An epidemiological study of health, injury, and long term outcomes in baseball players



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What you leave behind is not what is engraved on stone monuments, but what is woven into the lives of others

-Pericles from Thucydides' *"Pericles Funeral Oration"*

This thesis is dedicated to Gerald Clark "Mr. Yosef" Adams. Gerald Adams understood the power of sports as a teaching tool, and its ability to transform young people's lives. I hope that this thesis is one small step toward following in those footsteps.

Personal Acknowledgements

Gratitude is not only the greatest of virtues, but the parent of all others.

- Marcus Tillius Cicero

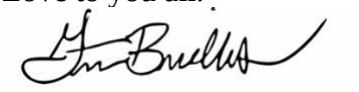
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Garrett Bullock
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Abstracts

Thesis title: An epidemiological study of health, injury, and long term outcomes in baseball players

Candidate name: Garrett Bullock (Wolfson College)

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Baseball injuries are a persistent and significant problem, with the greatest injury incidence to the elbow and shoulder. Baseball injuries can be prevented through a stepwise process that enables the identification of injury type, injury risk factors, etiology and injury mechanisms which is dependent upon high quality data. However, current injury risk and prediction research does not quantify the complexities related to athletic injuries. Therefore, the complex interaction of multiple risk factors and injury mechanisms are unclear and inhibits clinical examination and prevention. The primary aim of this thesis was to create an injury prediction model for shoulder and elbow injuries in a cohort of professional baseball pitchers. The secondary aims are to describe the musculoskeletal health and wellbeing of current and former baseball players and assess the clinical utility of the primary injury risk model.

I conducted a systematic scoping review of baseball health and wellbeing in 2019. It found that the greatest density of baseball research focused on injury incidence and prevalence. However, there was a paucity of research on the long-term health effect of baseball participation, health and wellbeing across all baseball playing standard, and injury prevention research.

I analyzed data of a survey of current and professional baseball players. Both current and former baseball players reported similar health related quality of life compared to the general population, high flourishing, and high physical activity. Former baseball players reported the greatest persistent joint pain prevalence to the shoulder and elbow, and decreased arm function compared to older total shoulder arthroplasty patients.

I conducted an interrupted time series analysis to assess the effectiveness of injury risk profiling and education on a five-year cohort of professional baseball players. Injury risk profiling and education decreased injury incidence by 33%.

I developed and internally validated an arm injury prediction model on a ten-year cohort of professional baseball pitchers. The prediction model demonstrated good discriminate ability and excellent calibration.

I developed and internally validated a humeral torsion prediction model on the same ten-year cohort of professional baseball pitchers. The prediction model demonstrated small error and excellent calibration.

I analyzed the clinical net benefit and utility of the developed injury prediction model in comparison to current evidence based practice. The prediction model demonstrated improved net benefit and utility compared to current practice standards.

Future research is needed to examine if findings are generalizable to different cohorts and playing standards, and the efficacy of this prediction model in a clinical setting

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List of Abbreviations

AIC: Akaike information criterion

ASES: American Shoulder and Elbow Surgeons Rating Scale

AUC: Area Under the Curve

BMI: Body mass Index

EPP: Events Per Parameter

ER: External Rotation

HA: Horizontal Adduction

HT: Humeral Torsion

HRQoL: Health Related Quality of Life

IPAQ-SF: The International Physical Activity Questionnaire-Short Form

IR: Internal Rotation

MAR: Missing at Random

MCAR: Missing Completely at Random

MCID: Minimal Clinical Important Difference

METS: Metabolic Equivalents

MiLB: Minor League Baseball

MLB: Major League Baseball

MNAR: Missing Not at Random

PED: Performance Enhancing Drug

QOL: Quality of Life

RMSE: Root Mean Square Error

ROM: Range of Motion

SANE: Single Assessment Numeric Evaluation

SLAP: Superior Labrum Anterior Posterior

TRIPOD: Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis

TRIPP: Translating Research into Injury Prevention Practice

TROM: Total Range of Motion

UCLR: Ulnar Collateral Ligament Reconstruction

US: United States

WHO-QOL: World Health Organization QOL

The undiscovered country…no traveller returns, puzzles the will…

-Hamlet, Act 3, Scene 1

Chapter One: Introduction

The beginning is the most important part of the work

-Plato “The Republic Book 1”

Prior Publication:

The theoretical prediction framework sections for this chapter are currently under review as an editorial, a clinical perspective, and a tutorial manuscript in three separate journals.

Bullock GS, Hughes T, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Clinical Prediction Model in Sports Medicine: A Tutorial. Journal of Orthopedic & Sports Physical Therapy.

Bullock GS, Hughes T, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Sports Medicine Prediction Models: A Brief Tutorial. British Journal of Sports Medicine.

Bullock GS, Hughes T, Arundale AH, Ward P, Collins GS, Kluzek S. Black box prediction methods in sport deserve a red card: to advance athlete care a substitute is needed. Sports Medicine.

1.1. Introduction

An overhead athlete is any athlete that performs the majority of their athletic pursuits over their head.[1] Overhead athletes can entail sports such as cricket, tennis, swimming, handball, javelin, or baseball. Not all overhead athletes are throwing athletes, with sports such as swimming not involving the throwing motion.[1-3] However, throwing is the predominant motion involved in overhead athletic activities.[1] The overhead throwing motion is a series of skilfully timed movements that produce the fastest motion produced by the human body at 7250 °/s.[1,4] This movement produces high forces throughout the arm, which can influence osseous and soft tissue adaptations,[5,6] and a high risk for injury.[7-9] Due to the unique skill and physical demands from overhand throwing,[1,4] the overhead throwing athlete is a unique athletic population that requires specific knowledge and evaluation.[3,10,11]

Overhead throwing sports are played throughout the world.[12] However, not all overhead throwing events should be considered equal. For example, javelin athletes throw the javelin 1 to 6 times per track and field meet,[13] in comparison to baseball or softball pitchers that throw the ball over 100 times per game.[14-16] Cricket bowlers and baseball pitchers require different throwing rules, causing different throwing force generation and attenuation strategies.[4,17] The physical characteristics of overhead athletes may also be dissimilar. Beyond different sex characteristics, baseball and softball pitchers have demonstrated different soft tissue and osseous adaptations in fully grown adults.[18] Due to the dissimilar overhead throwing match rules,[13-16] throwing biomechanics,[4,17] and physical characteristics between sports,[18] considering all overhead throwing athletes as the same is clinically not advised.

While investigating all overhead throwing athlete sports would be ideal, this is not be feasible due to time, money, and logistic constraints. As a result, only investigating one overhead

throwing sport is advisable. While this decreases the generalizability of this research to all overhead throwing athletes, investigating one sport that has a large and diverse population enables this research to have an increased reach and impact. One popular and worldwide overhead throwing sport is baseball.[12] Baseball is a ball and bat sport originated in the 19th century in the United States, and evolved from the popular games of town ball and rounders.[19] Baseball is now played throughout the world, with 160 countries associated with the World Baseball and Softball Federation.[12] It is estimated that over 16 million people participate in baseball within the United States, with professional leagues throughout Australasia, Latin America, and North America.[12,20] Due to high worldwide participation, and the involvement of multiple worldwide professional leagues,[12,20] baseball is an ideal overhead throwing sport to investigate.

1.2. Health and wellbeing

Almost one third of the world's population is sedentary.[21] Not meeting physical activity standards can increase the risk of mortality and morbidity.[22-24] To help counteract sedentary behaviour, sport has been proposed as a potential physical activity intervention.[25] Sport participation potentially increases physical activity habits throughout the lifespan.[26,27] Further, sport participation has other positive attributes included increased physical fitness[28,29] and community and social relations.[30-33] However sport participation can negatively impact quality of life[34,35] and mental health,[36,37] and increase the risk of negative coping habits (such as alcohol, tobacco, and drug use)[38-40] and risk of injury.[7,8] These negative consequences can have detrimental effects on overall health and wellbeing.

Currently it is unclear the positive and negative consequences of baseball participation in current or former baseball players. Understanding the health and wellbeing ramifications of

baseball participation can allow clinicians to inform baseball stakeholders on the long-term implications of playing baseball. Further, deciphering the health and wellbeing of baseball players can allow for the creation of holistic interventions and enable improved understanding and interventions for baseball players as they transition to retirement.

1.3. Current injury problems in baseball

Musculoskeletal injuries in baseball players are a persistent and significant problem.[7,41-43] The greatest incidence in acute and chronic injury is attributed to the shoulder,[42,43] elbow,[7,42,44] and trunk,[42] with throwing overuse injuries being the most common.[45,46] Baseball injury incidence ranges from 0.8 to 4.0 injuries per 1,000 athlete exposures.[45,47-53] The number of injuries is greater compared to other throwing sports.[50,51,53] Over a ten year period, ligament sprains and tears had a 1.70 greater odds of occurrence in baseball players compared to softball players, with a 4.57 greater odds in pitchers compared to position players.[51] Ulnar collateral ligament reconstruction rates are rising,[54,55] with the highest incidence at 6.3 per 100,000 persons.[55] The mean comprehensive cost of one high school baseball injury has been calculated to be 7,385 USD.[56] The high rates of injury incidence,[45,47-53] injury severity,[50,51,54] and the large health care and human capital costs, [56] in baseball players suggests that the approaches to understanding and preventing arm injuries within baseball are not effective.

Baseball arm injuries can be classified into shoulder and elbow injuries.[45,46] From these initial classifications, shoulder injuries can be further classified into acromion, deltoid, rotator cuff, labrum, bicep, or periscapular injuries.[57] Elbow injuries can be further classified into medial or lateral elbow injuries. Lateral elbow injuries are rare in baseball, with almost all elbow injuries sustained medially.[45,46] Medial injuries consist of ulnar collateral ligament, tendon flexor, or general forearm.[45,46] Within the baseball literature, arm injuries have been classified

as general arm injuries,[51] stratified by shoulder and elbow,[45,46] or more specific shoulder and elbow injuries such as ulnar collateral ligament or rotator cuff.[54,55,58] As stated above, baseball arm injuries are a persistent and significant problem,[7,41-43] with both shoulder and elbow injury mechanisms of injury sustained through throwing.[4] In order to account for the overall arm injury burden, general arm injuries must be analyzed due to the nature of the injury.[59]

1.4. Injury risk factors

Risk factors are divided into two main categories: intrinsic risk factors (e.g. age, strength, neuromuscular control) that are athlete related and extrinsic risk factors (e.g. workload, equipment, playing surface) that are related to environment.[60] Further, they can be divided into modifiable risk factors (e.g. workloads, neuromuscular control) and non-modifiable risk factors (e.g. age, sex).[60]

The available empirical evidence has identified only a fraction of complex interactions of risk factors in baseball. A primary limitation of current baseball research is that there are no prospective studies identifying intrinsic and extrinsic risk factors to inform injury prevention programs. Previous studies do not control for non-modifiable confounders that can affect modifiers.[43,61-63] Further, the focus of previous research was on one specific physical factor,[7,8,43,64] and an entire risk prediction model was not incorporated. Therefore, the complex interaction of multiple risk factors and injury mechanisms are unclear and inhibits clinical examination, prevention strategies and decision making. A novel multi-factorial injury risk model is warranted to protect the health of current players and promote their longevity.

Understanding injury risk factors are important to create and initiate effective injury prevention programs.[65] Adherence and use of designed injury prevention programs have been

effective in mitigating injuries in other sports such as soccer[66] and basketball,[67] with no current national injury prevention programs in baseball. However, most injury prevention programs are not effectively integrated into sport organizations.[68,69] Currently there are no studies that have investigated the efficacy and cost benefit of injury prevention programs compared to current evidence based practice in baseball. Having a better understanding of the efficacy and cost benefit of injury prevention programs will help inform clinicians and organizations on sustainable strategies to improve future injury prevention programs.

1.4.1. Intrinsic non modifiable factors

Humeral torsion

Baseball throwing generates high velocity and forces through the arm,[4,70,71] which contributes to unique osseous and soft tissue shoulder adaptations.[72,73] These shoulder adaptations contribute to changes in shoulder range of motion, specifically to increased external rotation and decreased internal rotation in comparison to the nondominant arm.[11] While soft tissue adaptations affect throwing specific shoulder range of motion,[5] the underlying osseous structural transformations also contribute to throwing shoulder range of motion.[6] These osseous shoulder structural adaptations are termed humeral torsion (HT). HT is measured through the line that bisects the humeral head articular surface and the transepicondylar axis.[74] During youth and adolescence, the high humeral forces generated during pitching effect osseous growth and development, contributing to the mitigation of natural humeral anatomical neck and head anteversion.[75] These structural adaptations are important for throwing development;[76] however, they are also linked to arm injury risk.[6] Following growth and development, HT ceases to change in throwing populations.[77-79] As a result, HT is a non-modifiable arm injury risk factor in adult baseball populations.

1.4.2. Intrinsic modifiable factors

Shoulder range of motion

Shoulder range of motion (ROM)[80] has been identified as a modifiable intrinsic risk factor in baseball player arm injuries. In a systematic review and meta-analysis, a side to side dominant shoulder internal rotation (IR) ROM deficit of greater than 5 degrees in pitchers demonstrated an increased likelihood to be injured.[80] While impaired shoulder ROM has been identified as an arm injury risk factor in baseball players, shoulder ROM is also modifiable through specific interventions. High school and college baseball players who received stretching and instrumented manual therapy interventions demonstrated increased ROM gain compared to stretching or no ROM intervention.[81] In another study, college baseball players that received posterior shoulder stretching demonstrated increased shoulder ROM compared to controls.[82] These randomized control trials demonstrate that shoulder ROM can be altered in baseball players at multiple competition levels.

1.4.3. Extrinsic modifiable factors

Pitching workload

Competition and training load are extrinsic modifiable factors that play an important role in facilitating performance and mitigating fatigue.[83-85] Within baseball, pitch counts and innings counts are conventional methods used to quantify pitching workload.[86-88] Individual game and season long pitch counts have been associated with increased fatigue, pain, and injury risk.[86,88-90] In a simulation study, each successive inning pitched increased pitching fatigue in pitchers.[88] In another study, there was a relationship between the number of pitches thrown in a game and in a season, and the incidence of shoulder and elbow pain in pitchers.[86] Due to the relationship between pitching workload and injury, baseball organizations have instituted pitch and inning count limits.[91,92]

Extrinsic and intrinsic injury risk factor consensus

Currently, there is no agreement on the specific intrinsic and extrinsic factors that predict baseball upper extremity injuries. The majority of research has focused on the upper extremity[7,43,93-95] and pitch workload,[15,86,96,97] while foregoing modifiable and nonmodifiable intrinsic risk factors.[6] Thus, it is imperative to study a combination of modifiable intrinsic and extrinsic factors to improve upper extremity injury prediction and enable targeted injury prevention programs.

1.5.Theoretical frameworks for injury prevention

Baseball injuries can be prevented through a stepwise process that enables the identification of injury type, injury risk factors, etiology and injury mechanisms which is dependent upon high quality data.[98] Without this data, designing and evaluating injury prevention programs lacks the appropriate focus and responsiveness.[98]

The 'Translating Research into Injury Prevention Practice' (TRIPP) framework is a six-step framework, established for injury surveillance in sports.[98] Step 1 establish the extent of the problem, typically using incidence and severity of injuries; Step 2 establish causes and injury mechanisms through epidemiological research; Step 3 develop preventative measures; Step 4 scientific evaluation of preventative measure under ideal conditions; Step 5 develop implementation strategies and Step 6 evaluate effectiveness of preventative measures in implementation context. The risk factor models describe below are related to Step 1 and 2 of the TRIPP framework.[98]

1.5.1. Injury risk factor models

In 1994, the dynamic, multifactorial model of sports injury aetiology was proposed to enable identification of intrinsic and extrinsic risk factors (Figure 1.1.).[60] However, merely establishing internal and external risk factors for baseball injuries is not sufficient.[99,100] Therefore, in 2005, injury mechanism was included in the comprehensive aetiology model to provide a comprehensive understanding of the causes of injuries (Figure 1.2.).[101] Then in 2007, this model was extended to include complex interaction between internal and external risk factors leading to an inciting event and resulting in injury.[102] Workloads (both training and competition) are strongly associated with injury.[103,104] Therefore, in 2017, this model was updated to include workloads and now refer to as the workload—injury aetiology model (Figure 1.3.).[105]

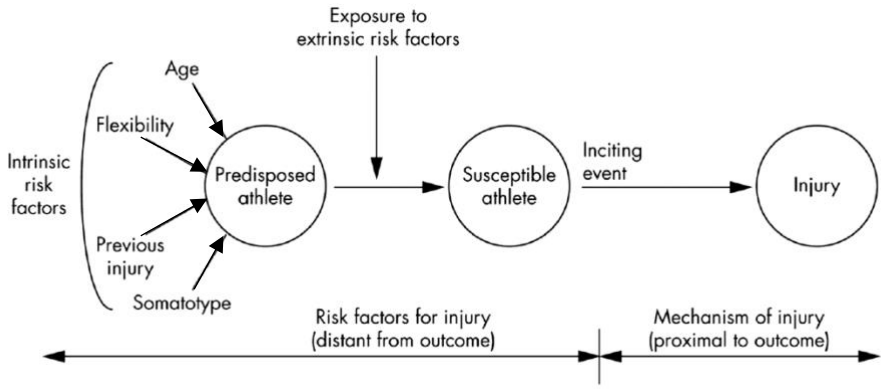


Figure 1.1. Meeuwisse et al.[60] Original Multifactorial Injury Model (Figure has been modified from its original version).

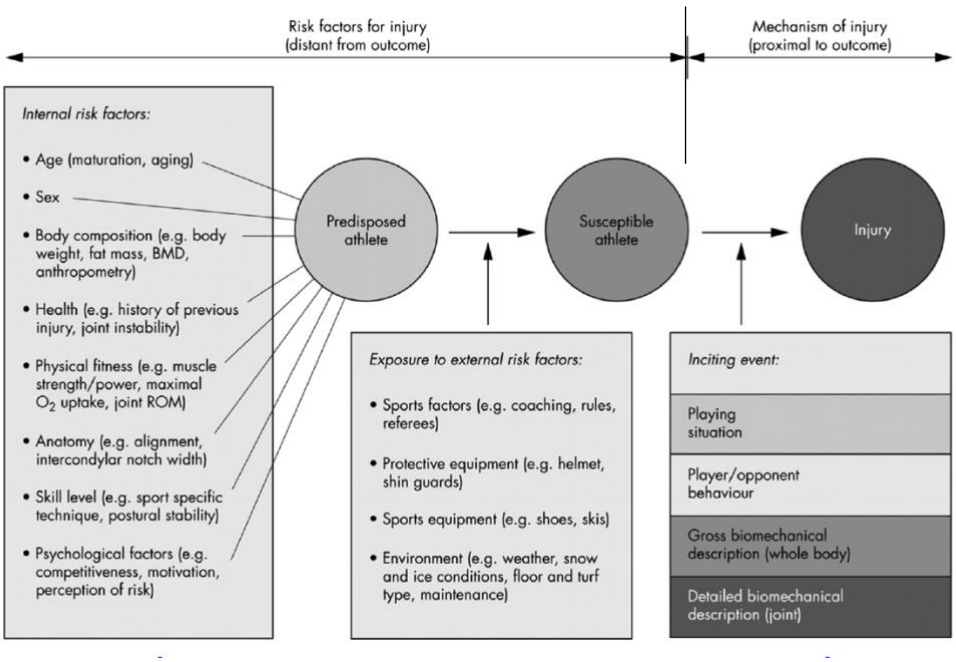


Figure 1.2. Bahr and Krausshaug[101] Comprehensive Injury Aetiology Model (Figure has been modified from its original version).

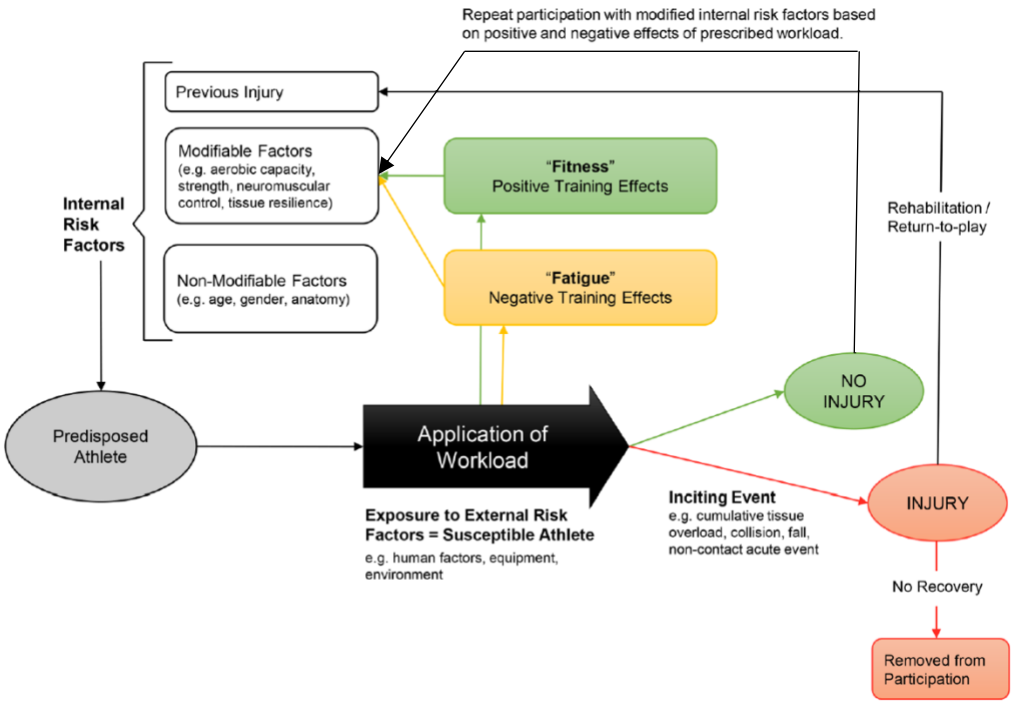


Figure 1.3. Windt and Gabbet[105] Workload-Injury Aetiology Model (Figure has been modified from its original version).

The aforementioned models highlight the pathway to injury, including (1) internal risk factors that predispose athletes to injury, (2) external risk factors, (3) injury mechanisms of the inciting event, where biomechanical breakdown of injury occurs, (4) workloads contribute to injury through exposure to external risk factors and potential inciting events, (5) fatigue, or negative physiological effects, and (6) fitness, or positive physiological adaptations. Therefore, the workload—injury aetiology model provides an established framework for injury risk factor explanation in sports and the theoretical underpinning of the research undertaken in this project.[105]

1.6. Risk prediction models

Sport participation has inherent injury risk at all standards of play,[9,106,107] which have a high healthcare and monetary burden.[108-110] Sport injuries can potentially have long term ramifications including osteoarthritis,[111,112] persistent joint pain,[113,114] and increased risk of obesity.[36,112] Due to these issues, sports medicine clinicians perform detailed physical examinations,[115,116] establish a diagnosis,[117] determine the prognosis,[118,119] and perform detailed and individualized interventions to help prevent or mitigate injury.[120,121]

The complexities involved in examination and interventions require high level clinical reasoning and decision making in order to create the best outcome for the patients involved.[117] However, while clinicians are highly knowledgeable and skilled,[122] it is not always clear what is the true prognosis or best personalised intervention for each individual patient.[123] As a result, clinicians are assisted by heuristics,[124,125] clinical decision rules,[126] and prognosis and prediction models.[127-129]

A more recent instrument that has been developed to assist clinicians are risk prediction tools.[130-132] Risk prediction tools, also known as prognostic prediction tools, are mathematical

models that use predictors to assess the risk or probability of an event.[133] These tools are not designed to supersede clinical experience and decisions; but, assist them in determining the best actions (or inaction) for their patients.[131] Risk prediction models have been used extensively in clinical medicine to help determine the prescription of cholesterol lowering drugs through the Framingham cardiovascular risk score,[128] to help evaluate the mortality risk with the acute physiology and chronic health evaluation (APACHE) score,[128] and identify patients at risk for osteoporotic fracture with the Fracture Risk Assessment Tool (FRAX).[127]

Within sports medicine, risk prediction tools are scarce. The majority of sports medicine clinical assessment and research is based on aetiology.[134] Aetiology research is focused on the causality of a certain variable or factor on an outcome, while controlling for other factors.[135] This is in contrast to risk prediction which uses multivariable factors to predict future outcomes.[131] While risk prediction can aid in understanding causality, it is not the overall goal.[136] Risk prediction tools incorporate causal and non-causal factors to help improve prediction. Within sports medicine, understanding causal links aid in determining the most appropriate interventions[137]; but, do not necessarily help the clinician identify the athlete in need of further examination and individualized interventions.[134] As a result, creating and incorporating high quality risk prediction tools could assist sports medicine clinicians to better identify and more appropriately intervene on athletes at risk for injury.

1.6.1. Risk prediction model development

General Overview

Risk prediction models use cohort or randomized control trial data to identify predictors that will provide the best predictive outcome performance.[130-132] Using multivariable methods to assign weights to each predictor, a total risk score is calculated.[131] The model performance (i.e. risk score) is assessed through multiple means, including calibration and

discrimination.[138] The developed model is then internally validated to assess for optimism and to correct for potential model overfitting.[139] The following sections underline specific methodological considerations (Figure 1.4.).

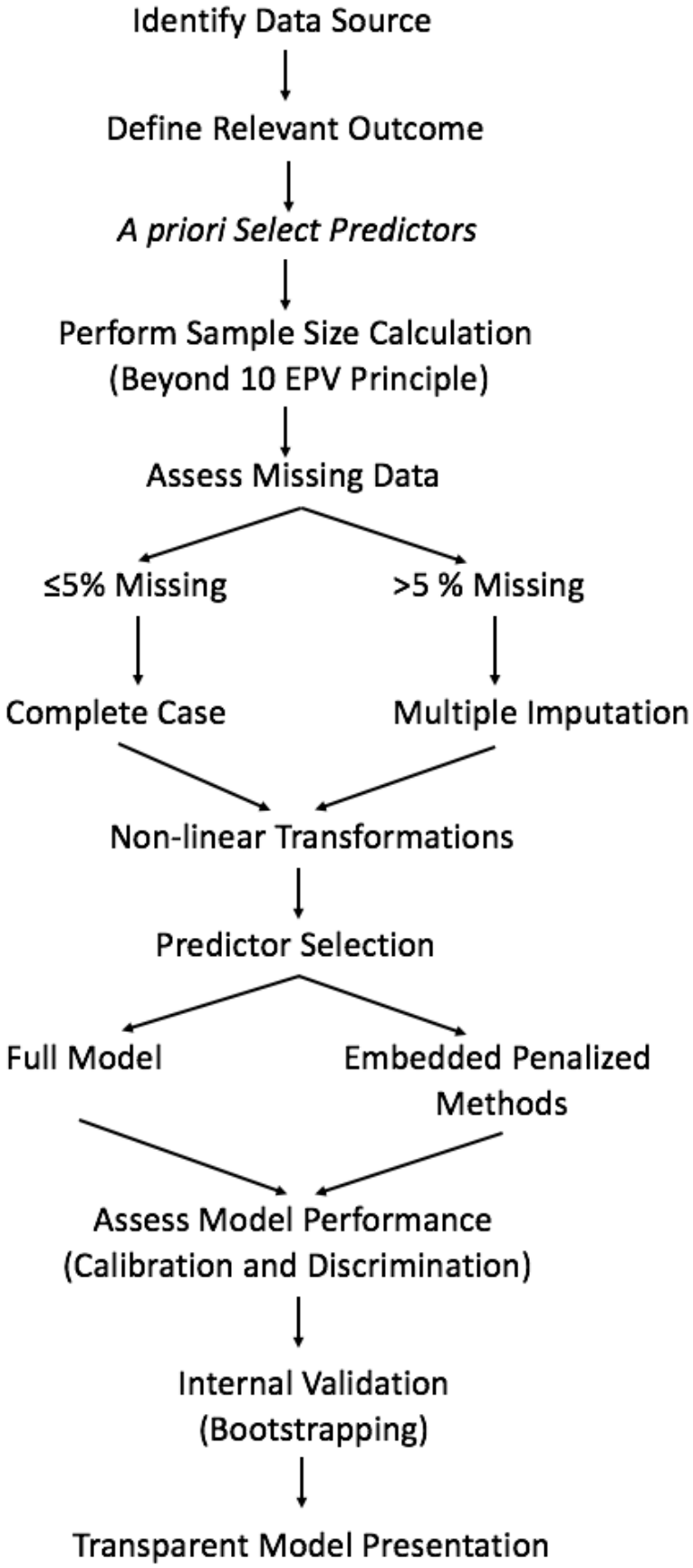


Figure 1.4. Risk Predictive Model Methodology Steps

Data

Data for risk prediction models is best utilized through prospective cohorts specifically designed to develop a risk prediction model. However, this is usually not feasible due to monetary and/or time constraints.[133] Thus, many risk prediction models are developed through cohorts that were recruited for other purposes. These cohorts have limitations concerning developing a risk prediction model due to the decreased precision in predictor selection.[131] The majority of risk prediction models are developed through retrospective cohorts, which is further limited by imprecision in predictor selection along with the general limitations of retrospective data.[140] Case control data can be used to develop a risk prediction model, however it is hard to assess the overall risk of the outcome due to the inability to discern the overall population size. Due to these methodological issues, case control data should be only used in nested cohort designs.[141] Case control data is best used when predictors are expensive or burdensome to obtain (such as imaging or surgery).[141,142] Finally, randomized control trial data can be used to develop a prediction model.[130,131] However, these data usually are constrained by tight inclusion and exclusion criterion, limiting generalizability.[131] Treatment and control data can be combined for risk prediction development, when both treatment and control data is found to have limited differences in risk; but, a separate treatment predictor should be included in the model.[143,144]

Outcomes

Outcomes should be focused on variables that are relevant to athletes, performance coaches, and/or sports medicine clinicians such as time loss injury,[145,146] pain,[147] or athletic performance factors.[147-149] The study design should have adequate follow up to accurately measure the desired outcome. Further, outcomes should be clearly defined.[145,146] If possible, examiners should be blinded to the outcome during data collection.[131]

Predictors

Predictors should be chosen for the potential predictive performance and should be based on the literature, expert opinion, and collinearity examination.[132] In case of predictor collinearity, predictors can be combined into one clinical meaningful predictor. For example, combining height and mass into body mass index, or using systolic and diastolic blood pressure to calculate mean arterial pressure.[150] As previously stated, risk prediction models do not necessarily need to include causal factors, but the predictors that best improve outcome prediction.[136] An example of a non-causal predictor is the Apgar score in predicting infant health.[151] Chosen predictors may not necessarily be incorporated into the final model, but should be considered for preliminary model development. Further predictor selection will be described in the predictor selection sub section.

Sample size considerations

Sample size calculations for risk prediction models have been traditionally derived from rules of thumb, such as the 10 events per variable rule (10 EPV) (i.e. outcome), not total number of observations.[152-154] However, there is misunderstanding concerning this rule.[155] Many predictors may have multiple degrees of freedom per predictor, increasing the number of parameters required per event. For example, an ordinal based predictor may have 3 levels, causing two degrees of freedom to be included in the model. Due to this methodological constraint, it has been proposed to change the events per variable to the events per parameter (EPP) rule.[155] Further, while this approach allows for simplistic use, this rule has been suggested to shrink or expand the events per parameter, demonstrating the complexity in this important issue.[156-158]

Sample size considerations are calculated in a four step process including determining the outcome proportion (i.e. the percentage of injuries in a defined cohort), the potential degrees of freedom incorporated into the model, and the potential overall model fit.[155] These model parameters are then inputted to an equation, which can be automated through R and Stata software packages.[155]

Data quality

Currently there is no clear method to assess data quality. Clinical tests and measures should be standardized across data collection sites and examiners should be adequately trained in data collection methods. Data should be analysed for error and potential biases in data collection methods. Large error or potential biases may affect outcome prediction, potentially altering future predicted outcomes.

Missing data

Missing data are frequent in clinical research.[159,160] Improper handling of missing data can create bias, leading to poor prediction.[161] It is common for missing data to be excluded from modelling, performing a complete case analysis. However, missing data is usually not completely at random, and excluding missing not at random data not only decreases power, but can also bias inferences and results.[162] Missing data is usually connected to other participant characteristics, predictors, and/or the outcome itself.[161] Thus, a thorough analysis needs to be performed to understand the relationship of the missing data to the rest of the data and the participants themselves.[162] Missing data can be identified as missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR). Only MCAR and MAR can be accounted for in the analyses, with MNAR providing substantial bias, inhibiting the ability to analyse these data.[163] When observing MNAR data, performing multiple sensitivity analyses to discern data biases is recommended.[164]

Once a missing data analysis has been completed and the relationships have been defined, there are specific methodologies that should be included to improve model development. A complete case analysis can be utilized if missing data is ≤5% for all participants.[165] However, such low missing data is rare. When missing data are above 5%, imputation is advised.[166] Many models that employ imputation only incorporate median or mean single imputation. Median or mean single imputation involves imputing the predictor median or mean for all missing data points.[167] However, this method is not recommended as it reduces data variance, decreasing predictive performance.[136] As a result, it is recommended to perform multiple imputation.[130-132] Multiple imputation is a statistical method in which missing values are imputed with a probable data point to estimate the distributional relationship of the data.[136] This method is performed multiple times (e.g. 20), creating multiple data sets in the process.[136] These data sets are then amalgamated to calculate the aggregated data. It is recommended that at least 20 imputations are performed, with imputations increasing in proportion to missing data (e.g. 30% missing data would equate to 30 imputations).[162]

Continuous predictors

Many predictors included in the risk prediction model will be continuous. Within sports medicine research, there is a trend to dichotomise and/or categorize continuous predictors.[72,168,169] While this method is simple and easy for clinical use, it greatly increases bias, decreases predictive power,[170-172] and has demonstrated decreased predictive performance in sports medicine injury models.[172] Dichotomising or categorizing continuous predictors is an extreme form of rounding which decreases predictor information, model power, and adds complexity to the analyses.[161] From a clinical perspective, dichotomizing and/or categorizing continuous predictors assumes large variability in each level, can underestimate risk, and is biologically implausible.[170,171] For example, categorizing blood pressure into normal (<130/90 mmHg) and hypertensive (≥130/90 mmHg) does not take into

account the true nature of blood pressure. In reality, there is only a minute difference between 129/89 mmHg and 130/90. However, dichotomizing this predictor, these two patients are grouped separately and 'bucketed' with 100/70 mmHg (normal) and 220/120 mmHg (hypertensive) respectively. While this is a simplistic example, this is to illustrate the bias introduced by dichotomizing and categorizing continuous predictors.

Continuous predictors should also not be assumed to be linear.[171] Within clinical medicine, many predictors have a non-linear relationship to the desired outcome. For example, there is a non-linear U shaped relationship between body mass index and mortality.[173] Assuming a linear relationship would not correctly identify patients with a low body mass index as having an increased mortality risk, decreasing the predictive ability of the model. As a result, non-linearity should be assumed until otherwise proven. There are multiple non-linear transformation options available, with restricted cubic splines and fractional polynomials recommended for model inclusion.[136,165,174,175] Non-linearity should be determined through the literature, visual inspection (i.e. graphical plotting), and statistical measures such as Akaike information criterion (AIC).[165] It should also be noted that when incorporating non-linearity transformations with multiple imputation, different imputation sets may have different non-linear transformations. In these cases, using the aggregated non-linear term for each predictor is recommended.

Model designs

Most risk prediction models will be focused on determining risk (i.e., predicting the risk of sustaining an athletic injury). These multivariable models can be implemented for logistic regression and survival analysis. Logistic regression models calculate the risk of sustaining an event, regardless of time, while survival analysis calculate the hazard of sustaining an event within a certain time period. Depending on the follow up and research question, both

model designs can be appropriate for sports medicine risk prediction. For example, a sports medicine practitioner may want to predict the risk of an athlete sustaining a second ankle sprain following initial injury over a 30-day period. In this case, a logistic regression would be most appropriate due to the small follow up time constraints. However, using the same example, the practitioner may want to predict the risk of the same athlete sustaining a second ankle sprain over the course of an entire season. In this case, a survival analysis would be more appropriate as knowing the time frame (early, middle, end of season) is important in determining the best plan of care. It should also be noted that linear regression methods can also be used in risk prediction modelling. While less utilized, these methods may be appropriate for certain clinical questions such as predicting the range of motion loss following surgery or injury.

Predictor selection

There are two main strategies for final model selection: full model and predictor selection.

Full model: The full model strategy entails incorporating all *a priori* predictors into the model. Using the full model can circumvent predictor selection bias and overfitting.[136,165] However, using all predictors can lead to decreased power and impede future model development.[136,165] Thus, when there is predictor high dimensionality (i.e. a greater number of predictors compared to the outcome) and/or uncertainty in the relationship between all predictors and the outcome, data driven predictor selection methods are advised.

Predictor selection: Many clinical studies incorporate single factor modelling and univariable analyses prior to the multivariable analysis used in building the predictor.[132] While single and univariable modelling approaches can inform the clinician on the relationship between the

outcome and predictor, these methods do not increase predictive performance.[136] Within risk prediction models, the goal is to improve prediction performance, not causality; thus, performing single or univariable methods does not take into account the interaction and confounding relationships of the other predictors. As a result, these methods are not recommended.[132]

The most common multivariable predictor selection methods are forward and backward selection. Forward selection is not advised due to not all predictors are assessed in each iteration, decreasing predictor performance.[176] Backward selection entails assessing all predictors and then systematically removing non-significant predictors.[177] It is recommended to use a lower P value when using backward selection, such a 0.20 or 0.50, in order to take into account the effect of weak predictors.[177,178] However, higher complexity predictor selection methods have been developed, which have greater predictor selection performance in sports medicine,[179] which are detailed below.

Within sports medicine, many predictors may have high multicollinearity, decreasing the ability of clinicians to isolate individual predictor effects upon the outcome.[179] Recent advances have allowed for advanced predictor selection techniques, including embedded penalized methods.[136] Embedded penalized methods include least absolute shrinkage and selection operator (Lasso)[180] and elastic net.[181] Both of these methods shrink coefficients (potentially down to zero), while simultaneously selecting predictors.[136] Further, they allow for multicollinearity assessment. Thus, using more traditional selection techniques (e.g. backward selection) decreases the predictive ability of models in comparison to embedded penalized techniques.[179] It is recommended to use an embedded penalized method when not performing a full model technique.

Assessing performance

Model performance should be assessed through calibration and discrimination. Calibration measures the agreement between the predicted model risks versus observed.[182] Calibration should be represented by the calibration slope with 95% confidence intervals, and graphically.[138] A calibration of <1 indicates that the risk is to extreme, while a calibration >1 suggests that the model under predicts the outcome. Discrimination is a model's ability to identify patients with the outcome versus patients without the outcome.[138] Discrimination is assessed through area under the curve (AUC) or the equivalent concordance index (c statistic).[165,183] An AUC of 0.5 is equivalent to a random prediction and an AUC of 1.0 a model's perfect ability to identify a patient with and without the outcome. Finally, logistic and continuous risk predictive models can be assessed with R^2. R^2 assesses the risk variance explained by the model and is on a scale of 0 to 1.[184]

Internal validation

Risk prediction models are expected to have improved performance on the original data set, in comparison to future (i.e. new) data.[185] This can be expected, as the original data optimistically predicts model performance on the developed data set (i.e. overfitting).[131] In order to attempt to control for this phenomenon, validation strategies have been introduced.[186] Traditionally, data sets have been split into training and testing sets to help control for overfitting.[132] However, data splitting has many methodological issues.[185] For small or moderate sized data sets, data splitting decreases overall power and uses an insufficiently small testing set to evaluate model performance.[186] If data sets are large, randomly splitting the data creates two identical data sets, which does not sufficiently test model performance.[132] As a result, it is recommended to use all data to develop the model and use internal validation methods to account for optimism.[139,186,187]

Internal validation is defined as using all study sample data to mitigate overfitting.[131] It is recommended to perform bootstrapping when internally validating a model. Bootstrapping involves taking a random sample of the data with replacement for *k* iterations. Bootstrapping allows for the overall model optimism to be assessed as well as can adjust individual coefficients, both potentially attenuating overfitting.[188] Historically, bootstrapping has been computationally expensive and only a few iterations could be employed. However, as computing power has increased, the number of bootstrap iterations has become more feasible.[136] It is recommended to perform at least 500 iterations[136]; but, completing ≥ 2000 iterations is feasible and may further evaluate model optimism. Following internal validation, model performance needs to be recalculated for best presentation. It should also be noted that while bootstrapping is the recommended internal validation method, cross validation can also be performed with similar performance.[189]

1.6.2. Risk prediction model presentation

The final risk predictive model should be reported as an equation. This includes the intercept and coefficients for all predictors. When using restricted cubic splines, the knots should be defined. The overall model mean, standard deviation, and R^2 should also be reported for future sample size calculations.[155] Models can also be reported as a calculator or a nomogram, to increase clinical usefulness.[165]

1.6.3. Risk prediction model external validation

Prior to risk prediction model clinical integration, further validation is required. It is important for risk prediction models to be generalisable beyond the original data. In order to assess the generalisability of the model, external validation is required.[190] External validation can consist of temporal (same institution, new individuals), geographic (new institution), or

domain (different type of individuals).[190] External validation should focus on model performance (i.e. calibration and discrimination), and potentially implement methods to update the model for increased generalisability. Within clinical medicine, the majority of risk prediction models are never externally validated, decreasing their usefulness.[191] However, due to the paucity of risk prediction models in sports medicine, emphasis needs to be placed on externally validating risk prediction models only once these risk prediction models are robustly developed.

1.6.4. Risk prediction model clinical utility

Risk prediction models are only useful if they improve clinical outcomes.[192] Increasing test and measure accuracy, determining the causality of different factors, or improving model performance are essential in enhancing clinical examination; however, these steps do not necessarily improve patient outcomes.[192,193] Risk prediction models need to be measured for clinical utility and impact.[139] Clinical utility is investigated through net benefit. Net benefit is defined as the number of true positives gained by making certain clinical decisions over a risk threshold range.[138,192,194] This analysis can directly compare the repercussions of using a risk prediction model to other clinical decisions, such as current evidence based practice.[192,193] Risk prediction model impact also needs to be assessed.[139] This is evaluated through clustered randomized trials, directly comparing athlete outcomes, such as time loss injury.[195] Sports medicine risk prediction models require development and multiple external validations prior to reaching this level.

1.6.5. Risk prediction model concluding remarks

Sports medicine clinicians use an assortment of knowledge and tools to provide the best outcomes for their patients.[115,116] With the rising complexity of sports medicine, including

data and technology integration,[196-198] load management,[199-201] and the merging of injury rehabilitation and performance testing,[134,202] there is a need more than ever to harness and harmonize these new tools and perspectives. However currently, sports medicine integrates this information in an isolationist manner, potentially inhibiting clinical examination and decision making. The goal of risk prediction modelling is to improve patient care.[139] Risk prediction models can improve prognostic accuracy through quantitative methods, while reducing complexity,[136,139] improving the clinician's ability to care for their patients.[136,139] Risk prediction models should be developed with rigorous methodology and be reported in a transparent manner for future clinical external validation, and utility. Within sports medicine, risk prediction models are nascent, giving the opportunity for new and exciting methodological opportunities that can make a direct impact on patient outcomes.

1.7. Aims

The overall goal of this thesis was to identify modifiable, intrinsic and extrinsic factors for the development of shoulder and elbow pitching injuries (TRIPP Step 2) and to inform the development of injury prevention strategies (TRIPP Step 3). The secondary goals were to describe the musculoskeletal health and wellbeing of baseball players and to measure and identify initial pain and injury history (TRIPP Step 1). Therefore, the primary aim of this study was to create an injury prediction model for shoulder and elbow injuries in a cohort of professional baseball pitchers. The secondary aims are to describe the musculoskeletal health and wellbeing of current and former baseball players and assess the clinical utility of the primary injury risk model. Steps 3 to 6 of the TRIPP framework are beyond the scope of this project (due to time and logistical limitations); however, the findings are expected to provide the foundation for future development and implementation of injury prevention strategies in baseball.

1.8. Structure of thesis

Chapter 1 introduces the definition of what encompasses an overhead athlete, current issues within baseball musculoskeletal health and wellbeing, the theoretical framework for injury prevention, and the theoretical framework and methodology for prediction models.

Chapter 2 reviews the current literature through a systematic scoping review and identifies research gaps concerning baseball health and wellbeing.

Chapter 3 assesses current and former baseball health and wellbeing through a developed questionnaire.

Chapter 4 details the research methodology employed for a ten-year prospective longitudinal professional baseball cohort previously collected.

Chapter 5 investigates the impact of injury risk profiling and education, through an interrupted time series analysis, on arm injury incidence in the professional baseball cohort.

Chapter 6 presents the development and performance of an arm injury prediction model using the professional baseball cohort.

Chapter 7 presents the development and performance of a humeral torsion prediction model using the professional baseball cohort.

Chapter 8 assesses the net benefit and clinical utility of the developed arm injury prediction model compared to current best evidence based practice.

Chapter 9 summarizes the overarching results and discusses the potential implications and limitations of the findings.

Chapter 2: The relationship between baseball participation, health, and wellbeing: A systematic scoping review

The knowledge of anything, since all things have causes, is not acquired or complete unless it is known by its causes.

-Avicenna "On Medicine"

Prior Publication:

The methods and results for this chapter were published as a manuscript. A conference abstract for presentation on this chapter has also been published (see Appendix G for further details).

Bullock GS, Uhan J, Harriss EK, Arden NK, Filbay SR. The relationship between baseball participation, health, and wellbeing: A systematic scoping review. Journal of Orthopaedic & Sports Physical Therapy. Feb, 2020;50(2):55-66.

2.1. Introduction

Playing baseball has been observed to produce physical attributes such as increased physical fitness, cardiovascular health, and strength.[28,29] However, playing baseball also entails a high risk for sustaining a musculoskeletal injury at all playing standards.[42,63,203] Due to the high risk for injury, baseball organizations have attempted to integrate strategies such as limiting pitch counts,[87] strength and conditioning programs,[204] and injury prevention and rehabilitation programs.[205] However, it is unclear if these programs have been successful in decreasing injury.[205] These injuries can increase the healthcare burden[56] and further the risk of osteoarthritis.[112] There is also a history of alcohol[38] and tobacco consumption in baseball,[206] which can increase the risk of morbidity[207,208] and decrease longevity.[209] Currently, it is unclear how playing baseball impacts overall health.

Playing sport can positively influence psychological health.[30] Psychological health entails multiple constructs including mental health and quality of life (QOL). [210] Sport participants have reported improved QOL[34] and mental health.[30] The psychological improvements from playing sport have been hypothesized to be related to enhanced social relationships[30] and improved physical activity and exercise.[30,33] However, playing sport is also related to worse QOL[34] and mental health.[37] The adverse relationship between playing sport and psychological health can be related to injury,[34] stress, and performance pressures.[211] For example, in a meta-analysis, athletes than incurred an anterior cruciate ligament injury reported decreased QOL compared to the general population 20 years following injury.[34] Further, 9% of former elite cricketers reported being depressed,[37] which is higher than the reported 3% general population prevalence.[212] Playing baseball, and the associated culture such as the high number of games,[213] travel,[214] and drug and alcohol consumption,[40] may

effect psychological health. Currently, it is unclear how playing baseball influences psychological health across the lifespan.

The purpose of this scoping review was to (1) investigate the relationship between baseball participation and health (i.e., musculoskeletal health, general health, and psychological health) at all ages and competition levels; (2) identify research gaps in the existing literature on baseball participation and health (i.e., musculoskeletal health, general health, and psychological health).

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2.2. Methods

2.2.1. Study Design

To investigate the relationship between baseball participation and health (i.e. musculoskeletal health, general health, and psychological health), and identify gaps in the literature, we adopted the scoping review process proposed for best practice.[215-217] This is a five-stage process in which the research question is identified, relevant studies are identified, studies are screened and selected from specific inclusion/exclusion criteria, data is charted, and results are collated, summarized, and reported.[216]

2.2.2. Identification of the research question

The primary research question (what is the relationship between baseball participation, health and wellbeing?) was informed by current knowledge gaps in the baseball literature, and the interests and needs of the baseball community.

2.2.3. Identification of relevant studies

To be eligible for inclusion in this review, articles had to meet the following criteria:

- Assesses a construct related to musculoskeletal health (e.g., injury, pain, physical activity, injury prevention), general health (physiological function, tobacco, alcohol use, BMI, nutrition, diabetes, cardiovascular disease), and/or psychological health (e.g., mental health, depression, mood, anxiety, QOL, fear of re-injury) in current or former baseball participants (of any age, sex or playing standard);
- Primary research studies, reviews, meta-analyses, guidelines or grey literature (including unpublished and ongoing trials, annual reports, dissertations and conference abstracts);
- Written in English.

Articles evaluating the following outcomes, without reporting or analyzing their relationship to health (i.e., musculoskeletal health, general health, or psychological health), were excluded from this review: i) baseball performance parameters (e.g. pitch velocity, wins and losses, earned run average); ii) biomechanics; iii) bony anatomy unrelated to health outcomes (e.g., humeral torsion); iv) player loading parameters (e.g., accelerometer data, global positioning systems, session rate perceived exertion, pitch count, innings count); v) joint range of motion/flexibility.

Additional exclusion criteria consisted of:

- Studies that only assessed musculoskeletal, general, or psychological health in baseball umpires, baseball spectators/fans, baseball coaches or baseball card owners/sellers;
- Editorials, periodicals, or letters to the editor
- Cadaveric, in situ, or animal models studies

2.2.4. Identification of key words and index terms

A librarian-assisted computerized search of Medline, CINAHL, Embase, Scopus, PsycINFO, SPORTDiscus, Cochrane Library, EBSCO, Web of Science and PEDro was conducted. A grey literature search was conducted of Google Scholar, Clinicaltrials.gov, ISRCTN Registry and Proquest Dissertation and Theses. The search was performed on all titles prior to 15 November, 2018. For the databases MEDLINE, Embase, CINAHL, PsycInfo, PEDro, clinicaltrials.gov, and ISRCTN Registry, only the term "*baseball**," was used to increase search inclusivity.[215] All other database searches yielded articles including a term related to *"baseball"* AND a term related to health or wellbeing (Appendix A.2). The following exclusion terms were applied: *"cadavers," "in situ", "in vitro,",* and *"animal studies"* (Appendix A.1.). References were extracted, imported, and tracked in EndNote (version X8, Thomas Reuters).

2.2.5. Study selection

One independent reviewer (GSB) screened all titles and abstracts for eligibility, before retrieving and screening the full text of all potentially eligible articles to confirm eligibility. A second reviewer (JU) completed the same screening process on a random sample of 30% of articles.[215] There was a 98% agreement regarding article eligibility between reviewers (Figure 1).

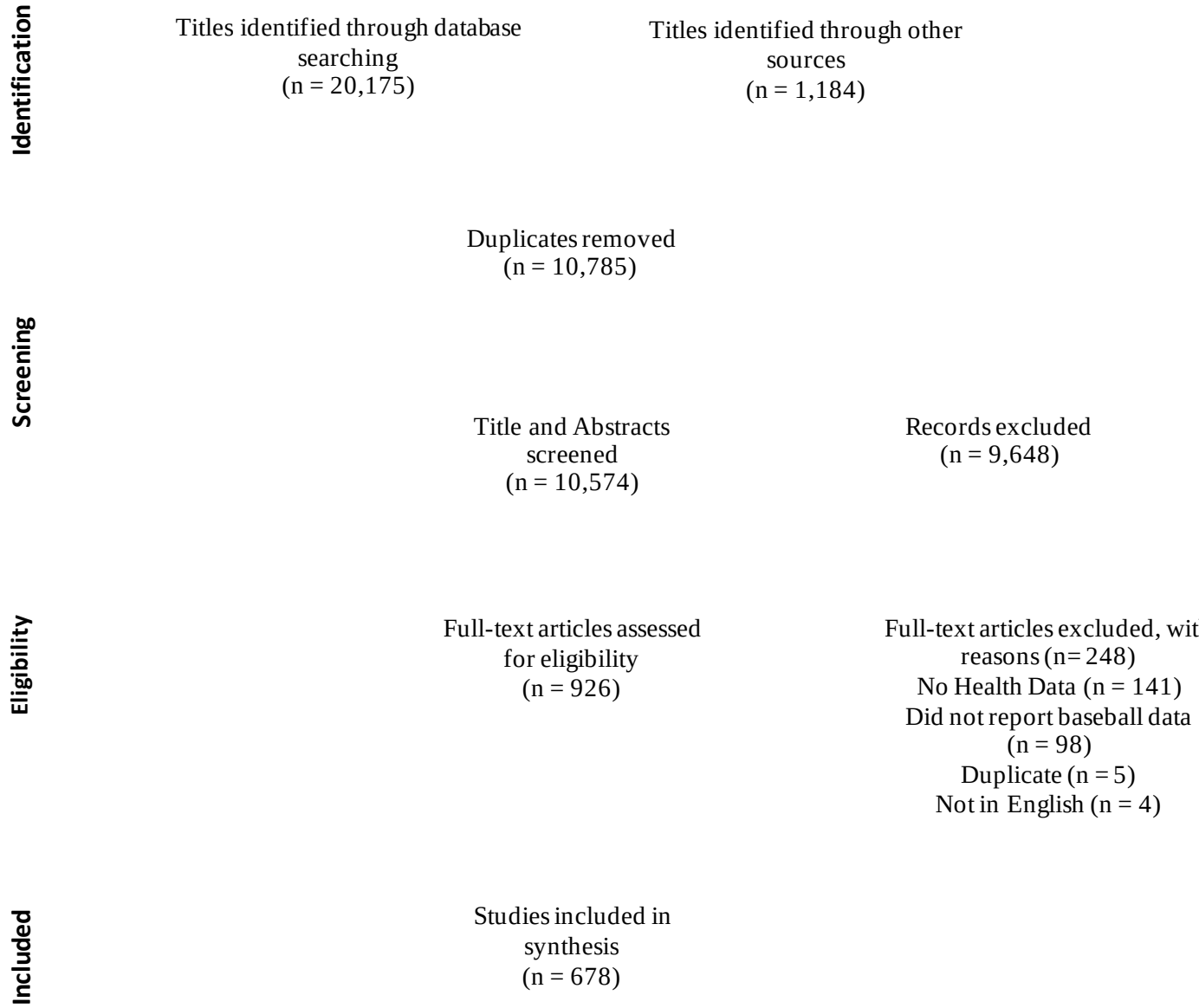


Figure 2.1. PRISMA Flow diagram demonstrating the scoping review of the literature for the relationship between baseball participation and physical and mental health

2.2.6. Extracting the results

Data were extracted by a single reviewer (GSB), and entered in a customized electronic database. Outcome data were stratified into *a priori* themes of musculoskeletal health, general health, and psychological health.[215] Data extracted included publication year, study type (primary, secondary, or grey literature), country of origin, age group, competition level, study design, study description, surgical procedure (if applicable), analysis design, and key findings.

2.2.7. Collating, summarizing and reporting the results

Data were collated and summarized for descriptive analysis. Data were explored to identify research gaps concerning the relationship between baseball participation, health and wellbeing.[215] Article characteristics were collated to map the overall trends in the data via publication year, country of origin, study design and theme.

2.3. Results

2.3.1. Search results

A total of 21,359 studies were identified in the initial search. After removing duplicates, 10,574 titles and abstracts were screened, resulting in 926 potentially eligible articles for full-text review (Figure 1). Of these, 678 articles (Appendix A.2) met the eligibility criteria and were included in the scoping review.

2.3.2. Year of publication of included studies

There was a substantial incremental increase in published studies over time, with most publications (371, 55%) published between 2010-2018 (Figure 2.2.).

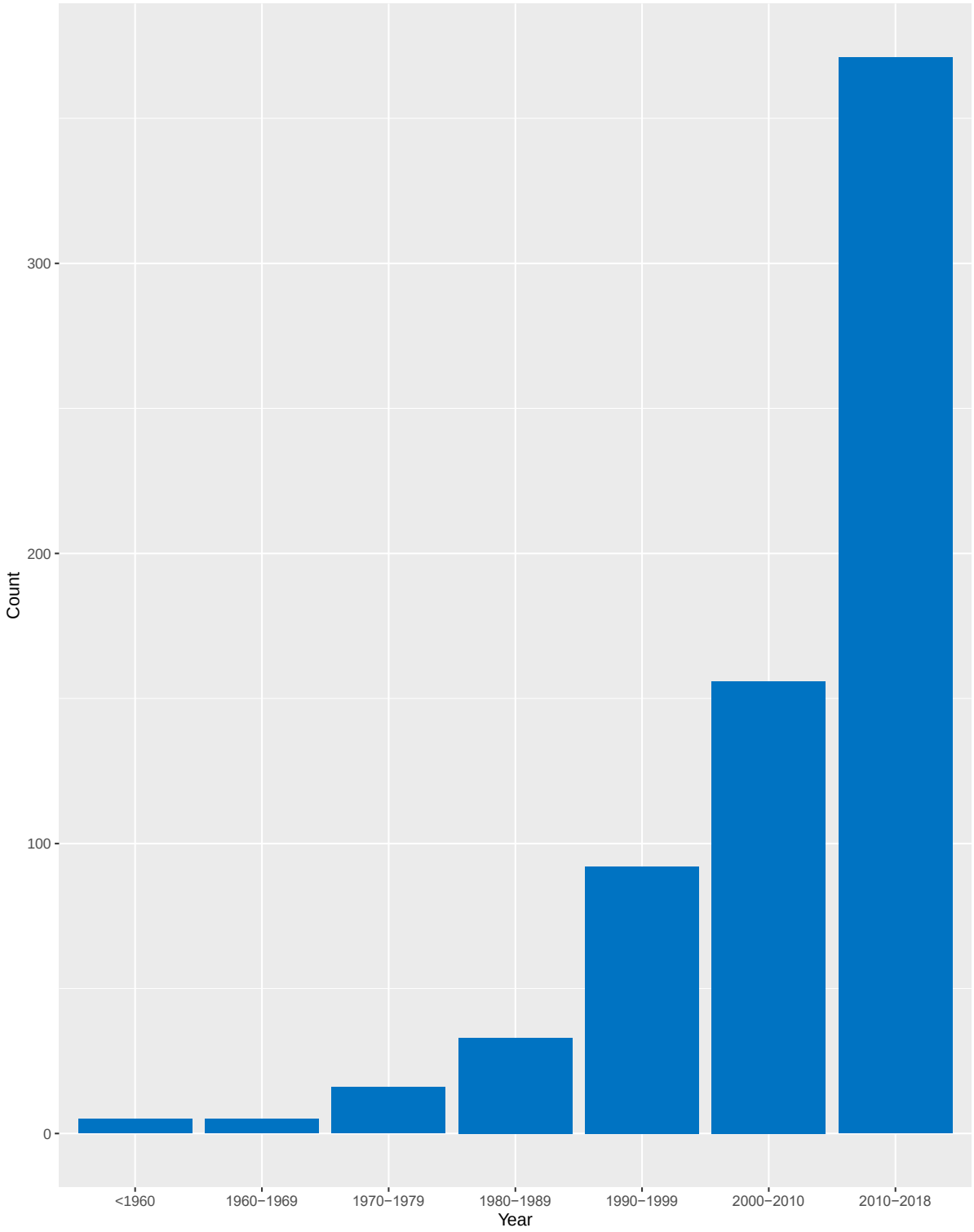


Figure 2.2. Year of Publication by Decade

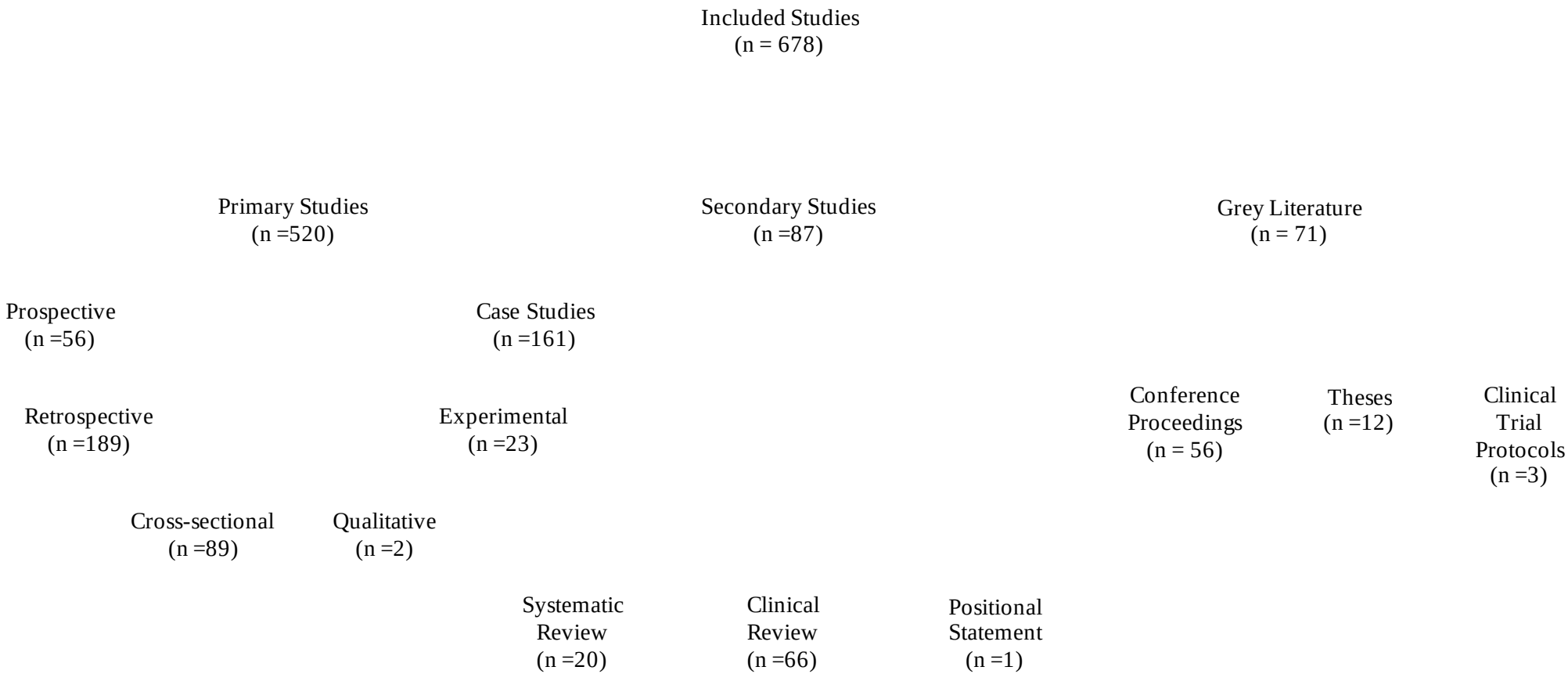
2.3.3. Geographic location of included studies

Of the 678 studies included in this review, 610 (90%) articles were from the United States (US), 59 (9%) articles were from Japan, 3 (<1%) articles were from Korea, 2 (<1%) articles were from the Netherlands, and <1% of articles were from Australia, Brazil, Indonesia, Puerto Rico, or the United Kingdom.

2.3.4. Study design

Most articles were primary studies (520, 77%) and the most common designs were retrospective (189, 36%) and case studies (161, 31%). There were 87 (13%) secondary studies, and 71 (10%) grey literature articles (Figure 2.3.).

Figure 2.3: Study Design for Included Literature



2.3.5. Participant characteristics

There were 424 (62%) studies that included only adult (>18 years old) baseball players, adolescents (13-18 years old) were investigated in 132 (20%) studies, and youth (≤12 years old) baseball players in 122 (18%) studies. 229 (34%) studies focused on professional baseball, 77 (11%) studies on collegiate baseball, and 111 (16%) studies on high-school baseball. Two studies (<1%) investigated female baseball players and 675 (>99%) included only male baseball players. 652 (96%) studies were in current baseball players and 26 (4%) studies investigated musculoskeletal, general, or psychological health in former baseball players.

2.3.6. Themes

Most articles (583, 86%) investigated musculoskeletal health, 77 (11%) articles investigated general health, and 19 (3%) articles investigated psychological health.

2.3.7. Musculoskeletal Health

523 (90%) articles that investigated musculoskeletal health assessed baseball injuries and 61 (10%) studies assessed surgical outcomes.

2.3.8. Injury

The most common baseball-related injuries investigated were elbow (218 articles, 35%) and shoulder (197 articles, 32%) injuries (Appendix 3). Of these, 193 (37%) were epidemiological studies, 153 (29%) were case studies, 66 (13%) were clinical commentaries, 57 (11%) were grey literature, 24 (5%) were studies comparing different physical attributes in injured versus non-injured baseball players, 13 (2%) were systematic reviews, 11 (2%)

were injury prevention studies, and 5 (1%) investigated the efficacy of rehabilitation exercises on pain.

Injury incidence ranged from 0.7 to 3.6 injuries per 1000 athlete exposures in professional baseball,[41,42,218-223] 4.7 to 5.8 injuries per 1000 athlete exposures in college baseball,[48,213,224,225] and from 0.8 to 4.0 injuries per 1000 athlete exposures in high school baseball.[45,47-53] Two studies observed increased injury prevalence from 2005-2015 and 1998-2015, at the high school[51] and professional levels, respectively.[41]

Professional baseball player upper extremity injury incidence accounted for 51% of all injuries,[42] with 21% involving the shoulder[41] and 10% involving the elbow.[221] College baseball players' upper extremity injury incidence accounted for 52% to 58% of all injuries,[224,225] with 0.37 and 0.18 injuries per 1000 athlete exposures for the shoulder and elbow.[213 224] High school baseball upper extremity injury incidence accounted for 63% of all injuries;[226] 1.39 to 1.90 shoulder injuries per 1000 athlete exposures,[47,49,52] and 0.86 to 0.92 elbow injuries per 1000 athlete exposures.[51,52]

Professional baseball lower extremity injury incidence was 0.7 and 1.2 per 1000 athletes exposures for the hamstring[218] and knee.[223] Lower extremity injury accounted for 27% of all injuries in college baseball players,[224] and 22% of all injuries in high-school baseball players.[226]

Injury prevention articles consisted of 5 grey literature,[65,227-230] 1 clinical commentary,[231] and 5 primary studies.[232-236] Injury reduction ranged from 25% to 57% in the injury prevention groups compared to controls.[232-236] Two studies[234,236] investigated hamstring injury

prevention programs in individual professional organizations, and observed a 40% reduction in hamstring injury incidence,[236] and a reduction of 50% days missed.[234] Three studies[232,233,235] investigated the efficacy of injury prevention strategies in high school baseballers, with injury incidence decreasing from a range of 27% to 57% in the prevention groups.[233,235] Using wood or metal bats did not change injury incidence.[232]

No studies investigated the relationship between sustaining an injury while playing baseball as a youth, adolescent, or collegiate athlete, and the long-term health effects across the lifespan. One study investigated the long-term musculoskeletal consequences of playing baseball as an adult, with 19% of retired baseball players in Australia having osteoarthritis and 24% having restricted mobility.[237]

2.3.9. Surgical outcomes

Fifty-five (90%) surgical outcome studies were primary studies and 6 (10%) were secondary studies. Forty-one (67%) studies evaluated ulnar collateral ligament reconstruction (UCLR) outcomes. The 3 studies that reported UCLR incidence or prevalence[238-240] found that 10% of all professional baseball players and 16% of professional pitchers had undergone UCLR,[238] annual UCLR incidence in professional baseball substantially rose from 1974 to 2015, [240] and 2.5% of college players underwent UCLR (0.86 UCLR's per team).[239] Five studies investigated UCLR revision surgery,[241-245] although only one study reported revision rate.[242] Time to return to play and total number of pitches were not associated with an increased risk of revision in professional baseball players.[241,245] No studies investigated UCLR revision outcomes in high school or collegiate baseball players.

Three studies[246-248] investigated rotator cuff surgical outcomes. Three studies investigated superior labrum anterior posterior (SLAP) surgical outcomes.[58,249,250] Other surgical studies investigated included Osteochondritis Dissecans, Latissimus Dorsi, Hamate, and Anterior Cruciate Ligament surgeries (each investigated in 2 studies). Bennet's lesion, bicep repair, femoral acetabular impingement, hip, and olecranon surgery were each investigated in one study. No studies investigated revision outcomes of these surgical procedures.

2.3.10. General Health

Forty-three (56%) studies that investigated general health in baseball participants assessed tobacco use, 16 (21%) studies investigated longevity, 5 (6%) studies investigated alcohol use, 5 (6%) studies investigated drug use, and 8 (10%) studies investigated markers of physiological health (BMI, body fat, cholesterol, diabetes, tuberculosis, and cardiovascular health).

2.3.11. Tobacco

Smokeless tobacco, or spit tobacco, was the most commonly used tobacco product, with prevalence ranging from 31% to 50% of professional baseball players.[251,252] High school, college, and professional baseball players all had an increased prevalence of smokeless tobacco use compared to the general population.[251,253,254] Tobacco use reduced following the implementation of organizational policy changes and tobacco cessation programs.[255,256]

2.3.12. Alcohol

High school baseball players were found to have a 50% increase in alcohol use, compared to high school non-athletes,[257] and consume similar amounts of alcohol compared to high-school American football players.[257] In two small studies, career professional baseball

alcohol consumption increased from 38% to 69% from rookie year to retirement.[38,40] One study discussed the negative health implications of alcohol in the professional baseball clubhouse.[258]

2.3.13. Drugs

Three (60%) studies investigated drugs including opioids, marijuana and amphetamines,[257,259,260] and two (40%) studies investigated anabolic steroid use in current professional baseball players.[261,262] High school baseball players were more likely to use marijuana compared to high school non-athletes.[257] There were four reported opioid overdose deaths in former professional baseball players over the last century[259] and one study described baseball drug-use media coverage and its implications for future baseball players.[263]

Amphetamine use was highly prevalent prior to their ban by Major League baseball. Use has greatly decreased.[260] No studies investigated drug use in current or former collegiate baseball players. Two studies reported on the overall bodily effects and cultural impact of steroid use in professional baseball players.[261,262] Specifically, future health risks due to steroid included increased risk of heart disease, cancer, and decreased mental health.[262] Baseball steroid use was allowed to become pervasive due to the established culture that valued winning above fair play or future health.[261] No studies investigated the prevalence of steroid use in baseball.

2.3.14. Longevity

All 16 studies that investigated longevity, included former professional baseball players. Six studies investigated factors affecting professional baseball player longevity. Birth date and handedness did not affect longevity.[264,265] Earlier professional debut and being a hall of fame

player negatively affected longevity.[266-268] Increased overall professional career length positively affected longevity.[269] Professional baseball players had longer life expectancies compared to US averages.[267,269-271]

2.3.15. Physiological Health

In current professional baseball players, 2 studies investigated cholesterol levels,[272,273] one study investigated body fat percentage,[274] one study investigated BMI,[275] two case studies investigated either diabetes[276] or tuberculosis[277] management in a single player, and one study investigated cardiovascular risk.[278] Twenty-eight per cent of professional baseball players had cholesterol levels over 200 mg/dl; 12% had triglycerides over 150 mg/dl.[272,273] Professional baseball players had similar body fat percentage to professional basketball and mixed martial arts athletes.[279] One study found that professional baseball players had increased BMI compared to the general US population, and that BMI had increased in professional baseball players over the last century.[275] Current professional baseball players had a 10% lower cardiovascular risk compared to current professional football players.[278]

2.3.16. Psychological Health

Sixteen (84%) articles investigated mental health and 3 (16%) investigated QOL.

2.3.17. Mental health

Six studies investigated former professional baseball player suicide risk factors and incidence. Prior to 1988, a suicide rate of 0.84[280] and 1%[281] was reported in professional baseball players, which was lower than the general population rate of 1.9%.[280] One study found professional baseball participation was protective against suicide,[280] and another study was inconclusive.[281] Birth month and baseball performance were not risk factors for suicide

in professional baseball players.[282-284] Of the 5 studies that investigated anxiety, only one small study evaluated anxiety prevalence and found 9 out of 22 college baseball players reported anxiety scores one standard deviation above the population normative mean.[285] Three case studies investigated pre-competitive anxiety,[286-288] and one study investigated the relationship between anxiety and recovery, finding that utilizing relaxation strategies decreased anxiety and improved recovery in collegiate baseball players.[289] Two studies investigated stress in youth athletes and found no association between baseball participation and stress levels.[290,291]

2.3.18. Quality of Life and life satisfaction

QOL or life satisfaction was investigated in 3 studies.[292-294] One study used the Short-Form 36, and observed that high school baseball players with shoulder pain had impaired physical components of QOL compared to high school baseball players without shoulder pain.[292] One study used the World Health Organization QOL (WHO-QOL) questionnaire and observed that youth baseball players involved in the national Brazilian baseball and softball training centre had decreased social relations and overall WHO-QOL scores compared to youth baseball players not involved in a training center.[293] The third study found that 51% of retired professional baseball players reported moderate life satisfaction and 15% reported low life satisfaction, although there was no comparison group in this study.[294]

2.4. Discussion

2.4.1. Summary

Most studies were primary research with the majority of studies employing retrospective (36%) or case studies (31%) designs, potentially representing a high risk of bias. Over 90% of studies examined US baseball players, which is not indicative of worldwide baseball

involvement. Baseball injury incidence ranged from 0.7 to 5.8 injuries per 1000 athletic exposures. 51% to 63% of baseball injuries were sustained in the upper extremity injury and for 22% to 27% were to the lower extremity. All baseball playing standards reported high tobacco, alcohol and drug consumption, compared to the general population. Professional baseball players demonstrated longer longevity compared to the general population. There were few studies examining the relationship between baseball participation and psychological health.

2.4.2. Baseball and Geographic Location

Baseball is played throughout the world,[295] and over 40% of professional baseball players are born outside of the US.[296] However, over 90% of studies were conducted within the US. Baseball players born on different continents have been observed to exhibit different levels of physical performance.[295,297] For example, similarly aged youth baseball players, from Latin America and Asia threw farther and with greater velocity compared to US baseball players.[295] Due to worldwide baseball play,[295,296] and the possibly different physical and cultural training and competing customs,[296] there is a need to investigate the relationship between baseball player musculoskeletal, general, and psychological health from different geographic and cultural regions.

2.4.3. Baseball and Musculoskeletal Health

The majority of studies examined baseball injury or surgery. Within the last 20 years, baseball injuries have increased at all playing standards.[41,51] This is comparable to soccer and football.[298,299] Only one Australian study has studied the long-term implications of playing baseball, with 1 in 5 former baseball players reported osteoarthritis and 1 in 4 suffered from decreased mobility and function.[237] These results are similar to other former athlete research,

with increased risk of osteoarthritis and joint pain potentially relating to previous injury or overall playing volume.[37,300] Within the previous 50 years, there has been a sustained increase in baseball-related surgery.[54,240] Surgery is costly and does not guarantee return to full function or a decrease in pain.[54,301] With the continued increased baseball injuries and surgery,[41,54] there is a need to implement injury prevention programs, and decipher the long-term injury consequences at all baseball playing standards.

2.4.4. Baseball and Tobacco Use

Smokeless tobacco consumption has a higher prevalence in baseball players at all playing standards compared to the general population. This is concerning as tobacco consumption is related to increased cancer risk and mortality,[302] and a higher prevalence of alcohol and drug use.[303] Smokeless tobacco consumption has continually declined in the US general population in the last ten years. However, use has increased over all major North American sports by almost 2%.[304] Baseball has a historical relationship to tobacco,[305] which is corroborated by the high tobacco consumption observed in this study.[253,306,307] However, tobacco use can be mitigated through tobacco cessation programs.[256,306,308] Thus, continuing to carry out organization- and team-based tobacco cessation programs to help attenuate tobacco use in baseball is essential.

2.4.5. Baseball, Alcohol, and Drug Use

Alcohol and drug consumption are related to increased risk of morbidity,[309] cancer,[310] and death.[311,312] High school and professional baseball players reported higher alcohol and recreational drug consumption compared to the general population; however, alcohol and drug use was similar to football, basketball, and soccer athletes.[257] Alcohol and drug consumption prevalence is high in collegiate athletes,[313] and has remained constant over

time.[39] Increased athlete alcohol and drug use have been connected to increased reporting of risky behavior, and sexual violence rates compared to non-athletes.[314,315] Alcohol and drug cessation programs have been observed to be successful in collegiate and professional athletes.[316] These results suggest that continued alcohol and drug testing, and cessation programs are needed for athletes at all playing standards.

No studies examined steroid use in baseball players. However, two studies investigated the physical and cultural impact of steroid use in professional baseball players.[261,262] Major League Baseball initiated performance enhancing drug (PED) testing in 2003, in order to internally investigate PED use.[317] However, steroid and PED testing has not been initiated at the college or high school level. The pressure to use such substances,[317] and the paucity of literature examining steroid use validates the necessity to investigate steroid and PED use in baseball players at all playing standards.

2.4.6. Baseball and Longevity

Professional baseball players were observed to live longer lives compared to the general US population. Sports participation, which involves physical activity,[318] can influence longevity.[319] However, sedentary behavior has increased in the US general population.[320] Increased sedentary behavior can impair health, and increase the risk of morbidity, such as type 2 diabetes[321] and cardiovascular disease,[321] and increased risk of mortality.[322] Professional football and basketball athletes have been observed to have similar increases in longevity compared to the general US population.[323] Increased longevity within professional athletes may be related to increased physical activity levels.[323] However, this has not been investigated in baseball. While there is evidence for increased longevity in professional athletes,[323] longevity has not been observed to be increased in amateur baseball populations.

2.4.7. Baseball and Physiological Health

Increased BMI can increase the risk of diabetes,[324] osteoarthritis,[325] cardiovascular disease[326] and stroke.[327] One study investigated BMI in baseball and observed that professional baseball players' BMI was greater than the general population.[275] Over the last hundred years, BMI has increased due to athlete body type selection, and changes in training methods.[328] Increased BMI has been related to greater cardiovascular disease risk in current or former football players.[278] However, one study found that current baseball players did not have an increased cardiovascular disease risk.[278] Over one in four professional baseball players had high cholesterol levels[272,273] compared to 39% of American men.[329] The lack of research investigating BMI, cholesterol, and cardiovascular risk in baseball,[275,278] illuminates a need to investigate the long-term health impacts of playing baseball across all playing standards.

2.4.8. Baseball and Psychological Health

Few articles studied psychological health in current or former baseball players at any playing standard. Suicide rates in baseball players prior to 1988 were almost half the US average of 1.9%.[280,281] However, since 1988, there have been many cultural and organization changes in baseball, such as the steroid era or the increased international participation in Major League Baseball, which may have an effect on suicide rates.[261] Professional athlete suicides have been attributed to steroid use, increased stress, or an inability to transition to life after sport,[330] which can all have a possible effect on mental health.[261,330]

Mental disorders such as anxiety, depression, and sleep disturbance also have a high prevalence in professional athletics.[331,332] For example, former professional cricket and soccer players have a depression prevalence between 37-39%,[331,332] which is higher than the

United Kingdom national prevalence of 3.4%.[212] Three studies investigated the prevalence of mental disorders such as anxiety and stress in baseball;[285,290,291] however, no studies investigated depression.

No studies compared QOL in current or former baseball players and non-baseball players. One construct relating to QOL, life satisfaction, was investigated in former professional baseball players, with 51% reporting moderate and 15% reporting low life satisfaction.[294] This is compared to 5.6% of the general U.S population reporting low or very low life satisfaction.[333] Former baseball players may report lower life satisfaction than the general population, emphasizing the need for further research investigating psychological health in current and former baseball players.

2.4.9. Further research priorities

A summary of the key knowledge gaps in relation to baseball, health and wellbeing is presented in Table 2.1.

Table 2.1: Research gaps in the literature regarding the relationship between baseball, health, and wellbeing

Research gap relating to baseball	Explanation
Injury prevention studies	Many studies investigated injury risk and prevalence. However, the majority were case studies or retrospective case series. Few were prospective, or randomized control trial injury prevention studies.
Long-term health and wellbeing implications of baseball participation	Very few studies investigated the long-term effect of playing baseball on health or wellbeing.
Current state of the health and wellbeing of collegiate baseball players	Only 11% of studies focused on collegiate baseball players. The majority of these were case studies. Further research is needed to evaluate health and wellbeing in collegiate baseball players.
The relationship between wellbeing and baseball participation at all competition levels	No studies compared QOL, life-satisfaction, anxiety or depression between current or former baseballers and the general population.
The health risks of weighted baseball training	Only one study reported on the effect of weighted-ball training and injuries. Weighted-ball training is poorly understood from a health perspective.

2.4.10. Strengths and potential limitations

This is the first study to review, summarize, and collate the literature on baseball, health, and wellbeing. This study screened a wide selection of databases and also incorporated grey literature, increasing the precision of these findings. Scoping reviews do not evaluate article methodological quality, which may lead to bias in interpretation. This review only included studies published in English. Due to worldwide baseball participation, this may have biased the results toward English speaking baseball players. A majority of included research was focused on professional baseball players, which decreases the generalizability of these results to amateur baseball players.

2.4.11. Conclusion

Baseball injury incidence ranged from 0.7 to 5.8 injuries per 1000 athlete exposures in high school, collegiate, and professional baseball. Professional baseball players have an increased life expectancy compared to the general population. Baseball players have a high prevalence of tobacco, alcohol, and drug compared, compared to the general population. Gaps in the literature in need of further prospective, longitudinal research within baseball include psychological health, long-term health implications of playing baseball, and injury prevention research.

Chapter 3: Health and wellbeing in current and former baseball players

Baseball is 90 percent mental. The other half is physical

-Yogi Berra

Prior Publication:

The methods and results for this chapter are currently under review as manuscripts in teo separate journals. A conference abstract for presentation on this chapter has also been published (see Appendix G for further details).

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Health conditions, substance use, physical activity and quality of life in current and former baseball players. Sports Health.

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Tokish J, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Persistent joint pain and arm function in former baseball players. Journal of Shoulder & Elbow Surgery

3. 1. Introduction

Baseball is a bat and ball sport that with 112 member countries in the international baseball federation.[12] Baseball is played at all playing standards and ages, with over 36,000 and 8,000 players participating at the collegiate and professional level in the United States.[334,335] Participating in baseball has many health benefits including enhanced cardiovascular health and physical fitness.[28,29,336] However, baseball players also have greater body mass index (BMI) compared to the general population,[275] which is associated with increased risk of comorbidities such as diabetes and high cholesterol.[337] Playing baseball also potentially increases the risk of stress and anxiety,[285,290,291] and baseball has a history of alcohol[38] and smokeless tobacco use,[206] which can further contribute to poor health outcomes.[207,208] In a systematic scoping review it was determined that there is currently a paucity of long-term general health research in baseball.[336]

One construct that assesses the multidimensions of health is health-related quality of life (HRQoL).[338] Health related quality of life encompasses several interconnected concepts including physical function, social function, general health, energy, and mental health.[338] While HRQoL is multifaceted,[338] HRQoL does not assess psychological constructs such as life purpose and meaning, which limits the full evaluation of health.[339] One psychological health construct that evaluates such topics is flourishing.[339,340] Flourishing incorporates physical, psychological, and social health, along with life purpose and meaning, which are not evaluated through HRQoL.[339] People with high flourishing have also been shown to have positive individual and societal impacts, and overall life satisfaction.[341-344] Few studies have investigated flourishing in athletes, with professional current and former cricketers reporting high flourishing compared to lower playing standards,[114] demonstrating the potential disparities between different playing standards. Within baseball, no studies have compared

HRQoL or flourishing in current or former baseball players.[336] However, one study has investigated one HRQoL and flourishing construct in retired professional baseball players, with 51% reported moderate life satisfaction and 15% reported low life satisfaction.[294] This is compared to 5.6% of the general U.S population reporting low or very low life satisfaction.[333] While there is a paucity of HRQoL or flourishing research in baseball, these data suggest the potential for worse life satisfaction compared to the general population, highlighting the need to investigate HRQoL and flourishing in current and former baseball players at all playing standards.

The 2011 Compendium of Physical Activities categorised baseball as a moderate-intensity physical activity endeavor,[345] however, baseball entails players to potentially sit for prolonged periods during batting, or stand for prolonged periods during fielding. Further, different positions can have different physical requirements, potentially affecting overall physical activity levels.[346] Currently, there is a paucity of scientific data exploring the relationship between playing baseball and physical activity. This research gap is significant because, former athletes may not maintain high physical activity levels following retirement from sport,[347,348] which may lead to greater risk of inactivity-related chronic diseases.[349] Understanding baseball player physical activity habits can help advise interventions that foster a sustainable, physically active lifestyle.

Baseball injuries are a significant burden.[42,110,203,350] These injuries have a high healthcare cost,[110,350] a large number of workplace days lost,[9,107] and have the potential for greater risk of osteoarthritis.[111,112] Post traumatic osteoarthritis ensues at a younger age, has a greater disability length, and is more resilient to treatment compared to idiopathic osteoarthritis.[351-353] Post traumatic osteoarthritis has a greater prevalence in former sport participants compared to

the general population,[112,351] which has been related to persistent joint pain.[354] Persistent joint pain is a significant contributor to osteoarthritis medical treatment,[354] and can inhibit physical function and activity.[35,355]

Baseball is an overhead sport, that requires the arm to propel a baseball at high velocities.[4] Due to these physical demands, the greatest injury incidence is to the shoulder and elbow.[9,107] Further, different baseball positions have demonstrated disparate arm and body part injury incidence,[9] potentially demonstrating the different physical requirements per position. As stated above, sport injuries are associated with future persistent joint pain.[351-353] While no research has investigated this issue in baseball, in one cricket study, after adjusting for injury, cricket bowlers had three times greater odds of reporting shoulder persistent pain compared to batters.[113] Arm persistent pain has different barriers to functional tasks compared to the lower extremity,[356,357] highlighting the need to understand arm specific pain and function. One tool to assess arm function is the Single Assessment Numeric Evaluation (SANE) for shoulder patients.[358,359] The SANE is a single item questionnaire that has demonstrated high validity, test retest validity, and responsiveness in comparison to other shoulder outcomes scores, such as the American Shoulder and Elbow Score and Rowe Score.[358,359] Utilizing this single validated item allows for ease of use and interpretability while concurrently employing little time and resources, increasing the utility of this tool.[359]

Currently, the majority of sport persistent pain research has concentrated on soccer, cricket, and rugby.[35,355,360] For example, professional soccer players reported greater lower extremity persistent pain compared to controls,[35,355] and former elite cricketers reported greater hand pain compared to former elite ruby players.[360] Further, the majority of sports participants do not reach the professional level.[334] Professional athletes have greater training and competition

demands and potentially greater sport exposure, compared to lower playing standards.[361] Understanding the relationship between persistent joint pain and baseball participation can inform use of resources to improve musculoskeletal health after retirement from baseball.

Currently there is a paucity of research investigating the long-term health effects of baseball participation. Persistent pain is a significant burden, and can be affected by musculoskeletal injury in sport.[351-353] Baseball has specific sport and positional demands that may modify persistent joint pain compared to other sports. Having a comprehensive understanding of lifestyle, HRQoL, flourishing, physical activity, persistent pain, and function can inform stakeholders of potential interventions to help improve long-term health and HRQoL across the lifespan. Therefore, the purpose of this study was to 1) to describe health conditions, lifestyle, HRQoL, flourishing, and physical activity in current and former baseball players; 2) evaluate persistent joint pain and arm function in former baseball players; 3) determine whether playing position is associated with an increased odds of joint pain and are related to reduced arm function in former baseball players.

3. 2. Methods

3.2.1. Study design

A cross-sectional questionnaire was employed for the Baseball Health and Wellbeing Study. This study was approved by the Wake Forest School of Medicine Institutional Review Board.

3.2.2. Participants and recruitment

Participants were recruited from college baseball teams, college baseball team alumni networks, professional baseball organizations, and social media. Recruitment was performed

between September 2019 through April 2020. A total of 260 participants opened up the survey, with 214 participants responded and consented to participate, and were included in the study (Figure 3.1.). Eligibility criteria consisted of: 1) played ≥1 baseball season, 2) aged ≥18 years old, 3) played college (junior college or four year) or professional baseball.

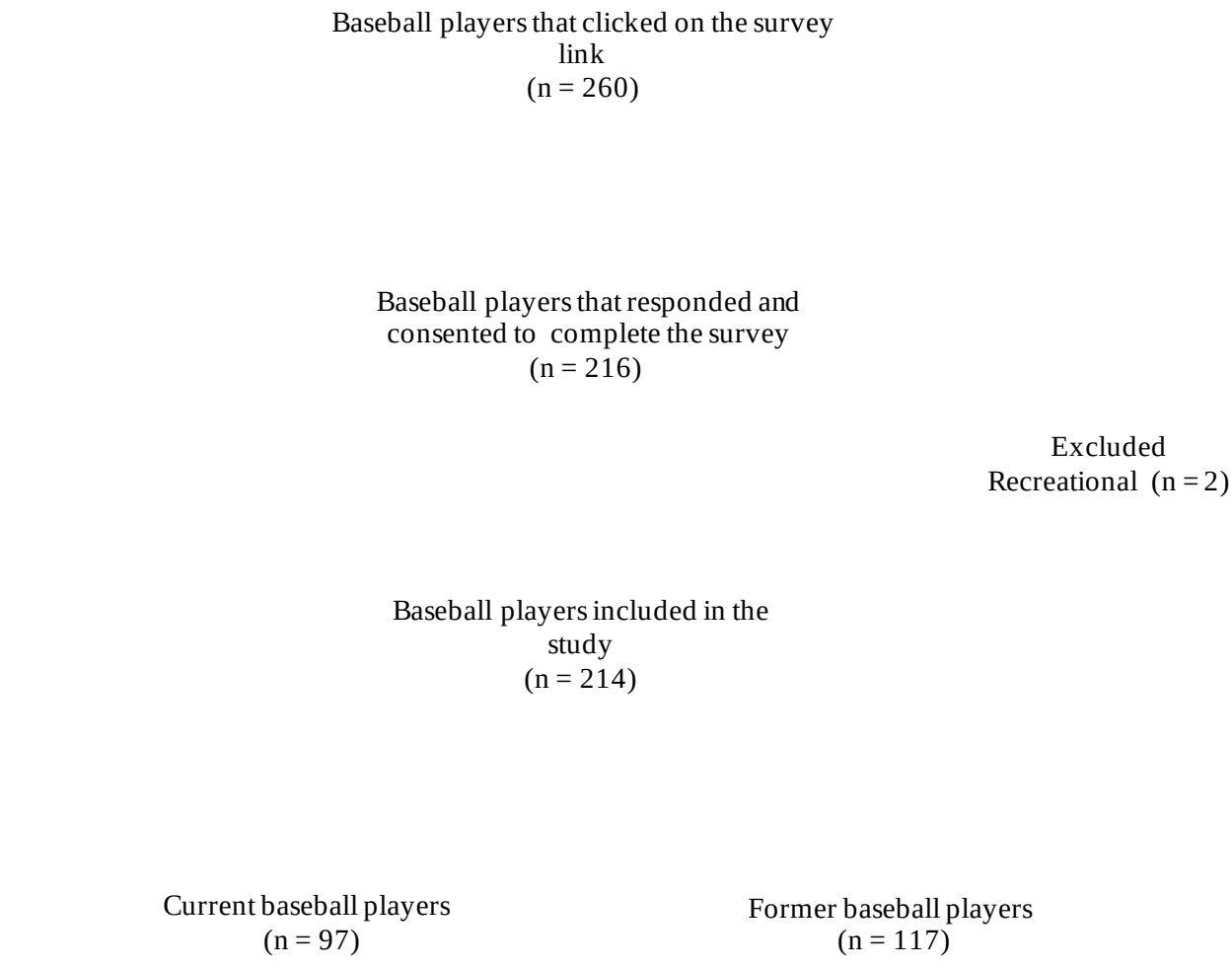


Figure 3.1. Study Participant Flow Chart

3.2.3. Questionnaire design

The questionnaire was created and then piloted on a group of current and former baseball players, collegiate and professional baseball coaches, and medical professionals (sport physician, physical therapists, and athletic trainers) who specialized in treating baseball players. The questionnaire was designed to evaluate five aspects of health and wellbeing: i. baseball-related injury; ii. joint pain and osteoarthritis; iii. general health and disease prevalence; iv. physical activity; v. resilience, quality of life and flourishing.[113,114] Participant data was inputted into an encrypted database. RedCap® software[362] was used, and participants could save their progress, and return to complete at a later time. The questionnaire gathered data on age, sex, body mass index (BMI), other sports played, number of baseball seasons played, years since retirement from baseball (if applicable), number of joints injured, number of orthopaedic surgeries, persistent joint pain, physician diagnosed osteoarthritis, history of playing sport while injured, health related quality of life (HRQoL), and flourishing. For full description of questionnaire, please refer to Appendix B.1.

3.2.4. Outcomes

Health Conditions

Health conditions were assessed with the following question *'Have you ever been told you have any of the following by a Doctor?*' If answered yes, participants were asked, *'Do you currently have any of the following, diagnosed by a Doctor?*' Health conditions assessed included: Asthma; Depression; Diabetes; High Blood Pressure; High Cholesterol.

Comorbidities: Comorbidities were assessed with the following question *'Have you ever been told you have any of the following by a Doctor?*' If answered yes, participants were asked,

'Do you currently have any of the following, diagnosed by a Doctor?' Comorbidities assessed included: Asthma; Depression; Diabetes; High Blood Pressure; High Cholesterol.

Lifestyle

Tobacco Use. Participants were asked smoking and smokeless tobacco questions. Questions included: '*Do you smoke?*' and *'Do you use smokeless tobacco products (chewing tobacco, snuff, dip, etc.)?'* Response options included Yes; No; Ex-smoker and Yes; No; Ex-smokeless user.

Electronic Cigarette Use. Participants were assessed for electronic cigarette use with the question, '*Do you use electronic cigarettes (e-cigarettes, vaping, juul, etc.)*?**'**
Response options included Yes; No; Ex-electronic cigarette user

Alcohol Use. Alcohol use was assessed with the following question, *'Over a typical week, how many units of alcohol do you consume (1 unit of alcohol is equal to: 1 small glass of wine (125ml, 4 ounces), OR 1 pub measure of spirits, OR 8 ounces of normal strength beer/lager).'*

Energy Drink Use. Participants were assessed for energy drink use with the following question, *'Do you drink energy drinks (Red Bull, Monster, All Star, etc.)?'* Response options included Yes; No. If participants answered yes, they were asked *'If so, how many energy drinks a day (one unit is 8 oz or one can of Red Bull or half a can of Monster Energy drink)'*.

Health related quality of life

Health related quality of life was assessed through the Veterans Rand 12 (VR-12). The VR-12 is non-proprietary version of the short form 12.[363] The VR-12 utilizes a five point scoring system per question, allowing for decreased floor and ceiling effects compared to the short form 12.[363] Health related quality of life is assessed on a 0 to 100 scale, with 0 representing full disability, and 100 representing no disability.[364] The VR-12 is comprised of the Physical Component Score (PCS) and Mental Component Score (MCS), which both have high reliability in general population samples.[365] The PCS and MCS are calculated using a normative based algorithm, using data from 2000 to 2002 United States Medical Expenditure Panel Survey (MEPS).[363] The VR-12 has demonstrated a minimum detectable change of 5.08 for the PCS and 11.15 for the MCS in spinal orthopaedic patients.[365] The VR-12 has also shown high responsiveness in knee arthroscopy patients.[366]

Flourishing

Flourishing was assessed using the Flourishing Scale.[340] The Flourishing Scale is an 8-item survey that measures perceived success in interpersonal relationships, self-esteem, purpose, competence, and optimism.[340,341] Each question is scored on a scale from 1 (strong disagreement) to 7 (strong agreement), with scores ranging from 8 (strong disagreement on all items) to 56 (strong agreement on all items). A higher score is considered greater flourishing.[340] The Flourishing Scale has been found to have high reliability (Intraclass Correlation Coefficient (ICC): 0.83 to 0.87) [340,341] and criterion and convergent validity in university students[340,341] and in adults from a variety of socioeconomic backgrounds, cultural origins, and age ranges.[367]

Physical activity

The International Physical Activity Questionnaire-Short Form (IPAQ-SF) was utilized to assess physical activity.[368] The IPAQ-SF has been used as a population surveillance and evaluation PA tool.[369,370] The IPAQ-SF has been observed to have fair agreement with accelerometer data (0.03-0.39)[371,372] and good validity compared to other PA questionnaires and PA logs (r>0.50).[372,373] Participants were asked to recall their PA in a usual week, as time spent in vigorous-intensity PA, moderate-intensity PA, and walking.[368] To reduce variability, a standardized approach outlined in the IPAQ-SF manual was utilized to clean and code the IPAQ-SF data.[368] In line with recommendations, bouts of weekly PA less than 10 minutes were recoded as zero minutes.[368] Time spent in vigorous PA, moderate PA, and walking was converted to Metabolic Equivalents (METS). One MET is 1 kcal/kg/h, or the resting metabolic rate, during quiet sitting.[368] Vigorous PA was calculated as 8 METS per min, moderate PA was calculated as 4 METS per min, and walking was calculated as 3.3 METS per min.[368] Metabolic equivalents were truncated at three hours (180 minutes) per day, per vigorous, moderate, and walking PA.[368] This was performed in order to reduce participant overestimation effect.[368] METS were then combined for vigorous PA, moderate PA, and walking, and reported as total weekly METS.

Persistent joint pain

Persistent joint pain was assessed with the following question, *'Do you currently experience pain, discomfort, or have any problems in any of your joints?'* If yes, participants were then asked *'Have you had pain in your [left/right] hip/groin, knee, ankle, foot, shoulder, elbow, hand/finger, spine/back, other joint <u>on most days of the last month</u>?'*. All participants that recorded persistent pain in the "other joint" category were hand searched for references of wrist, or toe persistent joint pain. These data were then recorded categories. Wrist persistent

pain was categorized with hand/finger, and toe persistent pain was added to foot persistent joint pain.

Single Assessment Numeric Evaluation (SANE)

The Single Assessment Numeric Evaluation (SANE) has been used to evaluate shoulder and elbow overall pain and function. The SANE was evaluated with the following question, 'How would you rate your shoulder today as a percentage of normal (0% to 100% scale with 100% being normal)?'[359] The SANE is scored on a scale of 0 to 100, with 0 demonstrating full disability and 100 demonstrating no pain and full function.[359] The SANE has previously been observed to have high validity in shoulder general population,[358] osteoarthritis patients,[374] arthroplasty,[375] military cadets,[376] shoulder surgical patients, shoulder anterior instability,[374] and athletics elbow surgical patients.[377] The SANE has also demonstrated a high correlation with the Rowe score and the American shoulder and elbow surgeons rating scale (ASES)[359,376] and the constant score.[374] The minimal clinical important difference (MCID) in bicep tenodesis patient was observed to be 3.5 points and the substantial clinical benefit of 5.8 points.[378]

3.2.5. Explanatory variables

Playing status

Participants were categorized into currently playing baseball, no longer playing baseball, or plan to return to baseball. If participants answered as plan to return to baseball, participants were categorized as no longer playing baseball for analyses.

Playing position

Playing position was assessed with the following question, *'what is/was you main position of play?'* Response items included pitcher; position player; or two way player (pitcher and position player).

3.2.6. Other data collected

Demographics

Participants were asked to report their age, height, weight, and hand dominance.

Playing standard

Standard-of-play was assessed with the following question, '*what was the highest standard of baseball that you played for at least one season*?' Response options included: Olympic or World Baseball Classic; Major League Baseball; Minor League Baseball; Independent Baseball; College (4 year), Junior College, High School; Recreation; don't know. Participants were stratified into professional (Olympic or World Baseball Classic; Major League Baseball; Minor League Baseball; Independent Baseball) and college (College (4 year), Junior College). Participants that reported their highest standard of play as high school, recreational, or *'Don't know'* were excluded from all analyses.

Injury history

Injury history was assessed with the following question, '*Have you ever had any baseball-related injuries leading to more than 4 weeks of reduced participation in exercise, training or sport?' Response items included yes, no, don't know. Don't know* responses were excluded from analyses. If answered yes, participants were then asked *'Please write the number of injuries for each joint and side for [left/right] hip/groin, knee, ankle, foot, shoulder, elbow, hand/finger, spine/back, other joint.'*

Years played baseball

Years played baseball was calculated from the age of first playing baseball to the age of the last year played baseball. Age first played baseball was assessed with the following question, 'What age were you when you played your *first* baseball game?' Age of the last year played baseball was assessed with the following question, 'If *no longer* playing baseball what age were you when you played your *last* baseball game?'

Education Level

Education was assessed with the following question, *'What is the highest level of education you have successfully completed?'* Response items included Did not finish high school; High school diploma; Did not finish college; Associate's degree or vocational certificate; Bachelor's degree; Master's or Professional degree (i.e., JD, MD, DPT, etc.); Doctorate degree (PhD, EdD, etc.); Other. Other responses were hand searched and categorized as appropriate. Participants were initially stratified into high school (High school diploma, did not finish college) university degree (Associate's degree or vocational certificate; Bachelor's degree), and graduate degree (Master's or Professional degree (i.e., JD, MD, DPT, etc.); Doctorate degree (PhD, EdD, etc.). Due to the disproportionate number of university or graduate degree former baseball participants, further cross tabular assessments were performed. It was determined that university and graduate level demographics, baseball participation, and playing standards were similar between groups. For full description of high school, university, and graduate degree participants, please refer to Appendix B.5.

3.3. Health conditions, lifestyle, and quality of life in current and former baseball players

3.3.1 Methods

Study design

Participant Recruitment and data collection is described in section 3.2. Outcomes assessed were health conditions (asthma; depression; diabetes; high blood pressure; high cholesterol), lifestyle (comorbidities, alcohol and tobacco use, electronic cigarette use, and energy drink consumption), HRQoL, flourishing, and PA.

Statistical Analyses

All data were assessed for missingness prior to analyses. Missing data were calculated as total and percentage of total data (Appendix B.2.). Missing data was varied (playing status: 0%; age: 6%; handedness: 0%; body mass index: 6%; comorbidities: 6%; flourishing: 17%; physical activity: 10%; joint injury: 7%). Missing data were categorized as missing at random. Multiple imputation with chained equations with 30 iterations (120 data sets) were performed. Multiple imputation data were pooled using Rubin's rules for all analyses.[379] Imputed data converged and were determined to have similar descriptive and variances compared to the original data (Appendix B.3.). Don't know' responses were excluded from all analyses.

Prior to data analysis, data were assessed for normality. Data were reported as mean (standard deviation), median (interquartile, range), or count (percentage). Data were calculated for all baseball players, and current and former baseball player subgroups. All analyses were performed in R version 4.02 (R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna,

Austria. URL http://www.R-project.org/), using the *dplyr* package[380] for cleaning and coding, the *naniar* package for missingness assessment,[381] the *mice* package for multiple imputation,[379] and *ggplot2* package[382] for data visualization.

3.3.2. Results

A total of 214 baseball players (Age: 29.8 (SD 13.3) years; Body Mass Index: 27.2 (SD 3.2) kg/m^2; Left Handed: 36 (17%); Current: 97 (45%); Former: 117 (55%)) participated in this study (Table 3.1.).

Table 3.1. Descriptive Statistics

Variable	All Baseball Players (n = 214)	Current Baseball Players (n = 97)	Former Baseball Players (n = 117)
Age (years)	29.8 (13.3)	20.9 (4.8)	36.8 (13.7)
Body Mass Index (kg/m^2)	27.2 (3.2)	26.3 (2.7)	28.0 (3.4)
Hand Dominance			
Left	36 (17%)	13 (13%)	23 (20%)
Right	178 (83%)	84 (87%)	94 (80%)
Baseball Seasons Played	16.4 (5.7)	14.9 (4.7)	17.8 (6.1)
Position			
Pitcher	76 (36%)	30 (31%)	46 (39%)
Position Player	81 (38%)	37 (38%)	44 (38%)
Two Way	57 (26%)	30 (31%)	27 (23%)
Highest Standard of Play			
College	175 (82%)	92 (95%)	83 (71%)
Professional	38 (18%)	5 (5%)	33 (39%)
Education			
High School Diploma	77 (38%)	64 (74%)	12 (10%)
Associate Degree	12 (6%)	12 (14%)	0 (0%)
University Degree	67 (33%)	7 (8%)	60 (51%)
Graduate Degree	48 (24%)	3 (3%)	45 (38%)
Asthma	9 (4%)	5 (5%)	4 (3%)
Diabetes	3 (1%)	1 (1%)	2 (2%)
High Blood Pressure	17 (8%)	1 (1%)	16 (14%)
High Cholesterol	23 (11%)	2 (2%)	21 (18%)
History of Depression	17 (8%)	11 (11%)	6 (5%)
Smokeless Tobacco			
Current User	44 (21%)	22 (23%)	22 (19%)
Former User	21 (10%)	3 (3%)	18 (15%)
Electronic Cigarette Use			
Current User	11 (5%)	9 (9%)	2 (2%)
Former User	6 (3%)	5 (5%)	1 (1%)
Alcohol Units per Week	3 (0, 7)	2 (0, 5)	4 (1, 8)
Current Energy Drink Use	46 (21%)	30 (31%)	16 (14%)
Energy Drink Units per Week	6 (4.5, 7.5)	6 (4.5, 7.5)	6 (4.6, 7.3)
Physical Activity Per Week (METS)	5880 (2272, 9488)	8667 (5069, 12272)	3931 (1662, 6200)
Flourishing Scale Score[a]	51.3 (5.8)	51.5 (5.7)	51.1 (6.0)
PCS[b]	48.96 (6.10)	49.90 (4.78)	48.07 (7.02)
MCS[b]	49.85 (9.13)	48.80 (9.69)	50.75 (8.63)
SANE[c]	74.9 (23.4)	80.3 (21.5)	70.2 (24.1)
History of Orthopaedic Surgery	95 (44%)	35 (36%)	60 (51%)
History of ≥4 week time loss injury	114 (53%)	41 (42%)	73 (62%)

Current Pain	100 (47%)	38 (39%)	62 (53%)

Descriptive statistics are reported as mean (standard deviation), median (interquartile range), or count (percentage)
1 alcohol unit is equivalent to one shot, 4 ounces of wine, or a half pint of beer
1 energy drink unit is equivalent to 8 ounces
METS = Metabolic Equivalents
PCS = Physical Component Score of the VR-12
MCS = Mental Component Score of the VR-12
SANE = Single Assessment Numeric Evaluation
[a] Flourishing total score is scored from 8 (strong disagreement on all items) to 56 (strong agreement on all items). A higher score is considered greater flourishing.
[b] Physical Component Scores (PCS) and Mental Component Scores (MCS) were calculated using norm based scoring (population norm 50 SD 10, high scorer = better health-related quality of life)
[c] The SANE is scored on a scale of 0 to 100, with 0 demonstrating full disability and 100 demonstrating no pain and full function

3.3.3. Discussion

Summary

31% of baseball players have used smokeless tobacco and 11% of current baseball players have used electronic cigarettes, compared to 3% of former baseball players. 31% of current baseball players consume energy drinks, while 14% of former baseball players, with both current and former baseball players consuming similar quantities of energy drinks per week. 14% and 18% former baseball players have either high blood pressure or high cholesterol. Both current and former baseball players reported similar HRQoL compared to the general United States population, and reported high flourishing and high physical activity.

Health Conditions and Lifestyle

26% of current and 34% of former baseball players reported using smokeless tobacco, which is comparable to past literature on professional, college, and high school baseball players.[251,253,254,306] However this prevalence is greater than the general United States population.[251,253,254] Tobacco use is related to increased risk of cancer[302,383] and to increased risk high risk of alcohol and drug consumption,[303] increasing overall morbidity and mortality risk. Baseball has a long history of tobacco use and culture, potentially explaining the high prevelance.[305,384] Interestingly, current baseball players reported lower smokeless tobaccos use compared to former baseball players. Tobacco cessation programs have demonstrated high efficacy,[256,306,308] and the National Collegiate Athletic Association and Major League Baseball have established a greater commitment to tobacco cessation programs in the last decade.[385,386] While beyond the scope of this study, these observations may demonstrate a potential mitigation of smokeless tobacco use. However, further research is needed to understand the impact of tobacco cessation policy on tobacco use in current and former baseball players at all playing standards.

Over 10% of current baseball players reporting using electronic cigarettes. While there is little research on this topic, this use is higher compared to general United States adult population of 1.4 to 6.8%.[5] In contrast, only 3% of former baseball players reported electronic cigarette use, which is comparable to the general population.[5] Currently there is sparse literature on the long-term health effects of electronic cigarette use. However, electronic cigarettes contain toxins and nicotine, which can adversely affect health.[387] The disparities between current and former baseball electronic cigarette prevalence may be due to electronic cigarette marketing strategies focusing on younger demographics.[388] Electronic cigarettes have been marketed as 'safe' and 'green', with the addition of flavours, which are not legally banned like in tobacco smoking, allowing for this shifting marketing strategy.[388] Due to this, there has been an inverse relationship between electronic cigarette use and age,[389] which supports our findings. Other potential explanations include electronic cigarette team sponsorship influencing use, using electronic cigarettes for nicotine consumption instead of smokeless tobacco due to tobacco cessation programs, and influence from peer pressure. However, these explanations are beyond the scope of this study. Further research is required to understand the electronic cigarette use age discrepancies in baseball.

21% of baseball players currently consume energy drinks, with current baseball players reporting a greater prevalence of energy drink consumption compared to former baseball players. The energy drink consumption prevalence is similar to a meta-analysis on general young adult population.[390] Energy drinks are not regulated for caffeine quantity, and have been associated with adverse cardiac events.[390] Since 2004, there has been an increasing trend of energy drink consumption, with a proportional increase in adverse events, particularly in young adult males.[391] Energy drink consumption has also been linked to increased risk taking behaviour and substance abuse, further highlighting the potential harmful effects.[392] The

increased energy drink prevalence in younger current baseball players compared to older former baseball players is similar to the aforementioned prevalence of electronic cigarette consumption. The increased marketing focus on younger demographics,[393] decreased sleep in younger populations,[394-396] increased screen time,[396] and general fatigue[394] may all play a role in the increased energy drink consumption in current baseball players. However currently, within baseball, no league wide policies have been enacted towards energy drink consumption. Therefore, there is a need to understand seasonal and career trends of energy drink consumption in baseball.

Former baseball players reported consuming a median of 4 units of alcohol per week. While previous literature has investigated baseball alcohol use, no studies reported number of units or frequency of alcohol consumption.[38,40] Baseball weekly alcohol consumption is similar to United States general population consumption.[397,398] Alcohol consumption is related to an increased risk of hypertension,[399] stroke,[399] morbidity[309] and cancer.[400,401] While there is no minimum clinical important difference prescribed for alcohol consumption, a meta-analysis concluded that there is a dose response relationship between alcohol consumption and stroke and cancer.[399] Specifically, consumption of two units of alcohol daily can increase the risk of stroke and cancer.[399] Besides the physical health consequences,[399-401] alcohol consumption is related to increased risk of sexual violence in athletes compared to non-athletes.[314,315] These descriptive relationships of alcohol consumption may be due to time commitments or the social and psychological requirement. Alcohol consumption is related to poorer mental health,[402] increased psychological stress,[403] and decreased mental components of HRQoL.[404,405] Due to these findings, position was stratified and compared descriptively (Appendix B.4.). Pitchers were found to have increased prevalence of being left handed, played on average two more seasons, and had a greater prevalence of playing at the

professional level compared to position and two way players. All other anthropomorphics measurements, health outcomes were similar. Further research is required to investigate the potential changes in alcohol consumption in baseball players across the lifespan and potential differences by position.

Health Related Quality of Life

Current and former baseball players demonstrated similar HRQoL compared to the United States general population. This is comparable to current and former recreational and elite cricketers;[113,114] but in contrast to a meta-analysis in which former collision sport athletes demonstrated poorer physical components of HRQoL compared to the general population.[406] Baseball collegiate and professional injuries have a similar prevalence and severity and similar body composition compared to cricket.[9,107,407] However, baseball players have different anthropometrics and less severe injury incidence and prevalence than collision sports.[107,408] Further, baseball participation has positive physical benefits such as improved physical fitness,[28,29,336] which has been shown to have a positive relationship to HRQoL,[409] potentially explaining this disparity. Investigating a more robust sample of former professional baseball players longitudinally to better understand the relationship between baseball exposure and HRQoL is required.

Flourishing

Baseball players demonstrated higher flourishing scores compared to a general population sample of Portuguese 25-60 year old adults (Flourishing Scale score: mean 43 SD 6),[341] college students from Singapore and the United States (mean 45 SD 7),[340] and a sample of New Zealand 50-59 year old adults (mean 44 SD 8).[367] These baseball player flourishing scores are similar to a sample of United Kingdom cricketers (median 49).[114] As there is no

minimal detectable difference established for the flourishing scale, it is not possible to determine if differences in flourishing scores a clinically meaningful. However, the similarities between baseball and cricket flourishing may be due to sport participation. Sport participation can improve social and community relations[30-32] and increased physical activity,[30,33] which can assist improving overall psychological health, and ultimately flourishing.[30,32,33] Other possible explanations include that this sample had a disparate bias towards higher educated baseball players. While no previous research has investigated the relationship of flourishing and education, similar wellbeing research has observed a positive relationship between education level and wellbeing.[410] Other explanations include the potential for improved socioeconomic status (relating to education status) of this sample,[411] improved familial and social connections,[339,340] and general flourishing disposition of this sample.

Physical Activity

Current and former baseball players reported performing 1238 and 562 daily METS of physical activity. While no other studies have investigated physical activity in baseball players, one study observed that former cricketers performed 120 METS per day.[113] Former baseball players are performing over 400 more METS per day compared to this sample of former United Kingdom cricketers, which is almost the recommended United States weekly physical activity level of 500 METS.[412] However, while this is a large discrepancy between these two moderate physical activity sports, this former baseball sample was 21.9 years younger (Baseball: 36.8 years, Cricket 58.7 years). As adults age, there is a propensity to decrease physical activity levels[413,414]; thus, these two samples cannot be directly compared. Nevertheless, this sample reported high levels of physical activity, despite retiring from baseball. A possible explanation of the retained high physical activity levels may be due to

the physical activity habits established in childhood and adolescence.[415] Physical activity habits are formed at an early age and are maintained through adulthood.[415] In this study, participants played their first baseball game at an average of five to six years old and played for an average of over 16 years. As a result, the physical activity habits learned and maintained through baseball training and competition may have been maintained once baseball participation had ceased.

3.4. Persistent joint pain and arm function in former baseball players

3.4.1. Methods

Study Design

Participant Recruitment and data collection is described in section 3.2. Eligibility criteria consisted of: 1) played ≥1 collegiate baseball season, 2) aged ≥18 years old, 3) played at least college baseball (junior college or four year); 4) Formerly played baseball (currently retired from baseball). Please refer to Figure 3.2. for participant flow chart. Outcomes assessed were persistent joint pain and the SANE. Explanatory variables include playing standard, playing position, injury history, and years played baseball. Confounders were identified through clinical reasoning and literature search. Confounders included age,[416] body mass index,[417] and handedness.[418-420]

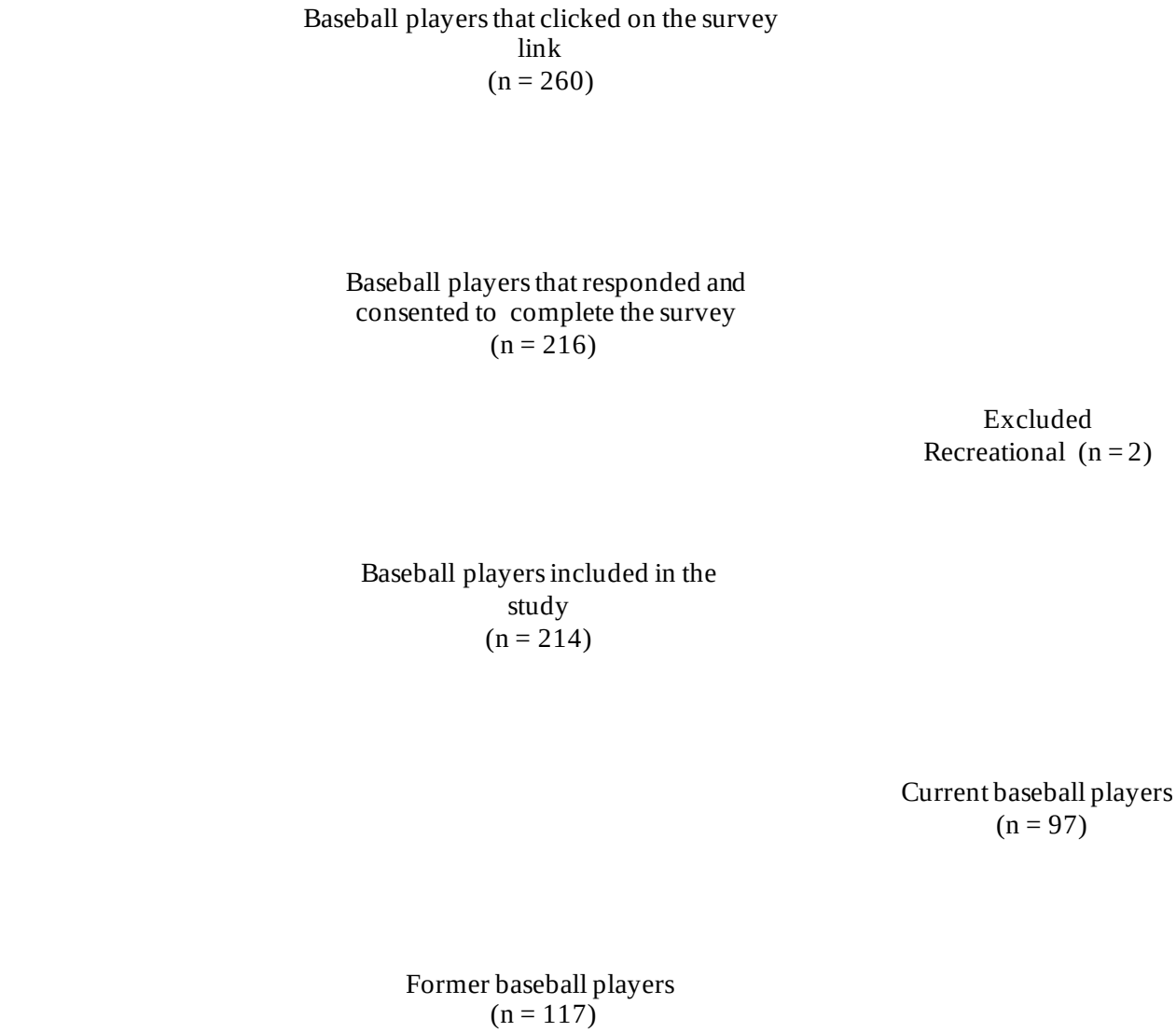


Figure 3.2. Second Study Participant Flow Chart

Statistical Analyses

All data were assessed for missingness prior to analyses. Missing data were calculated as total and percentage of total data (Appendix B.2.). Missing data was varied (playing status: 0%; age: 3%; handedness: 0%; body mass index: 3%; joint injury: 7%; SANE: 13%). Missing data were categorized as missing at random. Multiple imputation with chained

equations was performed for 20 iterations (100 data sets) using the *Mice* package. Multiple imputation data were pooled using Rubin's rules for all analyses.[379] Imputed data were evaluated for consistency and convergence through visual inspection and comparing descriptors and regression coefficients between complete case and imputed data (Appendix B.3).

Prior to data analysis, data were assessed for normality. Data were reported as mean (standard deviation), median (interquartile, range), or count (percentage). Multivariable logistic and linear regressions were performed to evaluate the relationship between joint pain, arm function and playing position. Unadjusted and adjusted odds ratios and coefficients and 95% confidence intervals (95% CI) were calculated. Models were adjusted for age, body mass index, playing standard, years playing baseball, and injury history. All assumptions for regressions were evaluated and satisfied.[421] Sensitivity analyses explored complete case analysis and shoulder and elbow persistent joint pain separately, whereby joint injury and surgery history variables were joint specific. Due to the wide confidence intervals demonstrated with the arm persistent pain analyses, a Firth corrected logistic regressions was performed to assess the potential for quasi variable separation. Sensitivity analyses were also performed assessing baseball players that only reported being pitchers versus non-pitchers (combining two way and position players). All analyses were performed in R version 4.02 (R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/), using the *dplyr* package[380] for cleaning and coding, the *naniar* package for missingness assessment,[381] and *ggplot2* package[382] for data visualization.

3.4.2. Results

A total of 117 former baseball players (Age: 36.8 (SD 13.7) years; Body Mass Index: 28.0 (SD 3.4) kg/m^2; Left Handed: 23 (20%); Baseball Seasons Played: 17.75 (SD 6.08)). A total of 62 (53%) of players reported joint pain, and the mean SANE score was 70.2 (SD 24.1; Table 3.5.). 52% of all former baseball players reported having persistent joint pain in at least one joint and 30% reported persistent joint pain in two or more joints. Shoulders had the greatest persistent joint pain prevalence (28%), with 94% being to the throwing shoulder. Knees had the second greatest persistent joint pain prevalence (26%), followed by elbows (21%), with 100% of persistent elbow pain being to the throwing elbow (Table 3.6.). Shoulders had the greatest joint injury prevalence (27%), with 94% of these shoulder injuries being to the throwing shoulder. Elbows had the second greatest joint injury prevalence (26%), with 100% of these elbow injuries being to the throwing elbow. Shoulders had the greatest joint surgery prevalence (24%), with 100% of these shoulder surgeries being to the throwing shoulder. Elbows had the second greatest joint surgery prevalence (19%), with 100% of these elbow surgeries being to the throwing elbow (Table 3.7.).

Table 3.5. Descriptive Statistics

Variable	Former Baseball Players (n = 117)	No Persistent Joint Pain (n = 56)	Current Persistent Joint Pain (n = 61)
Age (years)	36.8 (13.7)	33.5 (10.6)	38.9 (15.3)
Body Mass Index (kg/m^2)	28.0 (3.4)	27.1 (3.2)	28.5 (3.5)
Hand Dominance			
Left	23 (20%)	9 (16%)	14 (23%)
Right	94 (80%)	46 (84%)	48 (77%)
Baseball Seasons Played	17.8 (6.1)	18.2	17.6
Position			
Pitcher	46 (39%)	23 (42%)	23 (37%)
Position Player	44 (38%)	21 (38%)	23 (37%)
Two Way	27 (23%)	11 (20%)	16 (26%)
Highest Standard of Play			
College	83 (71%)	37 (67%)	47 (76%)
Professional	33 (39%)	18 (33%)	15 (34%)
Education			
High School Diploma	12 (10%)	5 (9%)	7 (11%)
Associate Degree	0 (0%)	0 (0%)	0 (0%)
University Degree	60 (51%)	29 (53%)	31 (50%)
Graduate Degree	45 (38%)	19 (19%)	24 (39%)
History of Orthopaedic Surgery	60 (51%)	22 (44%)	38 (61%)
History of 4+ week time loss injury	73 (62%)	34 (62%)	40 (65%)
Current Persistent Joint Pain	61 (52%)		

Descriptive statistics are reported as mean (standard deviation) or count (percentage)
Persistent pain is defined as having joint pain for ‘most days of the last month’

Table 3.6. Former Baseball Players Persistent Joint Pain

Variable	Former Baseball Players (n = 117)
Persistent Joint Pain (1+ joints)	61 (52%)
Persistent Joint Pain (2+ joints)	35 (30%)
Shoulder Persistent Pain	34 (29%)
Throwing Shoulder Persistent Pain	32 (28%)
Elbow Persistent Pain	25 (21%)
Throwing Elbow Persistent Pain	25 (21%)
Hand/Finger Persistent Pain	9 (8%)
Neck Persistent Pain	7 (6%)
Mid Back Persistent Pain	5 (4%)
Low Back Persistent Pain	14 (12%)
Hip Persistent Pain	9 (8%)
Knee Persistent Pain	30 (26%)
Ankle Persistent Pain	6 (5%)
Foot/Toe Persistent Pain	12 (10%)

Persistent pain is defined as having joint pain for ‘most days of the last month’

Table 3.7. Former Baseball Player Injury and Surgery History

Variable	Former Baseball Players (n = 117)
Injury History	
Shoulder Injury	32 (27%)
Throwing Shoulder Injury	29 (25%)
Elbow Injury	31 (26%)
Throwing Elbow Injury	31 (26%)
Hand Injury	8 (7%)
Neck Injury	1 (<1%)
Mid Back Injury	1 (<1%)
Low Back Injury	8 (7%)
Hip Injury	3 (3%)
Knee Injury	10 (9%)
Ankle Injury	3 (3%)
Foot Injury	2 (2%)
Surgery History	
Shoulder Surgery	24 (21%)
Throwing Shoulder Surgery	19 (16%)
Rotator Cuff	5 (4%)
Labrum and Rotator Cuff	14 (12%)
Shoulder Replacement	0 (0%)
Elbow Surgery	19 (16%)
Throwing Elbow Surgery	18 (15%)
UCLR	14 (12%)
Elbow Replacement	1 (<1%)
Other Surgery	3 (3%)
Hand Surgery	5 (4%)
Neck Surgery	0 (0%)
Mid Back Surgery	0 (0%)
Low Back Surgery	4 (3%)
Hip Surgery	4 (3%)
Knee Surgery*	15 (13%)
Meniscus	16 (14%)
ACLR	6 (5%)
Total Knee Arthroplasty	15 (13%)
Ankle Surgery	1 (<1%)
Foot Surgery	2 (2%)

An injury was defined as having a time loss injury of 4+ weeks
UCLR = Ulnar Collateral Ligament Reconstruction
ACL = Anterior Cruciate Ligament Reconstruction
*Knee surgery is for both left and right knees, and can include multiple surgeries

The odds of persistent joint pain and playing position

Playing position (Two Way: 1.41 (95% CI: 0.45, 4.35), p = 0.478; Pitcher: 0.40 (95% CI: 0.13, 1.21), p = 0.106) had similar odds of reporting persistent joint pain. Sensitivity analyses demonstrated similar results for complete case analyses (Table 3.9.). The Firth corrected logistic regression demonstrated similar results (Table 3.10.). There was no association between elbow or shoulder persistent pain and playing position in the adjusted analysis (Table 3.11.). Sensitivity analysis observed that pitchers reported an increased odds of persistent joint pain (3.79 (95% CI: 1.03, 14.02) and arm persistent joint pain (4.36 (1.28, 11.9) compared to non-pitchers (Table 3.12.)

The relationship of self-reported arm function and playing position

There was no relationship between SANE score and playing position (Position Player: -1.9 (95% CI: -14.3, 10.5), p = 0.764; Two Way: -1.7 (95% CI: 14.7, 11.3), p = 0.802). Sensitivity analyses demonstrated similar results for the complete case analyses (Table 3.9.) and comparing pitchers to non-pitchers (Table 3.12.).

Table 3.8. The odds and relationship of playing position and joint pain and arm function in former baseball players

Variable	Persistent Joint Pain (Any)	Persistent Shoulder/Elbow Pain	SANE
	Odd Ratios (95% CI)	Odd Ratios (95% CI)	Beta (95% CI)
Crude (Unadjusted)			
Two Way϶	1.32 (0.50, 3.50), p = 0.567	0.28 (0.05, 1.61) p = 0.157	-0.15 (-12.11, 11.81), p = 0.839
Pitcher϶	0.83 (0.37, 1.91), p = 0.674	1.82 (0.40, 8.24) p = 0.439	-0.08 (-14.43, 14.59), p = 0.974
Adjusted			
Two Way϶	1.41 (0.45, 4.35), p = 0.478	12.30 (0.50, 30.0), p = 0.130	-3.61 (-18.21, 11.00), p = 0.802
Pitcher϶	0.40 (0.13, 1.21), p = 0.106	9.20 (0.70, 11.9), p = 0.095	0.11 (-16.24, 16.45), p = 0.843
Professional*	0.72 (0.27, 1.91), p = 0.164	1.38 (0.71, 2.67), p = 0.342	1.03 (-3.03, 5.10), p = 0.996
Baseball Seasons	0.97 (0.90, 1.04), p = 0.361	1.12 (0.99, 1.23), p = 0.062	-0.08 (-0.99, 0.84), p = 0.717
History of Joint InjuryΦ	1.11 (0.45, 2.77), p = 0.822	1.04 (0.15, 8.51), p = 0.917	-3.66 (-16.67, 9.33), p = 0.402
Age	1.01 (0.98, 1.04), p = 0.469	1.04 (0.97, 1.11), p = 0.306	-0.31 (-0.72, 0.11), p = 0.244
Body Mass Index	1.10 (0.97, 1.25), p = 0.155	1.05 (0.79, 1.41), p = 0.720	-0.60 (-2.45, 1.23), p = 0.162
Right Handedψ	0.54 (0.18, 1.61), p = 0.272	0.01 (0.001, 0.09), p = 0.001	6.89 (-8.29, 22.07), p = 0.869
History of Orthopaedic SurgeryΘ	2.97 (1.24, 7.08), p = 0.016	1.70 (0.27, 10.6), p = 0.572	-0.07 (-13.91, 13.78), p = 0.658

SANE = Single Assessment Numeric Evaluation
95% CI = 95% Confidence Interval
Persistent pain was defined as pain on '*most days of the last most'*
϶ Position players were used as the reference category in the multivariable analyses
* College baseball players were used as the reference category in the multivariable analyses
ψ Left handed players were used as the reference category in the multivariable analyses
Φ For the persistent joint injury analyses, this is referring to a history of any joint injury, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm joint injury
ΘFor the persistent joint injury analyses, this is referring to a history of any orthopaedic surgery, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm orthopaedic surgery

Table 3.9. Sensitivity Analysis: The odds and relationship of playing position and joint pain and arm function in former baseball players using a complete case analysis

Variable	Persistent Joint Pain	Persistent Shoulder/Elbow Pain	SANE
	Odds Ratio (95% CI)	Odds Ratio (95% CI)	Beta (95% CI)
Two Wayϑ	1.42 (0.50, 4.02), p = 0.512	25.33 (0.68, 940.87), p = 0.080	-4.45 (-19.52, 10.62), p = 0.704
Pitcherϑ	0.74 (0.25, 2.1), p = 0.582	16.62 (0.95, 290.32), p = 0.05	2.46 (-18.67, 15.47), p = 0.704
Professional*	0.68 (0.25, 1.82), p = 0.437	4.56 (0.50, 41.62), p = 0.178	-0.11 (-13.18, 13.41), p = 0.860
Baseball Seasons	0.97 (0.90, 1.04), p = 0.362	1.16 (1.01, 1.34), p = 0.039	-0.07 (-1.00, 0.85), p = 0.947
History of Joint InjuryΦ	1.01 (0.40, 2.59), p = 0.980	3.21 (0.37, 28.07), p = 0.292	-3.75 (-17.27, 9.76), p = 0.706
Age	1.01 (0.97, 1.04), p = 0.693	1.05 (0.97, 1.13), p = 0.212	-0.36 (-0.82, 0.09), p = 0.105
Body Mass Index	1.11 (0.97, 1.26), p = 0.123	0.99 (0.72, 1.37), p = 0.979	-0.39 (-2.29, 1.52), p = 0.302
Right Handedψ	0.51 (0.17, 1.56), p = 0.238	0.01 (0.001, 0.09), p = 0.001	5.03 (-10.82, 20.87), p = 0.608
History of Orthopaedic SurgeryΘ	2.66 (1.10, 6.40), p = 0.029	0.39 (0.04, 3.84), p = 0.421	-1.52 (-15.94, 12.89), p = 0.576

SANE = Single Assessment Numeric Evaluation
95% CI = 95% Confidence Interval
Persistent pain was defined as pain on '*most days of the last most'*
ϑ Position players were used as the reference category in the multivariable analyses
* College baseball players were used as the reference category in the multivariable analyses
ψ Left handed players were used as the reference category in the multivariable analyses
Φ For the persistent joint injury analyses, this is referring to a history of any joint injury, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm joint injury
ΘFor the persistent joint injury analyses, this is referring to a history of any orthopaedic surgery, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm orthopaedic surgery

Table 3.10. Sensitivity Analysis: The Firth corrected adjusted odds of playing position and persistent arm pain in former baseball players

Variable	Persistent Joint Pain
	Odds Ratio (95% CI)
Two Wayϑ	6.72 (0.54, 83.1), p = 0.142
Pitcherϑ	6.44 (0.73, 57.2), p = 0.098
Professional*	1.24 (0.72, 2.15), p = 0.430
Baseball Seasons	1.12 (1.01, 1.24), p = 0.043
History of Joint InjuryΦ	2.24 (0.40, 12.6), p = 0.361
Age	1.04 (0.98, 1.09), p = 0.196
Body Mass Index	0.98 (0.76, 1.26), p = 0.849
Right Handedψ	0.01 (0.001, 0.16), p < 0.001
History of Orthopaedic SurgeryΘ	0.50 (0.08, 3.35), p = 0.478

95% CI = 95% Confidence Interval
Persistent pain was defined as pain on '*most days of the last most'*
ϑ Position players were used as the reference category in the multivariable analyses
* College baseball players were used as the reference category in the multivariable analyses
ψ Left handed players were used as the reference category in the multivariable analyses
Φ History of a throwing arm joint injury
Θ History of a throwing arm orthopaedic surgery

Table 3.11. Sensitivity Analysis: The adjusted odds of playing position and elbow or shoulder joint pain in former baseball players

Variable	Persistent Elbow Joint Pain	Persistent Shoulder Joint Pain
	Odd Ratios (95% CI)	Odd Ratios (95% CI)
Adjusted		
Two Way϶	1.78 (0.48, 6.57), p = 0.386	2.34 (0.12, 44) p = 0.574
Pitcher϶	2.14 (0.53, 8.70), p = 0.287	0.61 (0.04, 8.70) p = 0.717
Professional*	0.53 (0.18, 1.60), p = 0.263	2.07 (0.26, 16.6) p = 0.495
Baseball Seasons	1.01 (0.93, 1.10), p = 0.843	1.03 (0.90, 1.18) p = 0.637
History of Joint InjuryΦ	1.20 (0.30, 8.85), p = 0.801	7.61 (0.74, 78) p = 0.088
Age	1.04 (0.99, 1.08), p = 0.080	1.07 (0.98, 1.16) p = 0.117
Body Mass Index	0.96 (0.82, 1.13), p = 0.652	0.95 (0.69, 1.31) p = 0.743
Right Handedψ	0.96 (0.25, 3.70), p = 0.958	0.04 (0.01, 0.76) p = 0.032
History of Orthopaedic SurgeryΘ	0.41 (0.07, 2.44), p = 0.325	1.56 (0.14, 17) p = 0.716

95% CI = 95% Confidence Interval
Persistent pain was defined as pain on '*most days of the last most'*
϶ Position players were used as the reference category in the multivariable analyses
* College baseball players were used as the reference category in the multivariable analyses
ψ Left handed players were used as the reference category in the multivariable analyses
Φ For the elbow persistent pain analyses, this is referring to a history of elbow joint injury, in contrast to the shoulder persistent pain analyses, this is referring to a history of shoulder joint injury
Θ For the elbow persistent pain analyses, this is referring to a history of elbow orthopaedic surgery, in contrast to the shoulder persistent pain analyses, this is referring to a history of a shoulder orthopaedic surgery

Table 3.12. Sensitivity Analysis: The adjusted odds and relationship of pitchers and non-pitchers and joint pain and arm function in former baseball players

Variable	Persistent Joint Pain (Any)	Persistent Shoulder/Elbow Pain	SANE
	Odd Ratios (95% CI)	Odd Ratios (95% CI)	Beta (95% CI)
Pitcher϶	3.79 (1.03, 14.02), p = 0.046	4.36 (1.28, 11.9), p = 0.019	-2.29 (-15.67, 11.09), p = 0.734
Professional*	1.41 (0.44, 4.51), p = 0.562	1.74 (0.57, 5.29), p = 0.323	1.47 (-11.64, 14.58), p = 0.824
Baseball Seasons	1.02 (0.94, 1.10), p = 0.653	1.03 (0.95, 1.11), p = 0.471	-0.09 (-1.02, 0.84), p = 0.848
History of Joint InjuryΦ	0.63 (0.19, 2.06), p = 0.438	0.97 (0.31, 2.98), p = 0.951	-4.47 (-17.90, 8.96), p = 0.509
Age	1.04 (1.00, 1.09), p = 0.036	1.01 (0.97, 1.05), p = 0.620	-0.16 (-0.62, 0.28), p = 0.460
Body Mass Index	1.00 (0.85, 1.18), p = 0.984	1.05 (0.90, 1.23), p = 0.512	-0.97 (-2.86, 0.93), p = 0.312
Right Handedψ	0.11 (0.03, 0.49), p = 0.004	0.31 (0.08, 1.12), p = 0.073	0.92 (-13.88, 15.45), p = 0.915
History of Orthopaedic SurgeryΘ	2.86 (0.94, 8.72), p = 0.065	3.00 (1.04, 8.66), p = 0.041	-7.81 (-20.23, 4.60), p = 0.213

SANE = Single Assessment Numeric Evaluation
95% CI = 95% Confidence Interval
Persistent pain was defined as pain on '*most days of the last most'*
϶ Non pitchers (Two way and position players) were used as the reference category in the multivariable analyses
* College baseball players were used as the reference category in the multivariable analyses
ψ Left handed players were used as the reference category in the multivariable analyses
Φ For the persistent joint injury analyses, this is referring to a history of any joint injury, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm joint injury
ΘFor the persistent joint injury analyses, this is referring to a history of any orthopaedic surgery, in contrast to the arm persistent pain and SANE analyses, this is referring to a history of a throwing arm orthopaedic surgery

3.4.3. Discussion

Summary

52% of former baseball players reported having persistent joint pain in at least one joint, and 30% reported having persistent joint pain in two or more joints. Shoulders had the greatest prevalence of persistent pain, followed by knees, and elbows. 96% of all shoulder and elbow persistent pain was to the throwing arm. Despite the average age being 36.8 years, former baseball players reported a mean SANE score of 70.2. After controlling for confounders, playing position had similar odds and relationship to persistent joint pain and arm function.

52% of this former baseball player sample reported at least one joint with persistent pain, and 30% reported two or more joints with persistent pain. The reported persistent joint pain prevalence is higher than the United States general population of 11% to 19%.[422,423] However former high level sports participants have reported greater persistent joint pain prevalence compared to general population.[113,424,425] This sample's prevalence is similar to former athletes from other sports including cricket,[113,424] soccer,[355] and rugby.[425] However, the participants in all of these studies had greater mean ages, ranging from 56 to 62 years old.[113,355,424,425] Persistent joint pain has been observed to increase in prevalence during aging.[416] The similar persistent joint pain demonstrated by this former baseball sample, despite being 20 years younger, is concerning. Persistent joint pain has been associated with traumatic and overuse injury, along with overall sport exposure.[351-353] While baseball reports decreased traumatic injury compared to collision sports,[9,426] the high prevalence of overuse injuries and overall exposure may possibly explain this similar persistent joint pain prevalence. Other possible explanations include persistent joint pain is influenced by other sport participation, lifestyle,[427] chronic pain,[428] or depression and anxiety.[429,430] It should also be noted that players with worse pain and function may be more likely participate in this

study compared to healthy baseball players.[431] Previous research has reported that healthy patients are less likely to respond to surveys increasing the risk of non-response bias.[431,432] Considering the relatively young participant age and the prevalence of persistent joint pain, former baseball participants may be over represented in this sample. Prospective longitudinal studies, investigating persistent joint pain, in former baseball players are needed to further understand the etiology and persistent joint pain progression in this population.

The highest persistent joint pain prevalence was to the shoulder, knee and elbow. This is in contrast to previous former athlete literature in which the greatest persistent joint prevalence was to the knee, back, and hand,[113,355] and to the United States general population literature which the greatest prevalence was to the knee, back, and hand.[433] Knee persistent joint pain prevalence was similar to cricket,[113] but decreased compared to soccer.[35,355] These differences may be due to the specific sport tasks and physical requirements. Both cricket and baseball are overhead throwing sports,[4,434] while soccer is a field and court sport, which primarily involves the lower extremity.[435] Differences in baseball and cricket shoulder and elbow persistent joint prevalence may be due to the dissimilar throwing biomechanics employed by both sports.[4,434] Baseball utilizes a bent elbow during the late cocking throwing phase, increasing shoulder and elbow forces, and subsequently shoulder and elbow injuries.[4] In contrast, cricket bowling requires a straight arm, using increased spinal extension and rotation to propel the cricket ball, increasing spinal forces, and subsequent spinal injuries.[434] Over 95% of all shoulder and elbow persistent pain was to the throwing arm. As stated above, the throwing technique and high forces generated to the shoulder and elbow increase arm injury risk.[4] Shoulder persistent pain costs the United States $7 billion dollars a year, and rotator cuff injury and shoulder osteoarthritis are the primary drivers of this issue.[436] Within

this cohort, all former baseball players that sustained a shoulder surgery incurred a rotator cuff repair. In conjunction with the high shoulder injury incidence,[9] former baseball players may be at greater risk of persistent shoulder or elbow joint pain compared to other sport populations and the general population. Clinicians should consider these findings when creating fitness plans for athletes as they retire from baseball.

Former baseball players reported a mean SANE arm function score of 72. These scores are similar to a United States general population, mean age of 52.6 years old, following treatment of pathological shoulder conditions,[359] and a sample of American sports medicine shoulder patients, mean age 47 years old.[437] SANE scores were clinically decreased compared to a sample of total shoulder arthroplasty patients, mean age 68.9 years old, at two year follow up.[438] Arm function reported by this sample of former baseball players is concerning. This sample is younger, and is not a shoulder surgical or injury cohort in comparison to past literature.[359,437,438] The impaired SANE scores reported by this sample are potentially affected by the high shoulder and elbow persistent pain prevalence, and previous throwing arm injury and orthopaedic injury.[359] Further as stated above, these SANE scores may be influenced by nonresponse bias by healthy baseball players.[431,432] Other explanations include, unrealistic patient expectations concerning arm function[439] or currently participating in other sports and activities that require high level arm requirements such as swimming or javelin. While these SANE scores are potentially artificially reduced, overall arm function may still be decreased in baseball populations following retirement. Thus, former baseball players may require specific throwing arm examinations and potential interventions, such as physical therapy and surgery,[359,437,438] to improve overall arm function. Sports medicine clinicians need to educate baseball players of the risk of decreased arm function following retirement.

There was no relationship between playing position and persistent joint pain or arm function. It should be noted that the wide confidence intervals reported for playing position may demonstrate a potential relationship with persistent joint pain; however, the sample size may have hindered the precision in these analyses. To potentially control for the decreased sample size, a Firth corrected sensitivity analysis was performed, which also reported similar odds ratios. Further, due to two way players at the collegiate and professional levels reporting during the athlete public involvement sessions that these players primarily played a position and only pitched on minor occasions, another sensitivity analysis was performed. The sensitivity analyses investigating the relationship between pitchers and non-pitchers demonstrated increased odds of persistent joint pain in pitchers compared to non-pitchers, but similar results for reported arm function. While different baseball positions require different skills and physical attributes, all positions require high levels of throwing.[440] There is also the potential for residual confounding. As baseball players usually play multiple positions at younger ages, grouping players by college and professional position may only partially control for this explanatory variable. For example, baseball players that played outfield and pitcher through high school; but only outfield at the college and professional level would only be grouped as a position player within this study. As high school pitchers can pitch over 100 innings per year,[441] this grouping would miss significant pitching exposure. Despite these issues, the overall similarities in baseball participation between positions may incur similar risks for persistent joint pain and arm function. Baseball playing positions should potentially be given equal weight when examining former baseball player's joint health and arm function.

3.5. Strengths and Potential Limitations

This study utilized validated outcome measures to assess HRQoL,[363] flourishing,[340] physical activity,[368] arm function,[359] and persistent joint pain,[113,114] increasing the reliability and the ability to compare these results to the general population. Baseball stakeholders were used to develop and modify this survey, which increases the pertinence and applicability of this study. A one to six ratio between Major League Baseball (MLB) and Minor League Baseball players were recruited for this study. This is equal to the ratio of MLB and Minor League players, increasing the generalizability of these results to professional baseball players. This is the first study to investigate the relationship of baseball participation and health and wellbeing, allowing for novel insights into the implications of baseball participation.

These results are not generalizable to lower playing standards such as current or former high school, middle school, or recreational baseball players. These results are also not generalizable to female baseball players, softball players, or other overhead athlete sports such as tennis, swimming, or javelin. Due to the recruitment strategy, all current and former baseball players were from the United States. As baseball is played throughout the world,[295,296] these results are not generalizable to baseball participants from other countries of origin such as Latin America or Asia.

Due to using list serves and social media for recruitment, it is not possible to determine a true response rate, decreasing the capability of this study to understand selection bias. Further concerning selection bias, over 90% of all participants were recruited through college baseball alumni network list serves, with other recruitment strategies entailing MLB organizations, personal contact, or social media. Over 50% of professional baseball players do not play college baseball. This may bias this sample towards higher educated baseball

players. For example, only 10% of all former baseball players sampled reported having a high school diploma, compared to 90% earning a university degree or higher. As education can effect HRQoL,[442] substance use,[443] and physical activity[444] this sample may artificially inflate the true relationship between baseball participation and health and wellbeing.

Employing one data collection method potentially increases the risk of single method bias, which may deter data collection within individuals with poor computer literacy skills or access to technology. A previous study observed that using online based surveys may report different results compared to paper based methods.[445] Further, the mean age of former baseball players was 36.8 years old, which is decreased compared to previous cricket health and wellbeing literature, where the mean age was 60 years old.[113,114] Using an online recruitment strategy may bias participation to younger baseball players, decreasing the ability to compare these results to previous sport health and wellbeing literature.

No general population control data was collected in this survey. Only current and former baseball players were included in this sample to have direct methodological comparisons to previous work.[113,114] However, general population comparisons would increase the clinical applicability and understanding of these lifestyle and persistent pain data.

The cross-sectional nature of this study determines that participants must recall events that may have occurred in the past, which may create recall bias, decreasing the precision of these results.[446] This bias was attempted to be mitigated through the use of ‘don’t know’ answers, which allowed for a non-binary response. Further, outcomes such as alcohol consumption

and tobacco use may fluctuate throughout the season.[447] Longitudinal studies may better capture these outcomes through specific data collections throughout the year.

Physical activity self-reported measures[448] are extensively employed to evaluate population level physical activity. However, self-reported physical activity data can be over or underestimated due to recall bias[449] and response bias (e.g. social desirability).[450,451] Direct measures, such as accelerometers, provide increased physical activity measurement accuracy.[452] However, to increase response and utility of this survey, self-reported physical activity measures were utilized.[368]

Pain is a multidimensional construct that is affected by duration and intensity and can affect function and physical activity.[453] Further, osteoarthritis can affect pain, function, and physical activity.[351-353] It was not feasible to ascertain osteoarthritis diagnoses, as this would entail radiological and clinical examination.[454] These biases were attempted to be attenuated by using validated outcomes measures such as the SANE and the outcome of joint pain on most days of the last month. These measures were chosen as these outcomes are more a clinical relevant outcome, and allows for self-report. Further, only former baseball participants were analyzed in order to mitigate the confounding of current baseball injury. However, within this sample, former participants reported worse SANE scores than older total shoulder arthroplasty patients.[438] These findings may be artificially deflated due to the propensity of baseball players with worse pain and function to participate in this study compared to health baseball players.[431]

There may be unmeasured confounding regarding explaining lifestyle, persistent pain, and health outcome prevalence, such as socioeconomic status,[455] familial history of alcohol dependence,[456,457] or community relations,[455,458] which decreases the precision of these findings. Further, it is not possible through this survey to capture the underlying cause of these health outcomes, further decreasing the precision and clinical utility of these findings.

There is the potential for residual confounding concerning pitching exposure. While overall baseball exposure (through seasons played) was measured, pitching specific exposure may have confounded results. This was attempted to be mitigated by investigating persistent joint pain and reported arm function through baseball positions. Pitcher and two way positions both pitch at varying levels; however, the number of pitches or innings within a game or throughout the season could not be quantified. Further, a sensitivity analysis was performed investigating the relationship between pitchers and non-pitchers. As total pitch load can be related to arm injury and surgery,[336] improved quantification of pitching exposure may improve the precision in these results.

Missing data were observed within these data. The missing data mechanism was determined to be missing at random, explained through survey fatigue. In order to decrease this bias, best practice methodology was employed, consisting of implementing multiple imputation with chained equations.[379] Sensitivity analyses were conducted, analysing both imputed and complete case data, which demonstrated similar results. As a result, missing data only has minimal influence on these results.

3.6. Conclusions

Baseball players reported high smokeless tobacco use and current baseball players reported higher electronic cigarette and energy drink prevalence compared to former baseball players. Baseball players reported similar HRQoL compared to the general United States population, and high flourishing and physical activity. These results can be used to inform baseball stakeholders on the positives and negatives of high level baseball participation and to help create more effective interventions for baseball players as they transition from playing to retirement.

Former baseball players had a high prevalence of persistent joint pain compared to previous former athlete literature and to the general population. Almost 100% of all shoulder and elbow persistent joint pain was to the throwing arm, demonstrating the sport specific stresses sustained to baseball athletes. Further, while this sample of baseball players had a mean age below 40 years old, the mean reported arm function had clinically meaningful decreased scores compared to older arthroplasty patients. No relationships were observed between playing position and persistent joint pain or self-reported arm function, potentially demonstrating the similar overall throwing baseball exposure of pitchers, two way players, and position players. However, the persistent joint pain results should be interpreted with caution due to the wide confidence intervals and sensitivity analyses differences when investigating the relationship between pitchers and non-pitchers. Sports Medicine providers should consider throwing arm specific persistent joint pain and function when examining baseball players and when these athletes transition to retirement.

Chapter 4: Prospective Longitudinal Professional Baseball Cohort Methods

Science is organized knowledge. Wisdom is organized life
-Immanuel Kant

4.1. Introduction

There are 8,000 players participating at the professional level in the United States.[335] The professional baseball structure is split into the Major League Baseball (MLB) and Minor League Baseball (MiLB) systems. These two systems are each joined for each respective MLB organization. The MLB system, in descending order, is composed of the parent MLB club (e.g., New York Yankees or Los Angeles Dodgers), followed by the MiLB affiliates. Each MiLB affiliate is a successive playing standard below the MLB club. The highest MiLB is AAA, followed by AA, A+, A, short season A, rookie league, and the Dominican Summer League. The MLB season consists of 162 regular season games, not including spring training (i.e., preseason training camp). The MiLB levels AAA through A are comprised of 132 regular season games, not including spring training, while the short season A and rookie level teams play 76 games. Dominican Summer League plays 50 games.[335]

Each MLB team, and their MiLB affiliates, are required to have an athletic trainer on staff for each respective team. Further, each MLB organization has a medical coordinator that is the direct report for each athletic trainer. The medical coordinator is in charge of developing the overall medical and injury prevention philosophy, and is also responsible for designing the long-term rehabilitation plans for injured baseball players. All minor injury rehabilitation is designated to each team's athletic trainer (Personal communication, Robert Butler, Director of Performance and Medical Rehabilitation, St. Louis Cardinal Baseball Club).

Despite the large investments in medical staff within MLB, professional baseball injuries are significant, and continue to rise.[9,459] Baseball injuries can be prevented through a stepwise process that enables the identification of injury type, injury risk factors, aetiology and injury mechanisms which is dependent upon high quality data.[98] Without this data, designing and

evaluating injury prevention programs lacks the appropriate focus and responsiveness.[98] Deciphering injury risk will allow clinicians and coaches to better identify and create interventions in baseball players before they suffer an injury. The purpose of this chapter is to describe the research methods used to collect data in a prospective longitudinal professional baseball cohort.

4.2. Methods

4.2.1. Study design

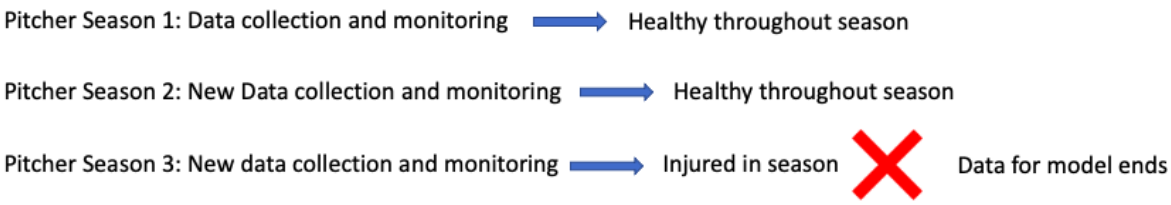
A prospective longitudinal study was conducted from 2009 to 2019 on MiLB pitchers in one organization. Prior to testing, all participants were detailed the risk and benefits of participation in verbal and written form. If a participant spoke a language other than English, an interpreter was used to verbally detail the study, and written consent forms were given in their own language. Participants were tested at the beginning of spring training (pre-season) and were randomized to either physical therapist for data collection. All data collectors were blinded to hand dominance.[460] Participants were tested for shoulder range of motion (ROM) and humeral torsion (HT). Following testing, participants were followed for the entire season for total athletic exposures and arm injuries (Figure 4.1.). All participant information was de-identified and coded into an encrypted centralized database. This investigation received favorable ethics approval from the University Institutional Review Board.



A. Timeline of data collection throughout the 10-year period



B. Timeline of season data collection



C. Hypothetical representation of data collection for a single pitcher

Figure 4.1. Pictorial representation of data collection.

4.2.2. Participants

Minor League Baseball pitchers, from every professional level, at one MLB club were included in this study. Participants were included if they were able to participate in all practices and competitions and were under a MiLB contract. Participants were excluded if they were currently injured or not participating in all spring training activities, participating in MLB spring training at time of data collection, or signed a professional contract in the middle of the season (e.g., draft, free agent, or international signing).[7]

4.2.3. Data Collectors

Two physical therapists performed all physical measurements for the entirety of cohort data collection. Prior to cohort data collection inception, reliability was performed for all physical measurements, which are detailed in the proceeding sections below. Physical therapy sports

residents, which rotate every two years, were trained as data collection assistants for all physical testing. Physical therapy sports resident training involved verbal and physical demonstration. Following demonstration, residents were tested on physical measurement skills and did not pass until intra-rater reliability was above 0.90.

4.2.4. Physical testing

Shoulder External and Internal Rotation Range of Motion

Shoulder external (ER) and internal (IR) ROM has been found to have high validity and reliability in general athletic,[461,462] overhead athlete,[461-463] youth overhead athletes,[464] and baseball populations.[63,73,461,462] Participants were placed supine on a standard plinth treatment table. Participants' shoulders were positioned in 90 degrees of shoulder abduction and elbow flexion. A small towel roll was placed under the humerus to maintain humeral position. Both dominant and non-dominant shoulders were measured.[465,466] Shoulder and scapula were stabilized by a study examiner placing a posterior pressure by the thenar eminence and thumb on the coracoid process before shoulder rotation.[461,465,467,468] Shoulder ER and IR were performed passively, with gravity acting upon the arm. A digital inclinometer was placed on the forearm midline and aligned to the olecranon process. Two examiners performed both ER and IR measurements, with one stabilizing the shoulder, and the other measuring shoulder rotation (Figure 4.2. and 4.3.).[469] Two trials were administered per shoulder, and the average of both trials were used in data analyses.[63] Prior to data collection, shoulder ER (intraclass correlation coefficient (ICC) (2,1) = 0.99; Standard error of measure (SEM) = 2.0; ICC (2,K) = 0.99; SEM= 0.95) and IR (ICC (2,1) = 0.97; SEM = 2.5; ICC (2,K) = 0.97 SEM = 2.6) reliability was observed to be excellent.



Figure 4.2. Shoulder External Rotation



Figure 4.3. Shoulder Internal Rotation

Horizontal Adduction

Shoulder horizontal adduction (HA) has been found to have high validity and reliability in overhead athletes[470] and baseball populations.[63,470,471] Both dominant and non-dominant

shoulders were measured. Subjects were placed supine on a standard plinth treatment table. The scapula was retracted and stabilized via the thenar eminence of one examiner placing an anterior to posterior pressure to the lateral scapular border. The upper extremity was then placed in 90 degrees abduction in zero degrees rotation.[63,470,471] The upper extremity was then passively horizontally adducted across the body.[470,471] A digital inclinometer was then placed on the posterior border of the humerus, in line with the olecranon and acromial processes. The angle between the humerus and the horizontal plane, from the superior aspect of the shoulder was then measured (Figure 4.4.).[63,470] Two trials were administered per shoulder, and the average of both trials were used in data analyses.[63] Prior to data collection, shoulder HA reliability (ICC (2,1) = 0.99; SEM =2.59; ICC (2,K) =0.97; SEM = 1.2) was determined to be excellent.

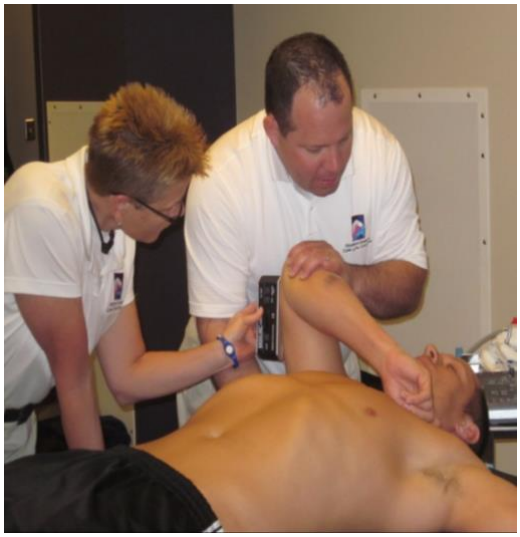


Figure 4.4. Shoulder Horizontal Adduction Range of Motion

Humeral Torsion

Humeral torsion indirect ultrasonographic measurement has been found to be valid and reliable in overhead athletes[472] and baseball players.[73,472] The standard error of measurement has been observed to range from 2 to 3. 8 degrees.[73,472] Participants were placed supine on a

standard plinth treatment table. Participants' shoulders were positioned in 90 degrees of shoulder abduction and elbow flexion. A 5-MHz transducer (Sonosite Inc., Bothell, WA, USA) was placed level on the anterior shoulder and aligned perpendicular to the long axis of the humerus (Figure 4.5.). The humerus was then rotated so that the intertubercular groove can be seen, with the apexes of the greater and lesser tubercles parallel to the horizontal plane. A digital inclinometer was then placed on the ulnar side of the forearm, measuring the forearm angle in the horizontal plane. These measurements indirectly measured the HT, in respect to the epicondylar axis.[73] Prior to data collection, shoulder HT reliability (ICC (2,1) = 0.97; SEM = 2.5; ICC (2,K) = 0.97 SEM= 2.6) was determined to be excellent.



Figure 4.5. Ultrasound Transducer Placement During Humeral Torsion Measurement

4.2.5. Exposure definition

An athlete-exposure (AE) was defined as one athlete participating in one practice or competition where a player was at risk of sustaining an injury.[9,473,474] Baseball exposure was

defined from the beginning of preseason (i.e. spring training) to the end of the minor league season.[475]

4.2.6. Injury definition

An injury was defined as an injury to a tendon, ligament, nerve, muscle, or bone that occurs during any baseball team sponsored activity or event[476] and was followed by at least one day of missed practice or at least one missed baseball game.[460] If a player was unavailable to play for injury prevention reasons (i.e., has reached league or individually determined pitch or innings count limits), then their absence was not considered as an injury.[475] Injuries were defined by the Orchard Sports Injury Classification system and arms injuries stratified by shoulder/clavicle, upper arm, elbow, and forearm.[57] All other injuries and illness were also recorded, but time loss was not taken into account for overall exposure nor included in the injury analyses.[146] Injury severity calculated as overall time loss,[146] with further injury severity stratified by seven and 28 days.[477] Injuries were further stratified into early (March, April), middle (May, June), and late (July, August, September).

Injury history was obtained from player medical records and previous professional baseball seasons. A pitcher was defined as having a history of arm injury if: previous elbow or shoulder surgery,[478,479] and/or sustaining 15 or more days of elbow or shoulder time loss injury in previous professional baseball seasons.[72,478]

4.2.7. Methodological strengths and potential weaknesses

Two physical therapists collected all physical measurements for all pitchers within this cohort, increasing the reliability and precision of these data. All measurements were assessed for high reliability prior to data collection, decreasing measurement bias. All second data

collectors were trained demonstrated high reliability prior to data collection. All data collectors were blinded to hand dominance, further decreasing measurement bias. All participants were randomly assigned for data collection, decreasing selection bias.

Reliability was only assessed for the primary data collectors prior to the inception of the cohort. As measurement reliability can change through time,[480] measurement drift may be instituted. While there is the potential for increased measurement precision due to a data collector learning effect,[481] increased measurement bias may be instituted due to increased time.[480]

Injury recording may not fully identify arm injuries. For example, a player may sustain a severe knee injury, but in the process sustain a subclinical arm injury. This injury would be designated as a knee, not an arm injury. As a previous injury increases risk of a subsequent injury,[482] this could potentially increase injury risk, decreasing the discriminant ability of the data.

Previous injury history was limited to professional baseball seasons and orthopaedic surgery prior to signing a professional baseball contract. Pitchers may sustain an injury without undergoing surgery. Previous injury has been observed to increase injury risk.[482] The inability to fully quantifying injury history creates the potential for residual confounding and decreases the precision in injury prediction.

Chapter 5: Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis

The universe is full of magical things patiently waiting for our wits to grow sharper

- William Butler Yeats

5.1. Introduction

Baseball has a high injury incidence,[9] and these injuries continue to increase.[459,483] The greatest injury incidence is to the shoulder and elbow, with pitchers having a higher injury incidence and prevalence than position players.[9,483-485] For example, 60% of all shoulder surgeries are performed on pitchers and 16% of all professional pitchers have undergone ulnar collateral reconstruction in their career.[484,485] These injuries have a high healthcare cost,[56] incur work time loss,[41] and inhibit performance.[486] Due to the severity and burden of baseball arm injuries,[110,459,483] baseball organizations have attempted to initiate injury risk identification and injury prevention programs.

One method to assess injury risk is through risk profiling.[7,72,128,460] Risk profiling is defined as the ability to screen individuals and subsequently identify individuals at high risk for the outcome (i.e., injury).[128] Within baseball, risk profiling has been performed, with shoulder range of motion (ROM) used as the risk profile gold standard.[7,72,460] In a meta-analysis, pitchers had a greater risk of arm injury with deficits greater than 5° between dominant and nondominant shoulder internal rotation ROM.[487] Pitchers were 6 times more likely to sustain an arm injury with deficits greater than 15° degrees between dominant and non-dominant shoulder horizontal adduction.[441] Injured pitchers exhibited greater than 5° difference between dominant and nondominant humeral torsion.[78]

While injury risk profiling is performed throughout baseball,[7,72,460] without proper education and interventions, identifying high injury risk athletes is inconsequential. Specific interventions have been employed for shoulder ROM deficits including stretching and manual therapy.[81] Other more global baseball injury mitigation strategies have been initiated

including implementing pitch counts,[87] individualized strength and conditioning programs,[204] and pitching biomechanical alterations.[70] However, despite the integration of injury risk profiling, education, and individualized interventions for high injury risk athletes, it is currently unclear how these strategies affect injuries in professional baseball pitchers.

Baseball arm injuries are a significant problem.[7,9,72] Risk profiling and education are strategies implemented to help reduce injury risk; however, currently there is little evidence on the effect of these interventions on arm injuries. Therefore, the purpose of this study was to evaluate the influence of risk profiling and education on arm injury incidence in minor league (MiLB) pitchers and to stratify by injury severity.

5.2. Methods

5.2.1. Study design

Participant recruitment and data collection are described in chapter 4. Beginning in the 2013 season, all MiLB pitcher injuries were recorded for date of onset and return to play. Prior to the 2013 season, only the occurrence and injury type were recorded. Thus, overall exposure was not possible to calculate prior to the 2013 season, and only baseball data from the 2013 to 2019 seasons were included in this study. Descriptive cross tabular analyses were performed to compare pitchers from the 2009-2012 seasons to the 2013-2014 seasons (Appendix C.1.). No descriptive physical differences were observed between groups.

5.2.2. Injury risk profiling and education

Beginning with the 2015 season, pitchers identified as at risk through preseason ROM and humeral torsion (HT) testing, were risk profiled for the Major League Baseball (MLB) organization. The MLB organization, including athletic trainers, physical therapists, and

strength and conditioning coaches were educated on what being risk profiled incurred. Further, the MLB organization was educated on potential shoulder ROM interventions, including posterior shoulder stretching and manual therapy.[81] These pitchers then received further physical examinations, and then were prescribed individualized interventions to potentially help mitigate arm injury risk. Potential interventions included posterior shoulder stretching and manual therapy,[81] reduced pitching workload, and/or altered strength and conditioning programs.

5.2.3. Statistical analyses

All data was investigated for missingness prior to analyses. Missing data was low (Shoulder range of motion: 3%, age: <1%, position: 0%), thus complete case analyses were performed. Investigation of normality was performed utilizing data visual inspection prior to analyses. Participant statistics were described using mean (standard deviation) for continuous normally distributed variables, median (interquartile range) for non-normally distributed continuous variables, and frequencies and percentages for categorical variables. Arm injury and combined trunk and lower extremity incidence was calculated by sum of arm injuries divided by sum of person-days multiplied by 1,000. χ^2 analyses were performed to investigate potential differences between shoulder ROM risk categories between the 2013-2014 and 2015-2019 seasons ($p < 0.05$). Interrupted time series analyses with quasipoisson distributions were performed to assess the effect of shoulder stretching and manual therapy on arm injury in professional minor league baseball (MiLB) players. These analyses were repeated for injury severity of 7+ and 28+ days. Sensitivity analyses were performed for elbow and shoulder injury, time to injury, and combined trunk and lower extremity injury. Unadjusted and adjusted odds ratios (ORs) with 95% confidence intervals (95% CI's) were reported for all analyses with alpha set at 0.05. Confounders controlled for included body mass index

(BMI),[488] arm dominance (left versus right arm),[489] seasonal pitch load, number of season pitching appearances, pitching position (i.e., starter versus reliever),[490] professional baseball seasons played, injury history,[478,479] HT difference,[6] shoulder internal rotation difference,[487] shoulder external rotation difference,[487] and shoulder horizontal adduction difference.[487] All assumptions for interrupted times series analyses were assessed and met. All analyses were performed in R version 3.5.1 (R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/), using the *naniar* package for missingness assessment,[491] and *tsModel f*or interrupted time series modelling. For complete code please refer to Appendix C.4.

5.3. Results

5.3.1. Participant characteristics

A total of 297 pitchers were included (Age: 23.0 (2.2) years, BMI: 24.8 (2.2), Left Handed: 21%), with a total of 119 pitchers in the 2013-2014 seasons and 178 pitchers in the 2015-2019 seasons. A total of 85,270 player days were observed, with 25,277 player days for the 2013-2014 seasons, and 59,993 player days for the 2015-2019 seasons. Overall injury history prevalence was 31%, the 2013-2014 season injury history prevalence was 27%, and the 2015-2019 season injury history prevalence was 33%.

Overall arm injury incidence was 1.15 arm injuries per 1000 AE's. For the 2013-2014 seasons arm injury incidence was 1.38 arm injuries per 1000 AE's, and for the 2015-2019 seasons, arm injury incidence was 1.63 arm injuries per 1000 AE's (Table 5.1.). Overall combined trunk and lower extremity injury incidence was 0.40 combined trunk and lower extremity injuries per 1000 AE's. For the 2013-2014 seasons combined trunk and lower

extremity injury incidence was 0.40 combined trunk and lower extremity injuries per 1000 AE's. For the 2015-2019 seasons combined trunk and lower extremity injury incidence was 0.40 combined trunk and lower extremity injuries per 1000 AE's.

5.3.2. Injury risk profiling

Differences were observed between the 2013-2104 and 2015-2019 seasons for shoulder injury risk categories. The 2013-2014 seasons demonstrated decreased preseason shoulder injury risk for IR shoulder risk (2013-2014: 32%, 2015-2019: 47%; $p = 0.003$) and ER shoulder risk (2013-2014: 35%, 2015-2019: 49%; $p = 0.007$). The 2015-2019 seasons demonstrated decreased dominant HA shoulder risk (2013-2014: 69%, 2015-2019: 58%; $p = 0.036$). There were no differences between seasons for TROM risk (2013-2014: 31%, 2015-2019: 33%; $p = 0.763$).

Table 5.1. Pitching Demographics for 2013-2019

	All Pitchers (n = 297)	2013-2014 (n = 119)	2015-2019 (n = 178)
Age (years)	23.0 (2.2)	23.4 (2.4)	22.7 (2.1)
Hand Dominance			
Left	62 (21%)	25 (17%)	57 (16%)
Right	235 (79%)	123 (83%)	292 (84%)
BMI (kg/m2)	24.8 (2.2)	25.1 (2.4)	24.6 (2.2)
Pitching Position			
Starter	122 (41%)	58 (49%)	100 (56%)
Reliever	175 (59%)	61 (51%)	78 (44%)
Seasonal Pitch Load	775 (394, 1156)	600 (213, 988)	860 (502, 1217)
Number of Pitching Appearances	25 (14)	26 (17, 35)	25 (14, 36)
Dominant Humeral Torsion	8.6 (13.1)	8.7 (12.9)	8.6 (13.3)
Dominant Internal Rotation	34.9 (10.9)	34.8 (10.3)	35.0 (11.1)
Dominant External Rotation	124.9 (10.2)	124.6 (9.3)	125.0 (10.6)
Dominant Horizontal Adduction	-2.3 (12.2)	-2.7 (11.6)	-2.1 (12.5)
Dominant Total Range of Motion	159.8 (12.9)	159.0 (12.3)	160.0 (13.1)
Non-Dominant Humeral Torsion	26.8 (13.5)	25.3 (13.0)	27.6 (13.7)
Non-Dominant Internal Rotation	47.6 (10.5)	45.2 (9.5)	48.7 (10.8)
Non-Dominant External Rotation	115.9 (11.3)	117.7 (9.8)	115.0 (11.0)
Non-Dominant Horizontal Adduction	15.6 (8.3, 24.6)	16.5 (7.8, 25.3)	15.7 (7.3, 24.1)
Non-Dominant Total Range of Motion	163.5 (13.5)	163.0 (11.6)	164.0 (14.3)
Humeral Torsion Difference	-18.2 (13.7)	-16.6 (12.0)	-19.1 (14.5)
Internal Rotation Difference	-12.8 (11.2)	-10.4 (10.4)	-13.8 (11.4)
External Rotation Difference	9.0 (9.1)	6.9 (8.3)	10.0 (9.3)
Total Range of Motion Difference	-3.8 (12.6)	-3.50 (12.3)	-3.92 (12.7)
Internal Rotation Risk			
Risk	42%	32%	47%
No Risk	58%	68%	53%
External Rotation Risk			
Risk	44%	35%	49%
No Risk	56%	65%	51%
Dominant Horizontal Adduction Risk			
Risk	62%	69%	58%
No Risk	38%	31%	42%
Total Range of Motion Risk			
Risk	32%	31%	33%
No Risk	68%	69%	67%
Arm Injuries 1+ Days	98 (33%)	35 (29%)	63 (35%)

Arm Injuries 7+ Days	84 (28%)	30 (25%)	54 (30%)
Arm Injuries 28+ Days	64 (22%)	22 (18%)	42 (24%)
Arm Injury Occurrence			
Early	43 (45%)	15 (43%)	28 (48%)
Middle	28 (32%)	13 (37%)	15 (26%)
Late	22 (23%)	7 (20%)	15 (26%)
Elbow Injuries	40 (13%)	17 (14%)	23 (13%)
Shoulder Injuries	64 (22%)	18 (14%)	46 (26%)

Data is reported as mean (standard deviation), median (interquartile range (IQR, IQR), or counts as percent
All range of motion is reported in degrees
Total Range of Motion = Sum of shoulder external and internal rotation range of motion
Range of motion difference is calculated as dominant – non-dominant shoulder
Internal Rotation Risk = Less than or equal to -15 degrees difference between dominant and non-dominant shoulder internal rotation
External Rotation Risk = Greater than or equal to +10 degrees difference between dominant and non-dominant shoulder external rotation
Dominant Horizontal Adduction Risk = Less than 0 degrees difference on dominant horizontal adduction
Total Range of Motion Risk = Less than or equal to -10 degrees difference between dominant and non-dominant shoulder total range of motion

5.3.3. Interrupted time series

There was a significant adjusted time loss arm injury reduction for the 2015-2019 seasons (Unadjusted: 0.76 (95% CI: 0.50, 1.15), p = 0.197; Adjusted: 0.67 (95% CI: 0.46, 0.99), p = 0.043) indicating a significant arm injury incidence reduction during these seasons (Figure 5.1.). Confounders that significantly influenced arm injuries included overall exposure (0.98 (95% CI: 0.97, 0.99), p < 0.001) and being a starting pitcher (1.87 (95% CI: 1.25, 2.80), p = 0.002). No other confounders significantly influenced arm injury incidence. Similar relationships were observed for 7 days (0.62 (95% CI: 0.42, 0.93), p = 0.019; Figure 5.2.), but not for 28 days (0.71 (95% CI: 0.47, 1.06), p = 0.093; Figure 5.3).

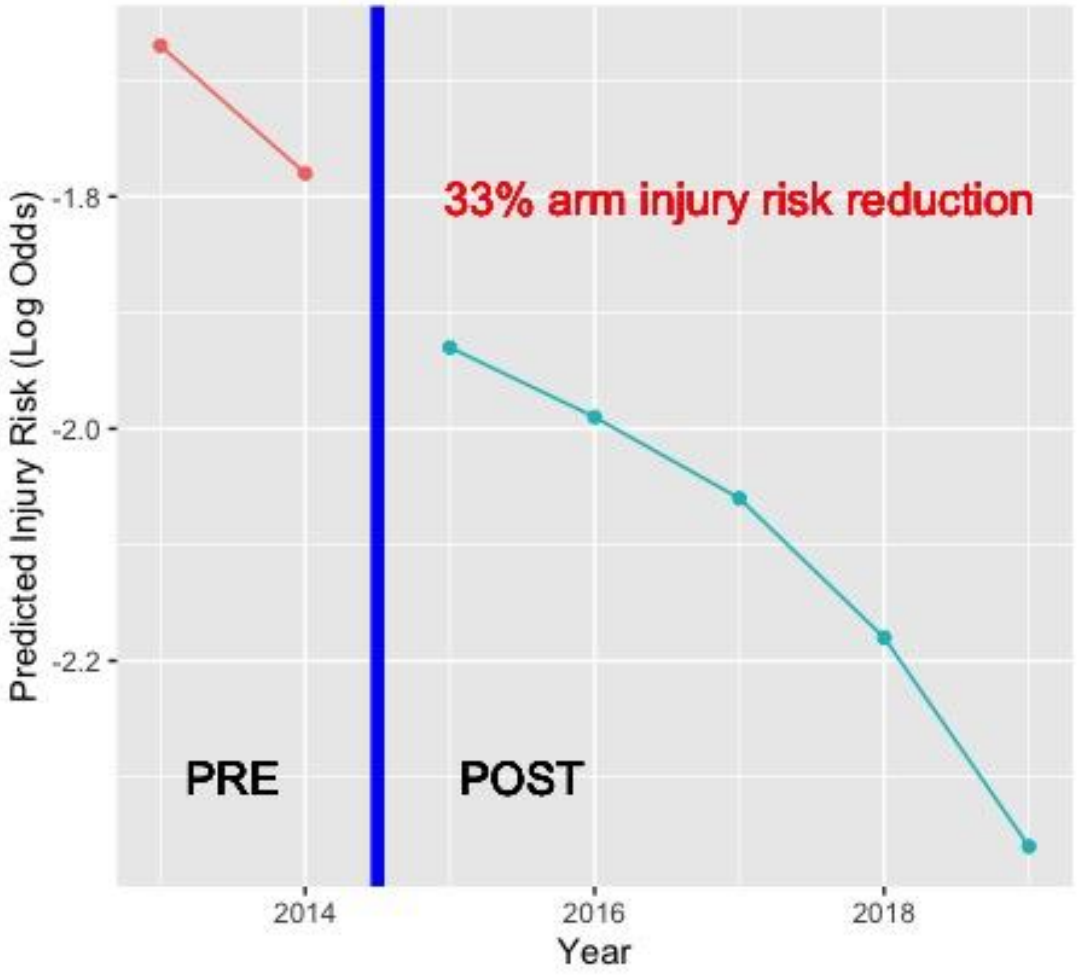


Figure 5.1. The relationship of injury risk profiling and education on overall arm injury incidence. Following organizational risk profiling and ecuations, there was a 33% arm injury incidence reduction over the subsequent seasons while controlling for other measurable factors.

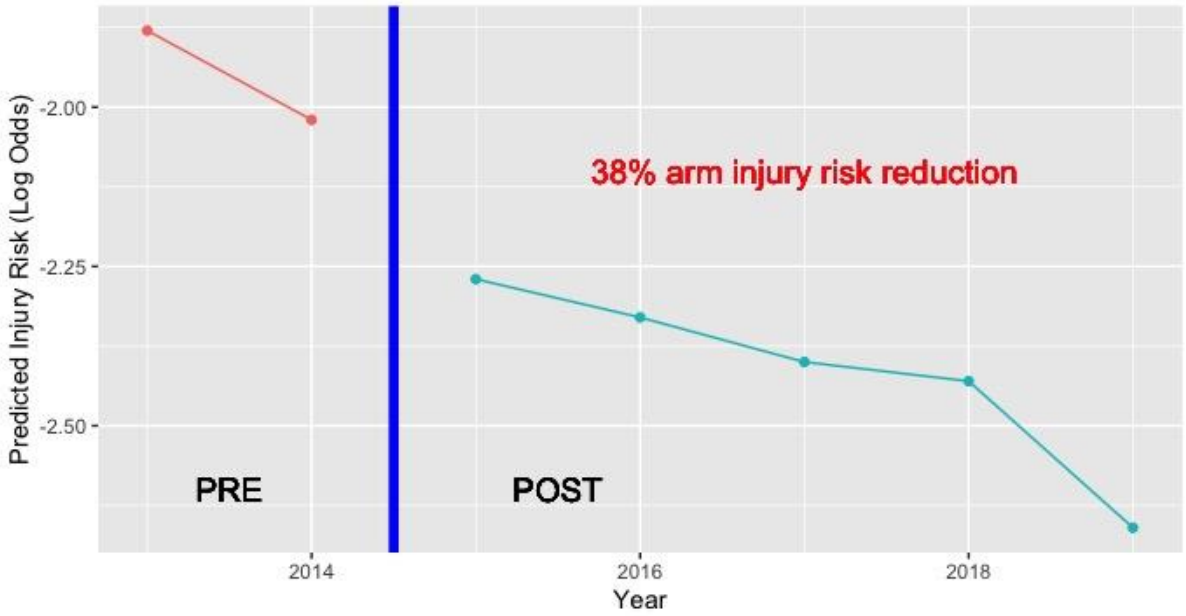


Figure 5.2. The relationship of injury risk profiling and education on 7+ day arm injury incidence. Following organizational risk profiling and education, there was a 38% arm injury incidence reduction over subsequent seasons while controlling for other measurable factors.

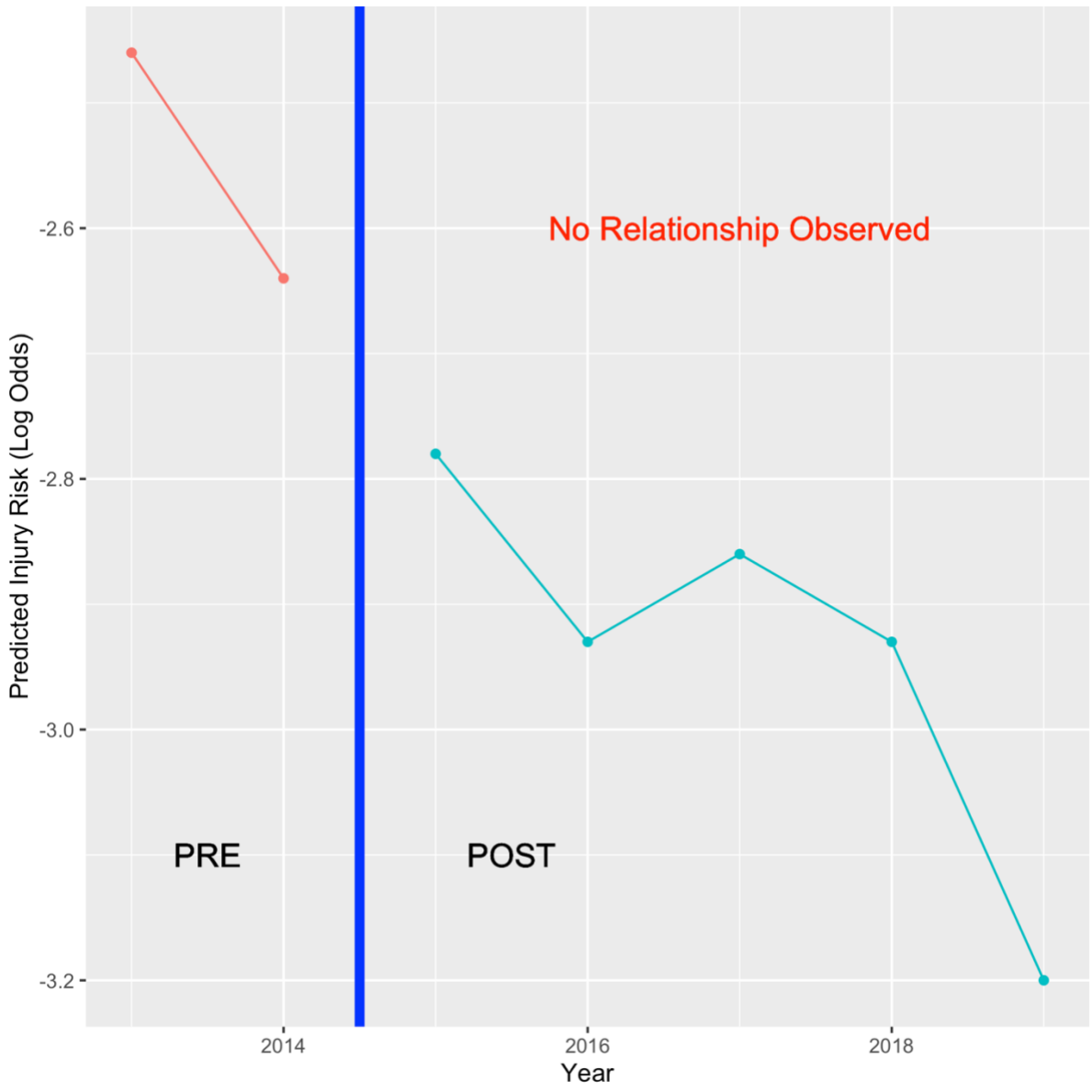


Figure 5.3. The relationship of injury risk profiling and education on 28+ day arm injury incidence. There was no relationship between organizational risk profiling and education and arm injury incidence over subsequent seasons.

5.3.4. Sensitivity analyses

There was a significant decrease in elbow injury for the 2015-2019 seasons (Unadjusted: 0.98 (95% CI: 0.97, 0.99), p = 0.039; Adjusted: 0.53 (95% CI: 0.30, 0.95), p = 0.034). There was no reduction in shoulder injuries for the 2015-2019 seasons (Unadjusted: 1.09 (95% CI: 0.68, 1.74), p = 0.773; Adjusted: 0.89 (95% CI: 0.53, 1.56), p = 0.690). There was no relationship

between arm injuries time occurrence within the baseball season (Unadjusted: 1.12 (95% CI: 0.78, 1.59), p = 0.548; Adjusted: 1.07 (95% CI: 0.74, 1.56), p = 0.723). There was no reduction in combined trunk and lower extremity injuries for the 2015-2019 seasons (Unadjusted: 1.42 (95% CI: 0.74, 2.72), p = 0.290; Adjusted: 1.55 (95% CI: 0.79, 3.01), p = 0.204).

5.4. Discussion

5.4.1. Summary

The main findings of this study were that no differences were observed between preseason shoulder ROM measures, demonstrating that shoulder ROM was similar and comparable between groups. However, the 2015-2019 seasons exhibited an increase in shoulder ROM clinically identified at risk groups. Injury risk profiling and education decreased overall and 7+ day arm injury incidence by 33%-38%. However, the relationship between injury risk profiling and education were inconclusive for 28+ day injury incidence, but the confidence intervals were wide. There were no descriptive or statistical differences for combined trunk and lower extremity injury incidence between the 2013-2014 and 2015-2019 seasons. These findings may demonstrate that injury risk profiling and education are potentially effective in mitigating arm injury incidence.

5.4.2. Effect of risk profiling and education on arm injury incidence

Risk profiling and education was observed to decrease arm injury incidence by 33-38% in overall and 7+ day arm injuries. Identifying athletes at risk for injury during preseason screening has been observed to be effective in attenuating injury incidence in other sports.[492] Identifying at risk athletes allows for injury prevention programs to be enacted, which have also demonstrated high efficacy in impacting sport injuries.[493-495] Following identifying pitchers at risk for an arm injury, sports medicine providers, and the respective baseball pitchers, were educated on potential injury risk reduction strategies such as shoulder ROM stretching and manual therapy,[81] pitching load reduction, and/or shoulder strengthening exercises.[496] Further, these players were more closely monitored throughout the season, allowing for alterations in individualized injury prevention strategies as the season progressed. Due to these injury risk mitigation strategies, a cross tabular exploratory analysis

was performed to assess potential mediating factors between those identified at risk and those identified not at risk for arm injury during spring training (Appendix C.2 & C.3). Pitchers identified as at risk threw almost 100 less pitches during the season and had two less appearances, the number of starters and relievers was almost equal. While no minimal clinically important difference has been identified for pitch count or appearances, this may be clinically relevant as this would equate to two starts and 50 pitches per start for a starting pitcher. While the timing of each individual pitch exposure was not within this data, traditionally pitch limiting strategies have been initiated at the beginning of the season for preseason identified at risk pitchers, for delayed or longer incremental increases in pitch loading. However, this is only speculative and further research is needed to understand how different potential pitch loading schemas (beginning of the season and throughout the season) could potentially affect arm injury incidence. It should be noted that risk profiling and education were inconclusive for 28+ day arm injuries. However, statistical power was substantially decreased for this analysis, demonstrated by the wide confidence intervals. While the exact injury prevention strategies were not recorded and were beyond the scope of this study, these data suggest that performing preseason injury risk screening, and educating sports medicine providers and their respective athletes, may allow for improved observation and greater precision in injury prevention intervention in higher risk athletes, potentially decreasing their arm injury risk.

Injury risk profiling and education interventions decreased elbow injury incidence by 47%, but was inconclusive for shoulder injury incidence. However, splitting the data decreased the power, limiting the interpretability of these findings. Further, within this particular professional organization, pitchers who sustained a shoulder injury were likely to be released, potentially biasing shoulder injury incidence towards the null. Elbow and shoulder injury risk

factors have been previously observed to be dissimilar in professional baseball pitchers.[7,72] For example, professional pitchers who sustained an elbow injury exhibited decreased dominant total shoulder ROM and shoulder flexion, while in the same cohort, professional pitchers that sustained a shoulder injury demonstrated decreased dominant shoulder external rotation.[7,72] These differences may be due to biomechanical changes caused by these different shoulder ROM deficits.[4] The greatest elbow valgus torque is sustained during the late cocking phase, which is a combination of shoulder rotation, scapulothoracic extension, and trunk extension.[4,497] Deficient dominant total shoulder ROM and shoulder flexion may create increased elbow valgus torque during the pitching late cocking phase due to decreased ability to produce the necessary shoulder and scapulothoracic motion.[497] In contrast, during the late cocking phase, decreased shoulder external rotation may not allow for sufficient lay back mechanism, putting undue stress on the shoulder.[77,78]

Descriptive combined trunk and lower extremity injury incidence was equal at 0.40 injuries per 1000 AE's between the 2013-2014 and 2015-2019 baseball seasons. Further, adjusted combined trunk and lower extremity injury incidence was similar between cohorts. This is in direct contrast to the steady decrease in adjusted arm injury incidence throughout the cohort. As baseball training and in game tactics have changed throughout the cohort time period, these modifications could have potentially explained the steady decrease in arm injury incidence. However, the similar combined trunk and lower extremity injury incidence throughout the cohort period potentially strengthens the association between incorporating risk profiling and education and the decreased arm injury risk.

There were no differences in time to injury before or after implementing risk profiling and education. This suggests that these interventions are indiscriminate in injury prevention

concerning time. Thus, other factors such as playing load and fatigue may also play a role in time to injury within a season.[498-500] For example there was a proportional relationship between increased pitch count and throwing arm pain in baseball pitchers.[498] In a systematic review, increased fatigue was associated with increased arm pain in pitchers.[499] It is advised to continue to monitor pitching load, through pitch count, and pitcher fatigue in association with risk profiling and education.

5.4.3. Strengths and potential limitations

This study used a seven-year prospective longitudinal professional baseball cohort, increasing the precision of these findings. All minor league affiliates were incorporated into the sample increasing the generalizability of these findings. All data were measured prior to baseball participation, by physical therapists, decreasing measurement bias. Missing data were low, allowing for a complete case analysis, increasing the precision and validity of these findings.

This cohort only evaluated one MLB organization, as each MLB organization has different training and play norms, these results may not be generalizable to other MLB organizations. Only professional baseball pitchers were integrated into this cohort, as baseball players play eight other positions, these results cannot be generalized to other positions such as catcher or outfielder. This cohort included MiLB players from different countries of origin, increasing the generalizability of these findings; however, different countries throughout the world have their own professional baseball leagues, which have different playing volume and training and practicing norms. As a result, these findings cannot be generalizable to different professional baseball leagues. Lower playing standards play a lower number of games, demonstrate decreased training volume, do not produce the same pitching velocity,[70,149] and have different access to sports medicine and performance resources compared to professional

organizations. Thus, these results also cannot be generalizable to lower playing standards such as college, high school, or middle school baseball. Other overhead athlete sports produce different forces throughout the arm,[497,501,502] and participate in different practice, training, and competition norms,[14] and thus are not generalizable to other overhead athletes such as tennis, softball, or swimming.

There were a decreased number of seasons and overall exposure for the pre intervention (2013-2014) compared to the intervention (2015-2019) groups. Due to the Major League Baseball Collective Bargaining Agreement, time of injury was not collected prior to 2013. It should not be assumed that the 2013-2014 pitchers were comparable to the 2009-2012 pitchers. Thus, a descriptive cross-tabular analysis was performed, which demonstrated similar results (Appendix C.1.). As a result, the 2013-2014 pitchers may be generalizable for the entire pre intervention group. The decreased number of pre intervention seasons decreased the power of the 28+ days lost to injury, demonstrated by the wide confidence intervals. This decreased pre intervention power compared to the intervention group inhibited conclusive results for this secondary analysis. However, despite the decreased precision, the decreased odds ratios for 28+ day analysis suggest that risk profiling and education may be associated with severe injury risk in professional MiLB pitchers.

There was a gradual decrease in adjusted arm injury incidence throughout the data collection period. The decreased number of seasons collected prior to intervention reduces the ability to fully quantify this potential trend. The greater number of years collected prior to the interrupted time, allows for improved inferences regarding the intervention.[503] While two years prior to interrupted time is sufficient for these analyses,[503] a greater number of years collected would have improved the ability to understand if this downward trend in adjusted

injury incidence is due to the implementation of injury risk profiling and education, or an overall improvement in training and injury prevention practices within the organization that started prior to the interrupted time. Combined trunk and lower extremity incidence calculations and analyses were performed to determine if these trends were similar for other body parts. As combined trunk and lower extremity injury incidence was similar between the pre intervention and intervention groups, it is believed that these interventions may explain some association in the decreased arm injury risk beginning in the 2015 season.

Elbow and shoulder injury risk factors have been previously observed to be dissimilar in professional baseball pitchers.[7,72] Sensitivity analyses were performed to explore the relationship of risk profiling and education on elbow and shoulder injuries separately; however, there was decreased power for these analyses, causing wide confidence intervals and inhibiting conclusions. While there was an observed relationship between risk profiling and education and elbow injuries, there was no observed relationship for shoulder injuries. As stated above, these discrepancies in injury risk may be due to differences in biomechanical and ROM impairments during the pitching motion.[4] However these results may also be affected by injury classification. Baseball elbow injuries are primarily to the medial elbow, due to the elbow stresses sustained during the late cocking phase.[4,9] This is in contrast to baseball shoulder injuries, which can be involve the deltoid, acromion, rotator cuff, and scapula.[504,505] The anatomical heterogeneity in shoulder compared to elbow injuries decreases the precision of these results.

A player may have sustained a subclinical injury that did not result in time lost to training, practice, or competition. As previous injury can influence future injury,[506] these subclinical injuries may bias these results toward the null. Baseball players may have also sustained an

arm injury coinciding with a lower extremity or trunk injury. These arm injuries may have been marked only as a lower extremity or trunk injury, biasing these results towards the null. However, due to the substantial decrease in adjusted injury incidence following risk profiling and education, these potential biases may have had minimal effect on these results.

Professional baseball service time was accounted for by creating an ordinal scaled variable. Best practice recommends keeping continuous variables as continuous when designing prediction models.[507] However, within this cohort, no player played more than six years within the organization. These data did not allow for a continuous variable to be implemented into the model, decreasing the precision of these results.

Player signing bonuses and salaries were not controlled for in these analyses. Player pay data were not available due to organizational contractual agreements. As organizational investment may play a role in player injury incidence and time loss for injury prevention and rehabilitation, higher paid players may have greater injury incidence and severity compared to lower paid players, potentially biasing these results towards the null.

On average, twelve (14%) pitchers a year were not included in this study as they were participating in MLB spring training during data collection. Pitchers that were participating in MLB spring training were higher level pitchers (AAA or AA); but, would play MiLB during the season. The exclusion of these pitchers from the model decreases the overall power and decreased the generalizability of these results to higher level MiLB pitchers. However, the small proportion of pitchers excluded from data analysis only has a small influence on results.

Pitchers were not considered injured if their season was ended prior to the end of the season due to injury prevention reasons such as reaching their season innings or pitch count limits. Upon inquiry to the MLB organization, sports medicine staff, and data collectors, no pitcher seasons were prematurely ended for injury prevention reasons during data collection. On average one to two pitchers were given more rest days between starts and/or appearance near the end of the season; but no pitchers ceased pitching within a season. There is a very small potential for immortal time bias due to this issue; however, this bias would not have an effect on results.

Previous injury history was limited to professional baseball seasons and orthopaedic surgery prior to signing a professional baseball contract. Pitchers may sustain an injury without undergoing surgery. Previous injury has been observed to increase injury risk.[482] The inability of fully quantifying injury history creates the potential for residual confounding and decreases the precision of these results.

All data were collected at the beginning of spring training. While this increases the feasibility of this project, this methodology may limit the clinical applicability of these results. For example, shoulder ROM can change between pitching appearances and throughout the season.[5] These potential changes in shoulder ROM can affect injury risk,[5,7,72] which could not quantified through these analyses. Baseball players may have changes in BMI throughout the season, and in between seasons. Body mass index data were extracted through publicly available means, and could not quantify inter or intra season changes, decreasing the precision of these results. Further, BMI is only one body composition measurement, and has been shown to have a decreased explanation of body composition in athletic populations.[508] Other body composition measurements such as fat free mass and body fat percentage may

decrease residual confounding. Psychological and biomechanical data were not collected within the professional baseball cohort. Both of these intrinsic factors have previously been observed to relate to baseball arm injuries,[509,510] decreasing the precision and clinical applicability of these results. Shoulder strength, lower extremity range of motion, and lower extremity dynamic balance were not incorporated into the analyses. As these intrinsic factors have demonstrated previous relationship to arm injuries,[61,511] the exclusion of these factors decreases the clinical interpretability of these findings and biases these findings towards the null.

The organization did not specify each intervention implemented to each individual due to risk profiling and education. While the overall interventions are recorded, such as shoulder manual therapy, pitch count reduction, individualized strength and conditioning plans, and further physical examinations, these interventions were not further detailed. This inhibits the ability to quantify the specific effect of individual or a combination of each intervention on arm injury risk. While a randomized control trial has investigated the effect of shoulder stretching and manual therapy on shoulder ROM,[81] no studies have investigated the effectiveness of any of these interventions on arm injury incidence at any level of baseball. As a result, these findings cannot quantify the effectiveness of these interventions on reducing arm injury incidence. These results can only conclude that risk profiling and education create an environment in which sports medicine clinicians and performance professionals can increase their awareness and time with higher risk baseball pitchers, which can potentially reduce arm injury risk in professional baseball pitchers.

5.4.4. Future research

These findings necessitate future research. The different relationships observed between injury risk profiling and education and elbow and shoulder injuries necessitate the need to understand how interventions potentially mitigate elbow and shoulder injuries separately. While injury risk profiling and education demonstrated a reduction in professional pitching arm injuries, it is not known what is the optimal amount of injury prevention interventions needed to decrease arm injury incidence. Posterior shoulder ROM stretching and instrumented assisted manual therapy was performed as part of the injury prevention interventions.[81] However, previous research has observed that shoulder flexion and elbow ROM can also increase injury risk.[5,7,72] Investigating the efficacy of other shoulder and elbow ROM and instrumented assisted manual therapy on baseball arm injuries is needed. Finally, risk profiling and education demonstrated effectiveness in reducing arm injury risk in professional baseball players; however, it is currently unclear the mechanism of arm injury mitigation when implementing these methods. A combination of quantitative and qualitative studies are needed to understand the mechanisms, barriers, and facilitators of risk profiling and education on arm injury risk reduction. Further, baseball is played at all ages and playing standards, with lower playing standards potentially having decreased access to sports medicine and performance support compared to professional baseball. Research is needed to understand the effectiveness of risk profiling and education on other playing standards, such as college, high school, and youth baseball players.

5.4.5. Conclusions

Organizational risk profiling and education appears to reduce professional pitching overall and 7+ day arm injury incidence by 33%-38%; but not for 28+ day injury risk. This suggests that while injury risk increased over time, organizational risk profiling mitigated the expected increase in arm injury incidence. Risk profiling and education can be used as a clinical

screening and intervention tool to help decrease arm injuries in professional baseball populations. Future research is required to understand the interplay of clinical and unmeasured factors on pitching injury risk.

Chapter 6: Development and internal validation of an arm injury prediction model for professional baseball pitchers

It's tough to make predictions, especially about the future

-Yogi Berra

Prior Publication:

The body of this manuscript is currently under review.

*Shanley E**,** *Bullock GS, Noonan TJ, Wyland J, Kissenberth T, Arden NK, Collins GS, Thigpen CS. Development and application of an arm injury prediction model for professional pitchers. American Journal of Sports Medicine.

*Joint first author

6.1. Introduction

Professional baseball injuries continue to rise and have been accompanied by increased time loss.[41,512] Recent advances in professional baseball injury tracking has further illuminated the extent of these injuries with baseball players sustaining over 8,000 injuries per year and over forty percent of these injuries credited to pitchers.[512]

Baseball pitching is a sequence of complex movements throughout the entire kinetic chain.[4] Pitching requires an interaction of multiple factors including intrinsic (range of motion, strength, biomechanical, neuromuscular, osseous, and anatomical) and extrinsic performance and environmental factors (pitch load).[513] The unilateral repetitive nature of the sport, and the high competition demands require baseball players to maintain a high level of performance without subsequent injury.[514] The physical demands of the sport, movement patterns, and injury risk appear to be interactive and dynamic rather than simple and stable over time. The traditional model of preseason injury risk profiling, through the implementation of screening programs, was commenced to identify range of motion deficits (ROM), scapular asymmetries, shoulder muscle weakness or imbalance, and have been used with the goal of attenuating injuries.[7,8,460,465,468,469,515-520] However, these methods are limited by the isolationist and simplistic approach, forgoing an attempt to take into account the complex and dynamic nature of the problem.[521]

A more complex approach to identify at risk athletes injury patterns have been suggested as an effective method to attenuate injuries.[134,522] This complex prediction model methodology necessitates the inclusion of a dynamic feedback system, the incorporation of non-linear assessment between predictors and injuries, and robust model performance evaluation.[134,513,522,523] Developing injury prediction models that acknowledge and attempt to

mathematically account for the complexities in athletic injuries are needed to understand the probability of injury and the most effective strategies to reduce injury risk in professional pitchers.[514] Therefore, purpose of this study was to develop an injury risk prediction model for identifying minor league (MiLB) pitchers at increased risk for a primary arm injury.

6.2. Methods

6.2.1. Study design

Participant recruitment and data collection are described in chapter 4. The entire prospective cohort from 2009 to 2019 were used within this study. Individual risk factors were identified by review of literature for study inclusion.[7,8,465,468-470,515-519,521,524-527] Those variables that were feasible to collect and deemed important for elevating the health and performance of the athletes participating within the organization were prioritized. Figure 6.1. details the variables collected during the study period.[513]

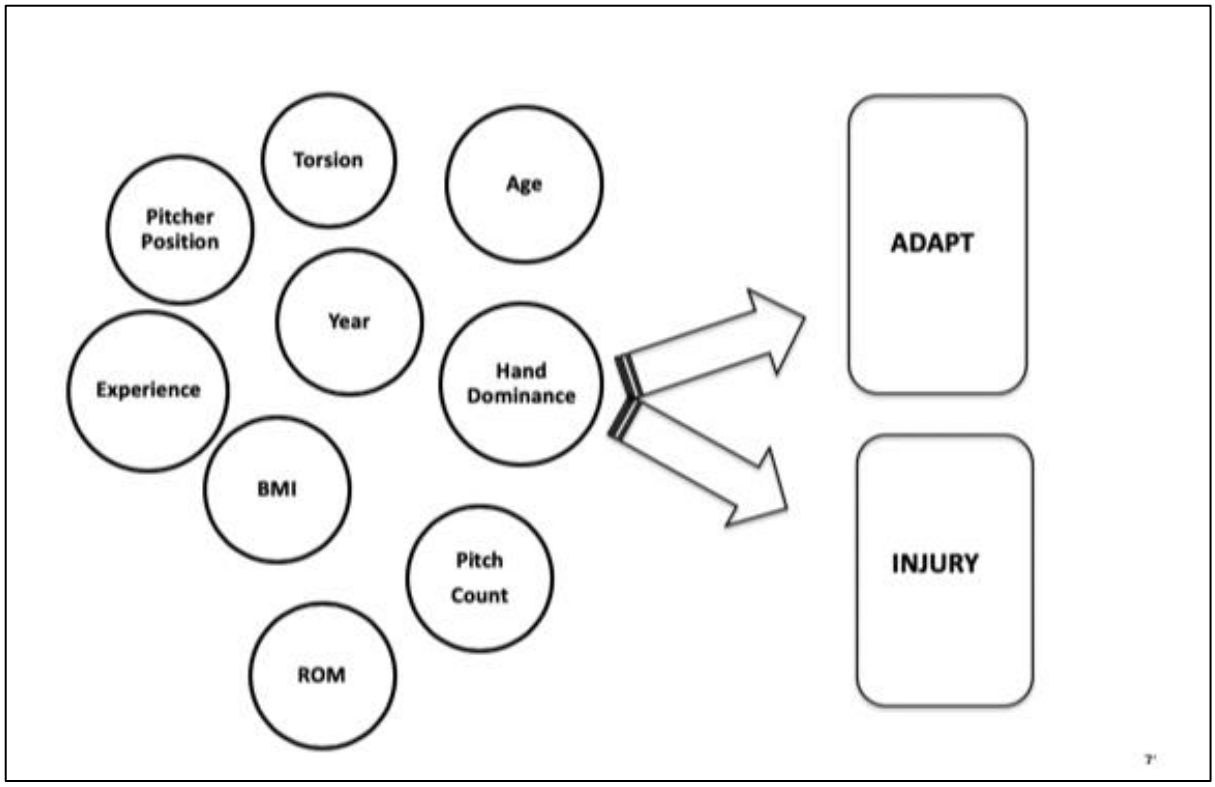


Figure 6.1. Initial Variables for the Prediction Model

6.2.2. Exposure definition

Pitching exposure was defined as total number of pitches in a season.[528] The number of pitches in a season was collected from team reports. However, team reports were inconsistent in reporting pitch counts, with only 45% of pitchers had season pitch counts. As a result, the remaining pitcher season pitch counts were accessed and recorded via publicly available data (thebaseballcube.com and baseball-reference.com). As these publicly available websites do not record the actual number of pitches in a season, indirect calculations were performed. Box score statistics including batters faced, strike outs, and walks were obtained from the publicly available websites and then calculated via a pitch count estimator formula (3.3xBatters Faced + 1.5xStrike Outs + 2.2xWalks).[528] This pitch count formula has found to be have excellent reliability (intraclass correlation coefficient = 0.98), with error of three pitches for a season.[528]

Beginning in the 2013 season (seasons 2013-2019) date of injury was recorded. This discrepancy between seasons 2009-2012 and 2013-2019 was due to changes in the Major League Baseball injury database reporting. As a result, time to injury was only available beginning in the 2013 season. Further definitions of athlete-exposure was defined as one athlete participating in one practice or competition where a player was at risk of sustaining an injury.[9,473,474] Baseball exposure was defined from the beginning of preseason (i.e. spring training) to the end of the minor league season.[475]

6.2.3. Outcome

Injury definition

An injury was defined as an injury to a tendon, ligament, nerve, muscle, or bone that occurs during any baseball team sponsored activity or event[476] and was followed by at least one day of missed practice or baseball games.[460] If a player was unavailable to play for injury prevention reasons (i.e., has reached league or individually determined pitch or innings count limits), then their absence was not considered as an injury.[475] Injuries were defined by the Orchard Sports Injury Classification system and arms injuries stratified by shoulder/clavicle, upper arm, elbow, and forearm.[57] All other injuries and illness were also recorded, and time loss was taken into account for overall exposure, but were not included in the injury analyses.[146]

6.2.4. Statistical analyses

All data was investigated for missingness prior to analyses. Missing data was low (Shoulder range of motion: 3%, age: <1%, position: 0%), thus complete case analyses were performed. An outlier analysis was also performed to identify any nonbiologically plausible data points,

and the influence of outliers on the data. It was determined that outliers were minimal, and demonstrated minimal influence on predictors. For full description, please refer to Appendix D.1. Participant characteristics were described using mean (standard deviation) for continuous normally distributed variables, median (interquartile range) for non-normally distributed continuous variables, and frequencies and percentages for categorical variables. Arm injury incidence was calculated per 1000 pitches.[529]

Preliminary analyses

Prior to analyses, an interrupted time series analysis was performed on the data collected between 2013-2019 (See Chapter 5). The 2009-2012 data was not included in the interrupted time series analysis due to this data did not report time to injury, or overall time loss to injury. The implementation of risk profiling and organizational education started in 2015 in an initiative to reduce the overall upper extremity risk in professional pitchers. Additional physical examination and arm injury prevention exercises were performed on pitchers identified as at risk for injury. As a result, it could not be assumed that overall upper extremity risk was the same throughout all prospective cohort years. In order to account for the differences between years, a binary variable was incorporated, identifying participants from 2009-2014, or 2015-2019. For inclusion into the prediction model, and to make predictions on future new data, this variable will be included as a binary variable if the pitcher is currently undergoing injury prevention arm care exercises on most days of the week.

Prior to model development, the relationship between continuous variables and upper extremity injury were assessed for non-linearity. Non-linearity was assessed through restricted cubic splines.[530] A restricted cubic spline is a non-linear piecewise polynomial

(non-linear calculation), joined at specific knots throughout the data. Knots are quantile mark points in which each segment (between each knot) is assessed for potential non-linear relationships.[530] The range of data is joined at each successive knot, allowing for different non-linear relationships to be assessed throughout the entirety of the data.[530] Non-linearity criterion was based on Akaike's Information Criteria (AIC), residuals, visual inspection, and biological plausibility. It was determined that BMI demonstrated a linear relationship, while pitch load and HT difference demonstrated a non-linear relationship with the best non-linear relationship explained by 4 knots. Dominant TROM and dominant HA also demonstrated a non-linear relationship, with the best non-linear relationship explained by 3 knots. For full description, please refer to Appendix D.2.

Sample size considerations

An a-priori sample size calculation was performed prior to model development to limit the number of predictor parameters based on the available data (n = 407 with 35% sustaining an arm injury). Sample size for binary prediction model development involves specifying three components: the potential R^2, the injury prevalence, and the total number of participants included in the study.[155] Nagelkerke R^2 was determined through preliminary work, with an R^2 of 0.32 utilized for calculations. The prevalence of arm injury was 0.35, and a total 407 participants were included in the study. It was determined that a total of 17 parameters could be included to reduce the risk of overfitting the prediction models. The R package *pmsampsize* was used to calculate prediction model sample size.

Model development

The transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) were followed for reporting the model development.[531] A prediction

model using logistic regression was performed, with the occurrence of a time loss upper extremity injury as the binary outcome. Following primary model development, an elastic net analysis was performed. Elastic net is a penalized method that assesses multicollinearity, and shrink the coefficients (down to zero) to reduce the risk overfitting.[181] Further, elastic net allows for predictor selection and incorporates these results into the overall model, and has been found to have improved results compared to more traditional statistical methods.[179] To find the optimal alpha and lambda shrinkage parameters, a tenfold cross-validation with ten iterations per fold was performed, with the greatest Kappa used to determine the best tuning parameters.[181] Predictor variables included: BMI, professional baseball years played (1-2, 3-4, 5+ years), upper extremity dominance (Left or Right handed), year of data collection (2009-2014, 2015-2019), total number of pitches, humeral torsion difference, dominant total range of motion (IR+ER), and dominant horizontal adduction. Internal validation was then performed to correct for optimism, using ten-fold cross validation. Sensitivity analyses were performed to better determine and understand the uncertainty in the results. Sensitivity analyses included: logistic regression for elbow and shoulder injuries separately, a mixed effects analysis for overall primary upper extremity injury, with individual participants as the random effect, and a Cox survival analysis in relation to time to primary upper extremity injury for the 2013-2019 seasons.

Model performance.

Model performance was investigated by calculating Nagelkerke R^2, calibration and discrimination. Calibration measures agreement between predicted risks from the model and what was observed, while discrimination evaluates how well the model differentiates between those with and without the outcome. Calibration was quantified by the calibration slope (with 95% confidence intervals) and graphically by plotting the predicted risk against

the observed outcome using a loess smoother. A calibration slope of one signifies perfect calibration and will be display a 45-degree line graphically. A calibration slope above one will demonstrate under predicted risk and a calibration slope below one will signify over predicted risk. Discrimination was evaluated by the Area Under Receiver Operating Characteristic Curve (AUC). An AUC of 0.5 equates to correctly predicting 50% of outcomes, which is no better than random guessing. An AUC of 1.0 demonstrates perfect (100%) outcome prediction. The AUC was categorized as Fail (0.5-0.6), Poor (0.61-0.7), Fair (0.71-0.8), Good (0.81-0.9), and Excellent (0.91-1.00).[532] All analyses were performed in R version 3.5.1 (R Core Team (2013). R: A language and environment for statistical computing. For full R code, please refer to Appendix D.3.

6.3. Results

A total 407 MiLB pitchers were included (Age: 23.2 (2.4) years, BMI: 25.1 (2.3), Left Handed: 17%), with a total of 141 primary arm injuries (Table 6.1.). A total of 527, 922 pitches were thrown from 2009-2019 seasons. Arm injury incidence was 0.267 arm injuries per 1000 pitches. Elbow injury incidence was 0.119 elbow injuries per 1000 pitches. Shoulder injury incidence was 0.163 shoulder injuries per 1000 pitches (Table 6.2.).

Table 6.1. Pitching Demographics

	All Pitchers (n = 407)	No Arm Injury (n = 266)	Arm Injury (n = 141)	Elbow Injury* (n = 63)	Shoulder Injury* (n = 86)
Age (years)	23.2 (2.4)	23.2 (2.2)	23.0 (2.2)	23.2 (2.4)	22.8 (2.1)
Hand Dominance					
Left	17%	17%	13%	16%	16%
Right	83%	83%	87%	84%	84%
BMI (kg/m2)	25.1 (2.3)	25.0 (2.3)	25.3 (2.5)	25.1 (2.3)	24.9 (2.3)
Pitching Position					
Starter	44%	61%	56%	52%	58%
Reliever	56%	39%	44%	48%	42%
Years within the Organization					
1-2 years	73%	71%	54%	42%	58%
3-4 years	22%	23%	36%	46%	32%
5+ years	5%	6%	10%	12%	10%
Dominant Humeral Torsion	8.3 (12.9)	8.1 (11.5)	9.4 (11.5)	8.3 (12.9)	9.9 (11.9)
Dominant Internal Rotation	35.5 (11.3)	35.7 (10.8)	34.8 (10.8)	35.5 (11.3)	36.2 (11.4)
Dominant External Rotation	126.8 (12.7)	126.8 (10.1)	127.1 (10.1)	126.8 (10.7)	125.7 (10.6)
Dominant Horizontal Adduction	-1.4 (12.6)	-1.6 (14.1)	-0.6 (14.1)	-1.4 (12.6)	-0.2 (13.2)
Non-Dominant Humeral Torsion	25.6 (13.0)	25.3 (11.7)	26.9 (11.7)	25.6 (13.0)	25.7 (11.9)
Non-Dominant Internal Rotation	48.1 (10.6)	48.0 (10.2)	48.3 (10.2)	48.1 (10.6)	48.9 (9.6)
Non-Dominant External Rotation	118.2 (11.6)	118.1 (11.3)	118.5 (11.3)	118.2 (11.6)	117.3 (11.5)
Non-Dominant Horizontal Adduction	16.8 (8.6, 24.9)	16.5 (8.3, 24.6)	18.0 (9.5, 26.5)	16.8 (8.6, 24.9)	14.65 (5.8, 23.5)
Humeral Torsion Difference	-17.3 (13.4)	-17.2 (12.9)	-17.5 (12.9)	-17.3 (13.4)	-15.9 (12.8)
Internal Rotation Difference	-12.6 (11.4)	-12.3 (11.4)	-13.6 (11.4)	-12.6 (11.4)	-12.7 (11.0)
External Rotation Difference	8.6 (9.5)	8.7 (9.1)	8.6 (9.1)	8.6 (9.5)	8.4 (9.3)

*8 pitchers sustained both elbow and shoulder injuries, and all of combined elbow and shoulder injuries were sustained at the same time

Table 6.2. A comparison of baseball demographics between different seasonal pitch counts

	Less than 1000 Season Pitchesψ (n = 376)	1000 to 1999 Season Pitchesψ (n = 145)	2000+ Season Pitchesψ (n = 61)
Age (years)	23.1 (2.4)	23.1 (2.3)	22.8 (2.4)
Hand Dominance			
Left	18%	13%	13%
Right	82%	87%	87%
BMI (kg/m2)	25.0 (2.4)	25.0 (2.3)	24.9 (2.4)
Pitching Position			
Starter	38%	54%	90%
Reliever	62%	46%	10%
Years within the Organization			
1-2 years	56%	46%	48%
3-4 years	36%	41%	39%
5+ years	8%	13%	13%
Number of Season Pitches	505 (300)	1334 (284)	2360 (203)
Dominant Humeral Retrotorsion	8.2 (12.6)	9.8 (12.2)	5.1 (14.0)
Dominant Internal Rotation	34.5 (11.5)	36.3 (10.8)	36.5 (10.2)
Dominant External Rotation	127.4 (10.5)	126.1 (11.6)	126.5 (11.4)
Dominant Horizontal Adduction	-2.1 (12.7)	-0.2 (12.5)	0.8 (10.9)
Non-Dominant Humeral Retrotorsion	25.6 (12.9)	26.7 (13.0)	23.8 (14.2)
Non-Dominant Internal Rotation	47.7 (10.5)	48.6 (10.8)	48.1 (10.6)
Non-Dominant External Rotation	118.4 (11.7)	118.0 (11.7)	119.0 (12.1)
Non-Dominant Horizontal Adduction	16.4 (8.6, 24.9)	17.1 (8.3, 24.6)	16.3 (9.5, 26.5)
Humeral Retrotorsion Difference	-17.4 (13.4)	-16.9 (13.5)	-18.7 (13.8)
Internal Rotation Difference	-13.3 (11.9)	-12.3 (11.3)	-11.7 (8.9)
External Rotation Difference	9.0 (9.9)	8.1 (9.0)	7.5 (8.6)
Horizontal Adduction Difference	-18.6 (17.1)	-17.2 (17.2)	-15.5 (16.3)

ψ Pitchers potentially played multiple seasons, and could be counted in different pitching seasonal load categories in different seasons

*****Descriptive data is reported as mean (standard deviation) or median (interquartile, range)

6.3.1 Arm injury prediction final model

Final model results are reported in Table 6.3. Of the nine predictors included in the model, all were included following elastic net analyses and optimism shrinkage. Final model development, following elastic net analyses and internal validation, demonstrated a Nagelkerke R^2 of 0.32, calibration slope of 1.05 (95% CI: 0.81, 1.30; Figure 6.2.), and an AUC of 0.74 (95% CI: 0.69, 0.80). Predictors with the highest influence for model development included number of season pitches, HT difference, and BMI. For every number of seasonal pitch count increase between 549 to 1,010 pitches explained an 0.012 increase in log odds arm injury risk (Odds Ratio: 1.01 (95% CI: 1.00, 1.03), $p<0.001$; Figure 6.3.). For every degree increase in HT difference between 17.0 degrees to 25 degrees explained an 0.162 increase in log odds arm injury risk (Odds Ratio: 1.18 (1.01, 1.38), $p = 0.009$; Figure 6.4.). For every point increase in BMI explained an 0.079 increase in log odds arm injury risk (1.08 (95% CI: 0.98, 1.19), $p = 0.084$). The mean distribution of the final model linear predictors was 1.543, the standard deviation was 0.950, the minimum was -3.538, and the maximum was 1.711.

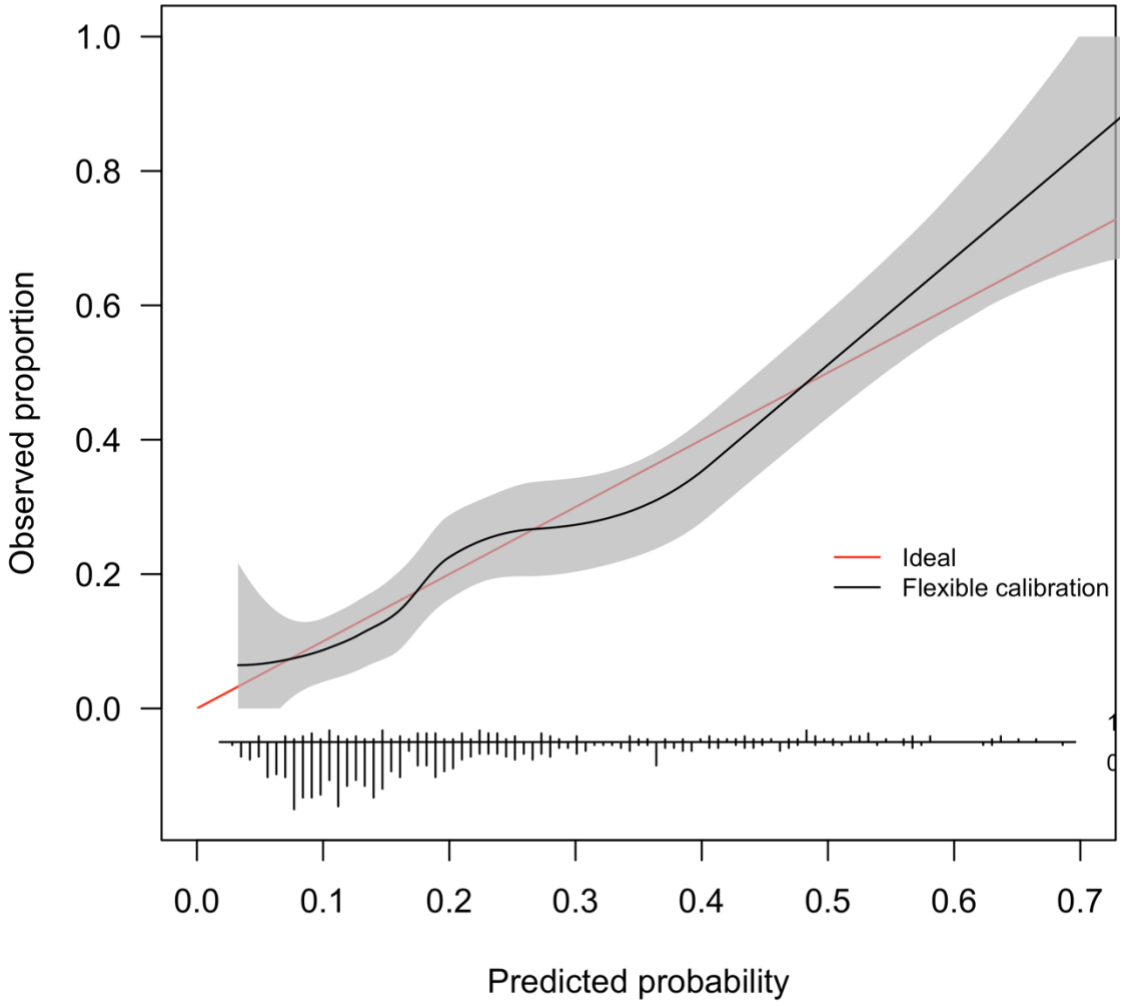


Figure 6.2. Calibration Plot Following Elastic Net and 10-Fold Internal Validation. Calibration the relationship between predicted and actual probability of the event. Perfect calibration would be a 45-degree line. There is a slight over prediction of injury risk between 0.2 to 0.4 predicted probability, and an under prediction of arm injury risk above 0.6 predicted probability.

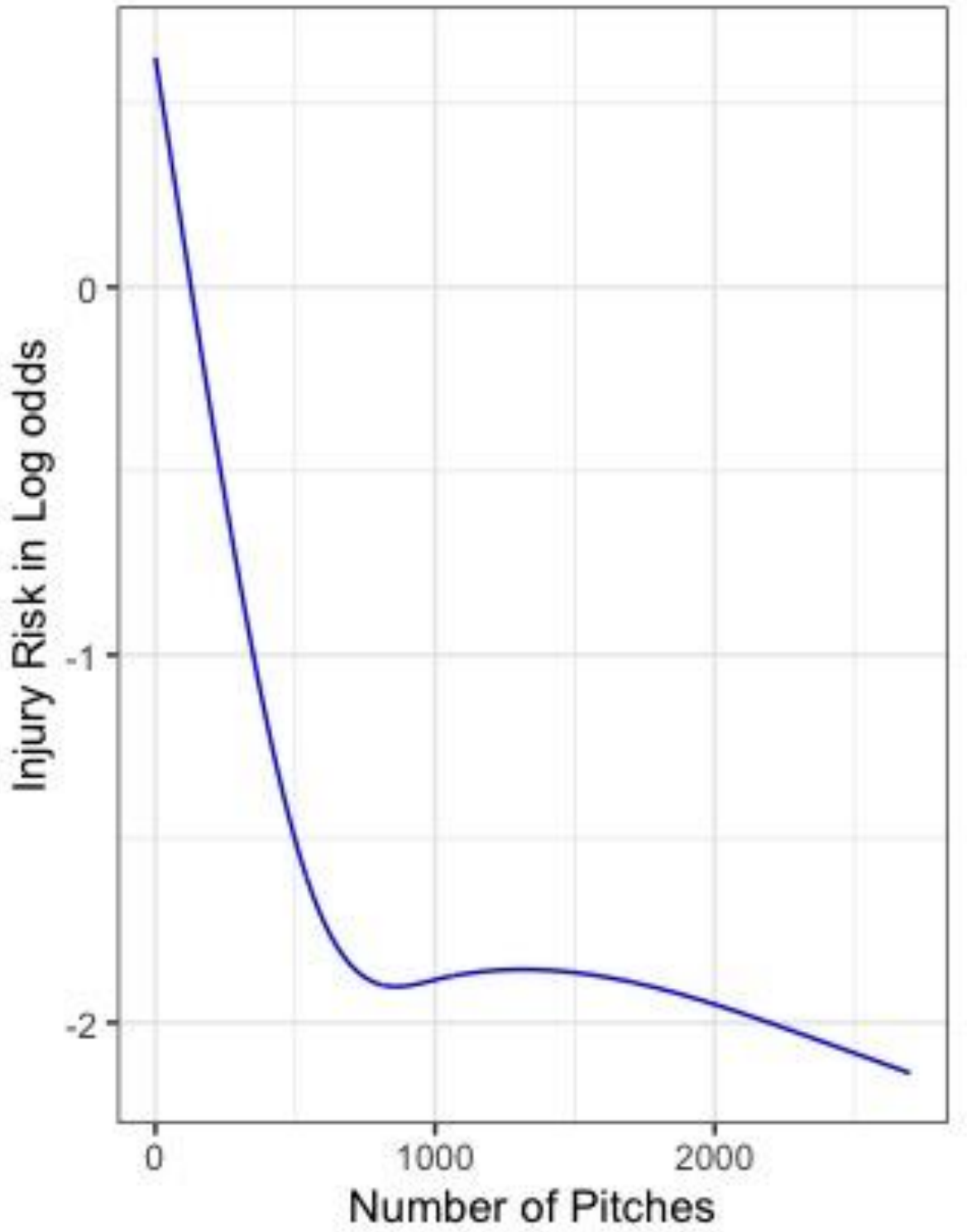


Figure 6.3. Non-linear relationship between number of pitches in a season and arm injury risk. Greater log odds is equivalent to greater arm injury risk and lower log odds (i.e. more negative) is less arm injury risk. As the number of seasonal pitches reaches 550 pitches, arm injury risk decreases. Injury risk slightly increases between 550 and 1010 pitches and arm injury risk further decreases as season pitch count reaches 2000 pitches.

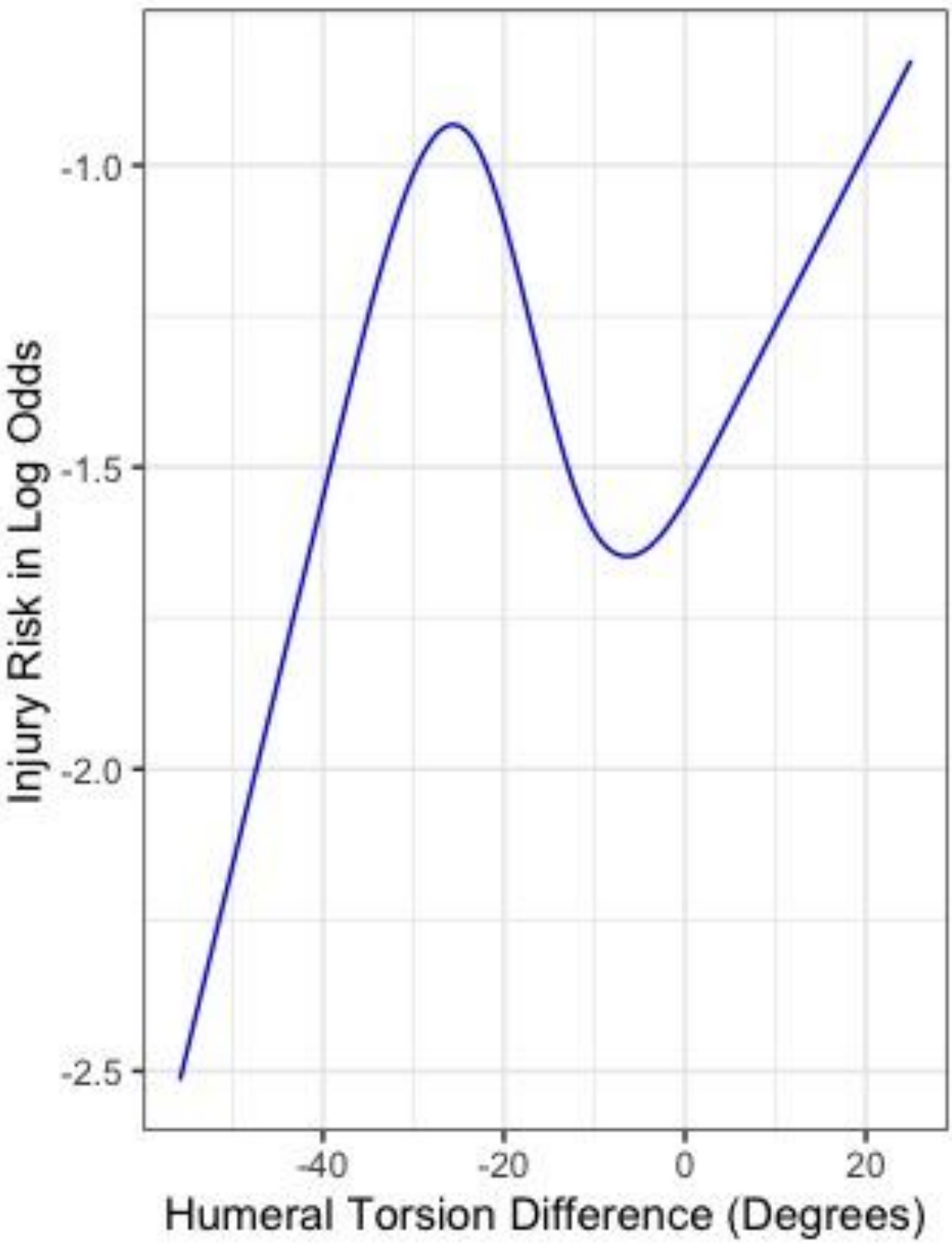


Figure 6.4. Non-linear relationship between dominant and nondominant humeral torsion difference and arm injury risk. Greater log odds is equivalent to greater arm injury risk and

lower log odds (i.e. more negative) is less arm injury risk. As humeral torsion difference reaches -23 degrees, arm injury risk increases. Arm injury risk decreases as humeral torsion reaches -8 degrees. Arm injury risk again increases as humeral torsion risk passes 0 degrees.

Table 6.3. Summary of Final Prediction Model for Arm Injury in Professional Pitchers

Predictor	Log Odds	Standard Error	P-Value
Intercept	-3.273	3.489	0.339
Body Mass Index	0.084	0.050	0.084
Arm Dominance (Right)	0.355	0.344	0.311
Year Played Professionally (3-4 years)	0.307	0.251	0.197
Year Played Professionally (5+ years)	-0.183	0.445	0.711
Professional Season (2015+)	-0.418	0.248	0.088
Number of Season Pitches (Knot 2: 52 to 548 pitches)	-0.005	0.001	<0.001
Number of Season Pitches (Knot 3: 549 to 1,010 pitches)	0.020	0.007	<0.001
Number of Season Pitches (Knot 4: 1,111 to 2,378 pitches)	-0.040	0.017	0.001
Humeral Torsion Difference (Knot 2: -38.5 to -25.9 degrees)	0.053	0.032	0.061
Humeral Torsion Difference (Knot 3: -25.8 to -12 degrees)	-0.214	0.092	0.007
Humeral Torsion Difference (Knot 4: -11.9 to 3.9 degrees)	0.850	0.323	0.005
Dominant Total Range of Motion (Knot 2: 144.5 to 161.7 degrees)	0.022	0.019	0.200
Dominant Total Range of Motion (Knot 3: 161.8 to 181.7 degrees)	-0.029	0.025	0.195

Dominant Horizontal Adduction (Knot 2: -15.2 to -3.2 degrees)	-0.018	0.019	0.313
Dominant Horizontal Adduction (Knot 3: -3.1 to 14.9 degrees)	0.030	0.027	0.268

6.3.2. Sensitivity analyses

A total of 63 primary elbow injuries were observed for the 2009-2020 seasons. Final model development demonstrated calibration slope of 1.00 (95% CI: 0.75, 1.28; Figure 6.5.) and an AUC of 0.81 (95% CI: 0.74, 0.87). Predictors with the highest influence for model development included number of season pitches, HT, and TROM. For every total number of season pitches increase between 549 to 1,010 pitches explained an 0.030 increase in log odds elbow injury risk (Odds Ratio: 1.03 (95% CI: 1.01, 1.05), p = 0.002). For every degree increase in TROM between 144.5 degrees to 161.7 degrees explained an 0.104 increase in log odds elbow injury risk (Odds Ratio: 1.11 (95% CI: 1.03, 1.18), p = 0.003). The mean distribution of the final model linear predictors was -2.76, the standard deviation was 1.34, the minimum was -6.92, and the maximum was 1.69.

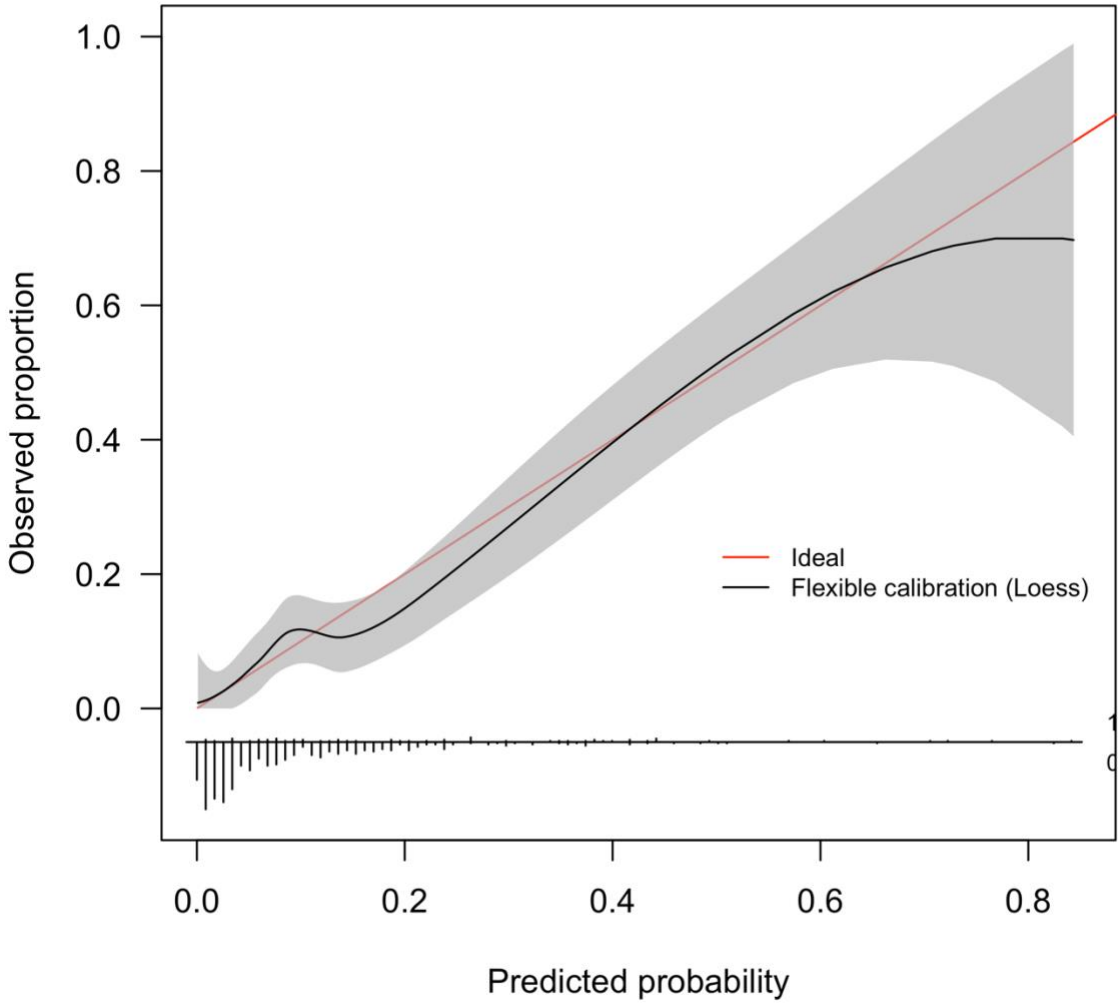


Figure 6.5. Calibration Plot for Elbow Injury Sensitivity Analysis. Calibration the relationship between predicted and actual probability of the event. Perfect calibration would be a 45-degree line. There is a slight over prediction of elbow injury risk between 0.2 to 0.4 predicted probability, and an over prediction of elbow injury risk above 0.7 predicted probability.

A total of 86 primary shoulder injuries were observed for the 2009-2020 seasons. Final model development demonstrated calibration slope of 1.00 (95% CI: 0.60, 1.41; Figure 6.6.) and an AUC of 0.66 (95% CI: 0.59, 0.72). Predictors with the highest influence for model development were number of season pitches. For every total number of season pitches

increase between 549 to 1,110 pitches explained an 0.099 increase in log odds shoulder injury risk (Odds Ratio: 1.01 (95% CI: 0.99, 1.02), p = 0.197). The mean distribution of the final model linear predictors was -1.96, the standard deviation was 0.60, the minimum was -3.50, and the maximum was 0.02.

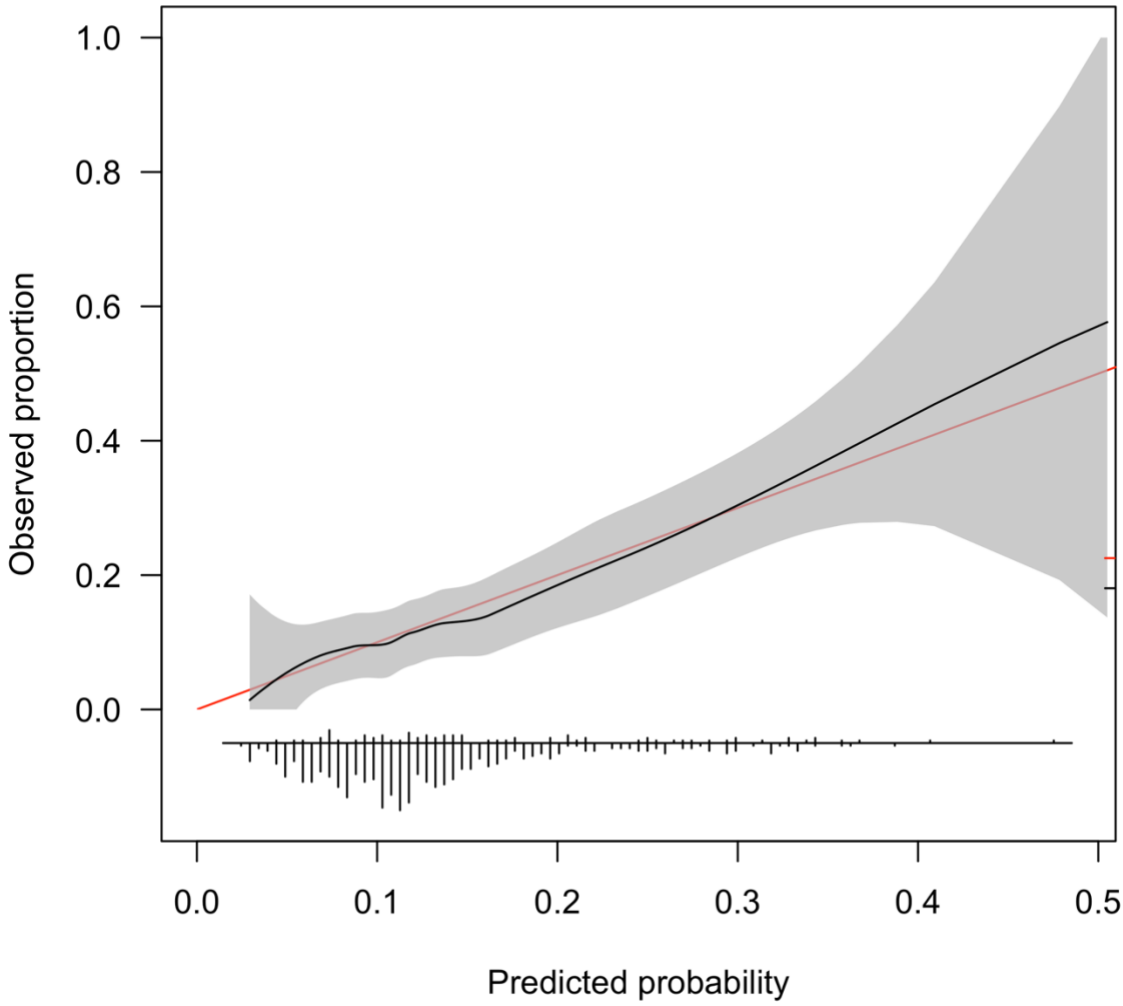


Figure 6.6. Calibration Plot for Shoulder Injury Sensitivity Analysis. Calibration the relationship between predicted and actual probability of the event. Perfect calibration would be a 45-degree line. There is a slight under prediction of shoulder injury risk above 0.3 predicted probability

Mixed effects analyses, with random effects calculated for individual pitchers, demonstrated similar results to original model, prior to internal validation. Final model development demonstrated calibration slope of 1.00 (95% CI: 0.77, 1.24) and an AUC of 0.74 (95% CI: 0.69, 0.80). Predictors with the highest influence for model development included number of season pitches, HT difference, and BMI. For every total number of season pitch increase between 549 to 1,010 pitches explained an 0.030 increase in log odds arm injury risk (Odds Ratio: 1.03 (95% CI: 1.01, 1.04), p<0.001). For every degree increase in HT difference between -38.5 degrees to -25.9 degrees explained an 0.058 increase in log odds arm injury risk (Odds Ratio: 1.06 (95% CI: 0.99, 1.13), p = 0.061). For every degree increase in HT difference between -11.9 degrees to 3.9 degrees explained an 0.900 increase in log odds arm injury risk (Odds Ratio: 2.46 (95% CI: 1.31, 4.63), p = 0.005). For every point increase in BMI explained an 0.086 increase in log odds arm injury risk (Odds Ratio: 1.09 (95% CI: 0.99, 1.21), p = 0.084).

Survival analyses, from seasons 2013 through 2019, reported a total of 84 arm injuries, with a total of 85,270 player days observed. Survival model results were similar to final model results prior to internal validation. Final model development demonstrated a calibration slope of 1.00 (95% CI: 0.80, 1.20) and an AUC of 0.76 (95% CI: 0.70, 0.81). Predictors with the highest influence for model development included number of season pitches and HT difference. For every total number of season pitch increase between 549 to 1,010 pitches explained an 0.020 increase in log of hazard arm injury risk (Hazard Ratio: 1.02 (95% CI: 1.01, 1.03), p = 0.002). For every degree increase in HT difference between -38.5 degrees to -25.9 degrees explained an 0.039 increase in log of hazard arm injury risk (Hazard Ratio: 1.04

(95% CI: 0.98, 1.11), p = 0.061). For every degree increase in HT difference between -11.9 degrees to 3.9 degrees explained an 0.802 increase in log of hazard arm injury risk (Hazard Ratio: 2.23 (95% CI: 1.20, 4.14), p = 0.002).

6.4. Discussion

6.4.1. Summary

The main findings of this study were that the development and internal validation of the multivariable prediction model established good calibration and discriminate abilities. Further, this prediction model demonstrated a pattern of intrinsic and extrinsic non-modifiable and modifiable predictors that influence arm injury risk in professional pitchers.

6.4.2. Clinical Applications

In spring training all athletes within this MLB organization participate in a medical and musculoskeletal physical screening process. From this physical examination, the included predictors were inputted into a prediction model (Figure 6.7.), which produces an overall risk score for each individual athlete (Figure 6.8.). This methodology allows for a more complex account of arm injury risk by mathematically accounting for the interplay of all predictors, instead of the more traditional sports medicine injury risk approach of assessing each individual risk factor.[7,8] Knowledge of the individuals primary risk factors can inform possible treatment interventions and workload management strategies to lower risk over the course of the season. Within this model, the most influential factors included seasonal pitch counts, difference in humeral torsion, and BMI. Further, this model allowed the identification of a functional safe zone for these predictors that demonstrated decreased injury risk for pitchers over a 10-year time frame.

In order to give greater clinical context, the actual results of a pitcher's preseason screening examination are given. The clinical examination findings will then be compared using both the best current evidence-based practice and the prediction model. A right-handed pitcher was entering his third season pitching in professional baseball, reported a BMI of 26 kg/m^2, and did not have history of previous injury. His ROM and HT screening demonstrated symmetrical side-to-side internal, total shoulder rotation, and humeral torsion (0°, 3°, -1° difference), respectively. The pitcher presented with 18° from neutral on the arm horizontal adduction test.

Current best evidence-based practice would disclose low risk for arm injury during the subsequent season.[7,8,517,526,533-535] However, the prediction model reported an 66% increase (risk score = 0.66) in arm injury risk. Individual predictor risk adjustments calculated that the pitcher's symmetrical side-to-side total shoulder rotation, years played, and pitch count would positively impact (decrease) arm injury risk; but that the pitchers arm dominance, BMI, side-to-side horizontal adduction and humeral torsion difference would negatively impact (increase) arm injury risk. This specific pitcher sustained a rotator cuff injury, which resulted in over one month of time loss injury. This pitcher was released in the subsequent spring training due to the rotator cuff injury in the prior season. For this athlete, potential interventions included better management of his posterior shoulder tightness (HA difference),[81] consistent monitoring of his pitch count, and maximizing his rest through increased days between pitching appearances could have decreased the risk and burden of his injury.

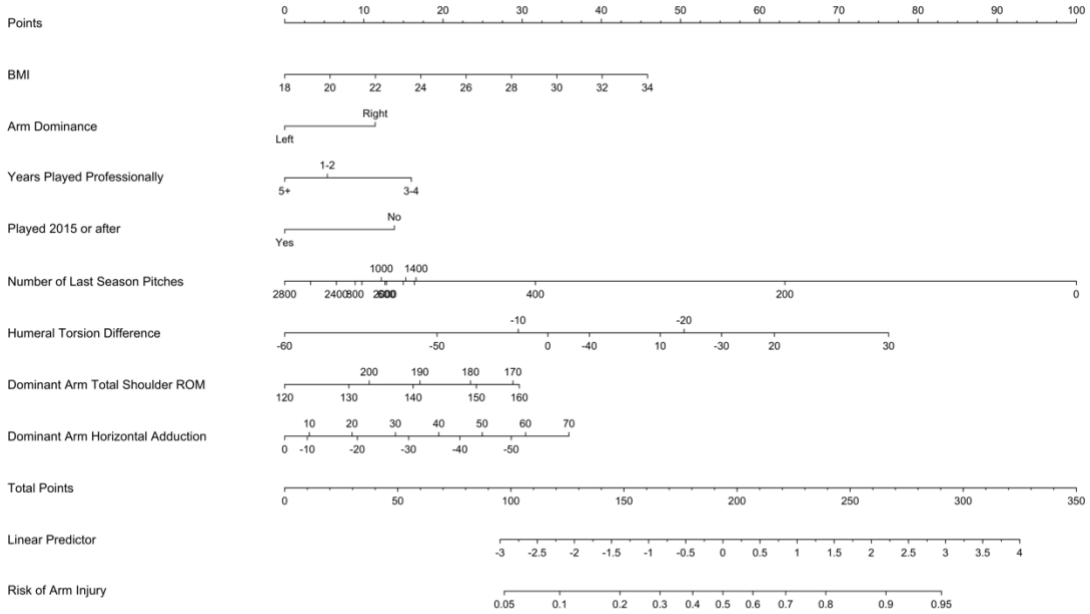


Figure 6.7. Arm Injury Prediction Model Nomogram

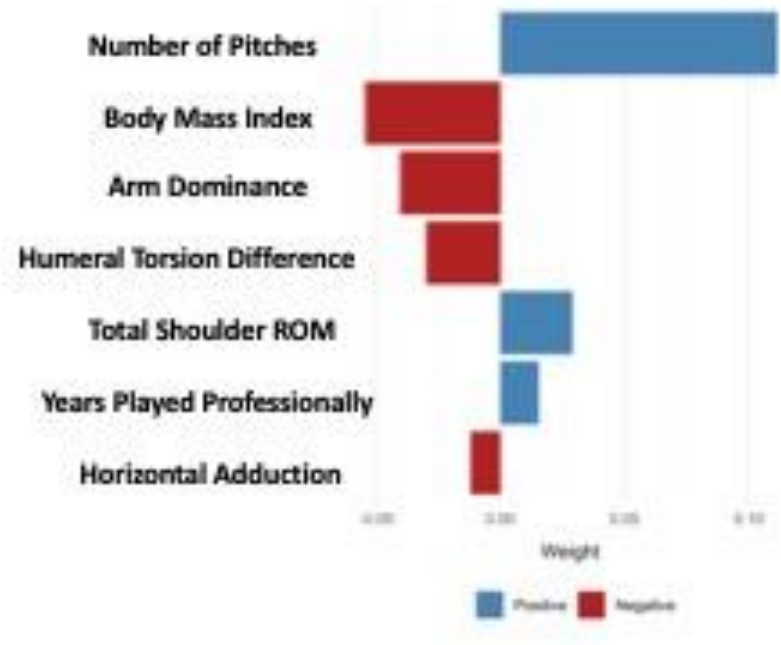


Figure 6.8. Example of an Individual Injury Risk Profile

6.4.3. The Influence of Individual Predictors

This prediction model calculated that every point increase in BMI resulted in an increase in arm injury risk. Overall pitcher anthropometrics have been hypothesized to influence performance, biomechanical stress, and potential for injury.[536] Youth and adolescent pitchers with higher BMI demonstrated greater medial elbow torque with pitching[537]; however, professional pitchers with greater BMI demonstrated decreased elbow stress and reinjury risk after UCL reconstruction.[538,539] BMI is traditionally used as a measure of obesity and hence increased BMI may potentially demonstrate pitchers with greater adipose tissue.[488] Increased fat mass has been related to poor conditioning and baseball arm injuries.[537,540] Another possible contributing factor is increased fat free mass. BMI may not be a good measure of fat mass in athletes[541] and previous literature has postulated that in baseball players, increased fat free mass (i.e. muscle) contribute to greater arm forces, potentially increasing arm injury risk.[488] Future prediction models should potentially incorporate body composition, through both fat and fat free mass, to have greater precision in arm injury risk prediction.

A non-linear relationship was observed between HT and arm injury risk. A specific 'safe zone' was observed for HT difference between -15 to - 8°. The non-linear relationship observed on both sides of this safe zone may be due to the mechanisms of injury for shoulder and elbow. If humeral torsion is too low, a pitcher is more at risk to sustain a shoulder injury due to decreased ability to externally rotate during late cocking. However, if humeral torsion is too great, then late cocking is too high, causing increased stress and increased risk of injury to the ulnar collateral ligament. Humeral torsion has been observed as a risk factor for arm injuries in professional pitchers.[526,527] Differences of greater than 4° between dominant and

nondominant HT have been associated with elbow and shoulder injuries.[526] However, a meta-regression concluded that differences between dominant and nondominant HT was not an arm injury risk factor.[6] However this meta-regression could not account for shoulder ROM, pitch load, and these results had high heterogeneity. While HT is an intrinsic non-modifiable factor, the relationship of HT and shoulder ROM must be considered when designing injury mitigation programs. The previously described meta-regression reported an increase of 0.65 degrees of HT per 1 degree of shoulder IR.[6] As a result, pitchers that demonstrate higher levels of HT difference may have less soft tissue influenced shoulder IR. These pitchers should be carefully monitored for changes in shoulder IR, which may further exacerbate arm injury risk, compared to pitchers with lower levels of HT difference.

Seasonal pitch volume was observed to have a non-linear relationship to arm injury risk. The relationship between seasonal pitch load and baseball arm injury risk has been investigated at all playing standards. Seasonal pitch load has included such metrics as pitching appearances, innings, pitch count per game, and number of pitches within a season with similar results.[521,542-544] Seasonal pitch count load has been positively associated with arm soreness in collegiate pitchers.[542] Other studies have used publicly available records for Major League Baseball (MLB) pitchers to determine the association of pitch load and injury. One study observed that overall pitch load was similar between pitchers who sustained an injury compared to pitchers who did not sustain an injury.[543] Another study concluded that the high variability in pitch load did not allow for an accurate investigation into the relationship between pitch load injury in professional pitchers.[521] Similar to our study, the pitchers throwing the most cumulative pitches had a lower frequency of injury.[521] Additionally, a

portion of injured pitchers threw less than 100 seasonal pitches, further demonstrating the complexity of this extrinsic modifiable factor. Descriptive analyses reported similar results for age, BMI, handedness, shoulder ROM, and HT. Higher seasonal pitch load groups reported a greater prevalence of starting pitchers, and a greater number of years playing within the organization. Starting pitchers may have inherent intrinsic factors that allow for decreased fragility, compared to pitchers who threw less seasonal pitch volume, instead of a direct relationship to overall pitch volume itself (Appendix D.4.). These intrinsic factors are currently unmeasured, and are nascent within the literature. Potential explanations include genetic, physiologic, and muscle quality differences between fragile and non-fragile pitchers. However, these are only speculative and inquiries are needed to investigate these potential relationships.

Shoulder ROM had less impact on model performance compared to seasonal pitch volume, HT, and BMI. Previous literature has observed a strong relationship between dominant and nondominant internal and total rotational ROM differences and arm injury in professional pitchers.[7,517,533-535,545-549] Shoulder dominant versus nondominant IR ROM differences of 5-25°[533,545,546,550] and total rotational ROM (ER+IR) differences of 5-15° have been associated with increased professional pitcher arm injury risk.[7,517,535,550] Current evidence is unclear how the difference of dominant versus nondominant or absolute horizontal adduction (HA) relates to arm injury risk.[487,550] Further, distinct differences in dominant versus nondominant shoulder range of motion ROM has demonstrated different clinical findings for shoulder and elbow injuries.[7,8,43,64] These differences may be due to mechanisms of injury during the pitching motion.[510] However, these studies did not control for nonmodifiable intrinsic factors, such as HT, when calculating arm injury risk. In a meta-regression, for every degree increase

in shoulder ROM was related to 0.65 degrees of HT.[6] As HT influences shoulder ROM,[6] these results suggest that HT is a confounder that impacts the relationship between shoulder ROM and arm injury risk in pitching populations. As a result, clinicians should measure and integrate HT results when performing pitching examinations.

6.4.4. Strengths and Potential Limitations

This study incorporated a 10-year prospective cohort, specifically designed to assess arm injuries in professional pitchers. All data were measured prior to baseball participation, by physical therapists, decreasing measurement bias. Missing data were low, allowing for a complete case analysis, increasing the precision and validity of these findings. This study had sufficient power to develop and internally validate a multifactorial prediction model, increasing the clinical relevance. The prediction model controls for prediction drift (related to the evolution of sports medicine and injury prevention within the sport and within the organization), increasing the precision of this model.

This cohort only evaluated one MLB organization, as each MLB organization has different training and play norms, these results may not be generalizable to other MLB organizations. Only professional baseball pitchers were integrated into this cohort, as baseball players play eight other positions, these results cannot be generalized to other positions such as catcher or outfielder. This cohort included MiLB players from different countries of origin, increasing the generalizability of these findings; however, different countries throughout the world have their own professional baseball leagues. As a result, these findings cannot be generalizable to different professional baseball leagues. These results also cannot be generalizable to lower

playing standards such as college, high school, or middle school baseball, nor generalizable to other overhead athletes such as tennis, softball, or swimming.

Shoulder IR was not included in the final prediction model. Shoulder IR is the most studied injury risk factor in baseball.[7,72] However, only a limited number of predictors could be included in the model. Prior to final model completion, three *a priori* prediction models were created, with one using shoulder IR instead of shoulder TROM. No differences were found in model performance. From a review of the literature, clinical reasoning, and discussion with the MLB organization, it was determined that the inclusion of HT difference, shoulder TROM, and HA would more accurately assesses shoulder ROM difference and posterior shoulder tightness while accounting for non-modifiable intrinsic factors compared to shoulder IR. Nevertheless, the exclusion of shoulder IR may decrease the clinical acceptance of this model.

Date of injury was not incorporated into this cohort until 2013, which does not allow for time to injury to be integrated into the model. However, a survival sensitivity analysis was performed to understand the influence of this bias on the results, which observed similar findings. Thus, this specific time to injury bias has a small influence on the precision of estimating injury risk in this cohort. Injury risk profiling and injury prevention strategies were not incorporated into the MLB organization until 2015. As reported in Chapter 5, implementing risk profiling and education attenuates arm injury incidence by 33% in this MLB organization. This change in evaluation and injury prevention strategies was inputted into the model to account for this bias through a binary classification. Using a binary classification has less precision compared to more continuous variable methods such as

inverse probability weighting.[551] However, inverse probability weighting, and other similar methods, were not feasible for this analysis due the assumptions violation.[552] Specifically, all participants must have the opportunity to receive treatment. As this was not possible, using a binary classification was the best option to account for changes in injury mitigation strategies. While there is decreased precision in using a dichotomised method to account for changes in treatment within the professional organisation, this predictor had little influence on the overall model.

Pitchers may have sustained a subclinical injury that did not result in time lost to training, practice, or competition. As previous injury can influence future injury,[506] these subclinical injuries may bias these results toward the null. Pitchers may have also sustained an arm injury coinciding with a lower extremity or trunk injury. These arm injuries may have been marked only as a lower extremity or trunk injury, biasing these results towards the null. However, these potential biases may have had minimal effect on these results.
Professional baseball service time was accounted for by creating an ordinal scaled variable. Best practice recommends keeping continuous variables as continuous when designing prediction models.[507] However, within this cohort, no player played more than six years within the organization. These data did not allow for a continuous variable to be implemented into the model, decreasing the precision of this model.

On average, twelve (14%) pitchers a year were not included in this study as they were participating in MLB spring training during data collection. Pitchers that were participating in MLB spring training were higher level pitchers (AAA or AA); but, would play MiLB during the season. The exclusion of these pitchers from the model decreases the overall

power and decreased the generalizability of these results to higher level MiLB pitchers. However, the small proportion of pitchers excluded from data analysis only has a small influence on results.

Pitchers were not considered injured if their season was ended prior to the end of the season due to injury prevention reasons such as reaching their season innings or pitch count limits. Upon inquiry to the MLB organization, sports medicine staff, and data collectors, no pitcher seasons were prematurely ended for injury prevention reasons during data collection. On average one to two pitchers per seasons were given more rest days between starts and/or appearance near the end of the season; but no pitchers ceased pitching within a season. There is a very small potential for immortal time bias due to this issue; however, this bias would not have an effect on prediction results.

Previous injury history was limited to professional baseball seasons and orthopaedic surgery prior to signing a professional baseball contract. Pitchers may sustain injury without undergoing surgery. Previous injury has been observed to increase injury risk.[482] The inability of fully quantifying injury history creates the potential for residual confounding and decreases the precision in injury prediction.

All data were collected at the beginning of spring training. While this increases the feasibility of this project, this methodology may limit the utility of the prediction ability of this model. For example, shoulder ROM can change between pitching appearances and throughout the season.[5] These potential changes in shoulder ROM can affect injury risk,[5,7,72] which could not quantified through this model. While seasonal pitch load was integrated in the model,

previous literature has observed that abrupt changes in the acute on chronic player load can affect injury risk.[553-555] Pitch count attempts to quantify pitching load and fatigue. However, pitch count is only a surrogate effect modifier and cannot quantify pitching intensity or effort, decreasing the precision of this variable to quantify load and of this model. Baseball players may have changes in BMI throughout the season, and in between seasons. Body mass index data were extracted through publicly available means, and could not quantify inter or intra season changes, decreasing the precision of this model. Further, BMI is only one body composition measurement, and has been shown to have a decreased explanation of body composition in athletic populations.[508] Other body composition measurements such as fat free mass and body fat percentage may allow for increased precision in this prediction model. Psychological and biomechanical data were not collected within the professional baseball cohort. Both of these intrinsic factors have previously been observed to relate to baseball arm injuries,[509,510] decreasing the precision and clinical applicability of the arm injury prediction model.

Elbow and shoulder injury risk factors have been previously observed to be dissimilar in professional baseball pitchers.[7,72] Subgroup analyses were performed to understand model precision for elbow and shoulder separately. Shoulder injury prediction demonstrated decreased performance compared to the standard model, while elbow injury prediction was improved compared to the primary model. Shoulder injury definitions are broad, with potential anatomical landmarks included involve the deltoid, acromion, rotator cuff, and scapula. The anatomical heterogeneity in potential shoulder injuries decreases the precision of this model.

Players' salaries and signing bonuses were not included as predictors within the model. The MLB organizations investment in a player may influence the degree in which injuries are rested or rehabilitated. This decreases the precision of these results.

The prediction model was not externally validated, decreasing the generalizability and clinical utility of these models. Before using a prediction model in the clinic, external validation is required.[5] However, prediction model development does not require external validation. Further, internal validation was performed to reduce overfitting.[556] Nevertheless, this prediction model should be used with caution until external validation is performed.

6.4.5. Conclusion

This prediction model demonstrated good discrimination and calibration when examining arm injury risk in professional pitchers. This prediction model may assist clinicians in elucidating the probability of arm injury risk. The interplay of intrinsic and extrinsic modifiable and non-modifiable factors allows for the potential for improved clarity when identifying athletes at risk for injury and intervening for injury risk attenuation. Future studies should attempt to add dynamic analysis of athlete biomechanical, neuromuscular, and environmental factors to add to the real-time application of the model throughout the competition season.

Chapter 7: Development and internal validation of a humeral torsion prediction model in professional baseball pitchers

Nature has only a single path and that path is run but once, and to each stage of existence has been allotted its own appropriate quality

-Marcus Tillius Cicero "On old Age"

Prior Publication:

The body of this manuscript is currently under review.

Bullock GS, Shanley E, Noonan TJ, Kissenberth T, Arnold A, Bailey L, Arden NK, Collins GS, Thigpen CS. Development and internal validation of a humeral torsion prediction model in professional baseball pitchers. Journal of Shoulder and Elbow Surgery.

7.1. Introduction

Professional baseball pitching arm injuries are a significant problem,[9] with players sustaining on average 71 days of time lost per injury.[59] Baseball pitching produces high forces throughout the shoulder,[4,70,71] creating sport specific adaptations that influence shoulder range of motion.[11] Due to the high healthcare and cost burden associated with professional baseball arm injuries,[9,59] sports medicine clinicians have sought to produce effective arm injury physical assessments.[72,557]

Baseball shoulder adaptations effect both the soft tissue and osseous structures, which in turn shifts the total arc of motion in the dominant compared to the nondominant shoulder.[72,73] Soft tissue adaptations influence changes in game and seasonal shoulder range of motion.[5,558] However, despite these acute and sub-acute shoulder range of motion changes,[5,558] shoulder range of motion is constrained by the underlying osseous adaptations, which is termed humeral torsion (HT).[76,559] HT is defined as humeral twisting,[560] with the high posterior forces shear involved in mitigating the natural humeral anteversion that occurs during youth and adolescents.[559] HT adaptations cease at the end of adolescent growth and development causing HT to stabilize by the time baseball players reach the professional ranks.

HT has been found to be an important factor in assessing professional pitcher arm injury risk, irrespective of shoulder range of motion.[6,561] For example, professional pitchers that sustained an elbow injury demonstrated 5 degrees greater HT compared to pitchers that did not sustain an elbow injury.[78] While HT has been determined to be an important factor in assessing baseball arm injury risk,[6,561] current technology hinders clinical examination. Presently, HT can be measured through indirect ultrasound evaluations, which require

expensive equipment and training.[73] However, many sports medicine clinics do not have access to this equipment, impeding baseball arm injury risk examination. One novel method to calculate clinical tests and measures is through prediction modelling.[562] Prediction modelling is a tool that implements statistical methods to calculate a risk or probability.[131] Prediction modelling has been used extensively in clinical medicine,[562,563] and has been shown to improve overall clinical examination and patient outcomes.[564,565] Thus, there is a need to implement prediction model methods to help improve baseball injury examination.

HT has been linked to pitching arm injury risk after controlling for shoulder range of motion.[78] Currently measuring HT uses expensive equipment and requires further training,[559] decreasing the ability of many clinicians to assess HT, which inhibits clinical assessment. Developing a HT prediction model using standard clinical tests and measures can aid clinical baseball arm injury risk examination. Therefore, the purpose of this study was to develop a humeral torsion prediction model in professional baseball pitchers.

7.2. Methods

7.2.1. Study design

Participant recruitment and data collection are described in chapter 4. The entire prospective cohort from 2009 to 2019 were used within this study.

7.2.2. Predictors

Shoulder external (ER) and internal rotation (IR) range of motion (ROM), shoulder horizontal addiction (HA), and injury history were collected and used as predictors in this study. Please refer to chapter 4 for full description of the ROM and injury history collection

methods.

7.2.3. Outcome

The outcome was HT. HT measurement was previously described in Chapter 4.

7.2.4. Statistical analyses

All data was investigated for missingness prior to analyses, using the R package naniar. Missing data was low (Professional Baseball Cohort: Shoulder ROM:3%, age: <1%, HT: 2%, position: 0%); thus, a complete case analysis was performed. Descriptive statistics were reported by mean (standard deviation), median (interquartile range), and frequencies and percentages for categorical variables.

Preliminary analyses

Linearity was not assumed, and thus prior to model development, continuous variables were assessed for a non-linearity in relation to HT. Non-linearity was assessed through restricted cubic splines at three, four, and five knots, through the R package rms.[566] It was observed that there was linear relationship for age, shoulder IR, shoulder ER, and shoulder HA. Interactions between shoulder ROM, between shoulder ROM and handedness, and shoulder ROM and continent of origin were assessed. No interaction relationships were observed during the preliminary analyses.

Sample size considerations

An *a-priori* sample size calculation was performed prior to model development. Continuous outcome prediction model sample size calculations involve specifying four step components,

the mean outcome value, the outcome standard deviation, overall null model variance (R^2), and number of parameters (degrees of freedom) potentially included in the model.[155] Using a previously published meta-analysis and meta-regression on HT in baseball pitchers, a mean HT of 27.5 degrees, with a standard deviation of 3.8 degrees was used to determine data variability.[6] The averaged variability explained by IR, ER, and HA concerning HT from the meta-regression was a Nagelkerke R^2 of 0.38.[6] Within the professional baseball prediction model, it was determined that a potential total of ten parameters would be utilized to predict HT. It was determined that a minimum of 244 participants would be needed to create a HT prediction model for the professional baseball cohort with low risk of overfitting. The R package *pmsampsize* was used to calculate the sample size needed to develop a prediction model using continuous outcome.[155]

Model development: primary analysis

Reporting of the model development followed the transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) recommendations.[531] A generalized linear regression model, using restricted cubic splines was performed to predict HT. Predictor variables included: (1) age, (2) arm dominance (Left or Right handed), (3) shoulder IR, (4) shoulder ER, (5) shoulder HA, (6) continent of origin (North America or Latin America), (7) previous shoulder or elbow injury. Internal validation to correct for optimism was performed by bootstrapping with 2000 iterations. Optimism corrected prediction model performance was assessed through root mean square error (RMSE), Nagelkerke R-Squared (R^2), and calibration.[562] Calibration is the agreement between predicted and actual values. Calibration was assessed by calculation the calibration slope with 95% confidence intervals and graphically plotting the actual versus the predicted

outcome. A calibration slope of one is equal to perfect calibration and is graphically depicted as a 45-degree line. A calibration slope above one (greater than a 45-degree line graphically) depicts a prediction model that under predicts values and a calibration slope below one (below 45-degree line graphically) over predicts values. Sensitivity analyses were performed with linear regressions using all predictors for dominant and nondominant shoulder. All analyses were performed in R version 3.5.1 (R Core Team (2013). R: A language and environment for statistical computing. The caret package was used to perform bootstrapping.

7.3. Results

A total 407 MiLB pitchers with a mean age of 23.2 year (sd = 2.4), BMI of 25.1 km/m^2 (sd = 2.3), and 17% were left handed were eligible and included (Table 7.1.).

Table 7.1. Pitching Demographics

	Professional Pitchers (n = 407)
Age (years)	23.2 (2.4)
Hand Dominance Left Right	 17% 83%
BMI (kg/m2)	25.1 (2.3)
Arm Injury History Prevalence	43%
Dominant Humeral Torsion	8.3 (12.9)
Dominant Internal Rotation	35.5 (11.3)
Dominant External Rotation	126.8 (12.7)
Dominant Horizontal Adduction	-1.4 (12.6)
Nondominant Humeral Torsion	25.6 (13.0)
Nondominant Internal Rotation	48.1 (10.6)
Nondominant External Rotation	118.2 (11.6)
Nondominant Horizontal Adduction	-1.4 (12.6)

*All shoulder range of motion and humeral torsion measures are reported in degrees

7.3.1. Professional baseball prediction model

Final model results are reported in Table 7.2. Final model RMSE was 11.86, Nagelkerke R^2 was 0.41, and calibration was 1.00 (95% CI: 0.94, 1.06; Figure 7.1.). Predictors with the highest influence for model include shoulder IR, shoulder ER, shoulder HA, and arm dominance. For every degree increase in shoulder IR explained an increase of 0.37 degrees of HT (0.37 (95% CI: 0.31, 0.43), $p < 0.001$). For every degree increase in shoulder ER explained a decrease of 0.30 degrees of HT (-0.30 (95% CI: -0.35, -0.24), $p < 0.001$). For every degree increase in shoulder HA explained an increase of 0.31 degrees of HT (0.31 (95% CI:0.26, 0.36), $p < 0.001$). Right handed pitchers demonstrated a decrease of 1.83 degrees of HT compared to left handed pitchers (Right Handed: -1.83 (95 CI: -3.67, 0.01), $p = 0.034$). The mean distribution of the final model linear predictors was 16.81 degrees, the

standard deviation was 9.95 degrees, the minimum was -19.00 degrees, and the maximum was 46.86 degrees.

Table 7.2. Summary of Final Prediction Model for Humeral Torsion in Professional Pitchers

Predictor	Beta Coefficients	Standard Error	P-Value
Intercept	33.01	5.28	< 0.001
Age	0.15	0.15	0.333
Arm Dominance (Right)	-1.83	0.94	0.034
Shoulder Internal Rotation	0.37	0.03	< 0.001
Shoulder External Rotation	-0.30	0.03	< 0.001
Shoulder Horizontal Adduction	0.31	0.02	< 0.001
Continent of Origin (Latin America)	0.35	0.91	0.692
Continent of Origin (Asia)	-2.09	1.46	0.585
Previous Shoulder or Elbow Injury	0.30	0.71	0.681

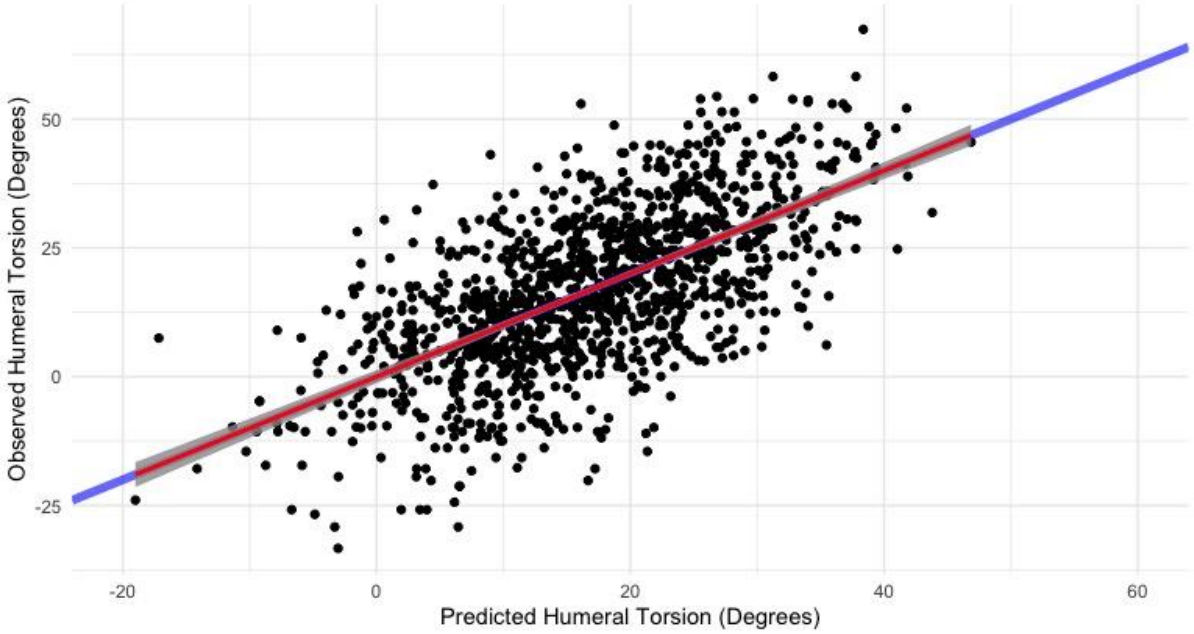


Figure 7.1. Professional Baseball Calibration Plot Following Bootstrapping with 2000 Iterations. The blue line represents perfect calibration, while the red line represents actual calibration.

7.3.2. Sensitivity analyses

Dominant Humeral Torsion. Final model RMSE was 11.89, Nagelkerke R^2 was 0.17, and calibration was 1.00 (95% CI: 0.84, 1.16) (Figure 7.2.). Predictors with the highest influence included shoulder IR, shoulder ER, shoulder HA, and arm dominance. For every degree increase in shoulder IR explained an increase of 0.34 degrees of HT (0.34 (95% CI: 0.25, 0.43), $p < 0.001$). For every degree increase shoulder ER explained a decrease of 0.12 degrees of HT (-0.12 (95% CI: -0.21, -0.03), $p = 0.007$). For every degree increase in shoulder HA explained an increase of 0.15 degrees of HT (0.15 (95% CI: 0.07, 0.23), $p < 0.001$). Right handed pitchers demonstrated a decrease of 3.82 degrees of HT compared to left handed pitchers (Right Handed: -3.82 (95% CI: -6.30, -1.38), $p = 0.002$). The mean

distribution of the final model linear predictors was 1.54 degrees, the standard deviation was 0.95 degrees, the minimum was -3.54 degrees, and the maximum was 1.71 degrees.

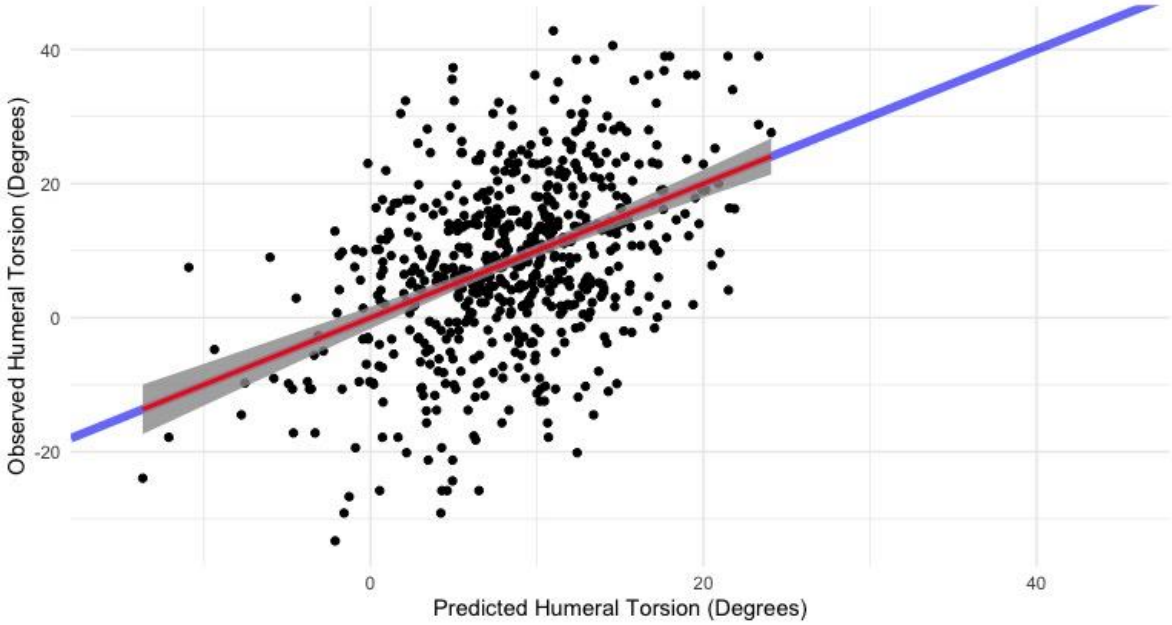


Figure 7.2. Dominant Humeral Torsion Professional Baseball Calibration Plot Following Bootstrapping with 2000 Iterations. The blue line represents perfect calibration, while the red line represents actual calibration.

Nondominant Humeral Torsion. Final model RMSE was 11.27, Nagelkerke R^2 was 0.24, and calibration was 1.00 (95% CI: 0.87, 1.13) (Figure 3). Predictors with the highest influence for included shoulder IR, shoulder ER, and shoulder HA. For every degree increase in shoulder IR explained an increase of 0.30 degrees of HT (0.30 (95% CI: 0.21, 0.39), $p < 0.001$). For every degree increase in shoulder ER explained a decrease of 0.32 degrees of shoulder HT (-0.32 (95% CI: -0.41, -0.23), $p < 0.001$). For every degree increase in shoulder HA explained an increase of 0.25 degrees of HT (0.25 (95% CI: 0.17, 0.33), $p < 0.001$). The mean distribution of the final model linear predictors was 1.54 degrees, the standard deviation was 0.95 degrees, the minimum was -3.54 degrees, and the maximum was 1.71 degrees.

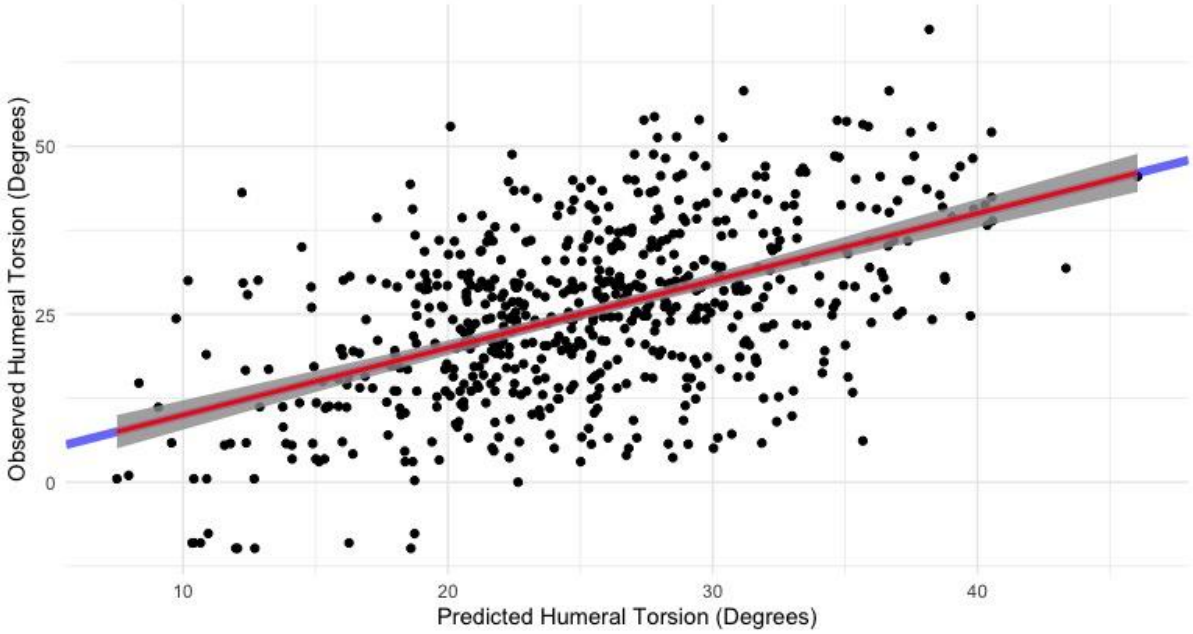


Figure 7.3. Nondominant Humeral Torsion Professional Baseball Calibration Plot Following Bootstrapping with 2000 Iterations. The blue line represents perfect calibration, while the red line represents actual calibration.

7.4. Discussion

7.4.1. Summary

The main findings of this study were that the prediction model demonstrated good performance. Predictors with the most influence in HT prediction were shoulder IR, ER, HA, and arm dominance. One degree increase in shoulder IR resulted in 0.37 degree increase in HT, while one degree increase in shoulder ER resulted in a 0.31 degree decrease in HT. Shoulder HA demonstrated similar findings compared to shoulder IR. Interestingly, right handed dominant pitchers demonstrated decreased HT compared to left handed dominant pitchers. These results suggest that clinicians can use these this prediction model equation to infer HT, potentially improving professional baseball physical examination.

7.4.2. Prediction model performance

The prediction model demonstrated a calibration of 1, with narrow confidence intervals. Calibration assesses the prediction versus the actual outcome, and a calibration slope of 1, with minimal derivation from the ideal 45-degree line, demonstrates excellent calibration. The model explained 41% of HT variance, suggesting that other factors may influence HT prediction. While no previous HT prediction models are within the literature, a previous study used regression analysis to investigate the variance explained by clinical measures.[76] While this study observed similar variance (46%), the previous study incorporated dominant HT as a predictor.[76] When excluding contralateral HT, model R^2 was significantly decreased (36%).[76] This is in contrast to our study which did not incorporate HT, since clinicians using this model will not have access to HT measurement, potentially increasing the clinical utility of this model. Model RMSE was 11.86, which is above the HT standard error of measure in professional pitchers of 2.3 degrees.[559] Further, HT differences of greater than 5 degrees

between dominant and nondominant limbs has been associated with greater elbow and shoulder injuries in professional pitchers.[78] RMSE was reported in degrees, suggesting that the prediction model error is potentially a clinically significant error. An almost 12 degree difference could potentially alter clinical decisions.[73] However, HT is only one factor incorporated in context with other clinical tests and measures[72,93,567] when determining appropriate clinical interventions.[81] Thus, the prediction HT should be used in conjunction with other clinical assessments in determining the individualized plan of care and interventions for the baseball athlete.

7.4.3 The relationship between intrinsic factors and humeral torsion

Both shoulder IR and ER demonstrated a significant influence on HT prediction performance, which supports previous literature.[6,76] As stated previously, baseball throwing during osseous growth and development attenuates humeral anteversion, affecting shoulder rotation range of motion.[75] It is thus not surprising that both shoulder IR and ER influenced HT. However, this model demonstrated a decreased relationship between shoulder IR and HT compared to a previous meta-analysis (0.37 vs 0.65).[6] These discrepancies may be due to the meta-analysis incorporated high school, college, and professional baseball pitchers into one analysis. While no HT differences were found between competition levels, this meta-analysis reported high heterogeneity, and these results were advised to be interpreted with caution.[6] Shoulder HA was also a significant factor in predicting HT. One previous study observed a moderate association between HA and HT.[559] HA is a cross body clinical test and does not directly measure shoulder rotation, but posterior shoulder tightness.[559,568,569] HT may impact posterior shoulder soft tissue and capsule positioning, demonstrating a clinical association between HT and HA.[559,568]

Right handed pitchers demonstrated decreased HT compared to left handed pitchers. Within professional baseball, on average, right handed pitchers throw at greater velocities compared to left handed pitchers.[570] As pitching velocity increases, greater force is transferred through the shoulder and elbow.[4] Greater posterior shear stress transmitted to the humeral epiphysis during adolescents may further mitigate humeral anteversion.[75] While beyond the scope of this study, it can be inferred that professional pitchers that throw at higher velocities, throw at greater velocities during adolescence. The potentiality for pitching velocity to further impact HT is further supported by the sensitivity analyses. Right handed pitchers demonstrated even greater decreases in dominant HT compared to left handed pitchers; however, hand dominance was not a significant factor in nondominant HT prediction. Clinicians should consider hand dominance when examining baseball pitchers.

7.4.4. Clinical Example

To aid in clinical applicability a brief clinical example is detailed. A right-handed pitcher professional pitcher is clinically examined at the beginning of spring training. During examination it is observed the pitcher's right shoulder has 35 degrees of shoulder IR, 111 degrees of shoulder ER, and 7 degrees of shoulder HA. Examining the pitcher's medical records, the pitcher is 24 years old, does not has a previous shoulder or elbow injury, and was born and raised in the United States. These data are then inputted into the equation: 33.01 (The Intercept) + 25*0.15 (Age) – 1.83 (Right-Handed) + 35*0.37 (IR) - 111*0.30 (ER) + 7*0.31 (HA) + 0 (North America) + 0 (No Injury History). The model predicts that this pitcher's right HT is 16.8 degrees. This equation can be inputted into an Excel spreadsheet or basic computer programs for ease of use within individual and/or team evaluations.

7.4.5. Future research

These results illuminate further research needs. HT can be influenced by throwing velocity and overall baseball throwing exposure.[76] Further research is required to understand how baseball exposure and throwing velocity impact HT. While not significant, continent of origin was assessed within this model. Future investigations are needed to understand potential continent of origin phenotype differences between baseball players. Other genetic phenotype components such as collagen and osseous morphology need to be considered when creating future prediction models. Investigating how this prediction model influences clinical assessment and decisions in real world practice is also needed.

7.4.6. Strengths and potential limitations

This study incorporated an *a priori* sample size calculation, with prediction model power exceeding minimal required power, improving the precision of these results. Current best practice methodological recommendations were utilized,[531] increasing the transparency and repeatability of this study. Internal validation was performed with bootstrapping, allowing for a realistic optimism corrected model estimate.

As osseous growth and development continues into adolescence,[75] these findings are not generalizable to youth and adolescent baseball players. These findings may be generalizable to college baseball pitchers, as most adults males have discontinued osseous growth by the time of reaching college.[6,76] However further study is required through transportation validation to examine the potential for the generalizability of this model to the collegiate ranks. These results are also not generalizable to other overhead athlete populations such as swimming, softball, or tennis. Previous research has observed that different overhead athlete

populations demonstrate dissimilar HT measurements.[571] Further, shoulder rotation velocities are dissimilar between different overhead athlete populations, potentially altering the overall exposure to high shoulder rotational forces,[71,571] further altering the potential for HT differences between sport populations.

Shoulder range of motion can change between pitching appearances throughout the season.[5] This study methodology did not allow for in season shoulder range of motion measurements. As shoulder ROM was observed to play an influential role in predicting HT, the inability to measures shoulder ROM throughout the season, and potential changes in shoulder ROM, decreases the clinical interpretability and utility of this model.

Pitchers may have sustained a subclinical injury that did not result in time lost to training, practice, or competition. As previous injury can effect shoulder ROM,[557] these subclinical injuries may bias these results toward the null. Pitchers may have also sustained an arm injury coinciding with a lower extremity or trunk injury. These arm injuries may have been marked only as a lower extremity or trunk injury, biasing these results towards the null. However, these potential biases may have had minimal effect on these results.

Previous injury history was limited to professional baseball seasons and orthopaedic surgery prior to signing a professional baseball contract. Pitchers may sustain injury without undergoing surgery. The inability of fully quantifying injury history creates the potential for residual confounding and decreases the precision in these models.

Professional baseball player baseball exposure during adolescence was not investigated. A previous study observed that throwing exposure during adolescent growth and development can influence HT.[76] The inability to quantify this exposure decreases the precision of these models.

Fastball velocity during was not evaluated, nor was fastball velocity recorded from adolescence. While no literature has evaluated the influence of fastball velocity on HT during growth and development nor into adulthood, the high shear forces upon the humerus initiated during throwing has demonstrated an influence on HT.[76] It is theoretically conceivable that increased throwing and pitching velocity may further attenuate humeral anteversion. Thus, the exclusion of pitching velocity may decrease the precision of the model.

Genetic factors were not evaluated for this study. Genetic factors such as collagen synthesis and osseous replication effect human morphology.[572] These genetic factors may play a role in specific HT adaptations, potentially providing further individual variation information. The exclusion of these factors decreases the precision of this model.

While this model exceeded sample size calculations, potentially allowing for a split sample training and testing approach, this was unadvised due to the sample homogeneity. Specifically, this sample was from one cohort of MiLB pitchers, from one organization. HT is also not affected by temporality, following the cessation of growth and development.[6] Previous methodological research has concluded that a split sample training and testing approach in a homogeneous sample decreases the efficacy and ability to generalize the model

compared to utilizing the entire data set for development internal validation.[139,186,187] As a results, external validation is required to evaluate the generalizability of these models.

Clinical utility and clinician translation was not evaluated. Prediction models are complex mathematical algorithms that require research and statistical training to understand. The feasibility and clinical translation of these models is imperative for proper clinical implementation. Following external validation, clinical translational and utility studies, using both quantitative and qualitative methods, are needed to identify the barriers and potential strengths in model implementation.

7.4.7. Conclusion

The prediction model demonstrated good humeral torsion prediction performance. However, the model RMSE was above the standard error of measure and above previous literature increased arm injury risk thresholds. For every degree increase in shoulder internal rotation explained an increase of 0.37 degrees of humeral torsion. For every degree increase in shoulder external rotation explained a decrease of 0.30 degrees of humeral torsion, and every degree increase in shoulder horizontal adduction explained an increase of 0.31 degrees of humeral torsion. Right handers demonstrated 1.86 degrees less humeral torsion compared to left handed. This prediction model can be used by clinicians to infer HT using standard clinical test and measures. These data can be used to potentially enhance professional baseball arm injury examination. External validation and clinical utility and translational studies are required prior to clinical implementation.

Chapter 8: Assessing the clinical benefit of an arm injury prediction model in professional pitchers compared to current evidence based practice: A decision curve analysis

It is impossible to begin to learn that which one thinks one already knows.

-Epictetus

8.1. Introduction

Professional baseball arm injuries are a significant problem, with injury incidence ranging from 0.7 to 3.6 injuries per 1000 athlete exposures.[336] Baseball injuries result in considerable cost,[56] lost work days,[41,56] and have potential long-term health consequences.[36,112] In order to help reduce baseball injuries, clinical tests and measures have been developed.[7,72,477] These clinical tests and measures have been incorporated into the physical examination and clinical decisions, becoming a part of standardized evidence based practice.[573]

The current baseball best evidence based practice is focused on shoulder range of motion.[7,72,477] A deficit in shoulder range of motion of the dominant compared to the nondominant shoulder has been significantly related to arm injury risk.[7,72,477] For example, professional pitchers with a deficit of greater than five degrees in their dominant compared to nondominant total shoulder range of motion were 2.6 times more likely to sustain an elbow injury.[7] Currently, baseball evidence based practice is focused on evaluating each specific physical factor in isolation.[7,8,43,64] Therefore, the complex interaction of multiple risk factors are unclear and may inhibit clinical examination, prevention strategies and decision making. One method to take into account the multi-factorial nature of injuries is through clinical prediction models. Prediction models are tools that can aid in clinical decision making,[531] and are used widely in various clinical settings.[574-576] However currently, prediction models have not been incorporated into sports medicine generally, or baseball specifically.

While prediction models can take into account the complex nature of clinical examinations,[531] a prediction model only has clinical value if it improves health outcomes.[192] While clinical accuracy, relationships to health outcomes, or significance of clinical tests and

measures are important steps in developing improved clinical examination, these analytical methods do not assess the true impact on patient outcomes or clinical decisions.[192,193] For example, common calculations such as sensitivity and specificity, which can then be used to calculate area under the curve (AUC), can measure overall test accuracy on a specific sample. While improved clinical test accuracy is desirable, it is not apparent what is the threshold accuracy required to impact clinical examination and ultimately clinical decisions.[564]

Decision analyses are another way to evaluate the impact of tests and measures on patient outcomes and clinical decisions. Decision analyses denotes possible clinical actions and consequences and evaluates the implications of these clinical actions across a threshold of probabilities.[577] A common decision analysis example is a decision tree, which classifies every possible decision and consequence, and then assigns a benefit probability for each potential decision.[577,578] While this method accurately quantifies each potential decision, decision trees are time consuming to compile, and difficult to interpret.[564]

A potential solution to this decision analytical problem is to define clinical decisions on a continuous scale, defining the best outcome as one and the worst outcome as zero.[564] Clinical decisions based off of tests and measures, such as prediction models, can then be calculated for overall potential benefit on a continuous scale.[193,565] A continuous scale allows for a direct test and measure comparison. Such comparisons can then analyze overall testing burden (prescribing unnecessary tests) and the improvement in allocation of resources, or in other words, the overall clinical impact.[564]

One method to assess clinical impact is through net benefit.[193,565] Net benefit calculates benefits and harms on the same scale, allowing for a direct comparison.[564] In other words, the net benefit directly assesses if a clinical test or measure, "does more harm than good." Net benefit can be compared to a treat all approach (i.e., assume every patient has the disease or will sustain an injury), treat none (i.e., wait until a patient has the disease or sustains an injury), and also other clinical decisions, such as current evidence based practice.[564] The formula to calculate net benefit is:[564]

*P denotes probability of disease

$$\frac{\text{True Positive Count} - \text{False Positive Count} \times (P / 1 - P)}{\text{Total Sample Size}}$$

This is equated to:[564]

$$\text{Sensitivity} \times \Pi - (1 - \text{Specificity}) \times (1 - \Pi) \times (P / 1 - P)$$

It should be noted that the treat all approach (i.e., assuming every patient has the disease or will sustain an injury) constitutes a perfect (i.e., 100%) sensitivity. The benefit of treating every patient is equivalent to the disease prevalence. As the disease prevalence decreases, the net benefit will also reduce, due to increasing the harm in prescribing clinical tests and measures (i.e., prescribing unnecessary tests). Further, net benefit ("good versus harm") calculations can also be equated to a cost benefit ratio (reported as Cost:Benefit). The cost benefit is in relation to the acceptable risk for an outcome. The cost benefit can be explained as the number of patients a clinician is willing to prescribe a test or measure to identify one patient with the outcome (i.e., disease or injury). A cost benefit of 1:4 would equate to a risk

0.2, or in other words, for every 5 patients tested, one patient would be identified with the outcome.[193,564,565]

To clarify net benefit with a brief example, the net benefit could be calculated to assess the number of correctly identified pitchers who will sustain an ulnar collateral ligament injury, without misidentifying pitchers as not at risk for injury, who go onto sustain an ulnar collateral ligament injury. Using a prediction model, the net benefit is calculated as 0.50, at 0.25 risk (cost benefit of 1:3). This is compared to the treat all approach for ulnar collateral ligament injury, which the net benefit was calculated as 0.25, at 0.25 risk (cost benefit of 1:3). The prediction model demonstrated a 0.25 net benefit improvement (0.50 versus 0.25) compared to the treat all approach, at 0.25 risk. In other words, the prediction model would improve resource allocation by 25 pitchers for every 100 pitchers evaluated, compared to the treat all strategy.

While calculating the net benefit of one particular injury risk is important,[194,565] within sport, injury risk varies between different teams, competition levels, and individual pitchers.[336] As a result, the net benefit of a prediction model must be analyzed over a range of thresholds.[564] These analyses are performed through decision curves.[138] A decision curve analyzes the net benefit through a range of risks, and depicted through graphical and numeric representation (Please refer for Figures 8.1-8.3 for graphical examples).[138] Within a decision curve, the x-axis depicts a range of risks and the subsequent net benefit. The y-axis represents the net benefit. The decision curves illustrate the net benefit through *a priori* defined risk thresholds. Decision curves have been used extensively in clinical research, to demonstrate the clinical utility of using prediction models.[192,563]

The negative impacts of baseball injuries have substantial monetary and healthcare ramifications.[41,56] Decision curve analysis incorporates the impact of clinical decisions; thus, allowing for the ability to quantify the net benefit of different baseball injury risk and prevention methods.[193,565] Currently, it is unclear what is the net benefit of current evidence based practice, nor novel prediction models. Therefore, the purpose of this study was to determine if a pitching arm injury prediction model improves clinical decision making in professional baseball pitchers in comparison to current best evidence based practice.

8.2. Methods

8.2.1. Study design

Participant recruitment and data collection are described in chapter 4. The entire prospective cohort from 2009 to 2019 were used within this study.

8.2.2. Statistical analyses

All data was investigated for missingness prior to analyses. Missing data was low (Shoulder range of motion: 3%, age: <1%, position: 0%), thus complete case analyses were performed. Participant statistics were described using mean (standard deviation) for continuous normally distributed variables, median (interquartile range) for non-normally distributed continuous variables, and frequencies and percentages for categorical variables.

A logistic regression was used to predict the occurrence of a time loss arm injury.[181] Predictor variables included: BMI, professional baseball years played (1-2, 3-4, 5+ years), upper extremity dominance (Left or Right handed), year of data collection (2009-2014, 2015-2019), total number of pitches, humeral torsion difference (dominant shoulder – nondominant

shoulder), dominant shoulder total range of motion (internal rotation + external rotation), and dominant shoulder horizontal adduction. Non-linearity of BMI, total number of pitches, humeral torsion differences, dominant shoulder total range of motion, and dominant shoulder horizontal adduction was assessed through restricted cubic splines.[566] Elastic net was used to reduce the risk of overfitting[181], where the tuning parameters (alpha and lambda) were obtained through tenfold cross-validation with ten iterations per fold, with best tuning parameters identified through the greatest Kappa. Internal validation of the prediction model was then performed using tenfold cross-validation to obtain optimism-adjusted measures of model performance. Prediction model performance was assessed through calibration and discrimination. Calibration was assessed by calculation the calibration slope with 95% confidence intervals, (where a slope < 1 suggests that estimated risks are too extreme, i.e., too high for individuals who are at high risk and too low for individuals who are at low risk, whilst a value > 1 suggests the opposite), and graphically plotting the actual versus the predicted outcome.[579] Discrimination was evaluated by the Area Under Receiver Operating Characteristic Curve (AUC), where a value of 0.5 indicates the model is no better than random predictions, whilst a value of 1.0 indicates the predictions from the model perfectly discriminate those with and without injury.

Decision curve analyses were performed to determine whether incorporating the arm injury prediction model into clinical practice improved pitcher outcomes.[138,194] The net benefit is the fraction of true positives gained by making decisions based on predictions over a range of plausible risk thresholds.[138,192,194] Within this study, the *a priori* threshold probability was defined as the population risk of arm injury within professional baseball.[9,336] As arm injury risk can vary between baseball players, the net benefit was calculated through a range of

predicted risks. Specifically, professional baseball injury incidence ranges from 15% to 30% from the literature.[9,336] After further consultation with key professional baseball sports medicine stakeholders, the risk threshold was *a priori* defined as 0.15-0.30. The net benefit of the prediction model was then compared through decision curve analyses to assume all are at high risk ('treat all') and assume all are at low risk ('treat none').[194,564] Further, the prediction model net benefit was compared to current baseball evidence based practice guidelines.[7,441] Specifically, the prediction model was compared to pitching injury risk profiling of greater than ten degrees difference between dominant and non-dominant shoulder total range of motion (internal rotation + external rotation)[7] and less than neutral (0 degrees) of shoulder horizontal adduction.[441] All analyses were performed in R version 3.5.1 (R Core Team (2013). R: A language and environment for statistical computing. The *rms* and *Hmisc* packages were used prediction model development, the caret package was used for internal validation, and the *rmda* package was used for decision curve analyses and plotting.

The reporting of the study followed the Transparent Teporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) reporting guideline.[531]

8.3. Results

A total 407 MiLB pitchers were included (Age: 23.2 (2.4) years, BMI: 25.1 kg/m^2 (2.3), Left Handed: 17%), with a total of 141 primary arm injuries (Table 8.1.). A total of 527, 922 pitches were thrown from 2009-2019 seasons. The prediction model exhibited a calibration slope of 1.05 (95% CI: 0.81, 1.30) and an AUC of 0.74 (95% CI: 0.69, 0.80). For full description of prediction model, please refer to Chapter 6.

Table 8.1. Pitching Demographics

	All Pitchers (n = 407)	No Arm Injury (n = 266)	Arm Injury (n = 141)
Age (years)	23.2 (2.4)	23.2 (2.2)	23.0 (2.2)
Hand Dominance			
Left	17%	17%	82%
Right	83%	83%	18%
BMI (kg/m^2)	25.1 (2.3)	25.0 (2.3)	25.3 (2.5)
Pitching Position			
Starter	44%	61%	56%
Reliever	56%	39%	44%
Years within the Organization			
1-2 years	73%	(71%)	61 (54%)
3-4 years	22%	(23%)	40 (36%)
5+ years	5%	(6%)	11 (10%)
Dominant Humeral Torsion	8.3 (12.9)	8.1 (11.5)	9.4 (11.5)
Dominant Internal Rotation	35.5 (11.3)	35.7 (10.8)	34.8 (10.8)
Dominant External Rotation	126.8 (12.7)	126.8 (10.1)	127.1 (10.1)
Dominant Horizontal Adduction	-1.4 (12.6)	-1.6 (14.1)	-0.6 (14.1)

*Humeral torsion and shoulder range of motion measurement are reported in degrees

At an aggregated team arm injury risk between 15-30%, the prediction model demonstrated greater net benefit (Table 8.2, Figure 8.1). For pitchers at an aggregated 20% team injury risk, assuming ‘treat all’ (i.e., all pitchers were at a high risk for injury) demonstrated a 0.06 net benefit, compared to 0.21 net benefit for the prediction model. This indicates that for

every 100 pitchers, the prediction model would improve resource allocation by 15 more pitchers as compared to the 'treat all' strategy. Similarly, at an aggregated 25% team injury risk, assuming 'treat all' (i.e., all pitchers were at a high risk for injury) demonstrated a negative net benefit of -0.26 (compared to 'treat none'), when the 'treat all' strategy was compared to the prediction model (net benefit of 0.07), the overall improvement of 0.33 was realized. This means that for every 100 pitchers the prediction model would improve resource allocation by 33 pitchers compared to the 'treat all' method.

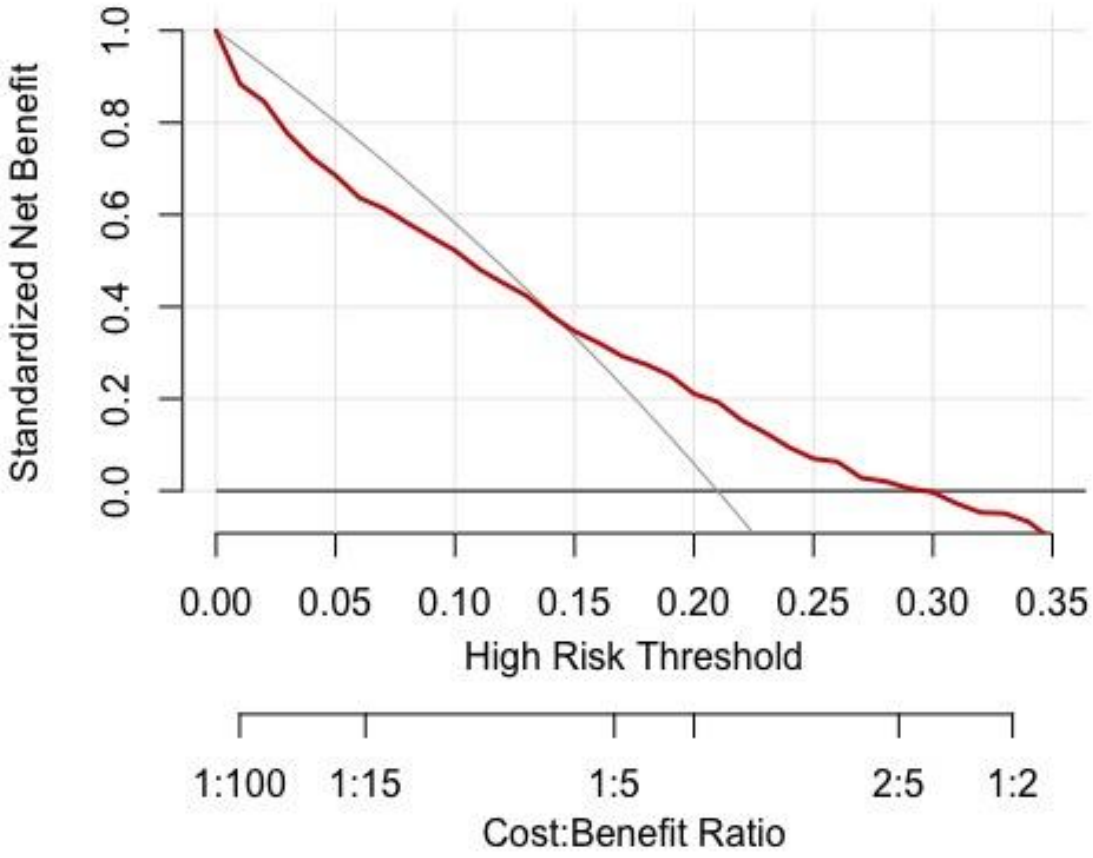


Figure 8.1. Decision curve for a prediction model to predict arm injury risk in professional baseball pitchers. Red line: Prediction Model. Light Grey Line: Treat All. The figure reports the expected net benefit compared to not treating any patients. Treat all assumes that all

pitchers are at a high risk for injury and should be intervened upon, while treat none assumes that all pitchers are at a low risk for injury and no interventions should be performed.

The current baseball evidence based practice guidelines of risk profiling demonstrated similar net benefit compared to the 'treat all' (i.e. all pitchers were at a high risk for injury) strategy up until aggregated 19% team arm injury risk, and improved net benefit compared to the prediction model until aggregated 15% team arm injury risk (Table 8.2.; Figure 8.2.; Figure 8.3.). At an aggregated 20% team arm injury risk, the prediction model demonstrated an improved net benefit compared to the total shoulder range of motion risk factor treatment of 0.08, or out of 100 pitchers the prediction model would improve resource allocation by eight pitchers compared to the total shoulder range of motion risk factor treatment, and an improved net benefit compared to shoulder horizontal shoulder adduction risk factor of 0.22, or out of 100 pitchers, the prediction model would improve resource allocation by 22 pitchers compared to the horizontal shoulder adduction risk factor method. At an aggregated 25% team arm injury risk, the prediction model demonstrated an improved net benefit compared to the total shoulder range of motion risk factor method of 0.03, or out of 100 pitchers the prediction model would improve resource allocation by 4 more pitchers compared to the total shoulder range of motion risk factor method, and an improved net benefit compared to horizontal shoulder adduction risk factor method of 0.08, or out of 100 pitchers, the prediction model would improve resource allocation by 8 pitchers compared to the horizontal shoulder adduction risk factor method.

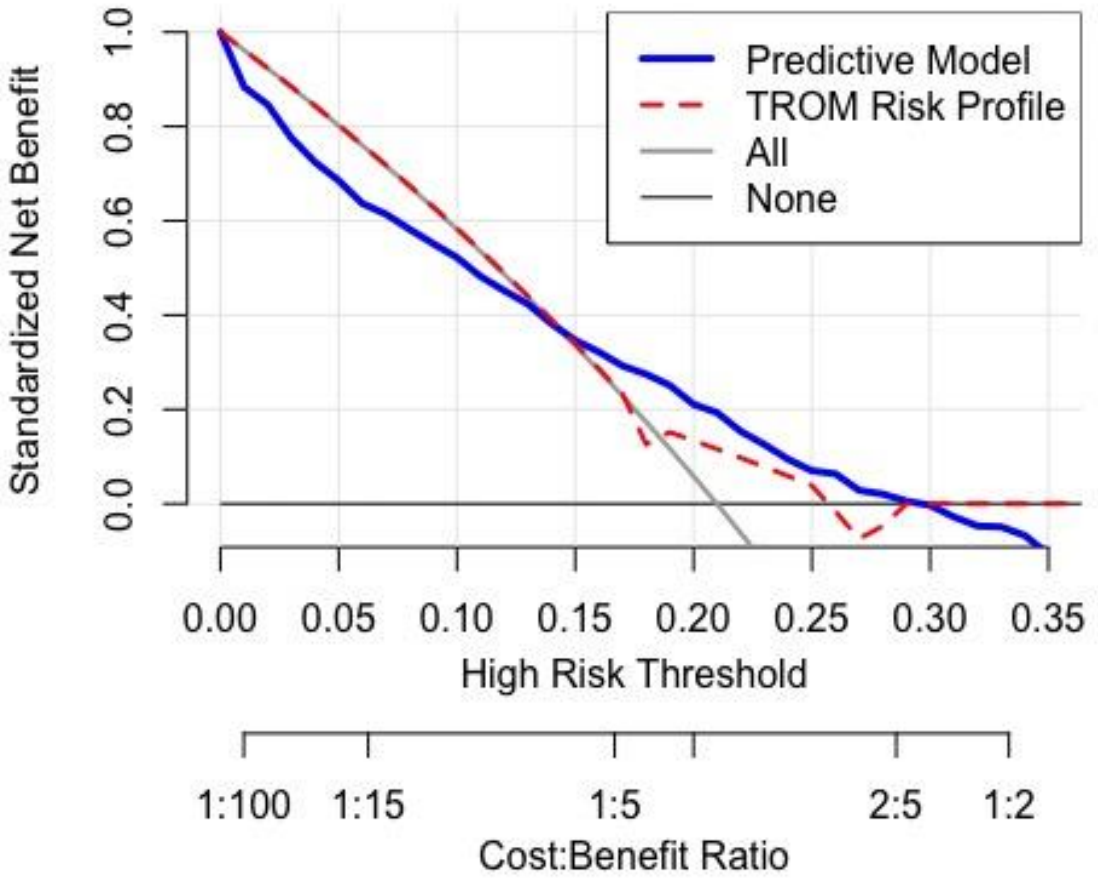


Figure 8.2. Decision curve for a prediction model to predict arm injury risk in professional baseball pitchers. The figure reports the expected net benefit compared to not treating any patients. TROM demonstrates baseball evidence based practice for injury risk identification. TROM = Total Range of Motion (Internal + External Shoulder Rotation). Treat all assumes that all pitchers are at a high risk for injury and should be intervened upon, while treat none assumes that all pitchers are at a low risk for injury and no interventions should be performed.

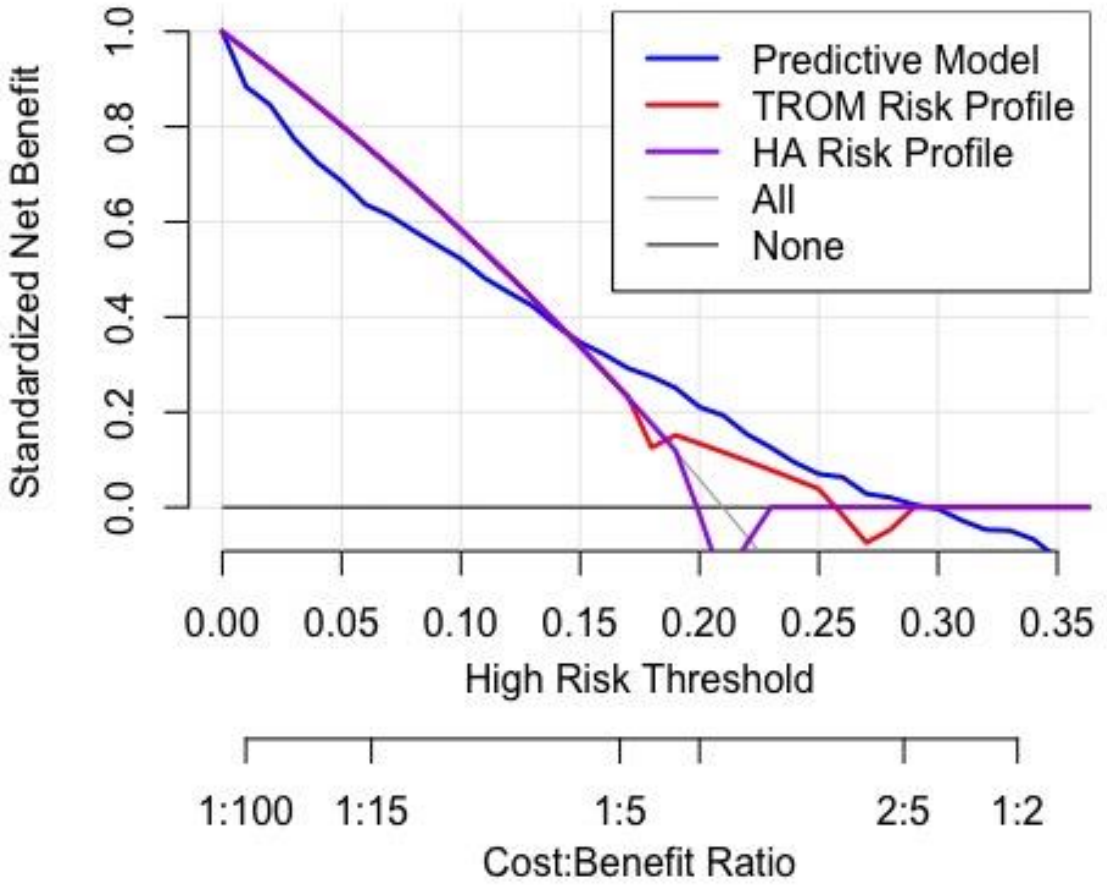


Figure 8.3. Decision curve for a prediction model to predict arm injury risk in professional baseball pitchers. The figure reports the expected net benefit compared to not treating any patients. TROM and HA demonstrate baseball evidence based practice for injury risk identification. TROM = Total Range of Motion (Internal + External Shoulder Rotation). HA = Horizontal Shoulder Adduction. Treat all assumes that all pitchers are at a high risk for injury and should be intervened upon, while treat none assumes that all pitchers are at a low risk for injury and no interventions should be performed.

Table 8.2. Net benefit of professional pitcher injury risk identification using a treat all approach, a prediction model, or current baseball evidence based practice

Injury Risk	Cost:Benefit	Treat All	Prediction Model	Total Range of Motion Risk Profiling	Horizontal Adduction Risk Profiling	Treat None
0	0:1	1.00	1.00	1.00	1.00	0.00
0.05	0:19	0.80	0.69	0.80	0.80	0.00
0.10	1:9	0.58	0.52	0.58	0.58	0.00
0.15	3:17	0.34	0.35	0.34	0.34	0.00
0.20	1:4	0.06	0.21	0.13	-0.01	0.00
0.25	1:3	-0.25	0.07	0.04	0.00	0.00
0.30	3:7	-0.61	0.00	0.00	0.00	0.00
0.35	7:13	-1.02	-0.11	0.00	0.00	0.00

Table Note: Net benefit is the net of false negatives and thus is the reduction in sports medicine resources utilized without a decrease in the number of pitchers who are incorrectly identified as sustaining an arm injury within a season. Treat all assumes that all pitchers are at a high risk for injury and should be intervened upon, while treat none assumes that all pitchers are at a low risk for injury and no interventions should be performed.

8.4. Discussion

8.4.1. Summary

The most important findings of this study were that the prediction model demonstrated improved net benefit compared to treat all and current best evidence based practice for the *a priori* defined 15-30% arm injury risk thresholds. These results suggest that the professional pitcher arm prediction model improves arm injury identification and clinical net benefit compared to treating all patients or current evidence based practice. Using the arm injury prediction model to identify which pitchers would most benefit from arm injury prevention appears to be an improved approach to enhance organizational resource allocation and reduction of arm injury risk.

8.4.2. Comparison of net benefit between the injury prediction model, treat all and current best evidence base practice

The current prediction model exhibited improved net benefit in comparison to the treat all and current best evidence based practice for injury risk of 15% to 30%. Previous baseball injury risk and injury identification studies have focused on statistical significance or clinical differences between groups.[7,64,72] However, establishing clinical relevance of different clinical test and measures (such as range of motion or strength) or clinical tools (such as a prediction model) must be able to establish that the findings can categorize athletes into different distinct subgroups.[192] Further, clinical context requires that clinical decisions be based off of overall prevalence or risk of the desired outcome.[193,194] While athlete categorization has been previously established in baseball players through risk profiling strategies, [7,72,73] most notably with shoulder range of motion deficits,[7,64,72] the overall clinical context and net benefit has not been evaluated. Professional pitcher baseball arm injury risk

ranges from 15% to 30% within a given season.[9,336] Within this context, the predictive model demonstrated improved net benefit compared to the treat all or current best evidence based practice. Specifically, the predictive model had an improved net benefit of 0.08 at 20% injury risk and 0.03 at 25% injury risk. In other words, the predictive model would correctly identify 8 more pitchers, out of 100, who would sustain an injury within a season compared to current evidence based practice risk profiling, and 3 more pitchers, out of 100, at 20% and 25% injury risk respectively.

As stated above, clinical usefulness must be evaluated in context of the clinical setting.[193,194] The prediction model demonstrated decreased net benefit compared to the treat all and current best evidence based practice when injury risk was below 15%. While pitching injury risk is above this threshold, other baseball players have lower arm injury risk. For example, position players, especially infielders and outfielders have lower arm injury risk,[9] decreasing the clinical utility of this prediction model. It is recommended from this clinical context that clinicians implement current best evidence practice, in the form of shoulder range of motion risk profiling, when evaluating injury risk in position players.

The prediction model demonstrated improved net benefit compared to best current evidence based practice at the *a priori* prescribed risk thresholds of 15-30%. However, the prediction model demonstrated 0 net benefit beginning at 0.30 risk. Further, the treat all and best current evidence based practice approaches also demonstrated a net benefit of 0 beginning at 0.30 risk. When clinically evaluating a pitcher, a clinician at the professional baseball level will likely have identified pitchers at a high risk for injury (risk > 0.30). It is advised if a prediction model risk score is calculated above 0.30, the clinician should assume that the

pitcher is at high risk for injury and proceed with further physical examinations, and potentially create an individualized plan of care to mitigate arm injury risk.

The observed arm injury risk prediction model net benefit suggests that valuable resources can be targeted towards the pitchers most at risk. For example, right handed pitchers with a high BMI, increased humeral torsion difference, a moderate pitch count, and poor HA would be identified as high risk by the prediction model during preseason, and individualized conditioning and manual therapy interventions would be enacted.[81] Throughout the season, pitch count[498] could be effectively monitored through the prediction model for these at risk pitchers, allowing for improved organizational wide monitoring and titration of pitch load. This is compared to pitchers identified at low risk, which would not require further physical examination or individualized injury prevention strategies. These low risk pitchers could be prescribed general organization wide injury prevention exercises (e.g., basic "arm care"), and the prediction model could be used to effectively monitor pitch load throughout the season. Abrupt changes in pitch load or physical measurements during the season, would change the pitchers' injury risk, instigating further physical examination and/or changes in pitch load. Using the prediction model to account for both modifiable factors including pitch load (i.e., pitch count)[498] and shoulder range of motion, [7,64,72] and non-modifiable factors such as humeral torsion[73] and injury history,[336] increases the potential for improved net benefit,[565] compared to current best evidence based practice within the prescribed injury risk threshold of 15-30% . This prediction model would allow for organization wide improvement in identify injury risk and individualized factors affecting this injury risk for more effective physical examination and interventions.

Future research

These results illuminate the need for future research. Baseball injuries, force production, and overall total games played are dissimilar at different age and competition levels.[71,498,580] Arm injury prediction models and clinical decision curve analyses need to be performed at the youth, high school and collegiate setting. Net benefit is only one factor in assessing clinical utility. This prediction model needs to be implemented in a real-world clinical setting to properly evaluate clinical usefulness. Other clinical measurements such as lower extremity range of motion and balance, and pitching biomechanics can affect arm injuries.[511,581] These clinical measures need to be incorporated into a prediction model to evaluate further prediction precision. The use of prediction models influences injury risk over time,[582,583] these models should be updated after incorporation, requiring the need for continued clinical decision analyses.

8.4.3. Strengths and potential limitations

This study incorporated a large prospective professional baseball cohort over an eleven-year period, which improves the precision of these results. Prediction model development utilized best practice guidelines,[531] improving the transparency and repeatability of the results.

External validation of the prediction model was not performed, decreasing the generalizability of the model. Only one professional baseball organization was included in the study, further decreasing generalizability. The prediction model demonstrated decreased net benefit compared to the 'treat all' and current best evidence based practice when aggregated team arm injury risk was below 15%. While pitching injury risk is above this threshold, other baseball players (such as infielders and outfielders) have lower arm injury

risk. Thus, these findings cannot be generalized to other playing positions. While similar arm injury risk factors have been observed at the high school and college levels,[441,477] these different competitions levels play different number of games per year and generate different levels of force.[71] Thus, these findings cannot be generalized to other baseball competition levels. Different overhead sports have been observed to have some dissimilar arm injury risk factors,[72,584,585] thus these findings cannot be generalizable to overhead sports such as swimming or tennis.

Range of motion can change throughout the season,[5] and seasonal fluctuations in pitching workload can increase injury risk.[586] Including range of motion over the season and a more precise measure of pitcher workload will potentially improve the net benefit of the model.

Players' salaries and signing bonuses were not included in the analyses. Major League Baseball organizations investment in a player may influence the degree of clinical impact of identifying true positive players. This decreases the clinically utility of these findings.

When comparing current best evidence based practice,[7,441] only shoulder range of motion injury risk profiling was incorporated. Other arm injury risk factors have been identified such as rotator cuff strength,[93] dynamic balance,[581] and hip range of motion.[567] However, these data were not available for prediction development nor for decision curve analyses. A more comprehensive decision curve analysis is required to better understand the net benefit differences between the developed prediction model and a comprehensive baseball physical examination.

This study did not evaluate real world clinical integration. but retrospective changes in an organization's use of regularly collected preseason data. Understanding the true clinical utility of this prediction model will involve clinical education, translation, and implementation analyses. These analyses will include both quantitative and qualitative methods to improve the strengths and weakness of this prediction model, concerning clinical implementation. Future studies are required to implement and assess the impact on reducing arm injuries and organizational resource allocation.

8.4.4. Conclusion

The prediction model demonstrated improved net benefit compared to 'treat all' and current evidence based practice at the prescribed 15-30% injury risk thresholds. The prediction model demonstrated decreased net benefit prior to 15% injury risk compared to treat all or current evidence based practice, which may demonstrate decreased clinical utility in baseball players such as outfielders and infielders; however, this was beyond the scope of this study. This prediction model can aid in identifying professional baseball pitchers at risk for arm injuries and improve resource allocation compared to current best evidence based practice. Incorporating the prediction model into clinical practice will likely improve professional baseball injury risk identification.

Chapter 9: Conclusions and Future Research

To arrive in the Rocky Mountains by plane would be to see them in one kind of context, as pretty scenery. But to arrive after days of hard travel across the prairies would be to see them in another way, as a goal, a promised land.

- Robert M. Pirsig "Zen and the Art of Motorcycle Maintenance: An Inquiry into Values"

9.1. Thesis summary and Implications

Chapter 2 found that the majority of baseball research is focused on musculoskeletal injury, and that most orthopaedic surgery research in baseball has concentrated on ulnar collateral ligament reconstruction. Further, baseball players have increased life expectancy, and high tobacco and drug use compared to the general population. However, no studies assessed baseball health and wellbeing across the lifespan, only one study investigated former baseball players, and there are few injury prevention studies.

Chapter 2 indicated that the research gaps in baseball health and wellbeing research are general health and health related quality of life research throughout the lifespan and injury prevention research. Baseball health and wellbeing research across the lifespan would provide information to inform baseball stakeholders (i.e., players, parents, policy makers, administrators, college and professional baseball organizations) of the risks and benefits of participating in baseball. Further, this research would allow for baseball organizations, such as the National Collegiate Athletic Association and Major League Baseball, to identify baseball players at risk for poor health related outcomes following retirement and begin to facilitate research (and ultimately interventions) that help mitigate poor health related outcomes in retired baseball players as they age. Lastly, baseball injury prevention research would help to attenuate injuries in baseball.

In Chapter 3 current and former baseball players reported high smokeless tobacco use and current baseball players reported greater electronic cigarette and energy drink consumption compared to former baseball players. Former baseball players reported a high prevalence of high blood pressure or high cholesterol and current baseball players reported a greater

prevalence of depression. Current and former baseball players reported similar health related quality of life compared to the general population and high flourishing.

These findings are concerning. While baseball has a long and storied history of tobacco use, these data demonstrate that baseball players at the collegiate and professional level may be participating in further unhealthy lifestyle choices that may be affecting health. Further, this cohort of current baseball players was almost exclusively from the collegiate ranks. The higher prevalence of electronic cigarette and energy drink consumption may be suggesting a change in college athlete substance use habits compared to older former baseball players. These Chapter 3 data suggest that tobacco cessation programs should be continued within all levels of baseball. Further, current baseball players reported a higher prevalence of electronic cigarette and energy drink consumption compared to former baseball players. As no baseball organization has banned either of these substances, the National Collegiate Athletic Association and baseball organizations need to consider educating current baseball players on the risks of consumption. Further, these organizations should consider incorporating cessation programs specifically designed for these substances.

Former baseball players reported similar persistent joint pain compared to former cricketers.[113,424] However, the greatest persistent joint pain prevalence was to the shoulder, knee, and elbow, which is disparate compared to past former athlete literature.[113,355,424,425] Former baseball players reported over 95% of shoulder and elbow persistent pain was to their throwing arm, and participants reported clinically significant decreased arm function compared to older total shoulder arthroplasty patients.

It is concerning that the mean age of these former baseball participants was below 40 years old. As people age, persistent joint pain can increase alongside functional decreases.[416] These data suggest that baseball players have a unique joint health disposition that should be considered when evaluating former baseball players. Further, the unilateral use of the dominant throwing arm when playing baseball may increase joint pain and reduce arm function. Baseball organizations should take this into account when educating baseball players as they retire. Specific arm focused interventions should be considered when designing baseball retirement transition programs. Potentially, former baseball players should be provided with semi-annual physical examinations where arm health and function are assessed, possibly helping to mitigate the likelihood of developing persistent pain symptoms and negative health outcomes.

In Chapter 5 injury risk profiling and education demonstrated decreased overall and 7+ day arm injury incidence in professional baseball players by 33%-35%. The results were inconclusive for 28+ day injury incidence. There were no differences in any shoulder ROM measures in preseason, demonstrating that shoulder ROM was similar and comparable for both groups. However, the 2015-2019 seasons demonstrated an increase in shoulder ROM injury risk groups.

Chapter 5 demonstrated that there is an association between injury risk profiling and education and a decreased arm injury incidence in professional baseball players. Preseason screening and injury risk education are easy to implement sports medicine strategies that can be incorporated at every level of play. Further, the use of current best evidence-based practice injury risk guidelines is easy to understand and explain to a wide range of baseball

stakeholders, beyond sports medicine trained professionals. Performing individualized injury prevention strategies, such as shoulder stretching and manual therapy, and limiting pitch load based off the preseason screening process, are commonly used injury prevention strategies. Implementing injury risk profiling and education is advisable within baseball organizations, teams, or individual players when more complex injury risk identification strategies are not available.

In Chapter 6, the arm injury prediction model demonstrated good discrimination and excellent calibration. When stratified by elbow and shoulder injury, the elbow injury prediction model demonstrated improved model performance compared to the primary model and to the shoulder injury prediction model. Sensitivity analyses observed that the survival and mixed effects models demonstrated similar model performance compared to the primary model.

Baseball injuries are complex and hard to predict as demonstrated by the innumerable studies and organizational, team, and individual interventions that have been attempted at all levels of baseball.[43,61-63] However, while this complexity has been a barrier to improving injury outcomes in baseball, past and current methodologies employed to solve this problem have not considered the complex intrinsic and extrinsic modifiable and non-modifiable factors that interplay with baseball arm injuries. Conventional research and sports medicine methodology has utilized in isolation, or in combination, with clinical heuristics and causal factors.[7,8,43,64] Thus, these conventional methodologies have not taken a plausible biological or complex approach to a difficult and complex problem, inhibiting clinical decisions and patient outcomes.

This is the first injury risk model to attempt to account for the complex relationship between arm injuries and intrinsic, extrinsic, modifiable, and non-modifiable factors. Previous baseball studies did not control for non-modifiable confounders that can affect modifiers.[43,61-63] Further, the focus of previous research was on one specific modifiable factor,[7,8,43,64] without accounting for the interdependent relationship of other non-modifiable factors. This work builds off of Meeuwisse et al.[60] and Bahr and Krausshaug[101] theoretical frameworks by including both modifiable and non-modifiable factors. Further, this model included season pitch count in order to control for the positive and negative adaptions to workload, which is based off of the Windt and Gabbett workload-injury aetiology framework.[105]

The multivariable arm injury risk prediction model demonstrated improved performance compared to previous more simplistic attempts at predicting arm injuries in baseball.[557] Further, the difference in dominant and non-dominant humeral torsion, a non-modifiable intrinsic factor, and seasonal pitch load, a modifiable extrinsic factor, were observed to have the greatest influence on injury risk. The non-linear relationship exhibited between these predictors and arm injuries demonstrated that there is a 'sweet spot' in difference in dominant and non-dominant humeral torsion and the number of season pitches. Sports medicine clinicians should consider the interplay between the non-modifiable and modifiable intrinsic and extrinsic factors when designing injury prevention strategies. For example, if the arm injury prediction model designated a pitcher with a large difference in humeral torsion as high injury risk, the sports medicine clinician would need to pay particular attention to shoulder internal rotation, as there would be less 'buffer' for internal rotation loss compared

to another pitcher that had decreased difference between dominant and non-dominant humeral torsion.[6] Further, this pitcher would be at greater at risk for loss in shoulder internal rotation and horizontal adduction during pitch load spikes, as decreased shoulder range of motion is associated with stressful pitching appearances.[5]

In Chapter 7, the professional humeral torsion prediction model demonstrated good predictive performance and excellent calibration. This model explained 41% of the humeral torsion sample variance. The strongest predictors within the model included shoulder internal rotation, external rotation, horizontal adduction, and arm dominance.

As humeral torsion requires expensive equipment and training to measure, inhibiting clinical utility, there is a need for a humeral torsion prediction model. The humeral torsion predictive model is reported as an equation that can be hand calculated or inputted into an excel document. Further, the predictors are derived using standard clinical tests and measures, improving the clinical utility of this model. This predictive model can assist in clinical examination and in measuring humeral torsion which then can be inputted as a predictor for the arm injury risk predictive model.

In Chapter 8, the primary arm injury prediction model demonstrated improved net benefit compared to assuming all patients were at risk for injury and injury risk profiling from 15% to 30% injury incidence. Using the arm injury prediction model to identify which pitchers would most benefit from arm injury prevention appears to be an improved approach to advance organizational resource allocation and reduction of arm injury risk. These data suggest that the arm injury prediction model can be used by clinicians to better identify

baseball pitchers at risk for injury compared to injury risk profiling. Finally, like the humeral torsion prediction model, the arm injury prediction model can be hand calculated or inputted into an excel document. This increases the ease of calculating injury risk for the average clinician.

As discussed within the introduction, baseball is an overhead athlete sport. These findings may have clinical implications to other overhead sporting athletes. Other overhead athlete sports, such as swimming, softball, cricket, and tennis have demonstrated changes in dominant humeral torsion compared to the nondominant arm.[587,588] The influence of humeral torsion on shoulder range of motion, and its implications concerning arm injury, may have clinical transferability in other overhead athlete sports. However, different sports have demonstrated different changes in humeral torsion. As a result, the exact humeral torsion relationships to injury and range of motion may be different compared to baseball. Performing risk profiling and individualized interventions has been performed in a wide variety of sports, with some success.[589,590] While the clinical phenotypes may be different between different overhead athlete sports, the principle of risk profiling may have clinical transferability to other throwing sports such as softball, javelin, and handball.[591] The baseball arm injury prediction model incorporated both modifiable and nonmodifiable factors, and demonstrated improved clinical net benefit compared to current best evidence practice. The specific prediction model algorithm should not be used to detect at risk athletes in other overhead athlete sports due to differences in clinical phenotypes and how throwing load is measured. However, in a previous study in handball, incorporating both modifiable and nonmodifiable factors improved injury risk assessment compared to modifiable factors

alone.[591] Other overhead athlete sports should incorporate both modifiable and nonmodifiable factors into a comprehensive model when assessing arm injury risk.

9.2. Limitations of this research

Scoping reviews are broad in nature and are intended to provide an outline of the literature. However, scoping reviews do not assess the quality of literature, potentially decreasing the interpretability of the results. Only studies written in English were searched, potentially biasing the scoping review results. The majority of included studies were from the United States, as baseball is played throughout the world on several continents, these results may not be generalizable to baseball players playing in other countries.

The baseball health and wellbeing questionnaire was disseminated through list servers and social media. As a result, the response rate cannot be determined, potentially adding selection bias to these results as possibly limiting the generalizability of the results. Baseball players with greater persistent pain and/or decreased function may have been more likely to respond to the survey, potentially disproportionally increasing the prevalence of persistent pain and reducing overall arm function compared to the actual persistent pain prevalence and arm function in this population. Questionnaire participants were asked to recall events from the past, which may produce recall bias, decreasing the precision of these results. Injuries and surgeries, which can confound persistent pain results, may not have been recalled, biasing the relationship of baseball exposure and persistent arm pain and function towards the null. Only computer-generated methods were used in questionnaire recruitment, which may hinder participants who have decreased computer and technological literacy and access from participating, also limiting the generalizability of the results. Older participants may

potentially not have computer access or skills necessary to participate in the questionnaire. Further, these participants are more likely to have persistent joint pain, decreasing the actual persistent joint pain prevalence in these results.

Major League Baseball players, or Minor League baseball players who were participating in Major League spring training were not included in the prospective professional baseball cohort, decreasing the generalizability of these results to all levels of professional baseball. Only one Major League Baseball organization participated in this cohort study. As there are 29 other Major League Baseball organizations, this decreases the generalizability of these findings. However, due to the uniform number of games played, days participating in a season, and the overall homogeneity of the population base, this only a minor limitation. Baseball is played at all playing standards, with this baseball cohort only focusing on professional baseball players. These results cannot be generalized to other playing standards such as college and high school. As college and high school baseball players play a smaller number of games per season, and have limited sports medicine and performance resources compared to professional players, these findings may not be transferable to lower competition levels. Only professional baseball pitchers were integrated into this cohort, as baseball players play eight other positions, these results cannot be generalized to other positions such as catcher or outfielder. Date of injury was not incorporated into this cohort until 2013, decreasing the clinical interpretability of these findings. Intrinsic and extrinsic factors can change throughout the baseball season,[5,16,592] however, only preseason measures were collected, decreasing the clinical interpretability and precision of these findings. As shoulder range of motion can change between starts and throughout the season,[5] and pitch count can vary between pitching appearances and starts, the preseason static nature of this

model inhibits in season usefulness.

Within the interrupted time series analysis, fewer seasons were included in the analysis pre risk profiling and education compared to the intervention group, potentially decreasing the precision of these results. However, a total of seven prospective seasons were included in the interrupted time series analysis, allowing for a large cohort analysis. Shoulder range of motion can change between pitching appearances and through the season,[5] however only preseason shoulder range of motion was collected, decreasing the clinical interpretability of these results. Only orthopaedic surgery history was included prior to signing a professional contract. As musculoskeletal injury that does not involve surgery can affect injury risk, there may be residual confounding.

Both prediction models were not externally validated, decreasing the generalizability and clinical utility of these models. Psychological and biomechanical data were not collected within the professional baseball cohort. Both of these intrinsic factors have previously been observed to relate to baseball arm injuries,[509,510] however there is currently not a consensus on specific psychological and biomechanical factors to potentially include in a prediction model. Nevertheless, the arm injury prediction model demonstrated good discrimination and excellent calibration, the inclusion of these psychological and biomechanical factors may potentially increase the performance and decreasing and clinical applicability of the model. Professional baseball player throwing and baseball playing exposure during adolescence was not collected. Throwing exposure during adolescent growth and development can influence humeral torsion,[76] decreasing the precision of the humeral torsion prediction model. Both of

these prediction models were not assessed for clinician usability nor their efficacy within a clinical setting, decreasing the clinical interpretability of these results.

9.3. Future research

This is the first research to quantify musculoskeletal health and wellbeing of current and former baseball players. As a result, cross-sectional methodology was employed. Future prospective longitudinal research is needed to understand how health related quality of life and persistent joint pain change throughout the lifespan. Further, investigating these longitudinal relationships will facilitate a greater understanding the interplay of musculoskeletal health (persistent joint pain, osteoarthritis, orthopaedic surgery, etc) and wellbeing (health related quality of life, flourishing, etc.) constructs, and how these factors change overtime. If prospective longitudinal research is not feasible, case control studies, evaluating differences between current and former baseball participants, other non-overhead sports such as soccer, and to the general population should be implemented. Deciphering these dynamic constructs throughout the lifespan and/or potential differences between baseball participants and controls can help sports medicine clinicians better identify appropriate interventions for baseball players as they transition to retirement.

The professional baseball prediction model demonstrated good discriminate ability and excellent calibration. However, only preseason and previous season factors were employed in the model. As intrinsic and extrinsic modifiable factors can change between pitching appearances,[5,16] throughout the season,[593-595] and between seasons,[558] future baseball injury prediction models need to account for dynamic changes in shoulder range of motion, body mass, pitch velocity, and pitching load. Specifically, pitching injury prediction models should

account for changes in shoulder internal and external range of motion at the minimum of three season points, seasonal changes in body mass index and body composition, and game to game changes in pitching load. Further, incorporating internal response to competition and training load, through specific psychological constructs such as session rate perceived exertion,[596] would increase the precision and clinical pertinence of these models. Beyond increasing the injury prediction precision, these prediction models require external validation. External validation is recommended through temporal methods (the same Major League Baseball organization at different time points) and through third party methods (other Major League Baseball organization). Transportation validation is also required to understand the generalizability of these models in American college and high baseball settings and in other countries that play baseball.

Once these validation methods have been instituted, clinical applicability and usefulness research is needed. The clinical net benefit and utility of this arm injury prediction model was demonstrated through the decision curve analyses. However, the clinical efficacy of these models is currently not understood. Further, while a basic injury prevention strategy demonstrated improved injury risk over a five-year span, it is unclear if implementing the complex injury prediction model improves injury outcomes within the Major League Baseball organization. A clustered randomized control trial is needed to decipher the clinical impact of implementing this prediction model.

This research is only the beginning of trying to solve this important problem. The future needs in baseball injury research can be best explained by Jiddu Krishnamurti, "*The more*

you know yourself, the more clarity there is. Self-knowledge has no end - you don't come to an achievement; you don't come to a conclusion. It is an endless river."

Updated list of conference abstracts, published papers, and submitted papers

Publications

Chapter 1

Bullock GS*, Hughes T*, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Clinical Prediction Model in Sports Medicine: A Tutorial. Journal of Orthopaedic & Sport Physical Therapy. In Press

*Joint first authors

Bullock GS*, Hughes T*, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Sports Medicine Prediction Models: A Brief Tutorial. British Journal of Sport Medicine. In Press.

*Joint first authors

Bullock GS, Hughes T, Arundale AH, Ward P, Collins GS, Kluzek S. Black box prediction methods in sport deserve a red card: to advance athlete care a substitute is needed. Sports Med. Under Review

Chapter 2

Bullock GS, Uhan J, Harriss EK, Arden NK, Filbay SR. The relationship between baseball participation, health, and wellbeing: A systematic scoping review. Journal of Orthopaedic & Sports Physical Therapy. Feb, 2020;50(2):55-66.

Chapter 3

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Health conditions, substance use, physical activity and quality of life in current and former baseball players. Orthopaedic Journal of Sports Medicine. Under Review

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Tokish J, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Persistent joint pain and arm function in former baseball players. Journal of Should & Elbow Surgery. In Press.

Chapter 5

**Thigpen CS, *Bullock GS,* Noonan TJ, Wyland J, Kissenberth T, Arden NK, Collins GS, Shanley E. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. American Journal of Sports Medicine. Under Review

*Joint first author

Chapter 6

*Shanley E**,** *Bullock GS, Noonan TJ, Wyland J, Kissenberth T, Arden NK, Collins GS, Thigpen CS. Development and application of an arm injury prediction model for professional pitchers. American Journal of Sports Medicine. Under Review

*Joint first author

Chapter 7

Bullock GS, Shanley E, Noonan TJ, Kissenberth T, Arnold A, Bailey L, Arden NK, Collins GS, Thigpen CS. Development and internal validation of a humeral torsion prediction model in professional baseball pitchers. Journal of Should & Elbow Surgery. In Press.

Chapter 8

*Bullock GS, *Shanley E, Noonan TJ, Wylans J, Kissenberth T, Arden NK, Collins GS, Thigpen CS. Assessing the clinical benefit of an arm injury prediction model in professional pitchers compared to current evidence-based practice: A decision curve analysis. American Journal of Sports Medicine. Under Review

*Joint first author

External Oral Presentations

Chapter 2

Bullock GS, Uhan J, Harriss EK, Arden NK, Filbay SR. The relationship between baseball participation, health, and wellbeing: A systematic scoping review. Presented at: Combined Sections Meeting. February 12-15, 2020, Denver Colorado.

Chapter 5

Bullock GS, Shanley E, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Thigpen CA. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. American Orthopaedic Society of Sports Medicine. Specialty Day. July 8-11, 2021.

Thigpen CA, Bullock GS, Shanley E, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. Combined Sections Meeting. February 24-27, 2021.

Chapter 6

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Development and application of an arm injury prediction model for professional pitchers. American Academy of Orthopaedic Surgeons. March 9-12, 2020, San Diego, CA.

Shanley E, Bullock GS, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Thigpen CA. Informing the Avoidance of Arm Injury for Professional Pitchers through Predictive Modelling. Combined Sections Meeting. February 24-27, 2021.

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Canada Sports Physiotherapy Conference. Toronto, Canada. May, 2021.

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Incorporating both modifiable and non-modifiable factors improve injury risk assessment in professional baseball pitchers. Canada Sports Physiotherapy Conference. Toronto, Canada. May, 2021.

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. A multivariable prediction model improves arm injury risk assessment and clinical net benefit in professional pitchers compared to ROM risk profiling alone. American Orthopaedic Society of Sports Medicine. Specialty Day. July 8-11, 2021.

Chapter 7

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Arnold A, Bailer LB, Shanley E. Development and internal validation of humeral torsion prediction model for professional baseball pitchers. Combined Sections Meeting. February 24-27, 2021. Orlando, FL.

Chapter 8

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Incorporating both modifiable and non-modifiable factors improve professional baseball pitch injury net benefit compared to current best evidence-based practice. Canada Sports Physiotherapy Conference. Toronto, Canada. May, 2021.

External Poster Presentations

Chapter 3

Bullock GS, Nicholson KF, Waterman BR, Niesen E, Salamh P, Thigpen CS, Shanley E, Collins GS, Arden NK, Filbay SR. Persistent pain and upper extremity function in former collegiate baseball players: An exploratory analysis. World Congress on Osteoarthritis (OARSI). April 30-May 3, 2020. Vienna, Austria.

Bullock GS, Nicholson KF, Waterman BR, Niesen E, Salamh P, Thigpen CS, Shanley E, Collins GS, Arden NK, Filbay SR. A high prevalence of persistent shoulder and elbow pain

and poor arm function amongst former baseball players. April 29-May 3, 2021. World Congress on Osteoarthritis (OARSI). Denver, CO.

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Appendices

All men dream: but not equally. Those who dream by night in the dusty recesses of their minds wake up in the day to find it was vanity, but the dreamers of the day are dangerous men, for they may act their dreams with open eyes, to make it possible.

-T.E. Lawrence “Seven Pillars of Wisdom”

Appendix A: Appendices for Chapter 2

Appendix A.1. Search strategies

PubMed, MEDLINE, Embase, CINAHL, Cochrane, PsycInfo, PEDro, clinicaltrials.gov, ISRCTN Registry: baseball*

SPORTDiscus:
(Baseball* or pitcher* or catcher* or hitter* or "position player*" or outfielder* or shortstop* or "first base*" or "third base*") AND (health* or tobacco or smoke* or smoking or alcohol* or illness or injur* or fitness* or mortalit* or death or morbidit* or inciden* or prevalen* or pain or wellbeing or "well being" or “quality of life” OR *QOL or “physical activity” or psych or depression or anxiet* or mental disorders or stress* or social or neurological or respiratory or metabolic or cardiovascular or longevity or musculoskeletal or osteoarthriti* or mood or rehab* or surger* or hamstring* or quadricep* or adductor or calf or plantar or shoulder or elbow or “ulnar collateral reconstruction” or “anterior cruciate ligament” or ACL or UCL or hand or foot or spine or neck or back or labrum or arm or forearm or concussion or head or TBI) NOT (cadaver* or "in situ" or "in vitro" or animals)

Web of Science:
(Baseball* or pitcher* or catcher* or hitter* or "position player*" or outfielder* or shortstop* or "first base*" or "third base*") AND (health* or tobacco or smoke* or smoking or alcohol* or illness or injur* or fitness* or mortalit* or death or morbidit* or inciden* or prevalen* or pain or wellbeing or "well being" or “quality of life” OR *QOL or “physical activity” or psych or depression or anxiet* or mental disorders or stress* or social or neurological or respiratory or metabolic or cardiovascular or longevity or musculoskeletal or osteoarthriti* or mood or rehab* or surger* or hamstring* or quadricep* or adductor or calf or plantar or shoulder or elbow or “ulnar collateral reconstruction” or “anterior cruciate ligament” or ACL or UCL or hand or foot or spine or neck or back or labrum or arm or forearm or concussion or head or TBI) NOT (cadaver* or "in situ" or "in vitro" or animals)

Scopus
((TITLE-ABS-KEY (baseball* OR pitcher* OR catcher* OR hitter* OR "position player*" OR outfielder* OR shortstop* OR "first base*" OR "third base*")) AND NOT (TITLE-ABS-KEY (cadaver* OR "in situ" OR "in vitro" OR animals))) AND (((TITLE-ABS-KEY (health* OR tobacco OR smoke* OR smoking OR alcohol* OR illness OR injur* OR fitness* OR mortalit* OR death OR morbidit* OR inciden* OR prevalen* OR “quality of life” OR *QOL OR “physical activity” OR psych* OR “mental disorders” OR cardiovascular OR respiratory or metabolic OR longevity OR wellbeing OR "well being" OR depression OR anxiet* OR mental AND disorders OR stress* OR osteoarthriti*)) OR (TITLE-ABS-KEY (musculoskeletal OR labrum OR hamstring* OR quadricep* OR adductor OR calf OR plantar OR shoulder OR elbow OR hand OR foot OR acl OR “anterior collateral ligament” OR “ulnar collateral ligament” OR UCL OR hamstring*)) OR (TITLE-ABS-KEY (mood OR rehab* OR surger* OR "tommy john" OR "ulnar collateral ligament reconstruction" OR "rotator cuff" OR labrum))) AND NOT (TITLE-ABS-KEY (cadaver* OR "in situ" OR "in vitro" OR animals))) AND (LIMIT-TO (LANGUAGE , "English"))

ProQuest:
((ti(Baseball* or pitcher* or catcher* or hitter* or "position player*" or outfielder* or shortstop* or "first base*" or "third base*") AND (health* or tobacco or smoke* or smoking or alcohol* or illness or injur* or fitness* or mortalit* or death or morbidit* or inciden* or prevalen* or pain or wellbeing or "well being" or “quality of life” OR *QOL or “physical activity” or psych or depression or anxiet* or mental disorders or stress* or social or neurological or respiratory or metabolic or cardiovascular or longevity or musculoskeletal or osteoarthriti* or mood or rehab* or surger* or hamstring* or quadricep* or adductor or calf or plantar or shoulder or elbow or “ulnar collateral reconstruction” or “anterior cruciate ligament” or ACL or UCL or hand or foot or spine or neck or back or labrum or arm or forearm or concussion or head or TBI))) NOT (ti(cadaver* OR "in situ" OR "in vitro" OR animals) OR ab(cadaver* OR "in situ" OR "in vitro" OR animals) OR diskw(cadaver* OR "in situ" OR "in vitro" OR animals))

Google Scholar
allintitle: (baseball| pitcher|catcher|hitter|"position player"|outfielder|shortstop|"first base"|"third base”) AND (health|tobacco|smoke|smokeless|alcohol|illness|injury|fitness|mortality|death|morbidity|incidence|prevalence|pain|”quality of life”|wellbeing|"well being"|depression|anxiety|"mental disorder"|stress|osteoarthritis|mood|QOL|”quality of life”|”rotator cuff”|leg|thigh|back|wrist|shoulder|elbow|”ulnar collateral ligament”|trunk|torso|foot|ankle|knee|”anterior cruciate ligament”|neck|spine|hamstring|quadriceps|calf|plantar|forearm|”tommy john”|labrum)

Appendix A.2. Count of studies by body part or condition

Body part or condition	Number	Percentage of injury studies (%)
Acromion Clavicular Joint	4	(<1%)
Ankle	4	(<1%)
Commotio Cordis	5	(<1%)
Dental	1	(<1%)
Elbow	218	(35%)
Eye	4	(<1%)
Face	5	(1%)
Foot	5	(<1%)
Forearm	1	(<1%)
Hand	12	(2%)
Hip	6	(1%)
Knee	11	(2%)
Leg	1	(<1%)
Neurological	16	(3%)
Shin	2	(<1%)
Shoulder	197	(32%)
Skin	5	(<1%)
Spine	22	(4%)
Testicular	2	(<1%)
Thigh	8	(1%)
Thoracic Outlet	2	(<1%)
Total Body	46	(8%)
Vascular	20	(3%)
Viscera	1	(<1%)
Wrist	1	(<1%)

Appendix B: Appendices for Chapter 3

Appendix B.1. Baseball health and wellbeing questionnaire



Thank you for agreeing to take part in The Baseball Health and Wellbeing Study, your participation is greatly appreciated. Please answer all questions as best you can by marking an X in the relevant box(s) or writing your answer on the line provided. If you have any questions about how to complete this questionnaire, please do not hesitate to contact our research team. Thanks again for your time.

1. Personal details and general health

1.1. **Gender:** Male ☐ Female ☐ Other ☐

1.2. **Age:** _____
M M Y Y Y Y

1.3. **Weight:** _____ kg ☐ pounds ☐

1.4. **Height:** _____ cm ☐ Feet/inches ☐

1.5. **Do you smoke?** Yes ☐ No ☐ Ex-smoker ☐

1.6. **Do you use smokeless tobacco products (chewing tobacco, snuff, dip, etc.)**

Yes ☐ No ☐ Ex-smokeless user ☐

1.7. **If yes, How old were you when you first used smokeless tobacco?** _____

1.8. **When did you most recently use smokeless tobacco?**

Never ☐ More than 12 months ago ☐ More than 30 da

Less than 30 days ago ☐

1.9. **Do you use smokeless tobacco regularly?**

Yes ☐ No ☐

1.10. **If yes, how many times a day? _____**

1.11. **Do you use electronic cigarettes (e-cigarettes, vaping, juul, etc.)**

Yes ☐ No ☐ Ex-electronic cigarette user ☐

1.12. **If yes, How old were you when you first used electronic cigarettes? _____**

1.13. **When did you most recently use electronic cigarettes?**

Never ☐ More than 12 months ago ☐ More than 30 da

Less than 30 days ago ☐

1.14. **Do you use electronic cigarettes pen regularly?**

Yes ☐ No ☐

1.15. **If yes, how many times a day? _____**

1.16. **Do you drink energy drinks (Red Bull, Monster, All Star, etc.)**

Yes ☐ No ☐

1.17. **If so, how many energy drinks a day (one unit is 8 oz or one can of Red Bull or half a can of Monster Energy drink)**

_____

1.18. **Over a typical week, how many units of alcohol do you consume (1 unit of alcohol is equal to: 1 small glass of wine (125ml, 4 ounces), OR 1 pub measure of spirits, OR 8 ounces of normal strength beer/lager)**

_____ units of alcohol

1.19. **How many minutes variation is your bed time on a typical weekday (i.e. by how many minutes does your bed time fluctuate during the week)? _____**

1.20. **How many minutes variation is your bed time on a typical weekend (i.e. by how many minutes does your bed time fluctuate during the weekend) ? _____**

1.21. **What is your optimal sleep length (i.e. how many hours would your best sleep be)? _____**

1.22. **What is your typical sleep length (i.e. how many hours of sleep do you get per night)? _____**

1.23. **Please select the ethnicity that is most applicable to you:**

☐ American Indian or Alaskan Native
☐ Asian
☐ Black or African American
☐ Hispanic or Latino
☐ Native Hawaiian or Other Pacific Islander
☐ White
☐ Do Not Wish To Answer

1.24.. **Have you ever been told you have any of the following by a Doctor?**

Asthma	Yes	☐	No	☐	Don't know	☐
Diabetes	Yes	☐	No	☐	Don't know	☐
Dementia	Yes	☐	No	☐	Don't know	☐
Epilepsy	Yes	☐	No	☐	Don't know	☐
High blood pressure	Yes	☐	No	☐	Don't know	☐
Depression	Yes	☐	No	☐	Don't know	☐
Heart problems (e.g. heart attack or angina)	Yes	☐	No	☐	Don't know	☐
High cholesterol	Yes	☐	No	☐	Don't know	☐
Stroke	Yes	☐	No	☐	Don't know	☐
Osteoporosis	Yes	☐	No	☐	Don't know	☐
Anxiety	Yes	☐	No	☐	Don't know	☐
Kidney problems	Yes	☐	No	☐	Don't know	☐
Memory impairment	Yes	☐	No	☐	Don't know	☐
Skin cancer	Yes	☐	No	☐	Don't know	☐
Other cancer	Yes	☐	No	☐	Don't know	☐
Any other medical problems?	Yes*	☐	No	☐	Don't know	☐

1.25.. * If yes, please list other medical problems: _____

_____

1.26. **Do you currently have any of the following, diagnosed a Doctor?**

	Yes	☐	No	☐	Don't k
s	Yes	☐	No	☐	Don't k
ia	Yes	☐	No	☐	Don't k
/	Yes	☐	No	☐	Don't k
od pressure	Yes	☐	No	☐	Don't k
ion	Yes	☐	No	☐	Don't k
roblems (e.g. heart attack or angina)	Yes	☐	No	☐	Don't k
olesterol	Yes	☐	No	☐	Don't k
	Yes	☐	No	☐	Don't k
rosis	Yes	☐	No	☐	Don't k
	Yes	☐	No	☐	Don't k
roblems	Yes	☐	No	☐	Don't k
y impairment	Yes	☐	No	☐	Don't k
ncer	Yes	☐	No	☐	Don't k
ancer	Yes	☐	No	☐	Don't k
er medical problems?	Yes*	☐	No	☐	Don't k

1.27. * If yes, please list other medical problems: _____

_____

1.28. **What is your current employment status?**

Full-time	☐	Part-time/casual	☐	Stu
Stay at home parent / caregiver	☐	Retired	☐	Unempl
				Don't k

1.29. **What is the highest level of education you have successfully completed?**

Did not finish High School	☐
High School diploma	☐
Did not finish College	☐
Associate's degree or Vocational certificate	☐
Bachelor's degree	☐
Master's or Professional degree (i.e. JD, MD, DPT, etc.)	☐
Doctorate degree (PhD, EdD, etc.)	☐
Other	☐

Don't know ☐

2. Baseball history

2.1. **Playing status:** Currently playing baseball ☐ *(go to question 2.4)* No longer playing baseball ☐ Plan to return to baseball ☐

2.2. **If *no longer* playing baseball what age were you when you played your *last* baseball game?**

_____ (years old)

2.3. **If you are no longer playing baseball, why did you stop playing baseball?** (please select all that apply)

Baseball related injury	☐	Age	☐
Non-baseball related injury	☐	No longer enjoyed it	☐
Chronic pain	☐	Too much of a time commitment	☐
Personal reasons	☐	To focus on another sport/ exercise	☐
Prioritized family life	☐	Work related commitments	☐
No longer good at it	☐	Didn't get along with teammates or coach	☐
Released or Cut	☐	Other	☐

Other, please specify: _____ __

2.4. **What age were you when you played your *first* baseball game?**

_____ (years old) Don't know ☐

2.5. **What was your main position(s) of play?** (select all that apply)**:**

Catcher ☐ Position Player ☐

Pitcher ☐ Please Specify Position _____

Starter ☐ Reliever ☐ Other ☐

Please Specify _____

2.6 **What age did you stop playing sports other than baseball?**

_____ (years old) Don't know ☐

2.7. **Do you throw with your left or right hand?**

Left ☐ Right ☐ Both ☐

2.8. **Do you bat left or right handed?**

Left ☐ Right ☐ Both ☐

2.9. **How often do/did you wear a helmet when batting in baseball?**

Never ☐ Most of the time ☐

Occasionally ☐ All of the time ☐

2.10. **Have you ever had a concussion as a result of playing baseball?**

Yes ☐ No ☐ Don't know ☐

2.11 **Have you ever played sport injured, despite feeling like doing so might make the injury worse?**

Yes ☐ No ☐ Don't know ☐

2.12. **Approximately how many seasons have you played baseball for?**

Number of seasons: _____

2.14. **What was the highest level of baseball that you played for at least one season? (please select only one)**

Major League Baseball	☐	Independent League	☐
Represented country at an international competition (i.e. Olympics, World Baseball Classic, etc.)	☐	College	☐
		High School	☐
		Recreational (i.e. Adult League, Babe Ruth, Little League, etc.)	☐
Minor League	☐		
International Professional League (i.e. Japan Korea, Mexico, etc.)	☐	Don't know	☐

3. Pain, injury and surgery

3.1. **Have you ever had orthopedic surgery (including bone, ligament or joint surgery)?**

Yes ☐ No ☐

3.2. **If yes, where? Please write the number of surgeries for each joint and side** (e.g. Hip left (L / 3, right (R / 0)

Hip
Number of surgeries: L ☐ R ☐

Shoulder
Number of surgeries: L ☐ R ☐

Knee
Number of surgeries: L ☐ R ☐

Elbow
Number of surgeries: L ☐ R ☐

Ankle
Number of surgeries: L ☐ R ☐

Hand/finger
Number of surgeries: L ☐ R ☐

Spine/back
Number of surgeries: ☐

Upper Back ☐ Middle Back ☐ Low Back ☐

Face/Jaw
Number of surgeries: L ☐ R ☐

Other joint(s), please specify: _____

3.3 **Have you ever had a hip replacement?**

Yes* ☐ No ☐ Don't know ☐

3.4 ***If yes, which side was your hip replacement on?**

Left ☐ *Right* ☐ Both sides ☐

3.5 **Have you ever had a knee replacement?**

Yes* ☐ No ☐ Don't know ☐

3.6 ***If yes, which side was your knee replacement on?**

Left ☐ *Right* ☐ Both ☐

3.7 **Have you ever had a shoulder replacement?**

Yes* ☐ No ☐ Don't know ☐

3.8 ***If yes, which side was your shoulder replacement on?**

Left ☐ *Right* ☐ Both ☐

3.9 **Have you ever had an elbow replacement?**

Yes* ☐ No ☐ Don't know ☐

3.10 ***If yes, which side was your elbow replacement on?**

Left ☐ *Right* ☐ Both ☐

3.11 **Have you ever had an Anterior Cruciate Ligament (ACL) Reconstruction:**

Yes* ☐ No ☐ Don't know ☐

3.12 ***If yes, which ACL was reconstructed?**

Left knee ☐ *Right knee* ☐ Both knees ☐

3.13 **Have you ever had knee cartilage or meniscus surgery?**

Yes* ☐ No ☐ Don't know ☐

3.14 ***If yes, which knee had cartilage or meniscus surgery?**

Left knee ☐ *Right knee* ☐ Both knees ☐

3.15 **Have you ever had Ulnar Collateral Reconstruction (i.e. "Tommy John") surgery?**

Yes* ☐ No ☐ Don't know ☐

3.16 ***If yes, which elbow had Ulnar Collateral Reconstruction (i.e. "Tommy John") surgery?**

Left elbow ☐ *Right elbow* ☐ Both elbows ☐

3.17 **Have you ever had rotator cuff surgery?**

Yes* ☐ No ☐ Don't know ☐

3.18 ***If yes, which shoulder had rotator cuff surgery?**

Left shoulder ☐ *Right shoulder* ☐ Both shoulders ☐

3.18 **Have you ever had labrum or SLAP shoulder surgery?**

Yes* ☐ No ☐ Don't know ☐

3.19 ***If yes, which shoulder had rotator cuff surgery?**

Left shoulder ☐ *Right shoulder* ☐ Both shoulders ☐

3.20 **Have you ever had a finger joint replacement?**

Yes* ☐ No ☐ Don't know ☐

3.21***If yes, which hand did you have the finger joint replacement?**

Left hand ☐ *Right hand* ☐ Both hands ☐

3.22. **Have you ever had any baseball-related injuries leading to more than *4 weeks* of reduced participation in exercise, training or sport?**

Yes ☐ No ☐ Don't know ☐

3.23. **If yes, where? Please write the number of injuries for each joint and side (eg Hip left (L / 3, right (R / 1)**

Hip Number of Injuries:	**L**	**R**	**Shoulder** Number of Injuries:	**L**	**R**
Knee Number of Injuries:	**L**	**R**	**Elbow** Number of Injuries:	**L**	**R**
Ankle Number of Injuries:	**L**	**R**	**Hand/finger** Number of Injuries:	**L**	**R**
Spine/back Number of Injuries:			**Face/Jaw** Number of Injuries:	**L**	**R**

Other joint(s), please specify: _____

3.24. **Do you currently experience pain, discomfort, or have any problems in any of your joints?**

Yes ☐ No ☐

3.25. **If yes, where? Please select all that apply and indicate which side(s)**

Hip/Groin ☐ Side(s): **L** ☐ **R** ☐ Both ☐	Shoulder ☐ Side(s): **L** ☐ **R** ☐ Both ☐
If yes, have you had pain in your Hip/Groin on most days of the last month? **Yes** ☐ **No** ☐	If yes, have you had pain in your Shoulder on most days of the last month? **Yes** ☐ **No** ☐
Knee ☐	Elbow ☐

Side(s): **L** ☐ **R** ☐ Both ☐

If yes, have you had pain in your Knee on most days of the last month? **Yes** ☐ **No** ☐

Side(s): **L** ☐ **R** ☐ Both ☐

If yes, have you had pain in your Elbow on most days of the last month? **Yes** ☐ **No** ☐

Ankle ☐

Sides(s): **L** ☐ **R** ☐ **Both** ☐

If yes, have you had pain in your Ankle on most days of the last month? **Yes** ☐ **No** ☐

Hand

Sides(s): **L** **R** **Both**

If yes, have you had pain in your Hand on most days of last month? **Yes** **No**

Spine ☐

Side(s) **Neck** ☐ **Mid** ☐ Low ☐

If yes, have you had pain in your Spine on most days of the last month? **Yes** ☐ **No** ☐

Face/Jaw ☐

Side(s): **L** ☐ **R** ☐ Both ☐

If yes, have you had pain in your Face/Jaw on most days of the last month? **Yes** ☐ **No** ☐

Other joint(s), please specify: _____

3.26. **Have you ever been told by a doctor that you have osteoarthritis (wear and tear or joint degeneration)?**

Yes ☐ No ☐ Don't know ☐

3.27. **If yes, which joint(s)?**

Hip ☐ **L** ☐ **R** ☐

Shoulder ☐ **L** ☐ **R** ☐

Knee ☐ **L** ☐ **R** ☐

Elbow ☐ **L** ☐ **R** ☐

Ankle ☐ L ☐ R ☐

Hand/finger ☐ L ☐ R ☐

Spine/back ☐ ☐

Face/Jaw ☐ L ☐ R ☐

Other joint(s), please specify: _____

4. Physical activity

4.1 **Have you participated in any of the following activities for at least one season/year?**
(Please indicate how many seasons/years you have took part in each activity)

Basketball ☐ No. Seasons: ____

Hockey ☐ No. Seasons: _____

Swimming ☐ Number of Years: _____

Football ☐ No. Seasons: ____

Soccer ☐ No. Seasons: _____

Biking ☐ Number of Years: _____

Golf ☐ No. Years: ____

Running ☐ Number of Years: _____

Tennis / Racquetball ☐ Number of Years: _____

Other sport(s), please specify:
(include number of seasons/years): _____

4.2 **If yes, are you currently playing these sports.**

Yes ☐ No ☐

4.2. **Out of all the sport and exercise that you have played over your lifetime (including baseball, what is your <u>favorite</u> sport or physical activity?**

Baseball ☐ **Biking** ☐ **Hockey** ☐

Swimming ☐ **Football** ☐ **Soccer** ☐

Track and Field ☐ **Golf** ☐ **Running** ☐

Tennis or Racquetball ☐ **Basketball** ☐ **Don't know** ☐

Other sport or physical activity (please specify): _____

4.3. **How important is being physically active to you?**

Very important ☐ Fairly important ☐

Not that important ☐ Not at all important ☐

4.4. **Are you as physically active as you would like to be?**

Yes ☐ No ☐

These questions will ask you about the time you spent being physically active in the last 7 days. Please answer each question even if you do not consider yourself to be an active person. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.

*Think about all the **vigorous activities** that you did in the last **7 days.** Vigorous physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think only about those physical activities that you did for **at least 10 minutes** at a time.*

4.5. **During the last 7 days, on how many days did you do vigorous physical activities?** (Think only about those physical activities that you do for at least 10 minutes at a time)

Days per week: _____ Don't know ☐

4.6. **How much time did you usually spend doing vigorous physical activities on one of those days?**

Hours per day: _____ Minutes per day: _____ Don't know ☐

*Think about all the **moderate activities** that you did in the **last 7 days**. Moderate activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least **10 minutes at** a time.*

4.7. **During the last 7 days, on how many days did you do moderate physical activities?** (Think only about those physical activities that you do for at least 10 minutes at a time)

Days per week: _____ Don't know ☐

4.8. **How much time did you usually spend doing moderate physical activities on one of those days?** (please answer in hours or minutes, or a combination of the two (eg, 1 hour, 15 minutes)

Hours per day: _____ Minutes per day: _____ Don't know ☐

*Think about the time you spent **walking** in the last **7 days.** This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.*

4.9. **During the last 7 days, on how many days did you walk for at least 10 minutes at a time?**

Days per week: _____ Don't know ☐

4.10. **How much time did you usually spend walking on one of those days?**

Hours per day: _____ Minutes per day: _____ Don't know ☐

*Now think about the time you spent **sitting on week days** during the last **7 days.** Include time spent at work, at home, while doing course work, and during leisure time. This may include time spent sitting at a desk, visiting friends, reading or sitting or lying down to watch television.*

4.11. **During the last 7 days, how much time did you usually spend sitting on a week day? (Include time spent lying down (awake) as well as sitting)**

Hours per day: _____ Minutes per day: _____

Don't know ☐

5. Wellbeing

Please indicate whether participating in baseball has impacted upon any of the following factors in a good way (positive impact), a bad way (negative impact) or not at all (no impact):

	Positive impact	Negative impact	No impact
5.1 **Quality of life**			
5.2 **Social skills**			
5.3 **Ability to cope with difficulties**			
5.4 **Stress**			
5.5 **Concentration and focus**			
5.6 **Self-esteem**			
5.7 **Work productivity**			
5.8 **Mood**			
5.9 **Anger and frustration**			
5.10 **Alcohol consumption**			
5.11 **Anxious or worried**			

5.12. **How much have you enjoyed playing baseball?**

I love/ loved playing baseball ☐ Somewhat ☐ Not at all ☐

A lot ☐ Not much ☐

5.13. **Have you experienced any *physical benefits* from playing baseball?**

Yes ☐ No ☐ Don't know ☐

5.14. **If yes, please tick all that apply:**

Improved strength ☐ Improved fitness ☐

Weight loss ☐ Improved co-ordination ☐

Improved body awareness	☐	Improved flexibility	☐
Better sleep	☐	More energy	☐

Other, physical benefit(s) (please specify): _____

_____

_____

_____

5.15. **Overall, how would you rate your health during the <u>past 4 weeks</u>?**

Excellent ☐ Very good ☐ Good ☐ Fair ☐ Poor ☐ Very poor ☐

5.16. **During the <u>past 4 weeks</u>, how much did physical health problems limit your usual physical activities (walking, climbing stairs)?**

Not at all ☐ Very little ☐ Somewhat ☐ Quite a lot ☐ Could not do physical activities ☐

5.17. **During the <u>past 4 weeks</u>, how much difficulty did you have doing your daily work, both inside and outside the home, because of your physical health?**

Not at all ☐ A little bit ☐ Somewhat ☐ Quite a lot ☐ Could not do daily work ☐

5.18. **How much <u>bodily</u> pain have you had during the <u>past 4 weeks</u>?**

None ☐ Very mild ☐ Mild ☐ Moderate ☐ Severe ☐ Very severe ☐

5.19 **During the <u>past 4 weeks</u>, how much energy did you have?**

Very much ☐ Quite a bit ☐ Some ☐ A little ☐ None ☐

5.20. **During the <u>past 4 weeks</u>, how much did your physical health or emotional problems limit your usual social activities with family or friends?**

Not at all ☐ Very little ☐ Somewhat ☐ Quite a lot ☐ Could not do social activities ☐

5.21. **During the <u>past 4 weeks</u>, how much have you been bothered by <u>emotional problems</u> (such as feeling anxious, depressed or irritable)?**

Not at all ☐ Slightly ☐ Moderately ☐ Quite a lot ☐ Extremely ☐

5.22. **During the <u>past 4 weeks</u>, how much did personal or emotional problems keep you from doing your usual work, school or other daily activities?**

Not at all ☐ Very little ☐ Somewhat ☐ Quite a lot ☐ Could not do daily activities ☐

5.23. **Please tell me to what extent you agree or disagree with this statement:**

When things go wrong in my life, it generally takes me a long time to get back to normal.

Agree strongly ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Disagree strongly ☐

Below are eight statements with which you may agree or disagree. Using the 1–7 scale below, indicate your agreement with each item by indicating that response for each statement.

7.	Strongly agree
6.	Agree
5.	Slightly agree
4.	Mixed or neither agree nor disagree
3.	Slightly disagree
2.	Disagree
1.	Strongly disagree

5.24.	I lead a purposeful and meaningful life	☐ ← (please write a number from 1 to 7 in each box, using the scale provided above)
5.25.	My social relationships are supportive and rewarding	☐
5.26.	I am engaged and interested in my daily activities	☐
5.27.	I actively contribute to the happiness and well-being of others	☐

5.28.	I am competent and capable in the activities that are important to me	
5.29.	I am a good person and live a good life	
5.30.	I am optimistic about my future	
5.31.	People respect me	

6. Further Contact

6.1 Can we contact you for future questions?

Yes* No Don't know

6.2 **If Yes, what is your email? _____**

<u>THANK YOU</u> for completing these questions, we really appreciate you taking the time to help out with this study! We will be in touch in the future to let you know the results of this study.

Appendix B.2. Baseball Health and Wellbeing Missing Data Assessment

Overall Takeaways

- 12 people filled out the first module, but did not proceed to the other 3 modules: 8/12 were currently playing ----Potential young attrition here for this but not clumped for one team, just a few interspersed throughout the study
- Former baseball players were slightly less likely to fill out IPAQ and alcohol intake
- Overall survey fatigue.
- No real issues with missing data, Missing at Random.

Missing Counts and Percentage
Playing Status: 0, 0%
Age: 12, 6%
Gender: 2, 6%%
Weight: 12, 5.6%
Height: 12, 5.6%
First Game Age: 4, 1.9%
Smoker: 12, 6%
Smokeless Tobacco: 12, 6%
Electronic Cigarettes: 12, 6%
Asthma: 12, 6%
Employment Status: 12, 6%
Education: 12, 6%
SANE: 26, 12%
QOL Impact: 35, 16%
Resilience Question: 35, 16%
Flourish: 38, 17%%
HRQOL: 35, 16%%
IPAQ: 21, 10%
Osteoarthritis: 16, 7%
Current Pain: 16, 7%
Persistent Joint Pain: 16, 7%
Surgery History: 16, 7%
Throwing Hand: 0, 0%

Figure B.2.1. Grouped Missing Data

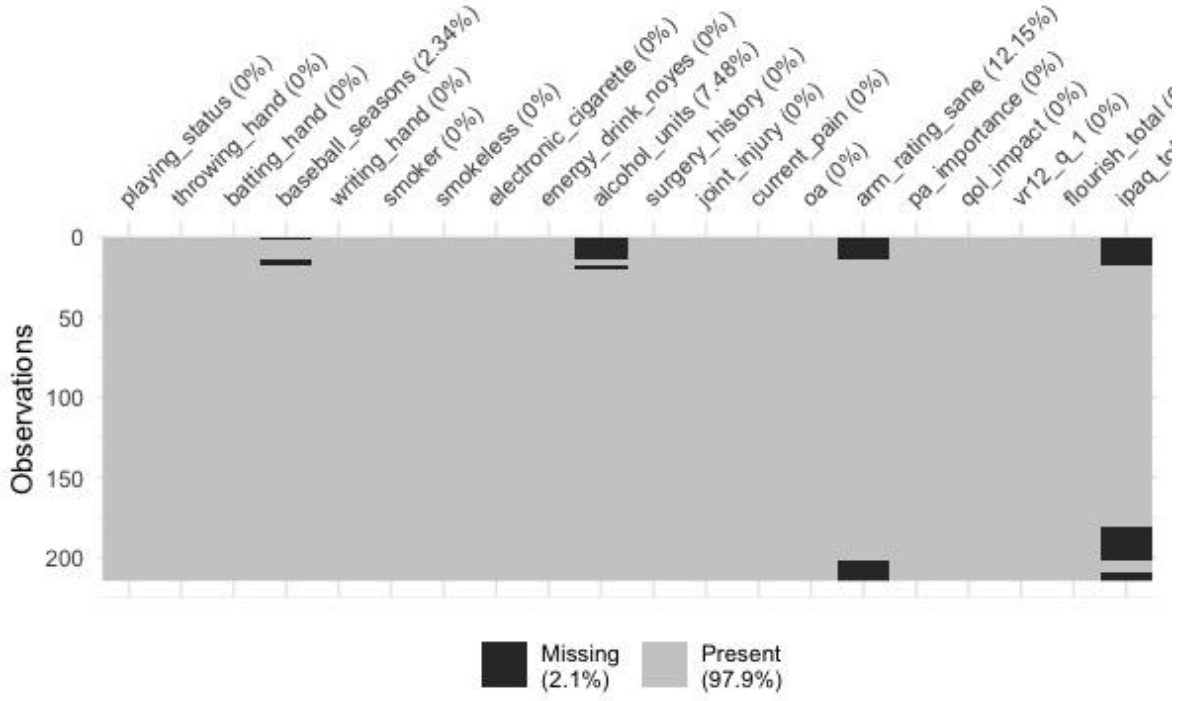


Figure B.2.2. Ungrouped Missing Data

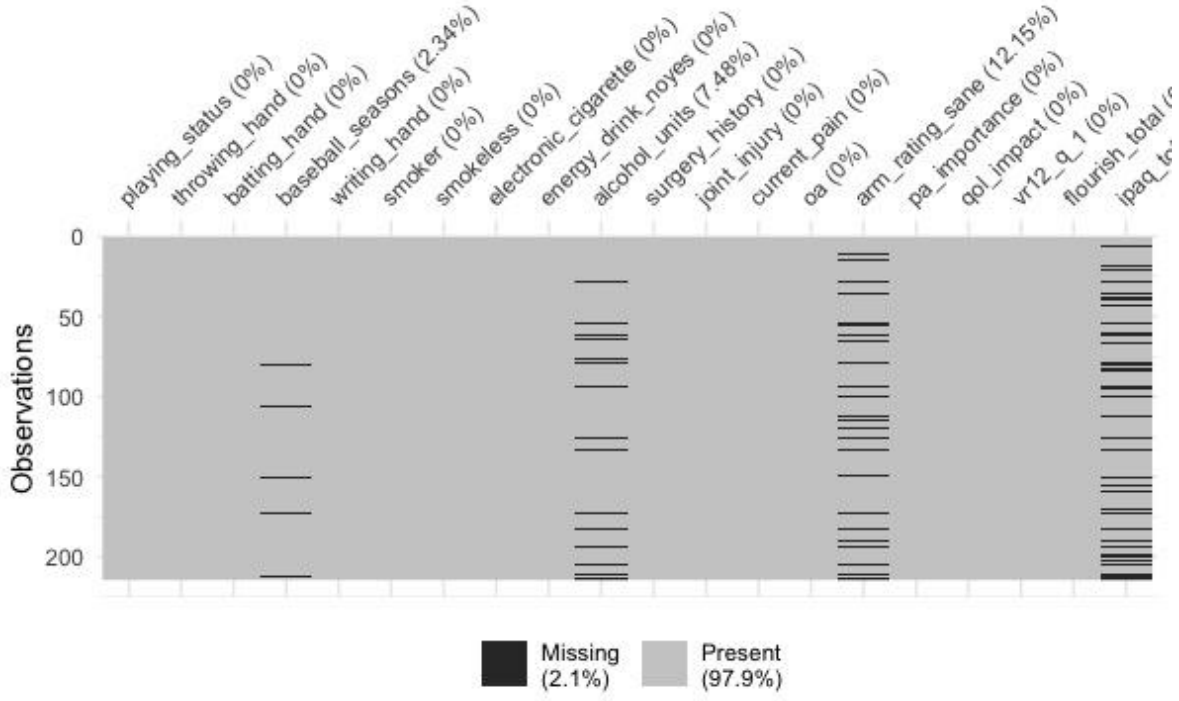
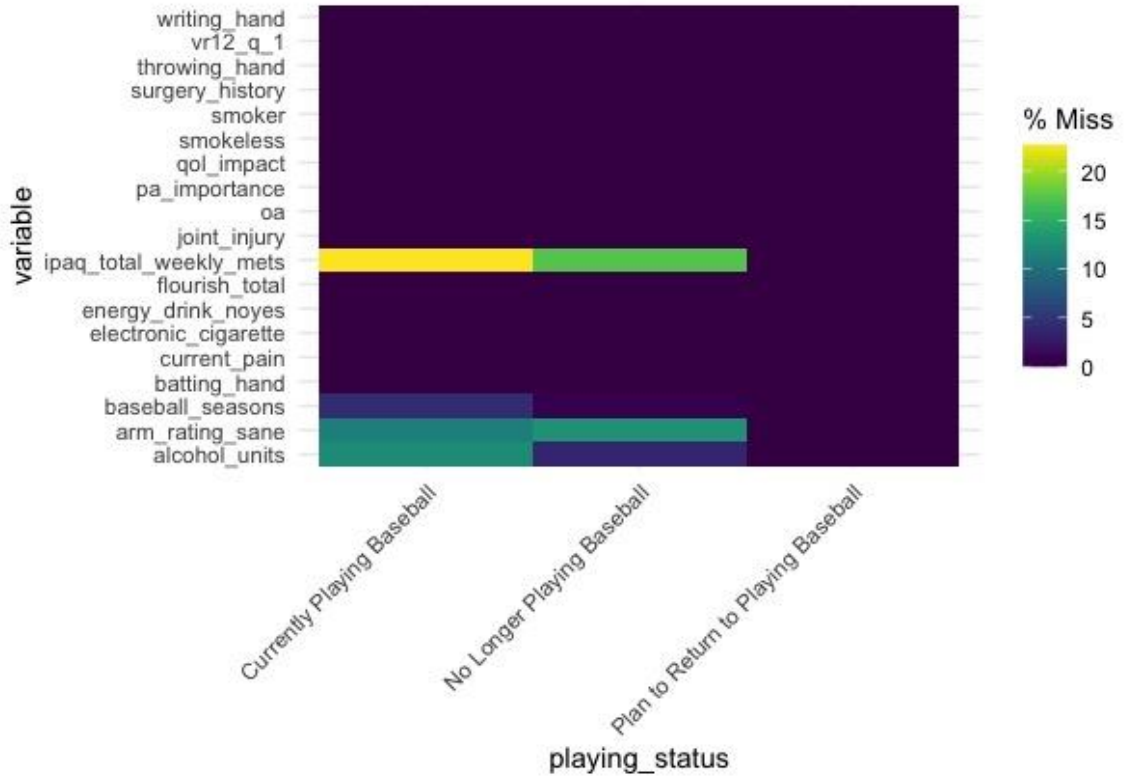


Figure B.2.3. Comparing Missing Data by Current and Former Baseball Players


writing_hand
vr12_q_1
throwing_hand
surgery_history
smoker
smokeless
qol_impact
pa_importance
oa
joint_injury
ipaq_total_weekly_mets
flourish_total
energy_drink_noyes
electronic_cigarette
current_pain
batting_hand
baseball_seasons
arm_rating_sane
alcohol_units
variable
% Miss
20
15
10
5
0
Currently Playing Baseball
No Longer Playing Baseball
Plan to Return to Playing Baseball
playing_status

Appendix B.3. Multiple imputation model R code and convergence assessment

B.3.1. Multiple imputation R code

```
#Mice Baseball HWB
library(dplyr)
library(ggplot2)
library(mice)

b_mice <- mice(base_formice2, m = 20, seed = 17)

stripplot(bf_mice, arm_rating_sane ~.imp)

imp_df <- complete(b_mice, "long", include = TRUE)

imp_df %>%
  ggplot( , mapping = aes(x= arm_rating_sane, group = factor(.imp), col = .imp)) +
geom_density(alpha = 0.25)
```

Table B.3.1. Imputed Former Baseball Player Descriptive Statistics

Variable	Former Baseball Players (n = 117)
Age (years)	36.6 (13.7)
Body Mass Index (kg/m^2)	27.9 (3.4)
Hand Dominance	
Left	23 (20%)
Right	94 (80%)
Baseball Seasons Played	17.7 (6.0)
Position	
Pitcher	46 (39%)
Position Player	44 (38%)
Two Way	27 (23%)
Highest Standard of Play	
College	83 (71%)
Professional	33 (39%)
Education	
High School Diploma	12 (10%)
University Degree	0 (0%)
High Blood Pressure	16 (14%)
Alcohol Units per Week	4 (1, 8)
Physical Activity Per Week (METS)	3972 (1698, 6246)
Flourishing Scale Score[a]	51.2 (6.0)
PCS[b]	48.9 (6.8)
MCS[b]	51.8 (8.4)
SANE[c]	70.3 (24.0)
History of Orthopaedic Surgery	60 (51%)
History of ≥4 week time loss injury	73 (62%)
Current Pain	62 (53%)

Descriptive statistics are reported as mean (standard deviation), median (interquartile range), or count (percentage)
Data were imputed for 20 iterations.
1 alcohol unit is equivalent to one shot, 4 ounces of wine, or a half pint of beer
METS = Metabolic Equivalents
PCS = Physical Component Score of the VR-12
MCS = Mental Component Score of the VR-12
SANE = Single Assessment Numeric Evaluation
[a] Flourishing total score is scored from 8 (strong disagreement on all items) to 56 (strong agreement on all items). A higher score is considered greater flourishing.
[b] Physical Component Scores (PCS) and Mental Component Scores (MCS) were calculated using norm based scoring (population norm 50 SD 10, high scorer = better health-related quality of life)
[c] The SANE is scored on a scale of 0 to 100, with 0 demonstrating full disability and 100 demonstrating no pain and full function

Figure B.3.1. Single Assessment Numeric Evaluation Imputation Convergence

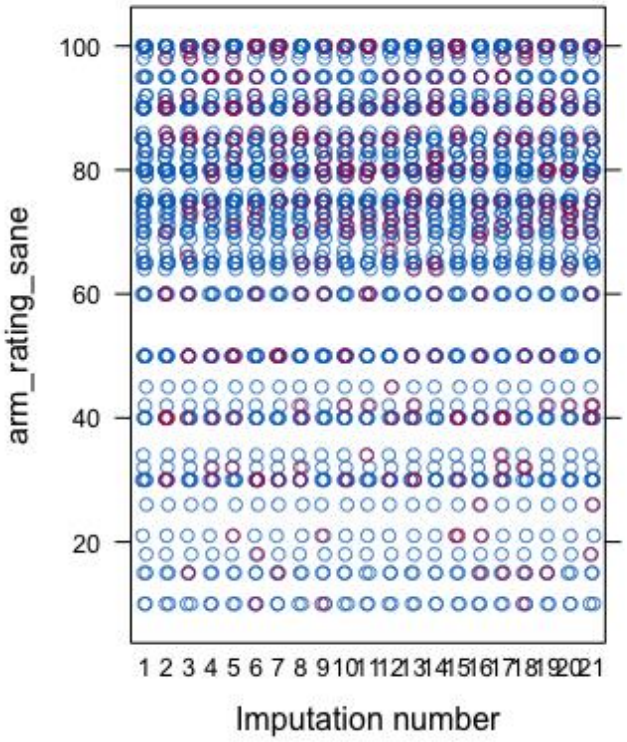
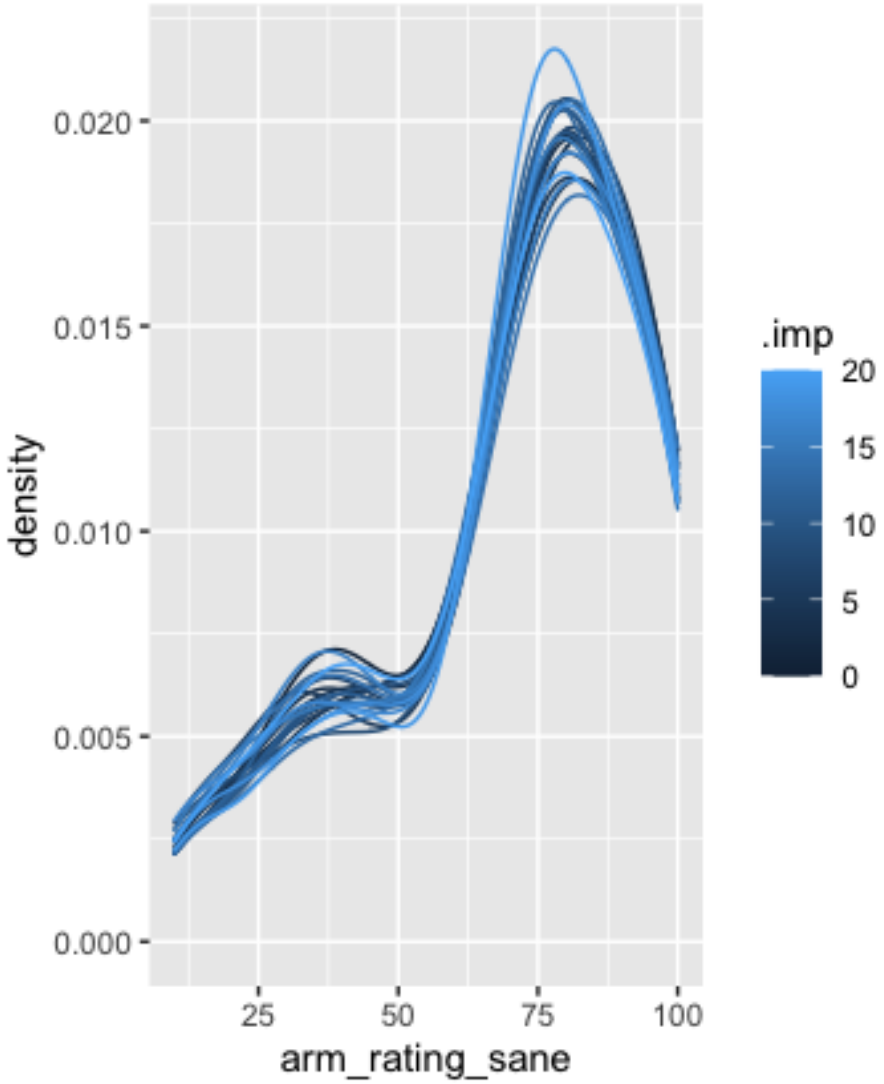


Figure B.3.2. Single Assessment Numeric Evaluation Imputation Density



Appendix B.4. Comparison of health outcomes between baseball playing positions

Variable	Pitchers (n = 76)	Position Players (n = 81)	Two Way Players (n = 57)
Age (years)	30.5 (13.7)	29.4 (12.0)	29.1 (14.5)
Body Mass Index (kg/m^2)	27.2 (3.0)	27.5 (3.0)	26.9 (3.8)
Hand Dominance			
Left	23 (30%)	4 (5%)	9 (16%)
Right	53 (70%)	77 (95%)	48 (84%)
Baseball Seasons Played	18.0 (7.5)	15.8 (4.5)	15.3 (3.6)
Highest Standard of Play			
College	50 (66%)	72 (89%)	54 (95%)
Professional	26 (34%)	9 (11%)	3 (5%)
Education			
High School Diploma	24 (32%)	32 (40%)	21 (37%)
Associate Degree	4 (5%)	4 (5%)	4 (7%)
University Degree	28 (37%)	19 (23%)	23 (40%)
Graduate Degree	20 (26%)	20 (25%)	6 (11%)
Asthma	4 (5%)	4 (5%)	1 (2%)
Diabetes	1 (1%)	1 (1%)	1 (2%)
High Blood Pressure	5 (6%)	8 (10%)	4 (7%)
High Cholesterol	9 (12%)	7 (9%)	7 (12%)
History of Depression	8 (11%)	7 (9%)	2 (4%)
Smokeless Tobacco			
Current User	15 (20%)	16 (20%)	13 (23%)
Former User	10 (13%)	11 (14%)	0 (0%)
Electronic Cigarette Use			
Current User	4 (5%)	4 (5%)	3 (5%)
Former User	1 (1%)	3 (4%)	2 (4%)
Alcohol Units per Week	4 (5%)	3 (4%)	2 (4%)
Current Energy Drink Use	15 (20%)	15 (19%)	17 (30%)
Energy Drink Units per Week	1 (0.8, 1.3)	1 (0.5, 1.5)	1 (0.5, 1.5)
Physical Activity Per Week (METS)	5256 (2390, 8123)	6144 (2318, 9971)	6480 (2319, 10641)
Flourishing Scale Score[a]	51.3 (5.8)	51.5 (5.7)	51.1 (6.0)
PCS[b]	49.1 (7.1)	49.1 (5.4)	48.5 (5.8)
MCS[b]	47.8 (10.9)	50.2 (7.6)	52.1 (8.0)
SANE[c]	76.6 (22.7)	71.9 (24.7)	76.9 (22.3)
History of Orthopaedic Surgery	37 (49%)	32 (40%)	26 (46%)
History of ≥4 week time loss injury	45 (59%)	42 (52%)	28 (49%)
Current Pain	37 (49%)	39 (48%)	24 (42%)

Descriptive statistics are reported as mean (standard deviation), median (interquartile range), or count (percentage)

1 alcohol unit is equivalent to one shot, 4 ounces of wine, or a half pint of beer

1 energy drink unit is equivalent to 8 ounces

METS = Metabolic Equivalents
PCS = Physical Component Score of the VR-12
MCS = Mental Component Score of the VR-12
SANE = Single Assessment Numeric Evaluation
[a] Flourishing total score is scored from 8 (strong disagreement on all items) to 56 (strong agreement on all items). A higher score is considered greater flourishing.
[b] Physical Component Scores (PCS) and Mental Component Scores (MCS) were calculated using norm based scoring (population norm 50 SD 10, high scorer = better health-related quality of life)
[c] The SANE is scored on a scale of 0 to 100, with 0 demonstrating full disability and 100 demonstrating no pain and full function

Appendix B.5. Comparison of health outcomes between education levels in former baseball players

Variable	High School Diploma (n = 12)	University Degree (n = 60)	Graduate Degree (n = 45)
Age (years)	38.2 (14.1)	35.9 (13.9)	37.3 (13.6)
Body Mass Index (kg/m^2)	29.7 (4.6)	27.8 (3.0)	27.8 (3.7)
Hand Dominance			
Left	2 (17%)	8 (13%)	12 (17%)
Right	10 (83%)	52 (87%)	33 (73%)
Baseball Seasons Played	19.4 (5.7)	18.1 (4.7)	16.9 (6.1)
Position			
Pitcher	5 (36%)	22 (38%)	18 (39%)
Position Player	5 (38%)	19 (32%)	20 (38%)
Two Way	2 (26%)	19 (32%)	27 (23%)
Highest Standard of Play			
College	6 (50%)	44 (73%)	31 (69%)
Professional	6 (50%)	16 (17%)	14 (31%)
Asthma	0 (0%)	3 (5%)	1 (2%)
Diabetes	1 (8%)	0 (0%)	1 (2%)
High Blood Pressure	1 (8%)	7 (12%)	8 (18%)
High Cholesterol	3 (25%)	5 (8%)	13 (29%)
History of Depression	1 (8%)	1 (2%)	3 (7%)
Smokeless Tobacco			
Current User	4 (21%)	12 (23%)	6 (19%)
Former User	1 (10%)	8 (3%)	9 (15%)
Electronic Cigarette Use			
Current User	1 (8%)	1 (2%)	0 (0%)
Former User	0 (0%)	1 (2%)	0 (0%)
Alcohol Units per Week	4 (1, 7)	3 (0, 7.5)	4 (1.5, 6.5)
Current Energy Drink Use	2 (21%)	11 (31%)	4 (14%)
Energy Drink Units per Week	6 (4.5, 7.5)	6 (4.5, 7.5)	6 (4.6, 7.3)
Physical Activity Per Week (METS)	4574 (2415, 6733)	4062 (1647, 6477)	3866 (2604, 5129)
Flourishing Scale score	48.6 (10.5)	51.7 (5.1)	51.0 (5.8)
PCS	45.7 (9.4)	48.2 (6.4)	48.3 (7.5)
MCS	51.1 (9.6)	51.5 (7.5)	49.5 (10.1)
SANE	58.2 (27.3)	70.9 (21.4)	72.5 (26.5)
History of Orthopaedic Surgery	6 (50%)	31 (52%)	23 (51%)
History of ≥4 week time loss injury	8 (67%)	41 (68%)	25 (56%)
Current Pain	7 (58%)	31 (52%)	24 (53%)

Descriptive statistics are reported as mean (standard deviation), median (interquartile range), or count (percentage)

1 alcohol unit is equivalent to one shot, 4 ounces of wine, or a half pint of beer

1 energy drink unit is equivalent to 8 ounces

METS = Metabolic Equivalents

PCS = Physical Component Score of the VR-12

MCS = Mental Component Score of the VR-12
SANE = Single Assessment Numeric Evaluation
[a] Flourishing total score is scored from 8 (strong disagreement on all items) to 56 (strong agreement on all items). A higher score is considered greater flourishing.
[b] Physical Component Scores (PCS) and Mental Component Scores (MCS) were calculated using norm based scoring (population norm 50 SD 10, high scorer = better health-related quality of life)
[c] The SANE is scored on a scale of 0 to 100, with 0 demonstrating full disability and 100 demonstrating no pain and full function

Appendix C: Appendices for Chapter 5

Appendix C.1. Comparison of descriptive data between 2009-2012 and 2013-2014 pitchers

	2009-2012 (n = 114)	2013-2014 (n = 119)
Age (years)	23.6 (2.6)	23.4 (2.4)
Hand Dominance		
Left	16%	17%
Right	84%	83%
BMI (kg/m2)	25.9 (2.4)	25.1 (2.4)
Pitching Position		
Starter	41%	49%
Reliever	59%	51%
Seasonal Pitch Load	790 (404, 1177)	600 (213, 988)
Number of Pitching Appearances	25 (17, 34)	26 (17, 35)
Dominant Humeral Torsion	7.5 (12.5)	8.7 (12.9)
Dominant Internal Rotation	37.0 (12.3)	34.8 (10.3)
Dominant External Rotation	132.0 (10.7)	124.6 (9.3)
Dominant Horizontal Adduction	0.9 (13.0)	-2.7 (11.6)
Dominant Total Range of Motion	169.1 (14.3)	159.0 (12.3)
Non-Dominant Humeral Torsion	22.8 (11.4)	25.3 (13.0)
Non-Dominant Internal Rotation	45.1 (10.7)	45.2 (9.5)
Non-Dominant External Rotation	124.4 (10.1)	117.7 (9.8)
Non-Dominant Horizontal Adduction	16.8 (8.5, 25.5)	16.5 (7.8, 25.3)
Non-Dominant Total Range of Motion	173.6 (14.2)	163.0 (11.6)
Humeral Torsion Difference	-15.3 (12.7)	-16.6 (12.0)
Internal Rotation Difference	-12.2 (12.0)	-10.4 (10.4)
External Rotation Difference	7.6 (10.1)	6.9 (8.3)
Total Range of Motion Difference	-4.5 (14.2)	-3.5 (12.3)
Internal Rotation Risk		
Risk	44%	32%
No Risk	54%	68%
External Rotation Risk		
Risk	36%	35%
No Risk	64%	65%
Dominant Horizontal Adduction Risk		
Risk	52%	69%
No Risk	48%	31%
Total Range of Motion Risk		
Risk	40%	31%
No Risk	60%	69%
Arm Injuries 1+ Days	25%	29%
Elbow Injuries	14%	14%
Shoulder Injuries	13%	14%

Data is reported as mean (standard deviation), median (interquartile range (IQR, IQR), or counts as percent
All range of motion is reported in degrees
Total Range of Motion = Sum of shoulder external and internal rotation range of motion
Range of motion difference is calculated as dominant – non-dominant shoulder
Internal Rotation Risk = Less than or equal to -15 degrees difference between dominant and non-dominant shoulder internal rotation
External Rotation Risk = Greater than or equal to +10 degrees difference between dominant and non-dominant shoulder external rotation
Dominant Horizontal Adduction Risk = Less than 0 degrees difference on dominant horizontal adduction
Total Range of Motion Risk = Less than or equal to -10 degrees difference between dominant and non-dominant shoulder total range of motion

Appendix C.2. Comparison of Pitchers Identified in Preseason as At Risk or Not At Risk for Sustaining an Arm Injury

	At Risk (n = 77)	Not at Risk (n = 156)
Age (years)	22.6 (2.2)	22.9 (2.1)
Hand Dominance		
Left	23%	13%
Right	84%	87%
BMI (kg/m2)	25.9 (2.4)	25.1 (2.1)
Pitching Position		
Starter	49%	47%
Reliever	51%	53%
Seasonal Pitch Load	714 (351, 1077)	812 (426, 1198)
Number of Pitching Appearances	24 (15, 33)	26 (17, 36)
Dominant Humeral Torsion	5.4 (13.5)	10.1 (12.8)
Dominant Internal Rotation	28.4 (11.2)	37.4 (9.5)
Dominant External Rotation	123.9 (10.8)	125.2 (9.9)
Dominant Horizontal Adduction	4.5 (12.8)	-1.5 (12.2)
Dominant Total Range of Motion	152.3 (11.7)	162.7 (12.0)
Non-Dominant Humeral Torsion	25.5 (14.4)	27.0 (12.9)
Non-Dominant Internal Rotation	50.3 (10.6)	46.3 (10.3)
Non-Dominant External Rotation	119.4 (10.5)	114.2 (11.2)
Non-Dominant Horizontal Adduction	16.6 (8.5, 25.5)	16.1 (7.8, 25.3)
Non-Dominant Total Range of Motion	170.0 (11.9)	160.4 (13.3)
Humeral Torsion Difference	-20.1 (13.3)	-16.9 (13.5)
Internal Rotation Difference	-21.9 (9.0)	-8.9 (9.7)
External Rotation Difference	4.5 (9.0)	11.1 (8.3)
Total Range of Motion Difference	-17.4 (6.4)	2.2 (9.3)

Data is reported as mean (standard deviation), median (interquartile range (IQR, IQR), or counts as percent
All range of motion is reported in degrees
Total Range of Motion = Sum of shoulder external and internal rotation range of motion
Range of motion difference is calculated as dominant – non-dominant shoulder
Range of Motion Risk = Less than or equal to -10 degrees difference between dominant and non-dominant shoulder total range of motion

Appendix C.3. Comparison of Pitchers Identified in Preseason as At Risk or Not At Risk for Sustaining an Arm Injury, Stratified by Pre or Post Risk Profiling and Education Seasons

	2013-2014		2015-2019	
	At Risk (n = 38)	Not at Risk (n = 81)	At Risk (n = 77)	Not at Risk (n = 156)
Age (years)	22.8 (2.1)	23.3 (2.3)	22.6 (2.2)	22.9 (2.1)
Hand Dominance				
Left	32%	11%	23%	13%
Right	68%	89%	77%	87%
BMI (kg/m2)	25.0 (2.6)	25.0 (2.4)	24.4 (2.4)	24.8 (2.1)
Pitching Position				
Starter	47%	48%	49%	47%
Reliever	53%	52%	51%	53%
Seasonal Pitch Load	467 (121, 813)	623 (229, 1017)	714 (351, 1077)	812 (424 , 1200)
Number of Pitching Appearances	24 (17, 31)	26 (17, 35)	24 (15, 33)	26 (18, 35)

Data is reported as mean (standard deviation), median (interquartile range (IQR, IQR), or counts as percent
All range of motion is reported in degrees
Total Range of Motion = Sum of shoulder external and internal rotation range of motion
Range of motion difference is calculated as dominant – non-dominant shoulder
Range of Motion Risk = Less than or equal to -10 degrees difference between dominant and non-dominant shoulder total range of motion

Appendix C.4. Complete interrupted time series R code

```
#Interrupted Times Series Analyses
library(foreign)
library(tsModel)
library("lmtest")
library("Epi")
library("splines")
library("vcd")

#Dataset
rockies_interrupted <- read.csv("/Users/student/Desktop/rockies_interrupted_data.csv")


#Overall Analysis (1+ Day Time loss )
injury_unadj_count <- glm(elbow_shoulder_injury_count_year ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                          family = quasipoisson, data = rockies_interrupted)

summary(injury_unadj_count) #Year: -0.222, p = 0.196; Exposure: -0.016 p <0.0001
summary(injury_unadj_count)$dispersion #0.75
round(ci.lin(injury_unadj_count,Exp=T),3) #0.801 (0.573, 1.120), p = 0.195


injury_count <- glm(elbow_shoulder_injury_count_year ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
                      BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                      IR_diff + HT_diff + HA_diff +ER_diff + as.factor(Previous_INJ),
                    family = quasipoisson, data = rockies_interrupted)

summary(injury_count) #Exposure: -0.016 p <0.0001
summary(injury_count)$dispersion #0.683
round(ci.lin(injury_count,Exp=T),3) #0.681 (0.468, 0.991) , p = 0.045



#7+ Day Injury
injury_unadj_7day <- glm(elbow_shoulder_injury_7days ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                         family = quasipoisson, data = rockies_interrupted)

summary(injury_unadj_7day) #Year: -0.279, p = 0.110; Exposure: -0.017 p <0.0001
summary(injury_unadj_7day)$dispersion #0.59
round(ci.lin(injury_unadj_7day,Exp=T),3) #0.756 (0.537, 1.064), p = 0.110

injury_7day <- glm(elbow_shoulder_injury_7days ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
```

```
                Age + BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                 IR_diff + HT_diff + HA_diff +ER_diff + as.factor(Previous_INJ),
               family = quasipoisson, data = rockies_interrupted)

summary(injury_7day) #
summary(injury_7day)$dispersion #0.54
round(ci.lin(injury_7day,Exp=T),3) #0.647 (0.438, 0.957), p = 0.029

#28+ Day Injury
injury_unadj_28day <- glm(elbow_shoulder_injury_28days ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                    family = quasipoisson, data = rockies_interrupted)

summary(injury_unadj_28day) #
summary(injury_unadj_28day)$dispersion #0.437
round(ci.lin(injury_unadj_28day,Exp=T),3) #0.788 (0.560, 1.108), p = 0.170


injury_28day <- glm(elbow_shoulder_injury_28days ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
                 BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                 IR_diff + HT_diff + HA_diff + ER_diff + as.factor(Previous_INJ),
               family = quasipoisson, data = rockies_interrupted)

summary(injury_28day) #
summary(injury_28day)$dispersion #0.433
round(ci.lin(injury_28day,Exp=T),3) #0.676 (0.450, 1.014), p = 0.059



#Sensitivity Analyses
#Elbow
elbow_unaj <- glm(elbowinjury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                family = quasipoisson, data = rockies_interrupted)
summary(elbow_unaj)
round(ci.lin(elbow_unaj,Exp=T),3) #0.983 (0.980, 0.986), p = 0.039

elbow <- glm(elbowinjury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
             BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
             IR_diff + HT_diff + HA_diff + ER_diff + as.factor(Previous_INJ),
           family = quasipoisson, data = rockies_interrupted)
summary(elbow)
round(ci.lin(elbow,Exp=T),3) #0.543 (0.279, 1.055), p = 0.072
```

```
#Shoulder
shoulder_unadj <- glm(shoulderinjury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                      family = quasipoisson, data = rockies_interrupted)
summary(shoulder_unadj)
round(ci.lin(shoulder_unadj,Exp=T),3) # 1.085 (0.679, 1.735), p = 0.773

shoulder <- glm(shoulderinjury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
                  BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                  IR_diff + HT_diff + HA_diff + ER_diff + as.factor(Previous_INJ),
                family = quasipoisson, data = rockies_interrupted)

summary(shoulder)
round(ci.lin(shoulder,Exp=T),3) #0.893 (0.529, 1.506), p = 0.670



#Early Middle Late Time of Injury

injur_unadj <- glm(elbow_shoulder_injury_count_year ~ year_2013_or2015above +
as.factor(three_tier_injurytime) + overall_exposure_arm_non_arminjuryloss,
                   family = quasipoisson, data = rockies_interrupted)
summary(injur_unadj)
summary(injur_unadj)$dispersion #0.811
round(ci.lin(injur_unadj,Exp=T),3) #1.115 (0.782, 1.588), p = 0.548


injury_count <- glm(elbow_shoulder_injury_count_year ~ year_2013_or2015above +
as.factor(three_tier_injurytime) + overall_exposure_arm_non_arminjuryloss +
                      BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                      IR_diff + HT_diff + HA_diff +ER_diff + as.factor(Previous_INJ),
                    family = quasipoisson, data = rockies_interrupted)

summary(injury_count)
summary(injury_count)$dispersion #0.738
round(ci.lin(injury_count,Exp=T),3) #1.095 (0.726, 1.653), p = 0.664


#Trunk and LE Injury
body_unadj <- glm(kinematic_chain_injury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss,
                   family = quasipoisson, data = rockies_2013plus_withle)
summary(body_unadj)
```

```
summary(body_unadj)$dispersion #0.811
round(ci.lin(body_unadj,Exp=T),3) #1.42 (0.74, 2.73), p = 0.290


body_count <- glm(kinematic_chain_injury ~ year_2013_or2015above +
overall_exposure_arm_non_arminjuryloss +
                    BMI + as.factor(ARM_DOM) + as.factor(Position) +
as.factor(years_played_ordinal) +
                    IR_diff + HT_diff + HA_diff +ER_diff + as.factor(Previous_INJ),
                  family = quasipoisson, data = rockies_2013plus_withle)

summary(body_count)
summary(body_count)$dispersion #0.738
round(ci.lin(body_count,Exp=T),3) #1.55 (0.79, 3.01), p = 0.204
```

Appendix D: Appendices for Chapter 6

Appendix D.1. Outlier Assessment

Dominant Internal Rotation
#Outliers identified: 5 nPropotion (%) of outliers: 0.8 nMean of the outliers: -0.91
#nMean without removing outliers: 35.52 nMean if we remove outliers: 35.8 n

Dominant External Rotation
#Outliers identified: 6 nPropotion (%) of outliers: 0.9 nMean of the outliers: 126.34
#nMean without removing outliers: 126.83 nMean if we remove outliers: 126.83 n

Dominant Horizontal Adduction
#Outliers identified: 8 nPropotion (%) of outliers: 1.2 nMean of the outliers: 0.32
#nMean without removing outliers: -1.36 nMean if we remove outliers: -1.38 n

Dominant Humeral Retrotorsion
#Outliers identified: 22 nPropotion (%) of outliers: 3.7 nMean of the outliers: -1.65
#nMean without removing outliers: 8.35 nMean if we remove outliers: 8.72 n

Internal Rotation Difference
#Outliers identified: 7 nPropotion (%) of outliers: 1.1 nMean of the outliers: -7.03
#nMean without removing outliers: -12.59 nMean if we remove outliers: -12.65 n

External Rotation Difference
#Outliers identified: 13 nPropotion (%) of outliers: 2 nMean of the outliers: 10.84
#nMean without removing outliers: 8.64 nMean if we remove outliers: 8.6 n

Horizontal Adduction Difference
#Outliers identified: 9 nPropotion (%) of outliers: 1.4 nMean of the outliers: -44.03
#nMean without removing outliers: -17.77 nMean if we remove outliers: -17.4 n

Appendix D.2. Non-linearity assessment of injury predictors

Figure D.2.1 Non-Linearity of Body Mass Index

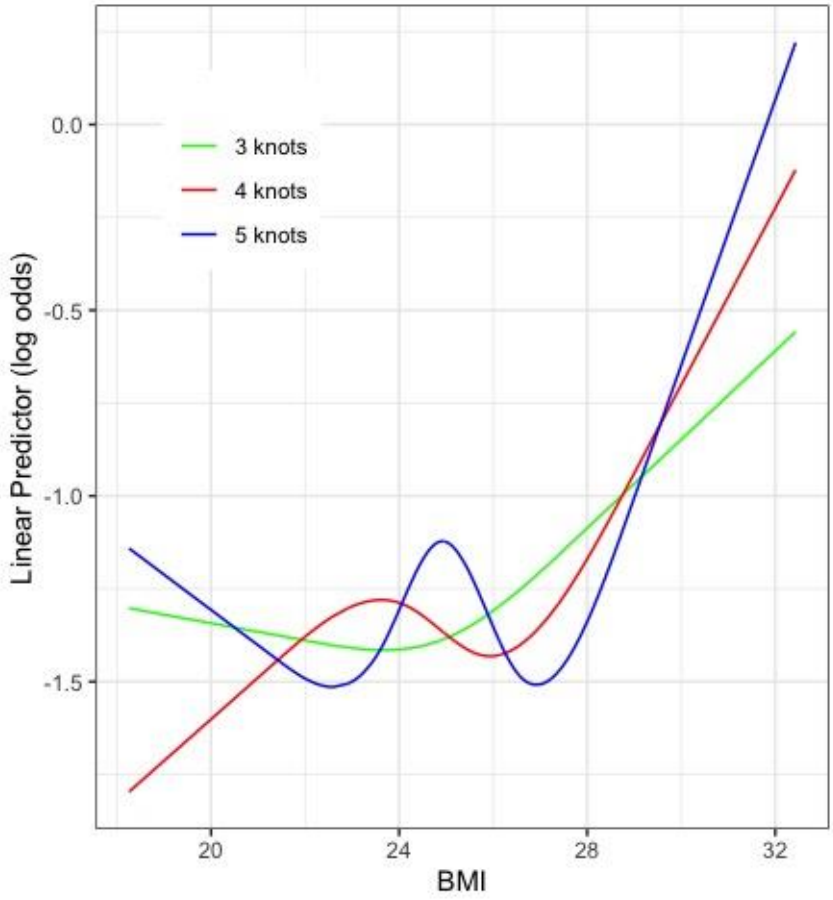


Figure D.2.2. Humeral Torsion Difference Non-Linearity Assessment

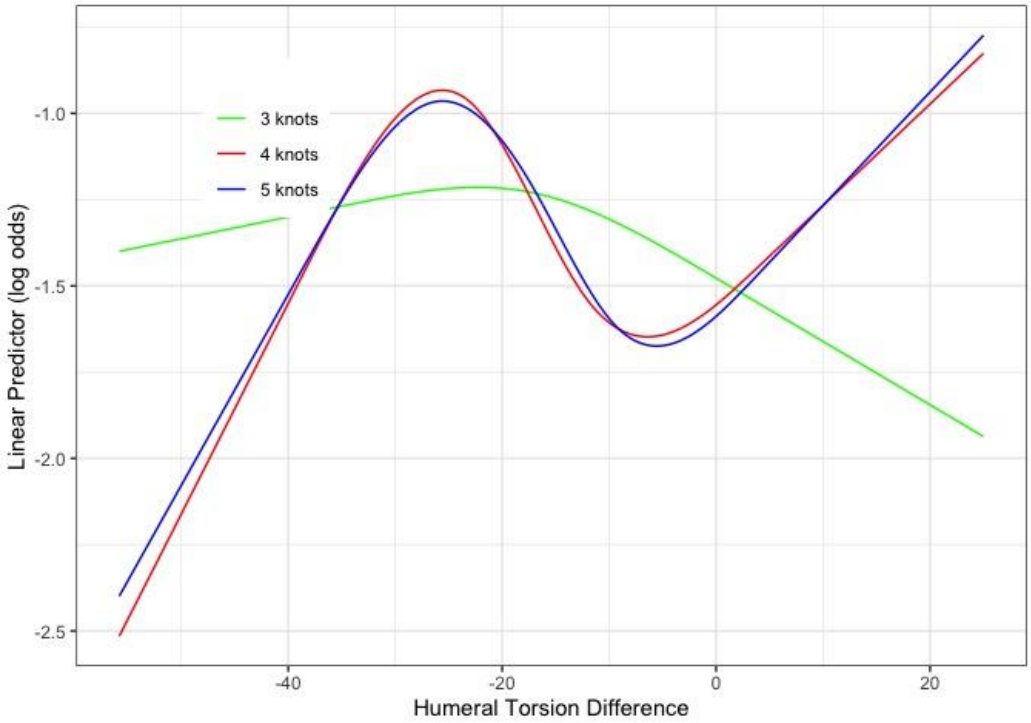


Figure D.2.3. Dominant Humeral Torsion Non-Linearity Assessment

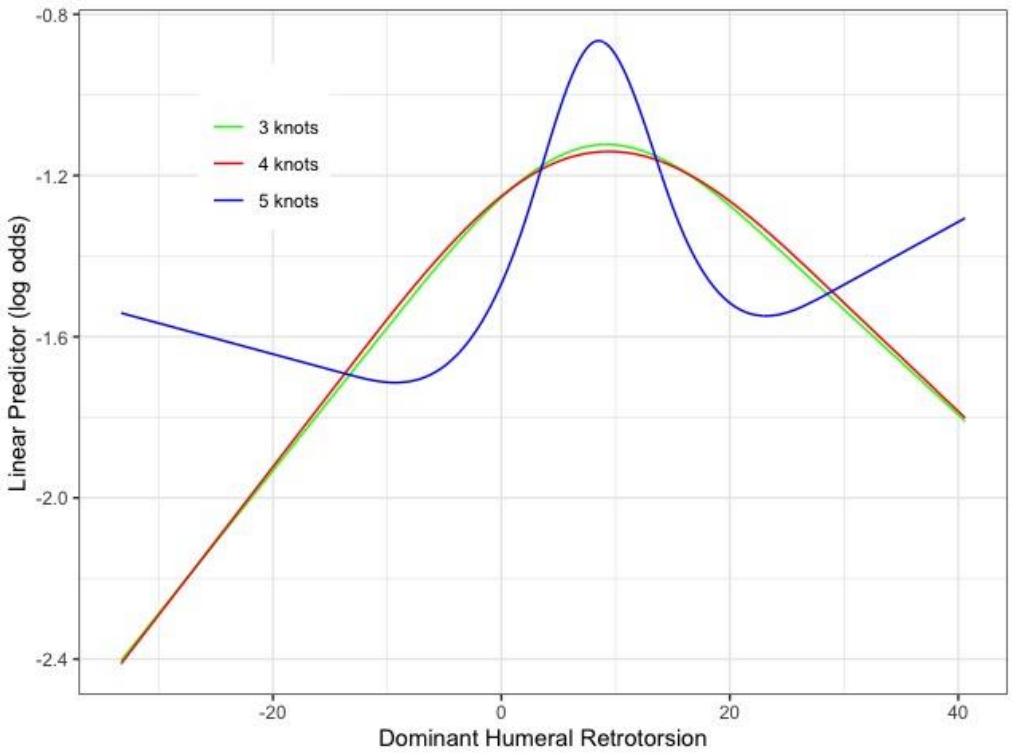


Figure D.2.4 Shoulder Total Range of Motion Difference Non-Linearity Assessment

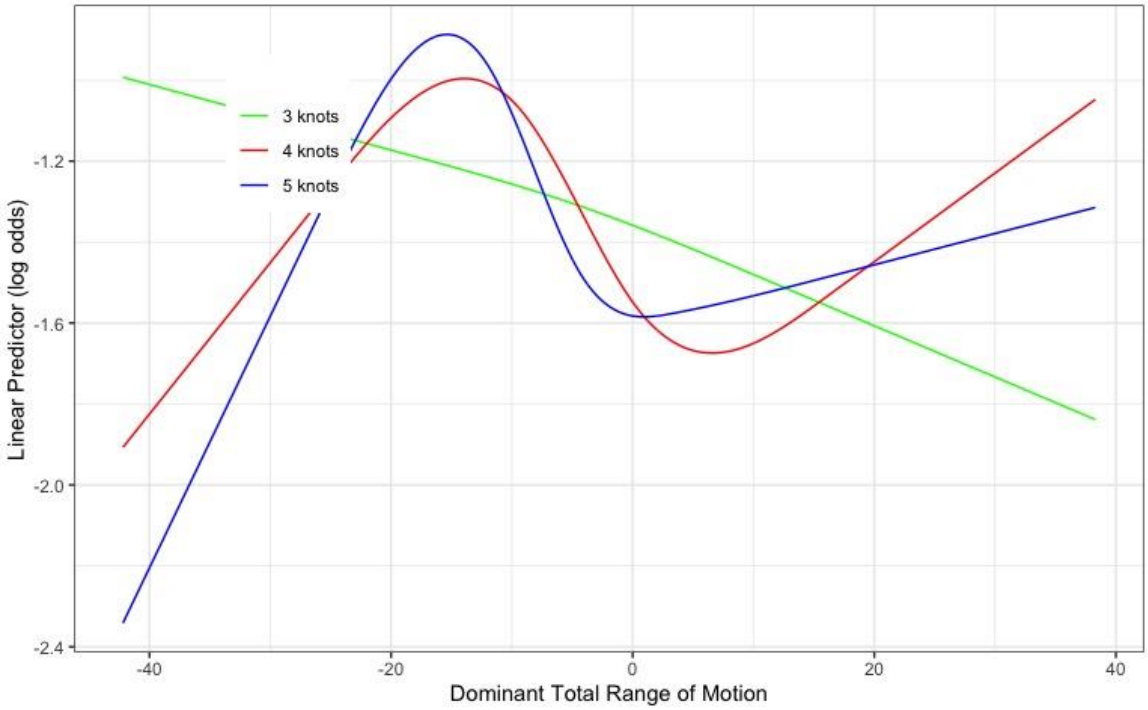
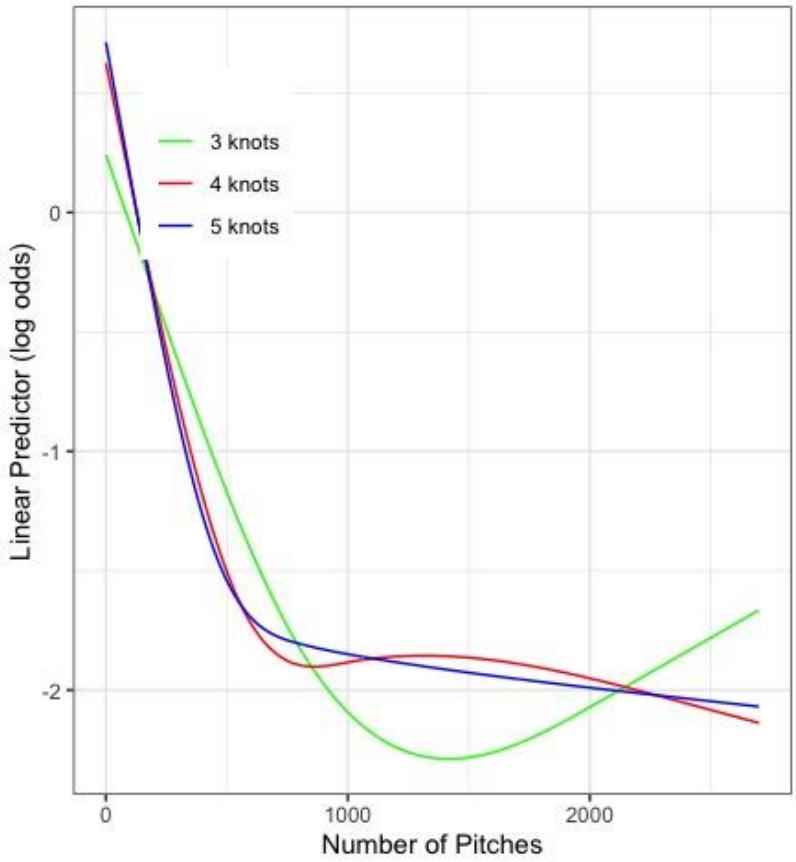


Figure D.2.5. Pitch Load Non-Linearity Assessment



Appendix D.3. Cross Tabulation Analyses Comparing Seasonal Pitch Counts

Table 2: A comparison of baseball demographics between different seasonal pitch counts

	Less than 1000 Season Pitches (n = 376)	1000 to 1999 Season Pitches (n = 145)	2000+ Season Pitches (n = 61)
Age (years)	23.1 (2.4)	23.1 (2.3)	22.8 (2.4)
Hand Dominance			
Left	18%	13%	13%
Right	82%	87%	87%
BMI (kg/m2)	25.0 (2.4)	25.0 (2.3)	24.9 (2.4)
Pitching Position			
Starter	38%	54%	90%
Reliever	62%	46%	10%
Years within the Organization			
1-2 years	56%	46%	48%
3-4 years	36%	41%	39%
5+ years	8%	13%	13%
Number of Season Pitches	505 (300)	1334 (284)	2360 (203)
Dominant Humeral Torsion	8.2 (12.6)	9.8 (12.2)	5.1 (14.0)
Dominant Internal Rotation	34.5 (11.5)	36.3 (10.8)	36.5 (10.2)
Dominant External Rotation	127.4 (10.5)	126.1 (11.6)	126.5 (11.4)
Dominant Horizontal Adduction	-2.1 (12.7)	-0.2 (12.5)	0.8 (10.9)
Non-Dominant Humeral Torsion	25.6 (12.9)	26.7 (13.0)	23.8 (14.2)
Non-Dominant Internal Rotation	47.7 (10.5)	48.6 (10.8)	48.1 (10.6)
Non-Dominant External Rotation	118.4 (11.7)	118.0 (11.7)	119.0 (12.1)
Non-Dominant Horizontal Adduction	16.4 (8.6, 24.9)	17.1 (8.3, 24.6)	16.3 (9.5, 26.5)
Humeral Torsion Difference	-17.4 (13.4)	-16.9 (13.5)	-18.7 (13.8)
Internal Rotation Difference	-13.3 (11.9)	-12.3 (11.3)	-11.7 (8.9)
External Rotation Difference	9.0 (9.9)	8.1 (9.0)	7.5 (8.6)
Horizontal Adduction Difference	-18.6 (17.1)	-17.2 (17.2)	-15.5 (16.3)

Appendix D.4. Professional baseball arm injury predictive model R code

```
library(plyr)
library(dplyr)
library(rms)
library(ggplot2)
library(reshape2)
library(pROC)
library(DescTools)
library(Hmisc)
library(boot)
library(glmnet)
library(Matrix)
library(caret)
library(classifierplots)
library(Epi)
library(lme4)
library(Matrix)
library(survival)
library(flexsurv)
library(lubridate)
library(survcomp)
library(rmda)

#Final Predictive Model
mod_final <- glm(elbow_shoulder_injury_7days~ BMI + ARM_DOM +
as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
            rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
          family="binomial", data = rockey_cutdown)
summary(mod_final)
round(ci.lin(mod_final,Exp=T),3)
lp_mod2 <- predict(mod_final)

## Calculating Discrimination Performance

# Predicted probabilities for each pitcher
pred_prob <- predict(mod_final,type="response")

# Obtain the linear predictor/PI for each patient
pred_LP <- predict(mod_final,type="link")


# Summarizing the distribution of linear predictor
mean(pred_LP) #-1.545047
sd(pred_LP) #0.9670456
min(pred_LP) #-3.651463
max(pred_LP) #2.192009
```

```
#Creating an array for ROC curve
injury_array <- rockey_cutdown %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M)) %>%
  select(ID, elbow_shoulder_injury_7days)


typeof(injury_array$elbow_shoulder_injury_7days) #593,

actual_v_predict_2 <- cbind(injury_array, lp_mod2)


# Obtain the c statistic / AUC
c1 <- roc(actual_v_predict_2$elbow_shoulder_injury_7days ~
actual_v_predict_2$lp_mod2,ci=TRUE)
c1 #0.7412 (95% CI: 0.688-0.7944)
#0.74 (95% CI: 0.69, 0.79)


## Another measure of separation
# Obtaining Somers' D statistic
Dstat <- rcorr.cens(pred_prob,actual_v_predict_2$elbow_shoulder_injury_7days)
Dstat["Dxy"] #0.4824

# Confidence interval calculation is based on c-statistic and then converted to D as D=2c-1
(2*(Dstat['C Index']-(1.96*(Dstat['S.D.']/2))))-1 #0.380
(2*(Dstat['C Index']+(1.96*(Dstat['S.D.']/2))))-1 #0.600
#0.48 (95% CI: 0.38, 0.59)

# Estimate R squared
PseudoR2(mod_final,"Nagelkerke") #0.316

# And the Brier score
BrierScore(mod_final) #0.138

# CITL
mod_log_1 <- glm(elbow_shoulder_injury_7days~offset(pred_LP),family="binomial", data
= actual_v_predict_2)
mod_log_1$coef
confint(mod_log_1) #3.287238e-12 (95% CI: -0.2284082,  0.2206741)

# E/O
prop.table(table(actual_v_predict_2$elbow_shoulder_injury_7days)) #0.2109 for event
O <- prop.table(table(actual_v_predict_2$elbow_shoulder_injury_7days))[2]
E <- mean(pred_prob)
E/O #1

# C-slope
```

```
mod_log_2 <- glm(elbow_shoulder_injury_7days ~
pred_LP,family="binomial",x=TRUE,y=TRUE, data = actual_v_predict_2)
mod_log_2 #1.00
confint(mod_log_2) #C Slope: 1.00 (95%CI: 0.773, 1.24)


# Obtain chi2
null_model <- glm(elbow_shoulder_injury_7days ~ 1,family="binomial", data =
actual_v_predict_2)
chisq <- anova(null_model,mod_final,test="Chisq")
summary(chisq)
chi2 <- chisq$Deviance[2]
chi2 #83.01

# display degress of freedom (df)
df_log <- chisq$Df[2]
df_log #15 DF's

# shrinkage of Van Houwelingen which is given by (chi2 - df)/chi2
# where df = 16 for the predictors here
vanH <- (chi2 - df_log)/chi2
vanH #0.819



#Performing Cross validation to find the best elastic net property
#Complete Case DF
injury_array <- rockey_cutdown %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M)) %>%
  select(ID, BMI, ARM_DOM, years_played_ordinal, year_2013_or2015above,
number_of_pitches, HT_diff, dtrom, DHA_M, elbow_shoulder_injury_7days)

#Changing L, R to 0 (Left), 1 (Right)
injury_array <- injury_array %>%
  mutate(ARM_DOM = ifelse(ARM_DOM == "L",
                          0,
                          1))
#Setting

#Elastic Net
set.seed(17)
model <- train(
  as.factor(elbow_shoulder_injury_7days) ~ BMI + as.factor(ARM_DOM) +
as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
    rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
  data = injury_array, method = "glmnet", family = "binomial",
  trControl = trainControl("cv", number = 10),
```

```
  tuneLength = 10
)

# Best tuning parameter
model$bestTune #Alpha: 0.8, Lamba: 9.680665e-05 (Lambda is shrinkage)
coef(model$finalModel, model$bestTune$lambda) #Really small shrinkage, which is good

plot(model)


#Testing
mod_test_elastic_prob <- model %>%
  predict(injury_array, type = 'prob')

#Getting Log Odds from Probability
predict_elastic_betas <- mod_test_elastic_prob %>%
  mutate(log_odds = log(`1`/`0`))

predict_elastic_onlybetas <- predict_elastic_betas$log_odds
predict_elastic_prob1 <- predict_elastic_betas$`1`



## Calculating Discrimination Performance
#Linear Predictor
predict_elastic_onlybetas <- predict_elastic_betas$log_odds
#Probability
predict_elastic_prob1 <- predict_elastic_betas$`1`


# Summarizing the distribution of linear predictor
mean(predict_elastic_onlybetas) #-1.532336
sd(predict_elastic_onlybetas) #0.9248481
min(predict_elastic_onlybetas) #-3.434258
max(predict_elastic_onlybetas) #2.027343


#Creating an array for ROC curve
injury_array <- rockey_cutdown %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M)) %>%
  select(ID, elbow_shoulder_injury_7days)


typeof(injury_array$elbow_shoulder_injury_7days) #593,

actual_v_predict_elastic <- cbind(injury_array, predict_elastic_onlybetas)
```

```
actual_predict_prob_elastic <- cbind(actual_v_predict_elastic, predict_elastic_prob1)

actual_predict_prob_elastic$elbow_shoulder_injury_7days <-
as.factor(actual_predict_prob_elastic$elbow_shoulder_injury_7days)

# Obtain the c statistic / AUC
c1_elastic <- roc(actual_v_predict_elastic$elbow_shoulder_injury_7days ~
predict_elastic_onlybetas,ci=TRUE)
c1_elastic # 0.7438 (95% CI: 0.691-0.7966)


## Calculating Discrimination Performance
#Linear Predictor
predict_elastic_onlybetas <- predict_elastic_betas$log_odds
#Probability
predict_elastic_prob1 <- predict_elastic_betas$`1`


## Another measure of separation
# Obtaining Somers' D statistic
Dstat_e <-
rcorr.cens(predict_elastic_prob1,actual_v_predict_elastic$elbow_shoulder_injury_7days)
Dstat_e["Dxy"] #0.488

# Confidence interval calculation is based on c-statistic and then converted to D as D=2c-1
(2*(Dstat_e['C Index']-(1.96*(Dstat_e['S.D.']/2))))-1 #0.380
(2*(Dstat_e['C Index']+(1.96*(Dstat_e['S.D.']/2))))-1 #0.600
#0.49 (95% CI: 0.38, 0.59)

# Estimate R squared
PseudoR2(model,"Nagelkerke") #0.3239

# And the Brier score
BrierScore(model) #0.136

# CITL
mod_log_elastic <-
glm(elbow_shoulder_injury_7days~offset(predict_elastic_onlybetas),family="binomial",
data = actual_v_predict_elastic)
mod_log_elastic$coef #3.096335e-06
confint(mod_log_elastic) #5.517992e-07  (95% CI: -0.2263445,  0.2186989 )

# E/O
prop.table(table(actual_v_predict_elastic$elbow_shoulder_injury_7days)) #0.2109 for event
O <- prop.table(table(actual_v_predict_elastic$elbow_shoulder_injury_7days))[2]
E <- mean(predict_elastic_prob1)
E/O #0.9999996

# C-slope
```

```
mod_log_elastic2 <- glm(elbow_shoulder_injury_7days ~
predict_elastic_onlybetas,family="binomial",x=TRUE,y=TRUE, data =
actual_v_predict_elastic)
mod_log_elastic2 #1.053
confint(mod_log_elastic2) #C Slope: 1.05 (95%CI: 0.806, 1.30)

# Visual assessment of calibration by risk groups

val.prob(y = actual_v_predict_elastic$elbow_shoulder_injury_7days, logit =
actual_v_predict_elastic$predict_elastic_onlybetas,
        pl=TRUE, smooth=TRUE, logistic.cal=TRUE,
        xlab="Predicted Probability", ylab="Actual Probability",
        lim=c(0, 1), emax.lim=c(0,1),
        legendloc=lim[1] + c(0.55 * diff(lim), 0.27 * diff(lim)),
        statloc=c(0,0.99), riskdist=c("predicted", "calibrated"),
        cex=.7, mkh=.02,
        connect.group=FALSE, connect.smooth=TRUE, g.group=4,
        evaluate=100, nmin=0)


typeof(actual_v_predict_elastic$elbow_shoulder_injury_7days)
typeof(predict_elastic_prob1)


# Calculate heuristic shrinkage

# Obtain chi2
null_model <- glm(elbow_shoulder_injury_7days ~ 1,family="binomial", data =
actual_v_predict_elastic)
chisq <- anova(null_model,model,test="Chisq")
summary(chisq)
chi2 <- chisq$Deviance[2]
chi2 #86.035

# display degress of freedom (df)
df_log <- chisq$Df[2]
df_log #15 DF's



# We can summarise the original & shrunken lp and compare the mean/SD/range
mean(pred_LP) #-1.545047
sqrt(var(pred_LP)) #0.9977146
min(pred_LP) #-3.651463
max(pred_LP) #2.192009

mean(heuristic_lp) #2.475459e-15
sqrt(var(heuristic_lp)) #0.568297
min(heuristic_lp) #-1.587253
```

```
max(heuristic_lp) #1.660098


# optimism adjusted statistics
c1_elastic$auc - (mean(c1_elastic$auc)-mean(c1_boot$auc)) # c-stat: 0.7433
mod_log_elastic$coef  #CITL: 5.517992e-07
mod_log_elastic2$coef[2]  # c-slope: 1.05

#optimism on its own
mean(c1_elastic$auc) - (mean(c1$auc)): #ROC Shrinkage: 0.002
mean(mod_log_elastic$coef)- (mean(mod_final$coef)) #Coefficient Shrinkage: 3.096329e-
06
mean(mod_log_elastic2$coef[2])-mean(mod_final$coef[2]) #C-Slope Shrinkage:
0.05339921

#Final Formula:

coef(model$finalModel, model$bestTune$lambda) # 3.096329e-06


calPlot2(mod_final, data = injury_array) #Line
calPlot2(mod_final, data = injury_array, method = "quantile", q = 10) #Bins


#Sensitivity Analyses

#Elbow
mod_elbow <- glm(elbowinjury ~ BMI + ARM_DOM + as.factor(years_played_ordinal) +
as.factor(year_2013_or2015above) +
                   rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
                 family="binomial", data = rockey_cutdown)
summary(mod_elbow)
round(ci.lin(mod_elbow,Exp=T),3)
lp_mod2 <- predict(mod_elbow)

## Calculating Discrimination Performance

# Predicted probabilities for each pitcher
pred_prob <- predict(mod_elbow,type="response")

# Obtain the linear predictor/PI for each patient
pred_LP <- predict(mod_elbow,type="link")


# Summarizing the distribution of linear predictor
mean(pred_LP) #-2.755687
sd(pred_LP) #1.342569
min(pred_LP) #-6.915187
max(pred_LP) #1.685251
```

```
#Creating an array for ROC curve
injury_array_elbow <- rockey_cutdown %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M)) %>%
  select(ID, elbowinjury)


typeof(injury_array_elbow$elbowinjury) #593,

actual_v_predict_elbow <- cbind(injury_array_elbow, lp_mod2)


# Obtain the c statistic / AUC
c_elbow <- roc(actual_v_predict_elbow$elbowinjury ~
actual_v_predict_elbow$lp_mod2,ci=TRUE)
c_elbow #0.764 (95% CI: 0.694-0.834)
#0.76 (95% CI: 0.69, 0.83)


## Another measure of separation
# Obtaining Somers' D statistic
Dstat <- rcorr.cens(pred_prob,actual_v_predict_elbow$elbowinjury)
Dstat["Dxy"] #0.611

# Confidence interval calculation is based on c-statistic and then converted to D as D=2c-1
(2*(Dstat['C Index']-(1.96*(Dstat['S.D.']/2))))-1 #0.380
(2*(Dstat['C Index']+(1.96*(Dstat['S.D.']/2))))-1 #0.600
#0.61 (95% CI: 0.49, 0.73)

# Estimate R squared
PseudoR2(mod_elbow,"Nagelkerke") #0.335

# And the Brier score
BrierScore(mod_elbow) #0.077

# CITL
mod_log_1 <- glm(elbowinjury~offset(pred_LP),family="binomial", data =
actual_v_predict_elbow)
mod_log_1$coef
confint(mod_log_1) #3.262141e-11  (95% CI: -0.3083046,  0.2905167 )

# E/O
prop.table(table(actual_v_predict_elbow$elbowinjury)) #0.2109 for event
O <- prop.table(table(actual_v_predict_elbow$elbowinjury))[2]
E <- mean(pred_prob)
E/O #1
```

```
# C-slope
mod_log_2 <- glm(elbowinjury ~ pred_LP,family="binomial",x=TRUE,y=TRUE, data =
actual_v_predict_elbow)
mod_log_2 #1.00
confint(mod_log_2) #C Slope: 1.00 (95%CI: 0.75, 1.28)


val.prob(y = actual_v_predict_elbow$elbowinjury, logit = actual_v_predict_elbow$lp_mod2,
        pl=TRUE, smooth=TRUE, logistic.cal=TRUE,
        xlab="Predicted Probability", ylab="Actual Probability",
        lim=c(0, 1), emax.lim=c(0,1),
        legendloc=lim[1] + c(0.55 * diff(lim), 0.27 * diff(lim)),
        statloc=c(0,0.99), riskdist=c("predicted", "calibrated"),
        cex=.7, mkh=.02,
        connect.group=FALSE, connect.smooth=TRUE, g.group=4,
        evaluate=100, nmin=0)




#Shoulder
mod_shoulder <- glm(shoulderinjury ~ BMI + ARM_DOM +
as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
                rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
              family="binomial", data = rockey_cutdown)
summary(mod_shoulder)
round(ci.lin(mod_shoulder,Exp=T),3)
lp_mod2 <- predict(mod_shoulder)

## Calculating Discrimination Performance

# Predicted probabilities for each pitcher
pred_prob <- predict(mod_shoulder,type="response")

# Obtain the linear predictor/PI for each patient
pred_LP <- predict(mod_shoulder,type="link")


# Summarizing the distribution of linear predictor
mean(pred_LP) #-1.961572
sd(pred_LP) #0.6048694
min(pred_LP) #-3.499988
max(pred_LP) #0.01988622


#Creating an array for ROC curve
```

```
injury_array_shoulder <- rockey_cutdown %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M)) %>%
  select(ID, shoulderinjury)


typeof(injury_array_shoulder$shoulderinjury) #593,

actual_v_predict_shoulder <- cbind(injury_array_shoulder, lp_mod2)


# Obtain the c statistic / AUC
c_shoulder <- roc(actual_v_predict_shoulder$shoulderinjury ~
actual_v_predict_shoulder$lp_mod2,ci=TRUE)
c_shoulder #0.656 (95% CI: 0.586-0.725)
#0.66 (95% CI: 0.59, 0.72)


## Another measure of separation
# Obtaining Somers' D statistic
Dstat <- rcorr.cens(pred_prob,actual_v_predict_shoulder$shoulderinjury)
Dstat["Dxy"] #0.311

# Confidence interval calculation is based on c-statistic and then converted to D as D=2c-1
(2*(Dstat['C Index']-(1.96*(Dstat['S.D.']/2))))-1 #0.380
(2*(Dstat['C Index']+(1.96*(Dstat['S.D.']/2))))-1 #0.600
#0.31 (95% CI: 0.17, 0.45)

# Estimate R squared
PseudoR2(mod_shoulder,"Nagelkerke") #0.210

# And the Brier score
BrierScore(mod_shoulder) #0.113

# CITL
mod_log_1 <- glm(shoulderinjury~offset(pred_LP),family="binomial", data =
actual_v_predict_shoulder)
mod_log_1$coef
confint(mod_log_1) #7.64894e-10   (95% CI: -0.2553156,  0.2416835)

# E/O
prop.table(table(actual_v_predict_shoulder$shoulderinjury)) #0.2109 for event
O <- prop.table(table(actual_v_predict_shoulder$shoulderinjury))[2]
E <- mean(pred_prob)
E/O #1

# C-slope
```

```
mod_log_2 <- glm(shoulderinjury ~ pred_LP,family="binomial",x=TRUE,y=TRUE, data =
actual_v_predict_shoulder)
mod_log_2 #1.00
confint(mod_log_2) #C Slope: 1.00 (95%CI: 0.60, 1.41)


val.prob(y = actual_v_predict_shoulder$shoulderinjury, logit =
actual_v_predict_shoulder$lp_mod2,
        pl=TRUE, smooth=TRUE, logistic.cal=TRUE,
        xlab="Predicted Probability", ylab="Actual Probability",
        lim=c(0, 1), emax.lim=c(0,1),
        legendloc=lim[1] + c(0.55 * diff(lim), 0.27 * diff(lim)),
        statloc=c(0,0.99), riskdist=c("predicted", "calibrated"),
        cex=.7, mkh=.02,
        connect.group=FALSE, connect.smooth=TRUE, g.group=4,
        evaluate=100, nmin=0)




#Mixed Effects for all arm injuries
#*********All singlular, not showing anything, ask Gary
mod_mixed <- glmer(elbow_shoulder_injury_7days ~ BMI + ARM_DOM +
as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
                   rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3)
+ (1 | ID),
                   data = rockey_cutdown, family=binomial, control = glmerControl(optimizer =
"bobyqa"), nAGQ = 10)
summary(mod_mixed)

se <- sqrt(diag(vcov(mod_mixed)))
# table of estimates with 95% CI
(tab <- cbind(Est = fixef(mod_mixed), LL = fixef(mod_mixed) - 1.96 * se, UL =
fixef(mod_mixed) + 1.96 *
              se)) #Log Odds
exp(tab) #OR's

#Survival Analysis
#Screening down to 13-19
rockey_cutdown <- read.csv("/Users/student/Documents/NDORMS /Rockies/Official Data
/rockies_totalload_5.4.20.csv")
rockey_cutdown$Year <- as_date(dmy(rockey_cutdown$Year))

rockey_cutdown$reported_date_arm_1 <-
as_date(dmy(rockey_cutdown$reported_date_arm_1))
```

```
rockey_cutdown_2013plus <- rockey_cutdown %>%
                    filter(Year >= "2013-01-01")

rockey_cutdown_2013plus$Year #GTG

rockey_cutdown_2013plus$reported_date_arm_1 #GTG

#Creating overall time to calculation to injury
rockey_cutdown_2013plus$max_player_days #Total exposure per year

rockey_13 <- rockey_cutdown_2013plus %>%
   filter(Year == "2013-01-01")

rockey_13 <- rockey_13 %>%
        mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                            difftime(reported_date_arm_1, "2013-03-03", units = c("days")),
                            max_player_days))

rockey_13 <- rockey_13 %>%
        mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                            overall_exposure_arm_non_arminjuryloss,
                            surv_arminj))

rockey_13[rockey_13$ID == "13-56", "surv_arminj"] <- 187.9583333


rockey_14 <- rockey_cutdown_2013plus %>%
  filter(Year == "2014-01-01")

rockey_14 <- rockey_14 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                      difftime(reported_date_arm_1, "2014-03-03", units = c("days")),
                      max_player_days))

rockey_14 <- rockey_14 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                      overall_exposure_arm_non_arminjuryloss,
                      surv_arminj))

rockey_14 %>%
  filter(is.na(surv_arminj)) %>%
  select(ID, f_name, Last_Name, elbow_shoulder_injury_7days, reported_date_arm_1)

rockey_14[rockey_14$ID == "14_73", "surv_arminj"] <- 187.9583333

rockey_15 <- rockey_cutdown_2013plus %>%
  filter(Year == "2015-01-01")
```

```
rockey_15 <- rockey_15 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                        difftime(reported_date_arm_1, "2015-03-03", units = c("days")),
                        max_player_days))

rockey_15 <- rockey_15 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                        overall_exposure_arm_non_arminjuryloss,
                        surv_arminj))

rockey_15 %>%
  filter(is.na(surv_arminj)) %>%
  select(ID, f_name, Last_Name, elbow_shoulder_injury_7days, reported_date_arm_1)

rockey_15[rockey_14$ID == "14_73", "surv_arminj"] <- 187.9583333


rockey_16 <- rockey_cutdown_2013plus %>%
  filter(Year == "2016-01-01")

rockey_16 <- rockey_16 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                        difftime(reported_date_arm_1, "2016-03-03", units = c("days")),
                        max_player_days))

rockey_16 <- rockey_16 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                        overall_exposure_arm_non_arminjuryloss,
                        surv_arminj))

rockey_16 %>%
  filter(surv_arminj < 0) %>%
  select(ID, f_name, Last_Name, elbow_shoulder_injury_7days, reported_date_arm_1)

rockey_16[rockey_16$ID == "16_013", "surv_arminj"] <- 67


rockey_17 <- rockey_cutdown_2013plus %>%
  filter(Year == "2017-01-01")

rockey_17 <- rockey_17 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                        difftime(reported_date_arm_1, "2017-03-03", units = c("days")),
                        max_player_days))

rockey_17 <- rockey_17 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                        overall_exposure_arm_non_arminjuryloss,
                        surv_arminj))
```

```
rockey_18 <- rockey_cutdown_2013plus %>%
  filter(Year == "2018-01-01")

rockey_18 <- rockey_16 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                        difftime(reported_date_arm_1, "2018-03-03", units = c("days")),
                        max_player_days))

rockey_18 <- rockey_16 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                        overall_exposure_arm_non_arminjuryloss,
                        surv_arminj))



rockey_19 <- rockey_cutdown_2013plus %>%
  filter(Year == "2019-01-01")

rockey_19 <- rockey_19 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 1,
                        difftime(reported_date_arm_1, "2019-03-03", units = c("days")),
                        max_player_days))

rockey_19 <- rockey_19 %>%
  mutate(surv_arminj = ifelse(elbow_shoulder_injury_7days == 0,
                        overall_exposure_arm_non_arminjuryloss,
                        surv_arminj))

rockey_19 %>%
  filter(is.na(surv_arminj)) %>%
  select(ID, f_name, Last_Name, elbow_shoulder_injury_7days, reported_date_arm_1)

rockey_19[rockey_19$ID == "16_074", "surv_arminj"] <- 52

#R Binding all the year data sets
r1314 <- rbind(rockey_13, rockey_14)
r131415 <- rbind(r1314, rockey_15)
r13_16 <- rbind(r131415, rockey_16)
r13_17 <- rbind(r13_16, rockey_17)
r13_18 <- rbind(r13_17, rockey_18)
rockey_cutdown_2013plus <- rbind(r13_18, rockey_19)

#Adding back in DTROM
rockey_cutdown_2013plus$dtrom <- rockey_cutdown_2013plus$DPIR_M +
rockey_cutdown_2013plus$D_PER_M
```

```
rockey_cutdown_2013plus$ndtrom <- rockey_cutdown_2013plus$ND_PIR_M +
rockey_cutdown_2013plus$ND_PER_M
rockey_cutdown_2013plus$trom_diff <- rockey_cutdown_2013plus$dtrom -
rockey_cutdown_2013plus$ndtrom


cox_arminjury <- coxph(Surv(surv_arminj, elbow_shoulder_injury_7days) ~ BMI +
ARM_DOM + as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
            rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
            data= rockey_cutdown_2013plus, ties="breslow")
cox_arminjury
summary(cox_arminjury)


# Calculate apparent discrimination performance

# Obtain the linear predictor/PI for each patient
pred_LP <- predict(cox_arminjury, type="lp",reference="sample")

# R automatically centres variables, to uncentered varaibles use this code
#pred_LP <- predict(surv_mod,type="lp",reference="sample") +
sum(coef(surv_mod)*surv_mod$means, na.rm=TRUE)

# Summarise the distribution of linear predictor
# Slightly different to sheet due to centering
mean(pred_LP) #-3.536802e-15
sd(pred_LP) #1.034938
min(pred_LP) #-2.299245
max(pred_LP) #4.406841

# Obtain Harrell's c statistic
summary(cox_arminjury)$concordance[1]
summary(cox_arminjury)$concordance[1]-(1.96*summary(cox_arminjury)$concordance[2])
summary(cox_arminjury)$concordance[1]+(1.96*summary(cox_arminjury)$concordance[2])
#AUC: 0.755 (95% CI: 0.699, 0.811)



# Other measures of discrimination / separation
# To obtain the Royston & Sauerbrei's D
#Not working for this
D <- D.index(pred_LP,surv.time= surv_arminj ,surv.event=
elbow_shoulder_injury_7days)$coef
D

# And R^2D
kap <- sqrt(8/pi)
sig2 <- (pi^2)/6
r2D <- (D^2 / kap^2) / (sig2 + (D^2 / kap^2))
```

r2D

```
##########
# Part 3 #
##########

# Calculate apparent calibration performance of the model in development data
#Making DF for complete case analysis

rockey_array <- rockey_cutdown_2013plus %>%
  filter(!is.na(BMI) & !is.na(ARM_DOM) & !is.na(years_played_ordinal)
&  !is.na(year_2013_or2015above) & !is.na(number_of_pitches) & !is.na(HT_diff)
& !is.na(dtrom) & !is.na(DHA_M) & !is.na(surv_arminj)) %>%
  select(ID, surv_arminj, elbow_shoulder_injury_7days)


# calibration slope
surv_arminjury2 <- coxph(Surv(rockey_array$surv_arminj,
rockey_array$elbow_shoulder_injury_7days)~pred_LP)
surv_arminjury2$coef
confint(surv_arminjury2) #C: 1.00 (95% CI: 0.80, 1.20)

actual_v_predict_surv <- cbind(rockey_array, pred_LP)

val.surv(fit = actual_v_predict_surv$elbow_shoulder_injury_7days, est.surv =
actual_v_predict_surv$pred_LP,
        pl=TRUE, smooth=TRUE, logistic.cal=TRUE,
        xlab="Predicted Probability", ylab="Actual Probability",
        lim=c(0, 1), emax.lim=c(0,1),
        legendloc=lim[1] + c(0.55 * diff(lim), 0.27 * diff(lim)),
        statloc=c(0,0.99), riskdist=c("predicted", "calibrated"),
        cex=.7, mkh=.02,
        connect.group=FALSE, connect.smooth=TRUE, g.group=4,
        evaluate=100, nmin=0)
```

Appendix E: Appendices for Chapter 7

Appendix E.1. Humeral torsion predictive model R code

```
library(dplyr)
library(ggplot2)
library(pmsampsize)
library(readxl)
library(lubridate)
library(reshape2)
library(rms)
library(finalfit)
library(naniar)
library(caret)
library(car)

#Getting Sample Size for the Cont Predictive Model for PRO
pmsampsize(type = "c",  rsquared = 0.38, parameters = 10, intercept = 27.5, sd = 3.8)
#244

combined_ht <- read_xlsx("/Users/student/Documents/NDORMS /Rockies/Official Data
/noPMmodel_rockies_alldata_continent_5.28.20.xlsx", sheet = 2)
#Complete Case (≤3% Missing data)

combined_ht <- combined_ht %>%
          filter(!is.na(Age) & !is.na(ARM_DOM) & !is.na(PIR_M) & !is.na(PER_M)
& !is.na(HA_M) & !is.na(Continent_Origin) & !is.na(Previous_INJ) & !is.na(HT_M))

combined_ht_model <- glm(HT_M ~ Age + as.factor(ARM_DOM) + PIR_M + PER_M +
HA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ),
                   family = 'gaussian', data = combined_ht)
summary(combined_ht_model)
confint(combined_ht_model)
with(summary(combined_ht_model), 1 - deviance/null.deviance) #0.417
plot(combined_ht_model)

set.seed(17)

full_boot <- train(HT_M ~ Age + as.factor(ARM_DOM) + PIR_M + PER_M + HA_M +
as.factor(Continent_Origin) + as.factor(Previous_INJ),
                   data = combined_ht, method = "glm", family = "gaussian",
                   trControl = trainControl("boot", number = 2000)
)
summary(full_boot$finalModel)
full_boot$results
#parameter    RMSE  Rsquared      MAE    RMSESD RsquaredSD     MAESD
#      none 11.8574 0.4084917 9.335472 0.3054831 0.02678569 0.2676185


set.seed(17)
```

```
boot_combined <- Boot(combined_ht_model, R = 2000)
summary(boot_combined)

boot_combined_predict <- predict.train(full_boot, newdata = combined_ht, type = "raw")


# Summarizing the distribution of linear predictor
mean(boot_combined_predict) #16.81128
sd(boot_combined_predict) #9.951723
min(boot_combined_predict) #-19.00404
max(boot_combined_predict) #46.8616



actual_v_predict_combined <- cbind(combined_ht, boot_combined_predict)

# C-slope
mod_combined_2 <- glm(HT_M ~
boot_combined_predict,family="gaussian",x=TRUE,y=TRUE, data =
actual_v_predict_combined)
mod_combined_2 #1.00
confint(mod_combined_2) #C Slope: 1.00 (95%CI: 0.94, 1.06)



#Calibration Plot
# Getting Quantiles
g3 <- mutate(actual_v_predict_combined, bin = ntile((boot_combined_predict), 10))

# Bin prediction into 10ths
g3 <-  g3 %>%
  group_by(bin) %>%
  mutate(n = n(), # Get ests and CIs
         bin_pred = mean(boot_combined_predict),
         bin_prob = mean(HT_M),
         standard_deviation = sd(HT_M),
         se = standard_deviation/(sqrt(n)),
         ul = bin_prob + 1.96 * se,
         ll = bin_prob - 1.96 * se) %>%
  ungroup()

#Plot Itself
ggplot(data = g3, aes(x = bin_pred, y = bin_prob, ymin = ll, ymax = ul)) +
  geom_pointrange(size = 0.5, color = "black") +
  geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
  # Smooth line fit through estimates
  geom_line(color = "red") +
  xlab("Predicted Humeral Torsion (Degrees)") +
```

```
  ylab("Observed Humeral Torsion (Degrees)") +
  theme_minimal()

ggplot(data = actual_v_predict_combined, aes(x = boot_combined_predict, y = HT_M)) +
  geom_point() +
  geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
  geom_smooth(method = lm, se = T, color = "red", size = 1, alpha = 0.8) +
  xlab("Predicted Humeral Torsion (Degrees)") +
  ylab("Observed Humeral Torsion (Degrees)") +
  theme_minimal() +
  xlim(-20, 60)


#########################################################################
#Sensitivity Analyses
#########################################################################

#Dominant HT
#Creating Prediction

model_ht <- glm(DHT_M ~ Age + as.factor(ARM_DOM) + DPIR_M + D_PER_M +
DHA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ),
            family = 'gaussian', data = rockey_continent_cutdown)
summary(model_ht)
confint(model_ht)
with(summary(model_ht), 1 - deviance/null.deviance) #Rsquared = 0.189
plot(model_ht) #Residuals Look fantastic, QQ Plot is right on the money.

model_ht_rcs <- glm(DHT_M ~ Age + as.factor(ARM_DOM) + rcs(DPIR_M, 3) +
rcs(D_PER_M, 3) + rcs(DHA_M, 3) + as.factor(Continent_Origin) +
as.factor(Previous_INJ),
            family = 'gaussian', data = rockey_continent_full_2)
summary(model_ht_rcs)
confint(model_ht_rcs)
with(summary(model_ht_rcs), 1 - deviance/null.deviance) #Rsquared = 0.195

model_ht_interact <- glm(DHT_M ~ Age + as.factor(ARM_DOM) + DPIR_M + D_PER_M
+ DHA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ) + DPIR_M*D_PER_M,
                  family = 'gaussian', data = rockey_continent_full_2)
summary(model_ht_interact)
confint(model_ht_interact)
with(summary(model_ht_interact), 1 - deviance/null.deviance) #0.190

noage <-glm(DHT_M ~ as.factor(ARM_DOM) + DPIR_M + D_PER_M + DHA_M +
as.factor(Continent_Origin) + as.factor(Previous_INJ) + DPIR_M*D_PER_M,
          family = 'gaussian', data = rockey_continent_full_2)
```

```
################## No Differences in all 3 models, will take the less complex
model###############

#Internal Validation for OPtmisim Shrinkage using Bootstrapping Methods
rockey_continent_cutdown <- rockey_continent_full_2 %>%
  filter(!is.na(Age) & !is.na(ARM_DOM) & !is.na(DPIR_M) & !is.na(D_PER_M)
& !is.na(DHA_M) & !is.na(Continent_Origin) & !is.na(Previous_INJ)
& !is.na(DHT_M)) %>%
  select(ID, Age, ARM_DOM, DPIR_M, D_PER_M, DHA_M, Continent_Origin,
Previous_INJ, DHT_M)

set.seed(17)

model_ht_boot <- train(DHT_M ~ Age + as.factor(ARM_DOM) + DPIR_M + D_PER_M +
DHA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ),
  data = rockey_continent_cutdown, method = "glm", family = "gaussian",
  trControl = trainControl("boot", number = 2000)
)
summary(model_ht_boot)
model_ht_boot$results
#parameter     RMSE  Rsquared      MAE    RMSESD RsquaredSD     MAESD
#1      none 11.89165 0.1687487 9.327384 0.4596245 0.03557731 0.3945517


boot_ht_predict <- predict.train(model_ht_boot, newdata = rockey_continent_cutdown, type
= "raw")

rockey_continent_cutdown$ARM_DOM <-
as.factor(rockey_continent_cutdown$ARM_DOM)
rockey_continent_cutdown$Continent_Origin <-
as.factor(rockey_continent_cutdown$Continent_Origin)
rockey_continent_cutdown$Previous_INJ <-
as.factor(rockey_continent_cutdown$Previous_INJ)

set.seed(17)

boot_HT_2 <- Boot(model_ht, R = 2000)
summary(boot_HT_2)
boot.ci(boot_HT_2, conf=0.95, type="all")




#Creating Array for only HT
HT_cutdown <- rockey_continent_cutdown %>%
  select(DHT_M)
```

```
# Summarizing the distribution of linear predictor
mean(boot_ht_predict) #8.432227
sd(boot_ht_predict) #5.62
min(boot_ht_predict) #-13.24
max(boot_ht_predict) #24.35


#Creating cut down DF for
rockey_continent_cutdown <- rockey_continent_full_2 %>%
  filter(!is.na(Age) & !is.na(ARM_DOM) & !is.na(DPIR_M) & !is.na(D_PER_M)
& !is.na(DHA_M) & !is.na(Continent_Origin) & !is.na(Previous_INJ)
& !is.na(DHT_M)) %>%
  select(ID, DHT_M)

actual_v_predict_ht <- cbind(rockey_continent_cutdown, boot_ht_predict)

# C-slope
mod_ht_2 <- glm(DHT_M ~ boot_ht_predict,family="gaussian",x=TRUE,y=TRUE, data =
actual_v_predict_ht)
mod_ht_2 #1.00
confint(mod_ht_2) #C Slope: 1.00 (95%CI: 0.84, 1.16)




############################################################
#Calibration Plot
####################################

# Getting Quantiles
g1 <- mutate(actual_v_predict_ht, bin = ntile((boot_ht_predict), 10))

# Bin prediction into 10ths
g1 <-  g1 %>%
  group_by(bin) %>%
  mutate(n = n(), # Get ests and CIs
         bin_pred = mean(boot_ht_predict),
         bin_prob = mean(DHT_M),
         standard_deviation = sd(DHT_M),
         se = standard_deviation/(sqrt(n)),
         ul = bin_prob + 1.96 * se,
         ll = bin_prob - 1.96 * se) %>%
  ungroup()

#Plot Itself
  ggplot(data = g1, aes(x = bin_pred, y = bin_prob, ymin = ll, ymax = ul)) +
  geom_pointrange(size = 0.5, color = "black") +
```

```
  geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
    # Smooth line fit through estimates
    geom_line(color = "red") +
  xlab("Predicted Humeral Torsion (Degrees)") +
  ylab("Observed Humeral Torsion (Degrees)") +
  theme_minimal()


  ggplot(data = actual_v_predict_ht, aes(x = boot_ht_predict, y = DHT_M)) +
    geom_point() +
    geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
    geom_smooth(method = lm, se = T, color = "red", size = 1, alpha = 0.8) +
    xlab("Predicted Humeral Torsion (Degrees)") +
    ylab("Observed Humeral Torsion (Degrees)") +
    theme_minimal()  +
    xlim(-15, 45)




#Non Dominant HT

rockey_continent_cutdown_ND <- rockey_continent_full_2 %>%
  filter(!is.na(Age) & !is.na(ARM_DOM) & !is.na(ND_PIR_M) & !is.na(ND_PER_M)
& !is.na(ND_HA_M) & !is.na(Continent_Origin) & !is.na(Previous_INJ)
& !is.na(NDHT_M)) %>%
  select(ID, Age, ARM_DOM, ND_PIR_M, ND_PER_M, ND_HA_M, Continent_Origin,
Previous_INJ, NDHT_M)




model_NDht <- glm(NDHT_M ~ Age + as.factor(ARM_DOM) + ND_PIR_M +
ND_PER_M + ND_HA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ),
                  family = 'gaussian', data = rockey_continent_cutdown_ND)
summary(model_NDht)
confint(model_NDht)
with(summary(model_NDht), 1 - deviance/null.deviance) #Rsquared = 0.262
plot(model_NDht) #Residuals Look fantastic, QQ Plot is right on the money.


#Internal Validation
set.seed(17)

model_NDht_boot <- train(NDHT_M ~ Age + as.factor(ARM_DOM) + ND_PIR_M +
ND_PER_M + ND_HA_M + as.factor(Continent_Origin) + as.factor(Previous_INJ),
                         data = rockey_continent_cutdown_ND, method = "glm", family = "gaussian",
```

```
                trControl = trainControl("boot", number = 2000)
)
summary(model_NDht_boot$finalModel)
model_NDht_boot$results
#parameter     RMSE Rsquared      MAE    RMSESD RsquaredSD     MAESD
#      none 11.27224 0.243482 9.018021 0.3934537 0.04064201 0.3570365


set.seed(17)

boot_NDHT_2 <- Boot(model_NDht, R = 2000)
summary(boot_NDHT_2)

boot_ht_predict <- predict.train(model_ht_boot, newdata = rockey_continent_cutdown, type
= "raw")

rockey_continent_cutdown$ARM_DOM <-
as.factor(rockey_continent_cutdown$ARM_DOM)
rockey_continent_cutdown$Continent_Origin <-
as.factor(rockey_continent_cutdown$Continent_Origin)
rockey_continent_cutdown$Previous_INJ <-
as.factor(rockey_continent_cutdown$Previous_INJ)

set.seed(17)

boot_HT_2 <- Boot(model_ht, R = 2000)
summary(boot_HT_2)
boot.ci(boot_HT_2, conf=0.95, type="all")




ndht_boot_predict <- predict.train(model_NDht_boot, newdata =
rockey_continent_cutdown_ND, type = "raw")

# Summarizing the distribution of linear predictor
mean(ndht_boot_predict) #25.30503
sd(ndht_boot_predict) #6.61282
min(ndht_boot_predict) #7.499581
max(ndht_boot_predict) #46.04552



actual_v_predict_NDht <- cbind(rockey_continent_cutdown_ND, ndht_boot_predict)

# C-slope
```

```
mod_NDht_2 <- glm(NDHT_M ~ ndht_boot_predict,family="gaussian",x=TRUE,y=TRUE,
data = actual_v_predict_NDht)
mod_NDht_2 #1.00
confint(mod_NDht_2) #C Slope: 1.00 (95%CI: 0.87, 1.13)



#Calibration Plot
# Getting Quantiles
g2 <- mutate(actual_v_predict_NDht, bin = ntile((ndht_boot_predict), 10))

# Bin prediction into 10ths
g2 <-  g2 %>%
  group_by(bin) %>%
  mutate(n = n(), # Get ests and CIs
         bin_pred = mean(ndht_boot_predict),
         bin_prob = mean(NDHT_M),
         standard_deviation = sd(NDHT_M),
         se = standard_deviation/(sqrt(n)),
         ul = bin_prob + 1.96 * se,
         ll = bin_prob - 1.96 * se) %>%
  ungroup()

#Plot Itself
ggplot(data = g2, aes(x = bin_pred, y = bin_prob, ymin = ll, ymax = ul)) +
  geom_pointrange(size = 0.5, color = "black") +
  geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
  # Smooth line fit through estimates
  geom_line(color = "red") +
  xlab("Predicted Humeral Torsion (Degrees)") +
  ylab("Observed Humeral Torsion (Degrees)") +
  theme_minimal() +
  ggtitle()


ggplot(data = actual_v_predict_NDht, aes(x = ndht_boot_predict, y = NDHT_M)) +
  geom_point() +
  geom_abline(slope = 1, color = "blue", size = 2, alpha = 0.6) + # 45 degree line indicating
perfect calibration
  geom_smooth(method = lm, se = T, color = "red", size = 1, alpha = 0.8) +
  xlab("Predicted Humeral Torsion (Degrees)") +
  ylab("Observed Humeral Torsion (Degrees)") +
  theme_minimal()  +
  xlim(-15, 45)
```

Appendix F: Appendices for Chapter 8

Appendix F.1. Decision curve analysis R code

```
library(rmda)

#Decision Curves for overall model

decision_curve <- cv_decision_curve(elbow_shoulder_injury_7days ~ BMI + ARM_DOM +
as.factor(years_played_ordinal) + as.factor(year_2013_or2015above) +
              rcs(number_of_pitches, 4) + rcs(HT_diff, 4) + rcs(dtrom, 3) + rcs(DHA_M, 3),
              rockey_cutdown, family = binomial(link = "logit"),
              thresholds = seq(0, 1, by = 0.01), folds = 10, study.design = "cohort",
               policy = "opt-in")

summary(decision_curve)

plot_decision_curve(decision_curve, cost.benefit.axis = TRUE,
                n.cost.benefits = 6, standardize = TRUE,
                confidence.intervals = T, xlim = c(0.0, 0.35),
                legend.position = "none")


risk_profile <- cv_decision_curve(elbow_shoulder_injury_7days ~ as.factor(trom_risk),
                          rockey_cutdown, family = binomial(link = "logit"),
                          thresholds = seq(0, 1, by = 0.01), folds = 10, study.design = "cohort",
                          policy = "opt-in")

summary(risk_profile)

ha_profile <- cv_decision_curve(elbow_shoulder_injury_7days ~ as.factor(ha_risk),
                          rockey_cutdown, family = binomial(link = "logit"),
                          thresholds = seq(0, 1, by = 0.01), folds = 10, study.design = "cohort",
                          policy = "opt-in")

summary(ha_profile)


plot_decision_curve(decision_curve, cost.benefit.axis = TRUE,
              n.cost.benefits = 6, standardize = TRUE,
              confidence.intervals = T, xlim = c(0.0, 0.35),
              legend.position = "none")

plot_decision_curve( list(decision_curve, risk_profile),
               curve.names = c("Predictive Model", "TROM Risk Profile"),
               xlim = c(0.0, 0.35),
               col = c("blue", "red"),
               lty = c(1,2),
               lwd = c(3,2, 2, 1),
               legend.position = "topright")
```

```
plot_decision_curve( list(decision_curve, risk_profile, ha_profile),
                     curve.names = c("Predictive Model", "TROM Risk Profile", "HA Risk Profile"),
                     xlim = c(0.0, 0.35),
                     col = c("blue", "red", "purple"),
                     legend.position = "topright")
```

Appendix G: Publications and Presentations

Appendix G.1. Publications and presentations derived from this thesis

Publications

Chapter 1

Bullock GS, Hughes T, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Clinical Prediction Model in Sports Medicine: A Tutorial. J Orthop Sport Phys Ther.

Bullock GS, Hughes T, Sergeant JC, Callaghan MJ, Riley RD, Collins GS. Sports Medicine Prediction Models: A Brief Tutorial. Br J Sport Med.

Bullock GS, Hughes T, Arundale AH, Ward P, Collins GS, Kluzek S. Black box prediction methods in sport deserve a red card: to advance athlete care a substitute is needed. Sports Med.

Chapter 2

Bullock GS, Uhan J, Harriss EK, Arden NK, Filbay SR. The relationship between baseball participation, health, and wellbeing: A systematic scoping review. Journal of Orthopaedic & Sports Physical Therapy. Feb, 2020;50(2):55-66.

Chapter 3

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Health conditions, substance use, physical activity and quality of life in current and former baseball players. Sports Health.

Bullock GS, Nicholson KF, Waterman BR, Shanley E, Thigpen CS, Tokish J, Salamh P, Devaney LL, Niesen E, Collins GS, Arden NK, Filbay SR. Persistent joint pain and arm function in former baseball players. J Should Elbow Surg

Chapter 5

**Thigpen CS, *Bullock GS,* Noonan TJ, Wyland J, Kissenberth T, Arden NK, Collins GS, Shanley E. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. Am J Sports Med.

*Joint first author

Chapter 6

*Shanley E**,** *Bullock GS, Noonan TJ, Wyland J, Kissenberth T, Arden NK, Collins GS, Thigpen CS. Development and application of an arm injury prediction model for professional pitchers. Am J Sports Med.

*Joint first author

Chapter 7

Bullock GS, Shanley E, Noonan TJ, Kissenberth T, Arnold A, Bailey L, Arden NK, Collins GS, Thigpen CS. Development and internal validation of a humeral torsion prediction model in professional baseball pitchers. J Should Elbow Surg.

Chapter 8

*Bullock GS, *Shanley E, Noonan TJ, Wylans J, Kissenberth T, Arden NK, Collins GS, Thigpen CS. Assessing the clinical benefit of an arm injury prediction model in professional pitchers compared to current evidence-based practice: A decision curve analysis. Am J Sports Med.

*Joint first author

External Oral Presentations

Chapter 2

Bullock GS, Uhan J, Harriss EK, Arden NK, Filbay SR. The relationship between baseball participation, health, and wellbeing: A systematic scoping review. Presented at: Combined Sections Meeting. February 12-15, 2020, Denver Colorado.

Chapter 5

Bullock GS, Shanley E, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Thigpen CA. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. American Orthopaedic Society of Sports Medicine. Specialty Day. July 8-11, 2021.

Thigpen CA, Bullock GS, Shanley E, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Organizational Risk Profiling and Education Associated with Reduction in Professional Pitching Arm Injuries: An interrupted time series analysis. Combined Sections Meeting. February 24-27, 2021.

Chapter 6

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Shanley E. Development and application of an arm injury prediction model for professional pitchers. American Academy of Orthopaedic Surgeons. March 9-12, 2020, San Diego, CA.

Shanley E, Bullock GS, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Thigpen CA. Informing the Avoidance of Arm Injury for Professional Pitchers through Predictive Modelling. Combined Sections Meeting. February 24-27, 2021.

Chapter 7

Bullock GS, Thigpen CA, Collins GS, Arden NK, Noonan TK, Kissenberth MJ, Wyland DJ, Arnold A, Bailer LB, Shanley E. Development and internal validation of humeral torsion prediction model for professional baseball pitchers. Combined Sections Meeting. February 24-27, 2021. Orlando, FL.

External Poster Presentations

Chapter 3

Bullock GS, Nicholson KF, Waterman BR, Niesen E, Salamh P, Thigpen CS, Shanley E, Collins GS, Arden NK, Filbay SR. Persistent pain and upper extremity function in former collegiate baseball players: An exploratory analysis. World Congress on Osteoarthritis (OARSI). April 30-May 3, 2020. Vienna, Austria.

Bullock GS, Nicholson KF, Waterman BR, Niesen E, Salamh P, Thigpen CS, Shanley E, Collins GS, Arden NK, Filbay SR. A high prevalence of persistent shoulder and elbow pain and poor arm function amongst former baseball players. April 29-May 3, 2021. World Congress on Osteoarthritis (OARSI). Denver, CO.

Every new beginning comes from some other beginning's end

-Seneca the Younger