

**OBJECTIVELY DIFFERENTIATING ANTERIOR CRUCIATE LIGAMENT INJURY
STATUS IN ADOLESCENTS THROUGH CLINICAL AND LABORATORY-BASED
MEASURES**

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TABLE OF CONTENTS

LIST OF ACRONYMS	vii
LIST OF FIGURES	ix
LIST OF TABLES	xii
ACKNOWLEDGEMENTS	xiii
PREFACE	xv
RESEARCH CONTRIBUTIONS.....	xvii
GENERAL ABSTRACT	xix
CHAPTER 1: INTRODUCTION	1
CHAPTER 2: LITERATURE REVIEW	3
2.1 ACL Injury and Changes to Joint Function	3
2.2 Influence of Puberty on ACL Injury Risk.....	4
2.3 Functional Capacity Measurement Tools.....	5
2.3.1 Subjective Measures	5
2.3.2 Objective Measures.....	6
2.3.3 Clinical Adoption of RTA Measures	7
2.4 IMU MoCap Trade-Off.....	8
2.5 Movement Analysis for Classification.....	11
2.6 Dimensionality Reduction Techniques	12
2.7 Principal Component Analysis.....	13
2.8 Classification Model Choices	15
CHAPTER 3: PURPOSE and HYPOTHESES	17
CHAPTER 4: GENERAL METHODOLOGY.....	21
4.1 Study Design.....	21
4.2 Participants.....	21
4.3 Protocol	23
4.4 Data Pre-Processing	26
4.5 Data Analysis	29
CHAPTER 5: ARTICLE 1	35
5.1 Preamble	36
5.2 Abstract.....	37
5.3 Introduction.....	38
5.4 Methods.....	39

Study Design.....	39
Participants.....	40
Procedure	40
Statistical Analyses	41
Reproducibility	41
Responsiveness	42
Limb Symmetry Index	42
5.5 Results.....	43
Reproducibility	43
Responsiveness	44
Limb Symmetry Index	44
Baseline Measures and Sex Differences	45
5.6 Discussion.....	46
5.7 Conclusion	48
5.8 References.....	49
5.9 Postamble.....	54
CHAPTER 6: ARTICLE 2	55
6.1 Preamble	56
6.2 Abstract.....	57
6.3 Introduction.....	58
6.4 Materials and Methods.....	59
6.5 Statistical Analysis.....	62
6.6 Results.....	64
6.7 Discussion.....	68
6.8 Conclusion	70
6.9 References.....	72
6.10 Postamble.....	80
CHAPTER 7: ARTICLE 3	81
7.1 Preamble	82
7.2 Abstract.....	83
7.3 Introduction.....	84
7.4 Methods.....	85
7.4.1 Participants.....	85
7.4.2 Protocol	86

7.4.3 Pre-processing.....	87
7.4.4 Application of Principal Component Analysis	88
7.4.5 Feature Selection.....	88
7.4.6 Classification.....	88
7.4.7 Model Performance.....	89
7.4.8 Post-hoc Analysis of Classification Outcomes	89
7.5 Results.....	90
7.5.1 Classification Performance of the Injured Limb (IL-CON).....	91
7.5.2 Classification Performance of the Contralateral Limb (CL-CON)	93
7.5.3 Misclassification Analysis	94
7.6 Discussion.....	96
7.7 Acknowledgments.....	98
7.8 References.....	99
7.9 Postamble.....	104
CHAPTER 8: IMU Validation.....	105
8.1 Preamble	105
8.2 Validation of Real IMUs and Simulated IMUs Against Marker-Based Kinematics	106
8.3 Participants and Available Data.....	111
8.4 Data Preparation and Reference Kinematics.....	111
8.5 Simulated Inertial Measurements from MoCap.....	112
8.6 Real IMU Fusion and Static Calibration.....	113
8.7 Knee Angle Estimation and Validation Metrics	113
8.8 Sensitivity Analyses and Implementation Considerations	114
8.9 Validation of the Processing Pipeline	115
8.10 Results.....	117
8.10.1 Validation Using the Present Dataset.....	117
8.10.2 Independent Validation Using the Scherpereel Dataset.....	119
8.11 Interpretation of Simulated IMU Outliers.....	121
8.12 Conclusion	122
8.12 Postamble.....	124
CHAPTER 9: ARTICLE 4	126
9.1 Preamble	127
9.2 Introduction.....	128
9.3 Methods.....	130

9.3.1 Participants.....	130
9.3.2 Protocol.....	130
9.3.3 Simulated IMU Generation.....	131
9.3.4 Pre-processing.....	132
9.3.5 Principal Component Analysis.....	133
9.3.6 Feature Selection.....	134
9.3.7 Classification.....	134
9.3.8 Model Performance.....	135
9.4 Results.....	135
9.4.1 Anterior Hop (Ant).....	135
9.4.2 Cross Hop (Crs)	136
9.4.3 Lateral Hop (Lat)	136
9.4.4 Triple Hop (Trp).....	136
9.4.5 Comparative Placement/Model Performance	138
9.4.6 Principal Component Interpretation.....	138
9.5 Discussion.....	140
9.6 References.....	142
9.7 Postamble.....	147
CHAPTER 10: GENERAL DISCUSSION	148
10.1 Functional Performance Reproducibility in Adolescents	149
10.2 Spatiotemporal Metrics for Classification	150
10.3 Kinematic Waveform Analysis and Classification	151
10.4 Simulated IMUs for Functional Classification	153
10.5 Comparison of Marker-Trajectory and Simulated IMU Classification Performance	154
10.6 Limitations	157
10.7 Clinical Implications.....	161
10.8 Future Directions	164
10.9 Conclusion	166
REFERENCES	168
APPENDICES	193
Appendix A: Summary of Participant Numbers.....	193
Appendix B: Patient Reported Outcome Measures (PROMs).....	195
Appendix C: CBRU Marker Placement.....	204
Appendix D: Description of Tasks.....	205

Maximum Voluntary Contractions	205
Functional Tasks	205
Appendix E: Trimming Trials Start and End Point Criteria for Movement Tasks	209
Appendix F: List of Spatiotemporal Variables	210
Appendix G: Summary of Injured-Limb Classification Metrics for Marker-Based and Simulated IMU Models	213

LIST OF ACRONYMS

AA-AE	Simulated IMU sensor configurations
AA	= low back, thighs, shanks, and feet
AB	= low back and hopping limb only
AC	= thighs and shanks
AD	= thighs, shanks, and feet
AE	= low back, thighs, and shanks
ACL	Anterior cruciate ligament
ACL _i	Anterior cruciate ligament injury/injured
ACL-QoL	Anterior Cruciate Ligament Quality of Life Questionnaire
ACL _r	Anterior Cruciate Ligament reconstructed
ACL-RSI	Anterior Cruciate Ligament Return to Sport Index
ANOVA	Analysis of variance
ANT	Maximal anterior hop
AUC	Area under the curve
BA	Bland-Altman analysis
CA	Correspondance analysis
CART	Classification and regression tree
CHEO	Children's Hospital of Eastern Ontario
CI	Confidence interval
CMC	Coefficient of Multiple Correlation
CMJ	Countermovement jump
CON	Control participant (uninjured)
CRS	Cross hop for distance
D	Dominant
DCrsDist	Dominant/Injured limb maximal perpendicular cross hop distance
DNormCrs	Dominant/Injured normalized cross hop distance
DR	Dimensional reduction
DT	Decision tree
DT _a	Decision tree of adolescents with and without injuries
DT _f /DT _m	Decision tree of female/male subgroups (f = female; m = male)
DTW	Dynamic Time Warping
DVJ	Drop vertical jump
EMG	Electromyography
EV	Ensemble voting (soft-voting across classifiers)
fACL	Females with ACL injury
fCON	Female controls
F ₁	<i>F</i> -measure (harmonic mean of precision & recall)
FR	French
HSS Pedi-FABS	Hospital for Special Surgery Pediatric Functional Activity Brief Scale
ICC	Intra-class correlation coefficient
IKDC-SKF	International Knee Documentation Committee Subjective Knee Form
IMU	Inertial measurement unit
KNN	k-Nearest Neighbours
κ	Kappa statistic
LAT	Maximal lateral hop
LCL	Lateral collateral ligament
LDA	Linear discriminant analysis

LOA	Limits of agreement
LOO/LOOCV	Leave-one-out cross-validation
LR	Logistic regression
LSI	Limb symmetry index
LSLAT	Limb symmetry of the maximal lateral hop for distance
LSTIME	Limb symmetry of the 6-meter timed hop
LSTRP	Limb symmetry of the triple hop for distance
mACL	Males with ACL injury
MCL	Medial collateral ligament
mCON	Male controls
ML	Machine learning
MoCap	Motion Capture
ND	Non-dominant
NE	Neighbour embedding
NMDS	Non-metric multidimensional scaling
NMF	Non-negative matrix factorization
NNormANT	Non-dominant normalized maximal anterior hop
OA	Osteoarthritis
PCA	Principal component analysis
PC	Principal component
PCoA	Principal coordinate analysis (classical multidimensional scaling)
PCL	Posterior cruciate ligament
Pedi-IKDC	Pediatric International Knee Documentation Committee Questionnaire
PR AUC	Precision-recall area under the curve
PRC	Precision-recall curve
PROMs	Patient-reported outcome measures
Q-angle	Quadriceps angle
REP	Reduced error pruning
REPT	Reduced error pruning tree
RL	Reinforcement learning
RMSE	Root mean squared error
ROME	Relative overall mean error
RTA	Return-to-activity
SD	Standard deviation
SEM	Standard errors of measurement
SENIAM	Surface Electromyography for the Non-Invasive Assessment of Muscles
SI	International System of Units (Système International)
SL	Supervised learning
SRD	Smallest real difference
SVM	Support vector machine
TIME/ 6m	6-meter timed hop
TRP	Triple hop for distance
UL	Unsupervised learning
3D	3-dimensional

LIST OF FIGURES

Figure 4.1 Single-limb hop tests: A. Maximal Anterior Hop; B. Maximal Lateral Hop; C. Triple Hop for Distance; D. Cross-Hop for Distance; and, E. Timed 6-meter Hop.	26
Figure 5.1. Single-limb hop tests on the right foot: A) anterior hop; B) lateral hop; C) triple hop; D) cross hop; and E) 6-meter timed hop.	41
Figure 6.1. Review of data breakdown for each model with the group, inputted features and differentiating classes outlined.	63
Figure 6.2: C5.0 decision tree model for both males and female adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) participants and uninjured controls (CON). NNormAnt, non-dominant/injured limb's maximal anterior hop normalized to body height; DCrsDist, dominant/uninjured limb's maximal perpendicular cross-hop distance; LSTRP, limb symmetry index of the triple hop distance; LSTIME, limb symmetry index of the 6-meter timed hop.	65
Figure 6.3: C5.0 decision tree model for male adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) and uninjured controls (CON). NNormAnt, non-dominant/injured limb's maximal anterior hop normalized to body height.	66
Figure 6.4: C5.0 decision tree model for female adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) and uninjured controls (CON). LSTRP, limb symmetry index of the triple hop distance; DNormCrs, dominant/uninjured limb's maximal cross hop distance normalized to body height; LSLAT, limb symmetry index of the maximal lateral hop distance.	67
Figure 7.1. The percent of correctly classified participants as injured or uninjured for the injured limb (IL-CON) and contralateral limb (CL-CON), compared with healthy uninjured limbs, using logistic regression (LR), decision tree (DT), k-nearest neighbour (KNN), linear discriminant analysis (LDA), naïve Bayes (NB), support vector machine (SVM), and ensemble voting (EV)...	90
Figure 7.2A-D. Confusion matrices for LDA classification of model IL-CON: the injured limb of the ACLi group and the healthy limbs of the control group across hopping tasks.	91
Figure 7.3A-D. Confusion matrices for LDA classification of model CL-CON: the contralateral limb of the ACLi group and the healthy limbs of the CON group across hopping tasks.	93
Figure 7.4. Counts of misclassified tasks and combinations for both injured (INJ) and contralateral (CONT) limbs in ACL-injured participants are presented, with stacked bars indicating the distribution of misclassifications for both single-task and multi-task activities.	94
Figure 7.5. Counts of misclassified tasks and combinations for both dominant (DOM) and non-dominant (NONDOM) limbs in control participants are presented, with stacked bars indicating the distribution of misclassifications for both single-task and multi-task activities.	95
Figure 8.1. Representative synchronized inertial measurements from a single hopping trial. Tri-axial accelerometer signals are shown for the thigh (A) and shank (B) IMUs, while tri-axial gyroscope signals are shown for the thigh (C) and shank (D) IMUs following synchronization and trimming according to the motion capture-defined trial boundaries.....	107
Figure 8.2. Representative tri-axial accelerometer signals recorded from the thigh-mounted Delsys Trigno IMU during a maximal triple hop trial. The X-, Y-, and Z-axis accelerometer measurements are displayed from top to bottom, with acceleration (m/s^2) plotted over time (s).....	109
Figure 8.3. Intermediate processing steps used to estimate knee flexion from the real IMU recordings during a representative hopping trial. (A) Sagittal orientations of the anatomically	

mapped thigh and shank segments following AHRS-based sensor fusion and anatomical calibration. (B) Relative thigh–shank angle computed from the segment orientations before baseline correction.....	110
Figure 8.4. Distribution of Pearson correlation coefficients between IMU-derived knee flexion angles and marker-based reference knee flexion across maximal anterior, maximal lateral, triple hop, and cross hop trials for participants with IMU recordings (n = 23, 160 trials), comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.	117
Figure 8.5. Boxplots of root mean squared error (RMSE) between IMU-derived and marker-based knee flexion angles across maximal anterior, maximal lateral, triple hop, and cross hop trials for participants with usable IMU recordings (n = 23, 160 trials), comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.	118
Figure 8.6. Representative knee flexion–extension time series from a single hopping trial showing marker-based reference angles (black), simulated IMU-derived angles (red, dashed), and real IMU-derived angles (blue, dotted) after baseline correction relative to the first 50 frames of the trial.	119
Figure 8.7. Boxplots of Pearson correlation coefficients between IMU-derived and marker-based knee flexion angles from the Scherpereel et al. (2003) open-source dataset ²¹⁷ during a squat trial, comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.	120
Figure 8.8. Boxplots of root mean squared error (RMSE) between IMU-derived and marker-based knee flexion angles from the Scherpereel et al. (2023) open-source dataset ²¹⁷ during a squat trial, comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.	120
Figure 8.9. Representative knee flexion–extension time series from a squat trial in the Scherpereel et al. (2023) open-source dataset ²¹⁷ showing marker-based reference angles (black), real IMU-derived angles (blue, dotted), and simulated IMU-derived angles (red, dashed) plotted over the same time axis to illustrate agreement between modalities.	121
Figure 9.1. Simulated IMU configurations (AA-AE) and lower-body placements including the lower back, thighs, shanks, and feet.	132
Figure 9.2. Injured class F1 scores ($\pm 95\%$ CI) across tasks (anterior hop = Ant, cross hop = Crs, lateral hop = Lat, and triple hop = Trp) and IMU configurations; AA = blue, AB = orange, AC = green, AD = red, AE = purple.	138
Figure 9.3. Relative contribution of each movement phase to classification performance for the best-performing model in each hop task (anterior hop = Ant, cross hop = Crs, lateral hop = Lat, triple hop = Trp), averaged across principal components.	139
Figure A.1. Flowchart detailing participant compliance and ability to complete single-limb hopping tasks (MaxAnt: maximal anterior hop; MaxLat: maximal lateral hop; Crs: cross hop; Trp: triple hop) with number of participants with anterior cruciate ligament injuries (ACLi) and trials contributing for both motion capture (MoCap) and inertial measurement unit (IMU) data.	193
Figure A.2. Flowchart detailing participant compliance and ability to complete single-limb hopping tasks (MaxAnt: maximal anterior hop; MaxLat: maximal lateral hop; Crs: cross hop; Trp: triple hop) with number of control (CON) participants and trials contributing for both motion capture (MoCap) and inertial measurement unit (IMU) data.	194
Figure C.1. Clinical Biomechanics Research Unit (CBRU) cluster marker set, adapted from the Human Movement Biomechanics Laboratory cluster marker set. Plug-in-Gait marker set acted as the basis with the additions of medial knee, ankle and elbow markers (LKNM, RKNM, LANM,	

RANM, LELBM, RELBM), three thigh, tibial, upper arm and forearm markers (THIGH CLUSTER, SHANK CLUSTER, UPPERARM CLUSTER, FOREARM CLUSTER), two iliac crest markers (LIC, RIC), four lower back markers (LOWER BACK CLUSTER), two pelvis markers (PELVIS CLUSTER) and two metatarsal markers (RM1, RM5, LM1, LM5) (figure adapted from Mantovani and Lamontagne, 2017).	204
Figure D.1. Squats	206
Figure D.2. Lunges	207
Figure D.3. Drop-vertical Jumps	207
Figure D.4. Side cuts	208

LIST OF TABLES

Table 5.1. Means and standard deviations of performance for each single-limb hop test in the two test locations for males and females for the dominant (D) and non-dominant limbs (ND).	43
Table 5.2. Test-retest reproducibility, agreement, and responsiveness for all participants in the laboratory versus gymnasium for the dominant (D) and non-dominant (ND) limbs.	44
Table 5.3. Bland-Altman analysis summary with the mean and limits of agreement between the laboratory and gymnasium for the dominant and non-dominant limbs.	44
Table 5.4. Limb symmetry indices (LSI) and number of participants who scored above 100% between locations (laboratory vs gymnasium) for the battery of single-limb hop tests for males and females.	45
Table 6.1. Participant characteristics and subjective functional scores.	60
Table 6.2. Number of ACL-injured participants contributing to each task.	62
Table 6.3. Descriptive statistics of the raw scores for the classifier variables chosen within the female and male C5.0 models.	67
Table 6.4. Evaluation metrics of the testing sets on the C5.0 models.	68
Table 7.1. Participant characteristics and subjective functional scores. Uninjured and ACL-injured male and female means and standard deviations.	86
Table 7.2. The number of participants broken down by sex and injury status, with the overall classification accuracy, F1 score, Cohen’s kappa, and area under the precision-recall curve when the optimal number of PCs was retained for each hopping task for both models IL-CON and CL-CON using LDA as the classifier.....	92
Table 7.3. Participants misclassified in both IL-CON and CL-CON models, by group and task...	94
Table 9.1. Best configuration and injured-class performance summary per task	137
Table 9.2. Top Contributing Features and Movement Phases	139
Table E.1. The start and end-point criteria used when trimming trial lengths for each single-limb hopping movement.	209
Table E.2. The start and end-point criteria used when trimming trial lengths for each functional movement.	209
Table G.1. Comparison of injured-limb (IL-CON) classification performance between marker-based motion capture and simulated IMU analyses (AA-AE) using linear discriminant analysis.	213

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PREFACE

Anterior cruciate ligament (ACL) injuries have been extensively studied in adult populations over the past several decades. More recently, evidence has begun to highlight important differences in adolescents; however, current rehabilitation guidelines remain largely derived from adult-based evidence. This discrepancy suggests that adolescents may not be receiving care optimized for their unique physiological and developmental characteristics. Addressing this gap is critical to advancing evidence-based rehabilitation for adolescents and to reducing the risk of both primary and secondary ACL injuries in this vulnerable cohort.

The overall aim of this doctoral thesis was to evaluate the measures used to assess functional performance following ACL injury, with a particular focus on comparing traditional spatiotemporal measures, which currently underpin rehabilitation guidelines for adults, with kinematic waveform analyses of the same tasks in adolescents. Specifically, this thesis sought (1) to quantify performance differences between adolescents with and without ACL injuries, and (2) to identify limb- and sex-specific differences in functional movement among adolescents with and without ACL injuries.

To achieve these objectives, four sub-aims were defined: (A) to establish both (i) the repeatability of functional tasks in various environments for uninjured adolescents, and (ii) a normative dataset of uninjured males and females to support clinicians and coaches; (B) to identify task- and variable-specific return-to-activity criteria for adolescent males and females with ACL injuries; (C) to investigate movement adaptations in the contralateral limbs of injured adolescents relative to uninjured peers; and (D) to examine the potential of wearable technology to objectively characterize movement differences between adolescents with ACL injuries and uninjured controls.

This thesis is structured in an article format, and research ethics approval was obtained from the University of Ottawa and CHEO Research Ethics Boards. Chapters 1 through 4 include the general introduction, literature review, purpose and hypotheses, and general methodology, respectively. Chapters 5, 6, 7, and 8 each present an independent study with their own references. Chapter 5, Article 1 has been published in the journal of *Communications in Kinesiology*. Chapter 6, Article 2 has been published in the journal of *Knee Surgery Sports Traumatology Arthroscopy*. Chapter 7, Article 3 has been formatted and submitted to *Frontiers in Bioengineering and Biotechnology*, section *Biomechanics*. Chapter 8 is a technical paper outlining the reasoning for

the methods of Chapter 9, Article 4. Chapter 9, Article 4 is in preparation for publication in *Gait & Posture*. Chapter 10 of this thesis provides a general discussion, summarizing the main findings of the four studies to the primary goals of this thesis and briefly discussing their impact and clinical relevance. It also addresses any findings, limitations, and suggestions for future research that were not discussed in each article's discussion section.

RESEARCH CONTRIBUTIONS

Chapter 5, Article 1: Girard, C. I., Del Bel, M., Bédard, V., Bradley, C., Comptour, A., O'Connor, K., Carsel, S., & Benoit, D. L. (2024). *Are single limb hopping scores the same when performed in a physical education class versus a laboratory setting in uninjured adolescents? Implications for future rehabilitation guidelines for adolescents with knee injuries. Communications in Kinesiology, 1(6).*

The first study of this thesis explored the reliability of a battery of single-limb hopping tasks in two environments: a gymnasium and a laboratory. All co-authors combined their efforts to conceptualize these experiments. Céline Girard helped supervise all data collections led by Virginie Bédard, Caroline Bradley, Andrea Comptour, and Kelly O'Connor. Céline Girard was responsible for all data and statistical analyses, and manuscript development. All co-authors edited and approved the final version of the manuscript.

Chapter 6, Article 2: Girard, C. I., Romanchuk, N. J., Del Bel, M. J., Carsen, S., Chan, A. D. C., & Benoit, D. L. (2025). *Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria. Knee Surgery, Sports Traumatology, Arthroscopy, 33(5), 1633-1644.*

The second study of this thesis explored the ability to classify injury status and sex among adolescents using functional tasks. The theoretical conception of the data collections was a combined effort from all co-authors. For all 134 data collections, either Céline Girard, Michael Del Bel, or Nicholas Romanchuk led. Céline Girard labelled all 5,535 trials manually using Vicon Nexus. Post-processing scripts, data analyses and manuscript development were predominantly written and completed by Céline Girard. All co-authors edited and approved the final manuscript.

Chapter 7, Article 3: Girard, C. I., Chan, A. D. C., Carsen, S., & Benoit, D. L. (2025). *Identifying movement differences in adolescents with and without ACL injury during hopping tasks. Manuscript under review.*

The third study of this thesis explored an objective data-driven method to differentiate injury status among adolescents using movement patterns during a series of single-limb hopping tasks. The theoretical conception of the data collections was a combined effort from all co-authors. For all 134 data collections, either Céline Girard, Michael Del Bel, or Nicholas Romanchuk led. Céline Girard labelled all 1,568 trials manually using Vicon Nexus. Post-processing scripts, data analyses

and manuscript development were also written and completed by Céline Girard. All co-authors edited the final manuscript.

Chapter 8, IMU Validation: Validation of Real IMUs and Simulated IMUs Against Marker-Based Kinematics

The fourth article of this thesis described the pipeline used to validate inertial measurements, both simulated from motion-capture and acquired from wearable sensors, against marker-based reference kinematics. The theoretical conception of the data collections was a combined effort from all co-authors. For all 134 data collections, either Céline Girard, Michael Del Bel, or Nicholas Romanchuk led. Céline Girard labelled all 946 trials manually using Vicon Nexus. Post-processing scripts for kinematics, data and statistical analyses, and manuscript development were completed by Céline Girard. All co-authors edited the final manuscript.

Chapter 9, Article 4: Girard, C. I., Chan, A. D. C., Carsen, S., & Benoit, D. L. (2026). Simulated IMUs for ACL Injury Classification in Adolescents: A Task- and Configuration-Specific Analysis of Single-Limb Hops. Manuscript in preparation.

The fifth study of this thesis explored the effectiveness of simulated inertial measurement unit sensor configurations and classification for adolescent populations with ACL injuries. The theoretical conception of the data collections was a combined effort from all co-authors. For all 134 data collections, either Céline Girard, Michael Del Bel, or Nicholas Romanchuk led. Céline Girard labelled all 1,568 trials manually using Vicon Nexus. Post-processing scripts for kinematic and simulated IMU outputs, data and statistical analyses, and manuscript development were also written and completed by Céline Girard. All co-authors edited the final manuscript.

GENERAL ABSTRACT

Background: Anterior cruciate ligament (ACL) injuries in adolescents are increasingly common and carry long-term consequences, including reduced return-to-activity (RTA) rates, elevated reinjury risk, and early-onset osteoarthritis. Current RTA assessments rely heavily on subjective questionnaires, strength measures, and spatiotemporal outcomes from a variety of functional tasks. While these tools are easy to administer, they often fail to capture the quality of the movement, leaving subtle but important deficits undetected. As a result, many athletes satisfy current clinical criteria despite exhibiting movement patterns that differ from those of healthy peers, which may contribute to persistent functional deficits and potentially elevated reinjury risk. There is a pressing need for approaches that move beyond simple distance- or time-based measures to capture the complexity of adolescent movement patterns and provide clinically relevant, portable solutions.

Purpose: This thesis aimed to evaluate whether adolescent functional performance following ACL injury can be more effectively characterized through kinematic analyses that extend beyond conventional spatiotemporal metrics. Four interrelated studies were conducted to determine whether hop tests are reproducible in adolescents, whether spatiotemporal outcomes alone provide sufficient classification accuracy, whether waveform-based analyses can identify movement adaptations not captured by conventional performance measures, and whether simulated inertial measurement units (sIMU) offer a clinically translatable alternative to motion capture (MoCap).

Methods: Across four studies, 170 adolescents completed a battery of single-limb hop tasks. The first study assessed the reproducibility and responsiveness of hop tasks in adolescents across environments, using test-retest analyses in a laboratory and gymnasium setting. This study also examined whether spatiotemporal outcomes from hop tasks could differentiate performance between sexes. The second study evaluated whether spatiotemporal variables from these hop tasks were sufficient for classifying ACL injury status. Decision tree models were employed to determine the most discriminative tasks and parameters, and classification outcomes were compared between males and females.

The third study shifted focus from spatiotemporal outcomes to continuous kinematic data, applying principal component analysis (PCA) to waveform features extracted from hop tasks. This study tested whether waveform-derived features provided superior classification of ACL injury status compared to spatiotemporal metrics and explored potential differences between injured and

contralateral limbs, with secondary exploratory analyses of sex effects. The fourth study extended these findings into a translational context by generating sIMU signals from motion capture trajectories. Multiple sensor configurations were simulated to evaluate whether sIMUs could replicate MoCap-based classification accuracy and to identify which sensor placements provided the most discriminative information for detecting ACL injury status.

Results/Discussion: Hop tasks demonstrated reproducibility in adolescents, confirming their suitability beyond laboratory conditions, with sex differences evident in hop distance and symmetry. Spatiotemporal variables provided modest classification accuracy, particularly in females, highlighting their limitations. Waveform-derived PCA features improved classification and revealed adaptations between injured and contralateral limbs, with exploratory analyses suggesting sex-related misclassification patterns. Finally, sIMUs demonstrated moderate classification performance, with results approaching those of MoCap in tasks characterized by larger dynamic movement signatures, with the thigh and shank placements providing the strongest discriminative power. Together, these findings demonstrate that while spatiotemporal outcomes remain useful, waveform and wearable approaches provide deeper insights and greater clinical translatability.

Conclusion: This thesis establishes that adolescent ACL injury assessment benefits from moving beyond traditional spatiotemporal outcomes toward kinematic waveform analysis and wearable sensor technologies. By confirming reproducibility, identifying the limitations of existing measures, advancing analytic techniques, and demonstrating the feasibility of sIMUs, this work builds a continuum from controlled laboratory testing to practical field-based applications. These findings contribute to developing more robust, ecologically valid assessments that may ultimately improve rehabilitation monitoring and reduce reinjury risk in adolescent athletes.

CHAPTER 1: INTRODUCTION

Anterior cruciate ligament (ACL) injuries remain a major concern in sports medicine due to their long-term impact on joint health, activity participation, and overall quality of life^{11,56,176}. Although decades of research have established evidence-based rehabilitation guidelines for adults, accumulating work indicates that adolescents differ meaningfully in risk profiles, biomechanics, and recovery trajectories^{150,208,260}. Despite these differences, current return-to-activity (RTA) criteria and rehabilitation protocols are primarily based on evidence from the adult population^{173,248}. This gap raises concerns that adolescent care may be suboptimal and that current assessments may not adequately capture adolescent-specific deficits or compensations.

These concerns are particularly important given the substantial risk of secondary ACL injury following RTA^{58,105,188}. Although females are considerably more likely than males to sustain a primary ACL injury¹⁹⁴, systematic reviews indicate that the overall risk of a second ACL injury following reconstruction is similar between sexes¹⁸⁵. However, the pattern of reinjury differs, with females demonstrating a greater risk of contralateral ACL injury and males exhibiting a slightly greater risk of ipsilateral graft rupture¹⁸⁵. These findings suggest that persistent movement adaptations and neuromuscular deficits may remain following rehabilitation, further emphasizing the need for objective RTA assessments capable of identifying residual biomechanical deficits in both limbs before unrestricted return to activity.

Clinical protocols commonly focus on spatiotemporal outcomes such as hop distances, completion time, and limb symmetry indices^{3,15,174,248}. These measures are appealing because they are easy to collect, familiar to clinicians, and play a central role in RTA decision-making. However, relying on single-value performance metrics may provide limited insight into how the task is performed and may mask persistent compensatory strategies, a particular concern for adolescents undergoing rapid developmental change^{128,133}. As a result, while spatiotemporal measures are informative, they may not provide sufficient detail to reveal subtle but clinically meaningful differences in functional performance across limbs, sexes, and injury status.

In contrast, kinematic waveform analysis preserves continuous time-series information across the entire movement cycle. Rather than collapsing execution into a single outcome, waveform methods capture timing, coordination, and local variations that more accurately reflect underlying motor strategies. Dimensionality-reduction techniques such as principal component

analysis (PCA) are well-suited for handling these high-dimensional data, allowing for the extraction of dominant movement patterns and latent biomechanical features that can subsequently be interpreted through waveform reconstruction and complementary analyses.^{12,64,81,211} Such techniques are particularly relevant in adolescent ACL cohorts, where variability in presentation and recovery can mask group differences when relying solely on spatiotemporal metrics²¹³.

Recent technological advancements have also introduced the possibility of incorporating wearable inertial measurement units (IMUs) into clinical assessments. While motion capture (MoCap) remains the gold standard for laboratory-based biomechanical analysis, IMUs offer portability, scalability, and real-world applicability^{43,192}. Their adoption into clinical practice, however, hinges on demonstrating that they can classify functional performance with accuracy comparable to MoCap for tasks of interest⁴². Identifying the best sensor placements and analysis methods for capturing injury-related differences is a critical step toward bridging the gap between laboratory research and applied rehabilitation practice.

The purpose of this thesis is to determine whether adolescent-appropriate evaluation of functional performance after ACL injury is better achieved by augmenting traditional spatiotemporal measures with kinematic waveform analysis, and to assess whether portable, wearable sensing technologies can support this shift from laboratory-based assessment to clinically accessible evaluation. To achieve these objectives, the thesis establishes normative adolescent reference data, quantifies the repeatability of functional tasks, compares the discriminative value of spatiotemporal and waveform-based measures, and evaluates the potential of IMUs against MoCap in classifying ACL injury status.

By integrating task repeatability, normative context, waveform-level analysis, and IMU-based classification, this thesis aims to provide clinically actionable evidence on what to measure, how to measure it, and how to interpret functional performance in adolescents following ACL injury. The expected outcome is a clearer, data-driven foundation for adolescent-specific assessment that can improve clinical decision-making, reduce the risk of re-injury, and contribute to safer and more effective rehabilitation protocols tailored to this unique and understudied population.

CHAPTER 2: LITERATURE REVIEW

2.1 ACL Injury and Changes to Joint Function

The knee joint is one of the most complex joints in the human body, with its six degrees of freedom, consisting of three rotations (internal/external, valgus/varus, and flexion/extension), and three translations (anterior/posterior, medial/lateral and compression/distraction)^{90,231}. It is exposed to high contact forces and moments during activities of daily living, requiring the knee to maintain a state of homeostasis by adjusting to external stimuli in a self-regulating process known as joint stability²⁰⁰. To maintain joint stability, the knee relies on a collaboration between the muscles, menisci, and ligaments, and if an injury to a ligament occurs, such as one to the anterior cruciate ligament (ACL), the neighboring components must compensate to restore joint stability.

The ACL is one of the four primary ligaments in the knee joint, including the posterior cruciate ligament (PCL), medial collateral ligament (MCL), and lateral collateral ligament (LCL), and provides structural resistance to the anterior translation of the tibia relative to the femur, especially at full extension¹⁵⁴. Its contribution to resisting anterior translation, however, decreases as the knee angle is increased¹⁵⁴. It is a secondary stabilizer for knee varus and valgus movements, and tibial rotation^{90,231}. Once the ACL is no longer intact, the surrounding musculature, the MCL and the posterolateral structures become a significant resistor to anterior tibial loads²¹⁶. The surrounding musculature must protect the menisci from shear forces during maneuvers such as landing, pivoting, and decelerating that put additional compressive forces in combination with anterior shear forces on the tibia⁹³. In addition to providing mechanical support, the ACL also uses stress and strain mechanoreceptors to provide proprioception and motor sensory feedback¹³⁶. As such, when injured, there is a resulting loss in mechanical knee joint stability and sensory feedback affecting the function of the knee¹³⁶. It is not surprising that these functional changes within the knee joint have the potential to cause long-term health consequences.

An injury to the ACL causes decreased structural stability and compromised neuromuscular control, which may lead to damaging long-term effects such as reduced stability leading to the shifting of joint contact regions, causing wear to thinner regions of articular cartilage¹⁰. Approximately 14% of the Canadian population is diagnosed with osteoarthritis (OA) and the degradation of articular surfaces caused by an ACL injury has the potential to cause early onset OA²⁶². Through the combination of high incidences of knee injuries occurring after the age of 12

years²²⁴, and the 50% increase in the likelihood of developing early onset OA within 5 to 20 years after a knee injury^{147,176,210}, it is not surprising that we are seeing adults in their early 20s and 30s being diagnosed with knee OA¹⁸⁰.

Given the increased likelihood of co-morbidities following a knee injury, it is astonishing that there is very little research on the current objective measures used in rehabilitative interventions, considering adolescent patients with ACL injury (ACLi). As such, we must first investigate whether the current guidelines and assessments are sensitive enough in distinguishing ACL injury status in this adolescent population to determine whether they are adequate for use during rehabilitation to mitigate the risk of re-injury. By doing so, clinical assessments and rehabilitation interventions can be tailored to provide greater insight into the patient's readiness to RTA, particularly for females who have a higher incidence of sustaining a knee injury¹⁹⁴.

2.2 Influence of Puberty on ACL Injury Risk

With the rise of ACL injury rates in youth from approximately 17 to over 50 per 100,000 person-years over the past two decades, and with adolescent females demonstrating the highest and fastest-growing rates^{22,69}, research must elucidate the injury mechanisms and biomechanically relevant variables in this population. A meta-analysis by Prodromos et al.¹⁹⁴ found that in all age groups for sports such as soccer and basketball, females had a 3 times greater incidence of ACL injuries compared to males. With this rapid growth in ACL injury incidence during pubescence^{22,69}, research on active adolescents is especially relevant, given that pubertal changes may affect their biomechanics and neuromuscular control, contributing to this increased risk.

Understanding the role that puberty plays in the biomechanics and neuromuscular control of an adolescent population is crucial when evaluating this population. Rapid growth occurs in bones and surrounding structures during puberty¹³⁹, which can lead to increases in external knee moments¹⁰⁹. Additionally, the increase in body weight and height throughout puberty can generate greater joint forces and raise the center-of-mass location, which can cause issues with balance^{108,139}. Males also have more testosterone during puberty, which facilitates the increase in muscular power and strength required to accommodate the rapid bone-growth occurrence¹³⁹. Pelvic growth is larger in females during puberty⁵¹, leading to an increased quadriceps angle (Q-angle)^{104,238}, accompanied by a higher pelvic width-femur length ratio². The Q-angle is the angle of the force vector of the quadriceps muscle group acting on the patella³⁵, and this increased angle

and consequently increased hip width is associated with greater strain on the knee's structures¹⁰⁴, and consequently, the ACL^{94,104,261}. This pelvic growth can predict increased knee valgus during dynamic movements, a primary predictor of non-contact ACL injury mechanisms¹²⁷. Following pubertal growth, females have also demonstrated a narrower intercondylar notch^{5,13,30,143,182,238}, and 20-35% smaller articular surfaces, leading to greater valgus moments compared to their male counterparts^{76,162}, all of which contribute to increased torques at the knee^{109,123}. These changes are especially relevant given that there are no age- or sex-specific ACL injury prevention and rehabilitation programs. Given that the ACL injury rates are similar between sexes in prepubescence²²⁴, exploring the current functional capacity tools used during return-to-activity (RTA) assessments and the strategies used to accomplish these tasks during this growth stage and after ACL injury is a crucial first step to enabling the future development of injury prevention protocols within an adolescent population.

2.3 Functional Capacity Measurement Tools

Functional capacity evaluations have been used in ergonomic settings designed to assess the capacity to return to work through work-related tasks¹¹⁸. For this thesis, functional capacity will therefore be explained as an individual's ability to achieve and adopt a movement pattern that accomplishes the task objective in a standardized environment while also minimizing injury risk. There are currently many subjective and objective measures using various tools during rehabilitation to evaluate different components of knee joint functional capacity to determine the speed and safety with which an athlete can return to sports or activities.

2.3.1 Subjective Measures

Subjective measures are primarily measured using patient questionnaires and aim to measure outcomes from a patient's perspective when recovering from injury. These range from evaluating global to ACL-specific to different domains of knee function. The International Knee Documentation Committee Subjective Knee Form (IKDC-SKF)¹¹⁷, one of the most widely used global knee function questionnaires, compares the scores of injured individuals to normative scores⁹. The IKDC-SKF has been developed for paediatric and adolescent populations (Pedi-IKDC)¹³², enabling its use among a variety of populations¹, and is reliable, valid, and responsive¹¹⁷.

¹ Both French and English versions of questionnaires are used in this thesis

Other global knee questionnaires, such as the KOOS-child, have also been developed for paediatric populations^{177,209}; however, some translated and culturally adapted versions have demonstrated lower responsiveness than the Pedi-IKDC (40% compared to 75%)²⁴⁶. In this context, responsiveness refers to the ability of an instrument to detect clinically relevant within-participant changes over time²³. The ACL Quality of Life (ACL-QoL) questionnaire¹⁶³ and the ACL Return to Sport Index (ACL-RSI)²⁴⁷ are two reliable injury-specific, subjective outcome measures for ACL-reconstructed patients and have been translated and adapted into several languages^{32,130,138,226}.

The ACL-RSI specifically evaluates psychological readiness to RTA by assessing constructs such as confidence, emotions, and fear of re-injury following ACL injury or reconstruction²⁴⁷. Lower ACL-RSI scores have been associated with reduced RTA rates and lower likelihood of returning to pre-injury levels of sport participation, whereas higher scores are generally associated with successful return to sport. Although reported thresholds vary across studies and populations, scores of approximately 65-70 have frequently been associated with successful return to sport²²². Clinically, the ACL-RSI may be used alongside objective measures such as strength testing and hop performance to identify athletes who appear physically recovered but may require additional psychological support before returning to activity²⁴⁷.

These questionnaires, whether global or domain-specific, are all used to assess a degree of self-reported symptoms, function, and capacity in ACLi and ACL-reconstructed (ACLR) populations and the final scores of these questionnaires have been reported to be significantly lower in ACLi compared to their CON counterparts^{74,82,107,145}. Furthermore, to get a clear understanding of a patient's ability to recover following an ACL injury or reconstructive surgery, several different constructs of knee function can be evaluated by clinicians. These constructs include a patient's fear of pain, fear of re-injury, and activity level, all of which can be evaluated through questionnaires and can be considered as knee function domains since they may be related to global knee function^{49,130,138}. These questionnaires provide some information on a patient's recovery. They can be easily measured in a clinical setting, yet must be used in conjunction with objective measures to provide a complete picture of the functional capacity of the patient's knee.

2.3.2 Objective Measures

Knee joint laxity, determined through the Lachman and Pivot-shift tests or the KT-1000 Knee Arthrometer, is considered the most basic measure of objective functional outcome¹⁵¹. Knee

joint laxity is determined in an unweighted and muscle-relaxed state, which is not reflective of a scenario leading to injury. It is therefore not surprising that joint laxity is not correlated to subjective measures of joint function^{17,50,223,229}. Knee strength, commonly defined as the peak isometric knee flexor torque, has shown moderate correlations to subjective measures³¹. Although this relationship is stronger than clinical laxity, isometric strength may not be truly representative of functional capacity during dynamic tasks¹²⁵. Rehabilitation and RTA protocols include a variety of dynamic tasks to evaluate different aspects of functional capacity^{3,255}. Among these, single limb hopping tasks have been shown to place high demands on the ACL and provide measures of functional capacity relating to quadriceps femoris weakness and dynamic knee stability closely resembling the demands of high-level sports and physical activities^{14,174,214,218}. The current performance metric in single-limb hopping tasks is the limb symmetry index (LSI), defined as the ratio of performance on the injured/non-dominant limb to that of the contralateral/dominant limb for a given outcome measure (e.g., hop distance or completion time)¹⁷⁴; however, compensatory changes have also been seen following injury^{19,102,144}, limiting the use of the uninjured limb as a control limb in this equation. Despite this limitation, differences in limb symmetries between these two cohorts have been seen in several studies^{15,92,174,206}. These findings suggest that single-limb hopping tasks warrant further examination beyond symmetry indices alone, as analysis of movement patterns between groups and limbs may reveal compensatory strategies and modifiable factors relevant to injury recovery and rehabilitation.

2.3.3 Clinical Adoption of RTA Measures

A combination of patient questionnaires and limb symmetry indices for strength and hopping performance is currently the most frequently used metric to determine readiness to RTA in clinics due to their simplicity and ease of implementation^{15,248}. These simple measures, although informative, do not provide a comprehensive picture of the problem. They provide insight into the individual's performance but do not explain how an individual achieved the desired outcome and their relation of these simple measures to functional capacity. There is evidence that objective measures obtained in laboratory settings provide greater insight into the functional capacity at the knee joint compared to clinical measures^{228,249}. One of the main issues with evaluating the functional capacity of the knee joint in a clinical setting is that it is difficult to accurately measure due to the limited space and time available during these assessments, and most of the equipment used is confined to laboratory space. There is also a lack of knowledge transfer between clinicians

and researchers regarding the clinical meaning of outcome variables obtained in a laboratory setting, combined with a lack of simple and accessible tools and platforms that can provide meaningful patient-specific movement profiles. With the abundance of measures and tools available, it can be difficult for clinicians to decide the appropriate test(s) and variables to use in their assessments. With the high re-injury rates seen among adolescents²⁴⁸, a re-evaluation of the current variables and criteria may be required to strengthen the RTA evaluation.

While much of the research on knee joint function and readiness to RTA is conducted using adult populations in controlled laboratory settings using motion capture, force plates, and electromyography (EMG), there has been a shift towards using portable inertial measurement units (IMU) and mobile-based applications for data collection in clinical or applied settings^{175,234,235}. Inertial measurement units can record tri-axial linear accelerations with an accelerometer, angular velocities through a gyroscope, and sometimes magnetic distortions with a magnetometer and can be fixed to body segments to provide direct acceleration, angular velocity, and magnetic-field measurements^{204,205}. Due to their size, IMUs can be used in various types of environments and spaces. They have also proven to be successful in estimating orientation and tracking motion in 3-dimensional (3D) space^{140,175,235}. Their increase in popularity may be attributed to their ability to collect, store, and analyze data outside of laboratory settings and provide real-time feedback^{71,193}.

Despite the increase in popularity of IMU-based movement quality assessments of knee function, IMUs have not yet been widely adopted into routine clinical practice²⁵¹. This is likely due to both a lack of time clinicians have to learn new technologies and the lack of outputs that are directly meaningful for functional tasks commonly used in RTA assessments, provided by these IMU-based movement quality analyses²⁵¹. To support their adoption, IMUs must be shown to classify movement patterns with at least the same level of accuracy as motion capture (MoCap) for the tasks of interest. Demonstrating that IMU-derived signals can provide classification performance comparable to motion capture will be essential for establishing them as clinically viable tools for monitoring movement and informing RTA decision-making.

2.4 IMU MoCap Trade-Off

Recent advances in technology have enabled the robust measurement of human movement using IMUs¹⁶⁴ and their miniaturization has enabled them to be smaller and lighter. They are often combined with portable devices, such as smartphones, for a variety of applications, such as fitness

tracking systems, gaming, and sports technology¹⁶⁵. When IMUs are combined with sensor fusion algorithms (e.g., Kalman filters) and a biomechanical model, full-body 3D kinematics can be obtained^{142,205,230}. In clinical practice, IMU technology has started to be used to replace MoCap for the assessment, screening, and diagnosis of various neurological disorders^{45,183,186}, captured through differences in motor coordination patterns during gait.

In replacing MoCap, IMU systems have been used to quantify various gait characteristics^{18,220} and have shown good agreement for lower body kinematics during cyclical movements such as running¹⁹⁸, skiing³⁹, and swimming⁶⁵. Motion capture systems conventionally track body-worn markers through a calibrated space to provide position and orientation measurements of body segments, whereas IMUs have the potential to provide this same level of information in uncontrolled environments without the restriction of a capture volume. Motion capture systems provide accurate and comprehensive analysis of the human body; however, they have limited portability, require complex setups, are constrained to small test areas, and are confined to one testing location per system, which is a potential reason why few studies have examined knee joint biomechanics during various jumping tasks outside the laboratory environment. In addition to wearable sensors, markerless MoCap approaches based on RGB or RGB-D cameras have emerged as promising alternatives to laboratory-based systems; however, their accuracy during dynamic sport-specific movements remains an active area of investigation.

Unlike camera-based approaches, IMUs directly measure segment motion and are not dependent on line-of-sight or camera placement. IMUs may therefore provide an alternative to traditional MoCap systems for measuring knee joint kinematics, as the knee angle estimation error using the root mean squared error (RMSE) ranges between approximately 1.5-4.0° for flexion/extension, 1.7-3.8° in abduction/adduction, and 1.4-3.3° in internal/external rotation for slow repetitive movements^{38,79,195,203,220}. A major disadvantage of using IMUs is that they typically suffer from accumulated errors and have not been validated for high-speed movements. Due to integration, a constant error in accelerations can result in linear errors in velocity and a quadratic error in positional data, whereas a constant error in the gyroscope data can result in quadratic error in angular velocity and cubic error growth in position⁷³. To mitigate these errors, including magnetometer-based drift typically in the gravitational axis, some have suggested different sensor-fusion algorithms and filters^{26,80,85,129}, whereas others have used calibration procedures to solve the issues with drift and segment alignment^{244,254}. In addition to drift, the validity of IMUs has been

reported to be related to the joint of interest and speed of the movement, ranging up to 12.8 m/s⁵⁵. Currently, rapid movements occurring during jumping tasks (e.g., knee angular velocities during drop vertical jump (DVJ) of 300 °/s¹¹⁶) might occur outside the validated speed ranges of IMUs. These tasks often push IMUs beyond validated ranges, and issues such as sensor drift, integration errors, and skin motion artifacts can compound measurement error. Various filtering approaches and calibration procedures have been proposed to address these limitations, but their effectiveness can depend on both the movement type and the segment of interest²²⁰.

The choice of segment location is particularly important when the goal is not simply to reproduce MoCap kinematics, but to identify real group differences relevant to functional tasks. For example, IMUs placed on the thighs and shanks provide detailed information about knee joint dynamics, which are critical for distinguishing ACL-injured from uninjured adolescents¹³³. Foot-mounted IMUs may enhance sensitivity to differences in landing mechanics⁹⁷, while trunk or low-back sensors capture global control strategies that may separate groups in tasks requiring balance or multiplanar stability⁴². Rather than pursuing a one-size-fits-all configuration, sensor placement should be guided by the functional question, whether the interest is in knee joint control, landing strategies, or whole-body coordination.

Although skin motion artifact and segment alignment remain concerns, several calibration algorithms and placement strategies have been developed to mitigate these issues. To counter the lack of IMU sensor placement guidelines for accurate joint angle estimations, several studies have developed and incorporated sensor calibration algorithms designed to mitigate sensor alignment and location differences^{78,131,244}. Several studies have investigated the validity of the lower-body kinematics during different tasks using various IMU systems with MoCap^{28,203,221,235}, and although the placements vary, the validity for knee flexion/extension was high for each task ($r \geq 0.8$), but the discriminatory power for functional classification may vary by segment. Thus, identifying which combination of segment placements best captures injury-related movement differences is essential for moving IMUs from validation studies into clinical adoption, ensuring that the information provided is both accurate and clinically meaningful for RTA decision-making. While these technologies enable increasingly detailed measurement of human movement, the challenge remains how to extract meaningful patterns from the resulting high-dimensional data, motivating the use of advanced movement analysis and classification approaches.

2.5 Movement Analysis for Classification

The use of IMUs may provide clinicians, coaches, and athletes with easier ways to quantify functional capacity in relation to movement patterns through the decision-making process regarding RTA. With the recent increase in popularity among portable tracking systems, IMUs have notably led to an increase in research for movement monitoring and analysis. At the simplest level, spatiotemporal metrics, such as step counts, event detection, or the recognition of broad activity types like walking, stair ascent, or running, have formed the foundation of IMU-based applications^{122,131,201}. These outcomes are attractive for their simplicity and have been extended to injury detection and recognition of abnormal movement patterns in clinical populations^{122,131,201}. However, spatiotemporal data alone often fail to capture the underlying quality of movement or the compensatory strategies that differentiate healthy and injured populations.

Movement screening tools, traditionally used in sport, occupational, and rehabilitation settings, aim to assess competency and identify poor patterns that may increase injury risk or indicate functional limitation^{70,135,158,159,178}. To date, movement screening for various applications is done using visual appraisals^{159,227} and provides excellent intra-rater reliability⁹¹. While visual appraisal is useful for clinicians, coaching, and rehabilitation, it is prone to errors due to inter-rater variability^{52,53}. Given that ACL re-injury rates remain high despite current RTA criteria, with meta-analytic estimates indicating that athletes younger than 25 who return to sport sustain a second ACL injury at a rate of approximately 23%, subjective assessments alone appear insufficient to provide robust decision-making in clinical practice^{248,252}. Therefore, to overcome limitations associated with the subjective scoring of movement quality, data-driven methods could improve the repeatability and reliability of the state of movement pattern recognition and assessments.

In recent years, there has been an increase in movement pattern recognition and analysis to differentiate different types of movements and extract fundamental patterns of coordination²⁴⁰. Several studies have used motion capture data to explore the variance in movements between and within groups using the trajectories of either marker positions^{199,211} or joint angles^{12,64} throughout the entire movement of interest. These continuous analyses take advantage of the redundancies inherent in the kinetic chain, where the motion of one segment is strongly related to another, and use dimensionality reduction or decomposition techniques to summarize high-dimensional data into interpretable patterns.

2.6 Dimensionality Reduction Techniques

Feature selection is the process of identifying and selecting relevant features for the classifier, either manually or programmatically. Heat maps and correlation plots are examples of manual processes to reduce the dimensionality of a dataset when there are redundancies among feature pairs^{115,121}. Statistical methods of dimensionality reduction include variance threshold¹⁶⁸ and univariate selection such as Pearson's correlation, ANOVA and Chi-square to evaluate feature relevance⁹⁹. These forms of feature selection are the simplest dimensionality reduction (DR) methods, as they are correlation-based and should be considered as a first choice before applying more complex methods.

Dimensionality reduction can be employed to overcome the 'curse of dimensionality'²⁴, which can manifest itself in a complex and overfitted model and draws on the bias-variance trade-off in predictive error⁸⁷. By reducing dimensionality, it is believed that we can reduce training variance at the cost of introducing some bias in the estimated parameters. Furthermore, standard DR methods can be used to compress large datasets²³⁷ and aid in data visualization^{113,120,190,250}. Nonlinear methods such as kernel principal component analysis (PCA)²¹⁹, Isomap²³³, nonmetric multidimensional scaling (NMDS)¹³⁷, and neighbour embedding (NE)¹¹¹ techniques are better at representing local interactions and have several applications in the field of computer vision. Alternatively, linear methods such as PCA^{113,120,190}, correspondence analysis (CA)¹¹², non-negative matrix factorization (NMF)^{67,103}, linear discriminant analysis (LDA)¹²⁰, or principal coordinates analysis (PCoA)²³⁹ preserve global structure and have been applied in various human movement studies^{81,86,157,225,240}. Preserving the global structure of the dataset in human movement waveforms while performing a DR technique can facilitate the interpretation of the motion of specific joints of interest.

Linear DR methods provide a faithful representation of the original data by capturing the main patterns, relationships, and trends present in the full dataset with fewer dimensions. However, considerations are needed when deciding the appropriate method for forming new features and/or extracting a smaller subset of the original features. Principal component analysis and LDA are the two most common DR methods employed for human movement studies, both creating new features from a linear combination of the original features. The major difference between LDA and PCA is that LDA is a supervised technique that seeks to optimize class separability, while PCA, an unsupervised DR technique, finds a set of uncorrelated components of maximum variance

in the dataset⁷². Linear discriminant analysis is closely related to ANOVA and regression analysis, which both attempt to express a dependent variable as a linear combination of other features¹⁶⁰. Principal component analysis' flexibility allows it to be used for both exploratory analyses, to reveal underlying patterns, and as a preprocessing step in predictive modelling, where reduced, uncorrelated features can improve model stability and limit overfitting. In biomechanics, PCA efficiently summarizes high-dimensional movement data into a small number of components that capture dominant patterns of variation and can be interpreted through waveform reconstruction. Among the available dimensionality reduction techniques, PCA has emerged as one of the most widely used approaches in biomechanics for summarizing complex movement data while preserving key patterns of variation.

2.7 Principal Component Analysis

The use of PCA for movement pattern recognition using motion capture to extract fundamental patterns of coordination has increased in recent years¹ and has been applied to both waveforms⁶⁴ and 3D motion capture marker data^{211,240}. Principal component analysis is a statistical data reduction technique that aims to identify and rank differences based on the amount of variance explained within a dataset. This technique identifies principal components (PC), a series of orthogonal patterns of variance, with the first component accounting for the largest variance within the dataset and the following components descending in variance^{1,119}. For categorical data, either converting categorical data to dummy binary features or using scaling categorical PCA (CATPCA) are two possible methods¹⁴⁶. These procedures not only quantify categorical variables but can then be used to reduce the dimensionality of the data into a smaller set of uncorrelated components that represent most of the information found in the original variables. In continuous data, PCA projects data to a lower-dimensional space along the direction of increasing variance and the features with the maximum variance are the PC^{72,113,120}. By reducing the data, PCA can identify redundancies and provide a subset of the data that will often explain a large portion of the variance^{64,240}.

For each PC, each participant's waveform has an associated PC score, representing the degree to which the participant expresses the specific pattern of variance (PC loading vector). Since the PCs are orthogonal, the estimate of the entire dataset can be expressed as a linear combination of these PCs using the following equation¹²⁴ :

$$X \approx \bar{x} + TP^T$$

where $\mathbf{X}$ is the reconstructed data matrix, $\bar{\mathbf{x}}$ is the mean waveform vector (added back after centring), $\mathbf{T}$ is the matrix of PC scores for all participants, and $\mathbf{P}$ is the matrix of PC loading vectors, each representing an orthogonal mode of variation. For an individual participant i , whose feature vector $\mathbf{x}_i$ contains all concatenated waveform measurements, the reconstruction is:

$$\mathbf{x}_i \approx \bar{\mathbf{x}} + \sum_{k=1}^m t_{ik} \mathbf{p}_k$$

where $\mathbf{x}_i$ represents the full set of waveform features for participant i , m is the number of retained PCs, t_{ik} is the score of participant i on PC k , and $\mathbf{p}_k$ is the loading vector for PC k .

The interpretation of PCs has previously involved a simultaneous inspection of the shape of the PC loading vector and the differences between extreme participant waveforms from high (95th) and low (5th) percentiles within the dataset^{12,64}. These representative extremes rely primarily on a visual comparison of the differences between two extreme waveforms representing a combination of magnitude, timing, or local peak difference features²⁵⁶. In contrast, a single-component reconstruction has provided a simplified and objective way to visualize biomechanical differences captured by each PC³⁴. This method also visualizes upper and lower bounds of waveforms for each PC by using the reconstructed upper (or lower) waveform, the mean temporal waveform for all participants, the pattern of variance (loading vector), and the percentile scalar PC-score³⁴. These visual representations, whether through the interpretation of the extreme waveforms or through single-component reconstruction, provide a visual comparison with respect to the mean waveform, highlighting trends from a normal distribution typically seen in biomechanical data.

Previous research has used PCA to identify these movement features that contribute to the greatest amount of variance to specific movements^{81,211,240,259}. This technique has been effectively used to detect and explain differences in cyclical^{64,81,240}, and non-cyclical movements^{81,199,211} within kinematic-based data sets to objectively analyze the movements. Using PCA to examine human motion could help to accurately identify complex movement patterns that may not be identified otherwise. One strength of using PCA to determine the variability is that the scores can then be used and analyzed through classification algorithms to detect and interpret differences between participants and/or trials⁷⁵.

2.8 Classification Model Choices

The choice of classification model determines how effectively extracted features are translated into clinically meaningful group discrimination. In orthopedic literature focused on the knee, several papers use regression models to predict varying indicators or risk factors of ligament injuries^{170,236}, rehabilitation success following reconstructive surgery^{49,179}, and the advancement of knee OA^{101,152,184}. Regression models are useful when determining a progression or continuous quantity output, such as estimating the degree of knee OA; however, if the output is binary, such as injury status (e.g., ACLi vs CON), a classification method may be more appropriate. An inherent limitation occurs in biomedical research, as there is not always a clear classification boundary despite its binary output measure. For instance, a patient with an ACL injury may exhibit movement strategies that more closely resemble those of their uninjured peer, whereas another injured participant may be more clearly labelled as an injured individual or ‘non-coper’^{7,40}. This ambiguity highlights the importance of model choice and careful interpretation when designing classifiers for clinical populations.

Among classification methods, logistic regression remains widely used because of its simplicity, transparency, and effectiveness across varied data types^{149,172,242}. However, it struggles with waveform data, which are typically high-dimensional and collinear, and therefore often underperforms in this context^{121,191}. Data transformation and dimensionality reduction techniques, such as PCA, can improve performance; however, different classification approaches may be better suited for modelling high-dimensional movement waveforms. Some common classifiers in orthopedic medical literature include k-nearest neighbours (k-NN), linear discriminant analysis (LDA), Gaussian naïve Bayes (GNB), decision trees (DT), and support vector machines (SVMs)⁴¹. Recent advances in deep learning, including convolutional neural networks (CNNs) and transformer-based architectures, have also been applied to biomechanical time-series data; however, these approaches typically require substantially larger datasets and may reduce interpretability. k-nearest neighbours is one approach, leveraging local neighbourhood relationships in the feature space to capture nonlinear class boundaries. While k-NN is intuitive and flexible, it is computationally demanding for large datasets and highly sensitive to irrelevant features or noise⁸. Linear discriminant analysis has proven particularly useful in biomechanics when paired with PCA, creating discriminative yet interpretable decision boundaries that are computationally efficient and transparent to clinicians^{64,211}. Gaussian naïve Bayes, while fast and

robust on small datasets, relies on an independence assumption that is rarely valid for waveform features, which can limit its performance compared to other models²⁰². Decision trees provide hierarchical decision rules that align well with clinical reasoning, making them appealing for translation to practice, though they risk overfitting if not carefully regularized³⁷. Support vector machines, on the other hand, are powerful for high-dimensional feature spaces and nonlinear class separation, often achieving high accuracy but at the cost of interpretability and the need for careful parameter tuning^{41,54}. These models illustrate a spectrum of options, ranging from highly interpretable but less powerful approaches to complex, high-performing black-box models.

Given that no single model consistently outperforms across all tasks, ensemble approaches such as voting classifiers offer a way to balance strengths and weaknesses. In hard voting, each model contributes equally to the final classification, while in soft voting, class probabilities are averaged, giving more influence to models with greater confidence²⁰⁷. Ensemble voting may be particularly valuable in biomechanics, where discriminative power may differ by hop task or sensor placement. By combining models, ensemble methods may mitigate the risk of misclassification associated with individual weaknesses, resulting in more stable and robust performance²⁰⁷. The trade-off is reduced transparency, as the rationale behind a majority or probability-weighted decision is less clear than the rules of a single model. Thus, ensemble methods can be leveraged in research to maximize classification accuracy, while interpretable models such as PCA-LDA or DTs remain essential for clinical translation, where decision-making must be transparent.

CHAPTER 3: PURPOSE and HYPOTHESES

The overall purpose of this doctoral thesis is to evaluate whether functional performance in adolescents with anterior cruciate ligament (ACL) injuries can be more effectively characterized by augmenting traditional spatiotemporal measures with kinematic waveform analyses, and whether wearable sensing technologies such as simulated inertial measurement units (sIMU) can provide classification accuracy comparable to laboratory-based motion capture. By addressing these questions, this thesis sought to bridge the gap between adult-derived rehabilitation guidelines and the unique needs of adolescent populations, thereby providing evidence that can inform adolescent-specific return-to-activity assessments and reduce the risk of re-injury.

Study 1: Reproducibility and Responsiveness of Hop Tasks

Given the current limitations for interpreting functional capacity in an injured population, there is a clear need to establish whether RTA tasks remain reproducible across environments representative of real-world assessment settings. Compared with laboratory environments, gymnasium settings may differ in surface characteristics, available space, and environmental distractions, thereby providing a practical test of the ecological validity of hop assessments. To address this, the first study of this thesis will address the following research questions:

SIQ1: Are single limb hopping tasks reproducible and responsive across environments to detect meaningful differences in adolescents?

Based on the current literature that has tested the single-limb hopping tasks for test-retest reliability in adult populations^{68,167,212}, it was hypothesized that the tasks would be reproducible and responsive between a physical activity class in a gymnasium setting and a laboratory setting in adolescents.

SIQ2: Are there sex-specific differences in spatiotemporal outcomes from single-limb hopping tasks commonly used in RTA assessments?

Based on prior findings that females demonstrate altered neuromuscular control, reduced strength, and different landing mechanics compared to males during adolescence^{59,83,208}, it was hypothesized that males would achieve greater absolute hop distances, while females may demonstrate different symmetry profiles or movement strategies.

Study 2: Spatiotemporal Metrics for Classification

With the high re-injury rate among adolescent populations, there is a clear need for significant research on the current rehabilitative assessments using adolescents. Given that current RTA assessments rely heavily on spatiotemporal metrics, it is important to determine whether these outcomes alone are sufficient for classifying ACL injury status in adolescents. To address this, the second study will explore:

S2Q1: Which functional tasks and spatiotemporal parameters typically used in return-to-activity (RTA) assessments are important in differentiating ACL-injury status in adolescent males and females?

Based on previous literature in adults using the battery of single-limb hopping tasks^{174,248} and on the evaluation of the spatiotemporal measures in these tasks with adolescent females⁸⁹, demonstrating that hop distance and limb symmetry indices differ between ACL-injured and uninjured individuals, it was hypothesized that the decision tree (DT) would identify the limb symmetries of the maximal anterior and lateral hops as the two measures and tasks that provided the best separation between adolescents with and without ACL injuries.

S2Q2: Do classification outcomes for distinguishing ACL-injured from uninjured adolescents differ between males and females?

Based on evidence of sex-specific biomechanical and neuromuscular differences during adolescence that contribute to higher ACL injury risk in females^{84,171,194,196}, it was hypothesized that the ability of spatiotemporal measures to distinguish ACL-injured from uninjured adolescents would differ between sexes, with different variables emerging as discriminative.

Study 3: Kinematic Waveform Analysis and Classification

Given the current limitations with the spatiotemporal measures used in RTA criteria providing limited insight into movement execution, there is a need to evaluate whether kinematic waveform features better capture injury-related differences. The overall objective of this study will answer the following questions:

S3Q1: Do kinematic waveform features derived from principal component analysis (PCA) provide superior classification of injury status compared to spatiotemporal measures?

Based on previous research showing that PCA applied to gait and hopping waveforms captures subtle injury-related differences beyond what spatiotemporal outcomes can detect^{64,81,166},

it was hypothesized that waveform-derived PCA features would outperform spatiotemporal metrics in classifying ACL injury status.

S3Q2: Can waveform-derived features identify limb- and sex-specific differences in adolescent movement strategies?

Based on evidence that PCA features can reveal compensatory differences between injured and contralateral limbs¹² and capture sex-specific landing mechanics in adolescents^{128,196}, it was hypothesized that waveform-derived features would reveal both limb- and sex-specific adaptations.

Study 4: Simulated IMUs for Functional Classification

Given the limitations of motion capture for routine clinical use, there is a need to determine whether portable IMUs can provide classification accuracy comparable to laboratory systems. To address this, the fourth study will evaluate:

S4Q1: Can simulated IMU signals classify hopping tasks in adolescents with and without ACL injuries with accuracy comparable to motion capture (MoCap)?

Based on literature demonstrating strong agreement between IMU-derived and MoCap-derived kinematics for dynamic movements such as running and jumping^{42,220}, it was hypothesized that simulated IMU configurations would achieve classification accuracy comparable to MoCap for hop tasks in adolescents.

S4Q2: Which segment placements provide the most discriminative information for differentiating adolescents with ACL injuries from uninjured controls and contralateral limbs?

Based on findings that thigh and shank segments capture knee mechanics most affected by ACL injury^{33,108}, it was hypothesized that IMUs placed on these segments would provide the greatest discriminative power.

Together, these four studies systematically investigate functional performance testing for adolescents with ACL injuries. Study 1 establishes the reproducibility, responsiveness, and sex-specific characteristics of hop tasks. Study 2 assesses whether traditional spatiotemporal outcomes can classify injury status. Study 3 extends the analysis to waveform-level features using PCA and classification models to uncover deeper movement patterns. Study 4 explores the potential for using sIMUs, identifying optimal sensor configurations for portable assessments. Collectively, these studies address the overall thesis purpose by determining what to measure, how best to

analyze it, and how to extend these approaches beyond the laboratory to clinical and applied settings.

CHAPTER 4: GENERAL METHODOLOGY

4.1 Study Design

This thesis is a portion of a larger and ongoing investigation that aims to identify changes in neuromuscular, biomechanical, and patient-reported measures pre- and post- ACL reconstruction with respect to control (CON) adolescent participants. Participants completed isometric and isokinetic strength testing and a battery of functional tasks, including single-limb hops, two-legged squats, lunges, countermovement jumps, drop-vertical jumps, and side cuts. This thesis primarily focuses on the single limb hopping tasks as they are commonly reported to be stressful to the anterior cruciate ligament (ACL)^{14,174,214} and used in various return-to-activity (RTA) assessments^{187,218,248}.

The analyses presented in this thesis are based on data collected at the Clinical Biomechanics Research Unit (CBRU) between 2017 and 2020. For this data collection, ACL-injured (ACLi) patients participated prior to their surgical reconstruction. This group was matched to a healthy, uninjured control (CON) adolescent group for age, sex, puberty stage, and competition level for physical activities.

This study has been approved by both the CHEO (17/74X) and University of Ottawa (H09-17-10) ethics committees.

4.2 Participants

Recruitment/Eligibility

Two groups of participants were recruited for this thesis: 1) ACLi patients, and 2) CON participants. The ACLi patients have been recruited from CHEO hospital to participate in the larger study program that includes three visits to the CBRU: pre-operatively (visit 1); 8-10 months post-operatively (visit 2); and approximately one year following visit 2 (visit 3). Inclusion criteria were a confirmed ACL rupture and no history of contralateral ACL ruptures, excluding those seeking an ACL reconstruction revision. All patients were between 10 and 18 years of age at the first testing session. The physician confirmed the ACL rupture through either a positive Lachman or Anterior Drawer test, magnetic resonance imaging, or arthroscopy, and cleared patients to perform all the study tasks.

Control participants were recruited from the community and local sports organizations through word of mouth, with inclusion criteria of no previous lower limb surgical operations, no

additional serious lower limb injury, including fractures or sprains within six months prior to testing or have no diseases that might affect neuromuscular function. The CON participants followed the same timeline after visit 1 for visits 2 and 3 to match the ACLi group timeline.

Sample sizes and effect sizes

The participants of Study 1 (S1) are independent of the remaining three studies and included thirty-four uninjured adolescents (18 F; 16 M) recruited from a local high school.

For Studies 2 through 4 (S2-S4), sixty-six (47 F; 19 M) ACLi and seventy (39 F; 31 M) CON had been recruited. The ACLi participants' first visit was analyzed for this project as previously mentioned. The CON group's age for visit 1 is 13 ± 2 years compared with 15 ± 1 years for the ACLi group. Since thirty-seven (26 F, 11 M) CON have come into the laboratory between 9-15 months after the first visit (visit 2) to match the time for ACLi's second visit after reconstructive surgery, their data was used instead of their first visit to match for age more closely. As a result, thirty-three (13 F; 20 M) CON from visit 1 and thirty-seven (26 F; 11 M) CON from visit 2 were included in the analysis. An outline of the number of participants used for further analysis can be found in Appendix A.

For S1, an a priori power analysis in G*Power software (3.1.9.7, Dusseldorf, Germany), based on previous data evaluating test-retest reliability in healthy adults for the anterior hop on the dominant leg⁶⁸, revealed that to achieve a power of 0.8, with an input effect size of 0.99 at $\alpha = 0.05$ using a dependent t-test comparing group means, a total sample size of 11 was required. All 34 participants were however used in the analysis.

For S2, an a priori power analysis in G*Power software (3.1.9.7, Dusseldorf, Germany), based on previous data evaluating sex differences in adults with an ACL reconstruction (ACLR) for side hop distances on the affected limb⁹², revealed that to achieve a power of 0.8, with an input effect size of 0.81 at $\alpha = 0.05$ using a two-way ANOVA comparing within-between group interactions, a total sample size of 50 was required. To account for missing data (Figure A1 and A2), all available participants (64 ACLi and 70 CON) were included in the analysis.

For S3 and S4, since entire waveforms are used in the analysis, all available processed data were used in the analysis, which accounted for 117 participants and 1,028 trials (53 ACLi and 64 CON).

For the validation of the IMUs in Chapter 8, based on previous research validating inertial sensors for the knee's sagittal plane during a CMJ⁴, a minimum sample size of 23 was required to

achieve a power of 0.8, with an input effect size of 0.63 at $\alpha = 0.05$ and using a two-sample t-test comparing group means. Accordingly, all available participants (n=23) were included in the IMU validation, encompassing a total of 195 associated trials.

4.3 Protocol

Informed Consent, Questionnaires, and Preparation

Prior to the first data collection, each participant received a phone call from the researcher to discuss the study's purpose, equipment, and tasks they would be asked to complete. Once the participants arrived at the laboratory, they were given a brief introduction and a tour of the laboratory space and equipment. The researcher then briefly explained the contents of the consent form and all questionnaires. All participants then read and signed an informed consent form approved by the CHEO (17/74X) and University of Ottawa (H09-17-10) ethics review boards. Following this, each participant completed a series of questionnaires pertaining to their self-reported functional performance. This includes the Tegner activity scale, an 11-point ordinal scale (0-10) used to quantify physical activity and sport participation²³²; the Pediatric International Knee Documentation Committee questionnaire (Pedi-IKDC), which assesses knee symptoms, function, and sport participation¹³²; the Pediatric Functional Activity Brief Scale (HSS Pedi-FABS or FR Pedi-FABS), which quantifies the frequency and intensity of physical activity and sport participation^{60,77}; Tanner Stages, a self-reported measure of biological maturation based on secondary sexual characteristics^{155,156}; and the ACL Return to Sport Index (ACL-RSI), which evaluates psychological readiness to return to activity following ACL injury²⁴⁷.

Participant and equipment preparation

After all consent forms and questionnaires were completed, participants changed into tight-fitting spandex shorts and a long-sleeved shirt. Anthropometric measurements were taken, including height (cm), weight (kg), leg and shank length (cm), width between the anterior superior iliac spine (ASIS) and between the posterior superior iliac spine (PSIS) (cm), thigh and shank circumferences (cm), and knee and ankle width (cm). Surface electromyography (EMG) electrodes (16-channel Trigno, Delsys, Boston, USA) were placed on the muscle bellies of the vastus lateralis (VL), vastus medialis (VM), biceps femoris (BF), semitendinosus (ST), lateral gastrocnemius (LG), and gluteus medius (GMED). Inertial/electromyography (IMU/EMG) sensors were placed on the rectus femoris (RF) and medial gastrocnemius (MG) following the guidelines set out by

SENIAM and De Luca^{63,106}. Sensor locations were prepared by shaving the hair, and skin oil removal with alcohol swabs.

Participants were then given the opportunity to stretch and bike on a cycle ergometer (Monark 828E, Vansbro, Sweden) with minimal resistance for 5 minutes as a warm-up. Maximum voluntary isometric contractions (MVICs) were then completed on a Biodex isokinetic dynamometer (System 4, Pro, Biodex Medical Systems, New York, USA) for all recorded muscle groups.

Following MVICs, participants were outfitted with 84 retroreflective markers according to a whole-body cluster marker set (Appendix C). Marker trajectories were recorded at 200 Hz using a 10-camera motion capture system (8 Vero, 2 Vantage, Vicon, Oxford, UK). The supporting Nexus software was also used to synchronously collect IMU/EMG signals sampled at 2000 Hz and EMG signals were band-pass filtered at 20-450 Hz. EMG signals were then normalized to the MVICs.

Dynamic Trials

Prior to performing the dynamic tasks, participants completed a static calibration trial with feet shoulder width apart on separate force plates with toes pointing straight forward and arms abducted to 90° with a 90° bend in the elbow. The static trial was used to align the participant to the laboratory global coordinate system as well as define local coordinate systems specific to each participant. Participants then completed a series of dynamic movement tasks, including a battery of single-limb hops, two-legged squats, lunges, countermovement jumps, drop vertical jumps, and side cuts. Each movement was explained and demonstrated by the researcher and participants were notified that they may skip or stop the performance of a task if it caused any pain or discomfort. Participants were asked to perform two practice trials on each limb and two successful trials for the single limb hop tasks and five successful trials for all other dynamic trials at a self-selected pace. The tasks were all chosen as they are often used in evaluating the relative between-limb difference in functional performance of patients during rehabilitation²⁴⁸.

This large data collection was broken into data sets for different research projects. The research for this thesis primarily uses the single limb hopping tasks for further analysis. These included maximal effort anterior, lateral, cross, triple, and a 6-meter timed hop. For the maximum anterior hop (ANT; Figure 4.1A), participants were instructed to begin facing forward and jump as far as they could on one foot. For the lateral hop (LAT) (Figure 4.1B), participants were

instructed to hop laterally as far as they could on one foot, facing perpendicular to the direction of the marked line on the laboratory floor. For the triple hop (TRP), participants completed three hops in a row for maximal distance (Figure 4.1C). For the cross-hop (CRS) for distance participants were asked to jump three times in a row across two marked lines separated by 15cm on the laboratory floor, while attempting to cover maximum distance forward (Figure 4.1D). To successfully complete a hop task, participants started on their testing leg with their hands on their hips, performed the maximal jump(s) for distance and maintained single-limb balance for three seconds. For the 6-meter timed hopping task (6-m), participants hopped the 6-meter distance as indicated by two taped lines as quickly as they felt comfortable on their testing limb. To account for variability in arm swing, participants were instructed to keep their hands on their hips throughout each trial. The distance and time to complete each task were measured with either a measuring tape or a stopwatch, as is typical in a clinical setting.

In addition, five successful trials of the following dynamic tasks were completed and used in Study 2: squats, lunges, CMJ, side cuts, and DVJs. The squats, lunges and CMJ required participants to keep their hands on their head and perform the movement to the best of their ability. Participants were asked to squat or lunge as low as possible and asked to jump as high as they could during the CMJ. For the side-cuts, participants were asked to run as quickly as they could, plant their foot on a force plate and accelerate at a 45° angle through a set of cones. Finally, for the DVJ, a platform was set to the height of the participant's tibial plateau, and participants were asked to step off the platform and jump as high as they could on the rebound. Additional descriptions and pictures of these dynamic tasks can be found in Appendix D.

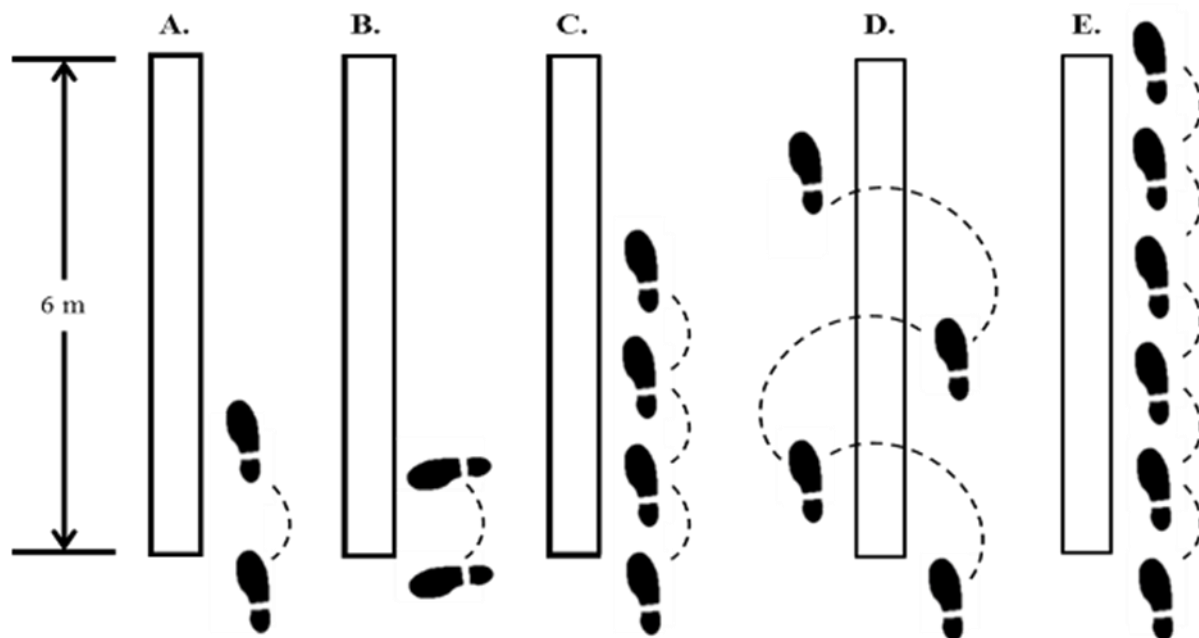


Figure 4.1 Single-limb hop tests: A. Maximal Anterior Hop; B. Maximal Lateral Hop; C. Triple Hop for Distance; D. Cross-Hop for Distance; and E. Timed 6-meter Hop.⁸⁸

4.4 Data Pre-Processing

Discrete Spatiotemporal Measures

Participants were included based on their ability to complete the single-limb maximal anterior hopping task, deemed as the least challenging task within the battery of single-limb hopping tasks. The variables are outlined in Appendix F, and all variables were chosen because they could be represented in a clinical setting using simple tools such as a stopwatch and a measuring tape. Accordingly, hop distances in Studies 1 and 2 were measured manually using a measuring tape, while completion time for the 6-meter timed hop was recorded using a stopwatch to reflect typical clinical assessment procedures. Outliers were identified through boxplots, and any value that exceeded 3 standard deviations from the sample mean was inspected and analyzed to determine the appropriate treatment. All outliers resulting from errors produced during data collection were excluded, and all other data were included in subsequent analyses to allow the inclusion of all the natural variability in participant performances.

The lunge and squatting depth were measured for the lunges and bilateral squats, respectively, based on the vertical difference in the pelvis origin. Similarly, the pelvic origin was used to compute the squatting depth (difference from the beginning of the trial to the lowest vertical height) and jump height (difference from the beginning of the trial to the highest vertical position)

for the CMJ. The squatting depth at both the initial takeoff after stepping off the platform onto the force plate (Figure C.3) and the final landing phase, and the jump height relative to their standing static trial, was used for the DVJ. The perpendicular distance from the planting foot on the force plate to the contralateral foot accelerating at a 45-degree angle was used to represent a potential measure for push-off power for the SC²⁵³. The distance between the starting position indicated by a zero on the measurement tape and the heel marker's landing position of the test limb was used to quantify hopping distance for the ANT, LAT, TRP and CRS hops. In addition, the maximal lateral distance between the three hops for the CRS was used to evaluate the control of the testing foot during these trials and the time to complete the 6-meter timed hop was measured. For all tasks performed on each limb separately, limb symmetry indices (LSI) were calculated using the following equation:

$$LSI = \frac{Non\ dominant/Injured}{Dominant/Uninjured}$$

Motion Capture Data

Marker trajectories for the single-limb hop tasks were labelled, gap-filled and filtered with a 4th order zero-lag dual low-pass Butterworth filter with cut-off frequencies of 15 Hz^{27,134} using custom pipelines in Vicon Nexus (Nexus v2.9, Vicon, UK). A modified Vicon Nexus model¹⁵³ was used for scaling and to compute inverse kinematics, relative to a standing reference trial for the hip, knee, and ankle sagittal and frontal planes.

Data were then exported and analyzed using MATLAB (The MathWorks, Natick, MA, USA). Joint centers were outputted bilaterally for the shoulder, foot, ankle, knee and hip; centers of mass for the trunk, head, and pelvis; and segment angular velocities and centers of mass (CoM) linear velocities of the head, trunk, pelvis, thighs, shanks, and feet^{61,62}. All positional data were first rotated so that the local coordinate system of the foot was aligned with the global coordinate system. The data were then translated so that the midpoint between the left and right hip of the first frame of the hopping trial was aligned with the global origin. The rotated data were then trimmed to specific start and end-point criteria (Appendix E) and normalized to 500 frames using a piecewise cubic, shape-preserving interpolation to control for differences in absolute movement time. To reduce the influence of limb dominance on the extracted principal components, all trials performed on the left limb were mirrored across the sagittal plane. Two matrices ($[n \times 21,000]$ and $[n \times m]$ for each hopping task were then constructed, where n was the number of contributing

participants and 21,000 was the time-normalized x, y, and z data for each joint center and center of gravity markers mentioned above (14 positions x 3 axes x 500 time points), and m corresponded to the number of concatenated signals (i.e. number of simulated sensors (3-7) x 6 signals x 500 time points) comprising of five different configurations of the lower back, thighs, shanks, and feet. Due to marker occlusion and some participants not completing all tasks, n was dependent on the hopping task (Appendix A).

Simulated Inertial Measurement Units

Inertial measurement units were simulated (sIMU) directly from the optical MoCap data so that the resulting time series would be dynamically consistent with the recorded marker trajectories and calculated joint centers. For each frame k , a right-handed cluster coordinate system $R_{seg}(k) \in \mathbb{R}^{3 \times 3}$ was constructed for the thigh, shank, trunk, and foot directly from the available cluster markers. When full clusters were present, the thigh and shank used the proximal posterior, proximal anterior, distal posterior and distal anterior markers. The proximal-distal (PD) axis was defined as the unit vector from the proximal to the distal centroid; the anterior-posterior (AP) axis as the unit vector from the anterior to the posterior centroid; the medial-lateral (ML) axis as the cross-product $PD \times AP$; and the third axis as $PD \times ML$ to complete an orthonormal triad^{44,257,258}. The trunk frame used a superior centroid formed by the sternum (SN) and C7 and an inferior centroid given by the mean of the available low-back markers, with at least two required at any frame; the AP direction was defined from SN toward the midpoint of the scapulae²⁵⁸. The foot frame used the heel for the proximal point, the midpoint of the first metatarsal and the fifth metatarsal for the distal point to define PD, and the line from the first to the fifth metatarsal for ML⁴⁴. When cluster markers were partially missing, anatomically grounded fallbacks ensured a well-posed frame: for the thigh, PD followed the line from the greater trochanter to the knee center, and for the shank, PD followed the line from the knee center to the ankle center; the remaining axes were obtained by the same cross-product construction^{44,258}. If fewer than two low-back markers were present for the trunk in a frame, no trunk frame was formed for that frame.

The sIMU orientation was taken to coincide rigidly with the cluster orientation, i.e., the sensor-to-world rotation at time k was $R_{sw}(k) \equiv R_{seg}(k)$. Angular velocity in the sensor frame was derived from the time derivative of the rotation matrix¹²⁶. Using a central difference,

$$\dot{R}(k) \approx \frac{R(k+1) - R(k-1)}{2\Delta t}$$

The body-rate skew matrix was computed as $S(k) = R(k)^\top \dot{R}(k)$, and the three components of angular velocity were read as

$$\omega(k) = \begin{bmatrix} S_{32}(k) \\ S_{13}(k) \\ S_{21}(k) \end{bmatrix},$$

yielding body-fixed rates in rad/s¹⁶⁹. Endpoints were set by copying the nearest central estimate to avoid one-sided differencing. Linear acceleration at each segment's center of mass (CoM) was first computed in the global frame by a second difference of the CoM position $p(k)$,

$$a_{gl}(k) \approx \frac{p(k+1) - 2p(k) + p(k-1)}{\Delta t^2},$$

after which gravity was removed and the result was expressed in the body frame,

$$f_{body}(k) = R(k)^\top (a_{gl}(k) - g), \quad g = \begin{bmatrix} 0 \\ 0 \\ -9.81 \end{bmatrix} m/s^2,$$

producing specific force⁹⁶. When available, the trajectories for the center of masses of the thigh, shank, trunk, and foot were used; if the foot CoM was unavailable, it fell back to the centroid of the heel, first and fifth metatarsals. Rotation matrices were constructed to be orthonormal at each frame; where averaging of axes was required (e.g., in static summaries), re-orthonormalization was performed via singular-value decomposition. No temporal filtering was applied to the simulated signals so as not to distort amplitudes or phases introduced by differentiation. The outputs consisted of synchronized, IMU-like body-fixed angular velocity $[w_x, w_y, w_z]$ and linear acceleration $[a_x, a_y, a_z]$ for each segment, together with the common time vector.

4.5 Data Analysis

All variables were first assessed for normality to determine whether parametric or non-parametric statistical tests were more appropriate. All statistical analyses were performed using R

(RStudio, Boston, MA) or SPSS Statistics 26.0 (IBM Corp, Armonk, NY, USA) with a significance set at $\alpha = 0.05$.

Study 1: Are Single Limb Hopping Scores the Same When Performed in a Physical Education Class Versus a Laboratory Setting in Uninjured Adolescents? Implications for Future Rehabilitation Guidelines for Adolescents with Knee Injuries

Understanding the ability of the single limb hopping tasks to be performed in different environments is an important step in providing clinicians, coaches, and patients with a reliable method to assess functional capacity.

To explore differences between female and male participants across various dimensions—including demographics, anthropometric measurements, self-reported questionnaires, and limb symmetry indices (LSIs) for single-limb hop tests—independent t-tests were employed. When the data distribution violated assumptions of normality, the non-parametric alternative, Mann-Whitney U-tests, was used to ensure valid comparisons (S1Q2).

To assess differences between limbs within the same group, dependent t-tests were conducted. For data that did not meet the normality assumptions, Wilcoxon tests were utilized as an appropriate non-parametric alternative (S1Q1). Parametric tests were preferred when their assumptions were satisfied because they generally provide greater statistical power and allow direct estimation of population parameters, whereas non-parametric alternatives were reserved for data that violated distributional assumptions.

The test-retest reproducibility of each single-limb hop test was examined using the intra-class correlation coefficients (ICC), a two-way random-effects model with absolute agreement. Test-retest reproducibility was defined as the degree to which measurement error relates to the variability in participants' performance on each single-limb hop test across both locations⁶⁶. The ICC calculated the ratio of the variance between participants and the total variance by assuming that the participants formed a random sample of a population⁶⁶. This method provided a robust estimate of the reliability of the measurements. To minimize systematic variation, the same assessors conducted evaluations across all sessions.

Agreement was defined as the statistical relationship between two measurements taken from the same participant during both initial and subsequent sessions of the hop tests, expressed in relevant units such as meters or seconds⁶⁶. The standard error of measurement (SEM) offered a quantifiable measure of error variance⁶⁶, while SEM% provided a percentage representation of

reproducibility in relation to the mean scores¹⁴¹. Systematic differences between the two limbs measured in the gymnasium and at the laboratory were investigated with Bland & Altman (BA) analysis²⁹, which graphically depicts the mean difference between limbs against the standard deviation (SD) of these differences. The limits of agreement (LOA) were calculated as the mean difference ± 1.96 times the SD of the differences²⁹, giving a visual representation of the degree of agreement.

Responsiveness, defined as the ability to detect clinically relevant changes in within-participant test-retest differences over time⁹⁸, was illustrated using BA plots²⁹. If analyses showed no significant systematic differences regarding the LOA, the smallest real difference (SRD) was calculated as $1.96 \times \sqrt{2} \times SEM$ and responsiveness as a percentage of the mean was calculated as $(SRD/mean) \times 100$ to represent the smallest measurement change and could be interpreted as a real (clinical) difference for an individual based on the LOA²³.

The hop distances and times of the dominant and non-dominant limbs were compared at both sessions using paired *t*-tests, and LSIs were calculated for each test (S1Q1). To determine possible location (S1Q1) and sex differences (S1Q2), a mixed ANOVA was used with locations as the within-subject factor and sex as the between-subject factor. Dependent *t*-tests were also performed to examine the learning effect between visit 1 and visit 2 (S1Q1).

Study 2: Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria.

Understanding the ability of the current measures used in RTA assessments in differentiating injury status in adolescents is crucial to determining whether they can then be used in an ACL-reconstructed cohort.

The C5.0 decision tree (DT) model, the successor to C4.5, was used due to its efficient memory usage and ability to produce smaller decision trees with lower error rates on testing sets¹⁸¹. Since missing values are present within this dataset, the C5.0 algorithm was chosen because it provides reduced error pruning and handles missing values by redistributing the weights of the variable branch with the missing value^{36,37}.

In this study, the C5.0 algorithm was set to seed 4, and the minimum number of cases required for a node to be eligible for splitting was determined relative to the size of the training set during each cross-validation iteration^{37,197}. The minimum number of cases required for a node to be eligible for splitting was determined relative to the size of the training set during each cross-

validation iteration to reduce overfitting and prevent the creation of overly specific terminal nodes. Global pruning was enabled, and leave-one-out cross-validation (LOO) was applied. In LOO, one observation (i.e., one participant) is designated as the testing set, while the model is built using the remaining $n - 1$ participants⁴⁷. This process is repeated n times, allowing each participant to be used as the test set, enabling hyperparameter tuning and model validation simultaneously. Hyperparameters were optimized separately for each decision tree model using only the training data within each cross-validation iteration. The final estimate averages all test error rates, ensuring every participant contributes to both training and validation. This model can then be tested for its generalizability with unseen data. Following hyperparameter selection using LOO within the training set, a final decision tree was trained using the entire 70% training dataset and evaluated on the independent 30% test set.

A two-pronged approach was employed to assess injury status and sex differences. First, a DT model (DTa) was created to differentiate adolescents with and without injuries (S2Q1 and S2Q2). Separate models were subsequently created for each sex to determine which functional tasks and spatiotemporal variables contributed most strongly to the classification of injury status among females (DTf) and males (DTm) (S2Q2).

Data were randomized into 70/30 splits, ensuring balanced classes and sexes. A class weight was assigned to address any imbalances in class distribution, calculated using the formula: $w_j = N_T / (C_j * N_j)$, where w_j is the weight for class j , N_T is the total number of participants in the dataset, C_j is the total number of unique classes (2), and N_j is the total number of participants in the respective class. These class weights were applied during model training to increase the penalty associated with misclassifying participants from the underrepresented class (ACLi), thereby reducing potential bias toward the majority class (CON). Class weights were not applied during testing, where model performance was evaluated on the independent test set.

The performance of each classifier was assessed on the test set (30% of the data) using several metrics: the F-measure (F_1), kappa statistic (κ), and the area under the precision-recall curve (PRC). The F_1 score represents the harmonic mean of precision and recall¹¹⁴, while the kappa statistic compares observed accuracy with expected accuracy, accounting for random chance⁴⁶. The PRC evaluates the model's effectiveness in predicting the positive class¹²¹ and reveals performance differences with imbalanced datasets²¹⁵. Confusion matrices were constructed for

each model, and sensitivity and specificity were outlined to represent clinically relevant performance measures¹⁰⁰.

Independent t-tests (or the non-parametric equivalent, Mann-Whitney U-tests) and effect sizes were also calculated for each important classifier identified through the DT model.

Study 3: Identifying movement differences in adolescents with and without ACL injury during hopping tasks

The battery of single-limb hop tasks was chosen for this study because the ANT and LAT were deemed the two tasks that provided the best separation between female adolescents with and without ACL injuries⁸⁹ and, as mentioned in Chapter 2, they are frequently used in rehabilitation protocols to assess readiness to return to pre-injury activities²⁴⁸. The 6-m timed hop was not used because participants began and ended the trials outside of the capture volume, preventing an accurate reconstruction of the data. In addition, only the final hop for CRS and TRP was analyzed since the landing of the final hop can highlight potential injury mechanisms, as it requires a stabilizing component not seen in the other hops¹¹⁰. A breakdown of the available data and the start and end criteria used for each task can be found in Appendix A and Appendix E, respectively.

Principal component analysis was applied to the pooled waveform data for each hop task, decomposing the signals into orthogonal components that represented distinct modes of movement variance. To prevent information leakage and overfitting, PCA was performed within each fold of leave-one-out cross-validation, fitted exclusively to the training set and applied to the test set. To select informative features, an ensemble approach combined ANOVA F-statistics, Chi-squared tests, Mutual Information, Random Forest importance, and LASSO regression. Components appearing in at least two rankings were retained, and the number of features was capped to the square root of the sample size to minimize overfitting.

Six supervised learning models were trained on the selected principal components: logistic regression, decision tree, k-nearest neighbours, linear discriminant analysis, Gaussian naïve Bayes, and a linear support vector machine. Within-fold class imbalance was addressed using SMOTE on the training set, followed by scaling and PCA before model fitting. A soft-voting ensemble averaged calibrated class probabilities from all six models to assess whether aggregation improved stability. Performance was summarized using accuracy, Cohen's κ , F1, and PR-AUC, emphasizing agreement beyond chance and minority-class discrimination. Two primary comparisons were

evaluated: IL-CON (injured limbs vs healthy control limbs) and CL-CON (contralateral limbs of ACL-injured vs healthy control limbs) (S3Q2).

To address S3Q1, Study 3 benchmarked its PCA-based classifiers against Study 2 using the same hop tasks and harmonized evaluation metrics (accuracy, κ , F1, PR-AUC). Since Study 2 and Study 3 used different resampling schemes (70/30 split with LOO on the training subset vs LOOCV), comparisons focused on metric magnitudes and confidence intervals rather than identical folds, providing an appropriate cross-study reference for relative performance.

A misclassification analysis was also conducted. Bilateral consistency of errors was examined by identifying participants misclassified at least once in both IL-CON and CL-CON models for each task, computing the proportion with bilateral misclassification among those misclassified on at least one limb, and quantifying error recurrence per limb and task. The distribution of bilateral errors across single tasks and task combinations was then stratified by sex and group (S3Q2). For controls, analyses were aligned to limb dominance to ensure consistent limb mapping across IL-CON and CL-CON.

Study 4: Simulated IMUs for ACL Injury Classification in Adolescents: A Task- and Configuration-Specific Analysis of Single-Limb Hops

The same cohort and hopping tasks described in Study 3 were used, with identical marker trajectory pre-processing for use as a comparison (S4Q1). Simulated IMU signals were generated from the marker-based kinematic data using a custom MATLAB pipeline that computed tri-axial angular velocities and linear accelerations for the thighs, shanks, trunk, and feet. Signals were expressed in local segment-fixed coordinate frames following removal of gravitational acceleration. Five sensor configurations were tested to determine the influence of placement on classification (S4Q2), ranging from full coverage across the trunk, thighs, shanks, and feet to reduced configurations focused on key segments. The outputs for the accelerometers and gyroscopes differed in scale. As such, features were normalized with the robust scaler to minimize the impact of outliers and ensure comparability. Feature selection, classification and model selection are identical to Study 3.

CHAPTER 5: ARTICLE 1

Are Single Limb Hopping Scores the Same When Performed in a Physical Education Class Versus a Laboratory Setting in Uninjured Adolescents? Implications for Future Rehabilitation Guidelines for Adolescents with Knee Injuries

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5.1 Preamble

Single-limb hop testing is widely used to evaluate the functional capacity of the lower extremities following injury and during rehabilitation. These tests are frequently incorporated into return-to-activity decision-making due to their simplicity, minimal equipment requirements, and ability to challenge lower-limb power, coordination, and dynamic stability. In clinical and field settings, performance outcomes such as hop distance and completion time are typically measured manually using simple tools, including measuring tapes and stopwatches. Despite their widespread use, the interpretation of hop performance relies on the assumption that outcomes are reproducible, responsive to meaningful change, and comparable across common testing environments.

In applied practice, functional testing is often performed outside controlled laboratory conditions, such as gymnasiums, rehabilitation clinics, and school-based physical activity settings. These environments introduce variability related to surface characteristics, footwear, visual and auditory distractions, and testing logistics. If such contextual factors influence hop performance, then observed differences in test outcomes may reflect environmental effects rather than true changes in functional capacity. Establishing the reproducibility of hop tests across environments is therefore necessary prior to their use as longitudinal outcome measures in adolescent populations.

Adolescence further complicates the interpretation of performance due to ongoing growth, maturation, and neuromuscular development. Variability in movement strategies during this period may differ between sexes and influence baseline hop outcomes and symmetry profiles. Understanding this variability in uninjured adolescents is an essential prerequisite for interpreting post-injury performance and identifying clinically meaningful deficits.

Accordingly, this chapter examines the reproducibility and responsiveness of a battery of single-limb hop tests performed in both an open gymnasium environment and a closed laboratory environment in uninjured adolescents. Baseline performance characteristics and sex-based differences are also evaluated. The findings establish foundational measurement properties required for the injury-focused and classification-based analyses presented in subsequent chapters, which build upon these clinically feasible performance measures using increasingly sophisticated biomechanical approaches.

5.2 Abstract

This study compared the performance of adolescents (11-13 years old) in two environments with five single-limb hopping tasks. The purpose was to assess the reproducibility and responsiveness of single-limb hop tests in two environments (gymnasium and laboratory) for uninjured adolescents, and determine whether there are differences in baseline measures between males and females. Thirty-four participants (12 ± 0.3 years) were randomly assigned the gymnasium during a regularly scheduled physical education class or the laboratory and completed five single-limb hop tasks. Two weeks later, participants completed the tasks in the other location. The performances were evaluated for reproducibility (intra-class correlation coefficients [ICC], and standard errors of measurement [SEM]), and responsiveness (Bland-Altman analyses [BA], and smallest real difference [SRD]). Limb symmetry indices (LSI) were also calculated for each task. Two-way mixed ANOVAs examined location and sex differences. All hops were reproducible ($ICC = 0.62-0.88$) with SEMs ranging between 6.7-13.0% of the mean of the group. BA showed location differences for the triple hop on the dominant limb ($d = -13.3$ cm, $p=0.03$). SRDs ranged between 18.5-35.9% of the mean of the group for all hops. Males scored higher (percent difference (%D) = 9.9-21.4%, $p<0.05$) for all hops except the anterior hop on both limbs, the 6-meter timed hop and lateral hop on the non-dominant limb. LSIs were 93.5-102.6% and 94.4-101.7% for all hopping tasks for females and males, respectively. In conclusion, this battery of single-limb hop tests offer a reliable method for clinicians and researchers to assess the functional capacity of uninjured adolescents in various environments.

5.3 Introduction

Approximately 75% of children and adolescents in North America participate in some form of organized sport (The National Federation of State High School Association, 2019). Unfortunately, more sports-related injuries are being reported and account for approximately 66% of all injuries in this population (Werner et al., 2016). Of those injuries, more than 50% occur in the lower extremities, with the knee and ankle accounting for many of these injuries that often lead to rehabilitation and, in some cases, surgical intervention (Hootman et al., 2007). Moreover, the risk for a subsequent injury is higher after a primary injury (Salmon et al., 2005). Despite the impact of these injuries, and considering adolescent females have a 1.5 times higher risk of a season-ending lower extremity injury compared to boys (Fernandez et al., 2007), there is surprisingly very limited sex-specific research on functional testing in an adolescent population.

Single-limb hop testing is one of the most common assessments to determine post-injury, post-surgical, and post-recovery/rehabilitation return-to-activity readiness in the lower extremities (Cristiani et al., 2019; Mattacola et al., 2002; Sharma et al., 2011). Four single-limb hop tests were developed and have been shown to be sensitive indicators of post-injury deficits in adult males (Barber et al., 1990; Noyes et al., 1991). Multiple authors have also established reliability (Dingenen et al., 2019; Ross et al., 2002); however, these single-limb hop tests have yet to be evaluated in an adolescent population and between sexes. It is also crucial to consider the environment in which functional performance is assessed during physical activities. Current testing is based in a closed environment such as a laboratory or clinician's office. These closed environments may not challenge the patient in the same way as an open environment, which is especially important when considering the environmental context within which actual activities and sports take place (Davies et al., 2017). Several laboratory-based experiments have confirmed an increased injury risk when movements are performed with additional cognitive or visual stimuli (Borotikar et al., 2008; Brown et al., 2009); however, typical functional testing does not incorporate different environments, which may limit a true assessment of the patient's performance. It is therefore important to ensure these tests can be performed outside a laboratory setting by measuring and establishing the reproducibility due to the varying locations and responsiveness of the scores within adolescent males and females to detect real and potentially clinically important changes over time.

Although limb symmetry indices (LSI) are commonly used to assess the functional capacity in adults with and without injuries (Cristiani et al., 2019; Johnson & Stoneman, 2007); there is limited evidence for their use in adolescent populations. Most studies calculate the LSI by dividing the dominant limb by the non-dominant limb's score, with an accepted threshold of 0.90 indicating symmetry (Barber-Westin & Noyes, 2011; Munro & Herrington, 2011). However, some studies have begun reporting lower thresholds in adolescents (Girard et al., 2020), and differences in asymmetry direction based on the task (Mulrey et al., 2020). This highlights the need to further examine this population's performance during functional testing.

Injury recovery among adolescents differs from adults, given the complex multifactorial nature of puberty (LaBella et al., 2014). As such, when evaluating an adolescent patient's recovery from injury, it is important to have insight into the functional capacity with respect to their age, sex, maturation state, and activity-matched cohort since it is with those individuals that they will be returning to full activity once they have recovered from their lower extremity injury. It is also important to ensure these tests can be performed outside the laboratory in a less controlled environment such as a gymnasium during a physical activity class and provide similar results. Therefore, the purpose of this study was to: i) assess the reproducibility and responsiveness of a battery of single-limb hop tests in two environments (open: physical activity class; and, closed: laboratory) for an uninjured adolescent population, and ii) determine whether there are differences in baseline measures between adolescent males and females. Once test-retest reproducibility has been established in an adolescent population, these measures can be used in various environments by clinicians, strength and conditioning professionals, and researchers alike.

5.4 Methods

Study Design

A multi-center (open: physical education class and closed: laboratory) counter-balanced study was designed to compare the performance of uninjured adolescent males and females with a battery of single-limb hop tests on two separate occasions with a 2-week interval. The testing session occurred during a regularly scheduled physical education class in a gymnasium providing an open environment with visual and auditory distractions whereas the laboratory session provided a closed, controlled environment with a maximum of four participants rotating through stations of

the single-limb hopping tasks at one time. Hop performances were evaluated by the same team of trained researchers in both locations.

Participants

Thirty-four adolescent participants, aged 11-13 years (18 females), were recruited from a local high school, and were randomly separated into two groups, with sex counterbalanced and began their first testing session either at the gymnasium or the laboratory. All participants provided informed consent, and approval for the study was obtained from the Institutional Research Ethics Board. At the laboratory session, participants had their height and weight recorded and then completed two questionnaires: the Hospital for Special Surgery Pediatric Functional Activity Brief Scale (HSS Pedi-FABS) in English or French (Del Bel et al., 2020; Fabricant et al., 2013), to assess physical activity levels and the Tanner Stage self-assessment for indicating their developmental stage in puberty (Marshall & Tanner, 1969,1970). Limb dominance was established as the limb typically used for mobility (i.e. kicking a soccer ball) while the non-dominant limb contributes to support (van Melick et al., 2017). Participants were deemed eligible for the study if they were injury-free at the time of testing.

Procedure

The first group completed the series of hop tasks at the gymnasium and the second group completed the hops in the laboratory. Two weeks later, participants completed the protocol in the opposite location. Participants were instructed to perform single-limb hops in a randomized order on each limb as described in previous studies including the anterior- (ANT), triple- (TRP), cross- (CRS), and 6-meter timed hop test (6m) (Barber et al., 1990; Noyes et al., 1991); a maximal lateral hop (LAT) was also added (Figure 5.1A-E). A minimum of one-minute rest between trials was provided and all hop tests were performed at a self-selected pace. Each participant was provided a demonstration from the researcher before completing two practice trials on each limb. Participants were instructed to jump as far as they could for the ANT, LAT, TRP and CRS hops without pausing between jumps for the TRP and CRS, and to jump as fast as they could for the 6m hop test. Participants then completed a minimum of three good trials, consisting of using proper technique (hands on their hips throughout testing), being in control throughout the task and holding the landing for a minimum of two seconds. Standardized shoes were provided in the laboratory to control for variability in shoe type as part of a larger study, and the participants wore their personal

footwear during their physical education class in the gymnasium setting. It was assumed that the different shoes would not have a significant effect on hopping performance.

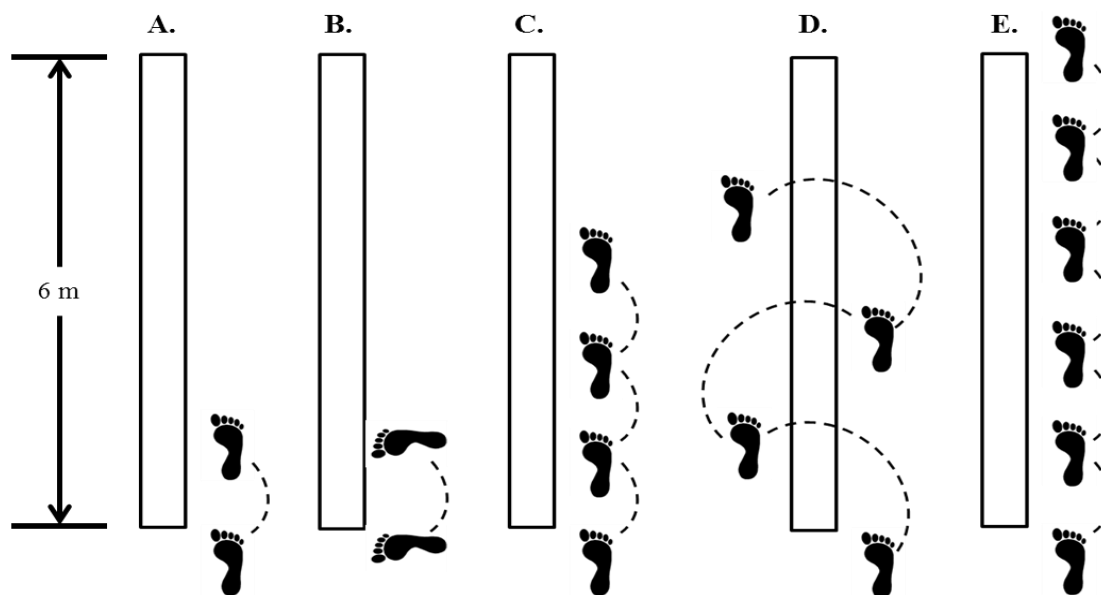


FIGURE 5.1. Single-limb hop tests on the right foot: A) anterior hop; B) lateral hop; C) triple hop; D) cross hop; and E) 6-meter timed hop.

Statistical Analyses

All variables were assessed for skewness/kurtosis and normality (Shapiro-Wilks tests). All statistical analyses were performed using SPSS (V25, IBM Corporation, Armonk, NY, USA) with the level of statistical significance set at $\alpha = 0.05$. Independent t-tests (or the non-parametric equivalent, Mann-Whitney U-tests) were used to evaluate group differences (female vs male) on the following variables: demographics and anthropometrics, questionnaires, and LSIs for all single-limb hop tests. Dependent t-tests (or the non-parametric equivalent, Wilcoxon tests) were used to evaluate between-limb differences within each group for the spatiotemporal variables.

Reproducibility

Test-retest reproducibility.

Test-retest reproducibility was defined as the degree to which the measurement error is related to the variability between the participants' performance on each single-limb hop test in both locations (de Vet et al., 2006). The test-retest reproducibility of each single-limb hop test was examined using the intra-class correlation coefficients (ICC), a two-way random-effects model with absolute agreement. The ICC calculated the ratio of the variance between participants and the total variance by assuming that the participants formed a random sample of a population (de Vet

et al., 2006). ICC values less than 0.40 were deemed poor, between 0.40 and 0.75 were moderate, 0.75-0.90 were good and greater than 0.90 were excellent (Fleiss, 2011). The assessors remained the same between sessions for each task reducing the potential for measurement error.

Agreement.

Agreement quantifies the relationship between two measurements made on the same participant during the first and second sessions of hop tests and was expressed on the measurement scale (i.e., meters or seconds) (de Vet et al., 2006). The standard error of measurement of agreement (SEM) represented the error variance (de Vet et al., 2006). SEM% was also calculated as a measure of reproducibility percentage against the mean scores (Lexell & Downham, 2005). Systematic differences between the two limbs measured in the gymnasium and at the laboratory were investigated with Bland & Altman (BA) analysis (Bland & Altman, 1986), by plotting the mean difference found between the limbs in each location against the standard deviation (SD) of the calculated difference. The limits of agreement (LOA) were calculated as the mean difference ± 1.96 times the SD of the differences (Bland & Altman, 1986).

Responsiveness

The ability to detect clinically relevant changes of the within-participant test-retest differences over time was defined as responsiveness (Guyatt et al., 1987). BA plots were used to visualize variations around the zero line if the mean difference between the two measures was significantly different from 0.0 cm (Bland & Altman, 1986). If BA analyses indicated no large systematic differences regarding the LOA, the smallest real difference (SRD) was calculated as $1.96 \times \sqrt{2} \times \text{SEM}$ responsiveness as a percentage of the mean was calculated as $(\text{SRD}/\text{mean}) \times 100$ to represent the smallest measurement change and could be interpreted as a real (clinical) difference for a single individual based on the LOA (Beckerman et al., 2001).

Limb Symmetry Index

The hop distances and times of the dominant and non-dominant limbs were compared at both sessions with paired t-tests. LSIs were then calculated for each test by dividing the score of the non-dominant limb by the dominant limb's score, multiplied by 100 (Abrams et al., 2014).

An analysis of variance (ANOVA) was performed to assess the ICCs, SEMs, and SRDs. To determine whether there were location and sex differences, a mixed ANOVA was used with locations being the within-subject factor and sex, the between-subject factor. Dependent t-tests were also performed to examine the learning effect between visit 1 and visit 2.

5.5 Results

Participants' demographics including age, height, body mass and puberty stage did not differ ($p > 0.05$) between sexes and were (mean $\pm$ SD): 12.0 ± 0.3 years, 1.58 ± 0.08 m, 50.1 ± 12.6 kg, and 3 ± 1 , respectively. All participants were physically active (16 ± 6 and 23 ± 5 for females and males respectively). Male participants scored on average higher than females on the HSS/FR Pedi-FABS questionnaire ($p < 0.01$) and were more active ($p < 0.001$), while no other differences existed in the population's demographics. As such, hop performances (Table 5.1) were not normalized to the participants' height.

Table 5.1. Means and standard deviations of performance for each single-limb hop test in the two test locations for males and females for the dominant (D) and non-dominant limbs (ND).

Limb	Gymnasium (mean $\pm$ SD)				Laboratory (mean $\pm$ SD)			
	D		ND		D		ND	
Sex	Male	Female	Male	Female	Male	Female	Male	Female
Anterior hop (cm)	110.1 $\pm$ 23.7	96.0 $\pm$ 20.2	107.4 $\pm$ 25.8	93.8 $\pm$ 22.3	109.4 $\pm$ 18.6	99.1 $\pm$ 15.2	106.3 $\pm$ 20.3	93.0 $\pm$ 19.2
Lateral hop (cm)	101.4* $\pm$ 19.6	83.5* $\pm$ 14.4	96.7 $\pm$ 17.0	83.3 $\pm$ 19.4	99.5* $\pm$ 14.5	87.9* $\pm$ 12.4	94.9 $\pm$ 14.5	88.3 $\pm$ 18.2
Triple hop (cm)	377.0* [†] $\pm$ 62.8	316.2* [†] $\pm$ 71.7	378.6* $\pm$ 76.3	307.6* $\pm$ 66.3	388.5* [†] $\pm$ 55.6	331.1* [†] $\pm$ 52.6	376.6* $\pm$ 63.3	327.1* $\pm$ 61.5
Cross hop (cm)	307.0* $\pm$ 60.2	250.1* $\pm$ 67.9	291.1* $\pm$ 79.9	243.9* $\pm$ 70.9	305.0* $\pm$ 58.9	246.4* $\pm$ 58.9	304.8* $\pm$ 63.6	247.4* $\pm$ 58.9
Timed 6-meter hop (s)	2.70* $\pm$ 0.47	2.99* $\pm$ 0.47	2.71 $\pm$ 0.54	2.98 $\pm$ 0.57	2.60* $\pm$ 0.46	2.95* $\pm$ 0.47	2.64 $\pm$ 0.56	3.02 $\pm$ 0.52

[†] Statistically significant sex differences evaluated using independent t-tests (*) and location differences ([†]) are identified ($p < 0.05$).

Reproducibility

ICC scores were moderate between locations for both limbs for ANT and LAT (0.62-0.70). The rest were all good between locations for both sexes (>0.75). SEM for dominant and non-dominant limbs had differences of less than 1.3 cm for ANT, 1.1 cm for LAT, 0.02 s for 6m, 0.5 cm for TRP, and 4.6 cm for CRS between limbs for all jumps and the absolute values for the five tests are shown in Table 5.2. The SEM% ranged between 6.7-13.0% (Table 5.2).

Table 5.2. Test-retest reproducibility, agreement, and responsiveness for all participants in the laboratory versus gymnasium for the dominant (D) and non-dominant (ND) limbs.

Limb	ICC (95% CI)		SEM (SEM%)		SRD (SRD%)		<i>p-value</i>	
	D	ND	D	ND	D	ND	D	ND
Anterior hop (cm)	0.70 (0.47-0.84)	0.70 (0.47-0.84)	11.10 (10.7)	12.40 (12.4)	30.75 (29.8)	34.38 (34.4)	0.62	0.77
Lateral hop (cm)	0.65 (0.40-0.81)	0.62 (0.36-0.79)	9.96 (10.8)	11.04 (12.2)	27.60 (29.8)	30.60 (33.8)	0.56	0.52
Triple hop (cm)	0.85 (0.71-0.93)	0.88 (0.77-0.94)	26.13 (7.4)	25.64 (7.4)	72.44 (20.6)	71.07 (20.6)	0.03*	0.13
Cross hop (cm)	0.80 (0.63-0.89)	0.77 (0.59-0.88)	30.38 (11.0)	35.03 (13.0)	84.22 (30.6)	97.10 (35.9)	0.70	0.34
Timed 6-meter hop (s)	0.81 (0.65-0.90)	0.86 (0.73-0.93)	0.19 (6.7)	0.21 (7.4)	0.52 (18.5)	0.59 (20.7)	0.13	0.82

¹ Statistically significant differences ($p < 0.05$) between locations are identified (*).

Responsiveness

The BA analysis mean (d) and LOA values are shown in Table 5.3. There was a significant location bias for the laboratory for the dominant limb's TRP scores ($d = -13.3$ cm; LOA = $-81.9 - 55.3$ cm; $p < 0.05$). Higher biases were found in the laboratory for the dominant ANT, dominant and non-dominant LAT, non-dominant TRP, and non-dominant CRS. Higher biases were found in the gymnasium for the non-dominant ANT, dominant and non-dominant 6m, and dominant CRS. Absolute values in SRD for the five tests are shown in Table 5.2. The SRD% ranged between 18.5-35.9% (Table 5.2).

Table 5.3. Bland-Altman analysis summary with the mean and limits of agreement between the laboratory and gymnasium for the dominant and non-dominant limbs.

Limb	Dominant limb (d (LOA))	Non-dominant limb (d (LOA))
Anterior hop (cm)	-1.3 (-32.4 – 29.8)	0.9 (-34.0 – 35.8)
Lateral hop (cm)	-1.4 (-29.3 – 26.5)	-1.8 (-32.6 – 29.1)
Triple hop (cm)	13.3 (-81.9 – 55.3)*	-9.4 (-79.1 – 60.3)
Cross hop (cm)	2.9 (-105.4 – 89.0)	-8.2 (-105.4 – 89.0)
Timed 6-meter hop (s)	0.88 (-0.02 – 0.68)	0.01 (-0.59 – 0.60)

¹ Statistically significant differences ($p < 0.05$) between locations are identified (*).

Limb Symmetry Index

No statistical location differences were found between LSIs. The mean LSIs were $96.3 \pm 8.9\%$ for ANT, $97.7 \pm 9.2\%$ for LAT, $101.1 \pm 9.5\%$ for 6m, $98.4 \pm 9.2\%$ for TRP, and $98.2 \pm 12.8\%$ for CRS with the scores for each sex and location displayed in Table 5.4. The percent of participants who had LSI above 100% for the different hops ranged between 22.2-66.7% and 25.0-62.5% in either location for females and males, respectively (Table 5.4).

Table 5.4. Limb symmetry indices (LSI) and number of participants who scored above 100% between locations (laboratory vs gymnasium) for the battery of single-limb hop tests for males and females.

Sex	Single-limb hop test	Laboratory		Gymnasium	
		LSI (%) (mean $\pm$ SD)	# participants > 100 LSI	LSI (%) (mean $\pm$ SD)	# participants > 100 LSI
Females	Anterior hop (cm)	93.5 $\pm$ 9.1	4	97.3 $\pm$ 7.6	6
	Lateral hop (cm)	99.8 $\pm$ 11.9	12	99.0 $\pm$ 7.8	6
	Triple hop (cm)	98.7 $\pm$ 9.1	11	97.8 $\pm$ 10.1	11
	Cross hop (cm)	100.6 $\pm$ 12.1	7	97.7 $\pm$ 12.3	5
	Timed 6-meter hop (s)	102.6 $\pm$ 8.6	8	100.0 $\pm$ 10.6	7
Males	Anterior hop (cm)	97.2 $\pm$ 8.8	6	97.4 $\pm$ 10.3	5
	Lateral hop (cm)	95.7 $\pm$ 8.0	5	95.9 $\pm$ 8.2	6
	Triple hop (cm)	96.9 $\pm$ 8.4	10	100.1 $\pm$ 9.6	7
	Cross hop (cm)	100.1 $\pm$ 9.7	4	94.4 $\pm$ 16.6	8
	Timed 6-meter hop (s)	101.7 $\pm$ 10.0	7	100.2 $\pm$ 9.4	6

Baseline Measures and Sex Differences

The mean distances and times were 101.5 ± 21.3 cm, 91.6 ± 17.3 cm, 348.6 ± 69.6 cm, 272.8 ± 69.8 cm, and 2.83 ± 0.52 s respectively for ANT, LAT, TRP, CRS, and 6m. A significant main effect of sex for LAT, $F(1, 32) = 9.918$, $p < 0.05$, 6m, $F(1, 32) = 4.302$, $p < 0.05$, TRP, $F(1, 32) = 8.599$, $p < 0.05$, and CRS, $F(1, 32) = 8.522$, $p < 0.05$ was found on the dominant limb; and TRP, $F(1, 32) = 7.351$, $p < 0.05$, and CRS, $F(1, 32) = 5.564$, $p < 0.05$ on the non-dominant limb, where males jumped significantly farther and faster than female participants (Table 5.1). Furthermore, significant improvements in scores were found over the two sessions except for the 6m on both limbs. The mean differences between the second and first visits for the dominant and non-dominant limbs respectively were 8.0 ± 13.7 cm and 8.8 ± 15.4 cm for ANT, 10.4 ± 9.6 cm, and 12.0 ± 10.1 cm for LAT, 18.1 ± 32.7 and 15.4 ± 33.3 cm for TRP, and 28.9 ± 32.3 cm and 33.3 ± 37.18 cm for CRS ($p < 0.01$). Finally, a significant effect of location was found for the TRP ($p < 0.05$), where both groups jumped significantly farther in the laboratory than during their physical education class in the gymnasium on their dominant limb.

5.6 Discussion

The objectives of this study were to: i) determine whether a battery of single-limb hop tasks could be reproducible and responsive in an adolescent population, and ii) determine whether sex differences existed. This study demonstrated that this battery of single-limb hop tasks is a highly reproducible and responsive method to assess the functional capacity of adolescents and their performances in both a laboratory and during a regularly scheduled physical education class. This study also found important sex differences that must be considered when evaluating functional capacity in adolescents.

This is the first study to determine the test-retest reproducibility of the anterior, lateral, triple, cross and 6-meter timed hop tests in an adolescent population. In line with previous studies on adults, the test-retest reproducibility coefficients for each of the single-limb hop tests were moderate to good (>0.60) (Ross et al., 2002). In addition, the 95% CI for all tests was narrow (Lai & Kelley, 2011), indicating good agreement. The ICC provides information about the reproducibility between two or more locations (Fleiss, 2011), and includes the variance term for individuals and is therefore affected by sample size heterogeneity, meaning that high correlations can still mean unacceptable measurement error (Atkinson & Nevill, 1998). In the present study, we further analyzed the absolute agreement, which is unaffected by the range of measurements using the SEM (Abrams et al., 2014; Lexell & Downham, 2005). The smaller the SEM, the more reliable and reproducible the measurement, often used to interpret the results of a true improvement after an intervention. The SRD also allows clinicians to determine whether a change in hop distance or time reflects a true change, rather than irrelevant variations when repeatedly testing an individual. The SRDs in Table 5.2 were 18.5-35.9% of the mean of the group, and similar across the different hop tests. This suggests that an improvement between 18.5-35.9% reflects a true change in performance when retesting an adolescent individual. These percentages are slightly higher than previous studies evaluating the test-retest of the anterior, triple, cross and timed hop (Dingenen et al., 2019; Munro & Herrington, 2011; Ross et al., 2002). Our study population is, however, comprised of recreationally active adolescents performing in both a closed and open environment suggesting a higher variability in SEMs and SRDs may be more reflective of this population.

When establishing baseline measures for an uninjured adolescent population, the LSI, typically used as an outcome measure in return-to-activity guidelines following an injury to the

lower extremity (Kivlan & Martin, 2012; Schmitt et al., 2015; Toole et al., 2017), must be examined. Most studies calculate LSI in uninjured individuals by dividing the score of the dominant limb by the non-dominant limb's score and obtain an average of >90% (Munro & Herrington, 2011; van Grinsven et al., 2010). Munro et al. (2011) found a mean LSI between 98.4-101.6% for the original set of four single-limb hop tests, which is in line with the results of our study (93.5-102.6% and 94.4-101.7% for females and males, respectively). However, a mean LSI of 100% or greater may mask the asymmetries of adolescents within an uninjured group as the dominant limb used in tasks requiring both limbs such as kicking a ball, may not be the same in unilateral tasks such as jumping and landing (van Melick et al., 2017). Approximately 44% (range of 22-66.7% depending on jumping task) of adolescents scored higher on their self-reported non-dominant limb compared to their dominant limb on any given single-limb hop task.

To further establish baseline measures for an adolescent population, it is important to ensure that the number of practice and test trials, and location do not influence the results. Ross et al. (2002) examined the test-retest reliability of the anterior, triple, cross and 6-meter timed hops in eighteen adult cadet males and had three practice trials followed by three test trials with a four-week interval between testing days. Others had 1-3 practice trials and 2-4 test trials with a one-week interval between testing days (Dingenen et al., 2019; Munro & Herrington, 2011). All studies consistently revealed significant improvements in scores between sessions that could be attributed to a learning effect. Our study used two practice trials and three test trials with a two-week interval between sessions and found significant improvements in all hops except for the 6-meter timed hop on both limbs. However, no significant differences in distances or times were found between locations except for the triple hop on the dominant limb. Although significant improvements from the first to the second testing session were found, we believe the lack of significance between locations in our adolescent population suggests that the battery of hop tests can be performed within acceptable limits of error in a gymnasium and laboratory. This learning effect should be taken into consideration within this population and further examined over repeated monthly intervals for 6-12 months or the length of a rehabilitation program for a serious lower extremity injury such as an anterior cruciate ligament injury. The repeated testing of these hopping tasks in adolescents would be beneficial since many rehabilitation programs use the patient's performance at different phases of rehabilitation to determine readiness to return to full activity.

Finally, the results of our study indicated there were sex differences within the scores of the hop tasks regardless of location. Female participants improved their performance in the laboratory compared to the gymnasium except for the cross-hop, whereas male participants scored higher for all hopping tasks except the timed 6-meter hop in the gymnasium. While it is difficult to speculate on why males and females responded differently, factors that may contribute include the psychosocial and physical nature associated with participation in different sports and activities. For example, females are more likely to engage in individual sports and activities, whereas males typically engage in team sports or group activities (Deaner et al., 2012), and the data collections done in the gymnasium were conducted in a group setting. These results suggest that the functional capacity of males and females should be evaluated separately when applying scores from one environment to another.

5.7 Conclusion

The battery of single-limb hop tests examined in this study offers clinicians, scientists and strength and conditioning experts a reliable method to assess the functional capacity of uninjured, adolescent males and females in various testing environments. This data and the methods can be used to guide LSI measures in adolescent males and females with lower extremity injury. Athletes participating in multidirectional sports often must multitask and providing an environment that more closely resembles an unplanned situation may provide a more accurate reflection of functional capacity and performance. Therefore, the performances obtained in a gymnasium during a regular physical education class may be an alternative option for patients to bring their scores directly to clinicians and health care providers to evaluate functional capacity compared to the traditional laboratory setting when such a facility is not available. These may also begin serving as baseline values for comparison of performance for adolescent individuals who have sustained a lower extremity injury.

5.8 References

- Abrams, G. D., Harris, J. D., Gupta, A. K., McCormick, F. M., Bush-Joseph, C. A., Verma, N. N., Cole, B. J., & Bach, B. R., Jr. (2014). Functional Performance Testing After Anterior Cruciate Ligament Reconstruction. *Orthopaedic Journal of Sports Medicine*, 2(1), 232596711351830. <https://doi.org/10.1177/2325967113518305>
- Atkinson, G., & Nevill, A. M. (1998). Statistical Methods For Assessing Measurement Error (Reliability) in Variables Relevant to Sports Medicine. *Sports Medicine*, 26(4), 217–238. <https://doi.org/10.2165/00007256-199826040-00002>
- Barber, S. D., Noyes, F. R., Mangine, R. E., McCloskey, J. W., & Hartman, W. (1990). Quantitative Assessment of Functional Limitations in Normal and Anterior Cruciate Ligament-Deficient Knees. *Clinical Orthopaedics and Related Research*, 255, 204–214. <https://pubmed.ncbi.nlm.nih.gov/2347154/>
- Barber-Westin, S. D., & Noyes, F. R. (2011). Factors Used to Determine Return to Unrestricted Sports Activities After Anterior Cruciate Ligament Reconstruction. *Arthroscopy: The Journal of Arthroscopic and Related Surgery*, 27(12), 1697–1705. <https://doi.org/10.1016/j.arthro.2011.09.009>
- Beckerman, H., Roebroeck, M. E., Lankhorst, G. J., Becher, J. G., Bezemer, P. D., & Verbeek, A. L. M. (2001). Quality of Life Research, 10(7), 571–578. <https://doi.org/10.1023/a:1013138911638>
- Bel, M. J. D., Kemp, L. G., Girard, C. I., Rossignol, J., Goulet, S. F., Bourgon, J.-F., Carsen, S., & Benoit, D. L. (2020). Translation and Validation of the Hospital for Special Surgery Pediatric Functional Activity Brief Scale for French Paediatric Populations. *Physiotherapy Canada*, 72(4), 348–354. <https://doi.org/10.3138/ptc-2019-0033>
- Bland, J. M., & Altman, D. G. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet*, 327(8476), 307–310. [https://doi.org/10.1016/s0140-6736\(86\)90837-8](https://doi.org/10.1016/s0140-6736(86)90837-8)
- Borotikar, B. S., Newcomer, R., Koppes, R., & McLean, S. G. (2008). Combined effects of fatigue and decision making on female lower limb landing postures: Central and peripheral

- contributions to ACL injury risk. *Clinical Biomechanics*,23(1), 81–92.<https://doi.org/10.1016/j.clinbiomech.2007.08.008>
- Brown, T. N., Palmieri-Smith, R. M., & McLean, S. G. (2009). Sex and limb differences in hip and knee kinematics and kinetics during anticipated and unanticipated jump landings: implications for anterior cruciate ligament injury. *British Journal of Sports Medicine*,43(13), 1049–1056.<https://doi.org/10.1136/bjsm.2008.055954>
- Cristiani, R., Mikkelsen, C., Edman, G., Forssblad, M., Engström, B., & Stålmán, A. (2019). Age, gender, quadriceps strength and hop test performance are the most important factors affecting the achievement of a patient-acceptable symptom state after ACL reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*,28(2), 369–380.<https://doi.org/10.1007/s00167-019-05576-2>
- Davies, G. J., McCarty, E., Provencher, M., & Manske, R. C. (2017). ACL Return to Sport Guidelines and Criteria. *Current Reviews in Musculoskeletal Medicine*,10(3), 307–314.<https://doi.org/10.1007/s12178-017-9420-9>
- de Vet, H. C. W., Terwee, C. B., Knol, D. L., & Bouter, L. M. (2006). When to use agreement versus reliability measures. *Journal of Clinical Epidemiology*,59(10), 1033–1039.<https://doi.org/10.1016/j.jclinepi.2005.10.015>
- Deaner, R. O., Geary, D. C., Puts, D. A., Ham, S. A., Kruger, J., Fles, E., Winegard, B., & Grandis, T. (2012). A Sex Difference in the Predisposition for Physical Competition: Males Play Sports Much More than Females Even in the Contemporary U.S. *PLoS ONE*,7(11), e49168.<https://doi.org/10.1371/journal.pone.0049168>
- Dingenen, B., Truijen, J., Bellemans, J., & Gokeler, A. (2019). Test–retest reliability and discriminative ability of forward, medial and rotational single-leg hop tests. *The Knee*,26(5), 978–987.<https://doi.org/10.1016/j.knee.2019.06.010>
- Fabricant, P. D., Robles, A., Downey-Zayas, T., Do, H. T., Marx, R. G., Widmann, R. F., & Green, D. W. (2013). Development and Validation of a Pediatric Sports Activity Rating Scale. *The American Journal of Sports Medicine*,41(10), 2421–2429.<https://doi.org/10.1177/0363546513496548>

- Fernandez, W. G., Yard, E. E., & Comstock, R. D. (2007). Epidemiology of Lower Extremity Injuries among U.S. High School Athletes. *Academic Emergency Medicine*, 14(7), 641–645. <https://doi.org/10.1197/j.aem.2007.03.1354>
- Fleiss, J. L. (2011). *The design and analysis of clinical experiments*. (Vol. 73).
- Girard, C. I., Warren, C. E., Romanchuk, N. J., Del Bel, M. J., Carsen, S., Chan, A. D. C., & Benoit, D. L. (2020). Decision Tree Learning Algorithm for Classifying Knee Injury Status Using Return-to-Activity Criteria. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) in conjunction with the 43rd Annual Conference of the Canadian Medical and Biological Engineering Society. IEEE. <https://doi.org/10.1109/embc44109.2020.9176010>
- Guyatt, G., Walter, S., & Norman, G. (1987). Measuring change over time: Assessing the usefulness of evaluative instruments. *Journal of Chronic Diseases*, 40(2), 171–178. [https://doi.org/10.1016/0021-9681\(87\)90069-5](https://doi.org/10.1016/0021-9681(87)90069-5)
- Hootman, J. M., Dick, R., & Agel, J. (2007). Epidemiology of Collegiate Injuries for 15 Sports: Summary and Recommendations for Injury Prevention Initiatives. *Journal of Athletic Training*, 42(2), 311–319. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1941297/>
- Johnson, M. R., & Stoneman, P. D. (2007). Comparison of a Lateral Hop Test Versus a Forward Hop Test for Functional Evaluation of Lateral Ankle Sprains. *The Journal of Foot and Ankle Surgery*, 46(3), 162–174. <https://doi.org/10.1053/j.jfas.2006.12.007>
- Kivlan, B. R., & Martin, R. L. (2012). Functional performance testing of the hip in athletes: a systematic review for reliability and validity. *International Journal of Sports Physical Therapy*, 7(4), 410–412. <https://www.ncbi.nlm.nih.gov/pmc/articles/pmid/22893860/>
- LaBella, C. R., Hennrikus, W., Hewett, T. E., Brenner, J. S., Brookes, M. A., Demorest, R. A., Halstead, M. E., Kelly, A. K. W., Koutures, C. G., LaBella, C. R., LaBotz, M., Loud, K. J., Martin, S. S., Moffatt, K. A., Schwend, R. M., Gordon, J. E., Otsuka, N. Y., Raney, E. M., Shaw, B. A., ... (2014). Anterior Cruciate Ligament Injuries: Diagnosis, Treatment, and Prevention. *Pediatrics*, 133(5), e1437–e1450. <https://doi.org/10.1542/peds.2014-0623>
- Lai, K., & Kelley, K. (2011). Accuracy in parameter estimation for targeted effects in structural equation modeling: Sample size planning for narrow confidence intervals. *Psychological*

- Methods,16(2), 127–148.<https://doi.org/10.1037/a0021764>Lexell, J. E., & Downham, D. Y. (2005). How to Assess the Reliability of Measurements in Rehabilitation. *American Journal of Physical Medicine and Rehabilitation*,84(9), 719–723.<https://doi.org/10.1097/01.phm.0000176452.17771.20>
- Marshall, W. A., & Tanner, J. M. (1969). Variations in pattern of pubertal changes in girls. *Archives of Disease in Childhood*,44(235), 291–303.<https://doi.org/10.1136/adc.44.235.291>
- Marshall, W. A., & Tanner, J. M. (1970). Variations in the Pattern of Pubertal Changes in Boys. *Archives of Disease in Childhood*,45(239), 13–23.<https://doi.org/10.1136/adc.45.239.13>
- Mattacola, C. G., Perrin, D. H., Gansneder, J. M., Gieck, J. H., Saliba, E. N., & McCue, F. C. (2002).Strength, functional outcome, and postural stability after anterior cruciate ligament reconstruction. *Journal of Athletic Training*,47, 262–268.
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC164354/>
- Mulrey, C. R., Shultz, S. J., Ford, K. R., Nguyen, A.-D., & Taylor, J. B. (2020). Methods of Identifying Limb Dominance in Adolescent Female Basketball Players: Implications for Clinical and Biomechanical Research. *Clinical Journal of Sport Medicine*,30(3), 279–281.<https://doi.org/10.1097/jsm.0000000000000589>
- Munro, A. G., & Herrington, L. C. (2011). Between-Session Reliability of Four Hop Tests and the Agility T-Test. *Journal of Strength and Conditioning Research*,25(5), 1470–1477.<https://doi.org/10.1519/JSC.0b013e3181d83335>
- Noyes, F. R., Barber, S. D., & Mangine, R. E. (1991). Abnormal lower limb symmetry determined by function hop tests after anterior cruciate ligament rupture. *The American Journal of Sports Medicine*,19(5), 513–518.<https://doi.org/10.1177/036354659101900518>
- Ross, M. D., Langford, B., & Whelen, P. J. (2002). Test-Retest Reliability of 4 Single-Leg Horizontal Hop Tests. *The Journal of Strength and Conditioning Research*,16(4), 617.[https://doi.org/10.1519/1533-4287\(2002\)016%3C0617:trros1%3E2.0.co;2](https://doi.org/10.1519/1533-4287(2002)016%3C0617:trros1%3E2.0.co;2)
- Salmon, L., Russell, V., Musgrove, T., Pinczewski, L., & Refshauge, K. (2005). Incidence and Risk Factors for Graft Rupture and Contralateral Rupture After Anterior Cruciate Ligament

- Reconstruction. *Arthroscopy: The Journal of Arthroscopic and Related Surgery*,21(8), 948–957.<https://doi.org/10.1016/j.arthro.2005.04.110>
- Schmitt, L. C., Paterno, M. V., Ford, K. R., Myer, G. D., & Hewett, T. E. (2015). Strength Asymmetry and Landing Mechanics at Return to Sport after Anterior Cruciate Ligament Reconstruction. *Medicine and Science in Sports and Exercise*,47(7), 1426–1434.<https://doi.org/10.1249/mss.0000000000000560>
- Sharma, N., Sharma, A., & Singh Sandhu, J. (2011). Functional Performance Testing in Athletes with Functional Ankle Instability. *Asian Journal of Sports Medicine*,2(4).<https://doi.org/10.5812/asjms.34741>
- The National Federation of State High School Association. (2019).2018-19 High School Athletic Participation Survey.
- Toole, A. R., Ithurburn, M. P., Rauh, M. J., Hewett, T. E., Paterno, M. V., & Schmitt, L. C. (2017).Young Athletes After Anterior Cruciate Ligament Reconstruction Cleared for Sports Participation: How Many Actually Meet Recommended Return-to-Sport Criteria Cutoffs? *Journal of Orthopaedic and Sports Physical Therapy*, 1–27.<https://doi.org/10.2519/jospt.2017.7227>
- van Grinsven, S., van Cingel, R. E. H., Holla, C. J. M., & van Loon, C. J. M. (2010). Evidence-based rehabilitation following anterior cruciate ligament reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*,18(8), 1128–1144.<https://doi.org/10.1007/s00167-009-1027-2>
- van Melick, N., Meddeler, B. M., Hoogeboom, T. J., Nijhuis-van der Sanden, M. W. G., & van Cingel, R.E. H. (2017). How to determine leg dominance: The agreement between self-reported and observed performance in healthy adults. *PLOS ONE*,12(12), e0189876.<https://doi.org/10.1371/journal.pone.0189876>
- Werner, B. C., Yang, S., Looney, A. M., & Gwathmey, F. W. (2016). Trends in Pediatric and Adolescent Anterior Cruciate Ligament Injury and Reconstruction. *Journal of Pediatric Orthopaedics*,36(5),447–452.<https://doi.org/10.1097/bpo.0000000000000482>

5.9 Postamble

The central contribution of this chapter is the establishment of reproducible and interpretable baseline performance characteristics for commonly used single-limb hop tests in adolescents. The results demonstrate that hop outcomes can be obtained with acceptable reproducibility across both laboratory and gymnasium environments, while also revealing measurable learning effects and task-specific variability that must be considered when interpreting repeated assessments.

The quantified measurement error and responsiveness thresholds reported in this chapter provide practical reference values for distinguishing true changes in performance from expected test–retest variability. In addition, the presence of sex-based differences in baseline hop performance highlights the importance of contextualizing functional outcomes within age- and sex-matched reference groups rather than relying solely on absolute performance values or symmetry thresholds.

This work establishes the measurement framework that we build upon in the following chapters. By demonstrating that hop tests can be administered outside the laboratory with comparable reliability, the findings support their use in applied settings where controlled biomechanical testing is not feasible. However, the observed variability within uninjured adolescents highlights the limitations of relying exclusively on spatiotemporal hop outcomes to characterize movement quality.

While the present chapter focuses on establishing reproducibility and baseline interpretation of functional performance, the chapters that follow extend this work by examining how hop-based metrics perform in the presence of injury, whether waveform-level kinematic features improve classification of limb status, and how wearable sensor technologies may further enhance clinical assessment. In this way, the current chapter provides the necessary foundation for progressing from measurement validation to injury characterization and translational implementation.

CHAPTER 6: ARTICLE 2

Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria.

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6.1 Preamble

Return-to-activity (RTA) decision-making following anterior cruciate ligament injury relies heavily on functional testing to assess readiness for sport participation. In clinical practice, these assessments often include a range of hopping and jumping tasks intended to evaluate lower-limb strength, power, symmetry, and movement control. Despite their widespread use, substantial variability exists in the selection, interpretation, and weighting of these functional tasks, particularly within adolescent populations. Current RTA guidelines have been developed using adult cohorts and have not been systematically evaluated for their ability to discern injury status in younger athletes.

Adolescents present unique challenges for functional assessment due to ongoing growth, maturation-related changes in neuromuscular control, and sex-specific differences that emerge during puberty. These factors may influence both task performance and the relevance of commonly used outcome measures. Consequently, spatiotemporal metrics that appear clinically meaningful in adults may not adequately capture injury-related deficits in adolescents or may differ in their discriminatory value between males and females.

Classification models provide an opportunity to evaluate multiple functional tasks simultaneously and to identify which measures contribute most strongly to differentiating injured and uninjured individuals. Decision tree-based approaches are particularly suited for this purpose due to their interpretability, transparency, and alignment with clinical decision-making frameworks. By identifying task-specific and sex-specific classifiers, such models may inform more targeted and evidence-based approaches to RTA assessment.

Therefore, this chapter investigates whether spatiotemporal variables derived from functional tasks commonly used in adult RTA guidelines can classify ACL injury status in adolescent males and females. The work aims to identify the tasks and variables strongly associated with injury status and to evaluate whether distinct classification profiles emerge between sexes. These findings provide a critical step toward understanding the limitations of current spatiotemporal measures and inform the need for more advanced biomechanical analyses explored in subsequent chapters.

6.2 Abstract

Purpose: A lack of standardization exists for functional tasks in return-to-activity (RTA) guidelines for adolescents with anterior cruciate ligament injury (ACLi). Identifying the variables that discern ACLi status among adolescents is a first step in the creation of such guidelines following surgical reconstruction. This study investigated the use of classification models to discern ACLi status of adolescents with and without injury using spatiotemporal variables from functional tasks typically used in RTA guidelines for adults.

Methods: Sixty-four adolescents with ACLi and seventy uninjured adolescents completed single-limb hops, lunges, squats, countermovement jumps and drop-vertical jumps. Jumping distances, heights, and depths were collected. Decision trees (DT) were used to classify ACLi status and were evaluated using the F -measure (F_1), kappa statistic (κ) and area under the precision-recall curve (PRC). Independent t-tests and effect sizes were calculated for each important classifier of the DT models.

Results: A five-variable model classified ACLi status with an accuracy of 67.5% ($F_1 = 0.6842$; $\kappa = 0.350$; PRC = 0.491) with sex as a classifier. Significant differences were found in three of the four spatiotemporal variables ($p \leq 0.002$). Separate models then classified ACLi status in males and females with an accuracy of 53.3% ($F_1 = 0.5882$; $\kappa = 0.0541$; PRC = 0.476) and 76.9% ($F_1 = 0.7692$; $\kappa = 0.541$; PRC = 0.528), respectively, with significant differences for all variables ($p \leq 0.013$).

Conclusions: Among the DT models, females were better able to classify ACLi status compared to males, highlighting the importance of sex-specific rehabilitation guidelines for adolescents.

6.3 Introduction

Annually, approximately 1 in 29 female athletes and 1 in 50 male athletes will experience an anterior cruciate ligament (ACL) injury [25, 43]. These injury rates have also been increasing by 2.3% every year for individuals between the ages of 10-18 [16, 68]. With these rising rates, particularly in females [25, 50, 68], there is a strong need to develop sex- and age-specific evidence for the creation of return-to-activity guidelines following an ACL injury in adolescent populations.

Adolescents' bodies are growing and changing throughout puberty. A knee injury in this key stage of their life, not only affects them physically but socially since they may be side-lined from their sports and activities with their friends for at least one year. Research in this area has increased to understand the injury mechanisms in adults [41, 46, 61] and create predictions for re-injury risk within adolescents [51]. Sex differences have also been identified after the onset of puberty for neuromuscular [6, 22], biomechanical [19, 31], and clinical measures [15, 26]. However, the current guidelines for ACL injury (ACLi) and post-operative rehabilitation do not account for sex differences in adults and have yet to be tested in adolescent males and females. Adolescents also reportedly have slower strength recovery following ACLi [33, 40], decreased neuromuscular control [53], and poor rates of passing return-to-activity criteria [27, 48, 65]. With the greater risk of sustaining a secondary injury within two years of the initial ACLi [16, 29, 52, 67] and a 50% greater chance of developing early onset osteoarthritis within 5 to 20 years as compared to the general population [39, 45, 58], evidence-based knowledge is needed to identify measures that can assess knee injury status following rehabilitation in adolescent patients with ACLi.

Clinicians use a range of functional capacity measures including questionnaires, strength tests, and functional tasks during the return-to-activity (RTA) assessment process to strengthen their clinical evaluations. Current functional tasks used in assessing rehabilitation progression and RTA include a series of single-limb hopping tasks and other functional movements, such as lunges, squats, countermovement jumps and drop-vertical jumps [4, 18, 70]; however, there is a lack of standardization for these functional tests in RTA assessments [57]. These tasks evaluate the control, strength, and power of the lower body limbs using a combination of raw scores, normalized scores, and limb symmetry indices to evaluate a patient's readiness to return to their pre-injury level of physical activities. The recovered patient would receive a negative finding if features of ACLi are found in the patient following surgery and rehabilitation. To the best of our

knowledge, there is no evidence identifying which spatiotemporal measures from functional tasks can differentiate uninjured and ACL-injured adolescent males and females.

A classification model using a variety of functional tasks currently used in RTA evaluations may allow a tailored approach to be used in clinical settings to identify the effects of the ACLi on functional capacity in an adolescent population. At a minimum, the tasks and variables must identify the effect of the injury on functional capacity, so that the clinician can then assess if the deficits are recovered following surgery and rehabilitation. Such an algorithm could be used in conjunction with current clinical criteria to provide additional information for whether the patient is displaying functional capacity comparable to an uninjured cohort. Decision trees are one of the most widely used techniques for classification [3, 60, 71] because of their simplicity [62], ease of implementation [3, 72], high interpretability, and transparency, and have been shown to provide a high accuracy across a variety of medical data sets [35, 38, 56]. This technique can be used to determine if a clinician should give consent for RTA based on the classification of ACLi status using objective measures since a decision tree is like a flow chart, where each node denotes a test on an attribute, each branch represents the outcome of the test, and each leaf represents a class [38]. Therefore, the purpose of this study was to 1) identify tasks and variables capable of classifying ACLi status in adolescents; and 2) identify unique tasks for ACLi status classification in both male and female adolescents. We hypothesized that the classifiers extracted would differ between models for male and female adolescents.

6.4 Materials and Methods

Sixty-four (45 female, 19 male) adolescents with an ACL injury (ACLi; 15.3 ± 1.3 yrs.; 167.7 ± 8.1 cm; 68.1 ± 19.6 kg; BMI: 24.1 ± 6.0 kg/m²; Tanner Stage: 4 ± 1) and seventy (39 female, 31 male) uninjured (CON; 13.8 ± 1.7 yrs.; 165.0 ± 10.8 cm; 54.0 ± 11.8 kg; BMI: 19.6 ± 2.9 kg/m²; Tanner Stage: 4 ± 1) adolescents participated in this study (Table 6.1). ACLi participants were included in this study if they had a confirmed ACL rupture by their physician via clinical assessment and/or MRI and subsequent arthroscopy, and no history of contralateral ACL ruptures, excluding those seeking an ACL reconstruction revision. The CON participants were recruited via convenience and snowball sampling of regional youth sports associations and club teams. The CON participants and the contralateral limb of the ACLi group were also required to not have any previous lower limb surgical operations, no additional serious lower limb injury

including fractures or sprains within six months prior to testing or have any diseases that might affect neuromuscular function. Each CON participant actively participated in organized sports at the time of testing, as assessed through the HSS Pedi-FABS or FR Pedi-FABS [17, 21]. Pre-injury and current physical activity level as defined by the Tegner activity level scale was included for all participants [64]. All participants provided written informed consent approved by the hospital and institutional ethics review boards and were part of a larger ongoing prospective, repeated measures cohort study.

Table 6.1. Participant characteristics and subjective functional scores.

Variable	Uninjured Male (n= 31) a) Mean $\pm$ SD b) Median (Range)	Uninjured Female (n= 39) a) Mean $\pm$ SD b) Median (Range)	ACL-injured Male (n= 19) a) Mean $\pm$ SD b) Median (Range)	ACL-injured Female (n= 45) a) Mean $\pm$ SD b) Median (Range)
Age (yrs.)	a) 13.7 $\pm$ 1.7*	a) 13.9 $\pm$ 1.8 [§]	a) 15.4 $\pm$ 1.2*	a) 15.3 $\pm$ 1.3 [§]
Height (m)	a) 1.67 $\pm$ 0.01	a) 1.63 $\pm$ 0.07	a) 1.74 $\pm$ 0.09	a) 1.65 $\pm$ 0.06
Weight (kg)	a) 54.4 $\pm$ 12.6*	a) 53.7 $\pm$ 11.3 [§]	a) 76.3 $\pm$ 31.0*	a) 64.7 $\pm$ 10.9 [§]
Time since injury (months)	-	-	a) 5.6 $\pm$ 2.9	a) 5.5 $\pm$ 4.2
HSS/FR Pedi-FABS (0-30)	a) 26 $\pm$ 4*	a) 21 $\pm$ 5 [§]	a) 9 $\pm$ 8*	a) 7 $\pm$ 6 [§]
Pre-injury Tegner activity scale (0-10)	-	-	b) 9 (10-6)	b) 9 (10-6)
Current Tegner activity scale (0-10)	b) 9 (10-5)*	b) 9 (9-5) [§]	b) 5 (9-0)*	b) 3 (9-0) [§]
Tanner Stage (1-5)	a) 4 $\pm$ 1	a) 4 $\pm$ 1	a) 4 $\pm$ 1	a) 4 $\pm$ 1

¹ Statistically significant differences ($p < 0.05$) between male and female (* and [§], respectively) CON vs ACLi are identified.

During the study, participants wore tight-fitting spandex shorts and a long-sleeved shirt. Anthropometric measurements were taken, including height (cm) and weight (kg). Participants were outfitted with 84 reflective markers (14mm diameter) placed on various landmarks according to a hybrid marker-cluster set [5]. Participants were then given the opportunity to stretch and spin on a cycle ergometer (Monark 828E, Vansbro, Sweden) with minimal resistance for 5 minutes as a warm-up.

Each participant was asked to complete a series of dynamic movement tasks, including a battery of single-limb hops [24, 44], lunges [1], bilateral squats [66], countermovement jumps (CMJ) [30], and drop vertical jumps (DVJ) [47]. The distance between the starting position indicated by a zero on the measurement tape and the heel marker's landing position of the test limb was used to quantify hopping distance for the maximal anterior (ANT), maximal lateral (LAT), triple (TRP), and cross (CRS) hops. In addition, the maximal lateral distance between the three hops for the CRS and the time to complete the 6-meter timed (TIME) hop were measured, totalling

12 variables for the single-limb hopping tasks. Two good trials were recorded for each hopping task and the best score (i.e., greatest distance or shortest time) was used in the model. These tasks and variables were chosen because they could all be measured in a clinical setting with a stopwatch and a measuring tape [23].

Three-dimensional motion capture data were recorded (8 Vero, 2 Vantage, Vicon, Oxford, UK), sampling at 200 Hz to extract the spatiotemporal variables from the other functional tasks including the lunges, squats, CMJ, and DVJ. The lunge and squatting depth were measured for the lunges and bilateral squats, respectively, based on the vertical difference in the pelvis origin. Similarly, the pelvic origin was used to compute the squatting depth and jump height for the CMJ. A good trial for the lunge, squat, and CMJ was defined by keeping their hands on their head and maintaining their balance throughout the trial. The squatting depth at both the initial takeoff after stepping off the platform onto the ground and the final landing phase, and the jump height relative to their standing static trial was used for the DVJ. A good DVJ trial consisted of participants stepping off the platform, not jumping off and maintaining their balance for two seconds after the final landing. Five good trials were recorded for the additional functional tasks and the best score (i.e., greatest depth or jump height) was used as the input variable in the model.

The number of participants contributing to each task varied as trials were deemed missing variables in the analysis where participants either did not perform a particular movement due to their comfort level or where missing data did not permit a complete marker reconstruction for the duration of the task (Table 6.2). Distances, depths, and jump heights were normalized to the participant's height and both raw and normalized variables were included in the decision tree model for all contributing participants. For all six distance-based jumping tasks and lunges performed on each limb separately, limb symmetry indices (LSI) were calculated using the following equation: $LSI = Injured/Uninjured \text{ or } Non-dominant/Dominant$. These 9 tasks and 4 Vicon variables were chosen because they could all be measured in a clinical setting with a stopwatch and a measuring tape to represent clinically available measures.

Table 6.2. Number of ACL-injured participants contributing to each task.

Task	Maximal anterior hop	Maximal lateral hop	Triple hop	Cross hop	6-meter timed hop	Lunges	Squats	Counter moveme nt jump	Drop vertical jump
Male (n= 19)	18	16	14	13	16	18	19	19	18
Female (n= 45)	40	38	39	31	38	45	45	43	40

6.5 Statistical Analysis

The C5.0 decision tree (DT) model was used, the successor to C4.5 and ID3, as its memory usage is more efficient and produces smaller decision trees with lower error rates on testing sets [49]. The C5.0 algorithm provides feature selection, cross-validation, and reduced error pruning [7, 9]. The algorithm treats missing values by redistributing the weights of the variable branch for which the value is missing using the C4.5 algorithm [55]. In this case, the C5.0 algorithm was set at seed 4, with the minimum number of cases used in at least two of the splits as the length of the training set divided by the number of splits used in each iteration of the cross-validation minus 1 [9, 54], with global pruning enabled, and leave-one-out-cross-validation (LOO).

The LOO was applied to 70% of the data, with the remaining 30% of the data used as the test set for performance analysis. LOO uses one observation (i.e. one participant) as the testing set and builds the model on the remaining $n - 1$ training participants and repeated n times so that each participant is used as the test set to tune the hyperparameters and validate the model simultaneously [13]. The LOO estimate is then the average of these n test error estimates. This process allows for all participants to be used in both training and validation to identify optimal hyperparameters for the DT model and can then be tested to evaluate its generalizability with unseen data.

A two-fold approach was used to assess injury status and sex differences. A DT model was first created to differentiate adolescents with and without injuries (DTa). All variables including sex, were used as features in the DTa model to explore their importance in the separation of ACLi status (Figure 6.1). Separate models were then created for each sex to explore the functional tasks chosen as classifiers for differentiating injury status among females (DTf) and males (DTm) (Figure 6.1).

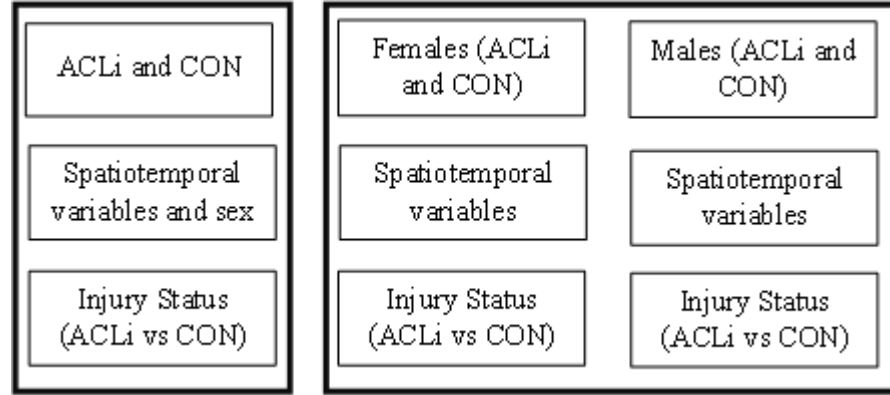


Figure 6.1. Review of data breakdown for each model with the group, inputted features and differentiating classes outlined.

The data for DTa were first randomized and split into training and testing sets with classes and sex equally distributed between sets for a 70/30 split. For DTf and DTm, the data were randomized with classes equally distributed between sets for the 70/30 split. A class weight was then assigned to account for imbalanced classes using the following equation: $w_j = NT / (C_j * N_j)$, where w_j is the weight for class j , NT is the total number of participants in the dataset, C_j is the total number of unique classes (2), and N_j is the total number of participants within the respective class.

The performance of each classifier was evaluated on the test set (30% of the data) using the F-measure (F1), kappa statistic (κ), and the area under the precision-recall curve (PRC). The F1 represents the harmonic mean between precision and recall [32], and the κ was used to compare the observed accuracy with the expected accuracy and takes into account random chance [12]. The PRC describes how good a model is at predicting the positive class [34] and can reveal differences in performance when using imbalanced datasets [59]. The confusion matrix for the models were constructed, and the sensitivity and specificity outlined to represent clinically relevant performance measures [28].

Independent t -tests (or the non-parametric equivalent, Mann-Whitney U-tests) and effect sizes were calculated for each important classifier determined through the DT model. Small effect size were considered to be $d < 0.3$, medium $0.3 < d < 0.5$, and large $d > 0.5$ [14]. All statistical analyses were performed using R (RStudio, Boston, MA) with a significance set at $\alpha = 0.05$.

6.6 Results

To differentiate ACLi status for the 94 participants in the training set, forty-seven variables were reduced to a five-variable model (DTa) including: non-dominant/injured limb ANT distance normalized to participants' heights (NNormANT), LSI of the TRP for distance (LSTRP), limb symmetry index for the TIME hop (LSTIME), sex, and dominant/uninjured limb maximal perpendicular CRS distance (DCrsDist) (Figure 6.2). Significant differences were identified for NNormANT ($p < 0.001$; $d = 0.838$), LSTRP ($p < 0.001$; $d = 0.789$), and LSTIME ($p = 0.002$; $d = 0.557$). The variable DCrsDist was not statistically different between groups.

The DT model for ACLi status prediction in the male adolescents (DTm) highlighted the NNormANT as the most important classifier ($p = 0.013$; $d = 0.783$) (Figure 6.3).

The LSTRP was identified as the most important classifier in the DT model for ACLi status prediction in the female adolescent group (DTf; $p < 0.001$; $d = 1.156$). After LSTRP, the dominant/uninjured limb's cross hop distance normalized to body height (DNormCrs) was identified as an additional classifier improving the model's predictability ($p = 0.012$; $d = 0.565$), with the LSI of the LAT (LSLAT) as the final classifier in the model ($p < 0.001$; $d = 0.749$) (Figure 6.4). Table 6.3 compares the descriptive results of the identified classifiers' scores between groups and Table 6.4 outlines the results of each of the three models studied using the reduced variables on the test set. The female group outperformed males and the entire group's DT models on all performance metrics when differentiating ACLi status.

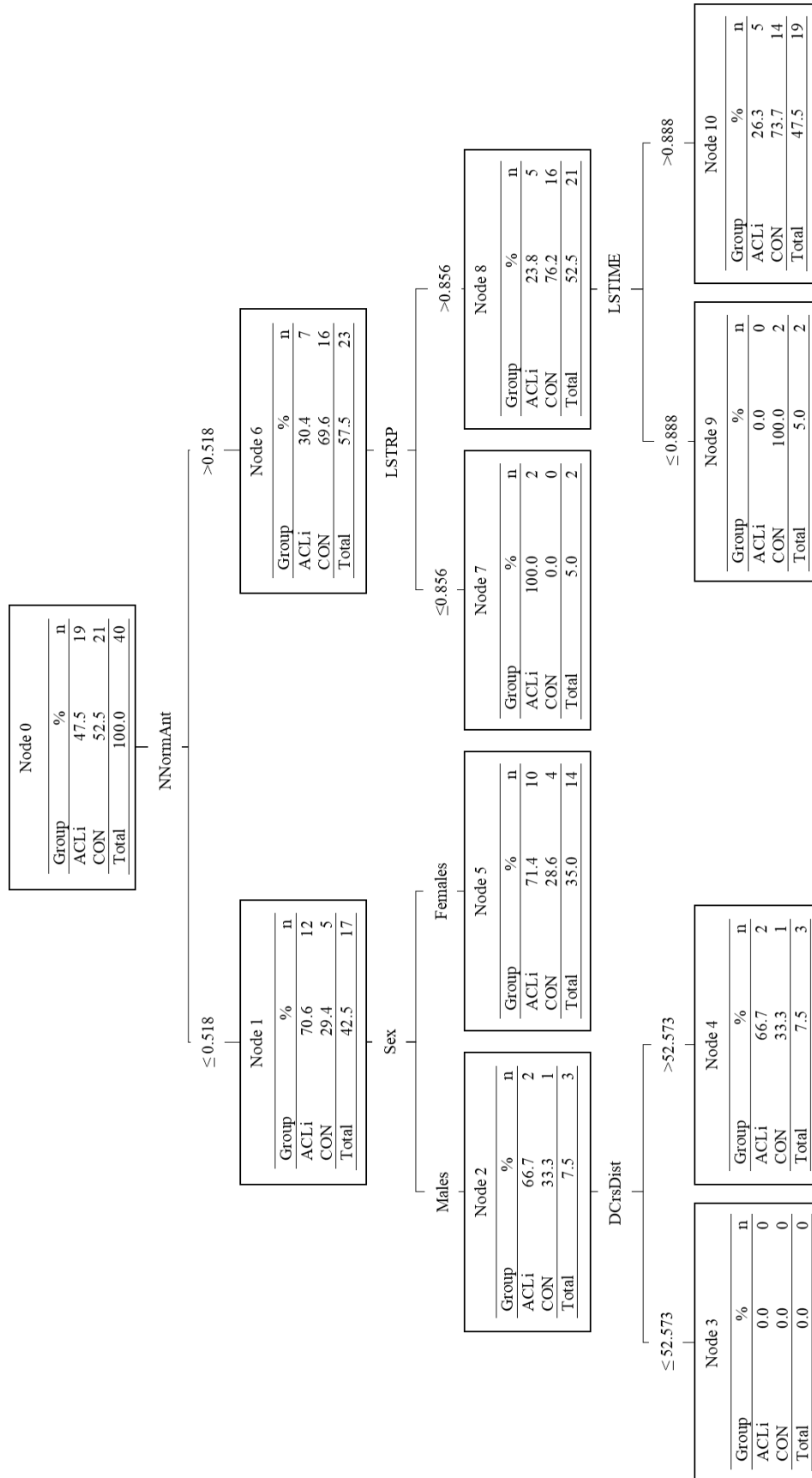


Figure 6.2. C5.0 decision tree model for both males and female adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) participants and uninjured controls (CON). NNNormAnt, non-dominant/injured limb's maximal anterior hop normalized to body height; DCrsDist, dominant/uninjured limb's maximal perpendicular cross-hop distance; LSTRP, limb symmetry index of the triple hop distance; LSTIME, limb symmetry index of the 6-meter timed hop.

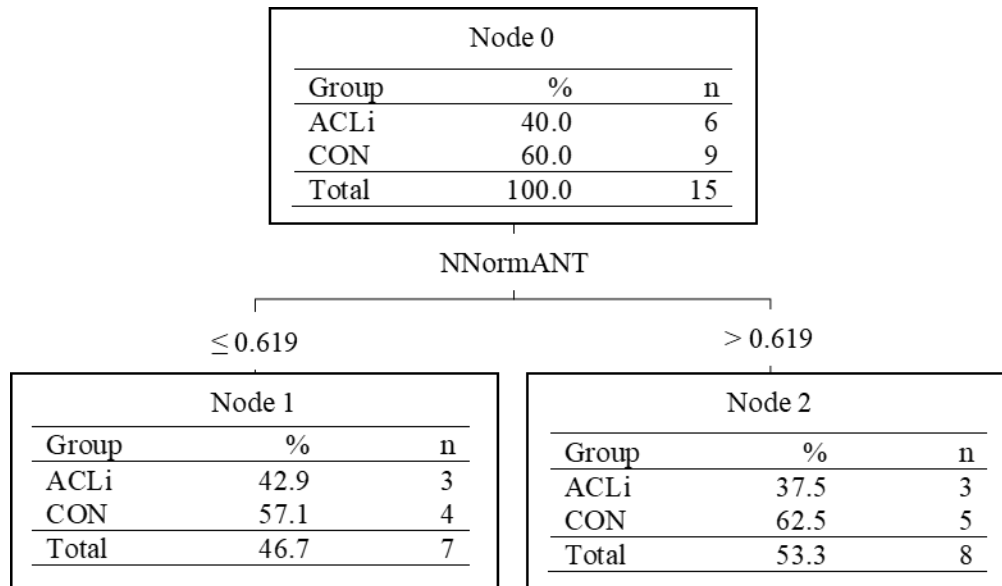


Figure 6.3: C5.0 decision tree model for male adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) and uninjured controls (CON). NNormAnt, non-dominant/injured limb's maximal anterior hop normalized to body height.

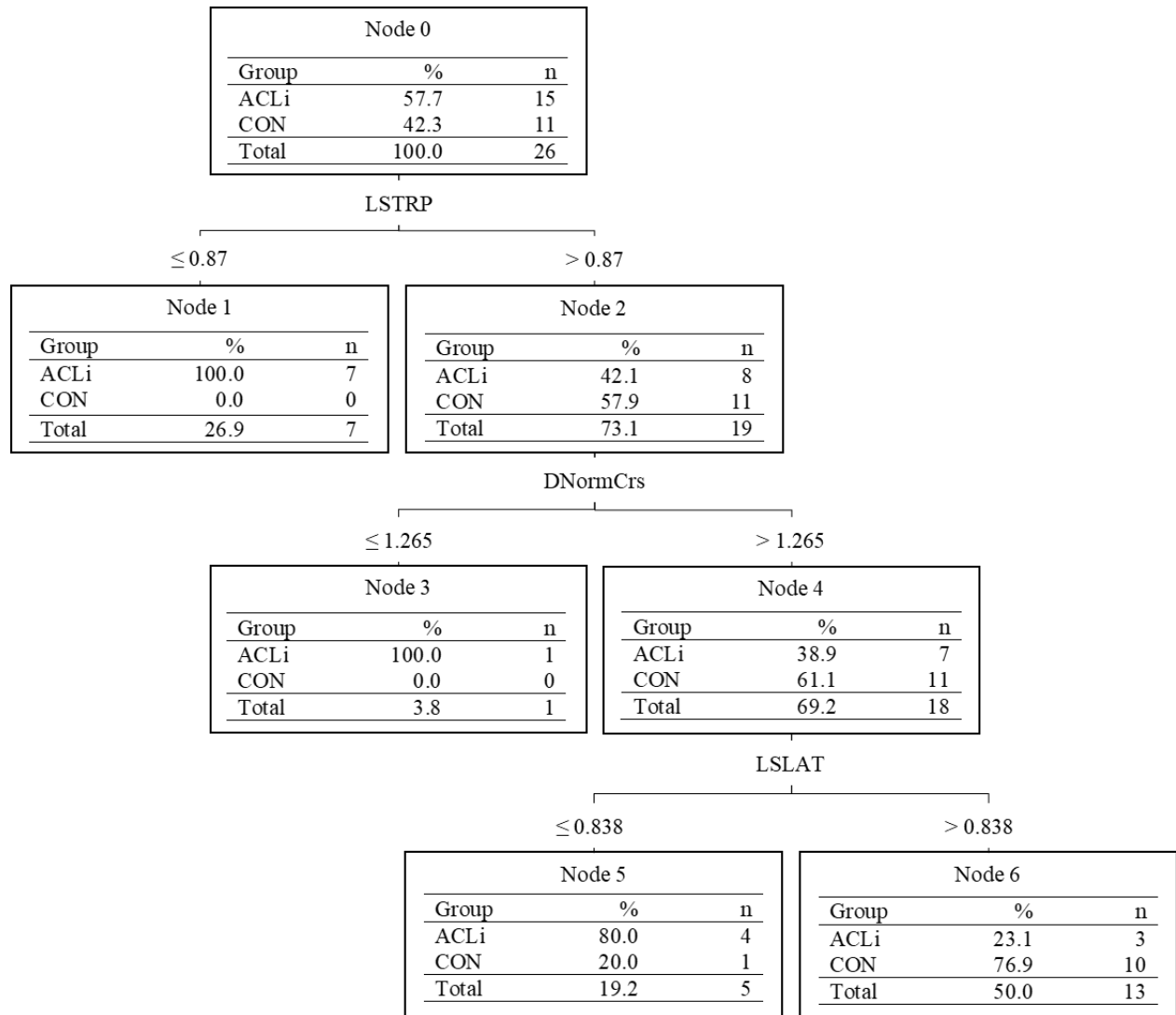


Figure 6.4: C5.0 decision tree model for female adolescents in the testing set differentiating those with anterior cruciate ligament injury (ACLi) and uninjured controls (CON). LSTRP, limb symmetry index of the triple hop distance; DNormCrS, dominant/uninjured limb's maximal cross hop distance normalized to body height; LSLAT, limb symmetry index of the maximal lateral hop distance.

Table 6.3. Descriptive statistics of the raw scores for the classifier variables chosen within the female and male C5.0 models.

Measure		Males	Females		
		NNormAnt	LSTRP	DNormCrS	LSLAT
Mean ± SD	ACLi	0.478 ± 0.166	0.870 ± 0.126	1.598 ± 0.394	0.856 ± 0.243
	CON	0.635 ± 0.166	0.990 ± 0.077	1.801 ± 0.346	1.001 ± 0.124
Range	ACLi	0.140-0.694	0.528-1.345	0.591-2.731	0.328-1.805
	CON	0.273-1.065	0.855-1.234	1.134-2.412	0.646-1.322

Table 6.4. Evaluation metrics of the testing sets on the C5.0 models.

Measure	Entire group (both males and females)	Males	Females
Accuracy	67.5%	53.3%	76.9%
Sensitivity	70.0%	62.5%	71.4%
Specificity	65.0%	42.9%	83.3%
<i>F</i> -measure	0.6842	0.5882	0.7692
Kappa statistics	0.350	0.0541	0.541
PRC area	0.491	0.476	0.528

6.7 Discussion

The purpose of this study was to examine if spatiotemporal variables extracted from functional tasks typically used in RTA assessments could differentiate ACLi status in adolescent males and females. The model differentiating the female adolescent groups correctly classified 76.9% of participants with three classifiers compared to 53.3% with one classifier and 67.5% with four classifiers for the males and the entire group respectively. The results suggest that a total of six variables (excluding sex) within the battery of five single-limb hopping tasks [24, 44] can differentiate ACLi status in adolescents. The male group demonstrated a classification ability slightly greater than chance ($>50\%$); however, had no agreement with the group truth (κ : 0.0541), whereas the female group offered an overall better classification performance. Differences in performance metrics between sexes were largely governed by the different tasks chosen by the C5.0 DT algorithm for classification of ACLi status. Furthermore, the addition of sex as a classifier within the model that included both males and females (Figure 6.2) further justifies separating sexes when evaluating their functional performance before and after injury to a lower limb.

After the onset of puberty, differences in males and females begin to emerge with respect to their anatomy and muscular composition. This can lead to differences in performance metrics which is why many studies normalize strength and functional task variables to either body weight or height [37]. We used a combination of raw and normalized scores for each task to evaluate their ability to differentiate the adolescent groups. Interestingly, limb symmetry indices and normalized values were used in the models despite no significant height differences between the injured and uninjured groups within each sex (Table 6.1). Although the injured participants were slightly older and therefore heavier than their uninjured counterparts, the LSIs observed in the younger uninjured group reflect those of an adult population [36, 42]. Furthermore, there were no group differences between the raw scores of the dominant limb for the CON group and the uninjured limb for the ACLi group in the single-limb hopping scores of the maximal anterior hop, maximal lateral hop,

cross hop and triple hop in both the male and female groups. These raw scores were similar to a previous study that examined the single-limb hopping scores in an adolescent population in both a laboratory setting and a physical education class [23]. These findings indicate that the age difference between our injured and uninjured cohorts would not have biased these findings. That being said, the female group remained easier to separate with larger ranges in the injured group compared to the uninjured group (Table 6.3). For example, the range for the injured group's LSLAT classifier is 0.328-1.805 which indicates highly asymmetrical values with either the injured or uninjured limbs having different performances with respect to the other limb. Furthermore, the female group's model used the DNormCrs classifier, which uses the dominant limb of the control group or the uninjured limb of the group with ACLi. Previous studies have reported worse self-reported outcomes for females than males [20, 63] with longer recovery times and strength recovery post-reconstruction [27, 37]. The decrease in physical activities compared to the male group (Table 6.1) may begin to explain the large differences between the two sexes, in addition to the deconditioning of the uninjured limb after injury. This suggests the importance for both males and females to remain physically active prior to their surgery. This further highlights the importance of sex-specific rehabilitation guidelines and monitoring to ensure female athletes are returning to their sport with confidence, adequate muscular strength and in a timely manner.

Most agree on using a battery of tests to assess RTA readiness, including muscle strength testing, functional tests, movement quality assessments, and patient-reported outcome measures (PROMs) [10, 11]. It can be difficult to decipher which tests to use especially when time and space are limited. Using a classification model that provides a logical order of tests and measures to use may aid in the decision-making process to determine readiness to return to pre-injury activities following reconstruction. Such a classification method does not however, come without its limitations and still requires some knowledge and expertise with respect to the decisions taken in the model.

The current C5.0 DT models that classified ACLi by sex in the test set misclassified six females (4 ACLi; 2 CON) and seven male participants (3 ACLi; 4 CON). One of the female ACLi participants had not completed any of the hop tasks because of their discomfort level. It can therefore be assumed this patient does not have the functional capacity required to be labelled as an uninjured adolescent; and should not have been labelled as such. If done manually, as is the case with Figures 6.2-6.4, the participant would be correctly classified as they did not achieve

values greater than the thresholds of each node. The correct classification of ACLi patients becomes more difficult when these patients have functional performances similar to their uninjured cohort. This was the case for six ACLi participants, whose performances fell within 1SD of the mean of the uninjured group and were mislabelled as uninjured. These ACLi participants may fall within a subgroup deemed copers whom would be able to return to the same activity level as before their injury [2], however, a deeper analysis is warranted to confirm whether they fall within this subgroup. In addition, traditionally, statistical tests have been geared towards the testing of a single hypothesis, whereas data mining through machine learning classifiers focuses on the search through multiple potential hypotheses [8, 69]. This approach allows for the testing and tailoring of multiple clinical tests for ACLi status classification and thereby may provide clinicians a set of tests for rehabilitation/RTA assessments following surgical reconstruction. Although a great first step in the tailoring of functional tasks in an adolescent population, additional measures such as their muscular strength and PROMs should be used in conjunction to functional tasks during a patient's rehabilitation and RTA assessment to minimize misclassification of the patient group.

In this work we have explored the use of an algorithm to discern knee injury status using clinically accessible measures across a variety of functional tasks currently used in RTA evaluations. The battery of single-limb hopping tasks classified participants with and without ACLi, with the maximal anterior hop classifying ACLi status in males, and the triple hop, maximal lateral hop, and cross hop classifying ACLi status in female adolescents. The C5.0 DT model was better able to classify females compared to their male counterparts highlighting the importance of sex-specific rehabilitation guidelines. This technique may be used to determine if a clinician should give consent for RTA based on the classification of ACL-injury status using objective measures with a flow-chart like decision-based algorithm [38]. Furthermore, the tasks and variables chosen as classifiers in each model can be easily completed in a clinical setting and may be utilized in conjunction with other current measures to help clinicians determine if patients are exhibiting performances similar to their uninjured counterparts at the time of a RTA decision.

6.8 Conclusion

Among the evaluated models, DTf had the highest classification performance for differentiating ACLi status in adolescents. Female adolescents were classified with 76.9% accuracy with three spatiotemporal variables including the limb symmetry of the triple hop, the

dominant/uninjured limb's normalized cross hop score, and the limb symmetry of the lateral hop. However, the inability to classify ACLi status among the male group with confidence suggests that these spatiotemporal measures are inadequate on their own for evaluating RTA readiness following surgical reconstruction. Therefore, future rehabilitation guidelines for adolescents should consider evaluating females and males separately to determine readiness to RTA using the cut-offs provided in this study as baseline ACLi status function.

6.9 References

1. Alkjær, T. , Henriksen, M. , Dyhre-Poulsen, P. & Simonsen, E.B. (2009) Forward lunge as a functional performance test in ACL deficient subjects: test–retest reliability. *The Knee*, 16, 176–182.
2. Alkjær, T. , Simonsen, E.B. , Peter Magnusson, S. , Aagaard, H. & Dyhre-poulsen, P. (2002) Differences in the movement pattern of a forward lunge in two types of anterior cruciate ligament deficient patients: copers and non-copers. *Clinical Biomechanics*, 17, 586–593.
3. Anyanwu, M.N. & Sajjan, G.S. (2009) Comparative analysis of serial decision tree classification algorithms. *International Journal of Computer Science and Security*, 230, 239.
4. Barber-Westin, S.D. & Noyes, F.R. (2011) Factors used to determine return to unrestricted sports activities after anterior cruciate ligament reconstruction. *Arthroscopy: The Journal of Arthroscopic & Related Surgery*, 27, 1697–1705.
5. Beaulieu, M.L. , Lamontagne, M. & Beaulé, P.E. (2010) Lower limb biomechanics during gait do not return to normal following total hip arthroplasty. *Gait & Posture*, 32, 269–273.
6. Del Bel, M.J. , Fairfax, A.K. , Jones, M.L. , Steele, K. & Landry, S.C. (2017) Effect of limb dominance and sex on neuromuscular activation patterns in athletes under 12 performing unanticipated side-cuts. *Journal of Electromyography and Kinesiology*, 36, 65–72.
7. Breiman, L. (1996) *Bias, variance, and arcing classifier*. Technical report 460. pp. 1–20.
8. Breiman, L. (2001) Statistical modeling: the two cultures. *Statistical Science*, 16, 199–231.
9. Breiman, L. , Friedman, J. , Stone, C.J. & Olshen, R.A. (1984) *Classification and regression trees*, 1st edition. New York: Chapman and Hall/CRC.
10. Burgi, C.R. , Peters, S. , Ardern, C.L. , Magill, J.R. , Gomez, C.D. , Sylvain, J. et al. (2019) Which criteria are used to clear patients to return to sport after primary ACL reconstruction? A scoping review. *British Journal of Sports Medicine*, 53, 1154–1161.
11. Capin, J.J. , Snyder-Mackler, L. , Risberg, M.A. & Grindem, H. (2019) Keep calm and carry on testing: a substantive reanalysis and critique of what is the evidence for and

- validity of return-to-sport testing after anterior cruciate ligament reconstruction surgery? A systematic review and meta-analysis'. *British Journal of Sports Medicine*, 53, 1444–1446.
12. Carletta, J. (1996) Assessing agreement on classification tasks: the kappa statistic. *Computational Linguistics*, 22, 249–254.
 13. Chapelle, O. , Vapnik, V. , Bousquet, O. & Mukherjee, S. (2002) Choosing multiple parameters for support vector machines. *Machine Learning*, 46, 131–159.
 14. Cohen, J. (2013) *Statistical power analysis for the behavioral sciences*. New York: Academic Press.
 15. Cristiani, R. , Mikkelsen, C. , Edman, G. , Forssblad, M. , Engström, B. & Stålmán, A. (2020) Age, gender, quadriceps strength and hop test performance are the most important factors affecting the achievement of a patient-acceptable symptom state after ACL reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*, 28, 369–380.
 16. Dekker, T.J. , Godin, J.A. , Dale, K.M. , Garrett, W.E. , Taylor, D.C. & Riboh, J.C. (2017) Return to sport after pediatric anterior cruciate ligament reconstruction and its effect on subsequent anterior cruciate ligament injury. *Journal of Bone and Joint Surgery*, 99, 897–904.
 17. Del Bel, M.J. , Kemp, L.G. , Girard, C.I. , Rossignol, J. , Goulet, S.F. , Bourgon, J.-F. et al. (2020) Translation and validation of the hospital for special surgery pediatric functional activity brief scale for french paediatric populations. *Physiother Canada*, 74, 348–354.
 18. Dingenen, B. & Gokeler, A. (2017) Optimization of the return-to-sport paradigm after anterior cruciate ligament reconstruction: a critical step back to move forward. *Sports Medicine*, 47, 1487–1500.
 19. Donelon, T.A. , Edwards, J. , Brown, M. , Jones, P.A. , O'driscoll, J. & Dos'santos, T. (2024) Differences in biomechanical determinants of acl injury risk in change of direction tasks between males and females: a systematic review and meta-analysis. *Sports Medicine – Open*, 10, 29.
 20. Ezzat, A.M. , Brussoni, M. , Mâsse, L.C. & Emery, C.A. (2021) Effect of anterior cruciate ligament rupture on physical activity, sports participation, patient-reported health

outcomes, and physical function in young female athletes. *The American Journal of Sports Medicine*, 49, 1460–1469.

21. Fabricant, P.D. , Robles, A. , Downey-Zayas, T. , Do, H.T. , Marx, R.G. , Widmann, R.F. et al. (2013) Development and validation of a pediatric sports activity rating scale. *The American Journal of Sports Medicine*, 41, 2421–2429.
22. Flaxman, T.E. , Smith, A.J.J. & Benoit, D.L. (2014) Sex-related differences in neuromuscular control: implications for injury mechanisms or healthy stabilisation strategies? *Journal of Orthopaedic Research*, 32, 310–317.
23. Girard, C.I. , Del Bel, M.J. , Bédard, V. , Bradley, C. , Comptour, A. , O'Connor, K. et al. (2024) Are single limb hopping scores the same when performed in a physical education class versus a laboratory setting in uninjured adolescents? implications for future rehabilitation guidelines for adolescents with knee injuries. *Commun Kinesiol*, 1(6).
24. Girard, C.I. , Warren, C.E. , Romanchuk, N.J. , Del Bel, M.J. , Carsen, S. , Chan, A.D.C. , et al. (2020) Decision tree learning algorithm for classifying knee injury status using return-to-activity criteria. In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. Institute of Electrical and Electronics Engineers Inc. pp. 5494–5497.
25. Gornitzky, A.L. , Lott, A. , Yellin, J.L. , Fabricant, P.D. , Lawrence, J.T. & Ganley, T.J. (2016) Sport-specific yearly risk and incidence of anterior cruciate ligament tears in high school athletes: a systematic review and meta-analysis. *The American Journal of Sports Medicine*, 44, 2716–2723.
26. Greenberg, E.M. , Dyke, J. , Leung, A. , Karl, M. , Lawrence, J.T. & Ganley, T. (2020) Uninjured youth athlete performance on single-leg hop testing: how many can achieve recommended return-to-Sport criterion? *Sports Health: A Multidisciplinary Approach*, 12, 552–558.
27. Greenberg, E.M. , Greenberg, E.T. , Ganley, T.J. & Lawrence, J.T.R. (2014) Strength and functional performance recovery after anterior cruciate ligament reconstruction in preadolescent athletes. *Sports Health: A Multidisciplinary Approach*, 6, 309–312.
28. Halinen, J. , Koivikko, M. , Lindahl, J. & Hirvensalo, E. (2009) The efficacy of magnetic resonance imaging in acute multi-ligament injuries. *International Orthopaedics*, 33, 1733–1738.

29. Heath, E.L. , Salmon, L.J. , Cooper, R. , Pappas, E. , Roe, J.P. & Pinczewski, L.A. (2019) 5-Year survival of pediatric anterior cruciate ligament reconstruction with living donor hamstring tendon grafts. *The American Journal of Sports Medicine*, 47, 41–51.
30. Hildebrandt, C. , Müller, L. , Zisch, B. , Huber, R. , Fink, C. & Raschner, C. (2015) Functional assessments for decision-making regarding return to sports following ACL reconstruction. Part I: development of a new test battery. *Knee Surgery, Sports Traumatology, Arthroscopy*, 23, 1273–1281.
31. Holden, S. , Boreham, C. , Doherty, C. , Wang, D. & Delahunt, E. (2015) Clinical assessment of countermovement jump landing kinematics in early adolescence: sex differences and normative values. *Clinical Biomechanics*, 30, 469–474.
32. Hripcsak, G. (2005) Agreement, the F-Measure, and reliability in information retrieval. *Journal of the American Medical Informatics Association*, 12, 296–298.
33. Ithurburn, M.P. , Paljieg, A. , Thomas, S. , Hewett, T.E. , Paterno, M.V. & Schmitt, L.C. (2019) Strength and function across maturational levels in young athletes at the time of return to sport after acl reconstruction. *Sports Health: A Multidisciplinary Approach*, 11, 324–331.
34. James, G. , Gareth, J. , Witten, D. , Hastie, T. & Tibshirani, R. (2013) *An introduction to statistical learning with applications in R*. New York: Springer.
35. Koh, H.C. & Tan, G. (2011) Data mining applications in healthcare. *Journal of Healthcare Information Management*, 19, 64–72.
36. Kotsifaki, A. , Van Rossom, S. , Whiteley, R. , Korakakis, V. , Bahr, R. , Sideris, V. et al. (2021) Symmetry in triple hop distance hides asymmetries in knee function after acl reconstruction in athletes at return to sports. *The American Journal of Sports Medicine*, 50, 441–450.
37. Kuenze, C. , Pietrosimone, B. , Lisee, C. , Rutherford, M. , Birchmeier, T. , Lepley, A. et al. (2019) Demographic and surgical factors affect quadriceps strength after ACL reconstruction. *Knee Surgery, Sports Traumatology, Arthroscopy*, 27, 921–930.
38. Lavanya, D. & Rani, K.U. (2011) Performance evaluation of decision tree classifiers on medical datasets. *International Journal of Computer Applications*, 26, 1–4.

39. Lohmander, L.S. , Englund, P.M. , Dahl, L.L. & Roos, E.M. (2007) The long-term consequence of anterior cruciate ligament and meniscus injuries. *The American Journal of Sports Medicine*, 35, 1756–1769.
40. Maguire, K. , Sugimoto, D. , Micheli, L.J. , Kocher, M.S. & Heyworth, B.E. (2021) Recovery after acl reconstruction in male versus female adolescents: a matched, sex-based cohort analysis of 543 patients. *Orthopaedic Journal of Sports Medicine*, 9, 232596712110548.
41. McLean, S.G. , Huang, X. & Van Den Bogert, A.J. (2005) Association between lower extremity posture at contact and peak knee valgus moment during sidestepping: implications for ACL injury. *Clinical Biomechanics*, 20, 863–870.
42. Mirković, S.V. , Đurić, S. , Sember, V. , Knezevic, O.M. , Pajek, M. , Mirković, M.M. et al. (2022) Evaluation of the limb symmetry index: the side hop test. *Frontiers in Physiology*, 13, 874632.
43. Montalvo, A.M. , Schneider, D.K. , Yut, L. , Webster, K.E. , Beynnon, B. , Kocher, M.S. et al. (2019) “What's my risk of sustaining an ACL injury while playing sports?” A systematic review with meta-analysis. *British Journal of Sports Medicine*, 53, 1003–1012.
44. Noyes, F.R. , Barber, S.D. & Mangine, R.E. (1991) Abnormal lower limb symmetry determined by function hop tests after anterior cruciate ligament rupture. *The American Journal of Sports Medicine*, 19, 513–518.
45. Øiestad, B.E. , Holm, I. , Engebretsen, L. & Risberg, M.A. (2011) The association between radiographic knee osteoarthritis and knee symptoms, function and quality of life 10-15 years after anterior cruciate ligament reconstruction. *British Journal of Sports Medicine*, 45, 583–588.
46. Olsen, O.E. , Myklebust, G. , Engebretsen, L. & Bahr, R. (2004) Injury mechanisms for anterior cruciate ligament injuries in team handball: a systematic video analysis. *The American Journal of Sports Medicine*, 32, 1002–1012.
47. Padua, D.A. , Marshall, S.W. , Boling, M.C. , Thigpen, C.A. , Garrett, W.E. & Beutler, A.I. (2009) The landing error scoring system (less) is a valid and reliable clinical assessment tool of jump-landing biomechanics: the jump-acl study. *The American Journal of Sports Medicine*, 37, 1996–2002.

48. Palmieri-Smith, R.M. , Curran, M.T. , Garcia, S.A. & Krishnan, C. (2021) Factors that predict sagittal plane knee biomechanical symmetry after anterior cruciate ligament reconstruction: a decision tree analysis. *Sport Heal A Multidiscip Approach*, 14, 194173812110049.
49. Pandya, R. & Pandya, J. (2015) C5.0 algorithm to improved decision tree with feature selection and reduced error pruning. *International Journal of Computer Applications*, 117, 975–8887.
50. Parsons, J.L. , Coen, S.E. & Bekker, S. (2021) Anterior cruciate ligament injury: towards a gendered environmental approach. *British Journal of Sports Medicine*, 55, 984–990.
51. Paterno, M.V. , Huang, B. , Thomas, S. , Hewett, T.E. & Schmitt, L.C. (2017) Clinical Factors that predict a second acl injury after ACL reconstruction and return to sport: preliminary development of a clinical decision algorithm. *Orthopaedic Journal of Sports Medicine*, 5, 232596711774527.
52. Paterno, M.V. , Rauh, M.J. , Schmitt, L.C. , Ford, K.R. & Hewett, T.E. (2012) Incidence of contralateral and ipsilateral anterior cruciate ligament (ACL) injury after primary ACL reconstruction and return to sport. *Clinical Journal of Sport Medicine*, 22, 116–121.
53. Paterno, M.V. , Schmitt, L.C. , Ford, K.R. , Rauh, M.J. , Myer, G.D. , Huang, B. et al. (2010) Biomechanical measures during landing and postural stability predict second anterior cruciate ligament injury after anterior cruciate ligament reconstruction and return to sport. *The American Journal of Sports Medicine*, 38, 1968–1978.
54. Quinlan, J.R. (1987) Simplifying decision trees. *International Journal of Man-Machine Studies*, 27, 221–234.
55. Quinlan, J.R. (1993) C4.5: programs for machine learning. San Mateo: Morgan Kaufman Publishers, Inc.
56. Rahimibashar, F. , Miller, A.C. , Salesi, M. , Bagheri, M. , Vahedian-Azimi, A. , Ashtari, S. et al. (2022) Risk factors, time to onset and recurrence of delirium in a mixed medical-surgical ICU population: a secondary analysis using Cox and CHAID decision tree modeling. *EXCLI Journal*, 21, 30–46.
57. Romanchuk, N.J. , Livock, H. , Lukas, K.J. , Del Bel, M.J. , Benoit, D.L. & Carsen, S. (2023) Criteria used to determine unrestricted return to activity after ACL reconstruction

- in pediatric and adolescent patients: a systematic review. *Orthopaedic Journal of Sports Medicine*, 11, 23259671231154540.
58. Roos, H. , Adalberth, T. , Dahlberg, L. & Lohmander, L.S. (1995) Osteoarthritis of the knee after injury to the anterior cruciate ligament or meniscus: the influence of time and age. *Osteoarthritis and Cartilage*, 3, 261–267.
 59. Saito, T. & Rehmsmeier, M. (2015) The precision-recall plot is more informative than the roc plot when evaluating binary classifiers on imbalanced datasets. *PLoS One*, 10, e0118432.
 60. Sarker, I.H. (2021) Machine learning: algorithms, real-world applications and research directions. *SN Computer Science*, 2, 160.
 61. Shimokochi, Y. & Shultz, S.J. (2008) Mechanisms of noncontact anterior cruciate ligament injury. *Journal of Athletic Training*, 43, 396–408.
 62. Su, J. & Zhang, H. (2006) A fast decision tree learning algorithm. *Association for the Advancement of Artificial Intelligence*, 6, 500–505.
 63. Sutton, K.M. & Bullock, J.M. (2013) Anterior cruciate ligament rupture: differences between males and females. *Journal of the American Academy of Orthopaedic Surgeons*, 21(1), 41–50.
 64. Tegner, Y. & Lysholm, J. (1985) Rating systems in the evaluation of knee ligament injuries. *Clinical Orthopaedics and Related Research*, 198, 42–49.
 65. Toole, A.R. , Ithurburn, M.P. , Rauh, M.J. , Hewett, T.E. , Paterno, M.V. & Schmitt, L.C. (2017) Young athletes cleared for sports participation after anterior cruciate ligament reconstruction: how many actually meet recommended return-to-sport criterion cutoffs? *Journal of Orthopaedic & Sports Physical Therapy*, 47, 825–833.
 66. Trulsson, A. , Miller, M. , Hansson, G.Å. , Gummesson, C. & Garwicz, M. (2015) Altered movement patterns and muscular activity during single and double leg squats in individuals with anterior cruciate ligament injury. *BMC Musculoskeletal Disorders*, 16, 28.
 67. Webster, K.E. & Feller, J.A. (2016) Exploring the high reinjury rate in younger patients undergoing anterior cruciate ligament reconstruction. *The American Journal of Sports Medicine*, 44, 2827–2832.

68. Werner, B.C. , Yang, S. , Looney, A.M. & Gwathmey, F.W. (2016) Trends in pediatric and adolescent anterior cruciate ligament injury and reconstruction. *Journal of Pediatric Orthopaedics*, 36, 447–452.
69. Witten, I.H. & Eibe, F. (2005) *Data mining: practical machine learning tools and techniques*, 2nd edition. San Francisco, CA: Morgan Kaufmann Publishers.
70. Wright, R.W. , Haas, A.K. , Anderson, J. , Calabrese, G. , Cavanaugh, J. , Hewett, T.E. et al. (2015) Anterior cruciate ligament reconstruction rehabilitation. *Sports Health: A Multidisciplinary Approach*, 7, 239–243.
71. Wu, X. , Kumar, V. , Ross Quinlan, J. , Ghosh, J. , Yang, Q. , Motoda, H. et al. (2008) Top 10 algorithms in data mining. *Knowledge and Information Systems*, 14, 1–37.
72. Zhang, Y. , Chi, Z.X. & Wang, D.G. (2005) Decision tree's pruning algorithm based on deficient data sets. In: *Sixth International Conference on Parallel and Distributed Computing Applications and Technologies (PDCAT'05)*, IEEE. pp. 1030–1032.

6.10 Postamble

The findings of this chapter demonstrate that spatiotemporal measures obtained from commonly used functional tasks possess a limited but informative capacity to differentiate ACL injury status in adolescents. The classification models revealed that only a small subset of variables contributed meaningfully to injury discrimination, and that the effectiveness of these variables differed between male and female participants. This task- and sex-dependent variability underscores the challenges associated with applying uniform RTA criteria across heterogeneous adolescent populations.

While the decision tree approach offered an interpretable framework for identifying clinically accessible classifiers, the modest classification performance, particularly among males, highlights important limitations of relying on spatiotemporal outcomes alone. These results suggest that traditional distance- and symmetry-based metrics may be insufficient for fully characterizing functional deficits following ACL injury in adolescents, even when multiple tasks are considered simultaneously.

Importantly, this chapter establishes that classification performance is strongly influenced by the choice of functional variables and by sex-specific movement strategies. The observed differences between male and female models emphasize the need for caution when interpreting group performance metrics and support the use of stratified analyses when evaluating adolescent functional capacity. It should also be noted that ACL-injured females demonstrated lower current Tegner activity scores than ACL-injured males, suggesting that differences in activity participation or recovery status may have contributed to some of the observed sex-specific findings. Furthermore, the wide range of Tegner scores observed within the ACL-injured group (0–9) reflects substantial variability in pre-operative functional status and activity restriction, highlighting the heterogeneity of adolescent presentations following ACL injury.

Within the broader context of this thesis, the present findings motivate the progression toward higher-dimensional biomechanical analyses. By demonstrating the constraints of spatiotemporal measures for injury classification, this chapter provides the rationale for exploring kinematic waveform features and dimensionality-reduction approaches in the following chapter. By doing so, it connects traditional clinical testing approaches with more comprehensive movement-based analyses aimed at improving the identification of injury-related adaptations in adolescent populations.

CHAPTER 7: ARTICLE 3

Identifying movement differences in adolescents with and without ACL injury during hopping tasks

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7.1 Preamble

Return-to-activity testing after anterior cruciate ligament injury commonly relies on functional performance tasks such as single-limb hopping. These tasks are attractive in clinical settings because they are time-efficient, require minimal equipment, and provide simple outcomes such as hop distance or completion time. Despite their practicality, these outcomes offer limited insight into how the movement was performed. Adolescents may achieve acceptable spatiotemporal scores while still demonstrating altered coordination strategies, compensatory patterns, or neuromuscular control deficits that are relevant to reinjury risk and longer-term function.

Quantitative movement analysis provides an opportunity to evaluate movement quality rather than performance outcomes alone. Principal component analysis (PCA) can reduce high-dimensional kinematic trajectories into a smaller set of components that capture dominant movement patterns across participants. When combined with supervised classification, this approach can test whether movement patterns differ systematically between groups and whether these differences are detectable at the level of the whole movement waveform. This is particularly relevant in adolescent ACL injury, where growth, maturation, and variable rehabilitation exposure may contribute to heterogeneous movement strategies that are not adequately characterized by discrete measures.

A second consideration is the validity of using the contralateral limb as a reference for normal function. Emerging evidence indicates that ACL injury can be associated with bilateral adaptations, which may reduce the utility of contralateral comparisons when evaluating readiness to return to activity. Comparing contralateral limbs to a healthy control cohort provides an alternative way to examine whether movement deviations persist beyond the injured side.

Accordingly, this chapter evaluates whether PCA-derived kinematic patterns during single-limb hopping can differentiate adolescents with ACL injury from uninjured peers and whether contralateral limbs exhibit detectable deviations relative to controls. The analyses extend prior work based on spatiotemporal outcomes by examining full kinematic trajectories and by explicitly testing both injured-limb and contralateral-limb comparisons.

7.2 Abstract

Objective tools capable of identifying persistent movement deviations during return-to-activity (RTA) assessment following anterior cruciate ligament (ACL) injury remain limited in adolescent populations, where current clinical evaluations are largely adapted from adult-based criteria. This study investigated whether movement patterns during hopping tasks could distinguish adolescents with ACL injuries from uninjured peers and whether contralateral limbs of injured participants exhibited residual deficits. Kinematic data from 117 adolescents (10–18 years) performing four single-limb hops were analyzed using principal component analysis (PCA) combined with linear discriminant analysis (LDA). The LDA classifier differentiated injured from control participants with accuracies of 81.8% (anterior hop), 73.1% (cross hop), 79.3% (lateral hop), and 77.5% (triple hop), with Cohen's κ ranging from 0.40–0.46 and F_1 scores of 0.53–0.62. Contralateral-limb classification accuracies ranged from 66.5% to 74.5%, confirming bilateral adaptations following ACL injury. Exploratory analyses indicated higher bilateral misclassifications among female participants across tasks. These results suggest that PCA-LDA models can effectively identify adolescent ACL-related movement deviations and highlight the importance of bilateral and sex-specific assessment frameworks. Integrating such quantitative, data-driven approaches into RTA protocols may enhance the precision of clinical decision-making and reduce the risk of reinjury among adolescent athletes.

Keywords: biomechanics, adolescent athletes, machine learning, hopping tasks, rehabilitation

7.3 Introduction

Anterior cruciate ligament (ACL) injuries remain a significant clinical and public health concern due to their high incidence and long-term functional consequences. Approximately 100,000 to 400,000 ACL injuries occur annually in North America¹, frequently managed with surgical reconstruction followed by prolonged rehabilitation lasting 8 to 12 months^{2,3}. Despite extensive rehabilitation, around half of individuals do not return to their pre-injury level of physical activity, adversely impacting their physical health, athletic identity, and psychological well-being⁴. These challenges are particularly concerning in adolescent athletes, who demonstrate elevated rates of secondary injury and may experience long-term consequences during critical stages of physical development.

Although research focusing on adolescent ACL injuries has increased, many rehabilitation and return-to-activity (RTA) protocols continue to be derived from adult populations⁵. These approaches may not adequately account for developmental differences in neuromuscular control, skeletal maturity, and movement strategies observed during adolescence⁶. Movement adaptations following ACL injury may therefore differ from those reported in adult populations, highlighting the need to evaluate objective and data-driven assessment approaches specifically within adolescent athletes.

In clinical practice, RTA assessments following ACL injury commonly combine strength testing, psychological readiness measures, and performance-based outcomes such as hop distance or completion time^{7,8}. While these metrics provide useful indicators of recovery, they offer limited insight into movement quality during dynamic tasks associated with ACL injury risk. Single-limb hopping tasks offer a functional evaluation of strength, balance, and neuromuscular control under dynamic conditions and commonly reveal interlimb performance deficits exceeding 10-20% following ACL injury⁹⁻¹³. However, interpretation typically relies on limb symmetry indices that assume the contralateral limb serves as a healthy reference.

The assumption that the contralateral limb represents a baseline has been increasingly challenged, as individuals with unilateral ACL injury often demonstrate bilateral neuromuscular adaptations, including altered loading patterns and compensatory movement strategies^{14,15}. As a result, comparisons with uninjured control populations may provide a more meaningful framework for identifying injury-related movement adaptations. Quantitative approaches capable of identifying injury-related movement patterns may provide clinicians with objective tools to

complement existing RTA assessments by detecting residual neuromuscular deficits not apparent through conventional clinical testing^{16–20}.

7.4 Methods

7.4.1 Participants

Kinematic data were collected from fifty-three (37 female, 16 male) adolescents with ACL injury (ACLi; 15.4 ± 1.3 yrs.; 167.3 ± 8.4 cm; 68.1 ± 20.9 kg; BMI: 24.2 ± 6.3 kg/m²; Tanner Stage: 4 ± 1) and sixty-four (37 female, 27 male) uninjured (CON; 13.8 ± 1.8 yrs.; 165.5 ± 10.9 cm; 54.8 ± 11.8 kg; BMI: 19.8 ± 2.9 kg/m²; Tanner Stage: 4 ± 1) adolescents (Table 7.1). ACL injury status was clinically confirmed by the treating orthopedic surgeon using standard diagnostic procedures, including manual ligament testing and/or magnetic resonance imaging where indicated. All ACLi participants were tested prior to surgical reconstruction when applicable, and none had undergone ACL reconstruction at the time of biomechanical assessment. Individuals were excluded if they had a history of contralateral ACL injury, were undergoing revision surgery, or presented with any condition that could compromise neuromuscular function.

The control group (uninjured adolescents; CON) was recruited within a comparable adolescent age range and from similar sport-participating populations from local community and sports organizations to approximate activity-level matching between groups. Inclusion criteria included no previous lower-limb surgical operations and no serious lower-limb injury, including fractures or sprains, within six months of testing. Participants reporting any chronic or acute condition that could impair neuromuscular control were excluded. All CON participants were actively engaged in organized sport at the time of testing, as assessed using the Hospital for Special Surgery Pediatric Functional Activity Brief Scale (HSS Pedi-FABS or FR Pedi-FABS)^{21,22}. Pre-injury and current physical activity level were recorded for all participants using the Tegner Activity Scale²³ and the development stage was recorded using the Tanner Stage self-assessment^{24,25}. Written informed assent was obtained from all participants, and written informed consent was obtained from their parent or legal guardian. Ethical approval was granted by the institutional research ethics boards prior to data collection.

Table 7.1. Participant characteristics and subjective functional scores. Uninjured and ACL-injured male and female means and standard deviations.

Variable	Uninjured Male (n=27)	Uninjured Female (n=37)	ACL-injured Male (n=16)	ACL-injured Female (n=37)
Age (yrs.)	13.7 ± 1.7*	13.9 ± 1.8§	15.5 ± 1.1*	15.3 ± 1.4§
Height (m)	1.68 ± 0.14	1.64 ± 0.07	1.73 ± 0.09	1.65 ± 0.07
Weight (kg)	55.4 ± 12.8*	54.3 ± 11.2§	77.5 ± 33.8*	63.9 ± 9.3§
Time Since Injury (months)	-	-	5.6 ± 2.9	5.5 ± 4.2
HSS/FR Pedi-FABS (0-30)	26 ± 4*	21 ± 5§	9 ± 7*	7 ± 6§
Tanner Stage (1-5)	3 ± 1	4 ± 1	4 ± 1	4 ± 1
Pre-injury Tegner Activity Scale (0- 10)	-	-	9 (6-10)	9 (7-10)
Current Tegner Activity Scale (0- 10)	9 (5-10)*	9 (5-9)§	5 (0-9)*	4 (0-9)§
Anterior Hop (cm)	108.6 ± 26.9	97.2 ± 20.8	105.3 ± 27.7	92.0 ± 18.6
Lateral Hop (cm)	87.3 ± 20.8	73.3 ± 15.3	81.2 ± 25.7	70.1 ± 17.8
Cross Hop (cm)	348.9 ± 84.7	209.0 ± 101.0§	314.6 ± 94.5	127.4 ± 63.7§
Triple Hop (cm)	412.4 ± 83.2	399.6 ± 96.1	344.1 ± 46.7	329.0 ± 55.0

¹ ACL = anterior cruciate ligament

² Statistical significant differences ($p < 0.05$) between male and female (* and §, respectively) CON vs ACLi are identified.

7.4.2 Protocol

Upon arrival at the clinical biomechanics laboratory, each participant reviewed and signed informed consent and completed an injury-history questionnaire. Demographic and anthropometric data were recorded, including height, body mass, thigh and shank circumferences, and bilateral leg and shank length. Each participant was then outfitted with 80 retroreflective markers to capture whole-body motion²⁶. Following marker placement, a static calibration was recorded to define the participant-specific skeletal model and local segment coordinate systems.

Participants completed a standardized hopping protocol consisting of a maximal anterior hop (Ant), maximal lateral hop (Lat), cross-hop for distance (Crs), and triple hop for distance (Trp)^{27,28}. Each task was performed unilaterally on both limbs following a standardized warm-up consisting of 5-10 minutes of stationary cycling followed by dynamic stretching. Hopping tasks were completed in a consistent order across participants, while limb testing order was counterbalanced to minimize potential order effects. Participants performed trials until two successful attempts were obtained per limb for each hopping task. For each task, participants were instructed to place their hands on their hips, perform maximal effort hops, and maintain balance for at least three seconds upon landing. In the Crs task, participants completed three consecutive hops forward, crossing two horizontal lines spaced 15 cm apart, while covering as much distance as possible. A successful

trial was defined as meeting all movement criteria (e.g., maintain hands on hips, maximal effort, and stable landing without compensatory steps). Trials were not excluded based on movement quality or visual appearance, ensuring that natural movement variability was preserved. Full body motion data were captured at a sampling frequency of 200 Hz using a 10-camera optical motion capture system (8 Vero, 2 Vantage, Vicon, Oxford, UK).

7.4.3 Pre-processing

Motion capture data were labelled and gap-filled using Vicon Nexus (Nexus v2.9, Vicon, UK), then exported and analyzed using MATLAB (The MathWorks, Natick, MA, USA). All trials were filtered using a dual-pass, low-pass Butterworth filter with a 15 Hz cut-off^{29,30}. Joint centers were outputted bilaterally for the hip, foot, knee and ankle; and centers of mass for the trunk, pelvis, thighs, shanks, and feet^{31,32}. The three-dimensional positional trajectories of joint centers and segment centers of mass were analyzed as entire movement waveforms, allowing characterization of global spatiotemporal movement patterns throughout task execution. All positional data were rotated so that the local coordinate system of the foot was aligned with the global coordinate system and translated so that the midpoint between the left and right hip of the first frame of the hopping trial aligned with the global origin. Data were then trimmed to specific start and end points and normalized to 500 frames using a piecewise-cubic, shape-preserving interpolation to account for differences in absolute movement time. For the Ant and Lat, task initiation was defined as the onset of heel or pelvis motion, and termination occurred when heel and pelvis velocities reached zero following landing stabilization. For the Trp and Crs, only the final hop was analyzed to ensure comparability with single-hop tasks. Movement initiation was defined following the final pre-takeoff minimum in toe vertical displacement together with the onset of heel or pelvis motion, while termination corresponded to post-landing stabilization using the same velocity-based criterion.

To standardize limb comparisons, trials performed on the left limb were mirrored about the sagittal plane so that all movements were represented in a consistent right-limb coordinate framework. This procedure allowed movement variability to reflect biomechanical differences rather than limb laterality. Uninjured adolescents generally exhibit a high degree of interlimb symmetry in kinetic and kinematic measures during single-limb tasks³³. Mirroring, therefore, helps reduce variance introduced solely by limb laterality, allowing PCA to focus on meaningful group-level differences. For uninjured participants, both limbs were treated as independent healthy

observations. This approach reduced dominance-related bias, as ACL injuries occurred in both dominant and non-dominant limbs. Limb dominance was recorded and incorporated in subsequent misclassification analyses. Two group comparisons were defined for classification: the injured limb of the ACLi group with the healthy limbs of the CON group (IL-CON), and the contralateral limb of the ACLi group with the healthy limbs of the CON group (CL-CON).

7.4.4 Application of Principal Component Analysis

The data were analyzed using principal component analysis (PCA). A [$n \times 21,000$] matrix was constructed for each hopping task, where n represented the number of contributing participants, and 21,000 was the time-normalized x, y, and z trajectories of 14 joint centers and segment centers of mass (14 positions $\times$ 3 axes $\times$ 500 time points). Due to marker occlusion and some participants not completing all tasks, n was dependent on the hopping task (see Table 7.2). Separate PCAs were performed for each task, with all participant data included to ensure consistent component structure across participants³⁴. All input features were standardized using z-scores.

7.4.5 Feature Selection

Given the high dimensionality of the kinematic datasets relative to the moderate sample size, dimensionality reduction and feature selection were used to mitigate overfitting and enhance generalization. PCA was performed within each leave-one-out cross-validation (LOOCV) fold using only the training data to prevent information leakage³⁵.

An ensemble feature selection strategy was then applied to the PCA-transformed training data. Five complementary methods (ANOVA F-statistic, Chi-squared test, Mutual Information³⁶, Random Forest feature importance³⁷, and least absolute shrinkage and selection operator (LASSO) regression coefficients³⁸) were used to rank components. The top 25 components from each method were identified, and only those selected by at least two methods were retained. To further limit model complexity, the final number of PCs entered into classification was restricted to the square root of the number of training samples for each task³⁹. Across tasks, the retained components collectively accounted for the majority of variance in the standardized waveform data.

7.4.6 Classification

To ensure that classification performance was not dependent on a single modelling assumption, classification was performed using six commonly used supervised machine learning models: logistic regression with balanced class weights, decision tree with class weighting, k-

nearest neighbours, linear discriminant analysis, Gaussian naïve Bayes, and support vector machine with a linear kernel and class weighting⁴⁰. Each model was assessed using LOOCV.

Within each cross-validation fold, the training data were first resampled using the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance and ensure adequate representation of the injured class⁴¹. Standard scaling was then applied to normalize the features, followed by PCA transformation. The PCA model was fit only to the training data and subsequently applied to the test sample. Selected PCs were used to train the classifier, which was then applied to the held-out test sample. Each model (IL-CON and CL-CON) was then trained on the selected components from the training set and used to predict the test participant's label.

In addition to evaluating the individual classifiers, a soft-voting ensemble classifier was constructed for each task. Each model's scores were converted to class-probability estimates using cross-validated calibration. Within each fold, the calibrated probability vectors from the six classifiers were averaged with equal weights, and the final label was assigned to the class with the highest average probability. The ensemble model was included to assess whether aggregating predictions from multiple classifiers could improve performance over any individual model.

7.4.7 Model Performance

For each hopping task, the model achieving the highest classification accuracy was identified. Performance metrics included classification accuracy derived from confusion matrices, Cohen's kappa coefficient, F1 score, and the area under the precision-recall curve (PR AUC)⁴². Cohen's kappa measures agreement between the predicted and true labels beyond chance, accounting for class imbalance⁴³, while F1 represents the harmonic mean between precision and recall⁴⁴. The PR AUC summarizes the trade-off between precision and recall, emphasizing the model's performance on the minority class⁴². Classification accuracy values above 70% were interpreted as acceptable discrimination in this context, while Cohen's κ values were interpreted according to conventional benchmarks (0.41–0.60 moderate, 0.61–0.80 substantial agreement). All post-processing analyses were conducted using Python (version 3.8) with the scikit-learn⁴⁰, imbalanced-learn⁴⁵, NumPy, Pandas, Matplotlib, and Seaborn libraries.

7.4.8 Post-hoc Analysis of Classification Outcomes

To provide additional context for model behaviour beyond overall classification accuracy, post-hoc analyses of classification outcomes were performed. Misclassification patterns were examined across hopping tasks and limb groups to determine whether classification errors

clustered within specific movements or participant characteristics. For each participant, classification results across all tasks were aggregated to evaluate the frequency and consistency of incorrect classifications across multiple tasks.

To explore potential sex-related differences in classification performance, model outcomes were additionally examined separately for male and female participants using the same trained models and evaluation metrics. These stratified analyses were exploratory and descriptive in nature and were not intended as formal sex-based comparisons or inferential statistical testing.

7.5 Results

Classification performance was comparable across models for both limb comparisons (Figure 7.1). Given this similarity, and its stable performance, interpretability, and minimal parameter tuning requirements^{46,47}, LDA was selected as the primary classifier for subsequent analyses to enable consistent cross-task comparisons.

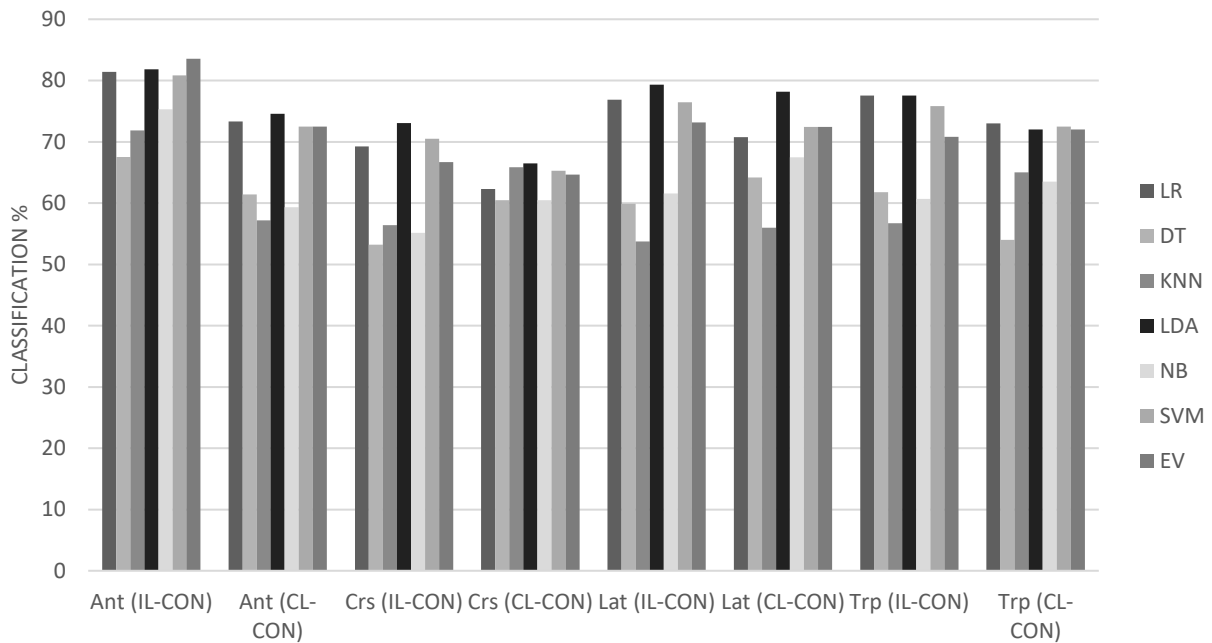


Figure 7.1. The percent of correctly classified participants as injured or uninjured for the injured limb (IL-CON) and contralateral limb (CL-CON), compared with healthy uninjured limbs, using logistic regression (LR), decision tree (DT), k-nearest neighbour (KNN), linear discriminant analysis (LDA), naïve Bayes (NB), support vector machine (SVM), and ensemble voting (EV).

7.5.1 Classification Performance of the Injured Limb (IL-CON)

Using LDA, classification accuracies were 81.8% (Ant), 73.1% (Crs), 79.3% (Lat), and 77.5% (Trp) (Table 7.2). Corresponding Cohen's κ values ranged from 0.40–0.46, F_1 scores from 0.53–0.62, and PR AUC from 0.61–0.66. Across tasks, specificity exceeded sensitivity (Figure 7.2A–D). For example, in Ant, 84.5% of CON trials were correctly identified (specificity) compared with 68.4% of ACLi trials (sensitivity). Similar patterns were observed for Crs (specificity = 73.0%, sensitivity = 73.1%), Lat (80.8% vs 71.8%), and Trp (80.9% vs 68.1%). Ensemble voting marginally improved Ant accuracy to 83.6% but did not enhance other tasks, confirming the minimal benefit of classifier aggregation. Consequently, LDA was retained for all further analyses to ensure interpretive and methodological consistency across tasks.

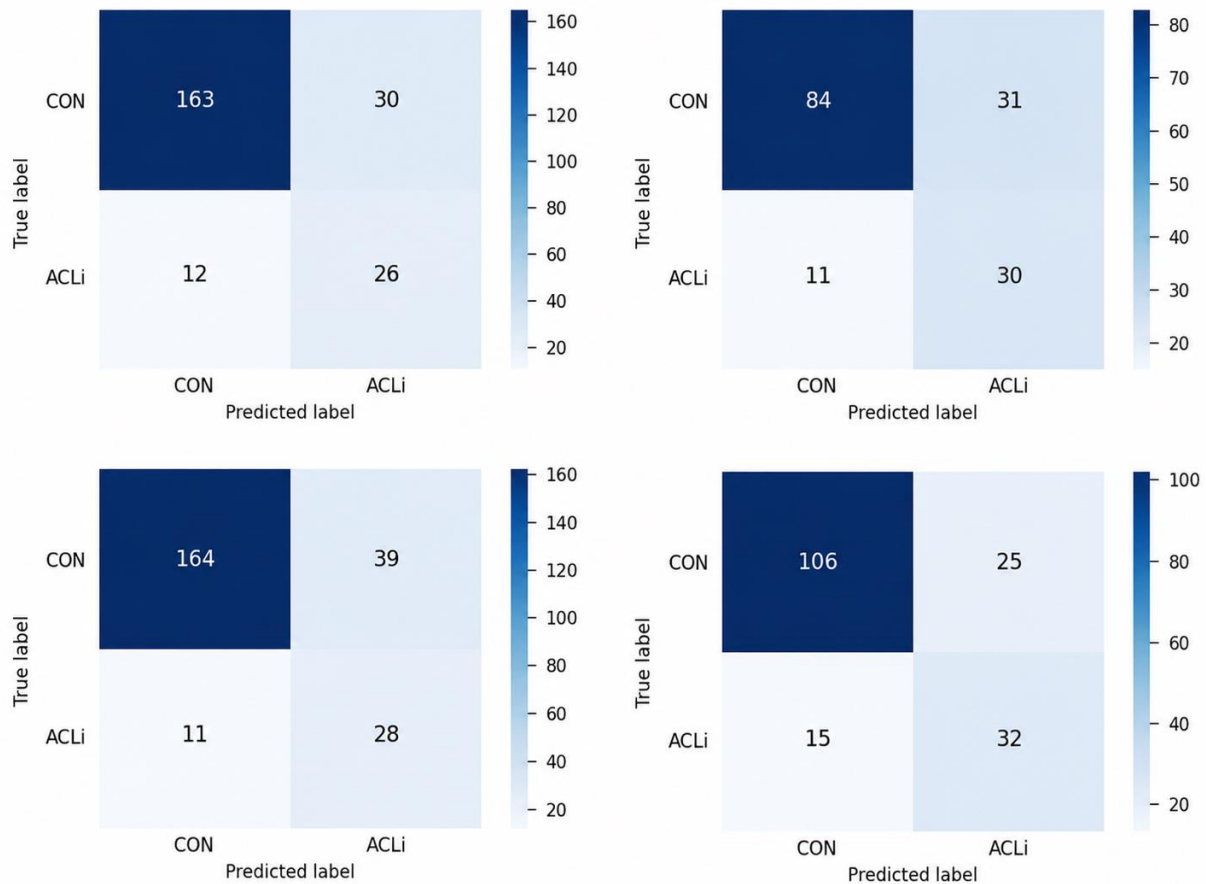


Figure 7.2A-D. Confusion matrices for LDA classification of model IL-CON: the injured limb of the ACLi group and the healthy limbs of the control group across hopping tasks. Rows represent the true group labels and columns represent the predicted group labels. Values indicate the number of trials classified into each category, with darker shading representing a greater number of trials. Correct classification of CON trials corresponds to specificity, whereas correct classification of ACLi trials corresponds to sensitivity.

Table 7.2. The number of participants broken down by sex and injury status, with the overall classification accuracy, F1 score, Cohen's kappa, and area under the precision-recall curve when the optimal number of PCs was retained for each hopping task for both models IL-CON and CL-CON using LDA as the classifier.

Limb	Task	n	Male		Female		# of PCs	Accuracy (%)	F1 score	Cohen's κ	PR AUC	Precision (%)	Recall (%)
			ACL	CON	ACL	CON							
ACLi injured limb vs CON (IL-CON)	Ant	81	6	27	17	31	15	81.8	0.44	0.55	0.61	68	46
	Crs	71	10	20	14	27	12	73.1	0.4	0.59	0.63	49	73
	Lat	83	6	27	18	32	15	79.3	0.41	0.53	0.64	42	72
	Trp	80	6	20	22	32	13	77.5	0.46	0.62	0.66	56	68
	Mean $\pm$ SD	79 $\pm$ 5	7 $\pm$ 2	24 $\pm$ 4	18 $\pm$ 3	31 $\pm$ 2	13.8 $\pm$ 1.5	77.9 $\pm$ 3.2	0.43 $\pm$ 0.02	0.57 $\pm$ 0.03	0.64 $\pm$ 0.02	53.8 $\pm$ 9.6	64.8 $\pm$ 11.0
ACLi contralateral limb vs CON (CL-CON)	Ant	84	7	27	19	31	15	74.6	0.36	0.51	0.63	39	72
	Crs	80	9	20	24	27	12	66.5	0.27	0.53	0.50	47	60
	Lat	82	5	27	18	32	15	78.2	0.35	0.48	0.45	39	60
	Trp	93	12	20	29	32	14	72	0.4	0.62	0.67	58	67
	Mean $\pm$ SD	85 $\pm$ 6	8 $\pm$ 3	24 $\pm$ 4	23 $\pm$ 5	31 $\pm$ 2	14.0 $\pm$ 1.4	72.8 $\pm$ 4.3	0.35 $\pm$ 0.05	0.54 $\pm$ 0.05	0.56 $\pm$ 0.09	45.8 $\pm$ 7.8	64.8 $\pm$ 5.1

Tasks: anterior hop (Ant), cross hop (Crs), lateral hop (Lat), triple hop (Trp). Groups: anterior cruciate ligament (ACL) injured (ACLi) and control (CON) participants

7.5.2 Classification Performance of the Contralateral Limb (CL-CON)

When the models were trained for CL-CON, LDA achieved accuracies of 74.2% (Ant), 66.5% (Crs), 74.5% (Lat), and 72.0% (Trp) (Table 7.2). Logistic regression slightly exceeded LDA for Trp (73.0% vs 72.0%), but differences across models were ≤ 1 percentage point for all metrics, supporting the continued use of LDA for consistency. Specificity again exceeded sensitivity across all tasks (Figure 7.3A–D). These results demonstrate that the contralateral limb retains distinguishable movement deviations relative to CON.

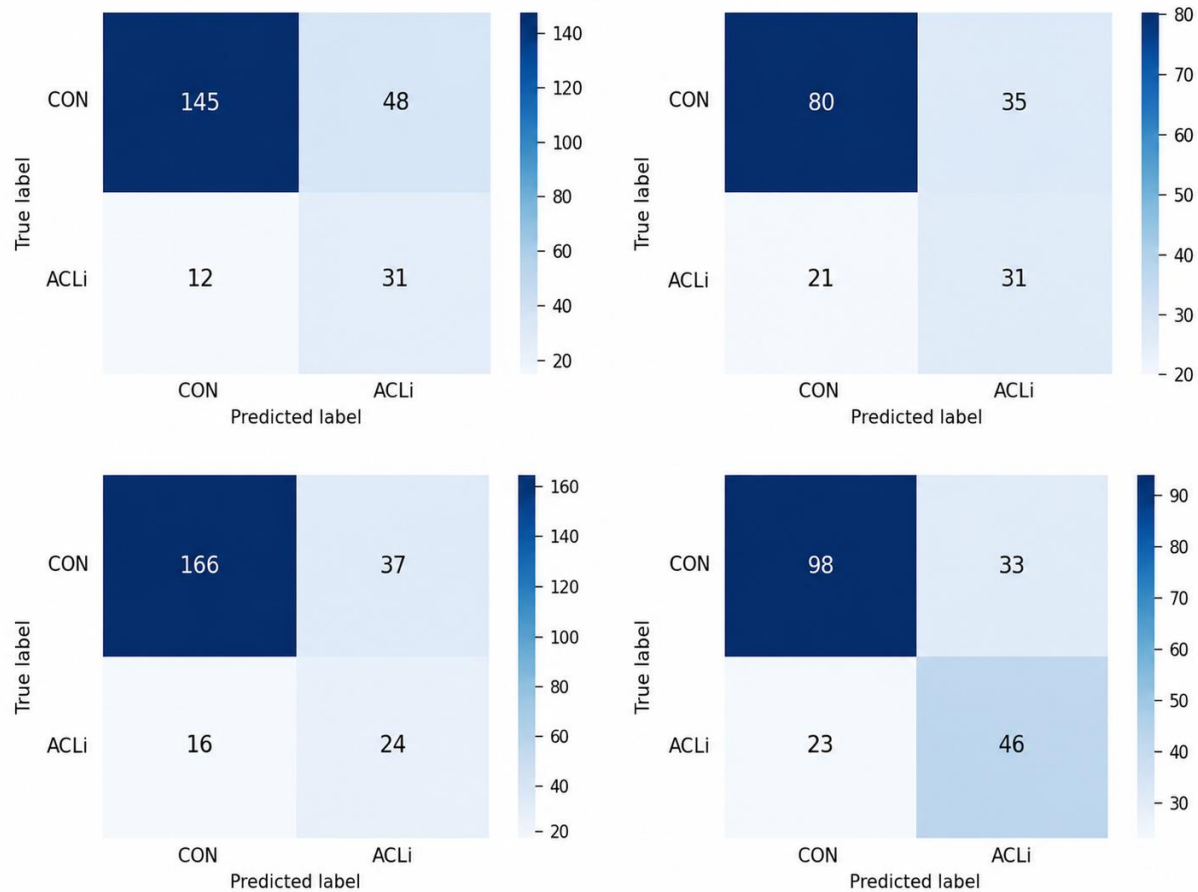


Figure 7.3A-D. Confusion matrices for LDA classification of model CL-CON: the contralateral limb of the ACLi group and the healthy limbs of the CON group across hopping tasks. Values represent the number of trials included in the analysis rather than unique participants. Rows represent the true group labels and columns represent the predicted group labels. Values indicate the number of trials classified into each category, with darker shading representing a greater number of trials. Correct classification of CON trials corresponds to specificity, whereas correct classification of ACLi trials corresponds to sensitivity.

7.5.3 Misclassification Analysis

Analysis of misclassification patterns revealed consistent bilateral trends. Participants misclassified on both limbs were identified for each task, representing those exhibiting systematic classification errors (Table 7.3). Control females (fCON) showed the highest bilateral misclassification rates across all tasks (>80%), whereas injured females (fACL) and injured males (mACL) exhibited moderate bilateral consistency (<60%). Lat produced the greatest number of bilateral misclassifications (68 participants), while Crs produced the fewest (51 participants).

Table 7.3. Participants misclassified in both IL-CON and CL-CON models, by group and task

Group	Ant	Crs	Lat	Trp
fACL	10 (47.6 %)	12 (46.2 %)	13 (59.1 %)	10 (35.7 %)
fCON	28 (90.3 %)	20 (74.1 %)	27 (84.4 %)	27 (81.8 %)
mACL	5 (62.5 %)	6 (46.2 %)	3 (50.0 %)	5 (45.5 %)
mCON	20 (71.4 %)	13 (56.5 %)	25 (78.1 %)	11 (55.0 %)

Note: Percentages reflect the proportion of participants in each group and task misclassified at least once in both the IL-CON and CL-CON LDA models. fACL = female ACL-injured; fCON = female control; mACL = male ACL-injured; mCON = male control.

Further inspection of misclassification distributions showed distinct task-specific patterns between groups (Figures 7.4 and 7.5). Among ACLi participants, Trp produced the largest number of misclassifications on the injured limb, while the contralateral limb exhibited the most errors during Trp and Crs. Multi-task combinations were also group-specific: Ant + Crs + Lat was most common for injured limbs, whereas Lat + Trp predominated for contralateral limbs. fACL participants accounted for 71.1% of all single-task misclassifications and all multi-task combinations.

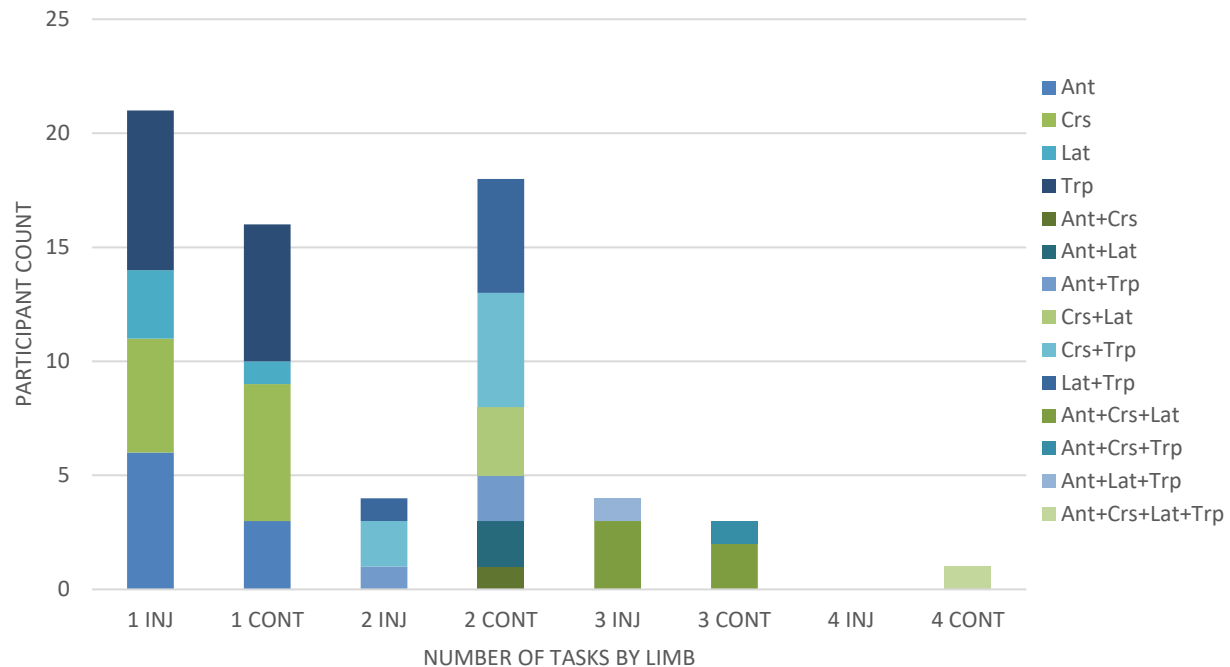


Figure 7.4. Counts of misclassified tasks and combinations for both injured (INJ) and contralateral (CONT) limbs in ACL-injured participants are presented, with stacked bars indicating the distribution of misclassifications for both single-task and multi-task activities.

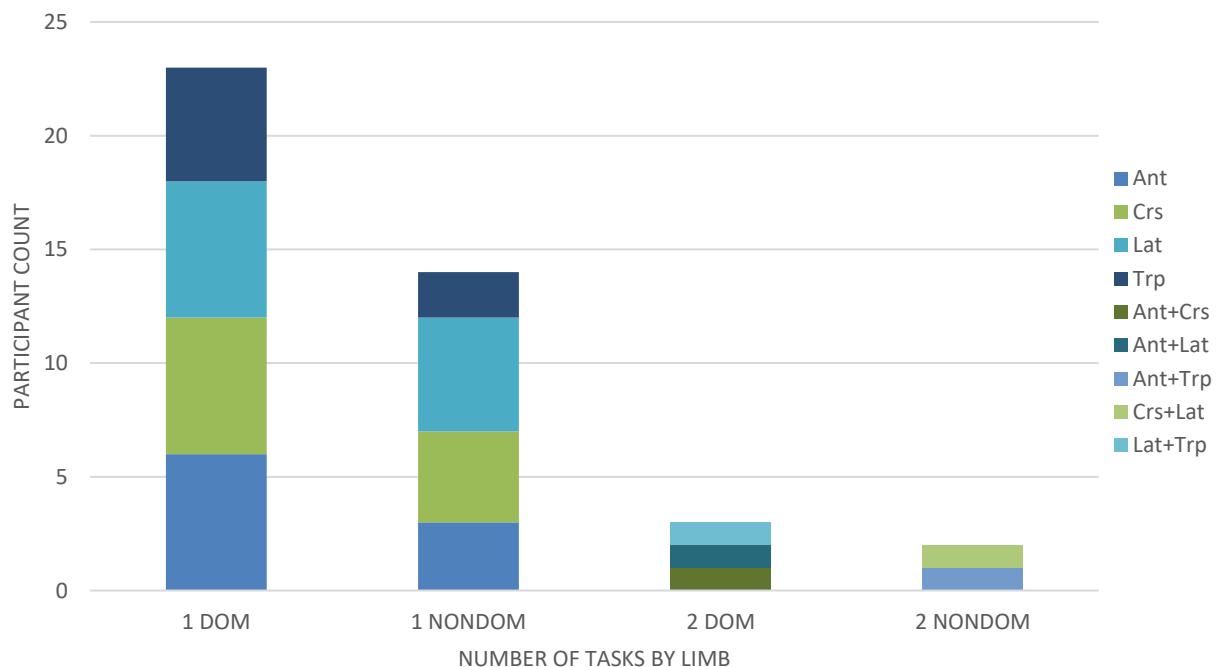


Figure 7.5. Counts of misclassified tasks and combinations for both dominant (DOM) and non-dominant (NONDOM) limbs in control participants are presented, with stacked bars indicating the distribution of misclassifications for both single-task and multi-task activities.

In the CON group, misclassification patterns reflected limb dominance. Ant, Crs, and Lat yielded the highest dominant-limb errors, whereas Lat predominated in non-dominant limbs (Figure 7.5). Only one male control (mCON) was misclassified on Trp for the dominant limb in both models, while all other single- and multi-task errors were attributed to fCON.

7.6 Discussion

The purpose of this study was to evaluate the ability of a PCA-driven classification framework to distinguish adolescents with ACL injury from uninjured peers during single-limb hopping and to determine whether the contralateral limb of injured participants exhibited deviations relative to uninjured controls. Both hypotheses were supported: PCA-LDA classifiers accurately differentiated injured from control limbs, achieving up to 81.8% accuracy on the anterior hop, and also detected movement deviations on the contralateral limb, indicating bilateral adaptations following ACL injury.

Several limitations should be acknowledged. The cross-sectional design precludes causal inference regarding whether the identified deviations represent pre-injury risk factors or residual post-injury adaptations. Subgroup sample sizes limited stratification by age, sex, and time since injury. Marker-based motion capture is also subject to soft-tissue artifact⁴⁸ and cannot capture muscle activity, which may obscure subtle muscular changes. Although LOOCV with SMOTE resampling reduced overfitting, the modest sample size constrained model complexity. Finally, PCA components provide abstract features that are not directly interpretable as joint-level mechanics. Moreover, since PCA was recalculated within each cross-validation fold and only selected components were retained for classification, individual PC loadings were not consistent across folds, limiting direct biomechanical characterization.

Our results demonstrate that PCA-LDA classifiers achieve robust discrimination on the injured limb with up to 81.8% accuracy on the anterior hop, with specificity (84%-94%) consistently higher than sensitivity (46%-73%) in all tasks (Table 1, Figure 2A-D). The anterior hop had the strongest discrimination and benefited slightly from ensemble voting, highlighting its utility in clinical RTA assessments. This finding underscores the critical role of sagittal-plane control in ACL injuries, in agreement with previous studies that highlight altered landing mechanics and quadriceps-hamstrings coordination in anterior hops following ACL injury^{27,49}.

The classification of contralateral limbs above chance confirms that ACL injury affects global neuromuscular coordination rather than a single limb. Similar contralateral deficits have been reported in adults, including bilateral proprioceptive changes and compensatory loading patterns following reconstruction^{50–52}. The comparable accuracies observed here suggest that these adaptations occur independently of age, likely reflecting central or systemic mechanisms that persist during adolescence.

Integration with previous literature suggests that classification performance may also reflect sex-related heterogeneity in movement strategies during adolescence. Exploratory stratified analyses indicated that female participants accounted for a greater proportion of single-task and multi-task misclassifications compared with males; these observations were descriptive and not intended as formal sex-based comparisons. The increased misclassification frequency in females may reflect greater variability in movement coordination during dynamic task execution. Previous adolescent literature has reported sex-related differences in neuromuscular control, including altered landing mechanics, increased knee valgus loading tendencies, and differences in muscle activation timing and joint stiffness regulation during high-demand tasks^{12,53–55}. Developmental changes occurring throughout adolescence, such as rapid growth, evolving strength profiles, and shifts in neuromuscular coordination, have been proposed as contributors to increased biomechanical variability in female athletes. Although maturation was not evaluated as a mechanistic factor in the present analyses, these developmental considerations may partially explain the greater heterogeneity observed in female classification patterns. Misclassification patterns among injured males appeared more uniform across tasks, suggesting comparatively consistent compensatory strategies within this subgroup. Although these findings should be interpreted cautiously, given subgroup sample sizes, these findings highlight the potential value of investigating sex- and development-informed reference datasets in future work.

Methodologically, the combined use of PCA, ensemble feature selection, and LDA provided an efficient classification framework capable of identifying consistent movement-pattern differences between groups while limiting model overfitting. Although PCA components do not permit direct interpretation at the level of individual joints or muscles, the stability of classification performance across tasks indicates that global coordination patterns differed systematically between injured and uninjured adolescents. Accordingly, interpretations are made at the level of overall movement behaviour rather than specific joint-level mechanics.

From a clinical standpoint, these findings highlight the value of quantitative, data-driven approaches to complement conventional hop test outcomes based solely on distance or time. Consistent with the task-combination misclassification patterns observed across participants, the ability of the model to consistently detect deviations across tasks suggests that cumulative classification evidence may strengthen clinical inference. When an individual is classified as injured in two or more hop tasks, the combined evidence may provide a more robust indicator of persistent asymmetry or incomplete recovery than single-task outcomes alone. Importantly, the purpose of this framework is not to diagnose ACL injury, but to identify persistent movement deviations that may remain despite acceptable hop performance. Classification outcomes, therefore, reflect movement quality rather than injury status and may complement conventional RTA assessments by identifying individuals who demonstrate injury-like movement patterns during functional tasks.

In summary, this study demonstrates that PCA–LDA models effectively differentiate ACL-injured from uninjured adolescents and reveal bilateral deviations consistent with neuromuscular adaptation. The anterior hop provided the clearest separation between groups, and observed variability among female participants suggests that future work should examine whether sex-specific reference data improve classification robustness in adolescent populations. Collectively, these results provide preliminary evidence that bilateral kinematic analysis may offer additional insight into residual movement adaptations during RTA evaluation in adolescents recovering from ACL injury.

7.7 Acknowledgments

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7.8 References

1. Majewski M, Susanne H, Klaus S. Epidemiology of athletic knee injuries: A 10-year study. *Knee*. 2006;13(3):184-188.
2. Kruse LMM, Gray B, Wright RW. Rehabilitation after anterior cruciate ligament reconstruction: A systematic review. *J Bone Joint Surg*. 2012;94:1737-1748.
3. Kvist J. Rehabilitation following anterior cruciate ligament injury: Current recommendations for sports participation. *Sports Medicine*. 2004;34(4):269-280.
4. Ardern CL, Webster KE, Taylor NF, Feller JA. Return to the preinjury level of competitive sport after anterior cruciate ligament reconstruction surgery: Two-thirds of patients have not returned by 12 months after surgery. *Am J Sports Med*. 2011;39(3):538-543.
5. Romanchuk NJ, Livock H, Lukas KJ, Del Bel MJ, Benoit DL, Carsen S. Criteria used to determine unrestricted return to activity after ACL reconstruction in pediatric and adolescent patients: A systematic review. *Orthopaedic Journal of Sports Medicine*. 2023;11(3):23259671231154540.
6. Myer GD, Jayanthi N, Difiori JP, et al. Sport specialization, part I: Does early sports specialization increase negative outcomes and reduce the opportunity for success in young athletes? *Sports Health*. 2015;7(5):437-442.
7. Webster KE, McPherson AL, Hewett TE, Feller JA. Factors associated with a return to preinjury level of sport performance after anterior cruciate ligament reconstruction surgery. *American Journal of Sports Medicine*. 2019;47(11):2557-2562.
8. Barber-Westin SD, Noyes FR. Factors used to determine return to unrestricted sports activities after anterior cruciate ligament reconstruction. *The Journal of Arthroscopic and Related Surgery*. 2011;27(12):1697-1705.
9. Sadeqi S, Norte GE, Murray A, Erbulut DU, Goel VK. Effect of whole body parameters on knee joint biomechanics: Implications for ACL injury prevention during single-leg landings. *American Journal of Sports Medicine*. 2023;51(8):2098-2109.
10. Ford KR, Myer GD, Smith RL, Vianello RM, Seiwert SL, Hewett TE. A comparison of dynamic coronal plane excursion between matched male and female athletes when performing single-leg landings. *Clinical Biomechanics*. 2006;21(1):33-40.

11. Chaudhari AM, Hearn BK, Leveille LA, Johnson ER, Andriacchi TP. The effects of dynamic limb alignment on knee moments during single limb landing: Implications for the analysis of the non-contact injury to the anterior cruciate ligament. 2003;(1):1-2.
12. Girard CI, Romanchuk NJ, Del Bel MJ, Carsen S, Chan ADC, Benoit DL. Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria. *Knee Surgery, Sports Traumatology, Arthroscopy*. 2025;33(5):1633-1644.
13. Johnston PT, McClelland JA, Webster KE. Lower limb biomechanics during single-leg landings following anterior cruciate ligament reconstruction: A systematic review and meta-analysis. *Sports Medicine*. 2018;48(9):2103-2126.
14. Gokeler A, Benjaminse A, Hewett TE, et al. Proprioceptive deficits after ACL injury: Are they clinically relevant? *Br J Sports Med*. 2012;46(3):180-192.
15. Paterno MV, Ford KR, Myer GD, Heyl R, Hewett TE. Limb asymmetries in landing and jumping 2 years following anterior cruciate ligament reconstruction. *Clinical Journal of Sports Medicine*. 2007;17(4):258-262.
16. Federolf P, Reid R, Gilgien M, Haugen P, Smith G. The application of principal component analysis to quantify technique in sports. *Scand J Med Sci Sports*. 2014;24(3):491-499.
17. Troje N. The little difference: Fourier-based synthesis of gender-specific biological motion. In: Würtz RP, Lappe M, eds. *Dynamic Perception*. Berlin: AKA Press; 2002:115-120.
18. Michalak J, Troje NF, Fischer J, Vollmar P, Heidenreich T, Schulte D. Embodiment of sadness and depression: Gait patterns associated with dysphoric mood. *Psychosom Med*. 2009;71(5):580-587.
19. Ross GB, Dowling B, Troje NF, Fischer SL, Graham RB. Objectively differentiating movement patterns between elite and novice athletes. *Med Sci Sports Exerc*. 2018;50(7):1457-1464.
20. Mavor MP, Gruevski KM, Ross GB, et al. A data-driven framework for assessing soldier performance, health, and survivability. *Appl Ergon*. 2022;104:103809
21. Del Bel MJ, Kemp LG, Girard CI, et al. Translation and validation of the Hospital for Special Surgery Pediatric Functional Activity Brief Scale for French paediatric populations. *Physiotherapy Canada*. 2020;74(4):348-354.

22. Fabricant PD, Robles A, Downey-Zayas T, et al. Development and validation of a pediatric sports activity rating scale. *Am J Sports Med.* 2013;41(10):2421-2429.
23. Tegner Y, Lysholm J. Rating systems in the evaluation of knee ligament injuries. *Clin Orthop Relat Res.* 1985;198:43-49.
24. Marshall WA, Tanner JM. Variations in pattern of pubertal changes in girls. *Arch Dis Child.* 1969;44(235):291-303.
25. Marshall WA, Tanner JM. Variations in the pattern of pubertal changes in boys. *Arch Dis Child.* 1970;45(239):13-23.
26. Beaulieu ML, Lamontagne M, Beaulé PE. Lower limb biomechanics during gait do not return to normal following total hip arthroplasty. *Gait Posture.* 2010;32(2):269-273.
27. Noyes FR, Barber SD, Mangine RE. Abnormal lower limb symmetry determined by function hop tests after anterior cruciate ligament rupture. *Am J Sports Med.* 1991;19(5):513-518.
28. Girard CI, Warren CE, Romanchuk NJ, et al. Decision tree learning algorithm for classifying knee injury status using return-to-activity criteria. In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*. Vol 2020-July. Institute of Electrical and Electronics Engineers Inc.; 2020:5494-5497.
29. Bisseling RW, Hof AL. Handling of impact forces in inverse dynamics. *J Biomech.* 2006;39(13):2438-2444.
30. Kristianslund E, Krosshaug T, Van den Bogert AJ. Effect of low pass filtering on joint moments from inverse dynamics: Implications for injury prevention. *J Biomech.* 2012;45(4):666-671.
31. De Leva P. Adjustments to zatsiorsky-seluyanov's segment inertia parameters. *J Biomech.* 1996;29(9):1223-1230.
32. De Leva P. Joint center longitudinal positions computed from a selected subset of Chandler's data. *J Biomech.* 1996;29(9):1231-1233.
33. Girard CI, Del Bel MJ, Bédard V, et al. Are single limb hopping scores the same when performed in a physical education class versus a laboratory setting in uninjured adolescents? Implications for future rehabilitation guidelines for adolescents with knee injuries. *Communications in Kinesiology.* 2024;1(6).

34. Troje NF. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. *J Vis (Tokyo)*. 2002;2(5):371-387. doi:10.1167/2.5.2
35. Jolliffe IT. Principal components in regression analysis. In: Springer, New York, NY; 1986:129-155.
36. Ross BC. Mutual information between discrete and continuous data sets. *PLoS One*. 2014;9(2):e87357.
37. Breiman L. Random forests. *Mach Learn*. 2001;45:5-32.
38. Tibshirani R. Regression shrinkage and selection via the lasso. *J R Stat Soc Series B Stat Methodol*. 1996;58(1):267-288.
39. Hastie T, Tibshirani R, Friedman J. *The elements of statistical learning: Data mining, inference, and prediction*. 2nd ed. Springer; 2017.
40. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine learning in Python. *J Mach Learn Res*. 2011;12:2825-2830.
41. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*. 2002;16:321-357.
42. Saito T, Rehmsmeier M. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLoS One*. 2015;10(3):e0118432.
43. Carletta J. Assessing agreement on classification tasks: The kappa statistic. *Computational Linguistics*. 1996;22(2):249-254.
44. Hripcsak G, Rothschild AS. Agreement, the F-measure, and reliability in information retrieval. *Journal of the American Medical Informatics Association*. 2005;12(3):296-298.
45. Lemaître G, Nogueira F, Aridas CK. Imbalanced-learn: A Python toolbox to tackle the curse of imbalanced datasets in machine learning. *Journal of Machine Learning Research*. 2017;18(17):1-5.
46. McLachlan GJ. *Discriminant analysis and statistical pattern recognition*. Hoboken, NJ, USA: John Wiley & Sons; 1992. doi:10.1002/0471725293
47. Martinez AM, Kak AC. PCA versus LDA. *IEEE Trans Pattern Anal Mach Intell*. 2001;23(2):228-233.

48. Benoit DL, Ramsey DK, Lamontagne M, Xu L, Wretenberg P, Renström P. Effect of skin movement artifact on knee kinematics during gait and cutting motions measured *in vivo*. *Gait Posture*. 2006;24(2):152-164.
49. Trigsted SM, Post EG, Bell DR. Landing mechanics during single hop for distance in females following anterior cruciate ligament reconstruction compared to healthy controls. *Knee Surgery, Sports Traumatology, Arthroscopy*. 2017;25(5):1395-1402.
50. Arockiaraj J, Korula RJ, Oommen AT, et al. Proprioceptive changes in the contralateral knee joint following anterior cruciate injury. *Journal of Bone and Joint Surgery - Series B*. 2013;95B(2):188-191.
51. Davey AP, Vacek PM, Caldwell RA, et al. Risk factors associated with a noncontact anterior cruciate ligament injury to the contralateral knee after unilateral anterior cruciate ligament injury in high school and college female athletes: A prospective study. *American Journal of Sports Medicine*. 2019;47(14):3347-3355.
52. Mausehund L, Krosshaug T. Knee biomechanics during cutting maneuvers and secondary ACL injury risk: A prospective cohort study of knee biomechanics in 756 female elite handball and soccer players. *American Journal of Sports Medicine*. 2024;52(5):1209-1219.
53. Myer GD, Ford KR, Paterno MV, Nick TG, Hewett TE. The effects of generalized joint laxity on risk of anterior cruciate ligament injury in young female athletes. *Am J Sports Med*. 2008;36(6):1073-1080.
54. DiCesare CA, Montalvo A, Barber Foss KD, et al. Sport specialization and coordination differences in multisport adolescent female basketball, soccer, and volleyball athletes. *J Athl Train*. 2019;54(10):1105-1114.
55. Donelon TA, Edwards J, Brown M, Jones PA, O'Driscoll J, Dos'Santos T. Differences in biomechanical determinants of ACL injury risk in change of direction tasks between males and females: A systematic review and meta-analysis. *Sports Medicine*. 2024;10(29).

7.9 Postamble

This chapter demonstrates that waveform-level kinematic information can differentiate adolescents with ACL injury from uninjured peers during single-limb hopping, and that deviations are detectable not only on the injured limb but also on the contralateral limb. These findings provide evidence that movement alterations following ACL injury in adolescents are not fully captured by discrete spatiotemporal outcomes and may reflect broader neuromuscular adaptation. The consistent pattern of higher specificity than sensitivity across tasks further suggests that some injured participants display movement strategies that overlap with control patterns, which is consistent with heterogeneity in injury presentation and recovery.

The results also highlight that task choice influences discrimination. The anterior hop produced the highest classification performance, although each hopping task demonstrated unique classification and misclassification patterns. These findings suggest that different hopping tasks may capture distinct aspects of movement behaviour and warrant consideration when assessing movement deviations beyond gross performance deficits. The misclassification analysis further indicates that errors can cluster within specific participants across tasks, which reinforces the potential value of considering classification consistency across tasks as an interpretive aid.

In contrast to traditional approaches that treat the contralateral limb as an internal control, the above-chance contralateral classification observed here supports the use of external reference cohorts when interpreting post-injury movement quality. This has direct relevance for clinical decision-making in adolescents, where visible symmetry may reflect bilateral adaptation rather than full restoration of pre-injury movement patterns.

Overall, this chapter provides the movement-based rationale for examining clinically feasible strategies that can approximate laboratory-grade kinematic discrimination. The subsequent work builds on these findings by evaluating whether similar classification performance can be achieved using inertial sensor features, with the longer-term goal of translating waveform-based assessment beyond the motion capture laboratory.

CHAPTER 8: IMU Validation

Validation of Real and Simulated IMUs for Knee Flexion Estimation During Functional Tasks

8.1 Preamble

Wearable inertial measurement units have become increasingly popular as a practical alternative to laboratory-based motion capture systems for the assessment of human movement. Their portability, lower cost, and feasibility for use in field and clinical environments make them especially appealing for return-to-activity monitoring following lower extremity injury. However, despite their increasing adoption, there is significant variability in reported accuracy across different tasks, joint motions, sensor placements, and processing pipelines. These inconsistencies highlight the importance of validating inertial sensor measurements against established marker-based references prior to their use in biomechanical modelling or classification analyses.

This chapter has two main objectives. First, it establishes and verifies a complete processing pipeline for estimating knee flexion angles from inertial data using anatomically consistent coordinate systems, static calibration procedures, and relative segment orientations. Second, it evaluates the agreement between marker-based knee kinematics and both real and simulated inertial measurements during single-limb functional hopping tasks commonly used in return-to-activity assessments.

Simulated inertial sensors derived from motion capture data are included as a methodological control. By generating inertial signals directly from known segment kinematics, the simulated IMUs allow the isolation of errors arising from sensor fusion, calibration, coordinate mapping, and joint-angle computation, independent of hardware-related limitations. Comparing the outputs between simulated and real IMUs therefore provides insight into whether discrepancies originate from the analytical framework itself or from the quality and stability of the recorded sensor signals.

Validating the accuracy and limitations of both real and simulated inertial measurement units is a necessary step prior to the application of inertial data in the subsequent chapter. This validation ensures that the conclusions drawn from subsequent classification and modeling analyses are based on verified measurement performance, rather than unquantified sensor errors.

8.2 Validation of Real IMUs and Simulated IMUs Against Marker-Based Kinematics

This chapter describes the processing pipeline used to validate inertial measurements, acquired from wearable sensors and simulated from motion-capture (MoCap), against marker-based reference kinematics data. The focus of this validation is the knee flexion angle during the maximal anterior, maximal lateral, triple hop, and cross hop tasks, derived from thigh and shank segment orientations. Start and stop criteria are outlined in Appendix E.

Real inertial measurements were collected using Delsys Trigno wireless EMG-IMU sensors (Delsys Inc., Natick, MA, USA) sampled at 200 Hz. Four sensors were placed on the rectus femoris and medial or lateral gastrocnemius muscle bellies according to the SENIAM guidelines as outlined in section 4.3 of this thesis. These devices were acquired primarily to record surface EMG. As such, sensor placement was optimized for EMG signal quality rather than inertial measurement, with the IMU embedded within each EMG sensor housing. Sensor recordings were synchronized with the Vicon motion capture system through the Delsys-Vicon integration framework, and manufacturer-provided Delsys software was used for sensor calibration prior to data collection. The recorded signals consisted of tri-axial accelerometer, gyroscope, and magnetometer measurements that were subsequently processed to estimate segment orientations and knee flexion angles.

To facilitate interpretation of the processing pipeline, a representative hopping trial was selected and visualized throughout the principal stages used to estimate knee flexion from the inertial measurements. The following figures illustrate the progression from the synchronized raw sensor recordings to orientation estimation and, ultimately, the comparison of IMU-derived knee flexion angles with the marker-based reference.

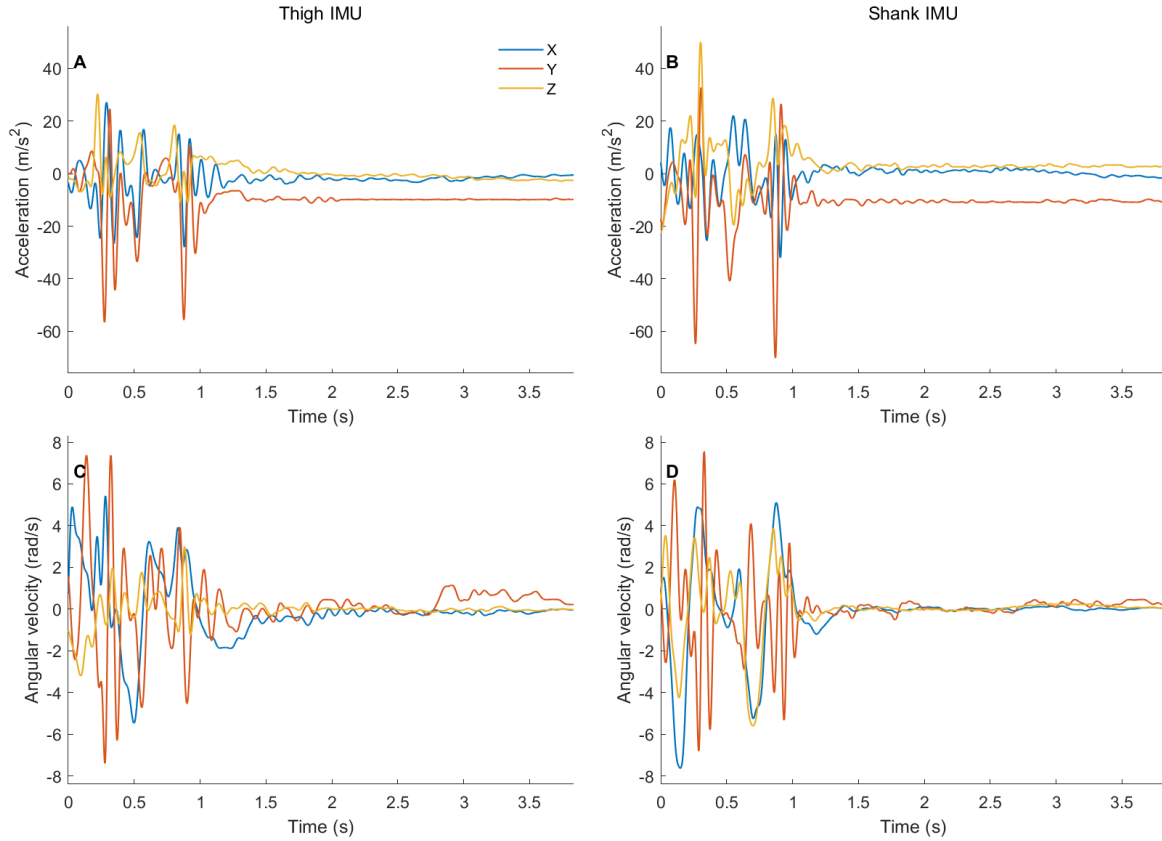


Figure 8.1. Representative synchronized inertial measurements from a single hopping trial. Tri-axial accelerometer signals are shown for the thigh (A) and shank (B) IMUs, while tri-axial gyroscope signals are shown for the thigh (C) and shank (D) IMUs following synchronization and trimming according to the motion capture-defined trial boundaries.

Real IMU recordings were collected from 80 participants across 946 hopping trials. Following quality assessment, only 160 trials from 23 participants met the criteria required for subsequent processing. Of the remaining 786 trials, 539 (68.6%) were missing, 236 (30.0%) exhibited signal saturation (ceiling or floor effects), and 11 (1.4%) were incomplete. At the participant level, 21 participants had no available IMU recordings, five participants had only saturated recordings, and the remaining participants demonstrated varying combinations of usable, missing, saturated, and incomplete trials. Consequently, trial-level quality assessment, rather than participant-level summaries, was used to determine inclusion in the validation analyses (Appendix A).

The 23 usable datasets were collected between January 1 and September 30, 2019. Within that period, 58 participants were recorded under the assumption that IMU data were available, but

only 23 yielded valid signals, with no discernible temporal pattern in data quality. The system appeared to function reliably for a maximum of three consecutive days during August 2019.

The substantial reduction from 80 recorded participants to 23 participants with usable IMU data highlights the practical challenges associated with collecting inertial measurements during high-impact functional tasks in pediatric populations. The original study was designed primarily to investigate biomechanical performance rather than to validate wearable sensors; therefore, detailed acquisition logs documenting the cause of each recording failure were not systematically maintained. Consequently, IMU signal quality was not evaluated during data collection, and recording failures were only identified retrospectively during processing. Although excluded datasets were categorized as missing, incomplete, or saturated, it was not possible to retrospectively determine the precise source of failure for every recording. These limitations motivated the subsequent validation analyses to determine whether the observed discrepancies originated from the sensor recordings themselves or from the processing pipeline used to estimate knee kinematics. A representative example of the abnormal accelerometer signals observed during quality assessment is shown in Figure 8.2. In addition to repeated clipping at apparent upper and lower recording limits, the magnitude of the recorded values was physiologically implausible for human movement and exceeded the expected measurement range of the Delsys Trigno IMU system. These signals were therefore interpreted as invalid sensor recordings rather than true segment accelerations. The scaling and source of these abnormal values could not be verified retrospectively; therefore, trials with these signal characteristics were excluded from further processing.

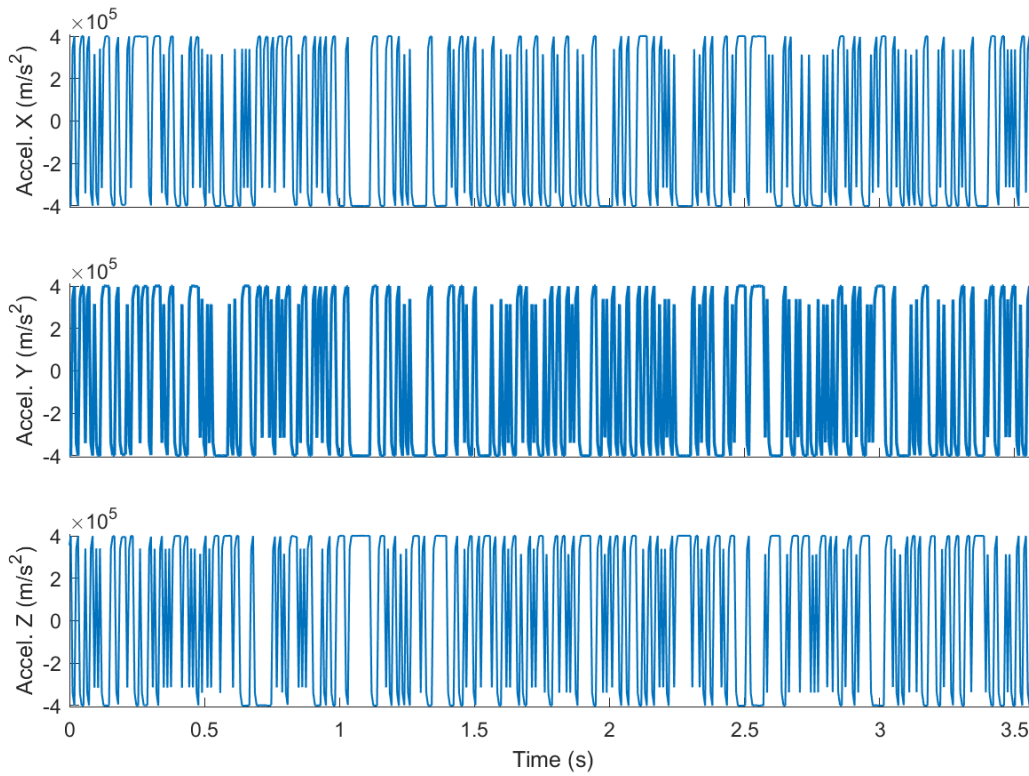


Figure 8.2. Representative abnormal tri-axial accelerometer signals recorded from the thigh-mounted Delsys Trigno IMU during a maximal triple hop trial. The X-, Y-, and Z-axis accelerometer measurements are displayed from top to bottom, with acceleration (m/s^2) plotted over time (s).

Initial validation analyses revealed substantial disagreement between real IMU-derived knee flexion angles and the marker-based reference kinematics. This raised the possibility that the observed discrepancies could arise either from limitations in the sensor recordings themselves or from errors in processing, calibration, or the joint-angle extraction pipeline. To distinguish between these possibilities, an additional validation step was performed using an independent open-source dataset containing synchronized IMU and marker data, allowing the processing pipeline to be evaluated under conditions where high-quality sensor recordings were known to be available.

To facilitate interpretation of the subsequent validation analyses, the principal stages of the knee-angle estimation pipeline are illustrated in Figure 8.3. Following synchronization and trimming, the raw inertial measurements were fused using an attitude and heading reference system (AHRS) filter to estimate sensor orientations. Anatomical calibration was then applied to express the thigh and shank orientations within anatomically meaningful reference frames, from

which the relative thigh–shank orientation was computed to estimate knee flexion prior to baseline correction.

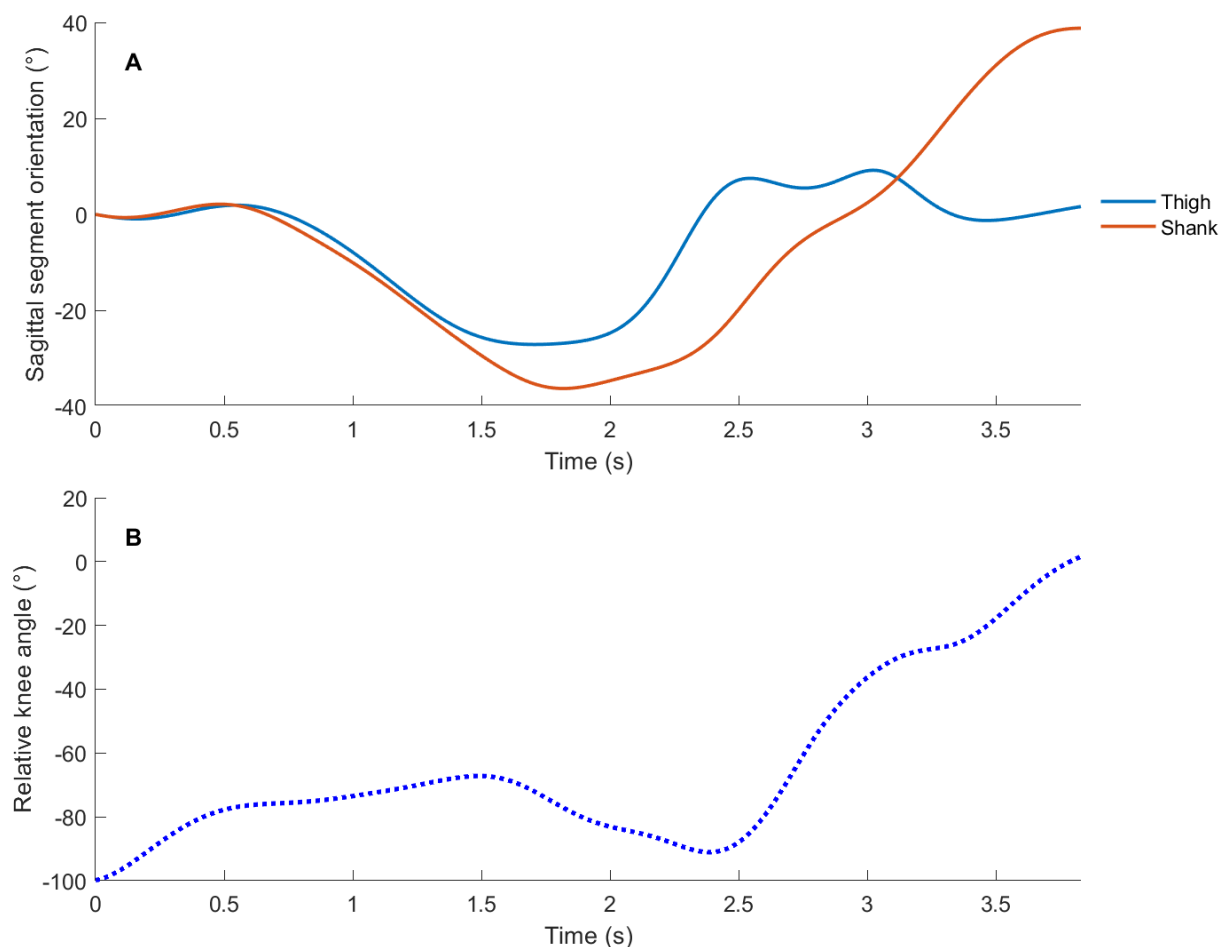


Figure 8.3. Intermediate processing steps used to estimate knee flexion from the real IMU recordings during a representative hopping trial. **(A)** Sagittal orientations of the anatomically mapped thigh and shank segments following AHRS-based sensor fusion and anatomical calibration. **(B)** Relative thigh–shank angle computed from the segment orientations before baseline correction.

An open-source dataset published by Scherpereel et al.²¹⁷ was analyzed to evaluate the generalizability and correctness of the processing pipeline under conditions where high-quality, well-synchronized data are known to be available. The squat trials from this dataset, using the right leg for comparison, were processed through the same pipeline applied to the present data. Agreement between modalities was quantified after static calibration, anatomical mapping, and time alignment^{95,192,257,258}. This comparison was designed to confirm that the pipeline yields accurate knee flexion estimates when applied to reliable IMU recordings, thereby isolating acquisition-related limitations from methodological implementation.

Together, the real IMU validation, simulated IMU (sIMU) comparison, and open-source dataset analysis allowed acquisition-related limitations to be distinguished from processing-related factors. Importantly, the purpose of the simulated IMUs was not to reproduce the acquisition errors observed in the wearable sensors. Rather, the simulated signals were used to isolate the biomechanical information theoretically available from each sensor location under ideal measurement conditions. This approach allowed the discriminatory potential of IMU-derived signals to be evaluated independently of hardware limitations, synchronization issues, sensor placement errors, and signal quality concerns present in the real recordings. The findings from this validation, therefore, motivated the use of simulated IMUs in the subsequent chapter to evaluate the upper limit of classification performance achievable when inertial measurements accurately represent the underlying segment kinematics.

8.3 Participants and Available Data

The validation analyses in this chapter are based on a subset of participants for whom usable real IMU data were available. A total of 23 participants contributed usable IMU data for this chapter. This subset included 3 female ACLi, 9 female CON, 1 male ACLi and 10 male CON participants. Multiple trials were available for each participant, resulting in 160 trials in total. The reduction from the original 946 trials collected across 80 participants to 160 usable trials from 23 participants reflects variability in IMU signal quality, rather than differences in protocol or task execution.

These participants represent a subset of the larger cohort used in Chapters 7 and 9 of the thesis, for which full marker-based kinematics and simulated IMUs were available. As such, the analyses in this chapter focus specifically on validating real and simulated IMU-derived knee flexion angles against marker-based reference data within this reduced dataset. The implications of this reduced sample size for subsequent analyses are addressed later in the chapter.

8.4 Data Preparation and Reference Kinematics

Full-body 3D marker trajectories included marker clusters on the thigh and shank, and calculated joint centers for the hip (HJC), knee (KJC), and ankle (AJC) for males and females⁶¹. Segment-fixed cluster frames were reconstructed at each frame from the cluster markers. For a generic segment, the proximal–distal (PD) axis was formed from the proximal to distal centroids, the anterior–posterior (AP) axis from anterior to posterior centroids, the medial–lateral (ML) axis

as $PD \times AP$, and a second out-of-plane axis as $PD \times ML$ to complete a right-handed triad. Anatomical frames were defined from joint centers and breadth markers following standard recommendations for bone embedded axes and reporting of joint motion^{44,257,258}. For the thigh, the PD axis pointed from HJC toward KJC, the ML axis along the knee width from medial (KNM) to lateral (KNL) markers, and the remaining axes were obtained by cross products. For the shank, the PD axis pointed from AJC toward KJC, and the ML axis followed the ankle width from the medial (ANM) to the lateral (ANL) markers.

For each frame, the hip-to-knee vector $v_{thigh}=HJC-KJC$ and the ankle-to-knee vector $v_{shank}=AJC-KJC$ were normalized and their dot product computed. The flexion angle was defined as the supplement of the arccosine to ensure an acute angle during flexion:

$$\theta_{markers} = 180^\circ - \cos^{-1}(\hat{v}_{thigh} \cdot \hat{v}_{shank})$$

For interpretability relative to clinical descriptions of knee motion, the relative orientation extraction and axis choices were made to be consistent with the Joint Coordinate System framework⁹⁵. A static trial provided per-frame cluster triads. These were averaged and re-orthonormalized via singular-value decomposition to define static cluster means. The cluster-to-anatomy rotation for each segment, R_{off} , was obtained by multiplying the transpose of the mean cluster triad by the mean anatomical triad⁴⁴.

8.5 Simulated Inertial Measurements from MoCap

To synthesize IMU signals from the marker data, the cluster rotation $R_{seg}(t)$ for each segment was taken as the IMU orientation. Angular velocity in the sensor frame was obtained from the skew-symmetric matrix $S = R^T \dot{R}$, where $\dot{R}$ was approximated by a central difference $(R(t + \Delta t) - R(t - \Delta t))/(2\Delta t)$; the body-fixed rates were then $\omega = [S_{32}, S_{13}, S_{21}]^T$. Linear acceleration at the segment center of mass (COM) was computed in the global frame by a second difference of the COM position and rotated into the body frame after gravity removal:

$$a_{gl} \approx \frac{p(t + \Delta t) - 2p(t) + p(t - \Delta t)}{\Delta t^2}, \quad f_{body} = R^T(a_{gl} - g), \quad g = [0, 0, -9.81]m/s$$

Simulated IMUs were generated for the thigh and shank using CMTHIGH and CMSHANK for COMs. A trunk IMU used a cluster defined by SN and C7 (falling back to SN and XP if C7

was unavailable) for the superior centroid and the average of available low-back markers (at least two required) for the inferior centroid; the AP direction was defined from SN toward the scapular midpoint (RSCAP/LSCAP). A foot IMU used HEE, M1, and M5 to define PD (heel to mid-metatarsal) and ML (M5 to M1), with CMFOOT for COM acceleration. Segment axes and anatomical mappings followed the same conventions as the marker reference^{44,257,258}.

8.6 Real IMU Fusion and Static Calibration

Real IMU orientations were estimated from gyroscope, accelerometer, and magnetometer data using MATLAB's *ahrsfilter* (and, for sensitivity checks, *imufilter*). These toolboxes provide quaternions/rotation matrices representing the rotation of the sensor body frame relative to a navigation frame. The Delsys Trigno sensors were synchronized with the Vicon motion-capture system during acquisition, allowing inertial and marker-based measurements to be recorded on a common timeline. Minor residual temporal offsets between systems were subsequently evaluated and corrected during processing using the time-alignment procedures described in Section 8.7.

Static calibration established a fixed mapping from the IMU's sensor axes to the segment's cluster axes. Instead of relying on AHRS in the static pose, which can be sensitive to drift, the static IMU triads were constructed directly from the IMU's accelerometer and magnetometer: the local Z axis was aligned with the opposite of gravity ($-\text{accel}$), the local X axis with $\text{mag} \times Z$, and the local Y axis with $Z \times X$. The optimal rotation from IMU to cluster over all static frames was then solved using the Kabsch (orthogonal Procrustes) method, ensuring a proper rotation (determinant +1)¹²⁶. Per-frame static helical-angle errors between the rotated IMU triads and the marker-derived cluster triads verified the calibration and were expected to be below one to two degrees on average. The final sensor-to-anatomy mapping for each segment combined this IMU-to-cluster rotation with the previously computed cluster-to-anatomy transformation. Additionally, widely used gradient-descent orientation filters (e.g. Madgwick) informed our sensitivity analyses¹⁴⁸. Despite these calibration and filtering procedures, substantial disagreement remained between the real IMU and marker-derived knee angles, motivating the additional validation steps described in Sections 8.8–8.10.

8.7 Knee Angle Estimation and Validation Metrics

For both markers and simulated IMUs, anatomical orientations were obtained by multiplying the cluster rotation by the cluster-to-anatomy offset for the thigh and shank, respectively. For real

IMUs, sensor-to-world rotations from the filter were transposed and then post-multiplied by the sensor-to-anatomy offsets computed from the static calibration. In all cases, the relative rotation between the thigh and shank anatomical frames, $R_{rel} = R_{thigh}^T R_{shank}$, was used to extract knee flexion. Flexion was measured about the anatomical ML axis using the *atan2* parameterization $\theta = \text{atan2}(R_{rel}(1,3), R_{rel}(3,3))$, which yields a signed, continuous angle consistent with the anatomical definition⁹⁵.

Each knee-angle series contained a static posture at the beginning of the trial. To remove pose offsets, the mean of the first 50 frames was subtracted from each time series. The IMU and marker timelines were then aligned. When the sampling rates differed or a slight lead-lag was suspected, an angular-velocity proxy (IMU body-rate projected onto the cluster-defined flexion axis) was cross-correlated to estimate a small time shift, after which all series were interpolated onto a common time grid. To diagnose orientation issues independently of joint angle extraction, a helical angle orientation error was computed between the anatomical frames derived from the IMU pipeline and those derived directly from the cluster markers, both in the static trial and dynamically¹⁴⁸.

Agreement between IMU-based and marker-based knee angles was quantified using Pearson’s correlation coefficient (*r*) and root-mean-square error (RMSE) in degrees, computed after baseline removal and time alignment. To diagnose orientation issues independently of the knee-angle extraction, a helical-angle orientation error was computed between the anatomical frames derived from the IMU pipeline and those derived directly from the cluster markers, both in the static trial (to verify calibration) and dynamically (to verify filter performance and mapping). A hinge-axis projection test provided an additional check: the IMU’s angular velocity was projected onto the cluster-defined flexion axis and compared to the cluster’s own angular-velocity component; high correlation in this projection indicates correct axis alignment even if absolute angles are offset^{44,95,257,258}.

8.8 Sensitivity Analyses and Implementation Considerations

Filter choice and configuration were examined by comparing *ahrsfilter* (with and without magnetometer) to *imufilter* (gyro + accel), and by varying noise parameters and magnetometer usage. Multiplication order (world-to-sensor versus sensor-to-world), sign conventions, and the combination of static mappings (IMU-to-cluster via Kabsch) with cluster-to-anatomy offsets were

verified explicitly. Missing markers were handled with principled fallbacks: when thigh clusters were incomplete, the PD axis was approximated by the line from the greater trochanter (GT) to the knee center (mean of KNM and KNL); when shank clusters were missing, the PD axis followed from knee to ankle centers (ANM and ANL). For the trunk, the superior centroid fell back from SN+C7 to SN+XP if C7 was unavailable, and at least two low-back markers were required to define the inferior centroid. Unit consistency and numerical differentiation were monitored, and gravity subtraction was always performed in the global Z-up frame prior to transformation into segment frames. We also compared axis projection correlations before and after any static or temporal corrections to isolate whether discrepancies arose from mounting, channel assignment, or fusion rather than from joint angle extraction^{126,148,243}.

Simulated IMUs served as a positive control and were expected to closely match marker-based knee angles (target $r > 0.9$, RMSE $< 5^\circ$) because their orientations are derived directly from the cluster frames. Real IMUs ideally approach similar performance under correct mounting and configuration. Orientation diagnostics targeted $\leq 1-2^\circ$ mean static error after calibration and $< 5^\circ$ mean dynamic error during movement; hinge axis- projection correlations were expected to exceed 0.9 when frames were correctly mapped^{44,95}.

All rotations used right-handed conventions. Cross products were ordered to enforce orthonormal frames, and singular-value decomposition-based re-orthonormalization was applied to mean triads. Angular velocity used central differences of rotation matrices with endpoint replication; linear acceleration used second differences of COM positions, with gravity subtracted in a Z-up global frame before rotation into body frames. The entire pipeline was implemented in MATLAB, with *ahrsfilter* and *imufilter* used for orientation fusion and standard linear algebra utilities for calibration and mapping.

Together, these steps provided a reproducible procedure to synthesize inertial signals from MoCap, to fuse and map real IMUs into anatomical frames, and to quantify agreement with a marker-based reference while isolating the source of any mismatch.

8.9 Validation of the Processing Pipeline

To verify the validity and generalizability of the full processing pipeline, an independent dataset containing synchronized optical motion capture and wearable IMU recordings was analyzed. This validation step was performed after the disagreement between real IMU signals and

marker-based knee kinematics was identified in the present dataset, in order to determine whether the discrepancies arose from limitations in the sensor recordings or from errors in the processing, calibration, or joint-angle extraction pipeline.

The dataset published by Scherpereel et al.²¹⁷ was used for this purpose. This dataset includes synchronized optical motion capture and wearable Delsys Trigno IMU recordings collected during a variety of cyclic and non-cyclic lower-limb tasks, including squatting. It includes tri-axial inertial measurements (accelerometer and gyroscope) together with corresponding three-dimensional marker trajectories acquired in a controlled laboratory environment. The dataset was specifically designed to support the development and validation of biomechanical and wearable sensing algorithms.

The squat trial from the right leg of this dataset was selected for validation. This dataset enables a direct comparison between IMU-derived joint kinematics and marker-based reference measurements. The same filtering, calibration, and relative rotation procedures described in Sections 8.6-8.8 were applied to the Scherpereel data.

To ensure compatibility with the present analysis pipeline, only minor adjustments were required. These consisted primarily of adapting marker and segment naming conventions to match those used in the present dataset. No modifications were made to the filtering procedures, orientation fusion methods, static calibration approach, anatomical frame construction, or joint-angle extraction algorithm. Knee flexion was computed using the same relative rotation formulation:

$$\theta = \text{atan2}(R_{rel(1,3)}, R_{rel(3,3)})$$

following orientation estimation and static baseline removal. Agreement between IMU-derived and marker-based knee angles was quantified using Pearson's correlation coefficient and RMSE. This comparison provided an independent validation of the processing pipeline under conditions where well-synchronized IMU and motion capture data were available, allowing acquisition-related limitations in the present dataset to be distinguished from potential methodological errors in the analytic framework. The resulting knee-angle comparisons are presented in Section 8.10.2.

8.10 Results

8.10.1 Validation Using the Present Dataset

Across participants and trials, the simulated IMUs, synthesized directly from the MoCap kinematics, showed substantially better agreement with the marker-based knee angle than the real IMUs (Figures 8.4 and 8.5). The mean ($\pm$ SD) Pearson correlation for simulated IMUs was 0.82 ± 0.27 , with an RMSE of $15.2^\circ \pm 11.4^\circ$. In contrast, the real IMUs yielded a mean correlation of 0.07 ± 0.43 and an RMSE of $83.4^\circ \pm 61.9^\circ$. Correlation values were summarized across trials after Fisher z-transformation to reduce bias associated with averaging Pearson correlation coefficients.

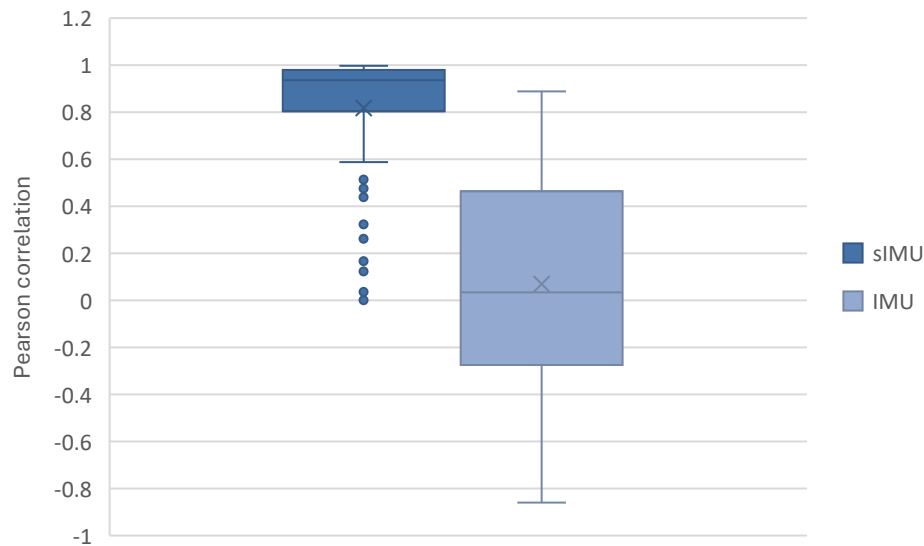


Figure 8.4. Distribution of Pearson correlation coefficients between IMU-derived knee flexion angles and marker-based reference knee flexion across maximal anterior, maximal lateral, triple hop, and cross hop trials for participants with IMU recordings ($n = 23$, 160 trials), comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.

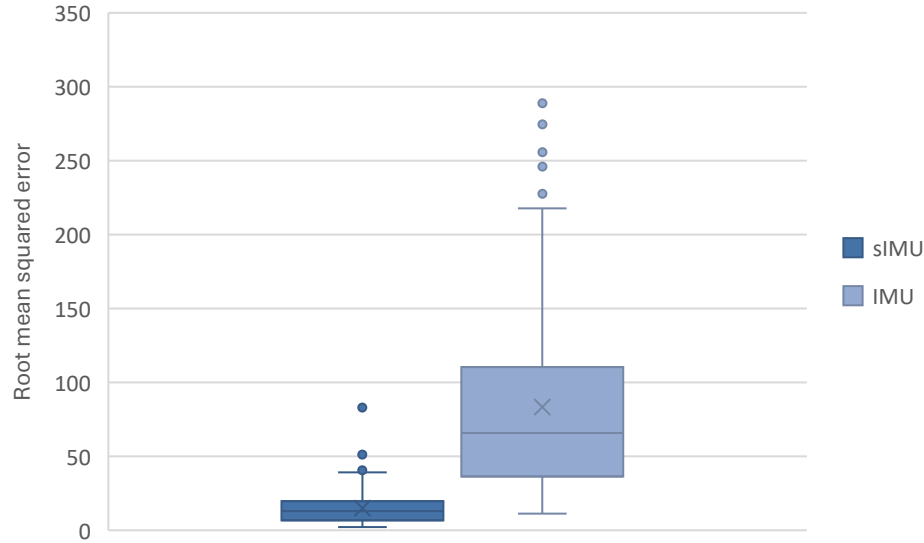


Figure 8.5. Boxplots of root mean squared error (RMSE) between IMU-derived and marker-based knee flexion angles across maximal anterior, maximal lateral, triple hop, and cross hop trials for participants with usable IMU recordings ($n = 23$, 160 trials), comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.

These results support the face validity of the processing pipeline when ground truth orientations are used (simulated IMUs), while simultaneously demonstrating a pronounced mismatch in the real sensor branch, consistent with mounting, channel, or fusion configuration issues rather than a failure of the mapping or joint angle extraction^{44,95}. Figure 8.6 illustrates representative knee flexion–extension traces for a single participant and trial, showing the marker-based reference, the simulated IMU angle, and the real IMU angle overlaid on the same time axis. The sIMU closely tracks the marker curve ($r = 0.97$, $\text{RMSE} = 3.4^\circ$), whereas the real IMU diverges in both amplitude and phase ($r = 0.23$, $\text{RMSE} = 34.0^\circ$).

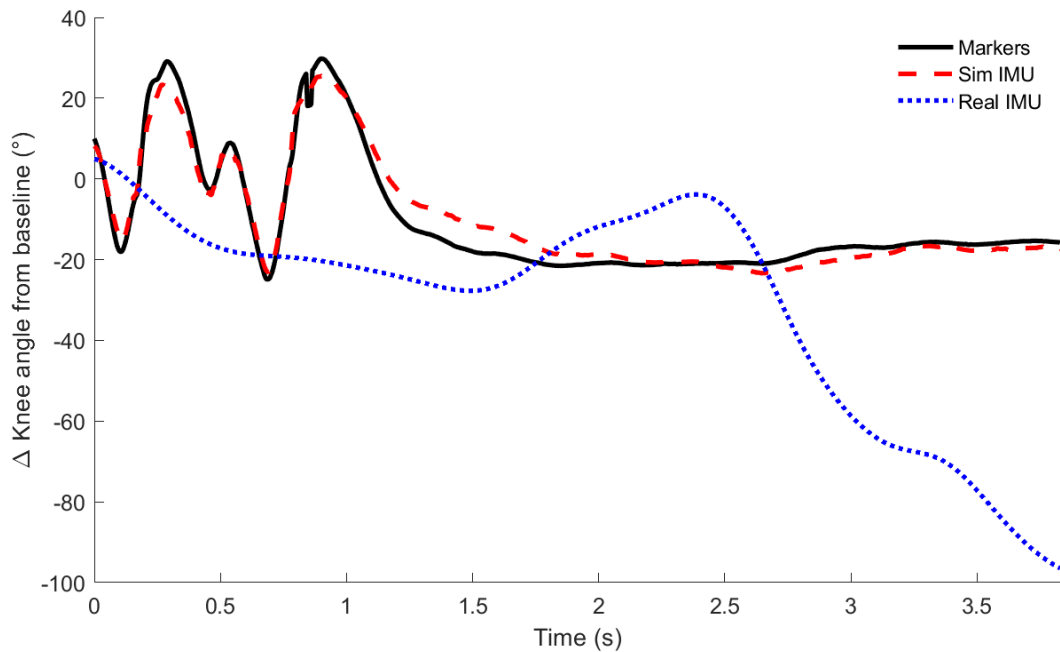


Figure 8.6. Representative knee flexion–extension time series from a single hopping trial showing marker-based reference angles (black), simulated IMU-derived angles (red, dashed), and real IMU-derived angles (blue, dotted) after baseline correction relative to the first 50 frames of the trial.

8.10.2 Independent Validation Using the Scherpereel Dataset

To independently confirm that the processing pipeline yields accurate knee-angle estimates when applied to well-synchronized IMU recordings, the procedures described above were applied to the Scherpereel dataset. The comparison using the open-source dataset²¹⁷ demonstrated that the IMU processing pipeline could accurately reproduce reference knee flexion when high-quality, synchronized IMU and marker data are available (Figures 8.7 and 8.8). The sIMUs using the marker clusters on the thigh and shank demonstrated excellent correspondence with the marker-based knee angle ($r = 0.966 \pm 0.034$, $RMSE = 20.56^\circ \pm 15.50$), while the physical thigh and shank IMUs also showed excellent agreement ($r = 0.969 \pm 0.035$, $RMSE = 21.91^\circ \pm 12.77$). Differences in RMSE magnitude between datasets likely reflect task differences (hopping versus squatting), movement amplitude, and trial duration rather than inconsistencies in the processing pipeline. Figure 8.9 illustrates representative knee flexion-extension traces over a six-second squat sequence, showing that both IMU and sIMU preserve the timing and shape of the movement pattern, with the simulated IMU (red, dashed) tracking slightly above the marker-based curve (black) and the real IMU (blue, dotted) slightly below. These findings confirm that the developed processing and calibration procedures yield accurate joint-angle estimates when applied to well-

aligned, fully synchronized data, reinforcing that the discrepancies observed in the original dataset likely reflect sensor-related acquisition issues rather than deficiencies in the analytical framework.

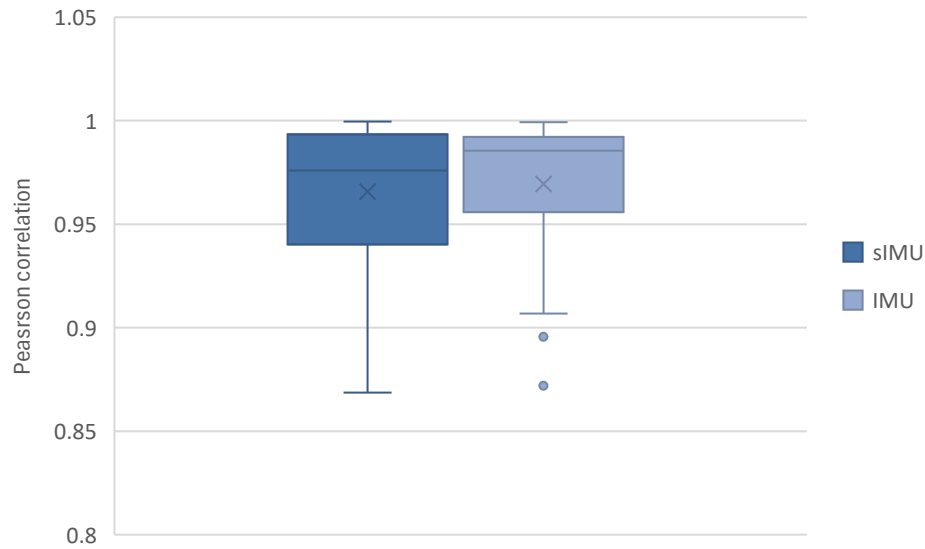


Figure 8.7. Boxplots of Pearson correlation coefficients between IMU-derived and marker-based knee flexion angles from the Scherpereel et al. (2003) open-source dataset²¹⁷ during a squat trial, comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.

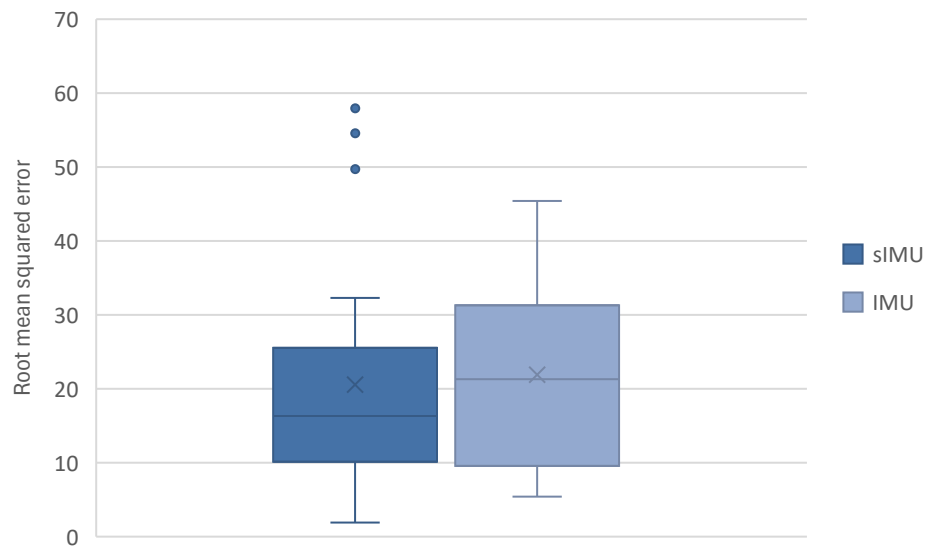


Figure 8.8. Boxplots of root mean squared error (RMSE) between IMU-derived and marker-based knee flexion angles from the Scherpereel et al. (2023) open-source dataset²¹⁷ during a squat trial, comparing real IMU signals with simulated IMU (sIMU) signals derived from motion capture kinematics.

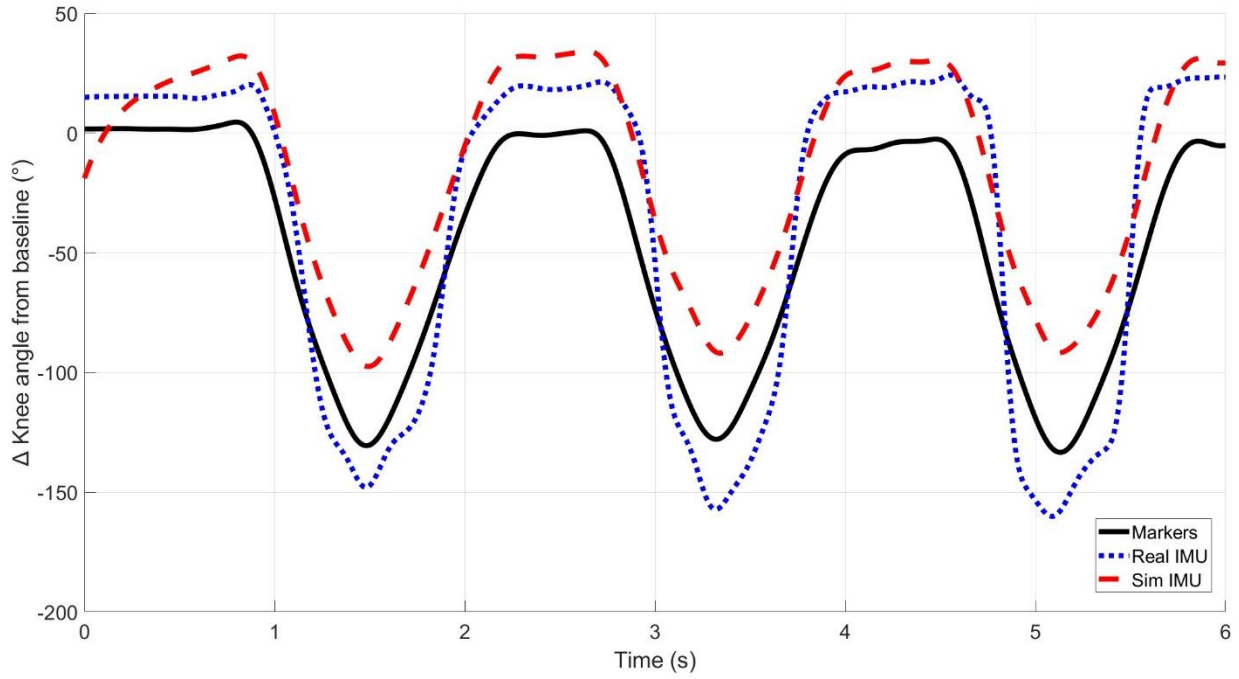


Figure 8.9. Representative knee flexion-extension time series from a squat trial in the Scherpereel et al. (2023) open-source dataset²¹⁷ showing marker-based reference angles (black), real IMU-derived angles (blue, dotted), and simulated IMU-derived angles (red, dashed) plotted over the same time axis to illustrate agreement between modalities.

Together, these results establish that the processing framework itself performs reliably under ideal conditions, and that the discrepancies in the collected data arise from limitations in the raw sensor recordings rather than from methodological implementation.

8.11 Interpretation of Simulated IMU Outliers

Although sIMUs demonstrated strong agreement with marker-based knee kinematics across most trials, a small subset exhibited low correlation and elevated RMSE relative to the marker-derived reference angle. These cases were examined to determine whether the discrepancies originated from instability in the simulated IMU generation pipeline or from limitations in the marker-based reference definition used for comparison.

Additional analyses were performed on the identified outlier trials by recomputing knee flexion using independently constructed anatomical coordinate systems derived directly from joint center and medial and lateral landmark markers at the knee and ankle. Unlike the sIMUs, which rely on rigid cluster-based segment frames, these anatomical rotations were defined from

instantaneous joint landmark geometry and therefore did not share identical marker inputs or frame construction assumptions.

Across the examined trials, anatomical rotation-based knee angles demonstrated reduced agreement with the sIMU signals, with correlations ranging from weak to moderate and substantially elevated RMSE values. Visual inspection revealed intermittent discontinuities and large amplitude excursions consistent with 180° orientation inversions arising from axis instability during dynamic movement. These inversions occur when anatomical axes defined by nearly collinear landmark configurations become numerically ill-conditioned, allowing small marker perturbations or soft-tissue motion to reverse the axis direction between frames.

Dynamic hopping tasks involve rapid impact loading, multiplanar motion, and transient marker occlusion, all of which increase the sensitivity of anatomical frame construction to local marker noise. The relative rotation formulation depends on consistent segment-axis orientation over time; therefore, intermittent axis reversal propagates directly into the extracted joint angle, despite otherwise reasonable segment motion. In contrast, the sIMU orientations are derived from rigid marker clusters whose spatial separation improves numerical stability and preserves frame continuity throughout the movement.

These findings indicate that the observed sIMU outliers do not reflect errors in signal synthesis or joint angle extraction. Rather, they arise from the sensitivity of the marker-based reference definition to anatomical frame instability under dynamic conditions. Consequently, disagreement in these trials reflects limitations of the reference representation rather than failure of the sIMU framework itself.

8.12 Conclusion

Across the majority of participants and trials, sIMUs reproduced the marker-based knee flexion with high correspondence, whereas real IMUs showed low and variable agreement despite exhaustive calibration, axis-projection checks, alternative fusion filters, and static and dynamic orientation diagnostics. The real sensors were affixed directly to the skin, not rigidly mounted, and only one dynamic trial lacked a complete thigh and shank cluster (fallback used for that trial), indicating that pervasive missing-marker issues are unlikely to explain the overall mismatch.

Although overall agreement between sIMUs and marker-based knee angles was high, a small subset of trials demonstrated reduced correlation or elevated RMSE. Additional investigation of

these outliers was therefore performed to determine whether they reflected instability in the sIMU generation pipeline or limitations in the reference kinematic definition. Knee flexion was recomputed using independently constructed anatomical coordinate systems derived directly from joint center and medial-lateral landmark markers, rather than cluster-based segment frames used for sIMU synthesis. In these trials, anatomical-frame reconstructions exhibited intermittent orientation discontinuities and large amplitude deviations relative to the sIMU signals, including apparent 180° inversions of segment orientation.

These findings indicate that the observed outliers primarily arose from instability in dynamically reconstructed anatomical reference frames rather than error in simulated inertial signal generation. Anatomical axes defined from joint centers and closely spaced medial-lateral markers are inherently sensitive to soft tissue motion artifact, marker noise, and temporary geometric degeneracy during rapid or multiplanar movements such as hopping. Small perturbations in landmark positions can cause axis flipping or loss of orthogonality, which propagates directly into relative rotation calculations and produces large apparent knee-angle errors despite otherwise consistent segment motion. In contrast, sIMU orientations are derived from technical marker clusters with larger spatial separation, resulting in numerically stable segment frames across the movement cycle.

Several additional factors could plausibly contribute to the variability observed in both real IMU signals and isolated sIMU outliers. Time-varying sensor-to-segment offsets due to soft-tissue motion artifact and intermittent sensor slip cannot be fully corrected using a single static calibration. Yaw observability limitations and magnetometer disturbance (soft- or hard-iron interference) may degrade heading estimates while roll and pitch remain reasonable. Axis-convention or sign inconsistencies between device firmware and analysis frames may preserve local angular velocity projections but corrupt integrated joint angles. High-impact landing phases may also introduce transient saturation or shock-induced bias. Sampling-rate mismatch and trigger timing were quantified as small following affine time correction and are unlikely, on their own, to account for the observed magnitudes.

Taken together, the pattern suggests that variability in the acquired real IMU signals and sensitivity of anatomical reference frame construction during dynamic tasks underlie the remaining disagreement with marker-based kinematics, rather than deficiencies in the analytical framework itself. Consequently, to address the thesis research questions without introducing avoidable bias

from sensor misalignment or unstable reference definitions, simulated IMUs were selected for the final analyses of Chapter 9, Article 4.

8.12 Postamble

This chapter evaluated the agreement between marker-based knee flexion angles and both real and simulated inertial measurements during functional hopping tasks in adolescents. The results demonstrated a clear divergence in performance between the two approaches. Simulated IMUs, generated directly from segment kinematics, consistently reproduced marker-based knee flexion patterns with substantially higher correlation and lower error. In contrast, real IMUs exhibited low and highly variable agreement despite extensive calibration procedures, orientation diagnostics, and sensitivity analyses.

The strong performance of the simulated IMUs confirms the validity of the anatomical mapping, relative orientation extraction, and joint angle computation pipeline developed in this work. When ground truth segment orientations were available, the framework reliably reconstructed knee flexion across tasks and participants. Validation using an independent open-source dataset further demonstrated that the same pipeline produced accurate results when applied to well-aligned and synchronized inertial recordings, supporting its generalizability across sensor systems and experimental contexts.

The poor performance of the real IMUs is therefore unlikely to reflect methodological shortcomings within the processing framework itself. Instead, the observed discrepancies are consistent with limitations in the acquired sensor data, including time-varying sensor-to-segment misalignment, soft tissue motion artifact, magnetometer disturbance, axis convention inconsistencies, and potential saturation during high-impact phases of hopping. These factors are difficult to correct retrospectively and may vary unpredictably across participants and trials.

Given these findings, the use of real IMU data in subsequent analyses would introduce substantial uncertainty unrelated to the biomechanical phenomena under investigation. To avoid propagating sensor-related error into classification models and interpretation of movement strategies, sIMUs were selected as the inertial data source for the analyses presented in Chapter 9. This decision allows the thesis to address its central research questions while maintaining consistency, transparency, and methodological rigour.

Together, the outcomes of this chapter establish sIMUs as a valid and defensible surrogate for wearable sensors within this dataset and provide a verified foundation for the final analyses examining inertial-based classification of functional performance in adolescent populations.

CHAPTER 9: ARTICLE 4

Simulated IMUs for ACL Injury Classification in Adolescents: A Task- and Configuration-Specific Analysis of Single-Limb Hops

In preparation for Gait & Posture

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9.1 Preamble

Wearable IMUs offer a feasible pathway for extending objective movement assessments from the biomechanics laboratory into clinical and field settings. Their portability and relatively low cost make them ideal for monitoring RTA progression after ACLi, particularly in adolescent populations who often have limited access to laboratory facilities. Previous chapters demonstrated that adolescents with ACLi exhibit task- and sex-dependent differences in functional performance using clinically accessible hop outcomes (e.g., hop distance, timed hop performance, and limb symmetry indices measured with a tape measure and stopwatch), as well as movement-pattern classifiers derived from laboratory motion capture. However, the practical adoption of laboratory-based movement-pattern approaches remains constrained by the reliance on optical motion capture.

The prior validation work established that the available real IMU recordings in this cohort were not of sufficient quality to support reliable kinematic reconstruction and would introduce substantial uncertainty into any classification analysis. To evaluate the feasibility of an inertial-sensor approach without additional data collection, this chapter uses motion-capture-derived simulated IMUs to generate accelerometer and gyroscope signals under idealized conditions. Simulated IMUs provide a controlled representation of inertial signals that preserves the task dynamics of the original movements while removing hardware-related limitations, enabling systematic investigation of sensor placement and configuration.

The purpose of this chapter is to determine whether simulated IMU signals can differentiate adolescents with ACLi from healthy controls during four single-limb hop tasks, and to identify which combinations of lower back, thigh, shank, and foot sensors provide the most informative representations for classification. By combining robust scaling, principal component analysis, ensemble feature selection, and supervised classification within a cross-validation framework, this work evaluates performance using metrics that emphasize injured-class detection rather than accuracy alone. The findings are intended to inform practical design choices for wearable assessment protocols in adolescents, including task selection, sensor placement, and analytic strategy.

9.2 Introduction

Adolescents experience high rates of anterior cruciate ligament (ACL) injury and re-injury, with only two-thirds of patients returning to their preinjury level of activity by 12 months post-surgery¹. Current return-to-activity criteria, such as strength symmetry and hop-test performance, were developed in adults and may not reflect the biomechanical and developmental complexities of the adolescent athlete. To begin addressing this gap, our previous work systematically characterized movement asymmetries and sex differences in adolescents following ACL injury using single-limb hopping tasks. That work included spatiotemporal analyses²² and whole-body movement pattern discrimination (Chapter 7) to understand how injury status, limb, and sex influence movement strategies and to support more individualized rehabilitation.

Our findings revealed significant sex-dependent differences in movement between adolescents with and without ACL injury, with classification accuracies of 53.3% for males and 76.9% for females based on spatiotemporal variables. Extending beyond those metrics, a combined principal component analysis and linear discriminant analysis framework was able to distinguish injured from uninjured movement patterns with high accuracy: comparing the injured limb of ACL-injured adolescents to healthy control limbs yielded accuracies between 73.1% and 81.8%, and the contralateral limb versus controls achieved 72.0% to 78.2%. Despite these promising results, reliance on laboratory-based optical motion capture limits scalability and real-world utility due to its high cost, long setup time, and infrastructure requirements.

While much of the foundational research on knee joint function and readiness for return-to-activity has been conducted in adult populations using controlled laboratory instruments, such as optical motion capture, isokinetic dynamometers, electromyography and force plates, there has been a notable shift toward portable wearable technologies^{38,51}. Inertial measurement units (IMUs) can capture tri-axial linear acceleration, angular velocity, and magnetic field information from body segments in clinical and field settings, and modern sensor fusion techniques have improved their ability to estimate three-dimensional orientation and kinematics in real time^{16,42,44,45}. Beyond portability, IMU-based workflows offer significantly lower capital and operational costs than camera-based MoCap (e.g., fewer sensors to purchase and maintain, minimal space and setup requirements, and no multi-camera calibration), thereby facilitating broader deployment in clinics, schools, and community settings. These characteristics make IMUs appealing for objective movement assessment outside the laboratory.

IMUs combined with machine learning have emerged as a powerful approach for extracting clinically meaningful movement patterns across a range of contexts. Both single- and multi-sensor configurations have been used to characterize neuromotor status, fatigue, risk factors, and functional performance across athletic and nonathletic populations^{27,28,34,49,58}. Multi-IMU systems, often coupled with advanced architectures such as convolutional neural networks or ensemble models, enhance robustness and enable more complex activity recognition and state estimation^{10,39,47}. Fusion of inertial signals has also been applied to infer internal biomechanical processes, such as joint loading⁵⁰, extending wearable sensing beyond surface-level motion tracking. Within this broader context, the configuration and placement of IMUs determine which aspects of segmental and intersegmental dynamics are captured, and analytic choices such as feature extraction and model selection govern how effectively those signals are translated into meaningful discrimination. Thoughtful alignment of sensor placement with data-driven feature selection and appropriate classifiers can amplify subtle injury-related movement differences and improve reliability across tasks. Given the high dimensionality of time-series IMU signals relative to typical clinical sample sizes, robust feature selection strategies are essential to reduce overfitting and enhance the generalizability of classification models. Similarly, evaluating multiple classification approaches can help ensure that observed discrimination is not dependent on a specific modelling assumption but reflects a consistent signal across analytic frameworks.

Despite these advances, the application of IMU-based machine learning to classify ACL injury status in adolescents remains limited. The literature on predicting re-injury risk and functional readiness using wearable-derived features is sparse, and key work, such as identifying individuals at heightened risk of secondary injury, has highlighted the need for more objective and sensitive tools⁴⁰. Moreover, while IMU based movement quality assessments have gained popularity, they have not been widely adopted in routine clinical practice, in part because clinicians often lack time to adopt new tools and because existing outputs are not always interpretable or actionable for functional decision-making⁵⁵. Demonstrating the ability to objectively differentiate movement patterns between adolescents with and without ACL injury is a necessary first step; these differences can inform care decisions, guide individualized rehabilitation, and serve as a reference for evaluating recovery trajectories.

To assess the feasibility of a wearable-sensor approach, MoCap-derived simulated IMUs were used to generate IMU-style signals directly from segment cluster frames. This approach

provides an upper bound on the discriminative potential of IMU signals under idealized rigid coupling and allows systematic exploration of sensor placements and configurations while leveraging the existing MoCap dataset.

Accordingly, this study had two primary objectives. First, to evaluate whether simulated IMU signals can differentiate ACL-injured adolescents from healthy controls during four single-limb hopping tasks. Second, to determine which simulated sensor configuration among combinations of low back, thighs, shanks, and feet is optimal for detecting meaningful injury-related movement differences. This work lays the foundation for translating wearable sensor-based assessments into clinical practice by identifying both effective sensor configurations and classification strategies for adolescent populations with ACL injuries.

9.3 Methods

9.3.1 Participants

One hundred and seventeen adolescents who participated in a prior biomechanical study investigating anterior cruciate ligament (ACL) injuries were included in this study (Chapter 7). The sample comprised both injured (37 females and 16 males; 15.4 ± 1.3 years old) and uninjured individuals (37 females and 27 males; 13.9 ± 1.8 years old). Participants in the ACL-injured (ACL_i) group had a confirmed complete rupture of the ACL, as diagnosed by a licensed physician. Individuals were excluded from this group if they had a history of contralateral ACL injury, were undergoing revision surgery, or had any other condition known to impair neuromuscular function.

The control group (CON) consisted of uninjured adolescents recruited from local schools and sports organizations. Participants were excluded if they reported a prior lower limb surgical procedure, a significant lower limb injury within six months of testing (such as a fracture or severe sprain), or a chronic or acute condition that could adversely affect neuromuscular control. Informed consent was obtained from all participants, and assent was collected from minors following institutional ethical approval. Parental or legal guardian consent was also obtained when appropriate.

9.3.2 Protocol

Upon arrival at the biomechanics laboratory, participants reviewed and signed informed assent/consent documentation, after which they completed a brief injury history questionnaire. Anthropometric measurements were then recorded, including height, body mass, thigh and shank

circumferences, and segment lengths. Participants were instrumented with 84 retroreflective markers to enable full-body motion tracking³. Following marker placement, a static pose was acquired to establish participant-specific skeletal geometry and segment coordinate frames. Full body motion data was sampled at 200 Hz using a 10-camera optical motion capture system (8 Vero, 2 Vantage, Vicon, Oxford, UK).

Each participant completed a battery of single-limb hopping tasks designed to assess lower limb function. These included the maximal anterior hop (Ant), lateral hop (Lat), cross-hop for distance (Crs), and triple hop for distance (Trp)^{23,37}. All tasks were performed unilaterally on both limbs, resulting in a total of eight trials per participant. During each trial, participants were instructed to place their hands on their hips, perform the hop at maximal effort, and maintain balance for a minimum of three seconds upon landing. The Crs task required participants to complete three consecutive forward hops while crossing two parallel lines spaced 15 cm apart. Each task was repeated as needed until two successful trials were recorded. A trial was deemed successful if all movement requirements were satisfied without compensatory actions or balance loss. Additional details on the experimental protocol can be found in Chapter 7.

For analysis, only contributing trials were included, defined as successful trials with complete motion-capture data sufficient to derive the simulated IMU signals. Not all participants completed every task on both limbs, and some trials were excluded for data quality reasons; therefore, the number of contributing trials differs by task and limb. Sample sizes are reported with each analysis.

9.3.3 Simulated IMU Generation

Simulated inertial signals were derived from the marker-based motion capture data using a custom MATLAB function that emulated segment-fixed IMUs¹⁴. Angular velocity was estimated by differentiating segment rotation matrices constructed from technical marker clusters, while linear acceleration was derived from the second derivative of the center of mass trajectory for each segment. To emulate accelerometer data, gravitational acceleration was subtracted in the global Z frame before rotating into the segment frame, and signals were expressed using standard SI units. No magnetometer signals were simulated; the simulated signals model a 6-DOF IMU (gyroscope + accelerometer) rather than a full 9-DOF unit. This choice reflects common practice in field settings, where magnetometer measurements can be unreliable due to soft-/hard-iron effects and

environmental interference and are therefore not always incorporated into fusion when the objective is to obtain linear accelerations and angular velocities rather than absolute headings.

Five sensor configurations were simulated to evaluate the influence of sensor placement on classification accuracy (Figure 9.1). Configuration AA includes a single low-back sensor with bilateral sensors on the thighs, shanks, and feet (seven IMUs total: 1 low back, 2 thighs, 2 shanks, 2 feet). Configuration AB comprised the low-back sensor plus sensors on the hopping limb only, defined as the thigh, shank, and foot on the limb performing the task (four IMUs total: 1 low back, 3 on the testing limb). Configuration AC used bilateral thigh and shank sensors without the feet (four IMUs total). Configuration AD placed sensors bilaterally on the thighs, shanks, and feet (six IMUs total, no low back). Configuration AE combined the low-back sensor with bilateral thigh and shank sensors (five IMUs total).

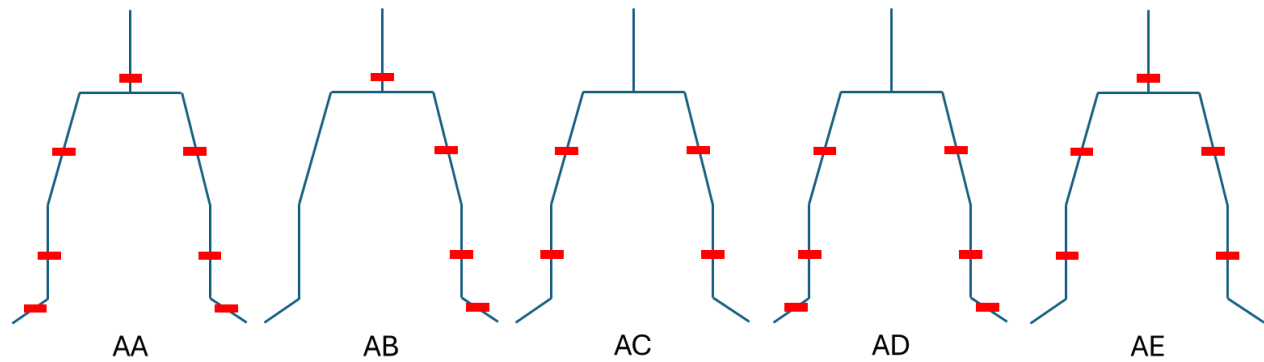


Figure 9.1. Simulated IMU configurations (AA-AE) and lower-body placements including the lower back, thighs, shanks, and feet.

9.3.4 Pre-processing

Marker trajectories used for IMU signal simulation were first rotated to align the local foot coordinate system with the global reference frame. The data were then translated such that the midpoint between the bilateral hip joint centers in the first frame of each trial coincided with the global origin. Time series data were trimmed according to task-specific movement onset and termination criteria, and all trials were normalized to 500 frames using a piecewise cubic Hermite interpolating polynomial to account for variability in task duration¹⁹. For interpretive purposes, each time-normalized hopping waveform was conceptually divided into functional phases reflecting task mechanics: preparatory/takeoff (propulsive phase preceding toe-off), landing

(initial ground contact to peak deceleration), and stabilization (post-landing control period). These phase labels were used descriptively to contextualize the temporal distribution of dominant feature contributions and were not used as inputs to classification. To remove high-frequency noise, a fourth-order, dual-pass low-pass Butterworth filter with a cut-off frequency of 15 Hz was applied to the simulated IMU signals⁵⁶.

To enable pooled analysis across limbs, trials performed on the left limb were mirrored across the sagittal plane to ensure a consistent spatial reference frame. This mirroring step prevented the principal components from capturing variance attributable solely to limb laterality rather than task-related movement patterns^{21,36}. For this study, only the injured limb of participants in the ACL-injured group (ACLi) was analyzed, and it was compared against the limbs of uninjured controls (CON).

Since simulated IMU features are expressed in different physical units (linear acceleration in meters per second squared (m/s^2) and angular velocity in radians per second (rad/s)), all IMU-derived features were robust-scaled per task within each cross-validation fold before dimensionality reduction and classification⁴¹. Robust scaling subtracts the median and divides the interquartile range (75th-25th percentile), limiting outlier influence and preventing unit-driven dominance of any feature family while avoiding data leakage by fitting the scaler within each training fold only.

9.3.5 Principal Component Analysis

Principal Component Analysis (PCA) was applied to the robust-scaled IMU features to obtain orthogonal principal components ordered according to the amount of variance explained. Subsequent feature selection retained a subset of these components for classification, providing a compact representation of the original data²⁹. For each hopping task, a separate PCA was performed. Data matrices were constructed such that each row represented one trial and each column contained the time-normalized angular velocity and linear acceleration values across all simulated sensors and axes. The resulting input matrix for each task had dimensions of $n \times m$, where n represented the number of contributing trials and m corresponded to the number of concatenated signals (i.e., number of sensors $\times$ 6 signals $\times$ 500 time points). PCA was applied within each fold of a leave-one-out cross-validation (LOOCV) framework⁵⁴. Within each fold, the robust scaler (median/IQR) was fit on the training trials for that task and applied to the held-out

trial, after which PCA was fit on the scaled training data and the learned loadings were applied to the held-out trial.

9.3.6 Feature Selection

Given the high dimensionality of the PCA-transformed dataset and the relatively small sample size, an ensemble feature selection strategy was employed to identify the most relevant components for classification⁶. Within each LOOCV fold, five feature selection methods were applied to the training data: 1) ANOVA F-statistic¹⁷, 2) chi-squared test²⁰, 3) mutual information², 4) random forest feature importance⁷, and 5) least absolute shrinkage and selection operator (LASSO) regression coefficients⁵³. Each method ranked the principal components based on their importance for distinguishing between ACLi and CON participants.

The top 25-ranked components from each method were retained, and components that appeared in the top 25 of at least two methods were selected for model training. This voting scheme was used to increase the robustness of the feature selection process by reducing reliance on any single ranking criterion while maintaining a sufficiently broad pool of high-importance components. To further prevent overfitting, the final number of selected components was limited to the square root of the number of training samples within each fold²⁵.

9.3.7 Classification

To evaluate robustness across modeling assumptions, six supervised machine learning classifiers were assessed for their ability to discriminate between ACL-injured and uninjured limbs: 1) logistic regression with class weighting, 2) decision tree classifier, 3) k-nearest neighbours, 4) linear discriminant analysis (LDA), 5) Gaussian naïve Bayes, and 6) support vector machine (SVM) with a linear kernel and balanced class weights⁴¹. Within each LOOCV fold, the training data were first augmented using the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance¹¹. SMOTE generated synthetic injured samples by interpolating between nearest neighbours in feature space, thereby improving the representation of the minority class. For the left-out test trial, the robust scaler, PCA projection, and set of retained components were applied to the raw test features prior to inference.

In addition to evaluating individual classifiers, an ensemble voting model was implemented for each task. Each classifier produced class-membership probabilities for the two classes (ACLi vs CON). For logistic regression and LDA, probabilities are obtained from the model's posterior estimates²⁵; for Gaussian naïve Bayes from normalized class posteriors¹⁵; for k-NN from the

proportion of neighbours in each class¹³; for decision trees from class frequencies in the terminal leaf⁸; and for the linear SVM via logistic calibration fitted on the training fold⁴³. Probabilities are normalized to sum to 1 across classes, and the soft-voting ensemble uses the average of model probabilities to form the final prediction³². The final class label was assigned based on the average probability, providing a consensus prediction that leveraged the strengths of all classifiers⁴⁶.

9.3.8 Model Performance

Model performance was assessed using multiple evaluation metrics, including overall classification accuracy, Cohen's kappa coefficient⁹, F1 score²⁶, and the area under the precision-recall curve (PR AUC)⁴⁸. To quantify uncertainty in injured-class precision, recall, and F1, a nonparametric bootstrap (1000 resamples) was performed for each model and the ensemble within each task, yielding 95% confidence intervals. Paired bootstrap differences (e.g., comparing the ensemble to the best single classifier, such as LDA on a given task) were computed to assess whether observed improvements were statistically meaningful; intervals excluding zero were interpreted as significant gains. For each hopping task and simulated IMU configuration, the classifier that achieved the most balanced injured-class profile through the F1 score, precision and recall was identified and reported.

All data processing, dimensionality reduction, analysis, model training, resampling, and evaluation were conducted using Python (version 3.8), with implementation through the scikit-learn⁴¹, imbalanced-learn³³, NumPy, Pandas, Matplotlib, and Seaborn libraries.

9.4 Results

9.4.1 Anterior Hop (Ant)

The highest F1 for the injured class for Ant was achieved using a Naïve Bayes classifier with configuration AE (low back, thighs, shanks; F1 = 0.39, 95% CI: 0.23-0.53; precision = 0.45 [0.26-0.63], recall = 0.34 [0.19-0.50]), indicating the most balanced detection of injured limbs for this task. In contrast, configuration AD with Naïve Bayes provided the highest single-model accuracy for Ant and yielded comparable injured precision (0.53) but lower recall (0.26). This suggests that the model was conservative in identifying injured cases. Ensemble voting under AD degraded injured-class performance for Ant (precision = 0.45, recall = 0.13), implying that aggregating the results in this context weakened the signal associated with identifying injured cases (Table 9.1).

9.4.2 Cross Hop (Crs)

Configuration AA with Naive Bayes achieved perfect injured recall (1.00 [0.85-1.00]) in the Crs task but did so at the expense of precision (0.36 [0.21-0.53]) and accuracy (37.5%), producing a large number of false positives. Configuration AE with LDA presented a more balanced injured-class profile (F1 = 0.49, 95% CI: 0.36–0.59; precision = 0.39 [0.28–0.50]; recall = 0.66 [0.50–0.80]), making it preferable when both sensitivity and specificity are important. The AB ensemble produced the same F1 score, with a lower accuracy (57.05%) while exhibiting elevated injured recall (0.78) paired with poor precision (0.36), reflecting a tendency to over-identify injured limbs without reliable specificity (Table 9.1).

9.4.3 Lateral Hop (Lat)

Injured-class discrimination for Lat was weak across all configurations. Configuration AE with Naïve Bayes provided the highest injured-class F1 (F1 = 0.28, 95% CI: 0.19–0.36; precision = 0.18 [0.12–0.24]; recall = 0.67 [0.51–0.81]; accuracy = 45.5%), indicating frequent failures to detect injured cases. No placement or model delivered acceptable injured-class sensitivity for Lat, and the high overall accuracies achieved by some classifiers, such as AD's KNN (81.7%), masked their inability to identify injured limbs reliably, revealing a critical separability limitation in this task (Table 9.1).

9.4.4 Triple Hop (Trp)

Performance on the Trp task was the most robust. AD's Decision Tree attained the best single-model injured-class balance (F1 = 0.66, 95% CI: 0.56–0.74), and ensemble voting under AD further enhanced this performance (F1 = 0.66, 95% CI: 0.55–0.75; precision = 0.57 [0.44–0.68]; recall = 0.82 [0.69–0.91]; accuracy = 78.1%), demonstrating that aggregation improved both sensitivity and precision for the injured class in this complex movement pattern (Table 9.1).

Table 9.1. Best configuration and injured-class performance summary per task

Task	Model	Config	# PCs	Precision (CI)	Recall/ Sensitivity (CI)	Specificity (CI)	F1 (CI)	Accuracy (%)	Cohen's Kappa	PRC AUC	Runner-up (F1, CI)
Ant	Naïve Bayes	AE	15	0.45 (0.26– 0.63)	0.34 (0.19– 0.50)	0.92 (0.88– 0.95)	0.39 (0.23– 0.53)	82.25	0.29	0.35	AD, NB (0.35, 0.18–0.51)
Crs	LDA	AE	12	0.39 (0.28– 0.50)	0.66 (0.50– 0.80)	0.63 (0.54– 0.72)	0.49 (0.36– 0.59)	63.46	0.23	0.47	AB, EV (0.49, 0.38–0.59)
Lat	Naïve Bayes	AE	15	0.18 (0.12– 0.24)	0.67 (0.51– 0.81)	0.41 (0.35– 0.48)	0.28 (0.19– 0.36)	45.45	0.04	0.18	AB, DT (0.24, 0.12–0.36)
Trp	Ensemble Voting	AD	—	0.57 (0.44– 0.68)	0.82 (0.69– 0.91)	0.75 (0.66– 0.82)	0.66 (0.55– 0.75)	78.09	0.51	—	AD, DT (0.66, 0.56–0.74)
Mean ± SD	—	—	—	0.40 ± 0.16	0.62 ± 0.20	0.68 ± 0.21	0.46 ± 0.16	67.31 ± 16.65	0.27 ± 0.19	0.33 ± 0.15	—

9.4.5 Comparative Placement/Model Performance

The injured-class F1 scores ($\pm 95\%$ CI) for the best-performing model within each IMU configuration and hop task are presented in Figure 9.2. Configuration AE, which used simulated IMUs on the lower back, thighs, and shanks, provided the most consistent performance for Ant, Crs, and Lat, while configurations AB and AD provided competitive injured-class metrics for all tasks. Ensemble voting yielded additional robustness for Trp but degraded or destabilized injured-class performance on Ant. The lateral task remained problematic regardless of sensor placement or model choice (Table 9.1).

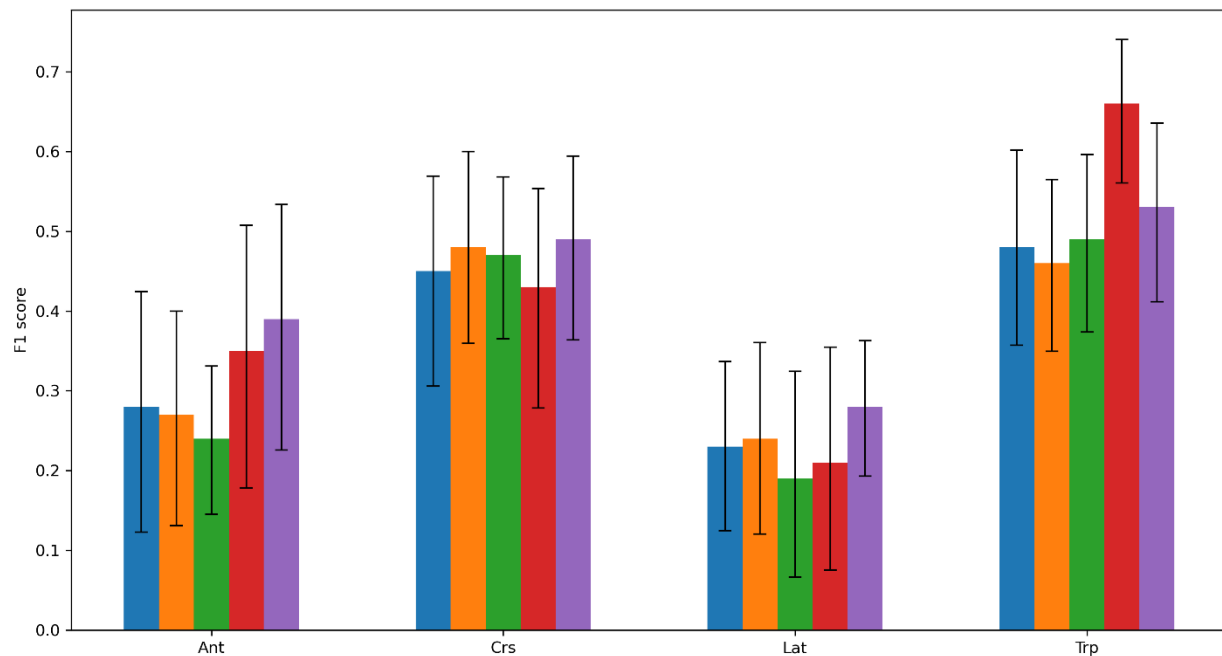


Figure 9.2. Injured class F1 scores ($\pm 95\%$ CI) across tasks (anterior hop = Ant, cross hop = Crs, lateral hop = Lat, and triple hop = Trp) and IMU configurations; AA = blue, AB = orange, AC = green, AD = red, AE = purple.

9.4.6 Principal Component Interpretation

Across tasks and configurations, the most discriminative PCs were dominated by the shank and foot IMUs, particularly medio-lateral and vertical accelerations, as well as sagittal and frontal plane angular velocities. These features were most influential during the early landing and stabilization phases, with additional contributions from the preparation and takeoff phases, especially in the multi-hop tasks (Figure 9.3).

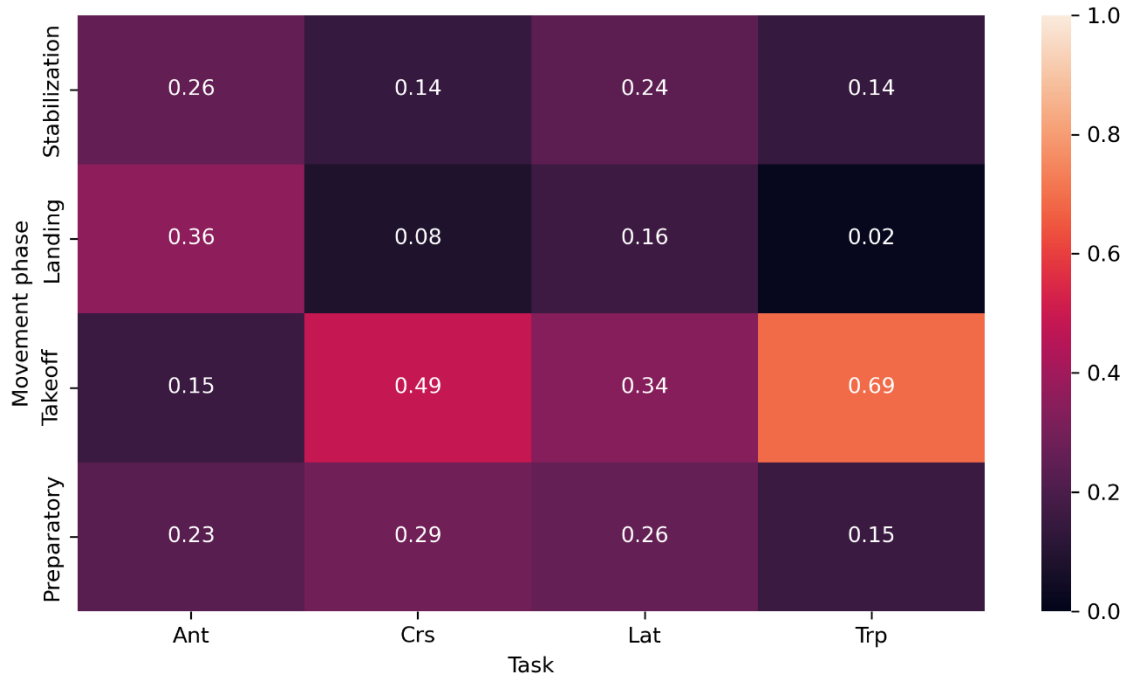


Figure 9.3: Relative contribution of each movement phase to classification performance for the best-performing model in each hop task (anterior hop = Ant, cross hop = Crs, lateral hop = Lat, triple hop = Trp), averaged across principal components.

For Ant, key components captured shank and thigh accelerations and angular velocities immediately following ground contact, highlighting the importance of post-landing control for distinguishing ACLi from CON participants. In Crs and Trp, high-magnitude loadings for foot and shank features during landing, stabilization, and takeoff suggested that coordinated limb control throughout multi-phase movement was essential for robust classification. Despite lower discriminatory power overall, Lat also exhibited top components weighted toward shank medio-lateral acceleration and angular velocity during landing and preparation (Table 9.2).

Table 9.2. Top Contributing Features and Movement Phases

Task	Component	Top Features/Segments	Key Movement Phase(s)
Ant	PC1	Shank ML acc., Thigh Z ang.vel., Foot acc.	Landing, Stabilization
Crs	PC2	Thigh/foot ML acc., Shank Y ang.vel.	Stabilization, Preparatory, Takeoff
Lat	PC1	Shank ML acc./vel., Foot acc.	Landing, Preparatory, Takeoff
Trp	PC3	Foot ML acc., Shank Y/Z ang.vel.	Landing, Preparatory, Takeoff

9.5 Discussion

The objectives of this study were to determine whether IMU signals could reliably classify ACL-injury status in adolescents during four single-limb hopping tasks, and to identify which lower-body sensor configurations and analytic approaches most effectively captured clinically meaningful movement deficits. Our findings demonstrate that task selection, model choice, and sensor configuration influence classification performance, with Trp and Crs achieving the highest F1 scores. These tasks were particularly informative when feature selection emphasized signal patterns during landing and takeoff phases, which are known to reflect compensatory strategies and neuromuscular control deficits following ACL injury^{24,30}. Given the need for scalable and objective movement assessment tools in adolescent rehabilitation and return-to-activity decision-making, these findings support the potential utility of wearable-based approaches.

The highest and most consistent precision and recall for the injured class were achieved during the triple hop and cross hop tasks, particularly when employing ensemble or LDA-based models. These task-level trends are consistent with our previous MoCap-based findings in adolescents, where multi-planar hopping tasks demonstrated strong discriminatory capacity between ACLi and CON groups (Chapter 7). While overall performance was not as strong for the lateral hop, the findings emphasize the need for reporting class-sensitive metrics such as precision and recall alongside accuracy to avoid overestimating model effectiveness, particularly when the outcome of interest is the detection of movement impairments^{12,22}.

Single-limb hop tests have traditionally relied on limb symmetries derived from hop distances or time³⁷. The addition of simulated wearable sensors provides key information on the movement patterns that differentiate between injured and control participants. For example, acceleration and angular velocity signals from the foot and shank during early landing and stabilization, as well as the thigh during takeoff, were consistently involved in discriminating between groups. These phases have previously been established as biomechanical mechanisms of ACL injury^{4,31,57} and are critical for detecting compensatory strategies in ACL-injured populations²⁴. This further justifies using an ensemble feature selection process to ensure that the most robust and informative components are prioritized, contributing to model stability and generalizability. The integration of feature selection, PCA-based dimensionality reduction, and cross-validation ensured that these findings reflect robust patterns rather than overfitting to specific signal features.

Sensor placement and configuration emerged as a key factor in classification performance. In this study, we simulated IMUs on the lower back, thighs, shanks, and feet, reflecting a practical approach for clinical translation^{35,50}. The decision to focus on lower-body placements for the simulated IMUs was based on both task design and biomechanics. During all hopping trials, participants kept their hands on their hips, minimizing upper limb motion and effectively rendering the arms and trunk as rigid bodies. As a result, including IMUs on the arms or upper trunk was unlikely to provide further discriminative information for injury status, while increasing complexity^{7,34}. This approach differs from a previous study where simulated IMUs were distributed across all body segments, resulting in improved classification accuracy for 12 out of 13 tested tasks compared to motion capture⁴⁷. However, that study did not isolate the independent contribution of each sensor location, and it remains unclear whether additional sensors directly improved discrimination or introduced redundant information. While comprehensive arrays may benefit highly complex or multi-segmental actions, the current results demonstrate that reliable differentiation of ACL injury status during single-limb hopping can be achieved using a streamlined lower-body configuration. Future work should systematically evaluate incremental sensor contributions to determine the optimal balance between classification performance and clinical feasibility.

A significant limitation of this study is the use of motion capture to calculate linear accelerations and angular velocities for the segments, rather than using raw sensor data from IMUs. Previous work has found strong agreement between IMU outputs and motion capture outputs^{5,52}. Nonetheless, simulations cannot fully capture all sources of noise and variability that may be present in practical field settings, such as electronic drift, noise, or attachment variability. Future studies should include direct comparison with physical IMUs in clinical or sporting environments to ensure the generalizability and robustness of these models.

In conclusion, this study provides evidence that simulated lower-body IMU configurations, when paired with ensemble feature selection and different classification algorithms, can reliably discriminate between ACL-injured and uninjured adolescents during single-limb hopping tasks. With the ideal configuration, IMU use may therefore provide an inexpensive way to objectively classify movement performance during single-limb hopping tasks in adolescents, offering a feasible tool for clinicians to objectively assess rehabilitation progression and readiness to return to activity.

9.6 References

1. Ardern CL, Taylor NF, Feller JA, Webster KE. Fifty-five per cent return to competitive sport following anterior cruciate ligament reconstruction surgery: An updated systematic review and meta-analysis including aspects of physical functioning and contextual factors. *Br J Sports Med*. 2014;48(21).
2. Battiti R. Using mutual information for selecting features in supervised neural net learning. *IEEE Trans Neural Netw*. 1994;5(4):537-550.
3. Beaulieu ML, Lamontagne M, Beaulé PE. Lower limb biomechanics during gait do not return to normal following total hip arthroplasty. *Gait Posture*. 2010;32(2):269-273.
4. Boden BP, Dean SG, Feagin JA, et al. Mechanisms of anterior cruciate ligament injury. *Orthopedics*. 2000;23(6):573-578.
5. Bolink SAAN, Naisas H, Senden R, et al. Validity of an inertial measurement unit to assess pelvic orientation angles during gait, sit-stand transfers and step-up transfers: Comparison with an optoelectronic motion capture system. *Med Eng Phys*. 2016;38(3):225-231.
6. Bolón-Canedo V, Sánchez-Marono N, Alonso-Betanzos A. Feature selection for high-dimensional data. *Progress in Artificial Intelligence*. 2016;5(2):65-75.
7. Breiman L. Random forests. *Mach Learn*. 2001;45:5-32.
8. Breiman L, Friedman J, Stone CJ, Olshen RA. *Classification and regression trees*. 1st ed. Chapman and Hall/CRC; 1984.
9. Carletta J. Assessing agreement on classification tasks: The kappa statistic. *Computational Linguistics*. 1996;22(2):249-254.
10. Chan VCH, Beaudette SM, Smale KB, Beange KHE, Graham RB. A subject-specific approach to detect fatigue-related changes in spine motion using wearable sensors. *Sensors*. 2020;20(9):2646.
11. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*. 2002;16:321-357.
12. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): The TRIPOD statement. *BMC Med*. 2015;13(1):1-10.

13. Cover TM, Hart PE. Nearest neighbor pattern classification. *IEEE Trans Inf Theory*. 1967;13(1):21-27.
14. Cutti AG, Ferrari A, Garofalo P, Raggi M, Cappello A, Ferrari A. "Outwalk": A protocol for clinical gait analysis based on inertial and magnetic sensors. *Med Biol Eng Comput*. 2010;48(1):17-25.
15. Domingos P, Pazzani M. On the optimality of the simple Bayesian classifier under zero-one loss. *Mach Learn*. 1997;29(2-3):103-130.
16. Dowling AV, Favre J, Andriacchi TP. Inertial sensor-based feedback can reduce key risk metrics for anterior cruciate ligament injury during jump landings. *Am J Sports Med*. 2012;40(5):1075-1083.
17. Fisher RA. Statistical methods for research workers. In: Kotz S, Johnson NL, eds. *Breakthroughs in Statistics*. Springer Series in Statistics. Vol 2. Springer, New York, NY; 1992:66-70.
18. Fort-Vanmeerhaeghe A, Bishop C, Busca B, Aguilera-Castells J, Vicens-Bordas J, Gonzalo-Skok O. Inter-limb asymmetries are associated with decrements in physical performance in youth elite team sports athletes. *PLoS One*. 2020;15(3):e0229440.
19. Fritsch FN, Carlson RE. Monotone piecewise cubic interpolation. *SIAM J Numer Anal*. 1980;17(2):238-246.
20. Pearson K. X. On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*. 1900;50(302):157-175.
21. Girard CI, Del Bel MJ, Bédard V, et al. Are single limb hopping scores the same when performed in a physical education class versus a laboratory setting in uninjured adolescents? Implications for future rehabilitation guidelines for adolescents with knee injuries. *Communications in Kinesiology*. 2024;1(6).
22. Girard CI, Romanchuk NJ, Del Bel MJ, Carsen S, Chan ADC, Benoit DL. Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria. *Knee Surgery, Sports Traumatology, Arthroscopy*. 2025;33(5):1633-1644.

23. Gokeler A, Benjaminse A, Welling W, Alferink M, Eppinga P, Otten B. The effects of attentional focus on jump performance and knee joint kinematics in patients after ACL reconstruction. *Physical Therapy in Sport*. 2015;16(2):114-120.
24. Hastie T, Tibshirani R, Friedman J. *The elements of statistical learning: Data mining, inference, and prediction*. 2nd ed. Springer; 2017.
25. Hripcsak G, Rothschild AS. Agreement, the F-measure, and reliability in information retrieval. *Journal of the American Medical Informatics Association*. 2005;12(3):296-298.
26. Johnston W, O'Reilly M, Dolan K, Reid N, Coughlan GF, Caulfield B. Objective classification of dynamic balance using a single wearable sensor. In: *IcSPORTS 2016 - Proceedings of the 4th International Congress on Sport Sciences Research and Technology Support*. SciTePress; 2016:15-24.
27. Johnston W, O'Reilly M, Duignan C, et al. Association of dynamic balance with sports-related concussion: A prospective cohort study. *American Journal of Sports Medicine*. 2019;47(1):197-205.
28. Jolliffe IT. Principal components in regression analysis. In: Springer, New York, NY; 1986:129-155.
29. Kotsifaki A, Van Rossom S, Whiteley R, et al. Symmetry in triple hop distance hides asymmetries in knee function after ACL reconstruction in athletes at return to sports. *Am J Sports Med*. 2021;50(2):441-450.
30. Krosshaug T, Slauterbeck JR, Engebretsen L, Bahr R. Biomechanical analysis of anterior cruciate ligament injury mechanisms: Three-dimensional motion reconstruction from video sequences. *Scand J Med Sci Sports*. 2007;17(5):508-519.
31. Kuncheva LI. *Combining pattern classifiers: Methods and algorithms*. John Wiley & Sons; 2014.
32. Lemaître G, Nogueira F, Aridas CK. Imbalanced-learn: A Python toolbox to tackle the curse of imbalanced datasets in machine learning. *Journal of Machine Learning Research*. 2017;18(17):1-5.
33. Mavor MP, Ross GB, Clouthier AL, Karakolis T, Graham RB. Validation of an IMU suit for military-based tasks. *Sensors*. 2020;20(15):4280.

34. McGrath T, Fineman R, Stirling L. An auto-calibrating knee flexion-extension axis estimator using principal component analysis with inertial sensors. *Sensors*. 2018;18(6):1882.
35. Mueske N, Katzel MJ, Chadwick KP, et al. Biomechanical symmetry during drop jump and single-leg hop landing in uninjured adolescent athletes. *Orthop J Sports Med*. 2019;7(3 Suppl):2325967119S00023.
36. Noyes FR, Barber SD, Mangine RE. Abnormal lower limb symmetry determined by function hop tests after anterior cruciate ligament rupture. *Am J Sports Med*. 1991;19(5):513-518.
37. Nüesch C, Roos E, Pagenstert G, Mündermann A. Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor-based system and a camera-based system. *J Biomech*. 2017;57:32-38.
38. Ordóñez FJ, Roggen D. Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. *Sensors*. 2016;16(1):115.
39. Paterno MV, Huang B, Thomas S, Hewett TE, Schmitt LC. Clinical factors that predict a second ACL injury after ACL reconstruction and return to sport: Preliminary development of a clinical decision algorithm. *Orthop J Sports Med*. 2017;5(12):1-7.
40. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine learning in Python. *J Mach Learn Res*. 2011;12:2825-2830.
41. Pizzolato C, Reggiani M, Saxby DJ, Ceseracciu E, Modenese L, Lloyd DG. Biofeedback for gait retraining based on real-time estimation of tibiofemoral joint contact forces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2017;25(9):1612-1621.
42. Platt JC. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. In: *Advances in Large Margin Classifiers*. 2000;10(3):61-74.
43. Roetenberg D, Slycke PJ, Veltink PH. Ambulatory position and orientation tracking fusing magnetic and inertial sensing. *IEEE Trans Biomed Eng*. 2007;54(5):883-890.
44. Roetenberg D, Luinge H, Slycke P. *Xsens MVN: Full 6DOF human motion tracking using miniature inertial sensors*. Xsens Motion Technologies BV, Tech Rep. Published online 2013.
45. Rokach L. Ensemble-based classifiers. *Artif Intell Rev*. 2010;33(1-2):1-39.

46. Ross GB, Dowling B, Troje NF, Fischer SL, Graham RB. Classifying elite from novice athletes using simulated wearable sensor data. *Front Bioeng Biotechnol.* 2020;8:520114.
47. Saito T, Rehmsmeier M. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLoS One.* 2015;10(3):e0118432.
48. Sgrò F, Mango P, Pignato S, Schembri R, Licari D, Lipoma M. Assessing standing long jump developmental levels using an inertial measurement unit. *Percept Mot Skills.* 2017;124(1):21-38.
49. Stetter BJ, Ringhof S, Krafft FC, Sell S, Stein T. Estimation of knee joint forces in sport movements using wearable sensors and machine learning. *Sensors (Switzerland).* 2019;19(17):1-12.
50. Teufl W, Lorenz M, Miezal M, Taetz B, Fröhlich M, Bleser G. Towards inertial sensor-based mobile gait analysis: Event-detection and spatio-temporal parameters. *Sensors (Switzerland).* 2018;19(1):1-20.
51. Teufl W, Miezal M, Taetz B, Fröhlich M, Bleser G. Validity of inertial sensor-based 3D joint kinematics of static and dynamic sport and physiotherapy-specific movements. *PLoS One.* 2019;14(2):1-18.
52. Tibshirani R. Regression shrinkage and selection via the lasso. *J R Stat Soc Series B Stat Methodol.* 1996;58(1):267-288.
53. Troje NF. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. *J Vis (Tokyo).* 2002;2(5):371-387.
54. Whelan D, O'Reilly M, Huang B, Giggins O, Kechadi T, Caulfield B. Leveraging IMU data for accurate exercise performance classification and musculoskeletal injury risk screening. In: *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* IEEE; 2016:659-662.
55. Winter DA. *Biomechanics and motor control of human movement.* 4th ed. 2009.
56. Yu B, Garrett WE. Mechanisms of non-contact ACL injuries. *Br J Sports Med.* 2007;41 Suppl 1(suppl_1):i47-i51.
57. Zago M, Sforza C, Dolci C, Tarabini M, Galli M. Use of machine learning and wearable sensors to predict energetics and kinematics of cutting maneuvers. *Sensors.* 2019;19(14):3094.

9.7 Postamble

This chapter evaluated the ability of simulated IMU signals to classify ACLi status in adolescents during single-limb hopping tasks and examined how sensor configuration and task selection influence classification performance. Using motion capture-derived inertial signals allowed a systematic investigation of wearable-style inputs while avoiding confounding error introduced by unreliable physical IMU recordings.

The results demonstrate that simulated IMUs can capture injury-related movement differences during functional hopping, but classification performance was strongly task- and configuration-dependent. The triple hop and cross hop consistently produced the most balanced injured-class performance, whereas the lateral hop remained challenging despite high apparent accuracy in some configurations, underscoring the importance of reporting class-sensitive metrics such as precision, recall, and F1 score rather than accuracy alone. Across tasks, configurations incorporating shank and foot sensors contributed most to discriminative features, particularly during landing and stabilization phases, highlighting the biomechanical relevance of distal segment control following ACL injury.

Comparison with the marker-based classification results presented earlier in the thesis indicates that, while simulated IMUs approach similar overall accuracies in some tasks, they exhibit reduced sensitivity to injured-class movement deviations. This difference reflects the loss of detailed spatial information when transitioning from full-body kinematics to inertial signals, even under idealized simulation conditions. Nonetheless, the consistency of performance across configurations and tasks provides important insight into the upper bound of wearable sensor-based classification under controlled conditions.

Taken together, these findings establish that simulated IMUs provide a defensible and informative surrogate for evaluating wearable-based injury classification in adolescents. The results identify task-specific and configuration-specific trade-offs that are critical for clinical translation and demonstrate that meaningful injury-related movement information can be extracted from inertial signals when analytic choices are carefully aligned with task biomechanics. This chapter, therefore, completes the methodological progression of the thesis and provides a validated foundation for interpreting inertial-based classification results in the broader context of RTA assessment.

CHAPTER 10: GENERAL DISCUSSION

The overarching aim of this doctoral thesis was to evaluate whether adolescent functional performance following anterior cruciate ligament (ACL) injury can be more effectively characterized through kinematic analyses that extend beyond conventional spatiotemporal outcomes. To achieve this aim, four interrelated studies were conducted. These studies collectively addressed whether single-limb hop tests are reproducible and clinically interpretable in adolescents, whether spatiotemporal metrics alone provide adequate classification accuracy, whether waveform analysis can capture subtle adaptations related to limb status, and whether simulated inertial measurement units (sIMU) can serve as a clinically translatable alternative to laboratory-based motion capture (MoCap).

The first study asked whether single-limb hop tasks were reproducible and responsive across environments in adolescents (S1Q1) and whether sex influenced spatiotemporal measures of these tasks (S1Q2). Consistent with the hypotheses, the hop tasks demonstrated reproducibility across settings, confirming their robustness for adolescent testing. Moreover, sex differences emerged in hop distances and symmetry measures, aligning with literature showing adolescent females exhibit altered neuromuscular control and landing mechanics compared to males^{59,83,208}. This established the foundation for using hop tasks as clinically meaningful assessments in youth.

The second study evaluated whether spatiotemporal measures alone could classify ACL injury status in adolescents (S2Q1) and whether classification accuracy differed between sexes (S2Q2). Decision tree modelling revealed that while spatiotemporal outcomes such as hop distance and limb symmetry indices contributed to group separation, classification accuracy was modest, particularly in females. This finding is consistent with prior research showing that distance-based hop indices often overestimate functional recovery^{174,249}. The decision trees further highlighted differences in discriminative parameters between sexes, underscoring the importance of sex-specific assessments given the higher injury risk in female adolescents^{84,171}.

The third study expanded upon these findings by testing whether kinematic waveforms could improve classification accuracy (S3Q1) and reveal limb- and sex-specific adaptations (S3Q2). Principal component analysis (PCA) of waveform features produced stronger classification of injury status than spatiotemporal outcomes, supporting the hypothesis and echoing findings in gait and osteoarthritis research where PCA captured subtle adaptations invisible to discrete metrics^{64,81}.

Moreover, exploratory misclassification analyses demonstrated that waveform features detected sex-specific adaptations, particularly in control females who exhibited consistent bilateral misclassifications across tasks. This supports the notion that adolescent females adopt unique movement strategies that may mask or exaggerate deficits^{108,128}.

The fourth study (Chapter 9) addressed the translational question of whether sIMU-derived features could approximate MoCap-based classification (S4Q1) and which sensor placements maximized discriminative power (S4Q2). Results demonstrated that sIMUs achieved comparable classification accuracy to MoCap, though injured-class detection remained lower, particularly for tasks requiring subtle multiplanar control. Sensor configurations incorporating thigh and shank placements produced the strongest classification performance, consistent with their role in capturing knee mechanics most affected by ACL injury^{33,108}. This study provides a critical step toward portable, field-based assessments that reduce reliance on costly laboratory systems.

Together, these studies establish that while spatiotemporal measures remain useful, they are insufficient for fully capturing the complexity of adolescent ACL injury. Waveform analyses provide deeper insights into compensatory movement patterns, and sIMUs extend this potential into applied settings. The thesis, therefore, builds a continuum from establishing reproducibility (Study 1), to testing current measures (Study 2), to advancing analytical approaches (Study 3), and finally to enabling clinical translation (Study 4).

10.1 Functional Performance Reproducibility in Adolescents

The first research question (S1Q1) examined whether single limb hopping tasks are reproducible and responsive across environments, specifically between a physical activity class in a gymnasium and a laboratory setting in adolescents. This was a critical step in determining the generalizability of hop-based assessments beyond controlled laboratory conditions. The results confirmed that hop tasks demonstrated reproducibility across both environments, with standard error of measurement (SEM) and smallest real difference (SRD) values indicating acceptable reliability. These findings align with adult research showing strong test–retest reliability of single-limb hop^{68,167,212}. Importantly, the responsiveness of these measures in adolescents suggests they can detect clinically meaningful changes in performance, a requirement for their use in monitoring rehabilitation or readiness to return to activity (RTA)^{23,66}. This extends the literature by confirming that hop tasks retain reproducibility in younger populations, even in less controlled environments, supporting their utility for schools, community sport settings, and clinical follow-ups outside the

laboratory. Moreover, demonstrating reproducibility across environments helps bridge the gap between laboratory-based biomechanics and applied practice, thereby enhancing the ecological validity of hop assessments for adolescents recovering from ACL injury.

Although the hop tests themselves require only simple equipment such as a measuring tape and stopwatch, standardized administration by trained assessors remains important to ensure consistent testing procedures and accurate measurement. The subsequent studies in this thesis build upon this foundation by incorporating waveform-based analyses and wearable sensor technologies that have the potential to automate movement quantification, thereby reducing the expertise required to objectively evaluate movement quality while retaining the practicality of functional hop testing.

The second research question (S1Q2) tested whether spatiotemporal parameters from single limb hopping tasks can differentiate sex in uninjured adolescents. This analysis was motivated by evidence that females exhibit distinct neuromuscular control strategies, lower strength, and altered landing mechanics compared to males, which collectively contribute to their elevated ACL injury risk^{59,83,108}. The present findings supported this hypothesis, revealing that males achieved greater absolute hop distances, consistent with higher strength and power outputs reported in adolescent males¹⁶⁷. Conversely, females demonstrated different symmetry patterns, suggesting reliance on compensatory strategies that could mask deficits in traditional symmetry indices. These results align with studies showing that standard hop-based limb symmetry indices can overestimate functional recovery in ACL-injured populations^{92,249}. By identifying sex-based differences in uninjured adolescents, this study emphasizes the importance of sex-specific normative data for hop performance and reinforces the need for tailored rehabilitation and injury-prevention protocols. The findings also highlight that spatiotemporal outcomes, while reproducible, may not fully capture underlying neuromuscular differences, reinforcing the rationale for subsequent waveform-based analyses explored in Study 3.

10.2 Spatiotemporal Metrics for Classification

The second study in this thesis evaluated whether spatiotemporal outcomes could classify ACL injury status in adolescents because RTA assessments rely heavily on these measures, despite evidence that hop distances and limb symmetry indices may overestimate recovery and fail to capture sex-specific neuromuscular differences^{84,174,249}. The first research question (S2Q1) investigated which spatiotemporal parameters from hop tasks are most important for

differentiating ACL-injured from uninjured adolescents. This investigation was critical because current RTA assessments are built primarily on hop distances and limb symmetry indices, despite concerns that these metrics may not fully reflect underlying movement deficits. The results supported the hypothesis that hop distance and symmetry measures from the anterior and lateral hops provided the best separation between groups. This aligns with earlier adult studies showing that distance-based hop tests are sensitive to ACL-related deficits^{174,187}, as well as adolescent work demonstrating the discriminative value of these tasks in females⁸⁹. However, the classification accuracy achieved using only spatiotemporal outcomes was modest, suggesting that while these metrics remain clinically useful, they are insufficient when used in isolation. This finding echoes evidence that hop-based symmetry indices often overestimate functional recovery, masking persistent neuromuscular impairments^{92,249}. The results of this study, therefore, underscore both the strengths and limitations of current RTA practices, demonstrating that spatiotemporal measures can contribute to classification but should not be viewed as comprehensive indicators of adolescent functional performance following ACL injury.

The second research question (S2Q2) examined whether classification outcomes differ between male and female adolescents. This analysis was motivated by well-documented sex differences in neuromuscular control and biomechanics during adolescence, with females often demonstrating increased valgus motion, reduced quadriceps strength, and altered landing strategies compared to males^{84,108,196}. The present findings supported the hypothesis, revealing that decision tree models identified different discriminative spatiotemporal variables for each sex, and overall classification accuracy varied between males and females. These outcomes highlight that adolescent females may rely on compensatory strategies that make classification more challenging, consistent with prior evidence of sex-specific adaptations in hop performance^{167,208}. Clinically, this suggests that RTA assessments relying solely on spatiotemporal metrics risk overlooking deficits in female athletes, who already face a higher risk of ACL injury and reinjury^{172,194}. The identification of sex-specific discriminative features emphasizes the need for tailored rehabilitation benchmarks and further supports the rationale for advancing beyond spatiotemporal measures toward waveform and wearable-based approaches explored in subsequent studies.

10.3 Kinematic Waveform Analysis and Classification

Traditional spatiotemporal outcomes from hop tests provide limited insight into movement quality, often missing subtle compensations that persist after ACL injury. To address this gap, the

first research question (S3Q1) asked whether kinematic waveform features derived from PCA provide superior classification of ACL injury status compared to spatiotemporal measures. Consistent with the hypothesis, waveform-derived features enhanced classification accuracy, supporting the idea that PCA can uncover injury-related adaptations that traditional distance or symmetry indices overlook. This finding extends the evidence base from adult gait and osteoarthritis studies^{64,81} into adolescent ACL-injured populations, demonstrating that complex multivariate patterns provide more discriminative power than discrete measures alone. Importantly, by showing that waveform analysis better differentiated injured from uninjured limbs, Study 3 confirmed that spatiotemporal outcomes, while reproducible and clinically interpretable, are not sufficient as standalone indicators of functional recovery. This highlights the clinical relevance of incorporating higher-dimensional movement analyses into rehabilitation assessment to ensure subtle but meaningful adaptations are not overlooked.

The second research question (S3Q2) examined whether waveform features could identify differences between limbs and sexes. The most robust finding was that classification accuracy was consistently stronger for the injured limb compared to the contralateral limb, supporting the hypothesis that waveform features would detect limb-specific adaptations. This suggests that deviations in the injured limb are more pronounced, whereas the contralateral limb may adopt compensatory strategies that obscure its differences from controls. These results are consistent with prior evidence that ACL injury induces bilateral neuromuscular adaptations, making the contralateral limb an imperfect comparator^{128,214}. Clinically, this highlights the need to interpret contralateral limb comparisons with caution, as apparent symmetry may mask systemic adaptations rather than true recovery.

These findings are particularly relevant in the context of secondary ACL injury. Although females have a substantially greater risk of sustaining a primary ACL injury than males¹⁰⁸, evidence suggests that the overall risk of a second ACL injury following ACL reconstruction is similar between sexes¹⁸⁵. However, females are more likely to sustain contralateral ACL injuries, whereas males demonstrate a slightly greater risk of ipsilateral graft rupture¹⁸⁵. These differences in reinjury patterns suggest that persistent bilateral neuromuscular adaptations may contribute to contralateral injury risk following RTA¹⁸⁹. While the present study was not designed to investigate mechanisms underlying secondary ACL injury, the observation that the contralateral limb

exhibited altered waveform characteristics reinforces the importance of assessing both limbs during rehabilitation rather than assuming the uninvolved limb represents normal function.

S3Q2 also included a secondary hypothesis that waveform-derived features would capture sex-specific adaptations in movement strategies. Due to the smaller number of male participants, robust statistical comparisons between sexes were not feasible. Instead, an exploratory analysis of misclassification patterns was conducted. This suggested a trend toward more frequent bilateral misclassifications in females, particularly among controls. While this aligns with literature showing that adolescent females adopt distinct landing strategies associated with ACL injury risk^{84,108}, the findings cannot be interpreted as conclusive. Thus, while the limb-specific hypothesis of S3Q2 was supported, the sex-specific hypothesis remains preliminary and highlights the need for larger, sex-balanced samples in future research.

10.4 Simulated IMUs for Functional Classification

The rationale for conducting Study 4 stemmed from the need to bridge the gap between laboratory-based biomechanical assessments and clinically feasible tools for widespread application. While optical motion capture (MoCap) remains the gold standard for movement analysis, its cost, infrastructure requirements, and limited ecological validity make it impractical for routine monitoring of adolescent ACL injury. Wearable IMUs provide a promising alternative, yet questions remain regarding whether sIMU signals can achieve classification accuracy comparable to MoCap and which segment placements yield the most discriminative information^{4,42}.

The first research question (S4Q1) examined whether sIMU signals could classify hopping tasks in adolescents with and without ACL injuries with accuracy comparable to MoCap. The results confirmed this hypothesis, showing that sIMU-derived features achieved classification accuracy similar to MoCap-based kinematics. This aligns with previous validation studies demonstrating strong agreement between IMU- and MoCap-derived measures of joint kinematics and dynamic movement quality^{38,203,221}. Importantly, the findings extend this literature by showing that IMU-derived data are not only valid for signal reconstruction but also effective for higher-level classification of injury status when combined with PCA and machine learning classifiers. This suggests that portable IMU systems may enable clinicians to monitor functional recovery in real-world environments, advancing toward ecologically valid, scalable injury assessment models.

The second research question (S4Q2) addressed which segment placements provide the most discriminative information for differentiating adolescents with ACL injuries from uninjured controls and contralateral limbs. Consistent with the hypothesis, the highest-performing configurations were those emphasizing signals from the thigh and shank segments, indicating that these locations contained the most informative biomechanical features for classification. Increasing the number of sensors beyond the thigh and shank did not consistently improve classification performance, indicating that these segments captured the majority of the discriminatory information relevant for distinguishing ACL-injured participants from uninjured controls. This finding is supported by prior research highlighting the thigh and shank as critical for capturing knee joint mechanics most affected by ACL injury^{33,108}. These results also mirror prior work in wearable-sensor studies, which emphasize placement sensitivity and highlight how improper placement can reduce classification performance^{45,131}.

Taken together, these findings demonstrate that sIMUs not only replicate the classification performance achievable using laboratory-based motion capture but also identify sensor placements with the greatest discriminatory potential under ideal measurement conditions. By demonstrating that thigh- and shank-based configurations provided the greatest discriminatory information under ideal measurement conditions, this study provides clear guidance for future clinical and field-based monitoring while acknowledging that real-world performance will also depend on factors such as sensor placement, signal quality, and acquisition protocols. These results underscore the translational potential of IMUs as cost-effective, portable tools for injury assessment, paving the way for large-scale adoption in youth rehabilitation and RTA evaluations.

10.5 Comparison of Marker-Trajectory and Simulated IMU Classification Performance

A comparison of the marker trajectory classification study (S3) and the simulated IMU study (S4) provides important context for interpreting the classification results across sensing modalities. Both studies evaluated multiple supervised classifiers within a PCA-based dimensionality reduction and ensemble feature selection framework. In S3, six classifiers and a soft-voting ensemble were tested, and LDA was selected for reporting because it achieved performance within 1-2% of the best models while offering greater interpretability and stability across tasks. In S4, multiple classifiers were again evaluated, and model selection emphasized injured-class metrics (F1, precision, and recall) rather than accuracy alone. To enable a harmonized comparison, Table

G.1 (Appendix G) presents LDA performance across modalities; however, this restriction is solely for matched comparison and does not imply that either study relied exclusively on LDA.

When examined using comparable classifiers (Table G.1), important differences between modalities remain. Across tasks, simulated IMUs generally demonstrated lower injured-class F1, precision, and recall compared to marker trajectories. The anterior and lateral hops exhibited the largest reductions in injured-class performance. Although overall accuracy occasionally remained similar between modalities, this was largely driven by the correct classification of the majority class (CON;²¹⁵). Injured-class recall was consistently reduced in the sIMU models, indicating that inertial signals did not preserve all injury-related discriminative features captured by full marker trajectories. Therefore, the results do not suggest equivalence between modalities. Rather, these findings indicate that classification performance is influenced by both the biomechanical demands of each task and how movement is quantified in the dataset, since marker-based kinematics and sIMU features emphasize different aspects of segment motion.

Task-specific patterns provide insight into why cross and triple hops showed closer agreement between modalities than anterior and lateral hops. Although the cross and triple hops involve repeated landing, stabilization, and takeoff phases, only the final hop was analyzed to maintain comparability with the anterior and lateral hop. Therefore, differences in performance cannot be attributed to cumulative impacts across repetitions. Instead, the distinguishing factor may relate to movement complexity and multiplanar control demands.

Even when considering only the final landing, the cross and triple hops involve dynamic propulsion and controlled landing following directional changes or forward momentum transfer. These movements generate pronounced segmental angular velocities and linear accelerations, particularly in the shank and foot segments. IMUs directly measure angular velocity and linear accelerations; therefore, tasks that produce larger and more distinct inertial signatures may preserve discriminative information more effectively after dimensionality reduction¹⁹². In contrast, the anterior hop is largely sagittal-plane dominant and more linear in its execution. Subtle differences in global center-of-mass trajectory and intersegment coordination, which are directly encoded in full marker trajectories, may not be fully captured by segment-fixed inertial signals⁵⁷.

The lateral hop presents a different limitation. Despite achieving relatively high overall accuracy under some configurations, injured-class recall remained low in the IMU models. The lateral hop requires frontal-plane control and multiplanar knee stabilization. However, frontal-

plane knee rotations during controlled athletic tasks are typically smaller in magnitude than sagittal-plane flexion-extension movements^{110,161}. IMU-derived signals may therefore struggle to detect small amplitude, short-duration multiplanar deviations, particularly when these are embedded within rapid stabilization phases and when no magnetometer information is included to stabilize heading estimates. Marker trajectories, which provide full three-dimensional segment positions and intersegment relationships, may retain greater sensitivity to subtle coordination differences across planes.

An additional consideration when comparing marker-based and simulated IMU classification performance is the trade-off between signal fidelity and data accessibility. Marker-based motion capture provides high-resolution kinematic data with a relatively high signal-to-noise ratio (SNR), whereas sIMUs, and by extension, real wearable sensors, capture a reduced representation of movement that may attenuate subtle biomechanical differences. As a result, classification models based on IMU-derived signals may exhibit lower discriminative performance when evaluated using a limited number of trials per participant. However, wearable sensors offer the practical advantage of enabling repeated, low-cost data collection in clinical or field environments. Increasing the number of trials or incorporating longitudinal measurements may enhance the effective SNR of IMU-based analyses by improving the stability and reliability of extracted features. Therefore, direct comparisons using single or limited trials may favour laboratory-based systems, but may not fully reflect the potential of wearable approaches when leveraged for higher-volume or repeated-measures data collection.

Taken together, these findings indicate that sIMUs did not fully replicate marker-based classification performance across all tasks, particularly for those requiring the detection of nuanced multiplanar control strategies. However, for tasks characterized by clearer dynamic transitions and larger inertial signatures, such as the cross and triple hops, IMU-based models approached marker-based performance more closely. These results suggest that the translational potential of IMU-based assessment may depend on task selection, movement-plane dominance, and the magnitude of the underlying biomechanical deviations. Rather than demonstrating equivalence between modalities, this comparison highlights the specific conditions under which wearable-sensor approaches may approximate laboratory-based kinematic discrimination.

10.6 Limitations

In addition to the limitations addressed in each study, there are general limitations to consider.

Cross-Sectional Study Design

One major limitation of this thesis is its cross-sectional design. Since participants were assessed at a single point in time, the ability to infer causal relationships between biomechanical features and long-term outcomes is restricted. Although classification models identified discriminative features that distinguished ACLi from uninjured adolescents, the findings cannot determine whether these features predict future injury risk, rehabilitation progress, or readiness to RTA. Longitudinal research is needed to track how these features evolve through the rehabilitation process and whether they can forecast successful outcomes, such as reduced risk of reinjury or avoidance of early-onset osteoarthritis^{147,187}.

Furthermore, a cross-sectional approach may obscure individual variability in adaptation trajectories. Adolescents are at a stage of rapid growth and neuromuscular development, meaning that biomechanical strategies may change naturally with maturation, independent of injury status^{155,156}. Without repeated measures, it is difficult to separate developmental changes from injury-related adaptations. This limitation highlights the need for prospective cohort studies that incorporate repeated biomechanical assessments at multiple stages of recovery and maturation to establish the temporal stability and clinical relevance of identified features.

Finally, cross-sectional analyses limit the translation of findings into clinical decision-making. Clinicians often need to know not only whether an athlete currently demonstrates deficits, but also how those deficits evolve and respond to intervention. While the present findings provide important baseline evidence that hop tasks and kinematic analyses are informative, they should be viewed as foundational rather than definitive. Future longitudinal work could validate whether these biomechanical markers offer prognostic value for tailoring rehabilitation or screening adolescents most at risk of reinjury.

Use of Simulated IMUs Rather than Real Devices

Another important limitation lies in the use of sIMUs in Study 4. Although simulating inertial signals from motion capture marker trajectories allowed generation of idealized inertial measurements, it does not replicate the real-world complexities of wearable sensor use. Physical IMUs are subject to soft tissue artifact²⁵, misalignment, calibration drift, and magnetic

interference, all of which can degrade signal quality and influence classification performance^{203,221}. The results presented here may therefore represent an optimistic upper bound on achievable accuracy, rather than reflecting true field performance.

Additionally, the simulation approach constrained analyses to idealized sensor placements. In clinical and sport settings, sensor placement may vary across clinicians or athletes, potentially altering the fidelity of captured signals. Small changes in placement have been shown to influence kinematic outputs, particularly for rotational measures^{38,140}. Since sIMUs were aligned perfectly to segment coordinate systems, they bypassed these practical sources of error. As such, while Study 4 demonstrates the theoretical promise of IMUs, real-world implementation studies are essential to confirm feasibility and robustness across diverse applied contexts.

Lastly, accelerometer, gyroscope, and magnetometer signals were simulated from the motion-capture data and processed using the same sensor fusion pipeline applied to the real IMU recordings. However, the simulated signals did not reproduce many of the factors that challenge orientation estimation during real-world data acquisition, including sensor drift, magnetic disturbances, soft tissue artifact, calibration error, signal saturation, and sensor placement variability. As a result, the sensor fusion algorithm was evaluated under ideal measurement conditions, and the resulting classification performance should be interpreted as an optimistic estimate of the discriminatory information available under ideal signal quality rather than the performance expected from wearable IMUs in clinical practice. Future studies using wearable IMUs are therefore required to evaluate the robustness of the complete acquisition and processing pipeline under real-world conditions.

Participant Characteristics and Group Heterogeneity

The participant sample also introduces limitations that affect the generalizability of findings. While the ACL-injured group consisted of adolescents with confirmed ACL ruptures, factors such as time since injury, time from injury to testing, and rehabilitation history were not standardized. These factors are known to influence neuromuscular adaptations, quadriceps strength, and movement strategies during functional tasks^{179,248}. The absence of these controls makes it difficult to isolate whether classification models detected injury status per se or secondary adaptations arising from heterogeneous management pathways.

Similarly, the control group for Studies 2 through 4 comprised adolescents recruited from community and sport organizations, representing a wide range of athletic backgrounds and

exposure levels. Some participants may have had higher sport-specific training, while others had minimal structured activity, potentially contributing to variability in hop performance. Sport exposure has been shown to shape neuromuscular control strategies⁵⁹, and without stratification, between-group differences may reflect athletic experience as much as injury status.

Another consideration is biological maturation. Adolescents between the ages of 10 and 18 span critical developmental stages marked by rapid changes in strength, coordination, and neuromuscular control^{155,156}. Although Tanner staging was recorded, it was not directly incorporated into the analyses, which could obscure maturation-related biomechanical patterns. Future studies should stratify or adjust for maturation status to disentangle developmental changes from injury-specific adaptations.

Ecological Validity of Laboratory-Based Measures

While Study 1 established reproducibility of hop tasks across laboratory and gymnasium settings, Studies 2 through 4 relied exclusively on laboratory-based motion capture data. Laboratory settings offer high precision and control, but they may not fully replicate the ecological demands of sport or rehabilitation environments. Factors such as footwear, surface compliance, and environmental distractions are likely to influence task performance and could reduce the external validity of the findings when applied outside controlled settings.

In clinical practice, assessments are often conducted in busy rehabilitation clinics, schools, or sports facilities where environmental conditions cannot be standardized. Differences in motivation and context can also affect performance, particularly in adolescents, who may respond differently in testing versus competition-like settings³⁴. The reliance on laboratory data, therefore, limits the immediate generalizability of the identified discriminative features.

Moreover, the ultimate translational goal of this thesis is to enable portable, wearable-based assessment. While the laboratory findings provide a strong foundation, ecological validation using IMUs in applied contexts is required to demonstrate that classification models remain robust when data are collected in field settings. Without this step, it remains uncertain whether the waveform and sIMU features identified here will translate effectively into clinical decision-making tools.

Methodological Considerations of PCA and Feature Selection

The analytical framework adopted in Studies 3 and 4, centred on PCA and ensemble feature selection, presents both strengths and limitations. PCA is a powerful method for reducing high-dimensional biomechanical data and identifying latent structures^{1,64}. However, the principal

components it produces are abstract mathematical constructs that do not always map intuitively onto discrete biomechanical features. While methods such as reconstruction and representative extremes can improve interpretability³⁴, interpretation remains inferential rather than direct. Consequently, clinicians may still find it challenging to translate these latent features into actionable rehabilitation targets without additional interpretive frameworks.

The ensemble feature selection approach enhanced robustness by combining multiple ranking methods, reducing reliance on any single metric of feature importance⁹⁹. However, this complexity comes at the cost of interpretability. The process of narrowing thousands of waveform features to a small subset of principal components, and then further filtering them through ensemble selection, introduces layers of abstraction that distance the final models from raw biomechanics. This may complicate clinical adoption unless future work develops interpretive frameworks that explicitly link selected principal components to observable movement patterns and clinically meaningful biomechanical adaptations.

Finally, while PCA was applied within a leave-one-out cross-validation loop to avoid information leakage, methodological decisions such as the number of components retained or the use of specific feature selection thresholds remain somewhat arbitrary. Although sensitivity analyses were conducted, the stability of selected features may still depend on dataset-specific factors. Replication in larger, independent cohorts will be necessary to confirm the generalizability of the identified discriminative components.

Beyond generalizability, translating laboratory-based classification models into clinical practice presents additional challenges. Importantly, the models developed in this thesis were not designed as diagnostic tools for ACL injury. Rather, they were developed to identify movement features that maximally distinguish adolescents with ACL injury histories from uninjured controls, thereby characterizing deviations from healthy movement patterns rather than injury mechanisms themselves. Consequently, model outputs should be interpreted as indicators of movement quality relative to healthy peers rather than as evidence of the presence or absence of injury. From a clinical perspective, this distinction may be particularly valuable, as persistent "ACLi-like" movement patterns following rehabilitation could indicate residual functional adaptations or incomplete recovery despite meeting conventional RTA criteria. However, before such approaches can be implemented clinically, further work is needed to establish clinically meaningful thresholds, externally validate the models in independent adolescent cohorts, and determine whether these

movement signatures are associated with outcomes such as reinjury risk, successful RTA, or long-term joint health. In addition, clinically deployable systems will require standardized protocols, automated processing pipelines, and interpretable outputs that can be readily integrated into routine rehabilitation and RTA decision-making.

Sample Size and Class Imbalance

The relatively modest sample size, particularly in the ACL-injured group, represents a final limitation of this thesis. Machine learning approaches, such as those applied here, typically benefit from large datasets that capture the full range of biological variability¹⁰³. Although leave-one-out cross-validation maximizes data use, smaller samples can lead to unstable decision boundaries and reduced generalizability when models are applied to new data.

Class imbalance further compounded this issue, as the number of uninjured participants exceeded injured participants. While SMOTE was used to augment the minority class and mitigate bias, synthetic oversampling cannot fully substitute for real biological variability⁴⁸. Moreover, SMOTE assumes that the minority class is homogenous enough to interpolate synthetic samples, which may not hold in ACL-injured adolescents with heterogeneous injury histories. This limitation raises the possibility that models may overfit to synthetic patterns rather than capturing true injury-related adaptations.

In addition, the use of leave-one-out cross-validation, while appropriate for small datasets, has been criticized for producing high-variance error estimates compared to methods like nested k-fold cross-validation²⁴⁵. Although this approach ensured that every trial contributed to model validation, reported accuracies should be interpreted cautiously. Future studies with larger, balanced samples are needed to confirm the stability of findings and enable the use of independent test sets for unbiased model evaluation.

10.7 Clinical Implications

The findings of this thesis carry several important clinical implications for how ACL injuries are assessed, monitored, and managed in adolescent populations. By moving beyond conventional spatiotemporal outcomes and incorporating waveform-based analyses and sIMU signals, this work demonstrates the potential to enhance objective movement assessment and support individualized rehabilitation strategies. Importantly, the classification frameworks developed throughout this thesis were designed to identify movement patterns associated with previous ACL injury rather than to function as standalone diagnostic tools. Their primary purpose is to provide objective

biomechanical information that complements existing RTA assessments and supports clinical decision-making.

First, the reproducibility of hop tasks across environments demonstrated in Study 1 confirms that these functional assessments can be reliably administered not only in biomechanics laboratories but also in school gyms and community clinics. This expands the feasibility of using hop tests as part of standard RTA protocols in adolescents, where laboratory access is limited. Reliable test-retest properties mean clinicians can confidently track progress over time and interpret changes as meaningful rather than measurement error^{23,68}. Importantly, the demonstrated responsiveness suggests that hop tasks can detect clinically relevant improvements, reinforcing their role in rehabilitation monitoring and outcome evaluation.

Second, the modest classification accuracy of spatiotemporal metrics alone, observed in Study 2, has direct implications for current clinical practice. RTA decisions in adolescents often rely heavily on measures such as hop distance and limb symmetry indices^{15,92}. The findings here confirm that while such metrics remain useful, they may not provide sufficient sensitivity to detect underlying movement deficits. This suggests that clinical guidelines may need to reconsider the weight placed on symmetry indices alone and instead integrate complementary assessments capable of capturing movement quality and compensatory strategies.

Study 3 provides evidence that waveform-based analyses can more effectively differentiate between injured and contralateral limbs than spatiotemporal outcomes. The classification results showed that the injured limb was consistently more separable from uninjured controls than the contralateral limb, indicating that waveform features capture compensatory adaptations that mask differences when only spatiotemporal metrics are considered. These findings underscore the complexity of contralateral limb involvement after ACL injury. While often assumed to function as a “healthy” comparator, the contralateral limb may itself adopt altered movement strategies that reduce its discriminative value. Clinically, this highlights the need to carefully interpret comparisons between limbs in adolescent athletes and suggests that waveform-based approaches provide a more nuanced assessment of residual deficits following ACL injury.

Finally, Study 4 offers critical insights into the potential for wearable IMUs to bridge the gap between laboratory biomechanics and clinical practice. Although the observed classification performance is not sufficient for independent clinical decision-making, the results demonstrate that wearable sensors can capture clinically relevant movement information comparable to

laboratory-based motion capture. Such systems are therefore best viewed as decision-support tools that complement existing assessments rather than replace them. By demonstrating that sIMU-derived features achieved classification accuracies comparable to motion capture, the findings support the feasibility of using wearable sensors for field-based assessment. This demonstrates the potential for future routine monitoring in schools, sports teams, and community rehabilitation programs where access to laboratory equipment is not feasible^{4,42}. In particular, the identification of thigh and shank placements as the most informative sensor configurations provides practical guidance for clinicians and researchers, ensuring that IMU deployment is both efficient and clinically meaningful.

From an implementation perspective, wearable IMUs may be integrated into routine pediatric sports medicine practice as an adjunct to existing RTA assessments rather than as a replacement for current clinical tools. For example, clinicians could instrument adolescents with a small number of sensors positioned on the lower body segments while performing functional tasks such as hopping or squatting during rehabilitation visits. These sensors could provide objective measures of movement quality and asymmetry that complement traditional metrics such as hop distance, limb symmetry indices, strength testing, and patient-reported outcomes. The portability and relatively low cost of IMUs may facilitate repeated assessments across rehabilitation, allowing clinicians to monitor recovery trajectories longitudinally in clinical, school, or community sport settings. Importantly, successful clinical implementation will depend on the development of standardized sensor placement protocols and user-friendly outputs that provide interpretable information to support decision-making.

The relative importance of precision and recall will ultimately depend on the intended clinical application. For screening or rehabilitation monitoring, higher sensitivity (recall) may be preferred to minimize the likelihood of overlooking adolescents who continue to demonstrate altered movement patterns, even if this results in additional false-positive classifications requiring further assessment. Conversely, applications intended to support high-stakes RTA decisions would require substantially greater precision and overall classification performance than demonstrated in the present work. Accordingly, the models developed in this thesis should be viewed as an initial proof-of-concept that establishes the feasibility of wearable biomechanical classification, while highlighting the need for further refinement and external validation before routine clinical implementation.

Across all four studies, the work underscores the importance of adopting a multimodal approach to ACL injury assessment in adolescents. Clinicians are encouraged to combine reproducible spatiotemporal outcomes, waveform-derived insights, and wearable sensor technologies to achieve a more comprehensive understanding of functional performance. Such integration has the potential to improve the accuracy of RTA decisions, reduce reinjury risk, and tailor interventions to individual needs, ultimately advancing evidence-based care for adolescents recovering from ACL injury.

The findings of this thesis also have implications for future RTA guidelines and rehabilitation protocols in adolescent populations. Current RTA decisions frequently emphasize performance-based measures such as hop distance, strength, and limb symmetry indices. However, the present findings suggest that these measures may not fully capture persistent movement adaptations, particularly in the contralateral limb. Future guidelines may therefore benefit from incorporating assessments of movement quality alongside traditional performance metrics. Wearable sensors offer a practical means of implementing such assessments in clinical settings by providing objective biomechanical information during functional tasks. Integrating spatiotemporal measures, patient-reported outcomes, and wearable-derived movement quality metrics may support more individualized rehabilitation progression and safer RTA decisions for adolescents recovering from ACL injury.

10.8 Future Directions

The findings of this thesis highlight both the potential and the limitations of current approaches to evaluating adolescent functional performance following ACL injury. Future research should move beyond isolated assessments or narrow methodological comparisons toward building a more integrated framework that can capture the complexity of adolescent recovery, support individualized rehabilitation, and facilitate real-world clinical application.

One overarching direction lies in the development of multi-modal assessment frameworks that combine spatiotemporal outcomes, kinematic waveforms, and wearable sensor data. While spatiotemporal metrics remain useful for quick, interpretable evaluations, waveform analyses provide richer insights into movement adaptations, and IMUs promise accessibility outside of the laboratory. Combining these approaches has the potential to enhance clinical decision-making by leveraging the strengths of each modality. Previous work has demonstrated that discrete hop

symmetry indices can mask deficits^{92,249}, whereas waveform analyses reveal subtle adaptations invisible to summary metrics^{64,81}. IMUs, meanwhile, have shown reliability and validity for dynamic task monitoring^{4,42}. Integrating these modalities would allow for a more complete characterization of performance and enhance the ecological validity of assessments. Future work may also explore alternative time-series feature extraction and representation-learning approaches to determine whether they provide improved performance or interpretability relative to PCA-based analyses.

Another priority is the advancement of prospective, longitudinal research designs. Much of the current work, including the studies in this thesis, focuses on cross-sectional classification of injury status. However, ACL injury and recovery are dynamic processes, and movement adaptations evolve. Longitudinal studies would enable the identification of early biomechanical markers predictive of re-injury or long-term functional decline. For example, abnormal symmetry indices and altered landing mechanics have been linked to subsequent contralateral ACL injuries and long-term osteoarthritis risk^{147,187}. Embedding waveform and IMU-based analyses into rehabilitation monitoring could shift assessments from static benchmarks to dynamic, individualized trajectories of recovery. In this context, wearable IMU systems are particularly well-suited for longitudinal designs, as their portability and low cost enable frequent or continuous data collection. Leveraging repeated measurements may improve the stability and interpretability of IMU-derived features and help mitigate the reduced signal fidelity relative to laboratory-based motion capture.

The incorporation of sex-specific and developmental considerations also warrants attention. Although exploratory analyses in this thesis suggested unique movement strategies in adolescent females, limited sample sizes prevented firm conclusions. Future studies should recruit larger, sex-balanced cohorts to better capture how sex and maturation interact with neuromuscular control. Literature consistently demonstrates that adolescent females exhibit greater valgus knee motion, altered landing mechanics, and higher ACL injury risk^{84,108,196}. Additionally, growth- and puberty-related changes influence joint kinematics and muscle activation patterns^{59,155,156}. Understanding these interactions will be critical for developing sex- and age-specific rehabilitation protocols and injury prevention strategies.

Finally, the translation of biomechanical assessment into field-based and technology-enabled practice represents a critical future step. Portable IMU systems, when validated against

gold-standard motion capture, could allow clinicians and coaches to monitor athletes in natural environments and during sport-specific tasks. Numerous validation studies have confirmed the concurrent validity of IMU-based systems for gait and sports movements^{28,203,220}. Emerging applications also show promise for integrating IMUs with machine learning pipelines for real-time classification of functional performance^{131,251}. Developing cloud-based platforms to aggregate and analyze wearable data could provide clinicians with interpretable feedback in real time, bridging the gap between biomechanics research and applied clinical decision-making. Importantly, future work should ensure that such systems balance analytical sophistication with usability and interpretability, so they are not only accurate but also feasible in everyday practice.

Collectively, these directions emphasize the importance of bridging laboratory-based biomechanics with applied rehabilitation and clinical monitoring. By combining methodological rigour with technological innovation, future research can advance toward assessment strategies that are not only accurate and reproducible but also feasible and impactful in the everyday contexts where adolescents train, recover, and compete.

10.9 Conclusion

This thesis set out to determine whether adolescent functional performance following ACL injury could be more effectively characterized through analyses that extend beyond conventional spatiotemporal outcomes. By combining reproducibility testing, classification modelling, waveform analysis, and simulated inertial sensing, the four studies created a continuum of evidence moving from the foundations of task reliability to clinically translatable sensor-based assessment.

The first two studies established that single-limb hop tests are reproducible in adolescents and capable of detecting sex-based differences in performance, while also showing that spatiotemporal measures alone provide only modest classification accuracy, particularly in females. Building on these findings, the third study demonstrated that kinematic waveform analysis using PCA offers superior classification power and revealed adaptations not captured by discrete hop outcomes, particularly in contralateral limbs. The fourth study extended this approach by confirming that sIMUs can replicate motion capture performance, with thigh and shank placements providing the most discriminative information, thereby supporting the feasibility of wearable sensor-based assessments. Although sIMUs demonstrated slightly reduced discriminative performance relative to marker-based kinematics, their scalability and capacity for

repeated data collection suggest that wearable sensor approaches may benefit from higher-volume or longitudinal sampling strategies to enhance robustness in applied settings.

Taken together, the findings of this thesis underscore that while spatiotemporal hop outcomes remain clinically valuable, they are insufficient for fully characterizing adolescent ACL injury. Waveform-based methods capture subtle adaptations in movement strategies, and the successful application of sIMUs points toward a future where portable, field-ready tools can provide deeper biomechanical insights. This work thus bridges the gap between controlled laboratory biomechanics and applied clinical practice, laying the groundwork for more precise rehabilitation monitoring, improved return-to-activity decision-making, and the development of scalable injury-prevention strategies for adolescent populations.

REFERENCES

1. Abdi H, Williams LJ. Principal component analysis. *Wiley Interdiscip Rev Comput Stat.* 2010;2(4):433-459.
2. Abitbol MM. The shapes of the female pelvis: Contributing factors. Vol. 41. 1996.
3. Adams D, Logerstedt DS, Hunter-Giordano A, Axe MJ, Snyder-Mackler L. Current concepts for anterior cruciate ligament reconstruction: A criterion-based rehabilitation progression. *J Orthop Sports Phys Ther.* 2012;42(7):601-614.
4. Al-Amri M, Nicholas K, Button K, Sparkes V, Sheeran L, Davies JL. Inertial measurement units for clinical movement analysis: Reliability and concurrent validity. *Sensors.* 2018;18(719):1-29.
5. Alentorn-Geli E, Myer GD, Silvers HJ, et al. Prevention of non-contact anterior cruciate ligament injuries in soccer players. Part 1: Mechanisms of injury and underlying risk factors. *Knee Surg Sports Traumatol Arthrosc.* 2009;17(7):705-729. doi:10.1007/s00167-009-0813-1
6. Alkjær T, Henriksen M, Dyhre-Poulsen P, Simonsen EB. Forward lunge as a functional performance test in ACL-deficient subjects: Test-retest reliability. *Knee.* 2009;16(3):176-182. doi:10.1016/j.knee.2008.11.011
7. Alkjaer T, Simonsen EB, Jørgensen U, Dyhre-Poulsen P. Evaluation of the walking pattern in two types of patients with anterior cruciate ligament deficiency: Copers and non-copers. *Eur J Appl Physiol.* 2003;89(3-4):301-308. doi:10.1007/s00421-002-0787-x
8. Altman NS. An introduction to kernel and nearest-neighbor nonparametric regression. *Am Stat.* 1992;46(3):175-185.
9. Anderson AF, Irrgang JJ, Kocher MS, Mann BJ, Harrast JJ. The International Knee Documentation Committee Subjective Knee Evaluation Form normative data. *Am J Sports Med.* 2006;34(1):128-135. doi:10.1177/0363546505280214
10. Andriacchi TP, Dyrby CO. Interactions between kinematics and loading during walking for the normal and ACL-deficient knee. *J Biomech.* 2005;38(2):293-298. doi:10.1016/j.jbiomech.2004.02.010
11. Ardern CL, Taylor NF, Feller JA, Webster KE. Fifty-five per cent return to competitive sport following anterior cruciate ligament reconstruction surgery: An updated systematic

- review and meta-analysis including aspects of physical functioning and contextual factors. *Br J Sports Med.* 2014;48(21):1543-1552. doi:10.1136/bjsports-2014-093842
12. Astephen JL, Deluzio KJ, Caldwell GE, Dunbar MJ, Hubley-Kozey CL. Gait and neuromuscular pattern changes are associated with differences in knee osteoarthritis severity levels. *J Biomech.* 2008;41(4):868-876. doi:10.1016/j.jbiomech.2007.10.037
 13. Bahr R, Krosshaug T. Understanding injury mechanisms: A key component of preventing injuries in sport. *Br J Sports Med.* 2005;39(6):324-329. doi:10.1136/bjsm.2005.018341
 14. Barber SD, Noyes FR, Mangine RE, McCloskey JW, Hartman W. Quantitative assessment of functional limitations in normal and anterior cruciate ligament-deficient knees. *Clin Orthop Relat Res.* 1990;255:204-214.
 15. Barber-Westin SD, Noyes FR. Factors used to determine return to unrestricted sports activities after anterior cruciate ligament reconstruction. *Arthroscopy.* 2011;27(12):1697-1705.
 16. Barengo NC, Meneses-Echávez JF, Ramírez-Vélez R, Cohen DD, Tovar G, Correa Bautista JE. The impact of the FIFA 11+ training program on injury prevention in football players: A systematic review. *Int J Environ Res Public Health.* 2014;11(11):11986-12000. doi:10.3390/ijerph111111986
 17. Barrett DS. Proprioception and function after anterior cruciate ligament reconstruction. *J Bone Joint Surg Br.* 1991;73-B(5):833-837.
 18. Bartlett HL, Goldfarb M. A phase variable approach for IMU-based locomotion activity recognition. *IEEE Trans Biomed Eng.* 2018;65(6):1330-1338. doi:10.1109/TBME.2017.2750139
 19. Baumgart C, Schubert M, Hoppe MW, Gokeler A, Freiwald J. Do ground reaction forces during unilateral and bilateral movements exhibit compensation strategies following ACL reconstruction? *Knee Surg Sports Traumatol Arthrosc.* 2017;25(5):1385-1394.
 20. Beaulieu ML, Lamontagne M, Beaulé PE. Lower limb biomechanics during gait do not return to normal following total hip arthroplasty. *Gait Posture.* 2010;32(2):269-273. doi:10.1016/j.gaitpost.2010.05.007
 21. Beaulieu ML, Lamontagne M, Xu L. Lower limb muscle activity and kinematics of an unanticipated cutting manoeuvre: A gender comparison. *Knee Surg Sports Traumatol Arthrosc.* 2009;17(8):968-976. doi:10.1007/s00167-009-0821-1

22. Beck NA, Lawrence JTR, Nordin JD, DeFor TA, Tompkins M. ACL tears in school-aged children and adolescents over 20 years. *Pediatrics*. 2017;139(3):e20161877. doi:10.1542/peds.2016-1877
23. Beckerman H, Roebroeck ME, Lankhorst GJ, Becher JG, Bezemer PD, Verbeek ALM. Smallest real difference, a link between reproducibility and responsiveness. *Qual Life Res*. 2001;10(7):571-578.
24. Bellman RE. *Adaptive Control Processes: A Guided Tour*. Princeton University Press; 1961.
25. Benoit DL, Ramsey DK, Lamontagne M, Xu L, Wretenberg P, Renström P. Effect of skin movement artifact on knee kinematics during gait and cutting motions measured in vivo. *Gait Posture*. 2006;24(2):152-164. doi:10.1016/j.gaitpost.2005.04.01226.
26. Bevly DM. Global Positioning System (GPS): A low-cost velocity sensor for correcting inertial sensor errors on ground vehicles. *J Dyn Syst Meas Control*. 2004;126:255-264. doi:10.1115/1.1766027
27. Bisseling RW, Hof AL. Handling of impact forces in inverse dynamics. *J Biomech*. 2006;39(13):2438-2444. doi:10.1016/j.jbiomech.2005.07.021
28. Blair S, Duthie G, Robertson S, Hopkins W, Ball K. Concurrent validation of an inertial measurement system to quantify kicking biomechanics in four football codes. *J Biomech*. 2018;73:24-32.
29. Bland JM, Altman DG. Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet*. 1986;327(8476):307-310.
30. Boden BP, Dean SG, Feagin JA, et al. Mechanisms of anterior cruciate ligament injury. *Orthopedics*. 2000;23(6):573-578. doi:10.3928/0147-7447-20000601-15
31. Bodkin S, Goetschius J, Hertel J, Hart J. Relationships of muscle function and subjective knee function in patients after ACL reconstruction. *Orthop J Sports Med*. 2017;5(7):1-7. doi:10.1177/2325967117719041
32. Bohu Y, Klouche S, Lefevre N, Webster K, Herman S. Translation, cross-cultural adaptation and validation of the French version of the Anterior Cruciate Ligament-Return to Sport after Injury (ACL-RSI) scale. *Knee Surg Sports Traumatol Arthrosc*. 2015;23(4):1192-1196. doi:10.1007/s00167-014-2942-4

33. Bose W, Beck C, Ambrosia RD. The synergistic action of the anterior cruciate ligament and thigh muscles in maintaining joint stability. *Am J Sports Med.* 1987;15(3):207-213.
34. Brandon SCE, Graham RB, Almosnino S, Sadler EM, Stevenson JM, Deluzio KJ. Interpreting principal components in biomechanics: Representative extremes and single component reconstruction. *J Electromyogr Kinesiol.* 2013;23(6):1304-1310. doi:10.1016/j.jelekin.2013.09.010
35. Brattström H. Shape of the intercondylar groove normally and in recurrent dislocation of patella: A clinical and X-ray anatomical investigation. *Acta Orthop Scand.* 1964;35(Suppl 68):1-148.
36. Breiman L. Bias, variance, and arcing classifier. Technical Report. 1996;460(April):1-20.
37. Breiman L, Friedman JH, Stone CJ, Olshen RA. *Classification and Regression Trees.* 1st ed. Chapman and Hall/CRC; 1984.
38. Brennan A, Zhang J, Deluzio K, Li Q. Quantification of inertial sensor-based 3D joint angle measurement accuracy using an instrumented gimbal. *Gait Posture.* 2011;34:320-323.
39. Brodie M, Walmsley A, Page W. Fusion motion capture: A prototype system using inertial measurement units and GPS for the biomechanical analysis of ski racing. *Sports Technol.* 2008;1(1):17-28. doi:10.1002/JST.6
40. Button K, Van Deursen R, Price P. Classification of functional recovery of anterior cruciate ligament copers, non-copers, and adapters. *Br J Sports Med.* 2006;40(10):853-858. doi:10.1136/bjsm.2006.028258
41. Cabitza F, Locoro A, Banfi G. Machine learning in orthopedics: A literature review. *Front Bioeng Biotechnol.* 2018;6:75.
42. Camomilla V, Bergamini E, Fantozzi S, Vannozzi G. Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. *Sensors.* 2018;18(3). doi:10.3390/S18030873
43. Capodaglio P, Cimolin V. Wearables for movement analysis in healthcare. *Sensors.* 2022;22(10). doi:10.3390/S22103720
44. Cappozzo A, Catani F, Leardini A, Benedetti MG, Della Croce U. Position and orientation in space of bones during movement: Experimental artefacts. *Clin Biomech (Bristol, Avon).* 1996;11(2):90-100. doi:10.1016/0268-0033(95)00046-1

45. Caramia C, Torricelli D, Schmid M, et al. IMU-based classification of Parkinson's disease from gait: A sensitivity analysis on sensor location and feature selection. *IEEE J Biomed Health Inform.* 2018;22(6):1765-1774.
46. Carletta J. Assessing agreement on classification tasks: The kappa statistic. *Comput Linguist.* 1996;22(2):249-254.
47. Chapelle O, Vapnik V, Bousquet O, Mukherjee S. Choosing multiple parameters for support vector machines. *Mach Learn.* 2002;46(1-3):131-159.
doi:10.1023/A:1012450327387
48. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: Synthetic minority over-sampling technique. *J Artif Intell Res.* 2002;16:321-357. doi:10.1613/JAIR.953
49. Chmielewski TL, Jones D, Day T, Tillman SM, Lentz TA, George SZ. The association of pain and fear of movement/reinjury with function during anterior cruciate ligament reconstruction rehabilitation. *J Orthop Sports Phys Ther.* 2008;38(12):746-753.
doi:10.2519/jospt.2008.2887
50. Christino MA, Fleming BC, Machan JT, Shalvoy RM. Psychological factors associated with anterior cruciate ligament reconstruction recovery. *Orthop J Sports Med.* 2016;4(3):1-9.
51. Coleman L, Coleman J. The measurement of puberty: A review. *J Adolesc.* 2002;25(5):535-550. doi:10.1006/jado.2002.0494
52. Cook G, Burton L, Hoogenboom B. Pre-participation screening: The use of fundamental movements as an assessment of function—Part 1. *N Am J Sports Phys Ther.* 2006;1(2):62-72.
53. Cook G, Burton L, Hoogenboom BJ, Voight M. Functional movement screening: The use of fundamental movements as an assessment of function—Part 2. *Int J Sports Phys Ther.* 2014;9(4):549-563.
54. Cortes C, Vapnik V. Support-vector networks. *Mach Learn.* 1995;20(3):273-297.
doi:10.1007/BF00994018
55. Cuesta-Vargas AI, Galán-Mercant A, Williams JM. The use of inertial sensor systems for human motion analysis. *Physiother Rev.* 2010;15(6):462-473.
doi:10.1179/1743288X11Y.0000000006

56. Culvenor AG, Collins NJ, Guermazi A, et al. Early patellofemoral osteoarthritis features one year after anterior cruciate ligament reconstruction: Symptoms and quality of life at three years. *Arthritis Care Res (Hoboken)*. 2016. doi:10.1002/acr.22761
57. Cutti AG, Ferrari A, Garofalo P, Raggi M, Cappello A, Ferrari A. "Outwalk": A protocol for clinical gait analysis based on inertial and magnetic sensors. *Med Biol Eng Comput*. 2010;48(1):17-25. doi:10.1007/s11517-009-0545-x
58. Dekker TJ, Godin JA, Dale KM, Garrett WE, Taylor DC, Riboh JC. Return to sport after pediatric anterior cruciate ligament reconstruction and its effect on subsequent anterior cruciate ligament injury. *J Bone Joint Surg Am*. 2017;99(11):897-904.
59. DelBel MJ, Fairfax AK, Jones ML, Steele K, Landry SC. Effect of limb dominance and sex on neuromuscular activation patterns in athletes under 12 performing unanticipated side-cuts. *J Electromyogr Kinesiol*. 2017;36:65-72.
60. DelBel MJ, Kemp LG, Girard CI, et al. Translation and validation of the Hospital for Special Surgery Pediatric Functional Activity Brief Scale for French paediatric populations. *Physiother Can*. 2022;74(4):348-354.
61. De Leva P. Adjustments to Zatsiorsky-Seluyanov's segment inertia parameters. *J Biomech*. 1996;29(9):1223-1230.
62. De Leva P. Joint center longitudinal positions computed from a selected subset of Chandler's data. *J Biomech*. 1996;29(9):1231-1233.
63. De Luca CJ, Gilmore LD, Kuznetsov M, Roy SH. Filtering the surface EMG signal: Movement artifact and baseline noise contamination. *J Biomech*. 2010;43(8):1573-1579. doi:10.1016/j.jbiomech.2010.01.027
64. Deluzio KJ, Astephen JL. Biomechanical features of gait waveform data associated with knee osteoarthritis: An application of principal component analysis. *Gait Posture*. 2007;25(1):86-93. doi:10.1016/j.gaitpost.2006.01.007
65. de Magalhães FA, Vannozzi G, Gatta G, Fantozzi S. Wearable inertial sensors in swimming motion analysis: A systematic review. *J Sports Sci*. 2015;33(7):732-745. doi:10.1080/02640414.2014.962574
66. de Vet HCW, Terwee CB, Knol DL, Bouter LM. When to use agreement versus reliability measures. *J Clin Epidemiol*. 2006;59(10):1033-1039.

67. Dhillon IS, Sra S. Generalized nonnegative matrix approximations with Bregman divergences. *Adv Neural Inf Process Syst*. 2005;18.
68. Dingenen B, Truijen J, Bellemans J, Gokeler A. Test-retest reliability and discriminative ability of forward, medial and rotational single-leg hop tests. *Knee*. 2019;26:978-987.
69. Dodwell E, Lamont LE, Green DW, Pan TJ, Marx RG, Lyman SL. Twenty years of pediatric anterior cruciate ligament reconstruction in New York State. *Am J Sports Med*. 2014;42(3):675-680. doi:10.1177/0363546513518412
70. Donà G, Preatoni E, Cobelli C, Rodano R, Harrison AJ. Application of functional principal component analysis in race walking: An emerging methodology. *Sports Biomech*. 2009;8(4):284-301. doi:10.1080/14763140903414425
71. Dowling AV, Favre J, Andriacchi TP. Inertial sensor-based feedback can reduce key risk metrics for anterior cruciate ligament injury during jump landings. *Am J Sports Med*. 2012;40(5):1075-1083. doi:10.1177/0363546512437529
72. Duda RO, Hart PE, Stork DG. *Pattern Classification*. 2nd ed. Wiley; 2000.
73. Dudek G, Jenkin M. Inertial sensors, GPS, and odometry. In: *Springer Handbook of Robotics*. Springer Berlin Heidelberg; 2008:477-490. doi:10.1007/978-3-540-30301-5_21
74. Eitzen I, Eitzen TJ, Holm I, Snyder-Mackler L, Risberg MA. Anterior cruciate ligament-deficient potential copers and noncopers reveal different isokinetic quadriceps strength profiles in the early stage after injury. *Am J Sports Med*. 2010;38(3):586-593. doi:10.1177/0363546509349492
75. Erickson BJ, Harris JD, Fillingham YA, et al. Anterior cruciate ligament reconstruction practice patterns by NFL and NCAA football team physicians. *Arthroscopy*. 2014;30(6):731-738. doi:10.1016/j.arthro.2014.02.034
76. Faber SC, Eckstein F, Lukasz S, et al. Gender differences in knee joint cartilage thickness, volume and articular surface area assessment with quantitative three-dimensional MR imaging. *Skeletal Radiol*. 2001;30(3):144-150.
77. Fabricant PD, Robles A, Downey-Zayas T, et al. Development and validation of a pediatric sports activity rating scale. *Am J Sports Med*. 2013;41(10):2421-2429.
78. Favre J, Aissaoui R, Jolles BM, de Guise JA, Aminian K. Functional calibration procedure for 3D knee joint angle description using inertial sensors. *J Biomech*. 2009;42(14):2330-2335. doi:10.1016/j.jbiomech.2009.06.025

79. Favre J, Jolles BM, Aissaoui R, Aminian K. Ambulatory measurement of 3D knee joint angle. *J Biomech.* 2008;41(5):1029-1035. doi:10.1016/j.jbiomech.2007.12.003
80. Favre J, Luthi F, Jolles BM, Siegrist O, Najafi B, Aminian K. A new ambulatory system for comparative evaluation of the three-dimensional knee kinematics, applied to anterior cruciate ligament injuries. *Knee Surg Sports Traumatol Arthrosc.* 2006;14(7):592-604. doi:10.1007/s00167-005-0023-4
81. Federolf P, Reid R, Gilgien M, Haugen P, Smith G. The application of principal component analysis to quantify technique in sports. *Scand J Med Sci Sports.* 2014;24(3):491-499. doi:10.1111/j.1600-0838.2012.01455.x
82. Fischer-Rasmussen T, Jensen PE. Proprioceptive sensitivity and performance in anterior cruciate ligament-deficient knee joints. *Scand J Med Sci Sports.* 2000;10(2):85-89. doi:10.1034/j.1600-0838.2000.010002085.x
83. Flaxman TE, Smith AJJ, Benoit DL. Sex-related differences in neuromuscular control: Implications for injury mechanisms or healthy stabilisation strategies? *J Orthop Res.* 2014;32(2):310-317. doi:10.1002/jor.22510
84. Ford KR, Myer GD, Hewett TE. Valgus knee motion during landing in high school female and male basketball players. *Med Sci Sports Exerc.* 2003;35(10):1745-1750. doi:10.1249/01.MSS.0000089346.85744.D9
85. Foxlin E. Inertial head-tracker sensor fusion by a complementary separate-bias Kalman filter. In: *Proceedings of the IEEE 1996 Virtual Reality Annual International Symposium.* IEEE; 1996:185-195.
86. Fransen J, Lenoir M, Pion J, Segers V. The value of non-sport-specific characteristics for talent orientation in young male judo, karate and taekwondo athletes. *Sci Martial Arts.* 2014;10:147.
87. Friedman JH. On bias, variance, 0/1-loss, and the curse of dimensionality. *Data Min Knowl Discov.* 1997;1(1):55-77. doi:10.1023/A:1009778005914
88. Girard CI, Romanchuk NJ, Del Bel MJ, Carsen S, Chan ADC, Benoit DL. Classifiers of anterior cruciate ligament status in female and male adolescents using return-to-activity criteria. *Knee Surg Sports Traumatol Arthrosc.* 2025;33(5):1633-1644. doi:10.1002/ksa.12462

89. Girard CI, Warren CE, Romanchuk NJ, et al. Decision tree learning algorithm for classifying knee injury status using return-to-activity criteria. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS). Vol. 2020. Institute of Electrical and Electronics Engineers Inc.; 2020:5494-5497.
90. Girgis FG, Marshall JL, Monajem A. The cruciate ligaments of the knee joint: Anatomical, functional and experimental analysis. *Clin Orthop Relat Res*. 1975;106:216-231.
91. Glaws KR, Juneau CM, Becker LC, Di Stasi SL, Hewett TE. Intra- and inter-rater reliability of the Selective Functional Movement Assessment (SFMA). *Int J Sports Phys Ther*. 2014;9(2):195-207.
92. Gokeler A, Welling W, Benjaminse A, Lemmink K, Seil R, Zaffagnini S. A critical analysis of limb symmetry indices of hop tests in athletes after anterior cruciate ligament reconstruction: A case-control study. *Orthop Traumatol Surg Res*. 2017;103(6):947-951.
93. Goldblatt JP, Fitzsimmons SE, Balk E, Richmond JC. Reconstruction of the anterior cruciate ligament: Meta-analysis of patellar tendon versus hamstring tendon autograft. *Arthroscopy*. 2005;21(7):791-803. doi:10.1016/j.arthro.2005.04.107
94. Gray J, Taunton JE, McKenzie DC, Clement DB, McConkey JP, Davidson RG. A survey of injuries to the anterior cruciate ligament of the knee in female basketball players. *Int J Sports Med*. 1985;6(6):314-316. doi:10.1055/s-2008-1025861
95. Grood ES, Suntay WJ. A joint coordinate system for the clinical description of three-dimensional motions: Application to the knee. *J Biomech Eng*. 1983;105(2):136-144.
96. Groves PD. Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems. 2nd ed. Artech House; 2013.
97. Gurchiek RD, Choquette RH, Beynnon BD, et al. Remote gait analysis using wearable sensors detects asymmetric gait patterns in patients recovering from ACL reconstruction. In: 2019 IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN). IEEE; 2019:1-4. doi:10.1109/BSN.2019.8771038
98. Guyatt G, Walter S, Norman G. Measuring change over time: Assessing the usefulness of evaluative instruments. *J Chronic Dis*. 1987;40(2):171-178.

99. Guyon I, Elisseeff A. An introduction to feature extraction. *Stud Fuzziness Soft Comput.* 2006;207:1-25. doi:10.1007/978-3-540-35488-8_1
100. Halinen J, Koivikko M, Lindahl J, Hirvensalo E. The efficacy of magnetic resonance imaging in acute multi-ligament injuries. *Int Orthop.* 2009;33(6):1733-1738. doi:10.1007/s00264-008-0689-6
101. Harrison AL. The influence of pathology, pain, balance, and self-efficacy on function in women with osteoarthritis of the knee. *Phys Ther.* 2004;84(9):822-831.
102. Harter RA, Osternig LR, Singer KM, James SL, Larson RL, Jones DC. Long-term evaluation of knee stability and function following surgical reconstruction for anterior cruciate ligament insufficiency. *Am J Sports Med.* 1988;16(5):434-443.
103. Hastie T, Tibshirani R, Friedman J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* 2nd ed. Springer; 2017.
104. Haycock CE, Gillette JV. Susceptibility of women athletes to injury: Myths vs reality. *JAMA.* 1976;236(2):163-165. doi:10.1001/jama.1976.03270020033020
105. Heath EL, Salmon LJ, Cooper R, Pappas E, Roe JP, Pinczewski LA. Five-year survival of pediatric anterior cruciate ligament reconstruction with living donor hamstring tendon grafts. *Am J Sports Med.* 2019;47(1):41-51. doi:10.1177/0363546518804502
106. Hermens HJ, Freriks B, Disselhorst-Klug C, Rau G. Development of recommendations for SEMG sensors and sensor placement procedures. *J Electromyogr Kinesiol.* 2000;10(5):361-374. doi:10.1016/S1050-6411(00)00027-4
107. Herrington L, Fowler E. A systematic literature review to investigate if we identify those patients who can cope with anterior cruciate ligament deficiency. *Knee.* 2006;13(4):260-265. doi:10.1016/j.knee.2006.02.010
108. Hewett TE, Ford KR, Myer GD. Anterior cruciate ligament injuries in female athletes. *Am J Sports Med.* 2006;34(3):490-498. doi:10.1177/0363546505282619
109. Hewett TE, Myer GD, Ford KR. Decrease in neuromuscular control about the knee with maturation in female athletes. *J Bone Joint Surg Am.* 2004;86(8):1601-1608.
110. Hewett TE, Myer GD, Ford KR, et al. Biomechanical measures of neuromuscular control and valgus loading of the knee predict anterior cruciate ligament injury risk in female athletes: A prospective study. *Am J Sports Med.* 2005;33(4):492-501.
111. Hinton G, Roweis S. *Stochastic Neighbor Embedding.* Vol. 15. 2002.

112. Hirschfeld HO. A connection between correlation and contingency. *Math Proc Cambridge Philos Soc.* 1935;31(4):520-524. doi:10.1017/S0305004100013517
113. Hotelling H. Analysis of a complex of statistical variables into principal components. *J Educ Psychol.* 1933;24(6):417-441. doi:10.1037/h0071325
114. Hripcsak G, Rothschild AS. Agreement, the F-measure, and reliability in information retrieval. *J Am Med Inform Assoc.* 2005;12(3):296-298. doi:10.1197/jamia.M1733
115. Huertas C, Ramírez RJ. Heat map based feature selection: A case study for ovarian cancer. *Lect Notes Comput Sci.* 2015;9028:3-13. doi:10.1007/978-3-319-16549-3_1
116. Iossifidou A, Baltzopoulos V, Giakas G. Isokinetic knee extension and vertical jumping: Are they related? *J Sports Sci.* 2005;23(10):1121-1127. doi:10.1080/02640410500128189
117. Irrgang JJ, Anderson AF, Boland AL, et al. Development and validation of the International Knee Documentation Committee Subjective Knee Form. *Am J Sports Med.* 2001;29(5):600-613.
118. Isernhagen SJ. Functional Capacity Evaluation: Rationale, Procedure, Utility of the Kinesiophysical Approach. Vol. 2. 1992.
119. Jackson JE. A User's Guide to Principal Components. John Wiley & Sons; 1991.
120. Jain AK, Duin RPW, Mao J. Statistical pattern recognition: A review. *IEEE Trans Pattern Anal Mach Intell.* 2000;22(1):4-37. doi:10.1109/34.824819
121. James G, Witten D, Hastie T, Tibshirani R. An Introduction to Statistical Learning with Applications in R. Casella G, Fienberg S, Olkin I, eds. Springer; 2013. doi:10.1007/978-1-4614-7138-7
122. Jayaraman C, Mummidisetty CK, Mannix-Slobig A, McGee Koch L, Jayaraman A. Variables influencing wearable sensor outcome estimates in individuals with stroke and incomplete spinal cord injury: A pilot investigation validating two research grade sensors. *J Neuroeng Rehabil.* 2018;15(1):1-18. doi:10.1186/s12984-018-0358-y
123. Jensen RK, Nassas G. Growth of segment principal moments of inertia between four and twenty years. *Med Sci Sports Exerc.* 1988;20(6):594-604. doi:10.1249/00005768-198812000-00013
124. Jolliffe IT. Principal components in regression analysis. In: *Principal Component Analysis.* Springer; 1986:129-155. doi:10.1007/978-1-4757-1904-8_8

125. Juneja H, Verma SK, Khanna GL. Isometric strength and its relationship to dynamic performance: A systematic review. *J Exerc Sci Physiother.* 2010;6(2):60-69.
126. Kabsch W. A solution for the best rotation to relate two sets of vectors. *Acta Crystallogr A.* 1976;32(5):922-923. doi:10.1107/S0567739476001873
127. Kiapour AM, Murray MM. Basic science of anterior cruciate ligament injury and repair. *Bone Joint Res.* 2014;3(2):20-31. doi:10.1302/2046-3758.32.2000241
128. King E, Richter C, Daniels KAJ, et al. Can biomechanical testing after anterior cruciate ligament reconstruction identify athletes at risk for subsequent ACL injury to the contralateral uninjured limb? *Am J Sports Med.* 2021;49(3):609-619. doi:10.1177/0363546520985283
129. King RC, Villeneuve E, White RJ, Sherratt RS, Holderbaum W, Harwin WS. Application of data fusion techniques and technologies for wearable health monitoring. *Med Eng Phys.* 2017;42:1-12. doi:10.1016/j.medengphy.2016.12.011
130. Kinikli GI, Celik D, Yuksel I, Atay OA. Turkish version of the Anterior Cruciate Ligament Quality of Life questionnaire. *Knee Surg Sports Traumatol Arthrosc.* 2015;23(8):2367-2375. doi:10.1007/s00167-014-3404-8
131. Kobsar D, Ferber R. Wearable sensor data to track subject-specific movement patterns related to clinical outcomes using a machine learning approach. *Sensors.* 2018;18(2828):1-12. doi:10.3390/s18092828
132. Kocher MS, Smith JT, Iversen MD, et al. Reliability, validity, and responsiveness of a modified International Knee Documentation Committee Subjective Knee Form (Pedi-IKDC) in children with knee disorders. *Am J Sports Med.* 2011;39(5):933-939.
133. Kotsifaki A, Van Rossom S, Whiteley R, et al. Symmetry in triple hop distance hides asymmetries in knee function after ACL reconstruction in athletes at return to sports. *Am J Sports Med.* 2022;50(2):441-450. doi:10.1177/03635465211063192
134. Kristianslund E, Krosshaug T, Van den Bogert AJ. Effect of low-pass filtering on joint moments from inverse dynamics: Implications for injury prevention. *J Biomech.* 2012;45(4):666-671. doi:10.1016/j.jbiomech.2011.12.011
135. Kritz M, Cronin J, Hume P. The bodyweight squat: A movement screen for the squat pattern. *Strength Cond J.* 2009;31(1):76-85. doi:10.1519/SSC.0b013e318195eb2f

136. Krogsgaard MR, Fischer-Rasmussen T, Dyhre-Poulsen P. Absence of sensory function in the reconstructed anterior cruciate ligament. *J Electromyogr Kinesiol*. 2011;21(1):82-86. doi:10.1016/j.jelekin.2010.09.012
137. Kruskal JB. Nonmetric multidimensional scaling: A numerical method. *Psychometrika*. 1964;29(2):115-129. doi:10.1007/BF02289694
138. Kvist J, Ek A, Sporrstedt K, Good L. Fear of re-injury: A hindrance for returning to sports after anterior cruciate ligament reconstruction. *Knee Surg Sports Traumatol Arthrosc*. 2005;13(5):393-397. doi:10.1007/s00167-004-0591-8
139. LaBella CR, Hennrikus WL, Hewett TE. Anterior cruciate ligament injuries: Diagnosis, treatment, and prevention. *Pediatrics*. 2014;133(5):e1437-e1450.
140. Lebel K, Boissy P, Nguyen H, Duval C. Inertial measurement systems for segments and joints kinematics assessment: Towards an understanding of the variations in sensor accuracy. *Biomed Eng Online*. 2017;16:56. doi:10.1186/s12938-017-0347-6
141. Lexell JE, Downham DY. How to assess the reliability of measurements in rehabilitation. *Am J Phys Med Rehabil*. 2005;84(9):719-723.
142. Li Q, Zhang JT, Novak AC, Brouwer B, Li Q. Concurrent validation of Xsens MVN measurement of lower limb joint angular kinematics. *Physiol Meas*. 2013;34(8):N63-N69. doi:10.1088/0967-3334/34/8/N63
143. Lim BO, Lee YS, Kim JG, An KO, Yoo J, Kwon YH. Effects of sports injury prevention training on the biomechanical risk factors of anterior cruciate ligament injury in high school female basketball players. *Am J Sports Med*. 2009;37(9):1728-1734. doi:10.1177/0363546509334220
144. Limbird TJ, Shiavi R, Frazer M, Borra H. EMG profiles of knee joint musculature during walking: Changes induced by anterior cruciate ligament deficiency. *J Orthop Res*. 1988;6(5):630-638. doi:10.1002/jor.1100060503
145. Lindström M, Felländer-Tsai L, Wredmark T, Henriksson M. Adaptations of gait and muscle activation in chronic ACL deficiency. *Knee Surg Sports Traumatol Arthrosc*. 2010;18(1):106-114. doi:10.1007/s00167-009-0886-x
146. Linting M, Meulman JJ, Groenen PJF, van der Kooij AJ. Nonlinear principal components analysis: Introduction and application. *Psychol Methods*. 2007;12(3):336-358. doi:10.1037/1082-989X.12.3.336

147. Lohmander LS, Englund PM, Dahl LL, Roos EM. The long-term consequence of anterior cruciate ligament and meniscus injuries. *Am J Sports Med.* 2007;35(10):1756-1769. doi:10.1177/0363546507307396
148. Madgwick SOH, Harrison AJL, Vaidyanathan R. Estimation of IMU and MARG orientation using a gradient descent algorithm. In: *Proceedings of the IEEE International Conference on Rehabilitation Robotics.* IEEE; 2011:1-7.
149. Magnussen RA, Lawrence JTR, West RL, Toth AP, Taylor DC, Garrett WE. Graft size and patient age are predictors of early revision after anterior cruciate ligament reconstruction with hamstring autograft. *Arthroscopy.* 2012;28(4):526-531.
150. Maguire K, Sugimoto D, Micheli LJ, Kocher MS, Heyworth BE. Recovery after ACL reconstruction in male versus female adolescents: A matched, sex-based cohort analysis of 543 patients. *Orthop J Sports Med.* 2021;9(11). doi:10.1177/23259671211054804
151. Makhni EC, Padaki AS, Petridis PD, et al. High variability in outcome reporting patterns in high-impact ACL literature. *J Bone Joint Surg Am.* 2015;97(18):1529-1542. doi:10.2106/JBJS.O.00155
152. Maly MR, Costigan PA, Olney SJ. Determinants of self-report outcome measures in people with knee osteoarthritis. *Arch Phys Med Rehabil.* 2006;87(1):96-104.
153. Mantovani G, Lamontagne M. How different marker sets affect joint angles in inverse kinematics framework. *J Biomech Eng.* 2017;139(4). doi:10.1115/1.4034708
154. Markolf KL, Mensch JS, Amstutz HC. Stiffness and laxity of the knee: The contributions of the supporting structures. A quantitative study. *J Bone Joint Surg Am.* 1976;58(5):583-594.
155. Marshall WA, Tanner JM. Variations in the pattern of pubertal changes in boys. *Arch Dis Child.* 1970;45(239):13-23.
156. Marshall WA, Tanner JM. Variations in the pattern of pubertal changes in girls. *Arch Dis Child.* 1969;44(235):291-303.
157. Masoud HI, Zerehsaz Y, Jin J. Analysis of human motion variation patterns using UMPCA. *Appl Ergon.* 2017;59(Pt A):1-10. doi:10.1016/j.apergo.2016.09.016
158. McCall A, Carling C, Nedelec M, et al. Risk factors, testing and preventative strategies for non-contact injuries in professional football: Current perceptions and practices of 44

- teams from various premier leagues. *Br J Sports Med.* 2014;48(18):1352-1357.
doi:10.1136/bjsports-2014-093439
159. McCunn R, aus der Fünten K, Fullagar HHK, McKeown I, Meyer T. Reliability and association with injury of movement screens: A critical review. *Sports Med.* 2016;46(6):763-781.
 160. McLachlan GJ. *Discriminant Analysis and Statistical Pattern Recognition.* John Wiley & Sons; 1992. doi:10.1002/0471725293
 161. McLean SG, Huang X, Van den Bogert AJ. Association between lower extremity posture at contact and peak knee valgus moment during sidestepping: Implications for ACL injury. *Clin Biomech (Bristol, Avon).* 2005;20(8):863-870.
doi:10.1016/j.clinbiomech.2005.05.007
 162. Mizuno K, Andrish JT, Van den Bogert AJ, McLean SG. Gender dimorphic ACL strain in response to combined dynamic 3D knee joint loading: Implications for ACL injury risk. *Knee.* 2009;16:432-440. doi:10.1016/j.knee.2009.04.008
 163. Mohtadi N. Development and validation of the Quality of Life Outcome Measure (Questionnaire) for chronic anterior cruciate ligament deficiency. *Am J Sports Med.* 1998;26(3):350-359.
 164. Morris JRW. Accelerometry: A technique for the measurement of human body movements. *J Biomech.* 1973;6(6):729-736. doi:10.1016/0021-9290(73)90029-8
 165. Mosa ASM, Yoo I, Sheets L. A systematic review of healthcare applications for smartphones. *BMC Med Inform Decis Mak.* 2012;12:67.
 166. Muniz AMS, Liu H, Lyons KE, et al. Comparison among probabilistic neural network, support vector machine and logistic regression for evaluating the effect of subthalamic stimulation in Parkinson disease on ground reaction force during gait. *J Biomech.* 2010;43:720-726. doi:10.1016/j.jbiomech.2009.10.018
 167. Munro AG, Herrington LC. Between-session reliability of four hop tests and the Agility T-test. *J Strength Cond Res.* 2011;25(5):1470-1477.
 168. Munson MA, Caruana R. On feature selection, bias-variance, and bagging. *Lect Notes Comput Sci.* 2009;5782(Pt 2):144-159. doi:10.1007/978-3-642-04174-7_10
 169. Murray R, Li Z, Sastry S. *A Mathematical Introduction to Robotic Manipulation.* 1st ed. CRC Press; 2017.

170. Myer GD, Ford KR, Brent JL, Hewett TE. Differential neuromuscular training effects on ACL injury risk factors in "high-risk" versus "low-risk" athletes. *BMC Musculoskelet Disord.* 2007;8:39. doi:10.1186/1471-2474-8-39
171. Myer GD, Ford KR, Hewett TE. The effects of gender on quadriceps muscle activation strategies during a maneuver that mimics a high ACL injury risk position. *J Electromyogr Kinesiol.* 2005;15(2):181-189. doi:10.1016/j.jelekin.2004.08.006
172. Myer GD, Ford KR, Paterno MV, Nick TG, Hewett TE. The effects of generalized joint laxity on risk of anterior cruciate ligament injury in young female athletes. *Am J Sports Med.* 2008;36(6):1073-1080. doi:10.1177/0363546507313572
173. Myer GD, Paterno MV, Ford KR, Quatman CE, Hewett TE. Rehabilitation after anterior cruciate ligament reconstruction: Criteria-based progression through the return-to-sport phase. *J Orthop Sports Phys Ther.* 2006;36(6):385-402.
174. Noyes FR, Barber SD, Mangine RE. Abnormal lower limb symmetry determined by function hop tests after anterior cruciate ligament rupture. *Am J Sports Med.* 1991;19(5):513-518.
175. Nüesch C, Roos E, Pagenstert G, Mündermann A. Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor-based system and a camera-based system. *J Biomech.* 2017;57:32-38. doi:10.1016/j.jbiomech.2017.03.015
176. Øiestad BE, Holm I, Engebretsen L, Risberg MA. The association between radiographic knee osteoarthritis and knee symptoms, function and quality of life 10-15 years after anterior cruciate ligament reconstruction. *Br J Sports Med.* 2011;45(7):583-588. doi:10.1136/bjsm.2010.073130
177. Örtqvist M, Roos EM, Broström EW, Janarv PM, Iversen MD. Development of the Knee Injury and Osteoarthritis Outcome Score for Children (KOOS-Child): Comprehensibility and content validity. *Acta Orthop.* 2012;83(6):666-673. doi:10.3109/17453674.2012.747921
178. Padua DA, Marshall SW, Boling MC, Thigpen CA, Garrett WE, Beutler AI. The Landing Error Scoring System (LESS) is a valid and reliable clinical assessment tool of jump-landing biomechanics: The JUMP-ACL Study. *Am J Sports Med.* 2009;37(10):1996-2002. doi:10.1177/0363546509343200

179. Palmieri-Smith RM, Lepley LK. Quadriceps strength asymmetry after anterior cruciate ligament reconstruction alters knee joint biomechanics and functional performance at time of return to activity. *Am J Sports Med.* 2015;43(7):1662-1669.
180. Palmieri-Smith RM, Thomas AC. A neuromuscular mechanism of posttraumatic osteoarthritis associated with ACL injury. *Exerc Sport Sci Rev.* 2009;37(3):147-153. doi:10.1097/JES.0b013e3181aa6669
181. Pandya R, Pandya J. C5.0 algorithm to improve decision trees with feature selection and reduced error pruning. *Int J Comput Appl.* 2015;117(16):1-6.
182. Papalia R, Franceschi F, Tecame A, D'Adamio S, Maffulli N, Denaro V. Anterior cruciate ligament reconstruction and return to sport activity: Postural control as the key to success. *Int Orthop.* 2015;39(3):527-534. doi:10.1007/s00264-014-2513-9
183. Parisi F, Ferrari G, Giuberti M, et al. Body-sensor-network-based kinematic characterization and comparative outlook of UPDRS scoring in leg agility, sit-to-stand, and gait tasks in Parkinson's disease. *IEEE J Biomed Health Inform.* 2015;19(6):1777-1793. doi:10.1109/JBHI.2015.2472640
184. Park HJ, Ko S, Hong M, Ok E, Lee JI. Factors related to standing balance in patients with knee osteoarthritis. *Ann Rehabil Med.* 2013;37(3):373-378. doi:10.5535/arm.2013.37.3.373
185. Patel AD, Bullock GS, Wrigley J, Paterno MV, Sell TC, Losciale JM. Does sex affect second ACL injury risk? A systematic review with meta-analysis. *Br J Sports Med.* 2021;55(15):873-882. doi:10.1136/bjsports-2020-103408
186. Patel S, Lorincz K, Hughes R, et al. Monitoring motor fluctuations in patients with Parkinson's disease using wearable sensors. *IEEE Trans Inf Technol Biomed.* 2009;13(6):864-873. doi:10.1109/TITB.2009.2033471
187. Paterno MV, Ford KR, Myer GD, Heyl R, Hewett TE. Limb asymmetries in landing and jumping 2 years following anterior cruciate ligament reconstruction. *Clin J Sport Med.* 2007;17(4):258-262.
188. Paterno MV, Rauh MJ, Schmitt LC, Ford KR, Hewett TE. Incidence of second ACL injuries 2 years after primary ACL reconstruction and return to sport. *Am J Sports Med.* 2014;42(7):1567-1573. doi:10.1177/0363546514530088

189. Paterno MV, Schmitt LC, Ford KR, Rauh MJ, Myer GD, Huang B, Hewett TE. Biomechanical measures during landing and postural stability predict second anterior cruciate ligament injury after anterior cruciate ligament reconstruction and return to sport. *Am J Sports Med.* 2010;38(10):1968-1978. doi:10.1177/0363546510376053
190. Pearson K. LIII. On lines and planes of closest fit to systems of points in space. *London Edinburgh Dublin Philos Mag J Sci.* 1901;2(11):559-572. doi:10.1080/14786440109462720
191. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine learning in Python. *J Mach Learn Res.* 2011;12:2825-2830.
192. Picerno P, Cereatti A, Cappozzo A. Joint kinematics estimate using wearable inertial and magnetic sensing modules. *Gait Posture.* 2008;28(4):588-595. doi:10.1016/j.gaitpost.2008.04.003
193. Pizzolato C, Reggiani M, Saxby DJ, Ceseracciu E, Modenese L, Lloyd DG. Biofeedback for gait retraining based on real-time estimation of tibiofemoral joint contact forces. *IEEE Trans Neural Syst Rehabil Eng.* 2017;25(9):1612-1621.
194. Prodromos CC, Han Y, Rogowski J, Joyce B, Shi K. A meta-analysis of the incidence of anterior cruciate ligament tears as a function of gender, sport, and a knee injury-reduction regimen. *Arthroscopy.* 2007;23(12):1320-1325. doi:10.1016/j.arthro.2007.07.003
195. Punchihewa NG, Miyazaki S, Chosa E, Yamako G. Efficacy of inertial measurement units in the evaluation of trunk and hand kinematics in baseball hitting. *Sensors.* 2020;20(24):1-11.
196. Quatman CE, Hewett TE. The anterior cruciate ligament injury controversy: Is "valgus collapse" a sex-specific mechanism? *Br J Sports Med.* 2009;43(5):328-335. doi:10.1136/bjsm.2009.059139
197. Quinlan JR. Simplifying decision trees. *Int J Man Mach Stud.* 1987;27(3):221-248.
198. Reenalda J, Maartens E, Homan L, Buurke JH. Continuous three-dimensional analysis of running mechanics during a marathon by means of inertial magnetic measurement units to objectify changes in running mechanics. *J Biomech.* 2016;49(14):3362-3367. doi:10.1016/j.jbiomech.2016.08.032

199. Remedios SM, Armstrong DP, Graham RB, Fischer SL. Exploring the application of pattern recognition and machine learning for identifying movement phenotypes during deep squat and hurdle step movements. *Front Bioeng Biotechnol.* 2020;8:364.
200. Riemann BL, Lephart SM. The sensorimotor system, Part I: The physiologic basis of functional joint stability. *J Athl Train.* 2002;37(1):71-79.
201. Rigas G, Tzallas AT, Tsipouras MG, et al. Assessment of tremor activity in the Parkinson's disease using a set of wearable sensors. *IEEE Trans Inf Technol Biomed.* 2012;16(3):478-487.
202. Rish I. An empirical study of the Naïve Bayes classifier. In: *IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence.* 2001:41-46.
203. Robert-Lachaine X, Mecheri H, Larue C, Plamondon A. Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis. *Med Biol Eng Comput.* 2017;55(4):609-619. doi:10.1007/s11517-016-1537-2
204. Roetenberg D, Slycke PJ, Veltink PH. Ambulatory position and orientation tracking fusing magnetic and inertial sensing. *IEEE Trans Biomed Eng.* 2007;54(5):883-890.
205. Roetenberg D, Luinge H, Slycke P. *Xsens MVN: Full 6DOF human motion tracking using miniature inertial sensors.* Xsens Motion Technologies BV; 2013.
206. Rohman E, Steubs JT, Tompkins M. Changes in involved and uninvolved limb function during rehabilitation after anterior cruciate ligament reconstruction: Implications for limb symmetry index measures. *Am J Sports Med.* 2015;43(6):1391-1398. doi:10.1177/0363546515576127
207. Rokach L. Ensemble-based classifiers. *Artif Intell Rev.* 2010;33(1-2):1-39. doi:10.1007/s10462-009-9124-7
208. Romanchuk NJ, Del Bel MJ, Benoit DL. Sex-specific landing biomechanics and energy absorption during unanticipated single-leg drop-jumps in adolescents: Implications for knee injury mechanics. *J Biomech.* 2020;113:110064.
209. Roos EM, Roos HP, Lohmander LS, Ekdahl C, Beynnon BD. Knee Injury and Osteoarthritis Outcome Score (KOOS): Development of a self-administered outcome measure. *J Orthop Sports Phys Ther.* 1998;28(2):88-96.

210. Roos H, Adalberth T, Dahlberg L, Lohmander LS. Osteoarthritis of the knee after injury to the anterior cruciate ligament or meniscus: The influence of time and age. *Osteoarthritis Cartilage*. 1995;3(4):261-267. doi:10.1016/S1063-4584(05)80017-2
211. Ross GB, Dowling B, Troje NF, Fischer SL, Graham RB. Objectively differentiating movement patterns between elite and novice athletes. *Med Sci Sports Exerc*. 2018;50(7):1457-1464. doi:10.1249/MSS.0000000000001571
212. Ross MD, Langford B, Whelan P. Test-retest reliability of four single-leg horizontal hop tests. *J Strength Cond Res*. 2002;16(4):617-622.
213. Rudolph KS, Axe MJ, Scholz JP, Snyder-Mackler L. Dynamic stability in the anterior cruciate ligament-deficient knee. *Knee Surg Sports Traumatol Arthrosc*. 2001;9(2):62-71. doi:10.1007/s001670000166
214. Rudolph KS, Axe MJ, Snyder-Mackler L. Dynamic stability after ACL injury: Who can hop? *Knee Surg Sports Traumatol Arthrosc*. 2000;8(5):262-269. doi:10.1007/s001670000130
215. Saito T, Rehmsmeier M. The Precision-Recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLoS One*. 2015;10(3):e0118432. doi:10.1371/journal.pone.0118432
216. Sakane M, Livesay GA, Fox RJ, Rudy TW, Runco TJ, Woo SLY. Relative contribution of the ACL, MCL, and bony contact to the anterior stability of the knee. *Knee Surg Sports Traumatol Arthrosc*. 1999;7(2):93-97. doi:10.1007/s001670050128
217. Scherpereel K, Molinaro D, Inan O, Shepherd M, Young A. A human lower-limb biomechanics and wearable sensors dataset during cyclic and non-cyclic activities. *Sci Data*. 2023;10(1):1-12. doi:10.1038/s41597-023-02840-6
218. Schmitt LC, Paterno MV, Ford KR, Myer GD, Hewett TE. Strength asymmetry and landing mechanics at return to sport after anterior cruciate ligament reconstruction. *Med Sci Sports Exerc*. 2015;47(7):1426-1434. doi:10.1249/MSS.0000000000000560
219. Schölkopf B, Smola A, Müller KR. Nonlinear component analysis as a kernel eigenvalue problem. *Neural Comput*. 1998;10(5):1299-1319.
220. Seel T, Raisch J, Schauer T. IMU-based joint angle measurement for gait analysis. *Sensors*. 2014;14(4):6891-6909. doi:10.3390/s140406891

221. Seel T, Schauer T. IMU-based joint angle measurement made practical. In: Proceedings of the 4th European Conference on Technically Assisted Rehabilitation. 2016.
222. Sell TC, Zerega R, King V, et al. Anterior Cruciate Ligament Return to Sport after Injury Scale (ACL-RSI) scores over time after anterior cruciate ligament reconstruction: A systematic review with meta-analysis. *Sports Med Open*. 2024;10(1):49. doi:10.1186/s40798-024-00712-w
223. Sernert N, Kartus J, Köhler K, et al. Analysis of subjective, objective and functional examination tests after anterior cruciate ligament reconstruction: A follow-up of 527 patients. *Knee Surg Sports Traumatol Arthrosc*. 1999;7(3):160-165.
224. Shea KG, Pfeiffer RP, Wang JH, Curtin M, Apel PJ. Anterior cruciate ligament injury in pediatric and adolescent soccer players: An analysis of insurance data. *J Pediatr Orthop*. 2004;24(6):623-628. doi:10.1097/00004694-200411000-00005
225. Shourijeh MS, Flaxman TE, Benoit DL. An approach for improving repeatability and reliability of non-negative matrix factorization for muscle synergy analysis. *J Electromyogr Kinesiol*. 2016;26:36-43. doi:10.1016/j.jelekin.2015.12.001
226. Silva LO, Mendes LMR, Lima POP, Almeida GPL. Translation, cross-adaptation and measurement properties of the Brazilian version of the ACL-RSI Scale and ACL-QoL Questionnaire in patients with anterior cruciate ligament reconstruction. *Braz J Phys Ther*. 2018;22(2):127-134. doi:10.1016/j.bjpt.2017.09.006
227. Sinden KE, McGillivray TL, Chapman E, Fischer SL. Survey of kinesiologists' functional capacity evaluation practice in Canada. *Work*. 2017;56(4):571-580. doi:10.3233/WOR-172519
228. Smale KB, Flaxman TE, Alkjaer T, Simonsen EB, Krogsgaard MR, Benoit DL. Anterior cruciate ligament reconstruction improves subjective ability but not neuromuscular biomechanics during dynamic tasks. *Knee Surg Sports Traumatol Arthrosc*. 2019;27(2):636-645. doi:10.1007/s00167-018-5189-7
229. Snyder-Mackler L, Fitzgerald GK, Bartolozzi AR, Ciccotti MG. The relationship between passive joint laxity and functional outcome after anterior cruciate ligament injury. *Am J Sports Med*. 1997;25(2):191-195.

230. Takeda R, Tadano S, Natorigawa A, Todoh M, Yoshinari S. Gait posture estimation using wearable acceleration and gyro sensors. *J Biomech.* 2009;42(15):2486-2494. doi:10.1016/j.jbiomech.2009.07.016
231. Takeda Y, Xerogeanes JW, Livesay GA, Fu FH, Woo SLY. Biomechanical function of the human anterior cruciate ligament. *Arthroscopy.* 1994;10(2):140-147.
232. Tegner Y, Lysholm J. Rating systems in the evaluation of knee ligament injuries. *Clin Orthop Relat Res.* 1985;198:43-49.
233. Tenenbaum JB, de Silva V, Langford JC. A global geometric framework for nonlinear dimensionality reduction. *Science.* 2000;290(5500):2319-2323. doi:10.1126/science.290.5500.2319
234. Teufl W, Lorenz M, Miezal M, Taetz B, Fröhlich M, Bleser G. Towards inertial sensor-based mobile gait analysis: Event detection and spatiotemporal parameters. *Sensors.* 2019;19(1):38. doi:10.3390/s19010038
235. Teufl W, Miezal M, Taetz B, Fröhlich M, Bleser G. Validity of inertial sensor-based 3D joint kinematics of static and dynamic sport and physiotherapy-specific movements. *PLoS One.* 2019;14(2):e0208681. doi:10.1371/journal.pone.0208681
236. Thomeé R, Neeter C, Gustavsson A, et al. Variability in leg muscle power and hop performance after anterior cruciate ligament reconstruction. *Knee Surg Sports Traumatol Arthrosc.* 2012;20(6):1143-1151. doi:10.1007/s00167-012-1912-y
237. Thorleuchter D, Van den Poel D, Prinzie A. Analyzing existing customers' websites to improve the customer acquisition process as well as the profitability prediction in B-to-B marketing. *Expert Syst Appl.* 2012;39(3):2597-2605. doi:10.1016/j.eswa.2011.08.115
238. Tillman MD, Smith KR, Bauer JA, Cauraugh JH, Falsetti AB, Pattishall JL. Differences in three intercondylar notch geometry indices between males and females: A cadaver study. *Knee.* 2002;9(1):41-46. doi:10.1016/S0968-0160(01)00135-1
239. Torgerson W. *Theory and Methods of Scaling.* John Wiley & Sons; 1958.
240. Troje NF. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. *J Vis.* 2002;2(5):371-387. doi:10.1167/2.5.2
241. Trulsson A, Miller M, Hansson GÅ, Gummesson C, Garwicz M. Altered movement patterns and muscular activity during single- and double-leg squats in individuals with

- anterior cruciate ligament injury. *BMC Musculoskelet Disord*. 2015;16:28.
doi:10.1186/s12891-015-0472-y
242. Uhorchak JM, Scoville CR, Williams GN, Arciero RA, St Pierre P, Taylor DC. Risk factors associated with noncontact injury of the anterior cruciate ligament: A prospective four-year evaluation of 859 West Point cadets. *Am J Sports Med*. 2003;31(6):831-842.
 243. Umeyama S. Least-squares estimation of transformation parameters between two point patterns. *IEEE Trans Pattern Anal Mach Intell*. 1991;13(4):376-380.
doi:10.1109/34.88573
 244. Vargas-Valencia L, Elias A, Rocon E, Bastos-Filho T, Frizera A. An IMU-to-body alignment method applied to human gait analysis. *Sensors*. 2016;16(12):2090.
doi:10.3390/s16122090
 245. Varma S, Simon R. Bias in error estimation when using cross-validation for model selection. *BMC Bioinformatics*. 2006;7:91. doi:10.1186/1471-2105-7-91
 246. van der Velden CA, van der Steen MC, Leenders J, van Douveren FQMP, Janssen RPA, Reijman M. Pedi-IKDC or KOOS-Child: Which questionnaire should be used in children with knee disorders? *BMC Musculoskelet Disord*. 2019;20(1):240. doi:10.1186/s12891-019-2600-6
 247. Webster KE, Feller JA, Lambros C. Development and preliminary validation of a scale to measure the psychological impact of returning to sport following anterior cruciate ligament reconstruction surgery. *Phys Ther Sport*. 2008;9(1):9-15.
doi:10.1016/j.ptsp.2007.09.003
 248. Webster KE, McPherson AL, Hewett TE, Feller JA. Factors associated with a return to preinjury level of sport performance after anterior cruciate ligament reconstruction surgery. *Am J Sports Med*. 2019;47(11):2557-2562. doi:10.1177/0363546519865537
 249. Wellsandt E, Failla MJ, Snyder-Mackler L. Limb symmetry indexes can overestimate knee function after anterior cruciate ligament injury. *J Orthop Sports Phys Ther*. 2017;47(5):334-338.
 250. Westad F, Hersleth M, Lea P, Martens H. Variable selection in PCA in sensory descriptive and consumer data. *Food Qual Prefer*. 2003;14(5-6):463-472. doi:10.1016/S0950-3293(03)00015-6

251. Whelan D, O'Reilly M, Huang B, Giggins O, Kechadi T, Caulfield B. Leveraging IMU data for accurate exercise performance classification and musculoskeletal injury risk screening. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2016:659-662.
doi:10.1109/EMBC.2016.7590788
252. Wiggins AJ, Grandhi RK, Schneider DK, Stanfield D, Webster KE, Myer GD. Risk of secondary injury in younger athletes after anterior cruciate ligament reconstruction: A systematic review and meta-analysis. *Am J Sports Med.* 2016;44(7):1861-1876.
doi:10.1177/0363546515621554
253. Winter DA, Patla AE, Frank JS, Walt SE. Biomechanical walking pattern changes in the fit and healthy elderly. *Phys Ther.* 1990;70(6):340-347. doi:10.1093/ptj/70.6.340
254. Wittmann F, Lambercy O, Gassert R. Magnetometer-based drift correction during rest in IMU arm motion tracking. *Sensors.* 2019;19(6):1312. doi:10.3390/s19061312
255. Wright RW, Haas AK, Anderson J, et al. Anterior cruciate ligament reconstruction rehabilitation: MOON guidelines. *Sports Health.* 2015;7(3):239-243.
doi:10.1177/1941738113517855
256. Wrigley AT, Albert WJ, Deluzio KJ, Stevenson JM. Differentiating lifting technique between those who develop low back pain and those who do not. *Clin Biomech (Bristol, Avon).* 2005;20(3):254-263. doi:10.1016/j.clinbiomech.2004.11.008
257. Wu G, Van der Helm FCT, Veeger HEJ, et al. ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: Shoulder, elbow, wrist and hand. *J Biomech.* 2005;38(5):981-992.
258. Wu G, Siegler S, Allard P, et al. ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part I: Ankle, hip, and spine. *J Biomech.* 2002;35(4):543-548.
259. Young C, Reinkensmeyer DJ. Judging complex movement performances for excellence: A principal components analysis-based technique applied to competitive diving. *Hum Mov Sci.* 2014;36:107-122. doi:10.1016/j.humov.2014.05.009
260. Zebis MK, Andersen LL, Brandt M, et al. Effects of evidence-based prevention training on neuromuscular and biomechanical risk factors for ACL injury in adolescent female

- athletes: A randomized controlled trial. *Br J Sports Med*. 2016;50(9):552-557.
doi:10.1136/bjsports-2015-094776
261. Zelisko JA, Noble HB, Porter M. A comparison of men's and women's professional basketball injuries. *Am J Sports Med*. 1982;10(5):297-299.
doi:10.1177/036354658201000507
262. Public Health Agency of Canada. Osteoarthritis in Canada. Government of Canada. Published 2020. Accessed October 14, 2021. <https://www.canada.ca/en/public-health/services/publications/diseases-conditions/osteoarthritis.html>

APPENDICES

Appendix A: Summary of Participant Numbers

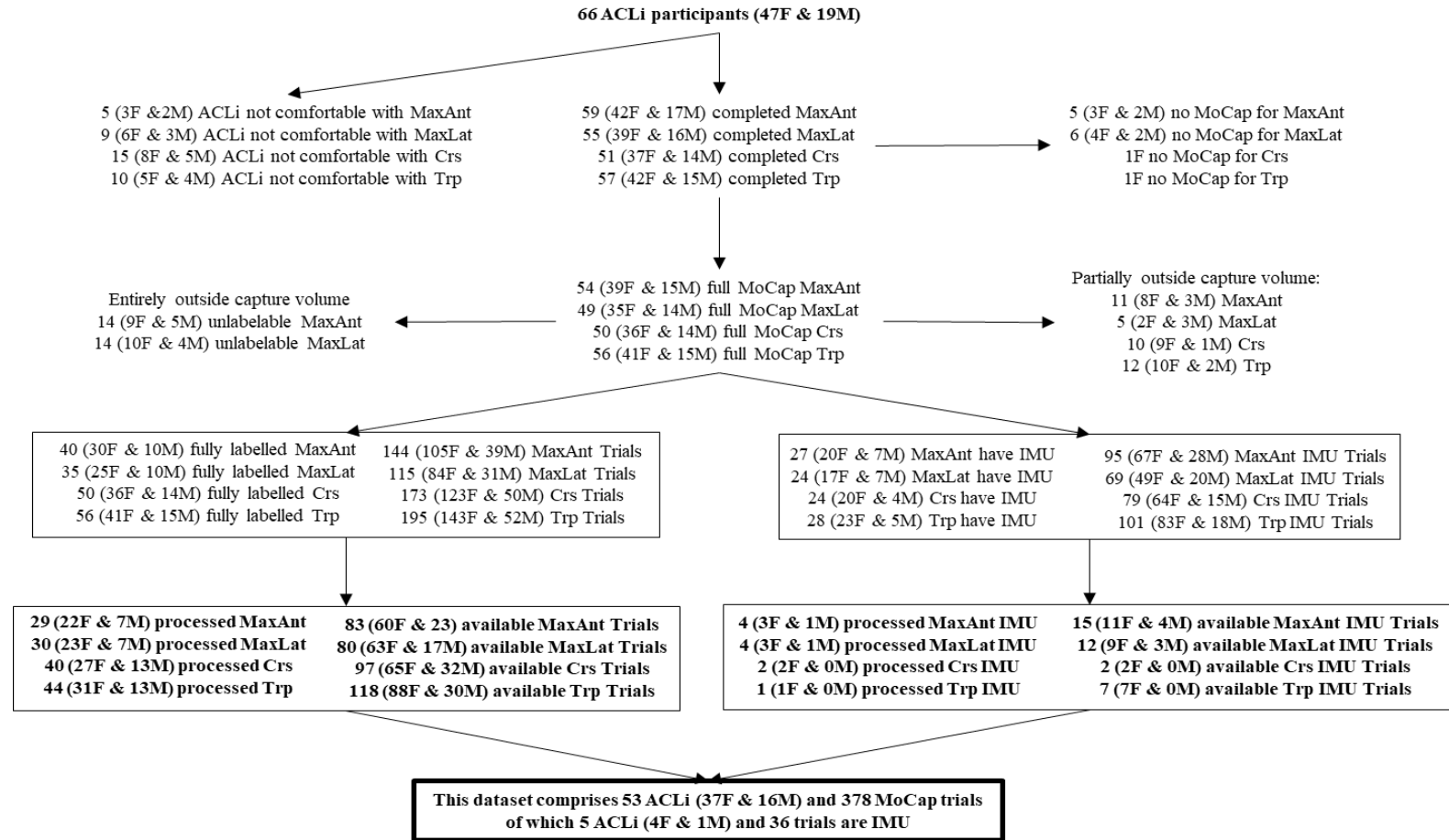


Figure A.1. Flowchart detailing participant compliance and ability to complete single-limb hopping tasks (MaxAnt: maximal anterior hop; MaxLat: maximal lateral hop; Crs: cross hop; Trp: triple hop) with number of participants with anterior cruciate ligament injuries (ACLi) and trials contributing for both motion capture (MoCap) and inertial measurement unit (IMU) data.

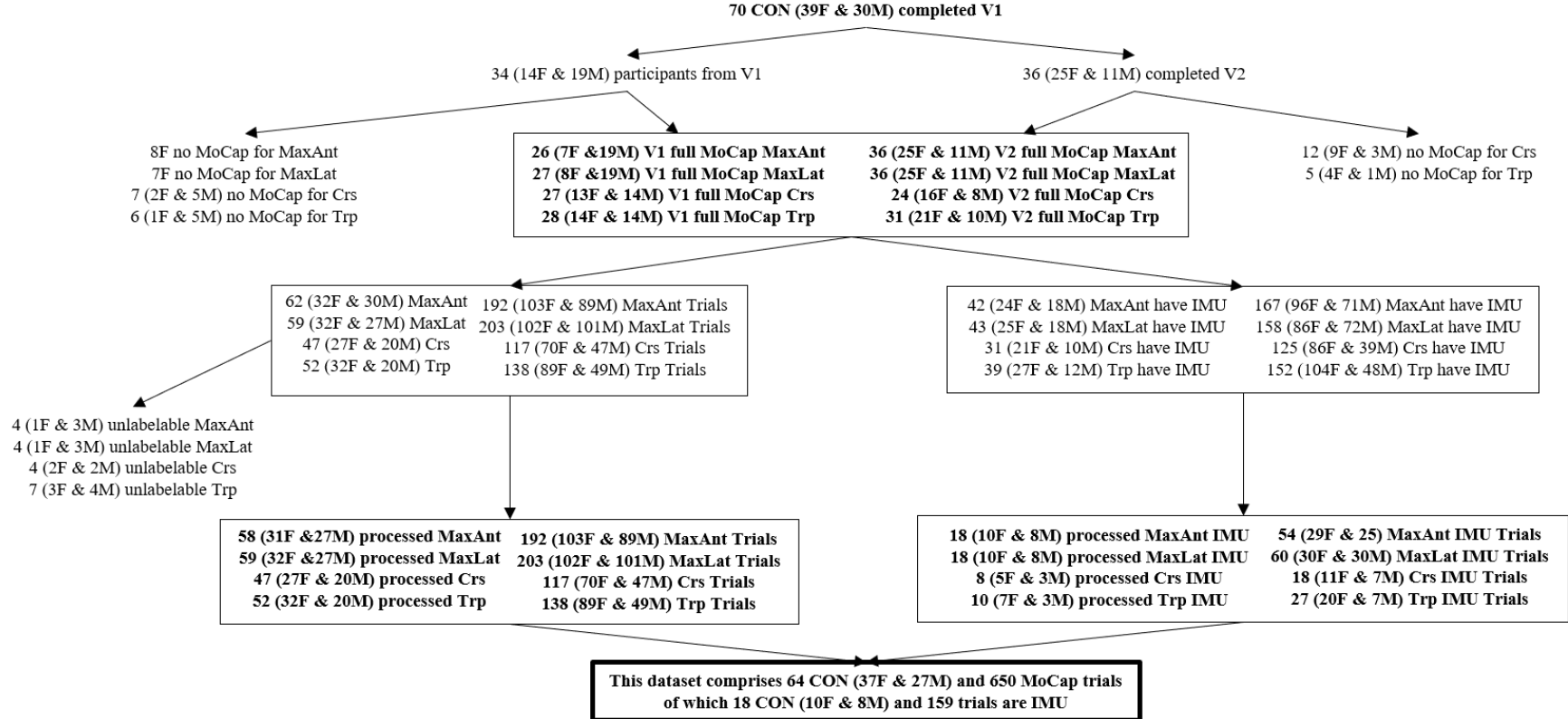


Figure A.2. Flowchart detailing participant compliance and ability to complete single-limb hopping tasks (MaxAnt: maximal anterior hop; MaxLat: maximal lateral hop; Crs: cross hop; Trp: triple hop) with number of control (CON) participants and trials contributing for both motion capture (MoCap) and inertial measurement unit (IMU) data.

Appendix B: Patient Reported Outcome Measures (PROMs)

Appendix B.1 Tegner Activity Scale

Date: _____

Participant: _____

TEGNER ACTIVITY LEVEL SCALE

Please indicate in the spaces below the **HIGHEST** level of activity that you participated in **BEFORE YOUR INJURY** and the highest level you are able to participate in **CURRENTLY**.

BEFORE INJURY: Level _____ CURRENT: Level _____

Level 10	Competitive sports- soccer, football, rugby (national elite)
Level 9	Competitive sports- soccer, football, rugby (lower divisions), ice hockey, wrestling, gymnastics, basketball
Level 8	Competitive sports- racquetball or bandy, squash or badminton, track and field athletics (jumping, etc.), down-hill skiing
Level 7	Competitive sports- tennis, running, motorcars speedway, handball Recreational sports- soccer, football, rugby, bandy, ice hockey, basketball, squash, racquetball, running
Level 6	Recreational sports- tennis and badminton, handball, racquetball, down-hill skiing, jogging at least 5 times per week
Level 5	Work- heavy labor (construction, etc.) Competitive sports- cycling, cross-country skiing, Recreational sports- jogging on uneven ground at least twice weekly
Level 4	Work- moderately heavy labor (e.g. truck driving, etc.)
Level 3	Work- light labor (nursing, etc.)
Level 2	Work- light labor Walking on uneven ground possible, but impossible to back pack or hike
Level 1	Work- sedentary (secretarial, etc.)
Level 0	Sick leave or disability pension because of knee problems

Y Tegner and J Lysohn. *Rating Systems in the Evaluation of Knee Ligament Injuries. Clinical Orthopedics and Related Research.* Vol. 198: 43-49, 1985.

List of Specific Activities:

Type	Duration	Sessions/week	Intensity (light/moderate/high)
BEFORE	_____	_____	_____
	_____	_____	_____
	_____	_____	_____
NOW	_____	_____	_____
	_____	_____	_____
	_____	_____	_____

Version date: 24-MAR-2018

Appendix B.2 Pedi-IKDC Subjective Knee Evaluation Form

Pedi-IKDC Subjective Knee Evaluation Form – PATIENT FORM																											
Section A: General Information																											
1. Participant ID:																											
2. Date distributed:	MM DD YYYY																										
Section B: Survey																											
Date you injured your knee: MM DD YYYY																											
We would like to learn more about your injured knee. Each of the questions asks you a different question about your injured knee. Please answer each question below.																											
SYMPTOMS																											
1. If you were asked to do the activities below, what is the most you could do <u>today</u> without making your injured knee hurt a lot? ☐ ₁ Very hard activities like jumping or turning fast to change direction, like in basketball or soccer ☐ ₂ Hard activities like heavy lifting, skiing or tennis ☐ ₃ Sort of hard activities like walking fast or jogging ☐ ₄ Light activities like walking at a normal speed ☐ ₅ I can't do any of the activities listed above because my knee hurts too much now																											
2. During the <u>past 4 weeks</u>, or <u>since your injury</u>, how much of the time did your injured knee hurt? <table style="width: 100%; border-collapse: collapse;"> <tr> <td style="width: 10%; text-align: right; vertical-align: bottom;">Never</td> <td style="width: 5%; text-align: center;">0</td> <td style="width: 5%; text-align: center;">1</td> <td style="width: 5%; text-align: center;">2</td> <td style="width: 5%; text-align: center;">3</td> <td style="width: 5%; text-align: center;">4</td> <td style="width: 5%; text-align: center;">5</td> <td style="width: 5%; text-align: center;">6</td> <td style="width: 5%; text-align: center;">7</td> <td style="width: 5%; text-align: center;">8</td> <td style="width: 5%; text-align: center;">9</td> <td style="width: 5%; text-align: center;">10</td> <td style="width: 10%; text-align: left; vertical-align: bottom;">Hurt all of the time</td> </tr> <tr> <td style="text-align: right; vertical-align: top;">hurt</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: left; vertical-align: top;"></td> </tr> </table>		Never	0	1	2	3	4	5	6	7	8	9	10	Hurt all of the time	hurt	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
Never	0	1	2	3	4	5	6	7	8	9	10	Hurt all of the time															
hurt	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐																
3. How badly <u>does</u> your injured knee hurt <u>today</u>? <table style="width: 100%; border-collapse: collapse;"> <tr> <td style="width: 10%; text-align: right; vertical-align: bottom;">Does not hurt at all</td> <td style="width: 5%; text-align: center;">0</td> <td style="width: 5%; text-align: center;">1</td> <td style="width: 5%; text-align: center;">2</td> <td style="width: 5%; text-align: center;">3</td> <td style="width: 5%; text-align: center;">4</td> <td style="width: 5%; text-align: center;">5</td> <td style="width: 5%; text-align: center;">6</td> <td style="width: 5%; text-align: center;">7</td> <td style="width: 5%; text-align: center;">8</td> <td style="width: 5%; text-align: center;">9</td> <td style="width: 5%; text-align: center;">10</td> <td style="width: 10%; text-align: left; vertical-align: bottom;">Hurts so much I can't stand it</td> </tr> <tr> <td style="text-align: right; vertical-align: top;"></td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: center;">☐</td> <td style="text-align: left; vertical-align: top;"></td> </tr> </table>		Does not hurt at all	0	1	2	3	4	5	6	7	8	9	10	Hurts so much I can't stand it		☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
Does not hurt at all	0	1	2	3	4	5	6	7	8	9	10	Hurts so much I can't stand it															
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐																
4. During the <u>past 4 weeks</u>, or <u>since your injury</u>, how hard has it been to move or bend your injured knee? ☐ ₁ Not at all hard ☐ ₂ A little hard ☐ ₃ Somewhat hard ☐ ₄ Very hard ☐ ₅ Extremely hard																											

Pedi-IKDC Subjective Knee Evaluation Form – **PATIENT FORM**

5. During the past 4 weeks, or since your injury, how **puffy (or swollen)** was your injured knee?
- ☐₁ Not at all puffy
 - ☐₂ A little puffy
 - ☐₃ Somewhat puffy
 - ☐₄ Very puffy
 - ☐₅ Extremely puffy
6. If you were asked to do the activities below, what is the most you could do today without making your injured knee **puffy (or swollen)**?
- ☐₁ Very hard activities like jumping or turning fast to change direction, like in basketball or soccer
 - ☐₂ Hard activities like heavy lifting, skiing or tennis
 - ☐₃ Sort of hard activities like walking fast or jogging
 - ☐₄ Light activities like walking at a normal speed
 - ☐₅ I can't do any of the activities listed above because my injured knee is puffy even when I rest
7. During the past 4 weeks, or since your injury, did your injured knee ever get **stuck in place (lock)** so that you could not move it? Yes No
☐₁ ☐₂
8. During the past 4 weeks, or since your injury, did your injured knee ever feel **like it was getting stuck (catching)**, but you could still move it? Yes No
☐₁ ☐₂
9. If you were asked to do the activities below, what is the most you could do today without your injured knee **feeling like it can't hold you up**?
- ☐₁ Very hard activities like jumping or turning fast to change direction, like in basketball or soccer
 - ☐₂ Hard activities like heavy lifting, skiing or tennis
 - ☐₃ Sort of hard activities like walking fast or jogging
 - ☐₄ Light activities like walking at a normal speed
 - ☐₅ I can't do any of the activities listed above because my injured knee feels like it can't hold me up

SPORTS ACTIVITIES

10. What is the most you can do on your injured knee **most of the time**?
- ☐₁ Very hard activities like jumping or turning fast to change direction, like in basketball or soccer
 - ☐₂ Hard activities like heavy lifting, skiing or tennis
 - ☐₃ Sort of hard activities like walking fast or jogging
 - ☐₄ Light activities like walking at a normal speed
 - ☐₅ I can't do any of the activities listed above most of the time

Pedi-IKDC Subjective Knee Evaluation Form – PATIENT FORM

11. Does your injured knee affect your ability to:

	No, not at all	Yes, a little	Yes, somewhat	Yes, a lot	I can't do this
a. Go up stairs?	1	2	3	4	5
b. Go down stairs?	1	2	3	4	5
c. Kneel on your injured knee?	1	2	3	4	5
d. Squat down like a baseball catcher?	1	2	3	4	5
e. Sit in a chair with your knees bent and feet flat on the floor?	1	2	3	4	5
f. Get up from a chair?	1	2	3	4	5
g. Run?	1	2	3	4	5
h. Jump and land on your injured knee?	1	2	3	4	5
i. Start and stop moving quickly?	1	2	3	4	5

FUNCTION

12. How well did your knee work **before** you injured it?

I could not do anything at all	0	1	2	3	4	5	6	7	8	9	10	I could do anything I wanted to
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	

13. How well does your knee work **now**?

I am not able to do anything at all	0	1	2	3	4	5	6	7	8	9	10	I am able to do anything I want to do
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	

14. Who completed the questionnaire? ☐ ₁ Child alone ☐ ₂ Child with help from parent/adult

Appendix B.3 HSS Pedi-FABS Questionnaire

Date: _____

Participant: _____

HSS Pedi-FABS Questionnaire

Instructions: Choose one answer for each activity or question. In the grid, please indicate how often you performed each activity in your healthiest and most active condition. **IN THE PAST MONTH:**

	Less than one time per month	One time per month	One time per week	2-3 times per week	More than 4 times per week
Running: running while playing a sport or jogging.					
Cutting: quickly changing directions while running.					
Decelerating: coming to a quick stop while running.					
Pivoting: turning your body with your foot planted (for example: skiing, skating, kicking, throwing, hitting a ball)					
Duration: perform athletic activity for as long as you would like to without stopping.					
Endurance: perform athletic activity for one whole hour without stopping.					

Competition: Do you participate in organized competitive sports or physical activities?

- ☐ No (or gym class only)
- ☐ Yes, but WITHOUT an official or judge (such as club or pickup games)
- ☐ Yes, WITH an official or judge
- ☐ Yes, at a national or professional level

Supervision: Do you participate in supervised (coach, trainer, instructor) sports practice or activities (other than gym class)?

- ☐ No
- ☐ Yes, 1-2 times per week
- ☐ Yes, 3-4 times per week
- ☐ Yes, 5 or more times per week

Version date: 27-JUN-2017

Appendix B.4. FR Pedi-FABS Questionnaire

Date: _____

Participant: _____

FC-Pedi-FABS

Instructions: Choisissez une réponse pour chaque activité ou question. Dans le tableau, indiquez combien de fois vous participez à chaque activité quand vous êtes dans votre état le plus actif et en santé.

DANS LE DERNIER MOIS:

	Moins qu'une fois par mois	Une fois par mois	Une fois par semaine	2-3 fois par semaine	Plus de 4 fois par semaine
Courir: courir quand vous faites du sport ou du jogging					
Couper: changer de direction rapidement quand vous courez					
Décélérer : faire un arrêt rapide quand vous courez					
Pivoter: tourner votre corps avec votre pied planté au sol (par exemple: skier, patiner, donner un coup de pied, lancer, frapper une balle)					
Durée: faire une activité physique aussi longtemps que vous voulez sans arrêter.					
Endurance: faire une activité physique pour une heure complète sans arrêt					

Compétition: Participez-vous à un sport ou une activité physique de façon compétitive et/ou organisée ?

- ☐ Non (ou seulement pendant vos cours d'éducation physique)
- ☐ Oui, mais SANS un arbitre ou un juge (comme des clubs ou des parties improvisées)
- ☐ Oui, AVEC un arbitre ou un juge
- ☐ Oui, au niveau national ou professionnel

Supervision: Participez-vous à un sport ou une activité (autre que les cours d'éducation physique) de façon supervisée (entraîneurs, soigneurs, instructeurs) ?

- ☐ Non (ou seulement pendant vos cours d'éducation physique)
- ☐ Oui, 1-2 fois par semaine
- ☐ Oui, 3-4 fois par semaine
- ☐ Oui, 5 fois ou plus par semaine

Tanner Scale of Sexual Maturity

Sexual-maturity ratings have replaced the traditional indicators of growth status such as height, weight and skinfold thickness. Sexual maturity ratings have proven useful in assessing growth and development during adolescence.

Classification of patients may be done as part of a general physical examination and does not require any special procedures.

The scale of development is based on secondary sexual characteristics. The ratings range from stage 1, which represents the pre-pubertal child, to stage 5, which represents the adult.

Boys: Genital Development

- Stage 1: Preadolescent. Testes, scrotum and penis are about the same size and proportion as in early childhood.
- Stage 2: Enlargement of scrotum and testes. Skin of scrotum reddens and changes in texture. Little or no enlargement of penis.
- Stage 3: Enlargement of penis, at first mainly in length. Further growth of testes and scrotum.
- Stage 4: Increased size of penis, with growth in breadth and development of glans. Testes and scrotum larger. Scrotal skin darkened.
- Stage 5: Genitalia are adult in size and shape.

Girls: Breast Development

- Stage 1: Preadolescent. Elevation of papilla only.
- Stage 2: Breast bud stage. Elevation of breast and papilla as small mound. Enlargement of diameter of areola.
- Stage 3: Further enlargement and elevation of the breast and areola, with no separation of their contours.
- Stage 4: Projection of areola and papilla to form a secondary mound above the level of the breast.
- Stage 5: Mature stage. Projection of papilla only, owing to recession of the areola to the general contour of the breast.

Both Sexes: Pubic Hair

- Stage 1: Preadolescent. Vellus over pubis is not developed further than that over abdominal wall (i.e., no pubic hair).
- Stage 2: Sparse growth of long, slightly pigmented downy hair, straight or slightly curled, chiefly at base of penis and along labia.
- Stage 3: Hair is considerably darker, coarser and more curled. It spreads sparsely over the junction of pubis.
- Stage 4: Hair is adult in type, but area covered is still considerably smaller than in adult. No spread to medial surface of thighs.
- Stage 5: Hair is adult in quantity and type, with distribution of horizontal (or classic "feminine" in females) pattern. Spread to medial surface of thighs but not up *linea alba* or elsewhere above base of inverse triangle (spread up *linea alba* occurs late and is rated Stage 6).

Adapted from the Public Health Agency of Canada: Canadian Guidelines on Sexually Transmitted Infections, Section VII, Appendix H. <http://www.phac-aspc.gc.ca/std-mts/sti-its/cgsti-lcdcits/app-ann-h-eng.php>

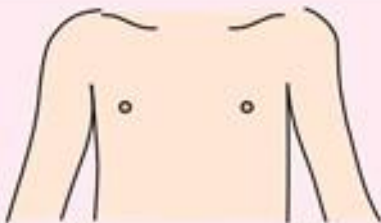
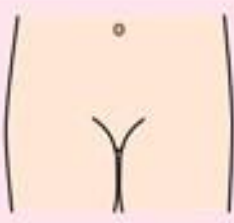
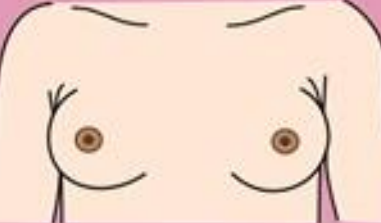
Classification of Tanner Stage: Male Pubescent Development

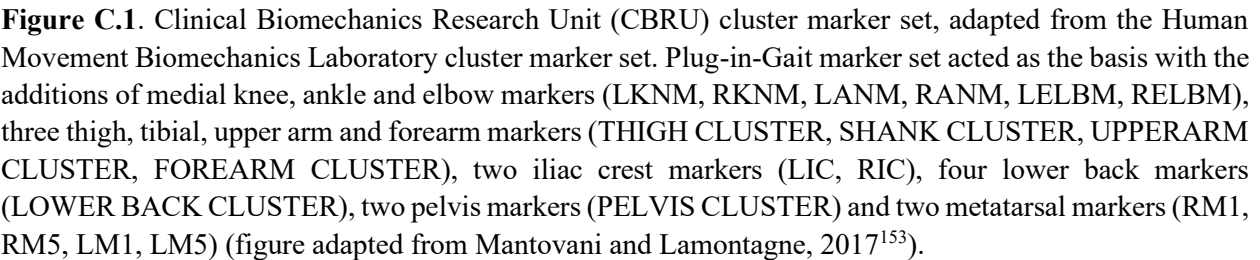
-Using the accompanied information "Tanner Scale of Sexual Maturity", please select the stage (I thru V) that you identify with the most.

☐	I		3 ↕<2,5
☐	II		4 ↕2,5-3,2
☐	III		10 ↕3,6
☐	IV		16 ↕4,1-4,5
☐	V		25 ↕>4,5

Classification of Tanner Stage: Female Pubescent Development

-Using the accompanied information "Tanner Scale of Sexual Maturity", please select the stage (I thru V) that you identify with the most.

☐	I			
☐	II			
☐	III			
☐	IV			
☐	V			



Appendix D: Description of Tasks

Maximum Voluntary Contractions

Maximum voluntary isometric contractions (MVICs) were used to record maximum activation magnitudes of the sixteen muscles on an isokinetic dynamometer (System 4 Pro, Biodex Medical Systems, New York, USA). MVICs were performed in the following positions: i) knee extension and ii) flexion in a seated position with the hip and knee flexed at 90° and 60° respectively ²⁰; iii) plantarflexion in a seated position with the hip and knee flexed at 90° and 0° respectively and the ankle at -10°; and, iv) hip abduction in a standing position with the hip and knee flexed to 0°. Participants were instructed to gradually increase their effort and to maintain their maximal force for 5 seconds. MVICs were repeated three times, with at least 1-minute rest between each trial. Verbal encouragement and on-screen feedback was provided by the researchers to elicit a maximal contraction.

Functional Tasks

Participants were given two practice trials for each task and completed as many trials as necessary to achieve five successful trials for all functional tasks. All trials were deemed unsuccessful if either of the participant's feet were not entirely on the force plate. For the side-cuts, the trial was deemed unsuccessful if the leading foot did not land entirely on the force plate.

Squats

The squats were performed by standing with one foot on each force plate with their hands on their head to account for variability in arm swing. Participants were instructed to begin in an upright position, squat down to a comfortable height and return to the upright starting position in a continuous movement. Minimal instructions were provided to ensure participants performed the movement naturally and to elicit potential differences in squatting depth and timing.

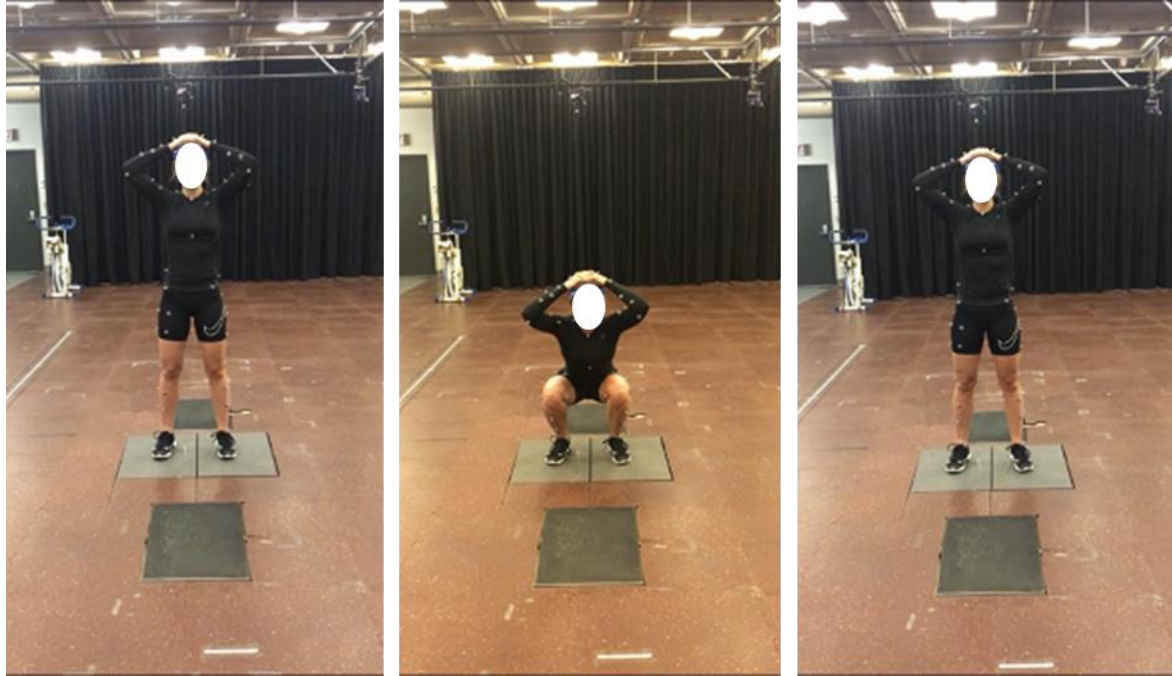


Figure D.1 Squats

Countermovement Jumps

The countermovement jumps (CMJ) were completed in the same location and position as the squat, with their feet shoulder width apart on separate force plates and their hands on their head. They are often used in injury prevention and rehabilitation programs by evaluating the relative difference in functional performance between limbs of the participant¹⁶. Participants were instructed to jump as high as they could while landing with one foot on each force plate and keeping their hands on their head. In addition to the aforementioned criteria for a successful trial, a CMJ trial was deemed successful if the participant held the landing without losing their balance and kept their hands on their head ²⁴¹.

Lunges

Participants began with their feet shoulder width apart on a single force plate. They were instructed to step forward with their testing leg on a second force plate in front of them, flex both knees to a comfortable depth and return to the starting position in a continuous movement ⁶. The trial was considered unsuccessful if their hands came off their head, if their knee touched the force plate, if their entire foot did not land on the respective force plates, or if they lost their balance at any point in the trial.



Figure D.2 Lunges

Drop-vertical Jumps

A platform was set to the height of the participant's tibial plateau to standardize take-off height. Participants began on the platform, stepped off with either foot onto the force plates, landing one foot on each plate, squatted down and immediately performed a vertical jump aiming to jump as high as possible and landing one foot on each force plate¹¹⁰.



Figure D.3 Drop-vertical Jumps

Side-cuts

Participants completed the side-cuts by running at a self-selected pace before planting the testing foot on the force plate and cutting at an angle of 45° ^{21,59}. A side-cut trial was deemed successful if the participant's planting foot was entirely on the force plate and accelerated out of the planting position at a 45° angle. We placed pylons in the lab to provide a $\pm 10^\circ$ target area for participants.



Figure D.4 Side cuts

Appendix E: Trimming Trials Start and End Point Criteria for Movement Tasks

Table E.1. The start and end-point criteria used when trimming trial lengths for each single-limb hopping movement

	Start	End
Maximum Anterior Hop	The initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data in vertical direction of the heel were close to that of the starting position.
Maximum Lateral Hop	The initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data in vertical direction of the heel were close to that of the start position.
Triple Hop for Distance	Once the toe has reached a valley prior to the final jump and a velocity of zero, and the initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data in vertical direction of the heel were close to that of the start position.
Cross Hop for Distance	Once the toe has reached a valley in the vertical direction and a velocity of zero prior to the final jump, and the initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data in vertical direction of the heel were close to that of the start position.

Table E.2. The start and end-point criteria used when trimming trial lengths for each functional movement.

	Start	End
Bilateral squats	The initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data were close to that of the starting position.
Lunges	The initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero and positional data were close to that of the start position.
Countermovement Jumps	Once the toe has reached a valley prior to the final jump (3/3) and a velocity of zero, and the initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis zero after peak jump height and positional data were close to that of the start position.
Drop vertical Jumps	Once the toe has reached a valley in the vertical direction and a velocity of zero prior to the final jump (3/3), and the initiation of the movement of either the heel or pelvis	Once the velocity of both the heel and pelvis reached zero after the second jump and positional data of the heel were close to that of the start position.
Side-cuts	The initiation of the cutting maneuver of the foot on the force plate	Once the contralateral foot's positional data in the vertical direction is close to zero.

Appendix F: List of Spatiotemporal Variables

1. Sex (0= female; 1= male)
2. Class (0=uninjured; 1=injured)
3. NMaxAnt = non-dominant/injured maximal anterior hop distance
4. NNormMaxAnt = non-dominant/injured maximal anterior hop distance normalized to height
5. DMaxAnt = dominant/contralateral maximal anterior hop distance
6. DNormMaxAnt = dominant/contralateral maximal anterior hop distance normalized to height
7. LSMaxAnt = limb symmetry index maximal anterior hop distance
8. NMaxLat = non-dominant/injured maximal lateral hop distance
9. NNormMaxLat = non-dominant/injured maximal lateral hop distance normalized to height
10. DMaxLat = dominant/contralateral maximal lateral hop distance
11. DNormMaxLat = dominant/contralateral maximal lateral hop distance normalized to height
12. LSMaxLat = limb symmetry index maximal lateral hop distance
13. NTimed = non-dominant/injured 6-meter timed hop time
14. DTimed = dominant/contralateral 6-meter timed hop time
15. LSTimed = limb symmetry index 6-meter timed hop
16. NCross = non-dominant/injured cross hop maximal distance
17. NNormCross = non-dominant/injured cross hop maximal distance normalized to height
18. DCross = dominant/contralateral cross hop maximal distance
19. DNormCross = dominant/contralateral cross hop maximal distance normalized to height
20. LSCross = limb symmetry index cross hop distance

21. NCrsDist = non-dominant/injured maximal vertical landing distance
22. NNormCrsDist = non-dominant/injured maximal vertical landing distance normalized to height
23. DCrsDist = dominant/contralateral maximal vertical landing distance
24. DNormCrsDist = dominant/contralateral maximal vertical landing distance normalized to height
25. LSCrsDist = limb symmetry index maximal vertical landing distance
26. NTripLe = non-dominant/injured triple hop distance
27. NNormTriple = non-dominant/injured triple hop distance normalized to height
28. DTriple = dominant/contralateral triple hop distance
29. DNormTriple = dominant/contralateral triple hop distance normalized to height
30. LSTripLe = limb symmetry index triple hop distance
31. CMJJumpHeight = countermovement jump height
32. CMJDepth = countermovement jump squatting depth pre jump
33. NormCMJJumpHeight = countermovement jump height normalized to height
34. NormCMJDepth = countermovement jump squatting depth pre jump normalized to height
35. DVJDropDepth = drop vertical jump dropping squat depth (pre jump)
36. DVJJumpHeight = drop vertical jump jump height
37. DVJLandDepth = drop vertical jump landing squatting depth
38. NormDVJDropDepth = drop vertical jump dropping squat depth (pre jump) normalized to height
39. NormDVJJumpHeight = drop vertical jump jump height normalized to height
40. NormDVJLandDepth = drop vertical jump landing squatting depth normalized to height

- 41. SquatDepth = squatting depth
- 42. NormSquatDepth = squatting depth normalized to height
- 43. NLungeDepth = non-dominant/injured lunge depth
- 44. NNormLungeDepth = non-dominant/injured lunge depth normalized to height
- 45. DLungeDepth = dominant/contralateral lunge depth
- 46. DNormLungeDepth = dominant/contralateral lunge depth normalized to height
- 47. LSLungeDepth = limb symmetry index lunge depth

Appendix G: Summary of Injured-Limb Classification Metrics for Marker-Based and Simulated IMU Models

Table G.1. Comparison of Injured-Limb (IL-CON) Classification Performance Between Marker-Based Motion Capture and Simulated IMU Analyses (AA-AE) Using Linear Discriminant Analysis

Task	Study / Configuration	# PCs	Accuracy (%)	F1 Score	Cohen's κ	PR AUC	Precision (%)	Recall (%)
Anterior Hop (Ant)	Markers – IL-CON (Chapter 7)	15	81.8	0.55	0.44	0.61	68	46
	Simulated IMU – AA (Chapter 9)	15	77.1	0.13	0.01	0.20	17	11
	Simulated IMU – AB (Chapter 9)	15	75.3	0.12	−0.02	0.17	15	11
	Simulated IMU – AC (Chapter 9)	15	78.4	0.17	0.05	0.24	23	13
	Simulated IMU – AD (Chapter 9)	15	81.8	0.19	0.11	0.23	36	13
	Simulated IMU – AE (Chapter 9)	15	74.0	0.12	−0.03	0.15	13	11
Cross Hop (Crs)	Markers – IL-CON (Chapter 7)	12	73.1	0.59	0.40	0.63	49	73
	Simulated IMU – AA (Chapter 9)	12	64.7	0.47	0.22	0.41	39	59
	Simulated IMU – AB (Chapter 9)	12	66.0	0.48	0.24	0.36	40	59
	Simulated IMU – AC (Chapter 9)	12	65.4	0.47	0.23	0.39	39	59
	Simulated IMU – AD (Chapter 9)	12	66.0	0.43	0.19	0.43	38	49
	Simulated IMU – AE (Chapter 9)	12	64.1	0.49	0.24	0.48	39	66
Lateral Hop (Lat)	Markers – IL-CON (Chapter 7)	15	79.3	0.53	0.41	0.64	42	72
	Simulated IMU – AA (Chapter 9)	15	71.1	0.08	−0.09	0.17	8	8
	Simulated IMU – AB (Chapter 9)	15	74.8	0.14	−0.01	0.17	16	13
	Simulated IMU – AC (Chapter 9)	15	75.2	0.14	0.00	0.20	16	13
	Simulated IMU – AD (Chapter 9)	15	80.6	0.20	0.11	0.25	30	15

Task	Study / Configuration	# PCs	Accuracy (%)	F1 Score	Cohen's κ	PR AUC	Precision (%)	Recall (%)
	Simulated IMU – AE (Chapter 9)	15	78.1	0.16	0.04	0.19	21	13
Triple Hop (Trp)	Markers – IL-CON (Chapter 7)	13	77.5	0.62	0.46	0.66	56	68
	Simulated IMU – AA (Chapter 9)	13	70.8	0.46	0.26	0.49	45	47
	Simulated IMU – AB (Chapter 9)	13	64.0	0.43	0.18	0.34	37	51
	Simulated IMU – AC (Chapter 9)	13	68.0	0.48	0.25	0.38	42	55
	Simulated IMU – AD (Chapter 9)	13	75.3	0.55	0.38	0.54	53	57
	Simulated IMU – AE (Chapter 9)	13	68.5	0.52	0.30	0.47	43	64