A Logistic Regression Model for Monitoring and Classifying Post-ACL Rehabilitation Individuals for Return to Sport

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Abstract
Over 250,000 anterior cruciate ligament (ACL) injuries occur every year in the United States alone, often during sports and fitness activities. Following an ACL injury and reconstruction, 44% of patients fail to return to healthy and functional levels due to unresolved neuromuscular impairments. These impairments can cause an individual to adopt adverse gait patterns resulting in detrimental compressive knee loading. Tools and methods for measuring, tracking, and classifying healthy knee function of an individual are needed. This paper proposes the use of time-based and frequency-based techniques to extract traditional and non-traditional metrics, such as, stride time variability, fast Fourier transform amplitudes, and ground reaction force peaks, to evaluate the restoration of healthy limb dynamics. These metrics will be used to develop a logistic regression model to aid in the classification of the healthy and ACL injured populations. This model will be helpful to clinicians and rehabilitation scientists in monitoring and developing programs for successful return to sport for post-ACL reconstruction individuals.

Key Words: Sports, logistic regression, athletic monitoring, modelling

1. Introduction

Anterior cruciate ligament (ACL) sprain or tear is encountered by one in 3,000 individuals annually (Boden et al. 2000). Despite advancements in research and ACL injury prevention programs, ACL injury rates have continued to rise (Donnelly et al. 2012). ACL injury results in loss of dynamic knee stability which is vital for movements like running and single-leg jump landing (Ardern et al. 2014). Many studies have been conducted to understand the causes of ACL injury. In their research, Morgan et al. (2014) revealed how elevated gastrocnemius forces compensate for decreased hamstring forces during the weight-acceptance phase of single-leg jump landing and highlighted the implications for anterior cruciate ligament injury risk. Most dynamic knee stability data recorded on individuals during running and jump landing studies are in a time series (i.e., a sequence of data points, typically consisting of successive measurements made over a time interval). However, quite often discrete measures are used to evaluate this data but additional information, not unveiled in the time domain, could possibly provide valuable insight into alterations in knee gait patterns in post-ACL reconstructed (ACLR) individuals. De Fontenay et al. (2014) and Gao et al. (2010) have assessed dynamic gait stability via methods such as Lyapunov exponents. Also, Morgan et al. (2016) used the Nyquist and

Bode stability criteria to assess changes in dynamic knee stability in healthy and anterior cruciate ligament reconstructed individuals during walking.

Given the large number of post-ACLR individuals with recurring knee issues, it is important to identify new and more advanced tools and methods for quantifying, monitoring, and classifying healthy knee function. In this study, strides of data were collected for each participant during a running protocol from which sixteen human biometric measurements were captured for each limb. This paper introduces a new, dimensionless, time-based metric (i.e., ratio of the active peak to the impact peak) to evaluate the restoration of healthy limb dynamics. We will investigate the seventeen variables as predictor(s) in a logistic regression model to aid in the classification of the healthy and post-ACLR injured limbs. The best model will be used to aid in establishing return-to-sport (RTS) decision-criteria. This model will also be valuable to clinicians and rehabilitation scientists in monitoring and making decisions related to successful limb dynamics for post-ACL reconstructed individuals.

2. Methods

2.1.1 Instrumented Gait Analysis

Thirty-one post-ACLR individuals (mean (standard deviation)); age: 20.4 (6.2) yrs; height: 1.8 (0.1) m; mass: 71.7 (11.1) kg; running speed: 2.7 (0.3) m/s; Tegnar (post-ACLR at 6 months): 6.4 (1.8); 16 males and 15 females) and 18 healthy controls (age: 20.9 (3.4) yrs; height: 1.7 (0.1) m; mass: 65.2 (13.8) kg; running speed: 2.7 (0.4) m/s; Tegnar: 6.9 (1.3); 10 males and 8 females) performed a running protocol. The age of the participants ranged from 18 to 31 years and each participant provided written informed consent as required by the institutional review board. All post-ACLR individuals participated in the study 6 months after surgery and were cleared by their physician. The ACLR surgery was performed by surgeons at the same orthopaedic practice with the participants receiving either a bone-patellar-bone or hamstring graft. All of the control participants were injury free for the six months prior to the study and had no history of knee surgery.

All participants performed a standard running protocol. They first performed a five-minute warm-up period where they jogged on the instrumented treadmill (Bertec Corporation, Columbus, Ohio) to get adapted to the equipment. After the participants were acclimated to the treadmill, they were then instructed to run at their self-selected speed. All participants wore the same type of WR662 sneakers (New Balance, Brighton, MA). This was done to minimize the effect that shoe-type variability could have on the results. The aforementioned acclimation period allowed individuals to adjust to both the treadmill and the shoes. Ground reaction force data were collected at 1200 Hz and a zero-lag, fourth-order Butterworth filter with a 35-Hz low-pass cutoff frequency was applied to the data.

2.1.2 Feature Extraction

Fifty-six markers were placed on each participant. Sagittal plane knee kinematics time-domain data were extracted using the fifty-six markers. Using fast Fourier transforms, the time-domain data were converted to a frequency-domain representation yielding a series of sinusoids. Power and phase spectrum were generated. The amplitude, frequency and phase data components of the ACLR injured limb, ACLR non-injured limb and both limbs of the healthy control individuals were obtained for analysis. The marker trajectories were recorded at 200Hz with a 12-camera motion analysis system (Motion Analysis Corp, Santa

Rosa, USA). Force data were collected at 1200 Hz and heel strike and toe off were determined when the vertical ground reaction force was greater or less than 30N.

Ten strides for each limb were collected during the running protocol. The peak ground reaction force was extracted from the vertical ground reaction force (vGRF) waveform data. The active peak was defined as the maximum vGRF peak and the impact peak was the peak that occurred during the first 50ms of stance. Sixteen human movement biometric variables were captured on each limb of each participant. Seven of the variables were time-domain metrics, including the active peak and the impact peak that were both normalized by bodyweight (BW), six were frequency-domain metrics and three were stability-based. For this study, a dimensionless number, AIP (i.e., the ratio of the active peak to the impact peak), was created and used in the model. The metrics were computed across the ten strides for each limb in the control and post-ACLR populations resulting in four limb groups - control right, control left, ACLR non-reconstructed and ACLR reconstructed.

3. Binary Logistic Regression Model

3.1.1 Overview

At present, diagnosing healthy knee post-ACLR is often based on qualitative observations of the patient's gait, physical examinations of the muscle tone, inspection of gait analysis metrics and the expertise of clinical professionals. This paper examines using a binary logistic regression model to uncover the best quantitative predictor variable(s) to aid in the classification of two population groups - healthy and post-ACLR injured limbs and to develop criteria for return to sport. The null hypothesis for the binary logistic regression model is that the probability of an event (e.g., healthy limb) is not associated with the value of a predictor variable (i.e., the line describing the relationship between the predictor variable and the probability of the response variable has a slope of zero which yields a horizontal line). If there is a relationship between the probability of a healthy limb and a predictor variable, then the model logistic curve should be a S-shaped curve.

3.1.2 Binary Logistic Regression Model

For the binary logistic model, Y is a binary response variable where

$Y_i = 1$ if the trait is present in an observation (e.g., healthy limb) i
$Y_i = 0$ if the trait is NOT present in an observation (e.g., post-ACLR injured limb) i

$X = (X_1, X_2, ..., X_k)$ be a set of explanatory variables which can be discrete, continuous, or a combination.

x_i is the observed value of the explanatory variables for observation i.

Y_i's are independently distributed, i.e., cases are independent and binomially distributed.

The homogeneity of variance does not need to be satisfied.

Use maximum likelihood rather than ordinary least squares to estimate model parameters.

For a single predictor variable, X, the logistic model is

$$Probability\ (Y_i = 1 \mid X = x_i) =$$

$$Probability\ (Y_i = Healthy\ Limb \mid X = x_i) = \frac{\exp(\beta_0 + \beta_1 * x_i)}{1 + \exp(\beta_0 + \beta_1 * x_i)}$$

4. Statistical Analyses

4.1.1 Exploratory Data Analysis (EDA)

Exploratory data analysis was used to aid in identifying any extraordinary observations and exposing any violations of distributional assumptions. For this study, EDA was beneficial in identifying a subset of the candidate seventeen variables that would be the best predictor variables for the logistic regression model. A review of the boxplot of each of the seventeen candidate predictor variables with each category of the four limb groups disclosed that the variable that showed strong location shifts with respect to the healthy and post-ACLR limbs was the new, dimensionless, variable AIP. In conducting the stepwise logistic regression analyses, it was determined that the AIP variable alone was the best predictor variable for the logistic regression model. Hence, for this study, the focus is on a single predictor variable, X, and the logistic model to be fit is

$$Probability\ (Y_i = Healthy\ Limb \mid X = AIP_i) = \frac{\exp(\beta_0 + \beta_1 * AIP_i)}{1 + \exp(\beta_0 + \beta_1 * AIP_i)}$$

In Figure 1, the boxplots of the AIP variable for each of the four limb groups - control right (0) , control left (1), post-ACLR non-reconstructed (2) and post-ACLR reconstructed (3) - highlight that the values of AIP for the post-ACLR reconstructed limb (3) are much lower in comparison to those of the healthy, control limbs (0 and 1). The values for the ACLR non-reconstructed (2) limb are also slightly lower. This may be due to the non-reconstructed limb of the post-ACLR individual making gait adjustments and thereby not functioning at its normal healthy status. So, data on the post-ACLR non-reconstructed limb was not used in the model. The control right and control left limbs were defined as the healthy, control population and the post-ACLR reconstructed limbs were defined as the injured limb population. The three post-ACLR limb observations (two males and 1 female) circled in the boxplot were removed from the study. It is clear they are outliers since their AIP values exceed those of all of the study participants, including the healthy ones.

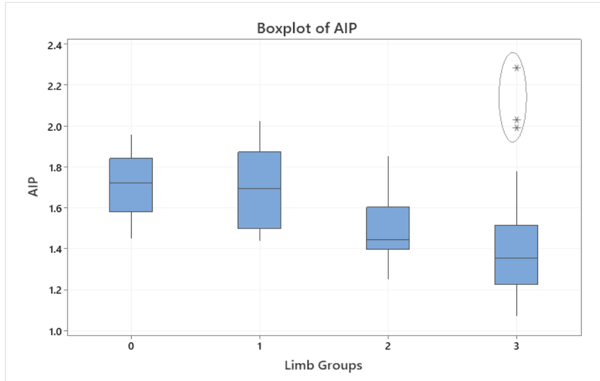

Figure 1: Boxplots of AIP for the four limb groups – control right (0), control left (1), control left (1), ACLR non-reconstructed (2) and ACLR reconstructed (3)

Hence, the study population in the logistic regression model included the 28 post-ACLR reconstructed limbs and the 36 healthy, control limbs. The descriptive statistics – mean, standard deviation, minimum, maximum, and the 95% confidence intervals on the mean - for the AIP variable for the two groups – healthy, control (1) and ACLR injured (0) – are provided in Table 1.

Table 1: Descriptive Statistics for AIP for Healthy (1) and post-ACLR Injured (0) Groups

Variable	Group	Total Count	Mean	StDev	Minimum	Maximum	95% CI
AIP	0	28	1.3552	0.1834	1.0700	1.7839	(1.2878, 1.4225)
	1	36	1.7217	0.1744	1.4379	2.0294	(1.6622, 1.7811)

Pooled StDev = 0.178374

4.1.2 Binary Logistic Regression Model Analysis

Logistic regression models were fit using each of the seventeen candidate predictor variables alone and test of hypotheses were conducted to assess the statistical significance of the model coefficients. In addition, stepwise, forward selection, and backward elimination analyses were also conducted using all seventeen candidate predictor variables. However, the model with AIP as the single predictor variable, as shown in Equation 1, yielded the most statistically significant findings and the estimated model coefficients are shown in Table 2 where $\beta_0 = -13.73$ and $\beta_1 = 8.98$.

Equation 1.

$$Probability\ (\ Y_i = Healthy\ Limb \mid X = AIP_i) = \frac{\exp(\ \beta_0 + \ \beta_1 * AIP_i)}{1+\ \exp(\ \beta_0 + \ \beta_1 * AIP_i\ )}$$

Table 2: Binary logistic regression model estimated coefficients and their 95% confidence intervals with the standard error, Z-value and P-value for each of the coefficients

Coefficients

Term	Coef	SE Coef	95% CI	Z-Value	P-Value
Constant	-13.73	3.96	(-21.49, -5.97)	-3.47	0.001
AIP	8.98	2.57	(3.94, 14.02)	3.49	0.000

Hence, for a given value of AIP = x_i, the binary logistic model prediction of the probability of a healthy limb is

$$\textit{Probability (Y= Healthy Limb} \mid x = x_i\,) \quad = \quad \frac{\exp(-13.73+8.98 * x_i\,)}{1+\ \exp(-13.73+8.98 * x_i)}$$

The p-values (< 0.05) for each of the coefficients, β_0 and β_1, are statistically significant at the significance level $\alpha = 0.05$. The 95% confidence intervals on the estimates of β_0 and β_1 do not include zero. Hence, for each of the coefficients, the test of the null hypothesis that the coefficient equals zero is rejected at the significance level $\alpha = 0.05$. Thus, you can conclude that the changes in AIP are associated with changes in the probability of a healthy limb. As a result, we reject the null hypothesis for the binary logistic regression model that the probability of the response event – a healthy limb - is ***not*** associated with the value of the predictor variable, AIP. The coefficient for AIP is 8.98 which suggests that the higher levels of the variable are associated with a higher probability of a healthy limb.

4.1.2 Binary Logistic Regression Goodness of Fit

Three tools were utilized to assess the overall goodness of fit of the logistic regression model. Approximately 70% of the 64 data cases in the study were used for the training set and 30% was used for the test set in developing the model. First, the Hosmer-Lemeshow Goodness of Fit test statistic was used to determine whether the model performs well in predicting the probabilities. If the p-value for this goodness of fit test is lower than the significance level, then the model does not perform well. The p-value for the goodness of fit statistic (p = 0.273) was greater than the significance level $\alpha = 0.05$ indicating the model performs well.

Next, the receiver operating characteristics (ROC) curve is a graphical plot that illustrates the diagnostic ability of a binary classifier and is another tool for assessing whether the model fits the data well. The area under the ROC curve values range from 0.5 to 1. When the binary model can perfectly separate the classes, then the area under the curve is 1. For this model, the area under the ROC curve is 0.90 for the training set and 0.99 for the test set. These values indicate that the model classifies much of the data correctly.

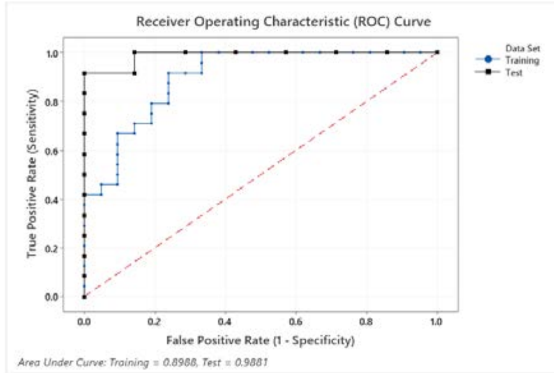

Figure 2: Receiver Operating Characteristic (ROC) Curves for the Training and Test Sets

Then, the residuals from the training and test sets were plotted on normal probability paper in Figure 3. Although two unusual observations were detected in the training set, in general the residuals tend to follow a straight line when plotted on Normal probability paper which also suggests the logistic model fits the data well.

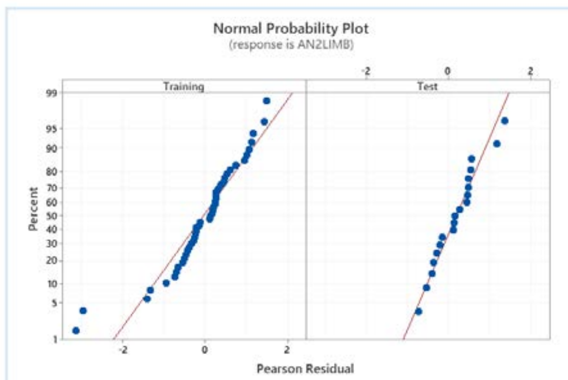

Figure 3: Normal Probability Plots of the Pearson Residuals for the Training and Test Sets

5. Discussion of Results

5.1.1 Binary Logistic Regression Fitted Curve

The plot of the fitted binary logistic regression model is shown as a solid red line in Figure 4. Indeed, it is an S-shaped curve with the estimated proportion of the population with a healthy limb performance (i.e., probability of a healthy limb) increasing as the AIP value increases. The dotted blue lines are the 95% upper and lower confidence interval bands about the fitted line.

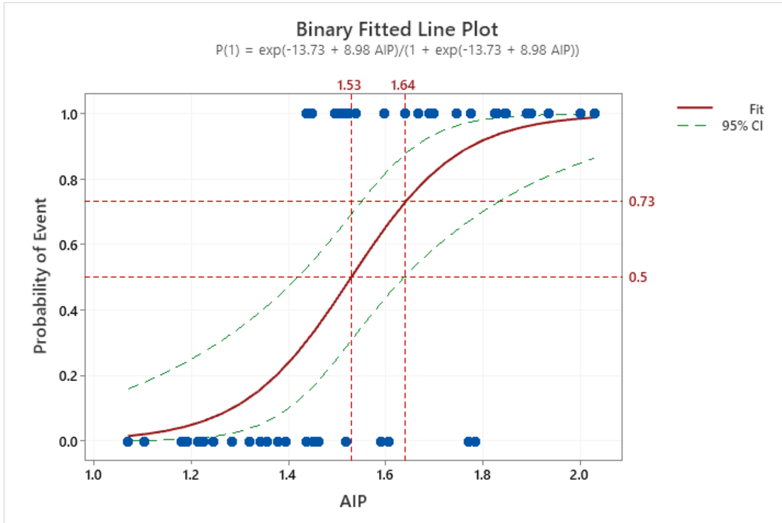

Figure 4: Binary Fitted Line Plot and 95% Confidence Interval Bands

At an AIP value of 1.53, the estimated proportion of population with (i.e., the probability of having) a healthy limb status is 0.50 with the 95% confidence interval of (0.31, 0.69). Thus, it is estimated that 50% of the individuals with an AIP limb value of 1.53 will have a healthy limb status. Roughly speaking, one can be 95% sure that the proportion of healthy limbs at an AIP value of 1.53 is between 31% and 69%. At an AIP value of 1.64, probability of having a healthy limb status is 0.73 with a 95% confidence interval of (0.50, 0.88) and it is estimated that 73% of the individuals with an AIP limb value of 1.64 will have a healthy limb status. Roughly speaking, one can be 95% sure that the proportion of healthy limbs at an AIP value of 1.64 is between 50% and 88%.

5.1.2 Odds Ratio

The odds ratio is an effect size statistic used to describe how changes in magnitude and direction of the predictor impact the probability of the event. In this study, it renders a comparison of the healthy limb group of the study relative to the post-ACLR group. Our study is evaluating the effect of the predictor variable on the probability of a healthy limb. If the effect of the predictor variable is the same in both groups, the odds ratio will be 1. For us, the odds ratio equals 2.45 and is greater than 1 which indicates that the probability of healthy limb is more likely to occur as the predictor increases as shown in the plot in Figure 4.

Binary Logistic Regression Model Odds Ratio ***For 0.1 increase in AIP Odds Ratio = 2.4548*** ***95% Confidence Interval on Odds Ratio (1.4833, 4.0628)***			
AIP	**Logistic Model Predicted Probability (Healthy Limb)**	**Logistic Model Predicted Probability (post-ACLR Injured Limb)**	**Odds Ratio = Prob(Healthy Limb) / Prob(post-ACLR Injured Limb)**
1.54	0.52	0.48	0.52/0.48 = **1.08**
1.64	0.73	0.27	0.73/0.27 = **2.70** ≅ 2.45*1.08
1.74	0.87	0.13	0.87/0.13 = **6.69** ≅ 2.45*2.70

Table 3: Binary Logistic Regression Model Odds Ratio and 95% Confidence Interval

The odds ratio and the 95% confidence interval for a given value of AIP are given in Table 3. Hence, likelihood of healthy limb performance to ACL Injured limb increased by a factor of approximately 2.45 for a 0.1 increase in AIP. Note, the 95% confidence interval does not include 1, which further supports the findings that the predictor variable has a positive effect on the probability of healthy limb. As highlighted in Table 3, for a 0.1 increase in AIP, the odds ratio increased by a factor of approximately 2.45. Hence, likelihood of healthy limb performance to post-ACLR injured limb performance increased by a factor of approximately 2.45.

5.1.3 Return-to-Sport (RTS) Decision Criteria

In reviewing the binary fitted line plot in Figure 4, it is important to note that for values of AIP less than 1.53, the estimated probability of a healthy limb is less than 0.50 and for values of AIP greater than 1.64, the estimated probability of a healthy limb is greater than 0.73. Based on the model estimates and summary information presented above, the following recommendations for return to sport outlined in Table 5 were developed.

Table 5: Return-to-Sport Decision Recommendation

AIP (Active peak/ Impact Peak)	Probability of Healthy Limb (Probability ACL Injured limb)	Return-to-Sport Decision
1.10 to 1.53	0.02 (0.98) to 0.50 (0.50)	No
1.54 to 1.63	0.52 (0.48) to 0.72 (0.23)	Caution
1.64 to 2.0	0.73 (0.27) to 0.99 (0.01)	Yes

6. Conclusion

The primary objective of this study was to develop a logistic regression model to aid in the classification of the healthy and post-ACLR populations. We were successful in identifying a new, non-invasive, easy to capture time-based metric - the ratio of the active peak to the impact peak - that could be used in a binary logistic regression model to predict the probability of healthy limb performance. Furthermore, we uncovered that, as this predictor variable increased, the probability of healthy limb performance increases. In summary, this predictor also served as a good metric to assign return-to-sport categories of poor, cautionary and good limb performance. We anticipate that these findings will be beneficial to clinicians and rehabilitation professionals in monitoring and developing programs for the successful return-to-healthy status for a post-ACL reconstruction individual, especially athletes.

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