Predicting Future Patients and Injuries

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Abstract

Using healthcare data provided by Integrated Musculoskeletal Care (IMC), we took first-visit patient information to form a predictive model for whether or not a patient will return for a second visit. Our best model was a Logistic Regression model which performed with 85.3% accuracy and a Nagelkerke R-squared score of .303. We then aggregated each patient's visit information and used 20 Logistic Regression models based on the aggregations to predict if a patient would return for an ailment to a body region other than the body region listed in their first visit. We found that a Logistic Regression model that uses binary data regarding all body regions afflicted across multiple visits is the best predictor for four of the top six body regions produces results with the best R-squared scores. These four body regions are Cervix, Knee, Non-Specific, and Shoulder, while the Lumbar and Anterior Foot are better predicted by continuous data regarding all body regions afflicted across multiple visits.

Introduction

We received data from patients with musculoskeletal disorders/injuries from Integrated Musculoskeletal Care (IMC), a firm that uses specialized orthopedic care procedures and measures to help patients treat and manage their conditions. The data was from patients outside of their network, meaning that they were not necessarily receiving the treatments and care that IMC recommends. IMC already uses data analytics techniques on the patients they care for, and they gave us this data to explore and see what insights we could gain from it. We hope to provide them with information that will help them expand their network and grow their business.

We began by exploring the data and looking at basic descriptive statistics for each field. The data contained nearly 350,000 records for 18,416 patients. The variables, descriptive statistics, and visualizations are included in our ***Data and Variables*** and ***Variable Creation*****,** and ***Data Exploration*** sections below. Once we were familiar with the data, we wanted to create a research question that would help IMC manage and grow their business and provide them with new insights. Since the data was from outside of IMC's network, we believed that if patients were not following IMC's strict and scientifically-backed guidelines of care that they would be likely to re-aggregate their existing injury or succumb to a new one (or multiple new ones). In our ***Methodology*** section, we decided to build a predictive model that would determine if a patient was likely to return for future care. We used a variety of classifiers, including Random Forest, Logistic Regression, an AdaBoost classifier on both Random Forest and Logistic Regression, and a separate XGboost classifier. We trained our data based off of the patient's first visit, and built models that were fairly accurate at determining if a patient was going to return for a second visit (~85% accuracy). While it is helpful to determine if a patient is likely to return again, we began to think it would be more useful to see what body part afflictions these patients were likely to return for and if they were going to return for issues involving multiple body parts. This could potentially allow care providers to staff more specific physicians and further investigate the relationship between how body regions interact and affect injuries between each other.

We further expanded our research to include the association between body regions. We started by exploring correlation and covariance matrices of body parts to see if any either positive or negative relationships with each other. After an initial look, we put the matrices into SPSS to test for statistical significance. After finding significant relationships, we moved on to testing our next model.

Expanding on our first model, we made a Random Forest classifier based on a patient's first visit to see if they were likely to return and if so for what body region injury. We didn't get a good predictive model for this, with an accuracy of only about 35%. We believe this result is due to limitations in the data, so we built another model that just predicted whether a patient was likely to return with injuries to multiple body regions, and our Logistic Regression model produced better results (~59% accuracy).

Finally, to further explore the relationships between body regions we ran logistic regressions on the top 6 body regions which we chose based on their covariance levels. Keeping the body region as our dependent variable and testing it against all other body regions and some other patient-specific variables, we were able to see if body regions truly have a significant effect on injuries to other body regions.

The results from our models are discussed in the ***Methodology*** and ***Insights*** sections.

Motivation, Problem Definition, and Existing Approaches

As the cost of healthcare continues to rise in the US, companies, governments, and individuals are continually tasked with finding the funds to pay for them, which can be an enormous burden. Musculoskeletal disorders are the leading cause of chronic disability in the US, costing these entities about half a trillion dollars each year in both direct and indirect costs. As this cost is very large, there is a need to find ways to reduce it and alleviate the financial burden on society. We were presented with data from Integrated Musculoskeletal Care (IMC), an orthopedic care company that promotes a strict and conservative care model aimed at treating orthopedic issues quicker and safer.

Besides the enormous cost of musculoskeletal disorders, the situation is further complicated by the short-staffing of medical professionals that is prevalent not only in this specific area but in the US healthcare system in general. Short-staffing does not mean scheduling and treating less patients, it most often means that those on staff are tasked with caring for more patients than they can manage and can lead to a decreased quality of care that can result in poor treatment and complications. In a study of oncology nurses, participants felt that they were more prone to near misses and errors when on a shift that was short-staffed and that they were "short-changing" the patients in their care (Nelson, 2011). While there have been many studies on the effects of poor working conditions on nurses, there are also reports of a potential shortage of physicians and other medical professionals as the demand for them continues to grow. In a study by the American Association of Medical Colleges, there could be a shortage of between 40,800 and 104,900 physicians by 2030 (Mann, 2017). While we do not aim at finding a solution to the overall problem of short-staffing medical professionals, we hope to build a model that will predict the number of patients that are likely to return so that IMC has time to schedule staff appropriately in advance.

To accomplish our objectives we intend to build a predictive model that will determine if a patient's characteristics make them likely to return for another case or injury. We also want to see if there is a significant correlation between different body parts relating to injuries, as identifying these relationships can help providers choose the correct preventative care long before other injuries are likely to occur. By building a good predictive model and identifying how injuries to certain body regions affect others, we can help TOC schedule adequate staffing levels based on the number of patients we expect to come in for future visits and provide them with relationships between body regions that they can further analyze to gain more insight as to why they are occuring.

Data and Variables

Our Data is a collection of patient healthcare data from Integrated Musculoskeletal Care (IMC). Before we received the data, it had been transformed and modified so that no one would be able to identify the patients and thus maintain patient confidentiality. Below is a list of the given variables:

- **EMID:** a unique, anonymous identifier for each patient (stands for Encrypted Member ID). In this data set, there are 18416 unique EMIDs
- **Date:** the date that a patient came for a specific procedure, in YYYY-MM format. This data set spans 4 years, from 2012-01 to 2016-12
- **Allowed:** the dollar amount allowed by the patient's insurance plan for each procedure. This variable ranges from $1 to $101,258 with a mean of $151.69 and a standard deviation of $948.06
- **ICD:** the International Classification of Diseases (ICD) Code and a description of it, there are 1607 unique codes in the data set, with the top being "7242 LUMBAGO", which is pain in the muscles and joints of the lower back and was seen 23362 times
- **Procedure:** code and description of the procedure performed. There are 2175 unique procedure types and total of 331011 procedures were performed, with the top being '97110 THERAPEUTIC EXERCISES', of which 39741 were performed
- **Gender:** sex of the patient (binary, Male or Female). Of the 331011 procedures performed, 192959 were done on women (~58.3%) and 138052 done on men (~41.7%)
- **DX:** the ICD Code only (no description); again, there are 1607 unique DXs as there were 1607 unique ICDs

- **BRalpha:** specific body region affected, abbreviated to several characters. There were 20 unique body parts and the number of issues related to each one is shown at a chart at the top of this report
- **PLalias:** Procedure Level Alias, there were 11 unique procedure types for this and the most common by far was “THRP” or “Therapy”, which has nearly twice as many cases as the next highest alias
- **MaxPL:** the maximum procedure for the case, case is defined as first visit for a specific condition/symptom. The values for this variable ranged from 1 to 9.2, with 5 being the most frequent and having a mean of 6.1 and a standard deviation of 2.3
- **FVL:** first visit for the case for life, expressed in MM-YYYY date format, this is the date a patient first comes in for a new case. The range is the same for the Date variable (2012-01 to 2016-12)
- **FVage:** corresponds with the FVL, this is the age of the patient when they came in for the first time for a new case. Age ranged from newborns (0) to elderly (103) with a mean of 43.4 years old and a standard deviation of 16.36 years. Age was expressed in years to one decimal place
- **FVrrisk:** First Visit Retrospective Risk (a comorbidity index), this is a scale designed by medical professionals to assign patients a risk factor, this is a scale from 1-100. The mean was 2.96 with a standard deviation of 3.51
- **CSID:** the Case ID, it is composed of the EMID and BRalpha

We created a chart for a breakdown of our continuous variables, which we will further explore (along with the categorical variables) in the following sections:

Breakdown of Continuous Variables

	FVage	FVrrisk	Allowed	MaxPL
count	331011	331011	331011	331011
mean	43.40	2.97	$ 151.69	6.15
std	16.37	3.51	$ 948.06	2.33
min	0	0	$ 1.00	1
25%	32	0.91	$ 21.00	5
50%	47	1.9	$ 36.00	6.2
75%	57	3.66	$ 76.00	8
max	103	100.36	$ 101,258.00	9.2

Variable Creation

After analyzing the given variables, we realized that there were more variables that we could create which could give us more insight to the data. First, we created a variable called “VisitCount” which tallied up the number of times each unique patient visited a clinic included in the data. After that, we created a dummy variable called “Returned” which returns a “1” if the customer visited a clinic more than once, otherwise the variable returns a “0”.

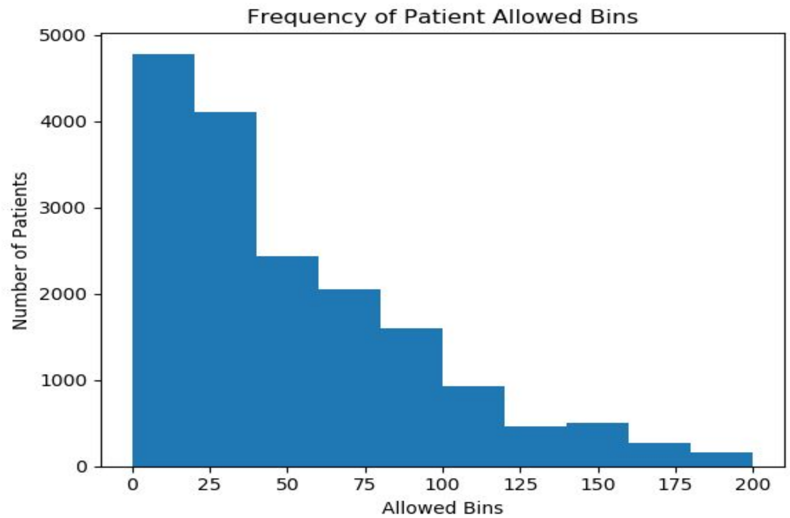
After creating that variable, we created a variable called “MultipleInjuries” that would tell us whether a patient visited for only one specific body region, such as lower back, or if they visited for more than one body region, such as lower back and upper arm. This variable returns a “0” if the patient only has information regarding one body region, and it return a “1” regardless of if the patient came in for two or twenty different body regions. We did not have this variable reflect the total number of body regions affected because our model will only concern itself with whether or not a patient returns for at least a second body region, plus we already calculated that information elsewhere.

We were also interested in how patients’ risk factor changed across visits. To check this, we took the difference between the maximum risk factor associated with a patient’s FVL and the minimum risk factor associated with a patient’s FVL. We call this variable “Risk Differential”. This attribute only applies to patients who had multiple FVLs (first time cases for a specific condition). Stemming off this, we also found the number of body parts associated with each FVL to see which body parts were most frequent, and to use in our later analysis which will see how injuries to some body parts may later affect other body parts.

Lastly, we created a variable called “MonthsAsPatient” that allows us to include a time element within the data. This category takes the initial dates we were given and then finds the date of the patient’s first and most recent visit and returns the amount of time in months that has elapsed since the two visits. For example, if a patient’s first visit was in May 2014 and their most recent visit was April 2016, the variable would return a “23” because 23 months have elapsed. If a patient only visited once, or if all of a patient’s visits were in the same month of the same year, the variable returns a “0”.

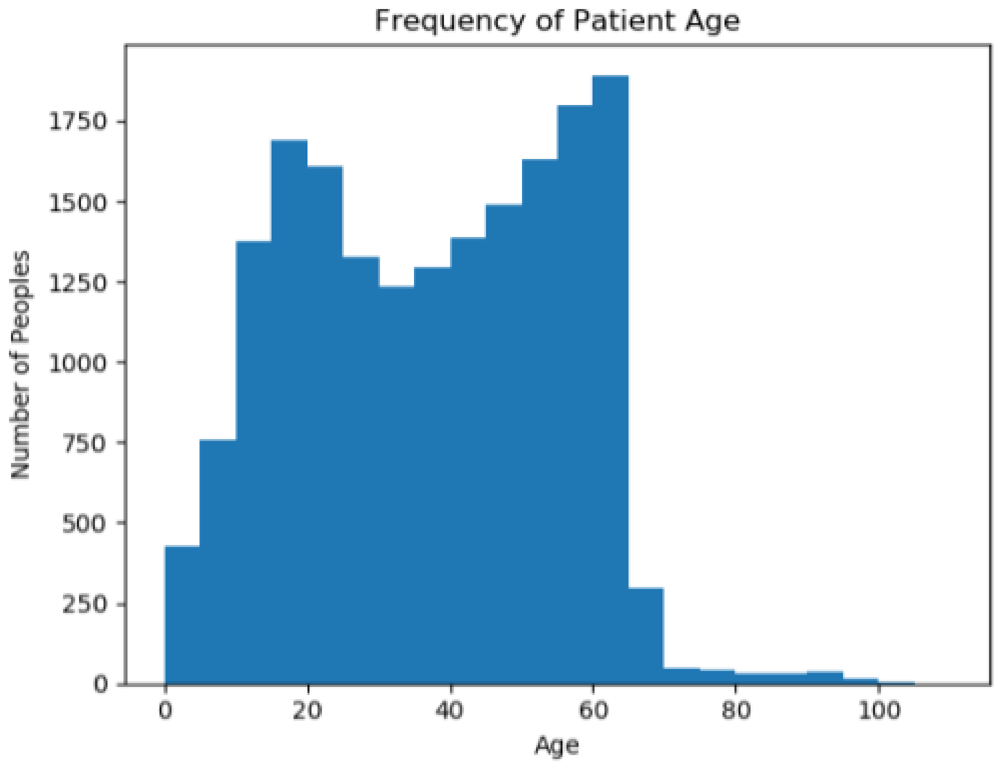
Data Exploration

When we began our exploration of the data, one variable we wanted to consider was the cost of treatment, as this is a generally recognized issue when it comes to healthcare in the U.S. We found that creating a histogram of the allowed amounts summed up the data pretty well:



Our histogram here shows counts of the allowed amounts in bins of 25 up until the cut-off of 200. There are patients with more than 200 allowed, but this will be included in its own category later of patients with allowed > 205 as a bin. As we can see, the most frequent case is an allowed amount between 0 and 25, and this measure is limited because it is the amount allowed by the patient's insurance plan, not the total cost of treatment. We wanted to see how much patients were spending on their treatments, and found that the average patient through all procedures spent about $2726.56. We can later compare this to the mean of 1 time visitors vs multiple visitors in order to see which customer base is able to pay more. A limitation of this data is that we only received information on the dollar amount allowed by each patient's insurance plan. Since insurance plans and providers vary in ways unexplained by our data, we cannot in good faith include this variable in our models. Additionally, we do not know how much the actual cost of the visits, which thus limits our analysis since costs can vary by geographical regions and our data set does not include information regarding locations.

Another factor we wanted to look at was the age of patients, as we assumed that musculoskeletal disorders would mostly impact the "older" population due to the eventual "wear and tear" and stresses our bodies deal with as we age.

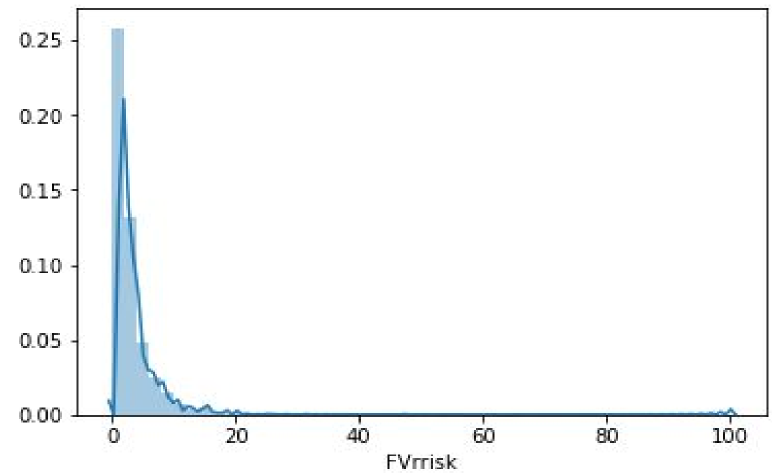


*Bins are in increments of 5 yrs

The age histogram above shows that patients are largely clustered between 15 and 65 years old. The results were surprising to us, namely that there is a nearly equal number of patients from 20-25 years old as there is 50-55 years old; there is a larger number of “young” people in the data than we expected.

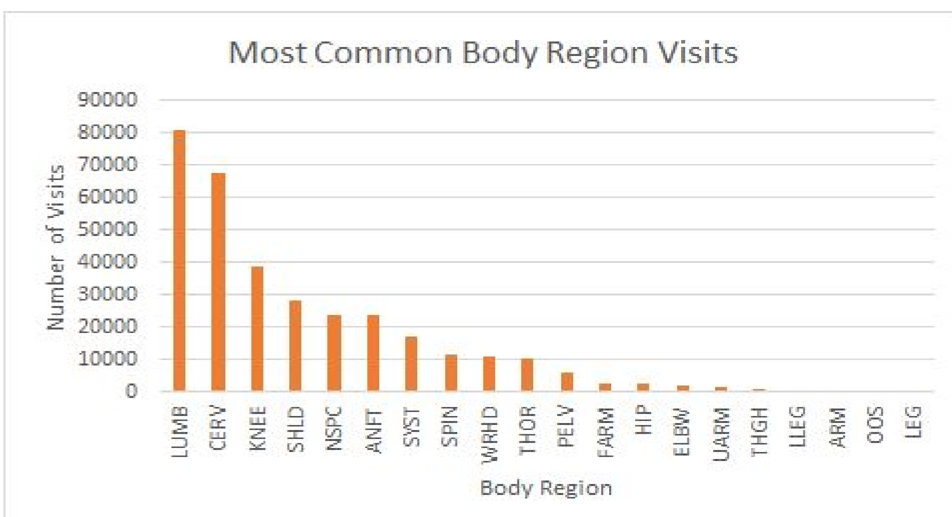
We also wanted to see the breakdown of patient’s first visit retrospective risk (FVrrisk), which is a scale from 1 to 100 created by medical professionals. We expected a fairly normal distribution here, but this expectation was formed without much knowledge of how the metric is determined. The plot below shows the actual distribution of patients’ risk, and the actual distribution is right-skewed.

Distribution Plot of Patients’ FVrrisk

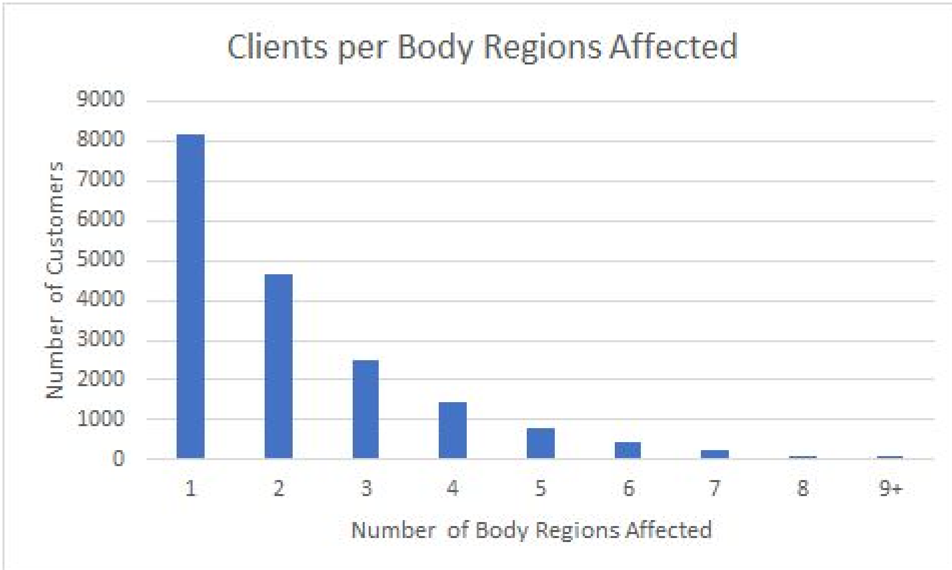


This plot shows that most patients have a low first visit retrospective risk (less than 20 out of a range of 100).

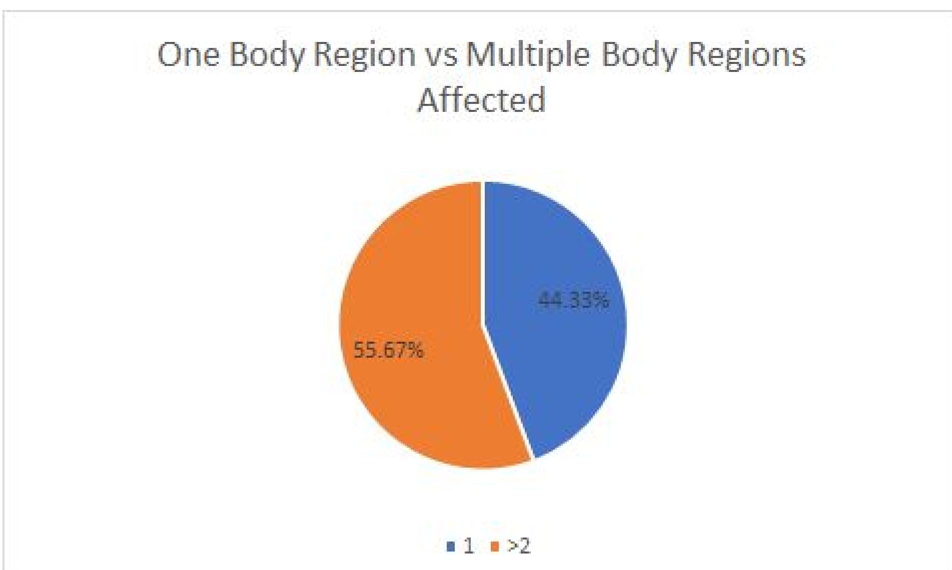
After we explored general information about the patients, we next looked into the breakdowns of the injuries/afflictions that were affecting patients. We started by looking at what body regions patients were coming in for and plotted the results in the bar chart below:



This chart shows which body region was taken care of for each visit. This includes multiple visits for the same customers. Lumbar and Cervix were the two body regions that customers come in for the most. To support our findings, we found a report by the World Health Organization which states: “Musculoskeletal conditions are the second largest contributor to disability worldwide, with low back pain being the single leading cause of disability globally.” This means our results make sense scientifically, as the lumbar spine directly contributes to low back pain and the cervical spine attributes to back and neck pain. After this finding, we went on to explore how many clients had injuries that afflicted multiple body regions:



The chart above shows how many clients have either one or more than one body region affected by an injury. As we can see, most clients come in for only one body region. What is interesting about this is that it appears that for every additional body region affected, the amount of clients is cut roughly in half.



The chart above shows the same data as the previous bar chart, but it classifies as either one body region or multiple body regions affected. As we can see, a large percentage of patients only come in for one type of body region, but a majority come in for multiple regions, meaning that there is room for our research to generate meaningful insights that has the potential to impact many patients.

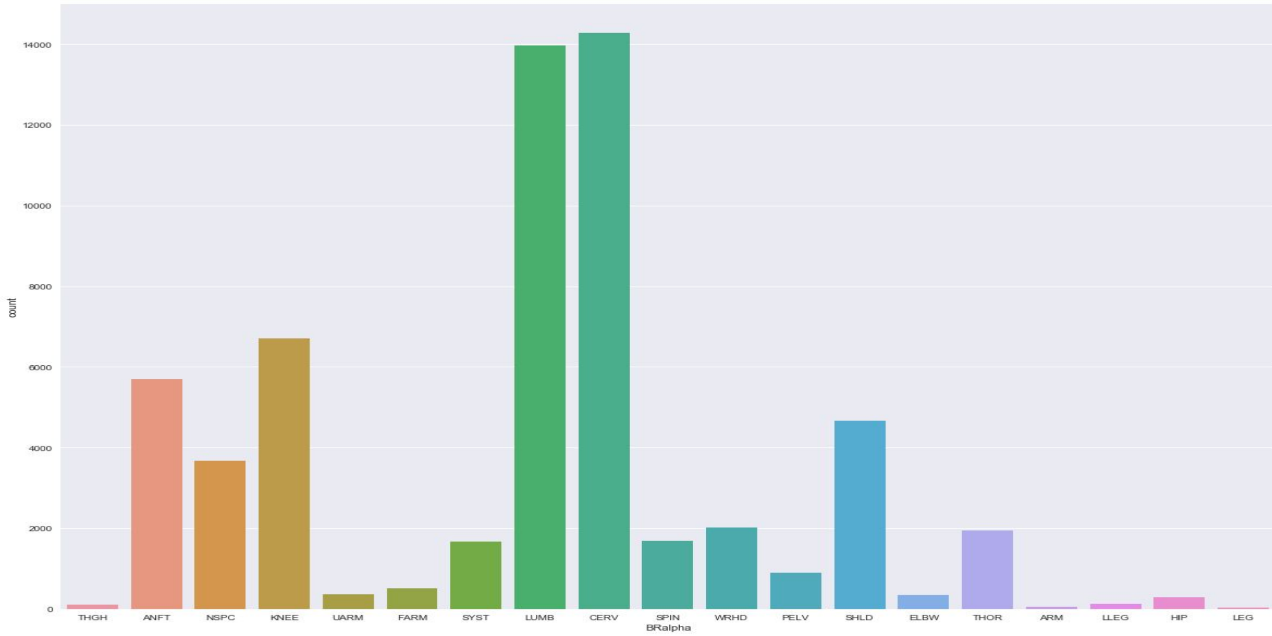
We also explore how many patients came in for FVLs, which are the first time a patient came in for a specific case and does not include the number of visits, just the number of unique cases they had. For example, from the image below, we see that 2,272 patients had 3 unique cases for which they sought medical treatment.

Counts of Number of Patients per Number of FVLs

FVL	Count
1	9158
2	4776
3	2272
4	1192
5	560
6	264
7	120
8	44
9	25
10	3
11	1
12	1

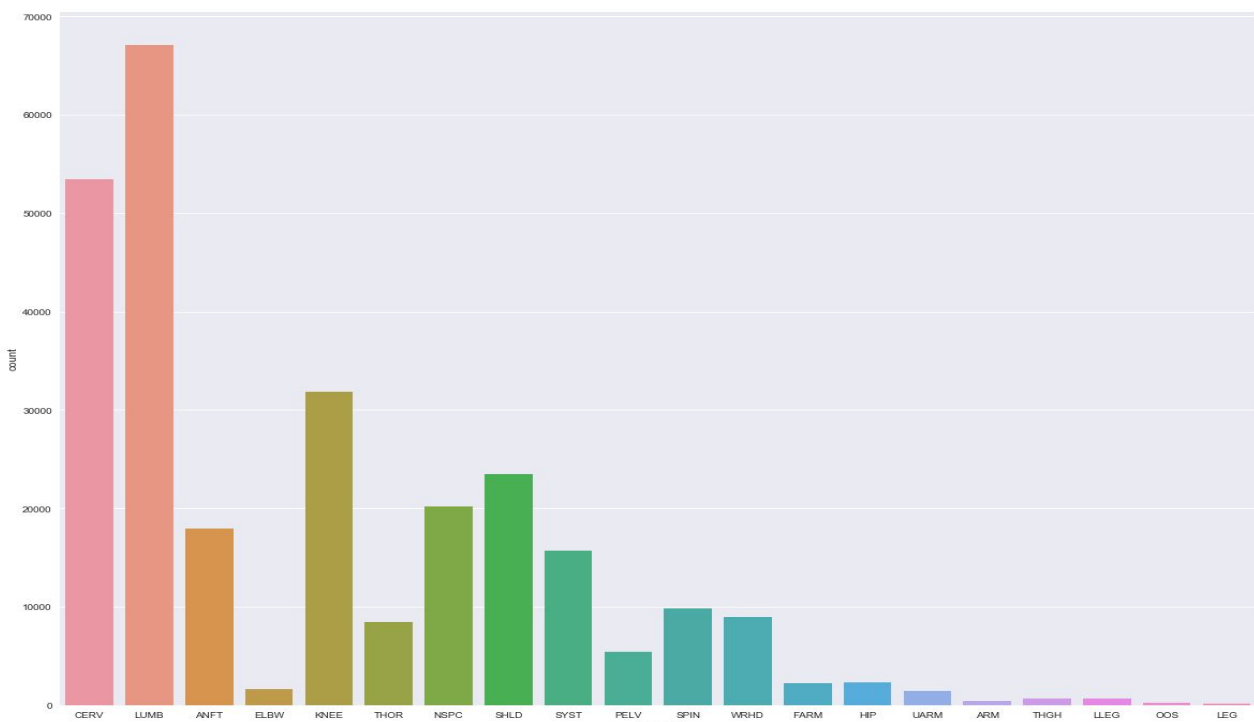
For patients who visited for one specific case (1 unique FVL), these are the counts of the body parts that they came in for:

Count of BRalpha for 1-Time FVL Patients



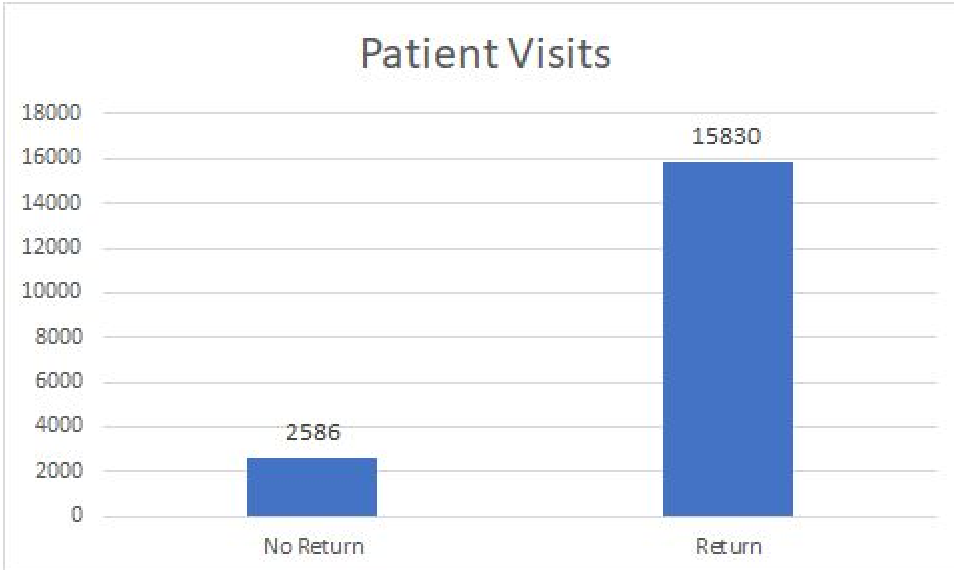
The top two body regions here are Lumbar and Cervical Spine. The next chart shows the same thing but for patients who made multiple FVLs:

Count of BRalpha for Multiple FVL Patients



Again, the top two are Lumbar and Cervical Spine.

While the FVLs are good for looking for specific cases, we are more interested in whether a patient is likely to return or not. For this, we split our data into patients that came in for one visit and those who came in for multiple visits:



As we can see, most patients returned for at least one more visit after their initial one, and we will use this information for later analysis in our ***Methods*** section.

We then wanted to begin to explore the relationships between body regions, namely if people with injuries to multiple body parts over time could have had subsequent injuries caused by a previous one. Our belief here is that if someone has one injury and does not treat it right, it could lead to subsequent injuries to other body regions over time due to a variety of factors. We also recognize that the opposite could be true: there may be some body regions with negative correlations to other body regions, which could possibly mean that treatment for one body region also helps reduce injury to a different body region. Or it could mean that if a patient has an injury to a specific body region, injury to the negatively correlated body region is not likely. To begin our exploration of these relationships, we created a correlation matrix of body regions:

Methodology

We began the data cleaning process by first dropping the columns that do not have any predictive value for our model. These variables were “ICD”, “Procedure”, “DX”, “MaxPL”, and “CSID”. We dropped these variables for the following reasons:

- **ICD:** Our study is concerned with the patient’s afflicted body region rather than their diagnoses
- **Procedure:** PLalias provides a more general variable with much of the same information
- **DX:** We are not concerned with the disease of the patient as we want the study to focus

on body regions

- **FVL** We have created the ‘Months as Patient’ variable that could be of more use
- **MaxPL:** Maximum Procedure Level could skew the data concerning the initial - more minor - visits
- **CSID:** Unique Case ID that lacks predictive power and, if included, would cause the data to overfit

After we dropped these columns, we then dropped any rows that had N/A values. This takes us from 349,023 rows down to 331,011. With dropping the N/A values, we lost 18,012 rows of data, which still leaves us with about 95% of our original data.

Next, we used a custom oneHotEncoder function to create dummy variables for the “Gender”, “BRalpha”, and “PLalias” variables. For binary categorical data, we create one new column that clearly states if the new category is true or false. For example, “Gender” becomes “Gender_Female”, and a ‘0’ indicates that the patient is a male while a ‘1’ indicates they are a female. On the other hand, if the column has multiple categories, we create multiple columns that are clearly labeled. For example, “BRalpha” becomes “BRalpha_ARM”, “BRalpha_HIP”, etc. If the patient came in for that specific category, they are given a “1”, else they receive a “0”.

With all of our variables created, we then merged our data frames into one larger data frame that contains all the variables that will be needed for our model. We ensured that the new variables are linked to the patients based on their “EMID’s”. After running our preliminary analyses described below, our next step in the process is to split our data using scikit-learn’s train_test_split function. We used 70% of our data to train our models and 30% of the data to test the models.

Our first step in our analyses was to explore the cleaned dataset. We found that there were 15,830 unique patients who had multiple patient visits. We focused on this set of patients in order to help with the transition to model building; since our project is concerned with patients who returned for multiple injuries, there would be no point in focusing on the correlation of body parts for patients that did not return. The one time unique patients will be re-assimilated into the analysis after correlation exploration.

To find the patients who returned, we created a separate data frame with each unique EMID and summed up the number of visits they had, and if the number was greater than 1 then they received a value of 1 in the Returned field and 0 otherwise.This is a sample of our code output where we demonstrate that we are able to see if a patient returned for a second visit or not:

Index	EMID	VisitCount	Returned
0	ZDYU-SO QLBU-ZVSD	3	1
1	ADYL-BO ZUSW-BWQF	9	1
2	ZDYU-ZA ZUMN-ZUZN	169	1
3	BDYV-AA ZFQW-BUGH	1	0
4	GDYU-SO ZUSX-GFPN	5	1
5	PDYL-YO ZHML-MFSX	8	1

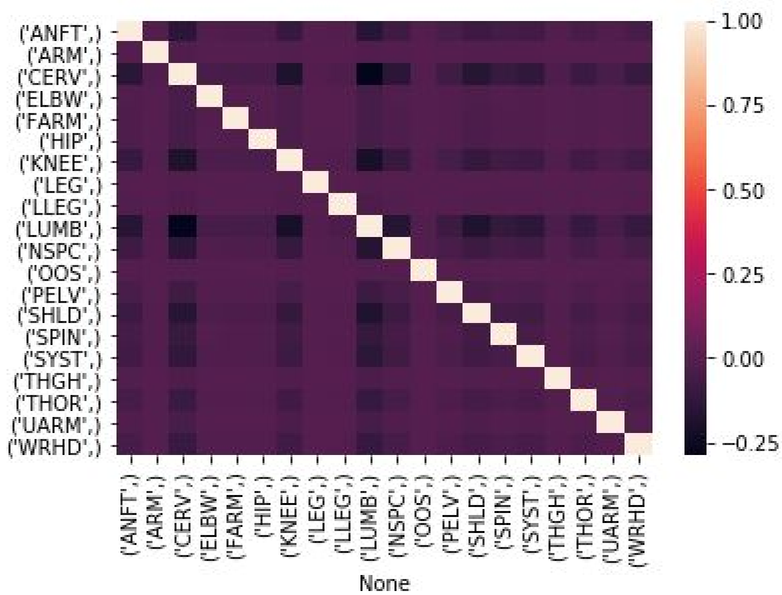
This will be helpful for later in the paper when we begin to make predictions on whether the customer returned or not. Our next step is to figure out, of the people who returned, who returned for a different type of injury.

Index	EMID	VisitCount	Returned	MultipleInjuries
0	ZDYU-SO QLBU-ZVSD	3	1	1
1	ADYL-BO ZUSW-BWQF	9	1	1
2	ZDYU-ZA ZUMN-ZUZN	169	1	1
3	BDYV-AA ZFQW-BUGH	1	0	0
4	GDYU-SO ZUSX-GFPN	5	1	0
5	PDYL-YO ZHML-MFSX	8	1	1

We were able to figure out the patients who returned, who returned for multiple injuries, and how many times they returned in total.

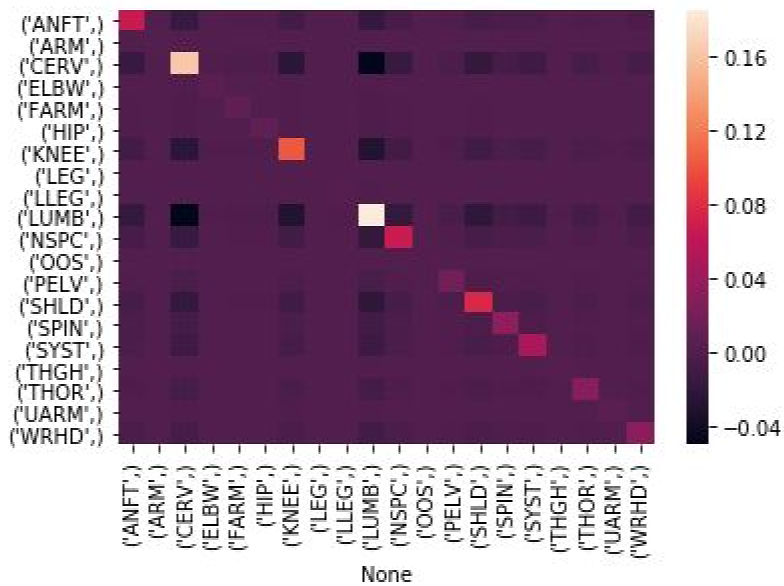
Moving forward, we wished to examine the correlation between body parts. To do this, we created dummy variables for the body part that was the cause of concern for the patient's visit. We then constructed a correlation matrix as well as a covariance matrix in python using numpy. The result of the visualizations are two 20 x 20 heat maps of the body parts and their correlations and covariances, respectively. See figures below for the data and visualizations of the body part correlations:

	ANFT	ARM	CERV	ELBW	FARM	HIP	KNEE	LEG	LLEG	LUMB	NSPC	OOS	PELV	SHLD	SPIN	SYST	THGH	THOR	UARM	WRHD
ANFT	1	-0.01013	-0.14062	-0.02121	-0.02521	-0.0248	-0.10071	-0.0058	-0.0134	-0.15786	-0.07722	-0.00712	-0.03861	-0.08444	-0.0527	-0.06519	-0.01351	-0.04993	-0.02081	-0.05144
ARM	-0.01013	1	-0.01853	-0.00279	-0.00332	-0.00327	-0.01327	-0.00076	-0.00176	-0.0208	-0.01017	-0.00094	-0.00509	-0.01112	-0.00694	-0.00859	-0.00178	-0.00658	-0.00274	-0.00678
CERV	-0.14062	-0.01853	1	-0.0388	-0.04612	-0.04537	-0.18426	-0.01062	-0.02451	-0.28882	-0.1413	-0.01302	-0.07064	-0.15449	-0.09642	-0.11927	-0.02472	-0.09135	-0.03808	-0.09412
ELBW	-0.02121	-0.00279	-0.0388	1	-0.00696	-0.00684	-0.02779	-0.0016	-0.0037	-0.04356	-0.02131	-0.00196	-0.01065	-0.0233	-0.01454	-0.01799	-0.00373	-0.01378	-0.00574	-0.0142
FARM	-0.02521	-0.00332	-0.04612	-0.00696	1	-0.00813	-0.03303	-0.0019	-0.00439	-0.05177	-0.02533	-0.00233	-0.01266	-0.02769	-0.01728	-0.02138	-0.00443	-0.01637	-0.00683	-0.01687
HIP	-0.0248	-0.00327	-0.04537	-0.00684	-0.00813	1	-0.03249	-0.00187	-0.00432	-0.05093	-0.02491	-0.0023	-0.01246	-0.02724	-0.017	-0.02103	-0.00436	-0.01611	-0.00671	-0.0166
KNEE	-0.10071	-0.01327	-0.18426	-0.02779	-0.03303	-0.03249	1	-0.0076	-0.01755	-0.20684	-0.10119	-0.00933	-0.05059	-0.11064	-0.06905	-0.08542	-0.0177	-0.06542	-0.02727	-0.06741
LEG	-0.0058	-0.00076	-0.01062	-0.0016	-0.0019	-0.00187	-0.0076	1	-0.00101	-0.01192	-0.00583	-0.00054	-0.00292	-0.00638	-0.00398	-0.00492	-0.00102	-0.00377	-0.00157	-0.00388
LLEG	-0.0134	-0.00176	-0.02451	-0.0037	-0.00439	-0.00432	-0.01755	-0.00101	1	-0.02751	-0.01346	-0.00124	-0.00673	-0.01472	-0.00918	-0.01136	-0.00235	-0.0087	-0.00363	-0.00897
LUMB	-0.15786	-0.0208	-0.28882	-0.04356	-0.05177	-0.05093	-0.20684	-0.01192	-0.02751	1	-0.15861	-0.01462	-0.0793	-0.17342	-0.10823	-0.13389	-0.02774	-0.10255	-0.04275	-0.10566
NSPC	-0.07722	-0.01017	-0.1413	-0.02131	-0.02533	-0.02491	-0.10119	-0.00583	-0.01346	-0.15861	1	-0.00715	-0.03879	-0.08484	-0.05295	-0.0655	-0.01357	-0.05017	-0.02091	-0.05169
OOS	-0.00712	-0.00094	-0.01302	-0.00196	-0.00233	-0.0023	-0.00933	-0.00054	-0.00124	-0.01462	-0.00715	1	-0.00358	-0.00782	-0.00488	-0.00604	-0.00125	-0.00462	-0.00193	-0.00476
PELV	-0.03861	-0.00509	-0.07064	-0.01065	-0.01266	-0.01246	-0.05059	-0.00292	-0.00673	-0.0793	-0.03879	-0.00358	1	-0.04242	-0.02647	-0.03275	-0.00679	-0.02508	-0.01045	-0.02584
SHLD	-0.08444	-0.01112	-0.15449	-0.0233	-0.02769	-0.02724	-0.11064	-0.00638	-0.01472	-0.17342	-0.08484	-0.00782	-0.04242	1	-0.0579	-0.07162	-0.01484	-0.05485	-0.02286	-0.05652
SPIN	-0.0527	-0.00694	-0.09642	-0.01454	-0.01728	-0.017	-0.06905	-0.00398	-0.00918	-0.10823	-0.05295	-0.00488	-0.02647	-0.0579	1	-0.0447	-0.00926	-0.03423	-0.01427	-0.03527
SYST	-0.06519	-0.00859	-0.11927	-0.01799	-0.02138	-0.02103	-0.08542	-0.00492	-0.01136	-0.13389	-0.0655	-0.00604	-0.03275	-0.07162	-0.0447	1	-0.01146	-0.04235	-0.01765	-0.04363
THGH	-0.01351	-0.00178	-0.02472	-0.00373	-0.00443	-0.00436	-0.0177	-0.00102	-0.00235	-0.02774	-0.01357	-0.00125	-0.00679	-0.01484	-0.00926	-0.01146	1	-0.00878	-0.00366	-0.00904
THOR	-0.04993	-0.00658	-0.09135	-0.01378	-0.01637	-0.01611	-0.06542	-0.00377	-0.0087	-0.10255	-0.05017	-0.00462	-0.02508	-0.05485	-0.03423	-0.04235	-0.00878	1	-0.01352	-0.03342
UARM	-0.02081	-0.00274	-0.03808	-0.00574	-0.00683	-0.00671	-0.02727	-0.00157	-0.00363	-0.04275	-0.02091	-0.00193	-0.01045	-0.02286	-0.01427	-0.01765	-0.00366	-0.01352	1	-0.01393
WRHD	-0.05144	-0.00678	-0.09412	-0.0142	-0.01687	-0.0166	-0.06741	-0.00388	-0.00897	-0.10566	-0.05169	-0.00476	-0.02584	-0.05652	-0.03527	-0.04363	-0.00904	-0.03342	-0.01393	1



The following figures are the results for data and visualizations regarding their covariances:

	ANFT	ARM	CERV	ELBW	FARM	HIP	KNEE	LEG	LLEG	LUMB	NSPC	OOS	PELV	SHLD	SPIN	SYST	THGH	THOR	UARM	WRHD
ANFT	0.066278	-9.5E-05	-0.01461	-0.00042	-0.00059	-0.00057	-0.00832	-3.1E-05	-0.00017	-0.01747	-0.00514	-4.7E-05	-0.00136	-0.00606	-0.00249	-0.00374	-0.00017	-0.00224	-0.0004	-0.00238
ARM	-9.5E-05	0.001331	-0.00027	-7.8E-06	-1.1E-05	-1.1E-05	-0.00016	-5.8E-07	-3.1E-06	-0.00033	-9.6E-05	-8.8E-07	-2.5E-05	-0.00011	-4.6E-05	-7E-05	-3.2E-06	-4.2E-05	-7.5E-06	-4.4E-05
CERV	-0.01461	-0.00027	0.162763	-0.00119	-0.00168	-0.00162	-0.02386	-9E-05	-0.00048	-0.0501	-0.01474	-0.00013	-0.00389	-0.01737	-0.00714	-0.01072	-0.00048	-0.00643	-0.00115	-0.00681
ELBW	-0.00042	-7.8E-06	-0.00119	0.005785	-4.8E-05	-4.6E-05	-0.00068	-2.5E-06	-1.4E-05	-0.00142	-0.00042	-3.8E-06	-0.00011	-0.00049	-0.0002	-0.0003	-1.4E-05	-0.00018	-3.3E-05	-0.00019
FARM	-0.00059	-1.1E-05	-0.00168	-4.8E-05	0.008132	-6.5E-05	-0.00096	-3.6E-06	-1.9E-05	-0.00201	-0.00059	-5.4E-06	-0.00016	-0.0007	-0.00029	-0.00043	-1.9E-05	-0.00026	-4.6E-05	-0.00027
HIP	-0.00057	-1.1E-05	-0.00162	-4.6E-05	-6.5E-05	0.007873	-0.00093	-3.5E-06	-1.8E-05	-0.00194	-0.00057	-5.2E-06	-0.00015	-0.00067	-0.00028	-0.00042	-1.9E-05	-0.00025	-4.4E-05	-0.00026
KNEE	-0.00832	-0.00016	-0.02386	-0.00068	-0.00096	-0.00093	0.102986	-5.1E-05	-0.00027	-0.02854	-0.00839	-7.7E-05	-0.00222	-0.0099	-0.00407	-0.00611	-0.00028	-0.00366	-0.00065	-0.00388
LEG	-3.1E-05	-5.8E-07	-9E-05	-2.5E-06	-3.6E-06	-3.5E-06	-5.1E-05	0.000438	-1E-06	-0.00011	-3.2E-05	-2.9E-07	-8.3E-06	-3.7E-05	-1.5E-05	-2.3E-05	-1E-06	-1.4E-05	-2.5E-06	-1.5E-05
LLEG	-0.00017	-3.1E-06	-0.00048	-1.4E-05	-1.9E-05	-1.8E-05	-0.00027	-1E-06	0.002324	-0.00057	-0.00017	-1.5E-06	-4.4E-05	-0.0002	-8.1E-05	-0.00012	-5.5E-06	-7.3E-05	-1.3E-05	-7.8E-05
LUMB	-0.01747	-0.00033	-0.0501	-0.00142	-0.00201	-0.00194	-0.02854	-0.00011	-0.00057	0.184891	-0.01763	-0.00016	-0.00466	-0.02078	-0.00854	-0.01283	-0.00058	-0.00769	-0.00137	-0.00815
NSPC	-0.00514	-9.6E-05	-0.01474	-0.00042	-0.00059	-0.00057	-0.00839	-3.2E-05	-0.00017	-0.01763	0.066822	-4.7E-05	-0.00137	-0.00611	-0.00251	-0.00377	-0.00017	-0.00226	-0.0004	-0.0024
OOS	-4.7E-05	-8.8E-07	-0.00013	-3.8E-06	-5.4E-06	-5.2E-06	-7.7E-05	-2.9E-07	-1.5E-06	-0.00016	-4.7E-05	0.000658	-1.3E-05	-5.6E-05	-2.3E-05	-3.5E-05	-1.6E-06	-2.1E-05	-3.7E-06	-2.2E-05
PELV	-0.00136	-2.5E-05	-0.00389	-0.00011	-0.00016	-0.00015	-0.00222	-8.3E-06	-4.4E-05	-0.00466	-0.00137	-1.3E-05	0.018665	-0.00162	-0.00066	-0.001	-4.5E-05	-0.0006	-0.00011	-0.00063
SHLD	-0.00606	-0.00011	-0.01737	-0.00049	-0.0007	-0.00067	-0.0099	-3.7E-05	-0.0002	-0.02078	-0.00611	-5.6E-05	-0.00162	0.077685	-0.00296	-0.00445	-0.0002	-0.00267	-0.00048	-0.00283
SPIN	-0.00249	-4.6E-05	-0.00714	-0.0002	-0.00029	-0.00028	-0.00407	-1.5E-05	-8.1E-05	-0.00854	-0.00251	-2.3E-05	-0.00066	-0.00296	0.033656	-0.00183	-8.3E-05	-0.0011	-0.0002	-0.00116
SYST	-0.00374	-7E-05	-0.01072	-0.0003	-0.00043	-0.00042	-0.00611	-2.3E-05	-0.00012	-0.01283	-0.00377	-3.5E-05	-0.001	-0.00445	-0.00183	0.049649	-0.00012	-0.00165	-0.00029	-0.00174
THGH	-0.00017	-3.2E-06	-0.00048	-1.4E-05	-1.9E-05	-1.9E-05	-0.00028	-1E-06	-5.5E-06	-0.00058	-0.00017	-1.6E-06	-4.5E-05	-0.0002	-8.3E-05	-0.00012	0.002363	-7.4E-05	-1.3E-05	-7.9E-05
THOR	-0.00224	-4.2E-05	-0.00643	-0.00018	-0.00026	-0.00025	-0.00366	-1.4E-05	-7.3E-05	-0.00769	-0.00226	-2.1E-05	-0.0006	-0.00267	-0.0011	-0.00165	-7.4E-05	0.030429	-0.00018	-0.00105
UARM	-0.0004	-7.5E-06	-0.00115	-3.3E-05	-4.6E-05	-4.4E-05	-0.00065	-2.5E-06	-1.3E-05	-0.00137	-0.0004	-3.7E-06	-0.00011	-0.00048	-0.0002	-0.00029	-1.3E-05	-0.00018	0.005573	-0.00019
WRHD	-0.00238	-4.4E-05	-0.00681	-0.00019	-0.00027	-0.00026	-0.00388	-1.5E-05	-7.8E-05	-0.00815	-0.0024	-2.2E-05	-0.00063	-0.00283	-0.00116	-0.00174	-7.9E-05	-0.00105	-0.00019	0.032178



As expected, many of the correlations between body parts were negative, but there were positive instances which stood out. The positive correlations were generally reflective; meaning for instance, if a patient came in for a knee issue, then there is a positive correlation that if the patient returned, it would also be for a knee issue. Though this may seem intuitive, it is interesting to note that this positive correlative pattern is not seen for every single (or even a majority) of the body parts. Rather, we see that lumbar, cervix, anterior foot, and knee problems are the most likely to have a patient return for the same issue.

The next step was testing the significance of these correlations. To do so, we exported to the excel file of the dummy variables of body parts that we created in python into SPSS. We then did a cross-tab analysis of the body regions observing the chi-squared statistic to see if these correlations were significant. Below is an example of the results of one such chi-squared test, which is of knee injuries with respect to thigh injuries:

KNEE * THGH

Crosstab

Count

		THGH		
		0	1	Total
KNEE	0	239440	676	240116
	1	31884	0	31884
Total		271324	676	272000

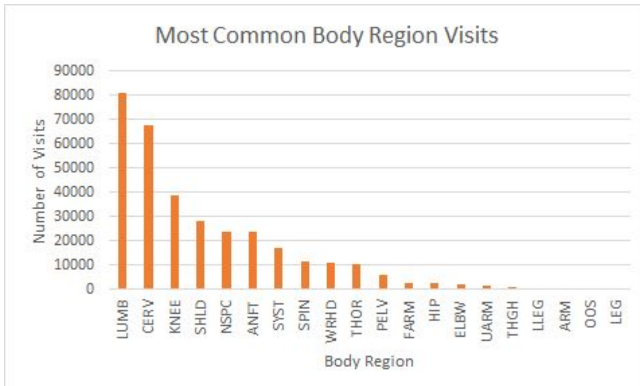
Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	89.987[a]	1	.000		
Continuity Correction[b]	88.855	1	.000		
Likelihood Ratio	168.791	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	89.987	1	.000		
N of Valid Cases	272000				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 79.24.

b. Computed only for a 2x2 table

With the large amount of significance tests we would need to run, we were thinking of limiting our analyses to lumbar and cervix injuries as the rows in the cross-tab analysis and compare these two body regions to all other body parts as the columns. The thought behind this is simply because the cervix and lumbar are the most common visit by an overwhelming margin. Below you can see the breakdown for number of visits by body part.



Since we found that the correlations were significant, we can continue with our analysis. We now plan to use the following variables as our features in order to build our model:

- Allowed
- FVage
- FVDiff
- Gender
- BRalpha (dummy variables)
- PLalias (dummy variables)
- VisitCount
- MonthsAsPatient
- Risk Differential

We will use the variable “returned” as our dependent variable. The patients which only visited once, which were removed so that the correlation and covariance analyses could the completed, will be re-inserted into the sample and test populations before we train our model. We hope to be able to reliably predict whether a patient will return or not after our model is fit. From there, the goal is to use the body part correlations and probabilities produced by the model and suggest the next body part that will afflict a patient, if it is predicted they will return at all.

To start, we first built models to predict simply whether or not a patient was going to return for another visit. We ran Logistic Regression, Random Forest, AdaBoost on Logistic Regression and Random Forest, and XGboost. All models had very similar accuracy scores with Random Forest having a slight edge. When we tested removing some variables from the models our accuracy scores only dropped by very insignificant amounts, so based on our data we don't think this would be a very valuable predictive model, as a large portion of patients returned for more than one visit and the data only spanned 4 years. Below are the accuracy score results from our five models:

Model	Logistic Regression	RandomForest	AdaBoost Logistic	AdaBoost Random Forest	XGBoost
All Variables	0.855	0.860	0.854	0.856	
Drop Fvrrisk	0.854	0.854	0.854		
Drop Year	0.854	0.854	0.855		
Drop Month	0.855	0.854	0.854		
Drop Month and Year	0.855	0.854	0.855		0.857
Drop Plalias, Month, and Year	0.854				
Drop Body Region, Plalias, Month, and Year	0.854				
Body Region, Plalias, and Gender ONLY	0.853	0.854			
Body Region and Gender ONLY	0.855	0.855			
Body Region ONLY	0.855	0.855			

We attempted to run a random forest classifier based on the patients' first visit information to try and predict the probability that the patient would come in for an injury to a different body region. For example, if we have first visit information about a patient with a lumbar injury, we tried to predict the probability that the patient would return for a cervix injury. After analyzing our data, we found that our models did not have enough information upon a patient's first visit to accurately predict the specific body regions that would afflict the patient. We used a random forest model, and the predictions were only about 35.873% accurate, with an R-squared score of .112. This means that our model had much difficulty accurately making this prediction as there is not enough data upon one visit to make a strong correlation. The R-squared score shows us that the results are largely due to random chance. With this in mind, we decided to take a step back and see if we could predict whether or not a patient would return for another body region injury in general.

Since we already predicted if a patient will return, we decided to use this prediction values in our analysis for multiple injuries. Although we have the actual return values for the data, a clinic would not know with certainty if a patient would return from only their first visit information, so it would be best for practicality to use our prediction model from phase one to predict multiple injuries. We again used Logistic Regression, Random Forest, XGBoost, and AdaBoost models to predict this variable. Our independent variables include gender, BRalpha, PLalias, and predicted return. The results of our models are depicted below:

Model	Accuracy Score	Recall Score
Logistic Regression	0.590	0.781
Random Forest	0.581	0.829
XGBoost	0.587	0.799
AdaBoost	0.587	0.796

The Logistic Regression model performs the best in accuracy scores. However, the random forest model has a slightly better recall score. This means that the random forest model does a slightly better job at positively predicting the patients who did return with multiple body injuries. Despite this, we decided that the Logistic Regression model would be the better model to use for several reasons. The major reason is because it is simple to understand how the results were calculated. Another reason is so that we remain consistent with the previous model that we used to predict if a patient returned.

Our next task was to aggregate the body regions for each patient by body region. For example, if on the first three visits, a patient came in for a lumbar injury, cervix injury, and then lumbar again, the results would look similar to the table below:

Visit Number	Lumbar	Cervix
Visit 1	1	0
Visit 2	1	1
Visit 3	2	1

Note: This is a simplified and fictitious example solely to help the reader better understand our process. The actual data frame included all 20 body regions.

In practice, the way we did this was by taking our original hcdata data frame and then sorting the table by EMID, Year, and then Month in that order. This way, we have each unique patient grouped together, and then we are able to preserve the order of the patient's visits by grouping by year and month in this manner. A limitation is that we do not have the exact day of the patient's visit, so it is highly likely that the data frame is not in the exact order. Models that can utilize the exact order of a patient's visits might have more predictive power.

After the data is properly sorted, we created a new data frame based on the hcdata data frame which only includes the EMID and BRalpha. This data frame was named multVisitEMID. We then one hot encoded the BRalpha category so that we would have a total of 20 unique body regions. Next, we created a new data frame called dfGrouped which takes the multVisitEMID data frame, groups the data frame by EMID, and then uses the “cumsum” method to produce a table of cumulative visits for each patient. It is important to note that this function is not simply taking the sum of the total visits for each patient, but rather it is taking the cumulative sum after each visit for every patient.

The next step was to merge the dfGrouped data frame with the EMIDDf data frame from earlier so that we know which patients returned and which did not. We used an “inner” join to do this, and dropped the VisitCount, MultipleInjuries, and MonthsAsPatient variables immediately after. We then included the Gender, FVage, Year, and Month from the hcdata data frame. After that, we removed any patient who did not return for multiple visits from the dfGrouped data frame, and then we one hot encoded the Gender variable. We then saved the data frame to an Excel document as “cumDf.xlsx” so that we could run some analyses in SPSS.

Even though we have the aggregate data, we also wanted to see if it would make a difference if we had all of the columns as binary variables, meaning that we only want to know if the patient returned for a specific body region at least once. For example, if on the first three visits, a patient came in for a lumbar injury, cervix injury, and then lumbar again, our results would look like the chart below:

Visit Number	Lumbar	Cervix
Visit 1	1	0
Visit 2	1	1
Visit 3	1	1

Note: Again, this is a fictitious example only used for illustrative purposes.

To get these results, we found that the greatest value across all columns in the dfGrouped data frame was a patient with 1,762 visits for Lumbar issues. With this number, we created a dictionary that included a reference to 0 if the value was zero, and a reference to 1 if the value was anywhere between 1 and 1,762. We then mapped this dictionary to all of the body region columns so that we have a similar data frame to cumDf, except this time each value is binary rather than continuous. We saved this data frame as “cumDfBinary” as an Excel file so that we can run further analyses in SPSS.

After we obtained these excel files, we used them in SPSS in order to create binary logistic regressions with a certain body region as the dependent variable and the remaining body regions as well as some control variables as the independent variables. For practicality, we chose to use the body regions which had the highest correlation and covariance magnitudes as our different dependent variables. This served to be useful, as by convenience, they also seemed to the regions which were most frequently visited for. These six body regions were:

- ANFT (Anterior Foot)
- KNEE (Knee)
- CERV (Cervix)
- LUMB (Lumbar)
- NSPC (Not Specific)
- SHLD (Shoulder)

We ran six regressions, with each of those body regions being a dependent variable, and the remaining 19 body regions and control variables are used as the independent variables. The combination of control variables which served to be most effective were:

- Max Risk
- Gender (Dummy Encoded)
- FV age
- Year
- Month

We ran these regression on both of the data frames: the cumulative sum for each patient data frame (cumDf), as well as the data frame which keeps each body region binary and does not sum each (cumDfBinary). Below you will see the results of these regressions. The results are organized by each body region that was the dependent variable and then into sub categories of which independent body region variables had positive beta coefficients, which had negative standardized beta coefficients, and which were insignificant (based off of their p-values from the regression. Significant values have a p-value below 0.05). The way this can be read, for example let's look at the ANFT regression. If someone came in for and arm injury previously, then using the beta coefficient of -.084, we can say that this person has a 8.4% less probability of coming in for an ANFT injury next time. The control variables were excluded from this ranking system because we were more interested in the effects of each body region on a specific body region as opposed to seasonal or demographic effects. It is interesting to note that there was a clear difference in the results from each of the two different data frames. The results from the cumulative sum data frame are on the left side, while the binary data frames results are on the right side. ANFT, KNEE, and CERV are on the page below, while the remaining three are on the following page.

Cumulative Data Frame

ANFT	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (.329)	1) ARM (-.084)	1) FARM (.132)
	2) THGH (.198)	2) HIP (-.015)	
	3) ELBW (.061)	3) UARM (-.014)	
	4) LEG (.045)	4) SPIN (-.012)	
	5) LLEG (.025)	5) THOR (-.009)	
	6) WRHD (.017)	6) LUMB (-.003)	
	7) NSPC (.007)	7) CERV (-.003)	
	8) SYST (.005)	8) PELV (-.002)	
	9)KNEE (.005)	9) SHLD (-.001)	

KNEE	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) LEG (.185)	1) ARM (-.042)	1) FARM (.493)
	2) LLEG (.145)	2) SPIN (-.026)	2) WRHD (.333)
	3) THGH (.032)	3) ELBW (-.019)	
	4) ANFT (.016)	4) HIP (-.018)	
	5) OOS (.016)	5) THOR (-.016)	
	6) PELV (.012)	6) CERV (-.006)	
	7) UARM (.005)	7) LUMB (-.004)	
	8) SYST (.003)	8) SHLD (-.003)	
		9) NSPC (-.001)	

CERV	Postive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (.122)	1) LLEG (-.064)	1) THGH (0.226)
	2) ARM (.066)	2) FARM (-.033)	2) PELV (.172)
	3) LEG (.064)	3) HIP (-.018)	
	4) ELBW (.045)	4) ANFT (-.016)	
	5) NSPC (.007)	5) WRHD (-.015)	
	6) UARM (.005)	6) KNEE (-.005)	
	7) THOR (.004)	7) SYST (-.001)	
	8) SHLD (.003)		
	9) SPIN (.002)		

Binary Data Frame

ANFT	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (1.799)	1) ARM (-.584)	1) LLEG (.28)
	2) THGH (.840)	2) LUMB (-.359)	
	3) LEG (.754)	3) CERV (-.329)	
	4) NSPC (.639)	4) PELV (-.278)	
	5) ELBW (.407)	5) FARM (-.185)	
	6) KNEE (.362)	6) HIP (-.13)	
	7) UARM (.326)	7)THOR (-.086)	
	8) SYST (.274)	8) SHLD (-.084)	
	9) SPIN (.074)		
	10) WRHD (.05)		

KNEE	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (.763)	1) LUMB (-.527)	1) SPIN (.972)
	2) THGH (.638)	2) CERV (-.498)	2) ARM (.097)
	3) LEG (.485)	3) ELBW (-.441)	
	4) LLEG (.398)	4) FARM (-.319)	
	5) NSPC (.392)	5) THOR (-.132)	
	6) HIP (.369)	6) SHLD (-.13)	
	7) ANFT (.353)	7) PELV (-.065)	
	8) SYST (.256)		
	9) UARM (.107)		
	10) WRHD (.038)		

CERV	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (1.241)	1) KNEE (-.513)	1) WRHD (.694)
	2) THOR (.558)	2) ANFT (-.341)	2) LEG (.613)
	3) SHLD (.381)	3) HIP (-.243)	3) FARM (.092)
	4) ARM (.127)	4) LLEG (-.211)	
	5) ELBW (.11)	5) LUMB (-.187)	
	6) SYST (.103)	6) UARM (-.135)	
	7) SPIN (.096)	7) PELV (-.055)	
	8) THGH (.092)		
	9) NSPC (.048)		

Cumulative Data Frame

LUMB	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (.074)	1) LEG (-.163)	
	2) LLEG (.053)	2) ARM (-.135)	
	3) THGH (.044)	3) UARM (-.097)	
	4) HIP (.031)	4) FARM (-.027)	
	5) PELV (.012)	5) ANFT (-.021)	
	6) SPIN (.007)	6) KNEE (-.013)	
	7) ELBW (.005)	7) SHLD (-.007)	
	8) NSPC (.004)	8) WRHD (-.006)	
	9) SYST (.001)	9) CERV (-.002)	
	10) THOR (.001)		

NSPC	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (.340)	1) SPIN (-.005)	1) ARM (.167)
	2) LEG (.088)	2) CERV (.003)	
	3) ELBW (.067)		
	4) LLEG (.064)		
	5) ANFT (.042)		
	6) WRHD (.042)		
	7) THGH (.037)		
	8) PELV (.028)		
	9) FARM (.028)		
	10) HIP (.014)		
	11) THOR (.009)		
	12) SYST (.009)		
	13) SHLD (.006)		
	14) KNEE (.004)		
	15) LUMB (.004)		
	16) UARM (.003)		

SHLD	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) ARM (.123)	1) LLEG (-.09)	1) LEG (.882)
	2) ELBW (.049)	2) THGH (-.033)	2) KNEE (.158)
	3) OOS (.034)	3) UARM (-.016)	3) NSPC (.146)
	4) FARM (.019)	4) SPIN (-.008)	
	5) WRHD (.019)	5) ANFT (-.005)	
	6) THOR (.011)	6) SYST (-.005)	
	7) CERV (.006)	7) PELV (-.002)	
	8) HIP (.004)	8)	
	9) LUMB (.00)		

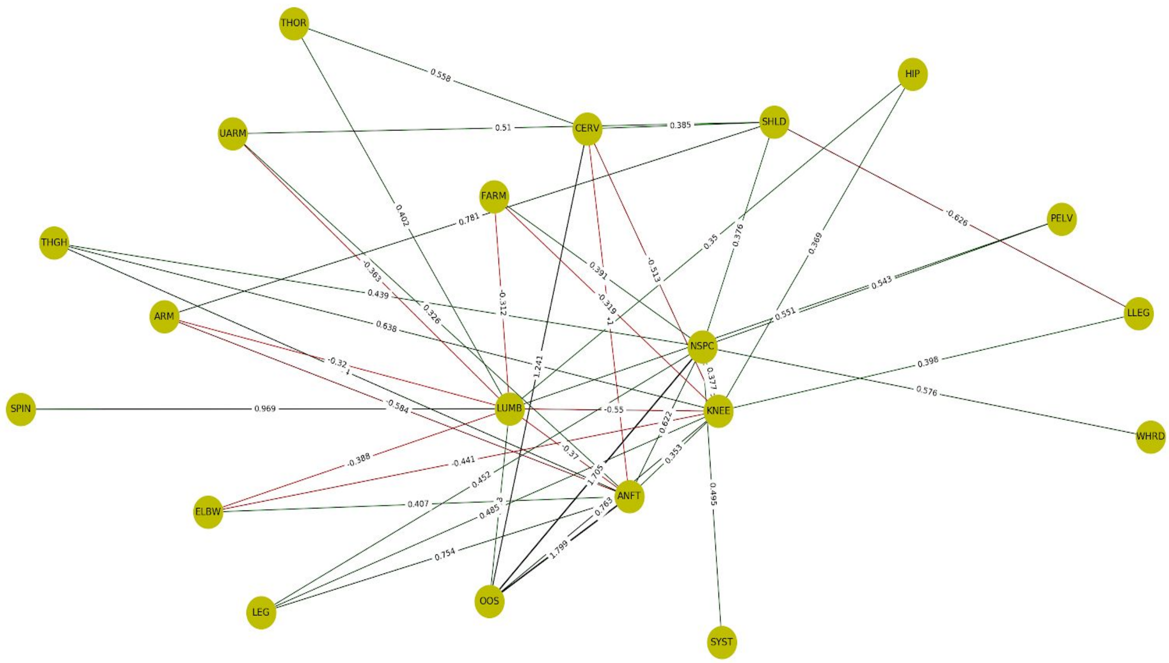
Binary Data Frame

LUMB	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) SPIN (.969)	1) KNEE (-.55)	1) LEG (.452)
	2) PELV (.551)	2) ELBW (-.388)	2) LLEG (.069)
	3) THOR (.402)	3) ANFT (-.37)	
	4) OOS (.38)	4) UARM (-.363)	
	5) HIP (.35)	5) ARM (-.320)	
	6) THGH (.121)	6) FARM (-.312)	
	7) SYST (.088)	7) CERV (-.185)	
	8) NSPC (.035)	8) SHLD (-.148)	

NSPC	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) OOS (1.705)		1) ARM (.806)
	2) ANFT (.622)		
	3) WRHD (.576)		
	4) PELV (.543)		
	5) SYST (.495)		
	6) LEG (.452)		
	7) THGH (.439)		
	8) FARM (.391)		
	9) KNEE (.377)		
	10) SHLD (.372)		
	11) UARM (.235)		
	12) THOR (.219)		
	13) LLEG (.173)		
	14) ELBW (.133)		
	15) HIP (.097)		
	16) SPIN (.065)		
	17) CERV (.027)		
	18) LUMB (.017)		

SHLD	Positive (Beta)	Negative (Beta)	Insignificant BR (p-value)
	1) ARM (.781)	1) LLEG (-.626)	1) THGH (.209)
	2) UARM (.510)	2) PELV (-.216)	
	3) CERV (.385)	3) KNEE (-.156)	
	4) NSPC (.376)	4) LUMB (-.155)	
	5) LEG (.263)	5) HIP (-.123)	
	6) WRHD (.248)	6) ANFT (-.098)	
	7) THOR (.233)	7) ELBW (-.075)	
	8) OOS (.128)	8) FARM (-.049)	
	9) SPIN (.116)		
	10) SYST (.107)		

For an easy way to visualize the significant beta coefficients, we also constructed a network graph using the regression results from the six most frequent body regions above with a beta coefficient above 0.3 or below -0.3:



For completion, we show the results of all forty logistic regression models below. The results on the left are the regression results of the cumulative data frame and the results on the right are the results for the binary data frame.

ANFT

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ARM	-.084	.014	36.810	1	.000	.918
	BRalpha_CERV	-.003	.000	304.575	1	.000	.997
	BRalpha_ELBW	.060	.003	306.612	1	.000	1.062
	BRalpha_FARM	.005	.003	2.832	1	.092	1.005
	BRalpha_HIP	-.017	.003	36.682	1	.000	.983
	BRalpha_KNEE	.005	.000	624.169	1	.000	1.005
	BRalpha_LEG	.047	.014	12.206	1	.000	1.048
	BRalpha_LLEG	.017	.010	2.577	1	.108	1.017
	BRalpha_LUMB	-.003	.000	635.252	1	.000	.997
	BRalpha_NSPC	.007	.000	664.664	1	.000	1.007
	BRalpha_OOS	.332	.016	440.875	1	.000	1.394
	BRalpha_PELV	-.002	.001	8.346	1	.004	.998
	BRalpha_SHLD	-.001	.000	18.257	1	.000	.999
	BRalpha_SPIN	-.012	.001	267.032	1	.000	.988
	BRalpha_SYST	.005	.000	388.472	1	.000	1.005
	BRalpha_THGH	.200	.009	509.526	1	.000	1.221
	BRalpha_THOR	-.008	.001	154.785	1	.000	.992
	BRalpha_UARM	-.013	.002	62.311	1	.000	.987
	BRalpha_WRHD	.017	.001	239.720	1	.000	1.017
	max risk	.035	.001	951.533	1	.000	1.036
	Gender_Female	.281	.009	950.272	1	.000	1.325
	FVage	-.006	.000	395.966	1	.000	.994
	Year	.283	.003	7665.748	1	.000	1.328
	Month	.041	.001	1028.450	1	.000	1.042
	Constant	-572.068	6.517	7705.283	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ARM	-.584	.047	156.439	1	.000	.558
	BRalpha_CERV	-.329	.009	1223.290	1	.000	.720
	BRalpha_ELBW	.407	.026	245.451	1	.000	1.502
	BRalpha_FARM	-.185	.021	80.883	1	.000	.831
	BRalpha_HIP	-.130	.025	27.900	1	.000	.878
	BRalpha_KNEE	.362	.010	1369.506	1	.000	1.436
	BRalpha_LEG	.754	.073	107.342	1	.000	2.126
	BRalpha_LLEG	-.054	.043	1.585	1	.208	.948
	BRalpha_LUMB	-.359	.010	1394.622	1	.000	.698
	BRalpha_NSPC	.639	.010	4491.618	1	.000	1.894
	BRalpha_OOS	1.799	.051	1229.720	1	.000	6.044
	BRalpha_PELV	-.278	.017	262.641	1	.000	.757
	BRalpha_SHLD	-.084	.011	56.479	1	.000	.919
	BRalpha_SPIN	.074	.013	34.561	1	.000	1.076
	BRalpha_SYST	.274	.011	573.705	1	.000	1.315
	BRalpha_THGH	.840	.030	762.666	1	.000	2.316
	BRalpha_THOR	-.086	.015	34.866	1	.000	.917
	BRalpha_UARM	.326	.028	140.224	1	.000	1.385
	BRalpha_WRHD	.050	.013	13.999	1	.000	1.051
	max risk	.023	.001	370.229	1	.000	1.023
	Gender_Female	.267	.009	816.912	1	.000	1.306
	FVage	-.007	.000	559.302	1	.000	.993
	Year	.260	.003	5845.993	1	.000	1.296
	Month	.037	.001	799.823	1	.000	1.037
	Constant	-524.328	6.838	5879.903	1	.000	.000

ARM

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.022	.002	88.907	1	.000	.978
	BRalpha_CERV	.000	.001	.053	1	.818	1.000
	BRalpha_ELBW	.027	.003	98.912	1	.000	1.027
	BRalpha_FARM	-.004	.008	.241	1	.623	.996
	BRalpha_HIP	-.031	.013	5.496	1	.019	.970
	BRalpha_KNEE	.004	.001	50.115	1	.000	1.004
	BRalpha_LEG	.130	.023	30.880	1	.000	1.139
	BRalpha_LLEG	.145	.018	64.786	1	.000	1.156
	BRalpha_LUMB	-.004	.000	58.444	1	.000	.996
	BRalpha_NSPC	-.001	.001	.422	1	.516	.999
	BRalpha_OOS	.199	.011	302.313	1	.000	1.220
	BRalpha_PELV	.011	.002	40.283	1	.000	1.011
	BRalpha_SHLD	.007	.001	108.994	1	.000	1.007
	BRalpha_SPIN	-.006	.003	6.072	1	.014	.994
	BRalpha_SYST	.001	.001	.452	1	.501	1.001
	BRalpha_THGH	-.300	.054	30.930	1	.000	.741
	BRalpha_THOR	.008	.001	40.978	1	.000	1.008
	BRalpha_UARM	.003	.002	1.496	1	.221	1.003
	BRalpha_WRHD	.055	.002	827.206	1	.000	1.056
	max risk	.053	.003	328.105	1	.000	1.055
	Gender_Female	-.054	.037	2.187	1	.139	.947
	FVage	.018	.001	216.224	1	.000	1.018
	Year	.320	.013	594.390	1	.000	1.377
	Month	.051	.005	96.128	1	.000	1.053
	Constant	-650.099	26.423	605.333	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.554	.047	138.763	1	.000	.575
	BRalpha_CERV	.174	.038	21.266	1	.000	1.190
	BRalpha_ELBW	1.198	.062	378.740	1	.000	3.313
	BRalpha_FARM	.114	.060	3.674	1	.055	1.121
	BRalpha_HIP	-.526	.106	24.851	1	.000	.591
	BRalpha_KNEE	-.022	.041	.297	1	.586	.978
	BRalpha_LEG	1.768	.152	134.858	1	.000	5.857
	BRalpha_LLEG	.802	.112	51.349	1	.000	2.230
	BRalpha_LUMB	-.345	.039	78.500	1	.000	.709
	BRalpha_NSPC	.043	.040	1.146	1	.284	1.044
	BRalpha_OOS	1.072	.129	69.055	1	.000	2.921
	BRalpha_PELV	-.320	.070	21.165	1	.000	.726
	BRalpha_SHLD	.826	.037	494.675	1	.000	2.284
	BRalpha_SPIN	-.475	.058	68.086	1	.000	.622
	BRalpha_SYST	.035	.045	.614	1	.433	1.036
	BRalpha_THGH	.188	.118	2.544	1	.111	1.207
	BRalpha_THOR	-.446	.066	45.017	1	.000	.640
	BRalpha_UARM	1.126	.062	331.921	1	.000	3.084
	BRalpha_WRHD	1.278	.040	1034.020	1	.000	3.589
	max risk	.039	.003	151.201	1	.000	1.040
	Gender_Female	-.073	.038	3.707	1	.054	.929
	FVage	.017	.001	181.104	1	.000	1.017
	Year	.226	.014	257.658	1	.000	1.254
	Month	.040	.005	58.359	1	.000	1.041
	Constant	-461.571	28.371	264.691	1	.000	.000

CERV

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.016	.001	568.933	1	.000	.984
	BRalpha_ARM	.063	.012	28.805	1	.000	1.065
	BRalpha_ELBW	.044	.003	223.267	1	.000	1.045
	BRalpha_FARM	-.031	.003	128.226	1	.000	.969
	BRalpha_HIP	-.019	.002	75.938	1	.000	.981
	BRalpha_KNEE	-.005	.000	687.060	1	.000	.995
	BRalpha_LEG	.065	.015	17.725	1	.000	1.067
	BRalpha_LLEG	-.081	.011	55.281	1	.000	.923
	BRalpha_LUMB	.003	.000	993.318	1	.000	1.003
	BRalpha_NSPC	.007	.000	496.369	1	.000	1.007
	BRalpha_OOS	.125	.007	314.811	1	.000	1.133
	BRalpha_PELV	.001	.001	3.066	1	.080	1.001
	BRalpha_SHLD	.003	.000	227.921	1	.000	1.003
	BRalpha_SPIN	.002	.000	28.742	1	.000	1.002
	BRalpha_SYST	-.001	.000	26.490	1	.000	.999
	BRalpha_THGH	-.001	.003	.225	1	.635	.999
	BRalpha_THOR	.005	.000	111.592	1	.000	1.005
	BRalpha_UARM	.006	.001	25.970	1	.000	1.006
	BRalpha_WRHD	-.015	.001	174.399	1	.000	.985
	max risk	.049	.001	2008.287	1	.000	1.050
	Gender_Female	.631	.008	6919.537	1	.000	1.880
	FVage	.001	.000	15.107	1	.000	1.001
	Year	.167	.003	3568.246	1	.000	1.181
	Month	.006	.001	28.214	1	.000	1.006
	Constant	-336.620	5.620	3587.585	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.341	.009	1322.044	1	.000	.711
	BRalpha_ARM	.127	.037	11.674	1	.001	1.135
	BRalpha_ELBW	.110	.024	20.721	1	.000	1.116
	BRalpha_FARM	-.030	.018	2.831	1	.092	.970
	BRalpha_HIP	-.243	.022	123.052	1	.000	.784
	BRalpha_KNEE	-.513	.009	3208.358	1	.000	.599
	BRalpha_LEG	.037	.072	.255	1	.613	1.037
	BRalpha_LLEG	-.211	.041	26.117	1	.000	.810
	BRalpha_LUMB	-.187	.008	565.422	1	.000	.829
	BRalpha_NSPC	.048	.008	31.876	1	.000	1.049
	BRalpha_OOS	1.241	.051	581.174	1	.000	3.460
	BRalpha_PELV	-.055	.014	14.698	1	.000	.947
	BRalpha_SHLD	.381	.009	1694.873	1	.000	1.464
	BRalpha_SPIN	.096	.011	81.968	1	.000	1.101
	BRalpha_SYST	.103	.010	98.946	1	.000	1.108
	BRalpha_THGH	.092	.030	9.263	1	.002	1.096
	BRalpha_THOR	.558	.012	2119.038	1	.000	1.748
	BRalpha_UARM	-.135	.026	26.331	1	.000	.874
	BRalpha_WRHD	.005	.012	.155	1	.694	1.005
	max risk	.058	.001	2499.807	1	.000	1.060
	Gender_Female	.659	.008	7281.736	1	.000	1.932
	FVage	.002	.000	70.983	1	.000	1.002
	Year	.183	.003	3932.916	1	.000	1.201
	Month	.009	.001	62.416	1	.000	1.009
	Constant	-369.674	5.880	3953.006	1	.000	.000

ELBW

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.019	.001	220.045	1	.000	1.019
	BRalpha_ARM	.212	.016	179.028	1	.000	1.236
	BRalpha_CERV	.001	.000	9.613	1	.002	1.001
	BRalpha_FARM	.060	.005	155.060	1	.000	1.062
	BRalpha_HIP	.037	.003	141.155	1	.000	1.037
	BRalpha_KNEE	-.014	.001	177.345	1	.000	.986
	BRalpha_LEG	-.132	.101	1.713	1	.191	.876
	BRalpha_LLEG	.126	.014	77.218	1	.000	1.134
	BRalpha_LUMB	-.003	.000	95.893	1	.000	.997
	BRalpha_NSPC	-.003	.001	10.019	1	.002	.997
	BRalpha_OOS	-.402	.069	33.512	1	.000	.669
	BRalpha_PELV	.006	.001	31.544	1	.000	1.006
	BRalpha_SHLD	-.002	.001	9.513	1	.002	.998
	BRalpha_SPIN	.000	.001	.000	1	.990	1.000
	BRalpha_SYST	.008	.000	323.701	1	.000	1.008
	BRalpha_THGH	.070	.005	199.477	1	.000	1.072
	BRalpha_THOR	.005	.001	30.056	1	.000	1.005
	BRalpha_UARM	.026	.001	297.925	1	.000	1.026
	BRalpha_WRHD	.002	.003	.405	1	.525	1.002
	max risk	.017	.003	38.931	1	.000	1.017
	Gender_Female	-.321	.023	188.942	1	.000	.725
	FVage	.010	.001	162.008	1	.000	1.010
	Year	.318	.008	1423.916	1	.000	1.375
	Month	.037	.003	121.889	1	.000	1.038
	Constant	-645.341	16.993	1442.313	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.416	.026	255.118	1	.000	1.515
	BRalpha_ARM	1.007	.063	258.576	1	.000	2.738
	BRalpha_CERV	.124	.025	25.643	1	.000	1.132
	BRalpha_FARM	.237	.042	31.239	1	.000	1.268
	BRalpha_HIP	-.206	.058	12.760	1	.000	.814
	BRalpha_KNEE	-.413	.029	202.640	1	.000	.662
	BRalpha_LEG	-.698	.186	14.009	1	.000	.498
	BRalpha_LLEG	-.106	.096	1.217	1	.270	.900
	BRalpha_LUMB	-.412	.026	252.719	1	.000	.662
	BRalpha_NSPC	.161	.026	38.282	1	.000	1.174
	BRalpha_OOS	-.926	.149	38.781	1	.000	.396
	BRalpha_PELV	.718	.035	427.162	1	.000	2.051
	BRalpha_SHLD	-.069	.028	5.969	1	.015	.933
	BRalpha_SPIN	.019	.033	.315	1	.575	1.019
	BRalpha_SYST	.277	.029	91.078	1	.000	1.320
	BRalpha_THGH	1.258	.052	581.982	1	.000	3.517
	BRalpha_THOR	.169	.035	23.685	1	.000	1.185
	BRalpha_UARM	2.540	.033	5944.901	1	.000	12.679
	BRalpha_WRHD	.078	.032	5.823	1	.016	1.082
	max risk	-.008	.003	6.680	1	.010	.992
	Gender_Female	-.329	.025	178.702	1	.000	.720
	FVage	.013	.001	290.778	1	.000	1.013
	Year	.264	.009	821.987	1	.000	1.302
	Month	.030	.003	78.623	1	.000	1.031
	Constant	-535.583	18.519	836.399	1	.000	.000

FARM

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.020	.002	157.378	1	.000	.980
	BRalpha_ARM	.087	.019	20.078	1	.000	1.091
	BRalpha_CERV	.000	.000	.025	1	.875	1.000
	BRalpha_ELBW	.011	.003	10.777	1	.001	1.011
	BRalpha_HIP	-.095	.008	128.970	1	.000	.910
	BRalpha_KNEE	-.003	.000	33.524	1	.000	.997
	BRalpha_LEG	.034	.022	2.363	1	.124	1.034
	BRalpha_LLEG	-.012	.023	.266	1	.606	.988
	BRalpha_LUMB	.005	.000	2847.785	1	.000	1.005
	BRalpha_NSPC	-.007	.001	73.016	1	.000	.993
	BRalpha_OOS	.189	.010	373.274	1	.000	1.208
	BRalpha_PELV	.020	.001	781.891	1	.000	1.021
	BRalpha_SHLD	.007	.000	306.423	1	.000	1.007
	BRalpha_SPIN	-.030	.002	159.136	1	.000	.970
	BRalpha_SYST	.004	.000	76.651	1	.000	1.004
	BRalpha_THGH	.076	.005	271.542	1	.000	1.079
	BRalpha_THOR	-.008	.001	32.724	1	.000	.992
	BRalpha_UARM	.035	.002	487.409	1	.000	1.036
	BRalpha_WRHD	.079	.001	3233.163	1	.000	1.082
	max risk	.055	.002	865.148	1	.000	1.056
	Gender_Female	.316	.019	288.563	1	.000	1.372
	FVage	-.021	.001	1451.343	1	.000	.979
	Year	.128	.007	375.208	1	.000	1.136
	Month	.034	.003	174.869	1	.000	1.034
	Constant	-260.455	13.295	383.803	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.138	.021	43.693	1	.000	.871
	BRalpha_ARM	.183	.057	10.249	1	.001	1.201
	BRalpha_CERV	-.022	.018	1.437	1	.231	.978
	BRalpha_ELBW	.253	.043	35.308	1	.000	1.288
	BRalpha_HIP	.391	.040	95.279	1	.000	1.478
	BRalpha_KNEE	-.311	.021	221.536	1	.000	.732
	BRalpha_LEG	.709	.111	40.411	1	.000	2.031
	BRalpha_LLEG	.456	.065	49.837	1	.000	1.577
	BRalpha_LUMB	-.323	.020	273.294	1	.000	.724
	BRalpha_NSPC	.416	.019	474.962	1	.000	1.516
	BRalpha_OOS	2.288	.053	1859.748	1	.000	9.858
	BRalpha_PELV	.217	.029	55.832	1	.000	1.242
	BRalpha_SHLD	-.009	.021	.161	1	.688	.991
	BRalpha_SPIN	-.412	.027	237.802	1	.000	.663
	BRalpha_SYST	.273	.022	159.933	1	.000	1.314
	BRalpha_THGH	.591	.049	146.482	1	.000	1.806
	BRalpha_THOR	.058	.028	4.295	1	.038	1.060
	BRalpha_UARM	1.501	.035	1873.629	1	.000	4.488
	BRalpha_WRHD	1.908	.018	10746.168	1	.000	6.740
	max risk	.037	.002	337.459	1	.000	1.037
	Gender_Female	.326	.019	287.134	1	.000	1.386
	FVage	-.014	.001	632.167	1	.000	.986
	Year	.031	.007	19.699	1	.000	1.031
	Month	.019	.003	56.837	1	.000	1.019
	Constant	-65.259	13.921	21.974	1	.000	.000

HIP

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.010	.001	75.008	1	.000	1.010
	BRalpha_ARM	-.041	.028	2.063	1	.151	.960
	BRalpha_CERV	-.002	.000	33.696	1	.000	.998
	BRalpha_ELBW	-.161	.021	57.621	1	.000	.852
	BRalpha_FARM	-.018	.008	4.328	1	.037	.983
	BRalpha_KNEE	-.001	.001	4.970	1	.026	.999
	BRalpha_LEG	.085	.022	14.526	1	.000	1.089
	BRalpha_LLEG	.205	.013	266.037	1	.000	1.228
	BRalpha_LUMB	.001	.000	419.423	1	.000	1.001
	BRalpha_NSPC	-.017	.001	213.115	1	.000	.983
	BRalpha_OOS	.110	.008	174.718	1	.000	1.116
	BRalpha_PELV	.073	.001	3133.534	1	.000	1.076
	BRalpha_SHLD	-.014	.001	151.026	1	.000	.986
	BRalpha_SPIN	-.006	.002	13.483	1	.000	.994
	BRalpha_SYST	.007	.000	383.910	1	.000	1.007
	BRalpha_THGH	.282	.011	672.258	1	.000	1.326
	BRalpha_THOR	-.008	.002	18.534	1	.000	.992
	BRalpha_UARM	-.016	.008	4.165	1	.041	.984
	BRalpha_WRHD	-.013	.003	17.092	1	.000	.987
	max risk	.065	.002	1083.888	1	.000	1.067
	Gender_Female	.604	.025	578.679	1	.000	1.829
	FVage	.018	.001	558.797	1	.000	1.018
	Year	.519	.009	3731.571	1	.000	1.681
	Month	.046	.003	206.364	1	.000	1.047
	Constant	-1051.218	17.126	3767.515	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.175	.025	47.129	1	.000	.839
	BRalpha_ARM	-.632	.107	34.866	1	.000	.531
	BRalpha_CERV	-.452	.024	367.059	1	.000	.636
	BRalpha_ELBW	-.350	.061	32.954	1	.000	.705
	BRalpha_FARM	.146	.043	11.462	1	.001	1.157
	BRalpha_KNEE	.382	.023	280.572	1	.000	1.466
	BRalpha_LEG	1.473	.117	158.123	1	.000	4.363
	BRalpha_LLEG	1.257	.055	525.396	1	.000	3.517
	BRalpha_LUMB	.356	.024	227.694	1	.000	1.428
	BRalpha_NSPC	.132	.024	30.202	1	.000	1.141
	BRalpha_OOS	1.297	.068	363.080	1	.000	3.660
	BRalpha_PELV	1.814	.024	5802.627	1	.000	6.133
	BRalpha_SHLD	-.175	.027	42.793	1	.000	.839
	BRalpha_SPIN	.157	.027	34.402	1	.000	1.170
	BRalpha_SYST	.192	.025	58.726	1	.000	1.212
	BRalpha_THGH	1.398	.040	1192.324	1	.000	4.045
	BRalpha_THOR	-.051	.033	2.382	1	.123	.950
	BRalpha_UARM	.171	.064	7.101	1	.008	1.187
	BRalpha_WRHD	-.368	.033	127.786	1	.000	.692
	max risk	.046	.002	456.046	1	.000	1.047
	Gender_Female	.554	.025	487.951	1	.000	1.740
	FVage	.016	.001	447.812	1	.000	1.017
	Year	.493	.009	3035.970	1	.000	1.637
	Month	.043	.003	186.153	1	.000	1.044
	Constant	-998.027	18.014	3069.379	1	.000	.000

KNEE

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.016	.001	674.295	1	.000	1.016
	BRalpha_ARM	-.043	.013	11.117	1	.001	.958
	BRalpha_CERV	-.005	.000	782.441	1	.000	.995
	BRalpha_ELBW	-.020	.003	48.405	1	.000	.981
	BRalpha_FARM	.003	.003	.767	1	.381	1.003
	BRalpha_HIP	-.020	.003	56.392	1	.000	.981
	BRalpha_LEG	.187	.022	74.216	1	.000	1.205
	BRalpha_LLEG	.132	.011	133.940	1	.000	1.141
	BRalpha_LUMB	-.004	.000	1004.954	1	.000	.996
	BRalpha_NSPC	-.001	.000	12.646	1	.000	.999
	BRalpha_OOS	.019	.007	8.095	1	.004	1.019
	BRalpha_PELV	.012	.001	322.791	1	.000	1.012
	BRalpha_SHLD	-.003	.000	93.049	1	.000	.997
	BRalpha_SPIN	-.026	.001	727.362	1	.000	.974
	BRalpha_SYST	.003	.000	116.093	1	.000	1.003
	BRalpha_THGH	.034	.003	118.815	1	.000	1.034
	BRalpha_THOR	-.016	.001	369.757	1	.000	.984
	BRalpha_UARM	.006	.001	26.152	1	.000	1.006
	BRalpha_WRHD	-.001	.001	1.109	1	.292	.999
	max risk	.083	.001	5230.275	1	.000	1.087
	Gender_Female	.066	.009	58.826	1	.000	1.068
	FVage	.004	.000	183.201	1	.000	1.004
	Year	.187	.003	3611.618	1	.000	1.206
	Month	.039	.001	1045.113	1	.000	1.040
	Constant	-379.120	6.281	3643.786	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.353	.010	1290.656	1	.000	1.423
	BRalpha_ARM	-.068	.041	2.746	1	.097	.934
	BRalpha_CERV	-.498	.009	3019.761	1	.000	.608
	BRalpha_ELBW	-.441	.029	235.279	1	.000	.643
	BRalpha_FARM	-.319	.021	239.448	1	.000	.727
	BRalpha_HIP	.369	.022	270.462	1	.000	1.446
	BRalpha_LEG	.485	.072	45.855	1	.000	1.625
	BRalpha_LLEG	.398	.041	95.050	1	.000	1.490
	BRalpha_LUMB	-.527	.009	3281.683	1	.000	.590
	BRalpha_NSPC	.392	.009	1785.999	1	.000	1.480
	BRalpha_OOS	.763	.048	250.566	1	.000	2.144
	BRalpha_PELV	-.065	.016	17.247	1	.000	.937
	BRalpha_SHLD	-.130	.011	147.786	1	.000	.878
	BRalpha_SPIN	.000	.012	.001	1	.972	1.000
	BRalpha_SYST	.256	.011	532.001	1	.000	1.291
	BRalpha_THGH	.638	.030	448.892	1	.000	1.893
	BRalpha_THOR	-.132	.014	84.490	1	.000	.876
	BRalpha_UARM	.107	.028	14.328	1	.000	1.113
	BRalpha_WRHD	.038	.013	8.306	1	.004	1.039
	max risk	.075	.001	3995.442	1	.000	1.078
	Gender_Female	.056	.009	39.657	1	.000	1.057
	FVage	.005	.000	265.313	1	.000	1.005
	Year	.156	.003	2232.135	1	.000	1.168
	Month	.036	.001	838.766	1	.000	1.036
	Constant	-314.796	6.628	2255.844	1	.000	.000

LEG

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.020	.004	31.549	1	.000	1.020
	BRalpha_ARM	.371	.037	98.978	1	.000	1.450
	BRalpha_CERV	.007	.001	50.562	1	.000	1.007
	BRalpha_ELBW	-.207	.091	5.161	1	.023	.813
	BRalpha_FARM	.086	.019	20.355	1	.000	1.090
	BRalpha_HIP	-.077	.031	6.285	1	.012	.926
	BRalpha_KNEE	-.005	.002	6.101	1	.014	.995
	BRalpha_LLEG	-.973	.476	4.175	1	.041	.378
	BRalpha_LUMB	-.011	.002	24.026	1	.000	.989
	BRalpha_NSPC	-.027	.006	18.066	1	.000	.974
	BRalpha_OOS	-10.713	189.526	.003	1	.955	.000
	BRalpha_PELV	-.212	.059	13.076	1	.000	.809
	BRalpha_SHLD	-.007	.003	6.777	1	.009	.993
	BRalpha_SPIN	-.094	.024	15.421	1	.000	.911
	BRalpha_SYST	-.032	.008	15.134	1	.000	.969
	BRalpha_THGH	.085	.014	36.982	1	.000	1.089
	BRalpha_THOR	-.073	.019	15.355	1	.000	.930
	BRalpha_UARM	.015	.009	2.563	1	.109	1.015
	BRalpha_WRHD	-.195	.039	25.206	1	.000	.823
	max risk	.088	.005	330.126	1	.000	1.092
	Gender_Female	.052	.070	.561	1	.454	1.054
	FVage	-.030	.002	210.264	1	.000	.970
	Year	.175	.025	49.199	1	.000	1.191
	Month	.079	.010	59.624	1	.000	1.082
	Constant	-356.899	50.133	50.680	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.813	.075	118.482	1	.000	2.256
	BRalpha_ARM	1.915	.154	154.530	1	.000	6.785
	BRalpha_CERV	.078	.074	1.124	1	.289	1.081
	BRalpha_ELBW	-.879	.191	21.309	1	.000	.415
	BRalpha_FARM	.547	.118	21.450	1	.000	1.728
	BRalpha_HIP	1.684	.124	183.850	1	.000	5.387
	BRalpha_KNEE	.574	.074	59.482	1	.000	1.775
	BRalpha_LLEG	-2.412	.718	11.267	1	.001	.090
	BRalpha_LUMB	.092	.080	1.336	1	.248	1.097
	BRalpha_NSPC	.492	.076	42.393	1	.000	1.635
	BRalpha_OOS	-16.676	766.582	.000	1	.983	.000
	BRalpha_PELV	-1.656	.197	70.346	1	.000	.191
	BRalpha_SHLD	.326	.084	15.174	1	.000	1.385
	BRalpha_SPIN	-.855	.136	39.473	1	.000	.425
	BRalpha_SYST	-.640	.109	34.279	1	.000	.528
	BRalpha_THGH	1.907	.119	257.431	1	.000	6.736
	BRalpha_THOR	-.828	.147	31.868	1	.000	.437
	BRalpha_UARM	2.371	.097	595.787	1	.000	10.708
	BRalpha_WRHD	-.912	.131	48.558	1	.000	.402
	max risk	.059	.006	110.697	1	.000	1.061
	Gender_Female	.073	.073	1.009	1	.315	1.076
	FVage	-.033	.002	236.817	1	.000	.968
	Year	-.037	.028	1.787	1	.181	.964
	Month	.050	.010	23.154	1	.000	1.051
	Constant	68.364	55.674	1.508	1	.219	489787234271769360000000000000.000

LLEG

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.022	.002	127.031	1	.000	1.022
	BRalpha_ARM	.187	.025	54.581	1	.000	1.205
	BRalpha_CERV	-.009	.001	53.492	1	.000	.991
	BRalpha_ELBW	.029	.005	36.094	1	.000	1.029
	BRalpha_FARM	.067	.010	44.591	1	.000	1.069
	BRalpha_HIP	.034	.006	34.007	1	.000	1.034
	BRalpha_KNEE	.002	.001	9.756	1	.002	1.002
	BRalpha_LEG	.037	.084	.193	1	.660	1.037
	BRalpha_LUMB	.002	.000	711.551	1	.000	1.002
	BRalpha_NSPC	-.009	.003	13.484	1	.000	.991
	BRalpha_OOS	-.073	.025	8.468	1	.004	.930
	BRalpha_PELV	-.004	.005	.667	1	.414	.996
	BRalpha_SHLD	-.015	.002	45.134	1	.000	.985
	BRalpha_SPIN	-.017	.005	12.975	1	.000	.983
	BRalpha_SYST	-.003	.001	7.466	1	.006	.997
	BRalpha_THGH	-.038	.030	1.668	1	.197	.962
	BRalpha_THOR	-.015	.004	15.713	1	.000	.986
	BRalpha_UARM	.013	.004	10.700	1	.001	1.013
	BRalpha_WRHD	-.039	.007	28.520	1	.000	.962
	max risk	.026	.005	27.477	1	.000	1.026
	Gender_Female	.068	.043	2.502	1	.114	1.071
	FVage	.002	.001	3.496	1	.062	1.002
	Year	1.319	.025	2798.832	1	.000	3.740
	Month	.144	.006	525.615	1	.000	1.155
	Constant	-2663.692	50.258	2809.035	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.007	.044	.025	1	.874	.993
	BRalpha_ARM	.629	.116	29.620	1	.000	1.875
	BRalpha_CERV	-.231	.043	28.195	1	.000	.794
	BRalpha_ELBW	-.165	.095	3.044	1	.081	.848
	BRalpha_FARM	.566	.067	70.934	1	.000	1.762
	BRalpha_HIP	1.044	.057	338.656	1	.000	2.841
	BRalpha_KNEE	.580	.042	190.248	1	.000	1.786
	BRalpha_LEG	-1.695	.713	5.658	1	.017	.184
	BRalpha_LUMB	-.018	.045	.170	1	.680	.982
	BRalpha_NSPC	.477	.045	113.269	1	.000	1.612
	BRalpha_OOS	.330	.159	4.299	1	.038	1.391
	BRalpha_PELV	.457	.061	56.852	1	.000	1.579
	BRalpha_SHLD	-.504	.054	86.288	1	.000	.604
	BRalpha_SPIN	-.515	.059	74.988	1	.000	.598
	BRalpha_SYST	-.107	.049	4.774	1	.029	.898
	BRalpha_THGH	-.585	.125	22.021	1	.000	.557
	BRalpha_THOR	.566	.052	119.165	1	.000	1.761
	BRalpha_UARM	.437	.094	21.451	1	.000	1.548
	BRalpha_WRHD	.126	.050	6.359	1	.012	1.134
	max risk	-.001	.006	.042	1	.837	.999
	Gender_Female	.009	.044	.037	1	.847	1.009
	FVage	.003	.001	6.321	1	.012	1.003
	Year	1.297	.025	2611.568	1	.000	3.656
	Month	.139	.006	495.609	1	.000	1.150
	Constant	-2618.487	51.136	2622.119	1	.000	.000

LUMB

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.022	.001	1035.026	1	.000	.979
	BRalpha_ARM	-.137	.013	119.853	1	.000	.872
	BRalpha_CERV	-.001	.000	80.840	1	.000	.999
	BRalpha_ELBW	.006	.001	16.817	1	.000	1.006
	BRalpha_FARM	-.026	.003	89.882	1	.000	.975
	BRalpha_HIP	.028	.002	137.248	1	.000	1.028
	BRalpha_KNEE	-.013	.000	2209.589	1	.000	.987
	BRalpha_LEG	-.154	.027	31.749	1	.000	.858
	BRalpha_LLEG	.027	.009	8.386	1	.004	1.027
	BRalpha_NSPC	.004	.000	196.244	1	.000	1.004
	BRalpha_OOS	.079	.006	163.230	1	.000	1.082
	BRalpha_PELV	.013	.001	213.202	1	.000	1.013
	BRalpha_SHLD	-.007	.000	705.375	1	.000	.993
	BRalpha_SPIN	.008	.000	300.060	1	.000	1.008
	BRalpha_SYST	.001	.000	9.588	1	.002	1.001
	BRalpha_THGH	.045	.006	59.202	1	.000	1.046
	BRalpha_THOR	.002	.000	19.272	1	.000	1.002
	BRalpha_UARM	-.095	.006	293.306	1	.000	.909
	BRalpha_WRHD	-.006	.001	28.347	1	.000	.994
	max risk	.072	.001	3706.819	1	.000	1.074
	Gender_Female	.086	.008	126.809	1	.000	1.090
	FVage	.021	.000	6987.228	1	.000	1.021
	Year	.170	.003	3634.956	1	.000	1.185
	Month	.015	.001	189.137	1	.000	1.015
	Constant	-343.504	5.674	3664.705	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.370	.010	1491.831	1	.000	.691
	BRalpha_ARM	-.320	.038	70.087	1	.000	.726
	BRalpha_CERV	-.185	.008	552.226	1	.000	.831
	BRalpha_ELBW	-.388	.026	230.813	1	.000	.679
	BRalpha_FARM	-.312	.019	266.561	1	.000	.732
	BRalpha_HIP	.350	.023	233.215	1	.000	1.419
	BRalpha_KNEE	-.550	.009	3542.866	1	.000	.577
	BRalpha_LEG	.057	.075	.564	1	.452	1.058
	BRalpha_LLEG	-.078	.043	3.303	1	.069	.925
	BRalpha_NSPC	.035	.009	15.943	1	.000	1.035
	BRalpha_OOS	.380	.051	55.331	1	.000	1.462
	BRalpha_PELV	.551	.015	1428.202	1	.000	1.735
	BRalpha_SHLD	-.148	.010	239.543	1	.000	.863
	BRalpha_SPIN	.969	.011	7921.014	1	.000	2.636
	BRalpha_SYST	.088	.011	70.471	1	.000	1.093
	BRalpha_THGH	.121	.031	14.883	1	.000	1.129
	BRalpha_THOR	.402	.012	1062.482	1	.000	1.495
	BRalpha_UARM	-.363	.028	169.530	1	.000	.696
	BRalpha_WRHD	-.181	.012	210.638	1	.000	.835
	max risk	.062	.001	2632.972	1	.000	1.064
	Gender_Female	.086	.008	119.466	1	.000	1.090
	FVage	.022	.000	7172.493	1	.000	1.022
	Year	.167	.003	3147.308	1	.000	1.182
	Month	.016	.001	222.800	1	.000	1.017
	Constant	-338.037	6.000	3174.639	1	.000	.000

NSPC

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.042	.001	2617.013	1	.000	1.043
	BRalpha_ARM	.015	.012	1.597	1	.206	1.015
	BRalpha_CERV	-.002	.000	211.478	1	.000	.998
	BRalpha_ELBW	.064	.004	220.296	1	.000	1.066
	BRalpha_FARM	.030	.003	117.688	1	.000	1.030
	BRalpha_HIP	.011	.002	26.783	1	.000	1.011
	BRalpha_KNEE	.003	.000	348.316	1	.000	1.004
	BRalpha_LEG	.095	.015	39.858	1	.000	1.100
	BRalpha_LLEG	.025	.011	5.045	1	.025	1.025
	BRalpha_LUMB	.004	.000	1553.553	1	.000	1.004
	BRalpha_OOS	.348	.023	220.189	1	.000	1.416
	BRalpha_PELV	.030	.001	746.942	1	.000	1.031
	BRalpha_SHLD	.006	.000	589.181	1	.000	1.006
	BRalpha_SPIN	-.004	.001	60.288	1	.000	.996
	BRalpha_SYST	.009	.000	937.461	1	.000	1.009
	BRalpha_THGH	.040	.005	74.523	1	.000	1.041
	BRalpha_THOR	.009	.000	418.493	1	.000	1.009
	BRalpha_UARM	.005	.001	13.477	1	.000	1.005
	BRalpha_WRHD	.041	.001	1076.861	1	.000	1.042
	max risk	.123	.001	9472.390	1	.000	1.131
	Gender_Female	.317	.008	1426.297	1	.000	1.373
	FVage	.006	.000	504.234	1	.000	1.006
	Year	.201	.003	4314.139	1	.000	1.222
	Month	.029	.001	590.151	1	.000	1.029
	Constant	-405.971	6.151	4356.079	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.622	.010	4176.766	1	.000	1.862
	BRalpha_ARM	.010	.040	.060	1	.806	1.010
	BRalpha_CERV	.027	.009	10.000	1	.002	1.027
	BRalpha_ELBW	.133	.026	26.531	1	.000	1.143
	BRalpha_FARM	.391	.019	403.293	1	.000	1.479
	BRalpha_HIP	.097	.024	16.738	1	.000	1.102
	BRalpha_KNEE	.377	.009	1611.587	1	.000	1.457
	BRalpha_LEG	.452	.075	36.345	1	.000	1.571
	BRalpha_LLEG	.173	.044	15.360	1	.000	1.189
	BRalpha_LUMB	.017	.009	3.921	1	.048	1.017
	BRalpha_OOS	1.705	.074	524.337	1	.000	5.501
	BRalpha_PELV	.543	.015	1305.128	1	.000	1.722
	BRalpha_SHLD	.372	.010	1380.225	1	.000	1.451
	BRalpha_SPIN	.065	.012	30.864	1	.000	1.067
	BRalpha_SYST	.495	.011	2133.452	1	.000	1.641
	BRalpha_THGH	.439	.033	175.227	1	.000	1.552
	BRalpha_THOR	.219	.013	270.706	1	.000	1.244
	BRalpha_UARM	.235	.028	71.784	1	.000	1.265
	BRalpha_WRHD	.576	.013	2088.843	1	.000	1.779
	max risk	.106	.001	6704.693	1	.000	1.111
	Gender_Female	.264	.009	953.563	1	.000	1.302
	FVage	.007	.000	630.111	1	.000	1.007
	Year	.148	.003	2153.846	1	.000	1.159
	Month	.021	.001	306.687	1	.000	1.021
	Constant	-299.827	6.411	2187.352	1	.000	.000

OOS

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.046	.001	1970.263	1	.000	1.047
	BRalpha_ARM	.243	.033	52.773	1	.000	1.275
	BRalpha_CERV	.013	.000	817.031	1	.000	1.013
	BRalpha_ELBW	-1.325	.201	43.249	1	.000	.266
	BRalpha_FARM	.158	.007	559.207	1	.000	1.171
	BRalpha_HIP	-.029	.014	4.205	1	.040	.971
	BRalpha_KNEE	.007	.001	78.560	1	.000	1.007
	BRalpha_LEG	-12.976	536.561	.001	1	.981	.000
	BRalpha_LLEG	.081	.045	3.183	1	.074	1.084
	BRalpha_LUMB	-.011	.001	68.865	1	.000	.989
	BRalpha_NSPC	.003	.001	5.847	1	.016	1.003
	BRalpha_PELV	.034	.001	1182.620	1	.000	1.035
	BRalpha_SHLD	-.010	.002	28.464	1	.000	.990
	BRalpha_SPIN	.001	.002	.134	1	.714	1.001
	BRalpha_SYST	.017	.001	826.907	1	.000	1.017
	BRalpha_THGH	.098	.008	151.331	1	.000	1.103
	BRalpha_THOR	-1.023	.130	61.781	1	.000	.360
	BRalpha_UARM	-.027	.013	4.387	1	.036	.974
	BRalpha_WRHD	.033	.003	98.905	1	.000	1.034
	max risk	.082	.004	476.783	1	.000	1.085
	Gender_Female	.956	.067	201.180	1	.000	2.601
	FVage	-.008	.002	23.153	1	.000	.992
	Year	-.032	.021	2.264	1	.132	.969
	Month	.050	.008	43.274	1	.000	1.051
	Constant	57.132	42.516	1.806	1	.179	6490307091483824000000000.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	1.801	.057	1010.991	1	.000	6.058
	BRalpha_ARM	.850	.142	35.833	1	.000	2.339
	BRalpha_CERV	.893	.057	244.728	1	.000	2.443
	BRalpha_ELBW	-1.546	.170	82.573	1	.000	.213
	BRalpha_FARM	2.199	.062	1246.954	1	.000	9.016
	BRalpha_HIP	1.315	.074	316.878	1	.000	3.724
	BRalpha_KNEE	.339	.053	40.964	1	.000	1.404
	BRalpha_LEG	-17.569	1091.688	.000	1	.987	.000
	BRalpha_LLEG	1.075	.165	42.661	1	.000	2.930
	BRalpha_LUMB	-.197	.059	11.213	1	.001	.821
	BRalpha_NSPC	1.630	.075	469.046	1	.000	5.105
	BRalpha_PELV	.740	.064	132.393	1	.000	2.097
	BRalpha_SHLD	-.064	.057	1.267	1	.260	.938
	BRalpha_SPIN	.619	.059	109.257	1	.000	1.858
	BRalpha_SYST	.848	.056	230.540	1	.000	2.336
	BRalpha_THGH	.265	.104	6.481	1	.011	1.303
	BRalpha_THOR	-3.486	.231	227.139	1	.000	.031
	BRalpha_UARM	.444	.105	18.031	1	.000	1.559
	BRalpha_WRHD	-.224	.064	12.147	1	.000	.799
	max risk	.040	.004	81.055	1	.000	1.041
	Gender_Female	.203	.069	8.570	1	.003	1.225
	FVage	-.006	.002	10.594	1	.001	.994
	Year	-.309	.023	186.548	1	.000	.734
	Month	-.006	.007	.734	1	.392	.994
	Constant	614.642	45.605	181.642	1	.000	8.625E+266

PELV

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.001	.001	.993	1	.319	1.001
	BRalpha_ARM	-.151	.025	37.567	1	.000	.860
	BRalpha_CERV	.000	.000	2.602	1	.107	1.000
	BRalpha_ELBW	-.003	.003	.895	1	.344	.997
	BRalpha_FARM	-.021	.005	16.754	1	.000	.979
	BRalpha_HIP	.091	.003	1124.287	1	.000	1.096
	BRalpha_KNEE	.000	.000	1.427	1	.232	1.000
	BRalpha_LEG	-.475	.107	19.640	1	.000	.622
	BRalpha_LLEG	.054	.014	15.498	1	.000	1.055
	BRalpha_LUMB	.004	.000	2089.695	1	.000	1.004
	BRalpha_NSPC	.006	.000	474.544	1	.000	1.006
	BRalpha_OOS	.076	.007	112.161	1	.000	1.079
	BRalpha_SHLD	-.004	.000	73.204	1	.000	.996
	BRalpha_SPIN	.000	.001	.388	1	.533	1.000
	BRalpha_SYST	.004	.000	122.957	1	.000	1.004
	BRalpha_THGH	.208	.007	837.696	1	.000	1.231
	BRalpha_THOR	.003	.001	19.326	1	.000	1.003
	BRalpha_UARM	-.024	.005	22.016	1	.000	.976
	BRalpha_WRHD	.006	.002	13.252	1	.000	1.006
	max risk	.070	.001	2706.608	1	.000	1.073
	Gender_Female	.227	.014	248.498	1	.000	1.255
	FVage	.017	.000	1329.516	1	.000	1.018
	Year	.094	.005	332.882	1	.000	1.099
	Month	.018	.002	86.952	1	.000	1.019
	Constant	-193.891	10.411	346.840	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.344	.018	379.613	1	.000	.709
	BRalpha_ARM	-.412	.068	36.349	1	.000	.662
	BRalpha_CERV	-.101	.015	47.618	1	.000	.904
	BRalpha_ELBW	.733	.035	428.203	1	.000	2.081
	BRalpha_FARM	.159	.029	30.080	1	.000	1.172
	BRalpha_HIP	1.749	.024	5531.487	1	.000	5.750
	BRalpha_KNEE	-.100	.016	38.793	1	.000	.905
	BRalpha_LEG	-2.118	.204	108.130	1	.000	.120
	BRalpha_LLEG	.103	.061	2.912	1	.088	1.109
	BRalpha_LUMB	.569	.015	1533.975	1	.000	1.766
	BRalpha_NSPC	.577	.015	1485.764	1	.000	1.780
	BRalpha_OOS	.932	.058	255.142	1	.000	2.540
	BRalpha_SHLD	-.200	.017	133.416	1	.000	.819
	BRalpha_SPIN	.028	.018	2.359	1	.125	1.028
	BRalpha_SYST	.370	.017	501.144	1	.000	1.448
	BRalpha_THGH	1.563	.034	2125.503	1	.000	4.775
	BRalpha_THOR	-.053	.022	5.737	1	.017	.949
	BRalpha_UARM	-.417	.050	69.800	1	.000	.659
	BRalpha_WRHD	.182	.020	82.230	1	.000	1.200
	max risk	.050	.001	1213.658	1	.000	1.052
	Gender_Female	.155	.015	107.649	1	.000	1.168
	FVage	.015	.001	864.755	1	.000	1.015
	Year	.037	.006	44.513	1	.000	1.037
	Month	.009	.002	17.878	1	.000	1.009
	Constant	-78.162	11.096	49.622	1	.000	.000

SHLD

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.005	.001	44.727	1	.000	.995
	BRalpha_ARM	.122	.011	114.156	1	.000	1.129
	BRalpha_CERV	.006	.000	1751.840	1	.000	1.006
	BRalpha_ELBW	.047	.003	217.892	1	.000	1.049
	BRalpha_FARM	.019	.003	49.831	1	.000	1.019
	BRalpha_HIP	.003	.002	1.351	1	.245	1.003
	BRalpha_KNEE	.000	.000	1.571	1	.210	1.000
	BRalpha_LEG	.001	.018	.003	1	.955	1.001
	BRalpha_LLEG	-.112	.013	69.952	1	.000	.894
	BRalpha_LUMB	.000	.000	24.119	1	.000	1.000
	BRalpha_NSPC	.001	.000	3.818	1	.051	1.001
	BRalpha_OOS	.038	.006	38.064	1	.000	1.039
	BRalpha_PELV	-.002	.001	6.833	1	.009	.998
	BRalpha_SPIN	-.007	.001	160.078	1	.000	.993
	BRalpha_SYST	-.005	.000	252.688	1	.000	.995
	BRalpha_THGH	-.031	.006	25.262	1	.000	.969
	BRalpha_THOR	.012	.000	652.988	1	.000	1.012
	BRalpha_UARM	-.014	.002	60.853	1	.000	.986
	BRalpha_WRHD	.019	.001	274.858	1	.000	1.019
	max risk	.057	.001	2498.051	1	.000	1.058
	Gender_Female	-.272	.009	877.842	1	.000	.762
	FVage	.017	.000	3020.179	1	.000	1.017
	Year	.146	.003	1867.138	1	.000	1.157
	Month	.023	.001	307.797	1	.000	1.023
	Constant	-296.563	6.809	1897.111	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.098	.011	76.463	1	.000	.906
	BRalpha_ARM	.781	.037	447.200	1	.000	2.185
	BRalpha_CERV	.385	.009	1725.149	1	.000	1.469
	BRalpha_ELBW	-.075	.028	7.294	1	.007	.928
	BRalpha_FARM	-.049	.021	5.489	1	.019	.952
	BRalpha_HIP	-.123	.026	22.857	1	.000	.884
	BRalpha_KNEE	-.156	.011	209.351	1	.000	.855
	BRalpha_LEG	.263	.080	10.785	1	.001	1.300
	BRalpha_LLEG	-.626	.053	139.892	1	.000	.535
	BRalpha_LUMB	-.155	.010	261.855	1	.000	.857
	BRalpha_NSPC	.376	.010	1428.293	1	.000	1.456
	BRalpha_OOS	.128	.051	6.294	1	.012	1.137
	BRalpha_PELV	-.216	.017	159.681	1	.000	.806
	BRalpha_SPIN	.116	.013	86.268	1	.000	1.123
	BRalpha_SYST	.107	.012	79.116	1	.000	1.112
	BRalpha_THGH	.043	.034	1.580	1	.209	1.044
	BRalpha_THOR	.233	.014	282.089	1	.000	1.263
	BRalpha_UARM	.510	.028	340.032	1	.000	1.665
	BRalpha_WRHD	.248	.014	334.704	1	.000	1.281
	max risk	.039	.001	1104.303	1	.000	1.040
	Gender_Female	-.352	.009	1405.451	1	.000	.703
	FVage	.018	.000	3503.068	1	.000	1.019
	Year	.121	.004	1172.314	1	.000	1.129
	Month	.019	.001	215.385	1	.000	1.019
	Constant	-245.988	7.110	1196.936	1	.000	.000

SPIN

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.005	.001	52.983	1	.000	1.005
	BRalpha_ARM	-.253	.024	106.630	1	.000	.777
	BRalpha_CERV	.001	.000	42.219	1	.000	1.001
	BRalpha_ELBW	-.001	.002	.160	1	.689	.999
	BRalpha_FARM	-.075	.005	199.038	1	.000	.928
	BRalpha_HIP	.007	.002	9.033	1	.003	1.007
	BRalpha_KNEE	-.003	.000	92.323	1	.000	.997
	BRalpha_LEG	-.240	.051	21.953	1	.000	.786
	BRalpha_LLEG	-.203	.017	149.883	1	.000	.816
	BRalpha_LUMB	.001	.000	221.774	1	.000	1.001
	BRalpha_NSPC	-.008	.000	301.837	1	.000	.992
	BRalpha_OOS	.100	.007	221.627	1	.000	1.105
	BRalpha_PELV	.006	.001	109.971	1	.000	1.006
	BRalpha_SHLD	-.002	.000	20.443	1	.000	.998
	BRalpha_SYST	.003	.000	159.039	1	.000	1.003
	BRalpha_THGH	.077	.005	220.047	1	.000	1.081
	BRalpha_THOR	.004	.000	66.947	1	.000	1.004
	BRalpha_UARM	-.022	.004	31.044	1	.000	.979
	BRalpha_WRHD	.003	.001	4.917	1	.027	1.003
	max risk	.078	.001	4107.454	1	.000	1.081
	Gender_Female	.239	.011	506.472	1	.000	1.270
	FVage	-.004	.000	152.981	1	.000	.996
	Year	.194	.004	2618.741	1	.000	1.214
	Month	.018	.001	144.461	1	.000	1.018
	Constant	-391.822	7.616	2646.544	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.034	.013	7.204	1	.007	1.035
	BRalpha_ARM	-.490	.058	72.205	1	.000	.613
	BRalpha_CERV	.054	.011	24.684	1	.000	1.055
	BRalpha_ELBW	.046	.033	1.924	1	.165	1.047
	BRalpha_FARM	-.441	.026	279.823	1	.000	.644
	BRalpha_HIP	.194	.026	56.516	1	.000	1.215
	BRalpha_KNEE	-.047	.012	14.753	1	.000	.954
	BRalpha_LEG	-.817	.128	40.946	1	.000	.442
	BRalpha_LLEG	-.667	.059	129.469	1	.000	.513
	BRalpha_LUMB	.974	.011	7940.247	1	.000	2.649
	BRalpha_NSPC	.067	.012	32.511	1	.000	1.069
	BRalpha_OOS	1.055	.050	446.569	1	.000	2.872
	BRalpha_PELV	.001	.018	.004	1	.947	1.001
	BRalpha_SHLD	.074	.013	33.945	1	.000	1.077
	BRalpha_SYST	.183	.013	188.591	1	.000	1.200
	BRalpha_THGH	.408	.034	140.520	1	.000	1.504
	BRalpha_THOR	.579	.014	1622.565	1	.000	1.785
	BRalpha_UARM	.091	.035	6.654	1	.010	1.096
	BRalpha_WRHD	.146	.016	85.149	1	.000	1.157
	max risk	.055	.001	1941.772	1	.000	1.057
	Gender_Female	.195	.011	315.866	1	.000	1.216
	FVage	-.009	.000	602.541	1	.000	.992
	Year	.135	.004	1122.379	1	.000	1.145
	Month	.012	.002	60.281	1	.000	1.012
	Constant	-274.963	8.134	1142.857	1	.000	.000

SYST

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.018	.001	648.544	1	.000	1.018
	BRalpha_ARM	.087	.012	51.646	1	.000	1.091
	BRalpha_CERV	.001	.000	25.721	1	.000	1.001
	BRalpha_ELBW	.057	.003	274.517	1	.000	1.059
	BRalpha_FARM	.013	.003	16.530	1	.000	1.013
	BRalpha_HIP	.012	.002	25.595	1	.000	1.012
	BRalpha_KNEE	.009	.000	1820.411	1	.000	1.009
	BRalpha_LEG	-.125	.037	11.363	1	.001	.882
	BRalpha_LLEG	-.085	.014	37.588	1	.000	.919
	BRalpha_LUMB	.003	.000	1612.538	1	.000	1.003
	BRalpha_NSPC	.009	.000	898.526	1	.000	1.009
	BRalpha_OOS	.089	.009	110.060	1	.000	1.094
	BRalpha_PELV	-.003	.001	16.489	1	.000	.997
	BRalpha_SHLD	-.001	.000	7.681	1	.006	.999
	BRalpha_SPIN	.003	.001	41.610	1	.000	1.003
	BRalpha_THGH	-.028	.005	28.690	1	.000	.972
	BRalpha_THOR	.003	.001	24.433	1	.000	1.003
	BRalpha_UARM	.047	.002	422.454	1	.000	1.048
	BRalpha_WRHD	.018	.001	232.471	1	.000	1.019
	max risk	.094	.001	6082.888	1	.000	1.099
	Gender_Female	.623	.011	3252.051	1	.000	1.864
	FVage	.009	.000	764.704	1	.000	1.009
	Year	.226	.004	3633.251	1	.000	1.254
	Month	.027	.001	350.036	1	.000	1.028
	Constant	-459.198	7.567	3682.799	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.242	.012	438.100	1	.000	1.273
	BRalpha_ARM	.064	.045	2.027	1	.155	1.066
	BRalpha_CERV	.052	.010	24.541	1	.000	1.053
	BRalpha_ELBW	.257	.029	78.499	1	.000	1.293
	BRalpha_FARM	.207	.021	93.557	1	.000	1.230
	BRalpha_HIP	.137	.025	31.225	1	.000	1.147
	BRalpha_KNEE	.217	.011	379.930	1	.000	1.243
	BRalpha_LEG	-.559	.104	28.862	1	.000	.572
	BRalpha_LLEG	-.127	.047	7.180	1	.007	.881
	BRalpha_LUMB	.046	.011	18.592	1	.000	1.047
	BRalpha_NSPC	.508	.011	2261.911	1	.000	1.663
	BRalpha_OOS	.403	.050	65.272	1	.000	1.497
	BRalpha_PELV	.332	.017	403.497	1	.000	1.394
	BRalpha_SHLD	.090	.012	55.587	1	.000	1.094
	BRalpha_SPIN	.186	.013	195.644	1	.000	1.204
	BRalpha_THGH	-.304	.036	71.371	1	.000	.738
	BRalpha_THOR	.236	.015	239.418	1	.000	1.266
	BRalpha_UARM	.177	.031	31.901	1	.000	1.193
	BRalpha_WRHD	.356	.014	632.917	1	.000	1.428
	max risk	.080	.001	4193.476	1	.000	1.084
	Gender_Female	.556	.011	2562.548	1	.000	1.744
	FVage	.008	.000	607.312	1	.000	1.008
	Year	.192	.004	2409.218	1	.000	1.212
	Month	.021	.001	212.145	1	.000	1.022
	Constant	-389.976	7.878	2450.692	1	.000	.000

THGH

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.020	.001	192.836	1	.000	1.020
	BRalpha_ARM	.298	.017	318.264	1	.000	1.347
	BRalpha_CERV	-.006	.001	70.143	1	.000	.994
	BRalpha_ELBW	.010	.004	5.871	1	.015	1.010
	BRalpha_FARM	.029	.008	14.397	1	.000	1.030
	BRalpha_HIP	.092	.002	1612.892	1	.000	1.096
	BRalpha_KNEE	.002	.001	18.537	1	.000	1.002
	BRalpha_LEG	.099	.023	18.745	1	.000	1.104
	BRalpha_LLEG	.047	.023	3.962	1	.047	1.048
	BRalpha_LUMB	-.001	.000	36.180	1	.000	.999
	BRalpha_NSPC	.009	.000	483.242	1	.000	1.009
	BRalpha_OOS	-.216	.023	86.468	1	.000	.805
	BRalpha_PELV	.034	.001	1535.310	1	.000	1.034
	BRalpha_SHLD	-.005	.001	21.272	1	.000	.995
	BRalpha_SPIN	.004	.002	4.959	1	.026	1.004
	BRalpha_SYST	.007	.001	158.936	1	.000	1.007
	BRalpha_THOR	.006	.001	24.882	1	.000	1.006
	BRalpha_UARM	-.195	.037	27.205	1	.000	.823
	BRalpha_WRHD	.013	.003	16.279	1	.000	1.013
	max risk	.072	.002	1028.294	1	.000	1.074
	Gender_Female	.164	.031	27.902	1	.000	1.179
	FVage	-.005	.001	28.453	1	.000	.995
	Year	.279	.011	653.587	1	.000	1.322
	Month	.041	.004	92.655	1	.000	1.042
	Constant	-567.593	22.018	664.547	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.803	.031	651.790	1	.000	2.231
	BRalpha_ARM	-.416	.135	9.560	1	.002	.660
	BRalpha_CERV	-.122	.032	14.061	1	.000	.885
	BRalpha_ELBW	1.226	.055	494.950	1	.000	3.408
	BRalpha_FARM	.423	.052	65.856	1	.000	1.526
	BRalpha_HIP	1.309	.042	984.658	1	.000	3.701
	BRalpha_KNEE	.573	.031	341.274	1	.000	1.774
	BRalpha_LEG	1.780	.120	218.922	1	.000	5.927
	BRalpha_LLEG	-.980	.127	59.396	1	.000	.375
	BRalpha_LUMB	-.066	.033	3.916	1	.048	.936
	BRalpha_NSPC	.463	.033	193.214	1	.000	1.588
	BRalpha_OOS	.369	.085	18.796	1	.000	1.446
	BRalpha_PELV	1.569	.035	2058.039	1	.000	4.802
	BRalpha_SHLD	-.054	.036	2.235	1	.135	.948
	BRalpha_SPIN	.265	.037	52.302	1	.000	1.304
	BRalpha_SYST	-.271	.037	53.359	1	.000	.763
	BRalpha_THOR	.600	.039	231.336	1	.000	1.822
	BRalpha_UARM	-.696	.089	61.001	1	.000	.499
	BRalpha_WRHD	-.115	.042	7.546	1	.006	.891
	max risk	.050	.003	337.815	1	.000	1.052
	Gender_Female	-.126	.032	15.247	1	.000	.881
	FVage	-.010	.001	97.803	1	.000	.990
	Year	.143	.012	141.332	1	.000	1.154
	Month	.027	.004	37.932	1	.000	1.027
	Constant	-293.297	24.233	146.489	1	.000	.000

THOR

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.006	.001	29.531	1	.000	.994
	BRalpha_ARM	-.062	.020	9.475	1	.002	.940
	BRalpha_CERV	.005	.000	884.854	1	.000	1.005
	BRalpha_ELBW	-.011	.004	9.830	1	.002	.989
	BRalpha_FARM	.013	.004	11.794	1	.001	1.013
	BRalpha_HIP	-.012	.004	10.152	1	.001	.988
	BRalpha_KNEE	-.002	.000	43.961	1	.000	.998
	BRalpha_LEG	-.123	.044	7.968	1	.005	.884
	BRalpha_LLEG	.106	.010	114.777	1	.000	1.112
	BRalpha_LUMB	.001	.000	153.973	1	.000	1.001
	BRalpha_NSPC	-.002	.000	17.073	1	.000	.998
	BRalpha_OOS	-1.497	.193	60.292	1	.000	.224
	BRalpha_PELV	-.021	.002	112.750	1	.000	.980
	BRalpha_SHLD	.002	.000	22.709	1	.000	1.002
	BRalpha_SPIN	.003	.001	20.143	1	.000	1.003
	BRalpha_SYST	-.003	.000	40.461	1	.000	.997
	BRalpha_THGH	.026	.004	55.568	1	.000	1.026
	BRalpha_UARM	-.013	.003	18.771	1	.000	.987
	BRalpha_WRHD	-.005	.002	8.622	1	.003	.995
	max risk	.054	.001	1619.515	1	.000	1.055
	Gender_Female	.043	.012	12.839	1	.000	1.044
	FVage	-.008	.000	423.329	1	.000	.992
	Year	.215	.004	2467.114	1	.000	1.240
	Month	.016	.002	86.330	1	.000	1.016
	Constant	-435.954	8.735	2490.989	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.124	.015	71.226	1	.000	.883
	BRalpha_ARM	-.525	.065	64.605	1	.000	.591
	BRalpha_CERV	.552	.012	2045.500	1	.000	1.737
	BRalpha_ELBW	.169	.035	23.743	1	.000	1.184
	BRalpha_FARM	.079	.027	8.323	1	.004	1.082
	BRalpha_HIP	-.015	.031	.242	1	.623	.985
	BRalpha_KNEE	-.173	.014	144.503	1	.000	.841
	BRalpha_LEG	-.706	.141	24.960	1	.000	.493
	BRalpha_LLEG	.586	.049	140.684	1	.000	1.798
	BRalpha_LUMB	.402	.013	1031.524	1	.000	1.495
	BRalpha_NSPC	.215	.013	262.881	1	.000	1.240
	BRalpha_OOS	-3.255	.227	206.352	1	.000	.039
	BRalpha_PELV	-.048	.021	5.103	1	.024	.953
	BRalpha_SHLD	.197	.014	196.947	1	.000	1.218
	BRalpha_SPIN	.585	.014	1675.697	1	.000	1.796
	BRalpha_SYST	.229	.015	227.434	1	.000	1.257
	BRalpha_THGH	.574	.038	229.773	1	.000	1.775
	BRalpha_UARM	.272	.037	55.469	1	.000	1.313
	BRalpha_WRHD	-.174	.019	85.757	1	.000	.840
	max risk	.024	.001	263.578	1	.000	1.024
	Gender_Female	-.075	.012	36.335	1	.000	.928
	FVage	-.010	.000	673.618	1	.000	.990
	Year	.160	.005	1213.072	1	.000	1.174
	Month	.011	.002	40.685	1	.000	1.011
	Constant	-325.577	9.276	1231.813	1	.000	.000

UARM

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	-.007	.002	13.147	1	.000	.993
	BRalpha_ARM	.436	.014	938.517	1	.000	1.547
	BRalpha_CERV	.000	.000	.069	1	.792	1.000
	BRalpha_ELBW	.039	.002	580.570	1	.000	1.040
	BRalpha_FARM	.092	.004	614.978	1	.000	1.097
	BRalpha_HIP	.022	.005	22.618	1	.000	1.022
	BRalpha_KNEE	.000	.001	.255	1	.614	1.000
	BRalpha_LEG	.166	.015	119.377	1	.000	1.181
	BRalpha_LLEG	.097	.017	32.473	1	.000	1.102
	BRalpha_LUMB	-.023	.001	484.022	1	.000	.977
	BRalpha_NSPC	-.003	.001	7.390	1	.007	.997
	BRalpha_OOS	.068	.012	34.667	1	.000	1.070
	BRalpha_PELV	-.021	.004	29.668	1	.000	.979
	BRalpha_SHLD	.004	.001	42.230	1	.000	1.004
	BRalpha_SPIN	-.037	.004	69.848	1	.000	.964
	BRalpha_SYST	.005	.001	56.378	1	.000	1.005
	BRalpha_THGH	.090	.005	292.939	1	.000	1.094
	BRalpha_THOR	.004	.001	15.059	1	.000	1.004
	BRalpha_WRHD	.039	.002	530.967	1	.000	1.040
	max risk	.038	.003	210.940	1	.000	1.039
	Gender_Female	-.203	.025	64.869	1	.000	.817
	FVage	-.005	.001	51.049	1	.000	.995
	Year	.278	.009	975.730	1	.000	1.321
	Month	.040	.004	123.597	1	.000	1.041
	Constant	-563.901	17.934	988.673	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	BRalpha_ANFT	.304	.028	119.369	1	.000	1.355
	BRalpha_ARM	1.109	.066	281.641	1	.000	3.032
	BRalpha_CERV	-.076	.027	8.117	1	.004	.927
	BRalpha_ELBW	2.541	.033	5908.411	1	.000	12.688
	BRalpha_FARM	1.500	.035	1864.841	1	.000	4.481
	BRalpha_HIP	.195	.065	8.937	1	.003	1.215
	BRalpha_KNEE	.049	.029	2.866	1	.090	1.050
	BRalpha_LEG	2.260	.097	547.698	1	.000	9.583
	BRalpha_LLEG	.276	.097	8.158	1	.004	1.318
	BRalpha_LUMB	-.423	.029	218.913	1	.000	.655
	BRalpha_NSPC	.293	.028	111.768	1	.000	1.341
	BRalpha_OOS	.374	.102	13.424	1	.000	1.454
	BRalpha_PELV	-.514	.053	93.976	1	.000	.598
	BRalpha_SHLD	.546	.028	385.329	1	.000	1.725
	BRalpha_SPIN	.067	.036	3.431	1	.064	1.069
	BRalpha_SYST	.227	.032	50.558	1	.000	1.255
	BRalpha_THGH	-.468	.088	28.065	1	.000	.626
	BRalpha_THOR	.337	.037	85.380	1	.000	1.401
	BRalpha_WRHD	.131	.033	15.420	1	.000	1.140
	max risk	-.004	.003	1.097	1	.295	.996
	Gender_Female	-.268	.026	104.371	1	.000	.765
	FVage	-.005	.001	39.752	1	.000	.995
	Year	.143	.010	213.087	1	.000	1.154
	Month	.017	.004	22.472	1	.000	1.018
	Constant	-292.639	19.758	219.371	1	.000	.000

WRHD

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	BRalpha_ANFT	.004	.001	25.209	1	.000	1.004
	BRalpha_ARM	.346	.013	670.484	1	.000	1.413
	BRalpha_CERV	.000	.000	.578	1	.447	1.000
	BRalpha_ELBW	.008	.002	18.514	1	.000	1.008
	BRalpha_FARM	.222	.004	3678.171	1	.000	1.249
	BRalpha_HIP	-.036	.004	66.072	1	.000	.965
	BRalpha_KNEE	-.002	.000	57.038	1	.000	.998
	BRalpha_LEG	-.347	.066	27.778	1	.000	.707
	BRalpha_LLEG	.027	.011	5.715	1	.017	1.028
	BRalpha_LUMB	.002	.000	693.913	1	.000	1.002
	BRalpha_NSPC	-.001	.000	13.673	1	.000	.999
	BRalpha_OOS	.024	.007	12.752	1	.000	1.024
	BRalpha_PELV	.000	.001	.283	1	.595	1.000
	BRalpha_SHLD	.002	.000	44.779	1	.000	1.002
	BRalpha_SPIN	.003	.001	23.201	1	.000	1.003
	BRalpha_SYST	-.001	.000	7.881	1	.005	.999
	BRalpha_THGH	-.016	.007	5.158	1	.023	.984
	BRalpha_THOR	-.022	.001	305.381	1	.000	.978
	BRalpha_UARM	.009	.001	36.254	1	.000	1.009
	max risk	.053	.001	1617.773	1	.000	1.055
	Gender_Female	.239	.012	398.126	1	.000	1.270
	FVage	-.004	.000	135.972	1	.000	.996
	Year	.355	.004	6937.893	1	.000	1.426
	Month	.040	.002	577.731	1	.000	1.041
	Constant	-716.888	8.578	6983.648	1	.000	.000

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	BRalpha_ANFT	.054	.013	15.915	1	.000	1.055
	BRalpha_ARM	1.269	.041	971.344	1	.000	3.558
	BRalpha_CERV	-.018	.012	2.223	1	.136	.982
	BRalpha_ELBW	.105	.033	10.474	1	.001	1.111
	BRalpha_FARM	1.908	.018	10705.683	1	.000	6.743
	BRalpha_HIP	-.253	.030	69.122	1	.000	.776
	BRalpha_KNEE	.024	.013	3.379	1	.066	1.025
	BRalpha_LEG	-1.021	.131	60.409	1	.000	.360
	BRalpha_LLEG	.187	.049	14.779	1	.000	1.205
	BRalpha_LUMB	-.221	.013	305.070	1	.000	.802
	BRalpha_NSPC	.593	.012	2248.249	1	.000	1.809
	BRalpha_OOS	-.448	.058	60.602	1	.000	.639
	BRalpha_PELV	.186	.020	85.131	1	.000	1.205
	BRalpha_SHLD	.262	.014	373.708	1	.000	1.299
	BRalpha_SPIN	.174	.016	121.093	1	.000	1.190
	BRalpha_SYST	.359	.014	641.743	1	.000	1.432
	BRalpha_THGH	-.071	.040	3.227	1	.072	.931
	BRalpha_THOR	-.158	.019	70.003	1	.000	.854
	BRalpha_UARM	.080	.033	5.849	1	.016	1.083
	max risk	.026	.001	330.338	1	.000	1.027
	Gender_Female	.144	.012	134.931	1	.000	1.155
	FVage	-.002	.000	34.381	1	.000	.998
	Year	.309	.005	4718.696	1	.000	1.363
	Month	.033	.002	373.499	1	.000	1.033
	Constant	-626.047	9.074	4760.311	1	.000	.000

Interpreting the Results from the Regressions

In order to better understand the meaning of our regression results, we can look an the example where ANFT is the dependent variable in the regression. If we look at the beta coefficient for ARM, the result is -.084. The way that this is interpreted is that the treatment for a person who has previously came in for an ARM injury results in a (e^-.084) =.92 less likely odds that they will come back again for an ANFT injury. On the reverse side, if the beta coefficient for the independent variable is positive, then the treatment that this person previously received, gives them (e^beta) more likely to return for the dependent body region variable. This allows us to see how past treatment could influence future visits.

Insights From Regressions

To further analyse which data frame proved to be the more reliable approach, we compared the Cox and Snell R squared and Nagelkerke R squared scores for each dependent body region variable.

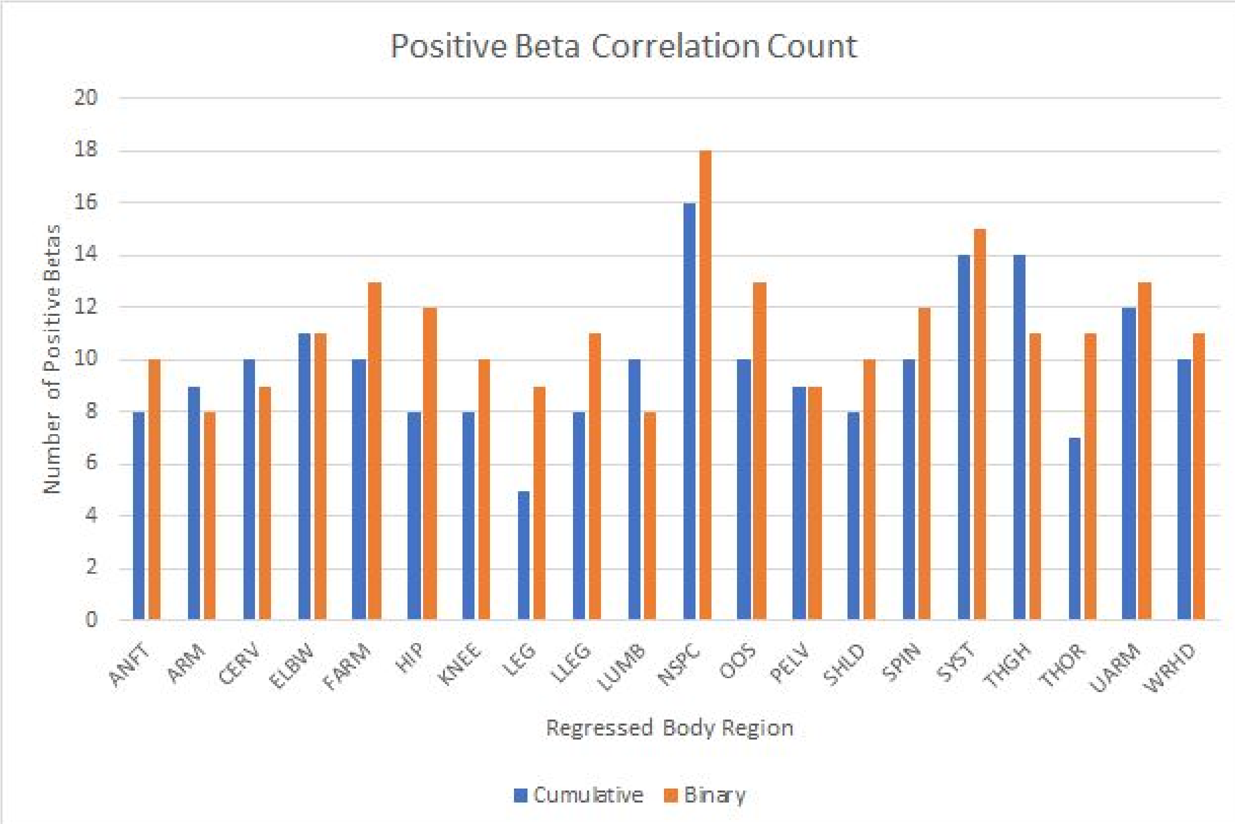
Dependent Variable	Cox and Snell R Squared	Nagelkerke R Squared	Data Frame
ANFT	0.08	0.123	Binary
ANFT	0.062	0.095	Cumulative
CERV	0.077	0.103	Binary
CERV	0.063	0.085	Cumulative
KNEE	0.074	0.109	Binary
KNEE	0.056	0.083	Cumulative
LUMB	0.112	0.15	Binary
LUMB	0.083	0.112	Cumulative
NSPC	0.15	0.209	Binary
NSPC	0.142	0.198	Cumulative
SHLD	0.052	0.081	Binary
SHLD	0.046	0.073	Cumulative

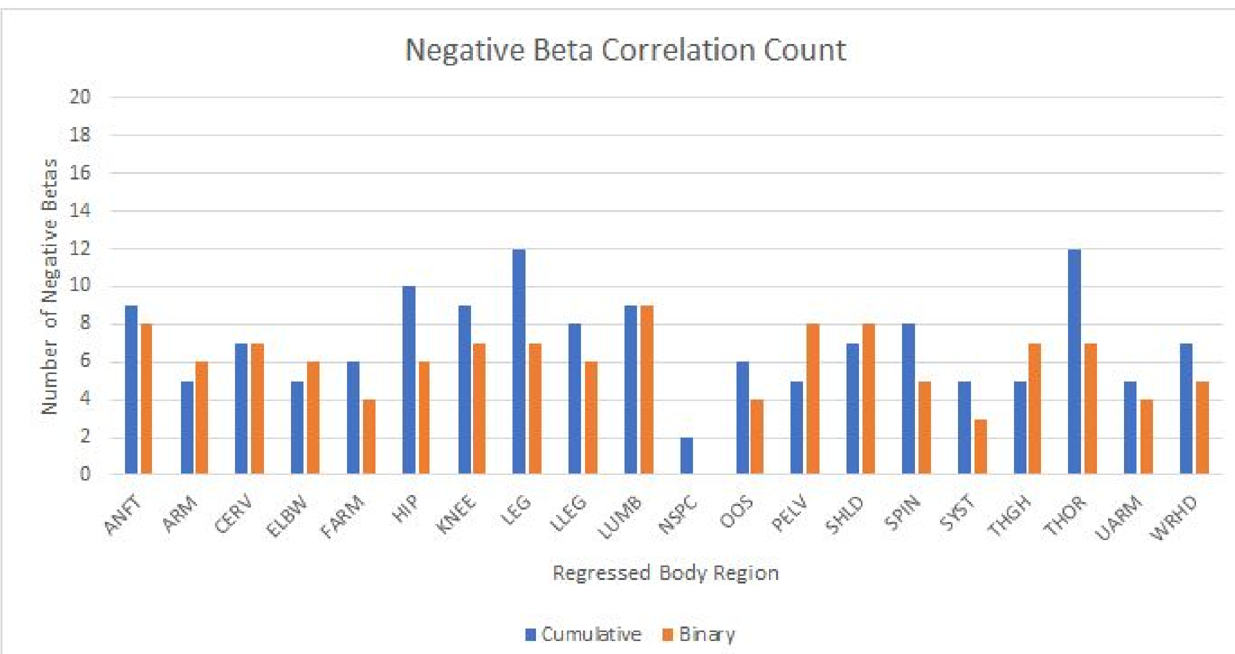
From looking at these comparisons, we see that the binary data frame produced more reliable results in all instances. These results apply both for both different criteria of R squared scores. From this, it would be justifiable to say that the binary data frame performed better. You can also come to this conclusion if you looked at the results in the regression tables pictured above. When it comes to medical knowledge, the results from the binary data frame produced results that were more intuitive as compared to the cumulative data frame. An example of this can be seen with LUMB as the dependent variable. The cumulative data frame resulted in OOS, LLEG, and THGH as the three most influencers in someone coming in for LUMB; while the binary data frame concluded SPIN, PELV, and THOR as the top influencing past injuries. It makes more medical sense that someone who had a past spinal, pelvic, or thoracic injury would letter come back for a lumbar issue; as opposed as someone having a leg, oos, or thigh injury. The R squared scores could still have had performed better, showing that we could be missing an important control variable in our regressions, this would take further analysis/ data collection.

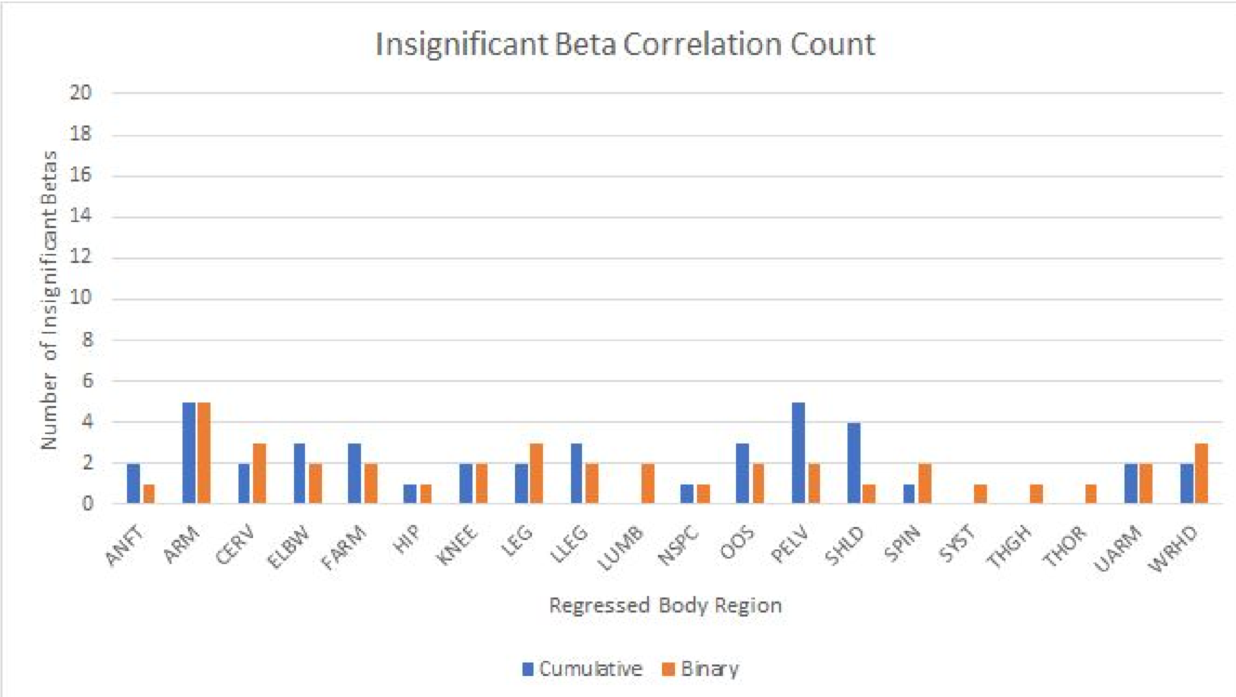
To further analyze the results of the models, we aggregated the betas from each model so that we can compare how the models differ. Below, we took the regression betas from each model and counted how many significant betas were positive, how many significant betas were negative, and how many betas were insignificant. We used p-values of < 0.05 to determine which betas were significant. The aggregate results are below:

Cumulative Regression Beta Coefficient Counts			
Body Region	Positive Beta	Negative Beta	Insignificant
ANFT	9	9	2
ARM	10	5	5
CERV	11	7	2
ELBW	12	5	3
FARM	11	6	3
HIP	9	10	1
KNEE	9	9	2
LEG	6	12	2
LLEG	9	8	3
LUMB	11	9	0
NSPC	17	2	1
OOS	11	6	3
PELV	10	5	5
SHLD	9	7	4
SPIN	11	8	1
SYST	15	5	0
THGH	15	5	0
THOR	8	12	0
UARM	13	5	2
WRHD	11	7	2

Binary Regression Beta Coefficient Counts			
Body Region	Positive Beta	Negative Beta	Insignificant
ANFT	11	8	1
ARM	9	6	5
CERV	10	7	3
ELBW	12	6	2
FARM	14	4	2
HIP	13	6	1
KNEE	11	7	2
LEG	10	7	3
LLEG	12	6	2
LUMB	9	9	2
NSPC	19	0	1
OOS	14	4	2
PELV	10	8	2
SHLD	11	8	1
SPIN	13	5	2
SYST	16	3	1
THGH	12	7	1
THOR	12	7	1
UARM	14	4	2
WRHD	12	5	3


Positive Beta Correlation Count
Number of Positive Betas
0
2
4
6
8
10
12
14
16
18
20
ANFT
ARM
CERV
ELBW
FARM
HIP
KNEE
LEG
LLEG
LUMB
NSPC
OOS
PELV
SHLD
SPIN
SYST
THGH
THOR
UARM
WRHD
Regressed Body Region
Cumulative
Binary


Negative Beta Correlation Count
Number of Negative Betas
0
2
4
6
8
10
12
14
16
18
20
ANFT
ARM
CERV
ELBW
FARM
HIP
KNEE
LEG
LLEG
LUMB
NSPC
OOS
PELV
SHLD
SPIN
SYST
THGH
THOR
UARM
WRHD
Regressed Body Region
Cumulative
Binary



The insignificant chart above shows us that the cumulative data frame has more insignificant beta values overall than does the binary data frame (41 total for cumulative and 39 for binary), which is aligned with our analysis of the top six body regions. We can also see that there is a greater variance for the count of some of the insignificant betas, such as PELV and SHLD. The binary version of the model only ever had a maximum of one more insignificant beta than did the cumulative model. From the graphs above, we can also see that the binary models tend to have more positive beta coefficients and the cumulative models tend to have more negative beta coefficients.

Business Applications

Using our two models could help in numerous ways to improve business operations. First, our preliminary logistic model is able to predict whether or not a patient is going to return based off very limited information from the patient on their first visit. This can help by aiding in predicting how many employees should be on staff based off of expected patients. Then using our body region regression model, you can predict what possible future injuries your patients could come in for based from their past injuries (as well as what types of injuries you should expect to see). From there, you could incorporate not only how many employees you should have on hand, but also what types of employees (e.g. specialists). For instance, if you see that a lot of patients are going to come back for back injuries in the following months, you could add more back specialists; the same theory goes for any other of the body regions.

Summary of Work

To begin, we built a logistic regression model which would predict whether or not a patient would return for a future visit. For business purposes, we only utilized information that was from a patient's first visit. This model, even through many adaptations, ran at approximately 85% accuracy level.

Next, we built another logistic regression. This time the model's purpose was to determine whether or not a patient returned for a different body region on their next visit(s) as opposed to the first. This model was not quite as accurate, but still performed with approximately 60% accuracy.

Finally, we used the patients that we found to have returned for different body regions in order to further predict what body region for which they would return. By using multiple logistic regression models with each individual body region as the dependent variable, we were able to further explore the associations between body regions. Each regression used all other body regions as independent variables and also included five control variables. The results were beta coefficients, which we could place in descending order based on the formula (e^ beta) to tell how likely past treatment on particular body regions would affect the likelihood that the patient would return for a specific other body region. Positive beta coefficients meant that their past treatment would increase the likelihood that they return for a specific body region, while negative beta coefficients meant that their past treatment reduced the likelihood to return for a particular body region. We were also able to us these beta coefficients in order to build a network between all the body regions which showed the interconnected influence among them.

Limitations

One possible issue with our results could be due to the fact that the data did not contain the magnitude or severity of the injury for each visit. We simply had the body region that was treated on each visit. We did try to control for the magnitude of injury based off of our risk differential variable that was created, but that can only account for so much in a predictive model. We believe that if we could have incorporated how severe the injury was in each visit, then this would have allowed our model to capture more of the randomness.

Also, the high number of patients that were in the data were those that came in for multiple visits could have skewed the accuracy results from our logistic model.

Moving Forward

Moving forward with our findings, we definitely would like to incorporate some data pertaining to actual cost of each visit to the patient as well as the business (not just the amount allowed). From this we could give better business insights into whether certain procedures wouldn't be worth covering or if there a speciality procedure in which you should focus in order to optimize profit. It would also beneficial moving forward if we had information on the cause of injury for each visit. With this additional information, it could allow us not only to give insights for the injury but also how it occurred. This would possibly allow us to build a more robust model, as well as better segment or patients treatment in a sense that a LUMB injury caused from falling is not the same as a LUMB treatment that was caused from a sports injury.

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