

ACLR Final Project

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Report

Audience

Our final report's audience/stakeholders include physicians and other researchers evaluating the health of patients who have undergone ACL reconstruction surgery.

Problem Statement

After athletes tear their anterior cruciate ligament (ACL), many undergo ACL reconstruction (ACLR) surgery. However, physicians and other researchers are still evaluating the recovery and health of patients who have undergone ACLR. It is important to note that a majority of patients do not get reinjured - in this study, 83% had no reinjuries after ACLR surgery. There are many features that can affect reinjury rates after the surgery, such as the gender of the patient, the graft type used, and even their mental readiness. Specifically, our stakeholders are interested in all of these factors and what combination will lead to the lowest reinjury rates in patients after ACLR surgery is performed.

Analysis

[insert graph analyses]

Conclusion

[insert conclusion]

1 Data Cleaning

1.0.0.1 Choosing our Variables:

With the given dataset, we decided to focus on the variables we deemed to be most relevant to our hypothesis regarding recovery trends. Categorical variables such as `sex_dashboard`, `graft_dashboard2`, `reinjury`, and `tss_dashboard` were included along with numerical values such as `age`, `ikdc`, `acl_rsi`, and `bmi`.

Our categorical variables provide key insight into grouping individuals and focusing on patterns relevant to them, as well as stratifying their respective outcomes. For example, `sex_dashboard` allowed us to explore sex-based differences in recovery. Both `graft_dashboard2` and `reinjury` helped us determine whether certain graft types experience reinjury more frequent with `tss_dashboard` establishing the time frame as to when individuals experienced their reinjury.

The numerical variables chosen are all continuous measures of both physical and psychological recovery factors that are key to affirming and establishing key numerical general descriptive statistics that provide a measure of evaluating outcome differences.

1.0.0.2 Cleaning Approach:

During our analysis, we took measures to address missing values, inconsistent data types, and outliers. For

For each variable, we assessed the proportion of missing values respective to the amount of observations. For our numerical columns, we decided to impute the missing values with the median, and for our categorical values decided to drop records entirely so that we could plot points accordingly when constructing our graphs and visualizations.

After completing our initial cleaning process, we went ahead with our next step, Exploratory Data Analysis (EDA), to examine any relations and patterns within our dataset.

2 Exploratory Data Analysis

Preview of the cleaned dataset (first five rows)

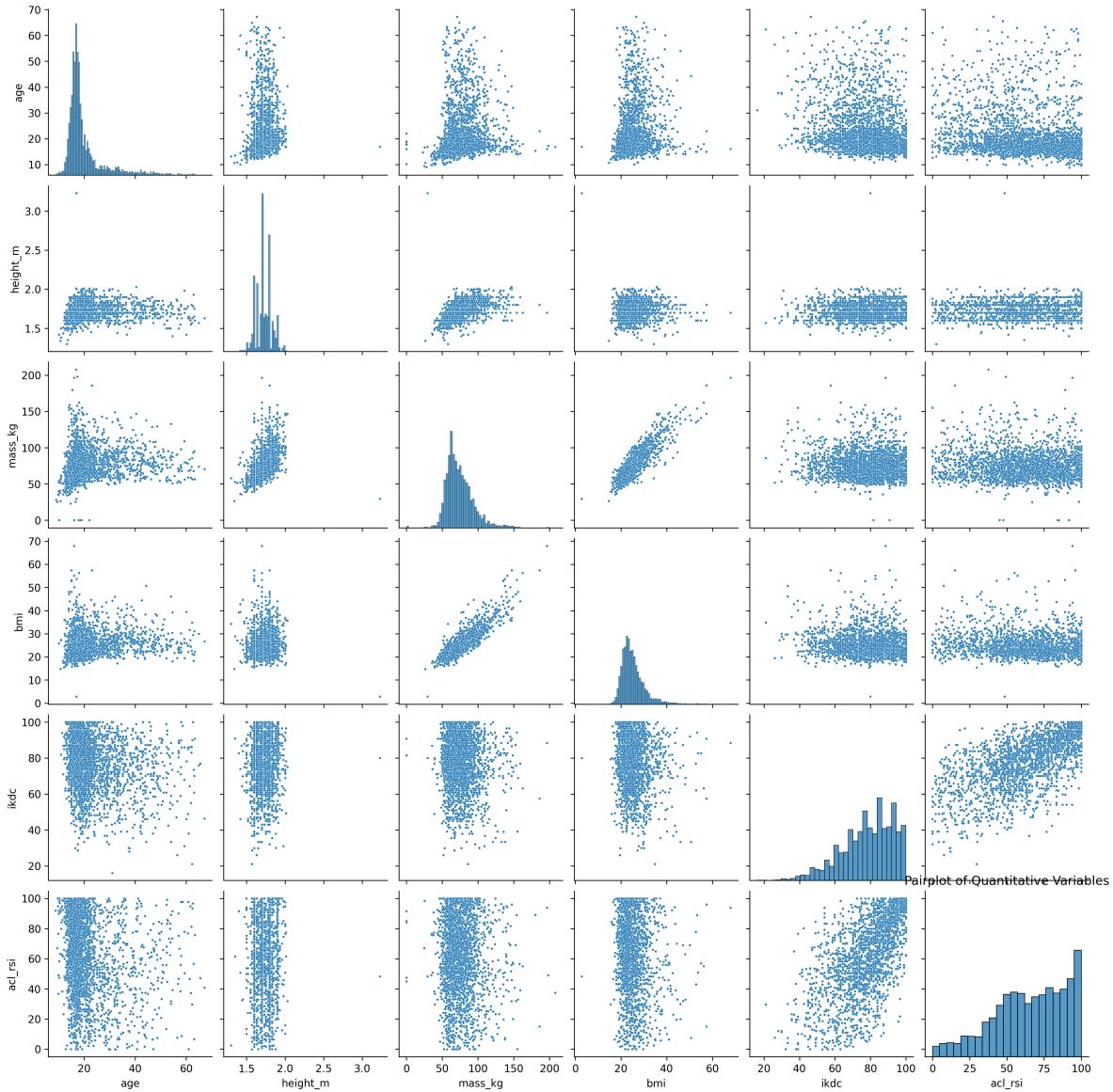
```
# setting up environment
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
# importing data as dataframe:
df = pd.read_csv('aclr data(in).csv')
# Including relevant variables into our dataframe and dropping the others:
df = df[['sex_dashboard', 'graft_dashboard2', 'reinjury', 'age', 'height_m', 'mass_kg', 'bmi',
df.head()
```

	sex_dashboard	graft_dashboard2	reinjury	age	height_m	mass_kg	bmi	ikdc	acl_rsi
0	Male	Other	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	No	21.7	1.9	87.4	24.210526	95.4	87.5
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Female	HS autograft	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	No	14.5	1.6	72.2	28.203125	79.3	8.3

```
# Filtering for numeric columns:
numeric_columns = df.select_dtypes(include=['int', 'float']).columns
# imputing missing values with the mean for each respective column
mean_values = df[numeric_columns].mean()
m_df = df.fillna(mean_values)
```

2.0.1 Pairplot of our chosen variables

```
# Pairplot of filtered variables:
sns.pairplot(df[['age', 'height_m', 'mass_kg', 'bmi', 'ikdc', 'acl_rsi']], plot_kws={"s": 5})
plt.title('Pairplot of Quantitative Variables')
plt.show()
```



This pairplot illustrates the relationship between each pair of variables in our dataset. This is a quick and straightforward tool to see if there are any obvious correlations/clusters between different elements. We can see that BMI and mass have the most positively correlated relationship, which is to be expected (since mass is used to calculate BMI). Other than that, there are no glaringly obvious trends between variables.

Looking at Specific Distributions

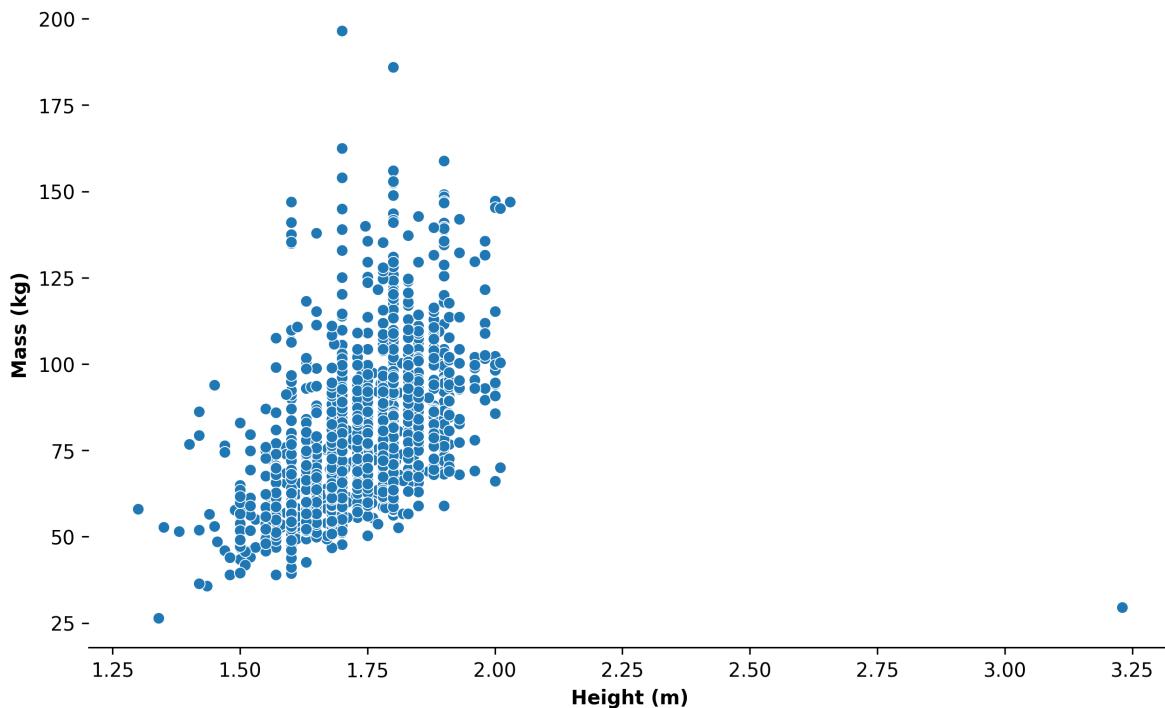
```
# Creating visualizations to illustrate distributions:
# SCATTERPLOT: Between height and mass_kg
```

```

plt.figure(figsize=(10,6))
sns.scatterplot(x='height_m', y='mass_kg', data=df)
# == SCAFFOLDING ==
plt.suptitle('Scatterplot of Height and Mass', weight = 'bold', fontsize = 16, x = 0.29)
# axis labels:
plt.xlabel('Height (m)', weight = 'bold')
plt.ylabel('Mass (kg)', weight = 'bold')
# removing spines
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['left'].set_visible(False)
plt.show()

```

Scatterplot of Height and Mass



This is a scatterplot that plots the distribution of height v mass between all the patients. There is a pretty positive correlation between the two variables, since as height increases, mass also tends to increase. There is one outlier where height is around 3.25 meters, or around 10 feet. This is most likely a typo and they intended to mark it as 1.25.

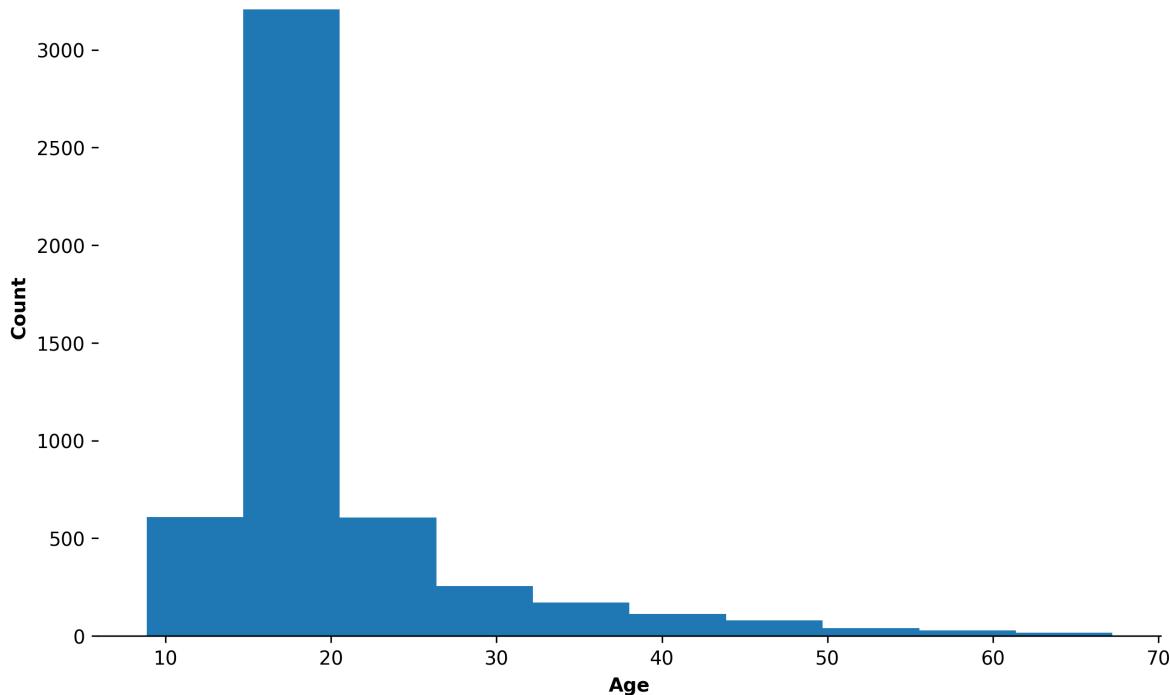
```

# Histogram for 'age':
plt.figure(figsize=(10,6))
df['age'].plot(kind='hist')
# == SCAFFOLDING ==
plt.suptitle('Histogram of Age', weight = 'bold', fontsize=16, x=0.20)
plt.title('Distribution of age values', fontsize=10, x=0.075)
plt.subplots_adjust(top = 0.91)
# axis labels:
plt.xlabel('Age', weight = 'bold')
plt.ylabel('Count', weight = 'bold')
# removing spines
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['left'].set_visible(False)
plt.show()

```

Histogram of Age

Distribution of age values



6. Examine Correlations (if relevant)

Interpret findings: What variables appear related?

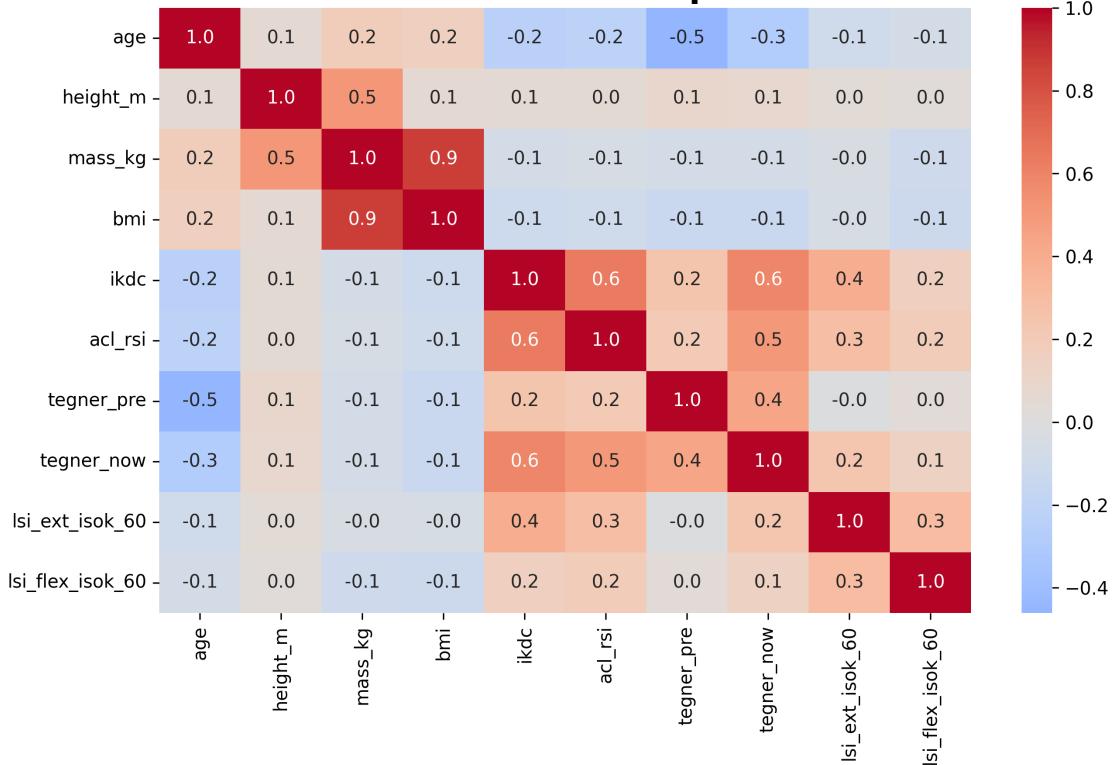
```

# setting filtered_df to be the relevant columns:
filtered_df = df[['sex_dashboard', 'graft_dashboard2', 'reinjury', 'age', 'height_m', 'mass_kg', 'bmi', 'ikdc', 'acl_rsi', 'tegner_pre', 'tegner_now', 'lsi_ext_isok_60', 'lsi_flex_isok_60']]
# dropping categorical columns:
num_fil_df = filtered_df.drop(['sex_dashboard', 'graft_dashboard2', 'reinjury'], axis=1)
# creating correlation matrix of our filtered numerical columns
corr_matrix = num_fil_df.corr()

# plotting correlation heatmap:
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, fmt=".1f", annot=True, cmap="coolwarm", center=0)
plt.title("Cleaned Dataframe: Correlation Heatmap", weight = 'bold', fontsize = 18, x=0.21)
plt.show()

```

Cleaned Dataframe: Correlation Heatmap



Positively correlated variables seem to include: - ikdc and acl_rsi - bmi and mass_kg - tegner_now and ikdc - tegner_now and acl_rsi

Negatively correlated variables seem to include: - tegner_pre and age - tegner_now and age

7. Explore Relationships (if relevant)

Dig into potential causal or descriptive relationships Use visualizations and statistical summaries.

```
# Records were mismatched so we shifted row values by 1
# (for every graft_type recorded, reinjury was blank so shifted by 1 to match)
df['reinjury_shifted'] = df['reinjury'].shift(-1)
df_cleaned = df[df['graft_dashboard2'].notna()][['graft_dashboard2', 'reinjury_shifted']]
df_cleaned.columns = ['graft_dashboard2', 'reinjury']
print(df_cleaned.head()) # previewing cleaned dataset

df_cleaned = df_cleaned[
    (df_cleaned['reinjury'].str.upper() != 'BLANK') &
    (df_cleaned['graft_dashboard2'].str.upper() != 'BLANK')]

grouped_counts = (
    df_cleaned.groupby(['graft_dashboard2', 'reinjury'])
    .size()
    .reset_index(name='count')
)

# #graft_order = ['HS allograft', 'BTB allograft', 'QT autograft', 'Allograft', 'Other']
# # Convert 'graft_dashboard2' to a categorical type w order
# #grouped_counts['graft_dashboard2'] = pd.Categorical(
# #    grouped_counts['graft_dashboard2'],
# #    categories=graft_order,
# #    ordered=True
# #)
# sort the DataFrame by this order for plotting
#grouped_counts = grouped_counts.sort_values('graft_dashboard2')

# plotting stacked bar chart:
plt.figure(figsize=(10, 6))
sns.barplot(
    data=grouped_counts,
    x='graft_dashboard2',
    y='count',
    hue='reinjury',
    palette='Set2'
)
# == SCAFFOLDING ==
plt.xlabel('Graft Type')
```

```

plt.ylabel('Count', weight = 'bold')
plt.title('Reinjury Types by Graft Type', weight = 'bold', fontsize = 16, x = 0.2)
plt.legend(title='Reinjury Type')
# removing spines
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['left'].set_visible(False)

plt.tight_layout()
plt.show()

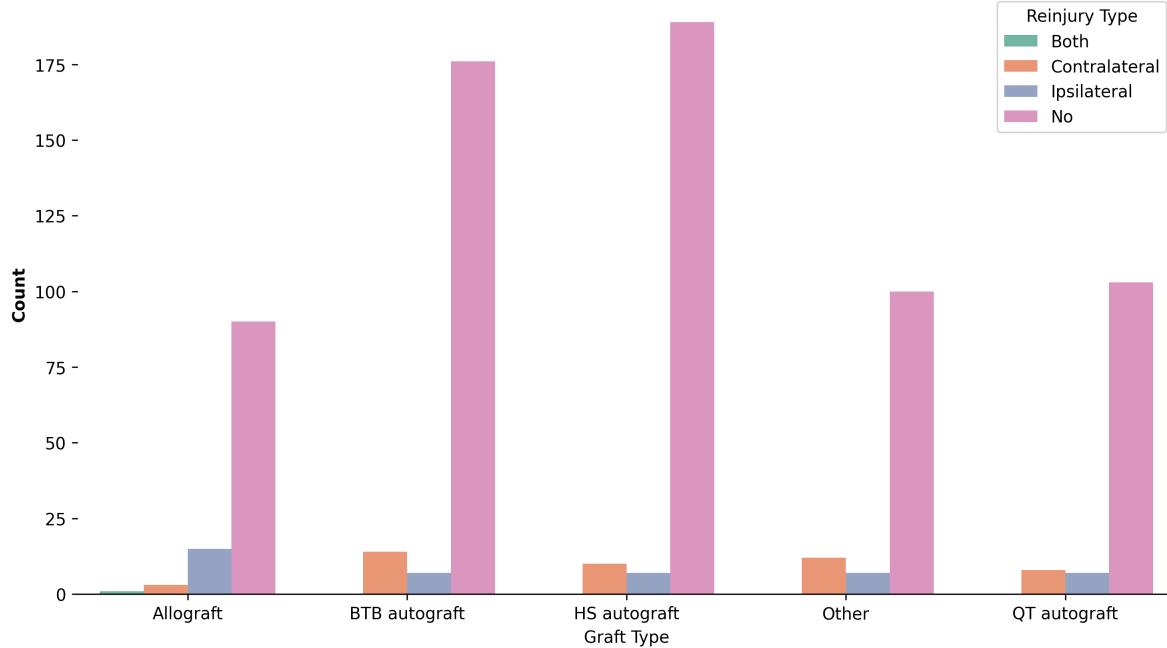
```

```

      graft_dashboard2 reinjury
0          Other      No
3      HS autograft      No
8      HS autograft    BLANK
10     HS autograft      No
15     HS autograft      No

```

Reinjury Types by Graft Type



HS Autograft has the highest proportion of no reinjuries, while the BTB autograft seems to have the highest recorded count of Contralateral reinjuries.

```

# Bar Chart: Focusing on Tegner as a metric since it assesses overall functionality

# calculating mean and std for both Tegner values:
mean_val = [filtered_df['tegner_pre'].mean(), filtered_df['tegner_now'].mean()]
std_val = [filtered_df['tegner_pre'].std(), filtered_df['tegner_now'].std()]

# == PLOTTING ==
plt.figure(figsize=(10,6))
plt.bar(['Pre', 'Now'], mean_val, yerr=std_val, capsize=5, color=['#7aa095', '#bf8b85'], alpha=0.8)

# SCAFFOLDING:
plt.suptitle('Tegner Performance Decreases after ACL Reconstruction ', weight='bold', fontsize=16)
plt.title('Comparing Tegner scores before surgery to scores recorded post-surgery', fontsize=14)

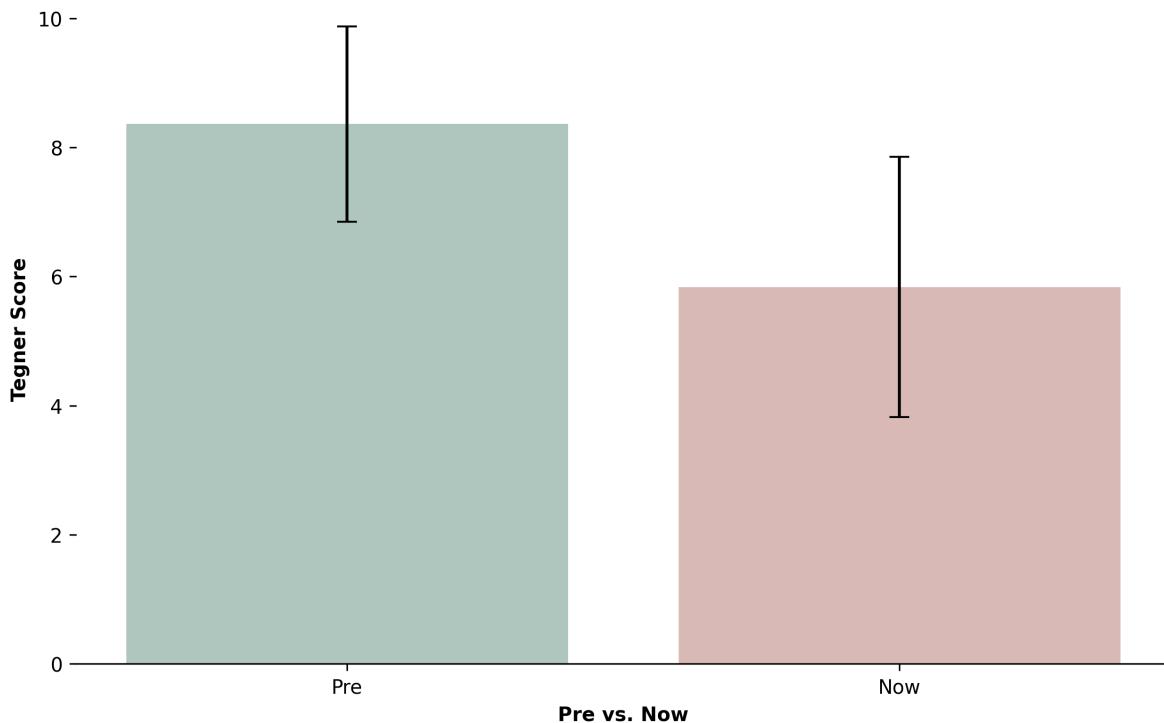
plt.subplots_adjust(top = 0.90) # adjusting space between the super title and the title
plt.ylabel('Tegner Score', weight='bold')
plt.xlabel('Pre vs. Now', weight='bold')

# removing spines
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['left'].set_visible(False)
plt.show()

```

Tegner Performance Decreases after ACL Reconstruction

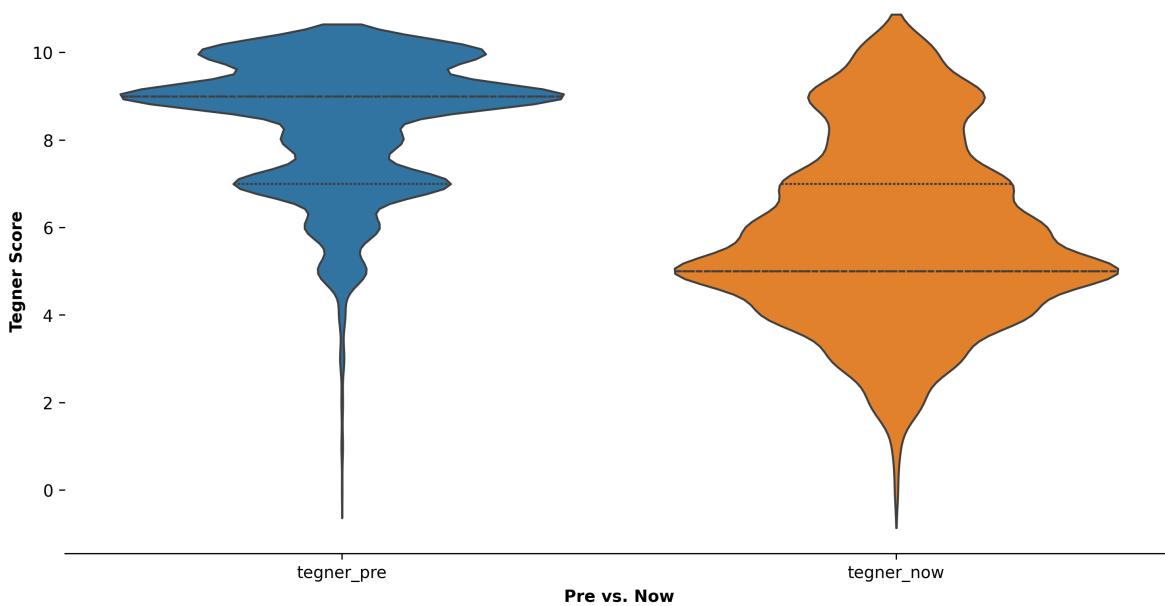
Comparing Tegner scores before surgery to scores recorded post-surgery



```
# Creating a violin plot to compare the tegner_pre and tegner_now by age:  
  
# PLOT  
plt.figure(figsize=(12, 6))  
sns.violinplot(data=filtered_df[['tegner_pre', 'tegner_now']], inner='quartile')  
  
# SCAFFOLDING:  
plt.suptitle('Tegner Scores are Lower After ACL Reconstruction', weight='bold', fontsize=16)  
plt.title('Comparing values from the pre_tegner to the current tegner values', fontsize=12, weight='bold')  
  
plt.subplots_adjust(top = 0.90) # adjusting space between the super title and the title  
plt.ylabel('Tegner Score', weight='bold')  
plt.xlabel('Pre vs. Now', weight='bold')  
  
plt.gca().spines['top'].set_visible(False)  
plt.gca().spines['right'].set_visible(False)  
plt.gca().spines['left'].set_visible(False)  
plt.show()
```

Tegner Scores are Lower After ACL Reconstruction

Comparing values from the pre_tegner to the current tegner values



3 Data Visualization

```
# Environment Setup:  
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import matplotlib  
import seaborn as sns  
from matplotlib import font_manager  
  
# importing data as dataframe:  
df = pd.read_csv('aclr data(in).csv')  
  
# filtering df to be consistent with relevant variables of interest:  
df = df[['sex_dashboard', 'graft_dashboard2', 'reinjury', 'age', 'height_m', 'mass_kg', 'bmi']]  
# previewing df with relevant columns:  
#df.head()  
# Filtering for numeric columns:  
numeric_columns = df.select_dtypes(include=['int', 'float']).columns  
# imputing missing values with the mean for each respective column  
mean_values = df[numeric_columns].mean()  
m_df = df.fillna(mean_values)  
# previewing the imputed dataframe:  
#print(m_df.head(5))  
df['sex_dashboard'] = df['sex_dashboard'].shift(-1)  
  
# == PLOT PREPARATION ==  
  
# data for graphing (getting rid of NaN values):  
df_clean = df[['ikdc', 'acl_rsi', 'sex_dashboard', 'tss_dashboard']].dropna()  
  
# Filter by sex  
df_male = df_clean[df_clean['sex_dashboard'] == 'Male']  
df_female = df_clean[df_clean['sex_dashboard'] == 'Female']  
# setting plot size:
```

```

plt.figure(figsize=(10, 6))
# male graph:
plt.scatter(df_male['ikdc'], df_male['acl_rsi'],
            marker='x', label='Male', color='#0070BB', alpha=0.7, s=40)
# Plot females with square markers
plt.scatter(df_female['ikdc'], df_female['acl_rsi'],
            marker='o', label='Female', color='#F653A6', alpha=0.5, s=40)

# == SCAFFOLDING ==

# setting titles:
plt.suptitle('Physical and Mental Recovery Go Hand in Hand', weight = 'bold', fontsize = 16,
             plt.title('Physical gains mirror mental gains in ACL Recovery Journey', color='#585757', font
             plt.subplots_adjust(top = 0.905) # adjusting spacing between sub and main title

# setting x-axis and y-axis labels:
plt.xlabel('IKDC (Knee Function)', weight = 'bold', fontsize = 12)
plt.ylabel('ACL_RSI (Mental Readiness)', weight = 'bold', fontsize = 12)

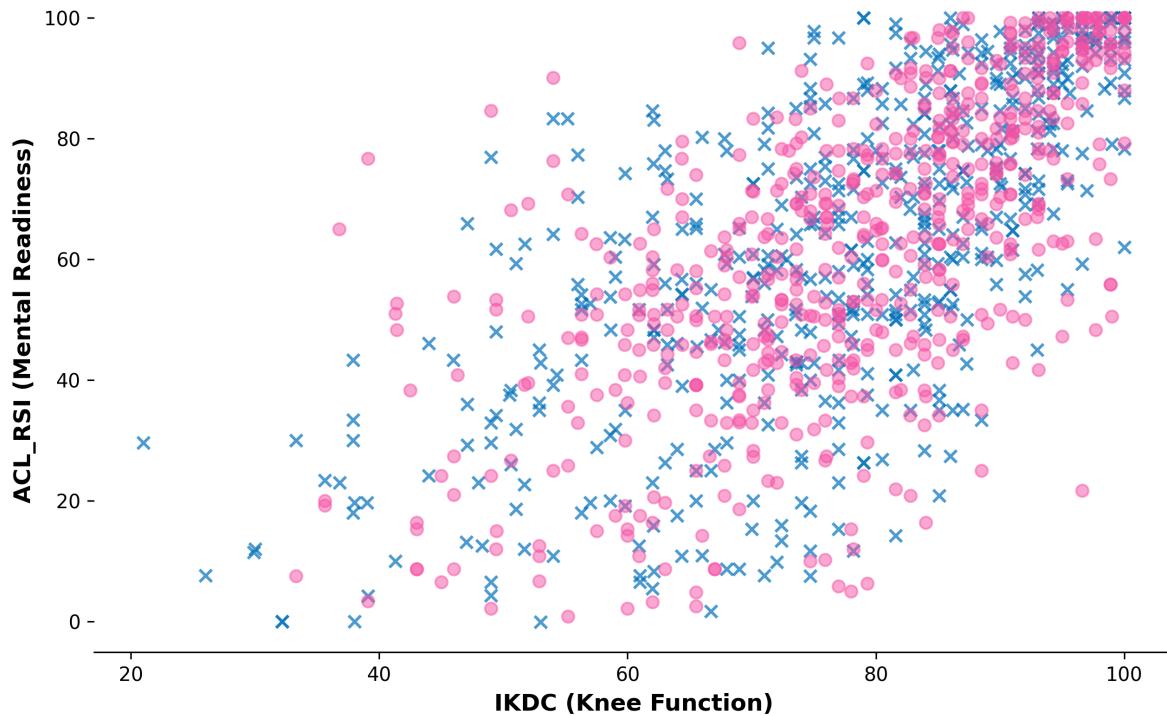
# reducing clutter on the end of the x-axis:
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.locator_params(axis='x', nbins=8) # reduces x-axis ticks

# extra formatting (removing spines for cleaner look):
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['left'].set_visible(False)
# adding source as annotation:
plt.figtext(0.1, -0.05, 'Source: UVA Department of Kinesiology and School of Data Science', l
plt.show()

```

Physical and Mental Recovery Go Hand in Hand

Physical gains mirror mental gains in ACL Recovery Journey



Source: UVA Department of Kinesiology and School of Data Science

Graph 2:

Planning on creating a scatterplot showing how both physical and mental readiness affect each other and the individual's overall confidence in returning to play.

```
# setting font
georgia_font = font_manager.FontProperties(family='Georgia')
plt.rcParams['font.family'] = georgia_font.get_name()

df = df[['sex_dashboard', 'graft_dashboard2', 'reinjury', 'age', 'height_m', 'mass_kg', 'bmi']
df = df[df['reinjury'].str.upper() != 'BLANK'] #get rid of all blank in reinjury

prop_noreinjury = df['reinjury'].value_counts(normalize=True).get('No', 0) #get proportion of no reinjury
print(f"Proportion of patients with no reinjury: {prop_noreinjury:.2%}") #print proportion

df['reinjury_shifted'] = df['reinjury'].shift(-1) #align reinjury with other values
df_cleaned = df[df['graft_dashboard2'].notna()][['graft_dashboard2', 'reinjury_shifted']] #get rid of rows with missing values
df_cleaned.columns = ['graft_dashboard2', 'reinjury'] #rename
```

```

counts = ( #get counts of graft and reinjury
    df_cleaned.groupby(['graft_dashboard2', 'reinjury'])
    .size()
    .reset_index(name='count')
)

graft_order = ['Allograft', 'QT autograft', 'HS autograft', 'BTB autograft', 'Other'] #order
counts['graft_dashboard2'] = pd.Categorical( #set order in counts
    counts['graft_dashboard2'],
    categories=graft_order,
    ordered=True
)
total_per_graft = counts.groupby('graft_dashboard2')['count'].transform('sum') #get sums
counts['proportion'] = counts['count'] / total_per_graft #calculate proportions
#show proportions
print(counts)
print('No reinjury proportions by Graft type:\n' +
'Allograft: 0.83\n' +
'BTB autograft: 0.89\n' +
'HS autograft: 0.92\n' +
'QT autograft: 0.87\n' +
'Other: 0.84\n')

counts_noreinjury = counts[counts['reinjury'] != 'No'] #get rid of no reinjury bar
plt.figure(figsize=(10, 6))
sns.barplot( #make grouped barplot
    data=counts_noreinjury,
    x='graft_dashboard2',
    y='proportion',
    hue='reinjury',
    palette='mako'
)
plt.xlabel('Graft Type')
plt.ylabel('Proportion of Reinjury Type')
plt.title('Undergoing ACLR Surgery? Consider a Hamstring (HS) Tendon Autograft', fontsize=14)
plt.text(0.01, 0.98, 'Comparing Proportions of Reinjury Types Across Different Graft Types',
         ha='left', va='center', transform=plt.gca().transAxes, fontsize=10, color='gray')
plt.legend(title='Reinjury Type', loc='upper left', bbox_to_anchor=(0.775, 1.0))
plt.text(-0.8, -0.02, 'Source: UVA Department of Kinesiology and School of Data Science', ha='right', va='bottom', color='gray')

sns.despine(top=True, right=True, left=True) #get rid of axes
plt.show()

```

```
findfont: Font family ['Georgia'] not found. Falling back to DejaVu Sans.  
/tmp/ipykernel_11986/934650589.py:27: FutureWarning:
```

```
The default of observed=False is deprecated and will be changed to True in a future version of pandas.
```

Proportion of patients with no reinjury: 87.47%

	graft_dashboard2	reinjury	count	proportion
0	Allograft	Both	1	0.009174
1	Allograft	Contralateral	3	0.027523
2	Allograft	Ipsilateral	15	0.137615
3	Allograft	No	90	0.825688
4	BTB autograft	Contralateral	14	0.071066
5	BTB autograft	Ipsilateral	7	0.035533
6	BTB autograft	No	176	0.893401
7	HS autograft	Contralateral	10	0.048544
8	HS autograft	Ipsilateral	7	0.033981
9	HS autograft	No	189	0.917476
10	Other	Contralateral	12	0.100840
11	Other	Ipsilateral	7	0.058824
12	Other	No	100	0.840336
13	QT autograft	Contralateral	8	0.067797
14	QT autograft	Ipsilateral	7	0.059322
15	QT autograft	No	103	0.872881

No reinjury proportions by Graft type:

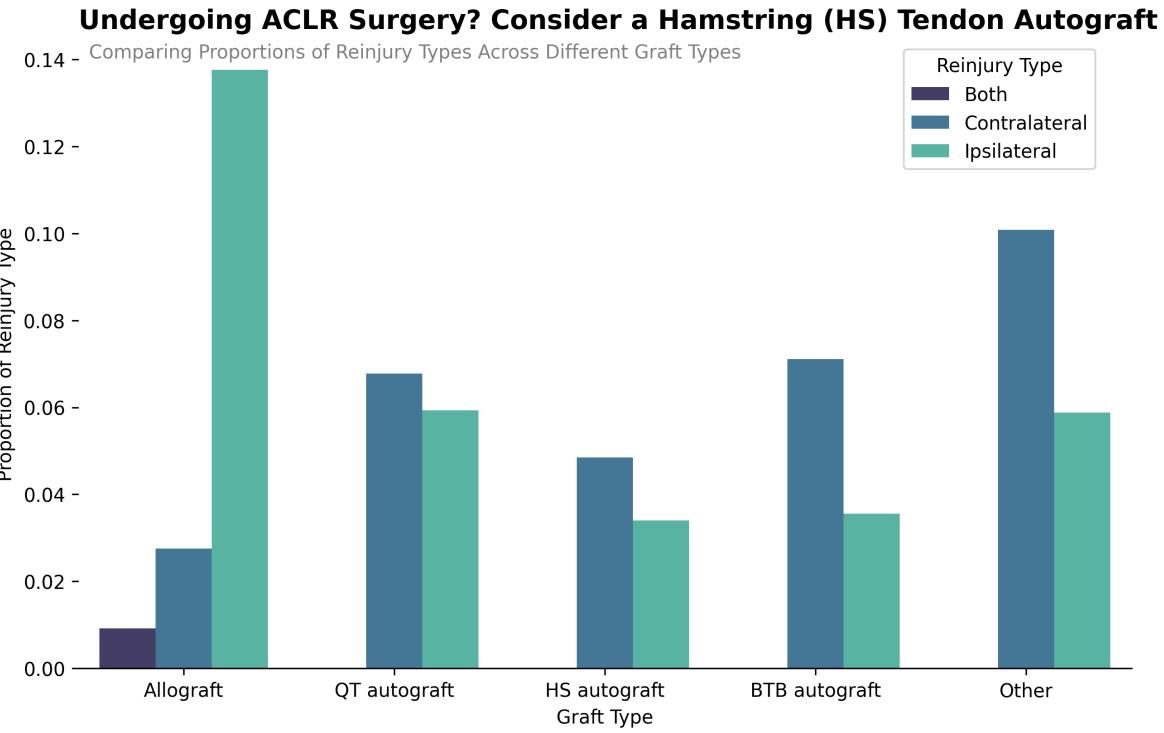
Allograft: 0.83

BTB autograft: 0.89

HS autograft: 0.92

QT autograft: 0.87

Other: 0.84



Source: UVA Department of Kinesiology and School of Data Science

Graph 3: Looking at the relationship between different reinjuries between the sexes.

```
# small multiples bar chart

# Set font family to Georgia
georgia_font = font_manager.FontProperties(family='Georgia')
plt.rcParams['font.family'] = georgia_font.get_name()

# Records were mismatched so we shifted row values by 1
# (for every graft_type recorded, reinjury was blank so shifted by 1 to match)
m_df['reinjury_shifted'] = m_df['reinjury'].shift(-1)
df2 = m_df[m_df['sex_dashboard'].notna()][['sex_dashboard', 'reinjury_shifted']]
df2.columns = ['sex_dashboard', 'reinjury']
# print(df2.head()) # previewing cleaned dataset

df2 = df2[
    (df2['reinjury'].str.upper() != 'BLANK') &
    (df2['sex_dashboard'].str.upper() != 'BLANK')]

df2 = df2[df2['reinjury'].str.upper() != 'NO'] # dropping 'no' reinjury records
```

```

df2= df2[df2['reinjury'].str.upper() != 'BOTH'] # dropping 'both' reinjury records

grouped_counts2 = (
    df2.groupby(['sex_dashboard', 'reinjury'])
    .size()
    .reset_index(name='count')
)

# Create sub-dataframes for Contralateral and Ipsilateral
df_contra = grouped_counts2[grouped_counts2['reinjury'] == 'Contralateral']
df_iphi = grouped_counts2[grouped_counts2['reinjury'] == 'Ipsilateral']

# Set up 1x2 subplot grid
fig, axs = plt.subplots(1, 2, figsize=(12, 5), sharey=True)

# Title
fig.suptitle('Males Reinjure Their ACLs More Than Females Overall', fontsize=14, weight='bold')

# Contralateral subplot
colors_contra = df_contra['sex_dashboard'].map({'Male': '#C8E7F5', 'Female': '#F6D2E0'}) # 1
bars_contra = axs[0].barh(df_contra['sex_dashboard'], df_contra['count'], color=colors_contra)
axs[0].set_title('Contralateral', loc='left', weight='bold', color='black')
axs[0].grid(axis='x', linestyle=':', color='gray')
axs[0].spines['top'].set_visible(False)
axs[0].spines['right'].set_visible(False)
axs[0].spines['bottom'].set_visible(False)
axs[0].tick_params(axis='x', length=0)
axs[0].tick_params(axis='y', length=0)

for bar in bars_contra:
    xval = bar.get_width()
    axs[0].text(xval + 0.5, bar.get_y() + bar.get_height()/2,
                round(xval), va='center', ha='left', fontsize=10)

# Ipsilateral subplot
colors_iphi = df_iphi['sex_dashboard'].map({'Male': '#C8E7F5', 'Female': '#F6D2E0'}) # 1
bars_iphi = axs[1].barh(df_iphi['sex_dashboard'], df_iphi['count'], color=colors_iphi)
axs[1].set_title('Ipsilateral', loc='left', weight='bold', color='black')
axs[1].grid(axis='x', linestyle=':', color='gray')
axs[1].spines['top'].set_visible(False)

```

```

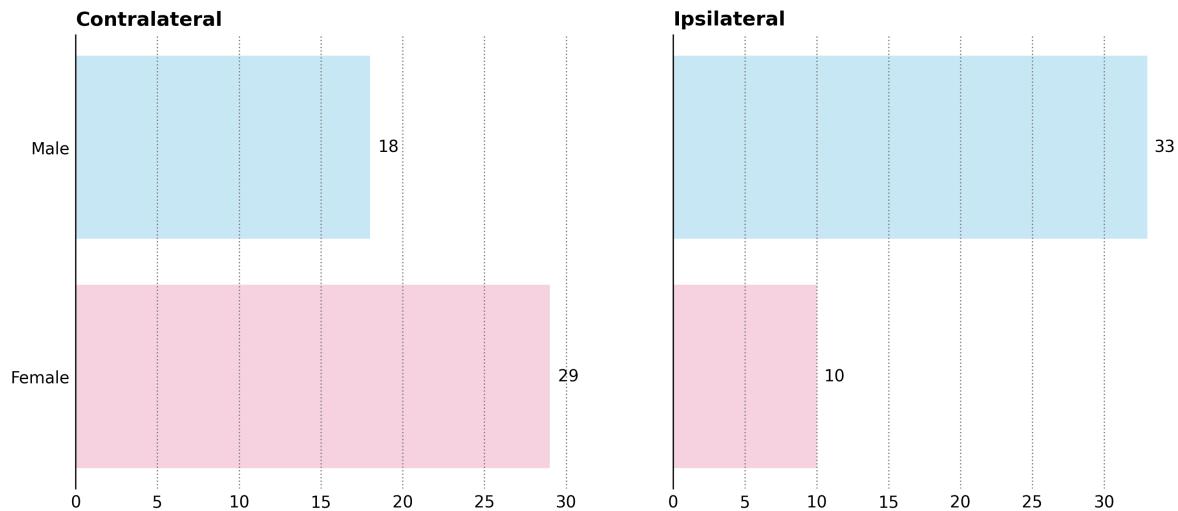
axs[1].spines['right'].set_visible(False)
axs[1].spines['bottom'].set_visible(False)
axs[1].tick_params(axis='x', length=0)
axs[1].tick_params(axis='y', length=0)

for bar in bars_ipsi:
    xval = bar.get_width()
    axs[1].text(xval + 0.5, bar.get_y() + bar.get_height()/2,
                round(xval), va='center', ha='left', fontsize=10)

# Final layout
plt.text(-42, -0.8, 'Source: UVA Department of Kinesiology and School of Data Science', ha='left')
# plt.tight_layout()
plt.show()

```

Males Reinjure Their ACLs More Than Females Overall



Source: UVA Department of Kinesiology and School of Data Science

4 Data Dictionary

Here are the relevant variables we used to complete our analysis with their meanings.

Variable	Description
acl_rsi	The return-to-sport-after-injury score is self-reported by the patient.
age	The age at which the patient received surgery.
bmi	Body mass index of the patient.
graft_dashboard2	The types of grafts used in surgery are allograft, QT autograft, HS autograft, BTB autograft, and others.
height_m	The height of the patient in meters.
ikdc	A patient-reported outcome measure used to assess knee function and symptoms.
mass_kg	The weight of the patient in kilograms.
reinjury	The different types of reinjuries: contralateral, ipsilateral, and both.
sex_dashboard	The gender of the patient: male or female.
tss_dashboard	Categorizes the months post-surgery into subsets.