ACLR Final Project

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Table of contents

Report

Audience

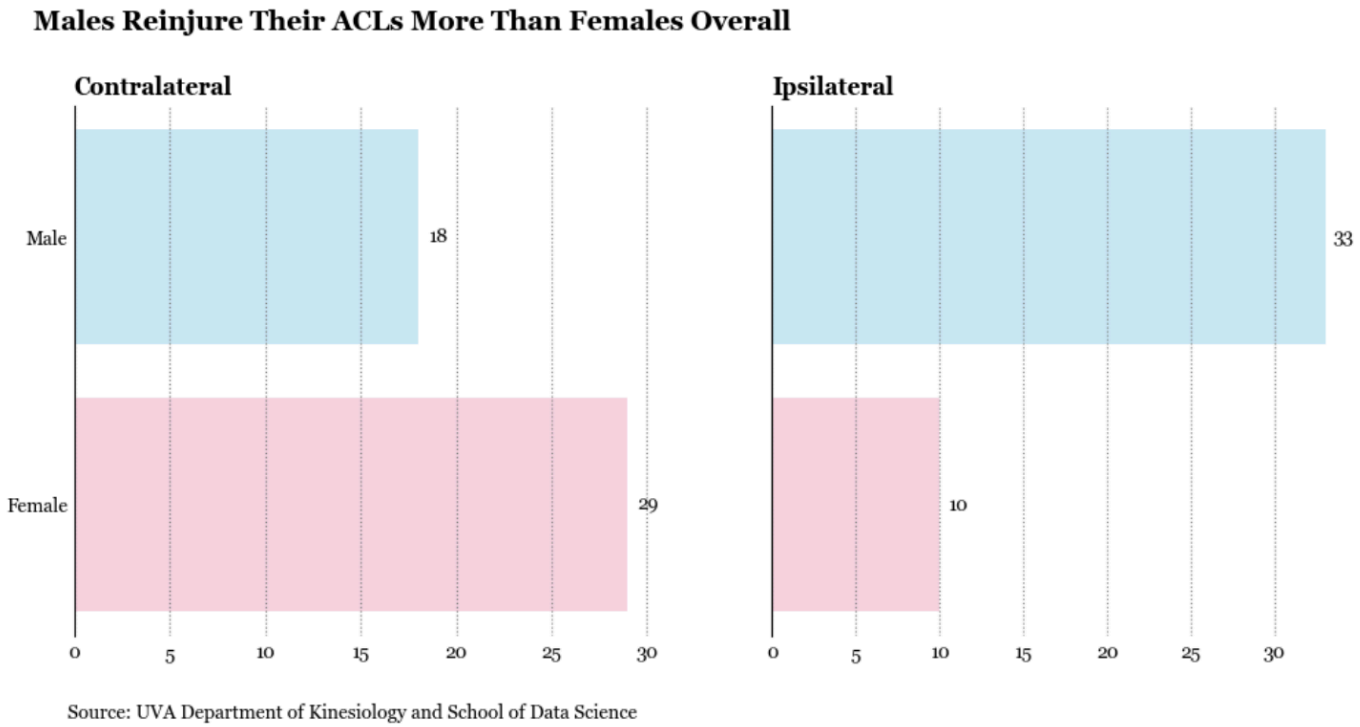
Our final report's audience/stakeholders include physicians and other researchers evaluating the health of patients who have undergone ACL reconstruction surgery.

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.

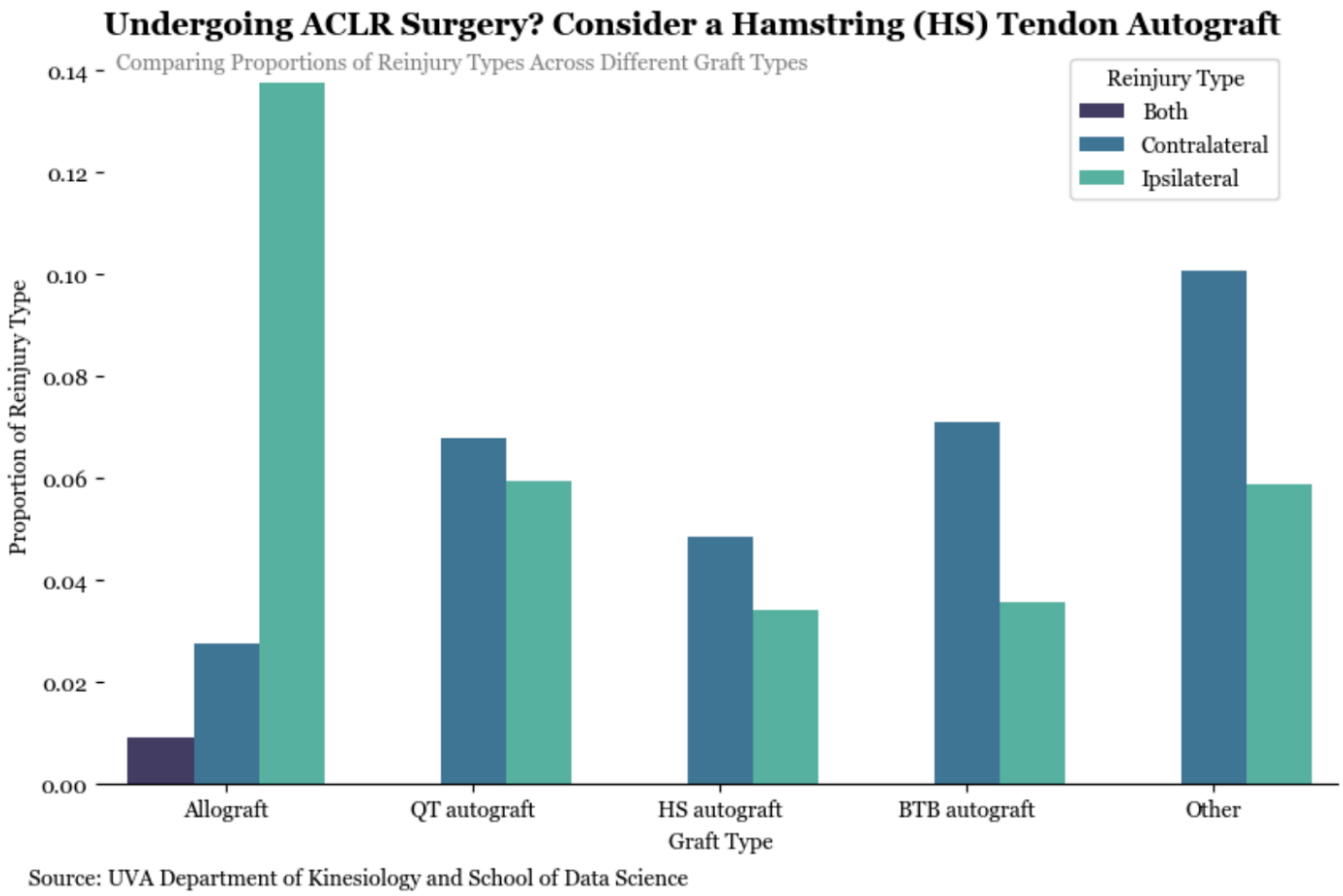
Analysis

Graph 1:



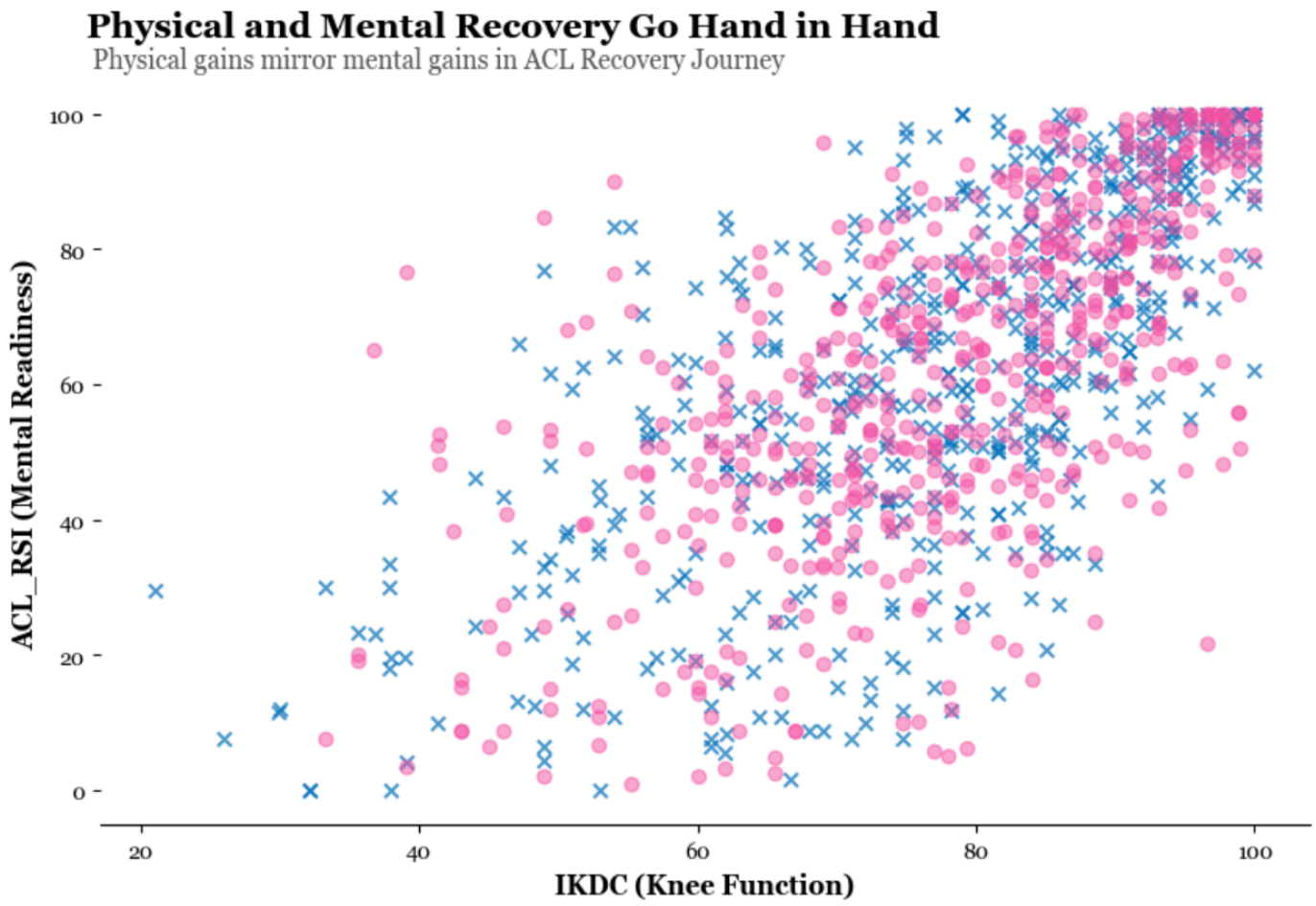
Throughout this simulated study, we found that overall, more males than females have reinjured their ACLs. As shown in this graph, men have a greater count of ipsilateral reinjuries than females, while women have a greater count of contralateral reinjuries than males. This finding is consistent with other research, as according to the National Institute of Health, female athletes were found to be 6 times more likely to suffer a contralateral reinjury than their male counterparts (Paterno et.al, 2). Further, the total count of contralateral reinjuries is greater than ipsilateral reinjuries, 47 and 43, respectively. Ipsilateral refers to the reinjury of the knee on the same side as the previous ACLR, reinjuring the same knee as before. Contralateral refers to the reinjury of the knee on the opposite side of the previous ACLR, reinjuring the other knee. We questioned why this might be the case, so we looked to see what grafts might be causing these reinjuries as well.

Graph 2:



The grafts in ACLR surgery are the ligaments used to replace the injured ACL. Most of the procedures in this case study were autografts, meaning that they were taken from the patient themselves. The grafts used in this study were the HS autograft, which uses the hamstring tendon. The BTB autograft, which uses the patellar tendon. The QT autograft, which uses the quadriceps tendon. An allograft, which uses tendon from a deceased donor to replace the ACL. Other, which uses tendon/tissue from the areas not listed above. Based on graph 2, which illustrates the proportions of graft types relative to their reinjury rates, we recommend undergoing ACLR surgery using the HS autograft, which has the highest proportion of no reinjuries and the average lowest proportion of contralateral and ipsilateral reinjuries. On the other hand, patients who undergo an allograft are much more likely to have ipsilateral reinjuries or even both types of reinjuries.

Graph 3:



In our final analysis, we examined the relationship between psychological readiness and perceived functional outcome by plotting ACL-RSI (psychological readiness) scores against IKDC (knee function) scores. The scatterplot revealed a clear positive correlation, suggesting that athletes who report feeling more psychologically prepared to return to sport (higher ACL-RSI) also tend to report better physical function and recovery (higher IKDC).This finding emphasizes the critical role of mental readiness in recovery outcomes, not just physical healing. Regardless of graft type or reinjury risk, it appears that athletes with stronger psychological confidence may have smoother functional recoveries—a reminder that holistic rehabilitation should integrate mental and emotional well-being alongside physical therapy.

Conclusion

Together, all three graphs demonstrate the nuance behind ACL reinjury and recovery. We found sex-specific risks, with men experiencing more ipsilateral tears and women experiencing more contralateral tears. Our graft analysis illustrated how different grafts may influence the type of reinjury, with each option carrying its own benefits and drawbacks. Lastly, we found that regardless of injury type, players who report higher mental readiness tend to experience better physical recovery. Overall, our findings underscore the importance of a personalized recovery approach—one that considers sex, surgical decisions, and the athlete's psychological readiness.

1 Data Cleaning Outline

Documentation for our data cleaning process, including decisions regarding how we handle missing values, outliers, and other data quality issues.

First, we import the necessary libraries and set the dataset which is a .csv file provided by the UVA School of Data Science and the UVA Department of Kinesiology as a pandas dataframe.

```
# Setting up our environment, importing all necessary libraries:
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Importing dataset as dataframe:
df = pd.read_csv('aclr data(in).csv')
```

```
# Previewing the dataframe:
df.head()
```

	record_id	redcap_event_name	redcap_repeat_instrument	sex_dashboard	graft_dashboa
0	1	baseline_arm_1	NaN	Male	Other
1	1	visit_1_arm_1	NaN	NaN	NaN
2	1	long_term_outcomes_arm_1	NaN	NaN	NaN
3	2	baseline_arm_1	NaN	Female	HS autograft
4	2	visit_1_arm_1	NaN	NaN	NaN

```
# Checking the dimensions of the dataframe:
print(df.shape)
```

```
(11150, 63)
```

The original dataframe has 11150 observations and 63 columns. We will be focusing on the variables we feel are most relevant to our hypothesis. We will be using the columns: `sex_dashboard`, `graft_dashboard2`, `reinjury`, `age`, `height_m`, `mass_kg`, `bmi`, `ikdc`, `acl_rsi` and dropping the rest from the dataframe.

```
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

Now that we have our columns of interest, we will first check for missing values across the dataset. We will use the `isnull()` method to check for missing values and the `sum()` method to get the total number of missing values in each column, as well as the percentage of missing values in each column.

```
# Checking for missing values:
missing_values = df.isnull().sum()

# Checking the percentage of missing values:
missing_percentage = (missing_values / len(df)) * 100
# Displaying missing values and their percentage:
missing_values = pd.DataFrame({'Missing Values': missing_values, 'Percentage': missing_percer

# Displaying the missing values:
print(missing_values)
```

```
                 Missing Values  Percentage
sex_dashboard              6413   57.515695
graft_dashboard2           6413   57.515695
reinjury                   5975   53.587444
age                        6024   54.026906
height_m                   8632   77.417040
mass_kg                    7899   70.843049
bmi                        8633   77.426009
ikdc                       8199   73.533632
acl_rsi                    7750   69.506726
tss_dashboard              5913   53.031390
```

Now we will proceed by separating the variables into categorical and continuous variables. We will use the `select_dtypes()` method to select the categorical variables and the continuous variables. For our numerical variables, we will impute missing values with the respective mean for each column.

```
# Filtering for numeric columns:
numeric_columns = df.select_dtypes(include=['int', 'float']).columns

# Imputing missing values with the mean for each respective column/varibale:
mean_values = df[numeric_columns].mean()
m_df = df.fillna(mean_values)

# Displaying the first 5 rows of the modified dataframe:
(m_df.head(5))
```

	sex_dashboard	graft_dashboard2	reinjury	age	height_m	mass_kg	bmi	ikdc
0	Male	Other	NaN	20.184761	1.725412	74.343033	25.201579	78.457377
1	NaN	NaN	No	21.700000	1.900000	87.400000	24.210526	95.400000
2	NaN	NaN	NaN	20.184761	1.725412	74.343033	25.201579	78.457377
3	Female	HS autograft	NaN	20.184761	1.725412	74.343033	25.201579	78.457377
4	NaN	NaN	No	14.500000	1.600000	72.200000	28.203125	79.300000

For our categorical variables, we have decided to fill the missing values with just an `Unknown` category, since this allows us to keep the rows with missing values without losing too much information so that we can continue with plotting later on.

```
# Filtering for Categorical columns:
categorical_columns = df.select_dtypes(include=['object']).columns
# Imputing missing values with the value 'Unknown' for each respective column/variable:
for column in categorical_columns:
    m_df[column] = m_df[column].fillna('Unknown')

# Displaying the first 5 rows of the modified dataframe:
(m_df.head(5))
```

	sex_dashboard	graft_dashboard2	reinjury	age	height_m	mass_kg	bmi	ikdc
0	Male	Other	Unknown	20.184761	1.725412	74.343033	25.201579	78.4573

	sex_dashboard	graft_dashboard2	reinjury	age	height_m	mass_kg	bmi	ikdc
1	Unknown	Unknown	No	21.700000	1.900000	87.400000	24.210526	95.40000
2	Unknown	Unknown	Unknown	20.184761	1.725412	74.343033	25.201579	78.45737
3	Female	HS autograft	Unknown	20.184761	1.725412	74.343033	25.201579	78.45737
4	Unknown	Unknown	No	14.500000	1.600000	72.200000	28.203125	79.30000

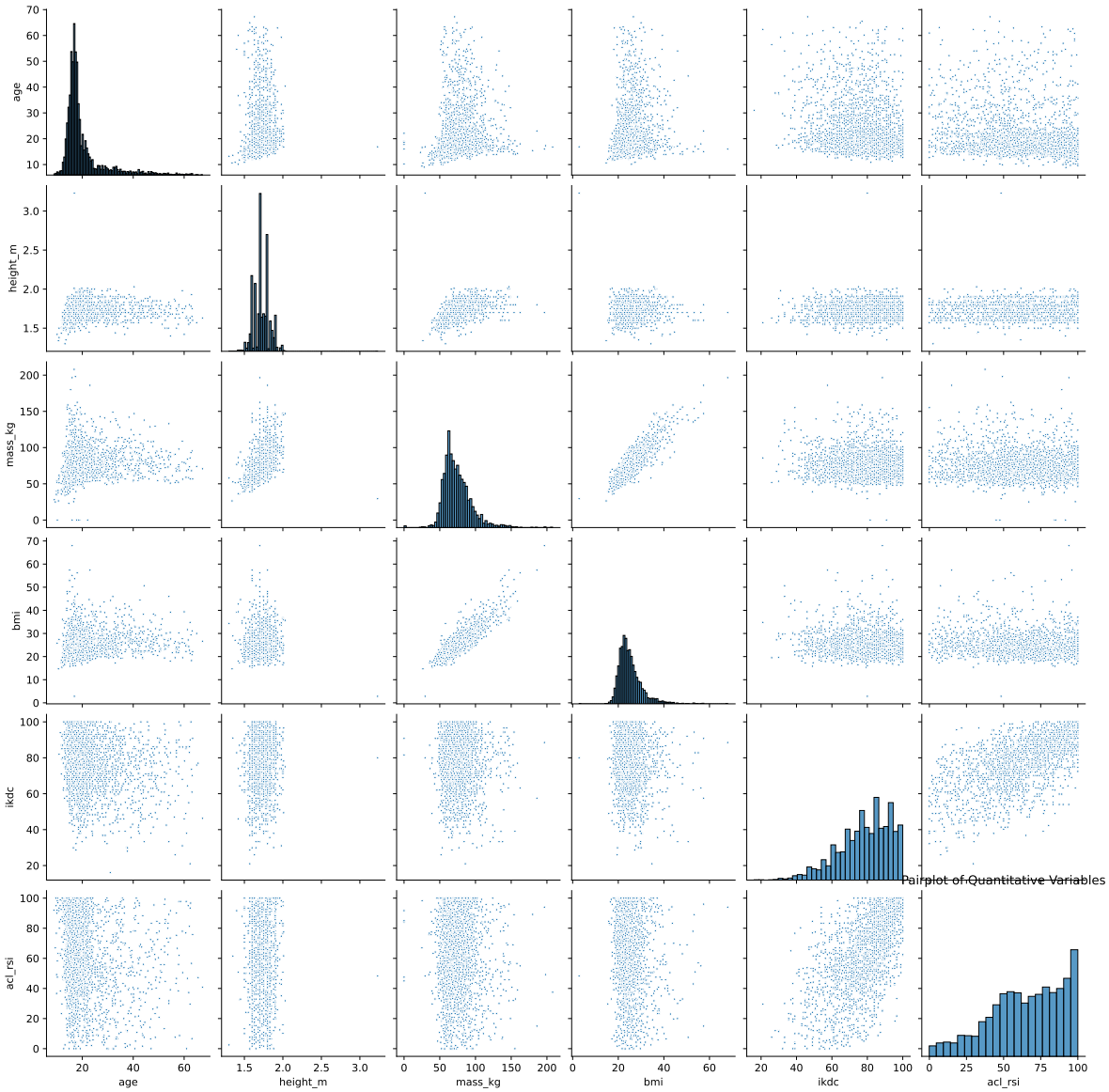
Now we have finished our early data cleaning process and are ready to explore relations in our EDA process.

2 Exploratory Data Analysis

Preview of the cleaned dataset: (first five rows)

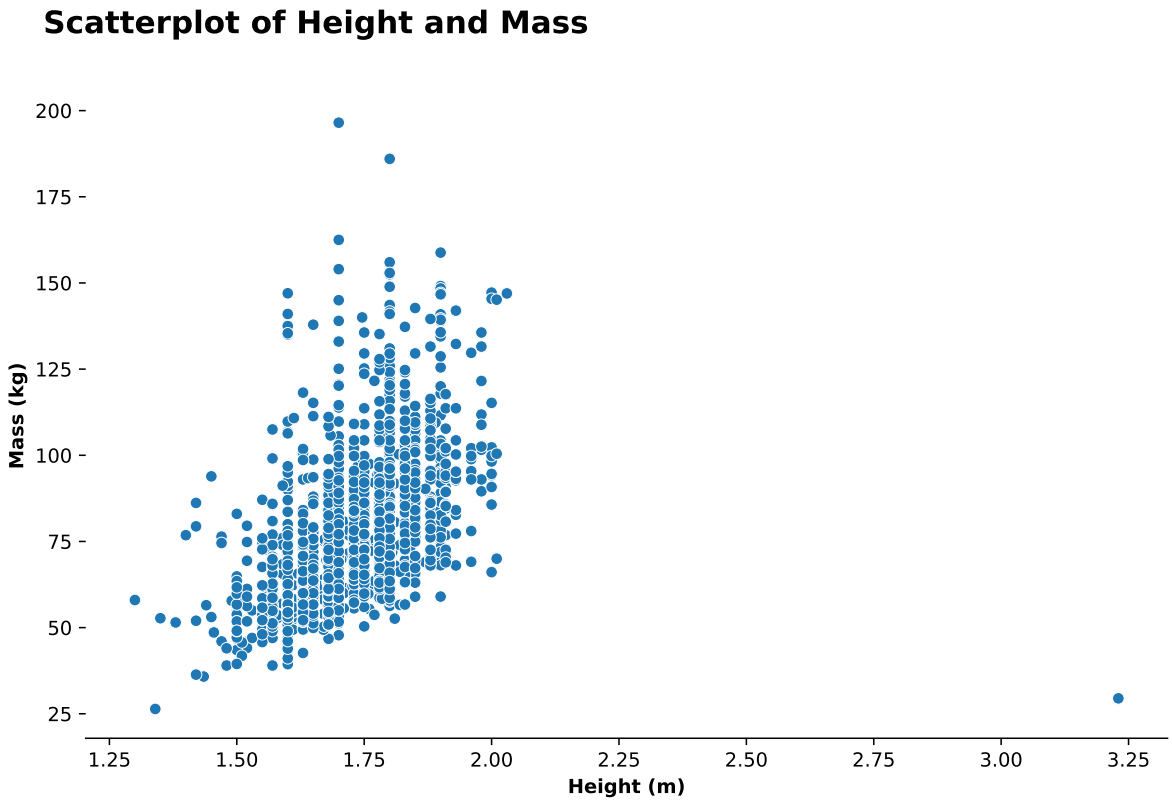
	sex_dashboard	graft_dashboard2	reinjury	age	height_m	mass_kg	bmi	ikdc	acl_rsi
0	Male	Other	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	No	21.7	1.9	87.4	24.210526	95.4	87.5
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Female	HS autograft	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	No	14.5	1.6	72.2	28.203125	79.3	8.3

2.1 Pairplot of our chosen variables



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 postively 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.

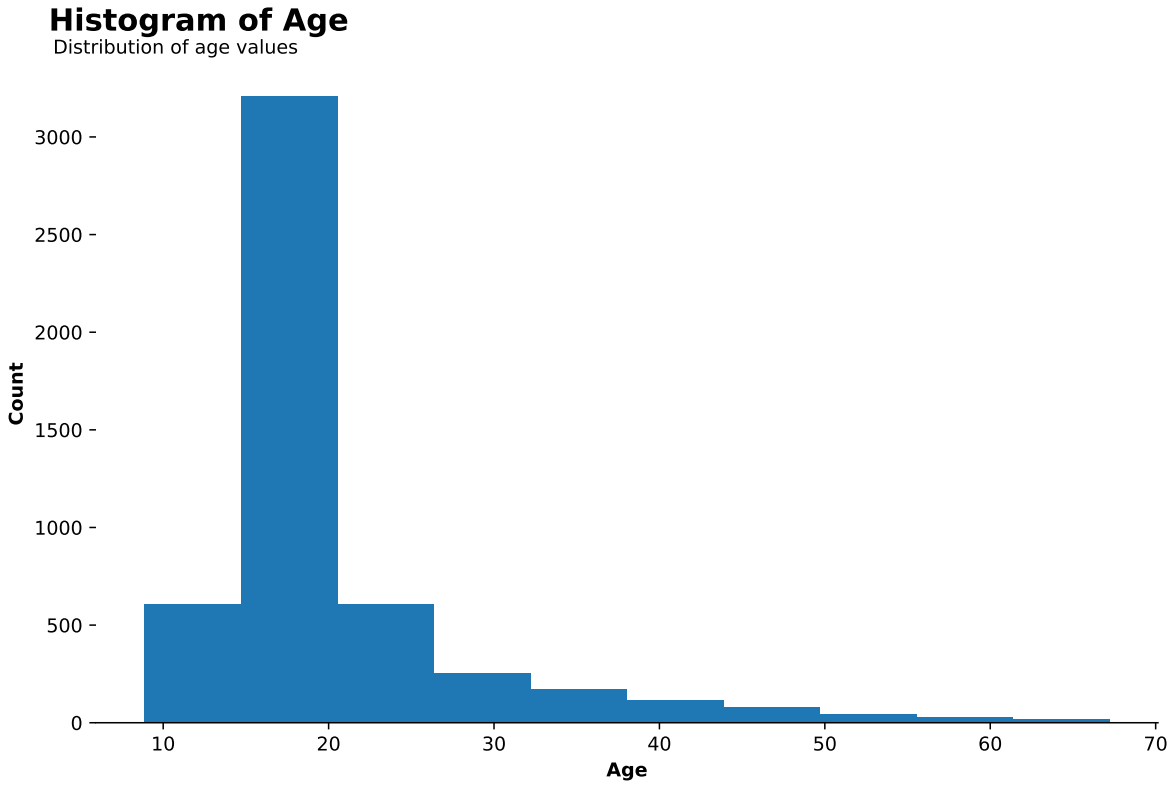
2.2 Looking at Specific Distributions



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.

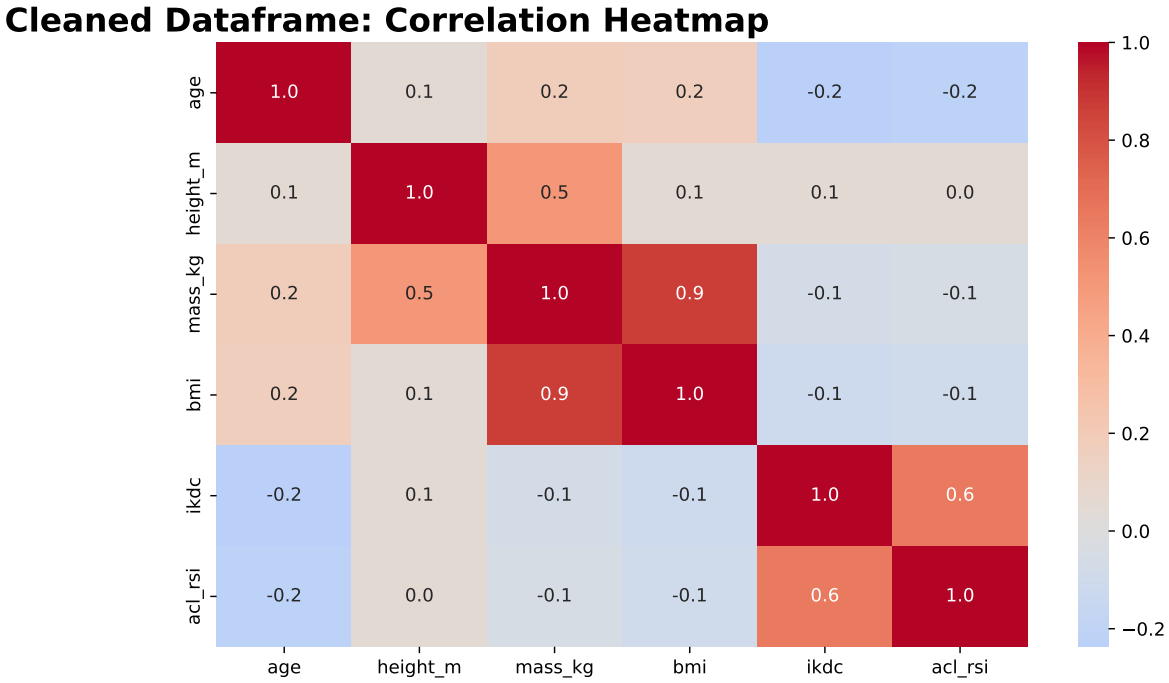
```
# Histogram for 'age'
plt.figure(figsize=(10,6))
df['age'].plot(kind='hist')

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()
```



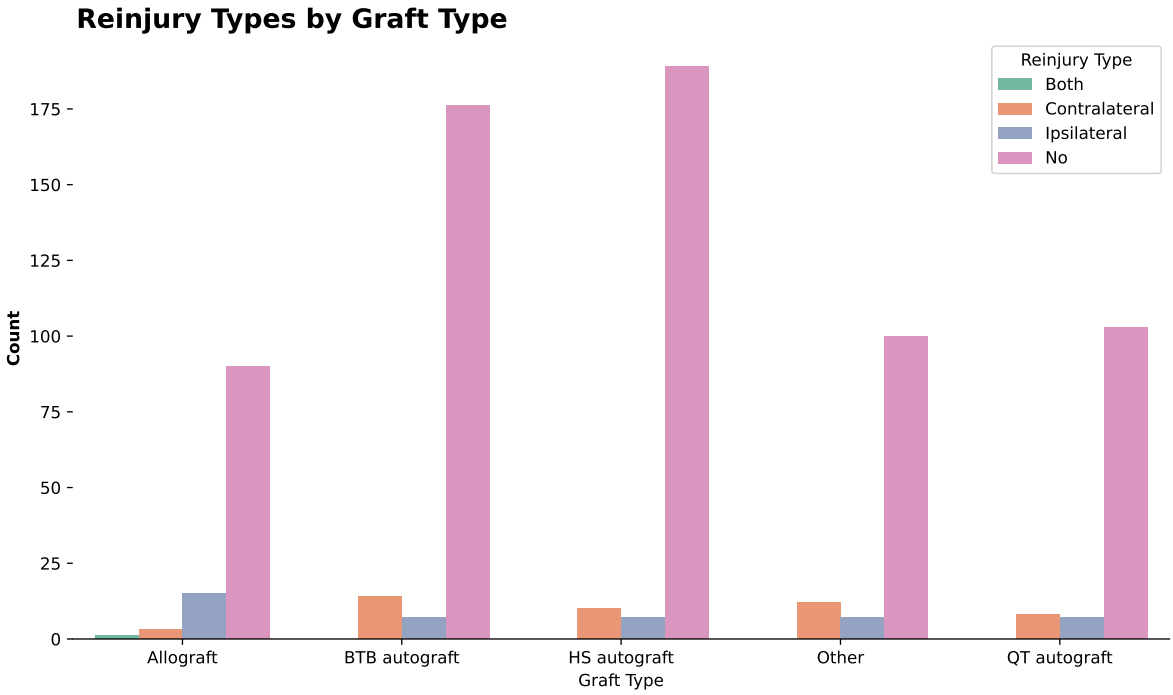
This is a histogram of the ages of all the patients in the study. As we can see there is a right tail skew; most participants are between the ages of 15-20. This makes sense since this study was likely done with many student athletes. There are a couple of older patients in their 50s and 60s, so it could be interesting to see how recovery is affected by age.

2.3 Examine Correlations



What variables appear related? The most positively correlated variables are between bmi and mass. This supports our earlier scatterplot that showed a positive trend between height and mass as well, which is great. Something interesting is there is a relatively positive relationship between ikdc and acl_rsi. This is also to be expected because both are patient reported - ikdc is a measure of knee function, while acl_rsi is the return-to-sport-after-injury score.

2.4 Looking into Reinjury Type and Graft Type



We were curious if there was any relationship between reinjury types across different graft types, so we made this grouped barplot. It seems that HS autograft has the highest proportion of no reinjuries, while the BTB autograft seems to have the highest recorded count of contralateral reinjuries. This is a super interesting visualization, so we decided to include this relationship in our data visualizations, along with some other characteristics on the next page! HS Autograft has the highest proportion of no reinjuries, while the BTB autograft seems to have the highest recorded count of Contralateral reinjuries.

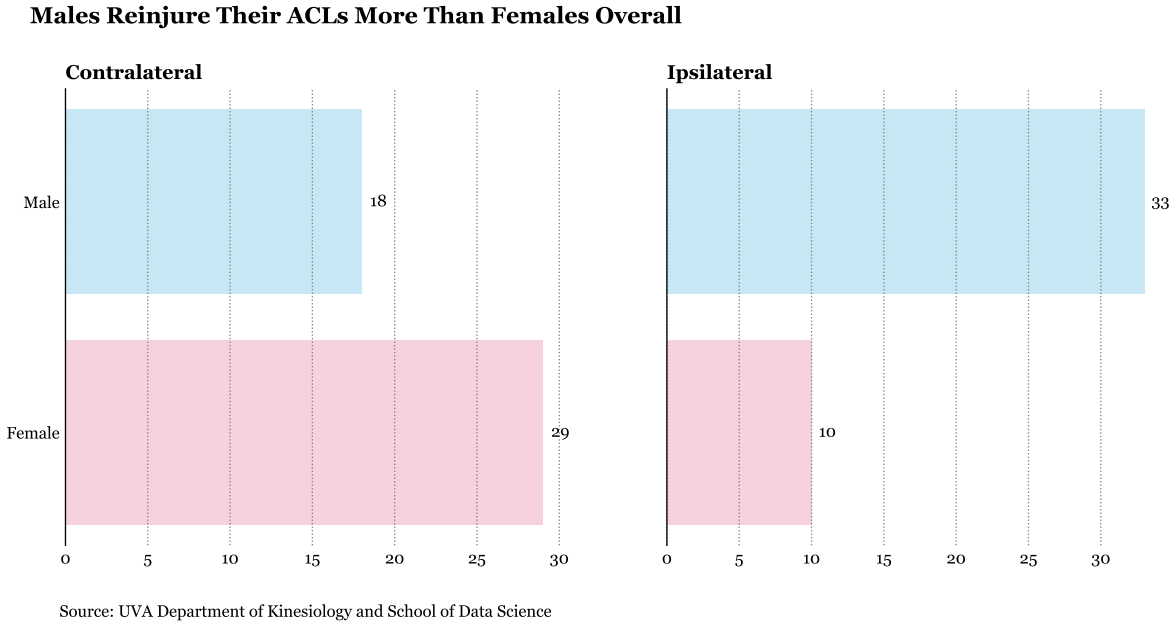
3 Data Visualization

3.1 Graph 1:

Breaking down reinjuries by type among both sexes.

```
# small multiples bar chart

from matplotlib import font_manager
# 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']

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 = ( # group by sex and reinjury
    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_ipsi = 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'})  # l
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: # adding labels to the ends of each bar
    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_ipsi = df_ipsi['sex_dashboard'].map({'Male': '#C8E7F5', 'Female': '#F6D2E0'})
bars_ipsi = axs[1].barh(df_ipsi['sex_dashboard'], df_ipsi['count'], color=colors_ipsi)
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: # adding labels to the ends of each bar
    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='l
# plt.tight_layout()
plt.show()
```



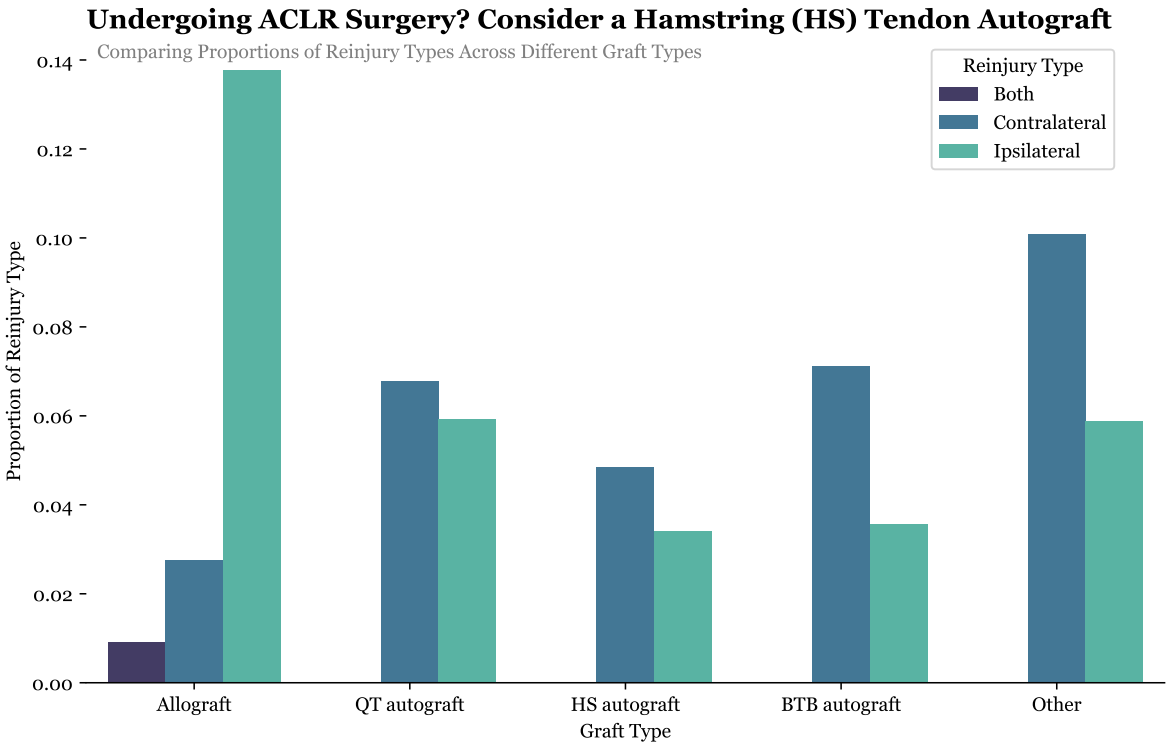
3.2 Graph 2:

Visualizing distribution of reinjuries as proportions to each respective graft type.

```
df = df[['sex_dashboard', 'graft_dashboard2', 'reinjury', 'age', 'height_m', 'mass_kg', 'bmi
# cleaning reinjury variable
df = df[df['reinjury'].str.upper() != 'BLANK']

#proportion of patients with no reinjury
prop_noreinjury = df['reinjury'].value_counts(normalize=True).get('No', 0)
print(f"Proportion of patients with no reinjury: {prop_noreinjury:.2%}")
# cleaning dataframe
df['reinjury_shifted'] = df['reinjury'].shift(-1) #align reinjury with other values
df_cleaned = df[df['graft_dashboard2'].notna()][['graft_dashboard2', 'reinjury_shifted']] #g
df_cleaned.columns = ['graft_dashboard2', 'reinjury']

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

```
#order of grafts
graft_order = ['Allograft', 'QT autograft', 'HS autograft', 'BTB autograft', 'Other']
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
# print(counts)
# print('No reinjury proportions by Graft type:\nAllograft: 0.83\nBTB autograft: 0.89\nHS au

#get rid of no reinjury bar for readability
counts_noreinjury = counts[counts['reinjury'] != 'No']
#make grouped barplot
plt.figure(figsize=(10, 6))
sns.barplot(
    data=counts_noreinjury,
    x='graft_dashboard2',
    y='proportion',
    hue='reinjury',
    palette='mako'
)

# graph labels and scaffolding
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=
sns.despine(top=True, right=True, left=True) #get rid of axes
plt.show()
```

```
Proportion of patients with no reinjury: 87.47%
```



Source: UVA Department of Kinesiology and School of Data Science

3.3 Graph 3:

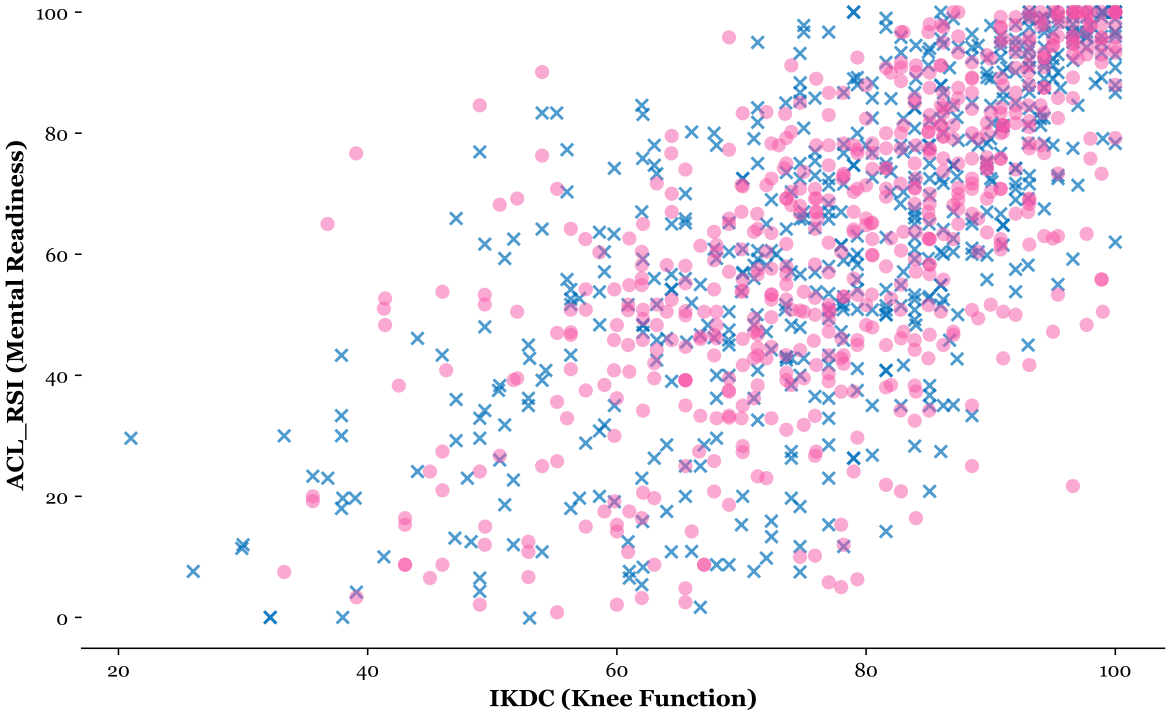
Visualizing the relation between mental fortitude and feelings of physcial recovery. Female athletes are represented by the pink circle markers, while males are the blue 'x'.

```
# == PLOT ==
# 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', h
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

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.