Sleep as a Predictor to Health in the Global Setting

Research Question:

Test if the combined data on sleep in relation to people's health and time allocation from each country can be used to predict the overall mental and physical healthiness (measured using the happiness index) of people from different global demographics.

Rationale:

Sleep is a critical biological function that affects physical health, mental health, and overall daily functioning. The quality and duration of sleep can significantly influence an individual's health outcomes and quality of life so understanding the relationship between physical and mental health and sleep across different global demographics can help us predict which country will be the healthiest overall.

Objective:

1) To determine the relationship between sleep quality and physical health indicators (like heart rate and blood pressure). 2) To analyze the sleep across global demographics and determine if there is a significant difference between people in different countries 3) Use this data to predict which country is overall the healthiest and check with a known happiness score from another database to see if we can predict a country's overall happiness and health using the amount of sleep they get.

Research Data:

1) Relationship between sleep, health and lifestyle of people: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset 2) World happiness report 2019: https://www.kaggle.com/datasets/mathurinache/world-happiness-report?resource=download 3) Time spent by people around the world https://www.kaggle.com/datasets/sujaykapadnis/what-humans-are-doing

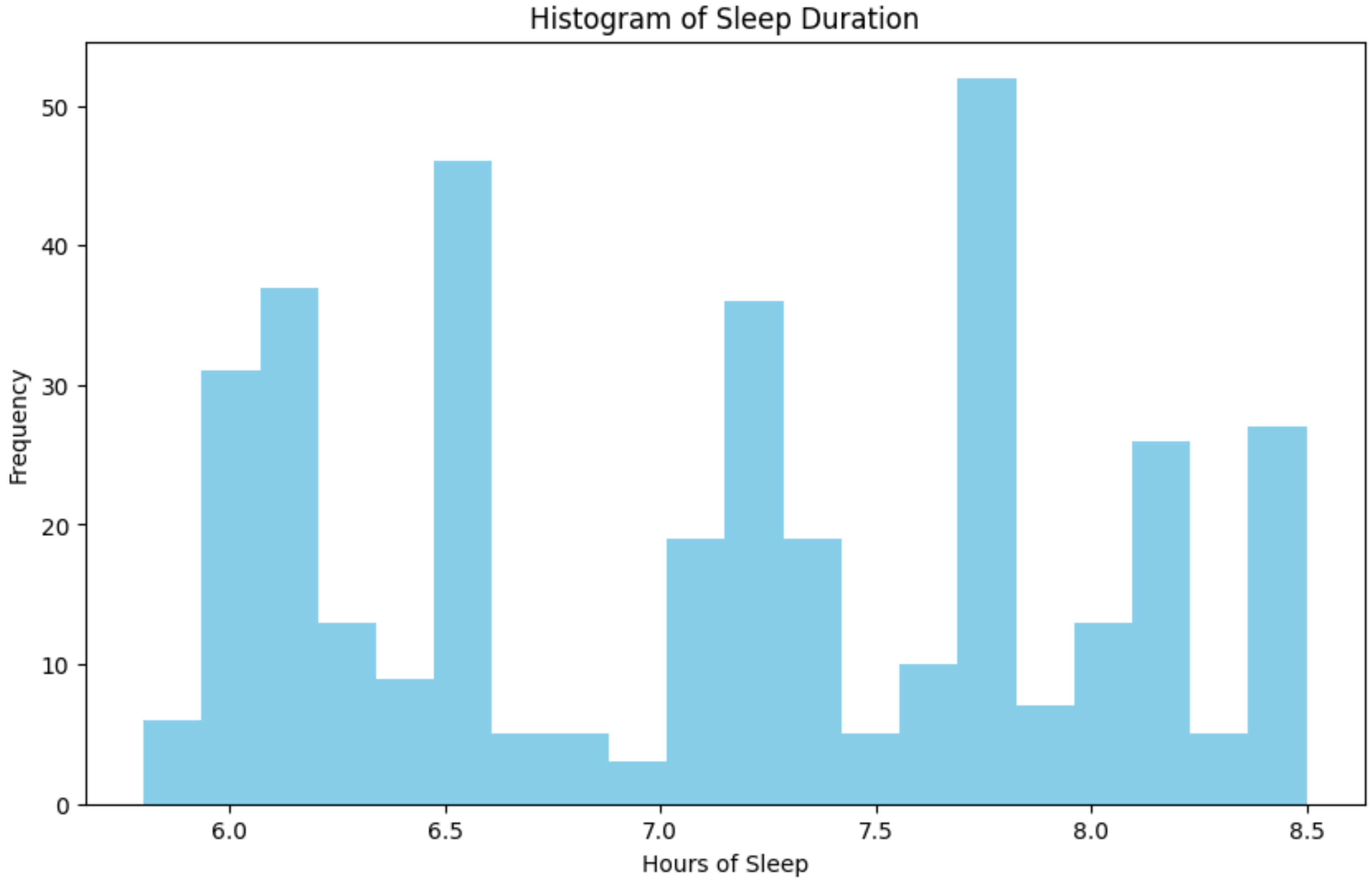
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset
sleep_health_lifestyle = pd.read_csv('Sleep_health_and_lifestyle_dataset.csv')

# https://www.kaggle.com/datasets/mathurinache/world-happiness-report?resource=download
happiness_data = pd.read_csv('./data-2019.csv')

# https://www.kaggle.com/datasets/sujaykapadnis/what-humans-are-doing
time_use = pd.read_csv('all-countries.csv')
print(happiness_data.head())

# summary stats for the dataset
```

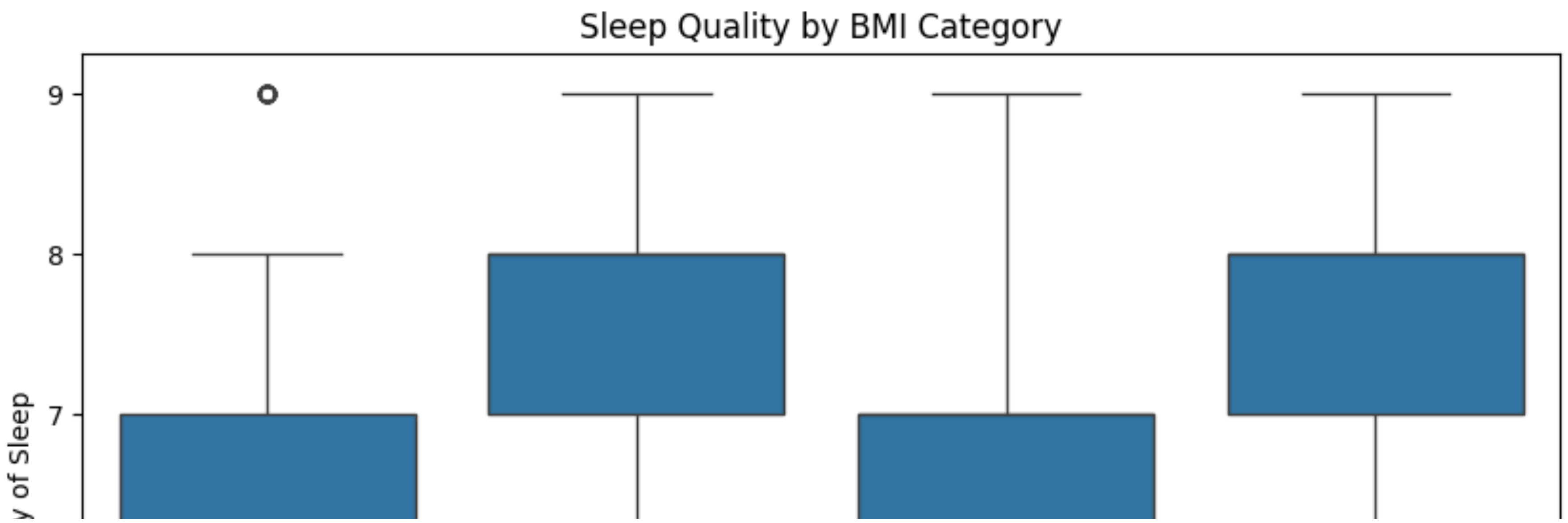
```
display(sleep_health_lifestyle.describe())

# histogram of Sleep Duration
plt.figure(figsize=(10, 6))
plt.hist(sleep_health_lifestyle['Sleep Duration'], bins=20, color='skyblue')
plt.title('Histogram of Sleep Duration')
plt.xlabel('Hours of Sleep')
plt.ylabel('Frequency')
plt.show()

# boxplot of Sleep Quality by BMI Category
plt.figure(figsize=(10, 6))
sns.boxplot(x='BMI Category', y='Quality of Sleep', data=sleep_health_lifestyle)
plt.title('Sleep Quality by BMI Category')
plt.xlabel('BMI Category')
plt.ylabel('Quality of Sleep')
plt.show()

# scatter plot of Sleep Duration vs. Heart Rate
plt.figure(figsize=(10, 6))
plt.scatter(sleep_health_lifestyle['Sleep Duration'], sleep_health_lifestyle['Heart Rate'], alpha=0.6)
plt.title('Sleep Duration vs. Heart Rate')
plt.xlabel('Sleep Duration (Hours)')
plt.ylabel('Heart Rate (Beats per Minute)')
plt.show()
```

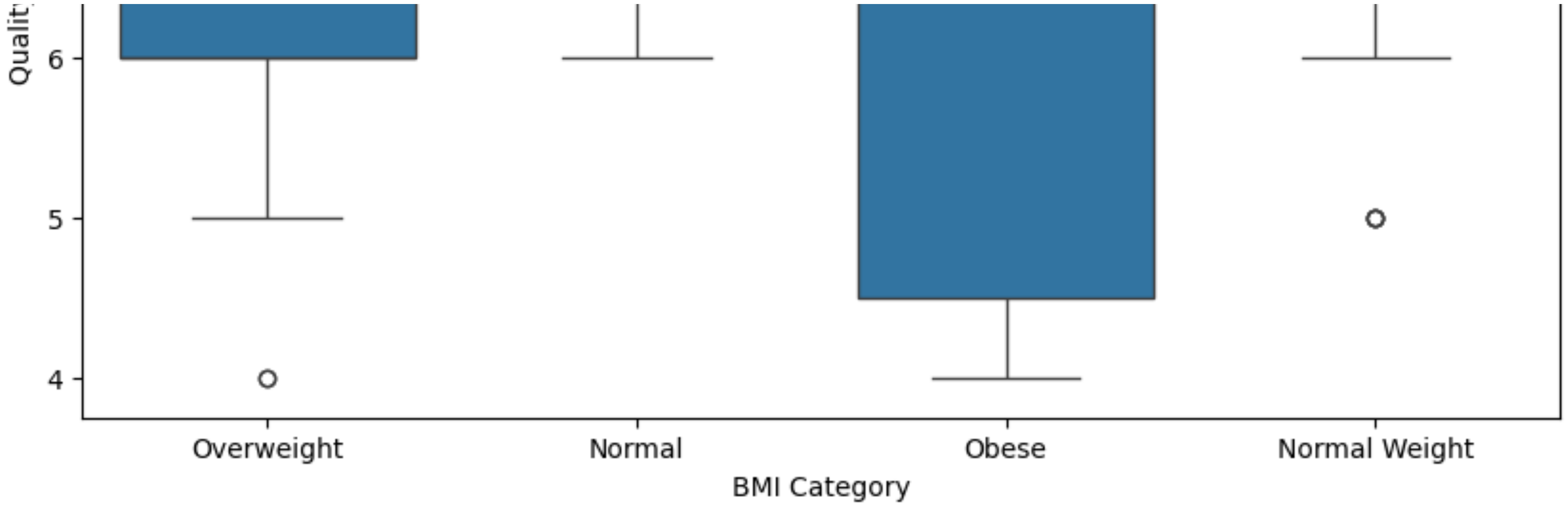
```
       Country                             Region  Rank 2019  Score 2019  \
0  Afghanistan                      Southern Asia        154       3.203
1      Albania       Central and Eastern Europe        107       4.719
2      Algeria  Middle East and Northern Africa         88       5.211
3    Argentina      Latin America and Caribbean         47       6.086
4      Armenia       Central and Eastern Europe        116       4.559

   GDP 2019  Family 2019  Life Expectancy 2019  Freedom 2019  Trust 2019  \
0     0.350        0.517                 0.361         0.000       0.025
1     0.947        0.848                 0.874         0.383       0.027
2     1.002        1.160                 0.785         0.086       0.114
3     1.092        1.432                 0.881         0.471       0.050
4     0.850        1.055                 0.815         0.283       0.064

   Generosity 2019
0            0.158
1            0.178
2            0.073
3            0.066
4            0.095
```

	Person ID	Age	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	Heart Rate	Daily Steps
count	374.000000	374.000000	374.000000	374.000000	374.000000	374.000000	374.000000	374.000000
mean	187.500000	42.184492	7.132086	7.312834	59.171123	5.385027	70.165775	6816.844920
std	108.108742	8.673133	0.795657	1.196956	20.830804	1.774526	4.135676	1617.915679

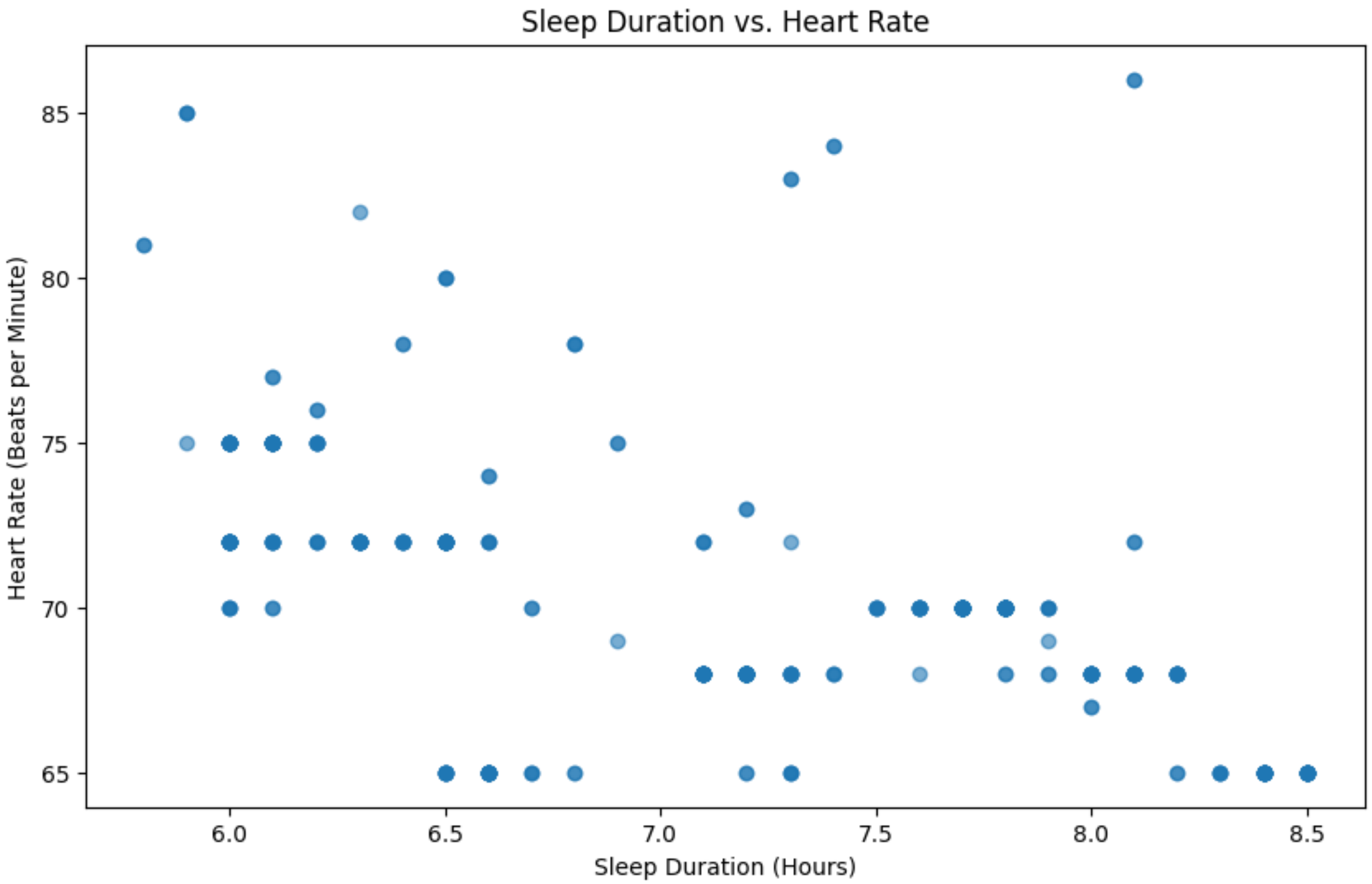
min	1.000000	27.000000	5.800000	4.000000	30.000000	3.000000	65.000000	3000.000000
25%	94.250000	35.250000	6.400000	6.000000	45.000000	4.000000	68.000000	5600.000000
50%	187.500000	43.000000	7.200000	7.000000	60.000000	5.000000	70.000000	7000.000000
75%	280.750000	50.000000	7.800000	8.000000	75.000000	7.000000	72.000000	8000.000000
max	374.000000	59.000000	8.500000	9.000000	90.000000	8.000000	86.000000	10000.000000





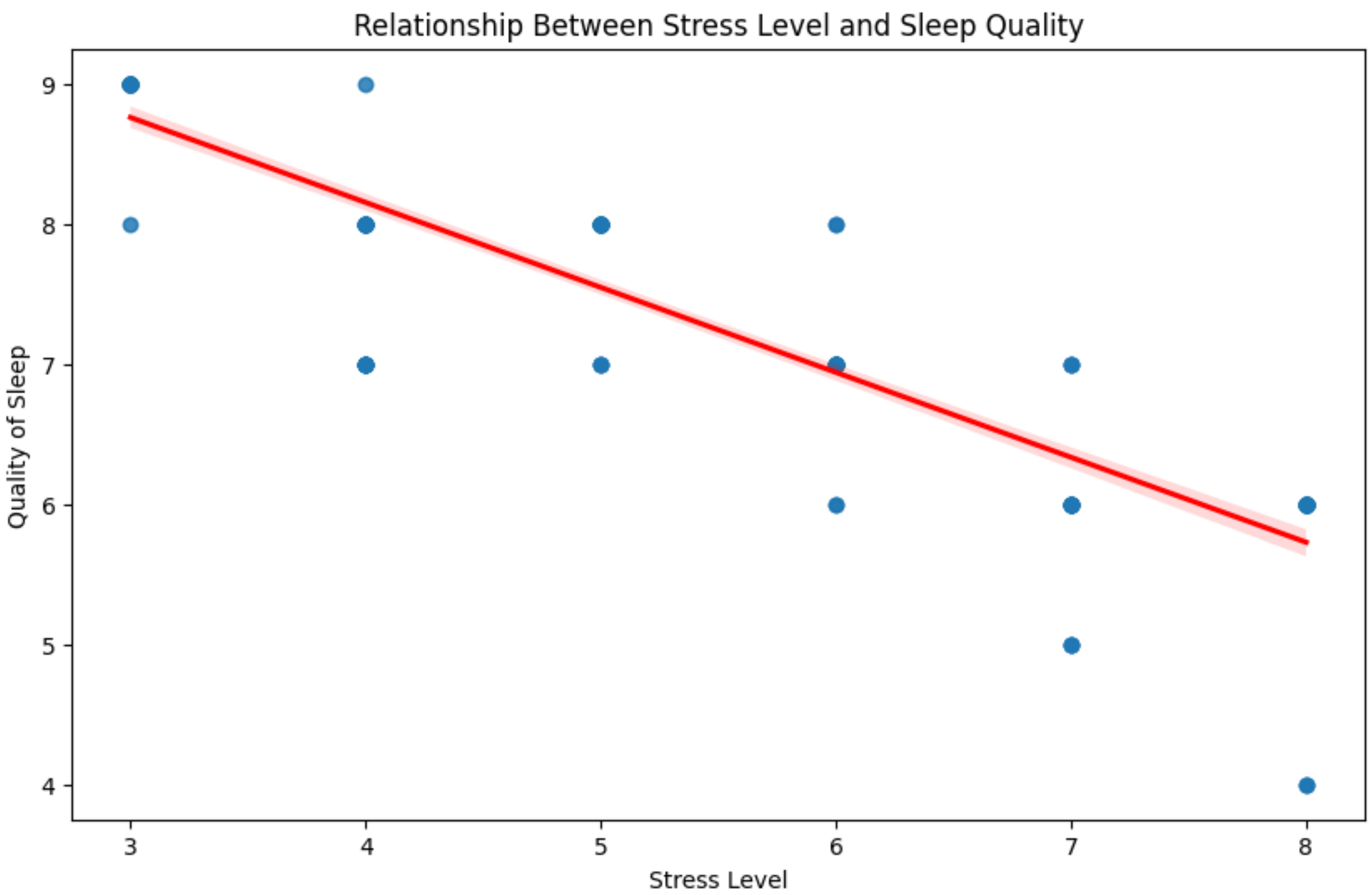


Quality
6
5
4
Overweight
Normal
Obese
Normal Weight
BMI Category



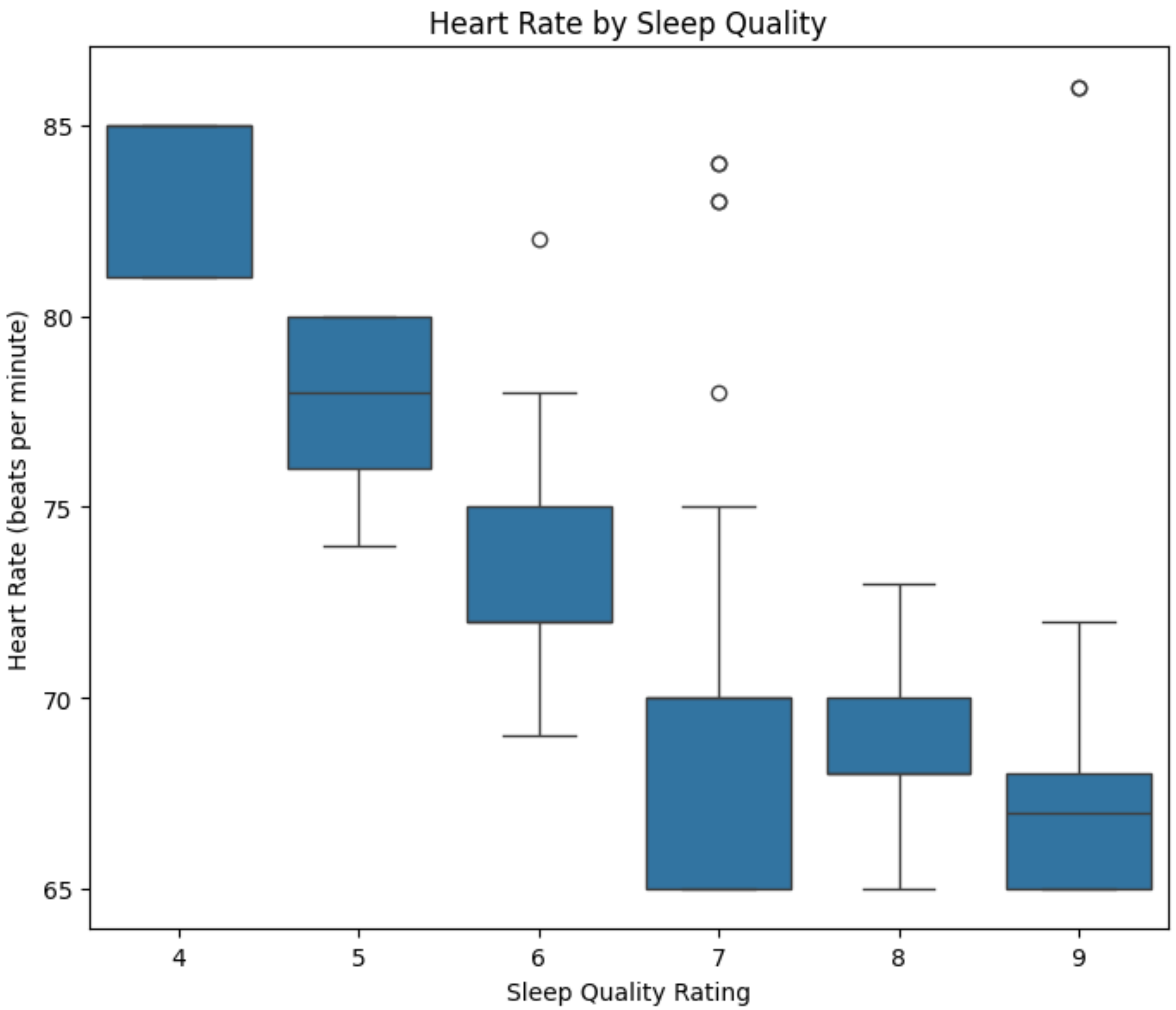
Sleep Duration vs. Heart Rate
Heart Rate (Beats per Minute)
85
80
75
70
65
6.0
6.5
7.0
7.5
8.0
8.5
Sleep Duration (Hours)

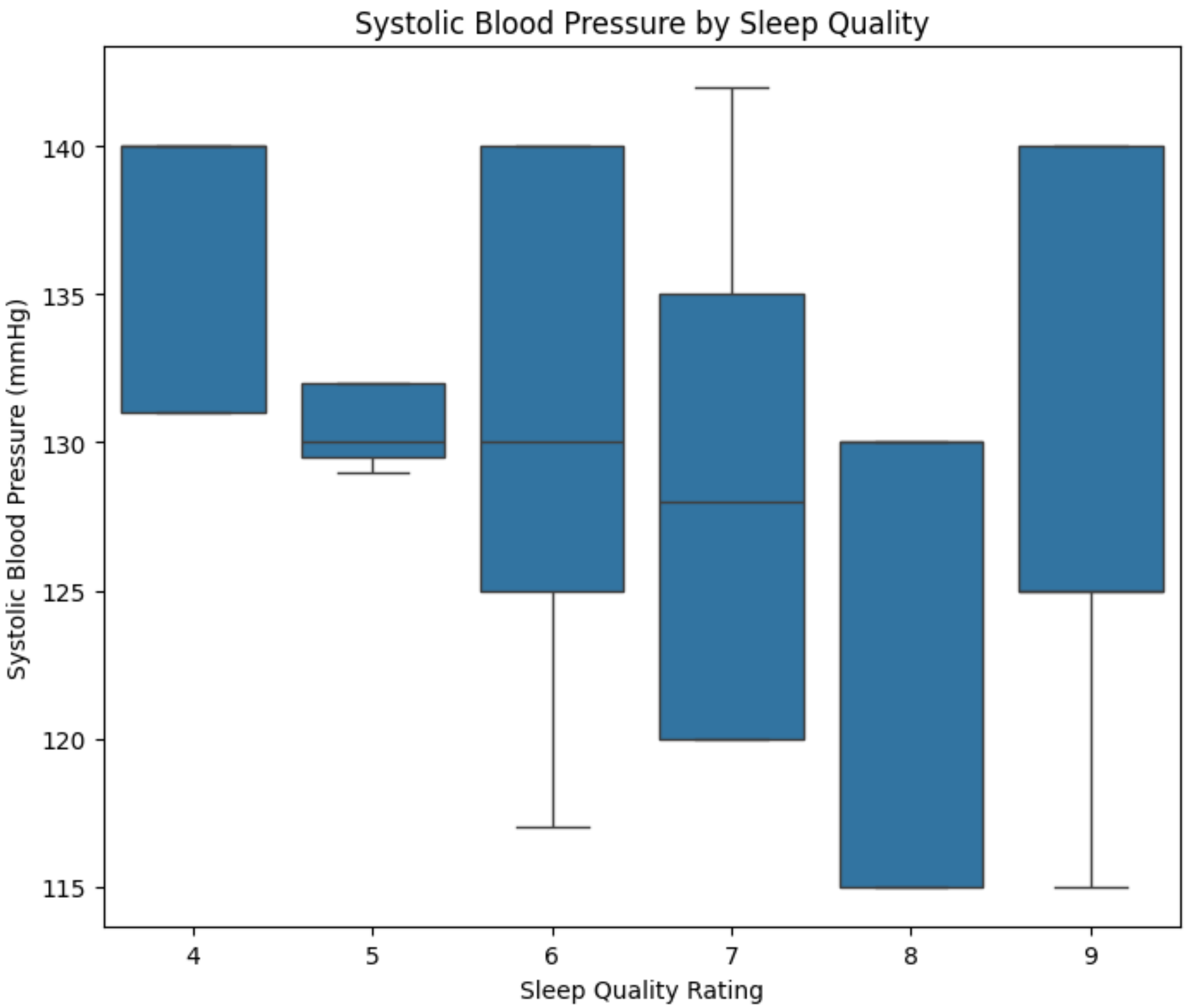
```
plt.figure(figsize=(10, 6))
sns.regplot(x='Stress Level', y='Quality of Sleep', data=sleep_health_lifestyle, scatter_kws={'alpha':0.6}, line_kws={'color':'red'})
plt.title('Relationship Between Stress Level and Sleep Quality')
plt.xlabel('Stress Level')
plt.ylabel('Quality of Sleep')
plt.show()
```

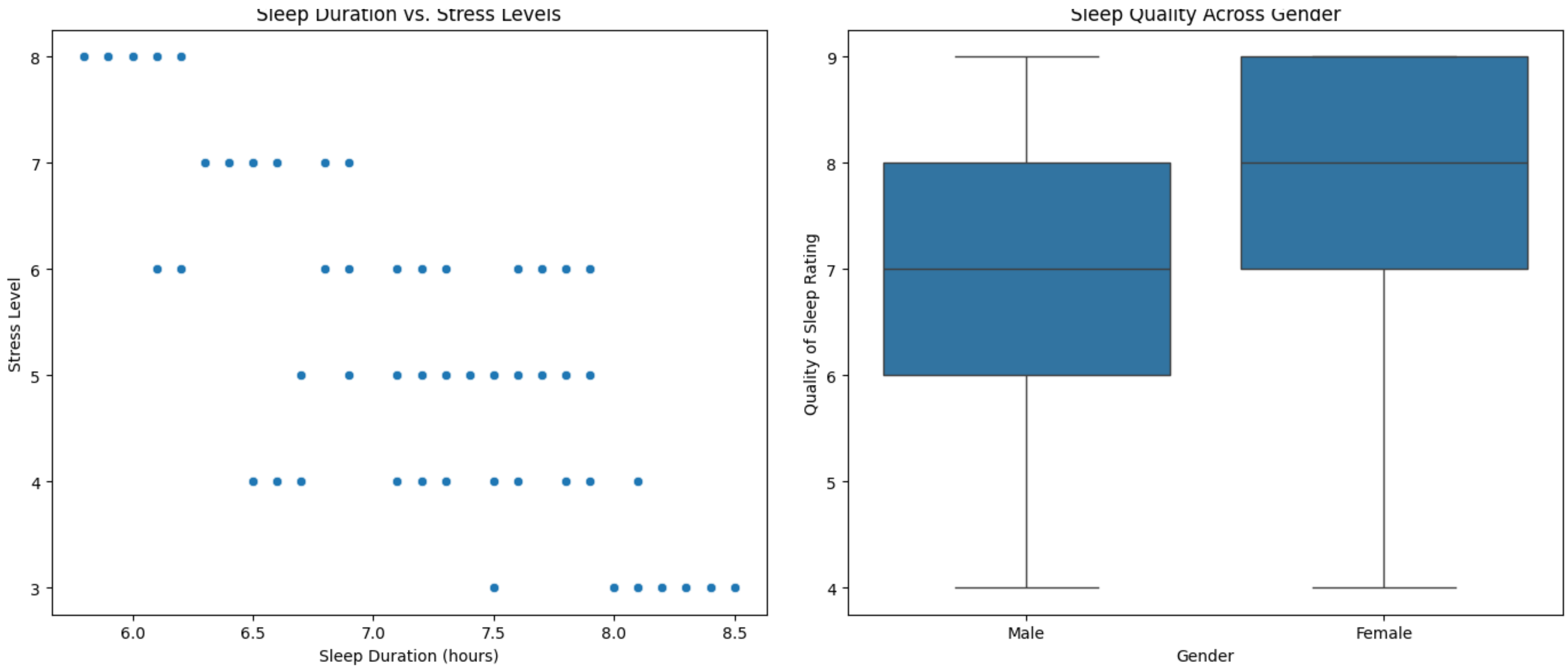



```
# Set up the figures for the plots
fig, axes = plt.subplots(2, 2, figsize=(14, 12))

# Plot 1: Heart Rate by Sleep Quality
sns.boxplot(x='Quality of Sleep', y='Heart Rate', data=sleep_health_lifestyle, ax=axes[0, 0])
axes[0, 0].set_title('Heart Rate by Sleep Quality')
axes[0, 0].set_xlabel('Sleep Quality Rating')
axes[0, 0].set_ylabel('Heart Rate (beats per minute)')

# Plot 2: Blood Pressure by Sleep Quality
sleep_health_lifestyle['Systolic BP'] = sleep_health_lifestyle['Blood Pressure'].apply(lambda x: int(x.split('/')[0]))
sns.boxplot(x='Quality of Sleep', y='Systolic BP', data=sleep_health_lifestyle, ax=axes[0, 1])
```

```
axes[0, 1].set_title('Systolic Blood Pressure by Sleep Quality')
axes[0, 1].set_xlabel('Sleep Quality Rating')
axes[0, 1].set_ylabel('Systolic Blood Pressure (mmHg)')

# Plot 3: Sleep Duration vs. Stress Levels
sns.scatterplot(x='Sleep Duration', y='Stress Level', data=sleep_health_lifestyle, ax=axes[1, 0])
axes[1, 0].set_title('Sleep Duration vs. Stress Levels')
axes[1, 0].set_xlabel('Sleep Duration (hours)')
axes[1, 0].set_ylabel('Stress Level')

# Plot 4: Sleep Quality Across Gender Groups
sns.boxplot(x='Gender', y='Quality of Sleep', data=sleep_health_lifestyle, ax=axes[1, 1])
axes[1, 1].set_title('Sleep Quality Across Gender')
axes[1, 1].set_xlabel('Gender')
axes[1, 1].set_ylabel('Quality of Sleep Rating')

plt.tight_layout()
plt.show()
```







T-test

The t-test conducted here is to compare between the mean heart rates between two groups: those with high sleep quality and those with low sleep quality.

```
from scipy.stats import ttest_ind, pearsonr, f_oneway

# Preparing data for t-test: Heart Rate across High vs Low Sleep Quality Groups
# Defining high quality as ratings 8 and above, low quality as ratings below 8
high_quality_hr = sleep_health_lifestyle[sleep_health_lifestyle['Quality of Sleep'] >= 8]['Heart Rate']
low_quality_hr = sleep_health_lifestyle[sleep_health_lifestyle['Quality of Sleep'] < 8]['Heart Rate']

# Conducting the t-test
t_test_results = ttest_ind(high_quality_hr, low_quality_hr, equal_var=False)

# Correlation test for Sleep Duration and Stress Levels
correlation_coefficient, p_value_corr = pearsonr(sleep_health_lifestyle['Sleep Duration'], sleep_health_lifestyle['Stress Level'])

t_test_results, (correlation_coefficient, p_value_corr)
```

```
(TtestResult(statistic=-11.129194972458267, pvalue=1.3898272008932421e-24, df=324.23637376114476),
 (-0.8110230278940431, 1.2378076181537574e-88))
```

In this section, I used a t-test and a pearson correlation test to determine the relationship between sleep and various factors such as heart rate, stress levels, and sleep quality differences across individuals.

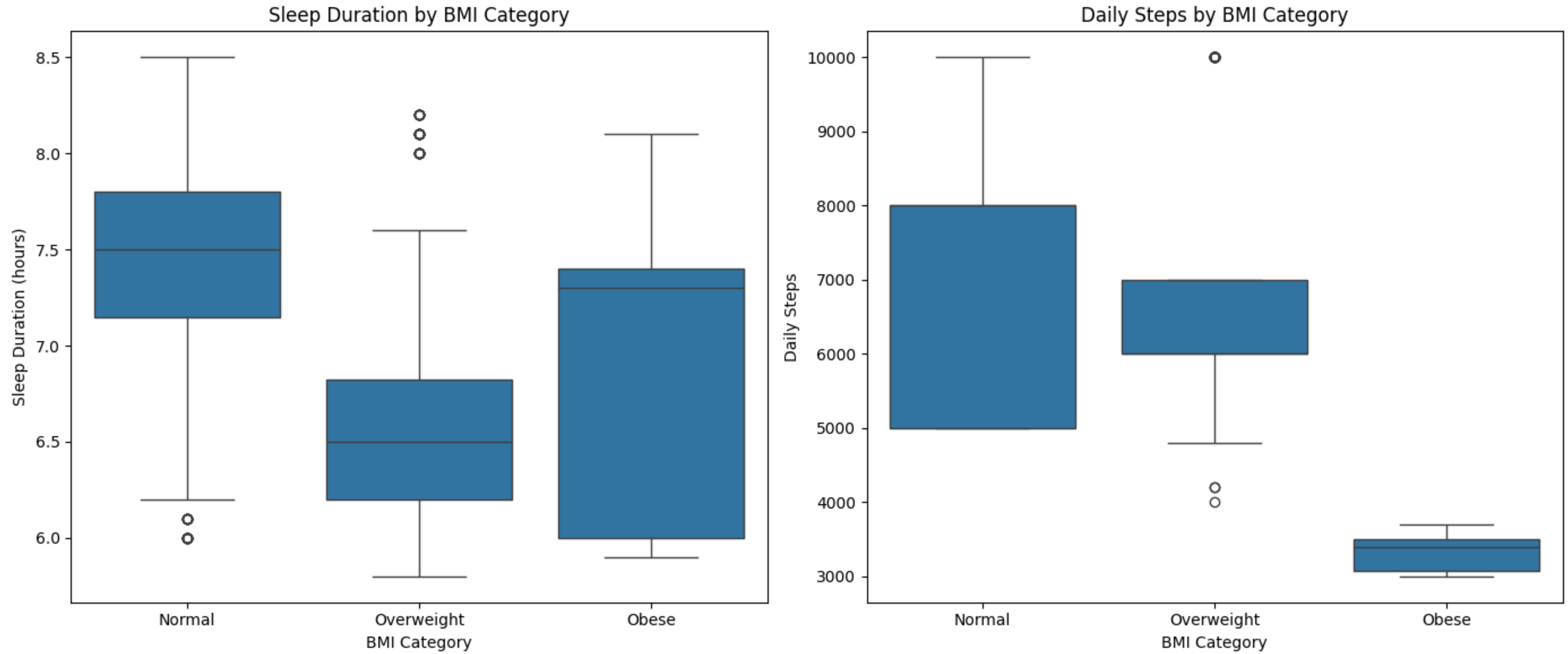
Results:

1) T-test: T-statistic: -11.129, P-value: 1.389e-24. This extremely low p-value suggests that there is a statistically significant difference in heart rates between the two sleep quality groups. (High vs Low sleep quality)

2) Pearson Correlation Test: Correlation Coefficient: -0.811, P-value: 1.238e-88. The negative correlation coefficient indicates a strong inverse relationship between sleep duration and stress levels, meaning that the lower your sleep quality, the higher your stress levels. The p-value further confirms that this relationship is statistically significant.

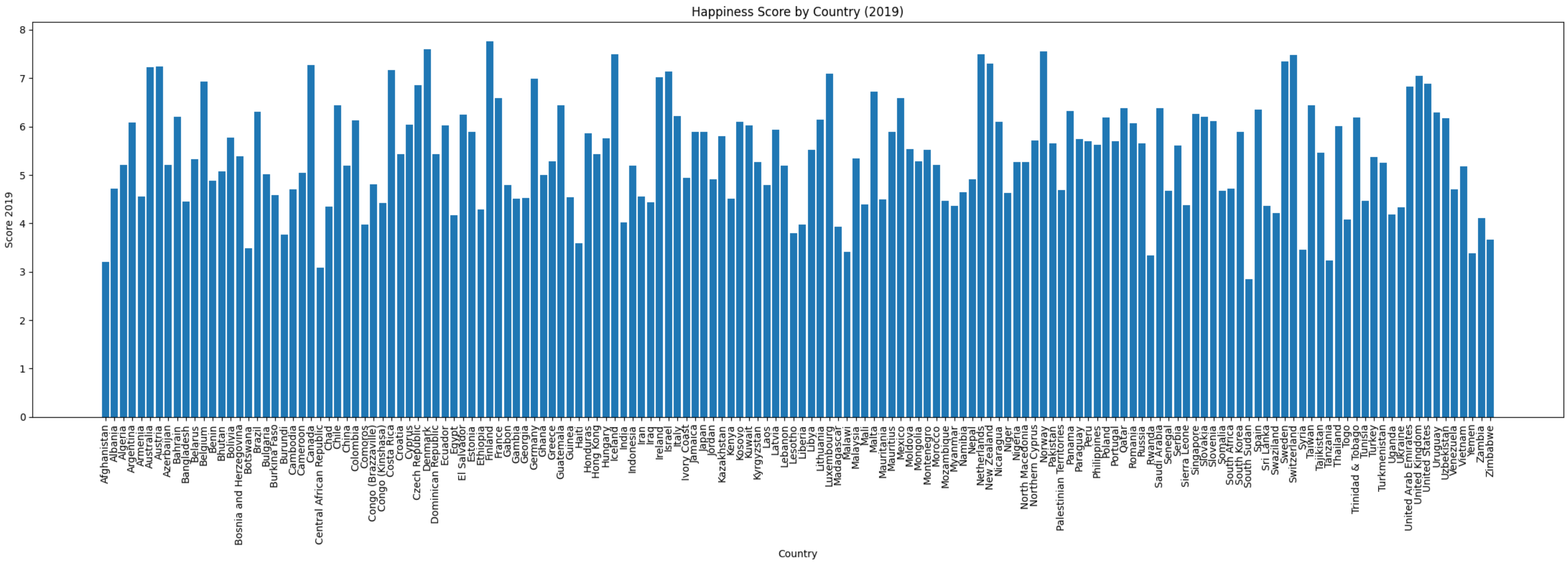
```
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plot 1: Sleep Duration by BMI Category
sns.boxplot(x='BMI Category', y='Sleep Duration', data=sleep_health_lifestyle, order=["Normal", "Overweight", "Obese"], ax=axes[0])
axes[0].set_title('Sleep Duration by BMI Category')
axes[0].set_xlabel('BMI Category')
axes[0].set_ylabel('Sleep Duration (hours)')

# Plot 2: Daily Steps by BMI Category
sns.boxplot(x='BMI Category', y='Daily Steps', data=sleep_health_lifestyle, order=["Normal", "Overweight", "Obese"], ax=axes[1])
axes[1].set_title('Daily Steps by BMI Category')
axes[1].set_xlabel('BMI Category')
axes[1].set_ylabel('Daily Steps')

plt.tight_layout()
plt.show()
```

```
# Preparing data for statistical tests
# Extracting sleep duration and daily steps for each BMI category
normal_sleep = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Normal']['Sleep Duration']
overweight_sleep = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Overweight']['Sleep Duration']
obese_sleep = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Obese']['Sleep Duration']

normal_steps = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Normal']['Daily Steps']
overweight_steps = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Overweight']['Daily Steps']
obese_steps = sleep_health_lifestyle[sleep_health_lifestyle['BMI Category'] == 'Obese']['Daily Steps']

# Perform ANOVA for sleep duration across BMI categories
anova_sleep = f_oneway(normal_sleep, overweight_sleep, obese_sleep)

# Perform ANOVA for daily steps across BMI categories
anova_steps = f_oneway(normal_steps, overweight_steps, obese_steps)

anova_sleep, anova_steps
```




```
(F_onewayResult(statistic=29.53721573917263, pvalue=1.4011965231114319e-12),
 F_onewayResult(statistic=27.472651379347422, pvalue=8.27072865567853e-12))
```

```
# Plotting the distribution of Happiness Scores by Country

df = happiness_data
plt.figure(figsize=(22, 8))
plt.bar(df['Country'], df['Score 2019'])
plt.xlabel('Country')
plt.ylabel('Score 2019')
plt.title('Happiness Score by Country (2019)')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```




```
# Pivot the data
stacked_data = time_use.pivot(index='countryISO3', columns='Subcategory', values='hoursPerDayCombined')

# Plot the stacked bar chart
ax = stacked_data.plot(kind='bar', stacked=True, figsize=(20, 10))

# Customize the plot
plt.xlabel('Country')
plt.ylabel('Time (hours)')
plt.title('Time Spent on Various Activities by Country')
```

```
plt.legend(title='Activity', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=90)

# Adjust layout to prevent cutting off labels
plt.tight_layout()

# Show the plot
plt.show()
```

Individual Assignment #3.1: Applying Regression to Your Project

The research problem and the hypothesis for this activity

2) The research problem and the hypothesis for this activity Question: Can a country's population's time use be used to predict their happiness?
Sub-problems:

1. Is there a correlation between sleep duration and stress level?
2. Is there a correlation between sleep duration and happiness ranking?
3. Is there a correlation between life expectancy and happiness?

```
Subproblem done in this assignment: Is there a correlation between sleep duration and stress level?
Hypothesis: There is a significant relationship between a person's sleep duration and their stress level
```

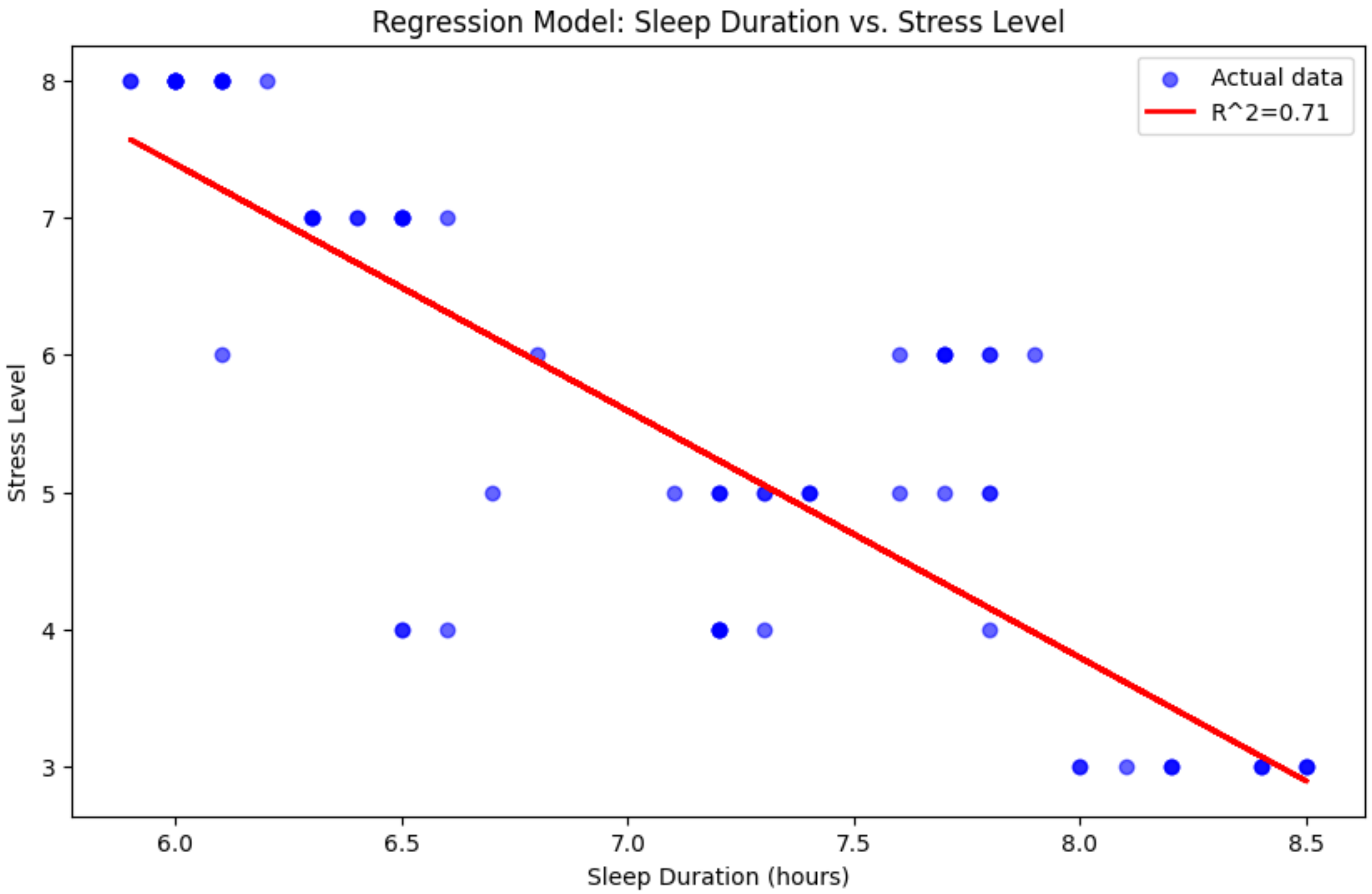
3) MSE: 0.911235988228852 R-squared: 0.7083360399574774

4) The conclusion to the hypothesis and to the research problem: To conclude, the results show that there is a significant relationship between sleep duration and stress level which supports my hypothesis. The R-squared value of 0.7083360399574774 from the model indicates that there is approximately 70.83% of the variance of stress levels can be explained by our sleep duration. The MSE of 0.911235988228852 shows us the average (squared) difference between predicted outcome and our actual stress levels. Overall we can conclude that our stress levels are being affected by sleep duration

```
# Regression model between sleep duration and stress level
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Prepare the data
X = sleep_health_lifestyle[['Sleep Duration']]
y = sleep_health_lifestyle['Stress Level']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Calculate mse
mse = mean_squared_error(y_test, y_pred)
mse
# Calculate r^2
r2_score = model.score(X_test, y_test)
```

```
print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2_score}')

plt.figure(figsize=(10, 6))
plt.scatter(X_test, y_test, color='blue', alpha=0.6, label='Actual data')
plt.plot(X_test, y_pred, color='red', linewidth=2, label=f"R^2={r2_score:.2f}")
plt.title('Regression Model: Sleep Duration vs. Stress Level')
plt.xlabel('Sleep Duration (hours)')
plt.ylabel('Stress Level')

plt.legend()

plt.show()
```

```
Mean Squared Error: 0.9112359882288514
R^2 Score: 0.7083360399574775
```



Multiple Linear Regression

To check which factor contributes most to a country's happiness level, multiple linear regression is used.

Independent Variables: Dependent Variable: "Score 2019": The happiness score of a country in 2019

```
data = happiness_data[['Country','Region','Rank 2019','Score 2019','GDP 2019','Family 2019',
                    'Life Expectancy 2019','Freedom 2019','Trust 2019','Generosity 2019']]
```

```
import statsmodels.api as sm

# Define the dependent and independent variables

# Exclude non-numeric variables 'Country' and 'Region'
X = data[['GDP 2019', 'Family 2019', 'Life Expectancy 2019', 'Freedom 2019', 'Trust 2019', 'Generosity 2019']]
y = data['Score 2019']

# Add a constant to the independent variables
X = sm.add_constant(X)

# Fit the regression model
model = sm.OLS(y, X).fit()

# Print the model summary
print(model.summary())


# Add a constant to the independent variables
# This is required for the statsmodels library because it does not add a constant by default
# We need this constant because the linear regression model is represented as y = b0 + b1*x1 + b2*x2 + ... + bn*xn
# If we do not include a constant, the model will be represented as y = b1*x1 + b2*x2 + ... + bn*xn
# Which will lead to incorrect results because the model will not have an intercept term to account for the bias
# in the data for example if all the independent variables are 0, the dependent variable will still have a value
X = sm.add_constant(X)

model = sm.OLS(y, X).fit()

print(model.summary())
```

```
==============================================================================
Dep. Variable:             Score 2019   R-squared:                       0.779
Model:                            OLS   Adj. R-squared:                  0.770
Method:                 Least Squares   F-statistic:                     87.62
Date:                Mon, 15 Jul 2024   Prob (F-statistic):           2.40e-46
Time:                        16:39:29   Log-Likelihood:                -119.76
No. Observations:                 156   AIC:                             253.5
Df Residuals:                     149   BIC:                             274.9
Df Model:                           6
```

```
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     1.7952      0.211      8.505      0.000       1.378       2.212
GDP 2019                  0.7754      0.218      3.553      0.001       0.344       1.207
Family 2019               1.1242      0.237      4.745      0.000       0.656       1.592
Life Expectancy 2019      1.0781      0.335      3.223      0.002       0.417       1.739
Freedom 2019              1.4548      0.375      3.876      0.000       0.713       2.197
Trust 2019                0.9723      0.542      1.793      0.075      -0.099       2.044
Generosity 2019           0.4898      0.498      0.984      0.327      -0.494       1.473
==============================================================================
Omnibus:                        8.188   Durbin-Watson:                   1.954
Prob(Omnibus):                  0.017   Jarque-Bera (JB):                7.971
Skew:                          -0.498   Prob(JB):                       0.0186
Kurtosis:                       3.483   Cond. No.                         28.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
                            OLS Regression Results
==============================================================================
Dep. Variable:             Score 2019   R-squared:                       0.779
Model:                            OLS   Adj. R-squared:                  0.770
Method:                 Least Squares   F-statistic:                     87.62
Date:                Mon, 15 Jul 2024   Prob (F-statistic):           2.40e-46
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Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
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Kurtosis:                       3.483   Cond. No.                         28.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Conclusion from multiple linear regression on a country's Happiness index

From earlier, we have found out that life expectancy has a positive correlation to a country's happiness score. Through research I have found from multiple sources backing the existence of a correlation between health factors (such as BMI, heart rate, stress level and blood pressure) to the longevity of a person.

Relevant Literature

Source:

1. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5418561/
2. https://www.nature.com/articles/s41398-021-01735-7#Sec8
3. https://www.reanfoundation.org/low-resting-heart-rate-and-lifespan/

So in order to figure out if we can use sleep quality as an indicator to a country's happiness, merge the datasets of what_humans_are_doingthe index.

```
# Extract relevant columns from the second dataset
sleep_data_2021 = time_use[time_use['Subcategory'] == 'Sleep & bedrest']
print("Sleep Time By Country")
print(sleep_data_2021.head())
```

```
Sleep Time By Country
                Category      Subcategory countryISO3 region_code  population  \
9    Somatic maintenance  Sleep & bedrest         ABW        AM_C    101665.0
33   Somatic maintenance  Sleep & bedrest         AFG        AS_S  36296111.0
57   Somatic maintenance  Sleep & bedrest         AGO        AF_M  31825299.0
81   Somatic maintenance  Sleep & bedrest         ALB        EU_S   2896307.0
105  Somatic maintenance  Sleep & bedrest         ARE        AS_W   9770526.0

     hoursPerDayCombined  uncertaintyCombined   dataStatus dataStatusEconomic
9                   8.21             3.883858  interpolated           observed
33                  9.49             0.977807  interpolated           observed
57                  9.79             1.291399  interpolated       interpolated
81                  9.40             0.170536      observed           observed
105                 9.45             1.334729  interpolated       interpolated
```

```
# Right now the name of the countries are represented by their ISO3 codes so we
# so that we can further combine the data with happiness index dataset.
# Source: https://www.kaggle.com/datasets/andradaolteanu/iso-country-codes-glol

# Load the ISO country codes dataset
iso_country_codes = pd.read_csv('wikipedia-iso-country-codes.csv')

iso_country_codes.columns = ['Country', 'Alpha-2 code', 'Alpha-3 code', 'Numeri

# Merge sleep_data_2021 with iso_country_codes to get full country names
sleep_data = pd.merge(sleep_data_2021, iso_country_codes[['Alpha-3 code', 'Cour
                           left_on='countryISO3', right_on='Alpha-3 code', how=

# Select and rename columns to match Dataset 1 format
sleep_data = sleep_data[['Country', 'hoursPerDayCombined']]
sleep_data = sleep_data.rename(columns={'hoursPerDayCombined': 'Sleep Time (mir

# Convert sleep duration from hours to minutes
sleep_data['Sleep Time (minutes)'] = sleep_data['Sleep Time (minutes)'] * 60


# Reorder columns to match Dataset 1 format
sleep_data = sleep_data[['Country', 'Sleep Time (minutes)']]

# Set 'Country' as the index
sleep_data = sleep_data.set_index('Country')

# Round 'Time (minutes)' to the nearest integer
sleep_data['Sleep Time (minutes)'] = sleep_data['Sleep Time (minutes)'].round()

print("Sleep Data")
print(sleep_data.head())
```

```
Sleep Data
                      Sleep Time (minutes)
Country
Aruba                                  493
Afghanistan                            569
Angola                                 587
Albania                                564
United Arab Emirates                   567
```

```
# Merge in happiness index (2019)
data = data.set_index('Country')

# Grab 'Country' and 'Score 2019' columns
happiness_data = happiness_data[['Country', 'Score 2019']]

# Merge with our sleep data
merged_data = pd.merge(sleep_data, happiness_data,
                       left_index=True, right_on='Country',
                       how='inner')

# Set 'Country' as the index again
merged_data = merged_data.set_index('Country')

merged_data = merged_data.rename(columns={'Sleep Time (minutes)': 'Sleep Time (
                                          'Score 2019': 'Happiness Score'})

print(merged_data.head())
```

```
                      Sleep Time (minutes)  Happiness Score
Country
Afghanistan                            569            3.203
Albania                                564            4.719
United Arab Emirates                   567            6.825
Argentina                              527            6.086
Armenia                                567            4.559
```

Here i normalize the data using MinMaxScaler so that all the features are on the same scale. This allow our model to learn the weights of the features more effectively and converge faster.

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

# Fit the scaler to your data and transform
normalized_data = scaler.fit_transform(merged_data)

# Convert back to a DataFrame
normalized_df = pd.DataFrame(normalized_data, columns=merged_data.columns, index=merged_data.index)

print(normalized_df.head())
```

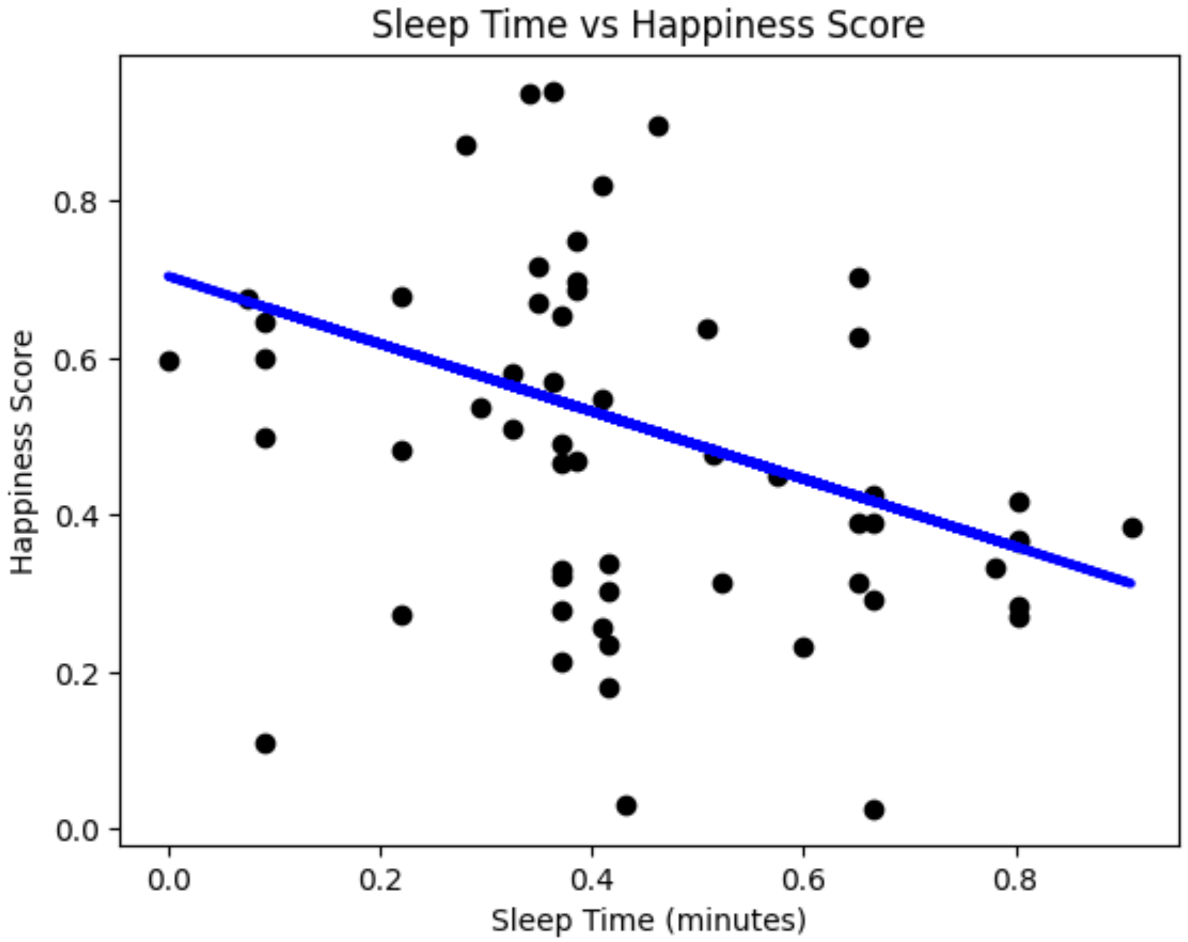
```
                      Sleep Time (minutes)  Happiness Score
Country
Afghanistan                       0.666667         0.025608
Albania                           0.628788         0.349125
United Arab Emirates              0.651515         0.798549
Argentina                         0.348485         0.640845
Armenia                           0.651515         0.314981
```

Modeling The Data

Now that we have extracted and cleaned the data, I will use Linear Regression to model our data. The data will be split in a 60:40 ratio.

```
from sklearn.metrics import r2_score as r2_score_func

X = normalized_df[['Sleep Time (minutes)']]
y = normalized_df['Happiness Score']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score_func(y_test, y_pred)

print(f"Mean squared error: {mse}")
print(f"R-squared score: {r2}")

# Plot the results
plt.scatter(X_test, y_test, color='black')
plt.plot(X_test, y_pred, color='blue', linewidth=3)
plt.xlabel('Sleep Time (minutes)')
plt.ylabel('Happiness Score')
plt.title('Sleep Time vs Happiness Score')
plt.show()

# Print the model coefficients
print(f"Intercept: {model.intercept_}")
print(f"Coefficient: {model.coef_[0]}")
```

```
Mean squared error: 0.044174066635616696
R-squared score: 0.05621186017827373
```

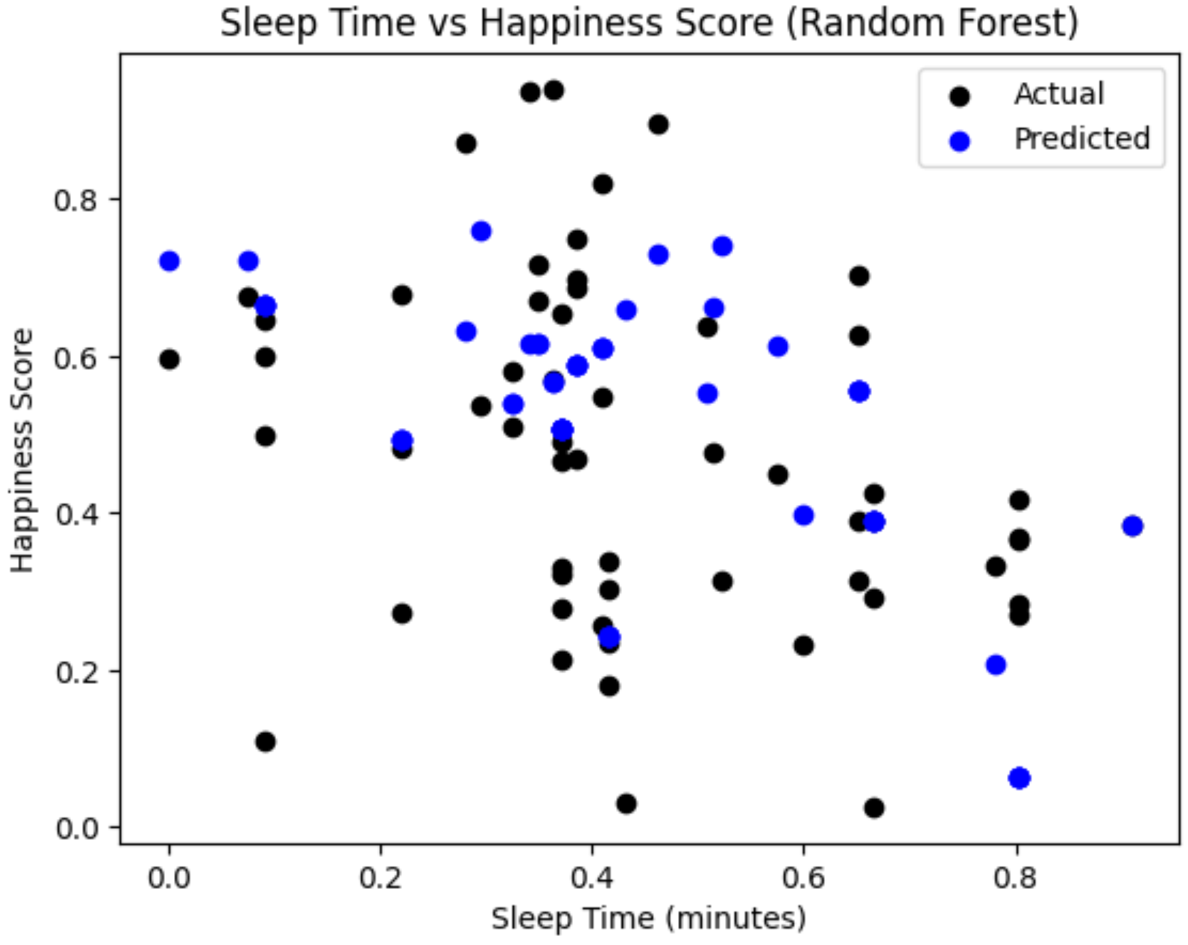



```
Intercept: 0.7041217128248263
Coefficient: -0.4306056703995436
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Prepare the data
X = normalized_df[['Sleep Time (minutes)']]
y = normalized_df['Happiness Score']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)

# Create and train the model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Make predictions
y_pred = rf_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
```

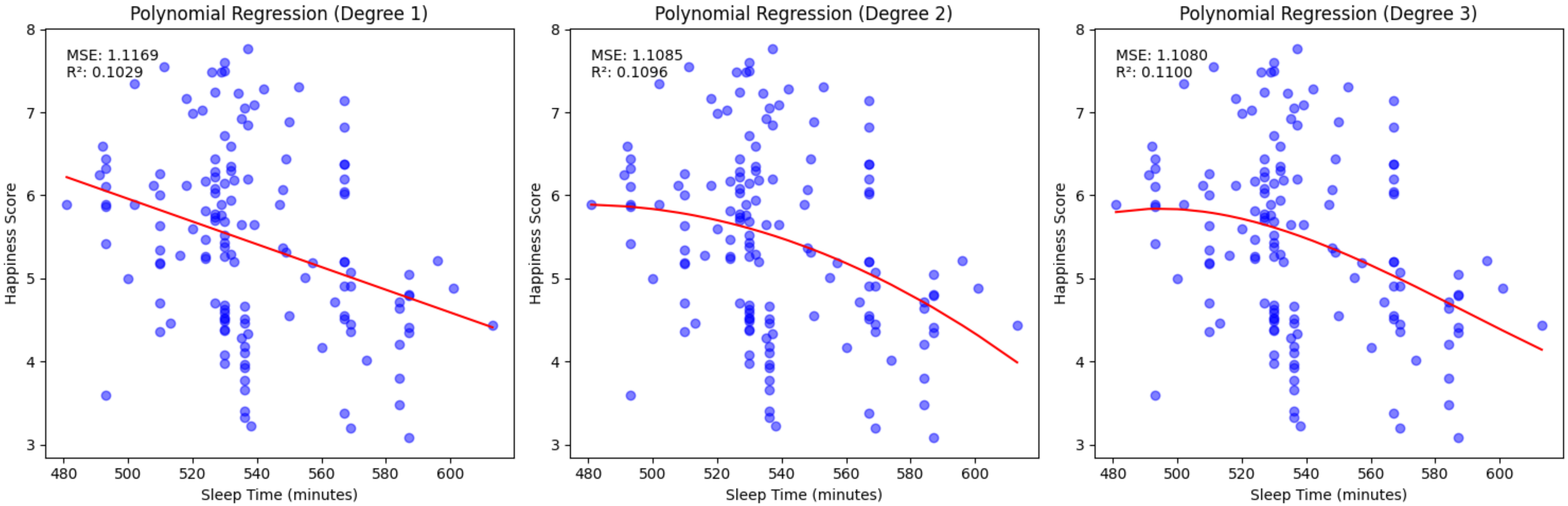
```
r2 = r2_score(y_test, y_pred)

print(f"Mean squared error: {mse}")
print(f"R-squared score: {r2}")

# Plot the results
plt.scatter(X_test, y_test, color='black', label='Actual')
plt.scatter(X_test, y_pred, color='blue', label='Predicted')
plt.xlabel('Sleep Time (minutes)')
plt.ylabel('Happiness Score')
plt.title('Sleep Time vs Happiness Score (Random Forest)')
plt.legend()
plt.show()
```

```
Mean squared error: 0.04585306549325808
R-squared score: 0.020339699670902323
```




```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Prepare the data
X = merged_data['Sleep Time (minutes)'].values.reshape(-1, 1)
y = merged_data['Happiness Score'].values
```

```
# Create polynomial features
# We'll try degrees 1, 2, and 3
degrees = [1, 2, 3]

plt.figure(figsize=(15, 5))

for i, degree in enumerate(degrees, 1):
    poly_features = PolynomialFeatures(degree=degree, include_bias=False)
    X_poly = poly_features.fit_transform(X)

    # Fit the model
    model = LinearRegression()
    model.fit(X_poly, y)

    # Make predictions
    y_pred = model.predict(X_poly)

    # Calculate MSE and R-squared
    mse = mean_squared_error(y, y_pred)
    r2 = r2_score(y, y_pred)

    # Plot the results
    plt.subplot(1, 3, i)
    plt.scatter(X, y, color='blue', alpha=0.5)

    # Sort X for smooth curve plotting
    X_sorted = np.sort(X, axis=0)
    X_poly_sorted = poly_features.transform(X_sorted)
    y_poly_pred = model.predict(X_poly_sorted)

    plt.plot(X_sorted, y_poly_pred, color='red')
    plt.title(f'Polynomial Regression (Degree {degree})')
    plt.xlabel('Sleep Time (minutes)')
    plt.ylabel('Happiness Score')
    plt.text(X.min(), y.max(), f'MSE: {mse:.4f}\nR²: {r2:.4f}', verticalalignment='top')

plt.tight_layout()
plt.show()
```



Polynomial Regression (Degree 1)
MSE: 1.1169
R²: 0.1029
Polynomial Regression (Degree 2)
MSE: 1.1085
R²: 0.1096
Polynomial Regression (Degree 3)
MSE: 1.1080
R²: 0.1100
Happiness Score
Sleep Time (minutes)
8
7
6
5
4
3
480
500
520
540
560
580
600

```
# Print the coefficients for the highest degree polynomial
highest_degree = max(degrees)
poly_features = PolynomialFeatures(degree=highest_degree, include_bias=False)
X_poly = poly_features.fit_transform(X)
model = LinearRegression()
model.fit(X_poly, y)

poly_features = PolynomialFeatures(degree=3, include_bias=False)
X_poly = poly_features.fit_transform(X)
poly_model = LinearRegression()
poly_model.fit(X_poly, y)
y_pred_poly = poly_model.predict(X_poly)
r2_poly = r2_score(y, y_pred_poly)
mse_poly = mean_squared_error(y, y_pred_poly)

print(f"\nCoefficients for {highest_degree}-degree polynomial:")
for i, coef in enumerate(model.coef_):
    print(f"x^{i+1}: {coef:.4f}")

print(f"Polynomial R^2: {r2_poly:.4f}, MSE: {mse_poly:.4f}")
```

```
Coefficients for 3-degree polynomial:
x^1: 0.7350
x^2: -0.0013
x^3: 0.0000
Polynomial R^2: 0.1100, MSE: 1.1080
```

Conclusion

This project aimed to explore the relationship between sleep duration and happiness scores across different countries. Through this project we can conclude that:

1. **Weak Correlation:** Our models consistently showed a weak relationship between sleep duration and happiness scores. This suggests that while sleep may play a role in happiness, it's not a strong predictor on its own at a country level.
2. **Model Performance:** The linear regression model performed similarly to more complex models like polynomial regression and Random Forest. This indicates that the relationship, while weak, is primarily linear in nature.
3. **Other Factors:** The low R-squared values across all models suggest that there are many other factors influencing a country's happiness score beyond sleep duration. This aligns with the complex, multifaceted nature of happiness as a concept.
4. **Data Limitations:** Since we're working with country-level averages, it may not be accurate on individual-level relationships between sleep and happiness.

Final Thoughts:

While sleep is often associated with well-being on an individual level, our analysis shows that this relationship isn't strongly reflected in country-level data.

It is possible that there is not enough data to precisely build the model. It would have been much better if I could get data for each year (for the happiness index and also sleep duration) instead of data that has been aggergated through surveys across multiple years like the one in my dataset.