```
In [2]:
          import pandas as pd
In [3]:
          import numpy as np
          import matplotlib.pyplot as plt
In [4]:
In [5]:
          import seaborn as sns
          data=pd.read_csv('gym_members_exercise_tracking.csv')
In [6]:
         data
In [7]:
Out[7]:
                              Weight Height
                                                                                 Session_Duration
                                                                                                   Calor
                                              Max_BPM Avg_BPM Resting_BPM
                Age Gender
                                (kg)
                                         (m)
                                                                                           (hours)
                 56
                                88.3
                                        1.71
                                                   180
             0
                        Male
                                                              157
                                                                             60
                                                                                              1.69
             1
                     Female
                                74.9
                                        1.53
                                                   179
                                                              151
                                                                             66
                                                                                              1.30
                 46
             2
                     Female
                                68.1
                                        1.66
                                                   167
                                                              122
                                                                             54
                                                                                              1.11
                 32
             3
                                                                                              0.59
                 25
                        Male
                                53.2
                                        1.70
                                                   190
                                                              164
                                                                             56
             4
                 38
                        Male
                                46.1
                                        1.79
                                                   188
                                                              158
                                                                             68
                                                                                              0.64
                  ...
                                 ...
                                                     ...
                                                               ...
           968
                 24
                        Male
                                87.1
                                        1.74
                                                   187
                                                              158
                                                                             67
                                                                                              1.57
           969
                 25
                        Male
                                66.6
                                        1.61
                                                   184
                                                              166
                                                                             56
                                                                                              1.38
           970
                 59
                     Female
                                60.4
                                        1.76
                                                   194
                                                              120
                                                                             53
                                                                                              1.72
           971
                                        1.83
                 32
                        Male
                               126.4
                                                   198
                                                              146
                                                                             62
                                                                                              1.10
           972
                 46
                        Male
                                88.7
                                        1.63
                                                   166
                                                              146
                                                                             66
                                                                                              0.75
          973 rows × 15 columns
```

In [8]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 973 entries, 0 to 972
Data columns (total 15 columns):

#	Column	Non-	-Null Count	Dtype
0	Age	973	non-null	int64
1	Gender	973	non-null	object
2	Weight (kg)	973	non-null	float64
3	Height (m)	973	non-null	float64
4	Max_BPM	973	non-null	int64
5	Avg_BPM	973	non-null	int64
6	Resting_BPM	973	non-null	int64
7	Session_Duration (hours)	973	non-null	float64
8	Calories_Burned	973	non-null	float64
9	Workout_Type	973	non-null	object
10	Fat_Percentage	973	non-null	float64
11	Water_Intake (liters)	973	non-null	float64
12	Workout_Frequency (days/week)	973	non-null	int64
13	Experience_Level	973	non-null	int64
14	BMI	973	non-null	float64

dtypes: float64(7), int64(6), object(2)

memory usage: 114.2+ KB

In [9]: data.describe()

Out[9]:

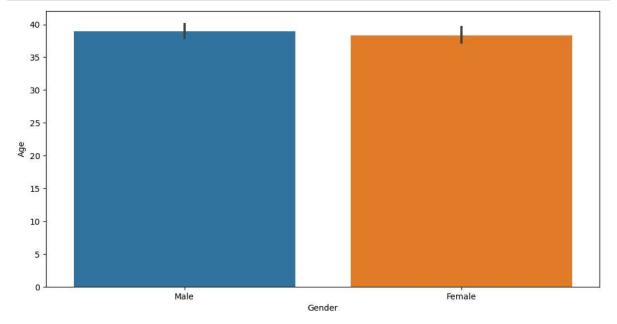
Session_Durati (hou	Resting_BPM	Avg_BPM	Max_BPM	Height (m)	Weight (kg)	Age	
973.0000	973.000000	973.000000	973.000000	973.00000	973.000000	973.000000	count
1.2564	62.223022	143.766701	179.883864	1.72258	73.854676	38.683453	mean
0.3430	7.327060	14.345101	11.525686	0.12772	21.207500	12.180928	std
0.5000	50.000000	120.000000	160.000000	1.50000	40.000000	18.000000	min
1.0400	56.000000	131.000000	170.000000	1.62000	58.100000	28.000000	25%
1.2600	62.000000	143.000000	180.000000	1.71000	70.000000	40.000000	50%
1.4600	68.000000	156.000000	190.000000	1.80000	86.000000	49.000000	75%
2.0000	74.000000	169.000000	199.000000	2.00000	129.900000	59.000000	max
>							4

In [10]: data.duplicated().sum()

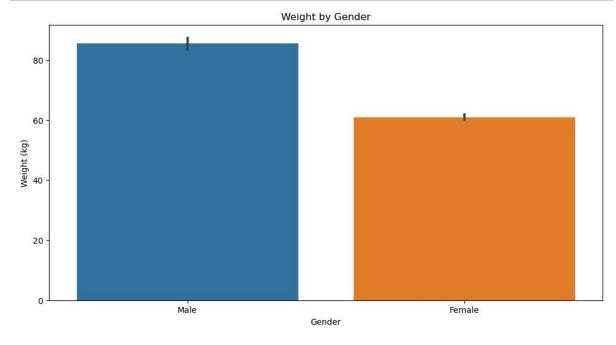
Out[10]: 0

```
In [11]: data.isna().sum()
Out[11]: Age
                                            0
         Gender
                                            0
         Weight (kg)
                                            0
         Height (m)
                                            0
                                            0
         Max_BPM
                                            0
         Avg_BPM
         Resting_BPM
                                            0
         Session_Duration (hours)
                                            0
         Calories_Burned
                                            0
                                            0
         Workout_Type
                                            0
         Fat_Percentage
         Water_Intake (liters)
                                            0
         Workout_Frequency (days/week)
                                            0
         Experience_Level
                                            0
         BMI
                                            0
         dtype: int64
```

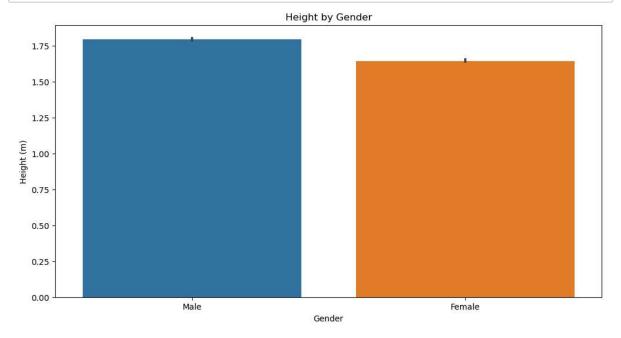




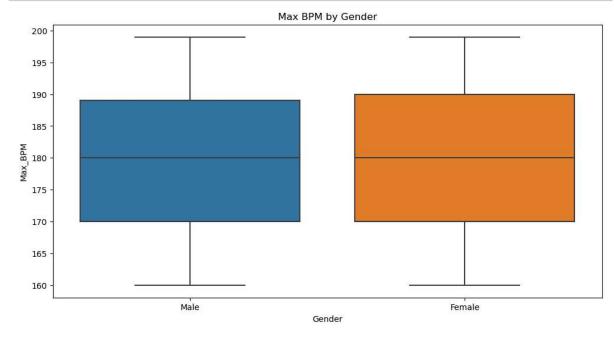
```
In [13]: # gender vs weight
plt.figure(figsize=(12,6))
sns.barplot(x='Gender',y='Weight (kg)',data=data)
plt.title('Weight by Gender')
plt.show()
```



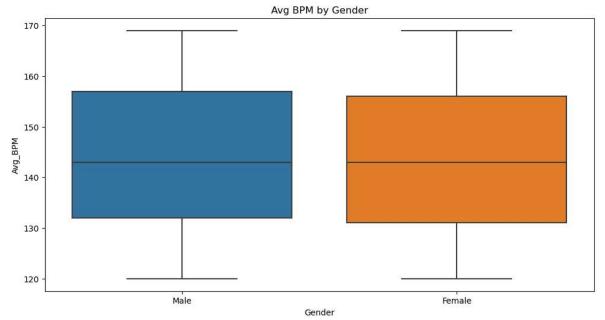
```
In [14]: # gender vs hight
    plt.figure(figsize=(12,6))
    sns.barplot(x='Gender',y='Height (m)',data=data)
    plt.title('Height by Gender')
    plt.show()
```



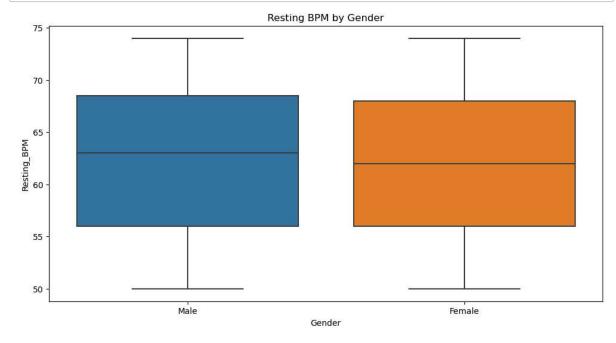
```
In [15]: #Max BPM by Gender'
    plt.figure(figsize=(12,6))
    sns.boxplot(x='Gender',y='Max_BPM',data=data)
    plt.title('Max BPM by Gender')
    plt.show()
```



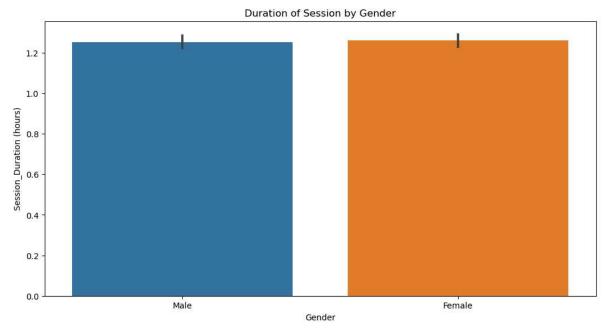




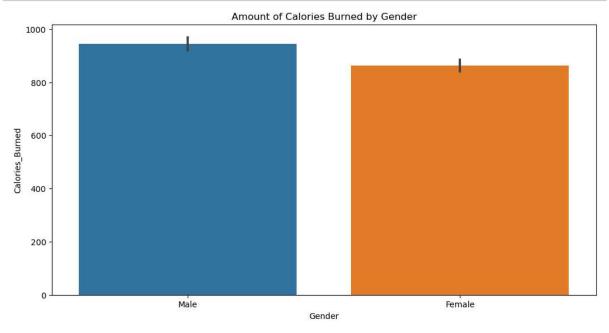
```
In [17]: #Resting BPM by Gender
plt.figure(figsize=(12,6))
sns.boxplot(x='Gender',y='Resting_BPM',data=data)
plt.title('Resting BPM by Gender')
plt.show()
```



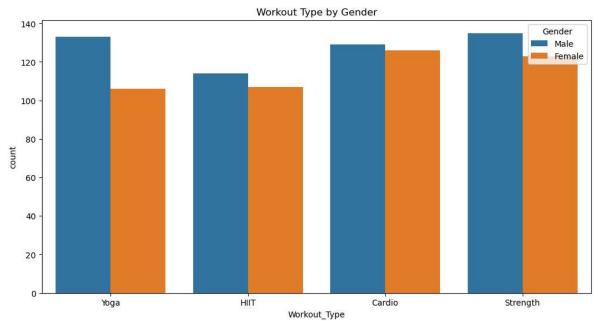
In [18]: #Duration of Session by Gender
plt.figure(figsize=(12,6))
sns.barplot(x='Gender',y='Session_Duration (hours)',data=data)
plt.title('Duration of Session by Gender')
plt.show()



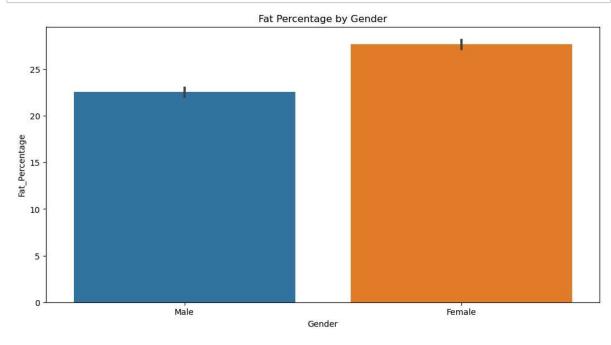
```
In [19]: #Amount of Calories Burned by Gender
plt.figure(figsize=(12,6))
sns.barplot(x='Gender',y='Calories_Burned',data=data)
plt.title('Amount of Calories Burned by Gender')
plt.show()
```

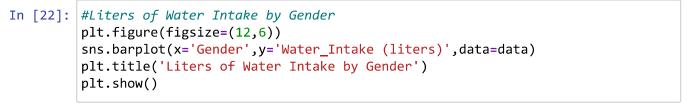


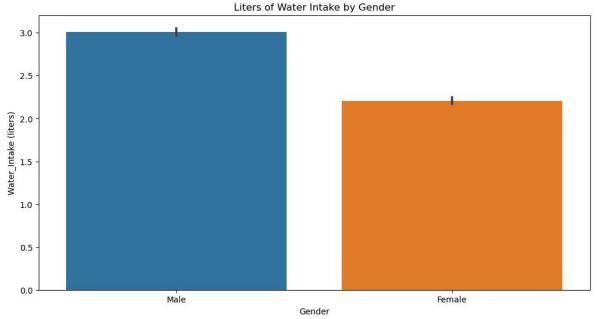




```
In [21]: #Fat Percentage by Gender
    plt.figure(figsize=(12,6))
    sns.barplot(x='Gender',y='Fat_Percentage',data=data)
    plt.title('Fat Percentage by Gender')
    plt.show()
```

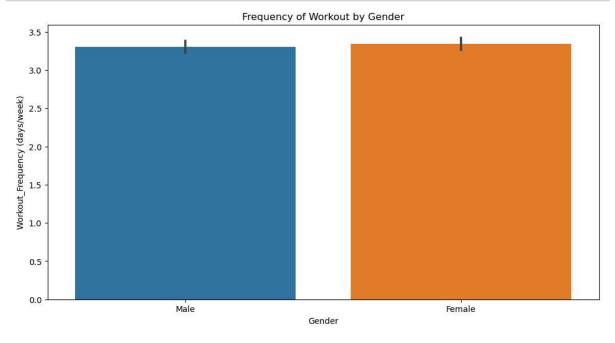




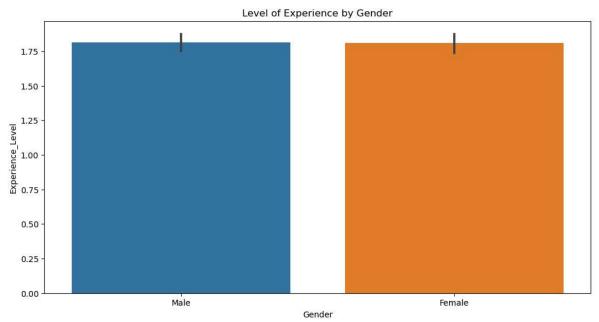


In [23]:

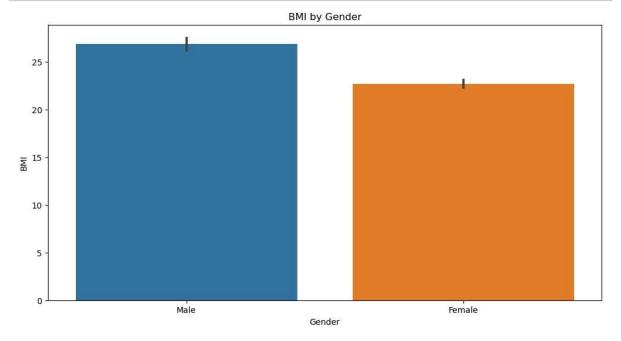
```
#Frequency of Workout by Gender
plt.figure(figsize=(12,6))
sns.barplot(x='Gender',y='Workout_Frequency (days/week)',data=data)
plt.title('Frequency of Workout by Gender')
plt.show()
```



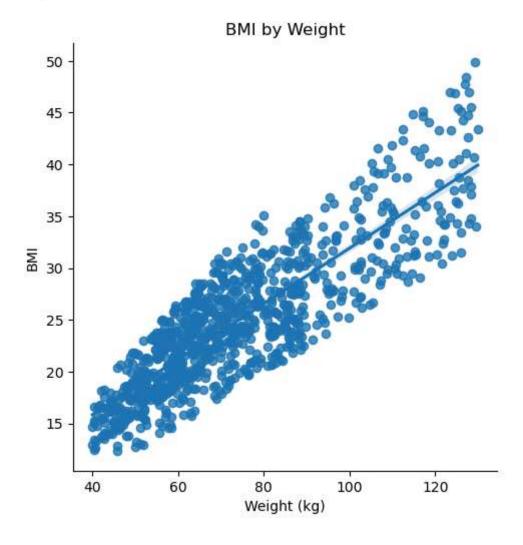




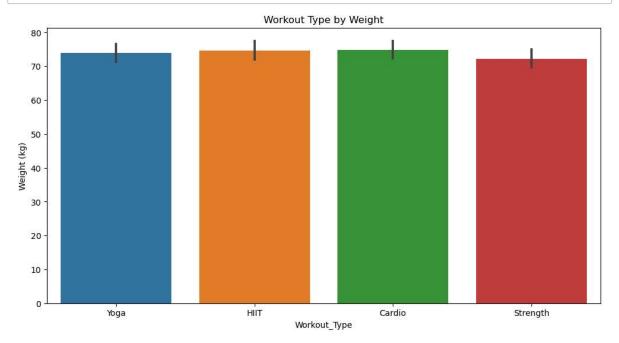
```
In [25]: #BMI by Gender
plt.figure(figsize=(12,6))
sns.barplot(x='Gender',y='BMI',data=data)
plt.title('BMI by Gender')
plt.show()
```



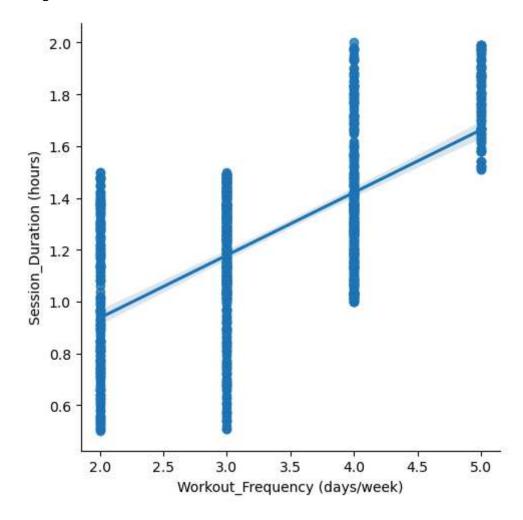
```
In [26]: #BMI by Weight
    plt.figure(figsize=(12,6))
    sns.lmplot(x='Weight (kg)',y='BMI',data=data)
    plt.title('BMI by Weight')
    plt.show()
```



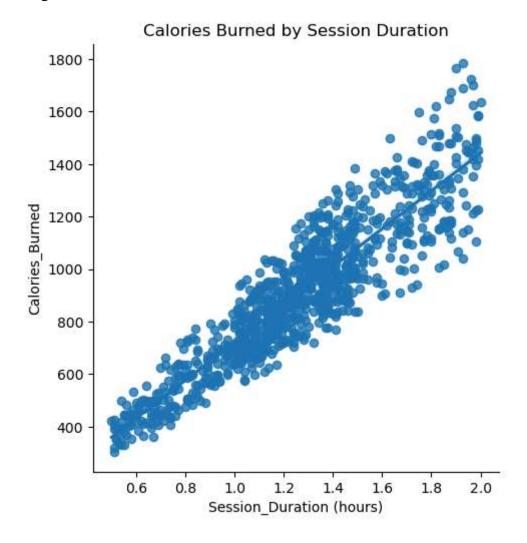
```
In [27]: #Workout Type by Weight
    plt.figure(figsize=(12,6))
    sns.barplot(y='Weight (kg)',x='Workout_Type',data=data)
    plt.title('Workout Type by Weight')
    plt.show()
```



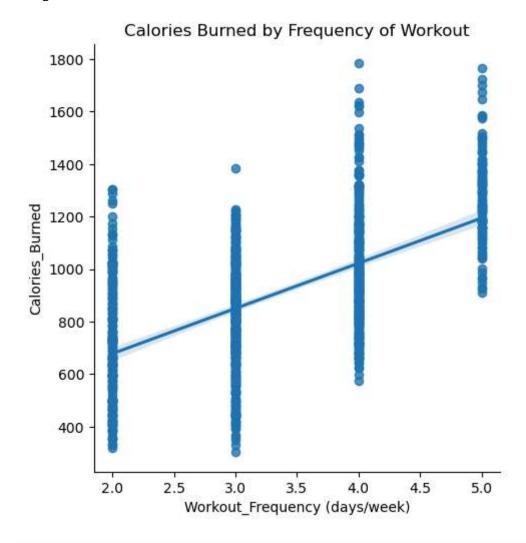
```
In [28]: plt.figure(figsize=(12,6))
    sns.lmplot(x='Workout_Frequency (days/week)',y='Session_Duration (hours)',data
    plt.show()
```



```
In [29]: plt.figure(figsize=(12,6))
    sns.lmplot(y='Calories_Burned',x='Session_Duration (hours)',data=data)
    plt.title('Calories Burned by Session Duration')
    plt.show()
```



```
In [30]: #Calories Burned by Frequency of Workout
    plt.figure(figsize=(12,6))
    sns.lmplot(x='Workout_Frequency (days/week)',y='Calories_Burned',data=data)
    plt.title('Calories Burned by Frequency of Workout')
    plt.show()
```



In [31]: import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter("ignore", category=pd.errors.SettingWithCopyWarning)

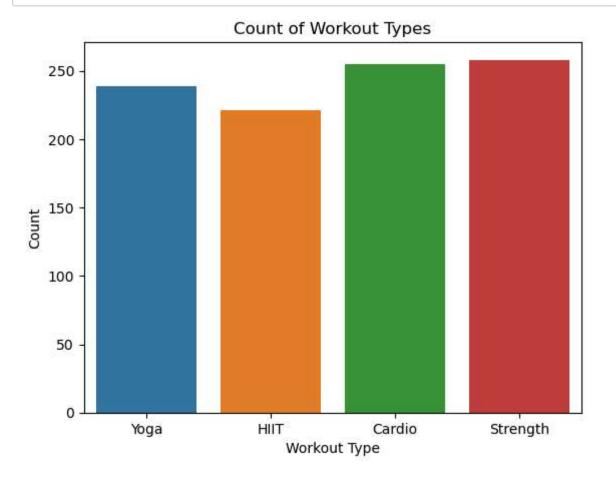
Comparing data between the Overweight and Healthy class and suggesting some improvements to reduce weigh

WHAT KIND OF TRAINING DO THEY MOSTLY DO?

```
In [32]: # Create a countplot to visualize the count of categories in 'Category' column
sns.countplot(x='Workout_Type', data=data)

# Set the title and labels
plt.title('Count of Workout Types')
plt.xlabel('Workout Type')
plt.ylabel('Count')

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

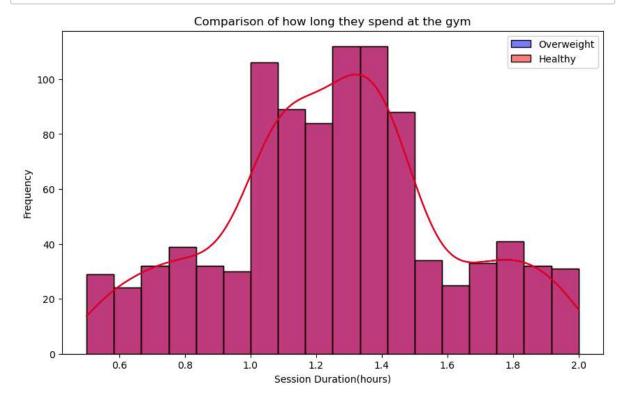


HOW LONG DO THEY SPEND THEIR TIME AT THE GYM?

```
In [33]: plt.figure(figsize=(10, 6))
    sns.histplot(data['Session_Duration (hours)'], color='blue', label='Overweight
    sns.histplot(data['Session_Duration (hours)'], color='red', label='Healthy', k

# Adding Labels and title
    plt.title('Comparison of how long they spend at the gym')
    plt.xlabel('Session Duration(hours)')
    plt.ylabel('Frequency')
    plt.legend()

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



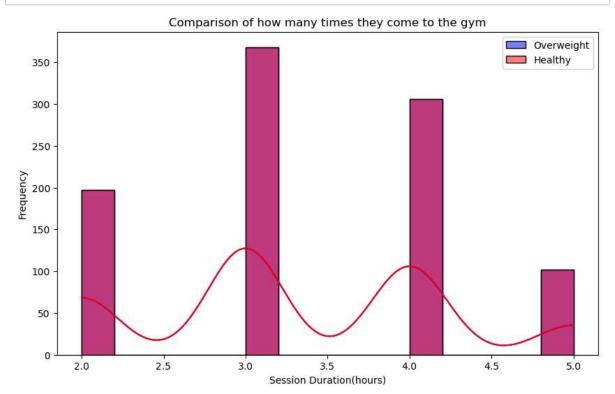
In [34]: #The healthier ones seems to be spending more hours at the gym than their over

HOW MANY TIMES IN A WEEK DO THEY GO TO THE GYM?

```
In [35]: # Plotting the histograms
plt.figure(figsize=(10, 6))
sns.histplot(data['Workout_Frequency (days/week)'], color='blue', label='Overw
sns.histplot(data['Workout_Frequency (days/week)'], color='red', label='Health

# Adding LabeLs and title
plt.title('Comparison of how many times they come to the gym')
plt.xlabel('Session Duration(hours)')
plt.ylabel('Frequency')
plt.legend()

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



WHAT IS THEIR AVERAGE EXPERIENCE LEVEL?

handling outliers

```
In [38]: Q1 = data['Calories_Burned'].quantile(0.25)
  Q3 = data['Calories_Burned'].quantile(0.75)
  IQR = Q3-Q1

min = Q1 - 1.5* IQR
MAX = Q3 + 1.5* IQR

data['Calories_Burned'] = np.where(data['Calories_Burned'] < min, min, data['Calories_Burned'] = np.where(data['Calories_Burned'] > MAX, MAX, data['Calories_Burned'] > MAX, MAX, data['BMI'] > MAX = Q3 + 1.5* IQR

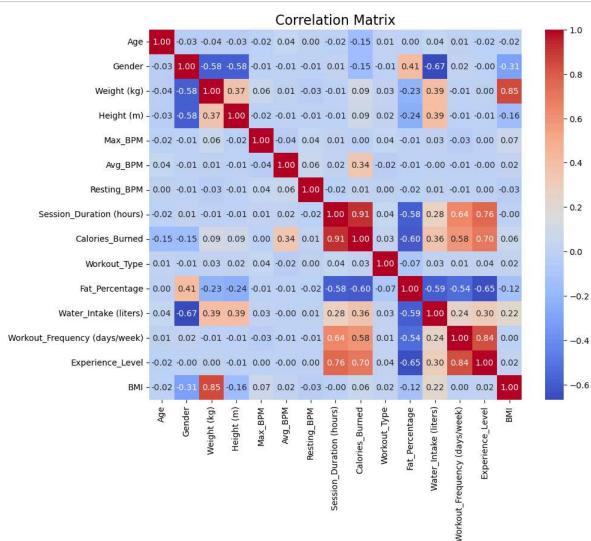
data['BMI'] = np.where(data['BMI'] < min, min, data['BMI'])
data['BMI'] = np.where(data['BMI'] > MAX, MAX, data['BMI'])
```

Corelation

```
In [40]: | data['Gender'].value_counts()
Out[40]: Gender
         Male
                    511
         Female
                    462
         Name: count, dtype: int64
In [41]: changes = {'Male': 0, 'Female':1}
In [42]: | data['Gender'] = data['Gender'].map(changes)
         data['Gender'].head()
Out[42]: 0
               0
         1
               1
         2
               1
               0
         3
         4
         Name: Gender, dtype: int64
```

```
In [43]: data['Workout_Type'].value_counts()
Out[43]: Workout_Type
         Strength
                      258
         Cardio
                      255
         Yoga
                      239
         HIIT
                      221
         Name: count, dtype: int64
In [44]: | changes2 = {'Strength': 0, 'Cardio':1, 'Yoga':2, 'HIIT':3}
In [45]: data['Workout_Type'] = data['Workout_Type'].map(changes2)
         data['Workout_Type'].head()
Out[45]: 0
               2
         1
               3
         2
               1
         3
               0
         4
               0
         Name: Workout_Type, dtype: int64
```

```
In [46]: correlation_matrix = data.corr()
   plt.figure(figsize=(10, 8))
   sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
   plt.title('Correlation Matrix', fontsize=16)
   plt.show()
```



Models

```
In [47]: threshold = 0.03
    correlation = data.corr()
    high_corr_features = correlation.index[abs(correlation['Calories_Burned']) > t
    high_corr_features.remove('Calories_Burned')
    print('Selected features based on corrolation with target:')
    print(high_corr_features)
    X_selected = data[high_corr_features]
    y = data['Calories_Burned']

Selected features based on corrolation with target:
    ['Age', 'Gender', 'Weight (kg)', 'Height (m)', 'Avg_BPM', 'Session_Duration
    (hours)', 'Fat_Percentage', 'Water_Intake (liters)', 'Workout_Frequency (day
    s/week)', 'Experience_Level', 'BMI']
```

```
In [48]:
         from sklearn.metrics import accuracy_score,confusion_matrix,classification_rep
         import warnings
         warnings.filterwarnings('ignore')
         from sklearn.preprocessing import MinMaxScaler
In [49]: | scaler = MinMaxScaler()
         X = scaler.fit_transform(X_selected)
In [50]: from sklearn.model_selection import train_test_split, GridSearchCV
         from sklearn.svm import SVC
         from sklearn.linear model import LogisticRegression
In [51]: X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.1, shuff
In [52]: model = LogisticRegression()
In [53]: X train.shape
Out[53]: (875, 11)
In [54]: model.fit(X_train, Y_train)
Out[54]: LogisticRegression()
         In a Jupyter environment, please rerun this cell to show the HTML representation or trust
         the notebook.
         On GitHub, the HTML representation is unable to render, please try loading this page
         with nbviewer.org.
In [55]: model.score(X_train, Y_train)
Out[55]: 0.04342857142857143
In [56]:
         y_pred = model.predict(X_test)
In [57]:
         print(accuracy_score(y_pred, Y_test))
         0.01020408163265306
```

```
In [63]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.model selection import train test split
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import mean squared error, mean absolute error, r2 score
         # Selected features based on correlation analysis
         selected_features = [
             'Session Duration (hours)', 'Experience Level', 'Workout Frequency (days/w
             'Water_Intake (liters)', 'Avg_BPM', 'Fat_Percentage', 'Gender'
         ]
         # Split the dataset
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
         # Scale features
         scaler = StandardScaler()
         X train scaled = scaler.fit transform(X train)
         X_test_scaled = scaler.transform(X_test)
         # Initialize and train Random Forest Regressor
         rf regressor = RandomForestRegressor(random state=42, n estimators=100)
         rf_regressor.fit(X_train_scaled, y_train)
         # Predictions
         y_train_pred = rf_regressor.predict(X_train_scaled)
         y_test_pred = rf_regressor.predict(X_test_scaled)
         # Evaluate the model
         train r2 = r2 score(y train, y train pred)
         test_r2 = r2_score(y_test, y_test_pred)
         train_mse = mean_squared_error(y_train, y_train_pred)
         test_mse = mean_squared_error(y_test, y_test_pred)
         train_mae = mean_absolute_error(y_train, y_train_pred)
         test_mae = mean_absolute_error(y_test, y_test_pred)
         print("Training R^2:", train_r2)
         print("Testing R^2:", test_r2)
         print("Training MSE:", train_mse)
         print("Testing MSE:", test mse)
         print("Training MAE:", train_mae)
         print("Testing MAE:", test_mae)
         Training R^2: 0.9966591492479834
         Testing R^2: 0.9761296949544783
         Training MSE: 236.55093097686378
```

Testing MSE: 1957.5072374358974 Training MAE: 11.756645244215939 Testing MAE: 34.138615384615385

```
In [ ]:
```

In []: