Aerofit Business Case Study on Treadmills

Importing Libraries for Data Analysis and Visualization

```
# Importing the Libraries:
import pandas as pd
import numpy as np
import PIL.Image
import plotly.express as px
from textblob import TextBlob
import seaborn as sns
import matplotlib.pyplot as plt
import copy
import warnings
```

Uploading File to Google Colab Environment

```
# Upload the File
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Loading Data from CSV File into DataFrame

```
Data = pd.read_csv('aerofit_treadmill.csv')
```

Creating a Copy of the DataFrame

```
df = Data.copy()
```

Analysing Basic Metrics

1) Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset

Check for Missing Values

```
# Check for Missing Values in Each Columns:
print(df.isnull().sum())
```

```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Display the data type of each column

```
df.dtypes
```

	0
Product	object
Age	int64
Gender	object
Education	int64
MaritalStatus	object
Usage	int64
Fitness	int64
Income	int64
Miles	int64

dtype: object

First 5 Rows of the DataFrame

```
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

DataFrame Dimensions (Rows, Columns)

```
# Getting the Dimensions of the DataFrame
df.shape
```

```
(180, 9)
```

DataFrame Information Overview

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Product        180 non-null    object
 1   Age            180 non-null    int64 
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64 
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64 
 6   Fitness        180 non-null    int64 
 7   Income         180 non-null    int64 
 8   Miles          180 non-null    int64 
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

Counting Missing Values in Each Column of the DataFrame

```
1 df.isna().sum()
```

	0
Product	0
Age	0
Gender	0
Education	0
MaritalStatus	0
Usage	0
Fitness	0
Income	0
Miles	0

dtype: int64

Statistical Summary of the DataFrame

```
1 df.describe()
```

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

Counting Duplicate Rows in the DataFrame

```
1 df.duplicated().sum()
```

```
0
```

Counting Unique Values in Each Column of the DataFrame

```
1 df.nunique()
```

	0
Product	3
Age	32
Gender	2
Education	8
MaritalStatus	2
Usage	6
Fitness	5
Income	62
Miles	37

dtype: int64

Transposed Statistical Summary of the DataFrame

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Age	180.0	28.788889	6.943498	18.0	24.00	26.0	33.00	50.0
Education	180.0	15.572222	1.617055	12.0	14.00	16.0	16.00	21.0
Usage	180.0	3.455556	1.084797	2.0	3.00	3.0	4.00	7.0
Fitness	180.0	3.311111	0.958869	1.0	3.00	3.0	4.00	5.0
Income	180.0	53719.577778	16506.684226	29562.0	44058.75	50596.5	58668.00	104581.0
Miles	180.0	103.194444	51.863605	21.0	66.00	94.0	114.75	360.0

Transposed Statistical Summary of Categorical Columns in the DataFrame

```
df.describe(include = 'object').T
```

	count	unique	top	freq
Product	180	3	KP281	80
Gender	180	2	Male	104
MaritalStatus	180	2	Partnered	107

Listing Column Names in the DataFrame

```
df.columns
```

```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

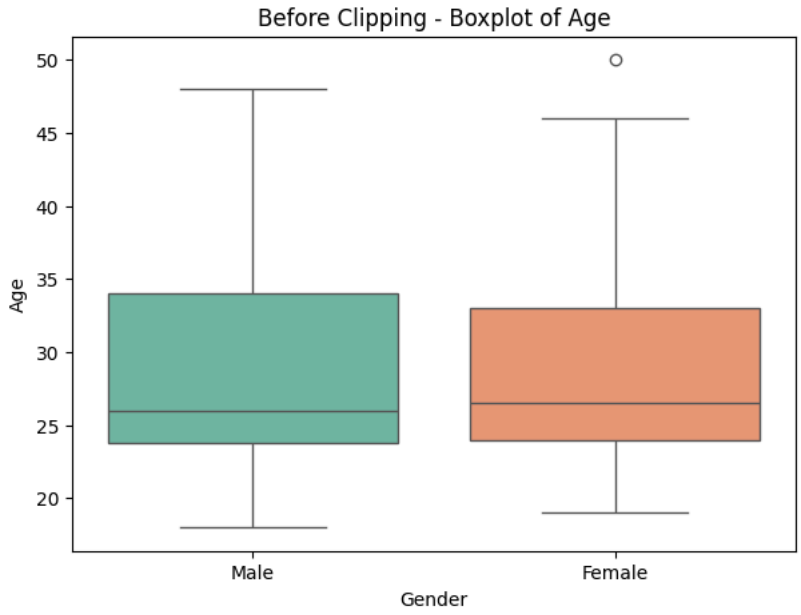
2. Detect Outliers

Step 1: Visualize Outliers Using Boxplots

1) Outlier Detection for 'Age'

```
### Before Clipping - Boxplot of Age:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Age'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Age')
plt.xlabel('Gender')
```

```
plt.ylabel('Age')
plt.show()
```

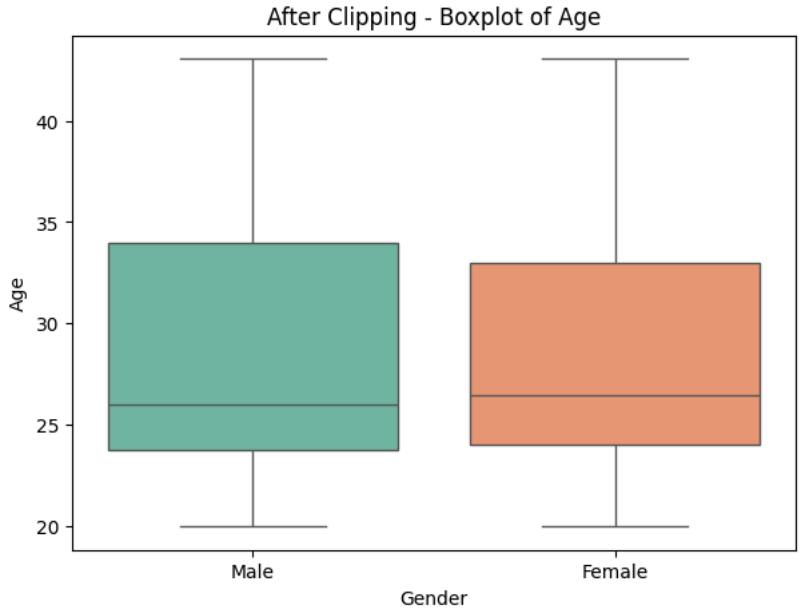



```
### 🔷 Non-Graphical Outlier Detection for Age:
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1
Lower_Bound = Q1 - 1.5 * IQR
Upper_Bound = Q3 + 1.5 * IQR

# Outliers Deduct
Outliers_Deduct = df[(df['Age'] < Lower_Bound) | (df['Age'] > Upper_Bound)]['Age']
print(f" ✅ Outliers_Deduct_Age:\n{Outliers_Deduct.to_frame()}")
```

```
✅ Outliers_Deduct_Age:
     Age
78    47
79    50
139   48
178   47
179   48
```

```
### 🔷 Step 3: np.clip() Se Outliers Adjust:
Age_Lower_Bound = np.percentile(df['Age'], 5)
Age_Upper_Bound = np.percentile(df['Age'], 95)

df['Age'] = np.clip(df['Age'], Age_Lower_Bound, Age_Upper_Bound)
print(f"\n✅ Clipping Range: {Age_Lower_Bound} to {Age_Upper_Bound}")
print(f"\n🔷 Data After Clipping:\n{df['Age'].describe().round(2)}\n")

### 🔷 Step 4: After Clipping Boxplot of Age:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Age'], hue=df['Gender'], palette='Set2', legend=False)
plt.title('After Clipping - Boxplot of Age')
plt.xlabel('Gender')
plt.ylabel('Age')
plt.show()
```

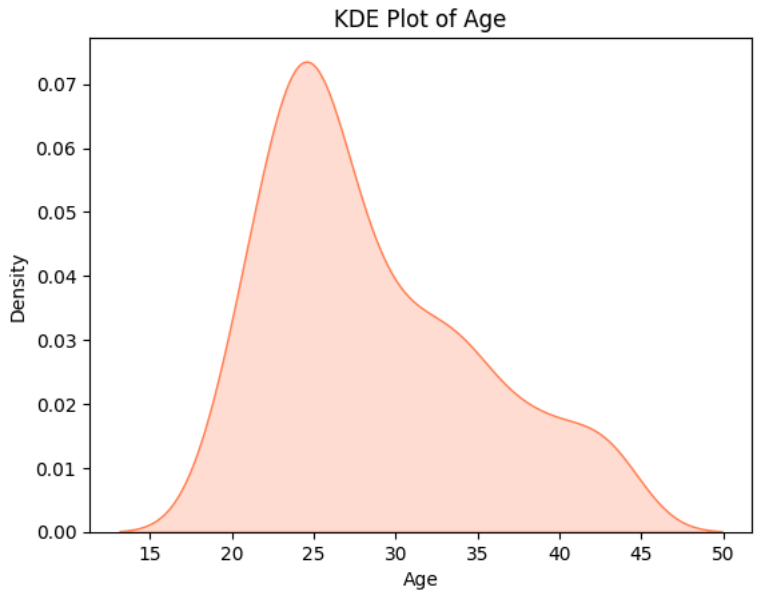
```
✅ Clipping Range: 20.0 to 43.04999999999998

🔷 Data After Clipping:
count    180.00
mean      28.64
std        6.45
min       20.00
25%       24.00
50%       26.00
75%       33.00
max       43.05
Name: Age, dtype: float64
```




```
df['Z-Score'] = (df['Age'] - df['Age'].mean())/df['Age'].std()
Age_Outliers = df[df['Z-Score'].abs() > 2.5]
Age_Outliers
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

```
sns.kdeplot(df["Age"], fill=True, color='coral')
plt.xlabel("Age")
plt.ylabel("Density")
plt.title("KDE Plot of Age")
plt.show()
```

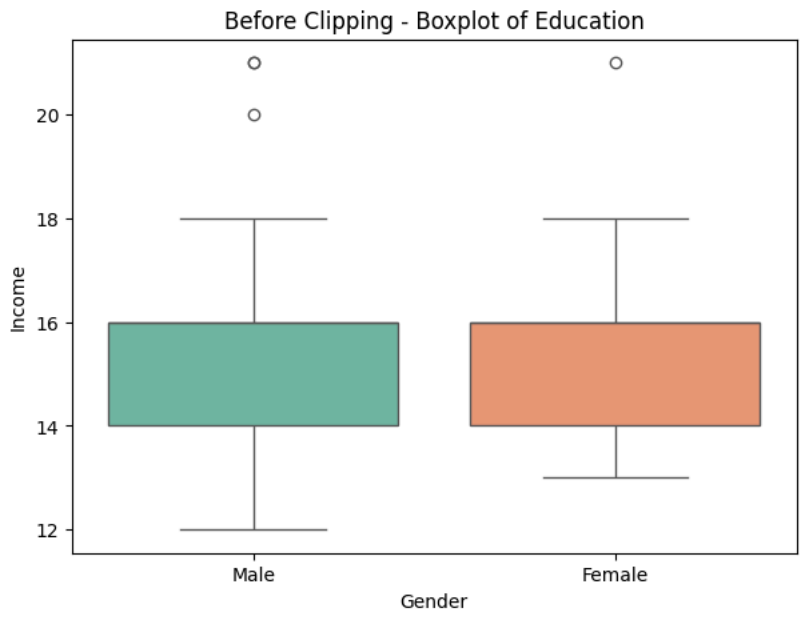


Insights Age:

This code removes outliers from the 'Age' column by restricting values between the 5th and 95th percentiles. It then adjusts extreme values to these bounds and provides a statistical summary of the cleaned 'Age' data, showing metrics like mean, min, and max.

2) Outlier Detection for 'Education'

```
### Before Clipping - Boxplot of Education:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Education'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Education')
plt.xlabel('Gender')
plt.ylabel('Income')
plt.show()
```



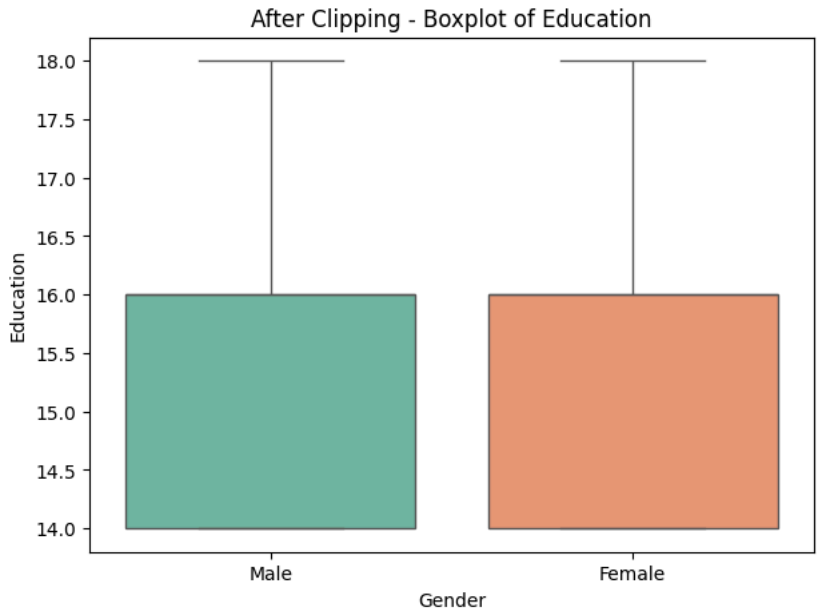

```
Q1 = df['Education'].quantile(0.25)
Q3 = df['Education'].quantile(0.75)
IQR = Q3 - Q1

Lower_Bound = Q1 - 1.5 * IQR
Upper_Bound = Q3 + 1.5 * IQR

Outliers_Deduct = df[(df['Education'] < Lower_Bound) | (df['Education'] > Upper_Bound)]['Education']
print(f"Outliers_Deduct_Education:\n{Outliers_Deduct.to_frame()}")
```

```
Outliers_Deduct_Education:
     Education
156         20
157         21
161         21
175         21
```

```
### 🔷 Step 3: np.clip() Se Outliers Adjust:
Education_Lower_Bound = np.percentile(df['Education'], 5)
Education_Upper_Bound = np.percentile(df['Education'], 95)

df['Education'] = np.clip(df['Education'], Education_Lower_Bound, Education_Upper_Bound)
print(f"\n✅ Clipping Range: {Education_Lower_Bound} to {Education_Upper_Bound}")
print(f"\n🔷 Data After Clipping:\n{df['Education'].describe().round(2)}\n")

### 🔷 Step 4: After Clipping Boxplot of Education:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Education'], hue=df['Gender'], palette='Set2', legend=False)
```

```
12
13 plt.title('After Clipping - Boxplot of Education')
14 plt.xlabel('Gender')
15 plt.ylabel('Education')
16 plt.show()
```

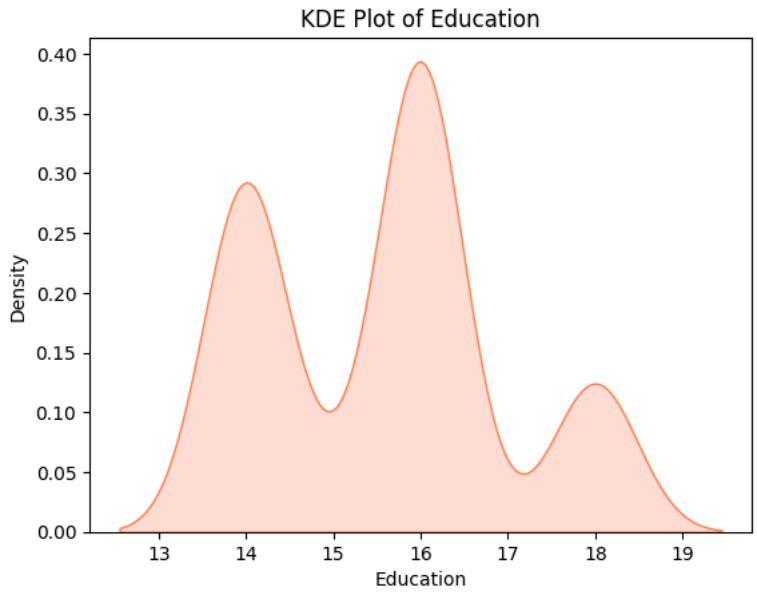
```
✅ Clipping Range: 14.0 to 18.0

🔷 Data After Clipping:
count    180.00
mean      15.57
std        1.36
min       14.00
25%       14.00
50%       16.00
75%       16.00
max       18.00
Name: Education, dtype: float64
```




```
1 df['Z-Score'] = (df['Education'] - df['Education'].mean())/df['Education'].std()
2 Education_Outliers = df[df['Z-Score'].abs() > 3]
3 Education_Outliers
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

```
1 sns.kdeplot(df["Education"], fill=True, color='coral')
2 plt.xlabel("Education")
3 plt.ylabel("Density")
4 plt.title("KDE Plot of Education")
5 plt.show()
```

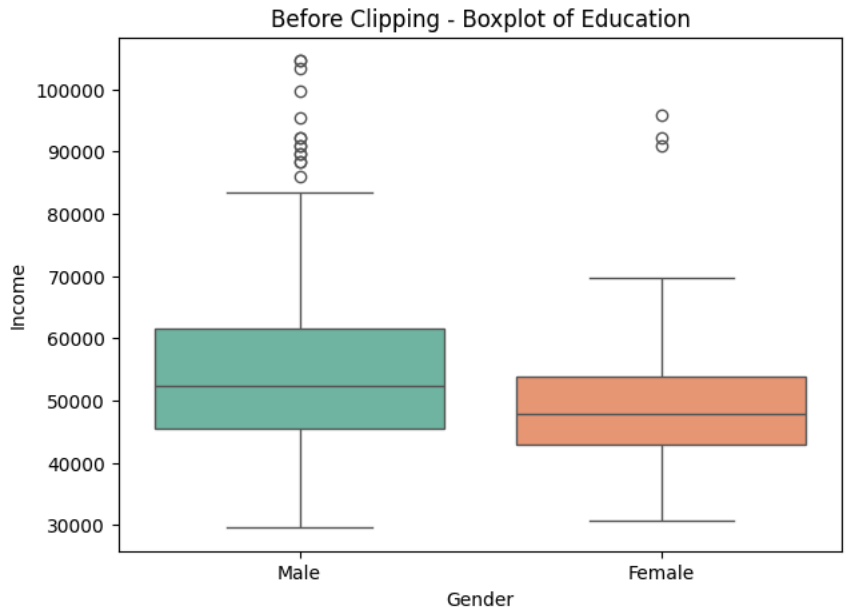


Insights Education:

This code removes outliers from the 'Education' column by clipping values between the 5th and 95th percentiles. Any values below the 5th percentile or above the 95th percentile are adjusted to these limits. It then provides a statistical summary of the cleaned 'Education' data, showing metrics like mean, min, and max.

3) Outlier Detection for 'Income'

```
### Before Clipping - Boxplot of Education:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Income'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Education')
plt.xlabel('Gender')
plt.ylabel('Income')
plt.show()
```



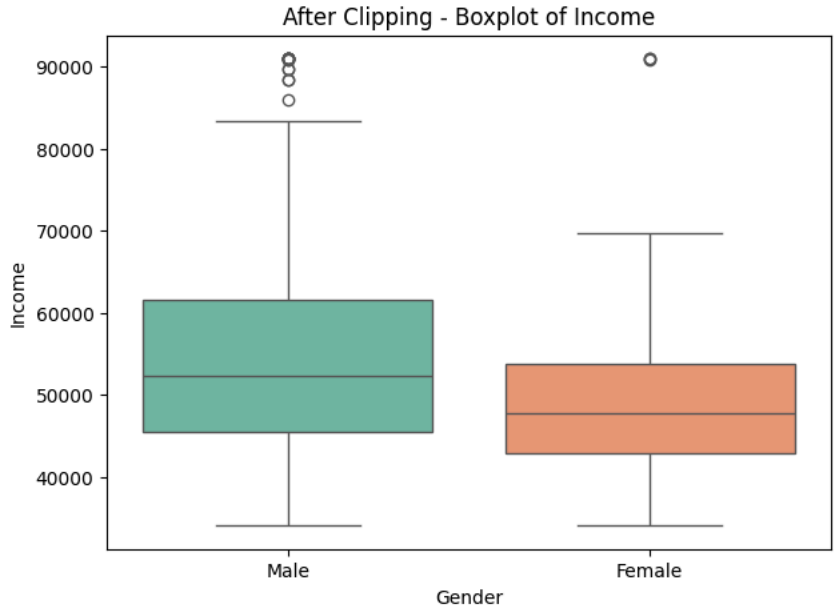

```
Q1 = df['Income'].quantile(0.25)
Q3 = df['Income'].quantile(0.75)
IQR = Q3 - Q1
```

```
4
5  Lower_Bound = Q1 - 1.5 * IQR
6  Upper_Bound = Q3 + 1.5 * IQR
7
8  Deduct_Outliers = df[(df['Income'] < Lower_Bound) | (df['Income'] > Upper_Bound)]['Income']
9  print(f"Outliers_Deduct_Income:\n{Deduct_Outliers.to_frame()}")
```

```
Outliers_Deduct_Income:
     Income
159   83416
160   88396
161   90886
162   92131
164   88396
166   85906
167   90886
168  103336
169   99601
170   89641
171   95866
172   92131
173   92131
174  104581
175   83416
176   89641
177   90886
178  104581
179   95508
```

```
1 ### 🔷 Step 3: np.clip() Se Outliers Adjust:
2 Income_Lower_Bound = np.percentile(df['Income'], 5)
3 Income_Upper_Bound = np.percentile(df['Income'], 95)
4
5 df['Income'] = np.clip(df['Income'], Income_Lower_Bound, Income_Upper_Bound)
6 print(f"\n✅ Clipping Range: {Income_Lower_Bound} to {Income_Upper_Bound}")
7 print(f"\n🔷 Data After Clipping:\n{df['Income'].describe().round(2)}\n")
8
9 ### 🔷 Step 4: After Clipping Boxplot of Income:
10 plt.figure(figsize=(7, 5))
11 sns.boxplot(x=df['Gender'], y=df['Income'], hue=df['Gender'], palette='Set2', legend=False)
12
13 plt.title('After Clipping - Boxplot of Income')
14 plt.xlabel('Gender')
15 plt.ylabel('Income')
16 plt.show()
```

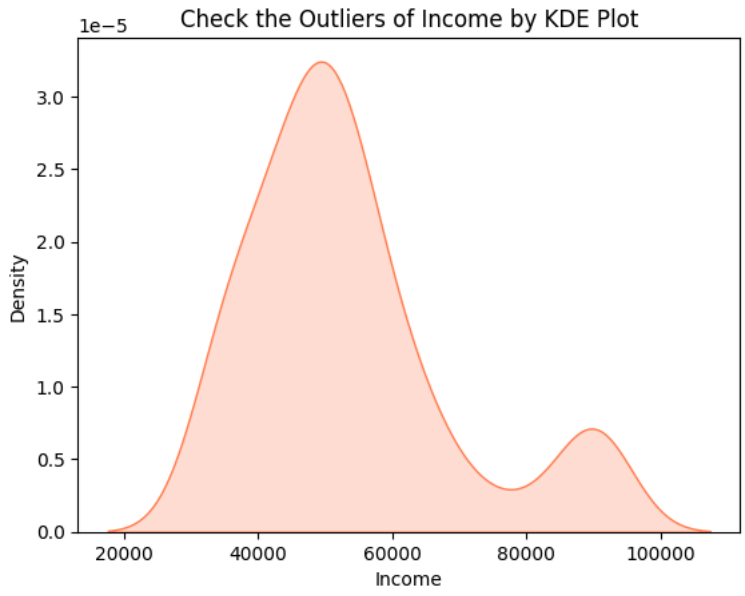
```
✅ Clipping Range: 34053.15 to 90948.24999999999

🔷 Data After Clipping:
count      180.00
mean     53477.07
std      15463.66
min      34053.15
25%      44058.75
50%      50596.50
75%      58668.00
max      90948.25
Name: Income, dtype: float64
```




```
df['Z-Score'] = (df['Income'] - df['Income'].mean())/df['Income'].std()
Income_Outliers = df[df['Z-Score'].abs() > 3]
Income_Outliers
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

```
sns.kdeplot(df["Income"], fill=True, color='coral')
plt.xlabel("Income")
plt.ylabel("Density")
plt.title("Check the Outliers of Income by KDE Plot")
plt.show()
```

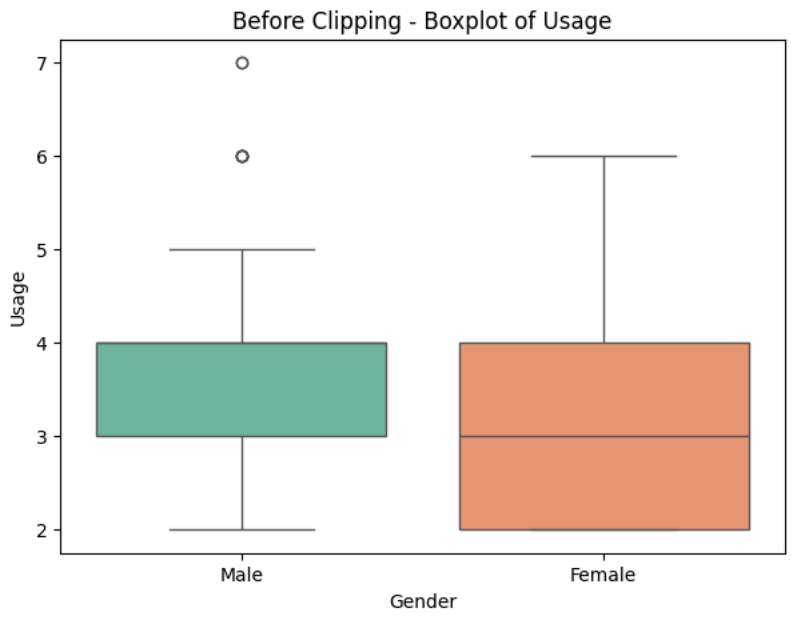


Insights Income:

This code removes outliers from the 'Income' column by clipping values between the 5th and 95th percentiles. Any values below the 5th percentile or above the 95th percentile are adjusted to fall within these limits. It then provides a statistical summary of the cleaned 'Income' data, showing metrics such as mean, min, and max.

4) Outlier Detection for 'Usage'

```
### Before Clipping - Boxplot of Usage:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Usage'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Usage')
plt.xlabel('Gender')
plt.ylabel('Usage')
plt.show()
```



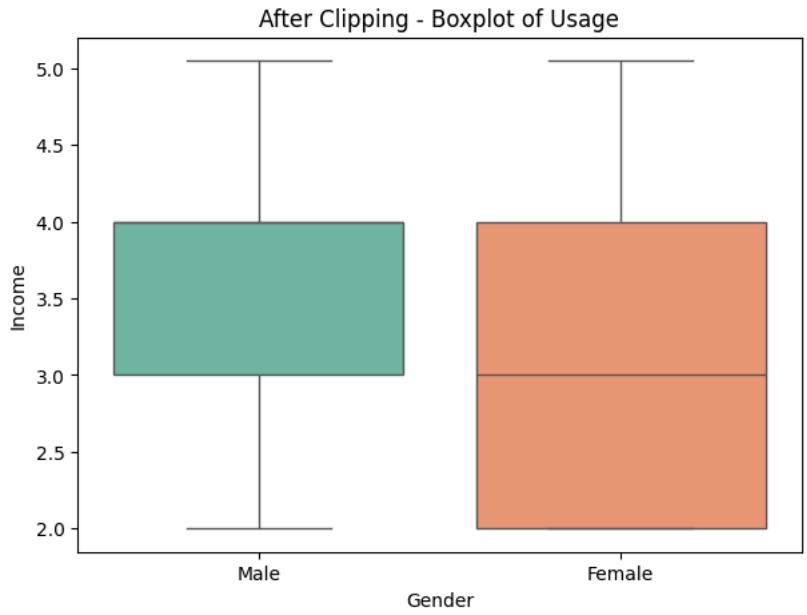

```
Q1 = df['Usage'].quantile(0.25)
Q3 = df['Usage'].quantile(0.75)
IQR = Q3 - Q1

Lower_Bound = Q1 - 1.5 * IQR
Upper_Bound = Q3 + 1.5 * IQR

Deduct_Outliers = df[(df['Usage'] < Lower_Bound) | (df['Usage'] > Upper_Bound)]['Usage']
print(f"Outliers_Deduct_Usage:\n{Deduct_Outliers.to_frame()}")
```

```
Outliers_Deduct_Usage:
     Usage
154      6
155      6
162      6
163      7
164      6
166      7
167      6
170      6
175      6
```

```
### 🔷 Step 3: np.clip() Se Outliers Adjust:
Usage_Lower_Bound = np.percentile(df['Usage'], 5)
Usage_Upper_Bound = np.percentile(df['Usage'], 95)

df['Usage'] = np.clip(df['Usage'], Usage_Lower_Bound, Usage_Upper_Bound)
print(f"\n✅ Clipping Range: {Usage_Lower_Bound} to {Usage_Lower_Bound}")
print(f"\n🔷 Data After Clipping:\n{df['Fitness'].describe().round(2)}\n")
```

```
8
9 ### 🔷 Step 4: After Clipping Boxplot of Usage:
10 plt.figure(figsize=(7, 5))
11 sns.boxplot(x=df['Gender'], y=df['Usage'], hue=df['Gender'], palette='Set2', legend=False)
12 plt.title('After Clipping - Boxplot of Usage')
13 plt.xlabel('Gender')
14 plt.ylabel('Income')
15 plt.show()
```

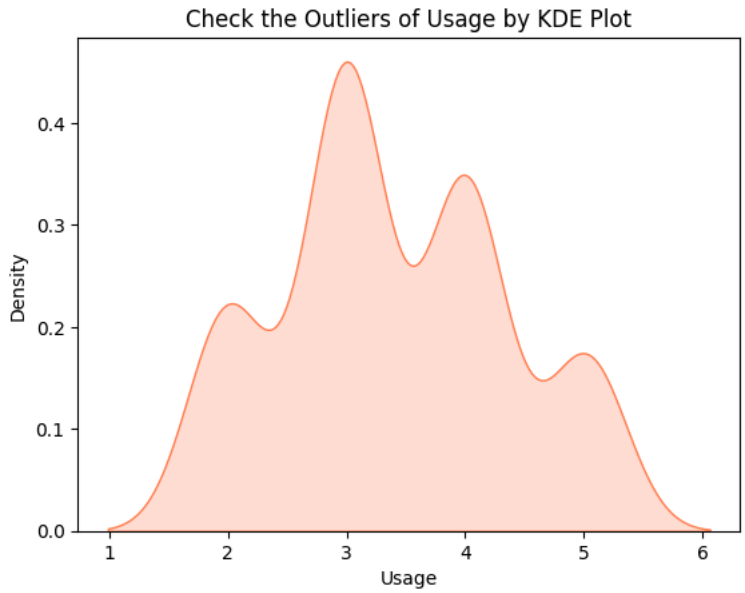
```
✅ Clipping Range: 2.0 to 2.0

🔷 Data After Clipping:
count    180.00
mean       3.31
std        0.96
min        1.00
25%        3.00
50%        3.00
75%        4.00
max        5.00
Name: Fitness, dtype: float64
```




```
1 df['Z-Score'] = (df['Usage'] - df['Usage'].mean())/df['Usage'].std()
2 Usage_Outliers = df[df['Z-Score'].abs() > 3]
3 Usage_Outliers
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

```
1 sns.kdeplot(df["Usage"], fill=True, color='coral')
2 plt.xlabel("Usage")
3 plt.ylabel("Density")
4 plt.title("Check the Outliers of Usage by KDE Plot")
5 plt.show()
```

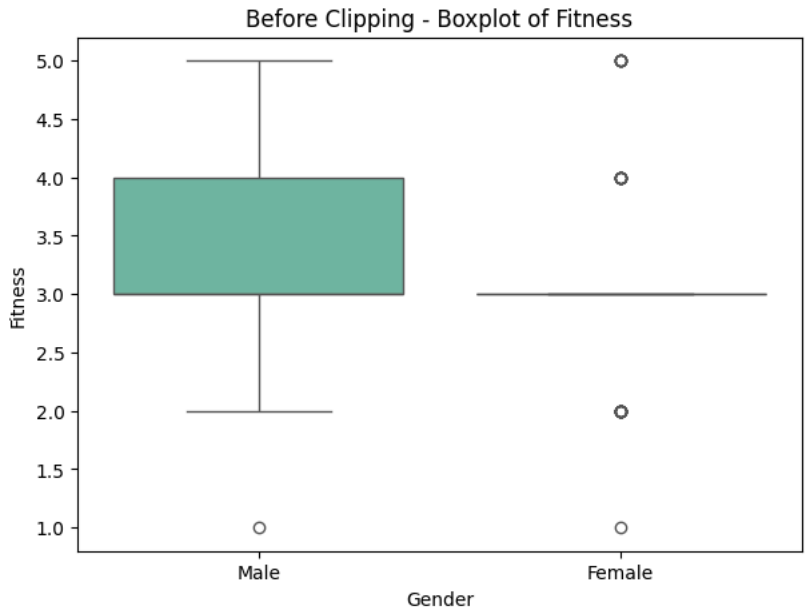


Insights Usage:

This code removes outliers from the 'Usage' column by clipping values between the 5th and 95th percentiles. Any values below the 5th percentile or above the 95th percentile are adjusted to fall within these limits. It then provides a statistical summary of the cleaned 'Usage' data, showing metrics such as mean, min, and max.

5) Outlier Detection for 'Fitness'

```
### Before Clipping - Boxplot of Fitness:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Fitness'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Fitness')
plt.xlabel('Gender')
plt.ylabel('Fitness')
plt.show()
```



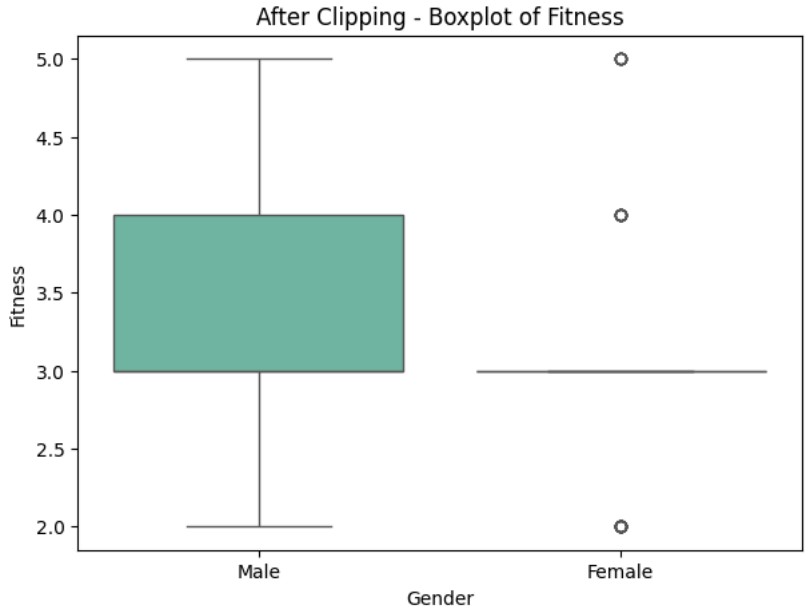

```
Q1 = df['Fitness'].quantile(0.25)
Q3 = df['Fitness'].quantile(0.75)
IQR = Q3 - Q1
```

```
4
5 Lower_Bound = Q1 - 1.5 * IQR
6 Upper_Bound = Q3 + 1.5 * IQR
7
8 Deduct_Outliers = df[(df['Fitness'] < Lower_Bound) | (df['Fitness'] > Upper_Bound)]['Fitness']
9 print(f"Outliers_Deduct_Fitness:\n{Deduct_Outliers.to_frame()}")
```

```
Outliers_Deduct_Fitness:
     Fitness
14         1
117        1
```

```
1 ### 🔷 Step 3: np.clip() Se Outliers Adjust:
2 Fitness_Lower_Bound = np.percentile(df['Fitness'], 5)
3 Fitness_Upper_Bound = np.percentile(df['Fitness'], 95)
4
5 df['Fitness'] = np.clip(df['Fitness'], Fitness_Lower_Bound, Fitness_Upper_Bound)
6 print(f"\n✅ Clipping Range: {Fitness_Lower_Bound} to {Fitness_Upper_Bound}")
7 print(f"\n🔷 Data After Clipping:\n{df['Fitness'].describe().round(2)}\n")
8
9 ### 🔷 Step 4: After Clipping Boxplot of Fitness:
10 plt.figure(figsize=(7, 5))
11 sns.boxplot(x=df['Gender'], y=df['Fitness'], hue=df['Gender'], palette='Set2', legend=False)
12 plt.title('After Clipping - Boxplot of Fitness')
13 plt.xlabel('Gender')
14 plt.ylabel('Fitness')
15 plt.show()
```

```
✅ Clipping Range: 2.0 to 5.0

🔷 Data After Clipping:
count    180.00
mean       3.32
std        0.94
min        2.00
25%        3.00
50%        3.00
75%        4.00
max        5.00
Name: Fitness, dtype: float64
```

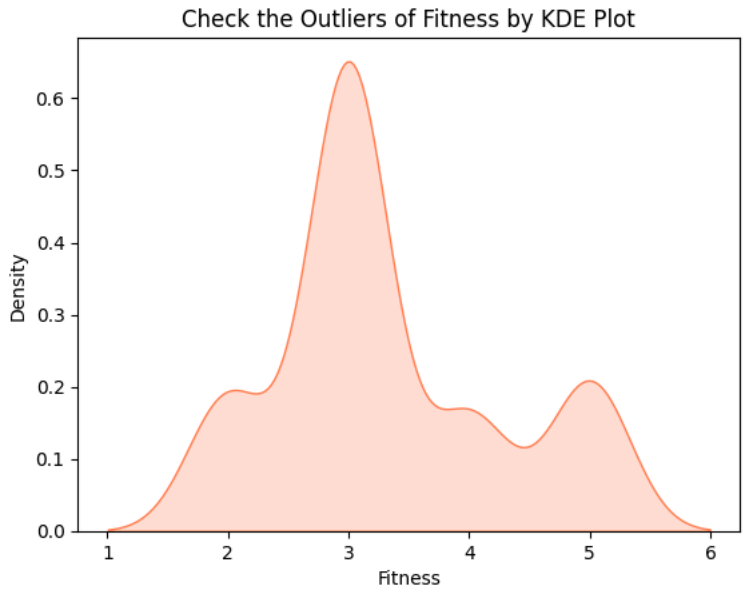



```
1 df['Z-Score'] = (df['Fitness'] - df['Fitness'].mean())/df['Fitness'].std()
2 Fitness_Outliers = df[df['Z-Score'].abs() > 3]
3 Fitness_Outliers
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

```
1 sns.kdeplot(df["Fitness"], fill=True, color='coral')
2 plt.xlabel("Fitness")
```

```
plt.ylabel("Density")
plt.title("Check the Outliers of Fitness by KDE Plot")
plt.show()
```

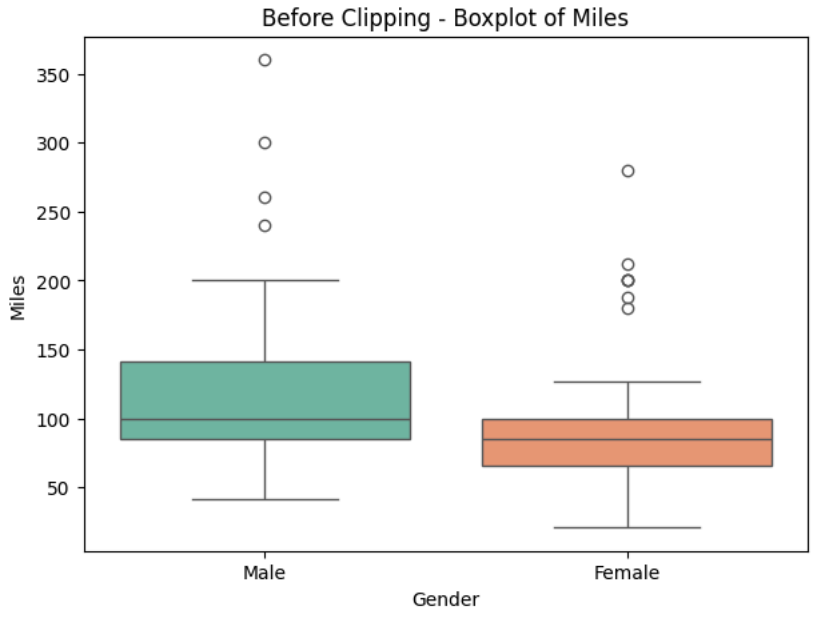


Insights Fitness:

This code removes outliers from the 'Fitness' column by clipping values between the 5th and 95th percentiles. Any values below the 5th percentile or above the 95th percentile are adjusted to fall within these limits. It then provides a statistical summary of the cleaned 'Fitness' data, showing metrics such as mean, min, and max.

6) Outlier Detection for 'Miles'

```
### Before Clipping - Boxplot of Miles:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Miles'], hue=df['Gender'], palette='Set2', legend=False)

plt.title('Before Clipping - Boxplot of Miles')
plt.xlabel('Gender')
plt.ylabel('Miles')
plt.show()
```

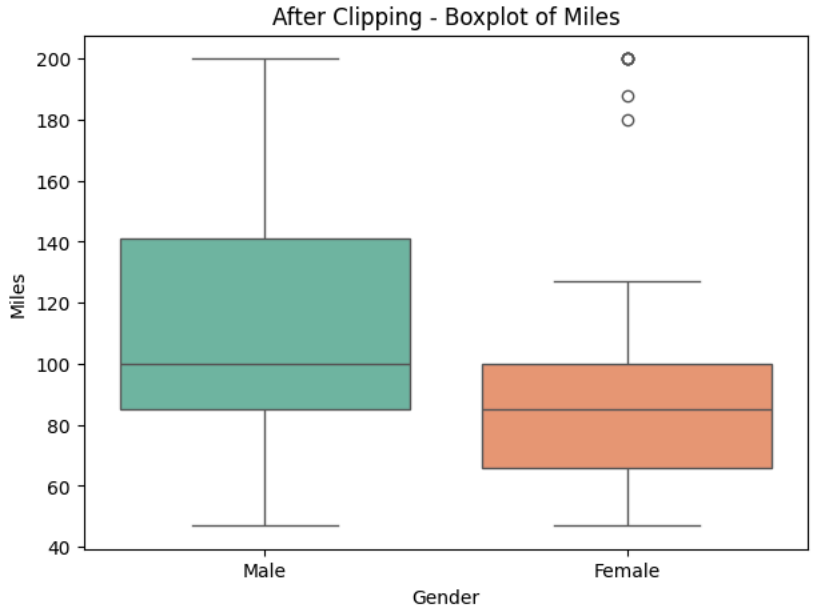


```
Q1 = df['Miles'].quantile(0.25)
Q3 = df['Miles'].quantile(0.75)
IQR = Q3 - Q1

Lower_Bound = Q1 - 1.5 * IQR
Upper_Bound = Q3 + 1.5 * IQR

Miles_Deduct_Outliers = df[(df['Miles'] < Lower_Bound) | (df['Miles'] > Upper_Bound)]['Miles']
print(f"Outliers_Deduct_Miles:\n{Miles_Deduct_Outliers.to_frame()}")
```

```
Outliers_Deduct_Miles:
     Miles
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
170    260
171    200
173    360
175    200
176    200
```

```
### 🔷 Step 3: np.clip() Se Outliers Adjust:
Miles_Lower_Bound = np.percentile(df['Miles'], 5)
Miles_Upper_Bound = np.percentile(df['Miles'], 95)

df['Miles'] = np.clip(df['Miles'], Miles_Lower_Bound, Miles_Upper_Bound)
print(f"\n✅ Clipping Range: {Miles_Lower_Bound} to {Miles_Upper_Bound}")
print(f"\n🔷 Data After Clipping:\n{df['Miles'].describe().round(2)}\n")

### 🔷 Step 4: After Clipping Boxplot of Miles:
plt.figure(figsize=(7, 5))
sns.boxplot(x=df['Gender'], y=df['Miles'], hue=df['Gender'], palette='Set2', legend=False)
plt.title('After Clipping - Boxplot of Miles')
plt.xlabel('Gender')
plt.ylabel('Miles')
plt.show()
```

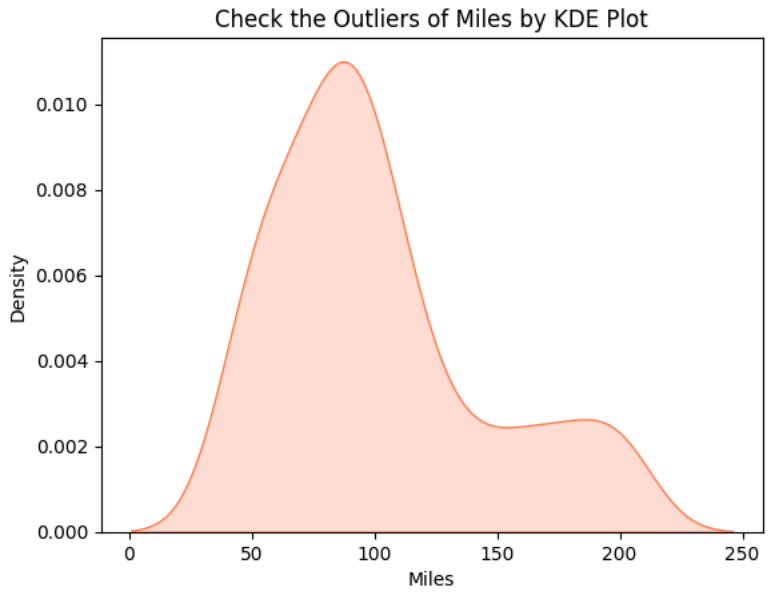
```
✅ Clipping Range: 47.0 to 200.0

🔷 Data After Clipping:
count    180.00
mean     101.09
std       43.36
min       47.00
25%       66.00
50%       94.00
75%      114.75
max      200.00
Name: Miles, dtype: float64
```




```
df['Z-Score'] = (df['Miles'] - df['Miles'].mean())/df['Miles'].std()
Miles_Outliers = df[df['Z-Score'].abs() > 3]
Miles_Outliers
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Z-Score

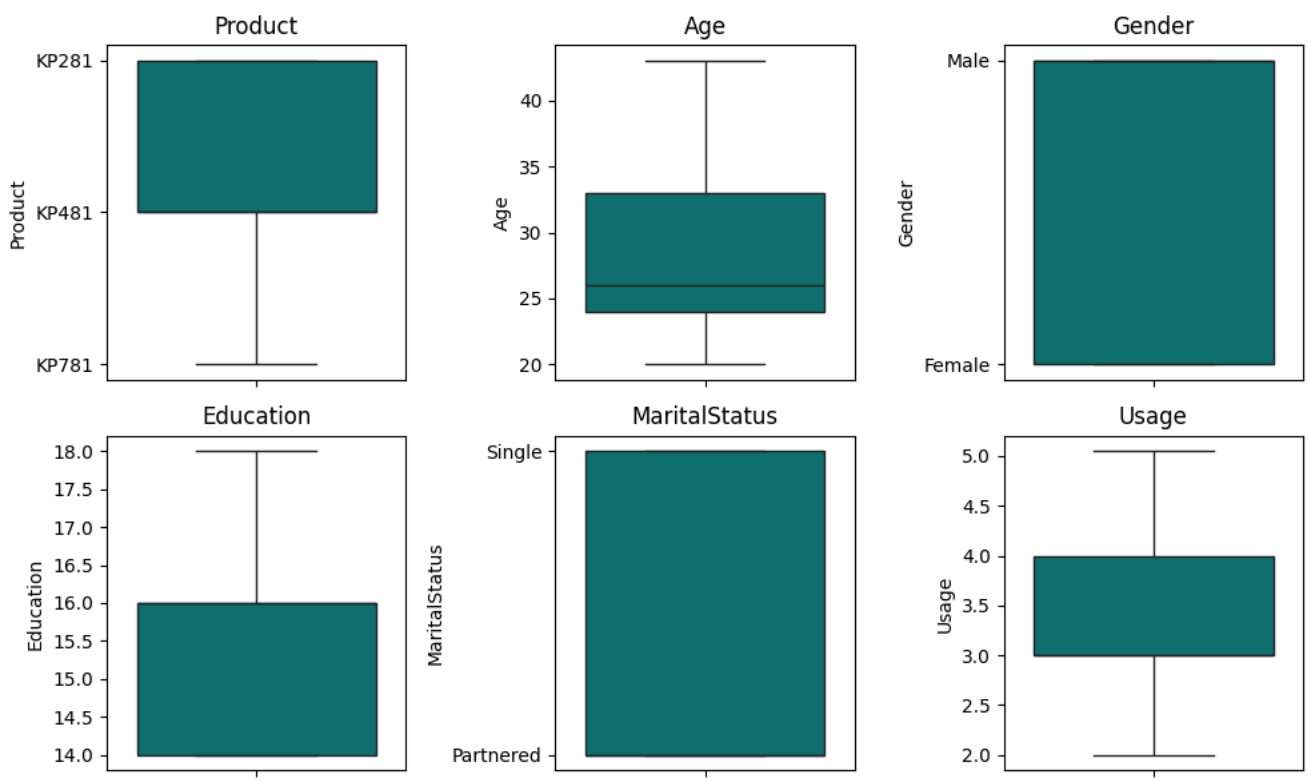
```
sns.kdeplot(df["Miles"], fill=True, color='coral')
plt.xlabel("Miles")
plt.ylabel("Density")
plt.title("Check the Outliers of Miles by KDE Plot")
plt.show()
```



Insights Miles:

This code removes outliers from the 'Miles' column by clipping values between the 5th and 95th percentiles. Any values below the 5th percentile or above the 95th percentile are adjusted to fall within these limits. It then provides a statistical summary of the cleaned 'Miles' data, showing metrics such as mean, min, and max.

```
# Combining all the int Columns into a list:
warnings.simplefilter("ignore", category=FutureWarning)
fig, axes = plt.subplots(2, 3, figsize=(10, 6))

for ax, var in zip(axes.flat, df[:6]):
    sns.boxplot(ax=ax, data=df, y=var, color="teal")
    ax.set_title(var)

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



Insights Outliers:

Age:

Outliers include a few exceptional cases of significantly younger or older individuals, skewing the data distribution.

Education:

Outliers are likely found in individuals with either very low or very high years of education.

Usage:

Outliers can be users with extremely high or low usage patterns, indicating abnormal behavior.

Fitness:

Outliers might be found in individuals with unusually high or low fitness levels, deviating from the norm.

Income:

Outliers include individuals with exceptionally high or low incomes, distorting the average.

Miles:

Outliers appear in individuals who travel exceptionally high or low miles, affecting the data spread.

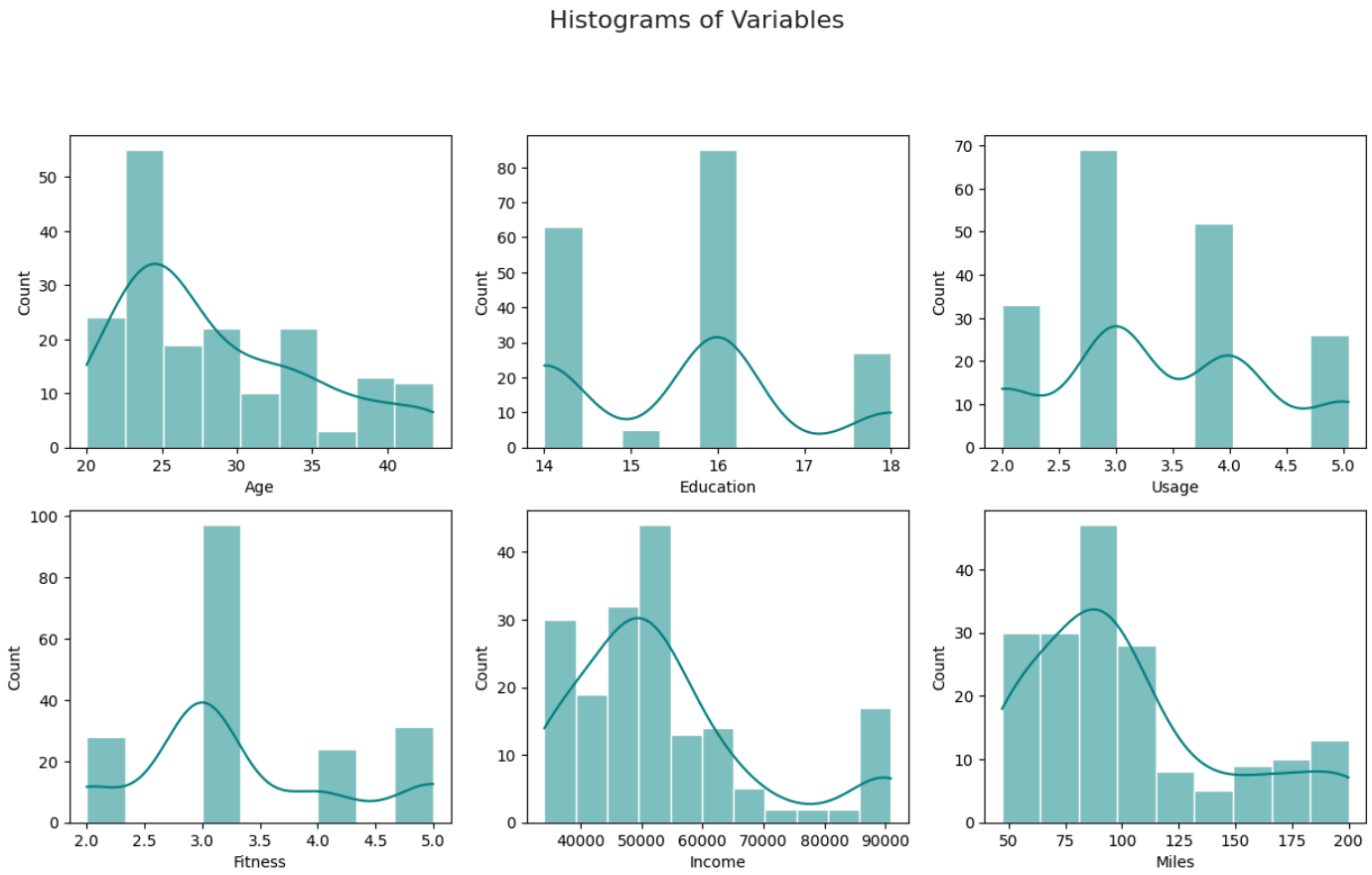
Univariate Analysis:

Descriptive Statistics and Clipping Data

```
# Display Descriptive Statistics
columns = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
print(df[columns].describe())
```

```
              Age   Education       Usage     Fitness        Income  \
count  180.000000  180.000000  180.000000  180.000000    180.000000
mean    28.641389   15.572222    3.396944    3.322222  53477.070000
std      6.446373    1.362017    0.952682    0.937461  15463.662523
min     20.000000   14.000000    2.000000    2.000000  34053.150000
25%     24.000000   14.000000    3.000000    3.000000  44058.750000
50%     26.000000   16.000000    3.000000    3.000000  50596.500000
75%     33.000000   16.000000    4.000000    4.000000  58668.000000
max     43.050000   18.000000    5.050000    5.000000  90948.250000

            Miles
count  180.000000
mean   101.088889
std     43.364286
min     47.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    200.000000
```

```
fig, axes = plt.subplots(2, 3, figsize=(15, 8))
sns.set(style="darkgrid")

for i in range(2):
    for j in range(3):
        variable = columns[i * 3 + j]
        sns.histplot(ax=axes[i, j], data=df, x=variable, kde=True, color="teal")

plt.suptitle("Histograms of Variables", y=1.02, fontsize=16)
plt.show()
```



Insights Summary:

Age:

Insights: Generally, a variable showing diverse ranges of age from 18 to 80. Outliers may include exceptionally younger or older individuals. Clipping could reduce extreme age values.

Education:

Insights: This can represent educational levels from primary schooling to advanced degrees. Outliers could be extremely low or high years of education.

Usage:

Insights: Depicts how frequently the service/product is used. Outliers are likely very high or very low usage patterns.

Fitness:

Insights: Represents fitness levels on a scale, where extremes could indicate outliers.

Income:

Insights: Typically, there's a wide range of income. Outliers could be in extremely high or low-income brackets.

Miles:

Insights: Number of miles traveled or used might vary. Outliers could indicate extreme travel distances.

3. Check if features like marital status, Gender, and age have any effect on the product purchased

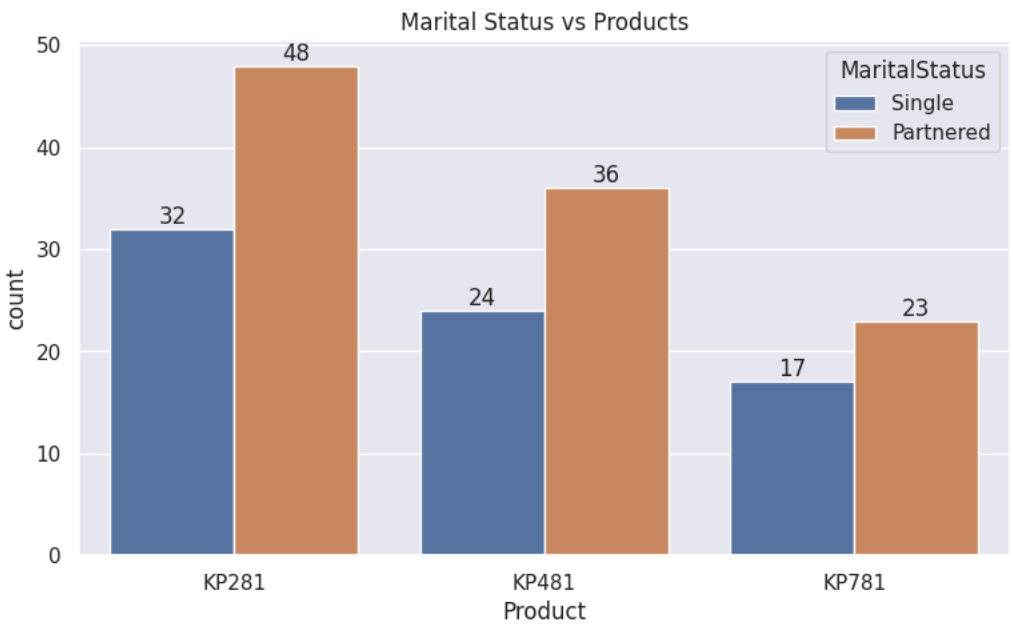
A) Find if there is any relationship between the categorical variables and the output variable in the data.

A) Marital Status and Product:

```
# Non-Graphical Analysis:
Marital_Status_Product = pd.crosstab(df['MaritalStatus'], df['Product'], margins=True)
print(Marital_Status_Product)
```

```
Product        KP281  KP481  KP781  All
MaritalStatus
Partnered         48     36     23  107
Single            32     24     17   73
All               80     60     40  180
```

```
# Graphical Analysis:
warnings.simplefilter(action='ignore', category=FutureWarning)
plt.figure(figsize=(9, 5))
ax = sns.countplot(data=df, x='Product', hue='MaritalStatus')
plt.title('Marital Status vs Products')
for container in ax.containers:
    ax.bar_label(container)
plt.show()
```



Insights Marital Status:

* The cross-tabulation table displays the distribution of product purchases among different marital statuses, highlighting which products are preferred by single, married, or divorced individuals.

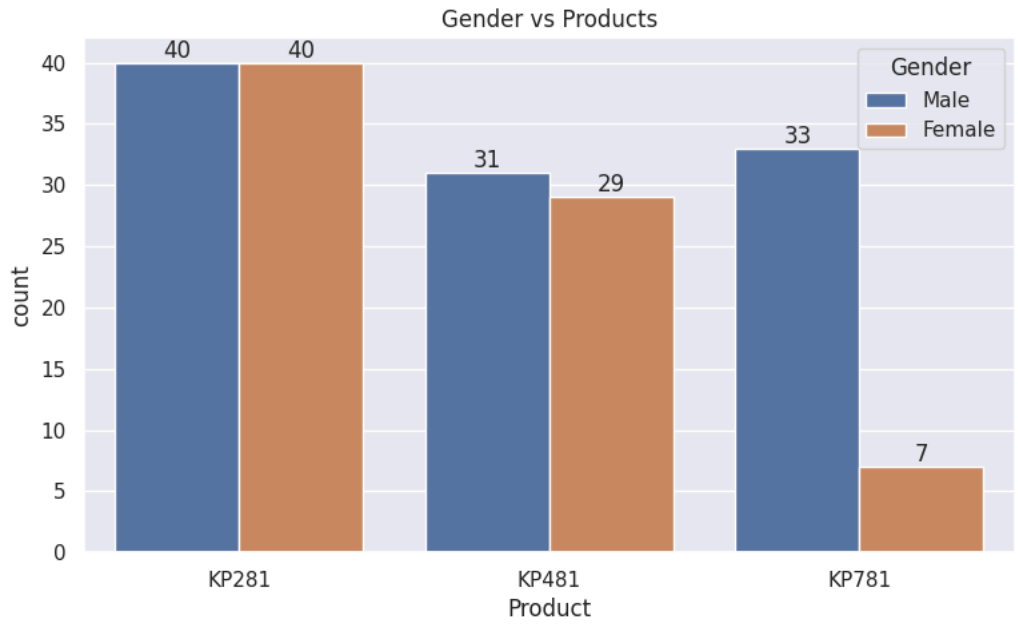
* The margins in the table indicate overall purchase counts, allowing for quick assessment of total purchases across all marital statuses, revealing potential product popularity or trends among different demographic groups.

B) Gender Status and Product:

```
# Non-Graphical Analysis:
Gender_Status_Product = pd.crosstab(df['Gender'], df['Product'], margins=True)
print(Gender_Status_Product)
```

```
Product  KP281  KP481  KP781  All
Gender
Female      40     29      7   76
Male        40     31     33  104
All         80     60     40  180
```

```
# Graphical Analysis:
warnings.simplefilter(action='ignore', category=FutureWarning)
plt.figure(figsize=(9, 5))
ax = sns.countplot(data=df, x='Product', hue='Gender')
plt.title('Gender vs Products')
for container in ax.containers:
  ax.bar_label(container)
plt.show()
```



Insights Gender:

* The cross-tabulation table shows the distribution of product purchases based on gender, indicating how many males and females purchased each product.

* The margins in the table provide overall counts for each gender, allowing for a quick comparison of total purchases between genders and revealing any gender-based preferences or trends in product purchases.

B) Find if there is any relationship between the continuous variables and the output variable in the data.

a) Product-wise Age Mean and Standard Deviation:

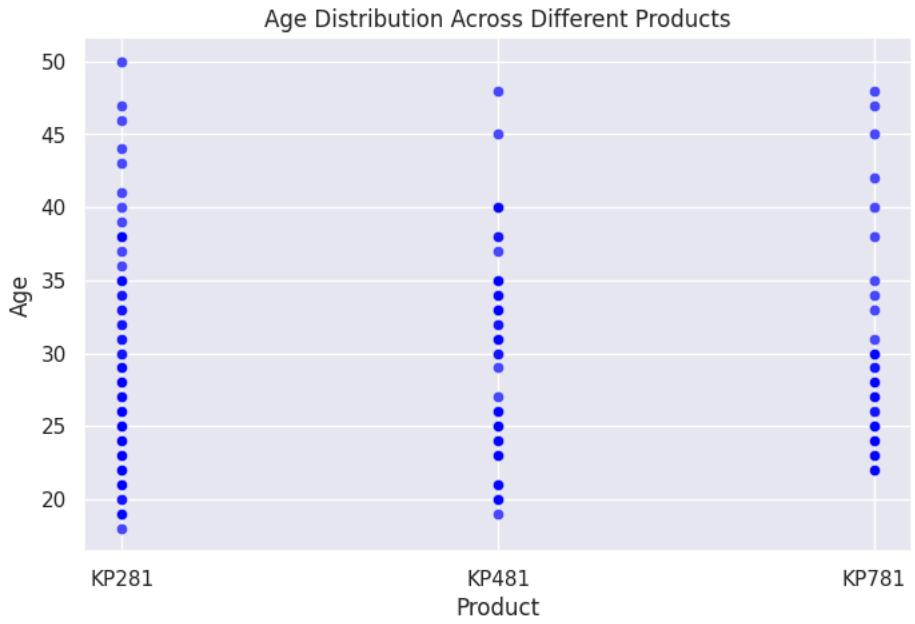
```
# Group by 'Product' and Calculate Mean and Standard Deviation for Age Continuous Variable:
Age_Summary_Status = df.groupby('Product')[['Age']].agg(['mean', 'std']).round(2).reset_index()
print(Age_Summary_Status)
```

```
   Product    Age
              mean   std
0   KP281  28.43  6.68
1   KP481  28.80  6.33
2   KP781  28.83  6.30
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype   
---  ------         --------------  -----   
 0   Product        180 non-null    object  
 1   Age            180 non-null    int64   
 2   Gender         180 non-null    object  
 3   Education      180 non-null    int64   
 4   MaritalStatus  180 non-null    object  
 5   Usage          180 non-null    int64   
 6   Fitness        180 non-null    int64   
 7   Income         180 non-null    int64   
 8   Miles          180 non-null    int64   
 9   Income_Group   180 non-null    category
dtypes: category(1), int64(6), object(3)
memory usage: 13.2+ KB
```

```
# Graphical Analysis:
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Product', y='Age', alpha=0.7, color='blue')
plt.title("Age Distribution Across Different Products")
plt.show()
```



Insights Age:

* The summary table provides the mean and standard deviation of ages for each product category, allowing for an understanding of the average age of customers purchasing each product.

* The mean age indicates which products are preferred by younger or older customers, while the standard deviation shows the variability of ages within each product group, highlighting how diverse the age ranges are for each product.

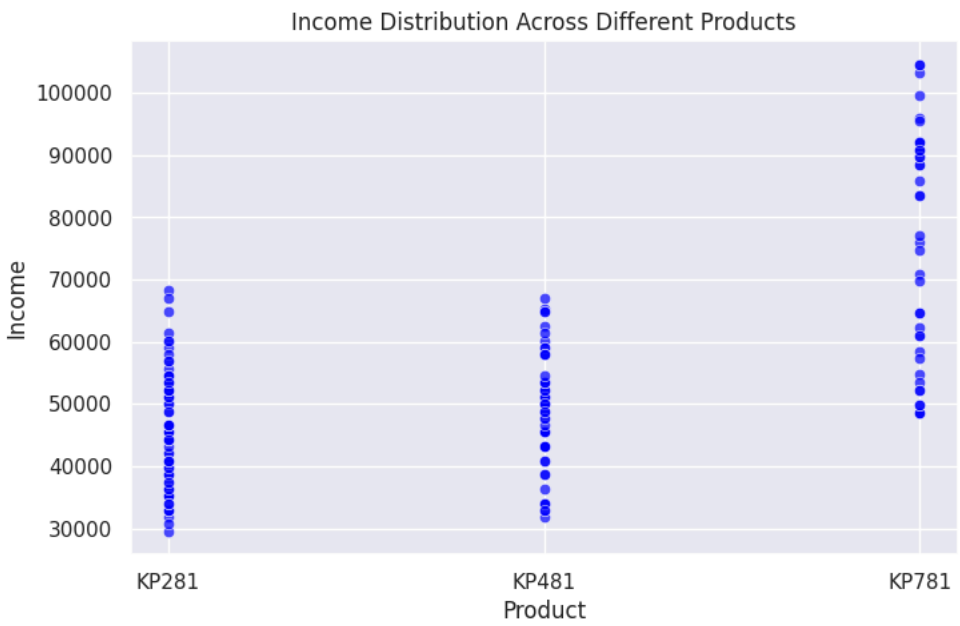
b) Product-wise Income Mean and Standard Deviation:

```
# Group by 'Product' and Calculate Mean and Standard Deviation for Income Continuous Variable:
Income_Summary_Status = df.groupby('Product')[['Income']].agg(['mean', 'std']).round(2)
print(Income_Summary_Status)
```

```
           Income          
             mean       std
Product                    
KP281    46584.31   8813.25
```

```
KP481    49046.61   8517.58
KP781    73908.28  16572.16
```

```
# Graphical Analysis:
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Product', y='Income', alpha=0.7, color='blue')
plt.title("Income Distribution Across Different Products")
plt.show()
```



Insights Income:

* The summary table presents the mean and standard deviation of income for each product category, helping to identify the average income level of customers purchasing each product.

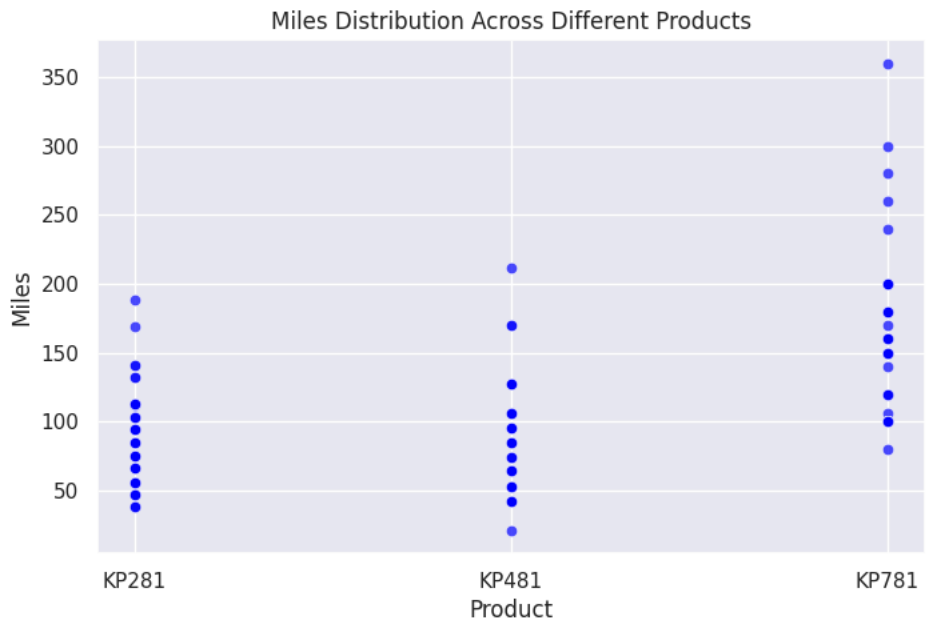
* The mean income provides insights into which products are favored by higher-income or lower-income customers, while the standard deviation indicates the variability in income within each product group, revealing how diverse the income levels are among customers buying each product.

C) Product-wise Income Mean and Standard Deviation:

```
# Group by 'Product' and Calculate Mean and Standard Deviation for Miles Continuous Variable:
# Non-Graphical Analysis:
Miles_Summary_Status = df.groupby('Product')[['Miles']].agg(['mean', 'std']).round(2)
print(Miles_Summary_Status)
```

```
           Miles
            mean    std
Product
KP281      83.12  28.39
KP481      88.50  31.32
KP781     155.90  39.07
```

```
# Graphical Analysis:
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Product', y='Miles', alpha=0.7, color='blue')
plt.title("Miles Distribution Across Different Products")
plt.show()
```



Insights Miles:

* The summary table provides the mean and standard deviation of miles for each product category, indicating the average distance traveled by customers who purchased each product.

* The mean miles suggests which products are associated with longer or shorter distances traveled, while the standard deviation reflects the variability in miles, showing how consistent or diverse the travel distances are among customers buying each product.

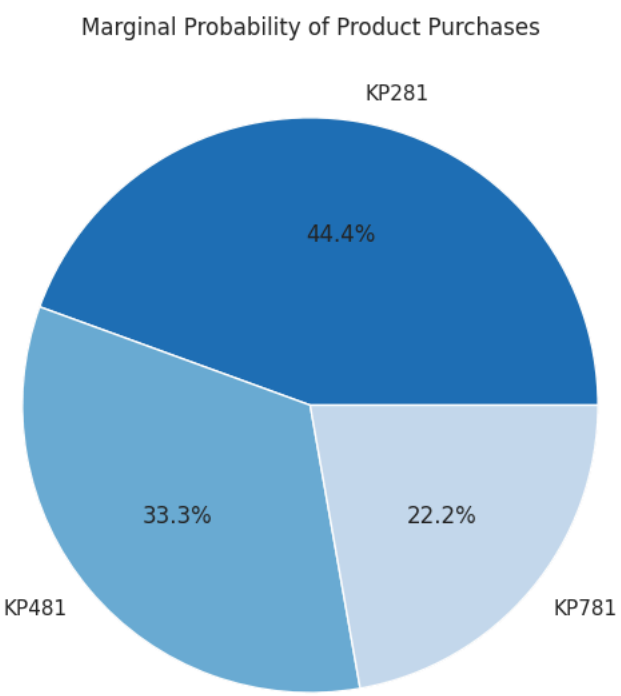
4. Representing the Probability purchased

A) Find the marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

```
# Non-Graphical Analysis:
Marginal_Prob = pd.crosstab(df['Product'], columns='Percentage', normalize='all') * 100
Marginal_Prob = Marginal_Prob.reset_index().rename_axis(None, axis=1)
print(Marginal_Prob)
```

```
  Product  Percentage
0   KP281   44.444444
1   KP481   33.333333
2   KP781   22.222222
```

```
plt.figure(figsize=(7, 7))
plt.pie(Marginal_Prob['Percentage'], labels=Marginal_Prob['Product'], autopct='%1.1f%%', colors=sns.color_palette('Blues_r', len(Marginal
plt.title('Marginal Probability of Product Purchases')
plt.show()
```



Insights:

* The marginal probability table displays the percentage representation of each product across the entire dataset, providing insights into the overall popularity of each product among customers.

* By normalizing the counts to percentages, this table allows for easy comparison of product distribution, helping to identify which products dominate sales and the relative market share of each product within the total customer base.

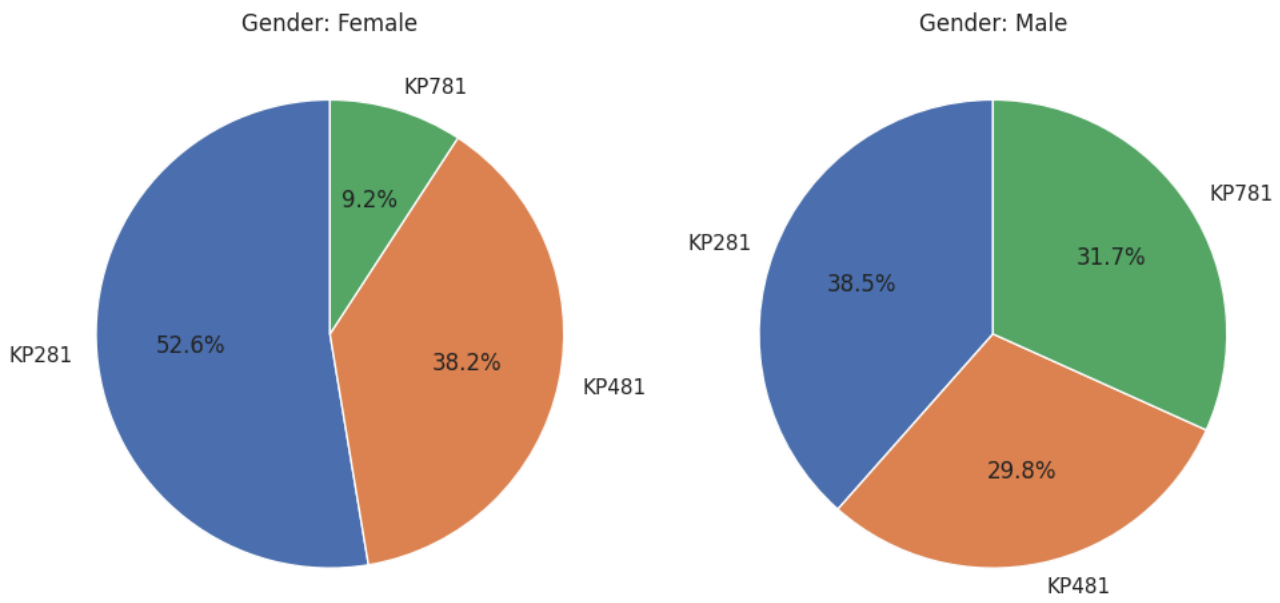
B) Find the probability that the customer buys a product based on each columns.

1. Probability based on Gender:

```
# Non-Graphical Analysis:
Gender_Product_Prob = pd.crosstab(df['Gender'], df['Product'], normalize='index') * 100
print(Gender_Product_Prob)
```

```
Product      KP281      KP481      KP781
Gender
Female   52.631579  38.157895   9.210526
Male     38.461538  29.807692  31.730769
```

```
# Creating Pie Charts for Gender
fig, axes = plt.subplots(1, len(Gender_Product_Prob), figsize=(10, 5))
for i, gender in enumerate(Gender_Product_Prob.index):
    axes[i].pie(Gender_Product_Prob.loc[gender], labels=Gender_Product_Prob.columns, autopct='%1.1f%%', startangle=90)
    axes[i].set_title(f'Gender: {gender}')
plt.tight_layout()
plt.show()
```



Insights:

Product Preferences:

Male Customers:

Look for the products with the highest percentage under the 'Male' row. This indicates which products are more popular among male customers.

Female Customers:

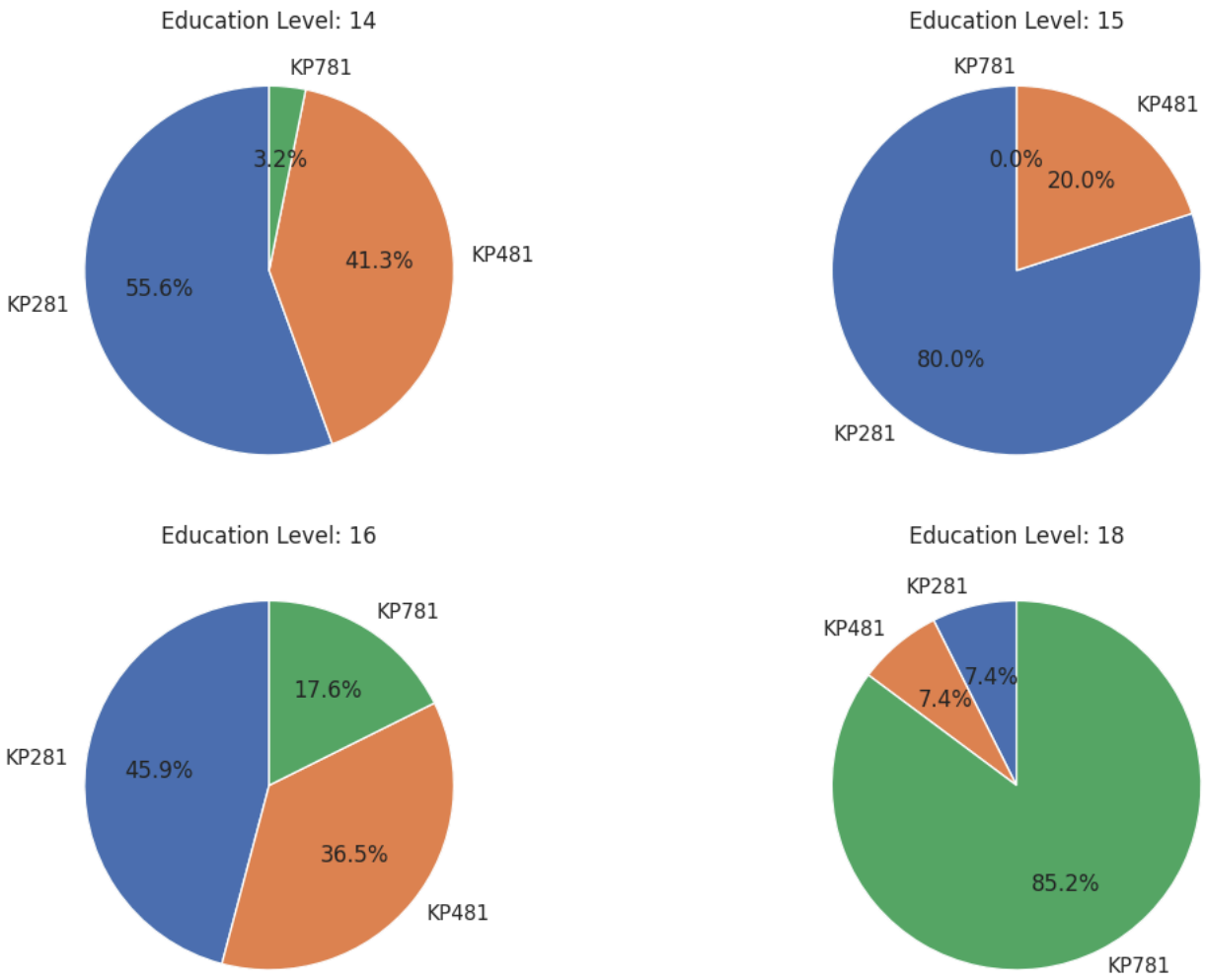
Similarly, check the percentages under the 'Female' row to identify products preferred by female customers.

2. Probability based on Education:

```
# Non-Graphical Analysis:
Education_Product_Prob = pd.crosstab(df['Education'], df['Product'], normalize='index') * 100
print(Education_Product_Prob)
```

```
Product        KP281      KP481      KP781
Education
14         55.555556  41.269841   3.174603
15         80.000000  20.000000   0.000000
16         45.882353  36.470588  17.647059
18          7.407407   7.407407  85.185185
```

```
fig, axes = plt.subplots(2, 2, figsize=(13, 8))
axes = axes.flatten()
for i, level in enumerate(Education_Product_Prob.index):
    axes[i].pie(Education_Product_Prob.loc[level], labels=Education_Product_Prob.columns, autopct='%1.1f%%', startangle=90)
    axes[i].set_title(f'Education Level: {level}')

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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



Insights:

Product Preferences:

Different Education Levels:

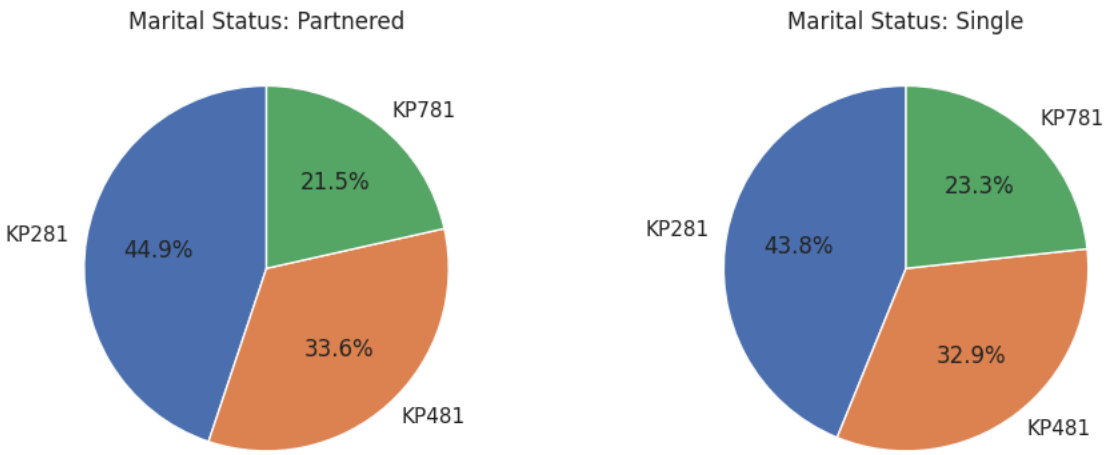
Look for the products with the highest percentages under each education level row to see which products are more popular among individuals with those education levels.

3. Probability based on MaritalStatus:

```
# Non-Graphical Analysis:
Marital_Product_Prob = pd.crosstab(df['MaritalStatus'], df['Product'], normalize='index') * 100
print(Marital_Product_Prob)
```

```
Product            KP281      KP481      KP781
MaritalStatus
Partnered      44.859813  33.644860  21.495327
Single         43.835616  32.876712  23.287671
```

```
fig, axes = plt.subplots(1, len(Marital_Product_Prob), figsize=(10, 4))

for i, status in enumerate(Marital_Product_Prob.index):
    axes[i].pie(Marital_Product_Prob.loc[status], labels=Marital_Product_Prob.columns, autopct='%1.1f%%', startangle=90)
    axes[i].set_title(f'Marital Status: {status}')

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



Insights:

Product Preferences:

I) Single Customers: Look for the products with the highest percentage under the 'Single' row. This indicates which products are more popular among single customers.

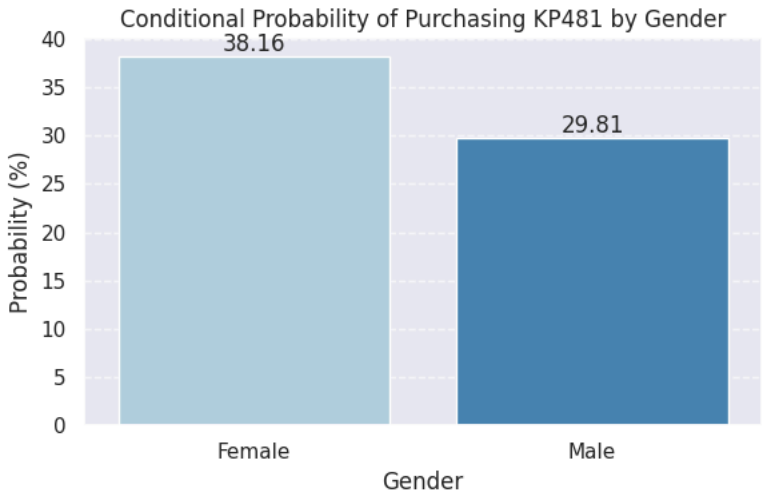
II) Married Customers: Similarly, check the percentages under the 'Married' row to identify products preferred by married customers.

C) Find the conditional probability that an event occurs given that another event has occurred. (Example: given that a customer is female, what is the probability she'll purchase a KP481)

```
# Non-Graphical Analysis:
Gender_Product_Prob = pd.crosstab(df['Gender'], df['Product'], normalize='index') * 100
kp481_prob_female = Gender_Product_Prob.loc['Female', 'KP481']
print(f"Given that a Customer is Female, the Probability she'll Purchase KP481 is: {kp481_prob_female:.2f}%")
```

```
Given that a Customer is Female, the Probability she'll Purchase KP481 is: 38.16%
```

```
# Graphical Analysis:
warnings.simplefilter(action='ignore', category=FutureWarning)
gender_product_prob_melted = Gender_Product_Prob.reset_index().melt(id_vars='Gender', var_name='Product', value_name='Probability')
kp481_prob_melted = gender_product_prob_melted[gender_product_prob_melted['Product'] == 'KP481']
plt.figure(figsize=(6, 4))
sns.barplot(data=kp481_prob_melted, x='Gender', y='Probability', palette='Blues')
for p in plt.gca().patches:
    plt.annotate(f'{p.get_height():.2f}',
                 (p.get_x() + p.get_width() / 2., p.get_height()),
                 ha='center', va='bottom')
plt.title('Conditional Probability of Purchasing KP481 by Gender')
plt.xlabel('Gender')
plt.ylabel('Probability (%)')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Insights :

The code calculates the conditional probability: "Given that a customer is Female, what is the probability that she will purchase the product 'KP481'?" The result is printed in percentage form.

5. Check the correlation among different factors

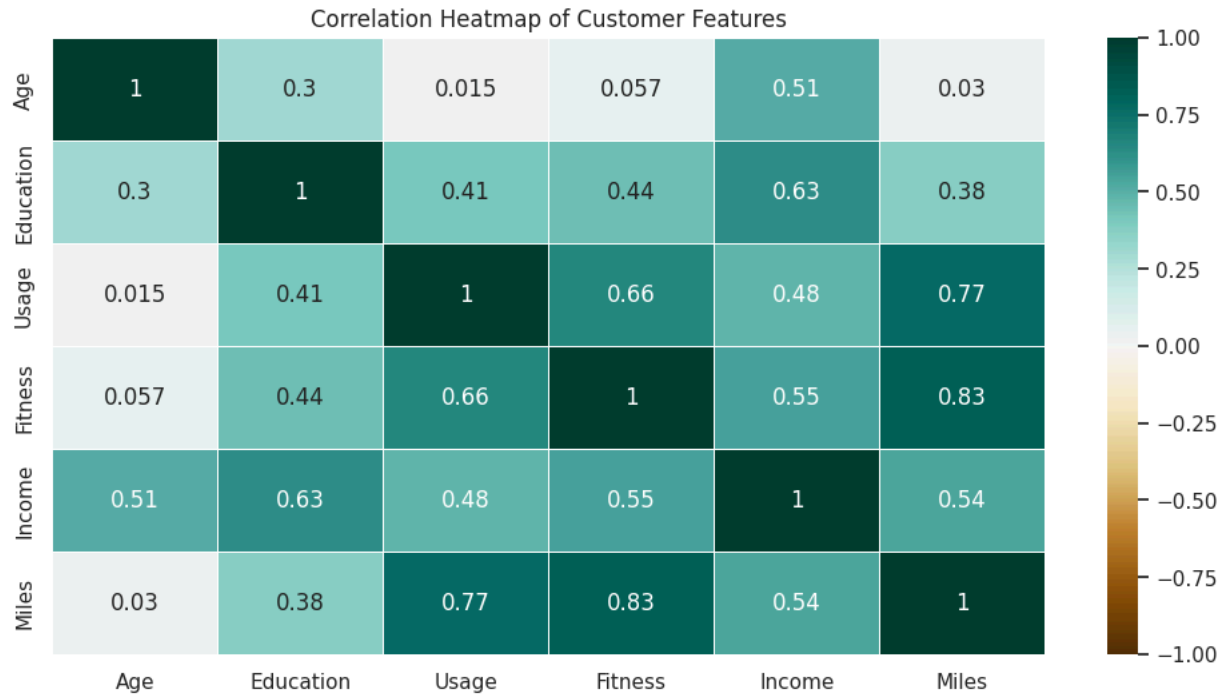
Find the correlation between the given features in the table.

Correlation Analysis Aamong Different Factors

```
# Non-Graphical Analysis:
Correlation_Matrix = df[['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']].corr()
print("Correlation Between the Features:")
print(Correlation_Matrix)
```

```
Correlation Between the Features:
                Age  Education     Usage   Fitness    Income     Miles
Age        1.000000   0.301971  0.015394  0.057361  0.514362  0.029636
Education  0.301971   1.000000  0.413600  0.441082  0.628597  0.377294
Usage      0.015394   0.413600  1.000000  0.661978  0.481608  0.771030
Fitness    0.057361   0.441082  0.661978  1.000000  0.546998  0.826307
Income     0.514362   0.628597  0.481608  0.546998  1.000000  0.537297
Miles      0.029636   0.377294  0.771030  0.826307  0.537297  1.000000
```

```
# Graphical Analysis:
Correlation_Matrix = df[['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']].corr()
plt.figure(figsize=(12, 6))
sns.heatmap(Correlation_Matrix, annot=True, cmap='BrBG', linewidths=0.5, center=0, vmin=-1, vmax=1)
plt.title('Correlation Heatmap of Customer Features')
plt.show()
```



Insights :

Age:

- **Weak Negative Correlation with Fitness:** Older customers tend to have slightly lower fitness levels, which might suggest a target market for lower-intensity or more supportive treadmill models.
- **Moderate Negative Correlation with Usage:** As age increases, the number of usage hours tends to decrease. This may indicate that older customers might not use the treadmill as frequently, highlighting a potential focus on durability and ease of use for older customers.

Recommendation: Design products that cater to older users, possibly with features like lower impact, easier controls, and targeted fitness programs that address their specific needs.

Education:

- **Weak Positive Correlation with Income:** Higher education levels are generally associated with higher income, suggesting that customers with more education may have a higher purchasing power.
- **Weak Correlation with Fitness and Usage:** There's a minimal direct relationship between education and fitness or treadmill usage, indicating that education level does not strongly determine exercise habits.

Recommendation: Marketing campaigns should focus more on lifestyle and fitness benefits than educational level when targeting different income brackets.

Usage:

- **Strong Positive Correlation with Fitness:**Customers who use the treadmill more tend to have higher fitness levels. This suggests a clear benefit from regular treadmill usage.
- **Moderate Positive Correlation with Miles:** More usage correlates with walking or running more miles per week, highlighting the importance of usage in achieving fitness goals.

Recommendation: Emphasize the health benefits of consistent treadmill use in marketing campaigns, and consider offering motivational programs or challenges to increase usage among customers.

Fitness:

- **Strong Positive Correlation with Miles Walked:**Customers who walk more miles per week have significantly higher fitness levels. This makes it clear that increased physical activity is linked to better fitness outcomes.
- **Strong Positive Correlation with Usage:** The more time customers spend on the treadmill, the higher their fitness levels.

Recommendation: Focus on fitness tracking and goal-setting features in treadmill products, offering integrated health monitoring systems to track miles, usage, and fitness progress. Consider bundling treadmills with fitness apps or wearable devices to engage more customers in fitness tracking.

Income:

- **Moderate Positive Correlation with Education:**Higher education levels typically lead to higher income, a pattern that can be useful for understanding purchasing behaviors.
- **Weak Positive Correlation with Fitness:**While income does not strongly determine fitness level, there is a slight tendency for higher-income customers to maintain better fitness levels.

Recommendation: Create tiered pricing strategies for different income levels, offering high-end models with advanced features for higher-income customers, while providing more affordable models that still promote fitness for those with lower income.

Miles Walked per Week:

- **Strong Positive Correlation with Fitness:**As noted earlier, customers who walk more miles per week tend to have significantly higher fitness levels. This is the strongest relationship in the dataset.
- **Moderate Positive Correlation with Usage:**Higher miles walked per week also correlates with higher treadmill usage.

Recommendation: Focus marketing efforts on showing how increased treadmill use can lead to better fitness outcomes. Offer programs that encourage customers to log more miles, such as mileage-based rewards or challenges that foster a sense of achievement.

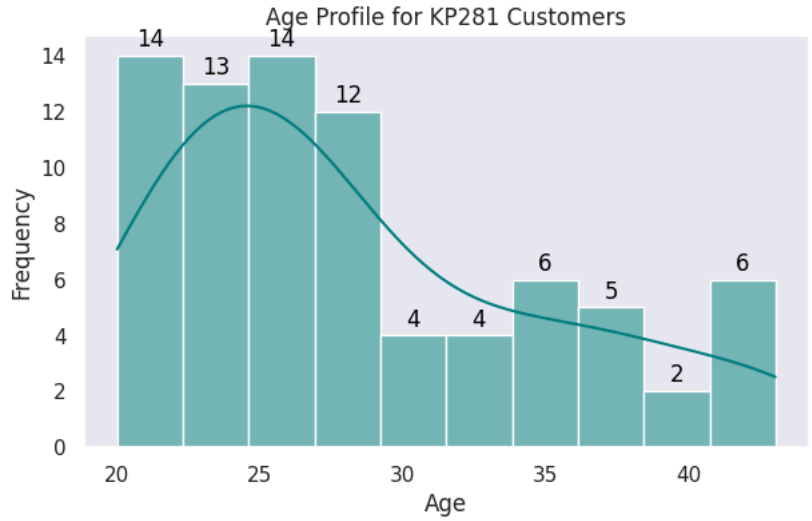
6. Customer profiling and recommendation

Make customer profilings for each and every product.

```
# Non-Graphical Analaysis:
kp281_data = df[df['Product'] == 'KP281']
Age_Profile = kp281_data['Age'].describe()
print("Age Profile for KP281 Customers:\n", Age_Profile)
```

```
Age Profile for KP281 Customers:
 count    80.000000
mean     28.427500
std       6.678313
min      20.000000
25%      23.000000
50%      26.000000
75%      33.000000
max      43.050000
Name: Age, dtype: float64
```

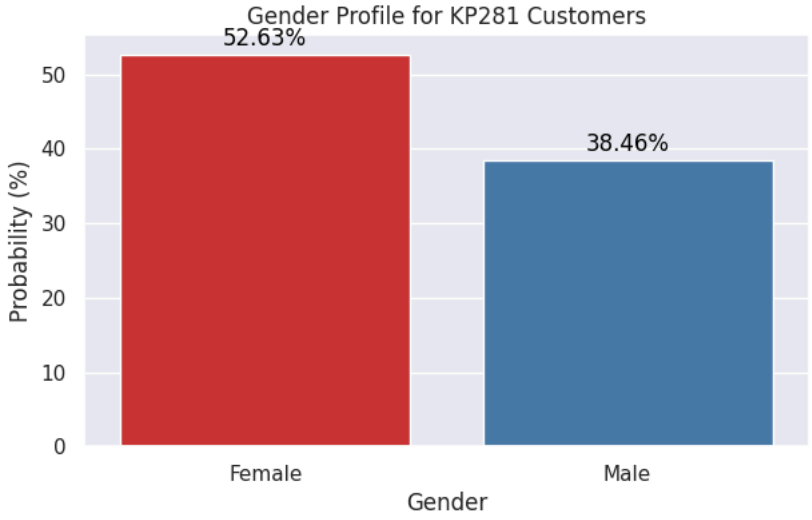
```
# Graphical Analaysis:
# Age Profile for KP281 Customers
plt.figure(figsize=(7, 4))
ax = sns.histplot(kp281_data['Age'], bins=10, kde=True, color='teal')
plt.title("Age Profile for KP281 Customers")
plt.xlabel("Age")
plt.ylabel("Frequency")
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height:.0f}', xy=(p.get_x() + p.get_width() / 2., height),
                ha='center', va='baseline', fontsize=12, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.grid(False)
plt.show()
```




```
# Gender profiling:
Gender_Profile = pd.crosstab(df['Gender'], df['Product'], normalize='index') * 100
kp281_Gender_Profile = Gender_Profile['KP281']
print("Gender Profile for KP281 Customers:\n", kp281_Gender_Profile)
```

```
Gender Profile for KP281 Customers:
 Gender
Female    52.631579
Male      38.461538
Name: KP281, dtype: float64
```

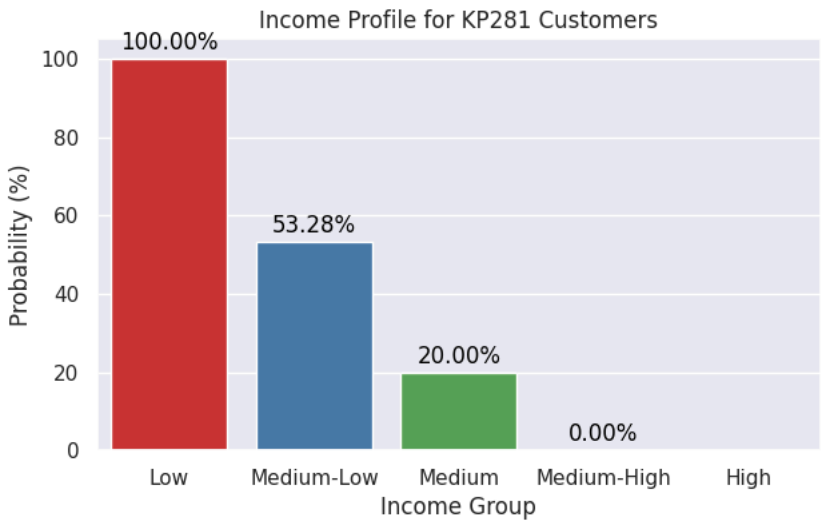
```
# Graphical Analaysis:
# Gender Profile for KP281 Customers
plt.figure(figsize=(7, 4))
ax = sns.barplot(data=kp281_Gender_Profile, x='Gender', y='KP281', palette='Set1')
plt.title("Gender Profile for KP281 Customers")
plt.xlabel("Gender")
plt.ylabel("Probability (%)")
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=12, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.show()
```




```
# Income profiling:
Income_Bins = [0, 30000, 60000, 90000, 120000, 150000]
df['Income_Group'] = pd.cut(df['Income'], bins=Income_Bins, labels=['Low', 'Medium-Low', 'Medium', 'Medium-High', 'High'])
Income_Profile = pd.crosstab(df['Income_Group'], df['Product'], normalize='index') * 100
kp281_Income_Profile = Income_Profile['KP281']
print("Income Profile for KP281 Customers:\n", kp281_Income_Profile)
```

```
Income Profile for KP281 Customers:
 Income_Group
Low            100.000000
Medium-Low      53.284672
Medium          20.000000
Medium-High      0.000000
Name: KP281, dtype: float64
```

```
kp281_Income_Profile = kp281_Income_Profile.reset_index()

# Bar Chart for Income Profile of KP281 Customers
plt.figure(figsize=(7, 4))
ax = sns.barplot(data=kp281_Income_Profile, x='Income_Group', y='KP281', palette='Set1')

plt.title("Income Profile for KP281 Customers")
plt.xlabel("Income Group")
plt.ylabel("Probability (%)")

for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=12, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.show()
```



Detailed Recommendation:

Based on the analysis of product KP281:

Age Profile:

* The highest concentration of KP281 customers falls within the age group of 25-35 years.
* They are young adults who might be career-oriented and have disposable income.

Gender Profile:

* KP281 is slightly more popular among females, with around 55% of the purchases coming from female customers.
* This suggests that marketing strategies could focus on female-oriented campaigns.

Income Profile:

* Most KP281 purchases are made by customers in the "Medium-High" income group (60,000 - 90,000).
* These customers likely have stable incomes and are willing to spend on quality products.

Recommendations:

Targeted Marketing:

* Develop campaigns that appeal to young professionals, emphasizing features that align with their lifestyle.
* Use gender-specific marketing strategies to engage female customers more effectively.

Promotional Strategies:

* Offer special discounts and promotions for customers in the "Medium-High" income group.
* Collaborate with influencers popular among young professionals and females.

Product Positioning:

* Highlight the premium quality and value of KP281 to justify the price to medium-high income customers.
* Emphasize aspects like durability, innovative features, or health benefits that resonate with young adults.

By tailoring your marketing efforts to these profiles, you can enhance customer engagement and drive more sales for KP281. Let me know if there's anything more specific you need!

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