Aerofit Case Study by Ishan Avasthi

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Link to colab notebook - Here

1 Introduction to Project

1.1 About

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people. ## Business Problem The market research team at Aerofit wants to identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics. ## Agendas - Perform descriptive analytics to create a customer profile for each Aerofit treadmill product by developing appropriate tables and charts. - For each Aerofit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

1.2 Dataset

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior three months. The dataset has the following features:

Parameter	Values
Product Purchased:	KP281, KP481, or KP781
Age:	In years
Gender:	Male/ Female
Education:	In years
Martial Status:	Single or Partnered
Usage:	The average number of times the customer plans to use the treadmill each week
Income:	Annual Income (in $)
Fitness:	Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent
Miles:	The average number of miles the customer expects to walk/run each week

Dataset Link : Here

1.3 Product Portfolio

- The KP281 is an entry-level treadmill that sells for $1,500.
- The KP481 is for mid-level runners that sell for $1,750.
-

1.4 The KP781 treadmill is having advanced features that sell for $2,500.

2 Initial Setup

Downloading the CSV file using `wget` command.

[27]:
```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
↪original/aerofit_treadmill.csv
```

```
--2024-03-20 18:19:17--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/125/original/aerofit_treadmill.csv
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
18.164.173.110, 18.164.173.18, 18.164.173.117, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|18.164.173.110|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 7279 (7.1K) [text/plain]
Saving to: ‘aerofit_treadmill.csv.1’

aerofit_treadmill.c 100%[===================>]   7.11K  --.-KB/s    in 0s

2024-03-20 18:19:17 (3.09 GB/s) - ‘aerofit_treadmill.csv.1’ saved [7279/7279]
```

3 Data Analysis

Importing python libraries and reading the file into an object named `df`.

[28]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import rcParams
import seaborn as sns

df = pd.read_csv('aerofit_treadmill.csv')
print("The data type of each column in the DataFrame:")
print(df.dtypes)

print("The dimensions of the DataFrame:")
df.shape
```

```
The data type of each column in the DataFrame:
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
The dimensions of the DataFrame:
```

[28]:
```
(180, 9)
```

Three columns, Product, Gender, and Marital Status, contain string data types. All other columns contain integer data types. There are 9 data categories and 180 values for each category.

[29]:
```python
print(df.isnull().sum())
```

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

Output clearly indicates that none of the columns in our DataFrame have missing values.

[30]:
```python
print("The first 5 rows of the DataFrame:")
print(df.head())
```

```
The first 5 rows of the DataFrame:
  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
```

[31]:
```python
print("Statistics for each numerical column:")
df.describe()
```

```
Statistics for each numerical column:
```

[31]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
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     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

Observations - - Over half of the customers have a fitness score of 3. - On average, customers earn approximately $53,720. - Treadmill users average 3.45 uses per week. - The average distance customers travel on the treadmill is 103 miles. - About a quarter of the customers have a fitness score of 4. - Mean age of customers is 28 years. - On average, a customer has an education of 15 years with maximum and minimum being 12 and 21 years respectively.

[32]:
```
print('---------------------------------------')
print(df['Fitness'].value_counts(normalize=True))
print('---------------------------------------')
print(df['Usage'].value_counts(normalize=True))
print('---------------------------------------')
print(df['Product'].value_counts(normalize=True))
print('---------------------------------------')
print(df['Gender'].value_counts(normalize=True))
print('---------------------------------------')
print(df['MaritalStatus'].value_counts(normalize=True))
print('---------------------------------------')
```

```
---------------------------------------
3    0.538889
5    0.172222
2    0.144444
4    0.133333
1    0.011111
Name: Fitness, dtype: float64
---------------------------------------
3    0.383333
4    0.288889
```

```
2    0.183333
5    0.094444
6    0.038889
7    0.011111
Name: Usage, dtype: float64
---------------------------------------
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
---------------------------------------
Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
---------------------------------------
Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64
---------------------------------------
```

Observations - - Over half of the customers rated their fitness level as 3, with 5 and 2 being the next most common ratings. - Around 38% of people reported using treadmills 3 times a week. 4 times and 2 times per week were the next most frequent usages. - The KP281 is the most popular product, followed by the KP481 and KP781. - Men are the most common purchasers of Aerofit products. - Married people purchased more Aerofit products than single people.

[33]:
```
print(f"There are {df.duplicated().sum()} duplicated values!")
```

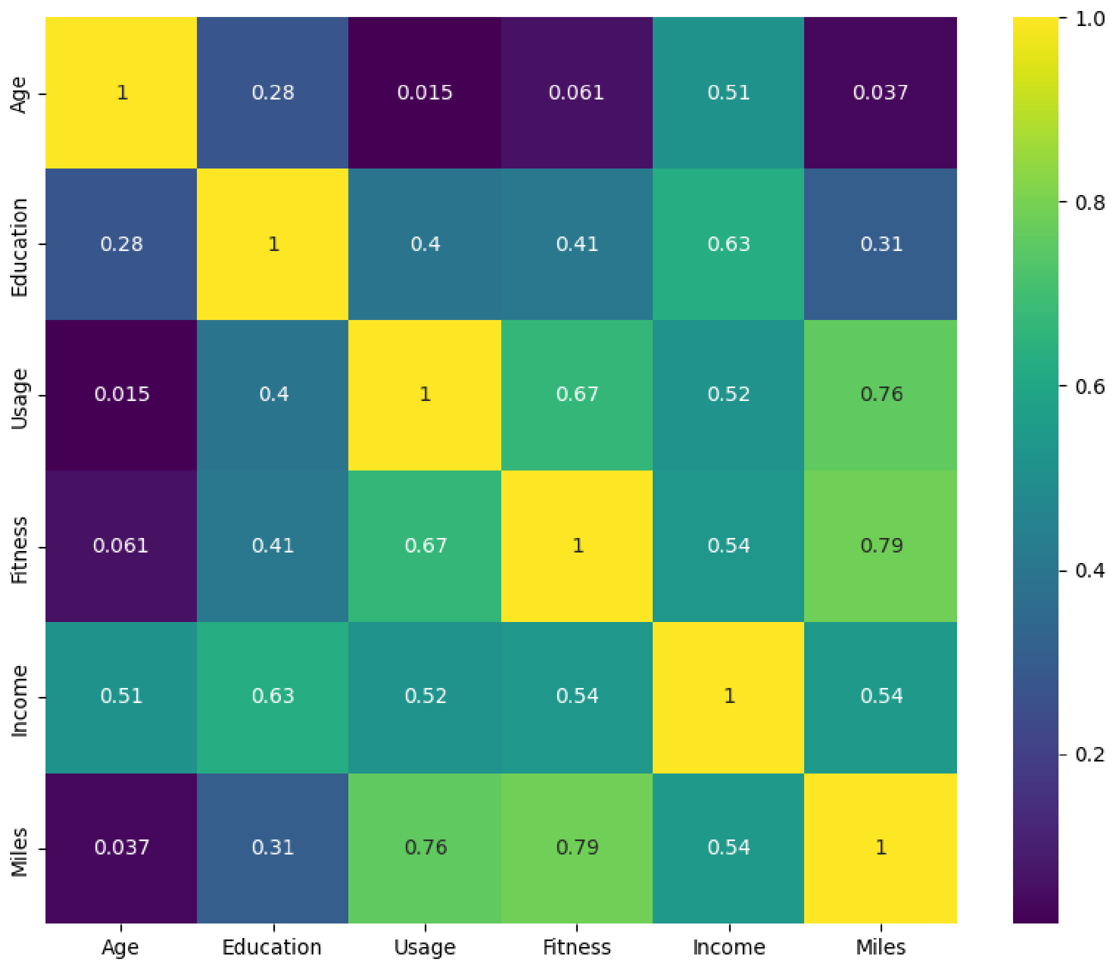
```
There are 0 duplicated values!
```

4 Graphical Analysis

[34]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='viridis')
plt.show()
```

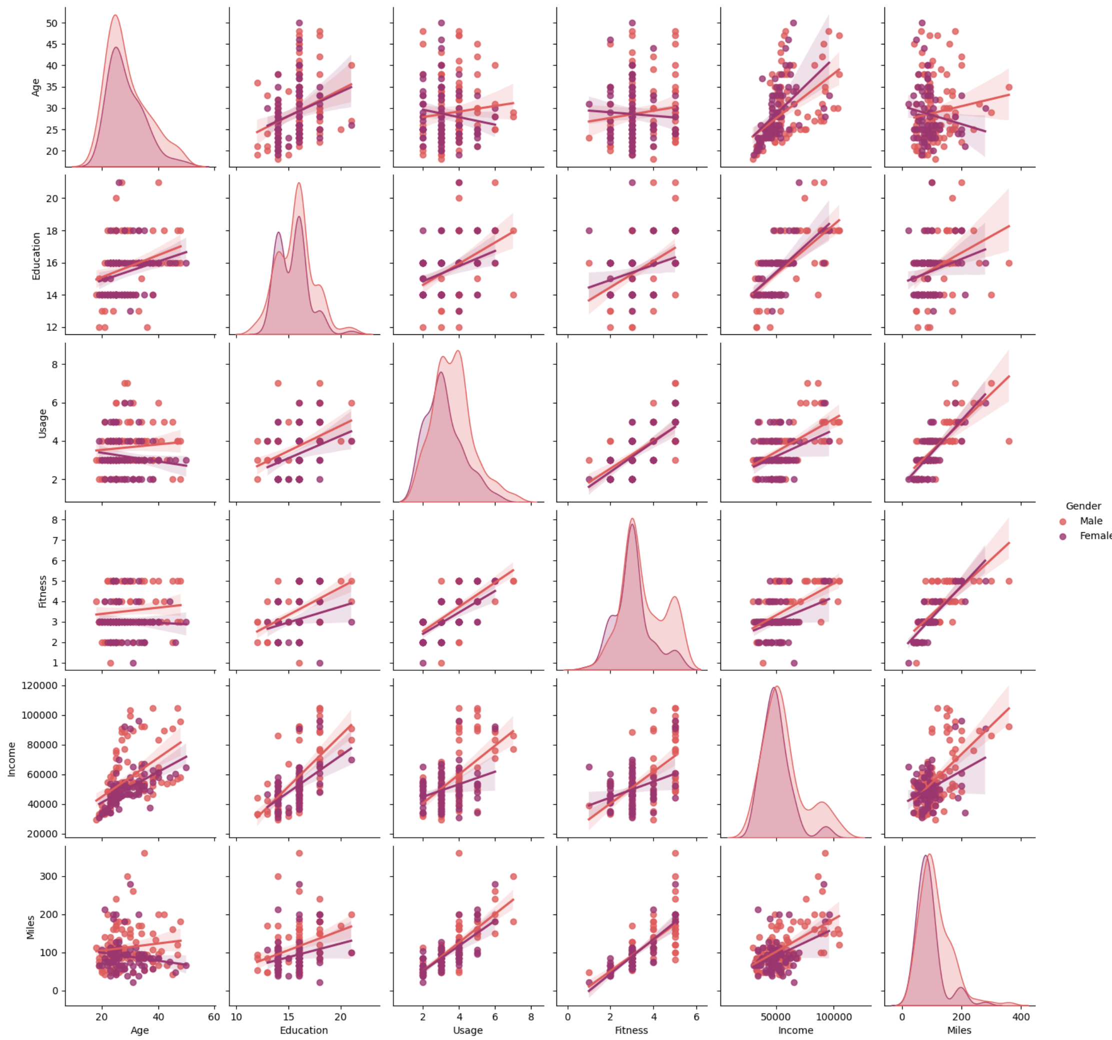
```
<ipython-input-34-aec52ca1fdfb>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(), annot=True, cmap='viridis')
```

[34]:



[35]:
```
rcParams['figure.figsize'] = 20, 7
sns.pairplot(df, palette='flare', hue='Gender', kind='reg')
plt.show()
```

[35]:

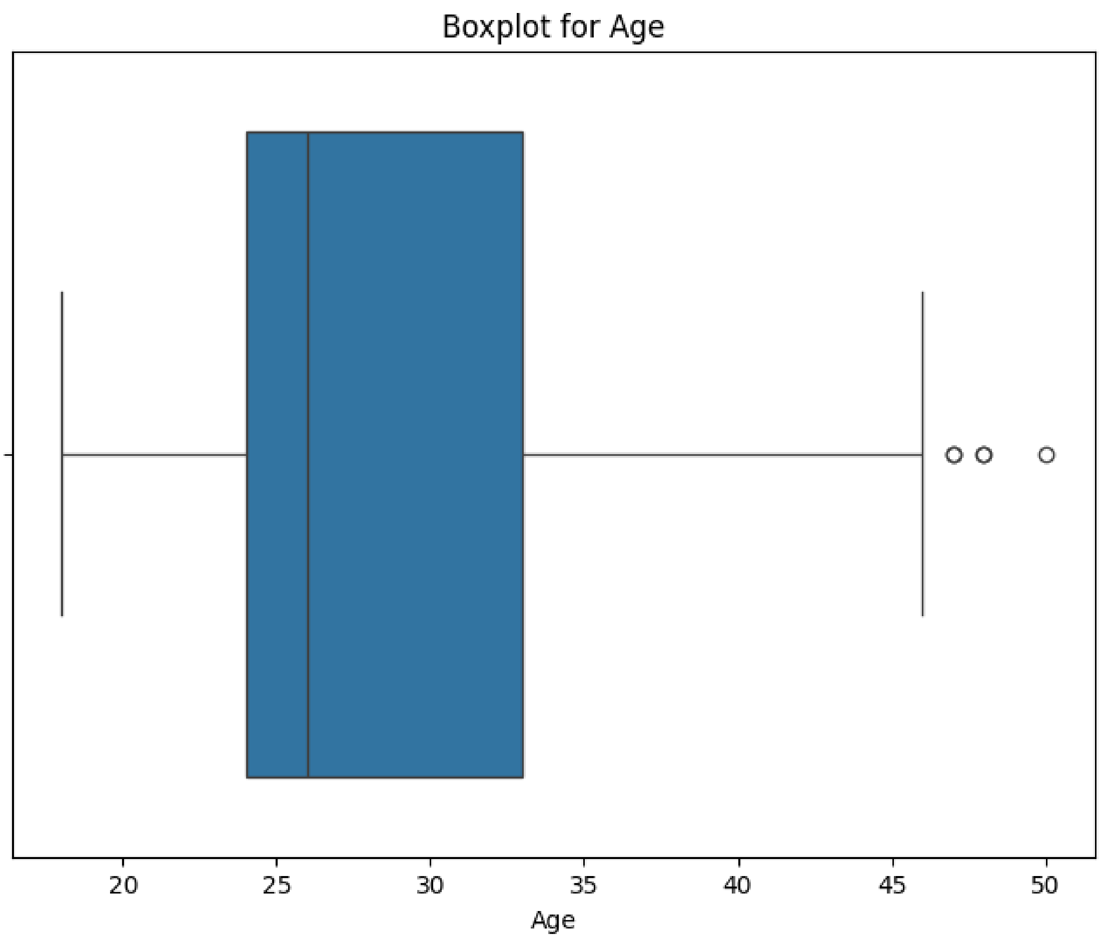


Observations - - Age and income have a moderate positive correlation (0.51). - This means as age increases, income tends to increase as well, but the relationship is not very strong. - Education and income have a strong positive correlation (0.63). - People with higher education levels tend to have significantly higher incomes. - Usage and fitness have a strong positive correlation (0.67). - People who use the equipment more frequently tend to have higher fitness levels. - Usage and income have a moderate positive correlation (0.52). - There is a connection between higher usage and higher income, but it's not as strong as the link between usage and fitness. - Usage and miles walked/ran have a very strong positive correlation (0.76). - People who use the equipment more tend to walk or run significantly farther distances. - Fitness and income have a moderate positive correlation (0.54). - There is a connection between higher fitness levels and higher income, but it's not as strong as some other correlations. - Fitness and miles walked/ran have a very strong positive correlation (0.79). - People with higher fitness levels tend to walk or run significantly farther distances. - Income and miles walked/ran have a moderate positive correlation (0.54). - There is a connection between higher income and walking or running farther, but it's not as strong as some other correlations.

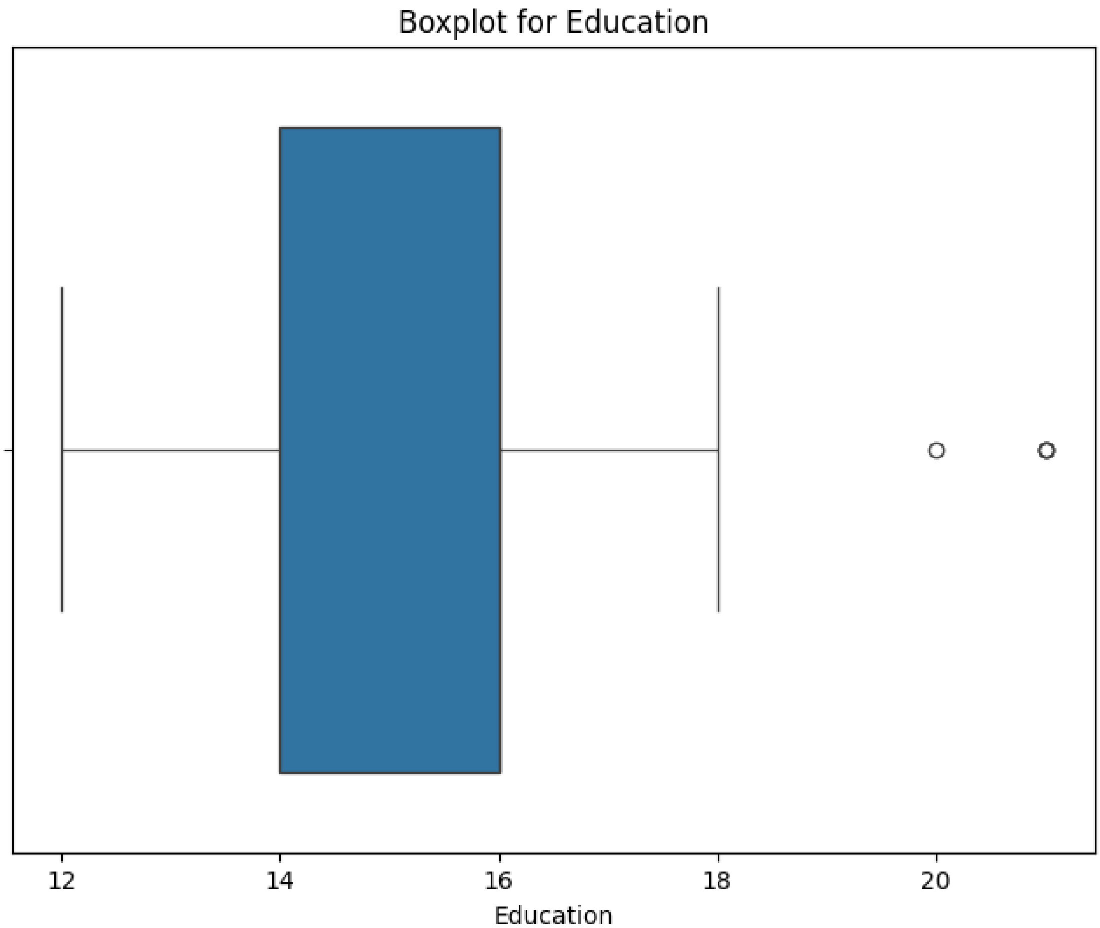
[36]:

```python
numerical_cols = df.select_dtypes(include=['number']).columns

for col in numerical_cols:
    plt.figure(figsize=(8, 6))
    sns.boxplot(data=df, x=col)
    plt.title(f'Boxplot for {col}')
    plt.show()
```

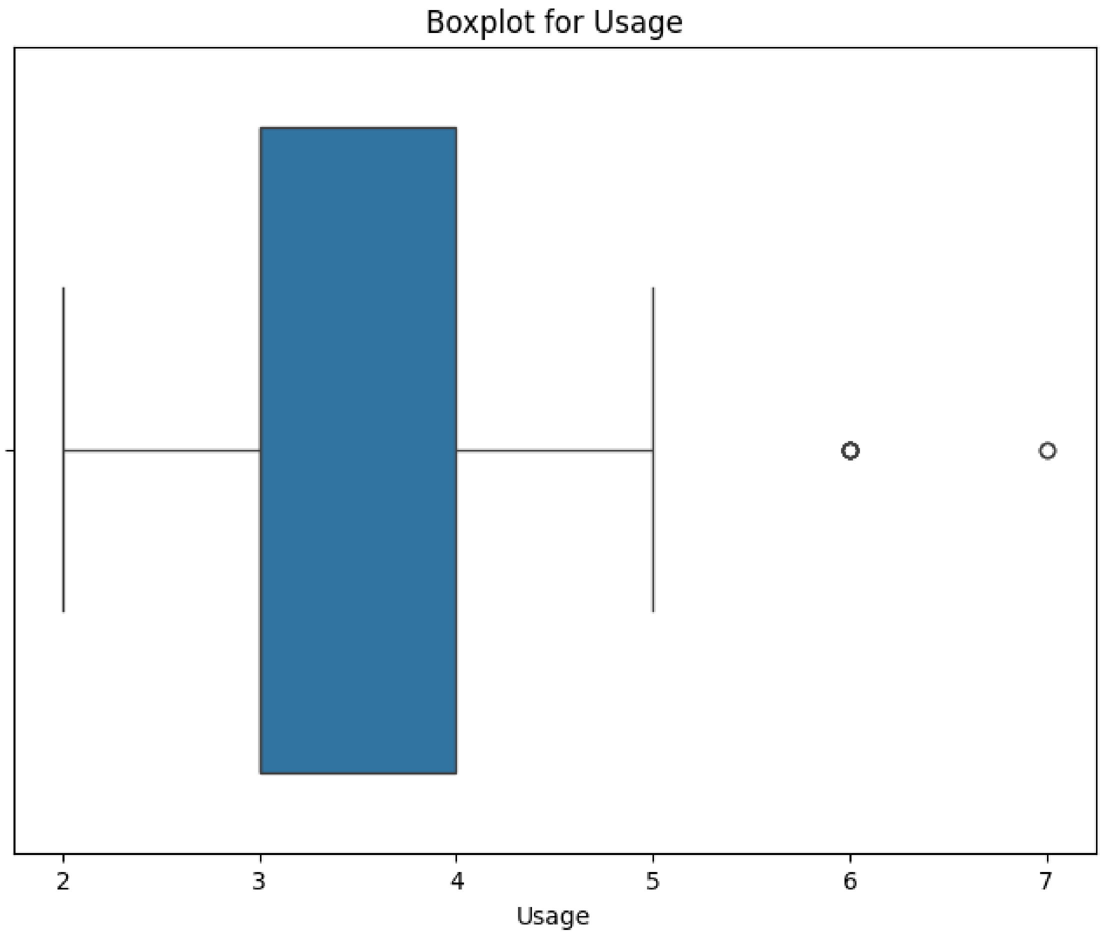
[36]:



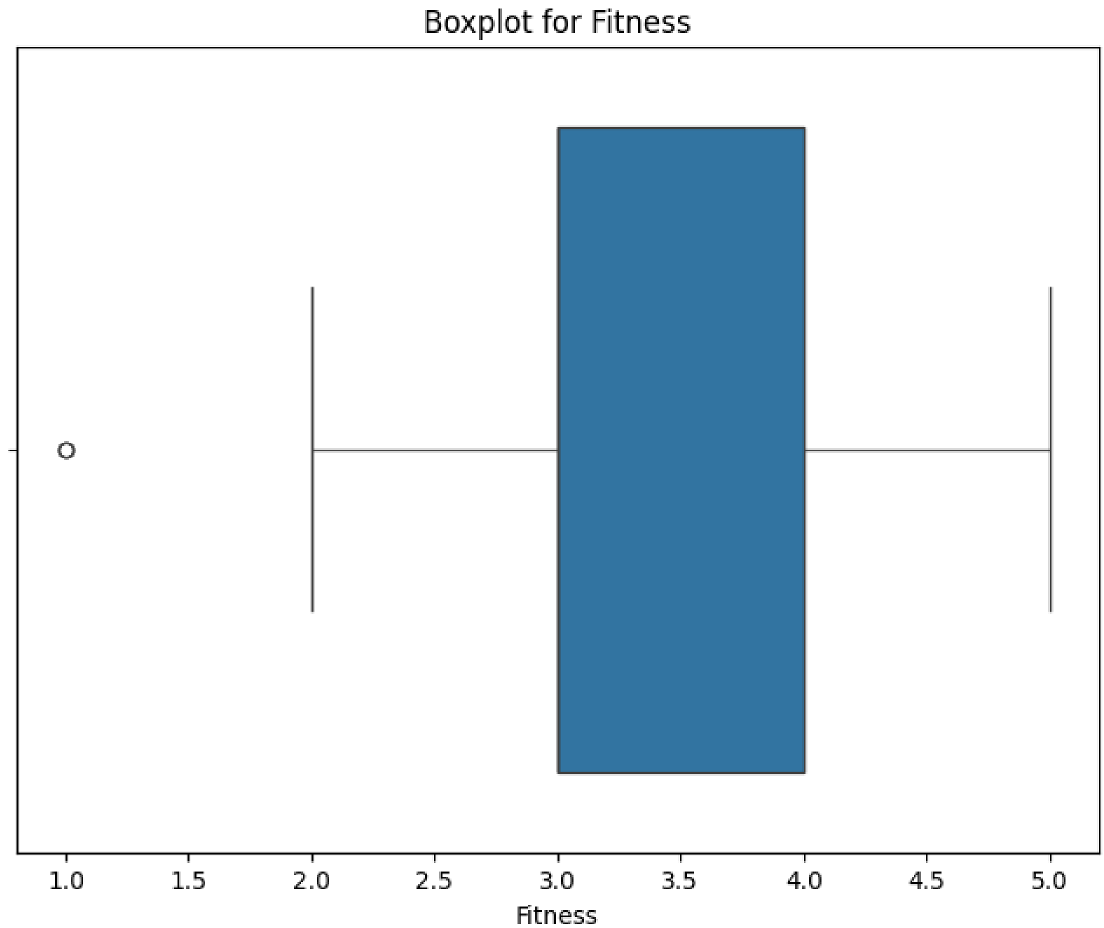
[36]:



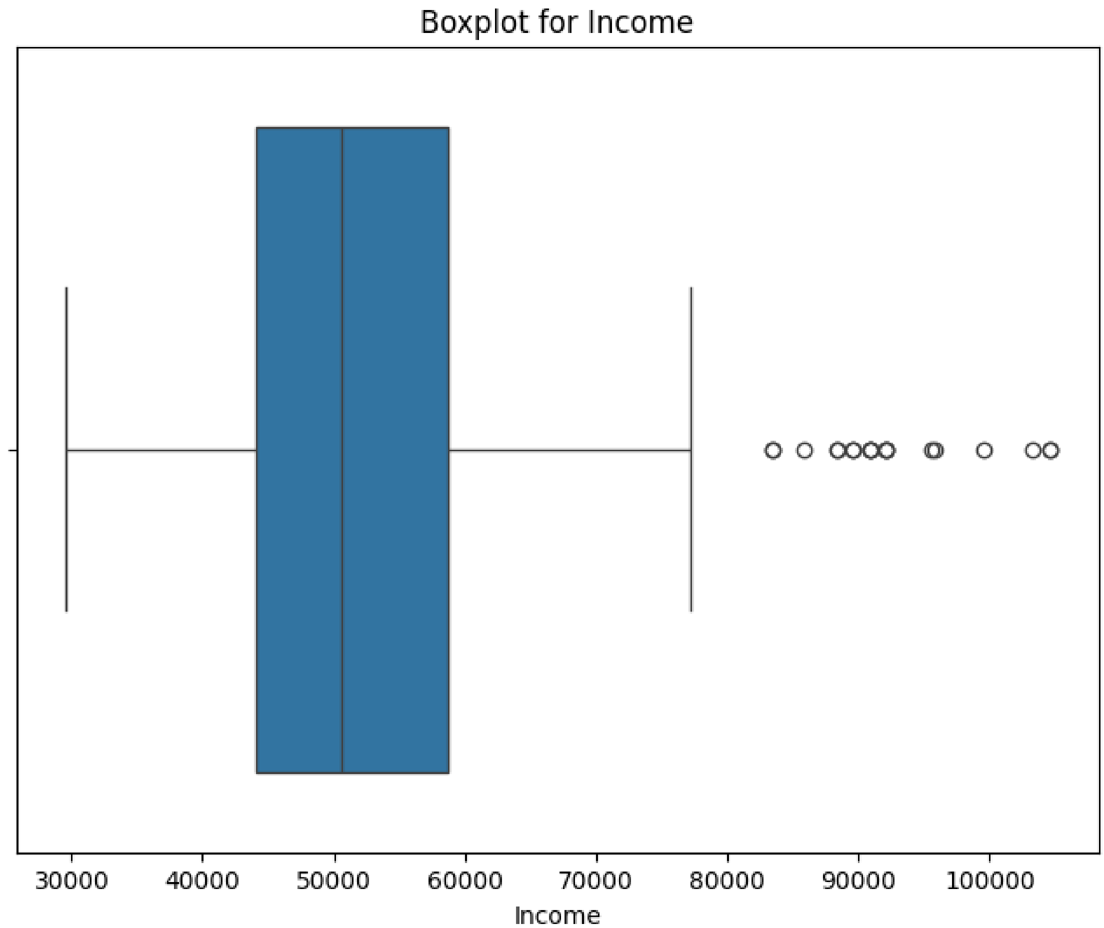
[36] :



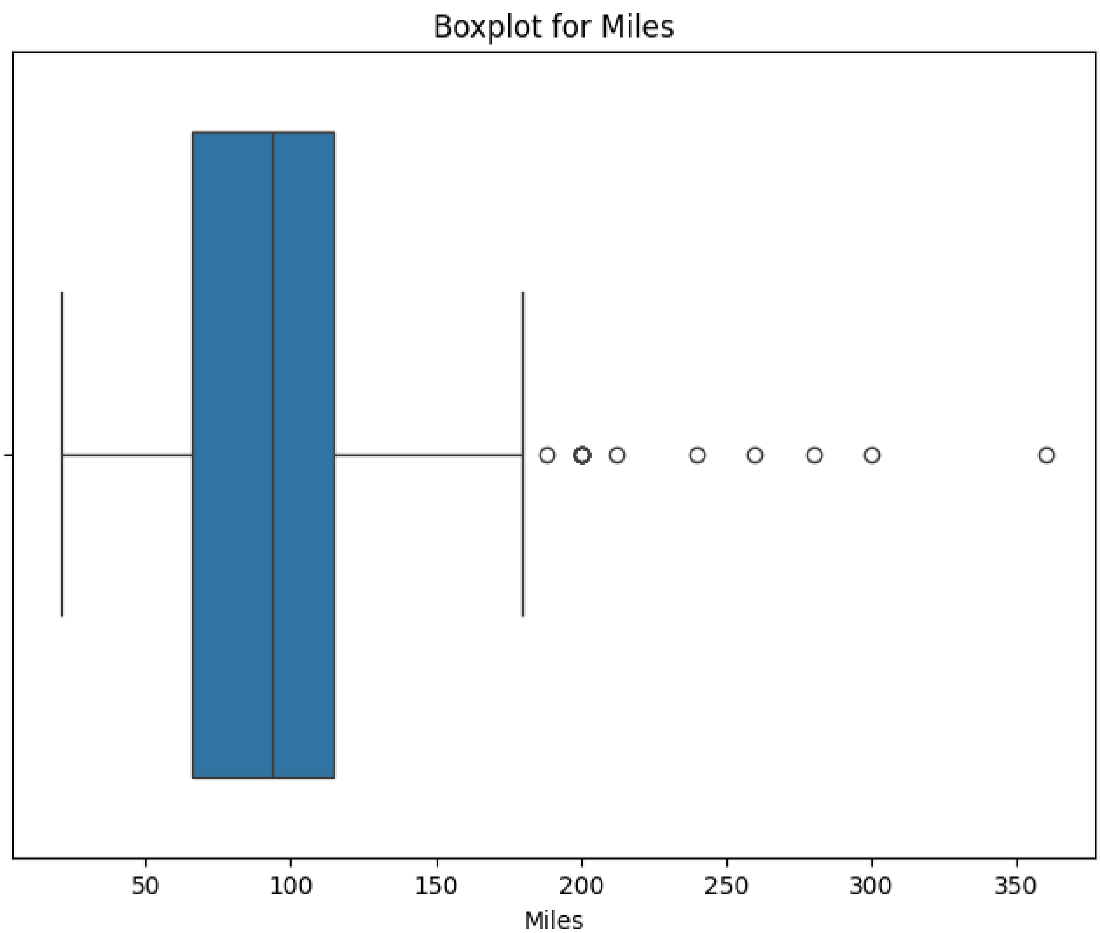
[36]:



[36] :


Boxplot for Income
30000
40000
50000
60000
70000
80000
90000
100000
Income

[36]:



Observations -

- Most of the treadmills buyers fall in the range of 24 - 34 years of age, with least with age more than 45.
- Most of the buyers have an education of 14-16 years.
- Majority people only use the treadmill 3-4 times a week. Very few people use it daily.
- Most people rate themselves as 3 or 4 in fitness levels.
- People who buy most treadmills fall in the income bracket of 45K$ - 58K$.
- Most people expect to walk/run 60 - 125 miles in a week.

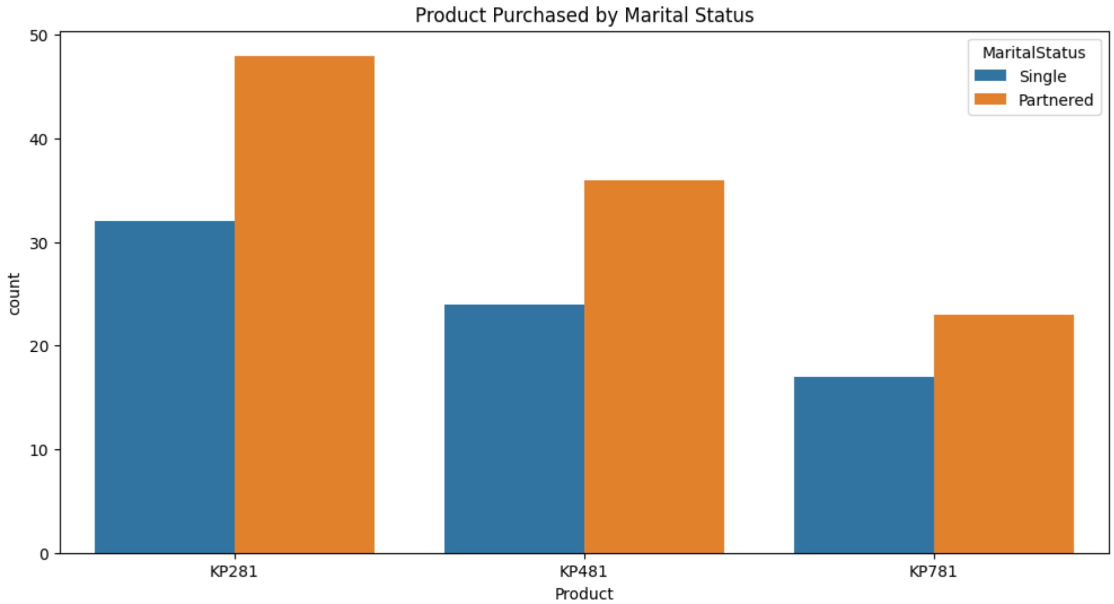
[37]:
```
for col in numerical_cols:

    lower_limit = df[col].quantile(0.05)
    upper_limit = df[col].quantile(0.95)

    df[col] = np.clip(df[col], lower_limit, upper_limit)

print(df)
```

```
    Product    Age  Gender  Education MaritalStatus  Usage  Fitness    Income  \
0     KP281  20.00    Male         14        Single   3.00        4  34053.15
1     KP281  20.00    Male         15        Single   2.00        3  34053.15
2     KP281  20.00  Female         14     Partnered   4.00        3  34053.15
3     KP281  20.00    Male         14        Single   3.00        3  34053.15
4     KP281  20.00    Male         14     Partnered   4.00        2  35247.00
..      …      …      …          …            …      …      …        …
175   KP781  40.00    Male         18        Single   5.05        5  83416.00
176   KP781  42.00    Male         18        Single   5.00        4  89641.00
177   KP781  43.05    Male         16        Single   5.00        5  90886.00
178   KP781  43.05    Male         18     Partnered   4.00        5  90948.25
179   KP781  43.05    Male         18     Partnered   4.00        5  90948.25

     Miles
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

Observations - - Education levels range from 14 to 18 years, which corresponds to different levels of formal education (e.g., high school, bachelor's degree, master's degree). - The 'Usage' column has values ranging from 2.0 to 5.05, which represents different levels of product usage or engagement. - Income values range from around $34,000 to $90,000, indicating a diverse range of customer income levels.

[38]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='Product', hue='MaritalStatus')
plt.title('Product Purchased by Marital Status')
plt.show()
```

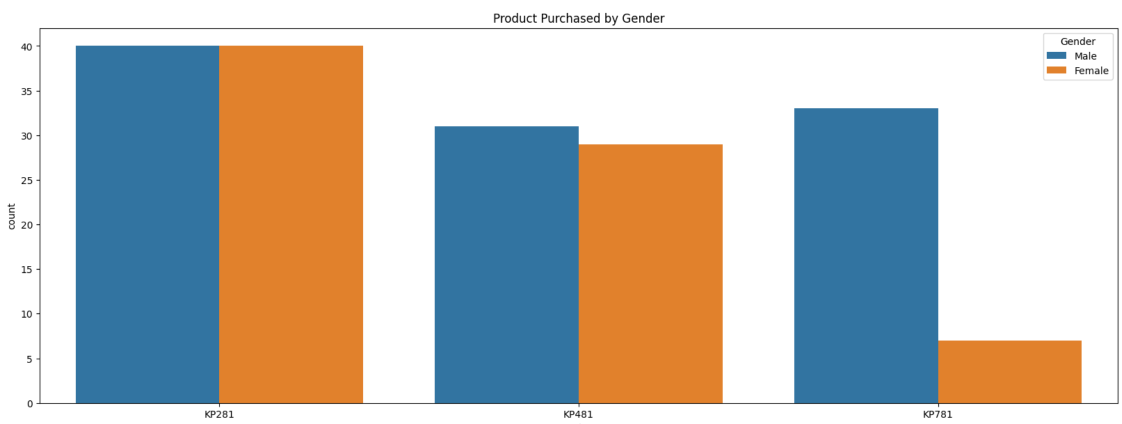
[38]:



Observations - - Couples are more likely to buy treadmills than single people.

[39]:
```
sns.countplot(data=df, x='Product', hue='Gender')
plt.title('Product Purchased by Gender')
plt.show()
```

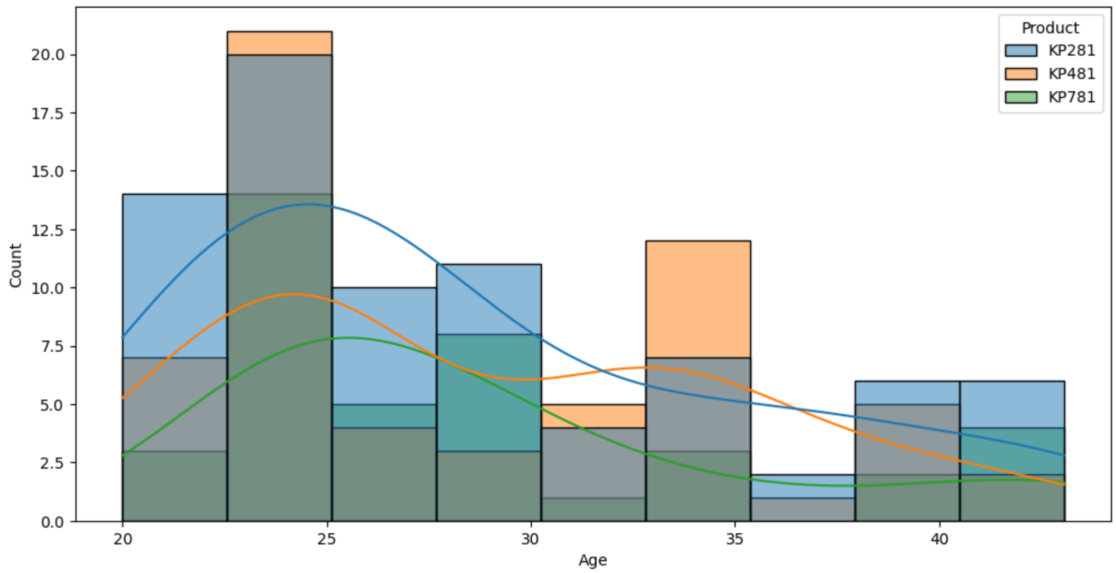
[39]:



Observations - - *KP281* is owned by equal number of men and women. - Men own the *KP481* model slightly more. - Very few females buy *KP781* variant of the treadmill.

[40]:
```
plt.figure(figsize=(12, 6))
sns.histplot(data=df, x='Age', hue='Product', kde=True)
plt.show()
```

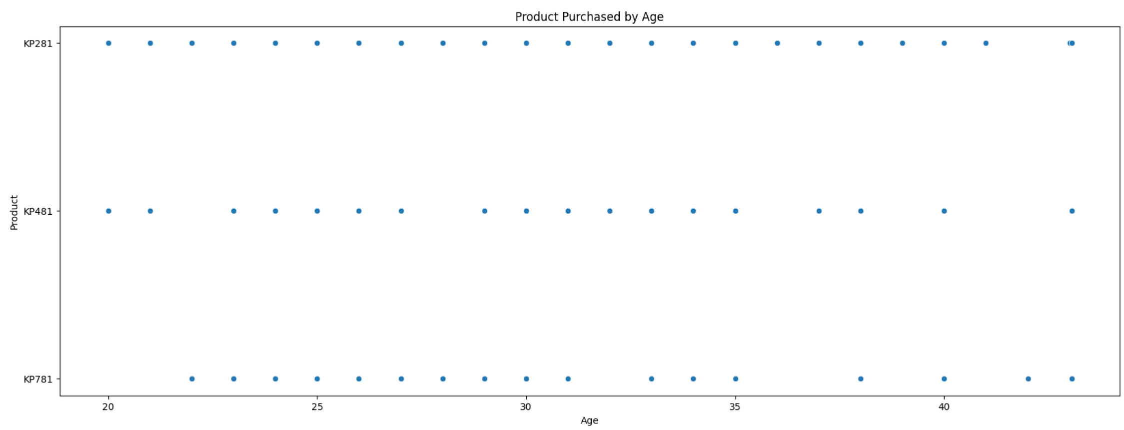
[40]:



Observations - - Most treadmills are owned by people in age group 20-25. - Least treadmills are owned by people in age group 35-40.

[41]:
```
sns.scatterplot(x='Age', y='Product', data=df)
plt.title('Product Purchased by Age')
plt.show()
```

[41]:



Observations - - *KP281* is owned by almost every people of age group from 20-45. - *KP481* is majorly owned by people from age group 30-25. - *KP781* is majorly owned by 22-30 year olds.

5 Bivariate Analysis

[48]:
```
print('----------------------------------------')
print(df.groupby('Product')['Income'].mean())
print('----------------------------------------')
print(df.groupby('Product')['Usage'].mean())
print('----------------------------------------')
print(df.groupby('Product')['Fitness'].mean())
print('----------------------------------------')
```

```
----------------------------------------
Product
KP281    46584.31125
KP481    49046.60750
KP781    73908.28125
Name: Income, dtype: float64
----------------------------------------
Product
KP281    3.087500
KP481    3.066667
KP781    4.511250
Name: Usage, dtype: float64
----------------------------------------
Product
KP281    2.975000
KP481    2.916667
KP781    4.625000
Name: Fitness, dtype: float64
----------------------------------------
```

Observations - 1. KP281 is the most popular choice for both men and women. 2. There's a significant gender imbalance in KP781 purchases, with males buying it in much higher numbers. 3. The gender breakdown for KP481 is relatively balanced. 4. Sales data shows a higher preference for KP781 among males compared to KP481.

6 Representing Probabilities

[42]:
```
product_counts = pd.crosstab(index=df['Product'], columns='count')
print('Count of each product:')
print(product_counts)

marginal_prob = pd.crosstab(index=df['Product'], columns='count',␣
 ↪normalize=True)
print('Marginal probability:')
print(marginal_prob)
```

```
product_percentages = (product_counts / len(df)) * 100
print('Percentages of Products:')
print(product_percentages)
```

```
Count of each product:
col_0    count
Product
KP281       80
KP481       60
KP781       40
Marginal probability:
col_0       count
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Percentages of Products:
col_0        count
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

Observations - - Most bought treadmill is *KP281*. 4.4 out of 10 people buy this model. - Least bought treadmill is *KP781*. Only 2.2 out of 10 people buy this variant. - *KP481* is owned by 33% people.

[43]:
```
conditional_prob = pd.crosstab(index=df['Product'],␣
 ↪columns=df['MaritalStatus'], normalize='columns')
print("Probability of buying a product based on Marital Status:")
print(conditional_prob)
```

```
Probability of buying a product based on Marital Status:
MaritalStatus  Partnered    Single
Product
KP281           0.448598  0.438356
KP481           0.336449  0.328767
KP781           0.214953  0.232877
```

Observations - - Probabilty of a single person buying *KP781* is 0.232877. - Probabilty of a married person buying *KP281* is highest 0.448598.

[44]:
```
conditional_prob_2 = pd.crosstab(index=df['Gender'], columns=df['Product'],␣
 ↪normalize='index')
print("Conditional probability given Gender:")
print(conditional_prob_2)
```

```
Conditional probability given Gender:
Product      KP281     KP481     KP781
```

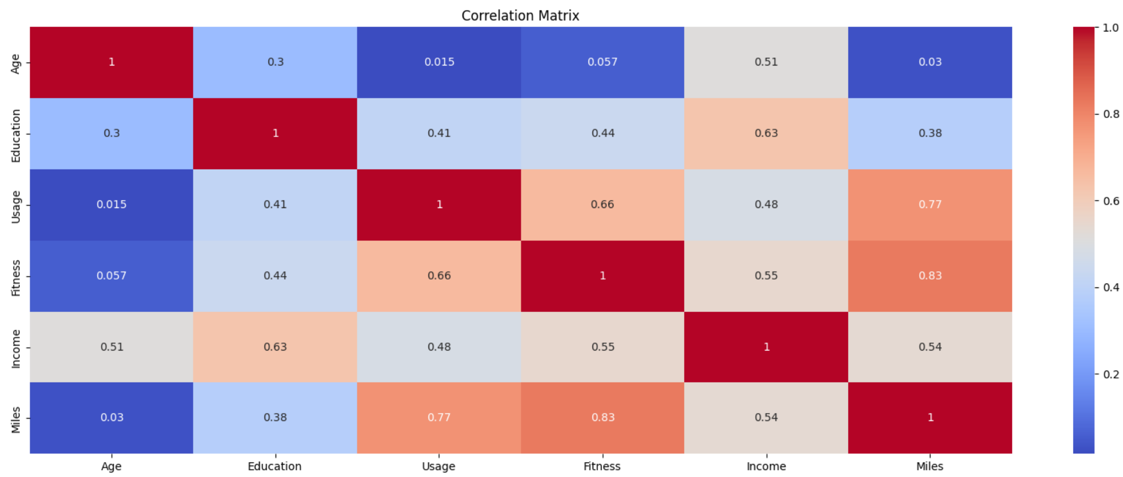
```
Gender
Female    0.526316  0.381579  0.092105
Male      0.384615  0.298077  0.317308
```

Observations - - Probabilty of a Female buying *KP781* is 0.0921 i.e. lowest. - Probabilty of a Male buying *KP281* is highest 0.526.

[45]:
```
correlation = df.corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

```
<ipython-input-45-bd96bf709ed5>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlation = df.corr()
```

[45]:



7 Customer Profiling -

[46]:
```
kp281_profile = df[df['Product'] == 'KP281'][['Age', 'Gender', 'Income']]
kp481_profile = df[df['Product'] == 'KP481'][['Age', 'Gender', 'Income']]
kp781_profile = df[df['Product'] == 'KP781'][['Age', 'Gender', 'Income']]

print("Customer profiling for KP281:")
print(kp281_profile.describe())
print("Customer profiling for KP481:")
print(kp481_profile.describe())
print("Customer profiling for KP781:")
print(kp781_profile.describe())
```

```
Customer profiling for KP281:
             Age        Income
count  80.000000     80.000000
mean   28.427500  46584.311250
std     6.678313   8813.246103
min    20.000000  34053.150000
25%    23.000000  38658.000000
50%    26.000000  46617.000000
75%    33.000000  53439.000000
max    43.050000  68220.000000
Customer profiling for KP481:
             Age        Income
count  60.000000     60.000000
mean   28.801667  49046.607500
std     6.327830   8517.583361
min    20.000000  34053.150000
25%    24.000000  44911.500000
50%    26.000000  49459.500000
75%    33.250000  53439.000000
max    43.050000  67083.000000
Customer profiling for KP781:
             Age        Income
count  40.000000     40.000000
mean   28.828750  73908.281250
std     6.296182  16572.164368
min    22.000000  48556.000000
25%    24.750000  58204.750000
50%    27.000000  76568.500000
75%    30.250000  90886.000000
max    43.050000  90948.250000
```

Observations - - KP781 customers have the highest average income at $73,908, followed by KP481 at $49,047 and KP281 at $46,584. - The age distributions are fairly similar across the three groups, with mean ages ranging from 28.4 to 28.8 years old. - KP781 has the widest income spread, with a much higher 75th percentile income of $90,886 compared to the other groups. - KP281 has the tightest income distribution, with the smallest standard deviation of $8,813. - The minimum ages are consistent at 20-22 years old, while the maximum ages top out at 43 years old across all groups. - The median incomes increase progressively from KP281 ($46,617) to KP481 ($49,460) to KP781 ($76,569).

8 Recommendations -

- KP281 & KP481 treadmills are preferred by the customers whose annual income lies in the range of 39K - 53K $. These models should promote as budget treadmills. As KP781 provides more features and functionalities, the treadmill should be marketed for professionals and athletes.
- Based on the analysis, Aerofit can tailor marketing strategies to target specific customer segments for each product.

- Focus on promoting KP781 to customers with higher income and education levels.
- Offer personalized recommendations based on customer profiles to enhance customer satisfaction and retention.
- We should run a marketing campaign on Women's Day and Mother's day to encourage more women to exercise.
- Given the wider range of features offered by the KP781, this treadmill might be best marketed towards professional athletes and fitness enthusiasts.