Business Case: AEROFIT

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.

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

INPUT:

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

```
data_path = "aerofit_treadmill.csv"
df = pd.read_csv(data_path)
df
```

OUTPUT:

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

INPUT:

```
print (f"Number of row: {df.shape[0]} \nNumber of columns:{df.shape[1]}")
```

OUTPUT:

```
Number of row: 180
Number of columns:9
```

INPUT:

```
df.info()
```

OUTPUT:

```
<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
```

INPUT:

```
df.describe()
```

OUTPUT:

	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

INPUT:

```
df.describe(include="all")
```

OUTPUT:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

OBSERVATIONS:

- There are no missing values in the data.
- There are 3 unique products in the dataset.
- KP281 is the most frequent product.
- Minimum & Maximum age of the person is 18 & 50, mean is 28.79 and 75% of persons have age less than or equal to 33.
- Most of the people are having 16 years of education i.e., 75% of persons are having education <= 16 years.
- Out of 180 data points, 104's gender is Male and rest are the female.
- Standard deviation for Income & Miles is very high. These variables might have the outliers in it.

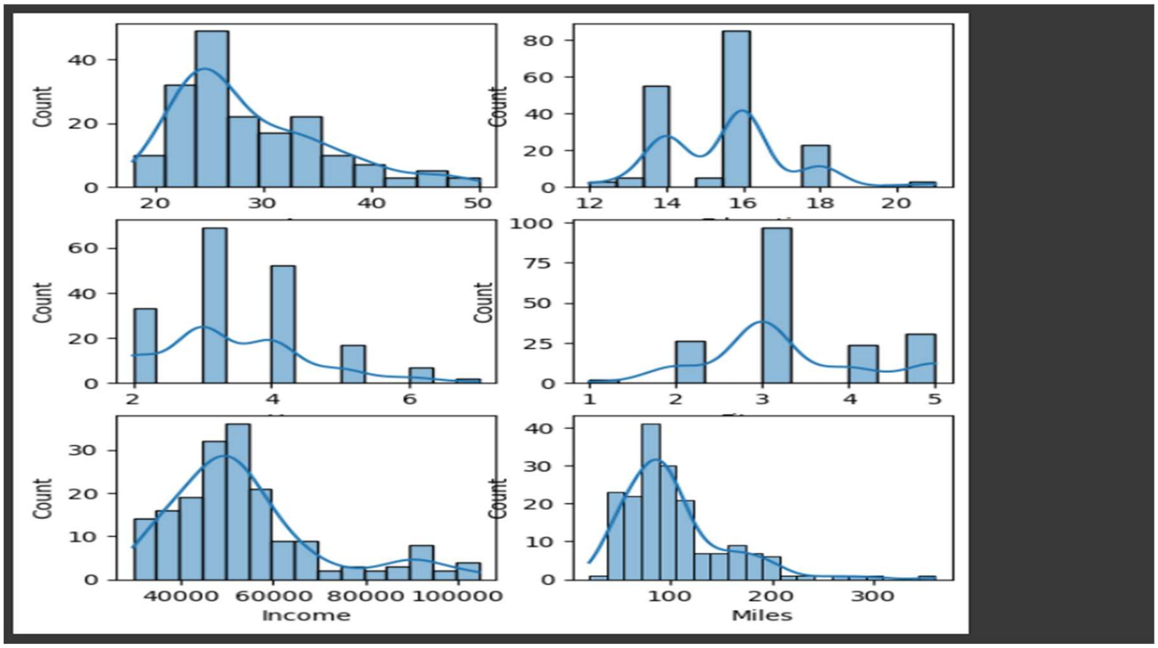
Univariate Analysis:

- Understanding the distribution of the data for the quantitative attributes:
- Age
- Education
- Usage
- Fitness
- Income
- Miles

INPUT:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(6, 5))
fig.subplots_adjust(top=1.2)
sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Education", kde=True, ax=axis[0,1])
sns.histplot(data=df, x="Usage", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Fitness", kde=True, ax=axis[1,1])
sns.histplot(data=df, x="Income", kde=True, ax=axis[2,0])
sns.histplot(data=df, x="Miles", kde=True, ax=axis[2,1])
plt.show()
```

OUTPUT:

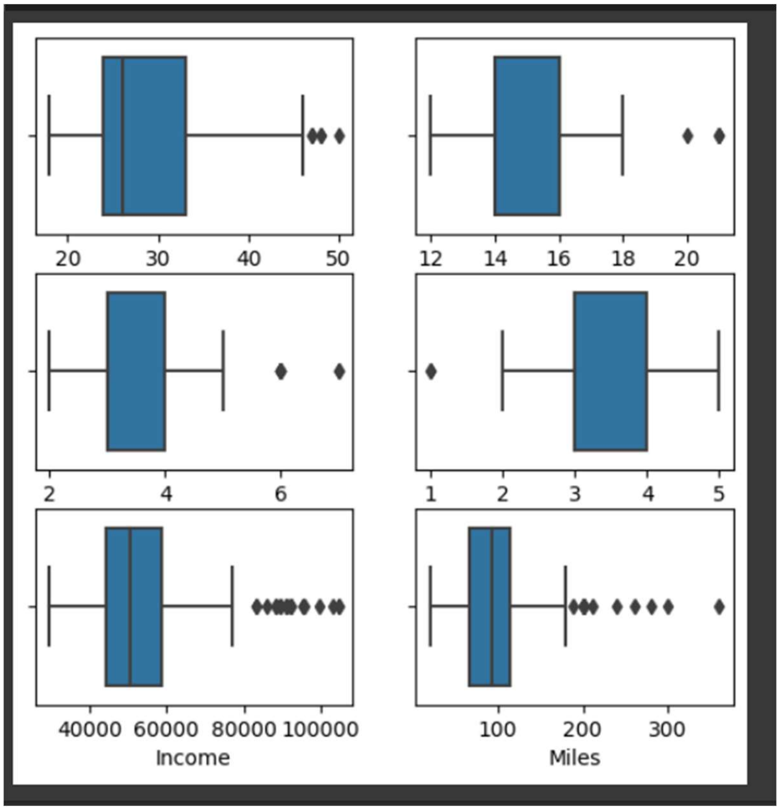


Outlier detection using Box Plots

INPUT:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(6, 5))
fig.subplots_adjust(top=1.0)
sns.boxplot(data=df, x="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, x="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, x="Usage", orient='h', ax=axis[1,0])
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, x="Miles", orient='h', ax=axis[2,1])
plt.show()
```

OUTPUT:



Observations:

- Even from the boxplots it is quite clear that:
- Age, Education and Usage are having very few outliers.
- While Income and Miles are having more outliers.

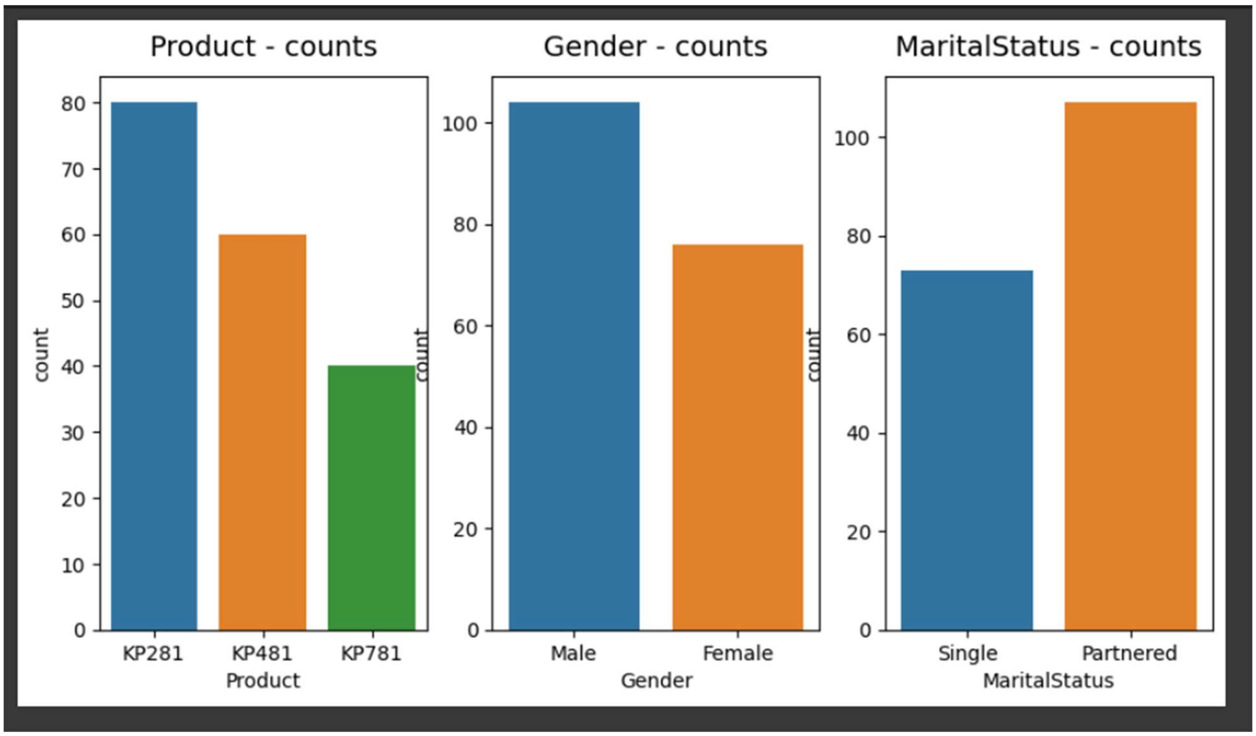
Understanding the distribution of the data for the qualitative attributes:

- Product
- Gender
- Marital Status

INPUT:

```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(10,5))
sns.countplot(data=df, x='Product', ax=axs[0])
sns.countplot(data=df, x='Gender', ax=axs[1])
sns.countplot(data=df, x='MaritalStatus', ax=axs[2])
axs[0].set_title("Product - counts", pad=10, fontsize=14)
axs[1].set_title("Gender - counts", pad=10, fontsize=14)
axs[2].set_title("MaritalStatus - counts", pad=10,
fontsize=14)
plt.show()
```

OUTPUT:



OBSERVATIONS:

- KP281 is the most frequent product.
- There are more Males in the data than Females.
- More Partnered persons are there in the data

To be precise - normalized count for each variable is shown below:

INPUT:

```
df1 = df[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count() / len(df)
```

OUTPUT:

variable	value	value
Gender	Female	0.422222
	Male	0.577778
MaritalStatus	Partnered	0.594444
	Single	0.405556
Product	KP281	0.444444
	KP481	0.333333
	KP781	0.222222

Observations:

Product:

- 44.44% of the customers have purchased KP2821 product.
- 33.33% of the customers have purchased KP481 product.
- 22.22% of the customers have purchased KP781 product.

Gender:

- 57.78% of the customers are Male.

Marital Status:

- 59.44% of the customers are Partnered.

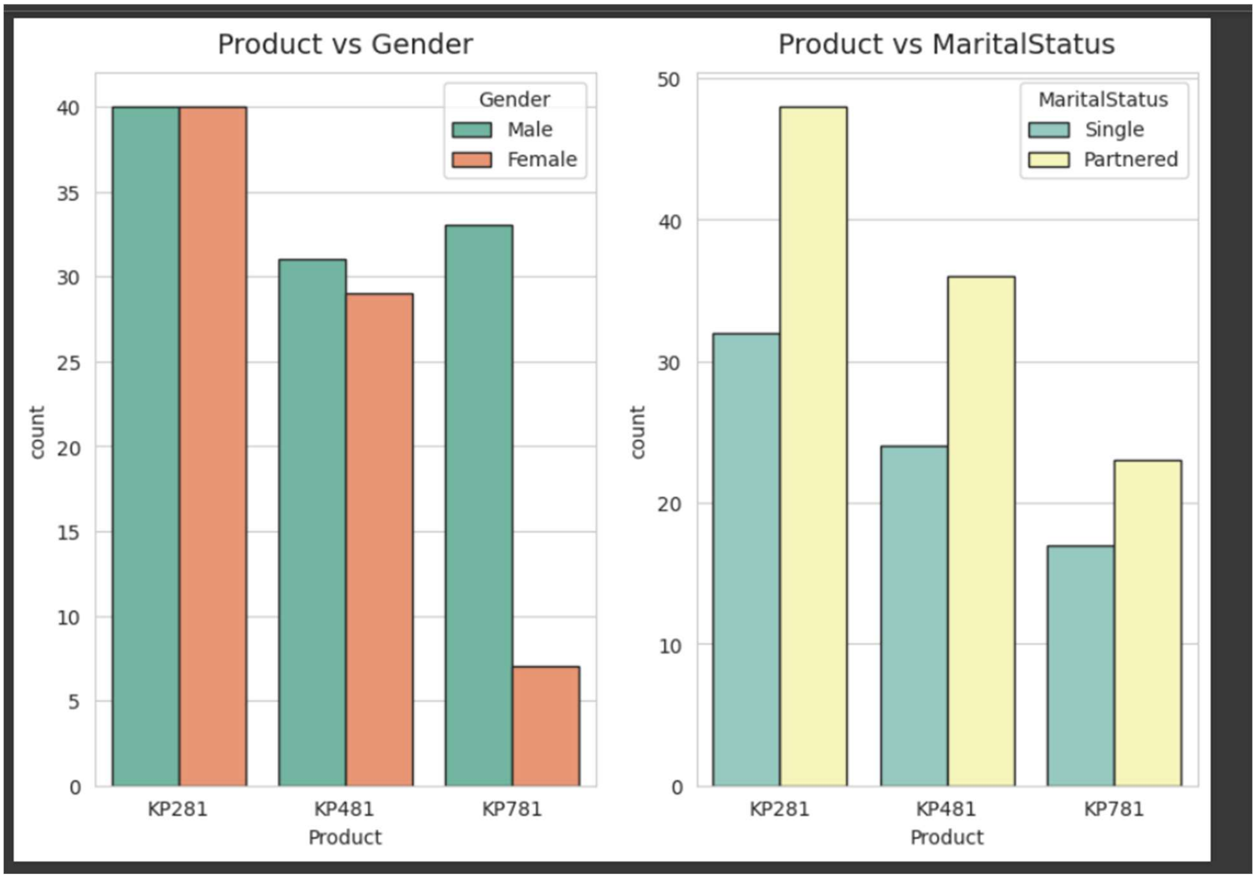
Bivariate Analysis:

- Checking if features - Gender or Marital Status have any effect on the product purchased.

INPUT:

```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(10, 6.5))
sns.countplot(data=df, x='Product', hue='Gender', edgecolor="0.15",
palette='Set2', ax=axs[0])
sns.countplot(data=df, x='Product', hue='MaritalStatus',
edgecolor="0.15", palette='Set3', ax=axs[1])
axs[0].set_title("Product vs Gender", pad=10, fontsize=14)
axs[1].set_title("Product vs MaritalStatus", pad=10, fontsize=14)
plt.show()
```

OUTPUT:



Observations:

Product vs Gender

- Equal number of males and females have purchased KP281 product and almost same for the product KP481

➢ Most of the Male customers have purchased the KP781 product.

Product vs Marital Status:

➢ Customer who is Partnered, is more likely to purchase the product.

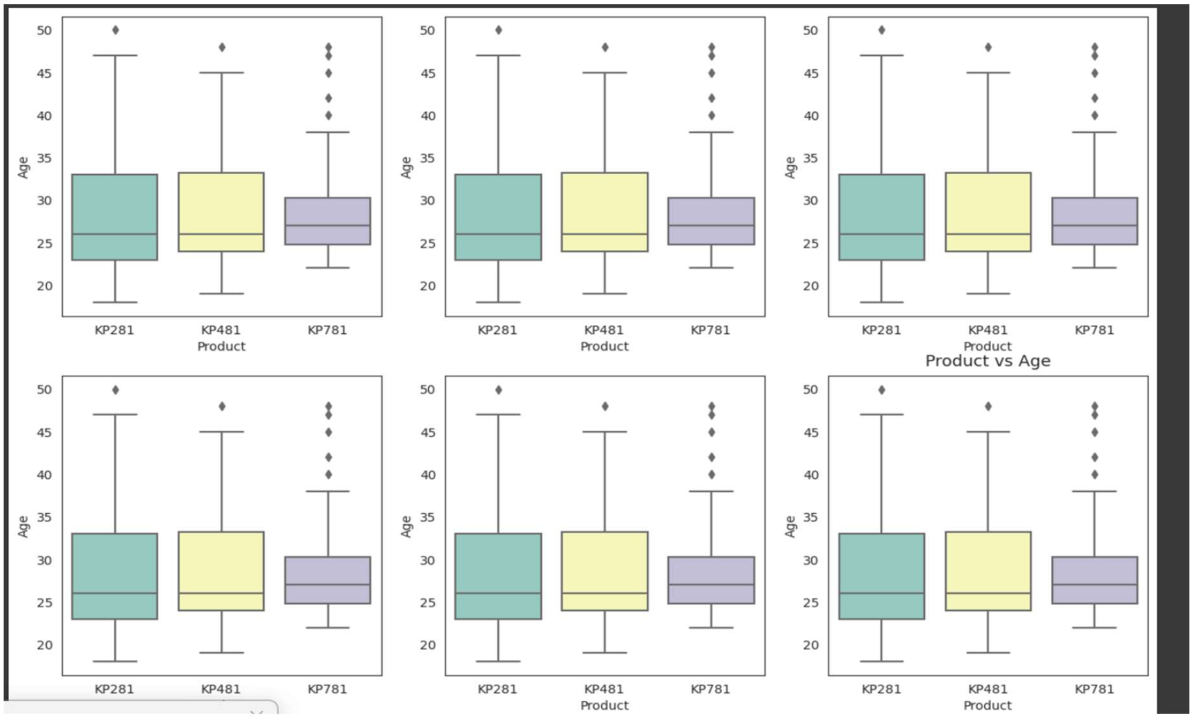
Checking if following features have any effect on the product purchased:

1. Age 2. Education 3. Usage 4. Fitness 5. Income 6. Miles.

INPUT:

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income',
'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(12, 8))
fig.subplots_adjust(top=1.2)
count = 0
for i in range(2):
  for j in range(3):
    sns.boxplot(data=df, x='Product', y=attrs[count],
ax=axs[i,j], palette='Set3')
axs[i,j].set_title(f"Product vs {attrs[count]}",
pad=8, fontsize=13)
count += 1
```

OUTPUT:



Observations:

1. **Product vs Age**
   - Customers purchasing products KP281 & KP481 are having same Age median value.
   - Customers whose age lies between 25-30, are more likely to buy KP781 product

   Product vs Education
   - Customers whose Education is greater than 16, have more chances to purchase the KP781 product.
   - While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481.

   Product vs Usage

   - Customers who are planning to use the treadmill greater than 4 times a week, are more likely to purchase the KP781 product.
   - While the other customers are likely to purchasing KP281 or KP481.

Product vs Fitness

- The more the customer is fit (fitness >= 3), higher the chances of the customer to purchase the KP781 product. 1. Product vs Income
- Higher the Income of the customer (Income >= 60000), higher the chances of the customer to purchase the KP781 product.

Product vs Miles

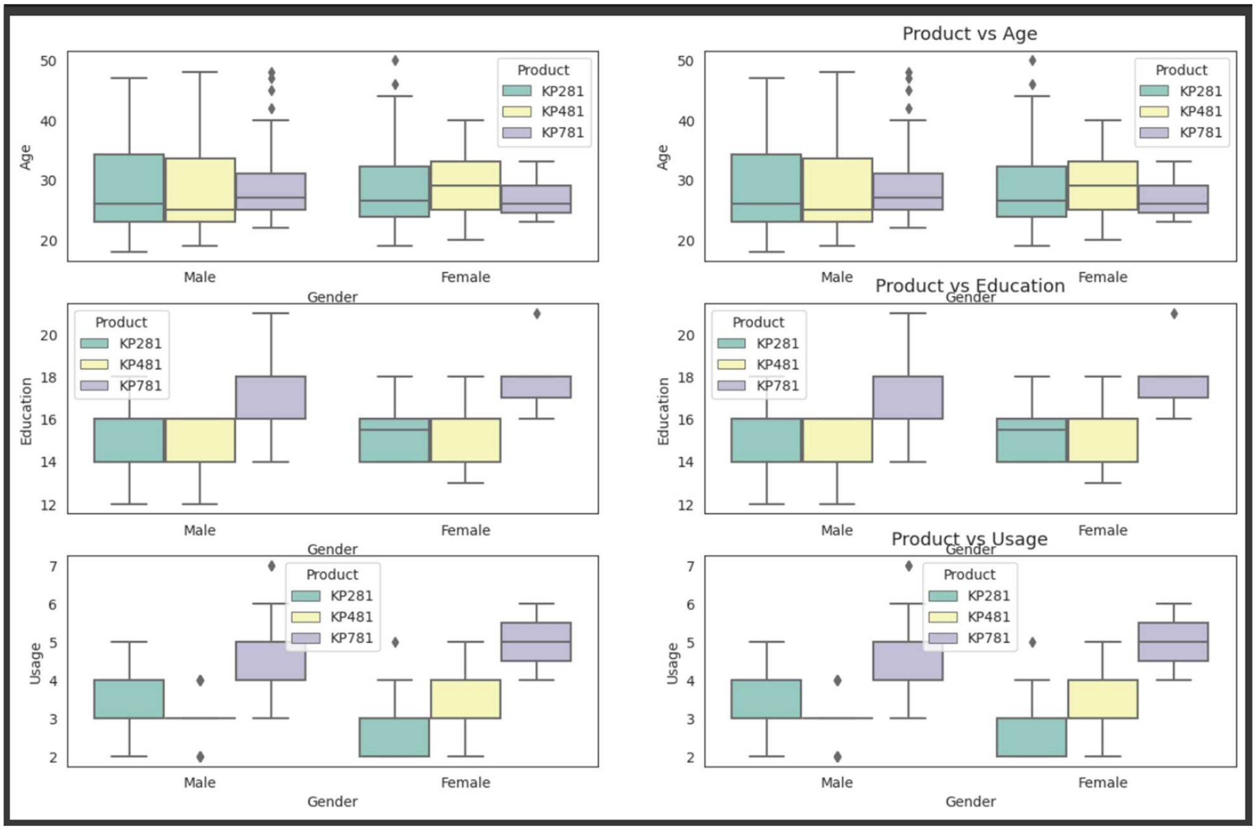
- If the customer expects to walk/run greater than 120 Miles per week, it is more likely that the customer will buy KP781 product.

Multivariate Analysis:

INPUT:

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(15, 8))
fig.subplots_adjust(top=1)
count = 0
for i in range(3):
 for j in range(2):
  sns.boxplot(data=df, x='Gender', y=attrs[count], hue='Product',
ax=axs[i,j], palette='Set3')
 axs[i,j].set_title(f"Product vs {attrs[count]}", pad=8,
fontsize=13)
 count += 1
```

OUTPUT:



OBSERVATIONS:

- Females planning to use treadmill 3-4 times a week, are more likely to buy KP481 product

Computing Marginal & Conditional Probabilities:

- Marginal Probability

INPUT:

```
df['Product'].value_counts(normalize=True)
```

OUTPUT:

```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

CONDITIONAL PROBABILITIES:

Probability of each product given gender:

INPUT:

```
def p_prod_given_gender(gender, print_marginal=False):
 if gender is not "Female" and gender is not "Male":
  return "Invalid gender value."

 df1 = pd.crosstab(index=df['Gender'], columns=[df['Product']])
 p_781 = df1['KP781'][gender] / df1.loc[gender].sum()
 p_481 = df1['KP481'][gender] / df1.loc[gender].sum()
 p_281 = df1['KP281'][gender] / df1.loc[gender].sum()

 if print_marginal:
  print(f"P(Male): {df1.loc['Male'].sum()/len(df):.2f}")
  print(f"P(Female): {df1.loc['Female'].sum()/len(df):.2f}\n")

 print(f"P(KP781/{gender}): {p_781:.2f}")
 print(f"P(KP481/{gender}): {p_481:.2f}")
 print(f"P(KP281/{gender}): {p_281:.2f}\n")

p_prod_given_gender('Male', True)
p_prod_given_gender('Female')
```

OUTPUT:

```
P(Male): 0.58
P(Female): 0.42

P(KP781/Male): 0.32
P(KP481/Male): 0.30
P(KP281/Male): 0.38

P(KP781/Female): 0.09
P(KP481/Female): 0.38
P(KP281/Female): 0.53
```