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.

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
df = pd.read_csv("/content/drive/MyDrive/CSV datasets/Aerofit.csv")
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

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.shape
```

```
(180, 9)
```

```
# Separate numerical and categorical columns
numerical_columns = df.select_dtypes(include=[np.number]).columns.tolist()
categorical_columns = df.select_dtypes(include=[object]).columns.tolist()
# Convert column names to a list:
# columns.tolist():converting the column Indexs  to a list for easy access
# Display the lists of columns
print("Numerical columns:", numerical_columns)
print("Categorical columns:", categorical_columns)
# Calculate the mean and standard deviation for numerical columns
numerical_means = df[numerical_columns].mean()
numerical_stds = df[numerical_columns].std()
print("\nMean values for numerical columns:")
print(numerical_means)
print("\nStandard deviation values for numerical columns:")
print(numerical_stds)
# Display value counts for categorical columns
print("\nValue counts for categorical columns:")
for column in categorical_columns:

    print(f"\n{column} value counts:")
    print(df[column].value_counts())
```

```
Numerical columns: ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
Categorical columns: ['Product', 'Gender', 'MaritalStatus']

Mean values for numerical columns:
Age             28.788889
Education       15.572222
Usage            3.455556
Fitness          3.311111
Income       53719.577778
Miles          103.194444
dtype: float64

Standard deviation values for numerical columns:
Age              6.943498
Education        1.617055
Usage            1.084797
Fitness          0.958869
Income       16506.684226
Miles           51.863605
dtype: float64
```

```
Value counts for categorical columns:

Product value counts:
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64

Gender value counts:
Gender
Male      104
Female     76
Name: count, dtype: int64

MaritalStatus value counts:
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

```
#conversion of categorical attributes to 'category' (If required)
for column in categorical_columns:
    df[column] = df[column].astype('category')
    print(df.dtypes)
```

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

Convereted object data types into categorical types

object---use more memory

category---use less memory

```
df.describe()#summary of statistics for numerical columns
```

	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

```
#Checking the characteristics of the data:
df.describe(include = 'all')#summary of statistics for (numerical columns + categorical columns)
```

	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

Non-Graphical Analysis: Value counts and unique attributes

```
#Value counts
df.value_counts()
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	count
KP281	**18**	**Male**	**14**	**Single**	**3**	**4**	**29562**	**112**	1
KP481	**30**	**Female**	**13**	**Single**	**4**	**3**	**46617**	**106**	1
	31	**Female**	**16**	**Partnered**	**2**	**3**	**51165**	**64**	1
			18	**Single**	**2**	**1**	**65220**	**21**	1
		Male	**16**	**Partnered**	**3**	**3**	**52302**	**95**	1
...	**...**	**...**	**...**	**...**	**...**	**...**	**...**	**...**	...
KP281	**34**	**Female**	**16**	**Single**	**2**	**2**	**52302**	**66**	1
		Male	**16**	**Single**	**4**	**5**	**51165**	**169**	1
	35	**Female**	**16**	**Partnered**	**3**	**3**	**60261**	**94**	1
			18	**Single**	**3**	**3**	**67083**	**85**	1
KP781	**48**	**Male**	**18**	**Partnered**	**4**	**5**	**95508**	**180**	1

180 rows × 1 columns

```
df['Usage'].value_counts()
```

Usage	count
3	69
4	52
2	33
5	17
6	7
7	2

out of 7days in a week :

1.69 cus used the treadmill 3 times/week.

2.52 cus used the treadmill 4 times/week.

3.similary remaining

4.only 2 cus used the treadmill 7 times/week

```
# Use value_counts() on a specific column
df['Product'].value_counts()
```

Product	count
KP281	80
KP481	60
KP781	40

```
# Check for null values in the DataFrame
null_counts = df.isnull().sum() # or df.isna()
print(null_counts)
```

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

df.isnull(): Use to check for missing values and understand where they are located in the DataFrame.

df.isnull().sum(): Use to get a quick summary of the number of missing values in each column

Observations:

There are no missing values in the data.

```
# Check for unique values in the DataFrame
df.nunique()
```

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

```
unique_values = df['Product'].unique()
print(unique_values)
```

```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

```
df['Product'].nunique()
```

```
3
```

```
print(unique_values)
```

```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

```
df['Age'].nunique()
```

```
32
```

Unique---what are the unique values in a feature

nunique...No of unique values (i.e..count of unique values)

value_counts...To get frequency of values(no of times a value repeating)

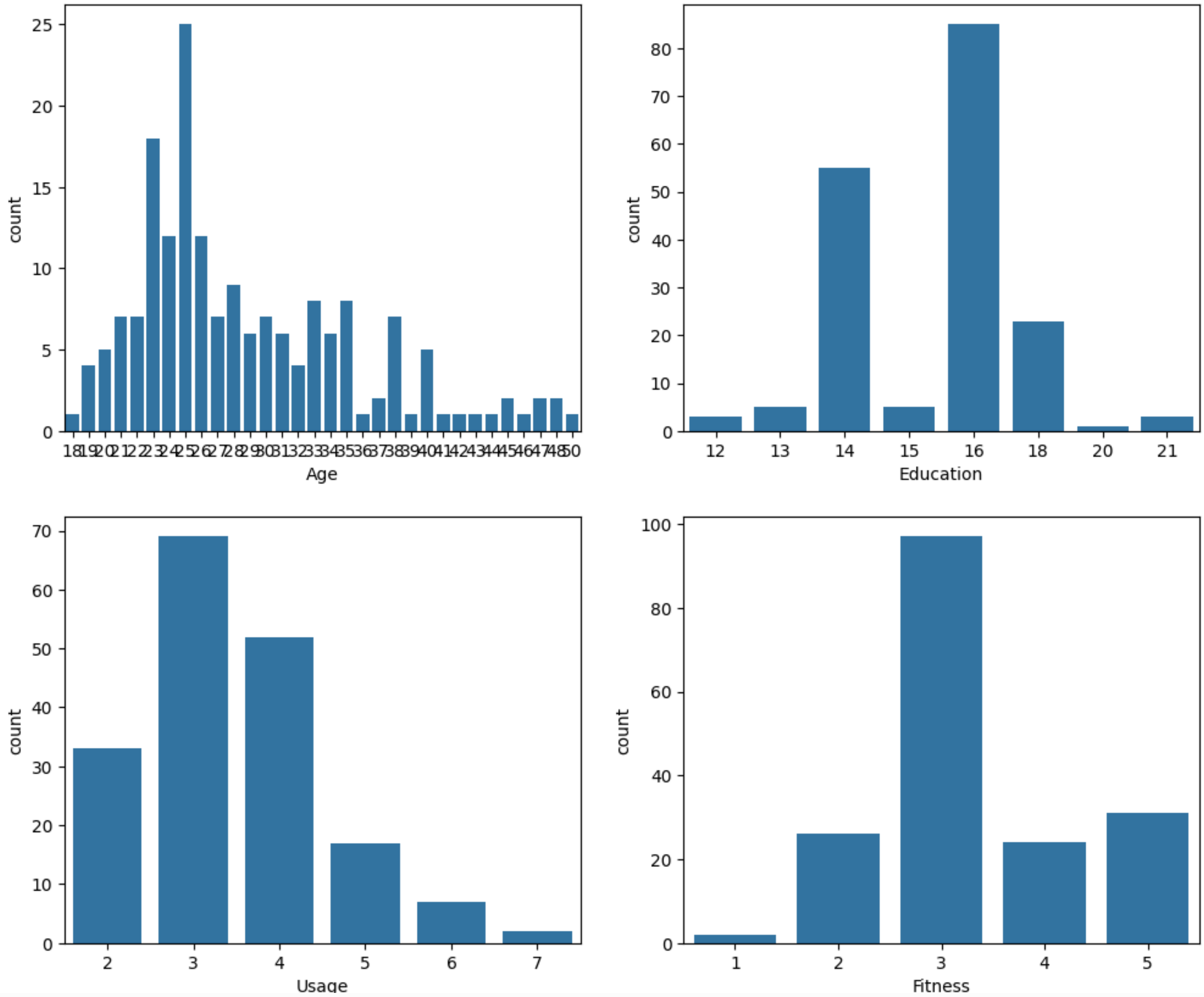
Univariate analysis

count plot

Quantitative data : counted or measured or numerical value.

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(12,10))
sns.countplot(data=df, x='Age', ax=axs[0,0])
sns.countplot(data=df, x='Education', ax=axs[0,1])
sns.countplot(data=df, x='Usage', ax=axs[1,0])
sns.countplot(data=df, x='Fitness', ax=axs[1,1])
```

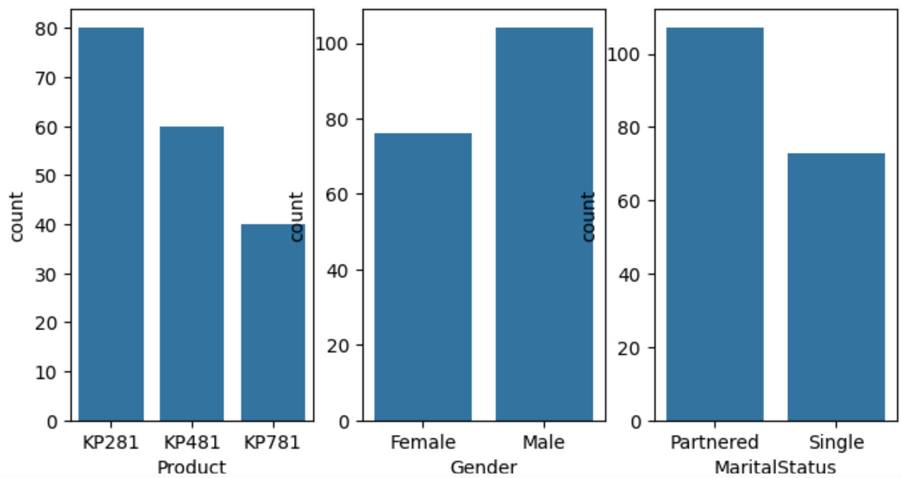
<Axes: xlabel='Fitness', ylabel='count'>



Qualitative data : descriptive data

1. Product
2. Gender
3. MaritalStatus

```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(8,4))
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])
plt.show()
```



Observations:

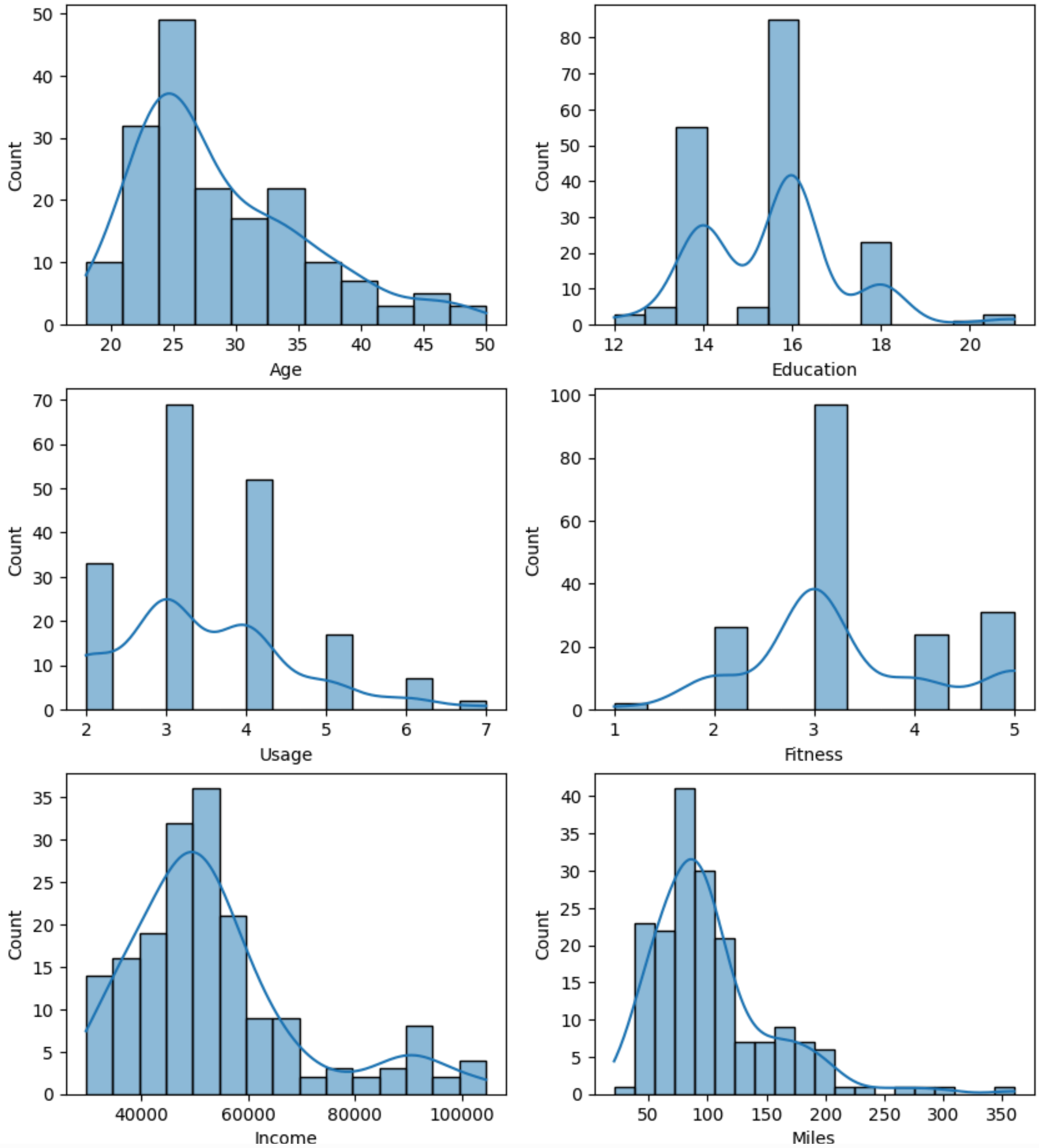
1.KP281 is the most frequent product.

2.There are more Males in the data than Females.

3.More Partnered persons are there in the data.

histplot/dist plot

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(10,8))
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()
```

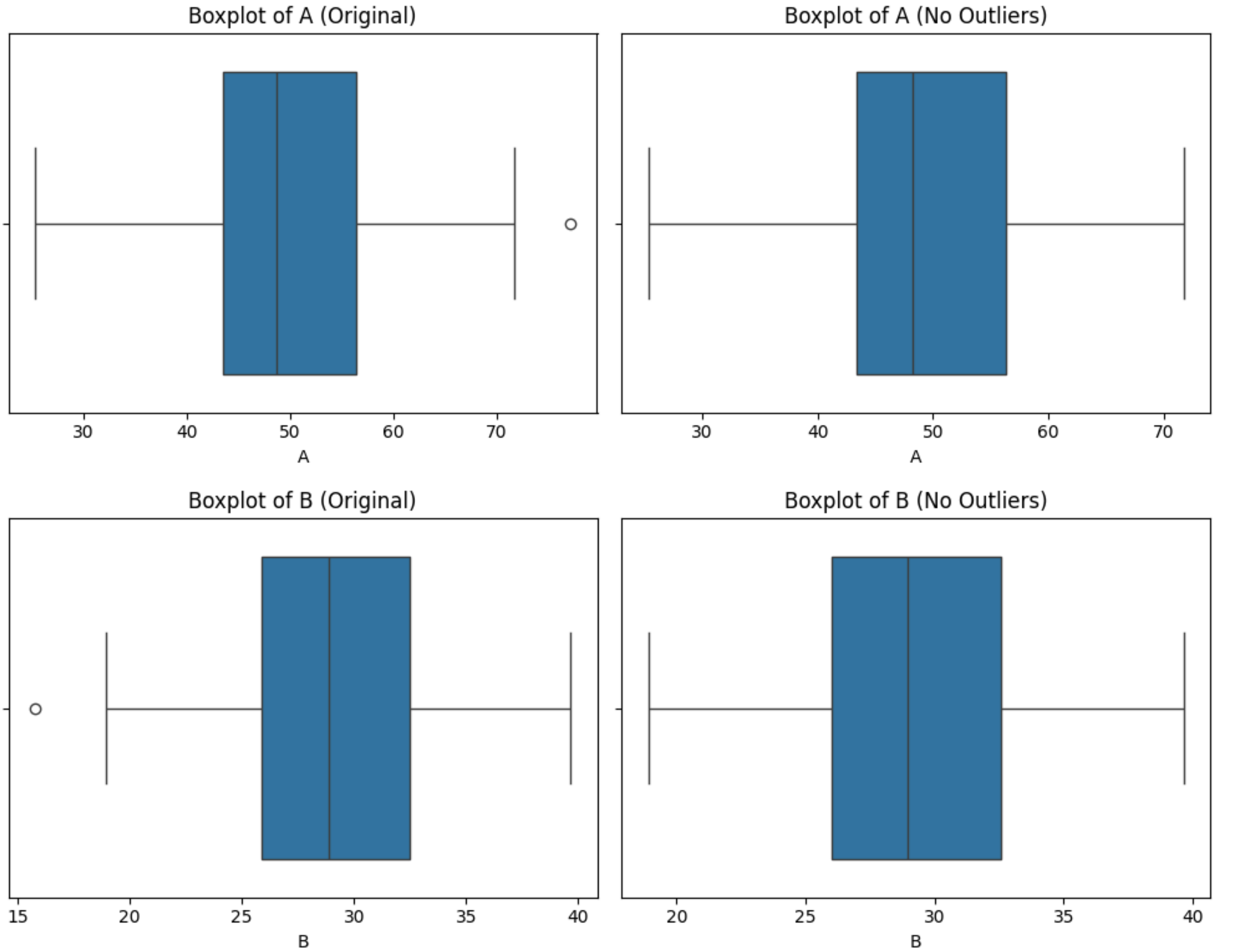


For categorical variable(s): Boxplot

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

# Separate numerical columns
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
```

```
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

# Load your DataFrame here (example placeholder)
df = pd.DataFrame({  # Example data
    'A': np.random.randn(100) * 10 + 50,
    'B': np.random.randn(100) * 5 + 30
})

# Identify numerical columns
numerical_columns = df.select_dtypes(include=[np.number]).columns.tolist()

# Remove outliers for all numerical columns
df_no_outliers = df.copy()
for column in numerical_columns:
    df_no_outliers = remove_outliers(df_no_outliers, column)

# Display the DataFrame without outliers
print("\nDataFrame without outliers:")
print(df_no_outliers.head())

# Function to create side-by-side boxplots for numerical columns
def plot_side_by_side(df, df_no_outliers, column):
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))

    # Original data boxplot
    sns.boxplot(x=df[column], ax=axes[0])
    axes[0].set_title(f'Boxplot of {column} (Original)')

    # Data without outliers boxplot
    sns.boxplot(x=df_no_outliers[column], ax=axes[1])
    axes[1].set_title(f'Boxplot of {column} (No Outliers)')

    plt.tight_layout()
    plt.show()

# Plot side-by-side for each numerical column
for column in numerical_columns:
    plot_side_by_side(df, df_no_outliers, column)
```

```
DataFrame without outliers:
           A          B
0  54.531112  27.499912
1  47.719781  18.918829
2  54.679580  34.520249
3  55.177609  25.846704
5  38.723414  27.915388
```



Outlier Removal:

Removes extreme values entirely.

Reduces dataset size.

May result in loss of valuable information.

Clipping:

Adjusts extreme values to boundary values.

Preserves dataset size.

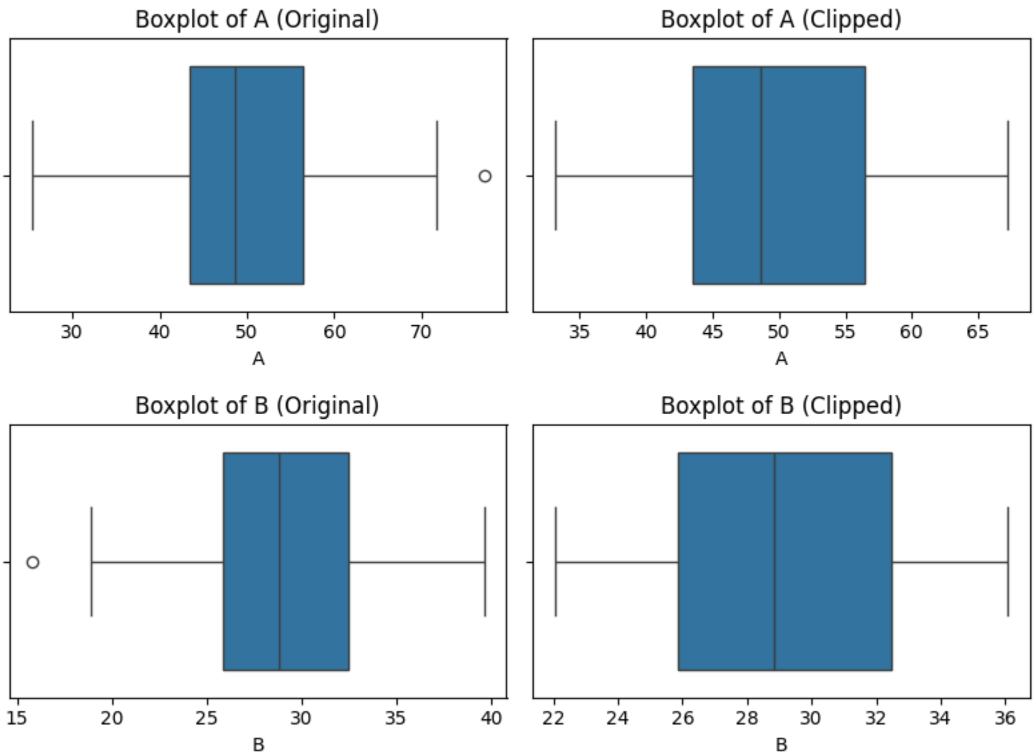
Reduces the impact of extreme values without discarding data.

Clipping--Adjusting O/L pts to 5 and 95% without removing those pts which may contain useful info

```
# Separate numerical and categorical columns
numerical_columns = df.select_dtypes(include=[np.number]).columns.tolist()
# Calculate the 5th and 95th percentiles for numerical columns
percentiles = df[numerical_columns].quantile([0.05, 0.95])
print("\n5th and 95th percentiles:")
print(percentiles)
# Clip the data between the 5th and 95th percentiles for numerical columns
clipped_df = df.copy()
for column in numerical_columns:
    lower_bound = percentiles.loc[0.05, column]
    upper_bound = percentiles.loc[0.95, column]
    clipped_df[column] = np.clip(df[column], lower_bound, upper_bound)
# Display the clipped DataFrame
```

```
print("\nClipped DataFrame for numerical columns:")
print(clipped_df.head())
# Function to create side-by-side boxplots for numerical columns
def plot_side_by_side(df, clipped_df, column):
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(8,3))
    # Original data boxplot
    sns.boxplot(x=df[column], ax=axes[0])
    axes[0].set_title(f'Boxplot of {column} (Original)')
    # Clipped data boxplot
    sns.boxplot(x=clipped_df[column], ax=axes[1])
    axes[1].set_title(f'Boxplot of {column} (Clipped)')
    plt.tight_layout()
    plt.show()
# Function to plot value counts for categorical columns
def plot_value_counts(df, column):
    plt.figure(figsize=(8, 4))
    sns.countplot(x=df[column])
    plt.title(f'Value Counts of {column}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
# Plot side-by-side for each numerical column
for column in numerical_columns:
    plot_side_by_side(df, clipped_df, column)
```

```
5th and 95th percentiles:
              A          B
0.05  33.178274  22.073525
0.95  67.208000  36.069745

Clipped DataFrame for numerical columns:
           A          B
0  54.531112  27.499912
1  47.719781  22.073525
2  54.679580  34.520249
3  55.177609  25.846704
4  53.985429  22.073525
```



Clipping data in the context of a box plot means adjusting the data to limit the in uence of extreme outliers

```
# Calculate the mean and standard deviation for numerical columns
numerical_means = df[numerical_columns].mean()
numerical_stds = df[numerical_columns].std()
print("\nMean values for numerical columns:")
print(numerical_means)
print("\nStandard deviation values for numerical columns:")
print(numerical_stds)
```

```
Mean values for numerical columns:
```

```
A    49.945339
B    29.140255
dtype: float64

Standard deviation values for numerical columns:
A    10.169437
B     4.481544
dtype: float64
```

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

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

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

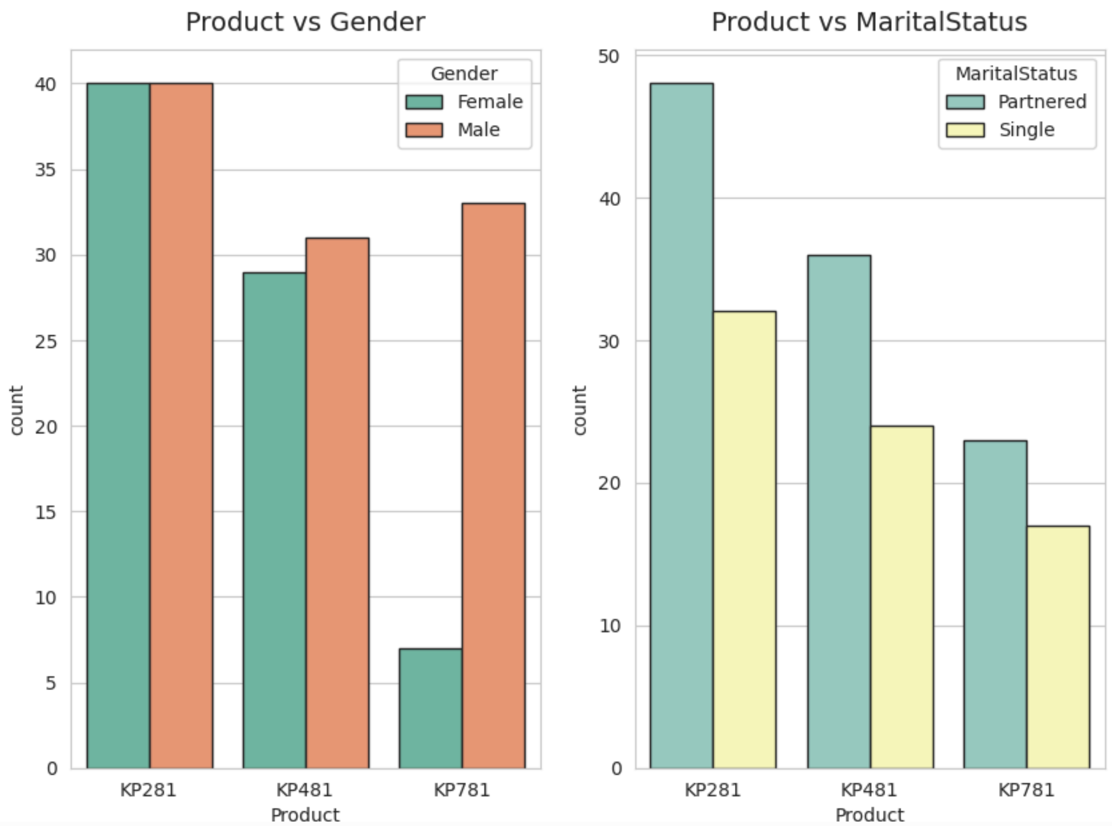
57.78% of the customers are Male.

MaritalStatus

59.44% of the customers are Partnered.

Bivariate Analysis:

```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(10,7))
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()
```



Observations:

Product vs Gender

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

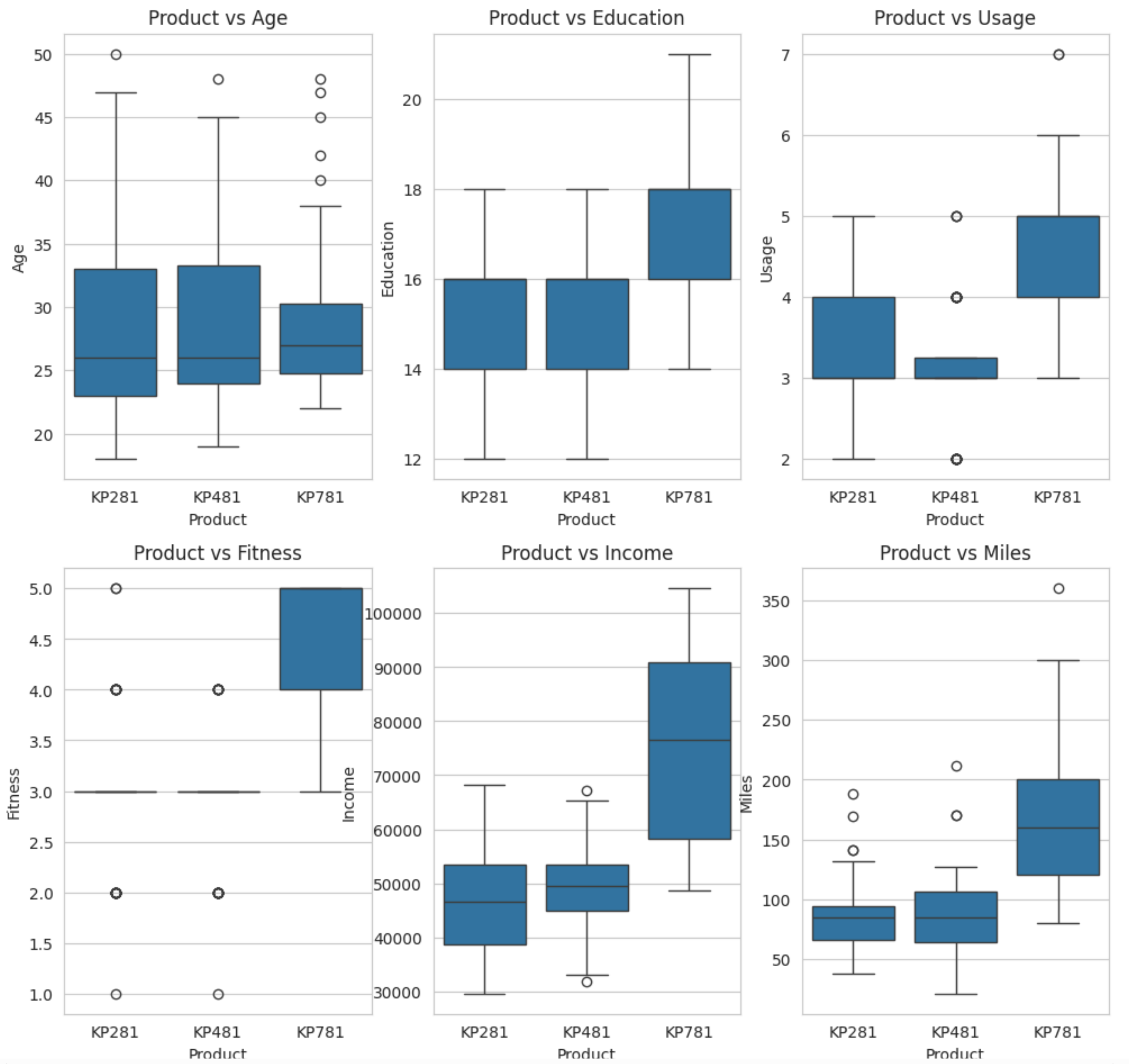
Most of the Male customers have purchased the KP781 product.

Product vs MaritalStatus 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

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income','Miles']
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])
   axs[i,j].set_title(f"Product vs {attrs[count]}")
   count += 1
```



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

2. 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.

3. 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.

4. Product vs Fitness

   The more the customer is t (tness >= 3), higher the chances of the customer to purchase the KP781 product.

5. Product vs Income

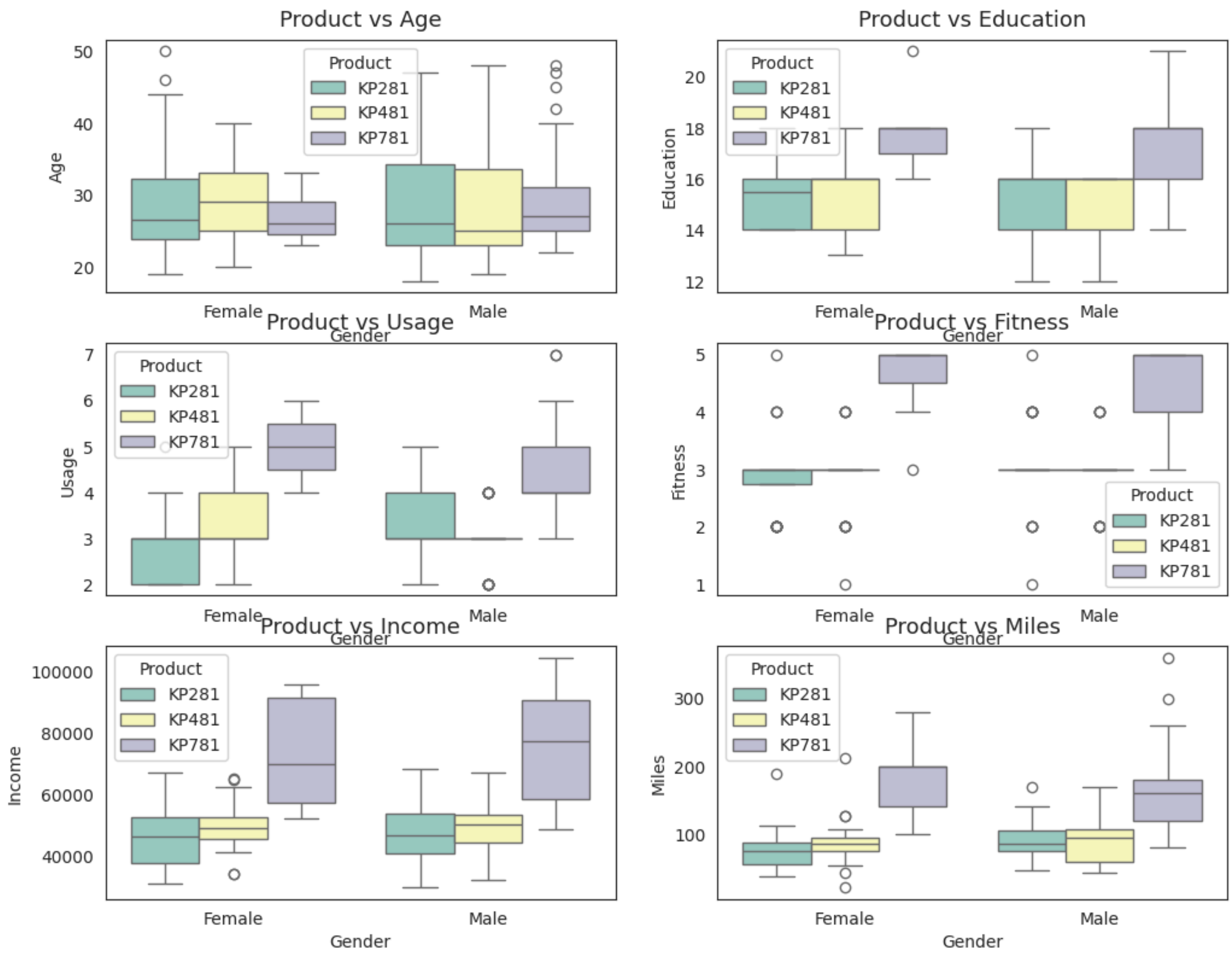
   Higher the Income of the customer (Income >= 60000), higher the chances of the customer to purchase the KP781 product.

6. 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:

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(12, 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
```



Observations:

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

Computing Marginal & Conditional Probabilities:

Marginal probability of an event is simply its frequency divided by the total count.

```
# Marginal probability of categorical variables
for col in ['Product', 'Gender', 'Education', 'MaritalStatus']:
    print(f"\nMarginal Probabilities for {col}:")
    print(df[col].value_counts(normalize=True))  # Normalized to get probabilities
```

```
Marginal Probabilities for Product:
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: proportion, dtype: float64

Marginal Probabilities for Gender:
Gender
Male      0.577778
```

```
Female    0.422222
Name: proportion, dtype: float64

Marginal Probabilities for Education:
Education
16    0.472222
14    0.305556
18    0.127778
15    0.027778
13    0.027778
12    0.016667
21    0.016667
20    0.005556
Name: proportion, dtype: float64

Marginal Probabilities for MaritalStatus:
MaritalStatus
Partnered    0.594444
Single       0.405556
Name: proportion, dtype: float64
```

For numerical columns, convert them into bins before computing probabilities:

```
# Example: Marginal probability for Age
df['Age_bin'] = pd.cut(df['Age'], bins=5)  # Adjust bins as needed
print("\nMarginal Probabilities for Age:")
print(df['Age_bin'].value_counts(normalize=True))
```

```
Marginal Probabilities for Age:
Age_bin
(24.4, 30.8]      0.366667
(17.968, 24.4]    0.300000
(30.8, 37.2]      0.194444
(37.2, 43.6]      0.088889
(43.6, 50.0]      0.050000
Name: proportion, dtype: float64
```

Compute Conditional Probabilities

Conditional probability P(A/B) is the probability of event A given that event B has occurred.

```
# Conditional probability: P(Gender | Product)
cond_prob = df.groupby('Product')['Gender'].value_counts(normalize=True).unstack()
print("\nConditional Probability P(Gender | Product):\n", cond_prob)
```

```
Conditional Probability P(Gender | Product):
 Gender     Female      Male
Product
KP281    0.500000  0.500000
KP481    0.483333  0.516667
KP781    0.175000  0.825000
<ipython-input-58-1249718a9a96>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a futur
  cond_prob = df.groupby('Product')['Gender'].value_counts(normalize=True).unstack()
```

```
# Bin Income for categorical probability
df['Income_bin'] = pd.qcut(df['Income'], q=4)  # Quartiles

# Compute P(Income | Education)
cond_prob_income_edu = df.groupby('Education')['Income_bin'].value_counts(normalize=True).unstack()
print("\nConditional Probability P(Income | Education):\n", cond_prob_income_edu)
```

```
Conditional Probability P(Income | Education):
 Income_bin  (29561.999, 44058.75]  (44058.75, 50596.5]  (50596.5, 58668.0]  \
Education
12                       0.666667             0.333333            0.000000
13                       0.600000             0.200000            0.200000
14                       0.400000             0.363636            0.218182
15                       0.800000             0.000000            0.000000
16                       0.164706             0.247059            0.341176
```