*Aerofit *

It 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.

Problem Statement

● 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 new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics. ● Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts. ● Construct two-way contingency tables for each AeroFit treadmill product and compute all conditional and marginal probabilities and their insights/impact on the business.

Start coding or generate with AI.

Getting the dataset

```
!gdown 1sNXswQ9OoGmzJqpuDGHZt1zcLCRiZLO3
!ls
```

```
Downloading...
From: https://drive.google.com/uc?id=1sNXswQ9OoGmzJqpuDGHZt1zcLCRiZLO3
To: /content/aerofit_treadmill.csv
100% 7.28k/7.28k [00:00<00:00, 16.2MB/s]
aerofit_treadmill.csv  sample_data
```

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

df=pd.read_csv('aerofit_treadmill.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

- Columns with categorical data are Product,Gender,MaritialStatus
- Columns with numerical value Age,Education,Usage,Fitness,Income,Miles

```
# Lets check the size of df as well

df.shape
```

```
(180, 9)
```

```
# Let's Check the Columns null values and datatype

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
```

1. As check the Shape of df which is (180,9) and checking info of columns all columns have 180 non null values which means there is no null values in this df.
2. Also all the columns datatype are properr.However we can create some new columns as per the requirement

```
# Let use df.describe for all the columns
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

```
df['Product'].value_counts()/df.shape[0]*100
```

	count
Product	
KP281	44.444444
KP481	33.333333
KP781	22.222222

```
df['Gender'].value_counts()/df.shape[0]*100
```

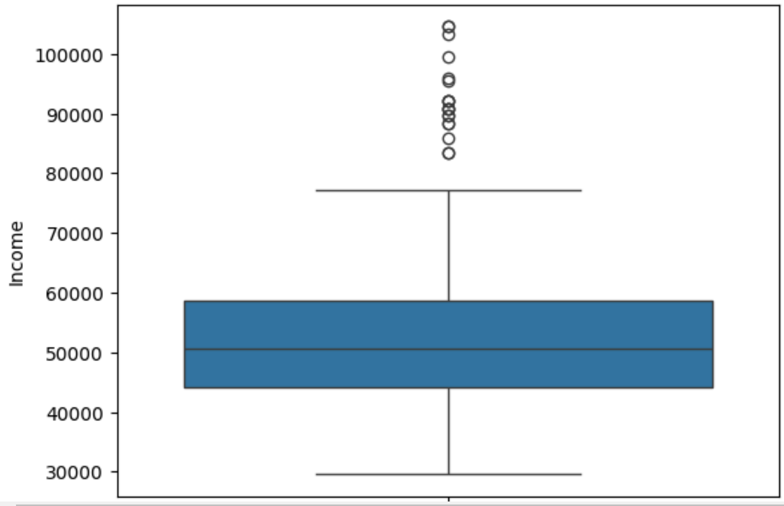
	count
Gender	
Male	57.777778
Female	42.222222

```
df['MaritalStatus'].value_counts()/df.shape[0]*100
```

	count
MaritalStatus	
Partnered	59.444444
Single	40.555556

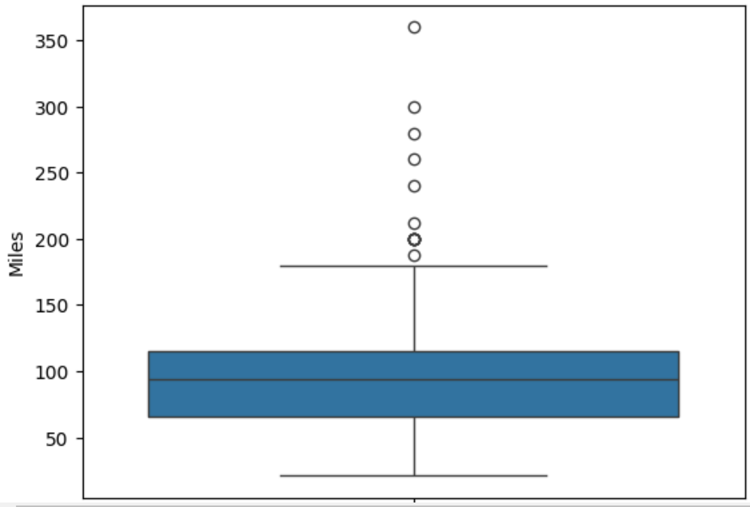
- There are 3 unique products in the dataset(KP281,KP481,KP781)
- KP281 is the most purchased product
- Minimum & Maximum age of the person is 18 & 50, mean is 28.79 and 75% of persons have age less than or equal to 33.
- Most of the people are having 16 years of education i.e., 75% of persons are having education <= 16 years.
- Data shows 57.7% male has purchased the product and rest by female.
- Due to high value of Standard Deviation for income and Miles columns.There is high probability of Outliers.

```
# Let's Check the Outliers in Income and Miles Column by plotting box plot
sns.boxplot(df['Income'])
plt.show()
```




```
sns.boxplot(df['Miles'])
```

```
<Axes: ylabel='Miles'>
```




```
# Let's Remove/clip the data between the 5 percentile and 95 percentile by using
# np.clip()

df['Income']=np.clip(df['Income'],df['Income'].quantile(0.05),df['Income'].quantile(0.95))
```

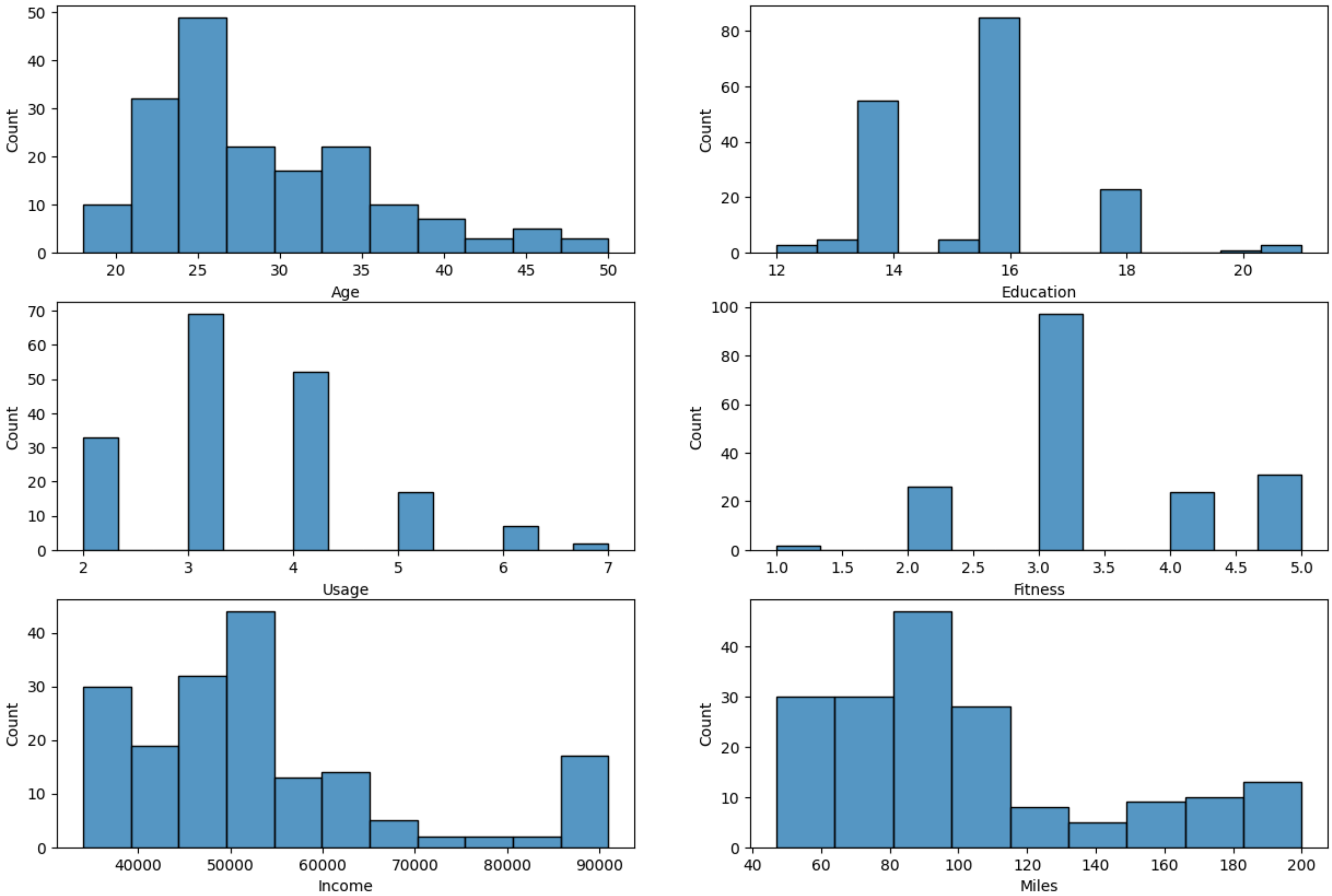
```
df['Miles']=np.clip(df['Miles'],df['Miles'].quantile(0.05),df['Miles'].quantile(0.95))
```

```
df.describe()
```

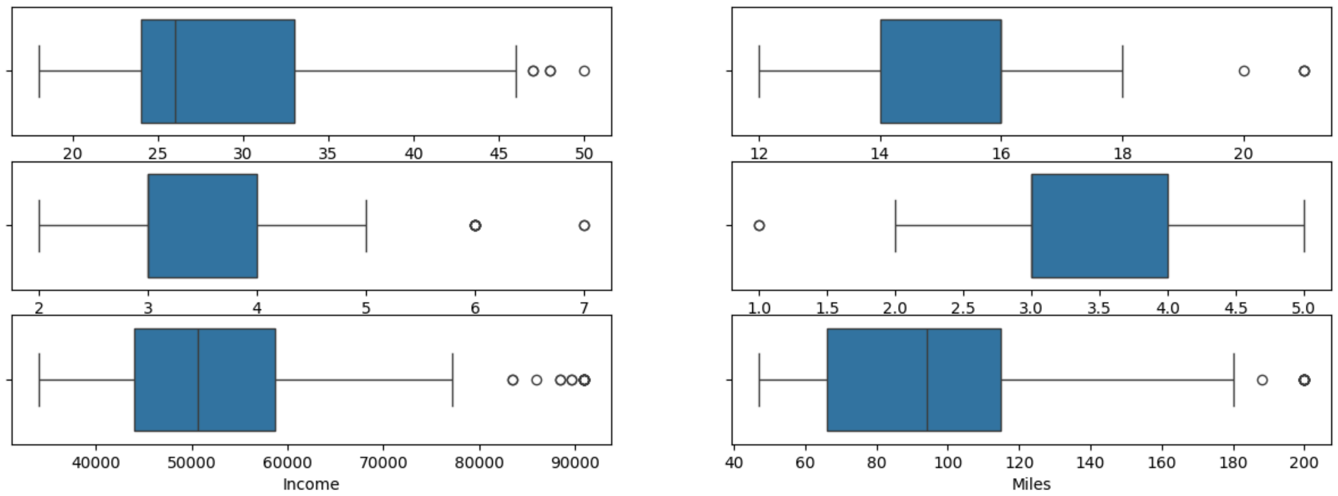
	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53477.070000	101.088889
std	6.943498	1.617055	1.084797	0.958869	15463.662523	43.364286
min	18.000000	12.000000	2.000000	1.000000	34053.150000	47.000000
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	90948.250000	200.000000

Univariate Analysis

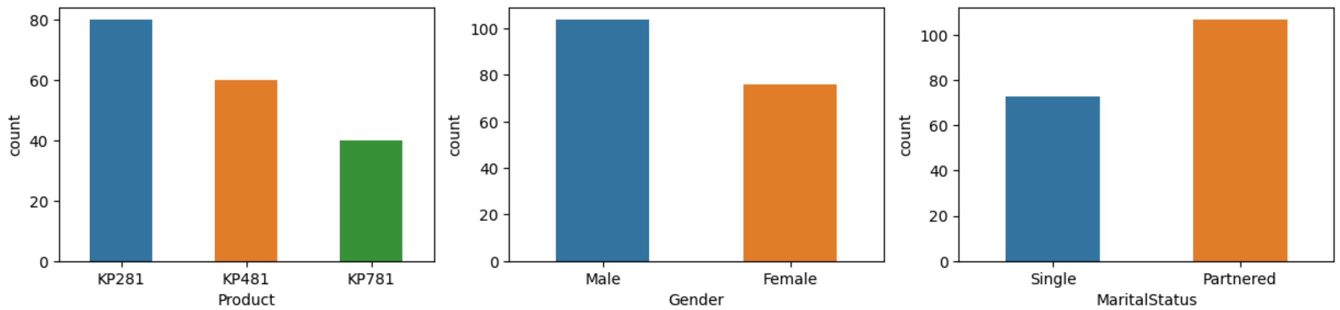
```
# Let's Plot the Histogram  for Age ,Education,Usage,Fitness,Income,Miles

fig,ax=plt.subplots(3,2,figsize=(15,10))
sns.histplot(data=df,x='Age',ax=ax[0,0])
sns.histplot(data=df,x='Education',ax=ax[0,1])
sns.histplot(data=df,x='Usage',ax=ax[1,0])
sns.histplot(data=df,x='Fitness',ax=ax[1,1])
sns.histplot(data=df,x='Income',ax=ax[2,0])
sns.histplot(data=df,x='Miles',ax=ax[2,1])
plt.show()
```




```
fig,ax=plt.subplots(3,2,figsize=(15,5))
sns.boxplot(data=df,x='Age',ax=ax[0,0])
sns.boxplot(data=df,x='Education',ax=ax[0,1])
sns.boxplot(data=df,x='Usage',ax=ax[1,0])
sns.boxplot(data=df,x='Fitness',ax=ax[1,1])
sns.boxplot(data=df,x='Income',ax=ax[2,0])
sns.boxplot(data=df,x='Miles',ax=ax[2,1])
plt.show()
```




```
# Lets Plot for the cateogrical data as well Product,Gender,Maritial Status
fig,ax=plt.subplots(1,3,figsize=(15,3))
sns.countplot(data=df,x='Product',hue='Product',width=0.5,ax=ax[0])
sns.countplot(data=df,x='Gender',hue='Gender',width=0.5,ax=ax[1])
sns.countplot(data=df,x='MaritalStatus',hue='MaritalStatus',width=0.5,ax=ax[2])
plt.show()
```

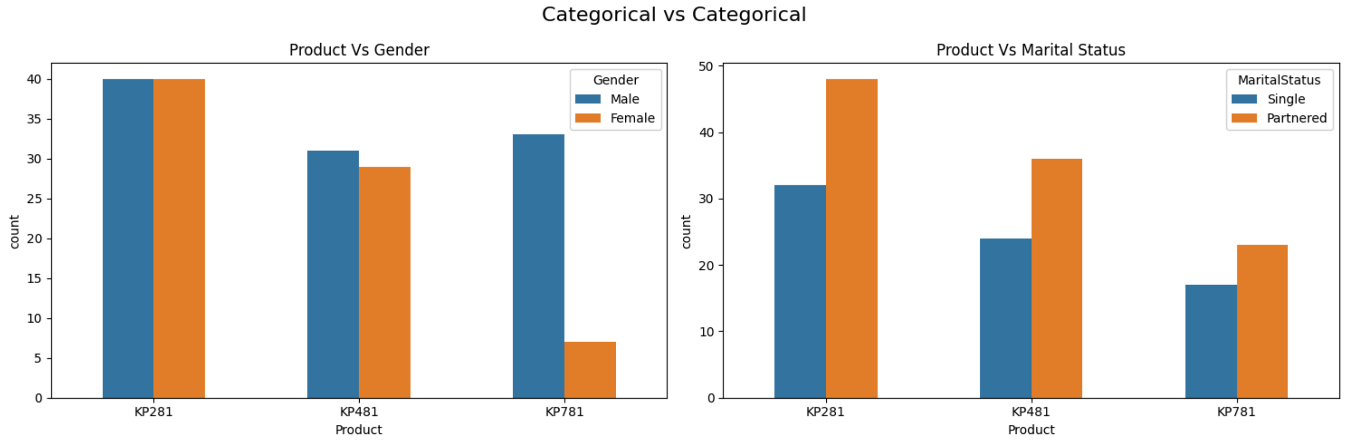


Bivariate Analysis

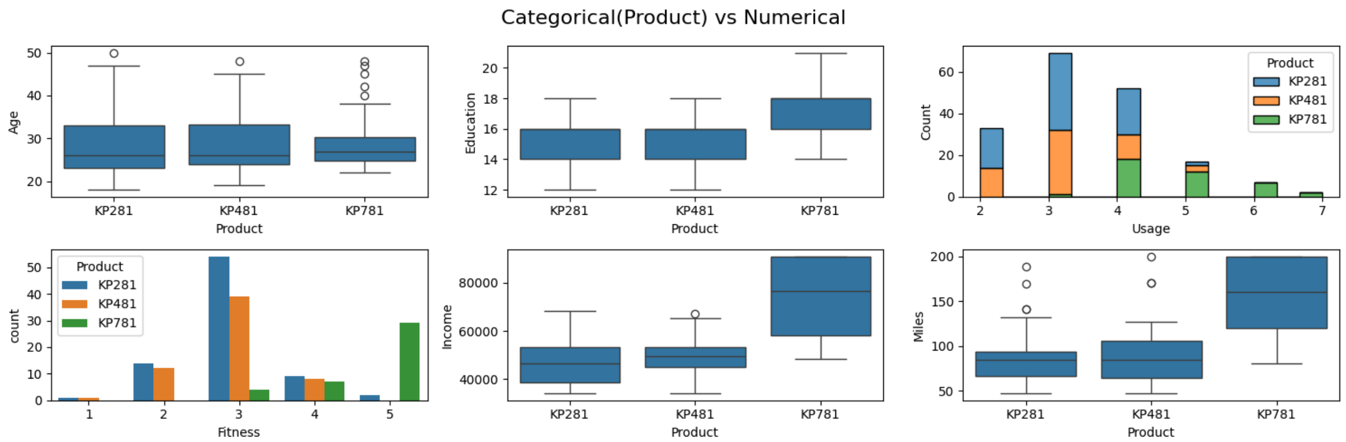
Let's Perform Bivarite analysis to study relationship between diffrent type of variable

- Numerical vs Numerical - We can use lineplot or scatter plot
- Categorical vs Numerical - we can use boxplot or barplot
- Categorical vs Categorical - we can use Dodged barplot or stacked barplot

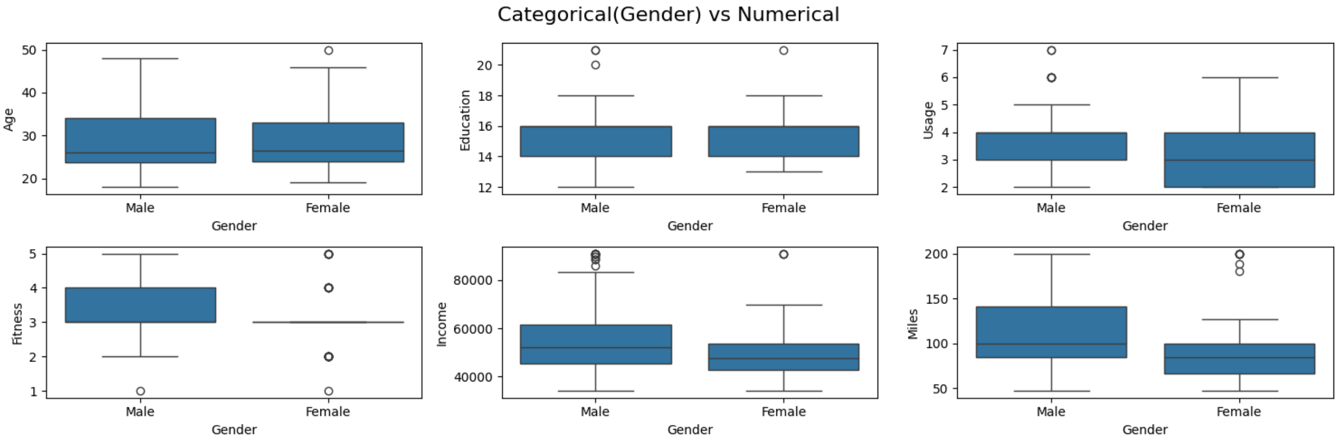
```
fig,ax=plt.subplots(1,2,figsize=(15,5))

sns.countplot(data=df,x='Product',hue='Gender',width=0.5,ax=ax[0])
sns.countplot(data=df,x='Product',hue='MaritalStatus',width=0.5,ax=ax[1])
ax[0].set_title('Product Vs Gender')
ax[1].set_title('Product Vs Marital Status')
plt.suptitle('Categorical vs Categorical', fontsize=16)
plt.tight_layout()
plt.show()
```



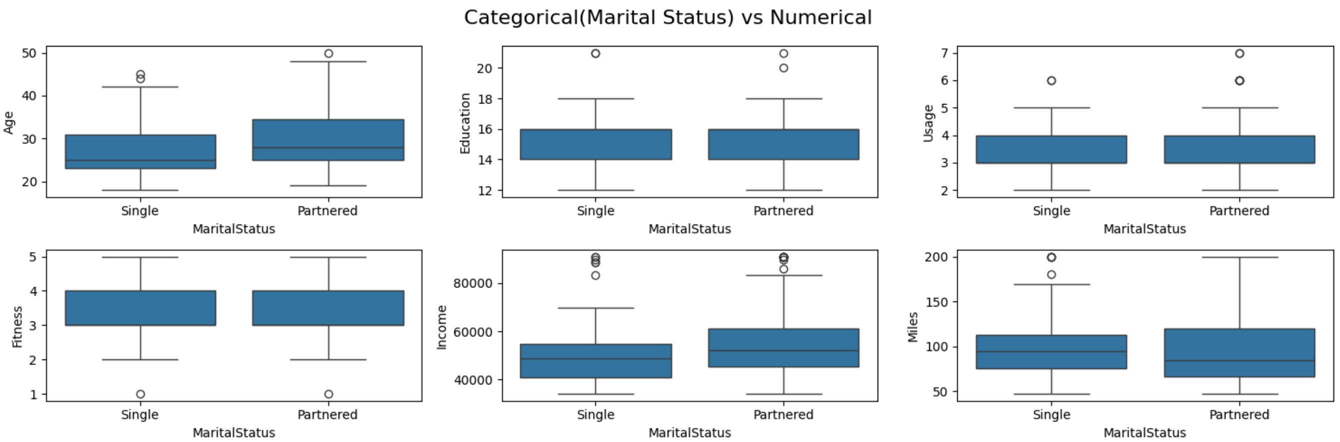

```
fig,ax=plt.subplots(2,3,figsize=(15,5))
sns.boxplot(data=df,x='Product',y='Age',ax=ax[0,0])
sns.boxplot(data=df,x='Product',y='Education',ax=ax[0,1])
sns.histplot(data=df,x='Usage',hue='Product',multiple='stack',ax=ax[0,2])
sns.countplot(data=df,hue='Product',x='Fitness',ax=ax[1,0])
sns.boxplot(data=df,x='Product',y='Income',ax=ax[1,1])
sns.boxplot(data=df,x='Product',y='Miles',ax=ax[1,2])
plt.suptitle('Categorical(Product) vs Numerical', fontsize=16)
plt.tight_layout()
plt.show()
```




```
fig,ax=plt.subplots(2,3,figsize=(15,5))
sns.boxplot(data=df,x='Gender',y='Age',ax=ax[0,0])
sns.boxplot(data=df,x='Gender',y='Education',ax=ax[0,1])
sns.boxplot(data=df,x='Gender',y='Usage',ax=ax[0,2])
sns.boxplot(data=df,x='Gender',y='Fitness',ax=ax[1,0])
sns.boxplot(data=df,x='Gender',y='Income',ax=ax[1,1])
sns.boxplot(data=df,x='Gender',y='Miles',ax=ax[1,2])
plt.suptitle('Categorical(Gender) vs Numerical', fontsize=16)
plt.tight_layout()
plt.show()
```

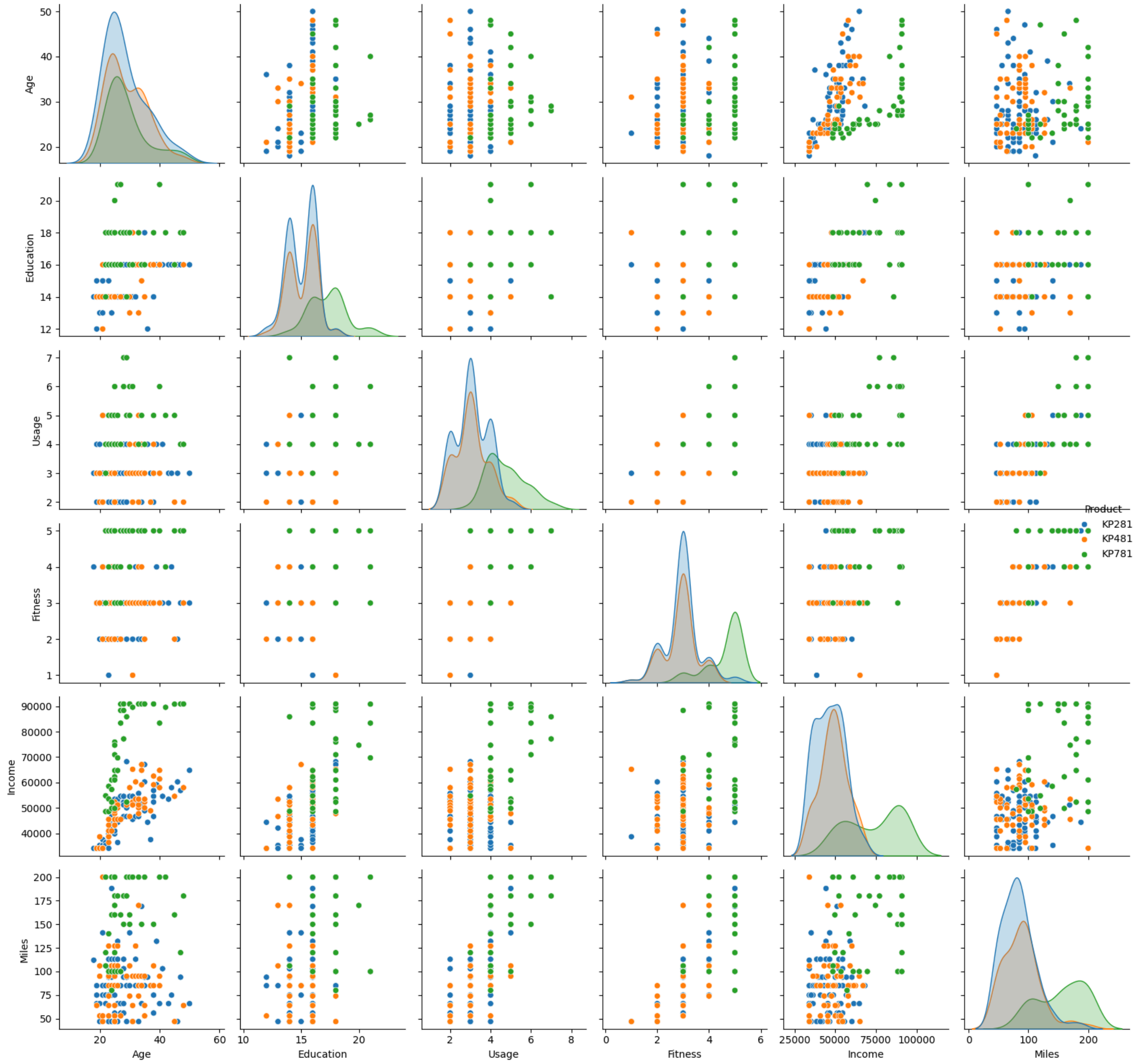



```
fig,ax=plt.subplots(2,3,figsize=(15,5))
sns.boxplot(data=df,x='MaritalStatus',y='Age',ax=ax[0,0])
sns.boxplot(data=df,x='MaritalStatus',y='Education',ax=ax[0,1])
sns.boxplot(data=df,x='MaritalStatus',y='Usage',ax=ax[0,2])
sns.boxplot(data=df,x='MaritalStatus',y='Fitness',ax=ax[1,0])
sns.boxplot(data=df,x='MaritalStatus',y='Income',ax=ax[1,1])
sns.boxplot(data=df,x='MaritalStatus',y='Miles',ax=ax[1,2])
plt.suptitle('Categorical(Marital Status) vs Numerical', fontsize=16)
plt.tight_layout()
plt.show()
```




```
plt.figure()
sns.pairplot(df,hue='Product')
plt.tight_layout()
plt.show()
```

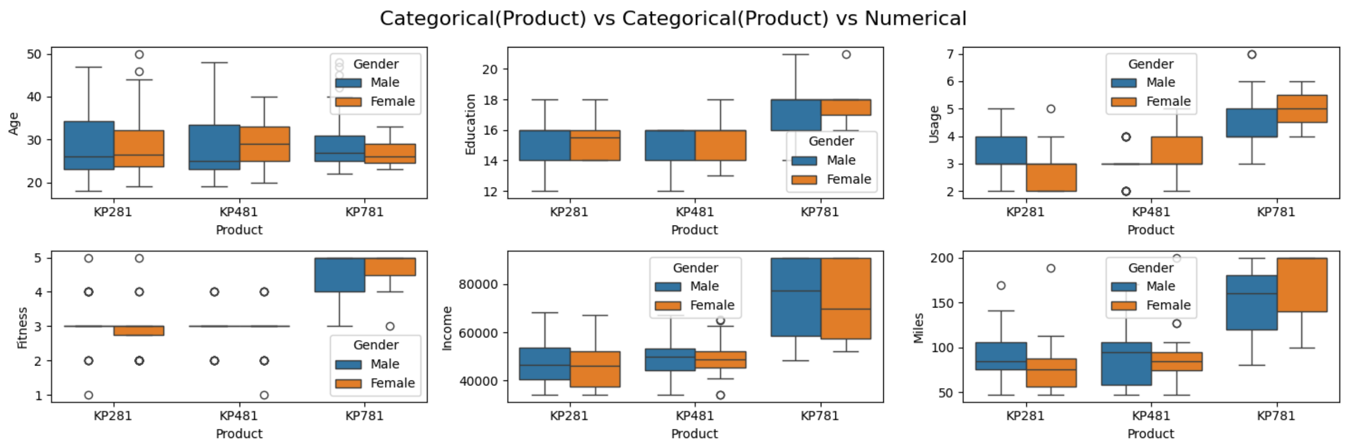
<Figure size 640x480 with 0 Axes>



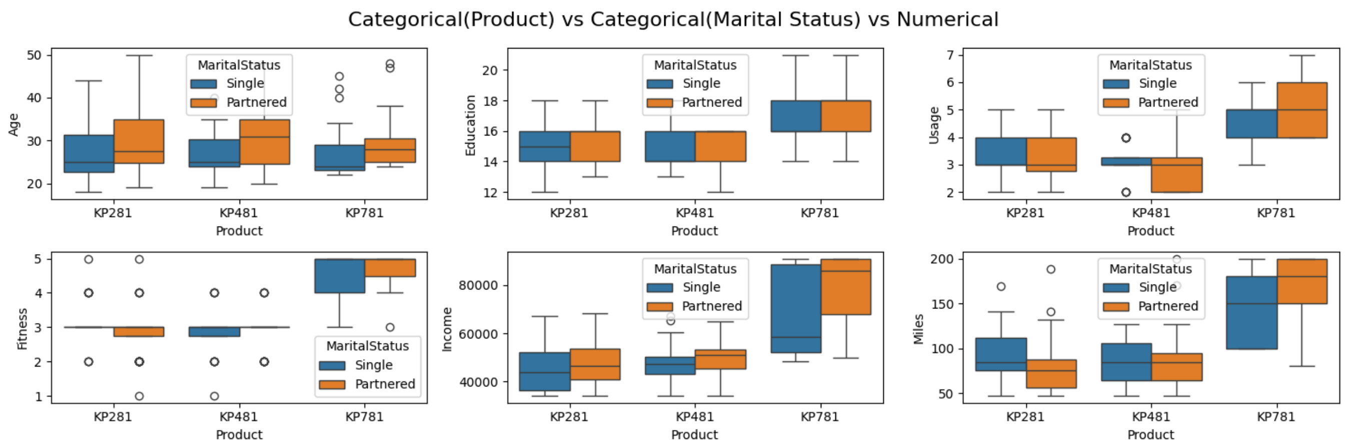
Multivariate Analysis

```
fig,ax=plt.subplots(2,3,figsize=(15,5))
sns.boxplot(data=df,x='Product',y='Age',hue='Gender',ax=ax[0,0])
sns.boxplot(data=df,x='Product',y='Education',hue='Gender',ax=ax[0,1])
sns.boxplot(data=df,x='Product',y='Usage',hue='Gender',ax=ax[0,2])
sns.boxplot(data=df,x='Product',y='Fitness',hue='Gender',ax=ax[1,0])
sns.boxplot(data=df,x='Product',y='Income',hue='Gender',ax=ax[1,1])
```

```
sns.boxplot(data=df,x='Product',y='Miles',hue='Gender',ax=ax[1,2])
plt.suptitle('Categorical(Product) vs Categorical(Product) vs Numerical', fontsize=16)
plt.tight_layout()
plt.show()
```




```
fig,ax=plt.subplots(2,3,figsize=(15,5))
sns.boxplot(data=df,x='Product',y='Age',hue='MaritalStatus',ax=ax[0,0])
sns.boxplot(data=df,x='Product',y='Education',hue='MaritalStatus',ax=ax[0,1])
sns.boxplot(data=df,x='Product',y='Usage',hue='MaritalStatus',ax=ax[0,2])
sns.boxplot(data=df,x='Product',y='Fitness',hue='MaritalStatus',ax=ax[1,0])
sns.boxplot(data=df,x='Product',y='Income',hue='MaritalStatus',ax=ax[1,1])
sns.boxplot(data=df,x='Product',y='Miles',hue='MaritalStatus',ax=ax[1,2])
plt.suptitle('Categorical(Product) vs Categorical(Marital Status) vs Numerical', fontsize=16)
plt.tight_layout()
plt.show()
```



Contigency Table

```
product_gender=pd.crosstab(df['Product'],df['Gender'],margins=True)
product_gender
```

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

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

```
# marginal probablity of the product

kp281=product_gender.loc['KP281','All']/product_gender.loc['All','All']
kp481=product_gender.loc['KP481','All']/product_gender.loc['All','All']
kp781=product_gender.loc['KP781','All']/product_gender.loc['All','All']
print(f'Marginal probablity of KP281 is {kp281}')
print(f'Marginal probablity of KP481 is {kp481}')
print(f'Marginal probablity of KP781 is {kp781}')
```

```
Marginal probablity of KP281 is 0.4444444444444444
Marginal probablity of KP481 is 0.3333333333333333
Marginal probablity of KP781 is 0.2222222222222222
```

```
# computing marginal probabilty for gender
male=product_gender.loc['All','Male']/product_gender.loc['All','All']
female=product_gender.loc['All','Female']/product_gender.loc['All','All']
print(f"Marginal probablity of Male is {male}")
print(f"Marginal probablity of Female is {female}")
```

```
Marginal probablity of Male is 0.5777777777777777
Marginal probablity of Female is 0.4222222222222222
```

```
# Condition probability for gender given the probablity for product

# what is the probability that a person purchasing a treadmill is male given that purchased treadmill is kp281
print("KP281")
kp281_male=product_gender.loc['KP281','Male']/product_gender.loc['KP281','All']
print(f"The probability that a person purchasing a treadmill is male given that purchased treadmill is kp281 is {kp281_male}")
kp281_female=product_gender.loc['KP281','Female']/product_gender.loc['KP281','All']
print(f"The probability that a person purchasing a treadmill is female given that purchased treadmill is kp281 is {kp281_female}")

print("KP481")
kp481_male=product_gender.loc['KP481','Male']/product_gender.loc['KP481','All']
print(f"The probability that a person purchasing a treadmill is male given that purchased treadmill is kp481 is {kp481_male}")
kp481_female=product_gender.loc['KP481','Female']/product_gender.loc['KP481','All']
print(f"The probability that a person purchasing a treadmill is female given that purchased treadmill is kp481 is {kp481_female}")

print("KP781")
kp781_male=product_gender.loc['KP781','Male']/product_gender.loc['KP781','All']
print(f"The probability that a person purchasing a treadmill is male given that purchased treadmill is kp781 is {kp781_male}")
kp781_female=product_gender.loc['KP781','Female']/product_gender.loc['KP781','All']
print(f"The probability that a person purchasing a treadmill is female given that purchased treadmill is kp781 is {kp781_female}")
```

```
KP281
The probability that a person purchasing a treadmill is male given that purchased treadmill is kp281 is 0.5
The probability that a person purchasing a treadmill is female given that purchased treadmill is kp281 is 0.5
KP481
The probability that a person purchasing a treadmill is male given that purchased treadmill is kp481 is 0.5166666666666667
The probability that a person purchasing a treadmill is female given that purchased treadmill is kp481 is 0.48333333333333334
KP781
The probability that a person purchasing a treadmill is male given that purchased treadmill is kp781 is 0.825
The probability that a person purchasing a treadmill is female given that purchased treadmill is kp781 is 0.175
```

```
product_marital=pd.crosstab(df['Product'],df['MaritalStatus'],margins=True)
product_marital
```

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

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

```
# Marginal Probability

single=product_marital.loc['All','Single']/product_marital.loc['All','All']
partnered=product_marital.loc['All','Partnered']/product_marital.loc['All','All']
print(f"Marginal probablity of Single is {single}")
print(f"Marginal probablity of Married is {partnered}")
```

```
Marginal probablity of Single is 0.40555555555555556
Marginal probablity of Married is 0.5944444444444444
```

```
# Conditional Probability

print("KP281")
kp281_single=product_marital.loc['KP281','Single']/product_marital.loc['KP281','All']
print(f"The probability that a person purchasing a treadmill is single given that purchased treadmill is kp281 is {kp281_single}")
kp281_partnered=product_marital.loc['KP281','Partnered']/product_marital.loc['KP281','All']
print(f"The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp281 is {kp281_partnered}")

print("KP481")
kp481_single=product_marital.loc['KP481','Single']/product_marital.loc['KP481','All']
print(f"The probability that a person purchasing a treadmill is single given that purchased treadmill is kp481 is {kp481_single}")
kp481_partnered=product_marital.loc['KP481','Partnered']/product_marital.loc['KP481','All']
print(f"The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp481 is {kp481_partnered}")

print("KP781")
kp781_single=product_marital.loc['KP781','Single']/product_marital.loc['KP781','All']
print(f"The probability that a person purchasing a treadmill is single given that purchased treadmill is kp781 is {kp781_single}")
kp781_partnered=product_marital.loc['KP781','Partnered']/product_marital.loc['KP781','All']
print(f"The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp781 is {kp781_partnered}")
```

```
KP281
The probability that a person purchasing a treadmill is single given that purchased treadmill is kp281 is 0.4
The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp281 is 0.6
KP481
The probability that a person purchasing a treadmill is single given that purchased treadmill is kp481 is 0.4
The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp481 is 0.6
KP781
The probability that a person purchasing a treadmill is single given that purchased treadmill is kp781 is 0.425
The probability that a person purchasing a treadmill is partnered given that purchased treadmill is kp781 is 0.575
```

```
# Customer Profiling on the basis of Product

'''

Customer Profiling

KP281

Age Distribution - for between 25-35
Income distribution - for between 40 to 50
Gender distribution - for both
Marital status distribution - partnered people purchase more as compare to single
Usage frequency - for people who will use 2 or 3 times a week
Fitness level - for 1 - 3

KP481

Age Distribution - for between 25-35
Income distribution -for between 45-50
Gender distribution - for male more likely to buy than female
Marital status distribution - partnered people purchase more as compare to single
Usage frequency - for people who will use 2 or 3 times a week
Fitness level - for 1 to 3

KP781

Age Distribution - for between 25 -30
Income distribution - more than 60 thousand
Gender distribution - for males is very high
Mmarital status distribution - partnered people purchase more as compare to single
Usage frequency - 4 or more
```