Importing libraries and Packages

Created by JV

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

Reading Aerofit CSV file

```
!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639992749
df = pd.read_csv("/content/aerofit_treadmill.csv?1639992749")
df
```

```
Downloading...
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
To: /content/aerofit_treadmill.csv?1639992749
100% 7.28k/7.28k [00:00<00:00, 19.3MB/s]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Mi
0	KP281	18	Male	14	Single	3	4	29562	
1	KP281	19	Male	15	Single	2	3	31836	
2	KP281	19	Female	14	Partnered	4	3	30699	
3	KP281	19	Male	12	Single	3	3	32973	
4	KP281	20	Male	13	Partnered	4	2	35247	
...	...	...	...	...	...	...	...	...	
175	KP781	40	Male	21	Single	6	5	83416	
176	KP781	42	Male	18	Single	5	4	89641	
177	KP781	45	Male	16	Single	5	5	90886	
178	KP781	47	Male	18	Partnered	4	5	104581	
179	KP781	48	Male	18	Partnered	4	5	95508	

180 rows × 9 columns

Next steps: Generate code with df View recommended plots

Section 1 . Defining Problem Statement and Analysing basic metrics (10 Points)

Defining Problem statement

We 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.

1. Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
2. 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.

Section 1.1 Basic Analysis

```
df.shape
```

```
(180, 9)
```

```
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
```

There is no missing Values and there is no requirement to change any data type of any variable

```
# statistical Summary of categorical data
df.describe( include = "object")
```

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

After analysing statistical Summary of categorical data, i can conclude:

1. There are 3 unique types of products in which KP281 have the highest sale
2. Male purchase the product more frequently than female
3. Most of the customers are married

```
# statistical Summary of numerical data
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.describe(include = "object")
```

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

Section 2 Non-Graphical Analysis: Value counts and unique attributes (10 Points)

Value Count of different types Of Products

```
product_counts = df['Product'].value_counts()
print(product_counts)
print()
# Calculate the percentage of males and females
total_count = len(df)
print("KP281 entry-level treadmill {}%".format(100*(product_counts['KP281'] / total_count).round(3)))
print("KP481 mid-level runners treadmill {}%".format(100*(product_counts['KP481'] / total_count).round(3)))
print("KP781 treadmill with advanced features {}%".format(100*(product_counts['KP781'] / total_count).round(3)))
```

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

KP281 entry-level treadmill 44.4%
KP481 mid-level runners treadmill 33.300000000000004%
KP781 treadmill with advanced features 22.2%
```

Value count of Male and Female

```
gender_counts = df['Gender'].value_counts()
print(gender_counts)
print()
# Calculate the percentage of males and females
total_count = len(df)
print("Percentage of Male Customer is {}%". format(100*(gender_counts['Male'] / total_count).round(3)))
print("Percentage of Female Customer is {}%". format(100*(gender_counts['Female'] / total_count).round(3)))
```

```
Gender
Male      104
Female     76
Name: count, dtype: int64

Percentage of Male Customer is 57.8%
Percentage of Female Customer is 42.199999999999996%
```

Value count of Married and Single Customers

```
marital_status = df['MaritalStatus'].value_counts()
print(marital_status)
print()
# Calculate the percentage of Partnered and Single
total_count = len(df)
print("Percentage of Married customers is {}%". format(100*(marital_status['Partnered'] / total_count)))
print("Percentage of Single customers is {}%".format(100*(marital_status['Single'] / total_count)))
```

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

Percentage of Married customers is 59.44444444444444%
Percentage of Single customers is 40.55555555555556%
```

Section 3 is after section 4

Section 4 Missing Value & Outlier Detection (10 Points)

Checking for Missing Values

```
df.isnull().sum()
```

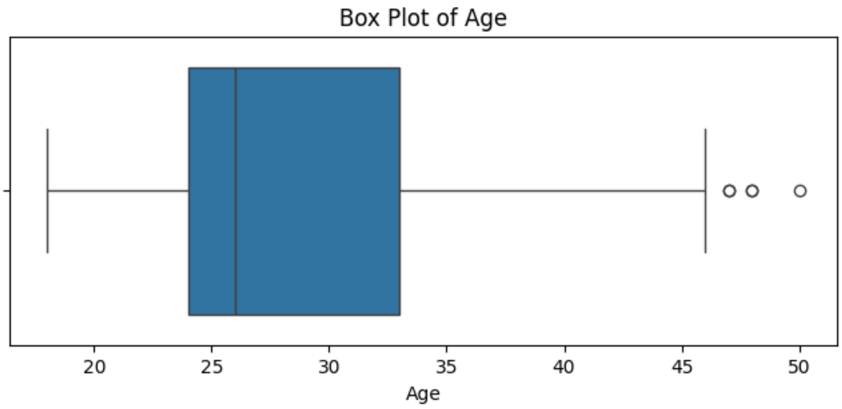
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

There where no Missing values

Checking for Outliers

Box plot of Age find outliers

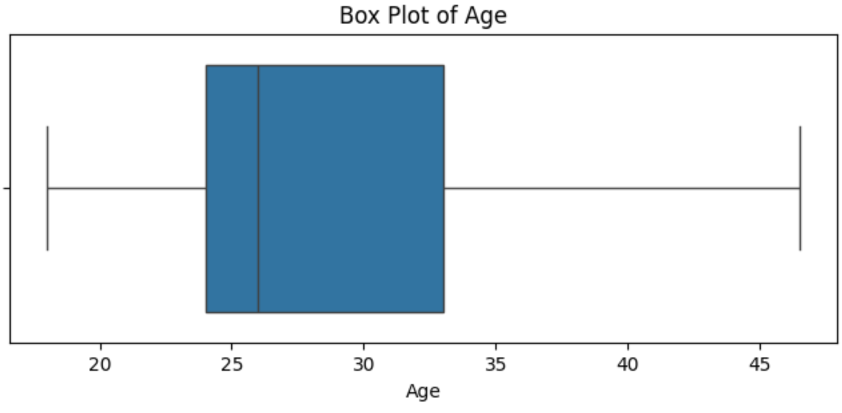
```
plt.figure(figsize=(8, 3))
sns.boxplot(x="Age", data = df)
plt.xlabel('Age')
plt.title('Box Plot of Age')
plt.show()
```



We detect few outliers in age, we need to treat this.

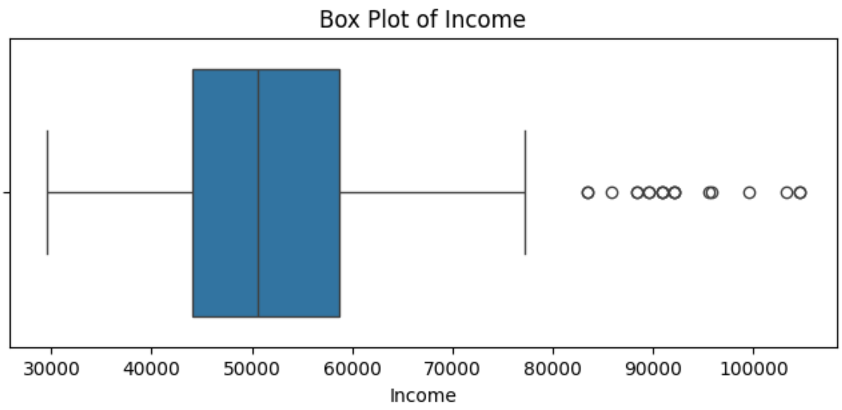
```
# Outlier treatment for Age
q1 = df["Age"].quantile(0.25)
q3 = df["Age"].quantile(0.75)
iqr = q3-q1
upperlimit = q3+(1.5*iqr)
lowerlimit = q1-(1.5*iqr)
#create function for condition
def limit_imputer(value):
  if value > upperlimit:
    return upperlimit
  if value < lowerlimit:
    return lowerlimit
  else:
    return value
# Apply def
df["Age"] = df["Age"].apply(limit_imputer)
```

```
#boxplot of age
plt.figure(figsize=(8, 3))
sns.boxplot(x="Age", data = df)
plt.xlabel('Age')
plt.title('Box Plot of Age')
plt.show()
```



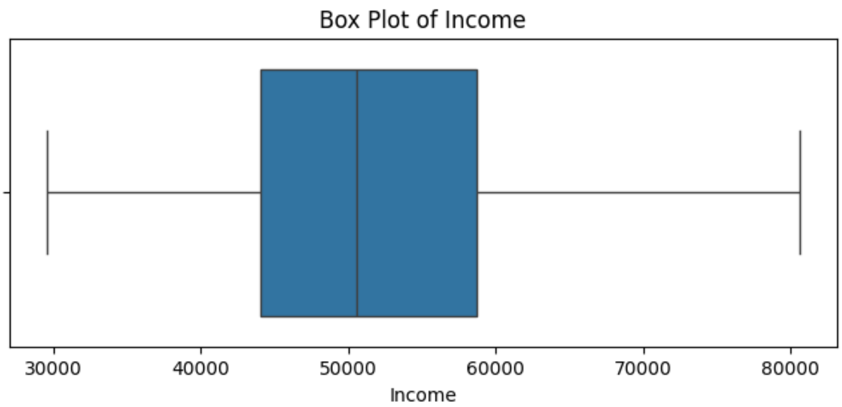
Boxplot of Income to find outlier

```
plt.figure(figsize=(8, 3))
sns.boxplot(x="Income", data = df)
plt.xlabel('Income')
plt.title('Box Plot of Income')
plt.show()
```



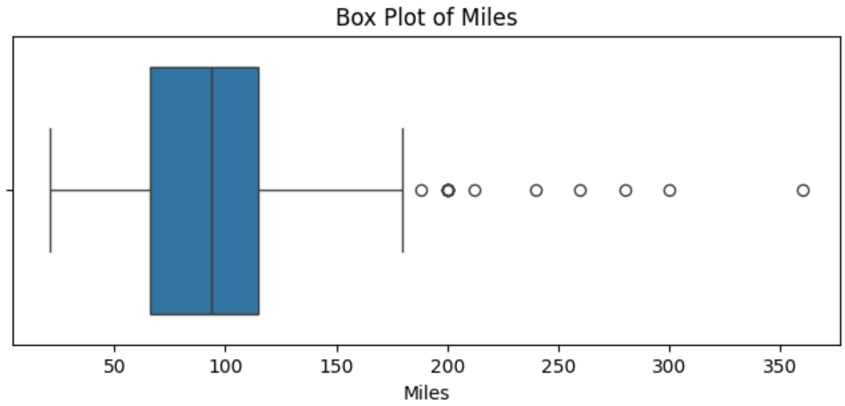

```
# Outlier treatment for Income
q1 = df["Income"].quantile(0.25)
q3 = df["Income"].quantile(0.75)
iqr = q3-q1
upperlimit = q3+(1.5*iqr)
lowerlimit = q1-(1.5*iqr)
#create function for condition
def limit_imputer(value):
  if value > upperlimit:
    return upperlimit
  if value < lowerlimit:
    return lowerlimit
  else:
    return value
# Apply def
df["Income"] = df["Income"].apply(limit_imputer)
```

```
plt.figure(figsize=(8, 3))
sns.boxplot(x="Income", data = df)
plt.xlabel('Income')
plt.title('Box Plot of Income')
plt.show()
```



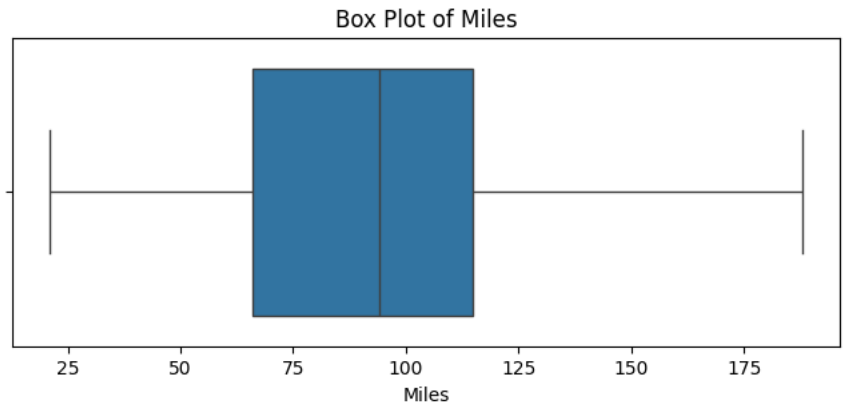
Boxplot of Miles to find Outliers

```
plt.figure(figsize=(8, 3))
sns.boxplot(x= "Miles", data = df)
plt.xlabel('Miles')
plt.title('Box Plot of Miles')
plt.show()
```




```
# Outlier treatment for Miles
q1 = df["Miles"].quantile(0.25)
q3 = df["Miles"].quantile(0.75)
iqr = q3-q1
upperlimit = q3+(1.5*iqr)
lowerlimit = q1-(1.5*iqr)
#create function for condition
def limit_imputer(value):
  if value > upperlimit:
    return upperlimit
  if value < lowerlimit:
    return lowerlimit
  else:
    return value
# Apply def
df["Miles"] = df["Miles"].apply(limit_imputer)
```

```
plt.figure(figsize=(8, 3))
sns.boxplot(x= "Miles", data = df)
plt.xlabel('Miles')
plt.title('Box Plot of Miles')
plt.show()
```



Outliers of miles are checked and Treated

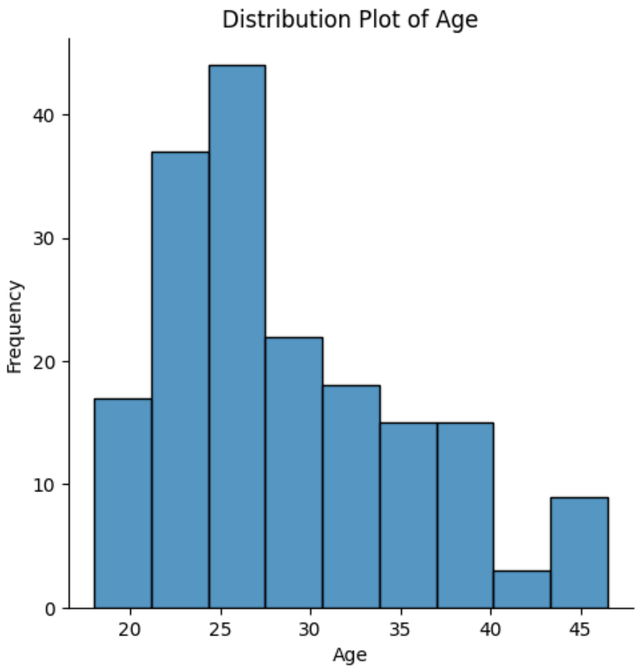
Box plot for all the Variables that can have Outliers are checked and treated

Section 3 Visual Analysis - Univariate & Bivariate (30 Points)

Section 3.1 For continuous variable(s): Part 1 Univariate

Histogram of Age to find the highest frequency of Customer Age Range

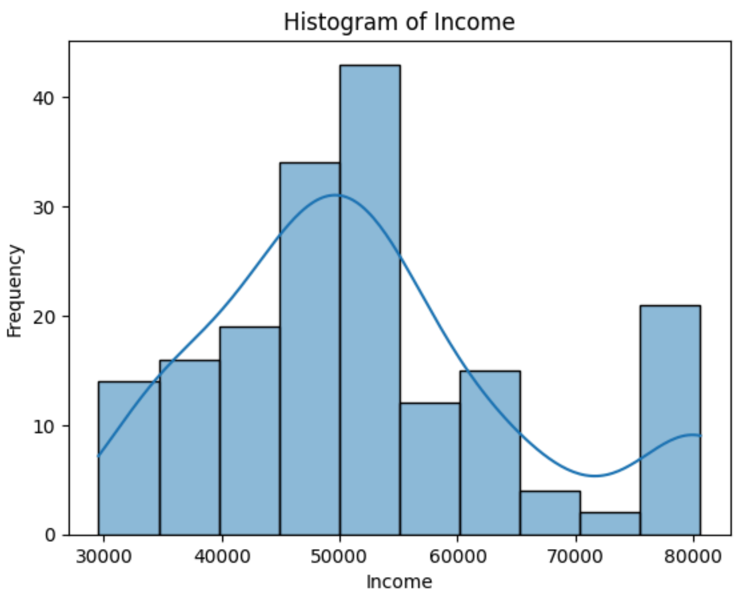
```
# Assuming your data is in a DataFrame called 'df'
sns.displot(df["Age"])

# Add labels and a title for better visualization
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Distribution Plot of Age')

# Display the plot
plt.show()
```



Person in age range 22-28 have the highest tendency to purchase the Product

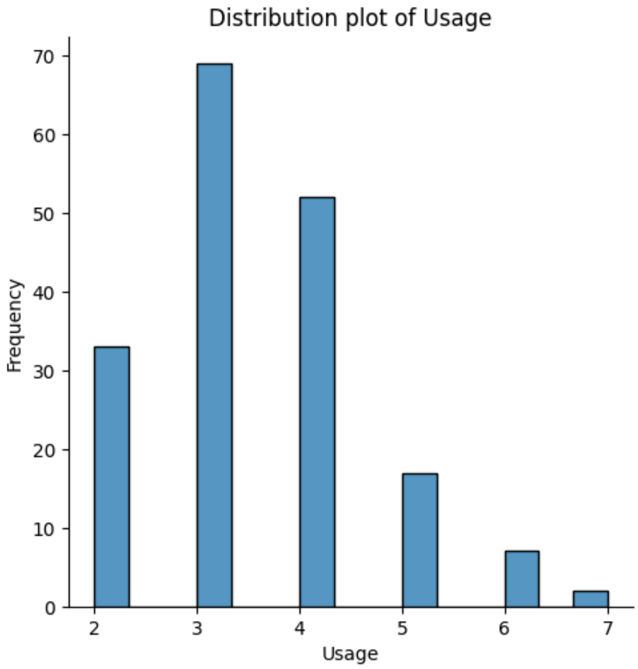
Histogram of Income to find the range of income where Max Customer Lie

```
# Assuming your data is in a DataFrame called 'df'
sns.histplot(df["Income"], kde=True)
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.title('Histogram of Income')


plt.show()
```



Custome having Income range in between 45-55 have the highest tendency to purchase the product. Exceptionally person having income approx 80K also have the equal tendency to purchase the product

```
sns.displot(df["Usage"])
plt.xlabel('Usage')
plt.ylabel('Frequency')
plt.title('Distribution plot of Usage')



plt.show()
```



Customer who mention the usage as 2,3,4 have the highest tendency to by the product

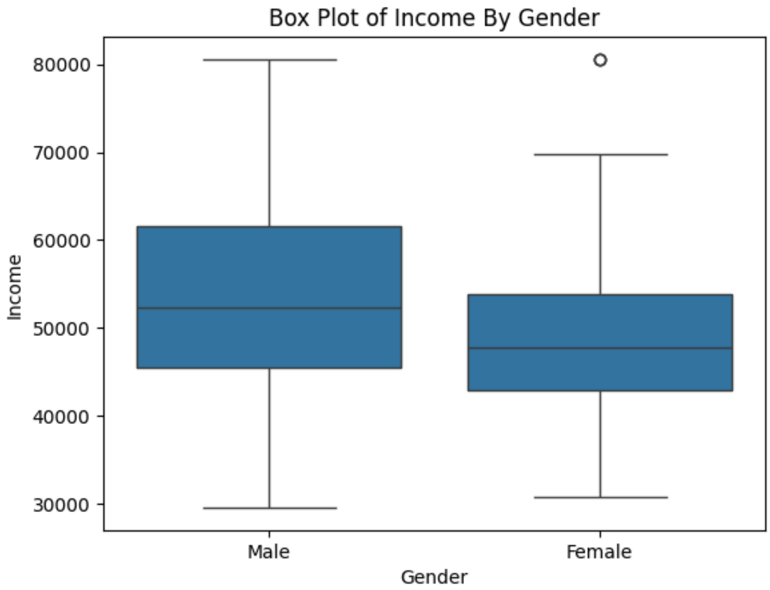
---

Section 3.1 For continuous variable(s): Part 2 Bivariate

Bivariate box plot of gender vs Income

```
sns.boxplot(x='Gender', y='Income', data=df)
plt.xlabel('Gender')
plt.ylabel('Income')
plt.title('Box Plot of Income By Gender')
```

```
Text(0.5, 1.0, 'Box Plot of Income By Gender')
```



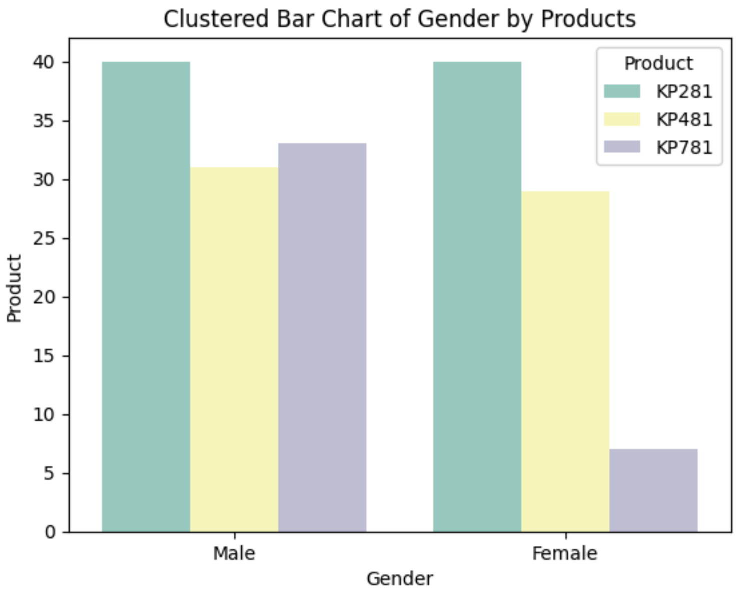
Male Income 75%tile Income of Male customer is approx 62 K and mean Income is approx 52K

Female Income 75%tile Income of Female customer is approx 53K and mean Income is approx 46K

Countplot of Gender vs Products

```
sns.countplot(x='Gender', hue='Product', data=df, palette='Set3')
plt.xlabel('Gender')
plt.ylabel('Product')
plt.title('Clustered Bar Chart of Gender by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of Gender by Products')
```



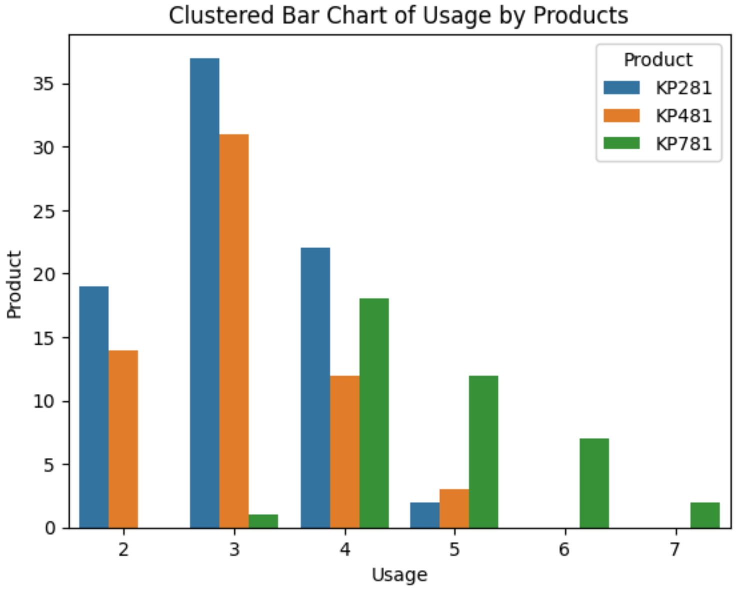
A Male customer have highest tendency to buy KP281, and approx equal tendency to buy KP418 and KP718.

A Female have the highest tendency to buy KP281, a bit lower tendency to buy KP418 and very least tendency to buy KP718.

Countplot of Usage vs Product

```
sns.countplot(x='Usage', hue='Product', data=df)
plt.xlabel('Usage')
plt.ylabel('Product')
plt.title('Clustered Bar Chart of Usage by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of Usage by Products')
```



Customer who plans to use the treadmill 2 or 3 times a week, there is very high probability the they will buy KP281 or KP481.

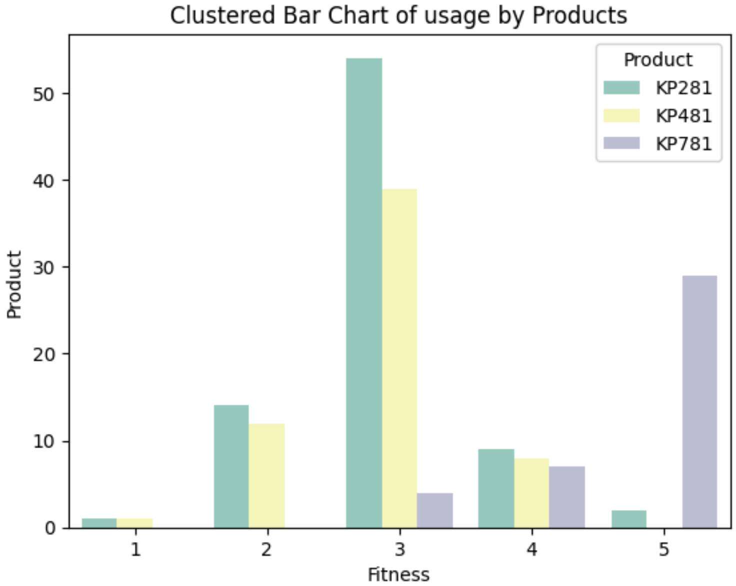
If customer planning to use treadmill 4 times a week there is approx equal probability that they will buy KP281 or KP781. Comparatively low tendency to buy KP481.

If customer wanted to use the treadmill 5, 6 or 7 times a week are mor likely to buy Kp781

Countplot of Fitness vs product

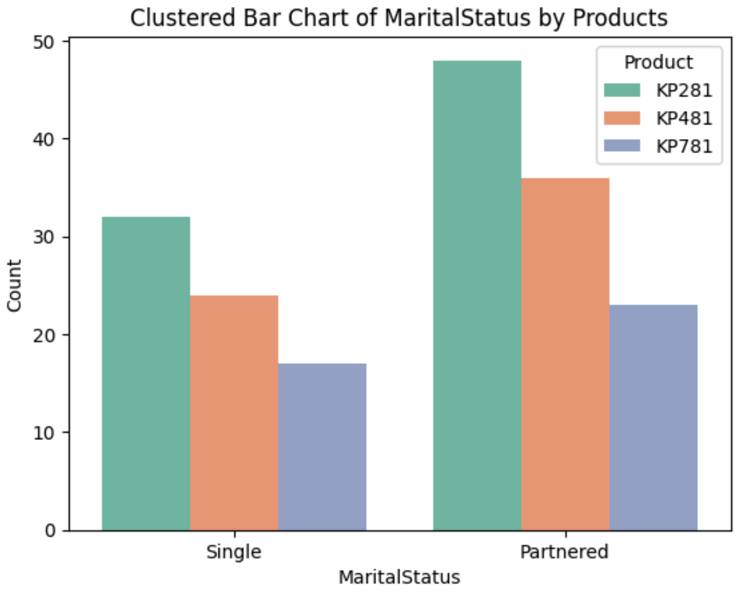
```
sns.countplot(x='Fitness', hue='Product', data=df, palette='Set3')
plt.xlabel('Fitness')
plt.ylabel('Product')
plt.title('Clustered Bar Chart of usage by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of usage by Products')
```



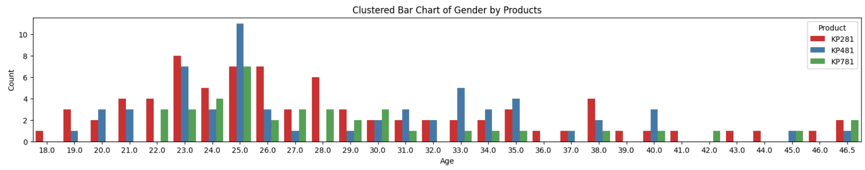

```
sns.countplot(x='MaritalStatus', hue='Product', data=df, palette='Set2')
plt.xlabel('MaritalStatus')
plt.ylabel('Count')
plt.title('Clustered Bar Chart of MaritalStatus by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of MaritalStatus by Products')
```




```
plt.figure(figsize=(20, 3))
sns.countplot(x='Age', hue='Product', data=df, palette='Set1')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Clustered Bar Chart of Gender by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of Gender by Products')
```



KP281 - Age range of most KP281 buyers is 19-28

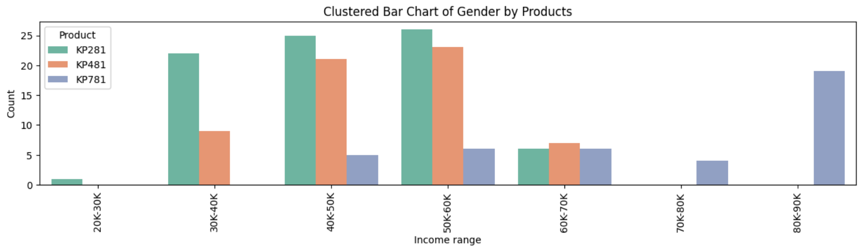
KP481 - Age range of most KP481 buyers is 20-25

KP781 - Age range of most KP781 buyers is 22-30

Segrigating Income into Bins

```
def Income_bin(value):
  if value <=30000:
    return "20K-30K"
  if value <=40000:
    return "30K-40K"
  elif value <=50000:
    return "40K-50K"
  if value <=60000:
    return "50K-60K"
  elif value <=70000:
    return "60K-70K"
  if value <=80000:
    return "70K-80K"
  elif value <=90000:
    return "80K-90K"
  elif value <=100000:
    return "90K-100K"
  else:
    return "100K-110K"
# Apply def
df["Income"] = df["Income"].apply(Income_bin)


plt.figure(figsize=(15, 3))
sns.countplot(x='Income', hue='Product', data=df, palette='Set2')
plt.xlabel('Income range')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.title('Clustered Bar Chart of Gender by Products')
```

```
Text(0.5, 1.0, 'Clustered Bar Chart of Gender by Products')
```



K281- Buyers of K281 have income range of 20K-70K

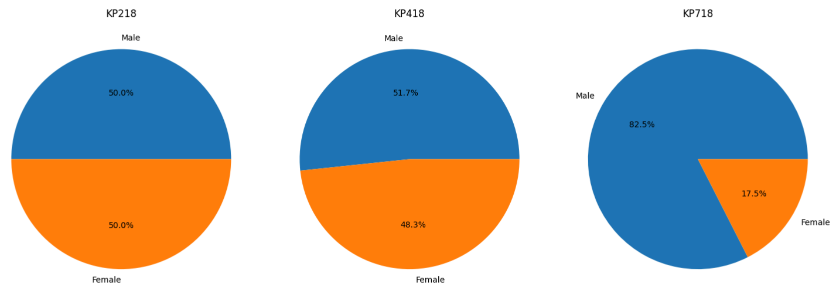
K481- Buyers of K481 have income range of 30K-70K

K781- Buyers of K781 have income range of 40K-110K

Section 3.2 For categorical variables (10 Points)

Pie chart of Gender, Product wise

```
kp281_total = df[df['Product']=="KP281"]
len_m = len(kp281_total[kp281_total["Gender"]=="Male"])
len_f = len(kp281_total[kp281_total["Gender"]=="Female"])
# Create a subplot 1
plt.figure(figsize=(15, 5))  # Adjust the figure size as needed
plt.subplot(1, 3, 1)  # Create the first subplot
plt.pie([len_m, len_f], labels =["Male", "Female", ], autopct = '%1.1f%%')
plt.title("KP218")


kp481_total = df[df['Product']=="KP481"]
len_m1 = len(kp481_total[kp481_total["Gender"]=="Male"])
len_f1 = len(kp481_total[kp481_total["Gender"]=="Female"])
# Create a subplot 2
plt.subplot(1, 3, 2)  # Create the second subplot
plt.pie([len_m1, len_f1], labels =["Male", "Female", ], autopct = '%1.1f%%')
plt.title("KP418")

kp781_total = df[df['Product']=="KP781"]
len_m2 = len(kp781_total[kp781_total["Gender"]=="Male"])
len_f2 = len(kp781_total[kp781_total["Gender"]=="Female"])
# Create a subplot 2
plt.subplot(1, 3, 3)  # Create the second subplot
plt.pie([len_m2, len_f2], labels =["Male", "Female", ], autopct = '%1.1f%%')
plt.title("KP718")

plt.tight_layout()  # Ensures that the plots don't overlap
plt.show()
```



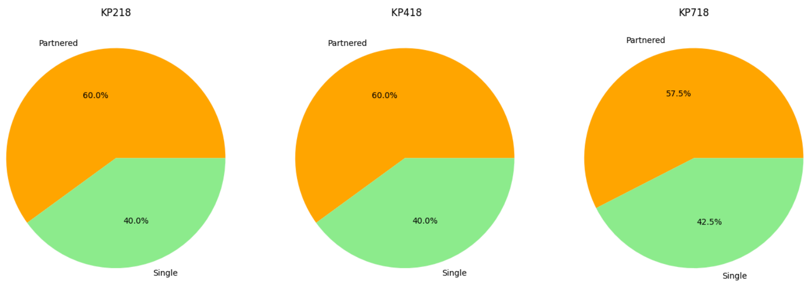
For KP218 and KP418 Male and Female customers are equal in ratio that is **1:1**

For KP781 Male and Female customers is 80:20 that is **4:1**

Pie chart of MaritalStatus, Product wise

```
kp281_total = df[df['Product']=="KP281"]
len_p = len(kp281_total[kp281_total["MaritalStatus"]=="Partnered"])
len_s = len(kp281_total[kp281_total["MaritalStatus"]=="Single"])
# Create a subplot 1
plt.figure(figsize=(15, 5))  # Adjust the figure size as needed
plt.subplot(1, 3, 1)  # Create the first subplot
plt.pie([len_p, len_s], labels =["Partnered", "Single" ], autopct = '%1.1f%%', colors = ['orange', 'lightgreen'])
plt.title("KP218")


kp481_total = df[df['Product']=="KP481"]
len_p1 = len(kp481_total[kp481_total["MaritalStatus"]=="Partnered"])
len_s1 = len(kp481_total[kp481_total["MaritalStatus"]=="Single"])
# Create a subplot 2
plt.subplot(1, 3, 2)  # Create the second subplot
plt.pie([len_p1, len_s1], labels =["Partnered", "Single", ], autopct = '%1.1f%%', colors = ['orange', 'lightgreen'] )
plt.title(" KP418")
```

```
plt.title("KP418")

kp781_total = df[df['Product']=="KP781"]
len_p2 = len(kp781_total[kp781_total["MaritalStatus"]=="Partnered"])
len_s2 = len(kp781_total[kp781_total["MaritalStatus"]=="Single"])
# Create a subplot 2
plt.subplot(1, 3, 3)  # Create the second subplot
plt.pie([len_p2, len_s2], labels =["Partnered", "Single", ], autopct = '%1.1f%%', colors = ['orange', 'lightgreen'] )
plt.title("KP718")

plt.tight_layout()  # Ensures that the plots don't overlap
plt.show()
```



Irrespective of any Model of Treadmill, the ratio of Partnered and Single customer is **60:40** that is **3:2**

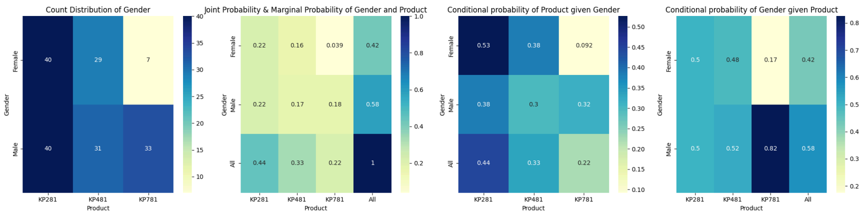
Section 3.3 For correlation: Heatmaps, Pairplots(10 Points)

Conditional and Marginal Probabilities

Gender vs Products

```
# First Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(df["Gender"], df['Product'], normalize = False)
plt.figure(figsize=(20, 5))  # Adjust the figure size as needed
plt.subplot(1, 4, 1)  # Create the first subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Count Distribution of Gender')

# Second Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Gender"], columns = df['Product'], dropna=True,margins=True, normalize=True)
plt.subplot(1, 4, 2)  # Create the second subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Joint Probability & Marginal Probability of Gender and Product')

# Third Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Gender"], columns = df['Product'], dropna=True,margins=True, normalize="index")
plt.subplot(1, 4, 3)  # Create the third subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Product given Gender')

# Fourth Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Gender"], columns = df['Product'], dropna=True,margins=True, normalize="columns")
plt.subplot(1, 4, 4)  # Create the fourth subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Gender given Product')

plt.tight_layout()  # Ensures that the plots don't overlap
```

```
plt.show()
```



Probability that a customer if wanted to buy KP281 and she is Female is 22% Probability that a customer if wanted to buy KP281 and he is Male is also 22%

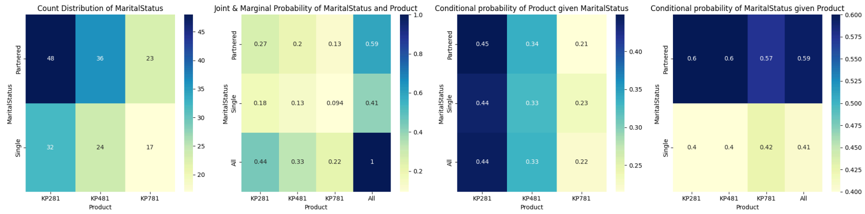
Probability that a customer if wanted to buy KP481 and she is Female is 16% Probability that a customer if wanted to buy KP481 and he is Male is also 17%

Probability that a customer if wanted to buy KP781 and she is Female is 3% Probability that a customer if wanted to buy KP781 and he is Male is also 18%

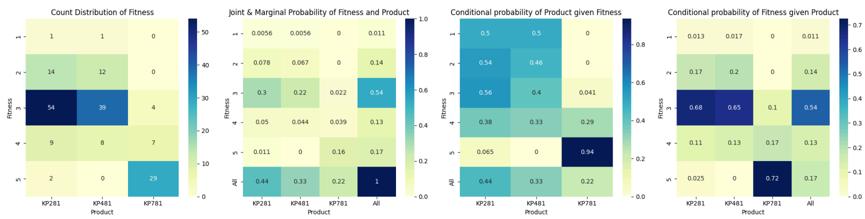
Probability that a customer will buy KP281 is 44% Probability that a customer will buy KP281 is 33% Probability that a customer will buy KP281 is 22%

Probability of a Male customer is 58% Probability of a Femaleale customer is 42%

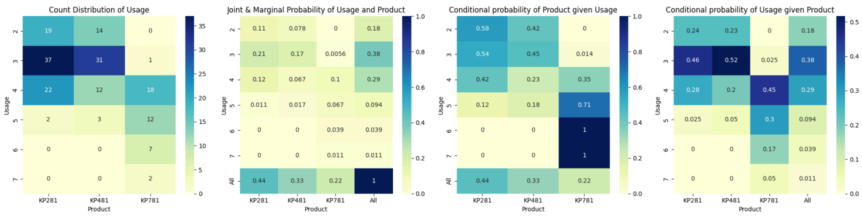
```
# First Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(df["MaritalStatus"], df['Product'], normalize = False)
plt.figure(figsize=(20, 5))  # Adjust the figure size as needed
plt.subplot(1, 4, 1)  # Create the first subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Count Distribution of MaritalStatus')

# Second Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["MaritalStatus"], columns = df["Product"], dropna=True,margins=True, normalize=T
plt.subplot(1, 4, 2)  # Create the second subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Joint & Marginal Probability of MaritalStatus and Product')

# Third Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["MaritalStatus"], columns = df["Product"], dropna=True,margins=True, normalize="
plt.subplot(1, 4, 3)  # Create the third subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Product given MaritalStatus')

# Fourth Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["MaritalStatus"], columns = df["Product"], dropna=True,margins=True, normalize="
plt.subplot(1, 4, 4)  # Create the fourth subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of MaritalStatus given Product')

plt.tight_layout()  # Ensures that the plots don't overlap
plt.show()
```




```
# First Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(df["Fitness"], df['Product'], normalize = False)
plt.figure(figsize=(20, 5))  # Adjust the figure size as needed
plt.subplot(1, 4, 1)  # Create the first subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Count Distribution of Fitness')

# Second Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Fitness"], columns = df["Product"], dropna=True,margins=True, normalize=True)
plt.subplot(1, 4, 2)  # Create the second subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Joint & Marginal Probability of Fitness and Product')

# Third Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Fitness"], columns = df["Product"], dropna=True,margins=True, normalize="index"
plt.subplot(1, 4, 3)  # Create the third subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Product given Fitness')

# Fourth Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Fitness"], columns = df["Product"], dropna=True,margins=True, normalize="column
plt.subplot(1, 4, 4)  # Create the fourth subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Fitness given Product')

plt.tight_layout()  # Ensures that the plots don't overlap
plt.show()
```



```
# First Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(df["Usage"], df['Product'], normalize = False)
plt.figure(figsize=(20, 5))  # Adjust the figure size as needed
plt.subplot(1, 4, 1)  # Create the first subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Count Distribution of Usage')

# Second Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Usage"], columns = df["Product"], dropna=True,margins=True, normalize=True)
plt.subplot(1, 4, 2)  # Create the second subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Joint & Marginal Probability of Usage and Product')

# Third Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Usage"], columns = df["Product"], dropna=True,margins=True, normalize="index")
plt.subplot(1, 4, 3)  # Create the third subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Product given Usage')

# Fourth Graph of Count distribution between Gender and Product
contingency_table = pd.crosstab(index = df["Usage"], columns = df["Product"], dropna=True,margins=True, normalize="columns"
plt.subplot(1, 4, 4)  # Create the fourth subplot
sns.heatmap(contingency_table, annot=True, cmap='YlGnBu')
plt.title('Conditional probability of Usage given Product')

plt.tight_layout()  # Ensures that the plots don't overlap
plt.show()
```



We find Positive Correlation between:

1. Fitness and Age
2. income and Age
3. Income and education
4. Income & education
5. Fitness & usage
6. Income & usage
7. miles & usage
8. Income & Fitness
9. miles & fitness

Section 5 Business Insights based on Non-Graphical and Visual Analysis (10 Points)

5.1 Comments on the range of attributes

1. Product - 3 unique products are there. KP281, KP481, KP781.
2. Age - Range of age is 18-50
3. Gender - 104 are Male and 76 are Female
4. MaritalStatus - 107 are Partnered and 73 are Single
5. Usage - Mode of usage is 3 times a week
6. Fitness- Mode of fitness is 3
7. Income- range of Income is 20K-110K