```
#import libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')  #to ignore warnings


plt.close('all')     #to close all running pyplot windows
```

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

```
#import dataset
df = pd.read_csv('https://drive.google.com/uc?id=12J5o4AC1YdL-UrDYvUnfi5zoPZ5nISUZ&export=download')
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   #shape of data
```

```
(180, 9)
```

there are 180 records and 9 columns in data

```
df.info()    #check data type of all columns
```

```
<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
```

Product,Gender and Marital Status are categorical values

Age,Education,Usage,Fitness,Income and Miles are Numerical Values

```
df.isnull().sum()     #checks null or missing value in data
```

	0
Product	0
Age	0
Gender	0
Education	0
MaritalStatus	0
Usage	0
Fitness	0
Income	0
Miles	0

dtype: int64

there is no missing values that means data is clean

```
df.duplicated().sum()   #check duplicate values
```

```
np.int64(0)
```

There is no duplicate value in data

```
df.nunique()   #check no of unique values in dataset
```

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

dtype: int64

```
df_product_count=df['Product'].value_counts().reset_index()    # total count of each type of product
df_product_count.columns=['Product','Count']
df_product_count
```

	Product	Count
0	KP281	80
1	KP481	60
2	KP781	40

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

There are 3 type of Products:

1. KP281
2. KP481
3. KP781

```
df_maritalstatus_count=df['MaritalStatus'].value_counts().reset_index()  #total count of each martial status
df_maritalstatus_count.columns=['MaritalStatus','Count']
df_maritalstatus_count
```

	MaritalStatus	Count
0	Partnered	107
1	Single	73

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

Marital Status divided into 2 types:

1. Single
2. Partnered

```
df_gender_count=df['Gender'].value_counts().reset_index()    # total count of each gender
df_gender_count.columns=['Gender','Count']
df_gender_count
```

	Gender	Count
0	Male	104
1	Female	76

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

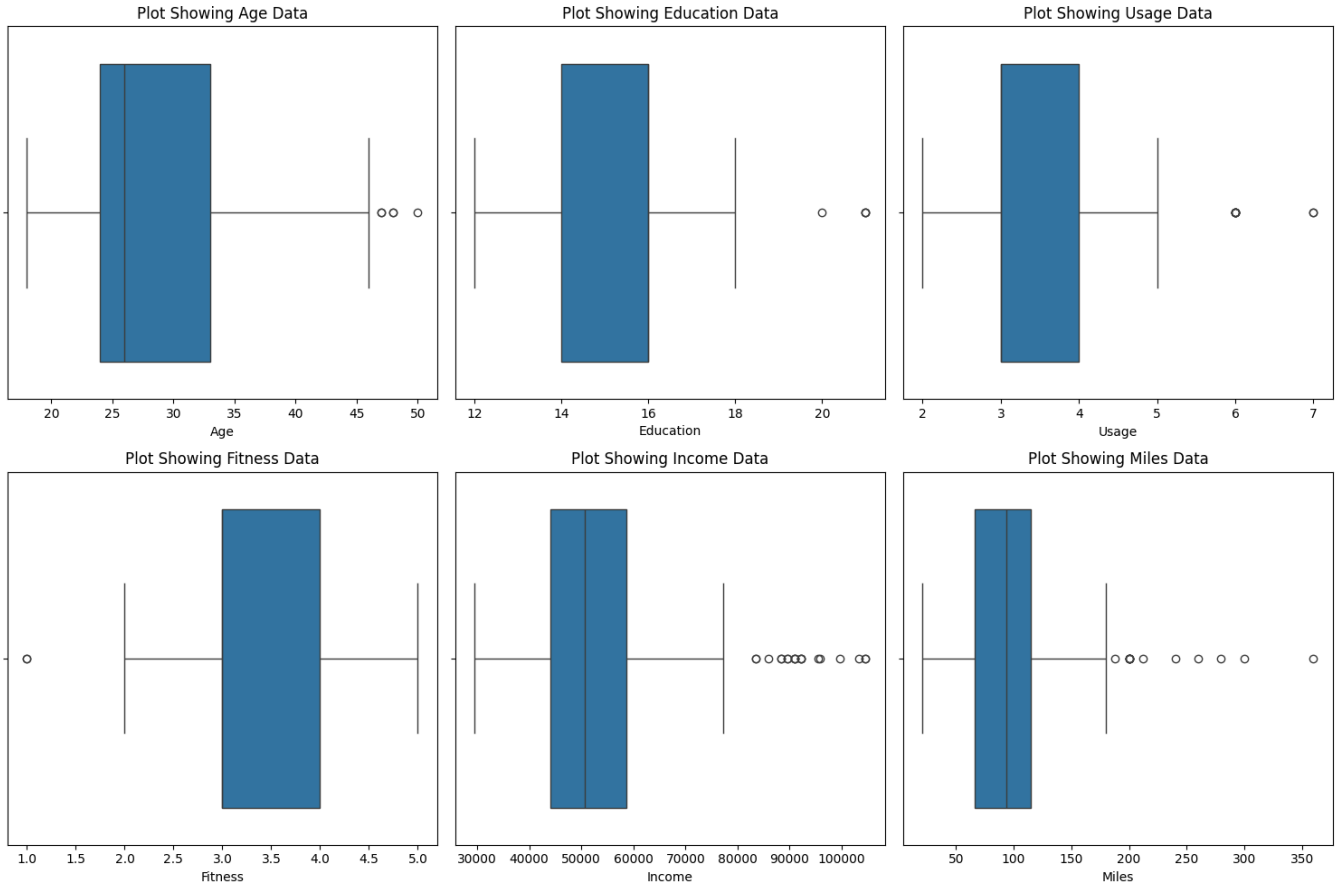
Detect Outliers (using boxplot, “describe” method by checking the difference between mean and median)

```
df.describe()   #describe the numerical data
```

	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

```
# Using Boxplot visualizing data

plt.figure(figsize=(15,10))

plt.subplot(2,3,1)
sns.boxplot(df['Age'],orient='h')
plt.title("Plot Showing Age Data")

plt.subplot(2,3,2)
sns.boxplot(df['Education'],orient='h')
plt.title("Plot Showing Education Data")

plt.subplot(2,3,3)
sns.boxplot(df['Usage'],orient='h')
plt.title("Plot Showing Usage Data")

plt.subplot(2,3,4)
sns.boxplot(df['Fitness'],orient='h')
plt.title("Plot Showing Fitness Data")

plt.subplot(2,3,5)
sns.boxplot(df['Income'],orient='h')
plt.title("Plot Showing Income Data")

plt.subplot(2,3,6)
sns.boxplot(df['Miles'],orient='h')
plt.title("Plot Showing Miles Data")
```

```
plt.tight_layout()
plt.show()
```




```
#Detect Outlier in Age
print("Detect Outliers in Age")

age_25=df['Age'].quantile(0.25)
print("age_25:",age_25)    #25% data
age_50=df['Age'].quantile(0.50)   #50% data
print("age_50:",age_50)
age_75=df['Age'].quantile(0.75)   #75% data
print("age_75:",age_75)
print("*"*100)
IQR_Age=age_75-age_25
print("IQR_Age: ",IQR_Age)    #Calculate IQR(Interquartile Range)

print("*"*100)
#lower and upper bounds for outlier
lower_bound_age=age_25-1.5*IQR_Age
upper_bound_age=age_75+1.5*IQR_Age
print("lower_bound:",lower_bound_age)
print("upper_bound:",upper_bound_age)
print("*"*100)

#Identify Outliers in Age
outliers_age=df[(df['Age']<lower_bound_age) | (df['Age']>upper_bound_age)]
print("Outliers in Age:")
print(outliers_age)
print("*"*100)

#Differnce b/w Mean and Median
```

```
mean_age=df['Age'].mean()
median_age=df['Age'].median()
difference=mean_age-median_age
print("Difference between mean and median Age:",difference)
```

```
Detect Outliers in Age
age_25: 24.0
age_50: 26.0
age_75: 33.0
**************************************************************************************************
IQR_Age:  9.0
**************************************************************************************************
lower_bound: 10.5
upper_bound: 46.5
**************************************************************************************************
Outliers in Age:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
78    KP281   47    Male         16     Partnered      4        3   56850
79    KP281   50  Female         16     Partnered      3        3   64809
139   KP481   48    Male         16     Partnered      2        3   57987
178   KP781   47    Male         18     Partnered      4        5  104581
179   KP781   48    Male         18     Partnered      4        5   95508

     Miles
78      94
79      66
139     64
178    120
179    180
**************************************************************************************************
Difference between mean and median Age: 2.788888888888888
```

```
#Detect Outlier in Education
print("Detect Outliers in Education")


Education_25=df['Education'].quantile(0.25)
print("Education_25:",Education_25)    #25% data
Education_50=df['Education'].quantile(0.50)   #50% data
print("Education_50:",Education_50)
Education_75=df['Education'].quantile(0.75)   #75% data
print("Education_75:",Education_75)
print("*"*100)
IQR_Education=Education_75-Education_25
print("IQR_Education: ",IQR_Education)    #Calculate IQR(Interquartile Range)

print("*"*100)
#lower and upper bounds for outlier
lower_bound_Education=Education_25-1.5*IQR_Education
upper_bound_Education=Education_75+1.5*IQR_Education
print("lower_bound:",lower_bound_Education)
print("upper_bound:",upper_bound_Education)
print("*"*100)

#Identify Outliers in Education
outliers_Education=df[(df['Education']<lower_bound_Education) | (df['Education']>upper_bound_Education)]
print("Outliers in Education:")
print(outliers_Education)
print("*"*100)

#Differnce b/w Mean and Median

mean_Education=df['Education'].mean()
median_Education=df['Education'].median()
print("mean_Education:",mean_Education)
print("median_Education:",median_Education)
difference=mean_Education-median_Education
print("Difference between mean and median Education:",difference)
```

```
Detect Outliers in Education
Education_25: 14.0
Education_50: 16.0
Education_75: 16.0
**************************************************************************************************
IQR_Education:  2.0
**************************************************************************************************
lower_bound: 11.0
upper_bound: 19.0
**************************************************************************************************
```

```
Outliers in Education:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
156   KP781   25    Male         20     Partnered      4        5   74701
157   KP781   26  Female         21        Single      4        3   69721
161   KP781   27    Male         21     Partnered      4        4   90886
175   KP781   40    Male         21        Single      6        5   83416

     Miles
156    170
157    100
161    100
175    200
**********************************************************************************************
mean_Education: 15.572222222222223
median_Education: 16.0
Difference between mean and median Education: -0.42777777777777715
```

```
#Detect Outlier in Usage
print("Detect Outliers in Usage")


Usage_25=df['Usage'].quantile(0.25)
print("Usage_25:",Usage_25)    #25% data
Usage_50=df['Usage'].quantile(0.50)   #50% data
print("Usage_50:",Usage_50)
Usage_75=df['Usage'].quantile(0.75)   #75% data
print("Usage_75:",Usage_75)
print("*"*100)
IQR_Usage=Usage_75-Usage_25
print("IQR_Usage: ",IQR_Usage)    #Calculate IQR(Interquartile Range)

print("*"*100)
#lower and upper bounds for outlier
lower_bound_Usage=Usage_25-1.5*IQR_Usage
upper_bound_Usage=Usage_75+1.5*IQR_Usage
print("lower_bound:",lower_bound_Usage)
print("upper_bound:",upper_bound_Usage)
print("*"*100)

#Identify Outliers in Usage
outliers_Usage=df[(df['Usage']<lower_bound_Usage) | (df['Usage']>upper_bound_Usage)]
print("Outliers in Usage:")
print(outliers_Usage)
print("*"*100)

#Differnce b/w Mean and Median

mean_Usage=df['Usage'].mean()
median_Usage=df['Usage'].median()
print("mean_Usage:",mean_Usage)
print("median_Usage:",median_Usage)
difference=mean_Usage-median_Usage
print("Difference between mean and median Usage:",difference)
```

```
Detect Outliers in Usage
Usage_25: 3.0
Usage_50: 3.0
Usage_75: 4.0
**********************************************************************************************
IQR_Usage:  1.0
**********************************************************************************************
lower_bound: 1.5
upper_bound: 5.5
**********************************************************************************************
Outliers in Usage:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
154   KP781   25    Male         18     Partnered      6        4   70966
155   KP781   25    Male         18     Partnered      6        5   75946
162   KP781   28  Female         18     Partnered      6        5   92131
163   KP781   28    Male         18     Partnered      7        5   77191
164   KP781   28    Male         18        Single      6        5   88396
166   KP781   29    Male         14     Partnered      7        5   85906
167   KP781   30  Female         16     Partnered      6        5   90886
170   KP781   31    Male         16     Partnered      6        5   89641
175   KP781   40    Male         21        Single      6        5   83416

     Miles
154    180
155    240
162    180
163    180
164    150
166    300
167    280
```

```
170    260
175    200
**********************************************************************************************
mean_Usage: 3.4555555555555557
median_Usage: 3.0
Difference between mean and median Usage: 0.4555555555555557
```

```
#Detect Outlier in Fitness
print("Detect Outliers in Fitness")


Fitness_25=df['Fitness'].quantile(0.25)
print("Fitness_25:",Fitness_25)    #25% data
Fitness_50=df['Fitness'].quantile(0.50)   #50% data
print("Fitness_50:",Fitness_50)
Fitness_75=df['Fitness'].quantile(0.75)   #75% data
print("Fitness_75:",Fitness_75)
print("*"*100)
IQR_Fitness=Fitness_75-Fitness_25
print("IQR_Fitness: ",IQR_Fitness)    #Calculate IQR(Interquartile Range)

print("*"*100)
#lower and upper bounds for outlier
lower_bound_Fitness=Fitness_25-1.5*IQR_Fitness
upper_bound_Fitness=Fitness_75+1.5*IQR_Fitness
print("lower_bound:",lower_bound_Fitness)
print("upper_bound:",upper_bound_Fitness)
print("*"*100)

#Identify Outliers in Fitness
outliers_Fitness=df[(df['Fitness']<lower_bound_Fitness) | (df['Fitness']>upper_bound_Fitness)]
print("Outliers in Fitness:")
print(outliers_Fitness)
print("*"*100)

#Differnce b/w Mean and Median

mean_Fitness=df['Fitness'].mean()
median_Fitness=df['Fitness'].median()
print("mean_Fitness:",mean_Fitness)
print("median_Fitness:",median_Fitness)
difference=mean_Fitness-median_Fitness
print("Difference between mean and median Fitness:",difference)
```

```
Detect Outliers in Fitness
Fitness_25: 3.0
Fitness_50: 3.0
Fitness_75: 4.0
**********************************************************************************************
IQR_Fitness:  1.0
**********************************************************************************************
lower_bound: 1.5
upper_bound: 5.5
**********************************************************************************************
Outliers in Fitness:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
14    KP281   23    Male         16     Partnered      3        1   38658
117   KP481   31  Female         18        Single      2        1   65220

     Miles
14      47
117     21
**********************************************************************************************
mean_Fitness: 3.311111111111111
median_Fitness: 3.0
Difference between mean and median Fitness: 0.3111111111111109
```

```
#Detect Outlier in Income
print("Detect Outliers in Income")


Income_25=df['Income'].quantile(0.25)
print("Income_25:",Income_25)    #25% data
Income_50=df['Income'].quantile(0.50)   #50% data
print("Income_50:",Income_50)
Income_75=df['Income'].quantile(0.75)   #75% data
print("Income_75:",Income_75)
print("*"*100)
IQR_Income=Income_75-Income_25
print("IQR_Income: ",IQR_Income)    #Calculate IQR(Interquartile Range)
```

```
print("*"*100)
#lower and upper bounds for outlier
lower_bound_Income=Income_25-1.5*IQR_Income
upper_bound_Income=Income_75+1.5*IQR_Income
print("lower_bound:",lower_bound_Income)
print("upper_bound:",upper_bound_Income)
print("*"*100)

#Identify Outliers in Income
outliers_Income=df[(df['Income']<lower_bound_Income) | (df['Income']>upper_bound_Income)]
print("Outliers in Income:")
print(outliers_Income)
print("*"*100)

#Differnce b/w Mean and Median

mean_Income=df['Income'].mean()
median_Income=df['Income'].median()
difference=mean_Income-median_Income
print("Difference between mean and median Income:",difference)
```

```
Detect Outliers in Income
Income_25: 44058.75
Income_50: 50596.5
Income_75: 58668.0
****************************************************************************************************
IQR_Income:  14609.25
****************************************************************************************************
lower_bound: 22144.875
upper_bound: 80581.875
****************************************************************************************************
Outliers in Income:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
159   KP781   27    Male         16     Partnered      4        5   83416
160   KP781   27    Male         18        Single      4        3   88396
161   KP781   27    Male         21     Partnered      4        4   90886
162   KP781   28  Female         18     Partnered      6        5   92131
164   KP781   28    Male         18        Single      6        5   88396
166   KP781   29    Male         14     Partnered      7        5   85906
167   KP781   30  Female         16     Partnered      6        5   90886
168   KP781   30    Male         18     Partnered      5        4  103336
169   KP781   30    Male         18     Partnered      5        5   99601
170   KP781   31    Male         16     Partnered      6        5   89641
171   KP781   33  Female         18     Partnered      4        5   95866
172   KP781   34    Male         16        Single      5        5   92131
173   KP781   35    Male         16     Partnered      4        5   92131
174   KP781   38    Male         18     Partnered      5        5  104581
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

     Miles
159    160
160    100
161    100
162    180
164    150
166    300
167    280
168    160
169    150
170    260
171    200
172    150
173    360
174    150
175    200
176    200
177    160
178    120
179    180
****************************************************************************************************
Difference between mean and median Income: 3123.0777777777766
```

```
#Detect Outlier in Miles
print("Detect Outliers in Miles")


Miles_25=df['Miles'].quantile(0.25)
print("Miles_25:",Miles_25)    #25% data
Miles_50=df['Miles'].quantile(0.50)   #50% data
print("Miles_50:",Miles_50)
```

```
Miles_75=df['Miles'].quantile(0.75)   #75% data
print("Miles_75:",Miles_75)
print("*"*100)
IQR_Miles=Miles_75-Miles_25
print("IQR_Miles: ",IQR_Miles)    #Calculate IQR(Interquartile Range)

print("*"*100)
#lower and upper bounds for outlier
lower_bound_Miles=Miles_25-1.5*IQR_Miles
upper_bound_Miles=Miles_75+1.5*IQR_Miles
print("lower_bound:",lower_bound_Miles)
print("upper_bound:",upper_bound_Miles)
print("*"*100)

#Identify Outliers in Miles
outliers_Miles=df[(df['Miles']<lower_bound_Miles) | (df['Miles']>upper_bound_Miles)]
print("Outliers in Miles:")
print(outliers_Miles)
print("*"*100)

#Differnce b/w Mean and Median

mean_Miles=df['Miles'].mean()
median_Miles=df['Miles'].median()
difference=mean_Miles-median_Miles
print("Difference between mean and median Miles:",difference)
```

```
Detect Outliers in Miles
Miles_25: 66.0
Miles_50: 94.0
Miles_75: 114.75
****************************************************************************************************
IQR_Miles:  48.75
****************************************************************************************************
lower_bound: -7.125
upper_bound: 187.875
****************************************************************************************************
Outliers in Miles:
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
23    KP281   24  Female         16     Partnered      5        5   44343
84    KP481   21  Female         14     Partnered      5        4   34110
142   KP781   22    Male         18        Single      4        5   48556
148   KP781   24  Female         16        Single      5        5   52291
152   KP781   25  Female         18     Partnered      5        5   61006
155   KP781   25    Male         18     Partnered      6        5   75946
166   KP781   29    Male         14     Partnered      7        5   85906
167   KP781   30  Female         16     Partnered      6        5   90886
170   KP781   31    Male         16     Partnered      6        5   89641
171   KP781   33  Female         18     Partnered      4        5   95866
173   KP781   35    Male         16     Partnered      4        5   92131
175   KP781   40    Male         21        Single      6        5   83416
176   KP781   42    Male         18        Single      5        4   89641

     Miles
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
170    260
171    200
173    360
175    200
176    200
****************************************************************************************************
Difference between mean and median Miles: 9.194444444444443
```

Fitness has less outliers than others as its difference b/w mean and median is lowest(0.311) than others

Incomes has most outliers as its difference b/w mean and median is highest(3123.07) than others

Education has negative difference(-0.42) means outliers mostly on left side of distribution whereas positive difference means outliers mostly on right side of distribution

Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc)

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

Education	count
16	85
14	55
18	23
15	5
13	5
12	3
21	3
20	1

dtype: int64

```
#function for converting education into 4 categories

def edu_cat(x):
  if x<13:
    return "Lower School"
  elif x>=13 and x<=15:
    return "Middle School"
  elif x>15 and x<18:
    return "High School"
  else:
    return "College"


df['Education_Cat']=df['Education'].apply(edu_cat)
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School
4	KP281	20	Male	13	Partnered	4	2	35247	47	Middle School

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

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

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

dtype: int64

```
#function for converting Usage into 4 categories

def usage_cat(x):
  if x<=3:
    return "Infrequent"
  elif x==4:
    return "Moderate"
  elif x==5:
    return "Regular"
  else:
    return "Dedicated"


df['Usage_Cat']=df['Usage'].apply(usage_cat)
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School	Infrequent
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School	Infrequent
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School	Moderate
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School	Infrequent
4	KP281	20	Male	13	Partnered	4	2	35247	47	Middle School	Moderate

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

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

Fitness	count
3	97
5	31
2	26
4	24
1	2

dtype: int64

```
#function for converting fitness into 3 categories

def fitness_cat(x):
  if x<=2:
    return "Poor Fitness"
  elif x==3:
    return "Good Fitness"
  else:
    return "Excellent Fitness"


df['Fitness_Cat']=df['Fitness'].apply(fitness_cat)
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat	Fitness_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School	Infrequent	Excellent Fitness
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School	Infrequent	Good Fitness
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School	Moderate	Good Fitness
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School	Infrequent	Good Fitness
4	KP281	20	Male	13	Partnered	4	2	35247	47	Middle School	Moderate	Poor Fitness

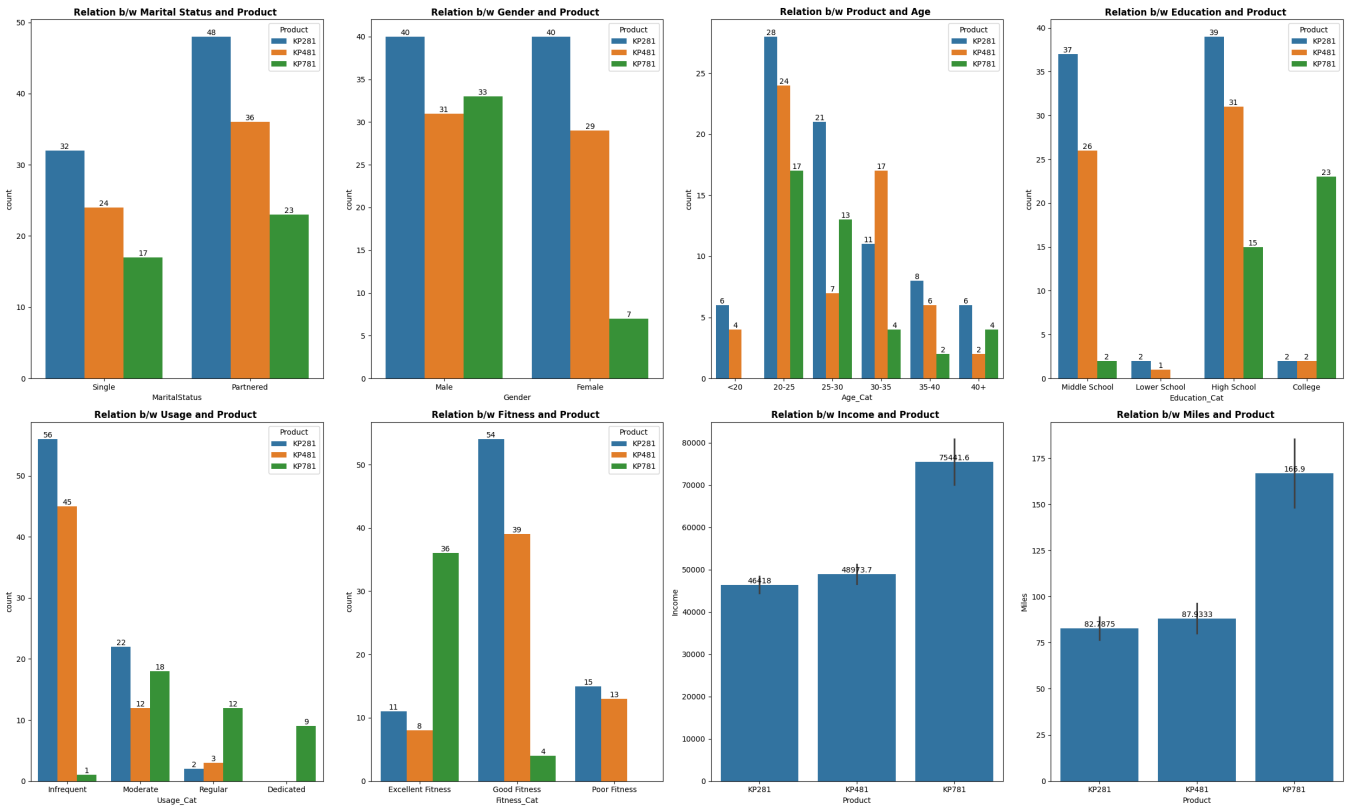
Next steps: Generate code with df | View recommended plots | New interactive sheet

```
# creating bins to categorize age
bins = [0,20,25,30,35,40,55]
labels = ['<20','20-25','25-30','30-35','35-40','40+']
df['Age_Cat'] = pd.cut(df['Age'], bins=bins, labels=labels)
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat	Fitness_Cat	Age_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School	Infrequent	Excellent Fitness	<20
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School	Infrequent	Good Fitness	<20
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School	Moderate	Good Fitness	<20
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School	Infrequent	Good Fitness	<20

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

```
# Show Relation b/w Product with different categoriess and check their effect by visualization

plt.figure(figsize=(25,15))   #figure size

plt.subplot(2,4,1)
ax1=sns.countplot(x=df['MaritalStatus'],hue=df['Product'])
plt.title("Relation b/w Marital Status and Product ",fontweight='bold')
for container in ax1.containers:
  ax1.bar_label(container)

plt.subplot(2,4,2)
ax2=sns.countplot(x=df['Gender'],hue=df['Product'])
plt.title("Relation b/w Gender and Product ",fontweight='bold')
for container in ax2.containers:
  ax2.bar_label(container)

plt.subplot(2,4,3)
ax3=sns.countplot(x='Age_Cat',hue='Product',data=df)
plt.title("Relation b/w Product and Age ",fontweight='bold')
for container in ax3.containers:
  ax3.bar_label(container)

plt.subplot(2,4,4)
ax4=sns.countplot(x=df['Education_Cat'],hue=df['Product'])
plt.title("Relation b/w Education and Product ",fontweight='bold')
for container in ax4.containers:
  ax4.bar_label(container)

plt.subplot(2,4,5)
ax5=sns.countplot(x=df['Usage_Cat'],hue=df['Product'])
plt.title("Relation b/w Usage and Product ",fontweight='bold')
for container in ax5.containers:
  ax5.bar_label(container)

plt.subplot(2,4,6)
ax6=sns.countplot(x=df['Fitness_Cat'],hue=df['Product'])
plt.title("Relation b/w Fitness and Product ",fontweight='bold')
for container in ax6.containers:
  ax6.bar_label(container)

plt.subplot(2,4,7)
ax7=sns.barplot(x=df['Product'],y=df['Income'])
plt.title("Relation b/w Income and Product ",fontweight='bold')
for container in ax7.containers:
  ax7.bar_label(container)

plt.subplot(2,4,8)
ax8=sns.barplot(x=df['Product'],y=df['Miles'])
plt.title("Relation b/w Miles and Product ",fontweight='bold')
for container in ax8.containers:
  ax8.bar_label(container)


plt.tight_layout()
plt.show()
```



People are partnered is likely to purchase a product then the people who are not.

Product KP281 is popular in both the genders.KP481 is popular higher in males as compare to females.KP781 is popular only in males.

People of age group 20-25 purchase more number of treadmills.

- 80% of purchasers are from 20 to 35 age group.
- 62% of purchases are from age group of 20-30 years

As per the education Middle school and high school likely to purchase the KP281 and KP481. College likely to purchase only KP781. Lower education is shouldn't be a traget audience as there is less chance that they will purchase a Treadmill

- Approx 83% people purchasers from Middle and High School group
- Less than 2% people purchasers from Lower School group

People who are infrequent user likely to purchase KP281 and KP481 and people are dedicated would purchase KP781. Rest of the class would randomly purchase any of the treadmill.

People who have Excellent fitness would purchase KP781 and people with Fair Fitness and Poor Fitness will purchase KP281 and KP481

People with high income would love to purchase the KP781 and lower to middle income group would love to purchase KP281 and KP481

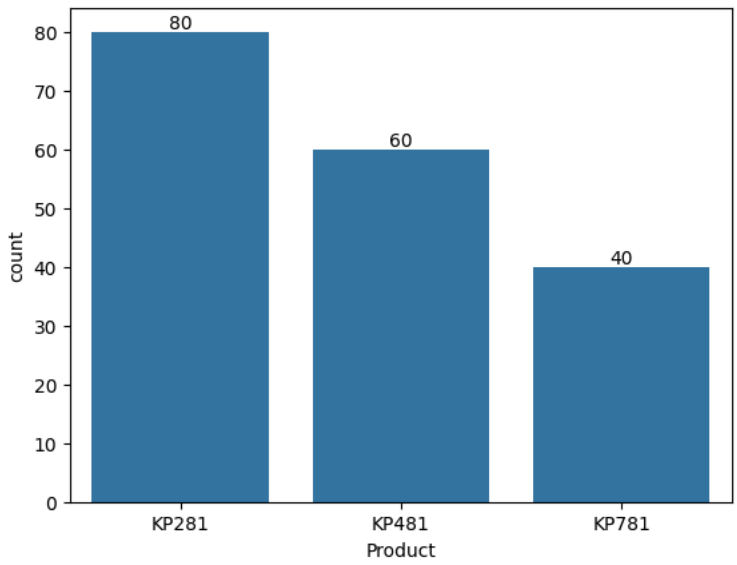
- People who have income under 50000 they like to purchase KP281 and KP481
- People who have income more then 50000 they like purchase KP781

If the miles run is higher cutsomer likely to purchase KP781

Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)

```
ax=sns.countplot(x=df['Product'])
for container in ax.containers:
```

```
  ax.bar_label(container)
plt.show()
```




```
product_count=pd.crosstab(index=df['Product'],columns='Count')
product_percentage=product_count/len(df)*100
product_percentage
```

Product	col_0 Count
KP281	44.444444
KP481	33.333333
KP781	22.222222

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

Probability of customers purchase KP281: ~0.44 or ~44%

Probability of customers purchase KP281: ~0.33 or ~33%

Probability of customers purchase KP281: ~0.22 or ~22%

Check correlation among different factors using heat maps or pair plots.**bold text**

```
df_copy=df.copy()
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat	Fitness_Cat	Age_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School	Infrequent	Excellent Fitness	<20
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School	Infrequent	Good Fitness	<20
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School	Moderate	Good Fitness	<20
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School	Infrequent	Good Fitness	<20

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

```
# changing categorical data to numerical to find correlation

df_copy['Product'].replace({'KP281':0,'KP481':1,'KP781':2},inplace=True)
df_copy['Gender'].replace({'Male':0,'Female':1},inplace=True)
df_copy['MaritalStatus'].replace({'Single':0,'Partnered':1},inplace=True)
df_copy.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat	Fitness_Cat	Age_Cat
0	0	18	0	14	0	3	4	29562	112	Middle School	Infrequent	Excellent Fitness	<20
1	0	19	0	15	0	2	3	31836	75	Middle School	Infrequent	Good Fitness	<20
2	0	19	1	14	1	4	3	30699	66	Middle School	Moderate	Good Fitness	<20
3	0	19	0	12	0	3	3	32973	85	Lower School	Infrequent	Good Fitness	<20

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

```
#dropping columns which not useful in finding correlation as these are redefining columns of previous ones

df_copy.drop(['Education_Cat','Fitness_Cat','Usage_Cat','Age_Cat'],axis=1,inplace=True)
df_copy.head()
```

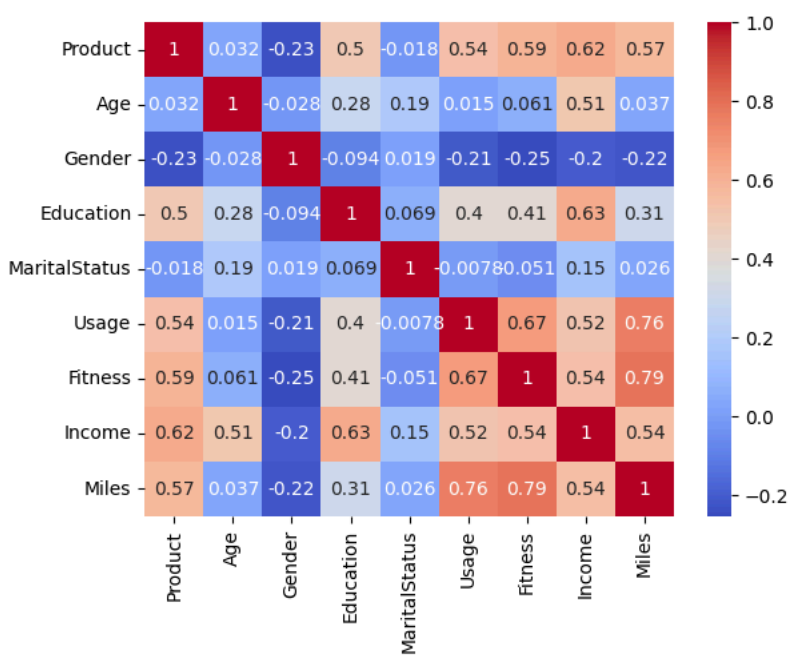
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	0	18	0	14	0	3	4	29562	112
1	0	19	0	15	0	2	3	31836	75
2	0	19	1	14	1	4	3	30699	66
3	0	19	0	12	0	3	3	32973	85
4	0	20	0	13	1	4	2	35247	47

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

```
#correlation of data

df_copy.corr()
```

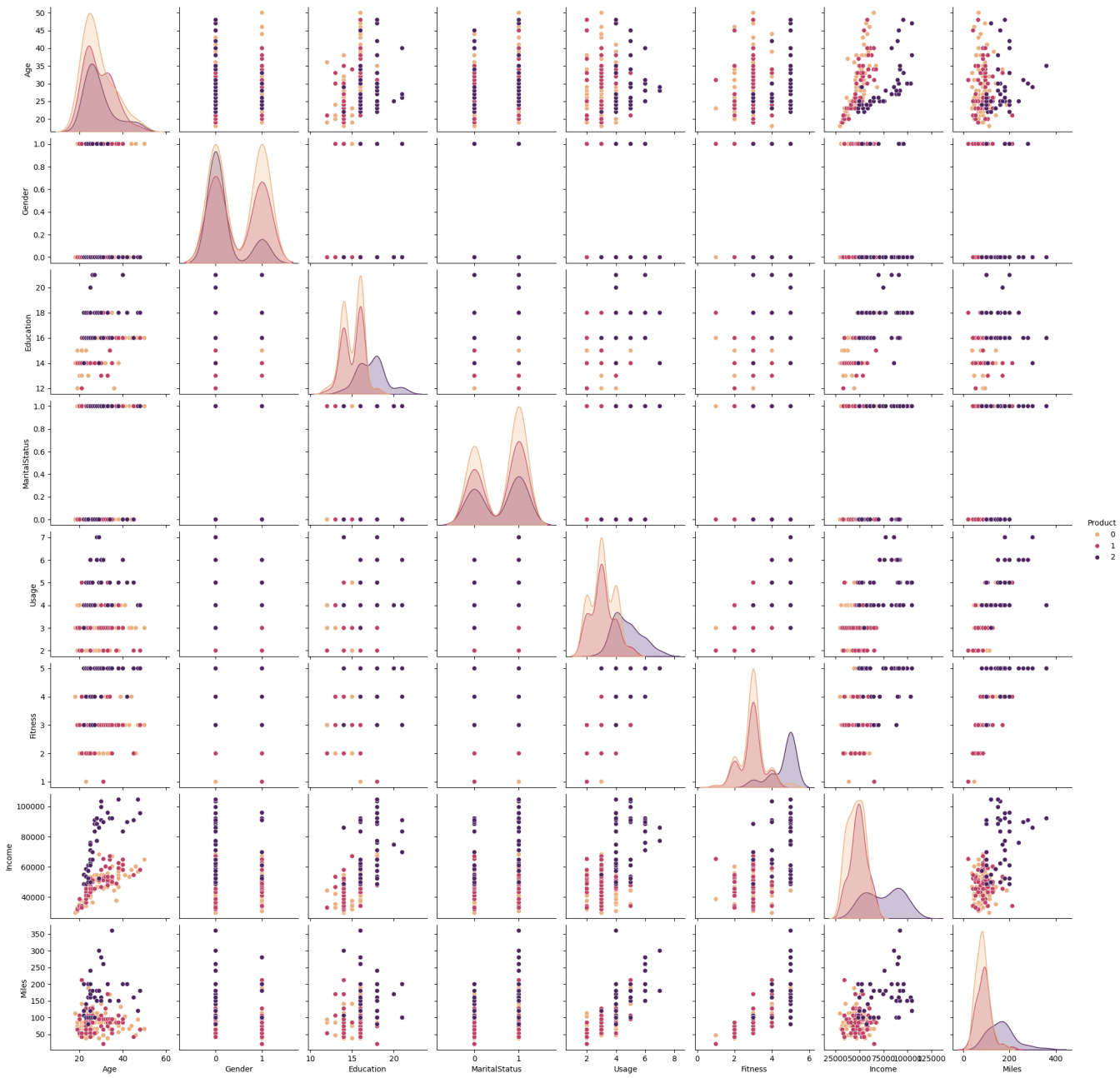
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
Product	1.000000	0.032225	-0.230653	0.495018	-0.017602	0.537447	0.594883	0.624168	0.571596
Age	0.032225	1.000000	-0.027544	0.280496	0.192152	0.015064	0.061105	0.513414	0.036618
Gender	-0.230653	-0.027544	1.000000	-0.094089	0.018836	-0.214424	-0.254609	-0.202053	-0.217869
Education	0.495018	0.280496	-0.094089	1.000000	0.068569	0.395155	0.410581	0.625827	0.307284
MaritalStatus	-0.017602	0.192152	0.018836	0.068569	1.000000	-0.007786	-0.050751	0.150293	0.025639
Usage	0.537447	0.015064	-0.214424	0.395155	-0.007786	1.000000	0.668606	0.519537	0.759130
Fitness	0.594883	0.061105	-0.254609	0.410581	-0.050751	0.668606	1.000000	0.535005	0.785702
Income	0.624168	0.513414	-0.202053	0.625827	0.150293	0.519537	0.535005	1.000000	0.543473
Miles	0.571596	0.036618	-0.217869	0.307284	0.025639	0.759130	0.785702	0.543473	1.000000

```
#Correlation Heatmap
sns.heatmap(df_copy.corr(),annot=True,cmap='coolwarm')
plt.figure(figsize=(15,12))
plt.show()
```




```
<Figure size 1500x1200 with 0 Axes>
```

```
#Pairplot
sns.pairplot(df_copy,hue='Product',palette='flare')
plt.show()
```



- Gender did not have any such correlation with other parameter that means it did not impact on purchasing.
- Educataion is highly correlated with income as its obvious. It also has impact on product purchased. Eductation also have significatnt correlation between fitness rating and Usage of the treadmill.
- Marital Status has smaller correlation between Age and Income.
- Usage is extremely correlated with Fitness and Miles and has a higher correlation with Income and Education as well.
- Income is highly correlated with Product and Education. It also had good correlation with Age, usage, Fitness, Miles.

- From above we can say that Product is extremely correlated with Income, Education, Fitness, Usage along with Miles.

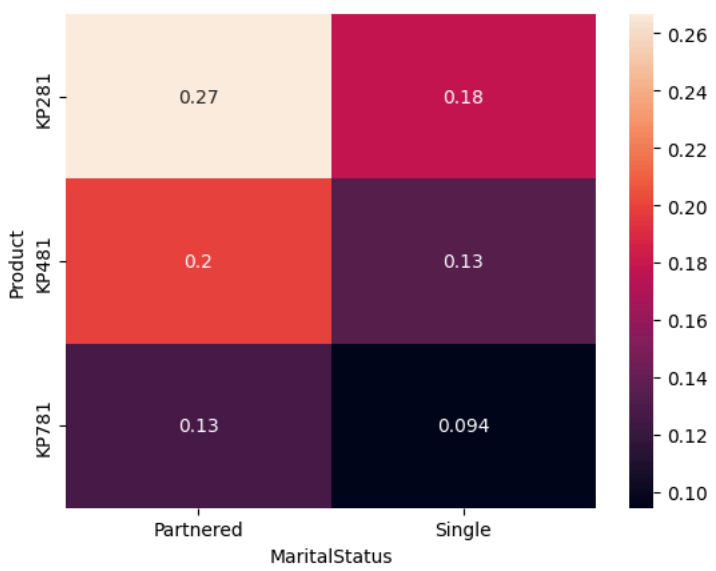
With all the above steps you can answer questions like: What is the probability of a male customer buying a KP781 treadmill?

```
#Using CrossTab finding what no of persons purchased as per their maritalstatus

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

MaritalStatus	Partnered	Single	All
Product			
KP281	0.266667	0.177778	0.444444
KP481	0.200000	0.133333	0.333333
KP781	0.127778	0.094444	0.222222
All	0.594444	0.405556	1.000000

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

```
sns.heatmap((pd.crosstab(df['Product'],df['MaritalStatus'],normalize=True)),annot=True)
plt.show()
```




```
#What is the probability of customers are partnered using any product?

print("Probability of customers which are partnered using any product:",107/180)

#What is the probability of customers are single using any product?

print("Probability of customers which are single using any product:",73/180)

#Probability of customers which are partnered using each product
print("Probability of customers which are partnered and using product K281:",48/80)

print("Probability of customers which are partnered and using product K481:",36/60)

print("Probability of customers which are partnered and using product K781:",23/40)

#Probability of customers which are single using each product

print("Probability of customers which are single and using product K281:",32/80)

print("Probability of customers which are single and using product K481:",26/60)

print("Probability of customers which are single and using product K781:",17/40)
```

```
Probability of customers which are partnered using any product: 0.5944444444444444
Probability of customers which are single using any product: 0.40555555555555556
Probability of customers which are partnered and using product K281: 0.6
```

```
Probability of customers which are partnered and using product K481: 0.6
Probability of customers which are partnered and using product K781: 0.575
Probability of customers which are single and using product K281: 0.4
Probability of customers which are single and using product K481: 0.43333333333333335
Probability of customers which are single and using product K781: 0.425
```

Partnered customers using more than single customers

Partnered Customers use products K281 and K481 i.e. 60% more then K781 i.e.57.5%

Single Customers use products K481(~ 43%) and K781(~ 42.5%) more then K281

```
#Using CrossTab finding what no of persons purchased as per their gender

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

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

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

```
print("Probability of male customers buy any product:",104/180)

print("Probability of female customers buy any product:",76/180)

print("Probability of male customers buying K281:",40/80)

print("Probability of male customers buying K481:",31/60)

print("Probability of male customers buying K781:",33/40)

print("Probability of female customers buying K281:",40/80)

print("Probability of female customers buying K481:",29/60)

print("Probability of female customers buying K781:",7/40)
```

```
Probability of male customers buy any product: 0.5777777777777777
Probability of female customers buy any product: 0.4222222222222222
Probability of male customers buying K281: 0.5
Probability of male customers buying K481: 0.5166666666666667
Probability of male customers buying K781: 0.825
Probability of female customers buying K281: 0.5
Probability of female customers buying K481: 0.48333333333333334
Probability of female customers buying K781: 0.175
```

```
#Probability of partnered customers buying each product

total_customers=len(df)
print("Total Customers:",total_customers)
print("*"*100)

#KP281
male_pratnered_kp281=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP281")])
print("Probability of male partnered customers buying K281:",male_pratnered_kp281/total_customers)

female_partnered_kp281=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP281")])
print("Probability of female partnered customers buying K281:",female_partnered_kp281/total_customers)
print("*"*100)
#KP481
male_pratnered_kp481=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP481")])
print("Probability of male partnered customers buying K481:",male_pratnered_kp481/total_customers)

female_partnered_kp481=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP481")])
print("Probability of female partnered customers buying K481:",female_partnered_kp481/total_customers)
print("*"*100)


#KP781
male_pratnered_kp781=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP781")])
print("Probability of male partnered customers buying K781:",male_pratnered_kp781/total_customers)
```

```
female_partnered_kp781=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Partnered")&(df["Product"]=="KP781")])
print("Probability of female partnered customers buying K781:",female_partnered_kp781/total_customers)
```

```
Total Customers: 180
****************************************************************************************************
Probability of male partnered customers buying K281: 0.11666666666666667
Probability of female partnered customers buying K281: 0.15
****************************************************************************************************
Probability of male partnered customers buying K481: 0.11666666666666667
Probability of female partnered customers buying K481: 0.08333333333333333
****************************************************************************************************
Probability of male partnered customers buying K781: 0.10555555555555556
Probability of female partnered customers buying K781: 0.022222222222222223
```

K281: Female partnered customers buying more approx 15%

K481: Male Partnered customers buying more approx 11.6%

K781: Male Partnered customers buying more approx 10.5%

```
#Probability of single customers buying each product

total_customers=len(df)
print("Total Customers:",total_customers)
print("*"*100)

#K281
male_single_kp281=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP281")])
print("Probability of male single customers buying K281:",male_single_kp281/total_customers)

female_single_kp281=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP281")])
print("Probability of female single customers buying K281:",female_single_kp281/total_customers)
print("*"*100)

#K481
male_single_kp481=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP481")])
print("Probability of male single customers buying K481:",male_single_kp481/total_customers)

female_single_kp481=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP481")])
print("Probability of female single customers buying K481:",female_single_kp481/total_customers)
print("*"*100)

#K781
male_single_kp781=len(df[(df["Gender"]=="Male")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP781")])
print("Probability of male single customers buying K781:",male_single_kp781/total_customers)

female_single_kp781=len(df[(df["Gender"]=="Female")&(df["MaritalStatus"]=="Single")&(df["Product"]=="KP781")])
print("Probability of female single customers buying K781:",female_single_kp781/total_customers)
```

```
Total Customers: 180
****************************************************************************************************
Probability of male single customers buying K281: 0.10555555555555556
Probability of female single customers buying K281: 0.07222222222222222
****************************************************************************************************
Probability of male single customers buying K481: 0.05555555555555555
Probability of female single customers buying K481: 0.07777777777777778
****************************************************************************************************
Probability of male single customers buying K781: 0.07777777777777778
Probability of female single customers buying K781: 0.016666666666666666
```

K281: Male Single customers buying more approx 10.5%

K481: Female Single customers buying more approx 7.7%

K781: Male Single customers buying more approx 7.7%

```
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Education_Cat	Usage_Cat	Fitness_Cat	Age_Cat
0	KP281	18	Male	14	Single	3	4	29562	112	Middle School	Infrequent	Excellent Fitness	<20
1	KP281	19	Male	15	Single	2	3	31836	75	Middle School	Infrequent	Good Fitness	<20
2	KP281	19	Female	14	Partnered	4	3	30699	66	Middle School	Moderate	Good Fitness	<20
3	KP281	19	Male	12	Single	3	3	32973	85	Lower School	Infrequent	Good Fitness	<20

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

```
pd.crosstab(df['Education_Cat'],df['Product'],margins=True,normalize=True)
```

Education_Cat	KP281	KP481	KP781	All
College	0.011111	0.011111	0.127778	0.150000
High School	0.216667	0.172222	0.083333	0.472222
Lower School	0.011111	0.005556	0.000000	0.016667
Middle School	0.205556	0.144444	0.011111	0.361111
All	0.444444	0.333333	0.222222	1.000000

Probability of customers from College Education Category purchase tredmills: 15%

- P(KP281|Education_Cat=College)= 1.1%
- P(KP481|Education_Cat=College)=1.1%
- P(KP781|Education_Cat=College)=15%

Probability of customers from High School Education Category purchase tredmills: 47.22%

- P(KP281|Education_Cat=High School)= 21.66%
- P(KP481|Education_Cat=High School)=17.22%
- P(KP781|Education_Cat=High School)=8.33%

Probability of customers from Lower School Education Category purchase tredmills: 1.66%

- P(KP281|Education_Cat=Lower School)= 1.1%
- P(KP481|Education_Cat=Lower School)=0.55%
- P(KP781|Education_Cat=Lower School)=0%

Probability of customers from Middle School Education Category purchase tredmills: 36.11%

- P(KP281|Education_Cat=Middle School)= 20.55%
- P(KP481|Education_Cat=Middle School)=14.44%
- P(KP781|Education_Cat=Middle School)=1.11%

```
pd.crosstab(df['Usage_Cat'],df['Product'],margins=True,normalize=True)
```

Usage_Cat	KP281	KP481	KP781	All
Dedicated	0.000000	0.000000	0.050000	0.050000