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.

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

```
[3] !curl -o aerofit_treadmill.csv "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv"
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100  7279  100  7279    0     0  41339      0 --:--:-- --:--:-- --:--:-- 41594
```

```
[4] df_aerofit = pd.read_csv('aerofit_treadmill.csv')
```

```
[9] df_aerofit.head(10)
```

	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
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
9	KP281	21	Female	15	Partnered	2	3	37521	85

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

Basic Data Analysis

```
#shape of the given data:
df_aerofit.shape
```

```
(180, 9)
```

```
#Checking data types of all the attributes
df_aerofit.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
```

```
#statistical summary
df_aerofit.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

```
#null values check##
df_aerofit.isnull().sum()
```

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

dtype: int64

Exploratory Data Analysis

```
# Unique Values
for i in df_aerofit.columns:
  print (f"{i}:", df_aerofit[i].nunique())
```

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

```
# Value counts
for i in df_aerofit.columns:
  print (f"{i}:", df_aerofit[i].value_counts())
```

```
Product: Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
Age: Age
25    25
23    18
24    12
26    12
28     9
33     8
35     8
22     7
30     7
27     7
38     7
21     7
31     6
34     6
29     6
20     5
40     5
19     4
32     4
37     2
45     2
48     2
47     2
18     1
41     1
39     1
36     1
43     1
46     1
44     1
50     1
42     1
Name: count, dtype: int64
Gender: Gender
Male      104
Female     76
Name: count, dtype: int64
Education: Education
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: count, dtype: int64
MaritalStatus: MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
Usage: Usage
```

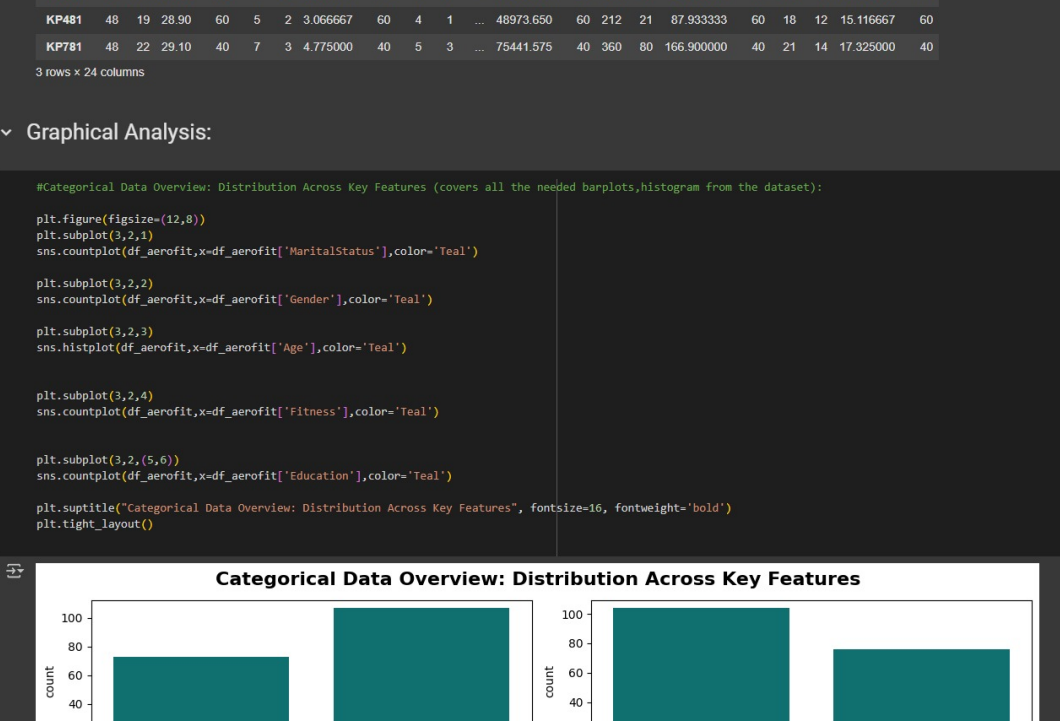
```
#overview table##
# A table to gain possible Business Insight (b/w the columns their max,min,count and mean values):##
df_aerofit.groupby('Product')[["Age", "Usage", "Fitness", "Income", "Miles", "Education"]].agg(['max', 'min', 'mean', 'size'])
```

	Age				Usage				Fitness		...	Income		Miles				Education			
	max	min	mean	size	max	min	mean	size	max	min	...	mean	size	max	min	mean	size	max	min	mean	size
Product																					
KP281	50	18	28.55	80	5	2	3.087500	80	5	1	...	46418.025	80	188	38	82.787500	80	18	12	15.037500	80
KP481	48	19	28.90	60	5	2	3.066667	60	4	1	...	48973.650	60	212	21	87.933333	60	18	12	15.116667	60
KP781	48	22	29.10	40	7	3	4.775000	40	5	3	...	75441.575	40	360	80	166.900000	40	21	14	17.325000	40

3 rows × 24 columns

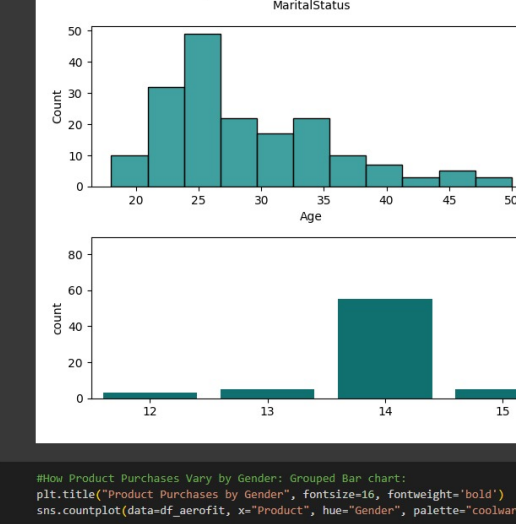
Graphical Analysis:

```
#Categorical Data Overview: Distribution Across Key Features (covers all the needed barplots,histogram from the dataset):

plt.figure(figsize=(12,8))
plt.subplot(3,2,1)
sns.countplot(df_aerofit,x=df_aerofit['MaritalStatus'],color='Teal')

plt.subplot(3,2,2)
sns.countplot(df_aerofit,x=df_aerofit['Gender'],color='Teal')

plt.subplot(3,2,3)
sns.histplot(df_aerofit,x=df_aerofit['Age'],color='Teal')


plt.subplot(3,2,4)
sns.countplot(df_aerofit,x=df_aerofit['Fitness'],color='Teal')


plt.subplot(3,2,(5,6))
sns.countplot(df_aerofit,x=df_aerofit['Education'],color='Teal')

plt.suptitle("Categorical Data Overview: Distribution Across Key Features", fontsize=16, fontweight='bold')
plt.tight_layout()
```



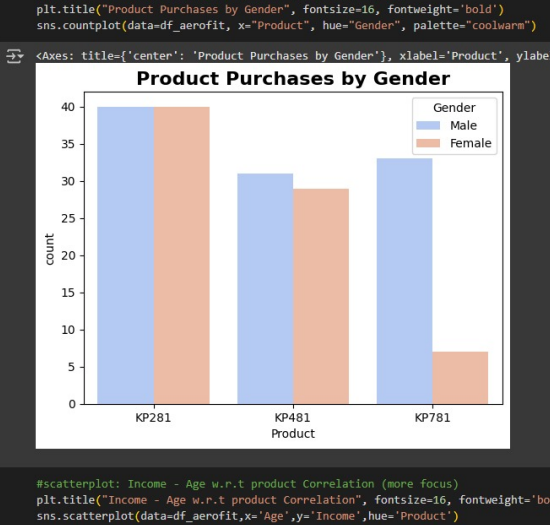
```
#How Product Purchases Vary by Gender: Grouped Bar chart:
plt.title("Product Purchases by Gender", fontsize=16, fontweight='bold')
sns.countplot(data=df_aerofit, x="Product", hue="Gender", palette="coolwarm")
```

```
<Axes: title={'center': 'Product Purchases by Gender'}, xlabel='Product', ylabel='count'>
```



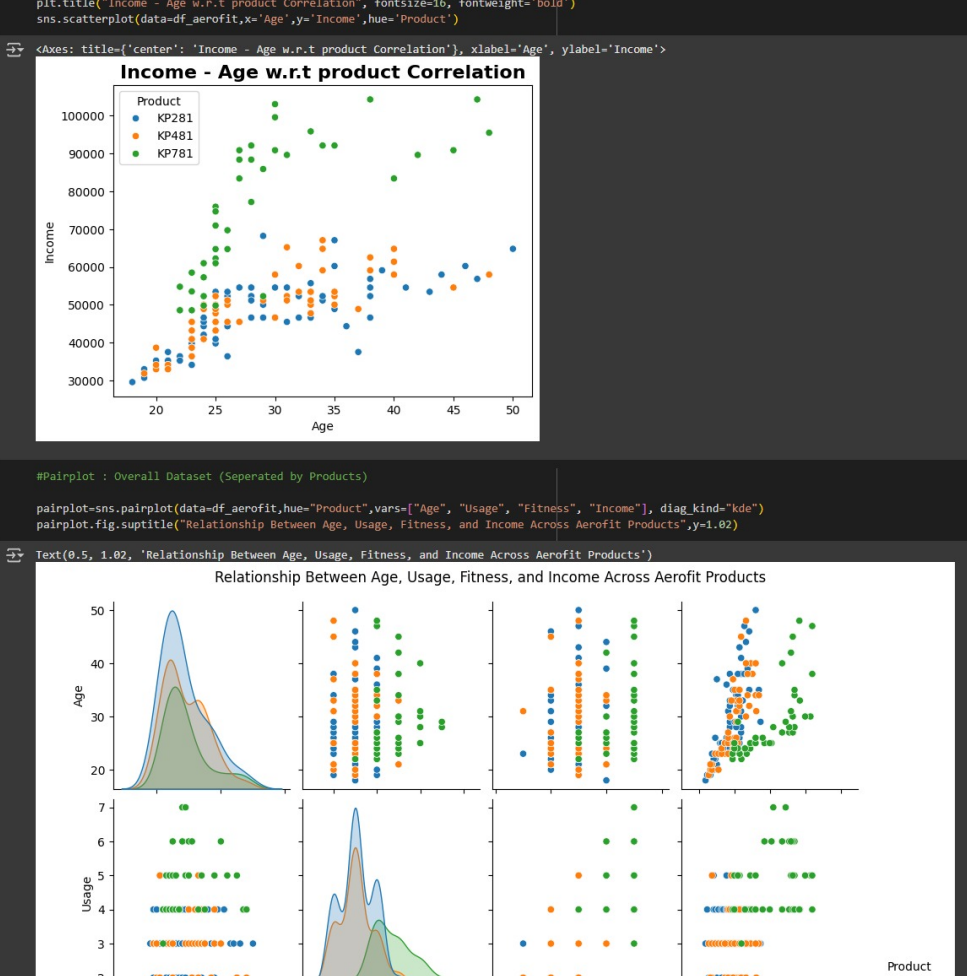
```
#scatterplot: Income - Age w.r.t product Correlation (more focus)
plt.title("Income - Age w.r.t product Correlation", fontsize=16, fontweight='bold')
sns.scatterplot(data=df_aerofit,x='Age',y='Income',hue='Product')
```

```
<Axes: title={'center': 'Income - Age w.r.t product Correlation'}, xlabel='Age', ylabel='Income'>
```



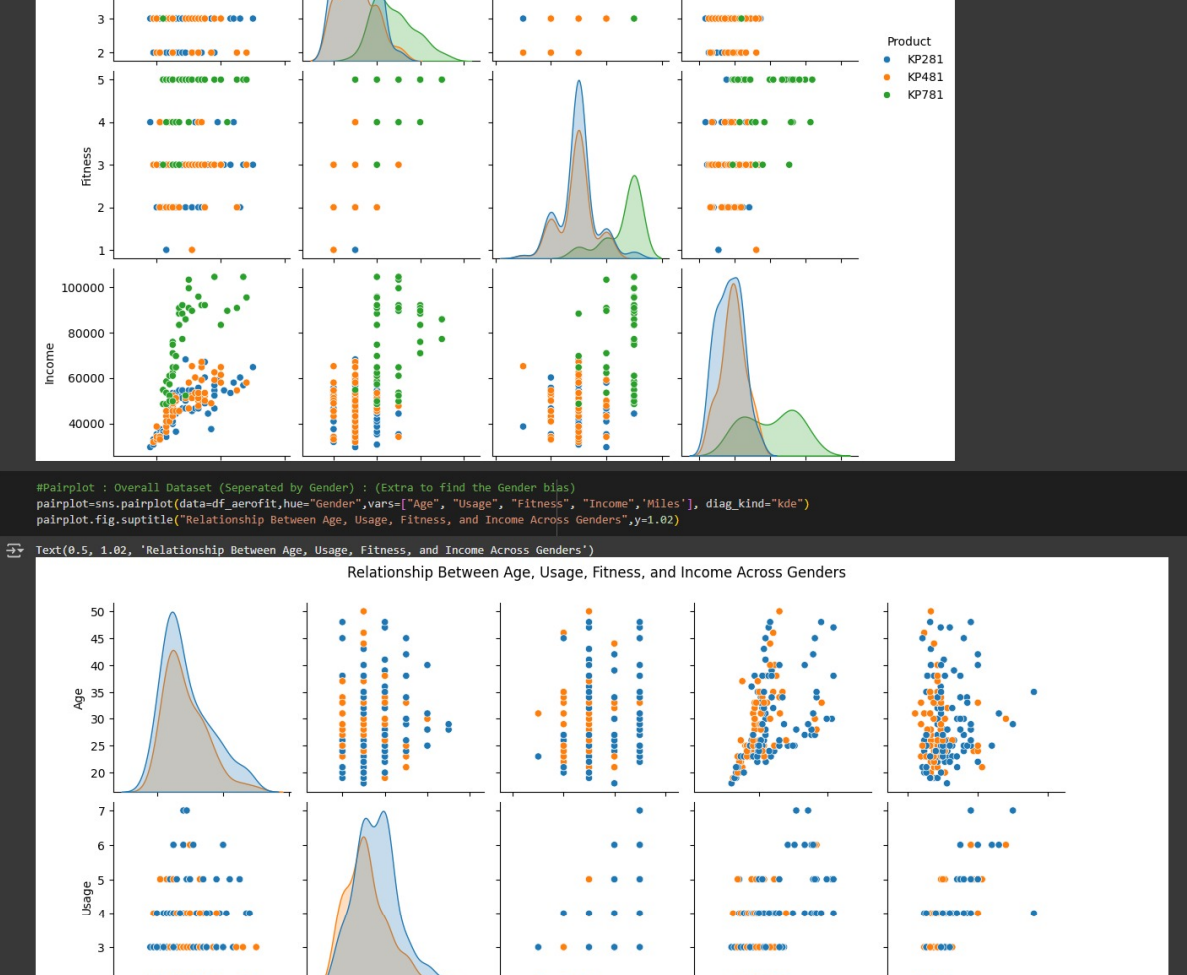
```
#Pairplot : Overall Dataset (Seperated by Products)

pairplot=sns.pairplot(data=df_aerofit,hue="Product",vars=["Age", "Usage", "Fitness", "Income"], diag_kind="kde")
pairplot.fig.suptitle("Relationship Between Age, Usage, Fitness, and Income Across Aerofit Products",y=1.02)
```

```
Text(0.5, 1.02, 'Relationship Between Age, Usage, Fitness, and Income Across Aerofit Products')
```



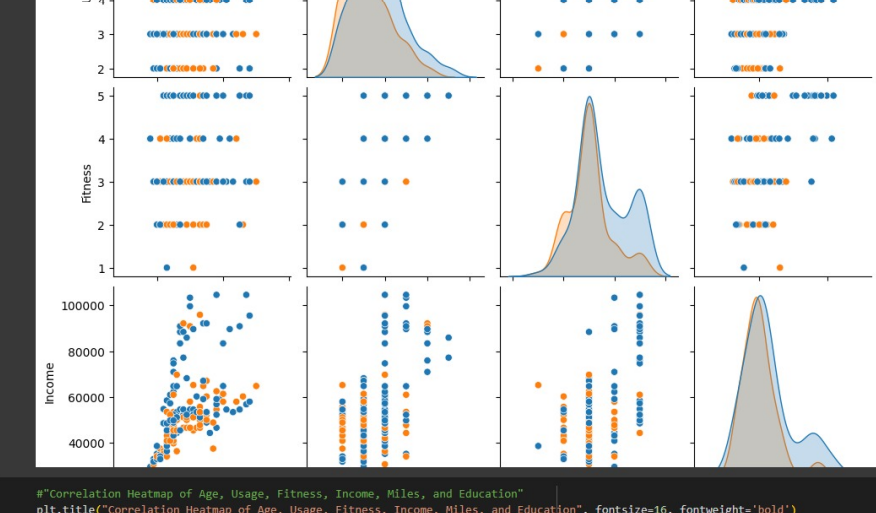
```
#Pairplot : Overall Dataset (Seperated by Gender) : (Extra to find the Gender bias)
pairplot=sns.pairplot(data=df_aerofit,hue="Gender",vars=["Age", "Usage", "Fitness", "Income","Miles"], diag_kind="kde")
pairplot.fig.suptitle("Relationship Between Age, Usage, Fitness, and Income Across Genders",y=1.02)
```

```
Text(0.5, 1.02, 'Relationship Between Age, Usage, Fitness, and Income Across Genders')
```



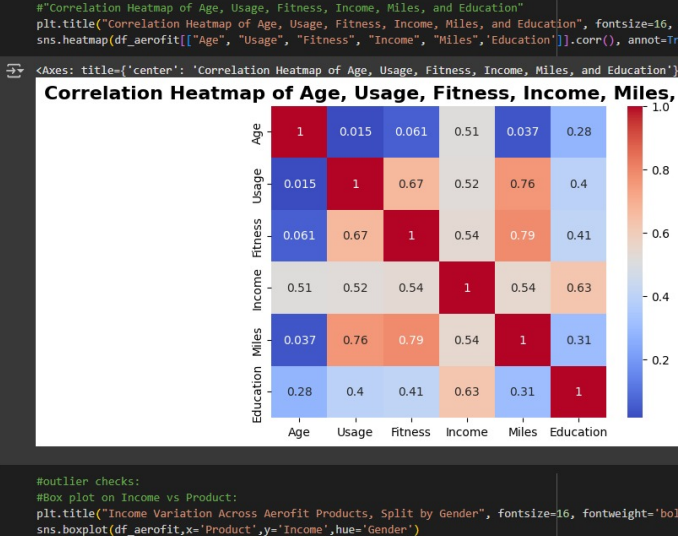
```
#"Correlation Heatmap of Age, Usage, Fitness, Income, Miles, and Education"
plt.title("Correlation Heatmap of Age, Usage, Fitness, Income, Miles, and Education", fontsize=16, fontweight='bold')
sns.heatmap(df_aerofit[["Age", "Usage", "Fitness", "Income", "Miles","Education"]].corr(), annot=True, cmap="coolwarm")
```

```
<Axes: title={'center': 'Correlation Heatmap of Age, Usage, Fitness, Income, Miles, and Education'}>
```



```
#outlier checks:
#Box plot on Income vs Product:
plt.title("Income Variation Across Aerofit Products, Split by Gender", fontsize=16, fontweight='bold')
sns.boxplot(df_aerofit,x='Product',y='Income',hue='Gender')
```

```
<Axes: title={'center': 'Income Variation Across Aerofit Products, Split by Gender'}, xlabel='Product', ylabel='Income'>
```



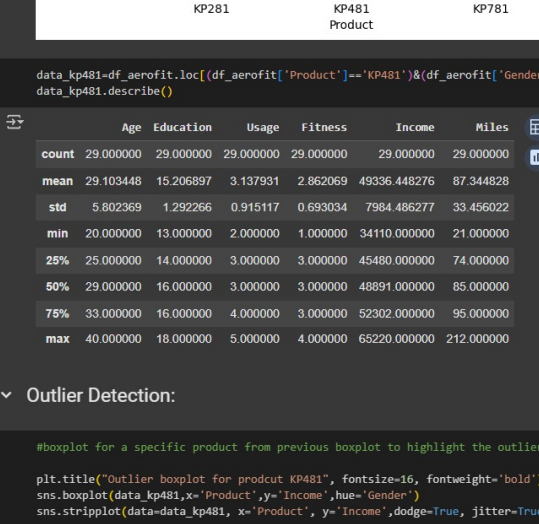
```
data_kp481=df_aerofit.loc[(df_aerofit['Product']=='KP481')&(df_aerofit['Gender']=='Female')]
data_kp481.describe()
```

	Age	Education	Usage	Fitness	Income	Miles
count	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000
mean	29.103448	15.206897	3.137931	2.862069	49336.448276	87.344828
std	5.802369	1.292266	0.915117	0.693034	7584.486277	33.456022
min	20.000000	13.000000	2.000000	1.000000	34110.000000	21.000000
25%	25.000000	14.000000	3.000000	3.000000	45480.000000	74.000000
50%	29.000000	16.000000	3.000000	3.000000	48891.000000	85.000000
75%	33.000000	16.000000	4.000000	3.000000	52302.000000	95.000000
max	40.000000	18.000000	5.000000	4.000000	63220.000000	212.000000

Outlier Detection:

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:

plt.title("Outlier boxplot for prodcut KP481", fontsize=16, fontweight='bold')
sns.boxplot(data_kp481,x='Product',y='Income',hue='Gender')
sns.stripplot(data=data_kp481, x='Product', y='Income',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP481'}, xlabel='Product', ylabel='Income'>
```



```
#upper limit
```

```
Q1_i=np.percentile(data_kp481['Income'],25)
Q1_i
```

```
np.float64(45480.0)
```

```
Q3_i=np.percentile(data_kp481['Income'],75)
Q3_i
```

```
np.float64(52302.0)
```

```
Q2_i=np.percentile(data_kp481['Income'],50)
Q2_i
```

```
np.float64(48891.0)
```

```
Iqr_income=Q3_i-Q1_i
Iqr_income
```

```
np.float64(6822.0)
```

```
upper_limit_income=Q3_i+(1.5*Iqr_income)
upper_limit_income
```

```
np.float64(62535.0)
```

```
outlier_income=data_kp481[data_kp481['Income']>upper_limit_income]
len(outlier_income)
```

```
2
```

```
#outliers in table format:(detected)

outlier_income
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
117	KP481	31	Female	18	Single	2	1	65220	21
126	KP481	34	Female	16	Partnered	4	3	64809	95

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

```
#lower limit
```

```
Q1_i
```

```
np.float64(45480.0)
```

```
lower_limit_income=Q1_i-(1.5*Iqr_income)
lower_limit_income
```

```
np.float64(35247.0)
```

```
outlier_income=data_kp481[data_kp481['Income']<lower_limit_income]
len(outlier_income)
```

```
2
```

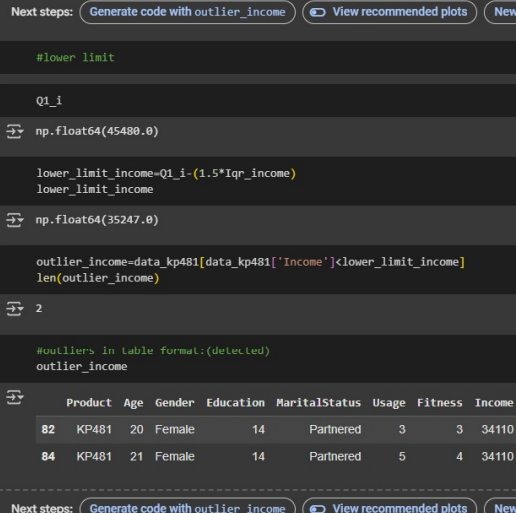
```
#outliers in table format:(detected)
outlier_income
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
82	KP481	20	Female	14	Partnered	3	3	34110	106
84	KP481	21	Female	14	Partnered	5	4	34110	212

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

```
#Box plot on age vs Product : Outlier Detection
plt.title("Variation in Age Across Products, Split by Gender", fontsize=16, fontweight='bold')
sns.boxplot(df_aerofit,x='Product',y='Age',hue='Gender')
```

```
<Axes: title={'center': 'Variation in Age Across Products, Split by Gender'}, xlabel='Product', ylabel='Age'>
```



```
kp_281_box=df_aerofit.loc[(df_aerofit['Product']=='KP281')&(df_aerofit['Gender']=='Female')]
kp_481_box=df_aerofit.loc[(df_aerofit['Product']=='KP481')&(df_aerofit['Gender']=='Male')]
kp_781_box=df_aerofit.loc[(df_aerofit['Product']=='KP781')&(df_aerofit['Gender']=='Male')]
```

```
kp_281_box.describe()
```

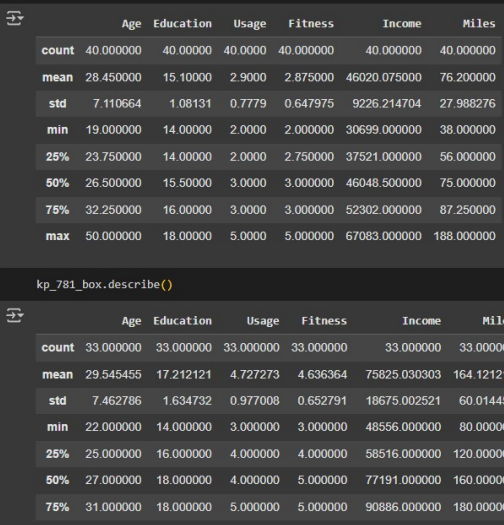
	Age	Education	Usage	Fitness	Income	Miles
count	40.000000	40.00000	40.0000	40.000000	40.000000	40.000000
mean	28.450000	15.10000	2.9000	2.875000	46020.075000	76.200000
std	7.110664	1.08131	0.7779	0.647975	9226.214704	27.968276
min	19.000000	14.00000	2.0000	2.000000	30699.000000	38.000000
25%	23.750000	14.00000	2.0000	2.750000	37521.000000	56.000000
50%	26.500000	15.50000	3.0000	3.000000	46048.500000	75.000000
75%	32.250000	16.00000	3.0000	3.000000	52302.000000	87.250000
max	50.000000	18.00000	5.0000	3.000000	67083.000000	188.000000

```
kp_781_box.describe()
```

	Age	Education	Usage	Fitness	Income	Miles
count	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000
mean	29.545455	17.212121	4.727273	4.636364	75825.030303	164.121212
std	7.462786	1.634732	0.977008	0.652791	18675.002521	60.014455
min	22.000000	14.000000	3.000000	3.000000	48556.000000	80.000000
25%	25.000000	16.000000	4.000000	4.000000	58516.000000	120.000000
50%	27.000000	18.000000	5.000000	5.000000	77191.000000	160.000000
75%	31.000000	18.000000	5.000000	5.000000	90886.000000	180.000000
max	48.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
plt.title("Outlier boxplot for prodcut KP281", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_281_box,x='Product',y='Age')
sns.stripplot(data=kp_281_box, x='Product', y='Age',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP281'}, xlabel='Product', ylabel='Age'>
```



```
Q1_a=np.percentile(kp_281_box['Age'],25)
Q1_a
```

```
np.float64(23.75)
```

```
Q3_a=np.percentile(kp_281_box['Age'],75)
Q3_a
```

```
np.float64(32.25)
```

```
Iqr_age=Q3_a-Q1_a
print('IQR (Age):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age ,',','lower limit:',lower_limit_age)
```

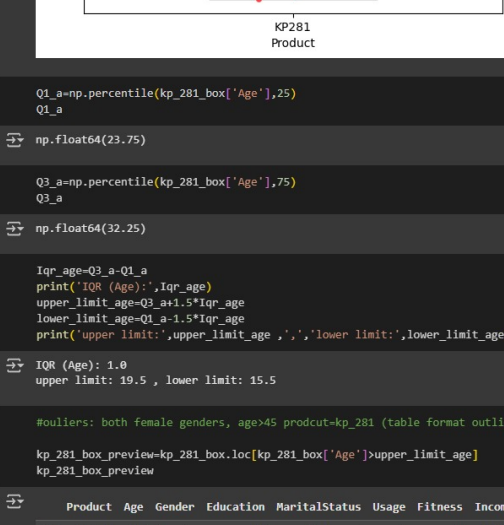
```
IQR (Age): 1.0
upper limit: 19.5 , lower limit: 15.5
```

```
#outliers: both female genders, age>45 product-kp_281 (table format outliers detected):

kp_281_box_preview=kp_281_box.loc[kp_281_box['Age']>upper_limit_age]
kp_281_box_preview
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
77	KP281	46	Female	16	Partnered	3	2	60261	47
79	KP281	50	Female	16	Partnered	3	3	64809	66

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
plt.title("Outlier boxplot for prodcut KP781", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_781_box,x='Product',y='Age')
sns.stripplot(data=kp_781_box, x='Product', y='Age',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP781'}, xlabel='Product', ylabel='Age'>
```



```
Q1_a=np.percentile(kp_781_box['Age'],25)
Q1_a
```

```
np.float64(25.0)
```

```
Q3_a=np.percentile(kp_781_box['Age'],75)
Q3_a
```

```
np.float64(31.0)
```

```
Iqr_age=Q3_a-Q1_a
print('IQR (Age):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age ,',','lower limit:',lower_limit_age)
```

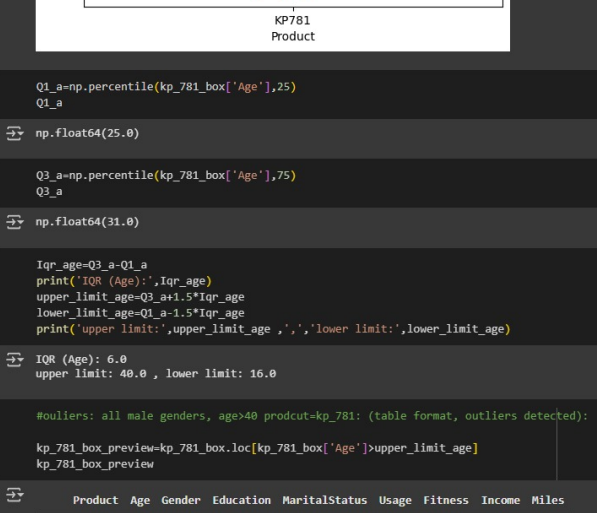
```
IQR (Age): 6.0
upper limit: 40.0 , lower limit: 16.0
```

```
#outliers: all male genders, age>40 product-kp_781: (table format, outliers detected):

kp_781_box_preview=kp_781_box.loc[kp_781_box['Age']>upper_limit_age]
kp_781_box_preview
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

```
#Box plot on Usage vs Product : Outlier Detection
plt.title("Variation in Usage Across Products, Split by Gender", fontsize=16, fontweight='bold')
sns.boxplot(df_aerofit,x='Product',y='Usage',hue='Gender')
```

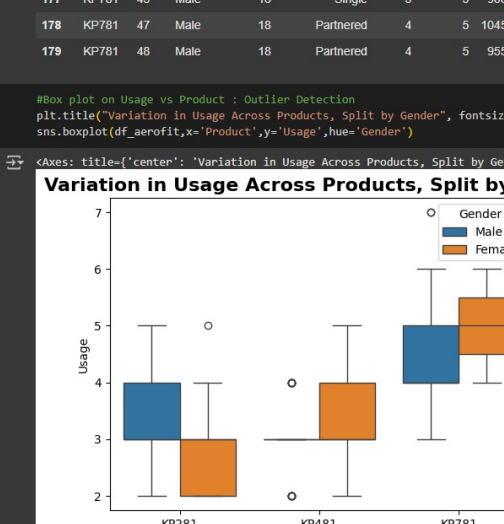
```
<Axes: title={'center': 'Variation in Usage Across Products, Split by Gender'}, xlabel='Product', ylabel='Usage'>
```



```
kp_281_box=df_aerofit.loc[(df_aerofit['Product']=='KP281')&(df_aerofit['Gender']=='Female')]
kp_481_box=df_aerofit.loc[(df_aerofit['Product']=='KP481')&(df_aerofit['Gender']=='Male')]
kp_781_box=df_aerofit.loc[(df_aerofit['Product']=='KP781')&(df_aerofit['Gender']=='Male')]
```

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
plt.title("Outlier boxplot for prodcut KP281", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_281_box,x='Product',y='Usage')
sns.stripplot(data=kp_281_box, x='Product', y='Usage',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP281'}, xlabel='Product', ylabel='Usage'>
```



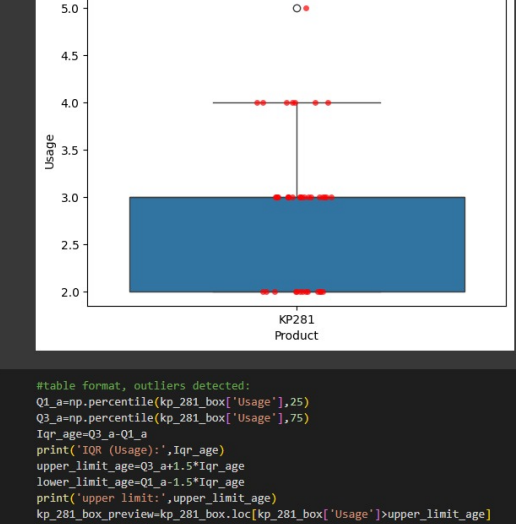
```
#table format, outliers detected:
Q1_a=np.percentile(kp_281_box['Usage'],25)
Q3_a=np.percentile(kp_281_box['Usage'],75)
Iqr_age=Q3_a-Q1_a
print('IQR (Usage):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age)
kp_281_box_preview=kp_281_box.loc[kp_281_box['Usage']>upper_limit_age]
kp_281_box_preview
```

```
IQR (Usage): 1.0
upper limit: 4.5
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
23	KP281	24	Female	16	Partnered	5	5	44343	188

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
plt.title("Outlier boxplot for prodcut KP481", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_481_box,x='Product',y='Usage')
sns.stripplot(data=kp_481_box, x='Product', y='Usage',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP481'}, xlabel='Product', ylabel='Usage'>
```



```
#table format, outliers detected:
Q1_a=np.percentile(kp_481_box['Usage'],25)
Q3_a=np.percentile(kp_481_box['Usage'],75)
Iqr_age=Q3_a-Q1_a
print('IQR (Usage):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age,'lower limit:',lower_limit_age)
kp_481_box_preview=kp_481_box.loc[kp_481_box['Usage']>upper_limit_age]
kp_481_box_preview
```

```
IQR (Usage): 0.0
upper limit: 3.0 lower limit: 3.0
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
90	KP481	23	Male	16	Partnered	4	3	45480	127
103	KP481	25	Male	14	Partnered	4	3	45480	170
107	KP481	25	Male	14	Single	4	3	48891	127
110	KP481	26	Male	16	Single	4	3	51165	106
111	KP481	27	Male	16	Single	4	2	45480	53
118	KP481	32	Male	16	Single	4	3	60261	127
120	KP481	33	Male	13	Partnered	4	4	53439	170

Next steps: Generate code with kp_481_box_preview View recommended plots New interactive sheet

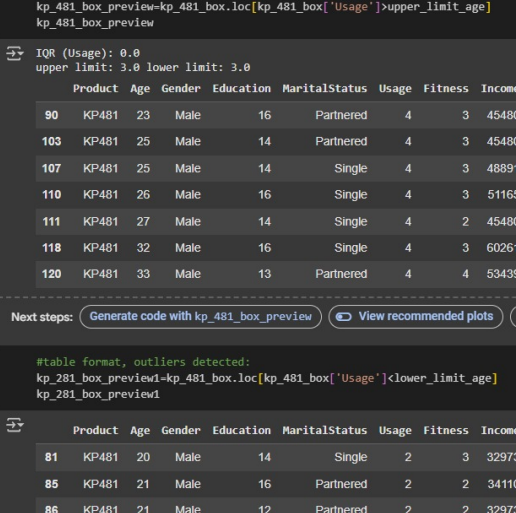
```
#table format, outliers detected:
kp_281_box_preview1=kp_481_box.loc[kp_481_box['Usage']<lower_limit_age]
kp_281_box_preview1
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
81	KP481	20	Male	14	Single	2	3	32973	53
85	KP481	21	Male	16	Partnered	2	2	34110	42
86	KP481	21	Male	12	Partnered	2	2	32973	53
99	KP481	25	Male	16	Partnered	2	2	52302	42
105	KP481	25	Male	16	Partnered	2	3	50028	53
138	KP481	45	Male	16	Partnered	2	2	54576	42
139	KP481	48	Male	16	Partnered	2	3	57987	64

Next steps: Generate code with kp_281_box_preview1 View recommended plots New interactive sheet

```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
plt.title("Outlier boxplot for prodcut KP781", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_781_box,x='Product',y='Usage')
sns.stripplot(data=kp_781_box, x='Product', y='Usage',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP781'}, xlabel='Product', ylabel='Usage'>
```



```
#table format, outliers detected:
Q1_a=np.percentile(kp_781_box['Usage'],25)
Q3_a=np.percentile(kp_781_box['Usage'],75)
Iqr_age=Q3_a-Q1_a
print('IQR (Usage):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age)
kp_781_box_preview=kp_781_box.loc[kp_781_box['Usage']>upper_limit_age]
kp_781_box_preview
```

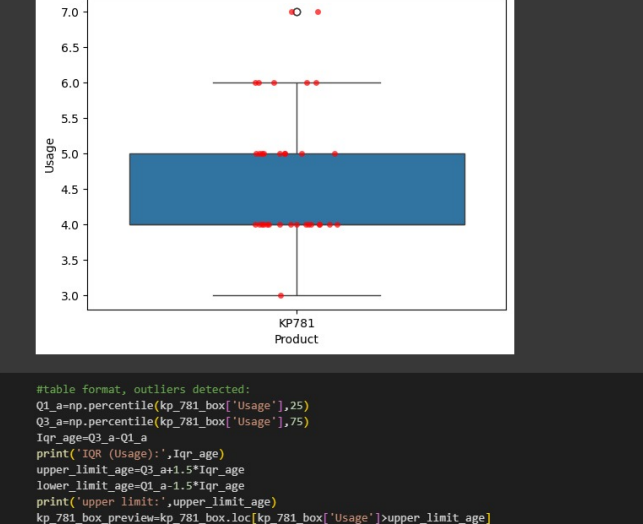
```
IQR (Usage): 1.0
upper limit: 6.5
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
163	KP781	28	Male	16	Partnered	7	5	77191	180
166	KP781	29	Male	14	Partnered	7	5	85906	300

Next steps: Generate code with kp_781_box_preview View recommended plots New interactive sheet

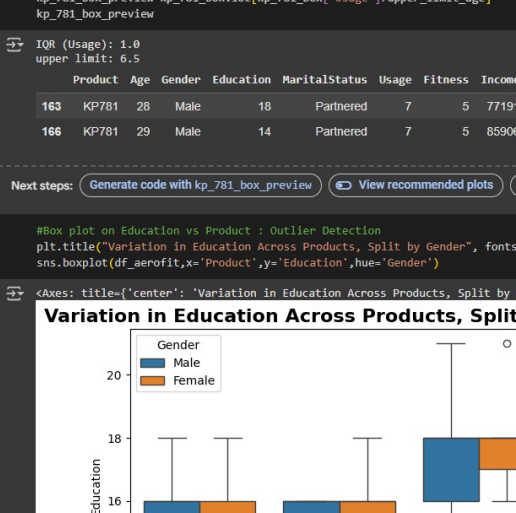
```
#Box plot on Education vs Product : Outlier Detection
plt.title("Variation in Education Across Products, Split by Gender", fontsize=16, fontweight='bold')
sns.boxplot(df_aerofit,x='Product',y='Education',hue='Gender')
```

```
<Axes: title={'center': 'Variation in Education Across Products, Split by Gender'}, xlabel='Product', ylabel='Education'>
```



```
#boxplot for a specific product from previous boxplot to highlight the outlier and the necessary calculations:
kp_781_boxf=df_aerofit.loc[(df_aerofit['Product']=='KP781')&(df_aerofit['Gender']=='Female')]
plt.title("Outlier boxplot for prodcut KP781", fontsize=16, fontweight='bold')
sns.boxplot(data=kp_781_boxf,x='Product',y='Education')
sns.stripplot(data=kp_781_boxf, x='Product', y='Education',dodge=True, jitter=True, marker='o', color='red', alpha=0.7)
```

```
<Axes: title={'center': 'Outlier boxplot for prodcut KP781'}, xlabel='Product', ylabel='Education'>
```



```
#table format, outliers detected:
Q1_a=np.percentile(kp_781_boxf['Education'],25)
Q3_a=np.percentile(kp_781_boxf['Education'],75)
Iqr_age=Q3_a-Q1_a
print('IQR (Education):',Iqr_age)
upper_limit_age=Q3_a+1.5*Iqr_age
lower_limit_age=Q1_a-1.5*Iqr_age
print('upper limit:',upper_limit_age)
kp_781_box_preview=kp_781_boxf.loc[kp_781_boxf['Education']>upper_limit_age]
kp_781_box_preview
```

```
IQR (Education): 1.0
upper limit: 19.5
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
157	KP781	26	Female	21	Single	4	3	69721	100

```
##Conversion##### for contingency tables
def income_range(x):
  if (x['Income']>=29562 and x['Income']<=54568.3):
    x['Income_range']="Low"
    return x
  elif(x['Income']>54568.3 and x['Income']<=75019):
    x['Income_range']="Medium"
    return x
  else:
    x['Income_range']="High"
    return x
temp=df_aerofit.apply(income_range,axis=1)
temp.head()

bins = [0, 20, 35,float("inf")]
labels = ["Young", "Teenagers", "Middle-aged"]
temp["Age"] = pd.cut(temp["Age"], bins=bins, labels=labels)

bins = [0, 14, 18,float("inf")]
labels = ["Low Education", "Medium Education", "High Education"]
temp["Education"] = pd.cut(temp["Education"], bins=bins, labels=labels)


bins = [0, 3, 5,float("inf")]
labels = ["Low Usage", "Medium Usage", "High Usgae"]
temp["Usage"] = pd.cut(temp["Usage"], bins=bins, labels=labels)


bins = [20, 100, 250,float("inf")]
labels = ["Low Miles", "Medium Miles", "High Miles"]
temp["Miles"] = pd.cut(temp["Miles"], bins=bins, labels=labels)


bins = [0, 2, 4,float("inf")]
labels = ["Poor Shape", "Fair Shape", "Excellent Shape"]
temp["Fitness"] = pd.cut(temp["Fitness"], bins=bins, labels=labels)
```

```
temp.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income_range
0	KP281	Young	Male	Low Education	Single	Low Usage	Fair Shape	29562	Medium Miles	Low
1	KP281	Young	Male	Medium Education	Single	Low Usage	Fair Shape	31836	Low Miles	Low
2	KP281	Young	Female	Low Education	Partnered	Medium Usage	Fair Shape	30699	Low Miles	Low
3	KP281	Young	Male	Low Education	Single	Low Usage	Fair Shape	32973	Low Miles	Low
4	KP281	Young	Male	Low Education	Partnered	Medium Usage	Poor Shape	35247	Low Miles	Low

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

Contingency tables:

Marginal Probability:

```
#generalised contingency table: On product vs Gender:
"Among all customers, 44.4% purchased KP281."
"Among all customers, 33.3% purchased KP481."
"Among all customers, 22.2% purchased KP781."

"Note: Only the above statements are common for the following tables. The distribution is different."


"Among all Male customers, 18.3% purchased KP781."
"Among all Female customers, 22.2% purchased KP281."
"Among all Male customers, 22.2% purchased KP281."
"Among all Male customers, 17.2% purchased KP481."

pd.crosstab(index=temp["Product"],columns=temp["Gender"],margins=True,normalize=True)*100
```

Gender	Female	Male	All
Product			
KP281	22.222222	22.222222	44.444444
KP481	16.111111	17.222222	33.333333
KP781	3.888889	18.333333	22.222222
All	42.222222	57.777778	100.000000

```
#contingency on Income range (High, medium, low income groups) vs products:
"Among all customers, 65.0% are in the Low-Income range."
"Among all customers, 23.3% are in the Medium-Income range."
"Among all customers, 11.7% are in the High-Income range."
"Among High-Income customers, 10.0% bought KP781 and are Male."
"Among Low-Income customers, 17.8% bought KP281 and are Female."
"Among Low-Income customers, 13.3% bought KP481 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Income_range'],margins=True,normalize=True)*100
```

	Income_range	High	Low	Medium	All
Product	Gender				
KP281	Female	0.000000	17.777778	4.444444	22.222222
	Male	0.000000	16.666667	5.555556	22.222222
KP481	Female	0.000000	12.777778	3.333333	16.111111
	Male	0.000000	13.333333	3.888889	17.222222
KP781	Female	1.666667	1.111111	1.111111	3.888889
	Male	10.000000	3.333333	5.000000	18.333333
All		11.666667	65.000000	23.333333	100.000000

```
#Contingency table### Marginal Probability###
"Among all customers, 59.4% are Partnered."
"Among all customers, 40.6% are Single."
"Among Partnered customers, 15.0% bought KP281 and are Female."
"Among Partnered customers, 11.7% bought KP481 and are Male."
"Among Single customers, 10.6% bought KP281 and are Male."
"Among Partnered customers, 10.6% bought KP781 and are Male."

pd.crosstab(index=[df_aerofit["Product"], df_aerofit["Gender"]],columns=df_aerofit["MaritalStatus"],margins=True,normalize=True)*100
```

	MaritalStatus	Partnered	Single	All
Product	Gender			
KP281	Female	15.000000	7.222222	22.222222
	Male	11.666667	10.555556	22.222222
KP481	Female	8.333333	7.777778	16.111111
	Male	11.666667	5.555556	17.222222
KP781	Female	2.222222	1.666667	3.888889
	Male	10.555556	7.777778	18.333333
All		59.444444	40.555556	100.000000

```
#Deeper contingency tables: On Product-Gender vs Age (in categories)
"Among all customers, 78.9% are Teenagers."
"Among all customers, 15.6% are Middle-aged."
"Among all customers, 5.6% are Young."
"Among Teenagers, 18.3% bought KP281 and are Female."
"Among Teenagers, 15.0% bought KP281 and are Male."
"Among Teenagers, 13.3% bought KP481 and are Female."
"Among Teenagers, 13.3% bought KP481 and are Male."
"Among Teenagers, 15.0% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Age'],margins=True,normalize=True)*100
```

	Age	Young	Teenagers	Middle-aged	All
Product	Gender				
KP281	Female	1.111111	18.333333	2.777778	22.222222
	Male	2.222222	15.000000	5.000000	22.222222
KP481	Female	0.555556	13.333333	2.222222	16.111111
	Male	1.666667	13.333333	2.222222	17.222222
KP781	Female	0.000000	3.888889	0.000000	3.888889
	Male	0.000000	15.000000	3.333333	18.333333
All		5.555556	78.888889	15.555556	100.000000

```
#Deeper contingency tables:On Product-Gender vs Education (in categories)
"Among all customers, 35.0% have Low Education."
"Among all customers, 62.8% have Medium Education."
"Among all customers, 2.2% have High Education."
"Among Medium Education customers, 12.2% bought KP281 and are Female."
"Among Medium Education customers, 12.7% bought KP281 and are Male."
"Among Medium Education customers, 8.8% bought KP481 and are Female."
"Among Medium Education customers, 10.0% bought KP481 and are Male."
"Among Medium Education customers, 15.6% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Education'],margins=True,normalize=True)*100
```

	Education	Low Education	Medium Education	High Education	All
Product	Gender				
KP281	Female	10.000000	12.222222	0.000000	22.222222
	Male	9.444444	12.777778	0.000000	22.222222
KP481	Female	7.222222	8.888889	0.000000	16.111111
	Male	7.222222	10.000000	0.000000	17.222222
KP781	Female	0.000000	3.333333	0.555556	3.888889
	Male	1.111111	15.555556	1.666667	18.333333
All		35.000000	62.777778	2.222222	100.000000

```
#Deeper contingency tables: On Product-Gender vs Usage(in categories)
"Among all customers, 56.7% are Low Usage users."
"Among all customers, 38.3% are Medium Usage users."
"Among all customers, 5.0% are High Usage users."
"Among Low Usage customers, 17.8% bought KP281 and are Female."
"Among Low Usage customers, 13.3% bought KP281 and are Male."
"Among Low Usage customers, 11.7% bought KP481 and are Female."
"Among Low Usage customers, 13.3% bought KP481 and are Male."
"Among Medium Usage customers, 13.9% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Usage'],margins=True,normalize=True)*100
```

	Usage	Low Usage	Medium Usage	High Usgae	All
Product	Gender				
KP281	Female	17.777778	4.444444	0.000000	22.222222
	Male	13.333333	8.888889	0.000000	22.222222
KP481	Female	11.666667	4.444444	0.000000	16.111111
	Male	13.333333	3.888889	0.000000	17.222222
KP781	Female	0.000000	2.777778	1.111111	3.888889
	Male	0.555556	13.888889	3.888889	18.333333
All		56.666667	38.333333	5.000000	100.000000

```
#Deeper contingency tables:On Product-Gender vs miles (in categories)
"Among all customers, 63.3% are Low Miles users."
"Among all customers, 34.4% are Medium Miles users."
"Among all customers, 2.2% are High Miles users."
"Among Low Miles customers, 18.9% bought KP281 and are Female."
"Among Low Miles customers, 15.6% bought KP281 and are Male."
"Among Low Miles customers, 12.2% bought KP481 and are Female."
"Among Low Miles customers, 12.2% bought KP481 and are Male."
"Among Medium Miles customers, 13.3% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Miles'],margins=True,normalize=True)*100
```

	Miles	Low Miles	Medium Miles	High Miles	All
Product	Gender				
KP281	Female	18.888889	3.333333	0.000000	22.222222
	Male	15.555556	6.666667	0.000000	22.222222
KP481	Female	12.222222	3.888889	0.000000	16.111111
	Male	12.222222	5.000000	0.000000	17.222222
KP781	Female	1.111111	2.222222	0.555556	3.888889
	Male	3.333333	13.333333	1.666667	18.333333
All		63.333333	34.444444	2.222222	100.000000

```
#Deeper contingency tables: On Product-Gender vs Fitness (in categories)
"Among all customers, 67.2% are in Fair Shape."
"Among all customers, 15.6% are in Poor Shape."
"Among all customers, 17.2% are in Excellent Shape."
"Among Fair Shape customers, 18.9% bought KP281 and are Male."
"Among Fair Shape customers, 16.1% bought KP281 and are Female."
"Among Fair Shape customers, 13.9% bought KP481 and are Male."
"Among Fair Shape customers, 12.2% bought KP481 and are Female."
"Among Excellent Shape customers, 13.3% bought KP781 and are Male"

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Fitness'],margins=True,normalize=True)*100
```

	Fitness	Poor Shape	Fair Shape	Excellent Shape	All
Product	Gender				
KP281	Female	5.555556	16.111111	0.555556	22.222222
	Male	2.777778	18.888889	0.555556	22.222222
KP481	Female	3.888889	12.222222	0.000000	16.111111
	Male	3.333333	13.888889	0.000000	17.222222
KP781	Female	0.000000	1.111111	2.777778	3.888889
	Male	0.000000	5.000000	13.333333	18.333333
All		15.555556	67.222222	17.222222	100.000000

Conditional Probability

```
#P(Gender|Product)
"Among customers who purchased KP281, 50.0% are Female and 50.0% are Male."
"Among customers who purchased KP481, 48.3% are Female and 51.7% are Male."
"Among customers who purchased KP781, 82.5% are Male."

pd.crosstab(index=temp["Product"],columns=temp["Gender"],normalize='index')*100
```

Gender	Female	Male
Product		
KP281	50.000000	50.000000
KP481	48.333333	51.666667
KP781	17.500000	82.500000

```
#P(Product|Gender)
"Among Female customers, 52.6% purchased KP281."
"Among Male customers, 38.5% purchased KP281."
"Among Female customers, 38.2% purchased KP481."
"Among Male customers, 29.8% purchased KP481."
"Among Female customers, only 9.2% purchased KP781."
"Among Male customers, 31.7% purchased KP781."

pd.crosstab(index=temp["Product"],columns=temp["Gender"],normalize='columns')*100
```

Gender	Female	Male
Product		
KP281	52.631579	38.461538
KP481	38.157895	29.807692
KP781	9.210526	31.730769

```
#P(Income_range|Product,Gender)
"Among Female customers who purchased KP281, 80.0% are in the Low-Income range."
"Among Male customers who purchased KP281, 75.0% are in the Low-Income range."
"Among Female customers who purchased KP481, 79.3% are in the Low-Income range."
"Among Male customers who purchased KP481, 77.4% are in the Low-Income range."
"Among Female customers who purchased KP781, 42.9% are in the High-Income range."
"Among Male customers who purchased KP781, 54.5% are in the High-Income range."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Income_range'],normalize='index')*100
```

	Income_range	High	Low	Medium
Product	Gender			
KP281	Female	0.000000	80.000000	20.000000
	Male	0.000000	75.000000	25.000000
KP481	Female	0.000000	79.310345	20.689655
	Male	0.000000	77.419355	22.580645
KP781	Female	42.857143	28.571429	28.571429
	Male	54.545455	18.181818	27.272727

```
#P(Product,Gender|Income_range)
"Among High-Income customers, 85.7% bought KP781 and are Male."
"Among Low-Income customers, 27.4% bought KP281 and are Female."
"Among Medium-Income customers, 23.8% bought KP281 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Income_range'],normalize='columns')*100
```

	Income_range	High	Low	Medium
Product	Gender			
KP281	Female	0.000000	27.350427	19.047619
	Male	0.000000	25.641026	23.809524
KP481	Female	0.000000	19.658120	14.285714
	Male	0.000000	20.512821	16.666667
KP781	Female	14.285714	1.709402	4.761905
	Male	85.714286	5.128205	21.428571

```
#P(MaritalStatus|Product,Gender)
"Among all customers who bought KP281 and are Female, 67.5% are Partnered."
"Among all customers who bought KP281 and are Male, 52.5% are Partnered."
"Among all customers who bought KP481 and are Female, 51.7% are Partnered."
"Among all customers who bought KP481 and are Male, 67.7% are Partnered."
"Among all customers who bought KP781 and are Female, 57.1% are Partnered."
"Among all customers who bought KP781 and are Male, 57.6% are Partnered."

pd.crosstab(index=[df_aerofit["Product"], df_aerofit["Gender"]],columns=df_aerofit["MaritalStatus"],normalize='index')*100
```

	MaritalStatus	Partnered	Single
Product	Gender		
KP281	Female	67.500000	32.500000
	Male	52.500000	47.500000
KP481	Female	51.724138	48.275862
	Male	67.741935	32.258065
KP781	Female	57.142857	42.857143
	Male	57.575758	42.424242

```
#P(Product,Gender|MaritalStatus)
"Among Single (Marital status),26% bought KP281 and are Male"
"Among Partnered (Marital status),25% bought KP281 and are Female"
"Among Single (Marital status),19.1% bought KP481 and are Female"
"Among Partnered (Marital status),19.6% bought KP481 and are Male"
"Among Partnered (Marital status),17.7% bought KP781 and are Male"
"Among Single (Marital status),19.1% bought KP781 and are Male"

pd.crosstab(index=[df_aerofit["Product"], df_aerofit["Gender"]],columns=df_aerofit["MaritalStatus"],normalize='columns')*100
```

	MaritalStatus	Partnered	Single
Product	Gender		
KP281	Female	25.233645	17.808219
	Male	19.626168	26.027397
KP481	Female	14.018692	19.178082
	Male	19.626168	13.698630
KP781	Female	3.738318	4.109589
	Male	17.757009	19.178082

```
#P(Age|Product,Gender):
"Among all customers who bought KP281 and are Female, 82.5% are Teenagers."
"Among all customers who bought KP281 and are Male, 67.5% are Teenagers."
"Among all customers who bought KP481 and are Female, 82.7% are Teenagers."
"Among all customers who bought KP481 and are Male, 77.4% are Teenagers."
"Among all customers who bought KP781 and are Female, 100% are Teenagers."
"Among all customers who bought KP781 and are Male, 81.8% are Teenagers."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Age'],normalize='index') * 100
```

	Age	Young	Teenagers	Middle-aged
Product	Gender			
KP281	Female	5.000000	82.500000	12.500000
	Male	10.000000	67.500000	22.500000
KP481	Female	3.448276	82.758621	13.793103
	Male	9.677419	77.419355	12.903226
KP781	Female	0.000000	100.000000	0.000000
	Male	0.000000	81.818182	18.181818

```
#P(Product,Gender|Age):
"Among all Teenagers, 23% bought KP281 and are Female."
"Among all Young-aged group, 40% bought KP281 and are Male."
"Among all Middle-aged group, 32% bought KP281 and are Male."
"Among all Young-aged group, 30% bought KP481 and are Male."
"Among all Middle-aged group, 21.4% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Age'],normalize='columns') * 100



#Just because all Female KP781 buyers are Teenagers doesn't mean Teenagers overwhelmingly choose KP781.
#Teenagers may prefer other products, making KP781 a niche choice.
```

	Age	Young	Teenagers	Middle-aged
Product	Gender			
KP281	Female	20.0	23.239437	17.857143
	Male	40.0	19.014085	32.142857
KP481	Female	10.0	16.901408	14.285714
	Male	30.0	16.901408	14.285714
KP781	Female	0.0	4.929577	0.000000
	Male	0.0	19.014085	21.428571

```
#P(Education|Product,Gender)
"Among Female who purchased KP281, 55% are with Medium Education"
"Among Male who purchaed KP281, 57% are with Medium Education"
"Among Female who purchaed KP481, 55% are with Medium Education"
"Among Male who purchaed KP481, 58% are with Medium Education"
"Among Female who purchaed KP781, 85% are with Medium Education"
"Among Male who purchaed KP781, 84.8% are with Medium Education"

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Education'],normalize='index')*100
```

	Education	Low Education	Medium Education	High Education
Product	Gender			
KP281	Female	45.000000	55.000000	0.000000
	Male	42.500000	57.500000	0.000000
KP481	Female	44.827586	55.172414	0.000000
	Male	41.935484	58.064516	0.000000
KP781	Female	0.000000	85.714286	14.285714
	Male	6.060606	84.848485	9.090909

```
#P(Product,Gender|Education)
"Among customers with High Education, 75.0% bought KP781 and are Male."
"Among customers with Medium Education, 24.8% bought KP781 and are Male."
"Among customers with Low Education, 28.6% bought KP281 and are Female."
"Among customers with Low Education, 27.0% bought KP281 and are Male."
"Among customers with Low Education, 20.6% bought KP481 and are Male and Female."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Education'],normalize='columns')*100
```

	Education	Low Education	Medium Education	High Education
Product	Gender			
KP281	Female	28.571429	19.469027	0.0
	Male	26.984127	20.353982	0.0
KP481	Female	20.634921	14.159292	0.0
	Male	20.634921	15.929204	0.0
KP781	Female	0.000000	5.309735	25.0
	Male	3.174603	24.778761	75.0

```
#P(Usage|Product,Gender)
"Among Female customers who purchased KP281, 80.0% are Low Usage."
"Among Male customers who purchased KP281, 60.0% are Low Usage."
"Among Male customers who purchased KP281, 40.0% are Medium Usage."

"Among Female customers who purchased KP481, 72.4% are Low Usage."
"Among Male customers who purchased KP481, 77.4% are Low Usage."

"Among Male customers who purchased KP781, 75.8% are Medium Usage."
"Among Female customers who purchased KP781, 71.4% are Medium Usage."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Usage'],normalize='index')*100
```

	Usage	Low Usage	Medium Usage	High Usgae
Product	Gender			
KP281	Female	80.000000	20.000000	0.000000
	Male	60.000000	40.000000	0.000000
KP481	Female	72.413793	27.586207	0.000000
	Male	77.419355	22.580645	0.000000
KP781	Female	0.000000	71.428571	28.571429
	Male	3.030303	75.757576	21.212121

```
#P(Product,Gender|Usage)
"Among High Usage customers, 77.8% bought KP781 and are Male."
"Among Low Usage customers, 31.4% bought KP281 and are Female."
"Among Medium Usage customers, 36.2% bought KP781 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Usage'],normalize='columns')*100
```

	Usage	Low Usage	Medium Usage	High Usgae
Product	Gender			
KP281	Female	31.372549	11.594203	0.000000
	Male	23.529412	23.188406	0.000000
KP481	Female	20.588235	11.594203	0.000000
	Male	23.529412	10.144928	0.000000
KP781	Female	0.000000	7.246377	22.222222
	Male	0.980392	36.231884	77.777778

```
#P(Miles|Product,Gender)
"Among Female customers who purchased KP281, 85.0% are Low Miles users."
"Among Male customers who purchased KP281, 70.0% are Low Miles users."
"Among Female customers who purchased KP481, 75.8% are Low Miles users."
"Among Male customers who purchased KP481, 70.9% are Low Miles users."
"Among Female customers who purchased KP781, 57.1% are Medium Miles users."
"Among Male customers who purchased KP781, 72.7% are Medium Miles users."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Miles'],normalize='index')*100
```

	Miles	Low Miles	Medium Miles	High Miles
Product	Gender			
KP281	Female	85.000000	15.000000	0.000000
	Male	70.000000	30.000000	0.000000
KP481	Female	75.862069	24.137931	0.000000
	Male	70.967742	29.032258	0.000000
KP781	Female	28.571429	57.142857	14.285714
	Male	18.181818	72.727273	9.090909

```
#P(Product,Gender|Miles)
"Among High Miles users, 75.0% bought KP781 and are Male."
"Among Medium Miles users, 38.7% bought KP781 and are Male."
"Among Low Miles users, 29.8% bought KP281 and are Female."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Miles'],normalize='columns')*100
```

	Miles	Low Miles	Medium Miles	High Miles
Product	Gender			
KP281	Female	29.824561	9.677419	0.0
	Male	24.561404	19.354839	0.0
KP481	Female	19.298246	11.290323	0.0
	Male	19.298246	14.516129	0.0
KP781	Female	1.754386	6.451613	25.0
	Male	5.263158	38.709677	75.0

```
#P(Fitness|Product,Gender)
"Among Female customers who purchased KP281, 72.5% are in Fair Shape."
"Among Male customers who purchased KP281, 85.0% are in Fair Shape."
"Among Female customers who purchased KP481, 75.8 are in Fair Shape."
"Among Male customers who purchased KP481, 80.6% are in Fair Shape."
"Among Female customers who purchased KP781, 71.4% are in Excellent Shape."
"Among Male customers who purchased KP781, 72.7% are in Excellent Shape."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Fitness'],normalize='index')*100
```

	Fitness	Poor Shape	Fair Shape	Excellent Shape
Product	Gender			
KP281	Female	25.000000	72.500000	2.500000
	Male	12.500000	85.000000	2.500000
KP481	Female	24.137931	75.862069	0.000000
	Male	19.354839	80.645161	0.000000
KP781	Female	0.000000	28.571429	71.428571
	Male	0.000000	27.272727	72.727273

```
#P(Product,Gender|Fitness)
"Among Excellent Shape customers, 77.4% bought KP781 and are Male."
"Among Poor Shape customers, 35.7% bought KP281 and are Female."
"Among Fair Shape customers, 28.1% bought KP281 and are Male."

pd.crosstab(index=[temp["Product"], temp["Gender"]],columns=temp['Fitness'],normalize='columns')*100
```

	Fitness	Poor Shape	Fair Shape	Excellent Shape
Product	Gender			
KP281	Female	35.714286	23.966942	3.225806
	Male	17.857143	28.099174	3.225806
KP481	Female	25.000000	18.181818	0.000000
	Male	21.428571	20.661157	0.000000
KP781	Female	0.000000	1.652893	16.129032
	Male	0.000000	7.438017	77.419355