Business Case: **Aerofit**

About Aerofit

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

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.

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

Downloading the dataset

```
! gdown 1YzcEnPQzFchTbYr7DvlV_hQo6R8wuPlB
```

```
Downloading...
From: https://drive.google.com/uc?id=1YzcEnPQzFchTbYr7DvlV_hQo6R8wuPlB
To: /content/Aerofit.csv
100% 7.28k/7.28k [00:00<00:00, 20.7MB/s]
```

Importing necessary Libraries

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

Reading the data

```
df = pd.read_csv('Aerofit.csv')
df
```

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
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

180 rows × 9 columns

```
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

Analysing basic metrics of the data like shape,data types of the attributes,checking for nulls and duplicates

```
df.shape
```

```
(180, 9)
```

```
df.columns
```

```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

```
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
```

```
df.Product.value_counts()
```

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

```
df.Gender.value_counts()
```

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

```
df.MaritalStatus.value_counts()
```

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

```
df.nunique()
```

```
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

```
df.loc[df.duplicated()]
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles

```
nulls = df.isnull().sum()
nulls
```

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

Non-Visual Analysis

The number of different treadmills purchased based on Gender

```
temp = df.groupby(['Product','Gender']).count().reset_index()
temp.rename(columns = {'Age':'Count'},inplace=True)
temp.iloc[:,:3]
```

	Product	Gender	Count
0	KP281	Female	40
1	KP281	Male	40
2	KP481	Female	29
3	KP481	Male	31
4	KP781	Female	7
5	KP781	Male	33

Modifying the data

- In order to include the prices in the dataframe as well, temporary dataframe 'pricing' is created & then we merge the original dataframe and pricing dataframe.

```
pricing = pd.DataFrame({
 "Product":["KP281","KP481","KP781"],
 "Product_pricing":[1500,1750,2500]
 })
```

```
pricing
```

	Product	Product_pricing
0	KP281	1500
1	KP481	1750
2	KP781	2500

```
df=df.merge(pricing, on='Product',how='left')
```

Creating a new column for deeper Analysis

```
df['Miles_per_use'] = df['Miles']/df['Usage']
```

Conversion of Numerical data to Categorical data for better analysis

- We converted Fitness rating into 5 categories ranging from Poor to Excellent.

```
df['Fitness_level'] = df['Fitness']
```

```
df["Fitness_level"].replace({1:"Poor", 2:"Mediocre", 3:"Average",4:"Good", 5:"Excellent"},inplace=True)
df
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Product_pricing	Miles_per_use	Fitness_leve
0	KP281	18	Male	14	Single	3	4	29562	112	1500	37.333333	Goo
1	KP281	19	Male	15	Single	2	3	31836	75	1500	37.500000	Averag
2	KP281	19	Female	14	Partnered	4	3	30699	66	1500	16.500000	Averag
3	KP281	19	Male	12	Single	3	3	32973	85	1500	28.333333	Averag
4	KP281	20	Male	13	Partnered	4	2	35247	47	1500	11.750000	Mediocr
...	...	...	...	...	...	...	...	...	...	...	...	.

Statistical Summary after modification of the Dataframe

```
df.describe()
```

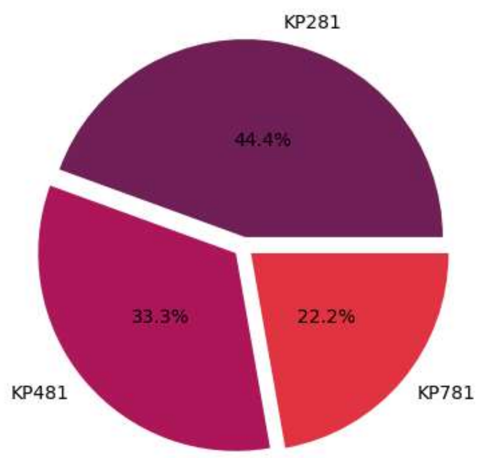
	Age	Education	Usage	Fitness	Income	Miles	Product
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000	1
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444	18
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605	3
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000	15
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000	15
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000	17
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000	17
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000	25

Insights from Visual Analysis

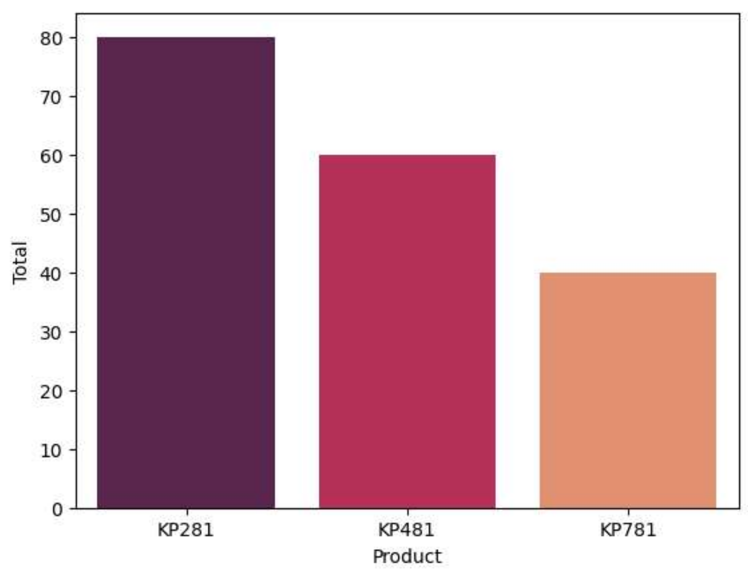
1. Highest sold product is KP281
2. Ratio of Male to Female customers is 57%-43%
3. Average Income is 53,719$
4. Average Age of the Customers is 28.7
5. Mean usage of a treadmill in a week is 3.45 times
6. Weekly average miles covered is 29.4

VISUAL ANALYSIS

```
colors = sns.color_palette('rocket')[1:4]
plt.pie(df.Product.value_counts(),labels = df.Product.value_counts().index,colors=colors,autopct="%.1f%%", explode=[0.05]*3, pctdistance=0.5)
plt.show()
```

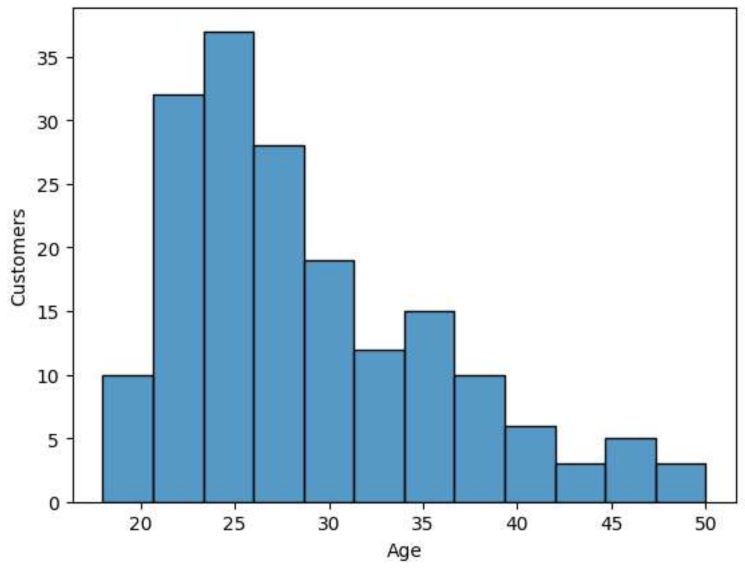



```
temp = sns.countplot(data=df,x='Product',palette='rocket')
plt.ylabel('Total')
plt.show()
```



From the above graphs we can see the distribution of sales of the 3 products, KP281 being the highest with 80 whereas KP781 being the lowest with 40.

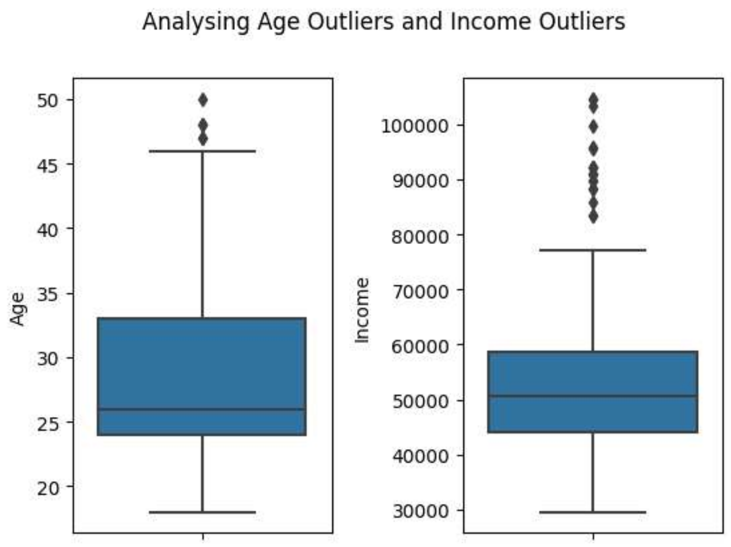
```
sns.histplot(df['Age'],bins=12)
plt.ylabel('Customers')
plt.show()
```



Age distibution of the Customers

```
fig , ax = plt.subplots(1,2)
fig.tight_layout(pad=4.0)

sns.boxplot(y=df.Age,ax=ax[0])
sns.boxplot(y=df.Income,ax=ax[1])
plt.suptitle("Analysing Age Outliers and Income Outliers")
plt.show()
```



Created a subplot plotting two boxplots in order to analyse the outliers.

```
q3 = np.percentile(df.Age,75)
q1 = np.percentile(df.Age,25)
IQR = q3-q1

Outliers = df.Age > q3 + (1.5*(IQR))
Outliers.value_counts()
```

```
False    175
True       5
Name: Age, dtype: int64
```

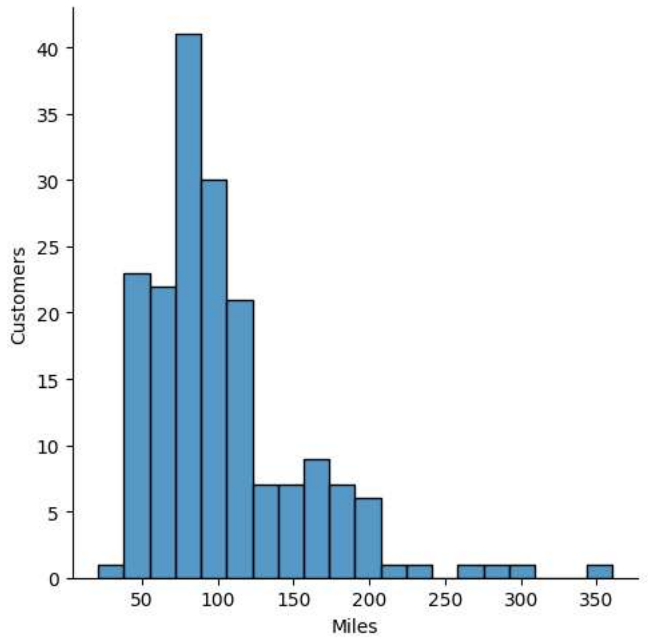
```
q3 = np.percentile(df.Income,75)
q1 = np.percentile(df.Income,25)
IQR = q3-q1

Outliers = df.Income > q3 + (1.5*(IQR))
Outliers.value_counts()
```

```
False    161
True      19
Name: Income, dtype: int64
```

After plotting the graphs we calculate the exact number of outliers for Age as well as Income

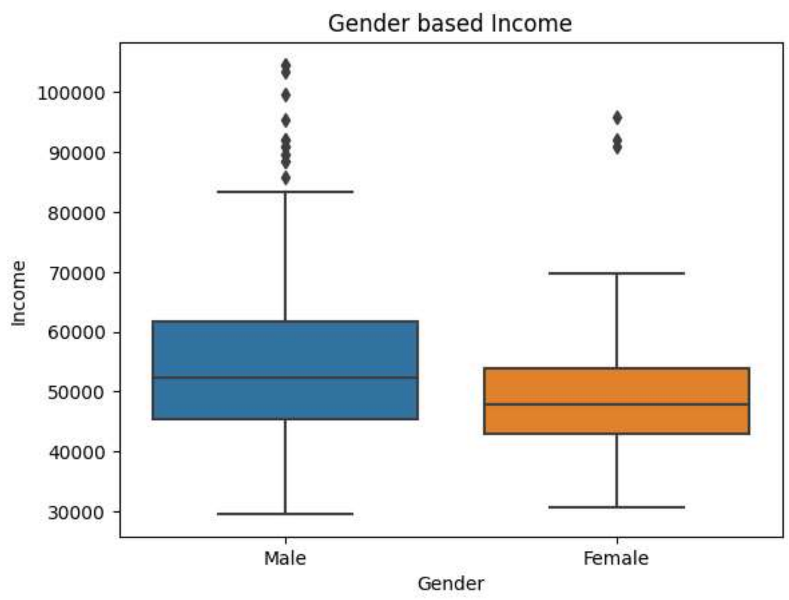
```
sns.displot(df.Miles)
plt.ylabel('Customers')
plt.show()
```



Distribution of weekly miles walked by the customers

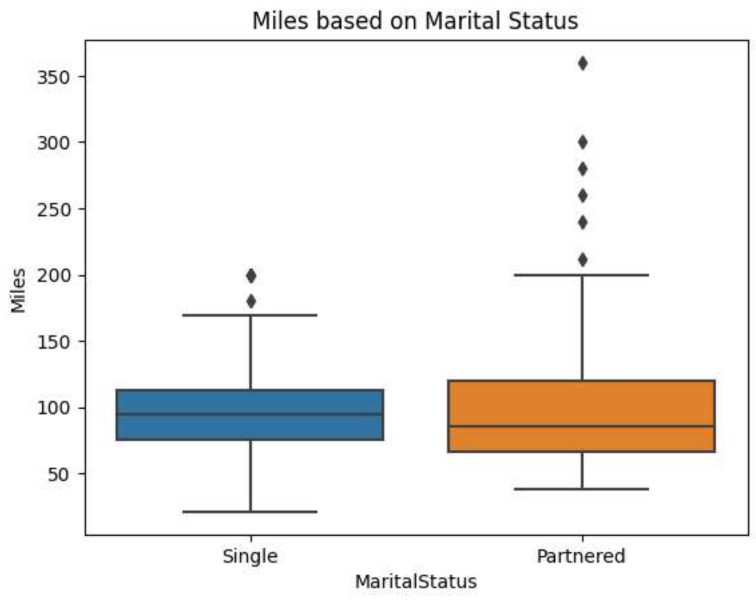
Bi-Variate Analysis

```
plt.xlabel("Gender")
plt.ylabel("Income")
sns.boxplot(x= 'Gender', y='Income', data=df)
plt.title("Gender based Income")
plt.show()
```



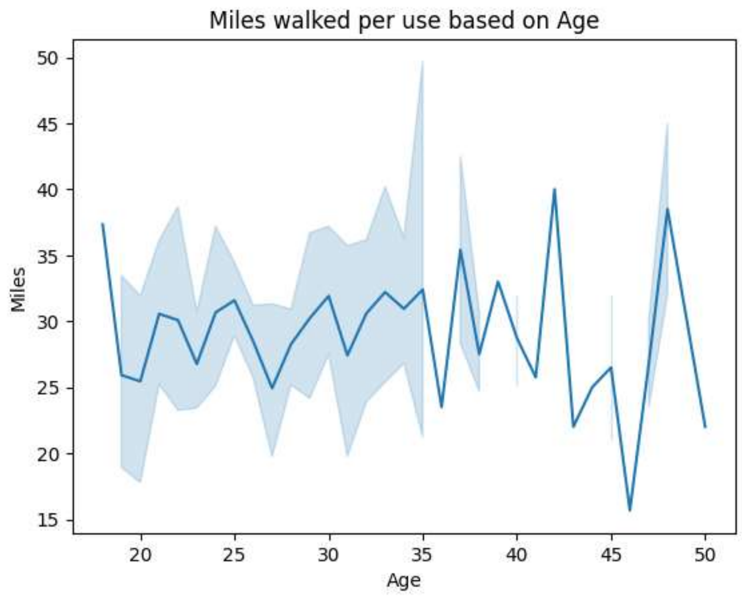
Comparisons of Income based on Gender through Box-plots

```
plt.xlabel("Gender")
plt.ylabel("Income")
x=sns.boxplot(x= 'MaritalStatus', y='Miles', data=df)
plt.title("Miles based on Marital Status")
plt.show()
```



Comparisons of Weekly Miles walked based on Marital Status through Box-plots

```
plt.xlabel("Age")
plt.ylabel("Miles")
x=sns.lineplot(data=df,x= 'Age', y='Miles_per_use')
plt.title("Miles walked per use based on Age")
plt.show()
```



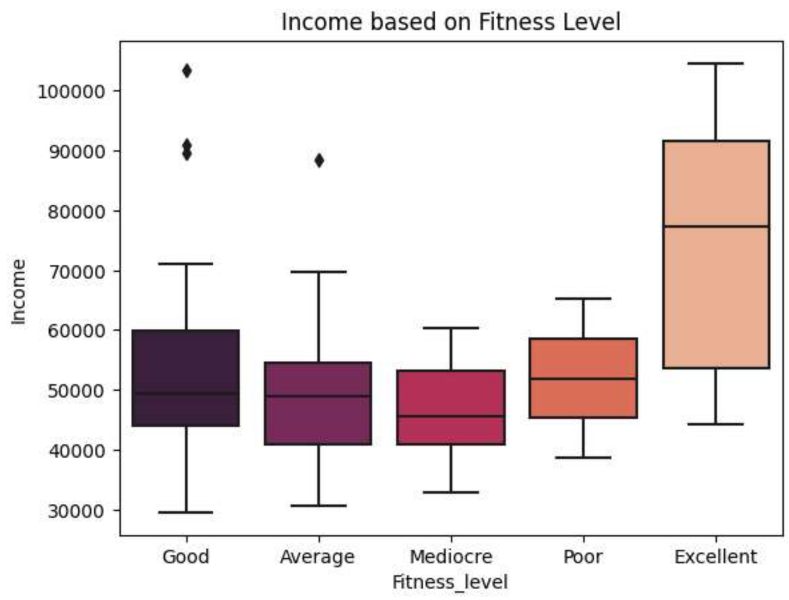
Distribution of miles walked per use of a treadmill based on Age

```
plt.xlabel("Age")
plt.ylabel("Miles")
```

```
x=sns.lineplot(data=df,x= 'Age', y='Miles',color = 'Green')
plt.title("Miles walked per week based on Age")
plt.show()
```

Distribution of miles walked per week on a treadmill based on Age

```
plt.xlabel("Income")
plt.ylabel("Fitness Level")
x=sns.boxplot(data=df,x= 'Fitness_level', y='Income',palette='rocket')
plt.title("Income based on Fitness Level")
plt.show()
```

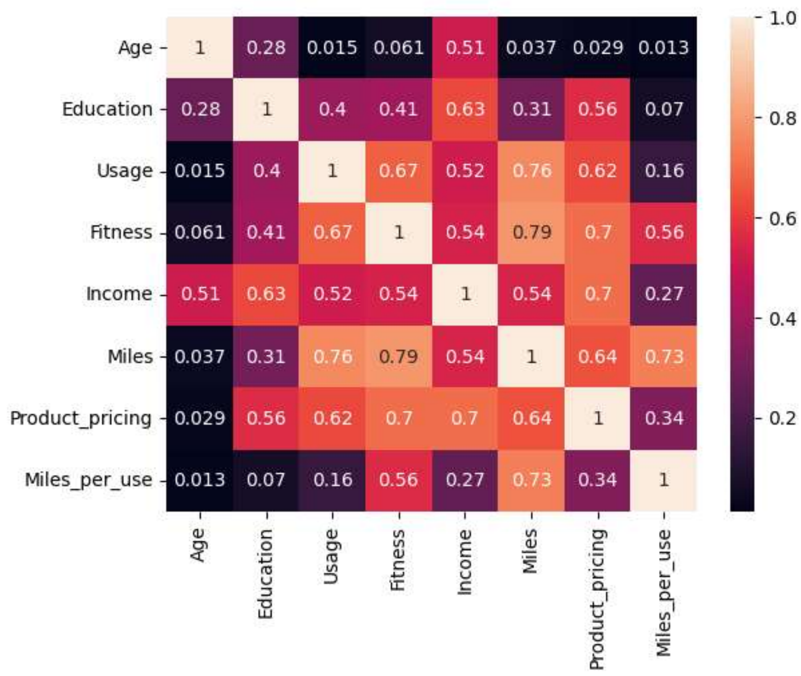


Created a relationship between income and Fitness Levels

```
correlation = df.corr()

sns.heatmap(correlation,annot=True)
```

```
<ipython-input-34-3ad7525823fd>:1: FutureWarning: The default value of numeric_only in
  correlation = df.corr()
<Axes: >
```



	Age	Education	Usage	Fitness	Income	Miles	Product_pricing	Miles_per_use
Age	1	0.28	0.015	0.061	0.51	0.037	0.029	0.013
Education	0.28	1	0.4	0.41	0.63	0.31	0.56	0.07
Usage	0.015	0.4	1	0.67	0.52	0.76	0.62	0.16
Fitness	0.061	0.41	0.67	1	0.54	0.79	0.7	0.56
Income	0.51	0.63	0.52	0.54	1	0.54	0.7	0.27
Miles	0.037	0.31	0.76	0.79	0.54	1	0.64	0.73
Product_pricing	0.029	0.56	0.62	0.7	0.7	0.64	1	0.34
Miles_per_use	0.013	0.07	0.16	0.56	0.27	0.73	0.34	1

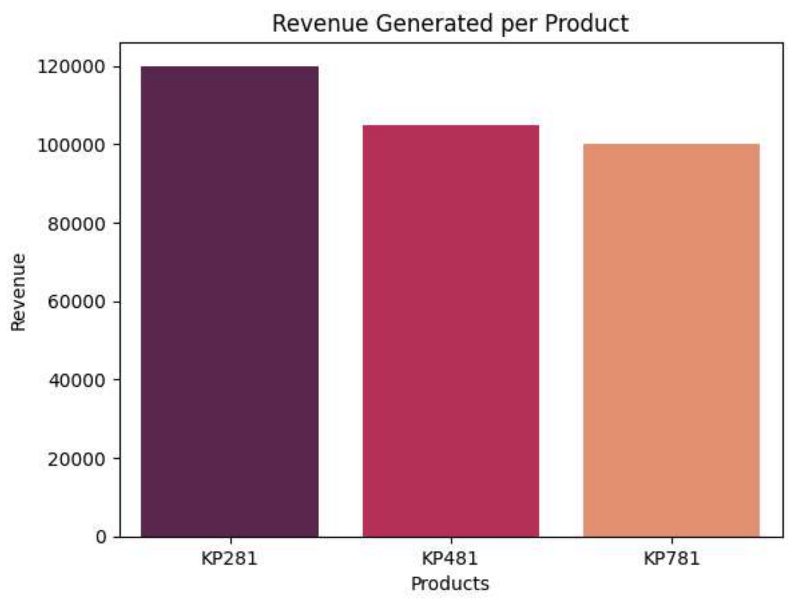
Correlation between all the attributes is displayed

Prior to this we dug deep into customer analysis, moving on we will deep dive into analysing the product with our customer analysis as well as calculating marginal probabilities.

```
revenue = df.groupby('Product')['Product_pricing'].sum().reset_index()
revenue
```

	Product	Product_pricing
0	KP281	120000

```
x=sns.barplot(data=revenue,x='Product',y='Product_pricing',palette='rocket')
plt.title("Revenue Generated per Product")
plt.xlabel("Products")
plt.ylabel("Revenue")
plt.show()
```



Calculated the revenue generated by each product in total and then plotted a bar graph

```
pd.crosstab(df.Product,df.Gender,margins = True,normalize = True)
```

Gender	Female	Male	All
Product			
KP281	0.222222	0.222222	0.444444
KP481	0.161111	0.172222	0.333333
KP781	0.038889	0.183333	0.222222
All	0.422222	0.577778	1.000000

Calculated Marginal Probability of a particular gender buying a certain product

```
pd.crosstab(df.Product,df.MaritalStatus,margins = True,normalize=True)
```

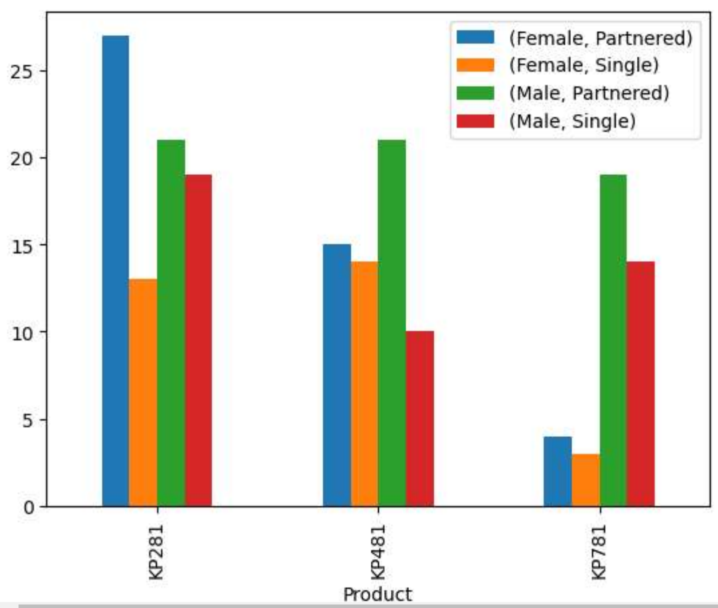
MaritalStatus	Partnered	Single	All
Product			
KP281	0.266667	0.177778	0.444444
KP481	0.200000	0.133333	0.333333
KP781	0.127778	0.094444	0.222222
All	0.594444	0.405556	1.000000

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

Gender	Product	Female		Male		All
MaritalStatus		Partnered	Single	Partnered	Single	
0	KP281	0.150000	0.072222	0.116667	0.105556	0.444444
1	KP481	0.083333	0.077778	0.116667	0.055556	0.333333
2	KP781	0.022222	0.016667	0.105556	0.077778	0.222222
3	All	0.255556	0.166667	0.338889	0.238889	1.000000

```
x= pd.crosstab(df.Product,[df.Gender,df.MaritalStatus],margins = True)
x= x.drop('All',axis=1)
x= x.drop('All',axis=0)
x.plot(kind='bar')
plt.legend()
plt.show()
```

```
<ipython-input-40-3d2cf8fe8695>:2: PerformanceWarning: dropping on a non-lexsorted multi-index without a level parameter may im
  x= x.drop('All',axis=1)
```

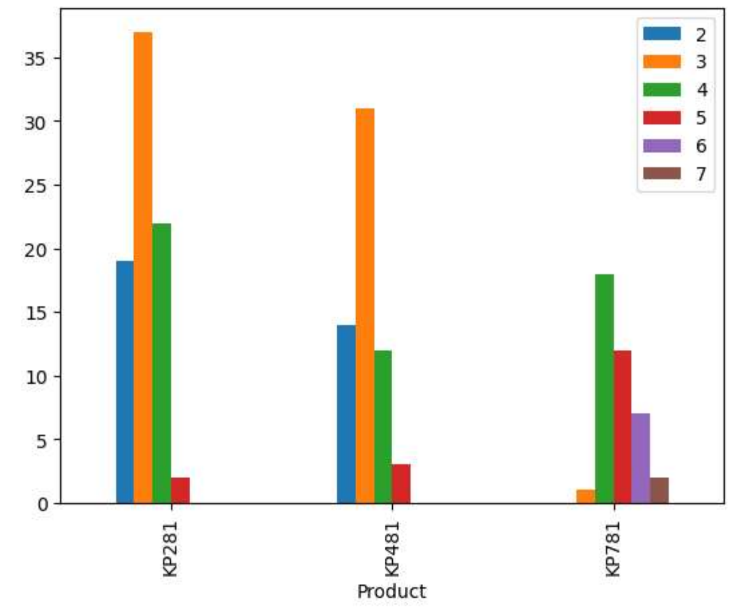


In the above graph we see the product distribution based on Gender as well as Marital Status.

```
pd.crosstab(df.Product,df.Usage,margins=True,normalize=True)
```

Usage Product	2	3	4	5	6	7	All
KP281	0.105556	0.205556	0.122222	0.011111	0.000000	0.000000	0.444444
KP481	0.077778	0.172222	0.066667	0.016667	0.000000	0.000000	0.333333
KP781	0.000000	0.005556	0.100000	0.066667	0.038889	0.011111	0.222222
All	0.183333	0.383333	0.288889	0.094444	0.038889	0.011111	1.000000

```
y= pd.crosstab(df.Product,df.Usage,margins=True)
y= y.drop('All',axis=1)
y= y.drop('All',axis=0)
y.plot(kind='bar')
plt.legend()
plt.show()
```

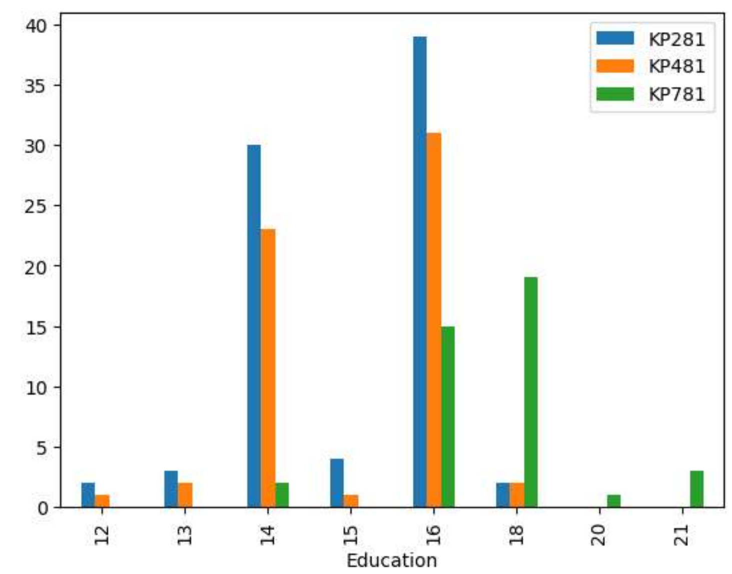


Above graph shows us how each product was picked by the customer based on the customer's usage per week

```
pd.crosstab(df.Education,df.Product,margins=True,normalize=True)
```

Product Education	KP281	KP481	KP781	All
12	0.011111	0.005556	0.000000	0.016667
13	0.016667	0.011111	0.000000	0.027778
14	0.166667	0.127778	0.011111	0.305556
15	0.022222	0.005556	0.000000	0.027778
16	0.216667	0.172222	0.083333	0.472222
18	0.011111	0.011111	0.105556	0.127778
20	0.000000	0.000000	0.005556	0.005556
21	0.000000	0.000000	0.016667	0.016667
All	0.444444	0.333333	0.222222	1.000000

```
a = pd.crosstab(df.Education,df.Product,margins=True)
a=a.drop('All',axis=1)
a=a.drop('All',axis=0)
a.plot(kind='bar')
plt.legend()
plt.show()
```

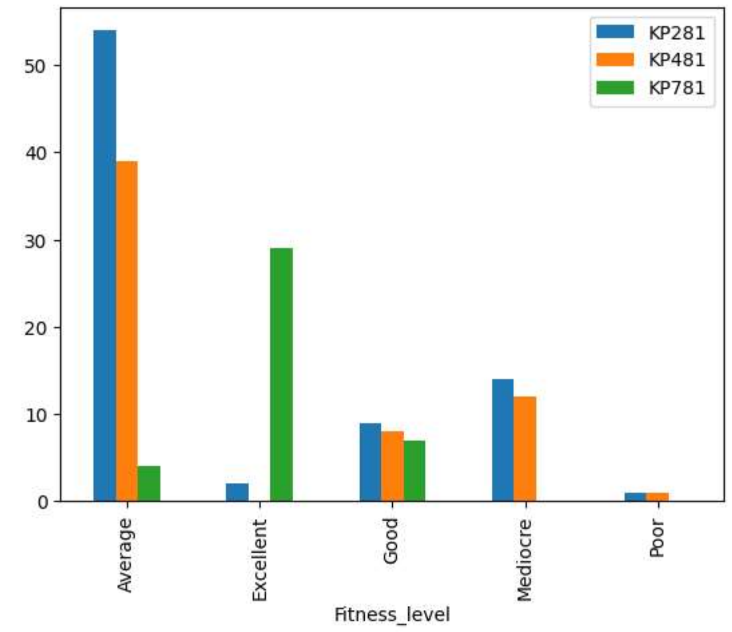


In order to get deeper analysis for customer profiling the above graphs shows us an analysis between education of a customer and the product.

```
pd.crosstab(df.Fitness_level,df.Product,margins=True,normalize=True)
```

Product	KP281	KP481	KP781	All
Fitness_level				
Average	0.300000	0.216667	0.022222	0.538889
Excellent	0.011111	0.000000	0.161111	0.172222
Good	0.050000	0.044444	0.038889	0.133333
Mediocre	0.077778	0.066667	0.000000	0.144444
Poor	0.005556	0.005556	0.000000	0.011111
All	0.444444	0.333333	0.222222	1.000000

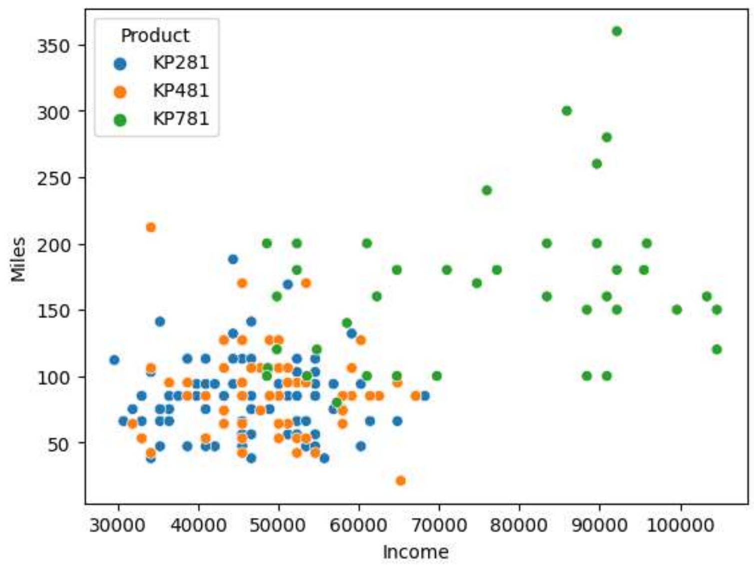
```
z= pd.crosstab(df.Fitness_level,df.Product,margins=True)
z=z.drop('All',axis=1)
z=z.drop('All',axis=0)
z.plot(kind='bar')
plt.legend()
plt.show()
```



What we have done here is seen the analysis of the product based on the fitness levels mentioned by the customer.

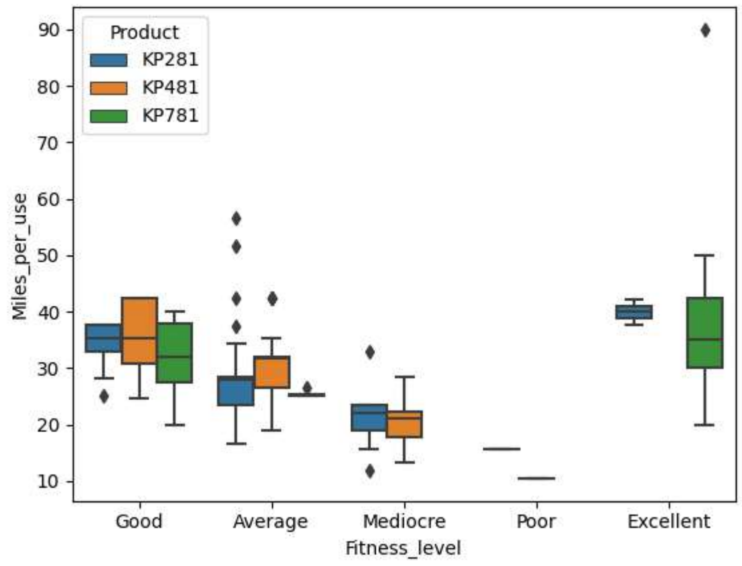
Multi-Variate Analysis

```
sns.scatterplot(data=df,x='Income',y='Miles',hue='Product')
plt.show()
```



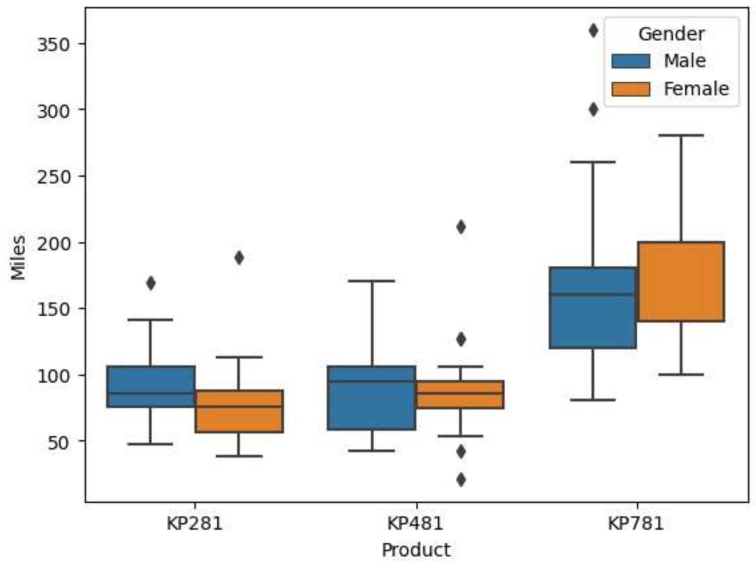
We see in the above graphs how customers with a certain income and a certain miles covered per week choose a specific product

```
sns.boxplot(data=df,x='Fitness_level',y='Miles_per_use',hue='Product')
plt.show()
```



The above graph helps us analyse product choices based on a customers Fitness level and Miles covered per use.

```
sns.boxplot(data=df,y='Miles',x='Product',hue='Gender')
plt.show()
```



Final Multi-variate analysis helps us understand Gender comparison based on Miles covered per week for each product

```
sns.pairplot(df)
plt.show()
```

Plotted a pairplot showing multiple variable comparison

CUSTOMER PROFILING

Based on the non-visual analysis as well as visual analysis as performed above the following customer profiles are created per product to help Aerofit increase sales with better insights on profiling

KP 281

- It is the highest selling product out of the three (80) Constitutes 44.4% out of total products sold
- Despite being the cheapest product out of the three $(1500) it brings in highest revenue (120,000)$
- Percentage of either a Male or Female customer buying KP281 is the same 22%
- KP 281 does fairly well with a partnered or single customer irrespective of their gender
- This particular treadmill is picked by those customers with a usage ranging from 2-4 times a week
- Widely popular treadmill with customers having education ranging from 14-16 years
- Customers with 'Average' or 'Mediocre' fitness levels majorly opt for this product
- Being the cheapest product this is widely popular with customers income ranging between (30k-55k$)
- Weekly miles walked on this treadmill would be 70-100

KP 481

- Second highest sold product (60), it forms 33.3% of the total products sold.
- With a median pricing of 1750$ it brings in a revenue of 105,000 dollars
- Percentage of Male Customers is one percent greater then percentage of Female customers for this product
- Most popular among Partnered Males
- Similar to KP281, it is popular with customers having a education range between 14-16
- Being a median priced treadmill customers with slightly higher income tend to go for this as well (30k-65k)
- Customers with 'Average' - 'Good' fitness level tend to opt for this product as well as customers with slightly higher weekly usage (3-5 times)
- Weekly miles walked on this treadmill would be 90-120

KP 781

- Least sold product (40) constituting 22.2% of total products sold.
- Being the costliest product 2500$ and despite it having the least sales it brings in a revenue of 100,000 dollars almost matching the KP481 revenue.
- The KP781 product is widely popular among Males (0.18),female customers are close to negligible for this product (0.03)
- This is a product that is mainly bought bys customers who are quite serious regarding their fitness and are seasoned, avg weekly use for these customers ranges from 4-7
- Customers with 'Good' & 'Excellent' Fitness levels majorly tend to buy this product.
- Being on the expensive side customers who have their income ranging from 50k-100k would go for this product
- Weekly miles walked on this treadmill would be 150-200
- Probability of a Customer with 'Poor' or 'Medicore' fitness levels is 0.

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