Problem Statement

Identify the characteristics of the target audience for each type of treadmill offered by a sports equipments manufacturing giant, to provide a better recommendation of the treadmills to the new customers.

Note: Although 44% of the products sold are KP281, there is no significant difference in the share of revenue generated by selling these products. Therefore, recommendations are made by giving equal importance to all three products.

In [793…

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

In [794…

```
df = pd.read_csv("treadmill.csv")
```

In [795…

```
df.head()
```

Out[795]:

	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

In [796…

```
df.tail()
```

Out[796]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
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

In [797…

```
df.shape
```

Out[797]:

```
(180, 9)
```

- There are 180 rows and 9 columns in the dataset. Each row represents a purchase and columns represent the product(treadmill) type and the customer attributes.

In [798…

```
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
```

- Categorical variables of type object - Product, Gender, MaritalStatus
- Numerical variables of type int - Age, Usage, Fitness, Income, Miles

- No null value in the dataset

In [799…

```
df.nunique()
```

Out[799]:

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

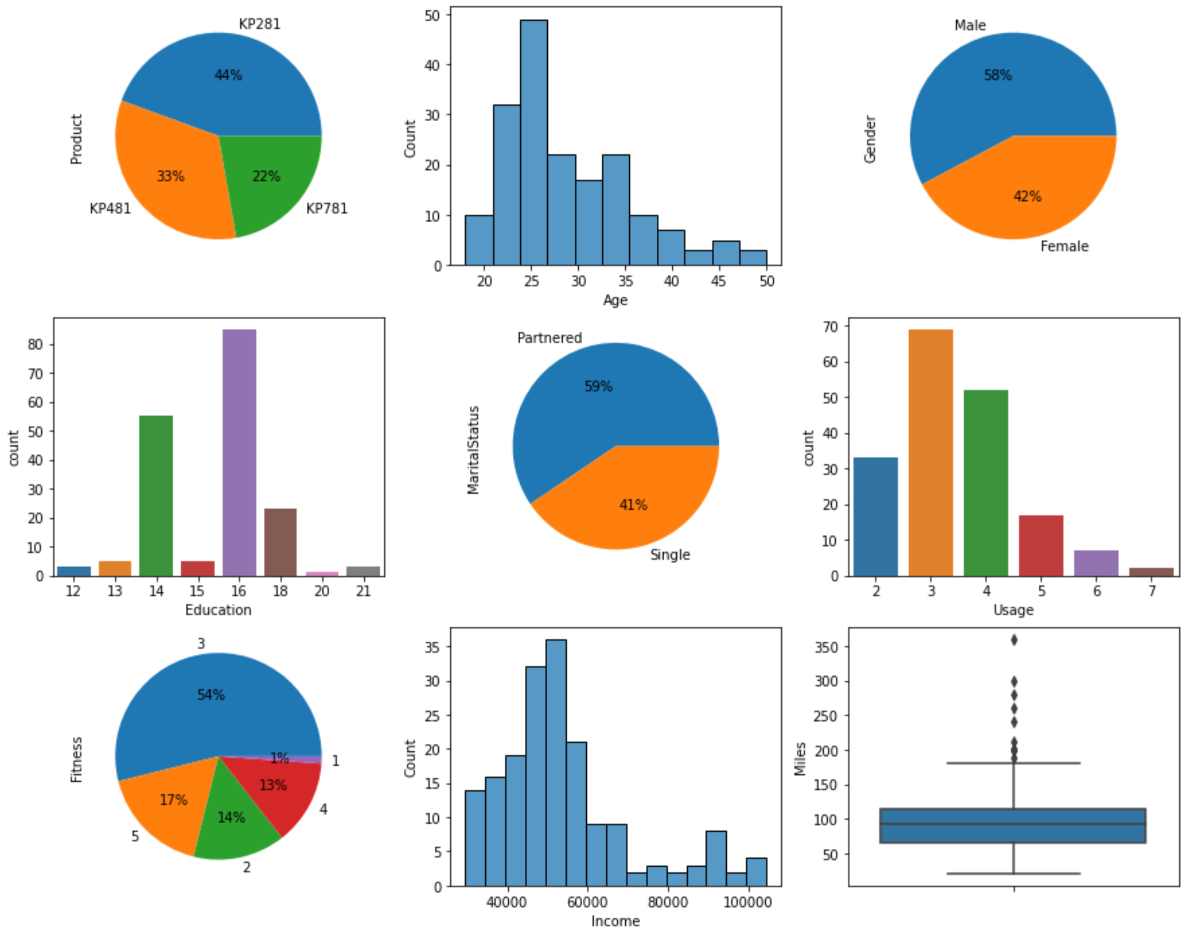
Univariate Analysis

Analysing the structure of data

In [800…

```
plt.figure(figsize=(15, 12))

## Product
plt.subplot(331)
df['Product'].value_counts().plot(kind='pie', autopct='%.f%%')

## Age
plt.subplot(332)
sns.histplot(data=df, x='Age')

## Gender
plt.subplot(333)
df['Gender'].value_counts().plot(kind='pie', autopct='%.f%%')

## Education
plt.subplot(334)
sns.countplot(data=df, x=df['Education'])
```

```python
## MaritalStatus
plt.subplot(335)
df['MaritalStatus'].value_counts().plot(kind='pie', autopct='%.f%%')

## Usage
plt.subplot(336)
sns.countplot(data=df, x='Usage')

## Fitness
plt.subplot(337)
df['Fitness'].value_counts().plot(kind='pie', autopct='%.f%%')

## Income
plt.subplot(338)
sns.histplot(data=df, x='Income')

## Miles
plt.subplot(339)
sns.boxplot(data=df, y='Miles')

plt.show()
```



- Most of the treadmills sold are the entry-level type (KP281) and advanced-type (KP781) are the least sold
- Majority of the customers are male (58%)
- 3 out of 5 customers are partnered and 2/5 are single
- 54% of the customers rate themselves 3 on a scale of 1 to 5 in fitness level, 5 being excellent and only 1% rate themselves 1

In [801…

```python
print('Percentage of customers who have had an eduction of 16 years -',
      ((df['Education'] == 16).sum()/1.8).round(0))
```

```
print('14 years -', ((df['Education'] == 14).sum()/1.8).round(0))
```

```
Percentage of customers who have had an eduction of 16 years - 47.0
14 years - 31.0
```

- Close to 50% of the customers have an education of 16 years and 78% of the customers have an education of either 14 or 16 years

Analysing the characteristics of numerical attributes

In [802…

```
df.describe()
```

Out[802]:

	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

- Median age of a customer is 26 and 50% of the customers are in age range 24-33.
- More than 50% of the people who have purchased the treadmill have a plan to use it 3-4 days a week
- 75% of the customers fall in an annual income between $30,000-60,000
- More than half of the total customers expect to run on an average 65-115 miles a week whereas the max distance a customer expects to run is 360 miles a week. These higher values of outliers are evident from the higher value of mean(103 miles) whereas median is at 94 miles.

Product

In [803…

```
df['Product'].unique()
```

Out[803]:

```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [804…

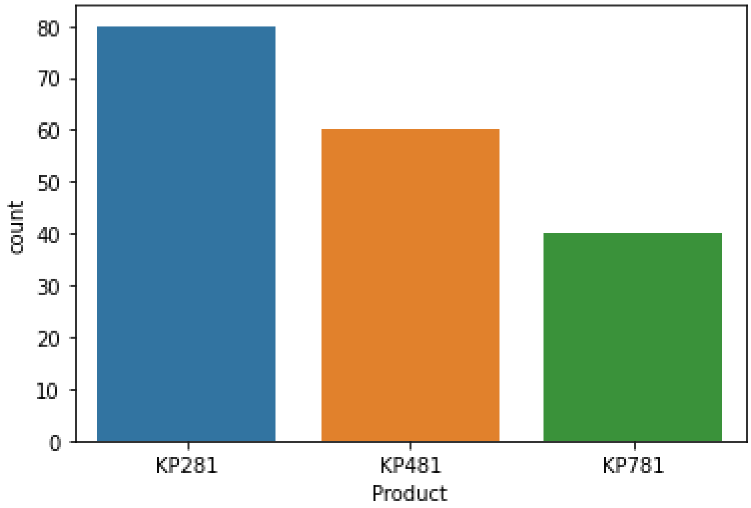
```
df['Product'].value_counts()
```

Out[804]:

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

In [805…

```
sns.countplot(data=df, x='Product')
plt.show()
```



Marginal Probability of products to be purchased

In [806…

```
(df['Product'].value_counts(normalize=True).round(2)).to_frame().rename(col
```

Out[806]:

	Probability
KP281	0.44
KP481	0.33
KP781	0.22

Revenue generation

In [807…

```
rev = df['Product'].value_counts().to_frame().rename(columns={'Product':'Re
rev.loc['KP281'] = rev.loc['KP281']*1500
rev.loc['KP481'] = rev.loc['KP481']*1750
rev.loc['KP781'] = rev.loc['KP781']*2500
((rev/rev.sum())*100).round(0)
```

Out[807]:

	Revenue%
KP281	37.0
KP481	32.0
KP781	31.0

- Although the sales of product KP281 is higher, there is no significant difference in the share of total revenue generated by each product.

Bivariate/Multivariate Analysis

In [808…

```
df.groupby(by='Product').median()
```

Out[808]:

Product	Age	Education	Usage	Fitness	Income	Miles
KP281	26.0	16.0	3.0	3.0	46617.0	85.0
KP481	26.0	16.0	3.0	3.0	49459.5	85.0
KP781	27.0	18.0	5.0	5.0	76568.5	160.0

In [809…

```
df.groupby(by='Product').mean()
```

Out[809]:

Product	Age	Education	Usage	Fitness	Income	Miles
KP281	28.55	15.037500	3.087500	2.9625	46418.025	82.787500
KP481	28.90	15.116667	3.066667	2.9000	48973.650	87.933333
KP781	29.10	17.325000	4.775000	4.6250	75441.575	166.900000

Average value of attributes of the customers who have purchased products KP281 and KP481 are almost the same

For product KP781, values are significantly higher, notably for fields like Fitness, Income and Miles run

In [810…

```
df.groupby(by=['Product', 'Gender']).mean()
```

Out[810]:

Product	Gender	Age	Education	Usage	Fitness	Income	Miles
KP281	Female	28.450000	15.100000	2.900000	2.875000	46020.075000	76.200000
	Male	28.650000	14.975000	3.275000	3.050000	46815.975000	89.375000
KP481	Female	29.103448	15.206897	3.137931	2.862069	49336.448276	87.344828
	Male	28.709677	15.032258	3.000000	2.935484	48634.258065	88.483871
KP781	Female	27.000000	17.857143	5.000000	4.571429	73633.857143	180.000000
	Male	29.545455	17.212121	4.727273	4.636364	75825.030303	164.121212

In [811…

```
df.groupby(by=['Product', 'MaritalStatus']).mean()
```

Out[811]:

Product	MaritalStatus	Age	Education	Usage	Fitness	Income	Miles
KP281	Partnered	29.666667	15.125000	3.041667	2.854167	47848.750000	77.229167
	Single	26.875000	14.906250	3.156250	3.125000	44271.937500	91.125000
KP481	Partnered	30.222222	15.250000	3.055556	2.916667	49522.666667	90.055556
	Single	26.916667	14.916667	3.083333	2.875000	48150.125000	84.750000
KP781	Partnered	29.826087	17.434783	4.913043	4.695652	82047.173913	183.043478
	Single	28.117647	17.176471	4.588235	4.529412	66504.588235	145.058824

Age vs Gender of customer

In [812…

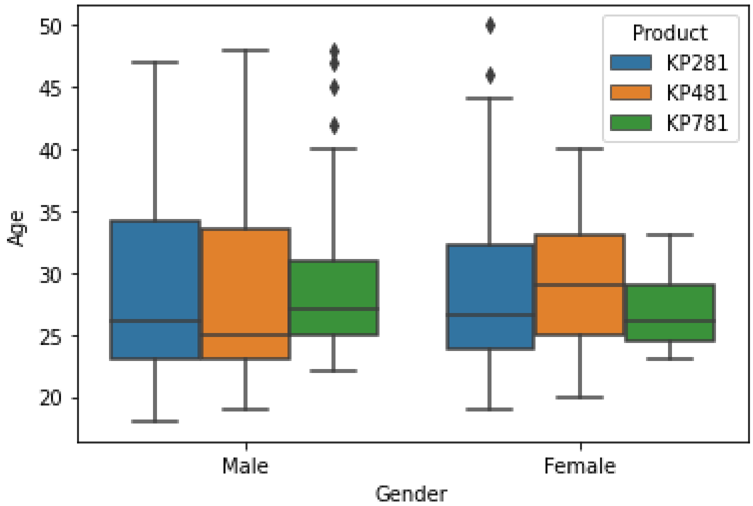
```
df.groupby(by=['Gender', 'Product']).describe()['Age']
```

Out[812]:

Gender	Product	count	mean	std	min	25%	50%	75%	max
Female	**KP281**	40.0	28.450000	7.110664	19.0	23.75	26.5	32.25	50.0
	KP481	29.0	29.103448	5.802369	20.0	25.00	29.0	33.00	40.0
	KP781	7.0	27.000000	3.559026	23.0	24.50	26.0	29.00	33.0
Male	**KP281**	40.0	28.650000	7.419828	18.0	23.00	26.0	34.25	47.0
	KP481	31.0	28.709677	7.439505	19.0	23.00	25.0	33.50	48.0
	KP781	33.0	29.545455	7.462786	22.0	25.00	27.0	31.00	48.0

In [813…

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

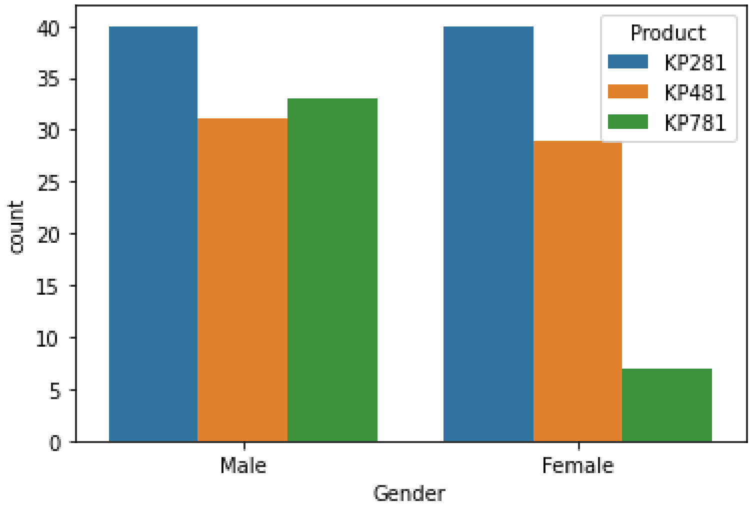


- Median age of customers who purchased different products are almost equal however, majority of KP781 customers fall into relatively narrow age range whereas the age is widely distributed for the customers of other two products

Product vs Gender

In [814…

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



Marginal Probability table

In [815…

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

Out[815]:

Gender	Female	Male	All
Product			
KP281	0.22	0.22	0.44
KP481	0.16	0.17	0.33
KP781	0.04	0.18	0.22
All	0.42	0.58	1.00

Conditional Probability table

In [816…

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

Out[816]:

Gender	Female	Male
Product		
KP281	0.50	0.50
KP481	0.48	0.52
KP781	0.18	0.82
All	0.42	0.58

- P(Product=KP781 and Gender=Male) = 0.18
- P(Male/KP781) = 0.82

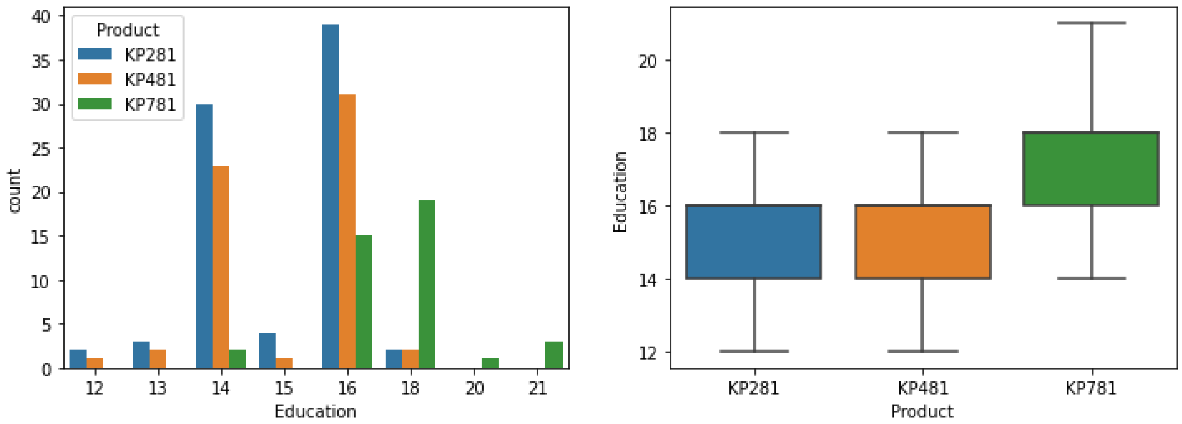
The likelihood of a male customer buying KP781 is 18% but if the product sold is KP781, there is 82% probability that it is bought by a male

Product vs Education

In [817…

```
plt.figure(figsize=(12, 4))

plt.subplot(121)
sns.countplot(data=df, x='Education', hue='Product')
```

```
plt.subplot(122)
sns.boxplot(data=df, y='Education', x='Product')

plt.show()
```



In [818…

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

Out[818]:

Education Product	12	13	14	15	16	18	20	21	All
KP281	0.01	0.02	0.17	0.02	0.22	0.01	0.00	0.00	0.44
KP481	0.01	0.01	0.13	0.01	0.17	0.01	0.00	0.00	0.33
KP781	0.00	0.00	0.01	0.00	0.08	0.11	0.01	0.02	0.22
All	0.02	0.03	0.31	0.03	0.47	0.13	0.01	0.02	1.00

- Around half of the customers have received 16 years of education which is the median years of education of those who purchased KP281 and KP481
- Incase of KP781, the medain years of eduation is 18 and the only product sold to customers with more than 18 years of education is KP781
- P(Product=KP781 and Education > 16) = 0.11 + 0.01 + 0.02 = 0.14
- P(Product=KP781/Education > 16) = 0.14/(0.13+0.01+0.02) = 0.14/0.16 = 0.875

There is an 87.5% chance that the product sold is KP781 given the customer has an eduction greater than or equal to 18 years

Product vs MaritalStatus

In [819…

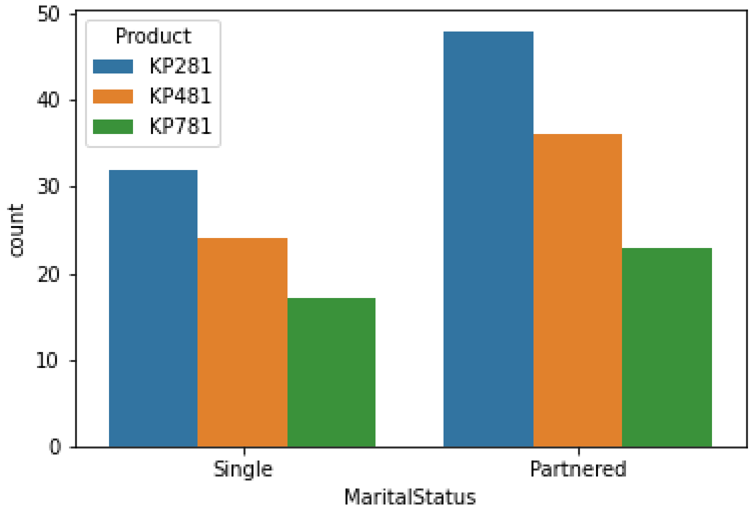
```
pd.crosstab(df['Product'], df['MaritalStatus'])
```

Out[819]:

MaritalStatus Product	Partnered	Single
KP281	48	32
KP481	36	24
KP781	23	17

In [820…

```
sns.countplot(data=df, x='MaritalStatus', hue='Product')
plt.show()
```



Prduct vs Usage

Marginal Probability

In [821…

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

Out[821]:

Usage Product	2	3	4	5	6	7	All
KP281	0.11	0.21	0.12	0.01	0.00	0.00	0.44
KP481	0.08	0.17	0.07	0.02	0.00	0.00	0.33
KP781	0.00	0.01	0.10	0.07	0.04	0.01	0.22
All	0.18	0.38	0.29	0.09	0.04	0.01	1.00

Conditional Probability

In [822…

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

Out[822]:

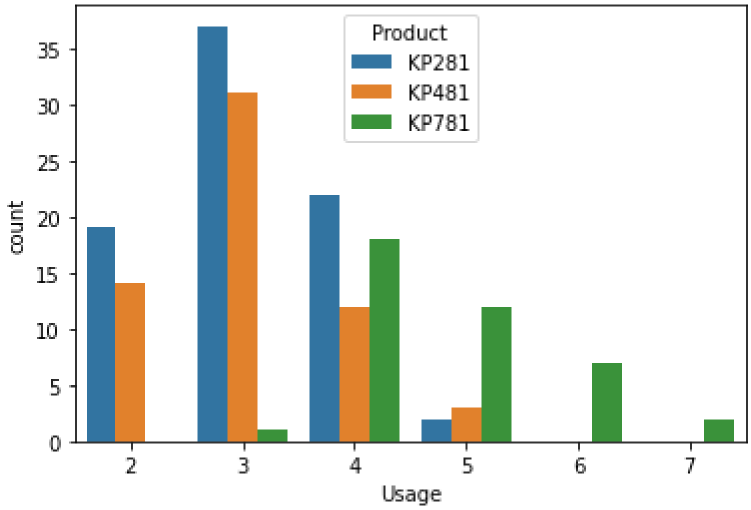
Usage Product	2	3	4	5	6	7
KP281	0.24	0.46	0.28	0.02	0.00	0.00
KP481	0.23	0.52	0.20	0.05	0.00	0.00
KP781	0.00	0.02	0.45	0.30	0.18	0.05
All	0.18	0.38	0.29	0.09	0.04	0.01

- P(KP781 and Usage >= 4) = 0.45+0.30+0.18+0.05 = 0.98

98% of KP781 customers use a treadmill 4+ days a week

In [823…

```
sns.countplot(data=df, x='Usage', hue='Product')
plt.show()
```



- The only product purchased by customers those who run more than 5 days a week is KP781

Product vs Fitness

Marginal Probability

In [824…

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

Out[824]:

Fitness Product	1	2	3	4	5	All
KP281	0.01	0.08	0.30	0.05	0.01	0.44
KP481	0.01	0.07	0.22	0.04	0.00	0.33
KP781	0.00	0.00	0.02	0.04	0.16	0.22
All	0.01	0.14	0.54	0.13	0.17	1.00

Conditional Probability

In [825…

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

Out[825]:

Fitness Product	1	2	3	4	5
KP281	0.01	0.18	0.68	0.11	0.02
KP481	0.02	0.20	0.65	0.13	0.00
KP781	0.00	0.00	0.10	0.18	0.72
All	0.01	0.14	0.54	0.13	0.17

In [826…

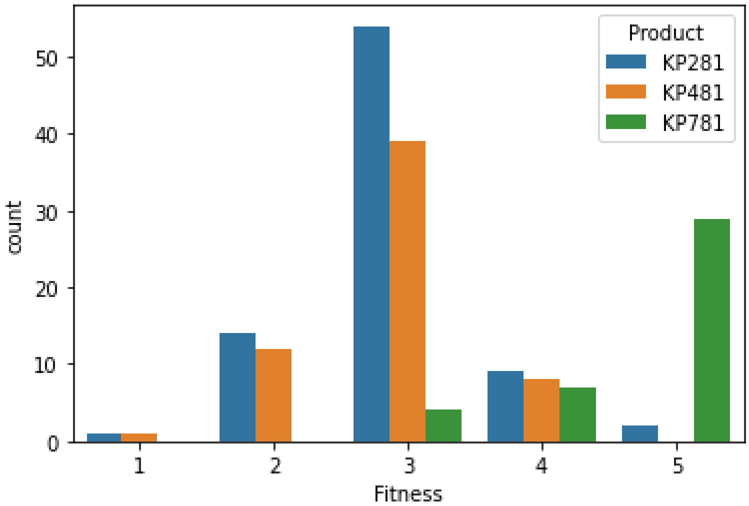
```
df.groupby(by=['Gender', 'Product']).describe()['Fitness']
```

Out[826]:

Gender	Product	count	mean	std	min	25%	50%	75%	max
Female	KP281	40.0	2.875000	0.647975	2.0	2.75	3.0	3.0	5.0
	KP481	29.0	2.862069	0.693034	1.0	3.00	3.0	3.0	4.0
	KP781	7.0	4.571429	0.786796	3.0	4.50	5.0	5.0	5.0
Male	KP281	40.0	3.050000	0.677476	1.0	3.00	3.0	3.0	5.0
	KP481	31.0	2.935484	0.573613	2.0	3.00	3.0	3.0	4.0
	KP781	33.0	4.636364	0.652791	3.0	4.00	5.0	5.0	5.0

In [827…

```
sns.countplot(data=df, x='Fitness', hue='Product')
plt.savefig('fitness_kp')
plt.show()
```



Product vs Miles

In [828…

```
df.groupby(by=['Gender', 'Product']).describe()['Miles']
```

Out[828]:

Gender	Product	count	mean	std	min	25%	50%	75%	max
Female	KP281	40.0	76.200000	27.988276	38.0	56.0	75.0	87.25	188.0
	KP481	29.0	87.344828	33.456022	21.0	74.0	85.0	95.00	212.0
	KP781	7.0	180.000000	63.245553	100.0	140.0	200.0	200.00	280.0
Male	KP281	40.0	89.375000	28.573511	47.0	75.0	85.0	105.25	169.0
	KP481	31.0	88.483871	33.625259	42.0	58.5	95.0	106.00	170.0
	KP781	33.0	164.121212	60.014455	80.0	120.0	160.0	180.00	360.0

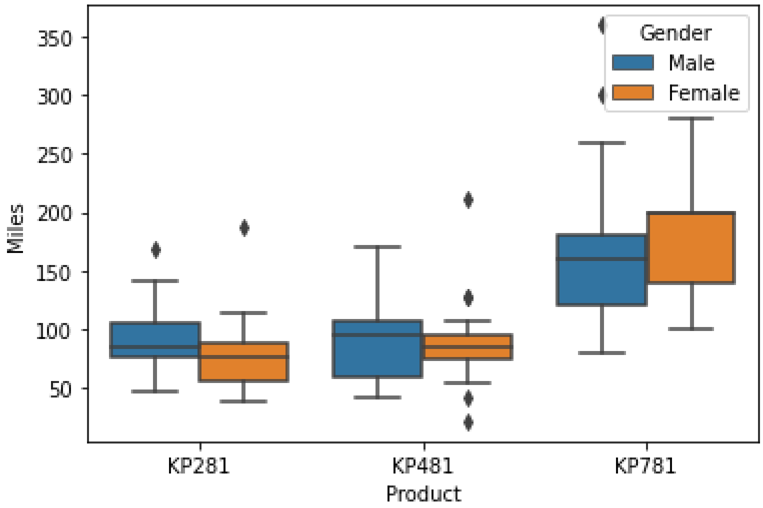
Outliers

There are outliers in both the sides of KP481 for a female customer

- IQR = 95-74 = 21
- Q1-1.5IQR = 74-31.5 = 42.5 wheras Q0 = 21
- Q3+1.5IQR = 95+31.5 = 126.5 wheras Q4 = 212 which is 68% more.

In [829…

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



Product-Income

In [830…

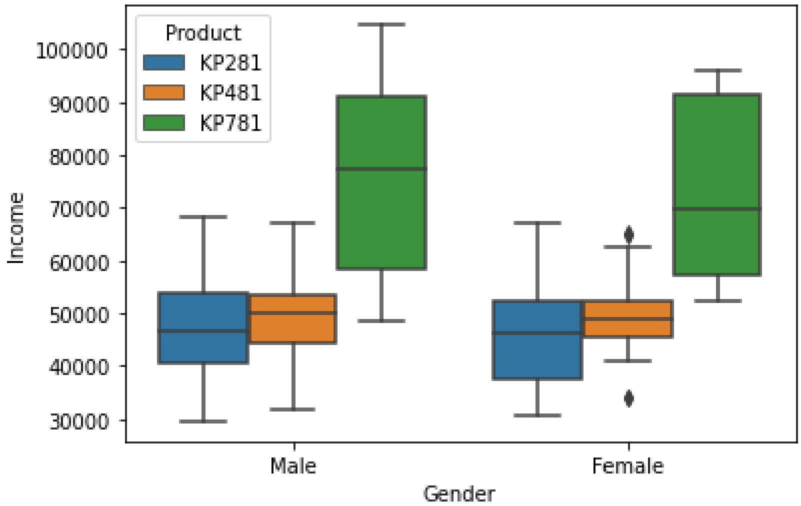
```
df.groupby(by='Product').describe()['Income']
```

Out[830]:

Product	count	mean	std	min	25%	50%	75%	max
KP281	80.0	46418.025	9075.783190	29562.0	38658.00	46617.0	53439.0	68220.0
KP481	60.0	48973.650	8653.989388	31836.0	44911.50	49459.5	53439.0	67083.0
KP781	40.0	75441.575	18505.836720	48556.0	58204.75	76568.5	90886.0	104581.0

In [831…

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



Product-Income-MaritalStatus

In [832…

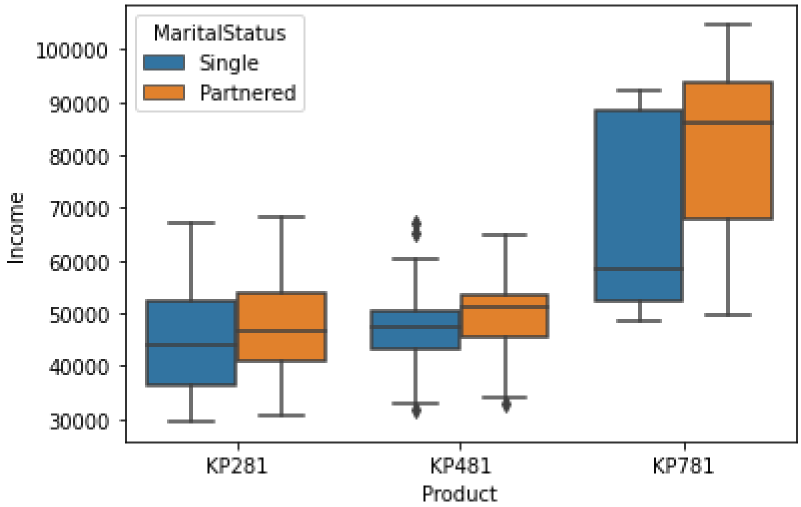
```
df.groupby(by=['Product', 'MaritalStatus']).describe()['Income']
```

Out[832]:

Product	MaritalStatus	count	mean	std	min	25%	50%	75%
KP281	Partnered	48.0	47848.750000	8806.643596	30699.0	40932.0	46617.0	53723.2
	Single	32.0	44271.937500	9186.952283	29562.0	36384.0	43774.5	52302.0
KP481	Partnered	36.0	49522.666667	8635.403820	32973.0	45480.0	51165.0	53439.0
	Single	24.0	48150.125000	8800.977467	31836.0	43206.0	47185.5	50312.2
KP781	Partnered	23.0	82047.173913	16387.308472	49801.0	67853.5	85906.0	93819.5
	Single	17.0	66504.588235	17830.525750	48556.0	52290.0	58516.0	88396.0

In [833…

```
sns.boxplot(data=df, y='Income', x='Product', hue='MaritalStatus')
plt.savefig('marital_income')
plt.show()
```



Product-Miles-Gender

In [834…

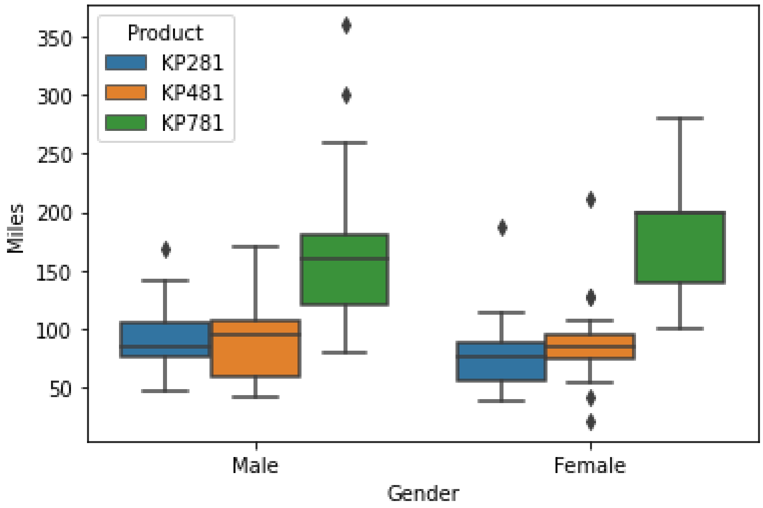
```
df.groupby(by=['Gender', 'Product']).describe()['Miles']
```

Out[834]:

Gender	Product	count	mean	std	min	25%	50%	75%	max
Female	KP281	40.0	76.200000	27.988276	38.0	56.0	75.0	87.25	188.0
	KP481	29.0	87.344828	33.456022	21.0	74.0	85.0	95.00	212.0
	KP781	7.0	180.000000	63.245553	100.0	140.0	200.0	200.00	280.0
Male	KP281	40.0	89.375000	28.573511	47.0	75.0	85.0	105.25	169.0
	KP481	31.0	88.483871	33.625259	42.0	58.5	95.0	106.00	170.0
	KP781	33.0	164.121212	60.014455	80.0	120.0	160.0	180.00	360.0

In [835…

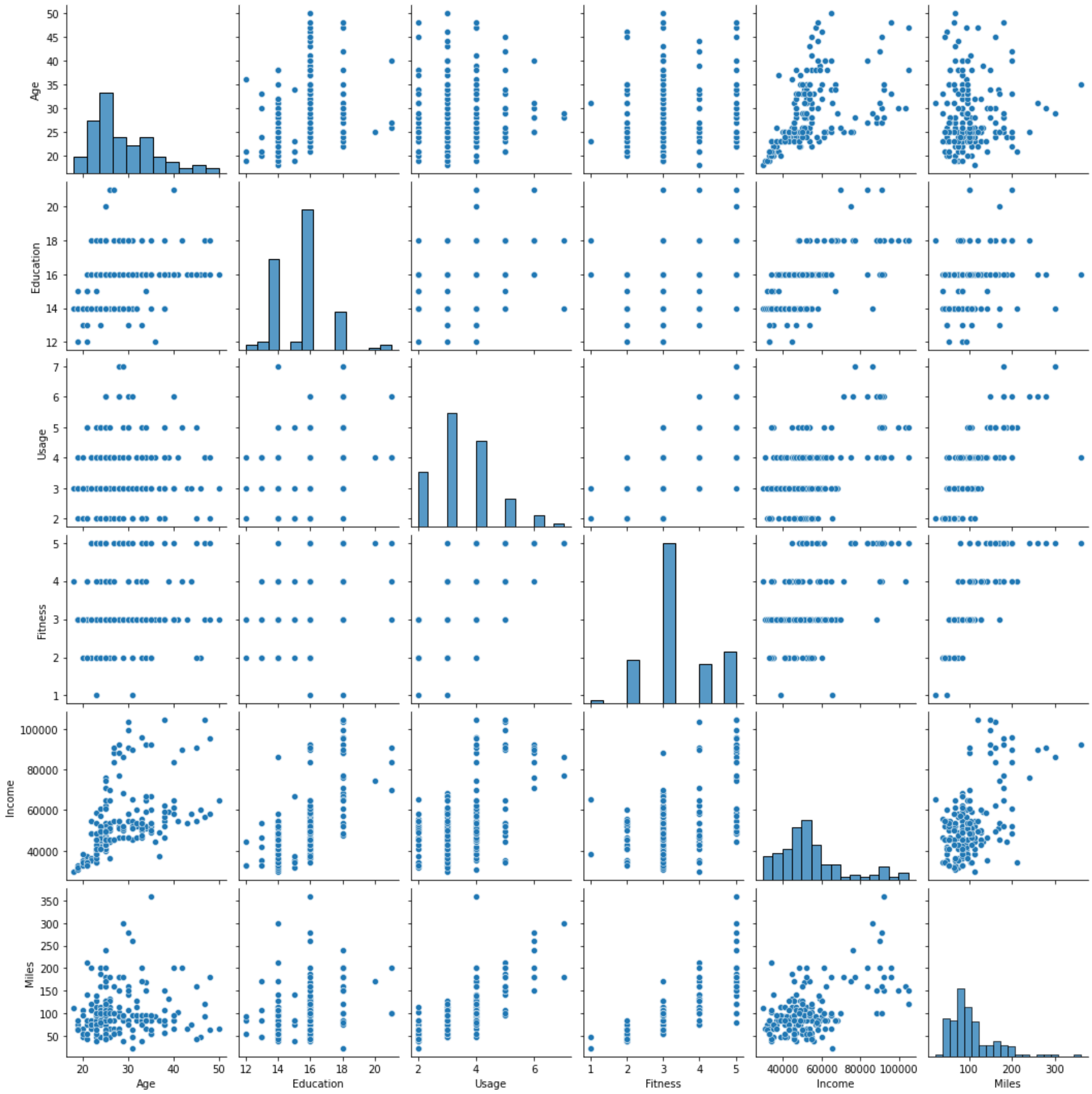
```
sns.boxplot(data=df, y='Miles', x='Gender', hue='Product')
plt.show()
```



Correlation

In [836…

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



In [837…

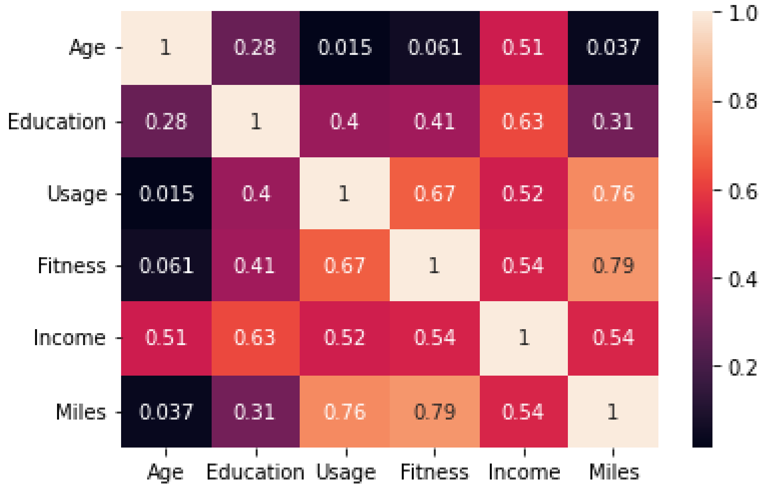
```
df.corr()
```

Out[837]:

	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000

In [838…

```
sns.heatmap(df.corr(), annot=True)
plt.show()
```



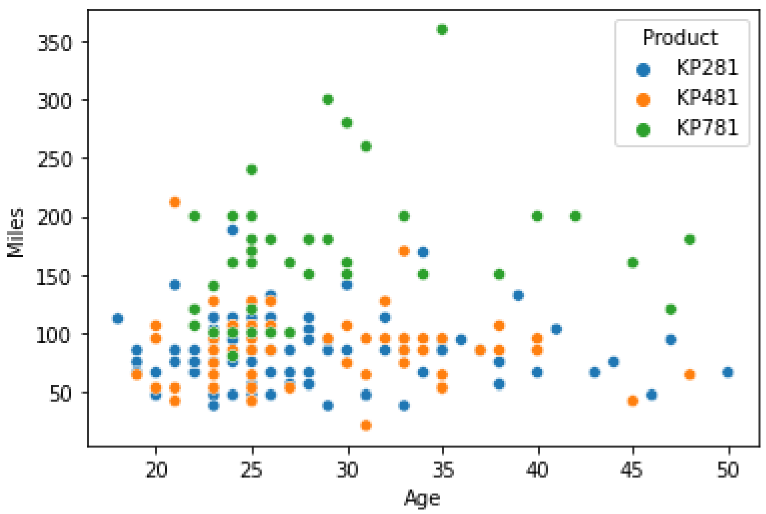
There is a strong correlation between Miles-Fitness and Miles-Usage

Income has a moderate correlation greater than 0.5 with Age, Usage, Fitness, Education and Miles

Product - Miles - Age

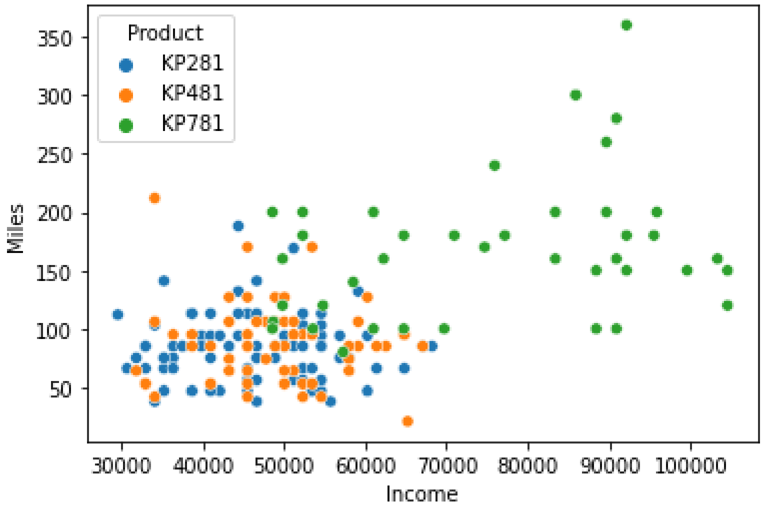
In [839…

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



Product - Income - Miles

```
In [840…  sns.scatterplot(data=df, x='Income', y='Miles', hue='Product')
          plt.savefig('income_miles')
          plt.show()
```



No significant relationship can be observed between income and miles run for the customers of product KP281 and KP481. However, KP781 customers tend to run more and have a relatively high annual income

Analysis Insights

I. KP781

```
 1. The likelihood of a male customer buying KP781 is 18% but,
if the product sold is KP781, there is 82% probability that it
is bought by a male. This implies that 4 out of 5 cutomers of
product KP781 are male.
 2. Overall, only 16% of the customers have had an education
of more than 16 years however, there is an 88% chance that the
product sold is KP781 given the customer has an eduction
greater than 16 years. Also, an average annual income over
$75,000 which 50% more than that of the other cutomers.
 3. Median Usage is 5 days and a running distance between 120-
200 miles a week. Also, a median customer rate themselves 5/5
in fitness.
```

II. KP281 and KP481

```
 1. 68% of KP281 customers and 65% of KP481 customers have
rated themselves 3 on a fitness scale 1-5. And no significant
difference can be seen between male and female customer
fitness levels.
 2. Median income of customers of both the product is found to
be almost same($47k-49k) however, majority of product KP481
customers fall into a relaively narrow income range and
partnered people found to have slightly higher income.
 3. No significant difference can be observed in the distance
run when income rises for either of the products.
```

Recommendations and Customer Profiling

1. Target Audience (KP281) - Moderately fit people of any gender with annual income between $35,000-55,000 and usage between 2-4 days a week.
2. Target Audience (KP481)- Moderately fit people of any gender with annual income between $45,000-55,000 and usage between 2-4 days a week.
3. Target audience(KP781) - Highly educated (16+ years) rich ($60k+) male customers who are already fit and expect to use a treadmill disproportionately high.
4. Since there is no significant difference between the customers of KP281 and KP481, the treadmill KP481 can be targeted to KP281 customers with an annual income greater than $45,000 for better revenue growth.

In [ ]: