Business Case_ Aerofit - Descriptive Statistics & Probability

May 13, 2024

1 Business Case: Aerofit - Descriptive Statistics & Probability

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.

1.1 Importing libraries and downloading dataset

[1]:
```
#Importing Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

#Downloading Aerofit Dataset
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
↪000/001/125/original/aerofit_treadmill.csv?1639992749')
```

1.2 Basic Metrics of Aerofit dataset

[ ]:
```
#first 5 rows
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
```

[ ]:
```
#last 5 rows
df.tail()
```

[ ]:
```
    Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
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
175    200
176    200
177    160
178    120
179    180
```

[ ]:
```
#shape
df.shape
```

[ ]: (180, 9)

[ ]:
```
#size
df.size
```

[ ]: 1620

[ ]:
```
#columns
df.columns
```

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

[ ]:
```
#indices
df.index
```

[ ]: RangeIndex(start=0, stop=180, step=1)

[ ]:
```
#information of dataset
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
```

[ ]:
```
#unique counts in each column
df.nunique()
```

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

[ ]:
```
#check nulls
df.isna().sum()
```

[ ]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
```

```
Miles           0
dtype: int64
```

[ ]:
```
#duplicates
df.duplicated().sum()
```

[ ]: 0

We can see that there are no duplicates and null values in the dataset

1.3 Descriptive Statistical Analysis

[ ]:
```
#statistical analysis for numerical columns
df.describe()
```

[ ]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

1. Age: Customer's age ranges from `18 to 50 years`, with an average age of `29 years`.

2. Education: Customer's education duration vary between `12 and 21 years`, with an average education of `16 years`.

3. Usage: Customer's usage of the product ranges from `2 to 7 times per week`, with an average usage frequency of `3 times per week`.

4. Fitness: Customers have rated their fitness on the scale of `1 to 5`, with an average being `3` reflecting a `moderate level of fitness`.

5. Income: Customer's annual income falls within the range of `$ 30,000 to $ 100,000`, with an average income of approximately `$ 54,000`.

6. Miles: Customer's running goals range from `21 to 360 miles per week`, with an average of `103 miles per week`.

```
[ ]: #statistical analysis for object type columns
jndf.describe(include = 'object')
```

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

7. Product: Based on the data, product `KP281` is sold more compared to the other two products having `80` sales.

8. Gender: Based on the data, most of the buyers are `Male` having count of `140`.

9. Marital Status: Based on the data, most of the buyers were `Married` having count of `107`.

1.4 Adding Grouped 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
```

We can group the following columns for further analysis:

- **Age**

  Categorizing the values in age column in 4 different buckets:

  1. Young Adult: 15 - 25 yrs of age
  2. Adults: 26 - 35 yrs of age
  3. Middle Aged: 36 - 45 yrs of age
  4. Elder : above 46 yrs of age

- **Education**

  Categorizing the values in education column in 3 different buckets:

  1. Secondary Education: 10 - 14 yrs of education
  2. Graduation: 15 - 18 yrs of education
  3. Post Graduation: above 19 yrs of education

- **Income**

  Categorizing the values in Income column in 4 different buckets:

  1. Low Income - Upto 40,000

2. Moderate Income - 40,000 to 60,000
3. High Income - 60,000 to 80,000
4. Very High Income - Above 80,000

- **Miles**

  Categorizing the values in miles column in 4 different buckets:

  1. Light Activity - Upto 50 miles
  2. Moderate Activity - 51 to 100 miles
  3. High Activity - 101 to 200 miles
  4. Very High Activity - Above 200 miles

[2]:
```
#grouping age
ages = [15, 25, 35, 45, df['Age'].max()]
age_group = ['Young Adult', 'Adult', 'Middle Aged', 'Elder']
df['AgeGroup'] = pd.cut(df['Age'], bins = ages, labels = age_group)

#grouping education
education = [10, 14, 18, df['Education'].max()]
edu_group = ['Secondary Education', 'Graduation', 'Post Graduation']
df['EducationGroup'] = pd.cut(df['Education'], bins = education, labels =␣
↪edu_group)

#groupingincome
income = [0, 40000, 60000, 80000, df['Income'].max()]
income_group = ['Low Income', 'Moderate Income', 'High Income', 'Very High␣
↪Income']
df['IncomeGroup'] = pd.cut(df['Income'], bins = income, labels = income_group)

#grouping miles
miles = [0, 50, 100, 200, df['Miles'].max()]
miles_group = ['Low Activity', 'Moderate Activity', 'High Activity', 'Very High␣
↪Activity']
df['MilesGroup'] = pd.cut(df['Miles'], bins = miles, labels = miles_group)
```

[ ]:
```
df.head()
```

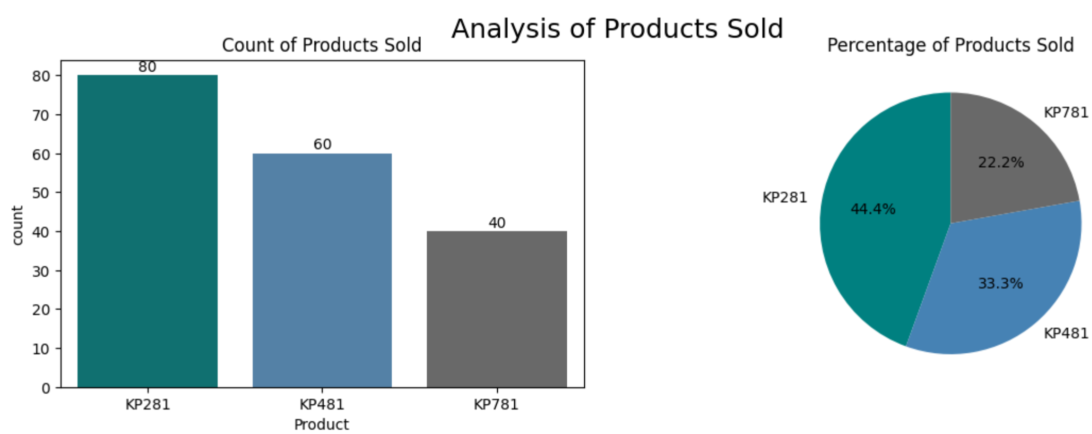
[ ]:
```
  Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0   KP281   18    Male         14        Single      3        4   29562
1   KP281   19    Male         15        Single      2        3   31836
2   KP281   19  Female         14     Partnered      4        3   30699
3   KP281   19    Male         12        Single      3        3   32973
4   KP281   20    Male         13     Partnered      4        2   35247

   Miles     AgeGroup       EducationGroup IncomeGroup         MilesGroup
0    112  Young Adult  Secondary Education  Low Income      High Activity
1     75  Young Adult           Graduation  Low Income  Moderate Activity
2     66  Young Adult  Secondary Education  Low Income  Moderate Activity
```

```
3      85  Young Adult  Secondary Education  Low Income  Moderate Activity
4      47  Young Adult  Secondary Education  Low Income       Low Activity
```

1.5 Product wise Analysis

1.5.1 Products Sold

```
[ ]: plt.figure(figsize=(14,4)).suptitle('Analysis of Products Sold',fontsize=18)

plt.subplot(1,2,1)
plt.title('Count of Products Sold', fontsize=12)
g1 = sns.countplot(df, x = 'Product', palette = {'KP281':'teal', 'KP481':
  ↪'steelblue', 'KP781':'dimgrey'})
for p in g1.patches:
    g1.text(p.get_x()+p.get_width()/2, p.get_height()+1, ha='center', s=round(p.
  ↪get_height()))

plt.subplot(1,2,2)
plt.title('Percentage of Products Sold', fontsize=12)
g2 = plt.pie(df['Product'].value_counts(),
             labels = df['Product'].unique(),
             autopct = '%1.1f%%',
             colors = ('teal','steelblue','dimgrey'),
             startangle = 90)

plt.show()
```



- The KP281 is an entry-level treadmill that sell for $1,500.
- The KP481 is for mid-level runners that sell for $1,750.
- The KP781 treadmill is having advanced features that sell for $2,500.

In the last quarter, product KP281 has showcased the strongest sales performance compared to the other two products constituting approximately 44.4% of the total sales.

1.5.2 Products Sales

[ ]:
```
sales = df.groupby('Product')['Product'].value_counts().
 ↪reset_index(name='UnitsSold')
sales['UnitPrice'] = [1500,1750,2500]
sales['Sales'] = sales['UnitsSold'] * sales['UnitPrice']
sales['UnitPrice'] = sales['UnitPrice'].apply(lambda x : '$'+ str(x))
sales['Sales'] = sales['Sales'].apply(lambda x : '$'+ str(x//1000) + 'K')
sales
```

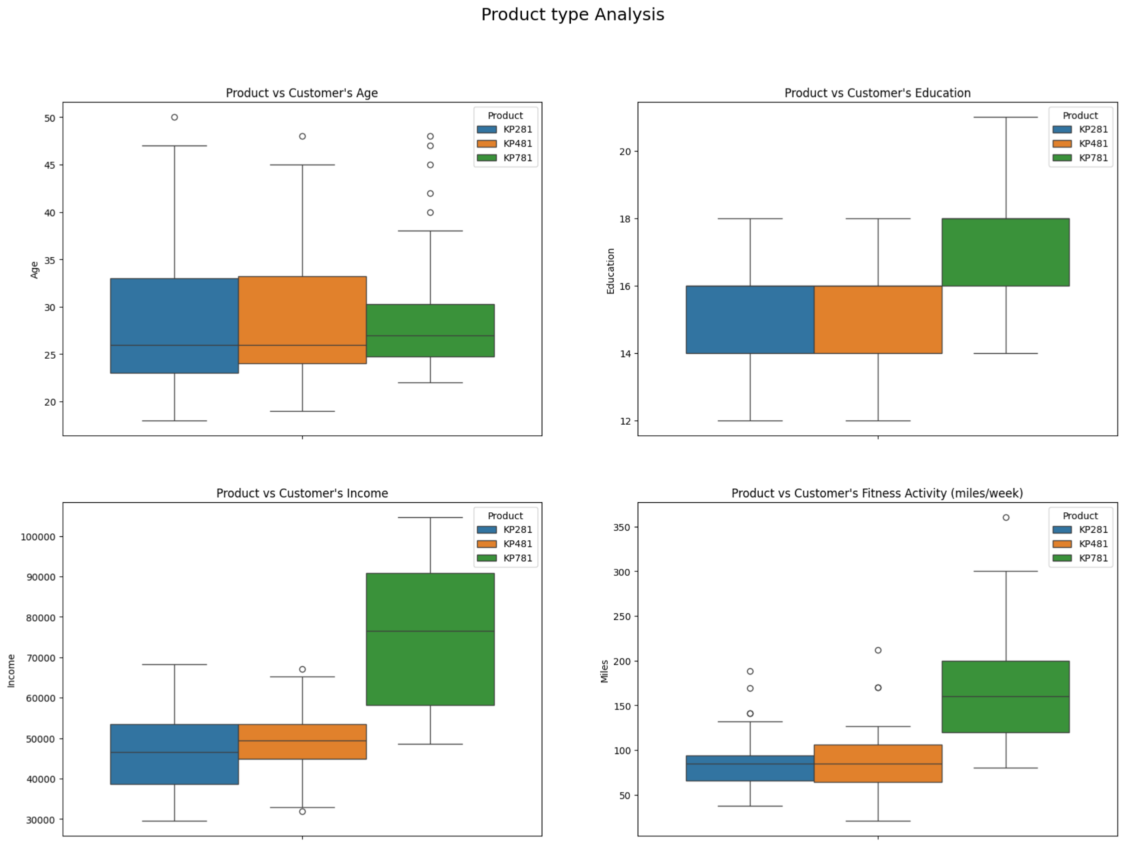
[ ]:

	Product	UnitsSold	UnitPrice	Sales
0	KP281	80	$1500	$120K
1	KP481	60	$1750	$105K
2	KP781	40	$2500	$100K

The sales revenue of the product KP281 is slightly larger than the other two but all three products have nearly equal contributions in terms of generating sales revenue.

1.5.3 Product type Analysis

[ ]:
```
plt.figure(figsize=(20,14)).suptitle('Product type Analysis',fontsize=18)

plt.subplot(2,2,1)
plt.title("Product vs Customer's Age", fontsize=12)
sns.boxplot(df, y='Age', hue='Product')

plt.subplot(2,2,2)
plt.title("Product vs Customer's Education", fontsize=12)
sns.boxplot(df, y='Education', hue='Product')

plt.subplot(2,2,3)
plt.title("Product vs Customer's Income", fontsize=12)
sns.boxplot(df, y='Income', hue='Product')

plt.subplot(2,2,4)
plt.title("Product vs Customer's Fitness Activity (miles/week)", fontsize=12)
sns.boxplot(df, y='Miles', hue='Product')

plt.show()
```

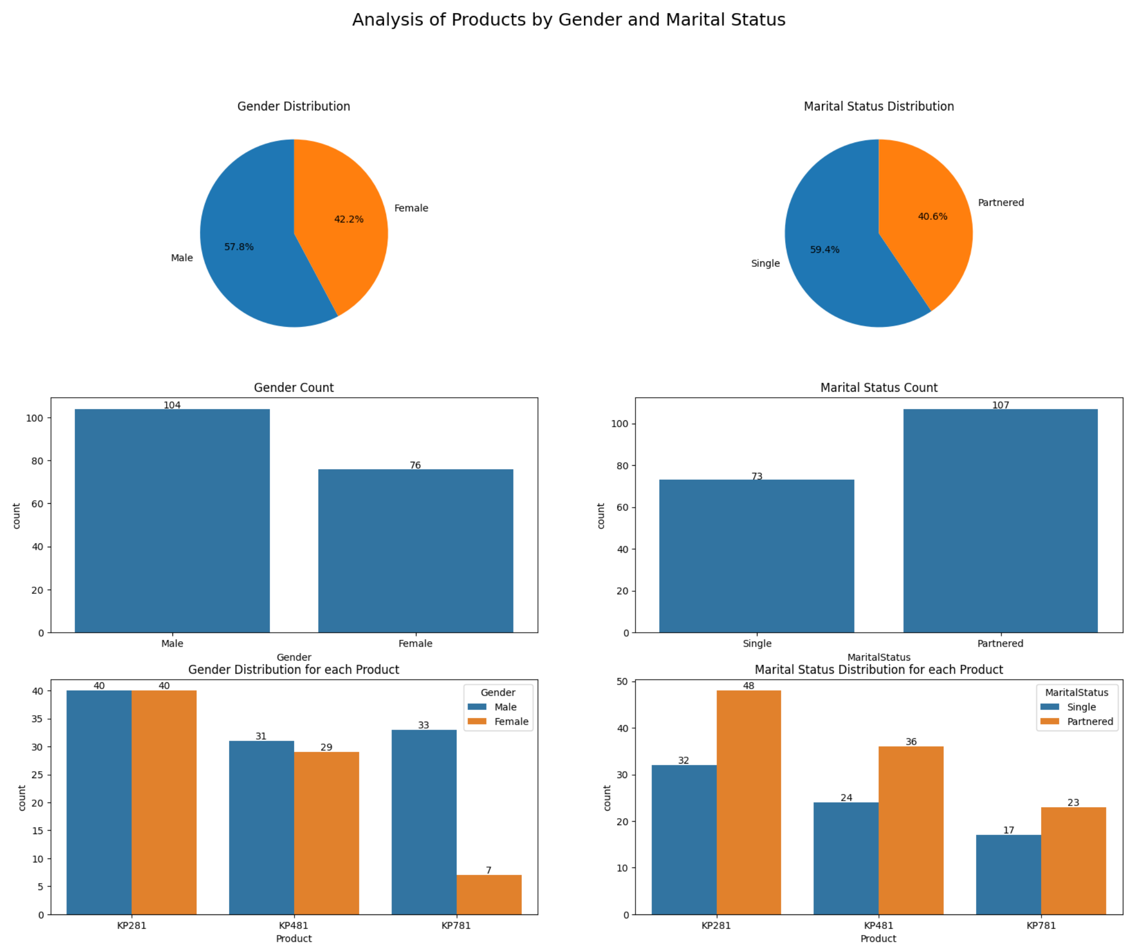


This shows that the product `KP781` has a strong preference among customers who possess **higher education and higher income levels, and are intended to have an active lifestyle by having average running activity greater than 150 miles/week.**

1.5.4 Based on Customer's Gender and Marital Status

[ ]:
```
plt.figure(figsize=(20,15)).suptitle('Analysis of Products by Gender and␣
↪Marital Status',fontsize=18)

plt.subplot(3,2,1)
plt.title('Gender Distribution', fontsize=12)
g2 = plt.pie(df['Gender'].value_counts(),
             labels = df['Gender'].unique(),
             autopct = '%1.1f%%',
             startangle = 90)

plt.subplot(3,2,3)
plt.title('Gender Count', fontsize=12)
ax = sns.countplot(df, x = 'Gender')
for p in ax.patches:
  if p.get_height():
```

```
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
  ↪s=round(p.get_height()))

plt.subplot(3,2,5)
plt.title('Gender Distribution for each Product', fontsize=12)
ax = sns.countplot(df, x = 'Product', hue = 'Gender')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
  ↪s=round(p.get_height()))

plt.subplot(3,2,2)
plt.title('Marital Status Distribution', fontsize=12)
g2 = plt.pie(df['MaritalStatus'].value_counts(),
             labels = df['MaritalStatus'].unique(),
             autopct = '%1.1f%%',
             startangle = 90)

plt.subplot(3,2,4)
plt.title('Marital Status Count', fontsize=12)
ax = sns.countplot(df, x = 'MaritalStatus')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
  ↪s=round(p.get_height()))

plt.subplot(3,2,6)
plt.title('Marital Status Distribution for each Product', fontsize=12)
ax = sns.countplot(df, x = 'Product', hue = 'MaritalStatus')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
  ↪s=round(p.get_height()))

plt.show()
```



- Around 58% of the buyers are `Male` and 42% are `female`.
- Around 60% of the buyers are `Married` and 40% are `single`.
- Product `KP781` which is the high end model is mostly bought by `Males`.

Probability and Conditional Probability for Customer's Gender

[ ]:
```
pd.crosstab(df['Product'], df['Gender'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:

Gender Product	Female	Male	All
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

- The **Probability** of a treadmill being purchased by a **`female is 42.2%`**.

- **`The conditional probability`** of purchasing the treadmill model given that the customer is **`female`** is :
    - For Product KP281 - **22.22%**
    - For Product KP481 - **16.11%**
    - For Product KP781 - **3.89%**
- The **`Probability`** of a treadmill being purchased by a **`male is 57.78%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer is **`male`** is :
    - For Product KP281 - **22.22%**
    - For Product KP481 - **17.22%**
    - For Product KP781 - **18.33%**

Probability and Conditional Probability for Customer's Marital Status

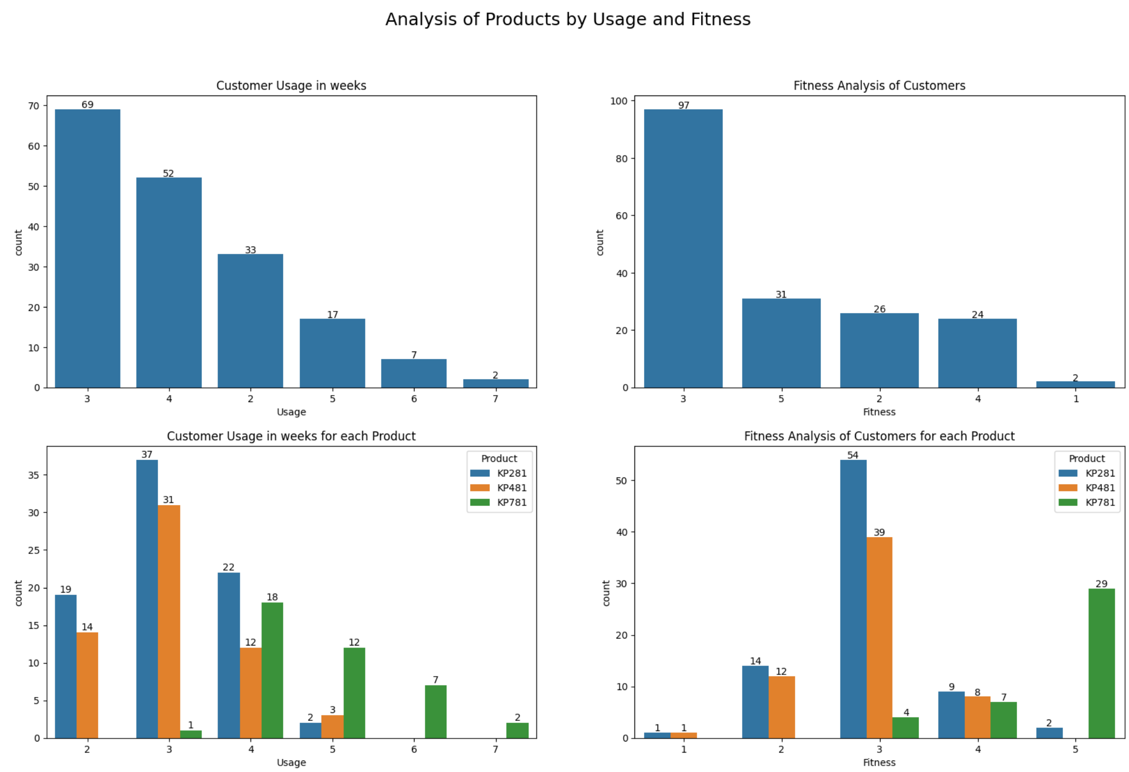
[ ]:
```python
pd.crosstab(df['Product'], df['MaritalStatus'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:
```
MaritalStatus  Partnered  Single     All
Product
KP281              26.67   17.78   44.44
KP481              20.00   13.33   33.33
KP781              12.78    9.44   22.22
All                59.44   40.56  100.00
```

- The **`Probability`** of a treadmill being purchased by a **`Married Customer is 59.44%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer is **`Married`** is :
    - For Product KP281 - **26.67%**
    - For Product KP481 - **20%**
    - For Product KP781 - **12.78%**
- The **`Probability`** of a treadmill being purchased by a **`Unmarried Customer is 40.56%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer is **`Unmarried`** is :
    - For Product KP281 - **17.78%**
    - For Product KP481 - **13.33%**
    - For Product KP781 - **9.44%**

1.5.5 Based on Customer's Usage and Fitness

[ ]:
```
plt.figure(figsize=(20,12)).suptitle('Analysis of Products by Usage and␣
↪Fitness',fontsize=18)

plt.subplot(2,2,1)
plt.title('Customer Usage in weeks', fontsize=12)
g2 = sns.countplot(df, x = 'Usage',  order = df['Usage'].value_counts().index)
for p in g2.patches:
  g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
↪get_height()))

plt.subplot(2,2,3)
plt.title('Customer Usage in weeks for each Product', fontsize=12)
ax = sns.countplot(df, x = 'Usage', hue = 'Product')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
↪s=round(p.get_height()))

plt.subplot(2,2,2)
plt.title('Fitness Analysis of Customers', fontsize=12)
g2 = sns.countplot(df, x = 'Fitness', order = df['Fitness'].value_counts().
↪index)
for p in g2.patches:
  g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
↪get_height()))

plt.subplot(2,2,4)
plt.title('Fitness Analysis of Customers for each Product', fontsize=12)
ax = sns.countplot(df, x = 'Fitness', hue = 'Product')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
↪s=round(p.get_height()))

plt.show()
```



- Almost 85% of the customers plan to use the treadmill for `2 to 4 times a week` and only `15% using 5 times and above each week`.
- Almost 54% of the customers have self-evaluated their `fitness rating at 3 on a scale of 1 to 5`. Furthermore, a substantial 84% of the total customers have rated themselves at `3 or higher`, indicating commendable fitness levels.

Probability and Conditional Probability for Customer's Usage

[ ]:
```
pd.crosstab(df['Product'], df['Usage'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:

Usage Product	2	3	4	5	6	7	All
KP281	10.56	20.56	12.22	1.11	0.00	0.00	44.44
KP481	7.78	17.22	6.67	1.67	0.00	0.00	33.33
KP781	0.00	0.56	10.00	6.67	3.89	1.11	22.22
All	18.33	38.33	28.89	9.44	3.89	1.11	100.00

- The **Probability** of a treadmill being purchased by a customer with **Usage 3 per week is 38.33%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Usage 3 per week** is :
    * For Product KP281 - **20.56%**

    * For Product KP481 - **17.22%**
    * For Product KP781 - **0.56%**

- The **Probability** of a treadmill being purchased by a customer with **Usage 4 per week is 28.89%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Usage 4 per week** is :
    * For Product KP281 - **12.22%**
    * For Product KP481 - **6.67%**
    * For Product model KP781 - **10%**
- The **Probability** of a treadmill being purchased by a customer with **Usage 2 per week is 18.33%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Usage 2 per week** is :
    * For Product KP281 - **10.56%**
    * For Product KP481 - **7.78%**
    * For Product KP781 - **0%**

Probability and Conditional Probability for Customer's Fitness level

[ ]:
```
pd.crosstab(df['Product'], df['Fitness'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:

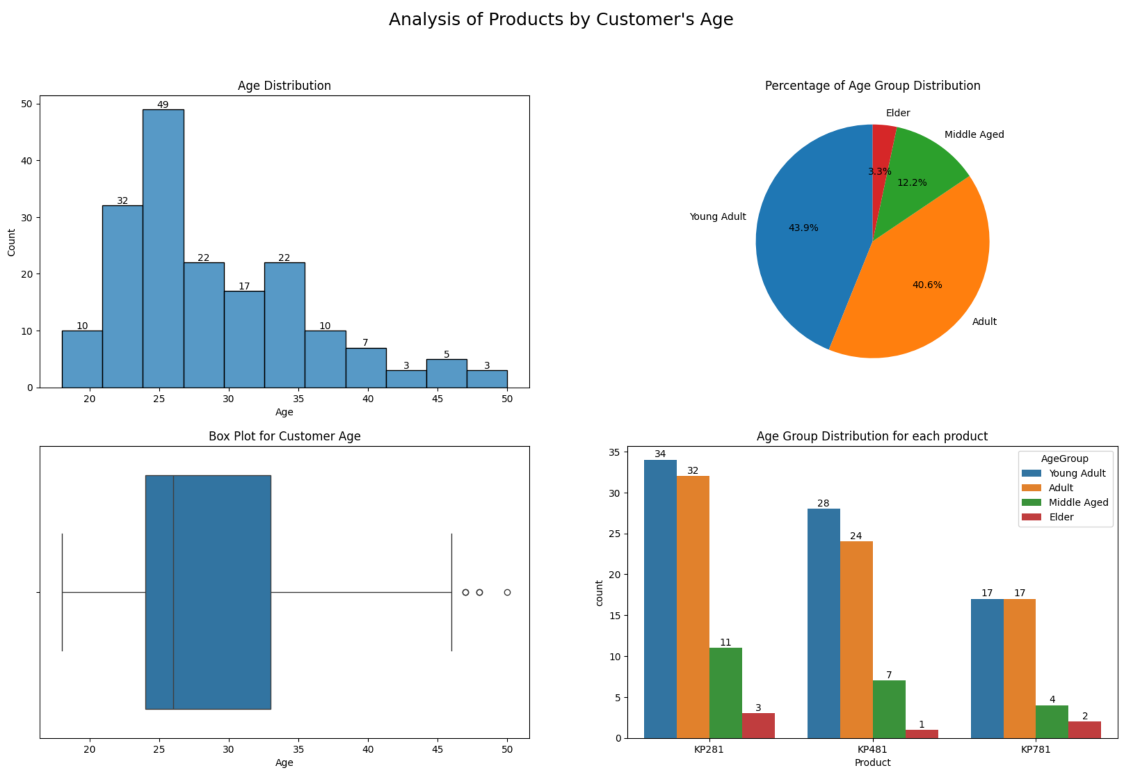
Fitness Product	1	2	3	4	5	All
KP281	0.56	7.78	30.00	5.00	1.11	44.44
KP481	0.56	6.67	21.67	4.44	0.00	33.33
KP781	0.00	0.00	2.22	3.89	16.11	22.22
All	1.11	14.44	53.89	13.33	17.22	100.00

- The **Probability** of a treadmill being purchased by a customer with **Average Fitness rating (3) is 54%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Average Fitness** is :
    * For product KP281 - **30%**
    * For product KP481 - **22%**
    * For product KP781 - **2%**
- The **Probability** of a treadmill being purchased by a customer having **Fitness rating 2 is almost 14%**.
- The **Probability** of a treadmill being purchased by a customer having **Fitness rating 4 is almost 13%**.

- The **Probability** of a treadmill being purchased by a customer having **Fitness rating 5 is almost 17%**.
- The **Probability** of a treadmill being purchased by a customer having **very low Fitness rating (1) is 1%**.

1.5.6 Based on Customer's Age

[ ]:
```
plt.figure(figsize=(20,12)).suptitle("Analysis of Products by Customer's␣
↪Age",fontsize=18)

plt.subplot(2,2,1)
plt.title('Age Distribution', fontsize=12)
g2 = sns.histplot(df, x = 'Age')
for p in g2.patches:
  g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
↪get_height()))

plt.subplot(2,2,3)
plt.title('Box Plot for Customer Age', fontsize=12)
sns.boxplot(df, x='Age')

plt.subplot(2,2,2)
plt.title('Percentage of Age Group Distribution', fontsize=12)
g2 = plt.pie(df['AgeGroup'].value_counts(),
             labels = df['AgeGroup'].value_counts().index,
             autopct = '%1.1f%%',
             startangle = 90)

plt.subplot(2,2,4)
plt.title('Age Group Distribution for each product', fontsize=12)
ax = sns.countplot(df, x = 'Product', hue='AgeGroup')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
↪s=round(p.get_height()))

plt.show()
```



[5]:
```python
df['Age'].describe()
```

[5]:
```
count    180.000000
mean      28.788889
std        6.943498
min       18.000000
25%       24.000000
50%       26.000000
75%       33.000000
max       50.000000
Name: Age, dtype: float64
```

- Almost `85%` of the customers falls under the age range of `18 to 35 (Young Adults and Adults)`, with a median age of `26`, suggesting young people showing more interest in the companies products
- There are `3 outliers` present in the age data.

Young Adult: 15 - 25 yrs of age

Adults: 26 - 35 yrs of age

Middle Aged: 36 - 45 yrs of age

Elder : above 46 yrs of age

Probability and Conditional Probability for Customer's Age

[ ]:
```
pd.crosstab(df['Product'], df['AgeGroup'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:

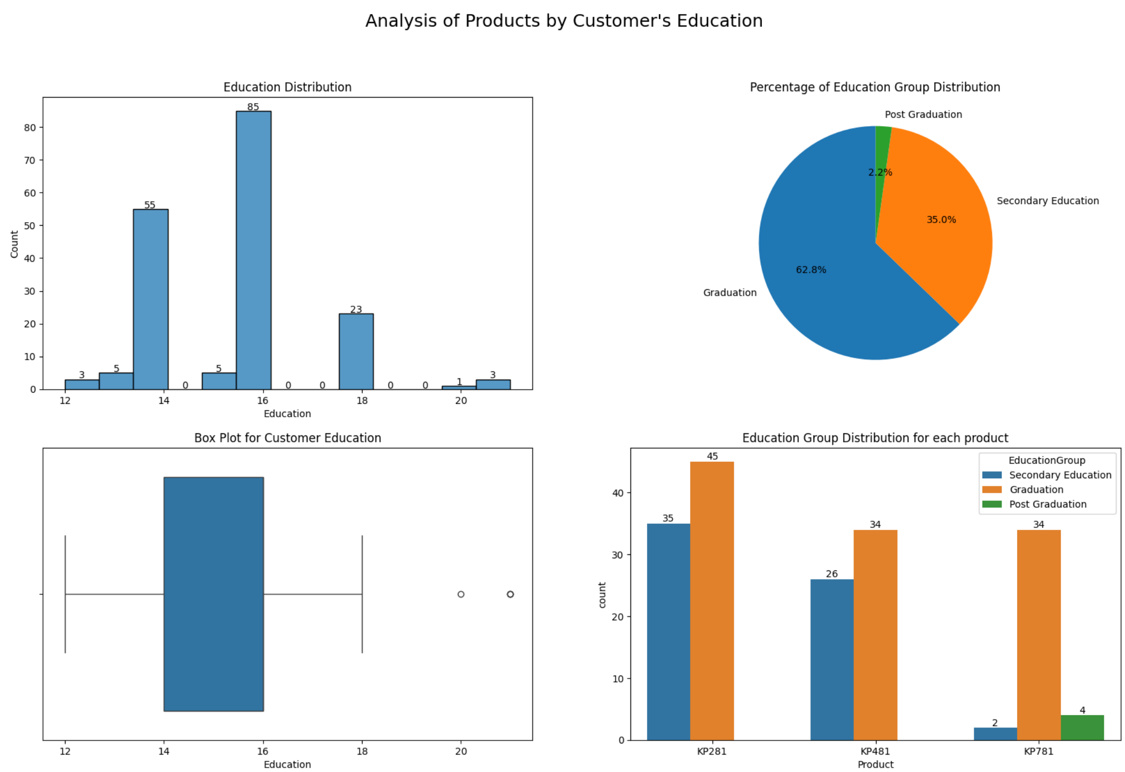
AgeGroup	Young Adult	Adult	Middle Aged	Elder	All
Product					
KP281	18.89	17.78	6.11	1.67	44.44
KP481	15.56	13.33	3.89	0.56	33.33
KP781	9.44	9.44	2.22	1.11	22.22
All	43.89	40.56	12.22	3.33	100.00

- The **Probability** of a treadmill being purchased by a **Young Adult (18-25) is 43.89%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer is **Young Adult** is :
    - For product KP281 - **18.89%**
    - For product KP481 - **15.56%**
    - For product KP781 - **9.44%**
- The **Probability** of a treadmill being purchased by a **Adult (26-35) is 40.56%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer is **Adult** is :
    - For product KP281 - **17.78%**
    - For product KP481 - **13.33%**
    - For product KP781 - **9.44%**
- The **Probability** of a treadmill being purchased by a **Middle Aged (36-45) is 12.22%**.
- The **Probability** of a treadmill being purchased by a **Elder (Above 45) is only 3.33%**.

1.5.7 Based on Customer's Education

[ ]:
```
plt.figure(figsize=(20,12)).suptitle("Analysis of Products by Customer's␣
↪Education",fontsize=18)

plt.subplot(2,2,1)
plt.title('Education Distribution', fontsize=12)
g2 = sns.histplot(df, x = 'Education')
for p in g2.patches:
  g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
↪get_height()))

plt.subplot(2,2,3)
plt.title('Box Plot for Customer Education', fontsize=12)
sns.boxplot(df, x='Education')
```

```
plt.subplot(2,2,2)
plt.title('Percentage of Education Group Distribution', fontsize=12)
g2 = plt.pie(df['EducationGroup'].value_counts(),
             labels = df['EducationGroup'].value_counts().index,
             autopct = '%1.1f%%',
             startangle = 90)

plt.subplot(2,2,4)
plt.title('Education Group Distribution for each product', fontsize=12)
ax = sns.countplot(df, x = 'Product', hue='EducationGroup')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
 ↪s=round(p.get_height()))

plt.show()
```




```
[6]: df['Education'].describe()
```

```
[6]: count    180.000000
     mean      15.572222
     std        1.617055
```

```
min        12.000000
25%        14.000000
50%        16.000000
75%        16.000000
max        21.000000
Name: Education, dtype: float64
```

- Almost 98% of the customers are pursuing `Secondary Education or Graduation (12 - 18 Years)`.
- The remaining 2% of the customers, a total of 4 pursued `Post Graduation (above 19 years)` and bought product `KP781` only which is the high end model.
- There are `2 outliers` present in the education data.
- 50% percentile (median) and 75% percentile are same i.e., 16 for education data.

Secondary Education: 10 - 14 yrs of education

Graduation: 15 - 18 yrs of education

Post Graduation: above 19 yrs of education

Probability and Conditional Probability for Customer's Education

[ ]:
```
pd.crosstab(df['Product'], df['EducationGroup'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:

EducationGroup Product	Secondary Education	Graduation	Post Graduation	All
KP281	19.44	25.00	0.00	44.44
KP481	14.44	18.89	0.00	33.33
KP781	1.11	18.89	2.22	22.22
All	35.00	62.78	2.22	100.00

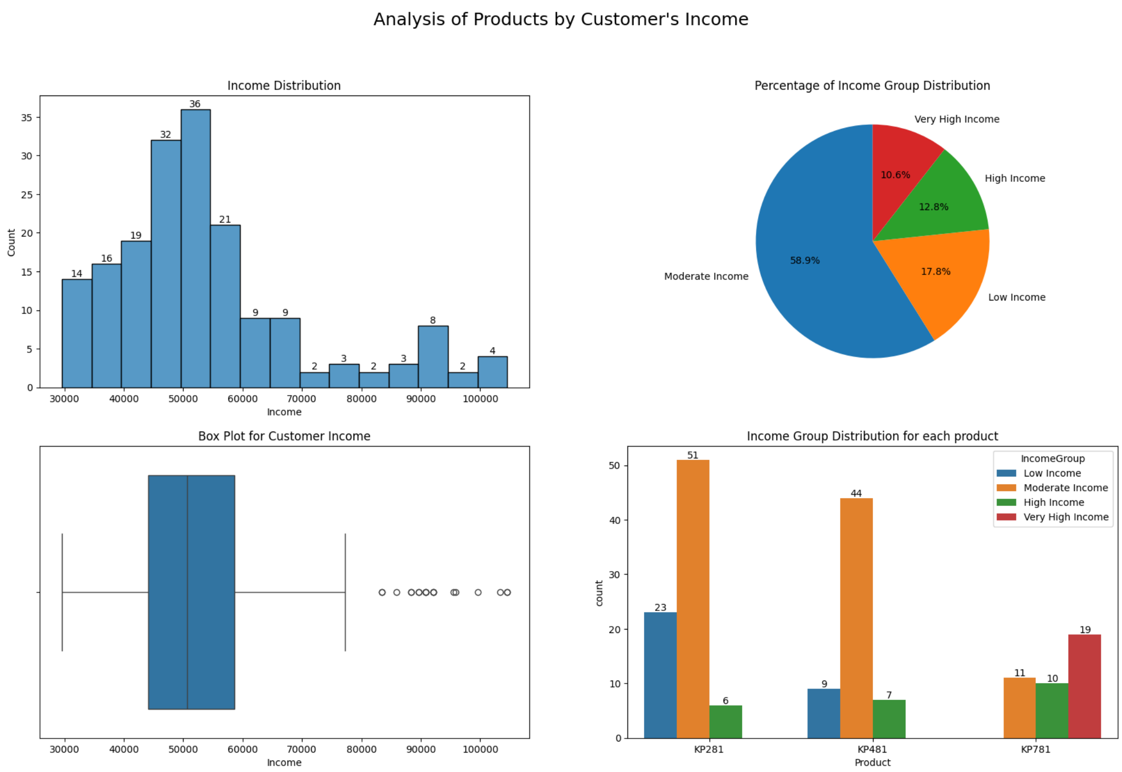
- The **`Probability`** of a treadmill being purchased by a customer pursuing **`Graduation (15 - 18 Years) is 62.78%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer is pursuing **`Graduation`** is :
    - For product KP281 - **25%**
    - For product KP481 - **18.89%**
    - For product KP781 - **18.89%**
- The **`Probability`** of a treadmill being purchased by a customer pursuing **`Secondary Education (10 - 14 Years) is 35%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer is pursuing **`Secondary Education`** is :
    - For product KP281 - **19.44%**

    * For product KP481 - **14.44%**
    * For product KP781 - **1.11%**

- The **Probability** of a treadmill being purchased by a customer pursuing **Post Graduation (19 Years) is 2.22%**.

1.5.8 Based on Customer's Income

[13]:
```
plt.figure(figsize=(20,12)).suptitle("Analysis of Products by Customer's␣
↪Income",fontsize=18)

plt.subplot(2,2,1)
plt.title('Income Distribution', fontsize=12)
g2 = sns.histplot(df, x = 'Income')
for p in g2.patches:
  g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
↪get_height()))

plt.subplot(2,2,3)
plt.title('Box Plot for Customer Income', fontsize=12)
sns.boxplot(df, x='Income')

plt.subplot(2,2,2)
plt.title('Percentage of Income Group Distribution', fontsize=12)
g2 = plt.pie(df['IncomeGroup'].value_counts(),
             labels = df['IncomeGroup'].value_counts().index,
             autopct = '%1.1f%%',
             startangle = 90)

plt.subplot(2,2,4)
plt.title('Income Group Distribution for each product', fontsize=12)
ax = sns.countplot(df, x = 'Product', hue='IncomeGroup')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
↪s=round(p.get_height()))

plt.show()
```




```
[7]: df['Income'].describe()
```

```
[7]: count       180.000000
     mean      53719.577778
     std       16506.684226
     min       29562.000000
     25%       44058.750000
     50%       50596.500000
     75%       58668.000000
     max      104581.000000
     Name: Income, dtype: float64
```

- Almost `18%` of the customers falls under `Low income (below 40K USD)` category.
- Almost `59%` of the customers falls under `Moderate income (40K to 60K USD)` category
- Almost `77%` of the total customers fall in income group of `below 60K` and only `23%` of them falling in `60K and above` income group
- There are `many outliers` present in the income data.

Low Income - Upto 40,000

Moderate Income - 40,000 to 60,000

High Income - 60,000 to 80,000

Very High Income - Above 80,000

Probability and Conditional Probability for Customer's Income

```
[ ]: pd.crosstab(df['Product'], df['IncomeGroup'], margins=True, normalize=True).
     ↪round(4)*100
```

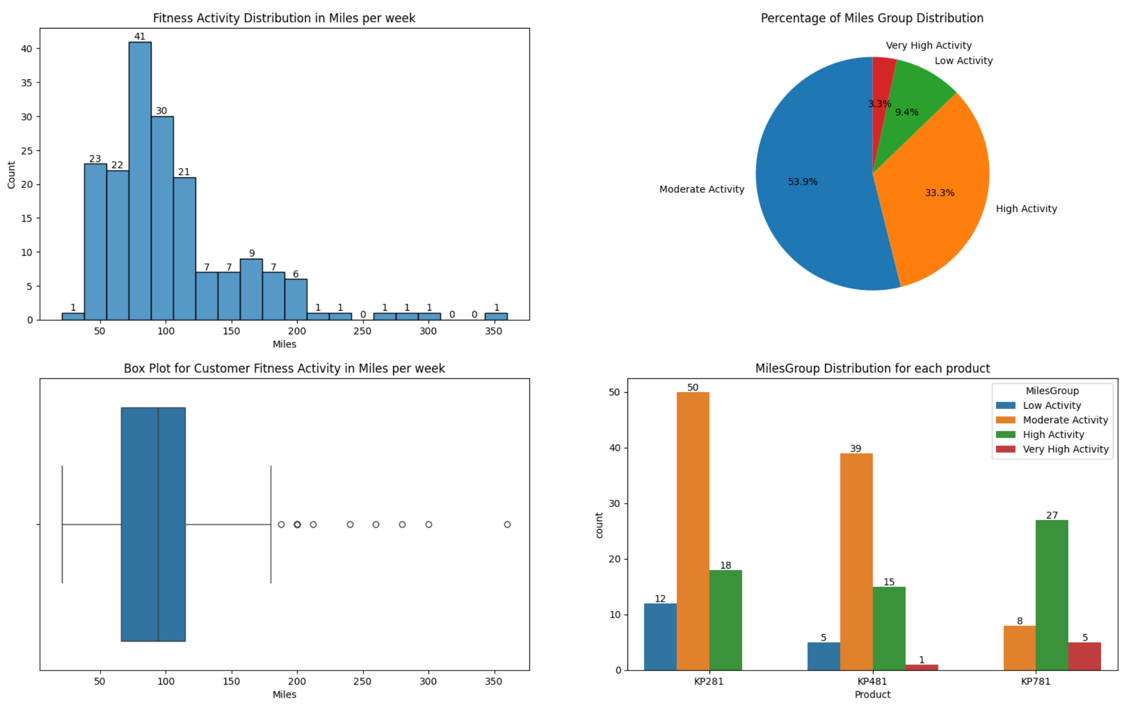
```
[ ]: IncomeGroup  Low Income  Moderate Income  High Income  Very High Income  \
     Product
     KP281             12.78            28.33         3.33              0.00
     KP481              5.00            24.44         3.89              0.00
     KP781              0.00             6.11         5.56             10.56
     All               17.78            58.89        12.78             10.56

     IncomeGroup     All
     Product
     KP281         44.44
     KP481         33.33
     KP781         22.22
     All          100.00
```

- The **`Probability`** of a treadmill being purchased by a customer with **`Low Income (below 40k) is 17.78%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer has **`Low Income`** is :
    - For Treadmill model KP281 - **12.78%**
    - For Treadmill model KP481 - **5%**
    - For Treadmill model KP781 - **0%**
- The **`Probability`** of a treadmill being purchased by a customer with **`Moderate Income (40k - 60k) is 58.89%`**.
  - **`The conditional probability`** of purchasing the treadmill model given that the customer has **`Moderate Income`** is :
    - For Treadmill model KP281 - **28.33%**
    - For Treadmill model KP481 - **24.44%**
    - For Treadmill model KP781 - **6.11%**
- The **`Probability`** of a treadmill being purchased by a customer with **`High Income (60k - 80k) is 12.78%`**
  - **`The conditional probability`** of purchasing the treadmill model given that the customer has **`High Income`** is :
    - For Treadmill model KP281 - **3.33%**
    - For Treadmill model KP481 - **3.89%**
    - For Treadmill model KP781 - **5.56%**
- The **`Probability`** of a treadmill being purchased by a customer with **`Very High Income(above 80k) is 10.56%`** and only bought product **`KP781`**

1.5.9 Based on Customer's Fitness Activity (Miles per week)

```
[ ]: plt.figure(figsize=(20,12)).suptitle("Analysis of Products by Customer's␣
     ↪Fitness Activity in Miles per week",fontsize=18)

     plt.subplot(2,2,1)
     plt.title('Fitness Activity Distribution in Miles per week', fontsize=12)
     g2 = sns.histplot(df, x = 'Miles')
     for p in g2.patches:
       g2.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center', s=round(p.
     ↪get_height()))

     plt.subplot(2,2,3)
     plt.title('Box Plot for Customer Fitness Activity in Miles per week',␣
     ↪fontsize=12)
     sns.boxplot(df, x='Miles')

     plt.subplot(2,2,2)
     plt.title('Percentage of Miles Group Distribution', fontsize=12)
     g2 = plt.pie(df['MilesGroup'].value_counts(),
                  labels = df['MilesGroup'].value_counts().index,
                  autopct = '%1.1f%%',
                  startangle = 90)

     plt.subplot(2,2,4)
     plt.title('MilesGroup Distribution for each product', fontsize=12)
     ax = sns.countplot(df, x = 'Product', hue='MilesGroup')
     for p in ax.patches:
       if p.get_height():
         ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
     ↪s=round(p.get_height()))

     plt.show()
```

Analysis of Products by Customer's Fitness Activity in Miles per week




```
[8]: df['Miles'].describe()
```

```
[8]: count    180.000000
     mean     103.194444
     std       51.863605
     min       21.000000
     25%       66.000000
     50%       94.000000
     75%      114.750000
     max      360.000000
     Name: Miles, dtype: float64
```

- Almost 87% of the customers plans to use the treadmill for `50 to 200 miles` per week with a median of `94 miles per week`.
- There are `9 outliers` present in the Miles data.

Low Activity - Upto 50 miles

Moderate Activity - 51 to 100 miles

High Activity - 101 to 200 miles

Very High Activity - Above 200 miles

Probability and Conditional Probability for Customer's Fitness Activity

[ ]:
```
pd.crosstab(df['Product'], df['MilesGroup'], margins=True, normalize=True).
↪round(4)*100
```

[ ]:
```
MilesGroup  Low Activity  Moderate Activity  High Activity  \
Product
KP281               6.67              27.78          10.00
KP481               2.78              21.67           8.33
KP781               0.00               4.44          15.00
All                 9.44              53.89          33.33

MilesGroup  Very High Activity     All
Product
KP281                     0.00   44.44
KP481                     0.56   33.33
KP781                     2.78   22.22
All                       3.33  100.00
```

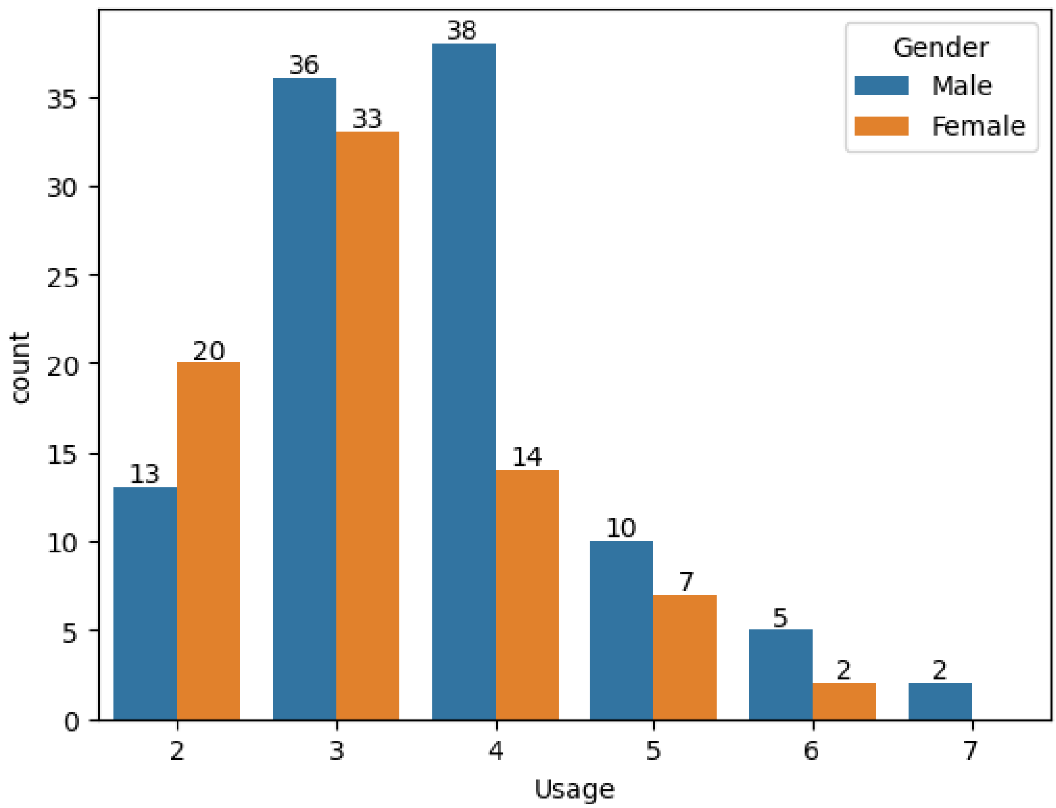
- The **Probability** of a treadmill being purchased by a customer with lifestyle of **Light Activity (0 to 50 miles/week) is 9.44%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Low Activity** is :
    - For Treadmill model KP281 - **6.67%**
    - For Treadmill model KP481 - **2.78%**
    - For Treadmill model KP781 - **0%**
- The **Probability** of a treadmill being purchased by a customer with lifestyle of **Moderate Activity (51 to 100 miles/week) is 53.89%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer with lifestyle of **Moderate Activity** is :
    - For Treadmill model KP281 - **27.78%**
    - For Treadmill model KP481 - **21.67%**
    - For Treadmill model KP781 - **4.44%**
- The **Probability** of a treadmill being purchased by a customer has lifestyle of **High Activity (100 to 200 miles/week) is 33.33%**.
  - **The conditional probability** of purchasing the treadmill model given that the customer has **Active Lifestyle** is :
    - For Treadmill model KP281 - **10%**
    - For Treadmill model KP481 - **8.33%**
    - For Treadmill model KP781 - **15%**

4. The **Probability** of a treadmill being purchased by a customer who is a **Fitness Enthusiast** i.e., having **Very high Activity (above 200 miles/week) is 3.33% only**

1.6 Gender wise Analysis

1.6.1 Gender vs Usage

[ ]:
```
ax = sns.countplot(df, x = 'Usage', hue = 'Gender')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',␣
  ↪s=round(p.get_height()))
plt.show()
```



[ ]:
```
pd.crosstab(df['Gender'],df['Usage'], normalize=True, margins=True).round(4)*100
```

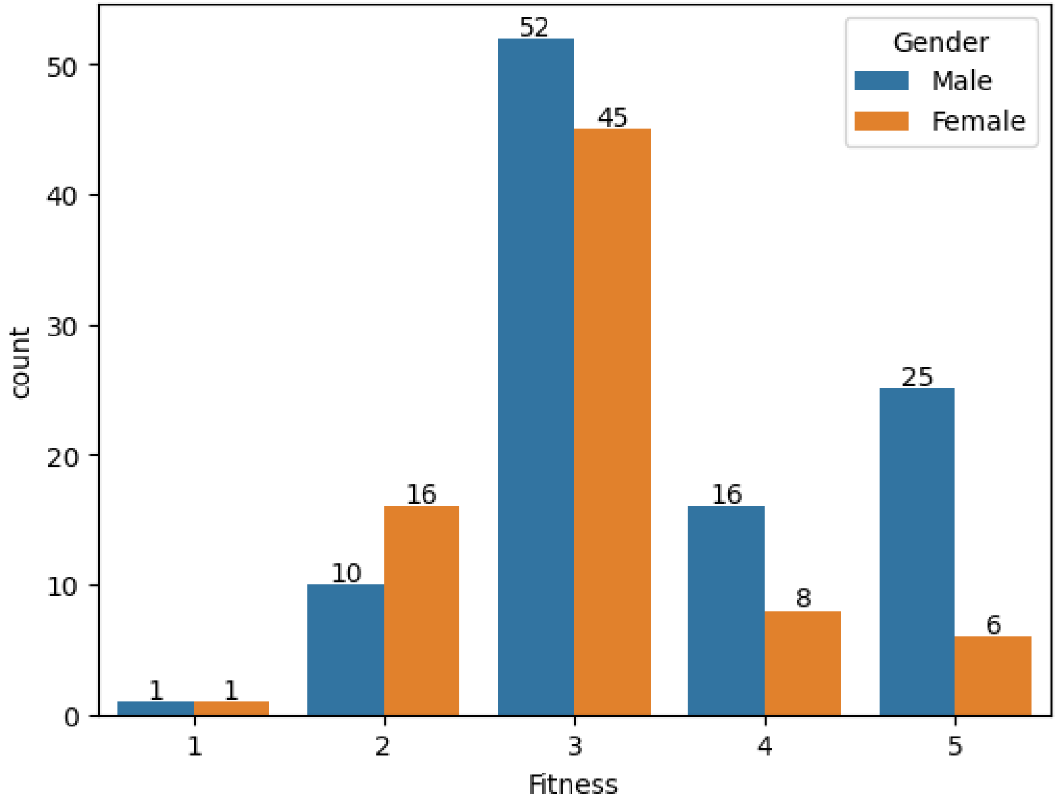
[ ]:

Usage	2	3	4	5	6	7	All
Gender							
Female	11.11	18.33	7.78	3.89	1.11	0.00	42.22
Male	7.22	20.00	21.11	5.56	2.78	1.11	57.78
All	18.33	38.33	28.89	9.44	3.89	1.11	100.00

- Almost 70% of Female customers plan to use the treadmill for 2 to 3 times a week whereas almost 70% of Male customer plan to use the treadmill for 3 to 4 times a week
- Only 2 Male customers are using treadmill for 7 times a week.

1.6.2 Gender vs Fitness

[ ]:
```
ax = sns.countplot(df, x = 'Fitness', hue = 'Gender')
for p in ax.patches:
  if p.get_height():
    ax.text(p.get_x()+p.get_width()/2, p.get_height()+0.3, ha='center',
 ↪s=round(p.get_height()))
plt.show()
```



[ ]:
```
pd.crosstab(df['Fitness'],df['Usage'], normalize=True, margins=True).
 ↪round(4)*100
```

[ ]:

Usage	2	3	4	5	6	7	All
Fitness							
1	0.56	0.56	0.00	0.00	0.00	0.00	1.11
2	7.78	5.56	1.11	0.00	0.00	0.00	14.44
3	10.00	26.11	16.67	1.11	0.00	0.00	53.89

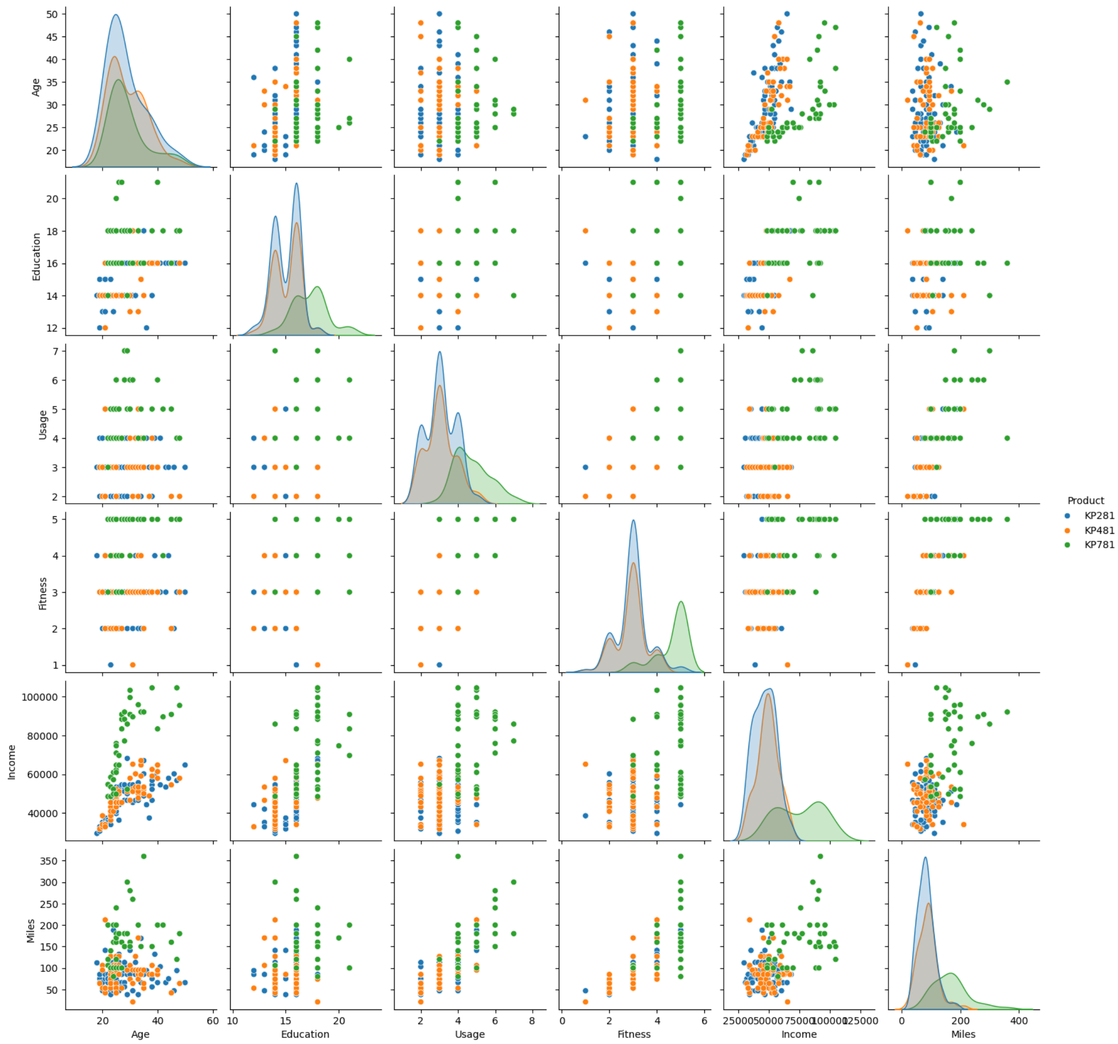
4	0.00	5.56	3.89	3.33	0.56	0.00	13.33
5	0.00	0.56	7.22	5.00	3.33	1.11	17.22
All	18.33	38.33	28.89	9.44	3.89	1.11	100.00

- Almost `80% of Female customers` rated themselves between `2 to 3` whereas almost `90% of Male customer` rated themselves between `3 to 5` on the fitness scale
- Rating `3` is mostly rated by customers with a count of `52 for Males` and `45 for Females`.

1.7 Correlation

1.7.1 Pair Plot

[ ]:
```
sns.pairplot(df, hue ='Product')
plt.show()
```



- By observing the Pair plot, we can say that Products KP281 and KP481 mostly lies under the same area whereas Product KP781 has area shifted towards higher values.

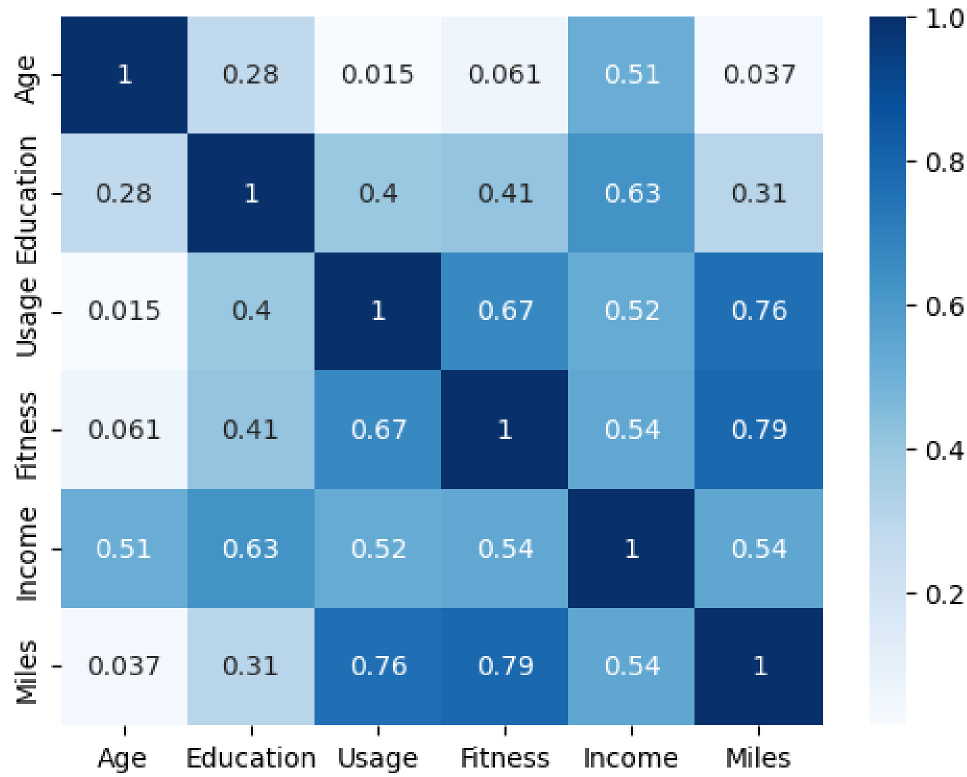
1.7.2 Heat Map

[ ]:
```
corr_mat = df.corr(numeric_only=True)
corr_mat
```

[ ]:

	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

[ ]:
```
sns.heatmap(corr_mat, annot = True, cmap='Blues')
plt.show()
```



- Eductaion and Income are highly correlated as its obvious. Eductation also has significatnt correlation between Fitness rating and Usage of the treadmill.
- Usage is highly correlated with Fitness and Miles as more the usage more the fitness and

mileage.

2 Insights

Based on above analysis

- Probability of purchase of KP281 = 44.4%
- Probability of purchase of KP481 = 33.3%
- Probability of purchase of KP781 = 22.2%
- `Customer Profile` for Product **`KP281`**:
  - Age of customer mainly between 18 and 35 years with few between 35 and 50 years
  - Education level between 13 and 18 years
  - Annual Income of customer mostly below USD 60,000
  - Weekly Usage - 2 to 4 times
  - Fitness Scale - 2 to 4
  - Weekly Running Mileage - upto 200 miles
- `Customer Profile` for Product **`KP481`**:
  - Age of customer mainly between 18 to 35 years with few between 35 to 50 years
  - Education level between 13 and 18 years
  - Annual Income of customer mostly between USD 40,000 and USD 80,000
  - Weekly Usage - 2 to 5 times
  - Fitness Scale - 2 to 4
  - Weekly Running Mileage - upto 200 miles
- `Customer Profile` for Product **`KP781`**:
  - Gender - Male
  - Age of customer mainly between 18 and 35 years with very few between 35 and 50 years
  - Education level mainly between 13 and 18 years and few above 19 years
  - Annual Income of customer mostly between USD 40,000 and USD 80,000 and some above USD 90,000
  - Weekly Usage - 4 to 7 times
  - Fitness Scale - 3 to 5
  - Weekly Running Mileage - 80 miles and above

3 Recommendations

3.1 Product KP281:

- **Target Audience:** This treadmill caters to Budget-conscious, young exercisers (aged 18-35) with moderate education level (13-18 years) and an annual income below USD 60,000. Their fitness goals may involve casual exercise, with a usage frequency of 2-4 times per week, fitness level of 2-4 out of 5 and weekly running mileage under 200 miles.
- **Recommendation:** Utilize social media platforms to promote the KP281 as an affordable entry point for fitness enthusiasts. Highlight its user-friendly features and emphasize its value

for casual runners or walkers.

3.2 Product KP481:

- **Target Audience:** This treadmill is ideal for value-conscious runners within 18-50 age range with moderate education level (13-18 years) and an annual income between USD 40,000 and USD 60,000. They may consider themselves occasional runners, using the treadmill 2-5 times per week, fitness level of 2-4 out of 5 and weekly running mileage under 200 miles.
- **Recommendation:** Leverage online advertising channels to reach this value-conscious demographic. Focus on the KP481's features that cater to occasional runners and highlight its durability for regular workouts.

3.3 Product KP781:

- **Target Audience:** This advanced treadmill targets Serious male runners within 18-35 age range pursued graduation or post graduation, most having (13-18 years) and a few having (above 19 years) of education level and their annual income likely fall within the USD 40,000 - USD 80,000 income bracket, with some exceeding USD 90,000. They are dedicated runners,using the treadmill 4-7 times per week, fitness level of 3-5 out of 5 and weekly running mileage is over 80 miles or more (mostly above 150).
- **Recommendation:** Advertise the KP781 in running magazines, websites, and events. Emphasize its advanced features, durability for high mileage, and ability to support dedicated training programs.

3.4 General Recommendations:

- **Customer Engagement:** Implement targeted email campaigns and personalized offers based on customer profiles.
- **Social Media:** Utilize social media platforms to engage with potential customers and share product benefits.
- **Customer Feedback:** Collect feedback through surveys or social media polls to understand customer preferences and improve product offerings.
- **Competitive Analysis:** Continuously monitor competitor products and pricing strategies to stay competitive in the market.
- **Customer Service:** Provide excellent customer service and post-purchase support to enhance brand loyalty and encourage repeat purchases.