AEROFIT BIZ CASE STUDY

To analyse,interprete and visualize the given Netflix data and to solve the related problems to get insights we need functions and methods, so we must import Python libraries into our work notebook.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.colors as col
from scipy.stats import norm
```

To get the data into our work space we use the below code(to read csv files) and saving the whole set of data into a single variable(dataframe) which makes analysis easier

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639992749 -O aerofit.csv
```

```
--2023-08-22 14:07:53--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 13.35.37.31, 13.35.37.7, 13.35.37.102, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|13.35.37.31|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 7279 (7.1K) [text/plain]
Saving to: ‘aerofit.csv’

aerofit.csv         100%[===================>]   7.11K  --.-KB/s    in 0s

2023-08-22 14:07:53 (2.41 GB/s) - ‘aerofit.csv’ saved [7279/7279]
```

```
data = pd.read_csv('aerofit.csv')
```

```
data.head(2)
```

	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

```
data.tail(2)
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

```
data.sample(2)
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
79	KP281	50	Female	16	Partnered	3	3	64809	66
123	KP481	33	Female	16	Partnered	5	3	53439	95

```
# TO GET NO. OF ROWS & COLUMNS:

data.shape
```

```
(180, 9)
```

```
# TO GET TOTAL ELEMENTS IN THE DATASET (i.e., the dot product of no. of rows & columns)

data.size
```

```
1620
```

```
# To get index

data.index
```

```
RangeIndex(start=0, stop=180, step=1)
```

```
# TO GET THE NAMES OF THE COLUMNS

data.columns
```

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

```
# TO GET THE NAMES OF THE COLUMNS(alternate method)

data.keys()
```

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

```
# To get memory usage of each column

data.memory_usage()
```

```
Index             128
Product          1440
Age              1440
Gender           1440
Education        1440
MaritalStatus    1440
Usage            1440
Fitness          1440
Income           1440
Miles            1440
dtype: int64
```

```
# TO GET THE TOTAL INFORMATION ABOUT THE DATASET.
# info function let us know the columns with their data types and no. of non-null values & the total memory usage


data.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
```

From the above analysis we get to know that all columns are integer data type except "Product","Gender" and "MaritalStatus" columns which is of object type

TO ANALYSE THE BASIC METRICS

```
# To get the data type of each column

data.dtypes
```

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

STATISTICAL SUMMERY

```
data.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

Describe function returns the glimpse of the data with the statistical values from all over the data just to predict the normal ranges and average ranges to the particular elements. Note: it will display only the numerical values and return from the numerical values.

INFERENCE:

1. Age group of the users is from 18 to 50
2. The Customers use the product atleast twice a week
3. Income range of the customers vary from 30,000(approx.) to maximum of 104581. This implies the Users are from varied income group

```
# To get statistical values for the object data type

data.describe(include = object)
```

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

```
# Accessing the rows with their iloc(integer location) values

data.iloc[:4]
```

	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

```
# Accessing selected range of rows using external location values

data.loc[3:6]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
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

```
# Accessing the specified columns for all rows using external location


data.loc[:,['Product','Gender','Usage']]
```

	Product	Gender	Usage
0	KP281	Male	3
1	KP281	Male	2
2	KP281	Female	4
3	KP281	Male	3
4	KP281	Male	4
...	...	...	...
175	KP781	Male	6
176	KP781	Male	5
177	KP781	Male	5
178	KP781	Male	4
179	KP781	Male	4

180 rows × 3 columns

NON-GRAPHICAL ANALYSIS:

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

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

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

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

INFERENCE:

The most used product is 'KP281'

```
data['Gender'].value_counts()
```

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

INFERENCE:

There are more MALE(104) users than Female(76) users

```
data['MaritalStatus'].value_counts()
```

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

INFERENCE:

The Aerofit products are more popular among the Partnered users

```
data.groupby(['Product','Gender']).agg({'Gender':'count'}).rename(columns={'Gender':'count'}).reset_index()
```

	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

INFERENCE:

For all Produts Male users dominate female users except for KP281 which has equal number of male and female users

```
data.groupby('Product').agg({'Miles':'mean'}).reset_index()
```

	Product	Miles
0	KP281	82.787500
1	KP481	87.933333
2	KP781	166.900000

INFERENCE:

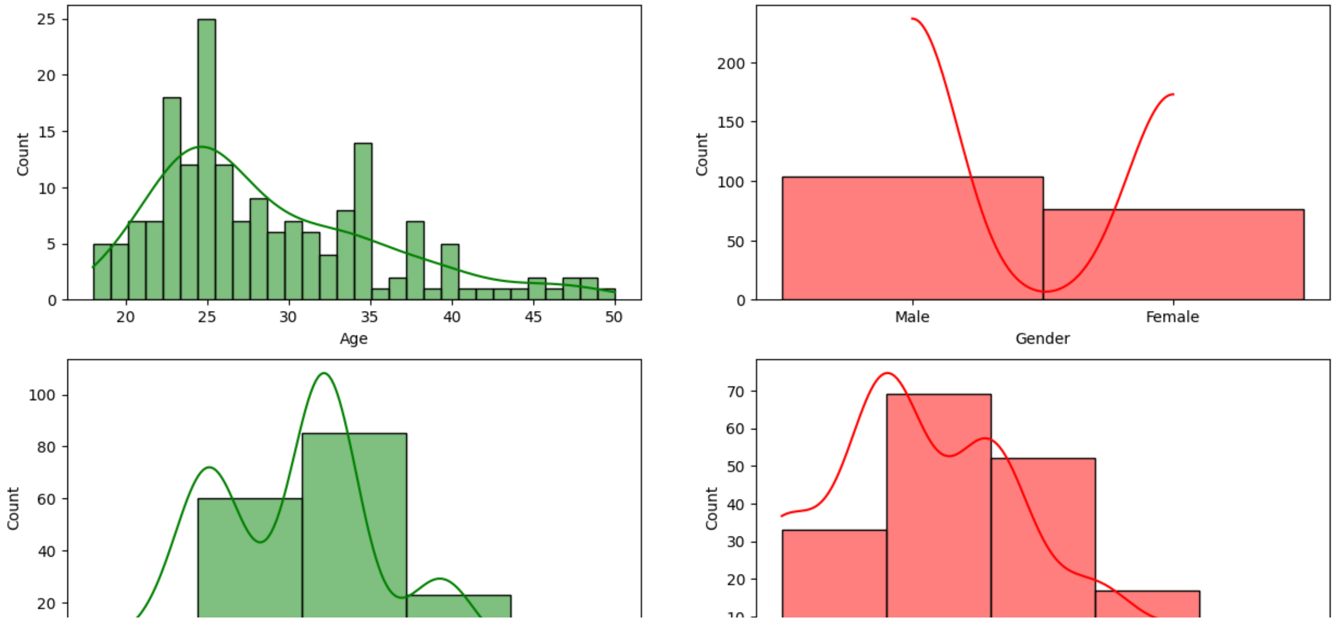
Outliers are present among KP781 users.

VISUAL ANALYSIS

UNIVARIATE

```
# plotting charts in subplots

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

plt.subplot(3,2,1)
sns.histplot(data = data, x='Age', kde=True, color='green', bins = 30)


plt.subplot(3,2,2)
sns.histplot(data = data, x='Gender', kde=True, color='red', bins = 10)


plt.subplot(3,2,3)
sns.histplot(data = data, x='Education', kde=True, color='green', bins = 5)

plt.subplot(3,2,4)
sns.histplot(data = data, x='Usage', kde=True, color='red', bins = 5)

plt.subplot(3,2,5)
sns.histplot(data = data, x='Fitness', kde=True, color='green', bins = 5)

plt.subplot(3,2,6)
sns.histplot(data = data, x='Income', kde=True, color='red', bins = 20)
```

```
<Axes: xlabel='Income', ylabel='Count'>
```



INFERENCE:

This analysis gives the overall idea about the distribution of all the parameters

COUNTPLOT ANALYSIS:

```
plt.figure(figsize=(12,8))

plt.subplot(2,2,1)
sns.countplot(data = data,x='Age')
plt.xticks(rotation =90)

plt.subplot(2,2,2)
sns.countplot(data = data,x='Product')

plt.subplot(2,2,3)
sns.countplot(data = data,x='Gender')

plt.subplot(2,2,4)
sns.countplot(data = data,x='MaritalStatus')

plt.show()
```

INFERENCE:

We have a visual evidence that,

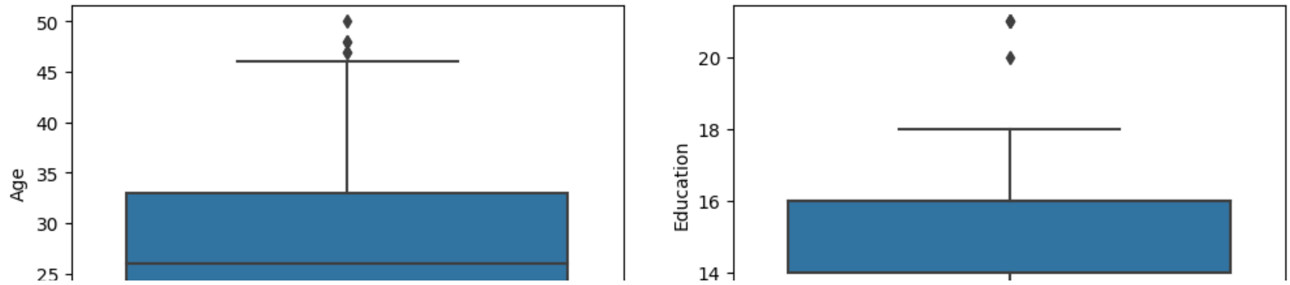
1. Users around the age group of 25 are more when compared to others.
2. As we already analysed the product KP281 is the most frequently used one.
3. Male Users are more than Female users
4. Aerofit products are more popular among the married people.

Age

BOXPLOT - CHECK FOR OUTLIERS

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

plt.subplot(3,2,1)
sns.boxplot(data = data, y='Age',orient='v')

plt.subplot(3,2,2)
sns.boxplot(data = data, y='Education',orient='v')

plt.subplot(3,2,3)
sns.boxplot(data = data, y='Usage',orient='v')

plt.subplot(3,2,4)
sns.boxplot(data = data, y='Fitness',orient='v')

plt.subplot(3,2,5)
sns.boxplot(data = data, y='Income',orient='v')

plt.subplot(3,2,6)
sns.boxplot(data = data, y='Miles',orient='v')
```

```
<Axes: ylabel='Miles'>
```



INFERENCE:

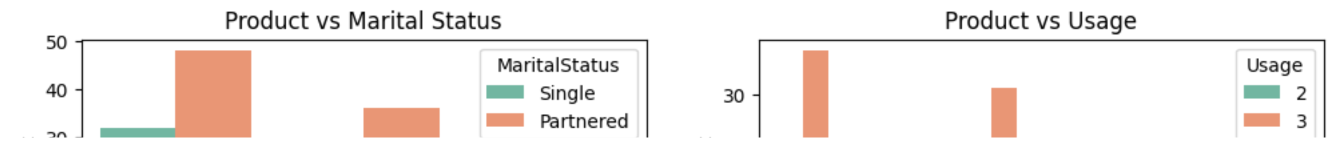
1. There are only very few outliers for 'Age','Education', 'Usage', 'Fitness'
2. In case of 'Income' and 'Miles' the outliers are more

BIVARIATE

Product-wise comparison of various parameters

```
plt.figure(figsize=(12,8))


plt.subplot(3,2,1)
sns.countplot(data=data, x='Product', hue='MaritalStatus',palette='Set2')
plt.title('Product vs Marital Status')

plt.subplot(3,2,2)
sns.countplot(data=data, x='Product', hue='Usage',palette='Set2')
plt.title('Product vs Usage')


plt.subplot(3,2,5)
sns.countplot(data=data, x='Product', hue='Fitness',palette='Set2')
plt.title('Product vs Fitness')


plt.subplot(3,2,6)
sns.countplot(data=data, x='Product', hue='Education',palette='Set2')
plt.title('Product vs Education')
```

```
Text(0.5, 1.0, 'Product vs Education')
```



INFERENCE:

We can clearly visualise that,

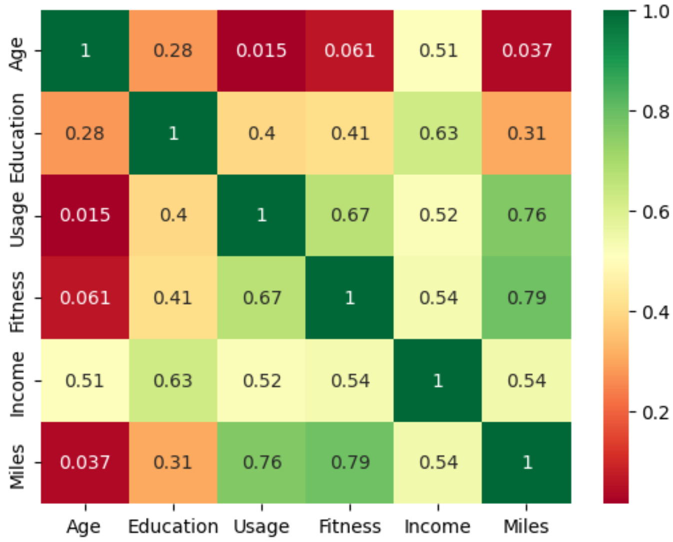
1. **Marital Status** - For all the Product types the Married/Partnered Users are more
2. **Usage** - KP281 aand KP481 users, use it mostly thrice a week whereas KP781 users, use it four times a week which means KP781 users are more frequent users
3. **Fitness** - Most users of products KP281 and KP481 belong to the fitness band 3 but most of KP781 users are more fit as they belong to fitness band 5
4. **Education** - Most of KP281 and KP481 users have 16 years of education where as KP781 users mostly have 18 years of education

MULTIVARIATE

HEATMAP:

```
sns.heatmap(data.corr(),cmap='RdYlGn',annot=True)
plt.show()
```

```
<ipython-input-43-b5ea03a19afe>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  sns.heatmap(data.corr(),cmap='RdYlGn',annot=True)
```



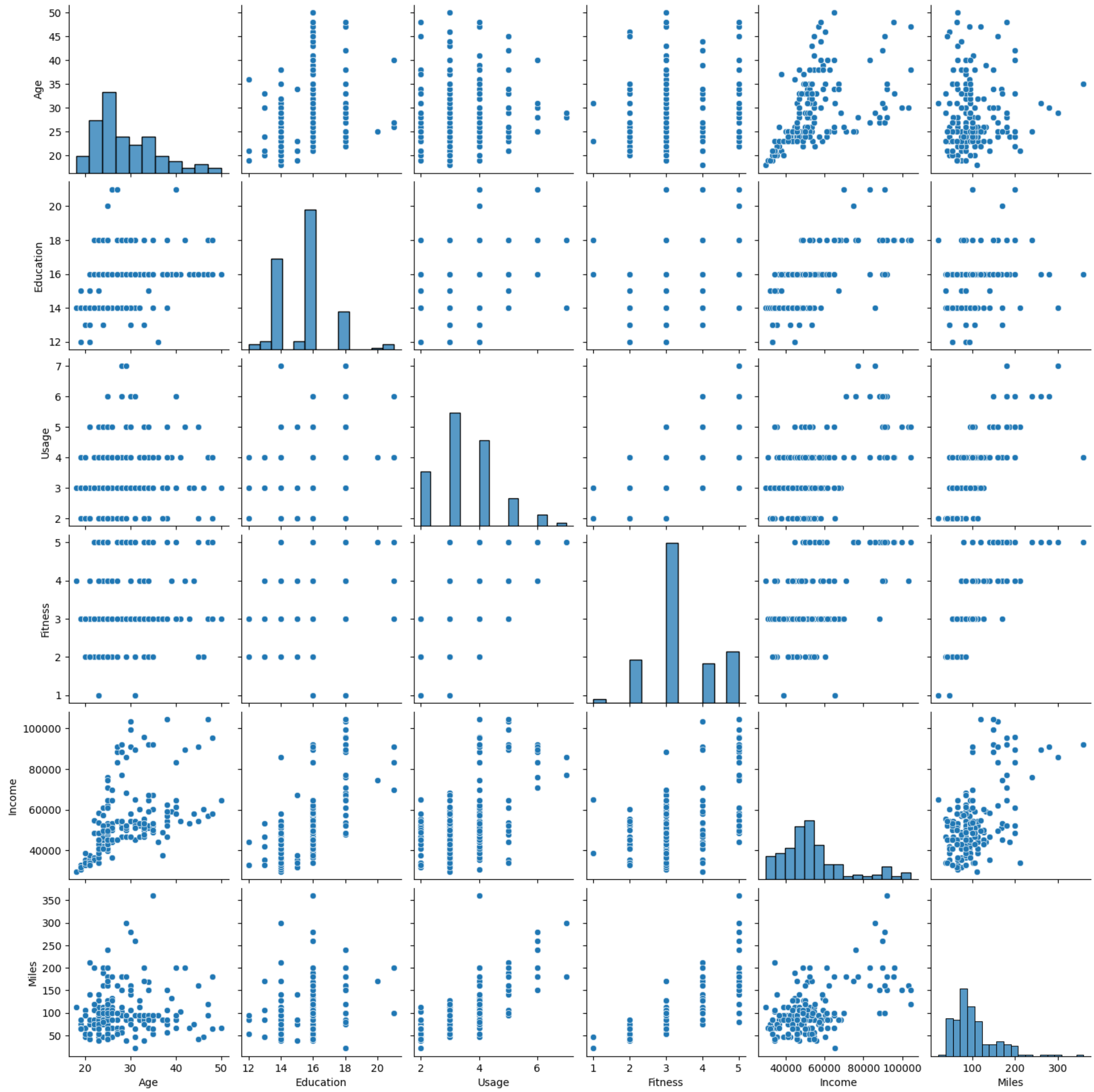
INFERENCE:

1. Fitness always have a strong correlation with usage and miles.
2. Income has a good correlation with all other parameters.
3. overall, we can say that all the parameters in this case are interdependent.

PAIRPLOT

```
# pairplot gives complete relation between all the range of statistical attributes in data

sns.pairplot(data = data)
```

<seaborn.axisgrid.PairGrid at 0x7b77e2ffe350>

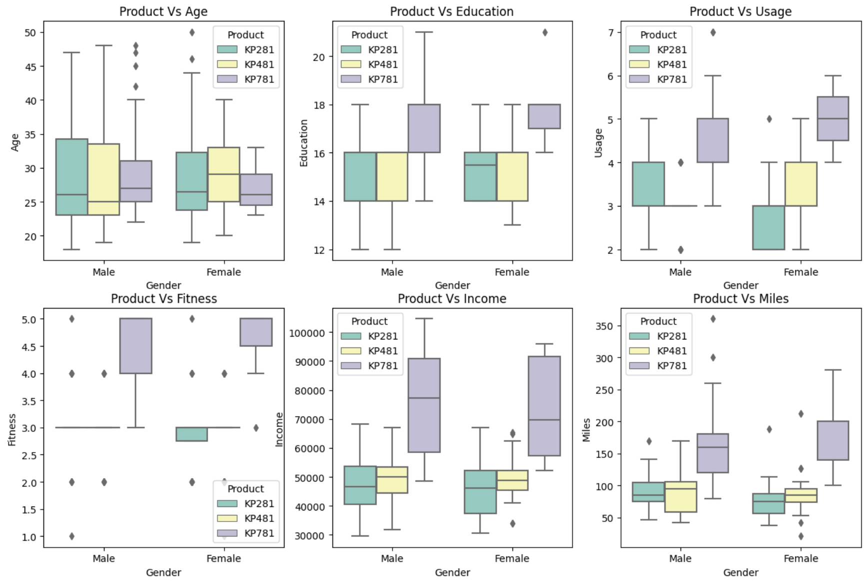


PRODUCT-WISE & GENDER-WISE ANALYSIS:

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

plt.subplot(3,3,1)
sns.boxplot(data = data,x='Gender', y='Age',hue='Product',palette='Set3')
plt.title('Product Vs Age')

plt.subplot(3,3,2)
sns.boxplot(data = data, x='Gender', y='Education',hue='Product',palette='Set3')
plt.title('Product Vs Education')


plt.subplot(3,3,3)
sns.boxplot(data = data,x='Gender', y='Usage',hue='Product',palette='Set3')
plt.title('Product Vs Usage')


plt.subplot(3,3,4)
sns.boxplot(data = data,x='Gender', y='Fitness',hue='Product',palette='Set3')
```

```
plt.title('Product Vs Fitness')


plt.subplot(3,3,5)
sns.boxplot(data = data,x='Gender', y='Income',hue='Product',palette='Set3')
plt.title('Product Vs Income')


plt.subplot(3,3,6)
sns.boxplot(data = data,x='Gender', y='Miles',hue='Product',palette='Set3')
plt.title('Product Vs Miles')
```

```
Text(0.5, 1.0, 'Product Vs Miles')
```



INFERENCE:

People with,

1. higher education,
2. more income,
3. tend to use treadmill more than 4 times a week,
4. walk more than 100 miles a week,
5. and are more fit

prefer using **KP781**

CHECK FOR DUPLICATE VALUES

```
data.duplicated().sum()
```

```
0
```

INFERENCE

This shows that there are no duplicate values

CHECK FOR MISSING VALUES:

```
data.isna().sum()
```

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

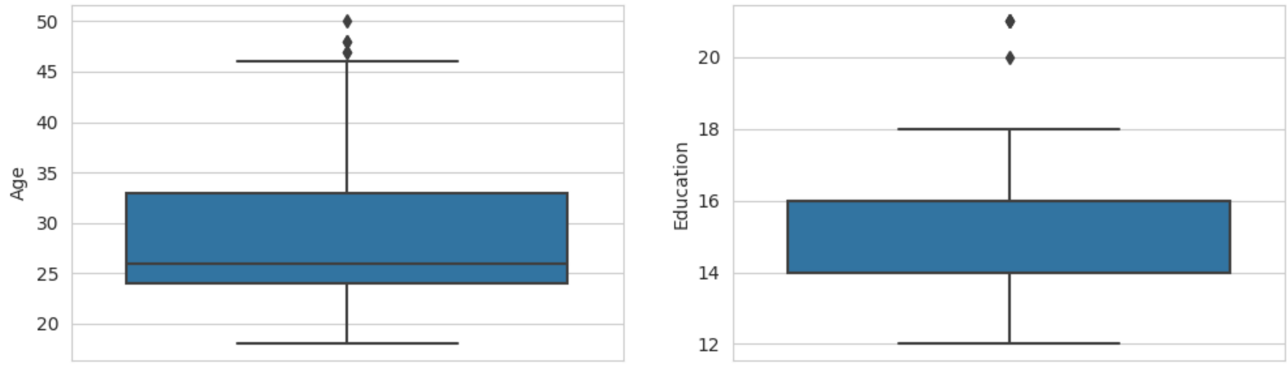
INFERENCE:

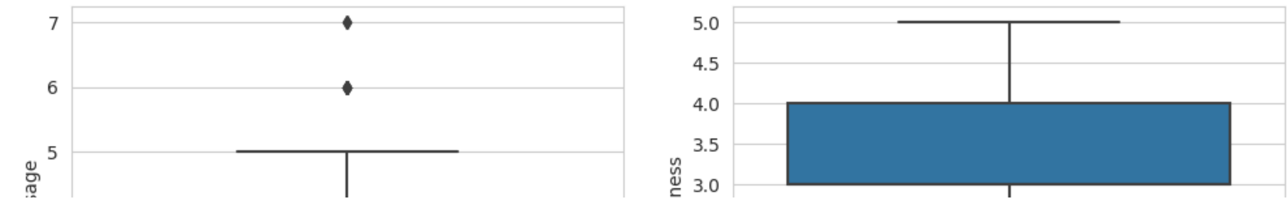
This shows that there are no null values

DETECTING DATA OF OUTLIER VALUES

```
sns.set_style(style='whitegrid')

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

plt.subplot(3,2,1)
sns.boxplot(data = data, y='Age',orient='v')

plt.subplot(3,2,2)
sns.boxplot(data = data, y='Education',orient='v')

plt.subplot(3,2,3)
sns.boxplot(data = data, y='Usage',orient='v')

plt.subplot(3,2,4)
sns.boxplot(data = data, y='Fitness',orient='v')

plt.subplot(3,2,5)
sns.boxplot(data = data, y='Income',orient='v')

plt.subplot(3,2,6)
sns.boxplot(data = data, y='Miles',orient='v')
```

```
<Axes: ylabel='Miles'>
```





DATA OF OUTLIERS IN AGE COLUMN

```
data[data['Age']>46]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
78	KP281	47	Male	16	Partnered	4	3	56850	94
79	KP281	50	Female	16	Partnered	3	3	64809	66
139	KP481	48	Male	16	Partnered	2	3	57987	64
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

DATA OF OUTLIERS IN EDUCATIION

```
data[data['Education']>18]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
156	KP781	25	Male	20	Partnered	4	5	74701	170
157	KP781	26	Female	21	Single	4	3	69721	100
161	KP781	27	Male	21	Partnered	4	4	90886	100
175	KP781	40	Male	21	Single	6	5	83416	200

```
data[data['Income']>80000]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
159	KP781	27	Male	16	Partnered	4	5	83416	160
160	KP781	27	Male	18	Single	4	3	88396	100
161	KP781	27	Male	21	Partnered	4	4	90886	100
162	KP781	28	Female	18	Partnered	6	5	92131	180
164	KP781	28	Male	18	Single	6	5	88396	150
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
168	KP781	30	Male	18	Partnered	5	4	103336	160

```
data[data['Miles']>175]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
23	KP281	24	Female	16	Partnered	5	5	44343	188
84	KP481	21	Female	14	Partnered	5	4	34110	212
142	KP781	22	Male	18	Single	4	5	48556	200
148	KP781	24	Female	16	Single	5	5	52291	200
152	KP781	25	Female	18	Partnered	5	5	61006	200
154	KP781	25	Male	18	Partnered	6	4	70966	180
155	KP781	25	Male	18	Partnered	6	5	75946	240
158	KP781	26	Male	16	Partnered	5	4	64741	180
162	KP781	28	Female	18	Partnered	6	5	92131	180
163	KP781	28	Male	18	Partnered	7	5	77191	180
165	KP781	29	Male	18	Single	5	5	52290	180
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
173	KP781	35	Male	16	Partnered	4	5	92131	360
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
179	KP781	48	Male	18	Partnered	4	5	95508	180

```
data[data['Usage']>5]
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
154	KP781	25	Male	18	Partnered	6	4	70966	180
155	KP781	25	Male	18	Partnered	6	5	75946	240
162	KP781	28	Female	18	Partnered	6	5	92131	180
163	KP781	28	Male	18	Partnered	7	5	77191	180
164	KP781	28	Male	18	Single	6	5	88396	150
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
170	KP781	31	Male	16	Partnered	6	5	89641	260
175	KP781	40	Male	21	Single	6	5	83416	200

INFERENCE:

1. There are only few outliers in case of **Age**, **Education** and **Usage**.
2. Thera are many outliers in case of **Income** and **Miles**

STATISTICAL ANALYSIS:

PROBABILITY:

MARGINAL PROBABILITY:

```
data['Product'].describe()
```

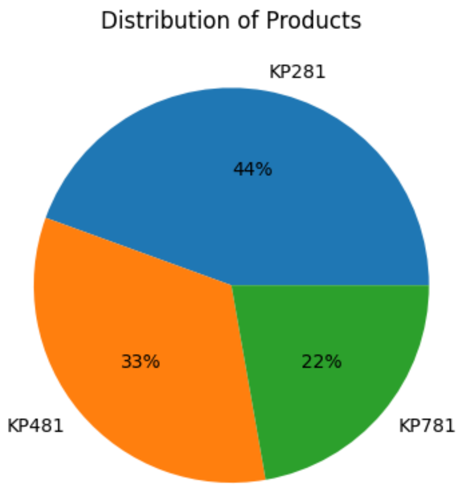
```
count       180
unique        3
top       KP281
freq         80
Name: Product, dtype: object
```

```
# To get the percentage contribution of each product
```

```
data['Product'].value_counts(normalize=True)
```

```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

```
pdt_cnt = data['Product'].value_counts()

plt.title('Distribution of Products')
plt.pie(pdt_cnt,labels=pdt_cnt.index,autopct='%.0f%%')
plt.show()
```



INFERENCE:

KP281 being the **most popular** product with KP481 in the second position followed by KP781

```
data.value_counts()
```

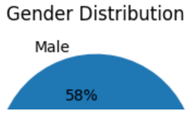
```
Product  Age  Gender  Education  MaritalStatus  Usage  Fitness  Income  Miles
KP281    18   Male    14         Single         3      4        29562   112      1
KP481    30   Female  13         Single         4      3        46617   106      1
         31   Female  16         Partnered      2      3        51165   64       1
                      18         Single         2      1        65220   21       1
              Male    16         Partnered      3      3        52302   95       1
                                                                                ..
KP281    34   Female  16         Single         2      2        52302   66       1
              Male    16         Single         4      5        51165   169      1
         35   Female  16         Partnered      3      3        60261   94       1
                      18         Single         3      3        67083   85       1
KP781    48   Male    18         Partnered      4      5        95508   180      1
Length: 180, dtype: int64
```

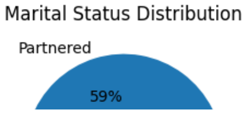
```
data['Gender'].value_counts(normalize=True)
```

```
Male      0.577778
Female    0.422222
```

```
Name: Gender, dtype: float64
```

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


plt.subplot(3,3,5)
pdt_cnt = data['Product'].value_counts()

plt.title('Products Distribution')
plt.pie(pdt_cnt,labels=pdt_cnt.index,autopct='%.0f%%')



plt.subplot(3,3,1)
gender_cnt = data['Gender'].value_counts()

plt.title('Gender Distribution')
plt.pie(gender_cnt,labels=gender_cnt.index,autopct='%.0f%%')



plt.subplot(3,3,3)
ms_cnt = data['MaritalStatus'].value_counts()

plt.title('Marital Status Distribution')
plt.pie(ms_cnt,labels=ms_cnt.index,autopct='%.0f%%')


plt.subplot(3,3,7)
us_cnt = data['Usage'].value_counts()

plt.title('Usage Distribution')
plt.pie(us_cnt,labels=us_cnt.index,autopct='%.0f%%')


plt.subplot(3,3,9)
ft_cnt = data['Fitness'].value_counts()

plt.title('Fitness Distribution')
plt.pie(ft_cnt,labels=ft_cnt.index,autopct='%.0f%%')

plt.show()
```





INFERENCE:

1. **KP281** - Most Popular Product
2. **Male** contibutes more than female
3. People with **Partnered** marital status use this product more
4. Most Aerofit Customers hit the treadmill **thrice** a week
5. Their Customers are mostly has fitness scale of **3**

CONDITIONAL PROBABILITY:

PROBABILITY OF EACH PARAMETER FOR A GIVEN PRODUCT

```
data['Gender'].where(data['Product']=='KP281').value_counts(normalize=True)
```

```
Male      0.5
Female    0.5
Name: Gender, dtype: float64
```

```
data['Gender'].where(data['Product']=='KP481').value_counts(normalize=True)
```

```
Male      0.516667
Female    0.483333
Name: Gender, dtype: float64
```

```
data['Gender'].where(data['Product']=='KP781').value_counts(normalize=True)
```

```
Male      0.825
Female    0.175
Name: Gender, dtype: float64
```

```
temp = data['Product'].unique()

# to get probability of each gender for the given product

for i in range(len(temp)):
  y = data['Gender'].where(data['Product']==temp[i]).value_counts(normalize=True)
  print('PROBABILITY OF EACH GENDER FOR THE PRODUCT',temp[i])
  print(y)
```

```
PROBABILITY OF EACH GENDER FOR THE PRODUCT KP281
Male      0.5
Female    0.5
Name: Gender, dtype: float64
PROBABILITY OF EACH GENDER FOR THE PRODUCT KP481
Male      0.516667
Female    0.483333
Name: Gender, dtype: float64
PROBABILITY OF EACH GENDER FOR THE PRODUCT KP781
Male      0.825
Female    0.175
Name: Gender, dtype: float64
```

INFERENCE:

KP281 and KP481 - almost equal contribution by both gender **KP781** - **Male** users dominate female with **82.5%**

```
temp = data['Product'].unique()

# to get probability of each MaritalStatus for the given product

for i in range(len(temp)):
  y = data['MaritalStatus'].where(data['Product']==temp[i]).value_counts(normalize=True)
  print('PROBABILITY OF EACH MARITAL STATUS FOR THE PRODUCT',temp[i])
  print(y)
```

```
PROBABILITY OF EACH MARITAL STATUS FOR THE PRODUCT KP281
Partnered    0.6
```

```
Single       0.4
Name: MaritalStatus, dtype: float64
PROBABILITY OF EACH MARITAL STATUS FOR THE PRODUCT KP481
Partnered    0.6
Single       0.4
Name: MaritalStatus, dtype: float64
PROBABILITY OF EACH MARITAL STATUS FOR THE PRODUCT KP781
Partnered    0.575
Single       0.425
Name: MaritalStatus, dtype: float64
```

INFERENCE:

Partnered users are more compared to single users for all product category

IMPACT OF INCOME ON THE PRODUCT TYPE

```
avg_income = data['Income'].where(data['Product']=='KP281').mean()
```

```
avg_income
```

```
46418.025
```

```
temp = data['Product'].unique()

# to get the average income of users of the given product

for i in range(len(temp)):
  avg_income = data['Income'].where(data['Product']==temp[i]).mean()
  print('AVERAGE INCOME OF USERS OF THE PRODUCT',temp[i])
  print(avg_income)
```

```
AVERAGE INCOME OF USERS OF THE PRODUCT KP281
46418.025
AVERAGE INCOME OF USERS OF THE PRODUCT KP481
48973.65
AVERAGE INCOME OF USERS OF THE PRODUCT KP781
75441.575
```

INFERENCE:

KP281 and KP481 - Preferred by Mid-level income group. **KP781** - Preferred by **High**-level **income** group

AGE VS PRODUCT

```
temp = data['Product'].unique()

# to get the average age of users of the given product

for i in range(len(temp)):
  avg_age = data['Age'].where(data['Product']==temp[i]).mean()
  print('AVERAGE AGE OF USERS OF THE PRODUCT',temp[i])
  print(avg_age)
```

```
AVERAGE AGE OF USERS OF THE PRODUCT KP281
28.55
AVERAGE AGE OF USERS OF THE PRODUCT KP481
28.9
AVERAGE AGE OF USERS OF THE PRODUCT KP781
29.1
```

INFERENCE:

Users of these Product are almost of the same age group of around **30 years** with some outliers.

FITNESS PERCENT OF EACH GENDER FOR THE GIVEN PRODUCT

```
temp = data['Product'].unique()
temp_gender = data['Gender'].unique()

# to get fitness percent of each gender for the given product

for i in range(len(temp)):
```

```
  for j in range(len(temp_gender)):
    y = data['Fitness'].where((data['Product']==temp[i])&(data['Gender']== temp_gender[j])).value_counts(normalize=True)
    print('FITNESS PERCENTAGE OF ',temp_gender[j],' FOR THE PRODUCT',temp[i])
    print(y)
```

```
FITNESS PERCENTAGE OF  Male  FOR THE PRODUCT KP281
3.0    0.700
4.0    0.150
2.0    0.100
1.0    0.025
5.0    0.025
Name: Fitness, dtype: float64
FITNESS PERCENTAGE OF  Female  FOR THE PRODUCT KP281
3.0    0.650
2.0    0.250
4.0    0.075
5.0    0.025
Name: Fitness, dtype: float64
FITNESS PERCENTAGE OF  Male  FOR THE PRODUCT KP481
3.0    0.677419
2.0    0.193548
4.0    0.129032
Name: Fitness, dtype: float64
FITNESS PERCENTAGE OF  Female  FOR THE PRODUCT KP481
3.0    0.620690
2.0    0.206897
4.0    0.137931
1.0    0.034483
Name: Fitness, dtype: float64
FITNESS PERCENTAGE OF  Male  FOR THE PRODUCT KP781
5.0    0.727273
4.0    0.181818
3.0    0.090909
Name: Fitness, dtype: float64
FITNESS PERCENTAGE OF  Female  FOR THE PRODUCT KP781
5.0    0.714286
4.0    0.142857
3.0    0.142857
Name: Fitness, dtype: float64
```

INFERENCE:

Irrespective of Gender, the Users of **KP781** are more **fit** with around **72%** of users comes under fitness band **5**

```
avg_income = data['Income'].mean()
data['Product'].where((data['Gender']=='Male')&(data['Income']>=avg_income)).value_counts(normalize=True)
```

```
KP781    0.613636
KP281    0.227273
KP481    0.159091
Name: Product, dtype: float64
```

```
avg_income = data['Income'].mean()
data['Product'].where((data['Gender']=='Female')&(data['Income']>=avg_income)).value_counts(normalize=True)
```

```
KP281    0.421053
KP481    0.315789
KP781    0.263158
Name: Product, dtype: float64
```

```
df = data[['Product','Gender','MaritalStatus']].melt()
df1=df.groupby(['variable','value'])[['value']].count()/len(data)
df1.rename(columns={'value':'% contribution'}).reset_index()
```

	variable	value	% contribution
0	Gender	Female	0.422222
1	Gender	Male	0.577778
2	MaritalStatus	Partnered	0.594444
3	MaritalStatus	Single	0.405556
4	Product	KP281	0.444444
5	Product	KP481	0.333333
6	Product	KP781	0.222222

BUSINESS INSIGHTS:

1. **PRODUCT:**

   1. 3 unique products - KP281, KP481, KP781
   2. **KP281** most **preferred** with overall contribution of 44%
2. **AGE:**
   1. Age group varies from 18 years to 50 years
   2. Most people belong to the age group of **25 years**
   3. KP781 users have most outliers when age is considered
3. **MARITAL STATUS:**
   1. **Partnered/Married** users are more than that of unmarried users
   2. Partnered users contribute **59%** of the total
4. **GENDER:**
   1. **Male** users dominate female users
   2. Male - 57%, Female - 42%
5. **USAGE:**
   1. KP281, KP481 - average usage is thrice a week
   2. **KP781** - average usage is **4 times** a week
6. **EDUCATION:**
   1. KP281, KP481 - average education of the users is 16 years
   2. KP781 - average education of the users is 18 year

OBSERVATION:

People with,

1. higher education,
2. more income,
3. tend to use treadmill more than 4 times a week,
4. walk more than 100 miles a week,
5. and are more fit

prefer using **KP781**

RECOMMENDATIONS:

1. KP281, KP481 - most suited for mid-level income group.
2. **KP781** - marketed among **premium** customers.
3. KP781 - Most suited for more fit persons who use treadmill almost 5 to 7 days a week and walk more than 100 miles which means its suited for a **sporty** persons and **fitness freak**.
4. Survey is recommended for income group **below 40,000** to get a wider graph.
5. Promote Products among **Single** (Marital status) with **workshops** and **free trials**.
6. Encourage **Female** users - emphazize on the **importance** of **fitness**.

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