1.Defining Problem Statement and Analysing basic metrics

Problem Statement:

The primary objective is to identify the characteristics of the target audience for each type of treadmill offered by AeroFit. This involves investigating potential differences across products concerning customer characteristics. The focus is on creating a customer profile for each treadmill product to enhance recommendations for new customers

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

df = pd.read_csv('/content/sample_data/aerofit_treadmill.csv')

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

print(f"Number of rows: {df.shape[0]}\nNumber of columns:
{df.shape[1]}")

Number of rows: 180
Number of columns: 9

print('Data Types: ')
print(df.dtypes)

Data Types:
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
```

```
Miles                int64
dtype: object
```

```
df.info() # provides summary information about data frame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

```
df.nunique()
```

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

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

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

```
df.isnull().sum()
```

```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
```

```
Income          0
Miles           0
dtype: int64
```

```
df.describe() #returns statistical summary of only numeric columns
```

```
              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
```

```
df.describe(include='object').T # this gives statistical summary of
all columns
```

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

2 .Non-Graphical Analysis: Value counts and unique attributes

```
df.nunique() # Gives count of unique values in each colum
```

```
Product           3
Age              32
Gender            2
Education         8
```

```
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

```python
for i in df.columns:   # to get unique values and count of unique values
    print(f"{i} Column has \n{df[i].unique()} values and \n{len(df[i].unique())} unique items\n\n")
```

```
Product Column has
['KP281' 'KP481' 'KP781'] values and
3 unique items


Age Column has
[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 43 44 46 47 50 45 48 42] values and
32 unique items


Gender Column has
['Male' 'Female'] values and
2 unique items


Education Column has
[14 15 12 13 16 18 20 21] values and
8 unique items


MaritalStatus Column has
['Single' 'Partnered'] values and
2 unique items


Usage Column has
[3 2 4 5 6 7] values and
6 unique items


Fitness Column has
[4 3 2 1 5] values and
5 unique items


Income Column has
[ 29562  31836  30699  32973  35247  37521  36384  38658  40932  34110
```

```
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508] values and
62 unique items


Miles Column has
[112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106
95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280
260
 360] values and
37 unique items
```

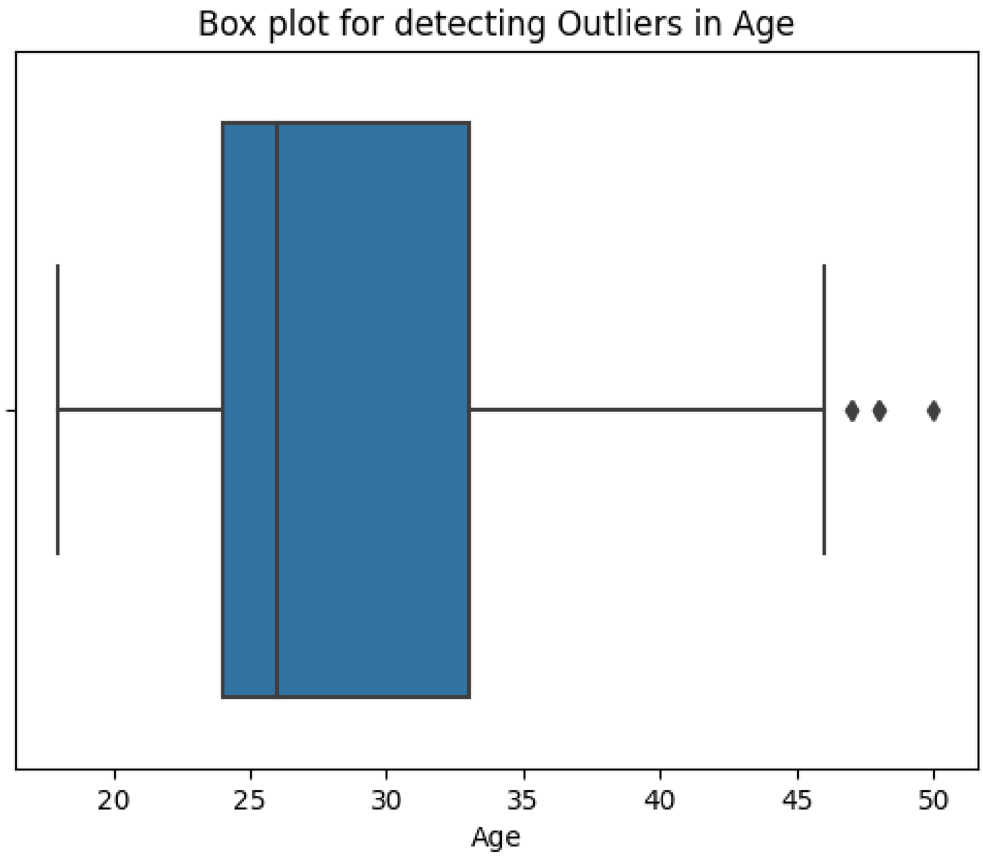
3 .Missing Value & Outlier Detection

```
df.isnull().sum()  # From below data we can confrim no missing vales
in given data and no need for pre-processing

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

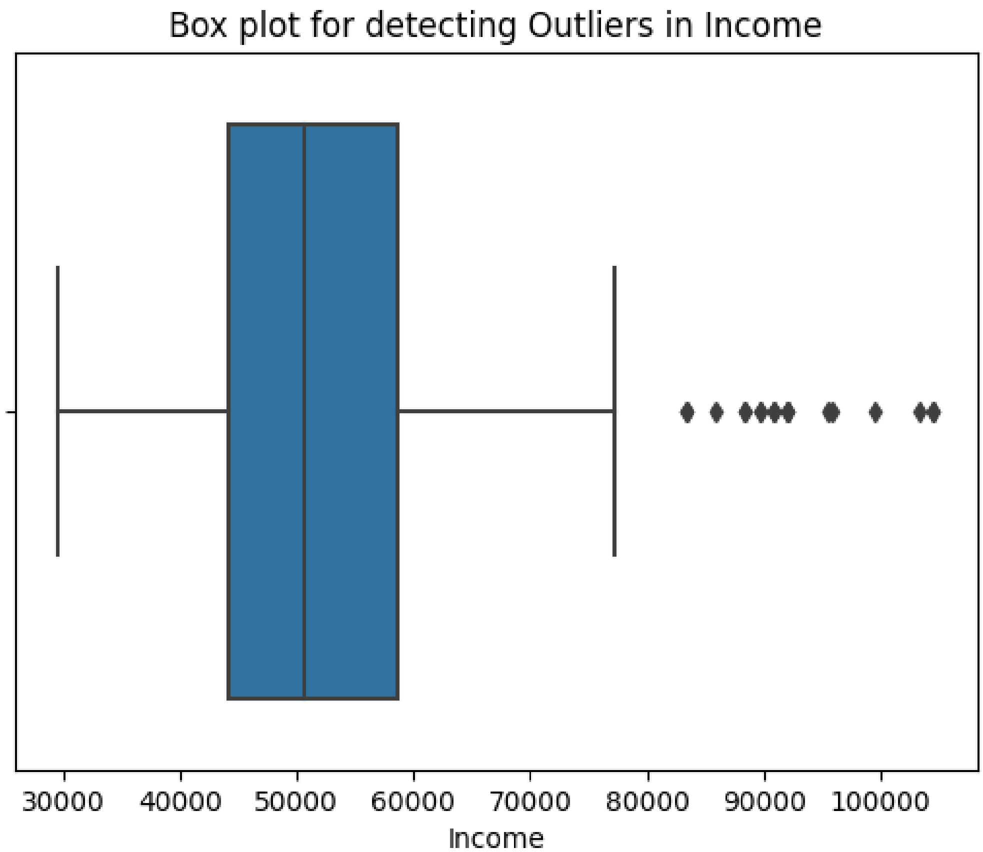
Outlier

```
df.nunique() # So for Age,Income and Miles we can find outliers as
theey are continouos rest are categorical values

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

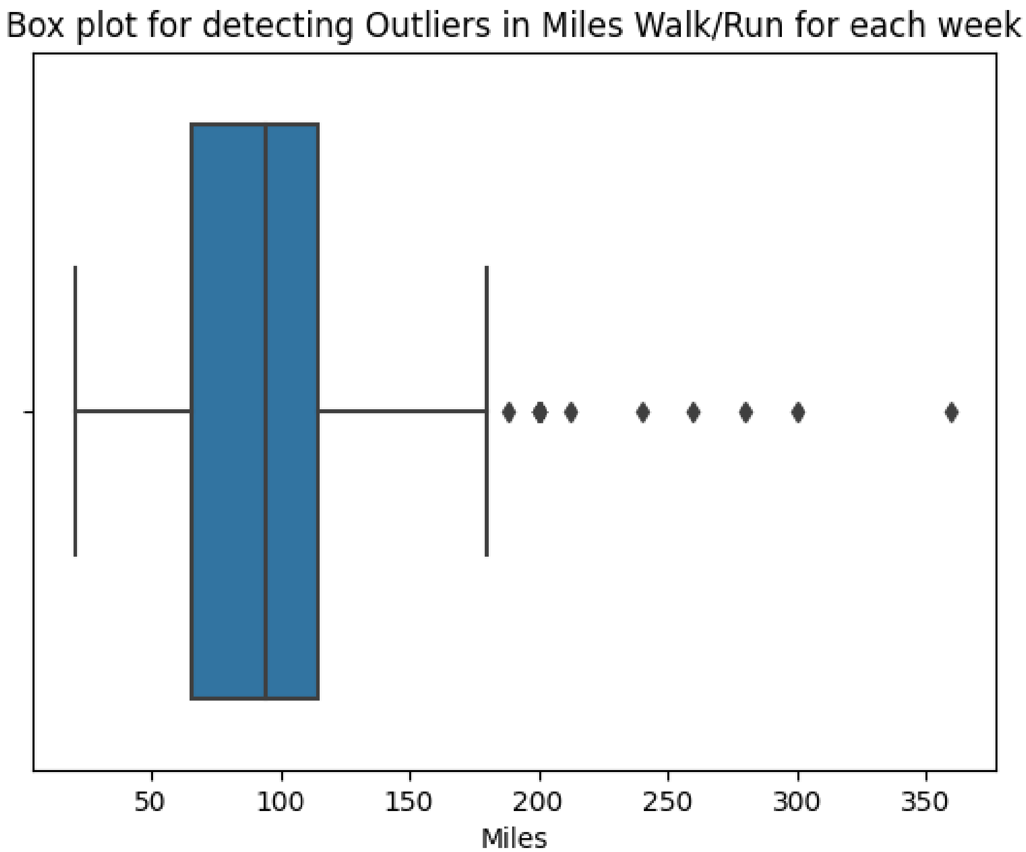
```
sns.boxplot(data=df,x='Age')
plt.title('Box plot for detecting Outliers in Age')
plt.show()
```




```
sns.boxplot(data=df,x='Income')
plt.title('Box plot for detecting Outliers in Income')
plt.show()
```




```
sns.boxplot(data=df,x='Miles')
plt.title('Box plot for detecting Outliers in Miles Walk/Run for each week')
plt.show()
```



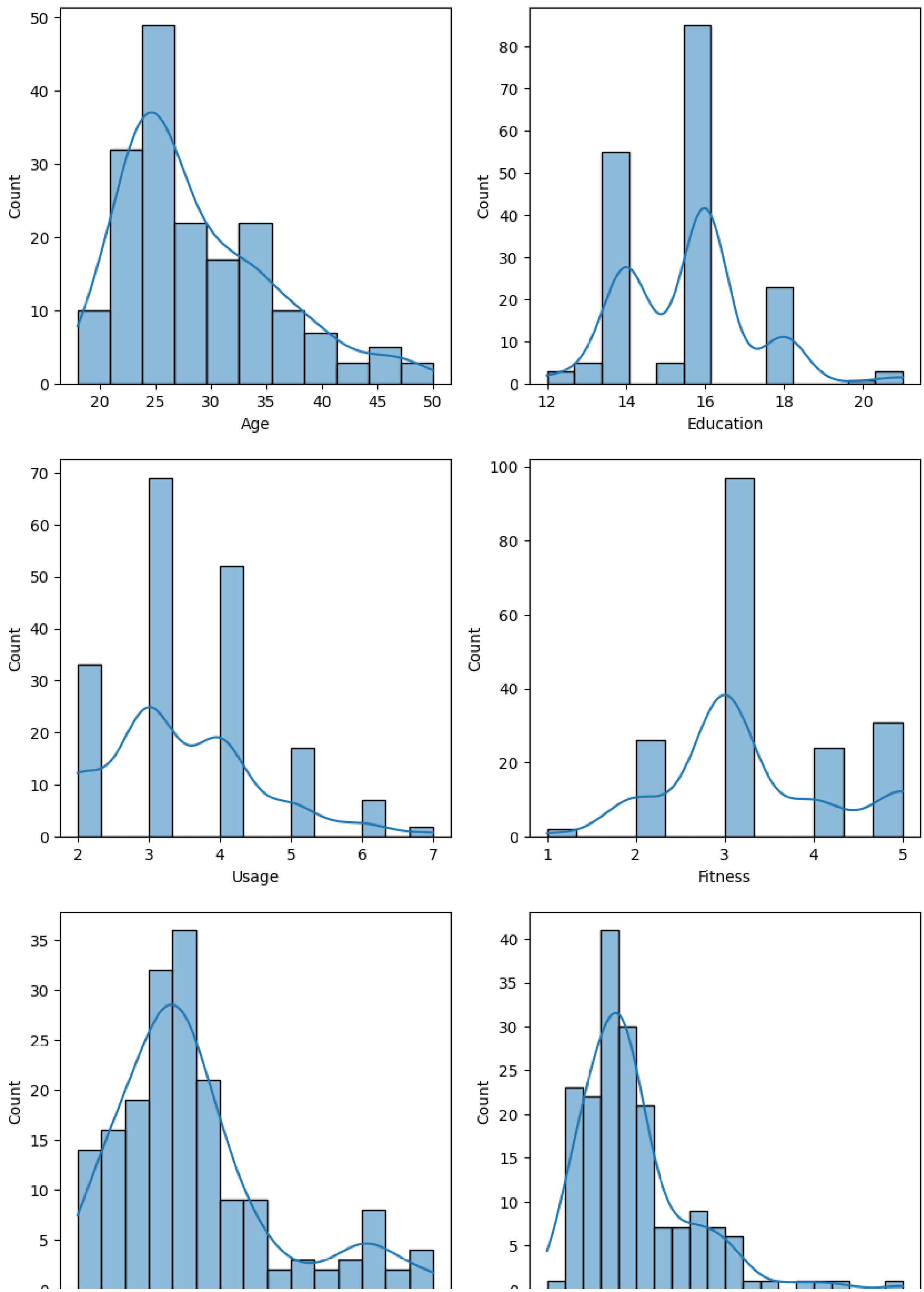
4 .Visual Analysis - Univariate & Bivariate

Understanding the distribution of the data for the quantitative attributes:

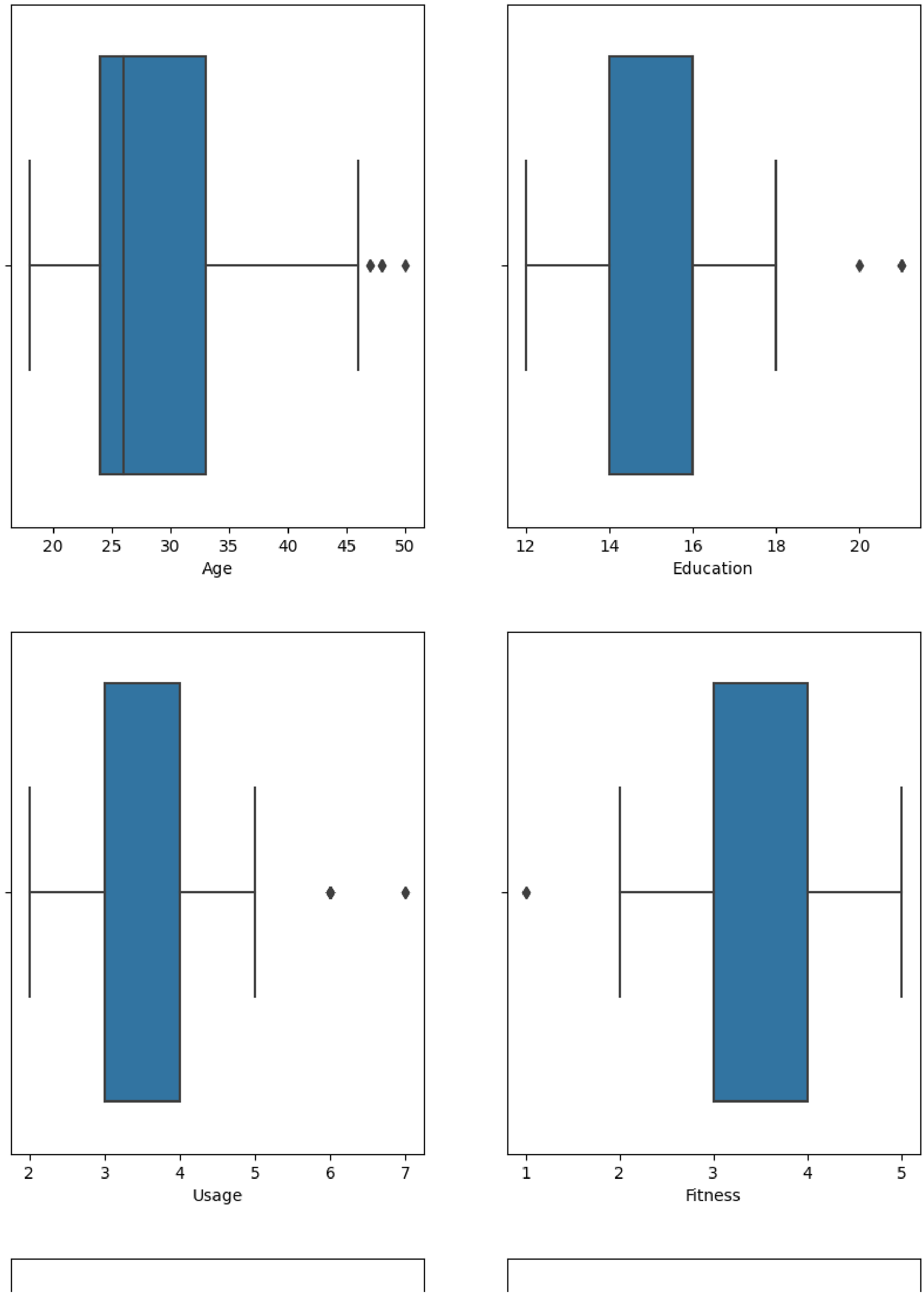
1. Age
2. Education
3. Usage
4. Fitness
5. Income
6. Miles

```
plt.figure(figsize=(10,15))
plt.subplot(3,2,1)
sns.histplot(data=df, x="Age", kde=True)
plt.subplot(3,2,2)
sns.histplot(data=df, x="Education", kde=True)
plt.subplot(3,2,3)
sns.histplot(data=df, x="Usage", kde=True)
plt.subplot(3,2,4)
sns.histplot(data=df, x="Fitness", kde=True)
plt.subplot(3,2,5)
sns.histplot(data=df, x="Income", kde=True)
plt.subplot(3,2,6)
```

```python
sns.histplot(data=df, x="Miles", kde=True)
plt.show()
```


Count
Age
20 25 30 35 40 45 50
0 10 20 30 40 50
Count
Education
12 14 16 18 20
0 10 20 30 40 50 60 70 80
Count
Usage
2 3 4 5 6 7
0 10 20 30 40 50 60 70
Count
Fitness
1 2 3 4 5
0 20 40 60 80 100
Count
5 10 15 20 25 30 35
Count
5 10 15 20 25 30 35 40

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(10, 17))
fig.subplots_adjust(top=1.0)
sns.boxplot(data=df, x="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, x="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, x="Usage", orient='h', ax=axis[1,0])
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, x="Miles", orient='h', ax=axis[2,1])
plt.show()
```



20
25
30
35
40
45
50
Age
12
14
16
18
20
Education
2
3
4
5
6
7
Usage
1
2
3
4
5
Fitness

```
outlier_detection = []

continuous_variables = ['Age', 'Income', 'Usage', 'Fitness', 'Miles',
'Education']

for col in continuous_variables:
  mean_val = df[col].mean()
  median_val = df[col].median()
  diff_val = mean_val-median_val

outlier_detection.append({'Variable':col,'Mean':mean_val,'Median':medi
an_val,'Difference':diff_val})

outlier_detection_df = pd.DataFrame(outlier_detection)
outlier_detection_df.set_index('Variable',inplace=True)

outlier_detection_df
```

	Mean	Median	Difference
Variable			
Age	28.788889	26.0	2.788889
Income	53719.577778	50596.5	3123.077778
Usage	3.455556	3.0	0.455556
Fitness	3.311111	3.0	0.311111
Miles	103.194444	94.0	9.194444
Education	15.572222	16.0	-0.427778

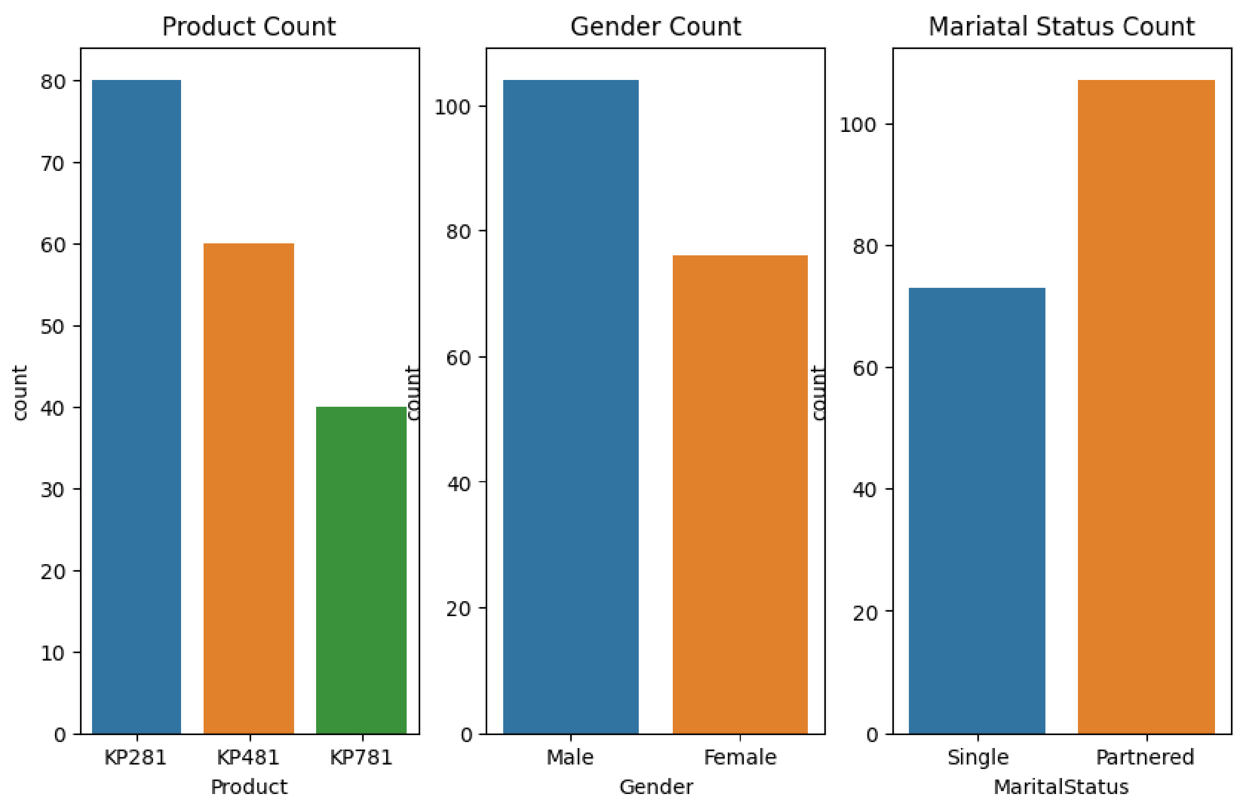
Observations:

1. Difference between Mean and Median is more for Miles and Income which shows that data is more spreaded and outliers are more
2. Whereas for remaining columns data is less spread and less outliers

Understanding the distribution of the data for the qualitative attributes:

1. Product
2. Gender
3. MaritalStatus

```
plt.figure(figsize=(10,6))
plt.subplot(1,3,1)
plt.title('Product Count')
sns.countplot(data=df, x="Product")
plt.subplot(1,3,2)
plt.title('Gender Count')
sns.countplot(data=df, x="Gender")
plt.subplot(1,3,3)
plt.title('Mariatal Status Count')
sns.countplot(data=df, x="MaritalStatus")
plt.show()
```



Observations

1. KP281 is the most frequent product.
2. Male count is more in data compared to Female.
3. Comitted people are more in data

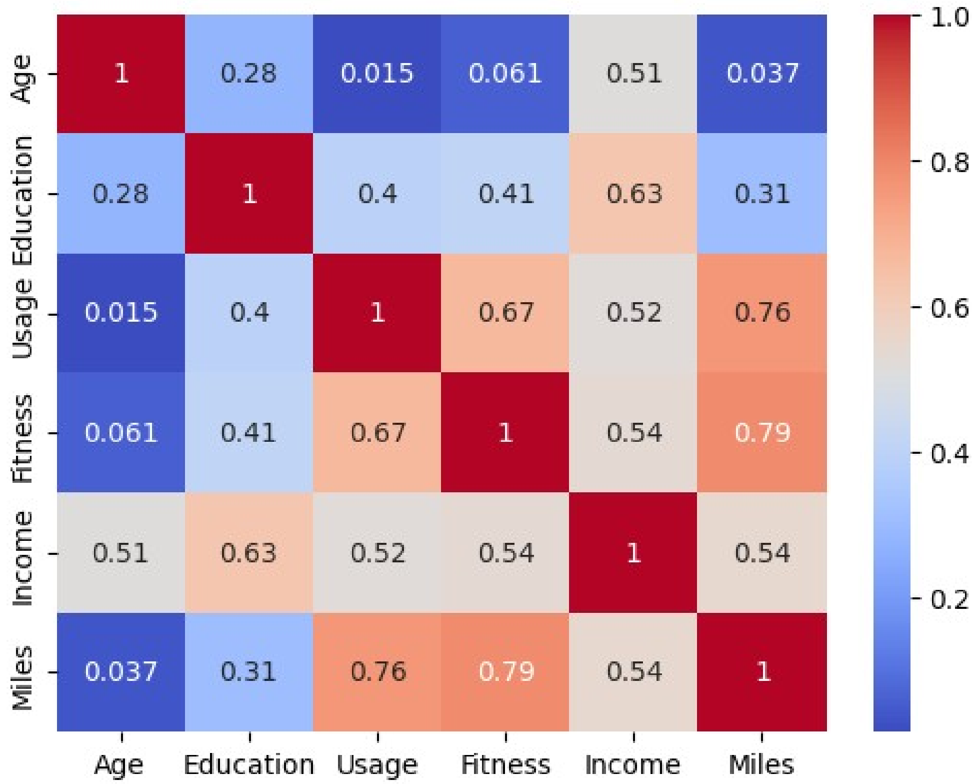
For correlation: Heatmaps, Pairplots

```
# Heat map can be formed only with numerical rows
numerical_columns = df.select_dtypes(exclude=['object']).columns
heatmap_df = df[numerical_columns]
heatmap_df.head()
```

	Age	Education	Usage	Fitness	Income	Miles
0	18	14	3	4	29562	112
1	19	15	2	3	31836	75
2	19	14	4	3	30699	66
3	19	12	3	3	32973	85
4	20	13	4	2	35247	47

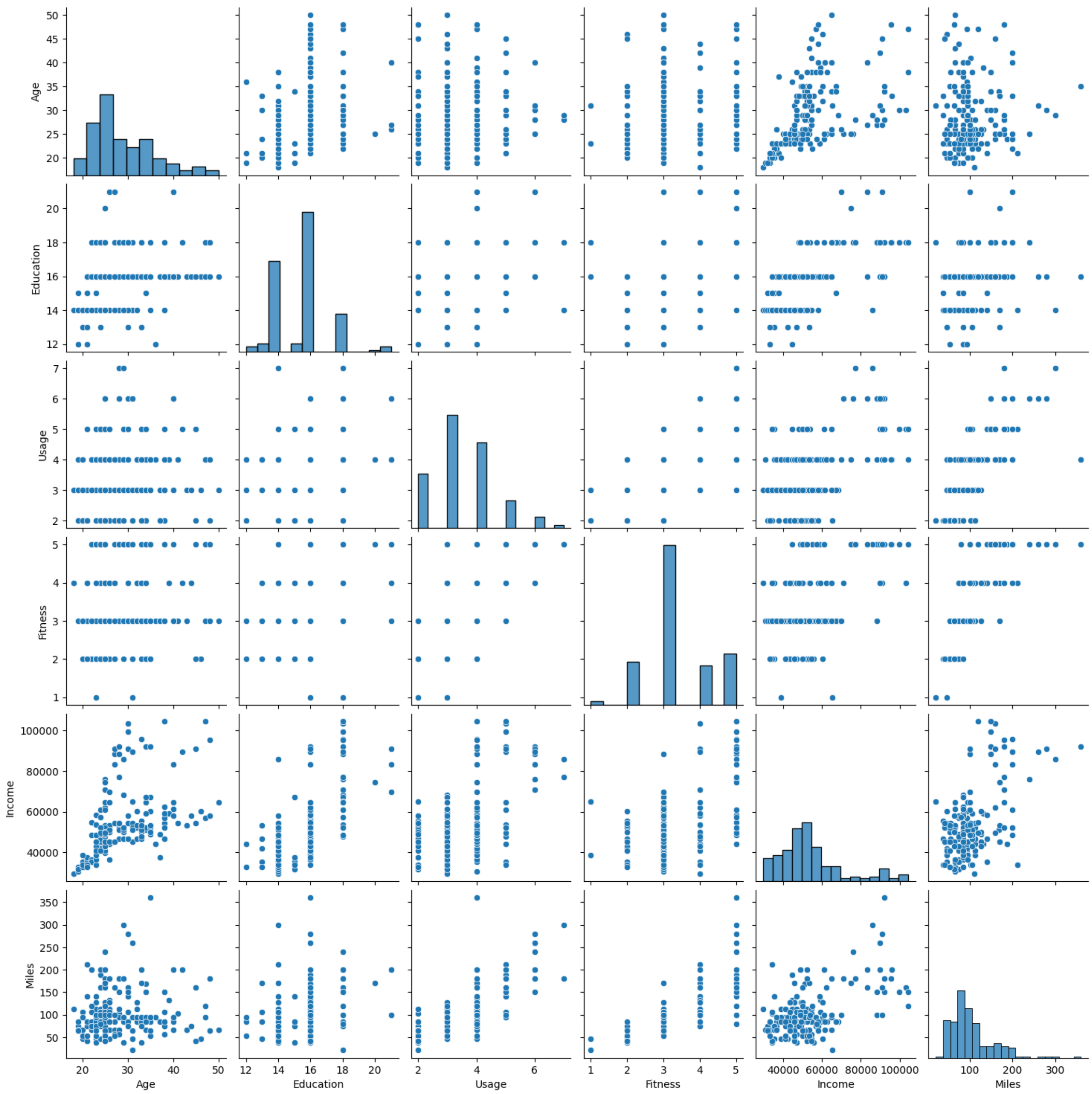
```
sns.heatmap(heatmap_df.corr(), annot = True, cmap = "coolwarm")
```

```
<Axes: >
```




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

```
<seaborn.axisgrid.PairGrid at 0x7afe6b637a30>
```



5. Business Insights based on Non-Graphical and Visual Analysis

1. Comments on the range of attributes
2. Comments on the distribution of the variables and relationship between them
3. Comments for each univariate and bivariate plot

```
outlier_detection_df
```

	Mean	Median	Difference
Variable			
Age	28.788889	26.0	2.788889
Income	53719.577778	50596.5	3123.077778
Usage	3.455556	3.0	0.455556

```
Fitness         3.311111       3.0      0.311111
Miles         103.194444      94.0      9.194444
Education      15.572222      16.0     -0.427778
```

Comment on ranges

1. **Based on the insights derived from the outlier detection section, we observed that the variables "Income" and "Miles" exhibit a notable spread, as evidenced by a considerable difference between their mean and median values.**

```
df.describe(include='object').T
```

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

1. **This shows that Most purchased product is KP281 by gender Male who marital ststus is Partnered**

Comments on the distribution of the variables and relationship between them

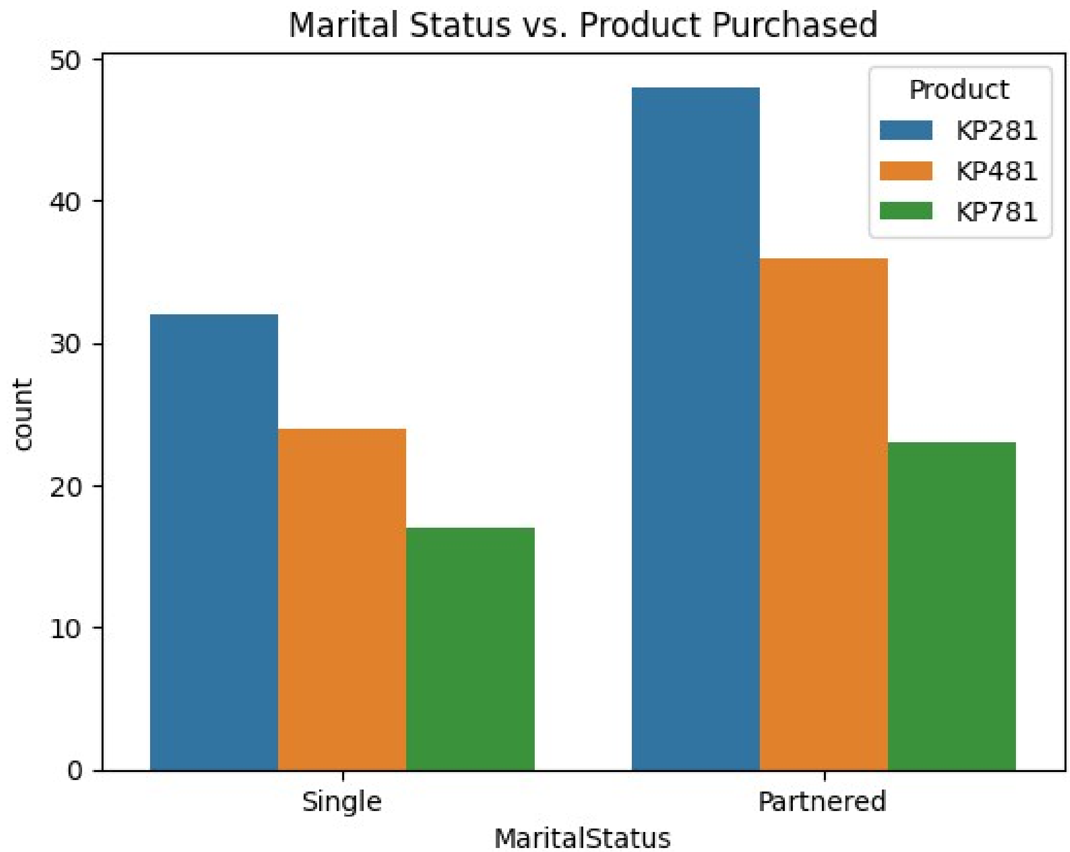
1. From the pair plot and co relation table we can see that most of the variables are independent except a few. Lets check them here

```
heatmap_df.corr()
```

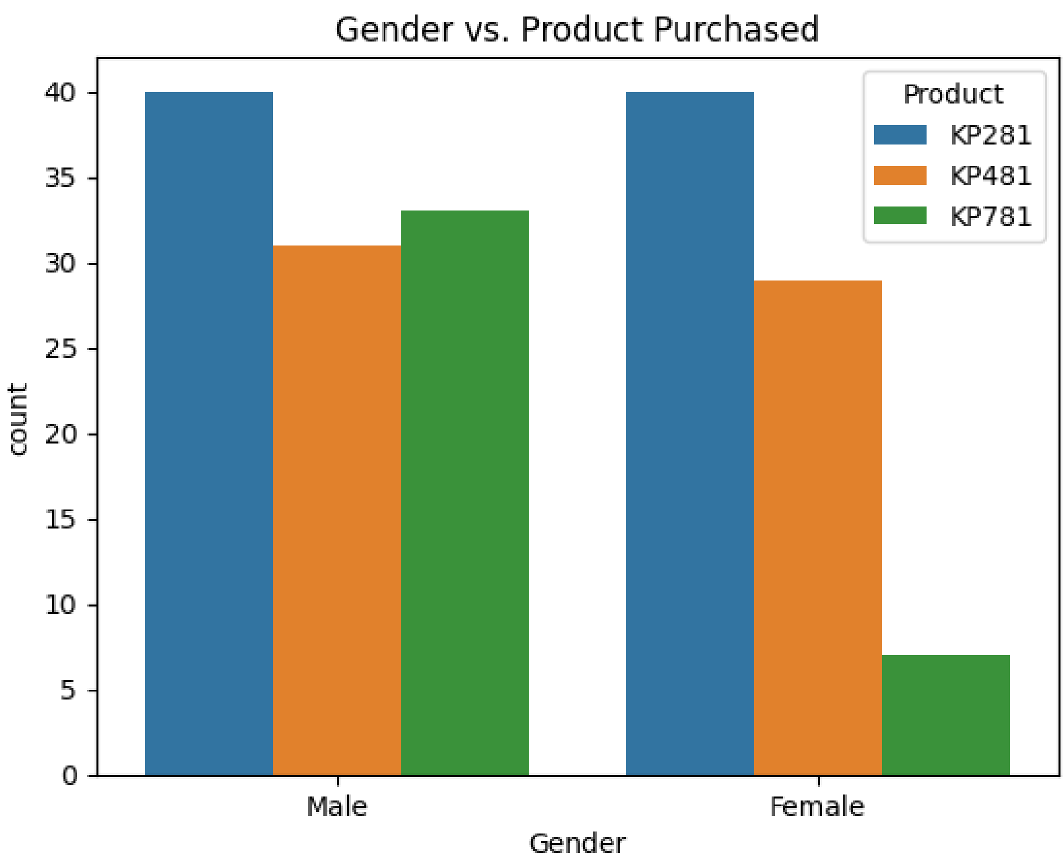
```
                Age  Education     Usage   Fitness    Income     Miles
Age        1.000000   0.280496  0.015064  0.061105  0.513414  0.036618
Education  0.280496   1.000000  0.395155  0.410581  0.625827  0.307284
Usage      0.015064   0.395155  1.000000  0.668606  0.519537  0.759130
Fitness    0.061105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

If we consider corr val >0.6 as co-related we can get pairs like (Age,Fitness), (Education,Income),(Usage,Fitness),(Usage,Miles) which are more co-related

```
# Relationship between the categorical variables and the output
variable in the data.)
sns.countplot(x='MaritalStatus', hue='Product', data=df)
plt.title('Marital Status vs. Product Purchased')
plt.show()
```



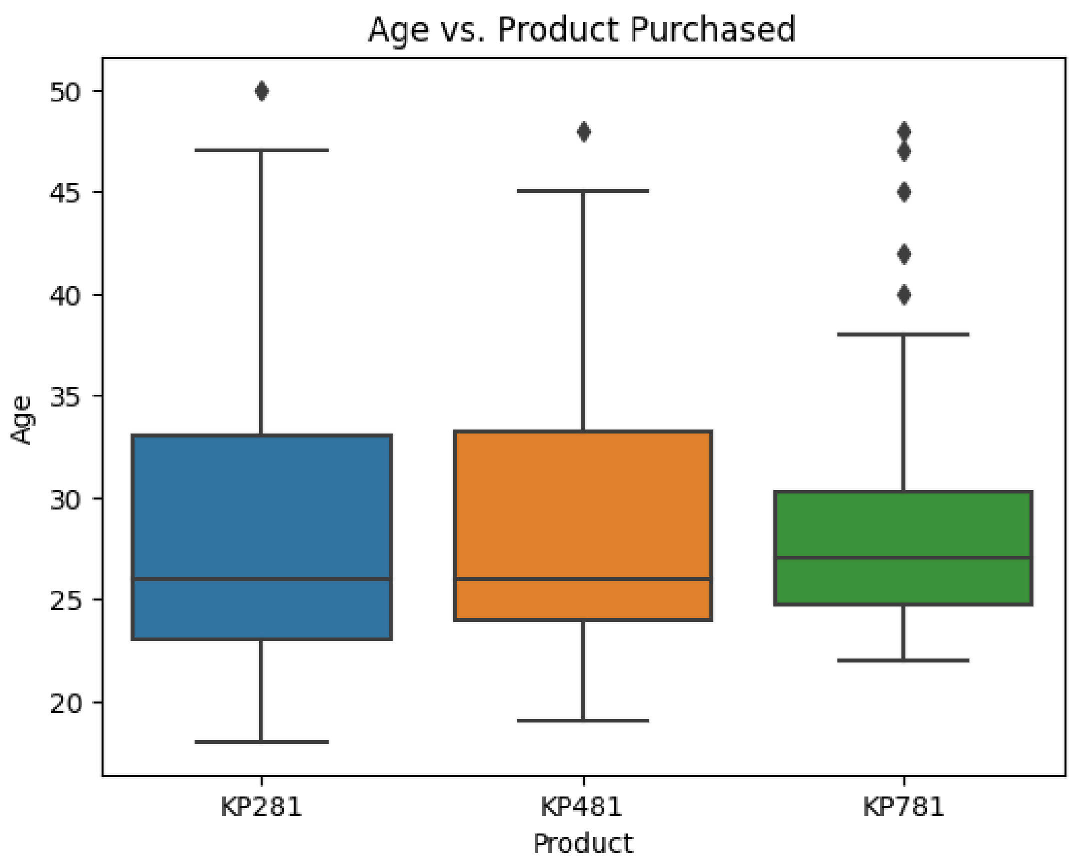

```
sns.countplot(x='Gender', hue='Product', data=df)
plt.title('Gender vs. Product Purchased')
plt.show()
```



Observation:

1. For all the available categorical columms MaritalStatus and Gender the most preferred product is KP281
2. For Females 2nd preferred product is KP481 where as for male it is KP781

```
sns.boxplot(x='Product',y='Age', data=df)
plt.title('Age vs. Product Purchased')
plt.show()
```



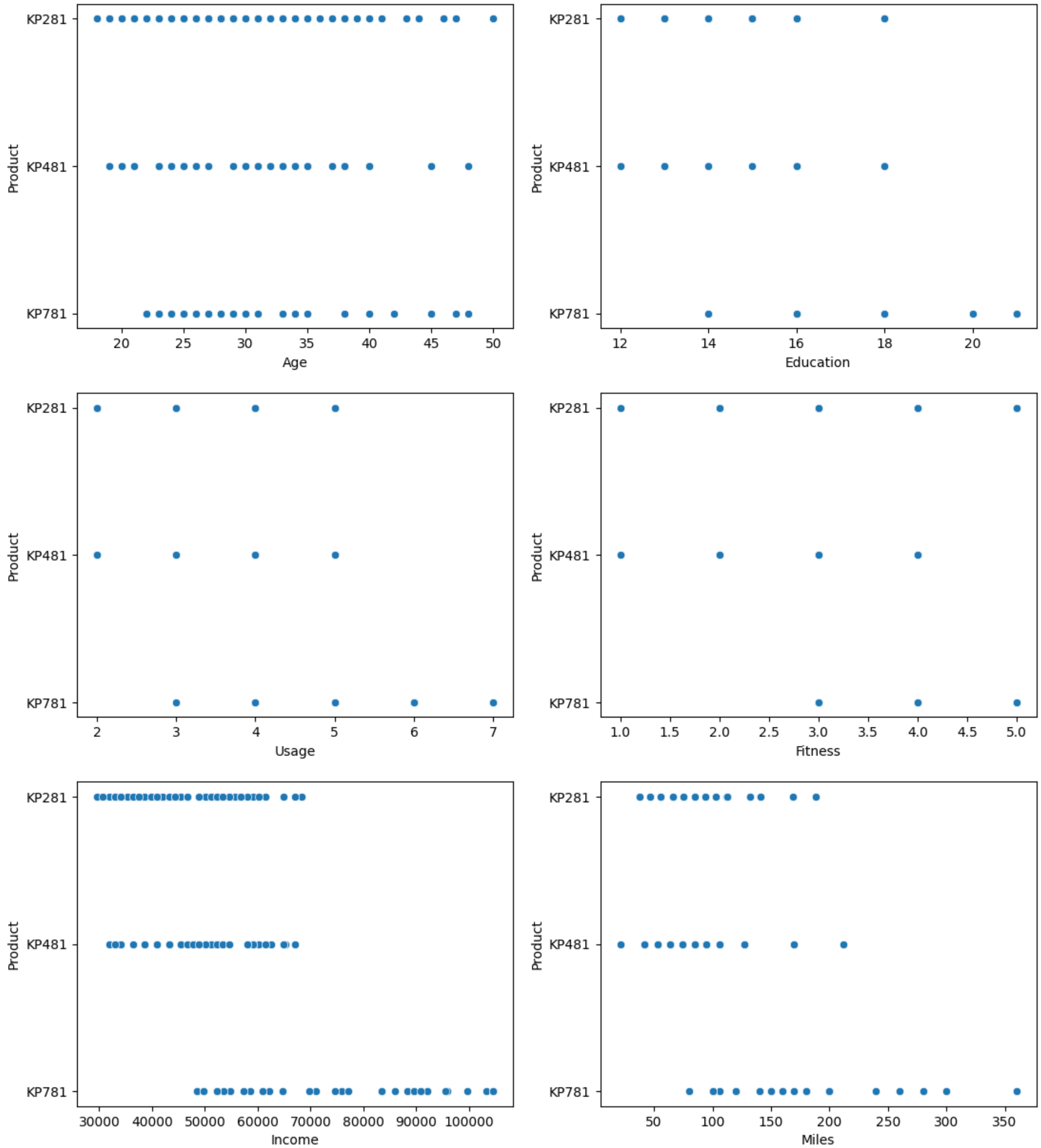
KP281 and KP481 is preferred by most of Age Groups

```
# Above data can be confirmed by below code as well
df1 = df[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count() / len(df) * 100
```

		value
variable	value	
Gender	Female	42.222222
	Male	57.777778
MaritalStatus	Partnered	59.444444
	Single	40.555556
Product	KP281	44.444444
	KP481	33.333333
	KP781	22.222222

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(13, 13))
fig.subplots_adjust(top=1.0)
sns.scatterplot(data=df, x="Age", y= 'Product', ax=axis[0,0])
sns.scatterplot(data=df, x="Education", y='Product', ax=axis[0,1])
sns.scatterplot(data=df, x="Usage", y='Product', ax=axis[1,0])
sns.scatterplot(data=df, x="Fitness", y='Product', ax=axis[1,1])
sns.scatterplot(data=df, x="Income", y='Product', ax=axis[2,0])
```

```
sns.scatterplot(data=df, x="Miles", y='Product', ax=axis[2,1])
plt.show()
```



Observation:

1. The data provided have less data points and most of columns have <=10 unique values thats why the scatter plot we have against Product forms different clusters

The marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

```
# probabilities of buying different Products can be calculated like
this
product_cross_tab = pd.crosstab(index=df['Product'], columns='count',
normalize=True) * 100
product_cross_tab
```

```
col_0        count
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

KP281 is most bought product followed by KP481 and KP781 which is observed many times in previous analysis

```
# Categorical columns for which we want to calculate probabilities
categorical_columns = ['Gender', 'MaritalStatus',
'Education','Fitness','Usage']

for col in categorical_columns:
    conditional_prob = pd.crosstab(index=df['Product'],
columns=df[col], normalize='columns') * 100
    print(f"\nConditional Probability based on {col}:")
    print(conditional_prob)
```

```

Conditional Probability based on Gender:
Gender      Female       Male
Product
KP281    52.631579  38.461538
KP481    38.157895  29.807692
KP781     9.210526  31.730769

Conditional Probability based on MaritalStatus:
MaritalStatus  Partnered     Single
Product
KP281          44.859813  43.835616
KP481          33.644860  32.876712
KP781          21.495327  23.287671

Conditional Probability based on Education:
Education         12    13         14    15         16         18
20  \
Product

KP281      66.666667  60.0  54.545455  80.0  45.882353   8.695652
0.0
```

```
KP481       33.333333  40.0  41.818182  20.0  36.470588   8.695652
0.0
KP781        0.000000   0.0   3.636364   0.0  17.647059  82.608696
100.0

Education     21
Product
KP281        0.0
KP481        0.0
KP781      100.0

Conditional Probability based on Fitness:
Fitness     1          2          3          4          5
Product
KP281    50.0  53.846154  55.670103  37.500000   6.451613
KP481    50.0  46.153846  40.206186  33.333333   0.000000
KP781     0.0   0.000000   4.123711  29.166667  93.548387

Conditional Probability based on Usage:
Usage            2          3          4          5      6      7
Product
KP281    57.575758  53.623188  42.307692  11.764706    0.0    0.0
KP481    42.424242  44.927536  23.076923  17.647059    0.0    0.0
KP781     0.000000   1.449275  34.615385  70.588235  100.0  100.0
```

From the above table we can find conditional probabilty for each column with product column

Eg1: **Given that a customer is female, what is the probability she'll purchase a KP481 is found as 38.16% which can be found in Conditional probabilty based on Gender table**

Eg2: **Given that a marital status is partnered, what is the probability KP281 is purchased is found as 44.86% which can be found in Conditional probabilty based on Marital Status table**

customer profilings for each and every product.

```
c = ['Age', 'Gender', 'Income']

for col in df['Product'].unique():
    customer_profile_pro = df[df['Product']==col][c]
    print(f'\nCustomer Profile for {col}:\
n',customer_profile_pro.describe(include='all'))


Customer Profile for KP281:
              Age Gender       Income
count   80.000000     80     80.00000
unique        NaN      2          NaN
top           NaN   Male          NaN
freq          NaN     40          NaN
mean    28.550000    NaN  46418.02500
```

```
std      7.221452    NaN   9075.78319
min     18.000000    NaN  29562.00000
25%     23.000000    NaN  38658.00000
50%     26.000000    NaN  46617.00000
75%     33.000000    NaN  53439.00000
max     50.000000    NaN  68220.00000

Customer Profile for KP481:
               Age Gender        Income
count   60.000000     60     60.000000
unique        NaN      2           NaN
top           NaN   Male           NaN
freq          NaN     31           NaN
mean    28.900000    NaN  48973.650000
std      6.645248    NaN   8653.989388
min     19.000000    NaN  31836.000000
25%     24.000000    NaN  44911.500000
50%     26.000000    NaN  49459.500000
75%     33.250000    NaN  53439.000000
max     48.000000    NaN  67083.000000

Customer Profile for KP781:
               Age Gender        Income
count   40.000000     40      40.00000
unique        NaN      2           NaN
top           NaN   Male           NaN
freq          NaN     33           NaN
mean    29.100000    NaN   75441.57500
std      6.971738    NaN   18505.83672
min     22.000000    NaN   48556.00000
25%     24.750000    NaN   58204.75000
50%     27.000000    NaN   76568.50000
75%     30.250000    NaN   90886.00000
max     48.000000    NaN  104581.00000
```

For Product KP281:

1. Total people who prefer this prouct is 80 out of 180
2. 50% of people who buy their Age is range 23 to 33
3. 50% people Salary is in range 38658 to 53439
4. Male and Female show equal interest to buy this product

For Product KP481:

1. Total people who prefer this prouct is 60 out of 180
2. 50% of people who buy their Age is range 24 to 33
3. 50% people Salary is in range 44911.5 to 53439
4. Male and Female show alomst equal interest to buy this product also

For Product KP781:

1. Total people who prefer this prouct is 40 out of 180
2. 50% of people who buy their Age is range 24 to 30
3. 50% people Salary is in range 58204.75 to 90886
4. This product is preferred mostly by males.

The Product KP781 is preferred mostly by Males who have more salary

6. Recommendations:

1. Targeted Marketing Strategies:

The Prouct KP281,KP481 is famous in both male and female genders with Salary < 6000 but KP781 is used mostly by male with Salary >6000. So Female with >6k salary can be targetted to increase sales of KP781. And also can provide good incentives and No cost EMI oprions for others as well

2. Product Feature Enhancements:

The Poduct KP281,KP481 are leading products in market. We can use customer feedback and insights to know what features made them to buy the product and implement the same features in KP781 as well, and also take feedback for any improvements

3. Customer Engagement:

For any business to be successfull customer engagement is must and should. Frequently interacting with customer and updating product to their requirements and implementing customer loyality programs to strengthen their relationship help boost in product sales

4. Pricing Strategies:

As we seen above most people prefer KP281,KP481 which prices could be low as people with salary < 6000 prefer these products. Maintaining these price the focus should be on sales of KP781 which can be improved by providing incentives on special days and also provide offers and EMI options

5. Promotional Campaigns:

These are part of letting people know about our business and business expansion plan. Promotional campaign can be organised that aligns with diff class customers. Lucky draw contestant can be conducted to reach the word out more

6.Continuous Monitoring:

Regularly update customer profiles and conduct ongoing analyses to adapt strategies based on changing market dynamics and customer preferences is must to survive in market