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.

Dataset

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior three months. The dataset has the following features:

Dataset link: Aerofit_treadmill.csv

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import math
from scipy import stats
from scipy.stats import binom
from scipy.stats import norm
from scipy.stats import poisson

df = 
pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/asset
s/000/001/125/original/aerofit_treadmill.csv?1639992749')
df

    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
```

```
..      ...  ...     ...        ...            ...     ...       ...
...
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
0      112
1       75
2       66
3       85
4       47
..     ...
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

```
df.head()
```

```
  Product  Age  Gender  Education MaritalStatus  Usage  Fitness
Income  Miles
0   KP281   18    Male         14        Single      3        4
29562    112
1   KP281   19    Male         15        Single      2        3
31836     75
2   KP281   19  Female         14     Partnered      4        3
30699     66
3   KP281   19    Male         12        Single      3        3
32973     85
4   KP281   20    Male         13     Partnered      4        2
35247     47
```

```
# to find lenghth of the dataset use:
len(df)
```

```
180
```

To find diferent data types in the dataset use:

```
df.dtypes
```

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

The following line displays a summary of the DataFrame, including descriptive statistics for each column

```
df.describe(include="all")
```

```
       Product         Age Gender   Education MaritalStatus
Usage  \
count      180  180.000000    180  180.000000           180
180.000000
unique       3         NaN      2         NaN             2
NaN
top      KP281         NaN   Male         NaN     Partnered
NaN
freq        80         NaN    104         NaN           107
NaN
mean       NaN   28.788889    NaN   15.572222           NaN
3.455556
std        NaN    6.943498    NaN    1.617055           NaN
1.084797
min        NaN   18.000000    NaN   12.000000           NaN
2.000000
25%        NaN   24.000000    NaN   14.000000           NaN
3.000000
50%        NaN   26.000000    NaN   16.000000           NaN
3.000000
75%        NaN   33.000000    NaN   16.000000           NaN
4.000000
max        NaN   50.000000    NaN   21.000000           NaN
7.000000

           Fitness        Income       Miles
count   180.000000    180.000000  180.000000
unique         NaN           NaN         NaN
top            NaN           NaN         NaN
freq           NaN           NaN         NaN
mean      3.311111  53719.577778  103.194444
```

```
std        0.958869   16506.684226   51.863605
min        1.000000   29562.000000   21.000000
25%        3.000000   44058.750000   66.000000
50%        3.000000   50596.500000   94.000000
75%        4.000000   58668.000000  114.750000
max        5.000000  104581.000000  360.000000
```

The following lines count the occurrences of each unique value in the specified columns.

```
df["Age"].value_counts()
```

```
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
38     7
21     7
22     7
27     7
31     6
34     6
29     6
20     5
40     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
43     1
41     1
39     1
36     1
42     1
Name: Age, dtype: int64
```

```
df["Gender"].value_counts()
```

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

```
df["MaritalStatus"].value_counts()
```

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

```
df["Usage"].value_counts()
```

```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

```
df["Fitness"].value_counts()
```

```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

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

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

The folowing line returns the number of unique values in each column of the DataFrame.

```
df.nunique()
```

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

The following line loop prints the name of each column in the DataFrame along with the number of unique values in that column.

```python
for i in df.columns:
  print(i,':',df[i].nunique())
```

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

This returns the number of missing values in each column of the DataFrame.

```python
df.isna().sum()
```

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

The following lines return the dimensions and total size of the DataFrame.

```python
df.shape
```

```
(180, 9)
```

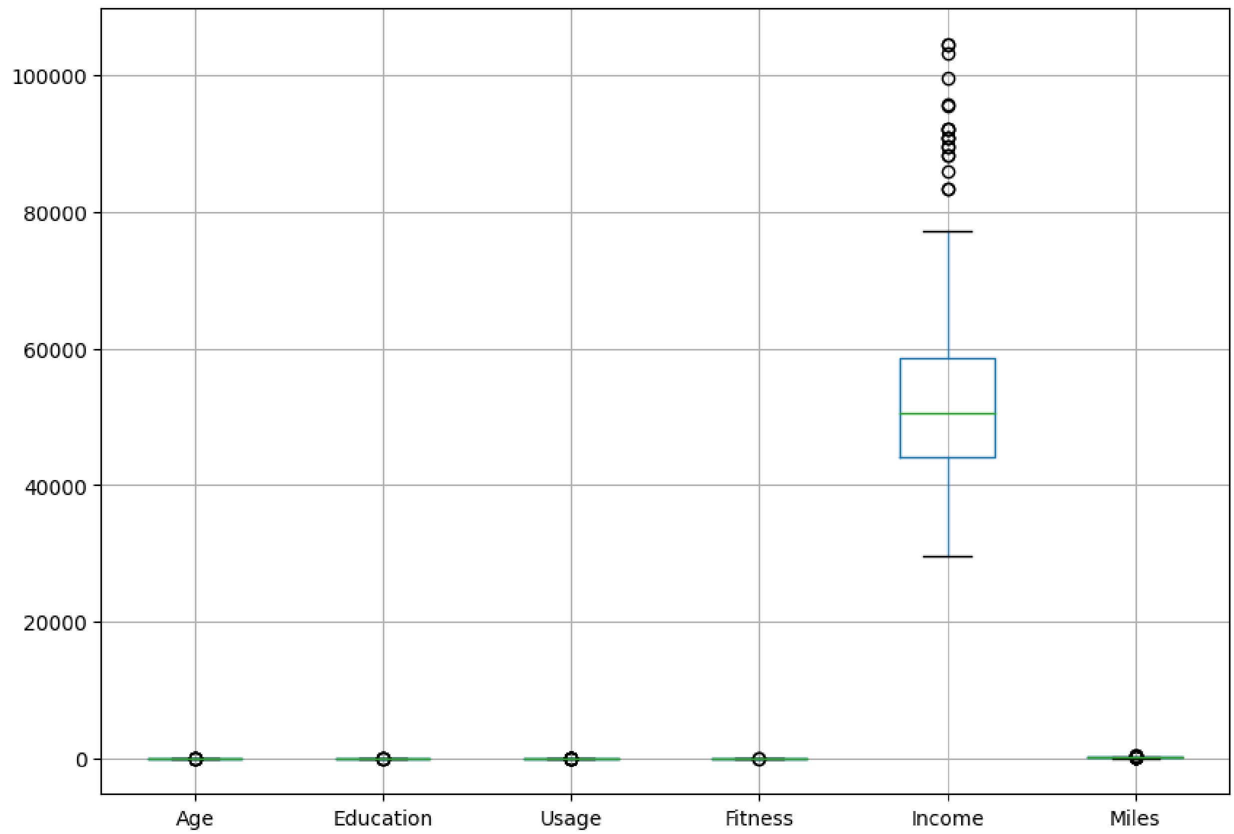
```python
df.size
```

```
1620
```

The following line creates a box plot of the DataFrame.

```python
plt.figure(figsize = (10, 7))
df.boxplot()
```

```
<Axes: >
```



The following lines return the mean and median values for each column in the DataFrame.

```
df.mean()
```

```
<ipython-input-18-c61f0c8f89b5>:1: FutureWarning: The default value of
numeric_only in DataFrame.mean is deprecated. In a future version, it
will default to False. In addition, specifying 'numeric_only=None' is
deprecated. Select only valid columns or specify the value of
numeric_only to silence this warning.
  df.mean()
```

```
Age              28.788889
Education        15.572222
Usage             3.455556
Fitness           3.311111
Income        53719.577778
Miles           103.194444
dtype: float64
```

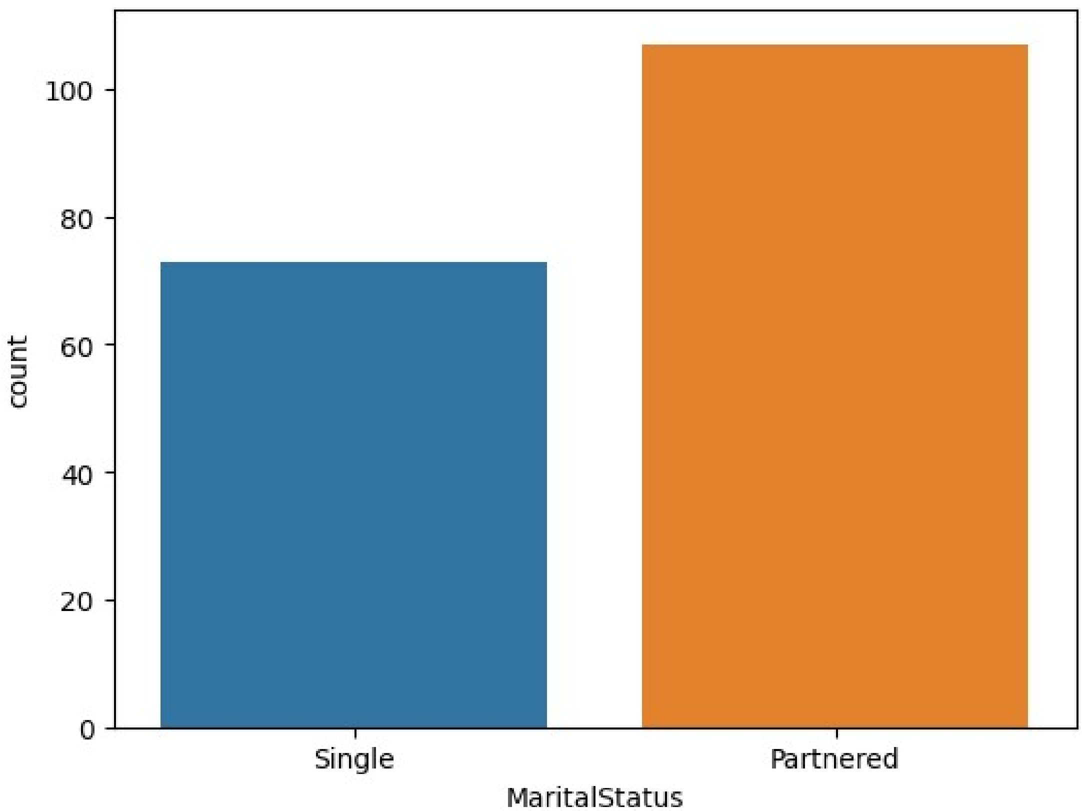
```
df.median()
```

```
<ipython-input-19-6d467abf240d>:1: FutureWarning: The default value of
numeric_only in DataFrame.median is deprecated. In a future version,
it will default to False. In addition, specifying 'numeric_only=None'
is deprecated. Select only valid columns or specify the value of
```

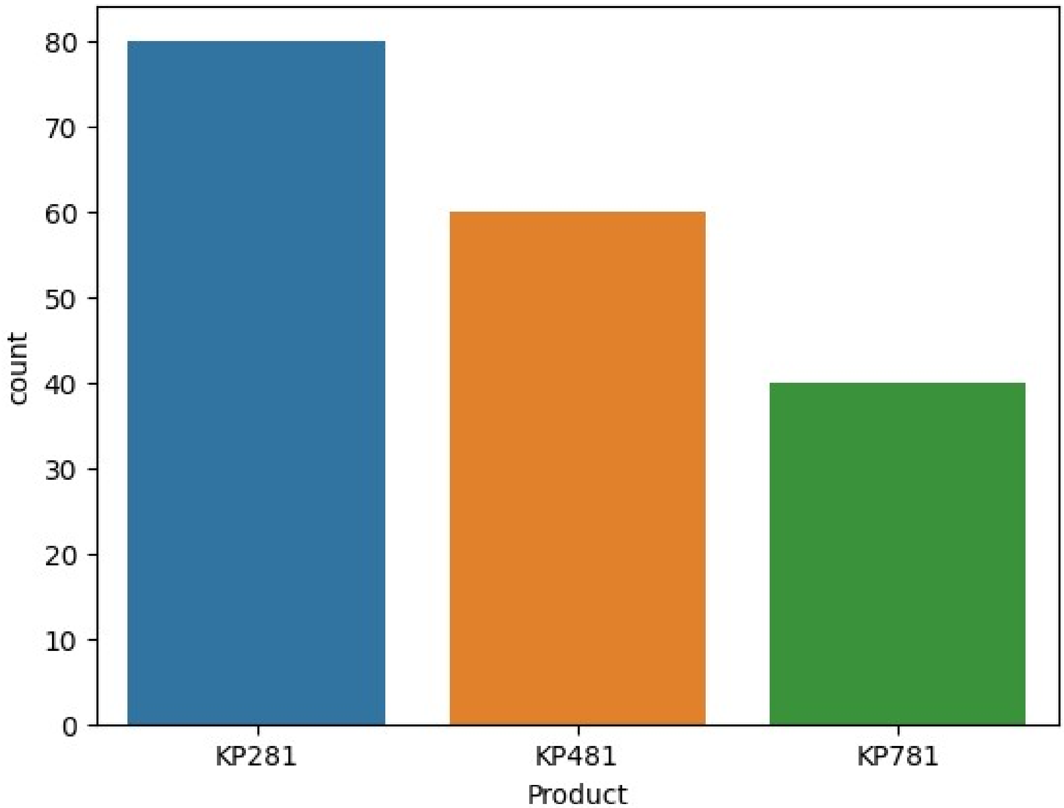
```
numeric_only to silence this warning.
  df.median()

Age                26.0
Education          16.0
Usage               3.0
Fitness             3.0
Income          50596.5
Miles              94.0
dtype: float64
```

The following lines create count plots of the "MaritalStatus", "Product", and "Gender" columns of the DataFrame using Seaborn.

```
sns.countplot(data=df, x='MaritalStatus')

<Axes: xlabel='MaritalStatus', ylabel='count'>
```

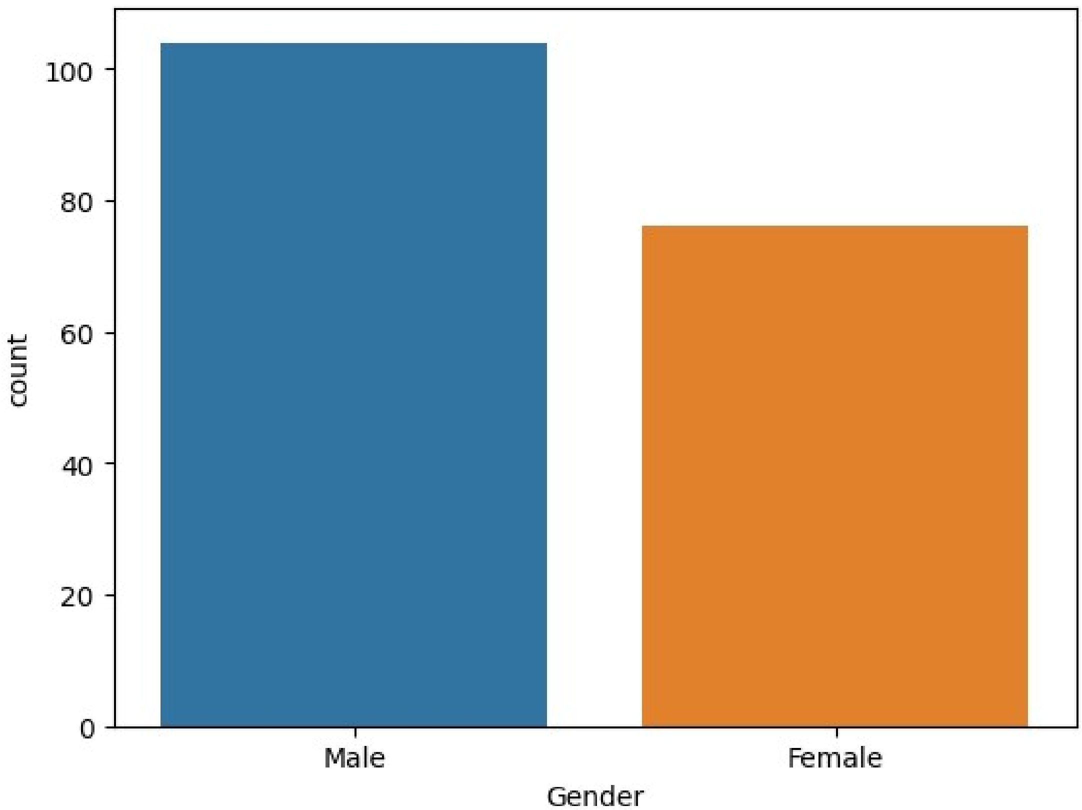



```
sns.countplot(data=df, x='Product')

<Axes: xlabel='Product', ylabel='count'>
```



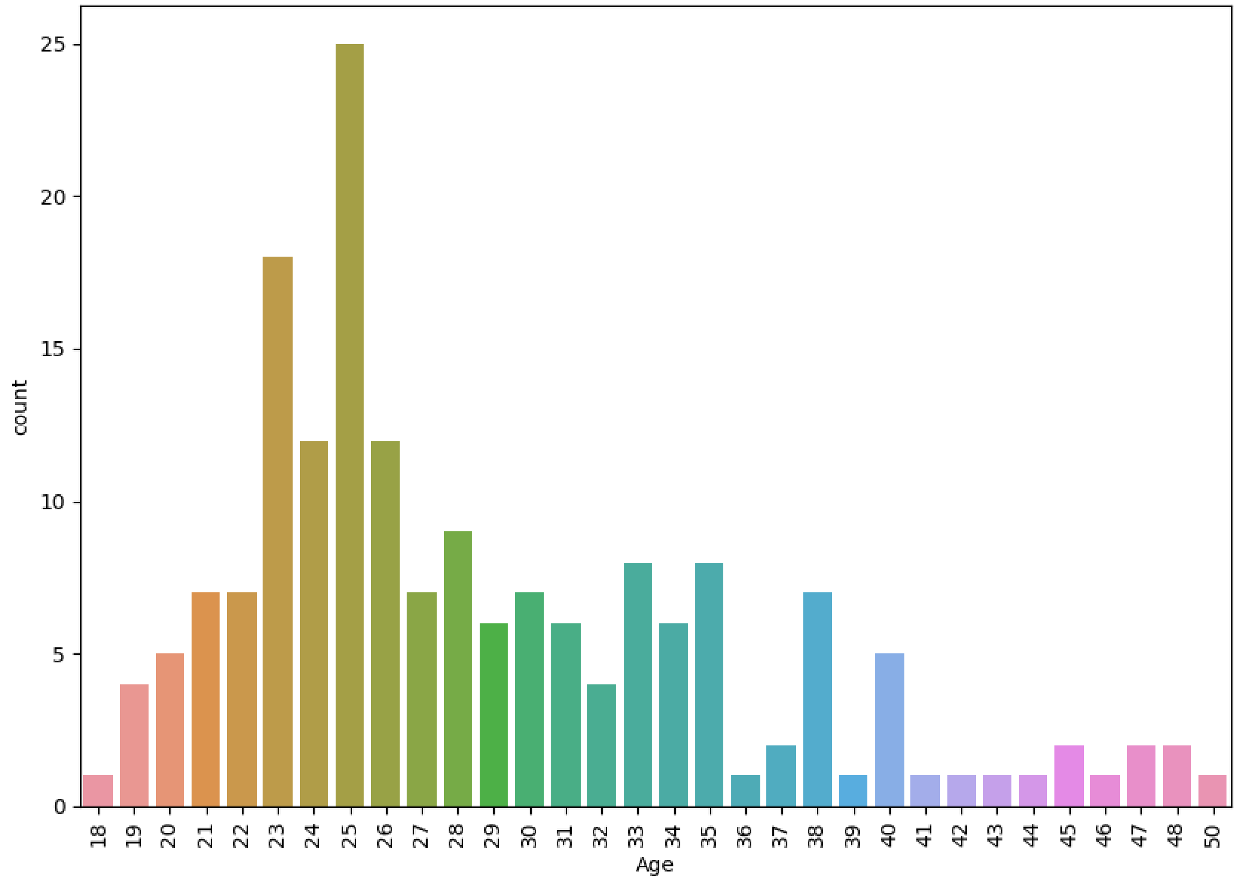

```
sns.countplot(data=df, x='Gender')
```

```
<Axes: xlabel='Gender', ylabel='count'>
```



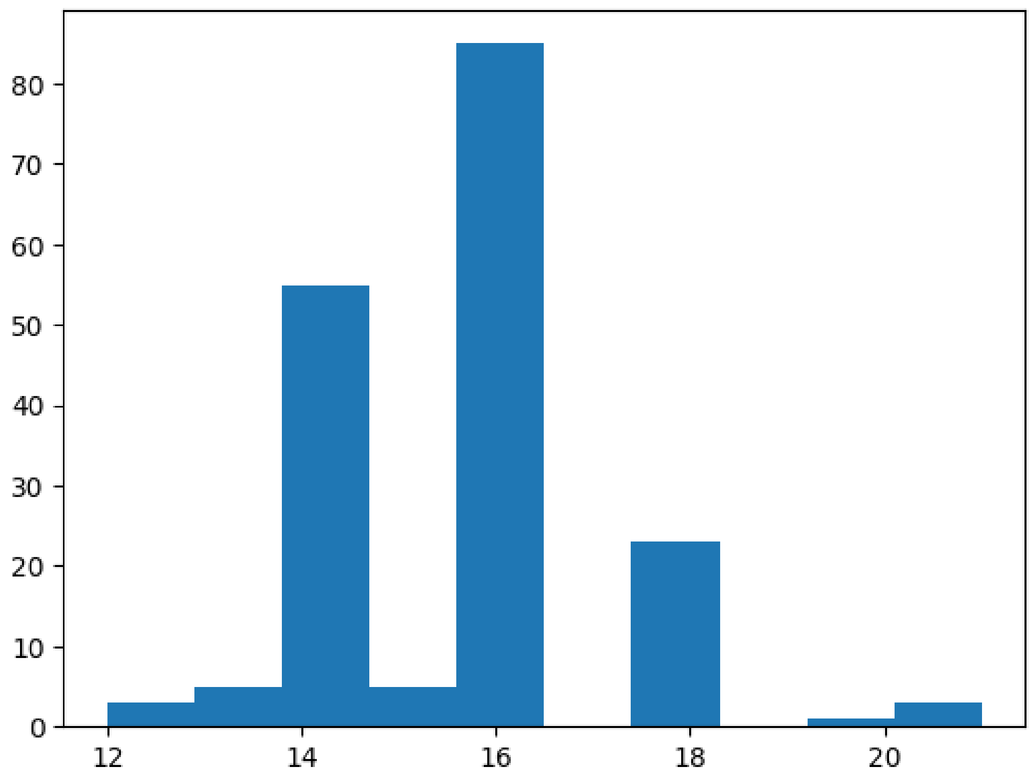
The following line creates a count plot of the "Age" column of the DataFrame using Seaborn, with the x-axis labels rotated 90 degrees.

```
plt.figure(figsize = (10, 7))
sns.countplot(data=df, x='Age')
plt.xticks(rotation=90)
plt.show()
```

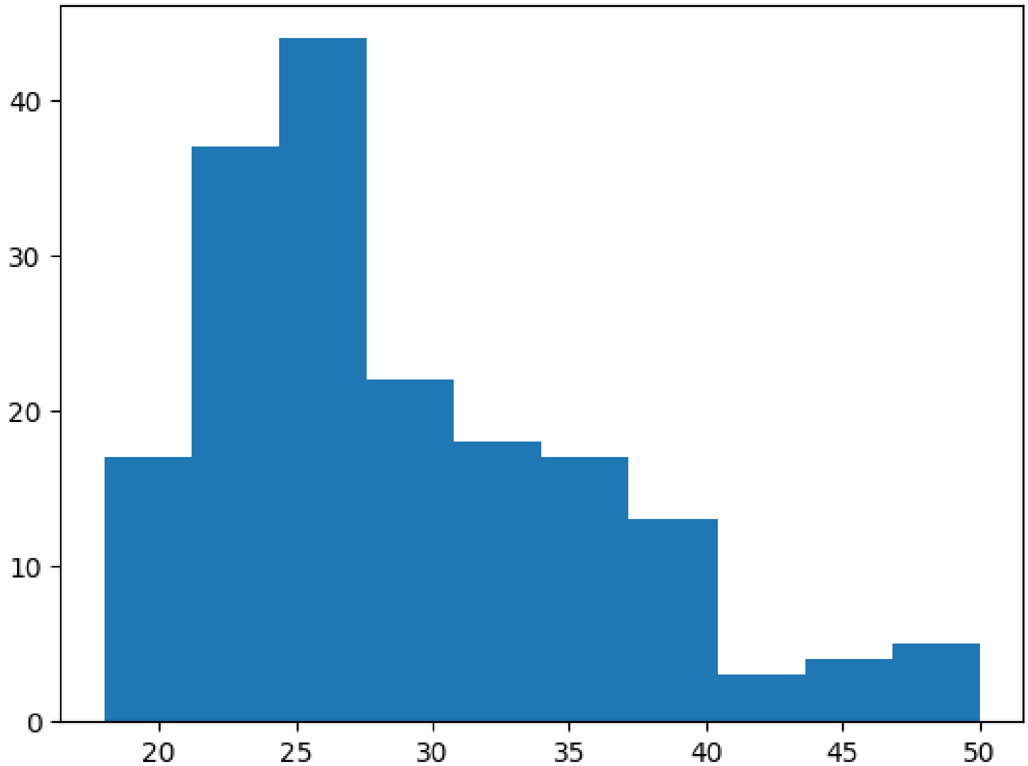


The following lines create histograms of the "Education", "Age", "Product", "Usage", and "Fitness" columns of the DataFrame using Matplotlib.

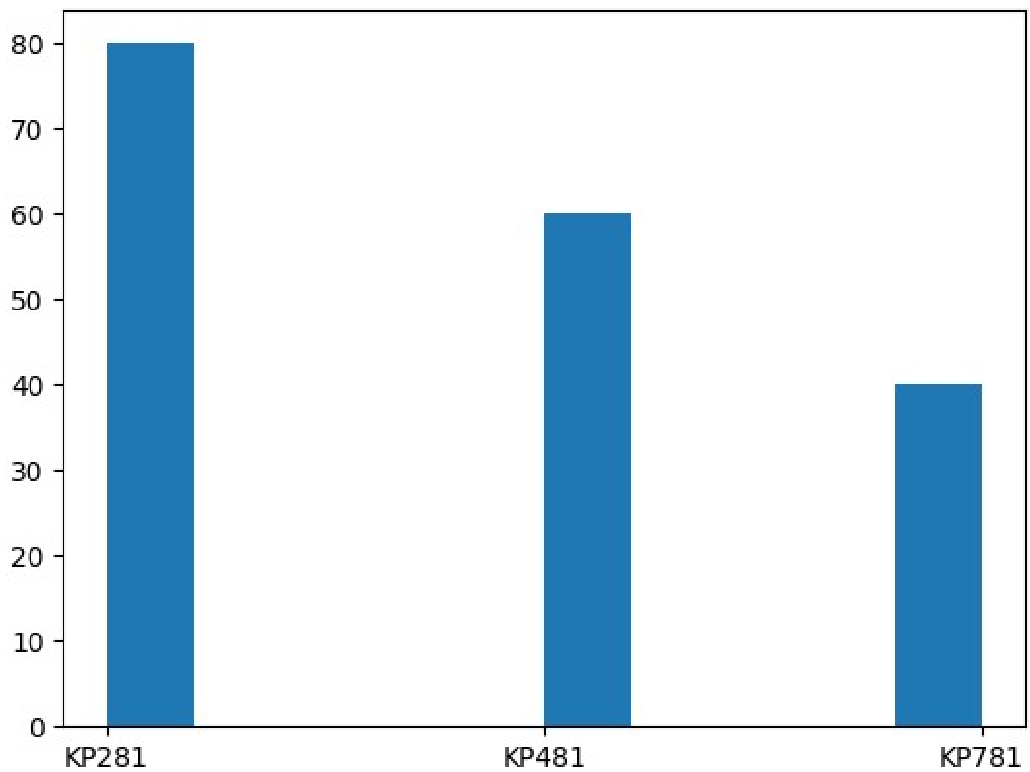
```
plt.hist(df["Education"])
plt.show()
```



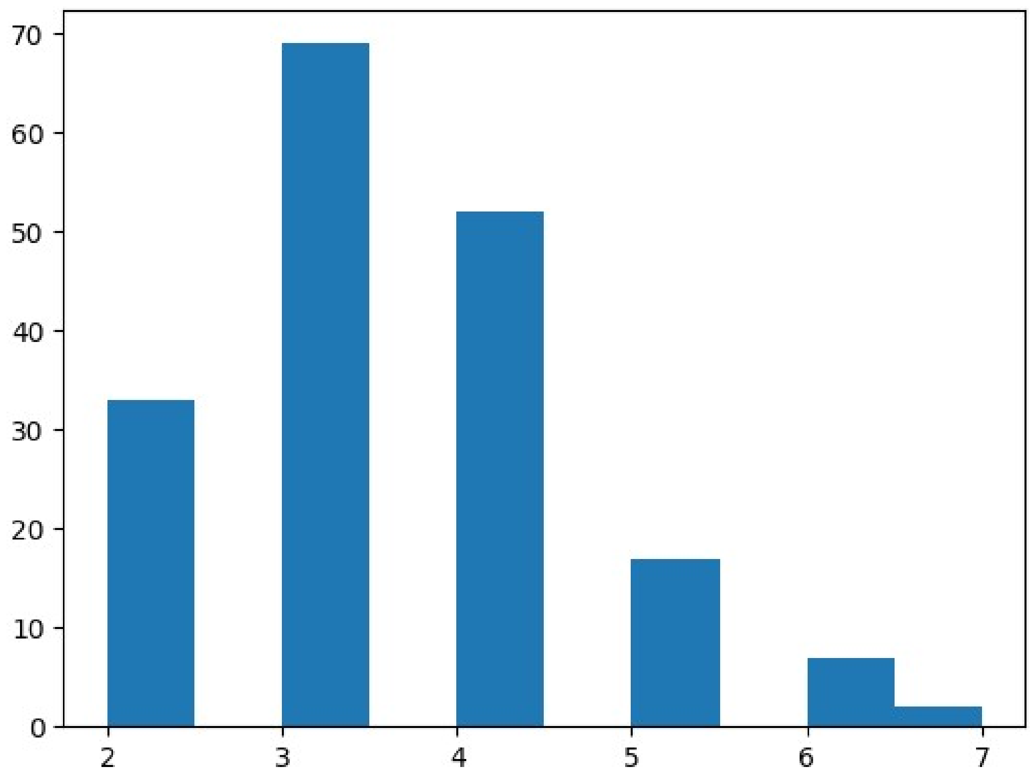

```
plt.hist(df["Age"])
plt.show()
```



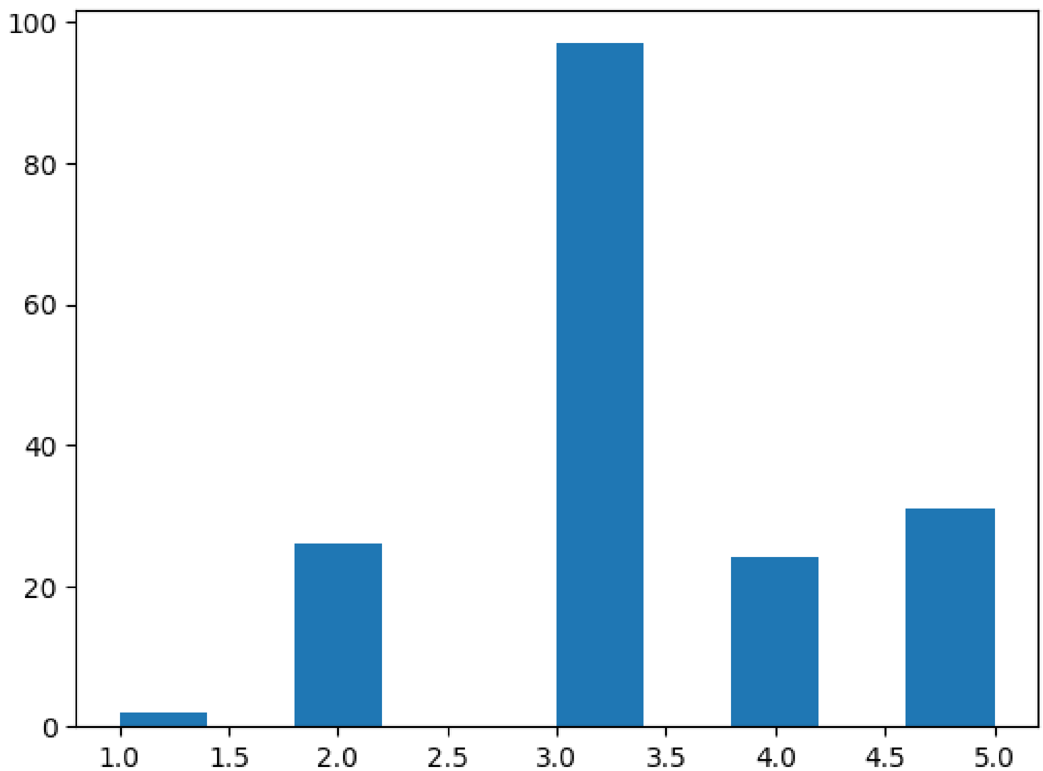

```
plt.hist(df["Product"])
plt.show()
```




```
plt.hist(df["Usage"])
plt.show()
```



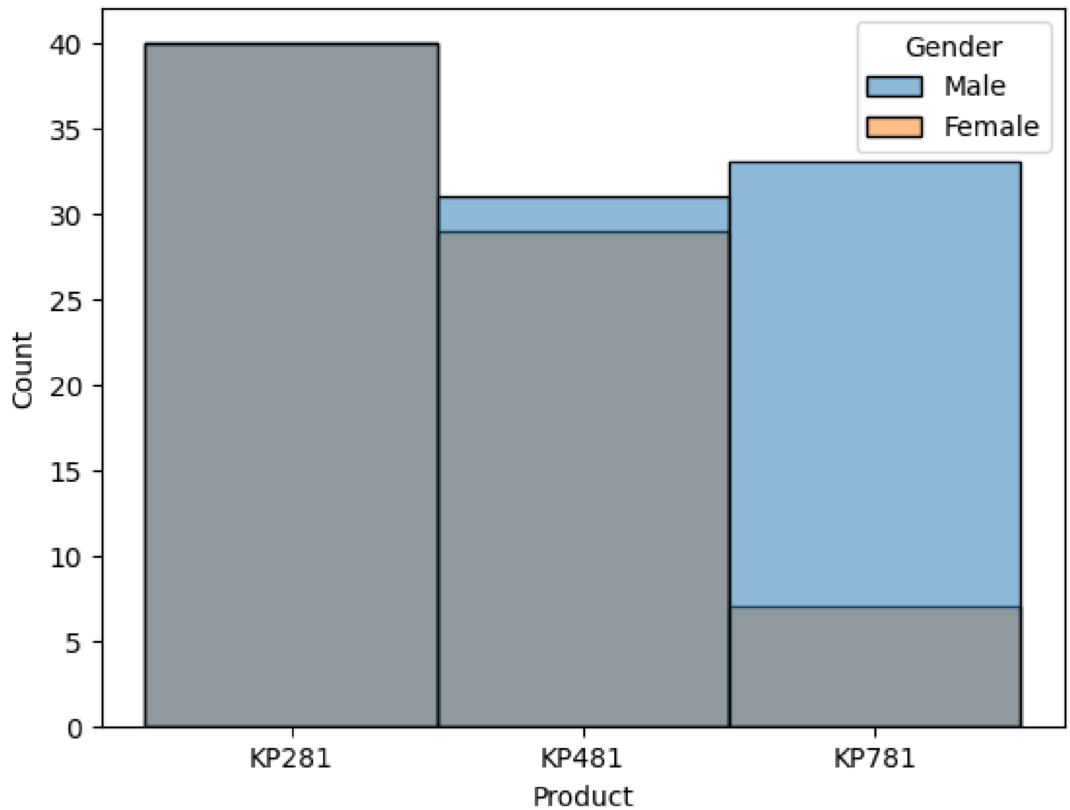

```
plt.hist(df["Fitness"])
plt.show()
```



Bivariate analysis : The following line create a histogram for Product and Gender columns of the DataFrame using Seaborn.

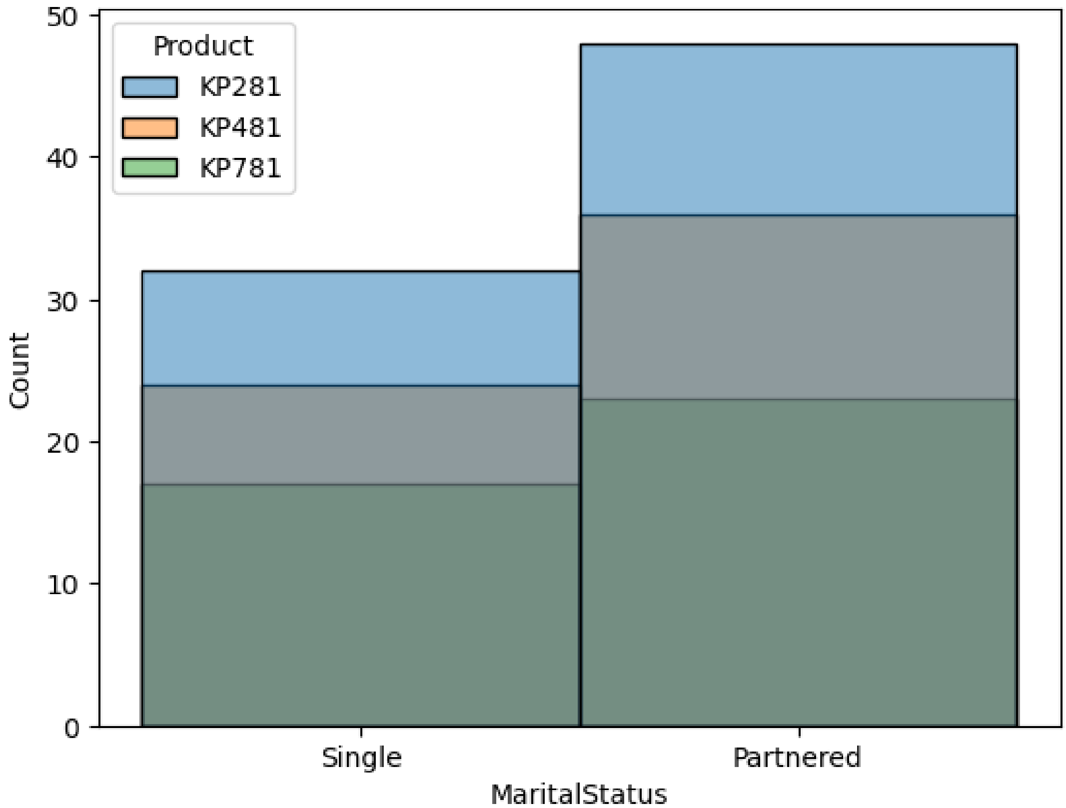
```
sns.histplot(data=df, x="Product", hue="Gender")
```

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



Bivariate analysis : The following line create a histogram for MaritalStatus and Product columns of the DataFrame using Seaborn.

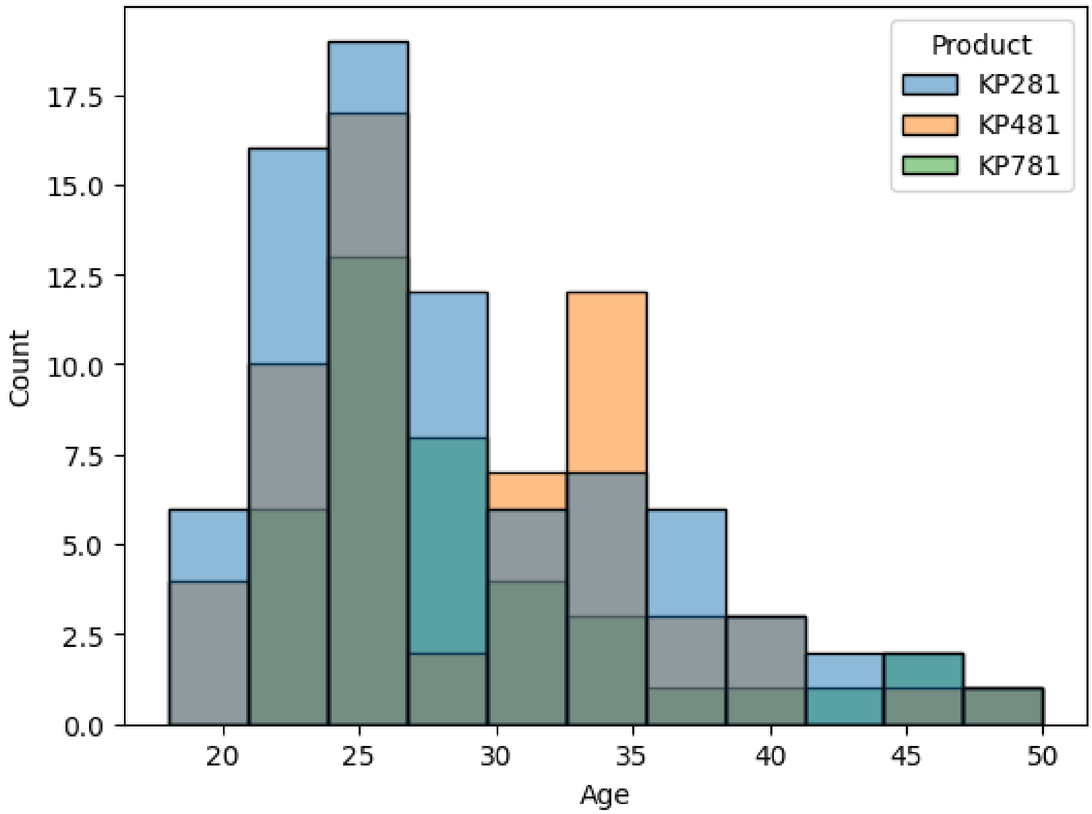
```
sns.histplot(data=df, x="MaritalStatus", hue="Product")

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



Bivariate analysis : The following line create a histogram for Age and Product columns of the DataFrame using Seaborn.

```
sns.histplot(data=df, x="Age", hue="Product")
```

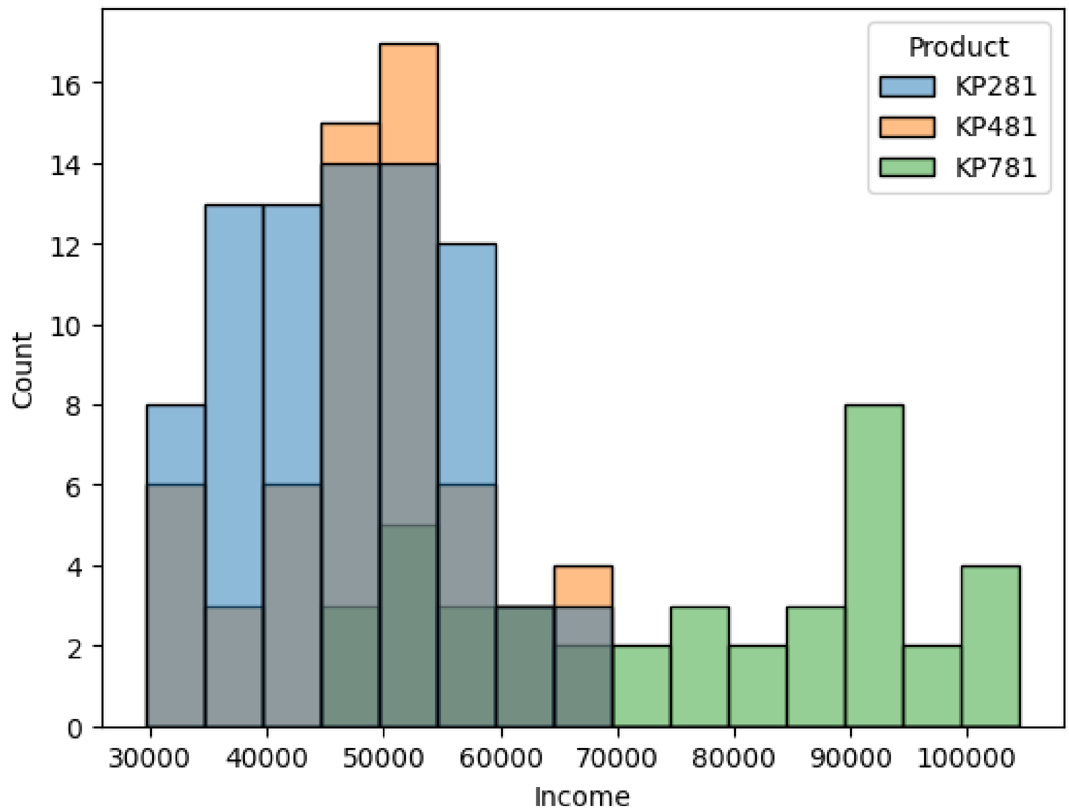
```
<Axes: xlabel='Age', ylabel='Count'>
```



Bivariate analysis : The following line create a histogram for Income and Product columns of the DataFrame using Seaborn.

```
sns.histplot(data=df, x="Income", hue="Product")
```

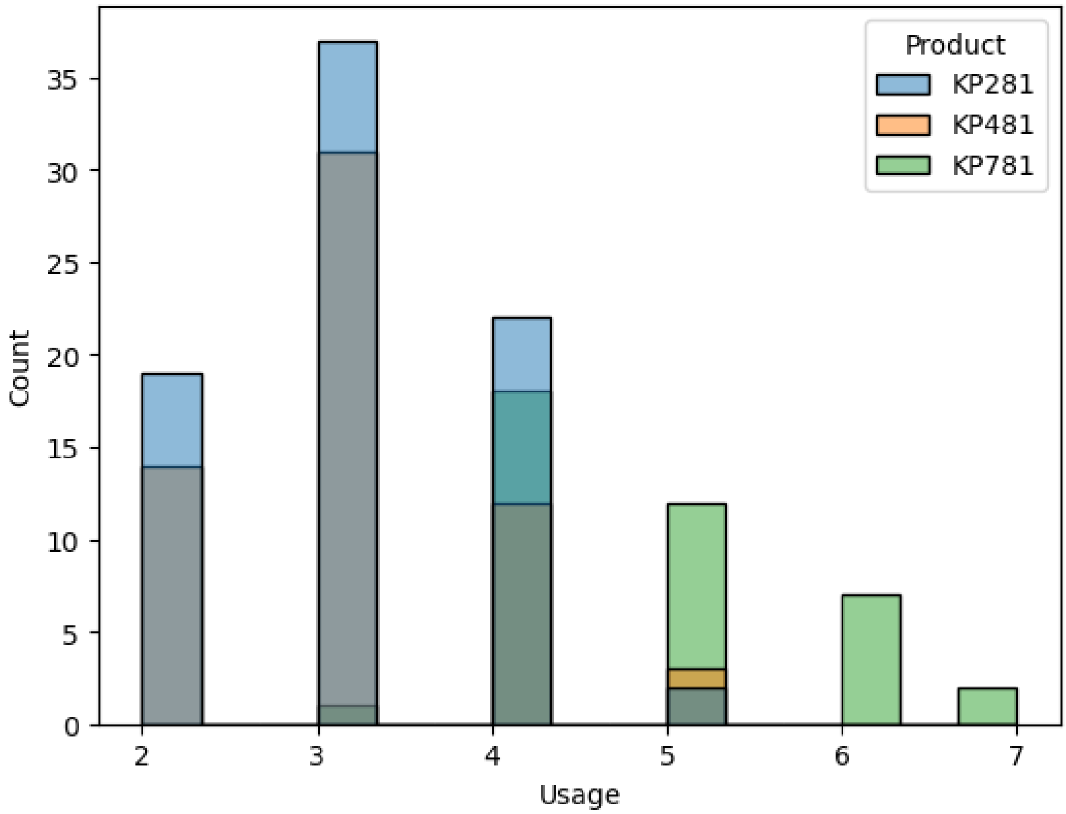
```
<Axes: xlabel='Income', ylabel='Count'>
```



Bivariate analysis : The following line create a histogram for Usage and Product columns of the DataFrame using Seaborn.

```
sns.histplot(data=df, x="Usage", hue="Product")
```

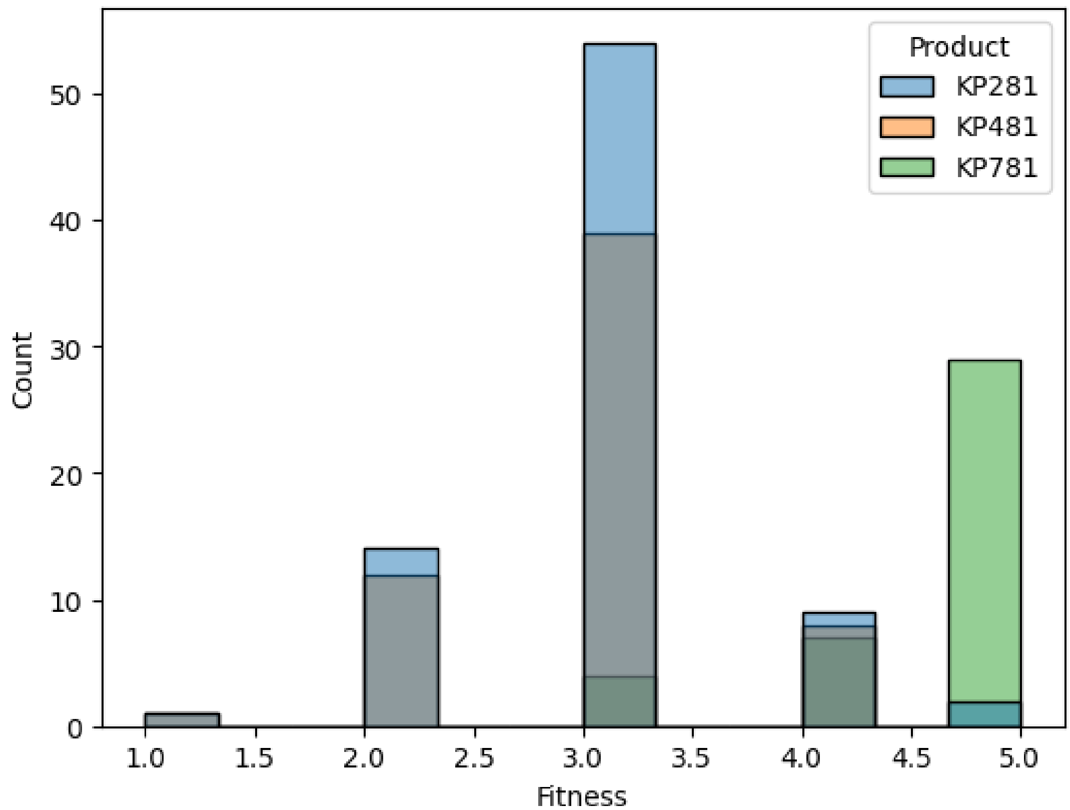
```
<Axes: xlabel='Usage', ylabel='Count'>
```



Bivariate analysis : The following line create a histogram for Fitness and Product columns of the DataFrame using Seaborn.

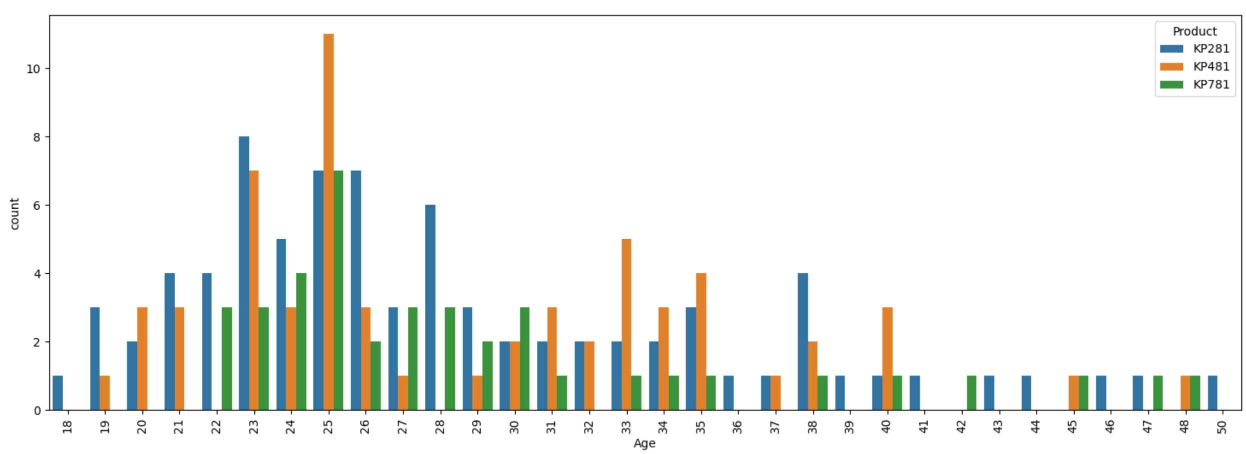
```
sns.histplot(data=df, x="Fitness", hue="Product")
```

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



Bivariate analysis : The following line create a Countplot for Fitness and Product columns of the DataFrame using Seaborn.

```
plt.figure(figsize = (18,6))
sns.countplot(data=df, x='Age',hue="Product")
plt.xticks(rotation=90)
plt.show()
```



The following line creates a crosstab between Gender and Product using Pandas . A crosstab is used to ompute a simple cross tabulation of two (or more) factors.

```
pd.crosstab(df["Gender"],df["Product"])
```

Product	KP281	KP481	KP781
Gender			
Female	40	29	7
Male	40	31	33

The following line creates a crosstab between Age and Product using Pandas

```
pd.crosstab(df["Age"],df["Product"])
```

Product	KP281	KP481	KP781
Age			
18	1	0	0
19	3	1	0
20	2	3	0
21	4	3	0
22	4	0	3
23	8	7	3
24	5	3	4
25	7	11	7
26	7	3	2
27	3	1	3
28	6	0	3
29	3	1	2
30	2	2	3
31	2	3	1
32	2	2	0
33	2	5	1
34	2	3	1
35	3	4	1
36	1	0	0
37	1	1	0
38	4	2	1
39	1	0	0
40	1	3	1
41	1	0	0
42	0	0	1
43	1	0	0
44	1	0	0
45	0	1	1
46	1	0	0
47	1	0	1
48	0	1	1
50	1	0	0

The following line creates a crosstab between MaritalStatus and Product using Pandas

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

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

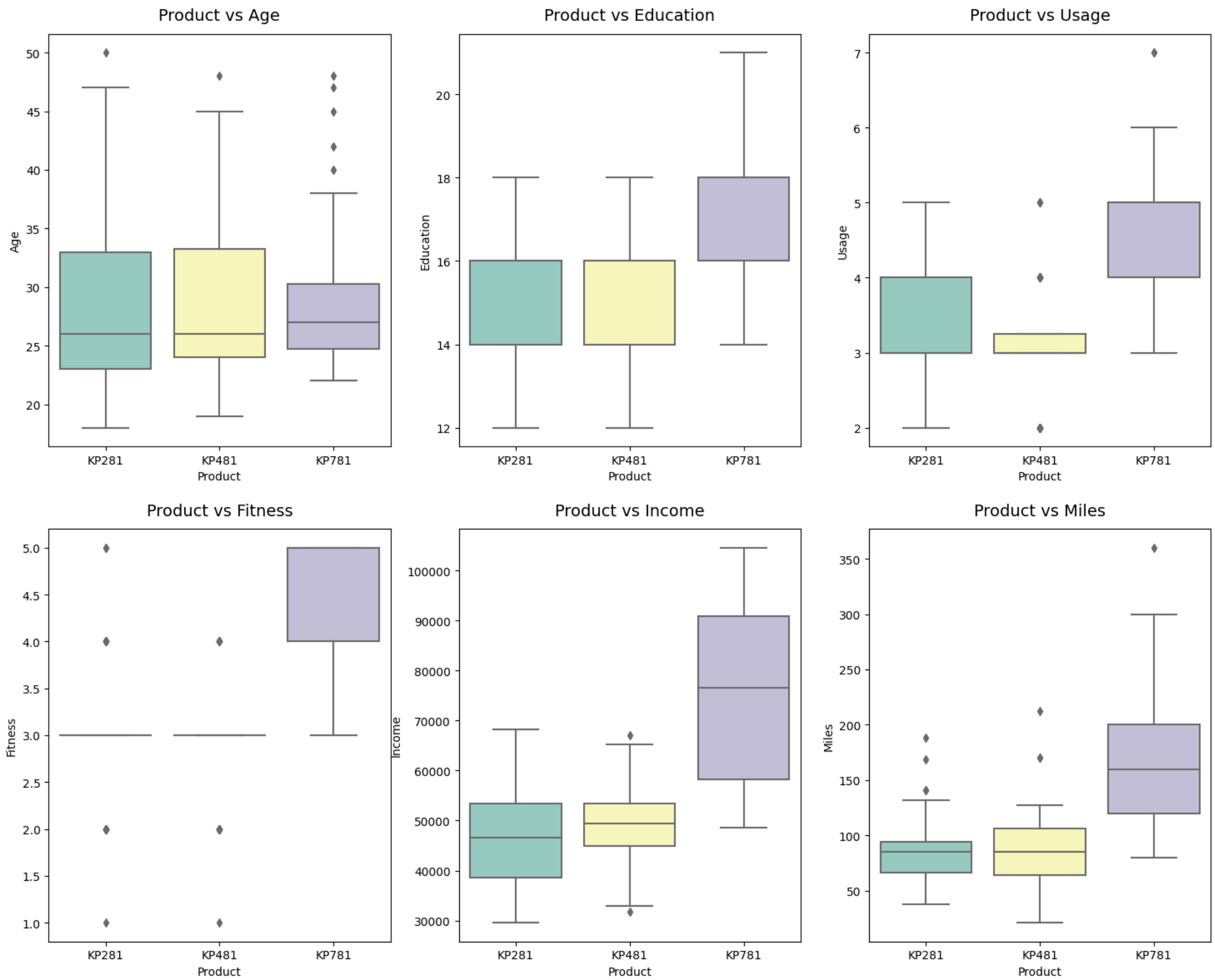
The following line creates a crosstab between Incomeand Product using Pandas

```
pd.crosstab(df["Income"],df["Product"])
```

```
Product  KP281  KP481  KP781
Income
29562        1      0      0
30699        1      0      0
31836        1      1      0
32973        3      2      0
34110        2      3      0
...        ...    ...    ...
95508        0      0      1
95866        0      0      1
99601        0      0      1
103336       0      0      1
104581       0      0      2

[62 rows x 3 columns]
```

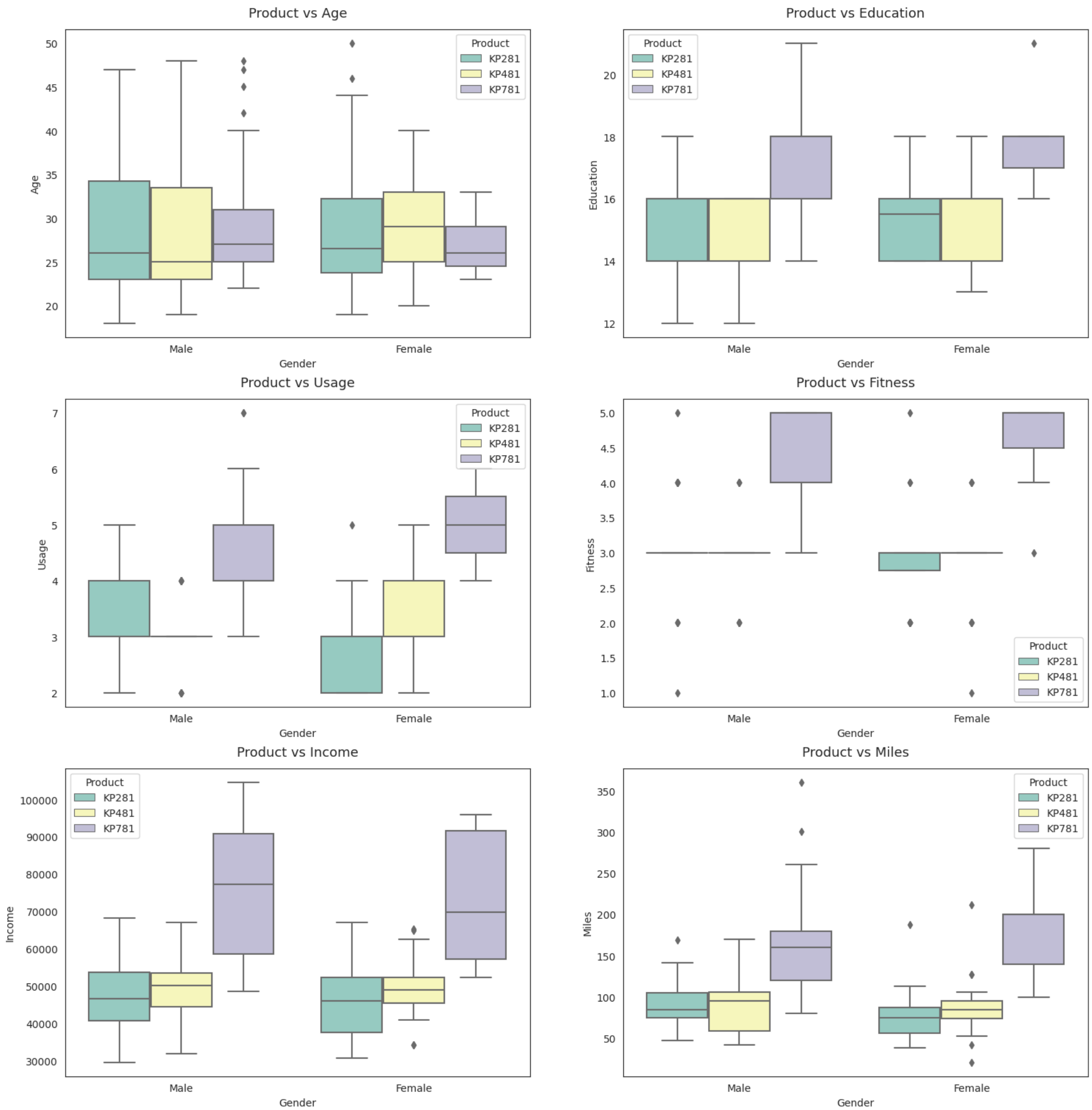
Multivariate Analysis : Analysis is done on continuous values like Age,Education,Usage,Fitness,Income,Miles against Product using Seaborn. It is used to find outliers which can be seen from the graph as points staying away from the regular graphs.

```
feat = ["Age","Education","Usage","Fitness","Income","Miles"]
fig,axs = plt.subplots(nrows = 2,ncols = 3,figsize = (18,10))
fig.subplots_adjust(top=1.2)
count=0
for i in range(2) :
    for j in range(3) :

sns.boxplot(data=df,x="Product",y=feat[count],ax=axs[i,j],palette="Set
3")
        axs[i,j].set_title(f"Product vs
{feat[count]}",pad=12,fontsize=14)
        count+=1
```



Multivariate Analysis : Analysis is done on continuous values like Age,Education,Usage,Fitness,Income,Miles against Product and Gender using Seaborn.

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 12))
fig.subplots_adjust(top=1.3)
count = 0
for i in range(3):
    for j in range(2):
        sns.boxplot(data=df, x='Gender', y=attrs[count],
hue='Product', ax=axs[i,j], palette='Set3')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12,
fontsize=13)
        count += 1
```



Conditional Probability : The probability of each Product is taken given that the Gender is male or female.

```
def prod_gender(gender, print_marginal=False):
    if gender is not "Female" and gender is not "Male":
        return "Invalid gender value."

    df1 = pd.crosstab(index=df['Gender'], columns=[df['Product']])
    p781 = df1['KP781'][gender] / df1.loc[gender].sum()
    p481 = df1['KP481'][gender] / df1.loc[gender].sum()
    p281 = df1['KP281'][gender] / df1.loc[gender].sum()
```

```
    if print_marginal:
        print(f"P(Male): {df1.loc['Male'].sum()/len(df):.2f}")
        print(f"P(Female): {df1.loc['Female'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{gender}): {p781:.2f}")
    print(f"P(KP481/{gender}): {p481:.2f}")
    print(f"P(KP281/{gender}): {p281:.2f}\n")

prod_gender('Male', True)
prod_gender('Female')
```

```
P(Male): 0.58
P(Female): 0.42

P(KP781/Male): 0.32
P(KP481/Male): 0.30
P(KP281/Male): 0.38

P(KP781/Female): 0.09
P(KP481/Female): 0.38
P(KP281/Female): 0.53


<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<ipython-input-42-476470736745>:2: SyntaxWarning: "is not" with a
literal. Did you mean "!="?
  if gender is not "Female" and gender is not "Male":
<ipython-input-42-476470736745>:2: SyntaxWarning: "is not" with a
literal. Did you mean "!="?
  if gender is not "Female" and gender is not "Male":
```

From the above code it is clear that :

- 58% of customers are male and 42% of the customers are female.
- Out of all males 32% bought KP781 ,30% bought KP481 , 38% bought KP281.
- Out of all females 9% bought KP781 ,38% bought KP481 , 53% bought KP281.

Conditional Probability : The probability of each Product is taken given that the MaritalStatus of the customer.

```
def prod_maritalstatus(status, print_marginal=False):
    if status is not "Single" and status is not "Partnered":
        return "Invalid marital status value."

    df1 = pd.crosstab(index=df['MaritalStatus'],
columns=[df['Product']])
    p781 = df1['KP781'][status] / df1.loc[status].sum()
```

```
    p481 = df1['KP481'][status] / df1.loc[status].sum()
    p281 = df1['KP281'][status] / df1.loc[status].sum()

    if print_marginal:
        print(f"P(Single): {df1.loc['Single'].sum()/len(df):.2f}")
        print(f"P(Partnered): 
{df1.loc['Partnered'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{status}): {p781:.2f}")
    print(f"P(KP481/{status}): {p481:.2f}")
    print(f"P(KP281/{status}): {p281:.2f}\n")

prod_maritalstatus('Single', True)
prod_maritalstatus('Partnered')

P(Single): 0.41
P(Partnered): 0.59

P(KP781/Single): 0.23
P(KP481/Single): 0.33
P(KP281/Single): 0.44

P(KP781/Partnered): 0.21
P(KP481/Partnered): 0.34
P(KP281/Partnered): 0.45


<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<ipython-input-43-c1282818332a>:2: SyntaxWarning: "is not" with a 
literal. Did you mean "!="?
  if status is not "Single" and status is not "Partnered":
<ipython-input-43-c1282818332a>:2: SyntaxWarning: "is not" with a 
literal. Did you mean "!="?
  if status is not "Single" and status is not "Partnered":
```

From the above code it is clear that :

- Out of all the customers 41% is single and 59% is partnered.
- Out of all the customers who are single 23% bought KP781,33% bought KP481,44% bought KP281.
- Out of all the customers who are partnered 21% bought KP781,34% bought KP481,45% bought KP281

A heatmap is drawn using Searborn on all continuous values. Using a heatmap to visualise a confusion matrix, time-series movements, temperature changes, correlation matrix and SHAP interaction values.

```
plt.figure(figsize=(16, 6))
sns.heatmap(df.corr(),cmap="YlGnBu", annot=True)
plt.show()
```

```
<ipython-input-44-46cee23e128a>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  sns.heatmap(df.corr(),cmap="YlGnBu", annot=True)
```

A correlation matrix is found between product and other continuous values. Since product is of type object it is changed into 'int' data type.It helps to understand the relation between the continuous values and product.

```
df['Product'] =df['Product'].astype('category').cat.codes
corr_matrix=df.corr()
corr_matrix["Product"].sort_values(ascending=False)
```

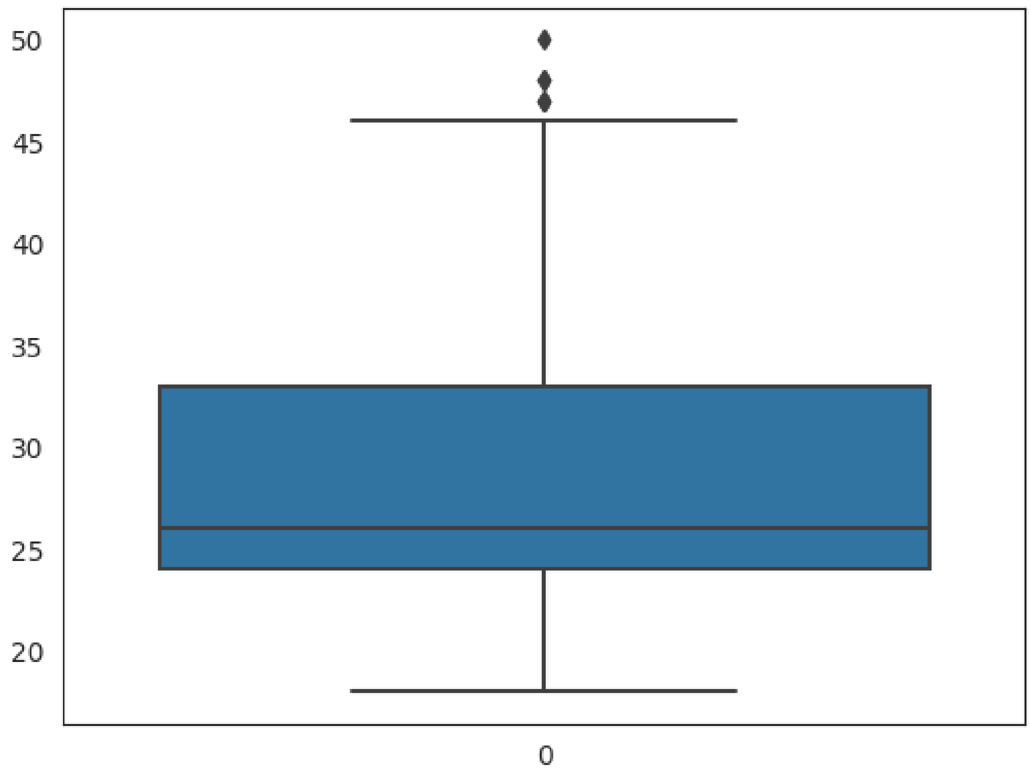
```
<ipython-input-45-e35a225e4fc5>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  corr_matrix=df.corr()
```

```
Product      1.000000
Income       0.624168
Fitness      0.594883
Miles        0.571596
Usage        0.537447
Education    0.495018
Age          0.032225
Name: Product, dtype: float64
```

The following code helps us to find the outliers and the values of the outliers.

```
sns.boxplot(df['Age'])
```

```
<Axes: >
```

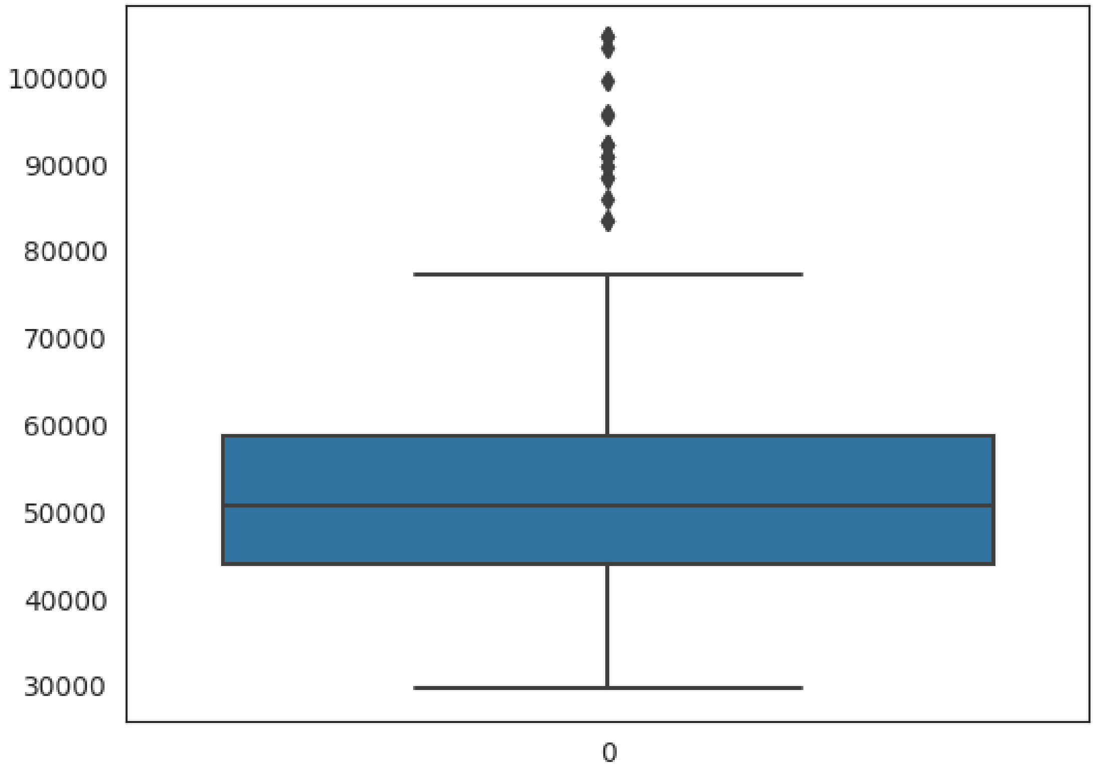



```
np.where(df['Age']>46)
```

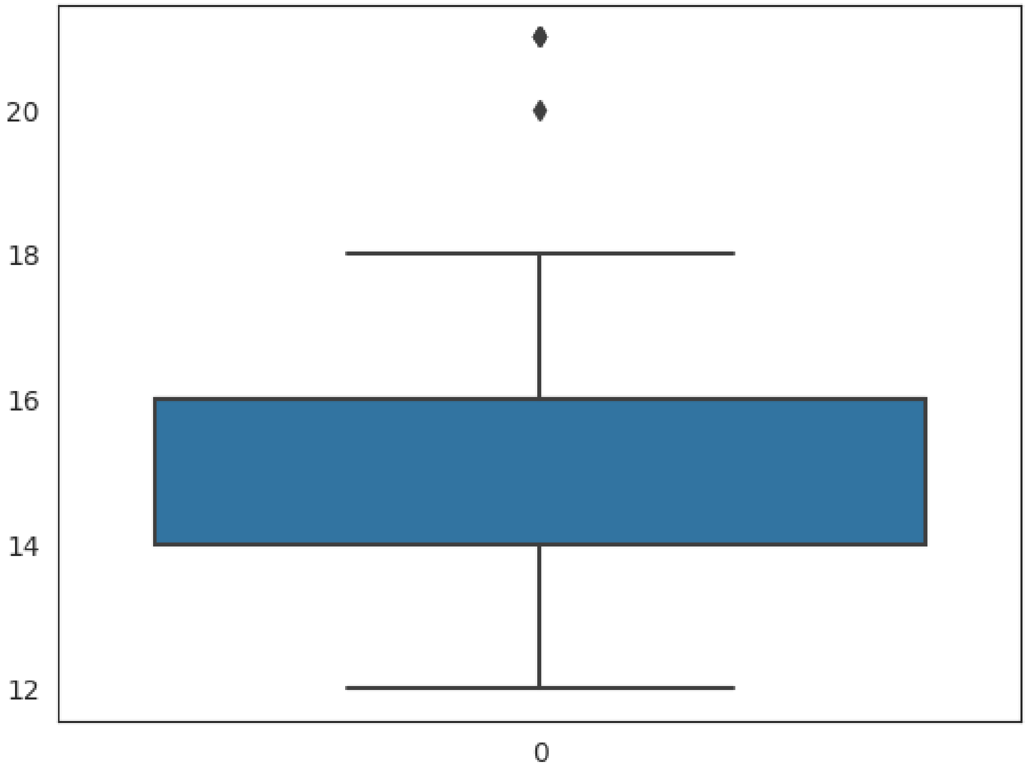
```
(array([ 78,  79, 139, 178, 179]),)
```

```
sns.boxplot(df['Income'])
```

```
<Axes: >
```




```
np.where(df['Income']>80000)

(array([159, 160, 161, 162, 164, 166, 167, 168, 169, 170, 171, 172,
173,
        174, 175, 176, 177, 178, 179]),)

sns.boxplot(df['Education'])

<Axes: >
```

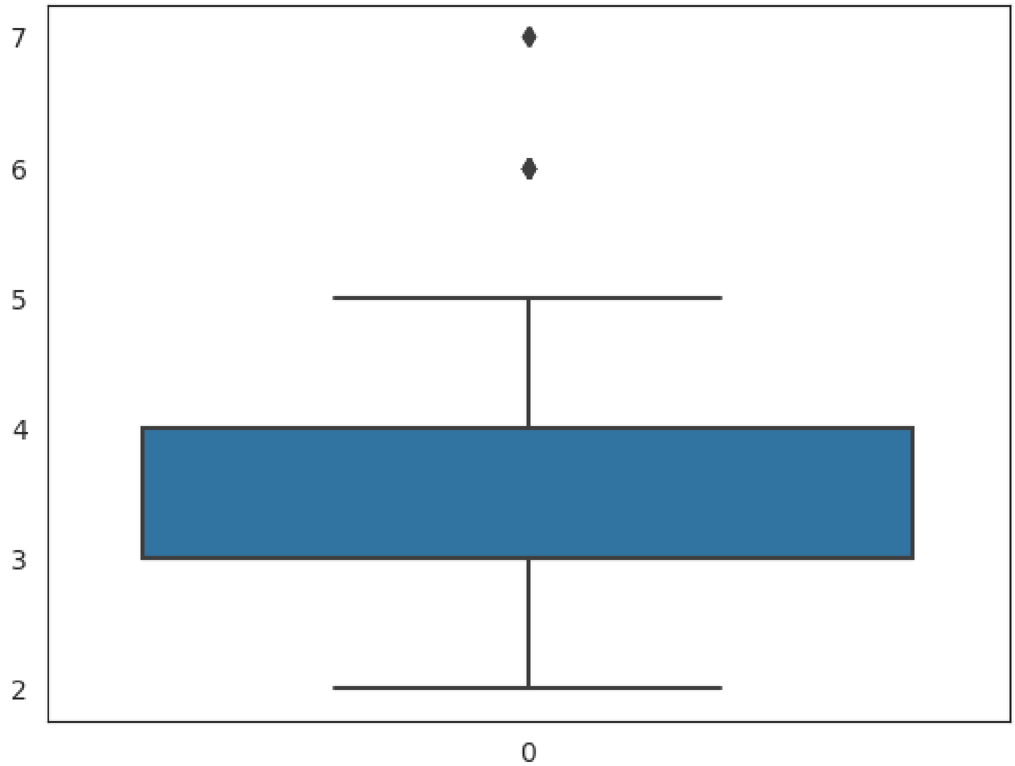



```
np.where(df['Education']>18)
```

```
(array([156, 157, 161, 175]),)
```

```
sns.boxplot(df['Usage'])
```

```
<Axes: >
```

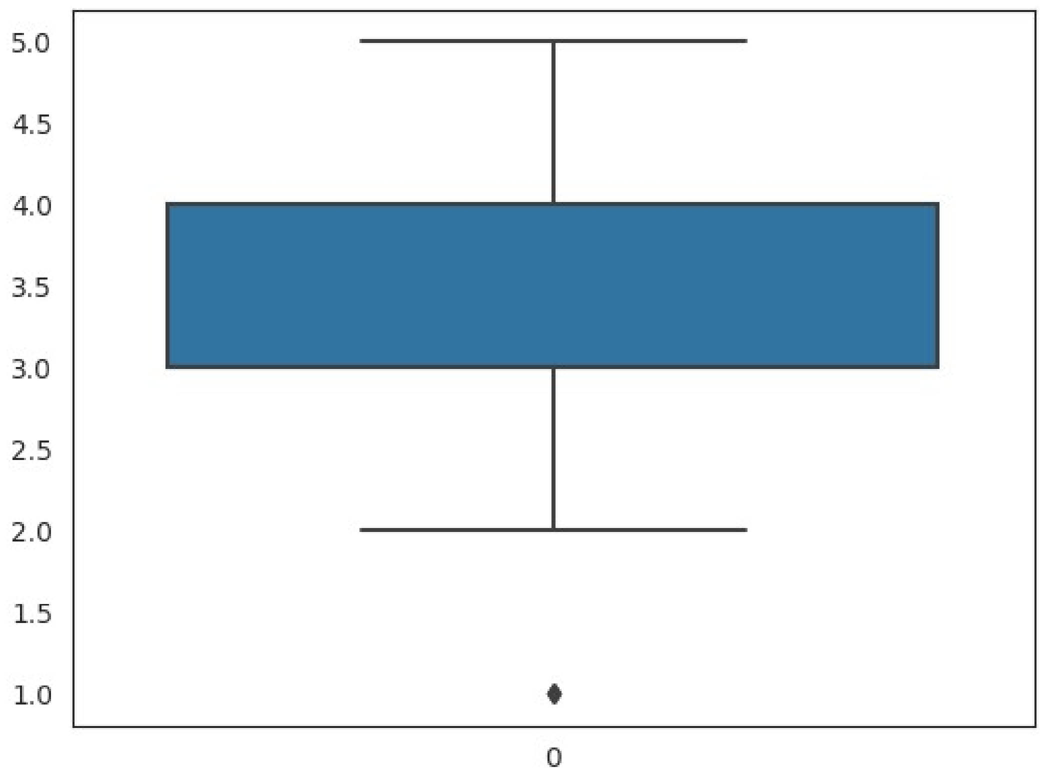



```
np.where(df["Usage"]>5)
```

```
(array([154, 155, 162, 163, 164, 166, 167, 170, 175]),)
```

```
sns.boxplot(df['Fitness'])
```

```
<Axes: >
```

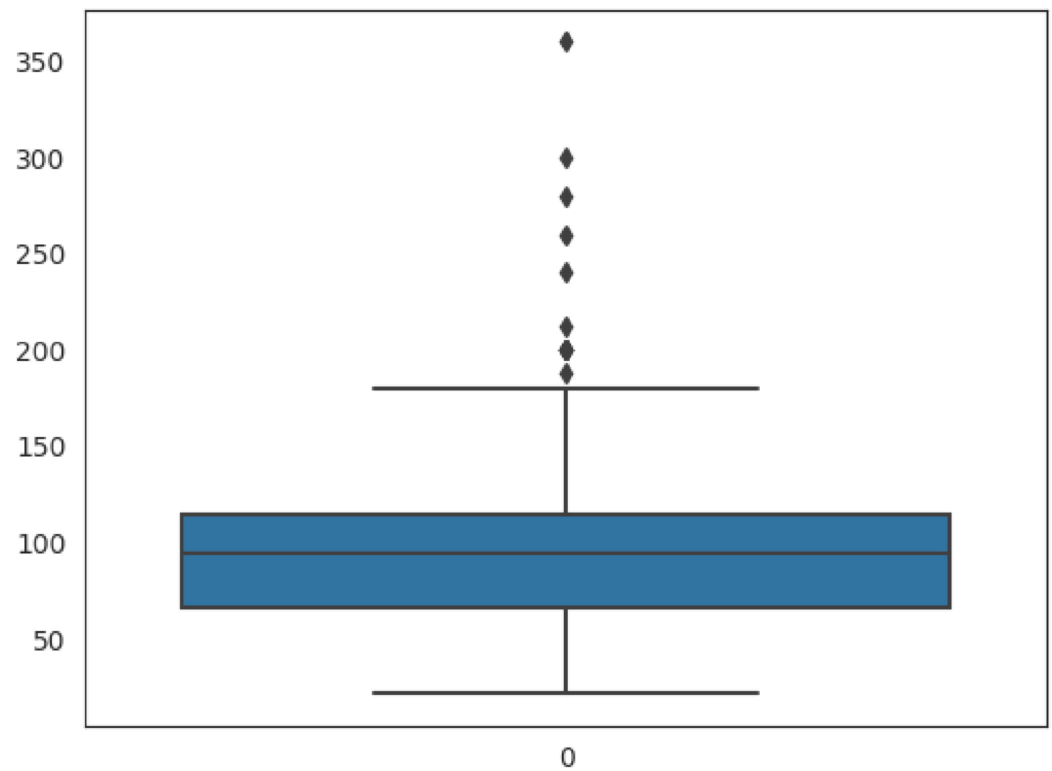



```
np.where(df["Fitness"]<2)
```

```
(array([ 14, 117]),)
```

```
sns.boxplot(df['Miles'])
```

```
<Axes: >
```




```
np.where(df["Miles"]>180)
```

```
(array([ 23,  84, 142, 148, 152, 155, 166, 167, 170, 171, 173, 175,
176]),)
```

Observations

- Since most of the customers who bought KP781 are male we can say that it is best suited for male not for female
- Cutomers who are in age between 25-30 are buying KP781 treadmill more, so it is adviced that people belong to 30+ and below 25 are not recommended to buy this treadmill.
- Customers who are less educated shouldn't buy KP781 treadmill.
- Customers who are not using treadmill less than 4 times a week shouldn't buy this treadmill.
- Customers with fitness less than 3 shouldn't buy KP781 treadmill.
- Customers who don't walk/run greater than 120 miles per week shouldn't nuy KP781 treadmill.
- There are no missing values in the data.
- There are 3 unique products in the dataset.
- KP281 is the most frequent product.
- Minimum & Maximum age of the person is 18 & 50, mean is 28.79 and 75% of persons have age less than or equal to 33.

- Most of the people are having 16 years of education i.e. 75% of persons are having education <= 16 years.
- Out of 180 data points, 104's gender is Male and rest are the female.
- Standard deviation for Income & Miles is very high. These variables might have the outliers in it.
- Females planning to use treadmill 3-4 times a week, are more likely to buy KP481 product