tlre0mmyh

March 9, 2023

1 Introduction

[64]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[65]:
```
df = pd.read_csv("aerofit_treadmill.csv")
print(df.shape)
df.head()
```

```
(180, 9)
```

[65]:

	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

[66]:
```
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
```

[132]:
```
df.describe()
```

[132]:
```
              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
```

[137]:
```
df[['Product', 'Gender', 'MaritalStatus']].describe()
```

[137]:
```
       Product Gender MaritalStatus
count      180    180           180
unique       3      2             2
top      KP281   Male     Partnered
freq        80    104           107
```

[67]:
```
df.isna().sum()
```

[67]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

2 Defining Problem Statement and Analysing basic metrics

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.

1. Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
2. 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.
3. No nulls values present in the data
4. The data is fully cleaned and best categorised
5. Top customers as of Product is KP281, Gender Male, MaritalStatus is Partnered

3 Non-Graphical Analysis: Value counts and unique attributes

[68]:
```
data = []
df.columns
```

[68]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

[69]:
```
# Product value counts

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

[69]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

[70]:
```
# Product unique attributes

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

[70]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

[71]:
```
# Ages value counts

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

[71]:
```
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
```

[72]:
```
# Age unique attributes

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

[72]:
```
array([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])
```

[73]:
```
# Gender value counts

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

[73]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

[74]:
```
# Gender unique attributes

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

[74]:
```
array(['Male', 'Female'], dtype=object)
```

[75]:
```
# Education value counts

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

[75]:
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

[76]:
```
# Education unique attributes

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

[76]:
```
array([14, 15, 12, 13, 16, 18, 20, 21])
```

[77]:
```
# MaritalStatus value counts

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

[77]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

[78]:
```
# MaritalStatus unique attributes

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

[78]:
```
array(['Single', 'Partnered'], dtype=object)
```

[79]:
```
# Usage value counts

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

[79]:
```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

[80]:
```python
# usage unique attributes

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

[80]:
```
array([3, 2, 4, 5, 6, 7])
```

[81]:
```python
# Income value counts

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

[81]:
```
45480    14
52302     9
46617     8
54576     8
53439     8
         ..
65220     1
55713     1
68220     1
30699     1
95508     1
Name: Income, Length: 62, dtype: int64
```

[82]:
```python
# Income unique attributes

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

[82]:
```
array([ 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])
```

[83]:
```python
# Fitness value counts

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

[83]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

[84]:
```python
# Fitness unique attributes

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

[84]:
```
array([4, 3, 2, 1, 5])
```

[85]:
```python
# Miles value counts

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

[85]:
```
85     27
95     12
66     10
75     10
47      9
106     9
94      8
113     8
53      7
100     7
180     6
200     6
56      6
64      6
127     5
160     5
42      4
150     4
38      3
74      3
170     3
120     3
103     3
132     2
141     2
280     1
260     1
300     1
240     1
112     1
212     1
80      1
140     1
21      1
169     1
188     1
360     1
```

```
Name: Miles, dtype: int64
```

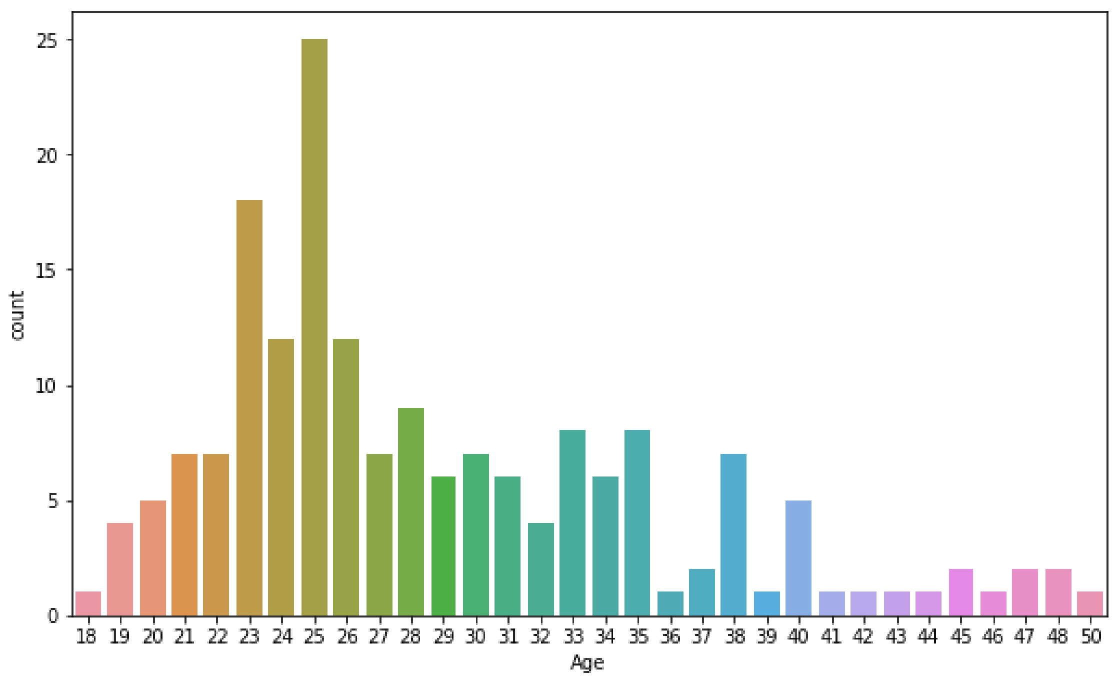
[86]:
```
# Miles unique attributes

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

[86]:
```
array([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])
```

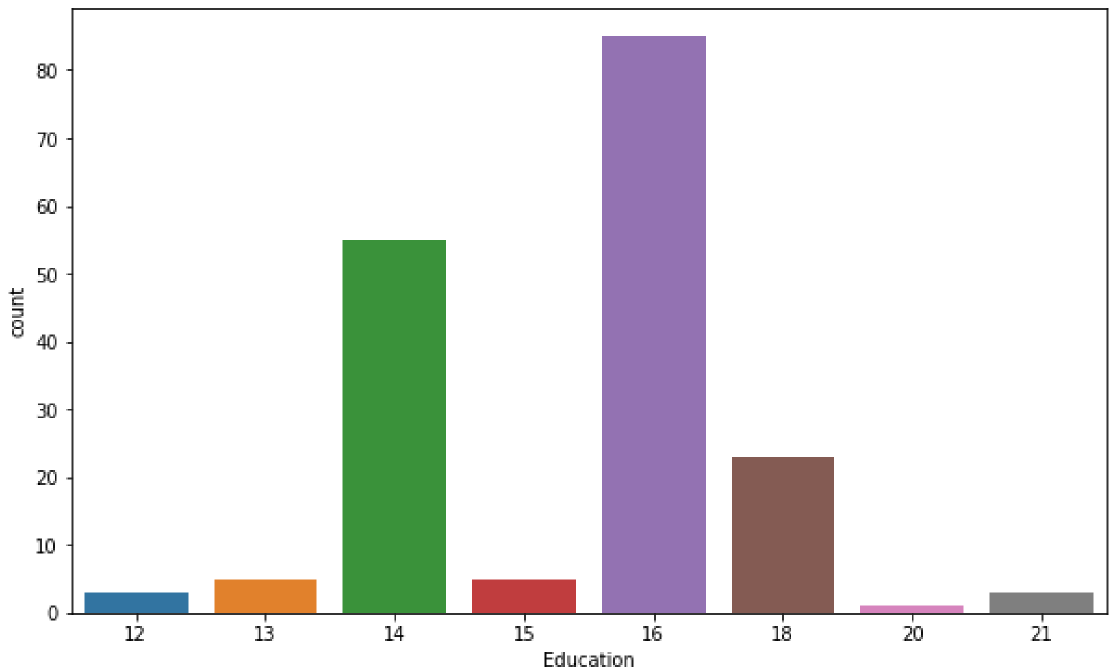
4 Visual Analysis - Univariate & Bivariate

4.1 For continuous variable(s): Distplot, countplot, histogram for univariate analysis

[87]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Age', data = df)
plt.show()
```

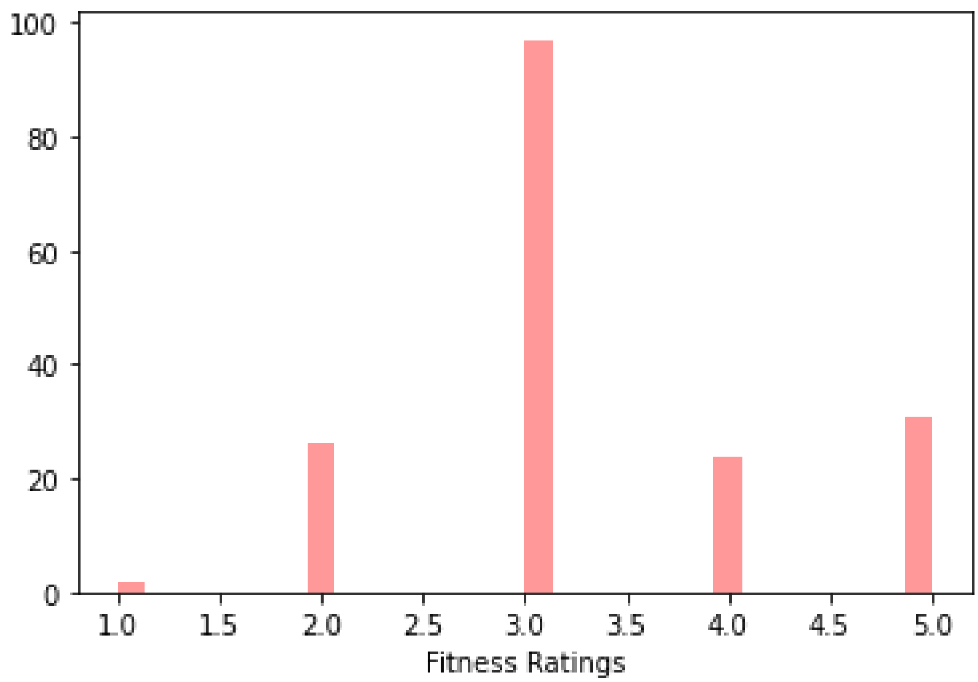


[88]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Education', data = df)
plt.show()
```



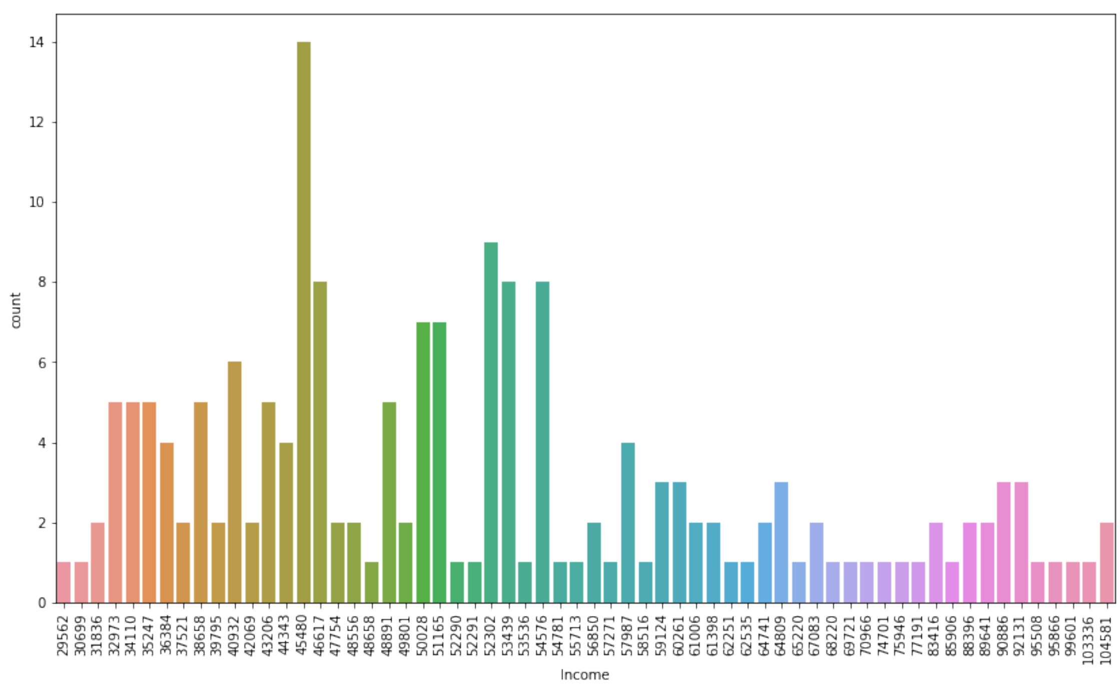
[89]:
```
sns.distplot(df['Fitness'], kde = False, color ='red', bins = 30)
plt.xlabel('Fitness Ratings')
plt.show()
```

```
/usr/local/lib/python3.9/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

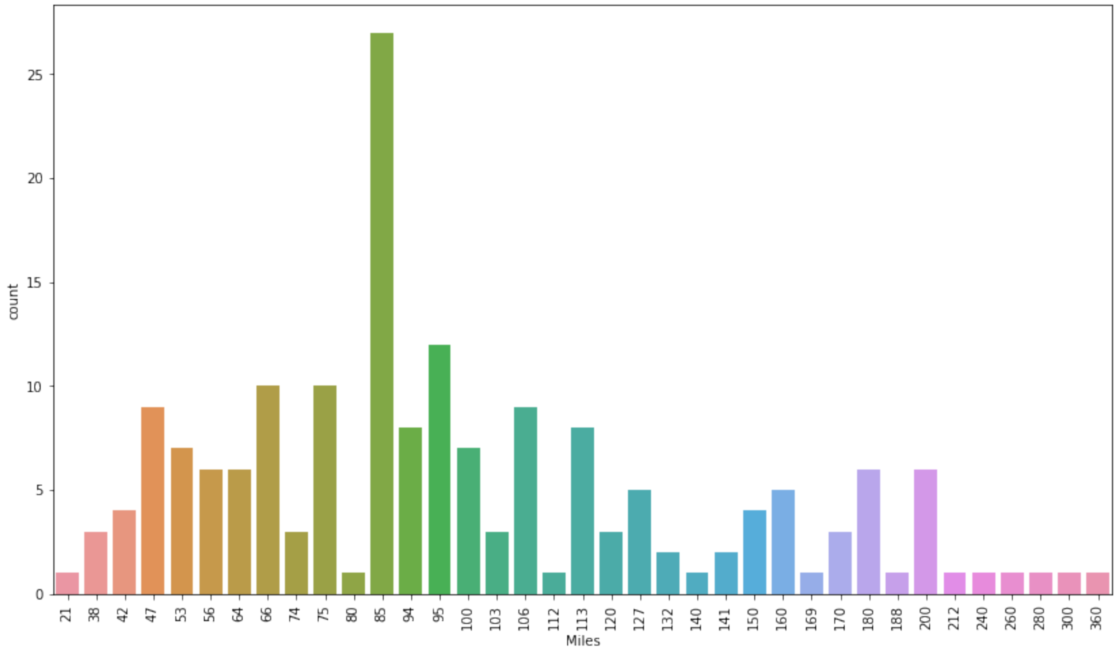


[90]:

```
plt.figure(figsize = (14, 8))
sns.countplot(x = 'Income', data = df)
plt.xticks(rotation = 90)
plt.show()
```

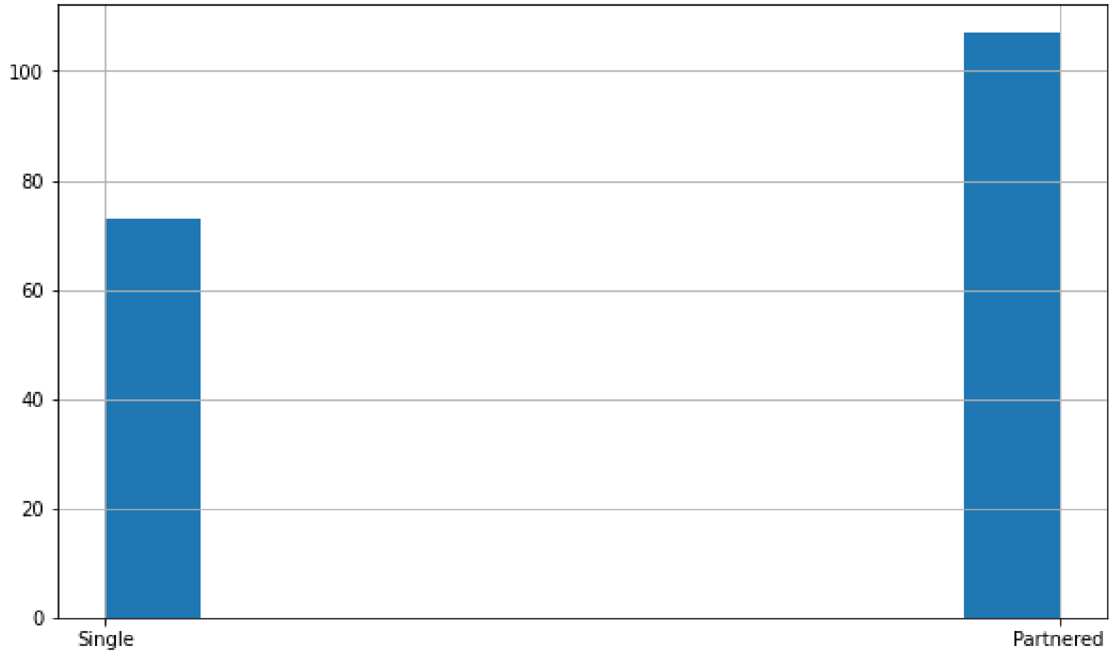


[91]:
```
plt.figure(figsize = (14, 8))
sns.countplot(x = 'Miles', data = df)
plt.xticks(rotation = 90)
plt.show()
```



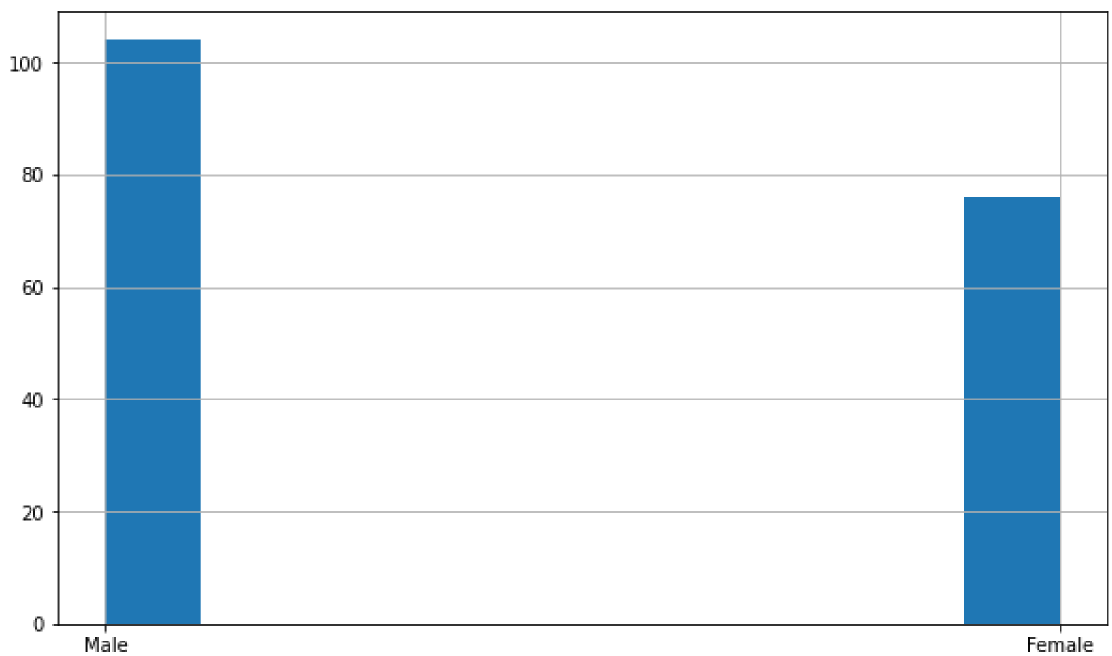
[92]:
```
plt.figure(figsize = (10, 6))
df['MaritalStatus'].hist()
```

[92]: <AxesSubplot:>



[93]:
```
plt.figure(figsize = (10, 6))
df['Gender'].hist()
```

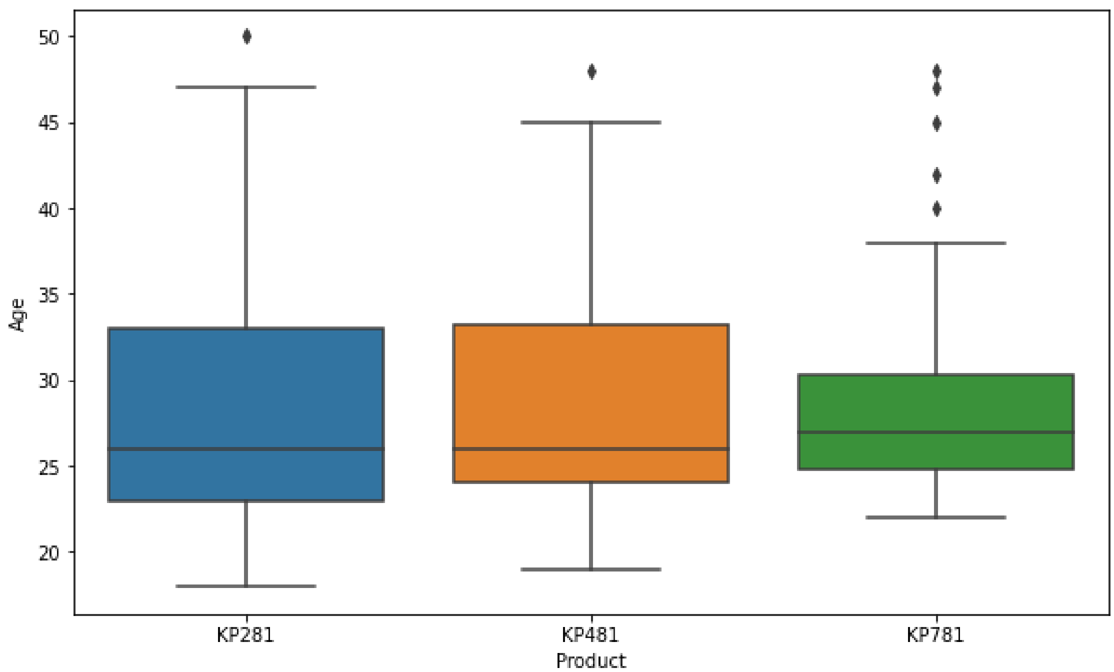
[93]: <AxesSubplot:>



4.2 For categorical variable(s): Boxplot

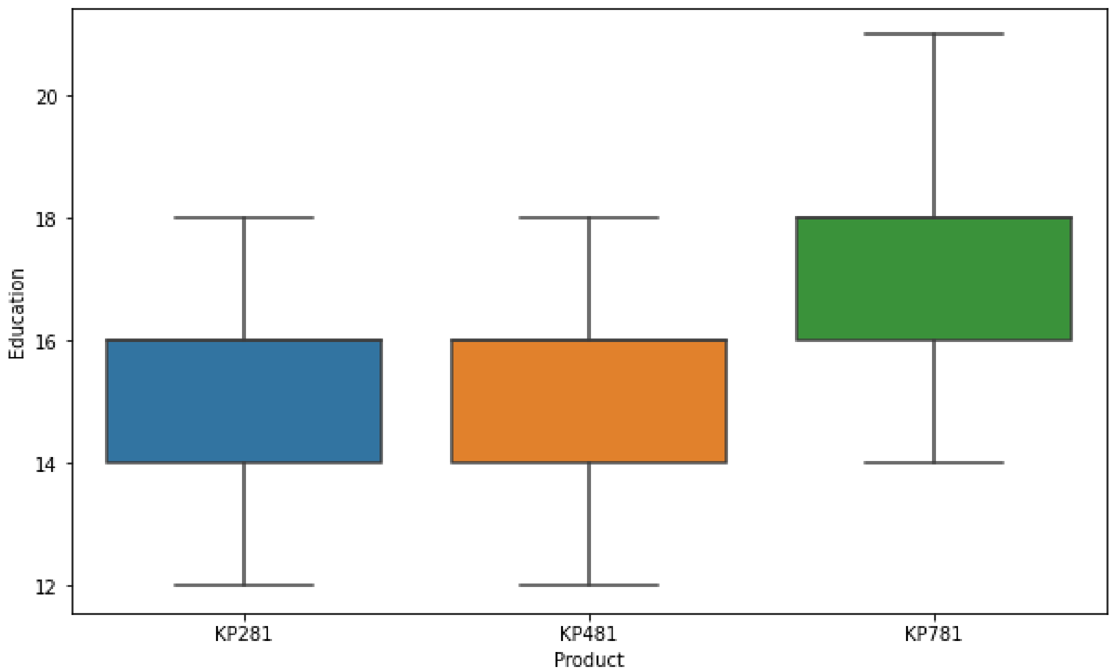
[94]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Age'])
```

[94]: <AxesSubplot:xlabel='Product', ylabel='Age'>



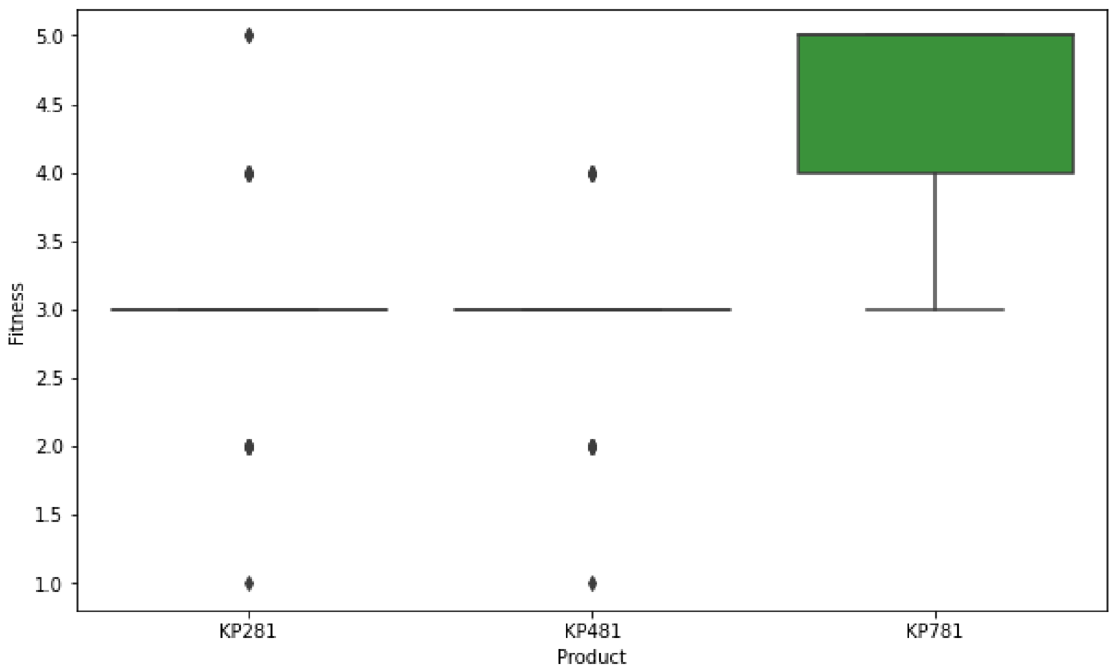
[95]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Education'])
```

[95]: <AxesSubplot:xlabel='Product', ylabel='Education'>



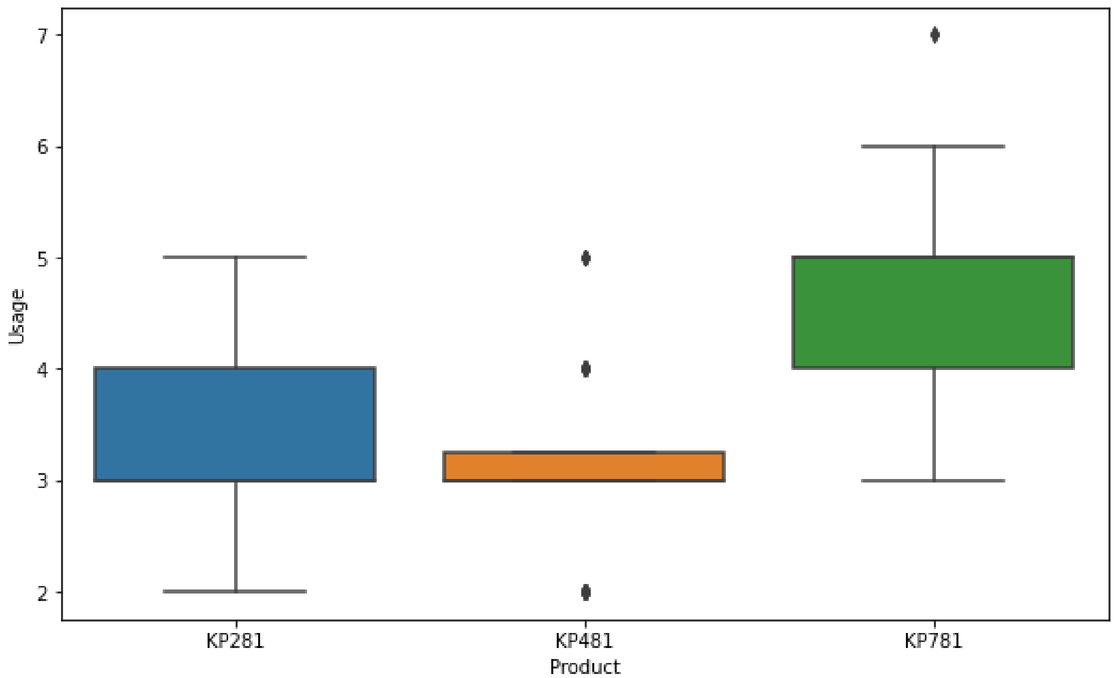
[96]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Fitness'])
```

[96]: <AxesSubplot:xlabel='Product', ylabel='Fitness'>



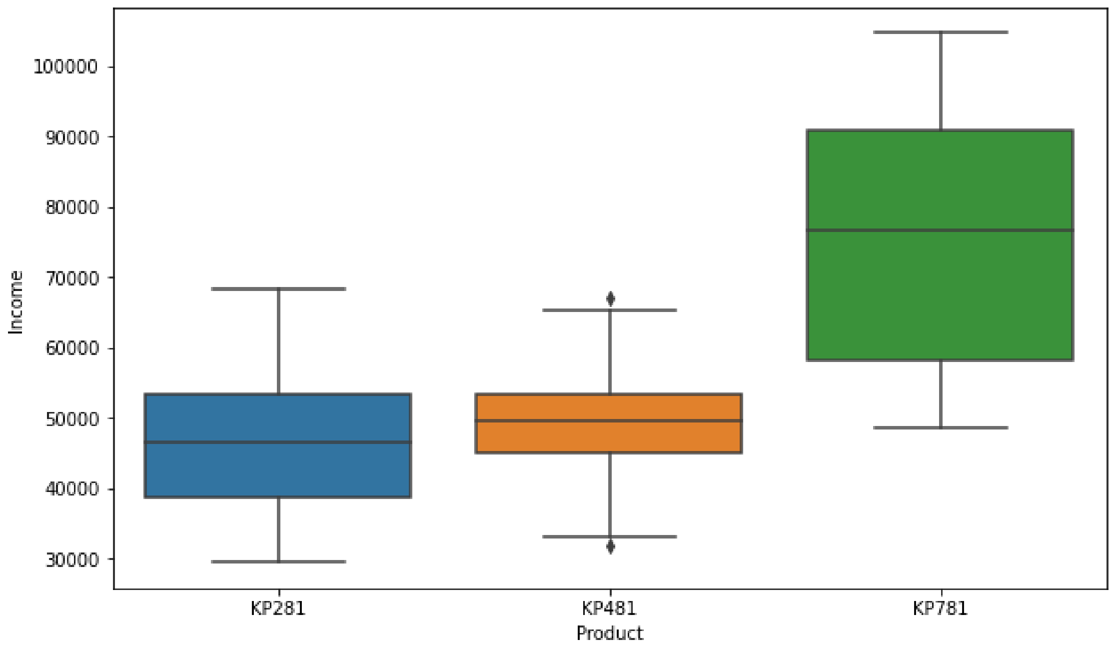
[97]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Usage'])
```

[97]: <AxesSubplot:xlabel='Product', ylabel='Usage'>



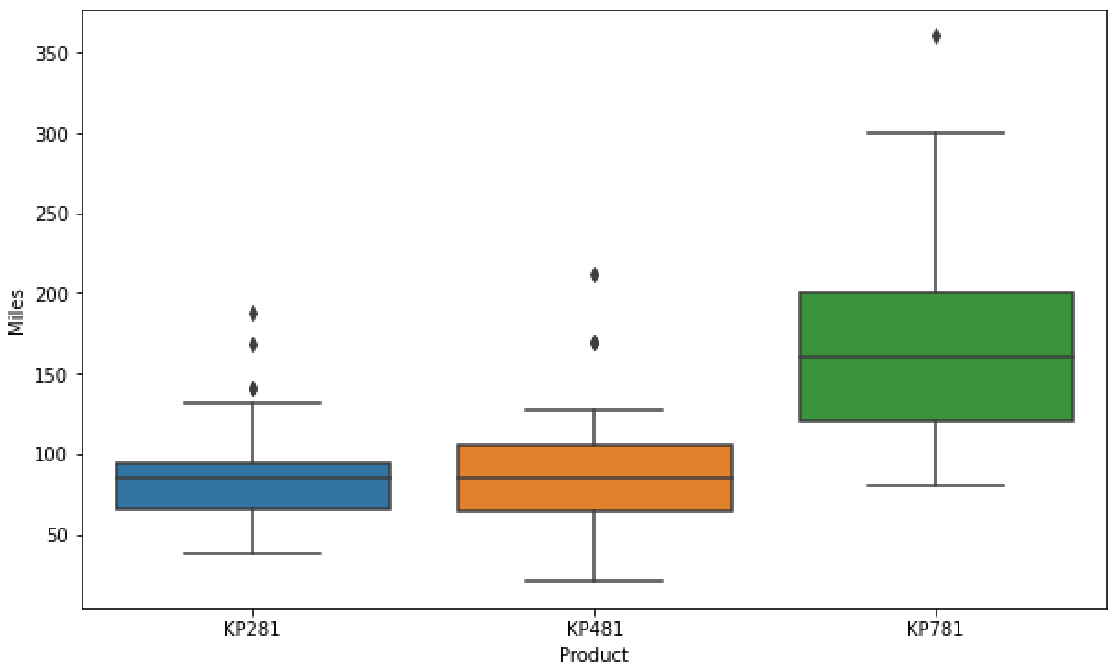
[98]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Income'])
```

[98]: <AxesSubplot:xlabel='Product', ylabel='Income'>



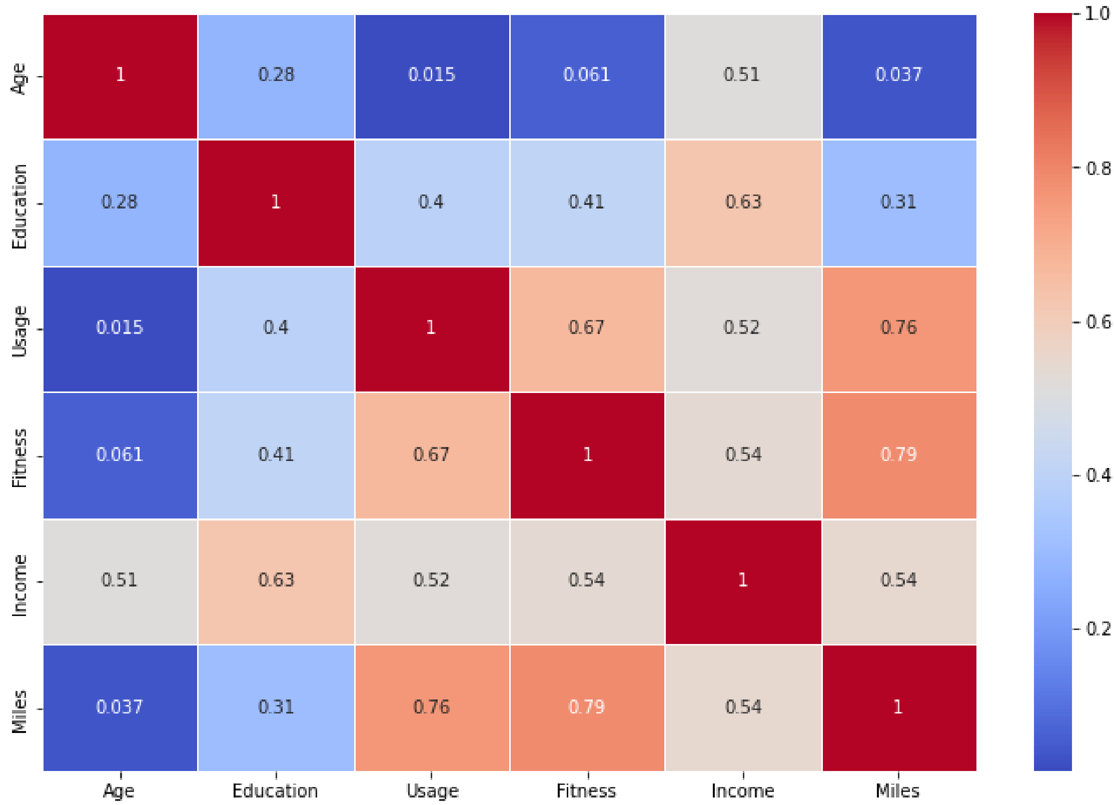
[99]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = df['Product'], y = df['Miles'])
```

[99]: <AxesSubplot:xlabel='Product', ylabel='Miles'>



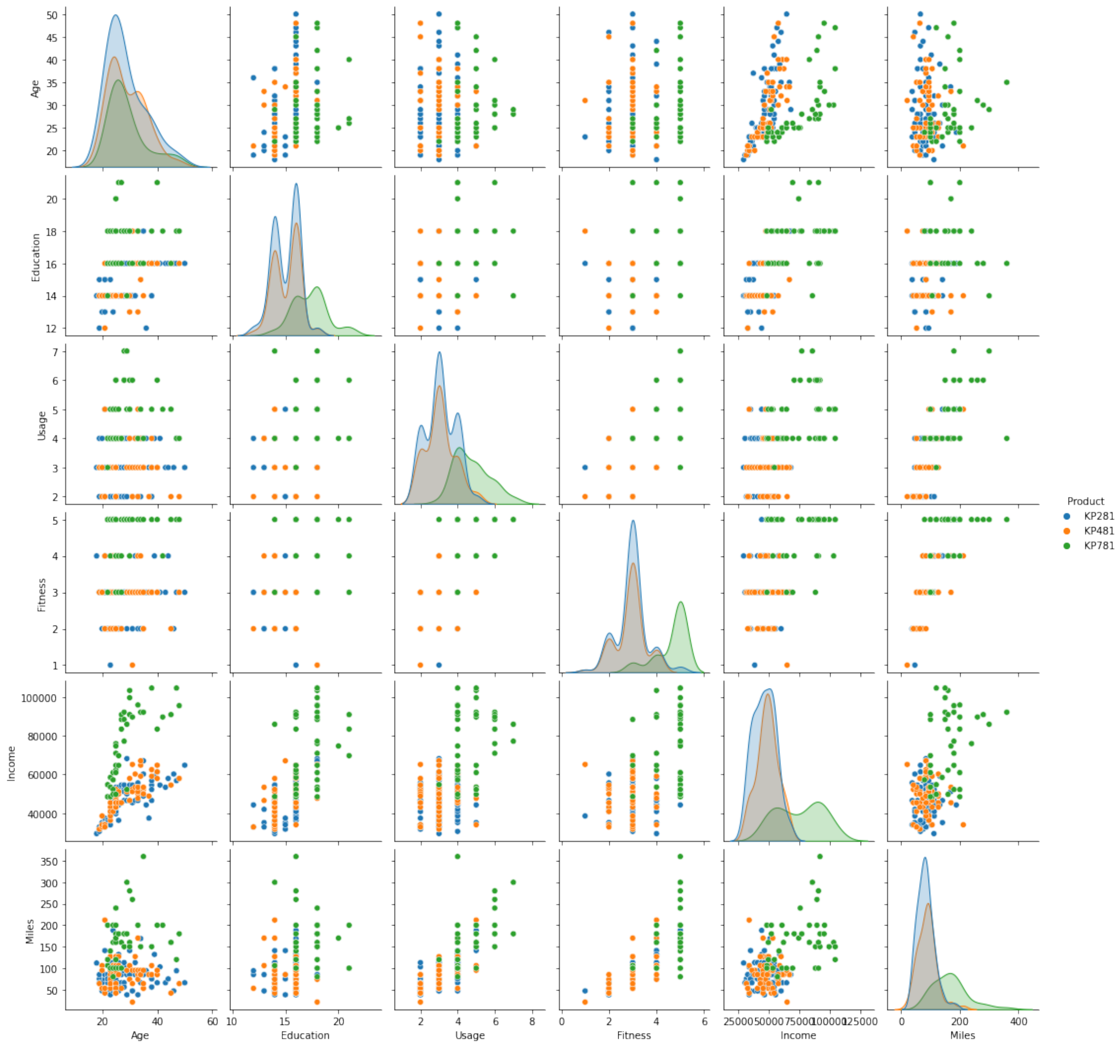
4.3 For correlation: Heatmaps, Pairplots

[100]:
```
plt.figure(figsize = (12, 8))
sns.heatmap( df.corr() , annot=True,linewidth = 0.5 , cmap = 'coolwarm')
plt.show()
```



[101]:
```
sns.pairplot(df, hue = 'Product')
```

[101]: <seaborn.axisgrid.PairGrid at 0x7f41748ae190>



5 Missing Value & Outlier Detection

[102]:
```
# No missing values

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

[102]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
```

```
Miles              0
dtype: int64
```

Their are no missing values ____

[103]:
```python
data = []
for Att in ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']:
  for model in ['KP281', 'KP481', 'KP781']:
    obj = {}

    q1 = df.loc[df['Product'] == model, Att].quantile(.25)
    q3 = df.loc[df['Product'] == model, Att].quantile(.75)

    iqr = q3 - q1

    upper_w = q3 + 1.5*iqr
    lower_w = q1 - 1.5*iqr

    outliers = len(df.loc[(df['Product'] == model) & (df[Att] > upper_w)]) +
 ↪len(df.loc[(df['Product'] == model) & (df[Att] < lower_w)])

    obj['Attributes'] = Att
    obj['Model'] = model
    obj['Upper_Whisker'] = upper_w
    obj['Inter Quartile Range'] = iqr
    obj['Lower_Whisker'] = lower_w
    obj['Outliers'] = outliers

    data.append(obj)

pd.DataFrame(data)
```

[103]:

	Attributes	Model	Upper_Whisker	Inter Quartile Range	Lower_Whisker	\
0	Age	KP281	48.000	10.00	8.000	
1	Age	KP481	47.125	9.25	10.125	
2	Age	KP781	38.500	5.50	16.500	
3	Education	KP281	19.000	2.00	11.000	
4	Education	KP481	19.000	2.00	11.000	
5	Education	KP781	21.000	2.00	13.000	
6	Usage	KP281	5.500	1.00	1.500	
7	Usage	KP481	3.625	0.25	2.625	
8	Usage	KP781	6.500	1.00	2.500	
9	Fitness	KP281	3.000	0.00	3.000	
10	Fitness	KP481	3.000	0.00	3.000	
11	Fitness	KP781	6.500	1.00	2.500	
12	Income	KP281	75610.500	14781.00	16486.500	
13	Income	KP481	66230.250	8527.50	32120.250	

```
14      Income  KP781      139907.875               32681.25        9182.875
15       Miles  KP281         136.000                  28.00          24.000
16       Miles  KP481         169.000                  42.00           1.000
17       Miles  KP781         320.000                  80.00           0.000

    Outliers
0          1
1          1
2          5
3          0
4          0
5          0
6          0
7         29
8          2
9         26
10        21
11         0
12         0
13         2
14         0
15         4
16         3
17         1
```

As their are very less outliers Its doesn't effect the data as such

---

6 Business Insights based on Non-Graphical and Visual Analysis

6.1 Comments on the range of attributes

[105]:
```
# For Non Categorical Values

data = []
for att in df.columns:
  if df[att].dtype == 'int64':
    obj = {}
    obj['Attributes'] = att
    obj['Min_Value'] = df[att].min()
    obj['Mean'] = df[att].mean()
    obj['Max_Value'] = df[att].max()

    data.append(obj)

pd.DataFrame(data)
```

[105]:

	Attributes	Min_Value	Mean	Max_Value
0	Age	18	28.788889	50
1	Education	12	15.572222	21
2	Usage	2	3.455556	7
3	Fitness	1	3.311111	5
4	Income	29562	53719.577778	104581
5	Miles	21	103.194444	360

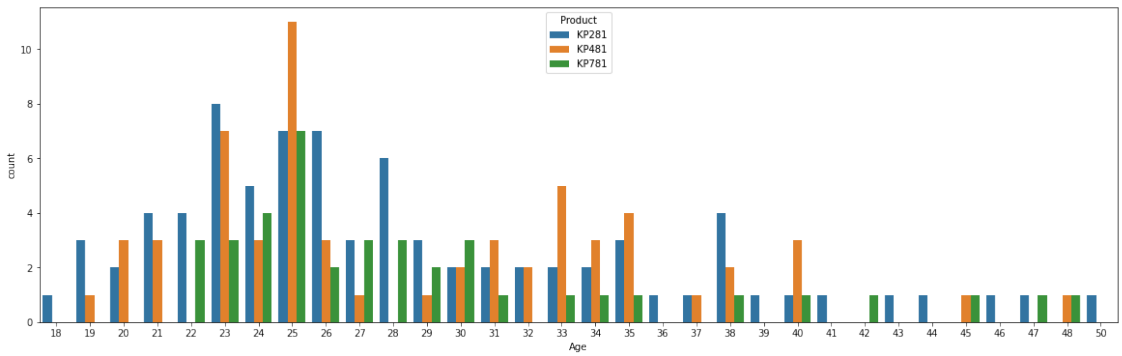
[106]:
```
# For categorical Values

data = []
for att in df.columns:
  if df[att].dtype == 'object':
    obj = {}
    most_freq = df[att].value_counts().index[0], df[att].value_counts()[0]
    less_freq = df[att].value_counts().index[-1], df[att].value_counts()[-1]

    obj['Attributes'] = att
    obj['Most Frequent'] = most_freq
    obj['Less Frequent'] = less_freq

    data.append(obj)


pd.DataFrame(data)
```

[106]:

	Attributes	Most Frequent	Less Frequent
0	Product	(KP281, 80)	(KP781, 40)
1	Gender	(Male, 104)	(Female, 76)
2	MaritalStatus	(Partnered, 107)	(Single, 73)

6.2 Comments on the distribution of the variables and relationship between them AND Comments for each univariate and bivariate plot

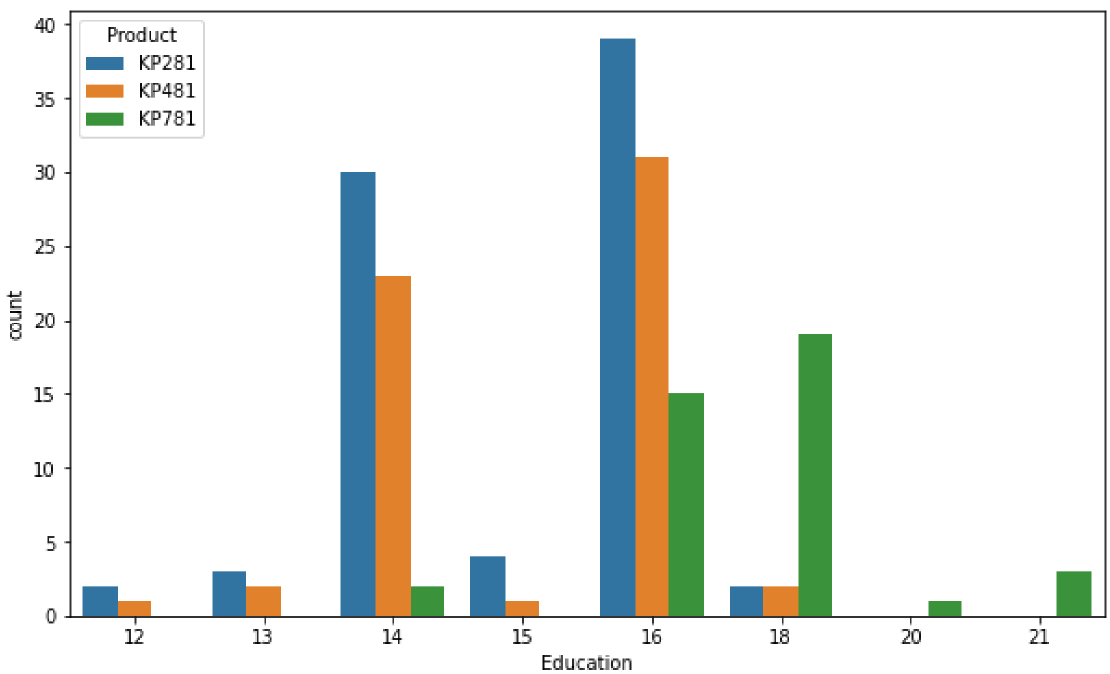
[107]:
```
plt.figure(figsize = (20, 6))
sns.countplot(x = 'Age', data = df, hue = 'Product')
plt.show()
```



Above is the Relationship between Product and Age

1. The Product **KP281** is mostly bought by the people of age **23**
2. The Product **KP481** is mostly bought by the people of age **25**
3. The Product **KP781** is mostly bought by the people of age **25**

[108]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Education', data = df, hue = 'Product')
plt.show()
```

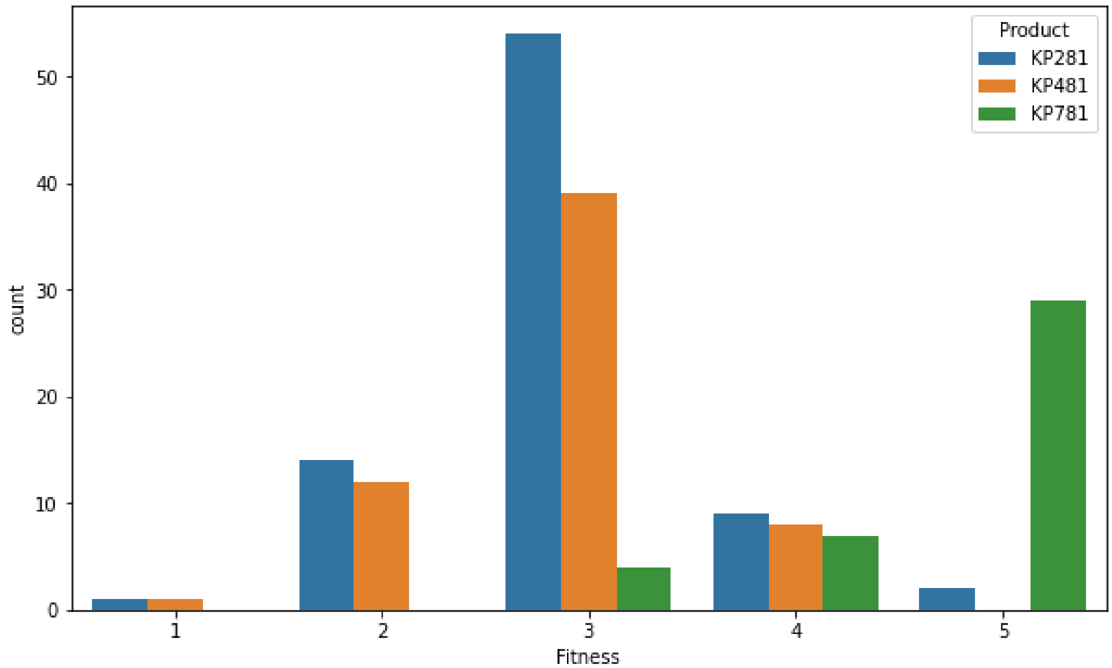


Above is the Relationship between Product and Education in years

1. The Product **KP281** is mostly bought by the people of Education years of **16**
2. The Product **KP481** is mostly bought by the people of Education years of **16**

3. The Product **KP781** is mostly bought by the people of Education years of **18**

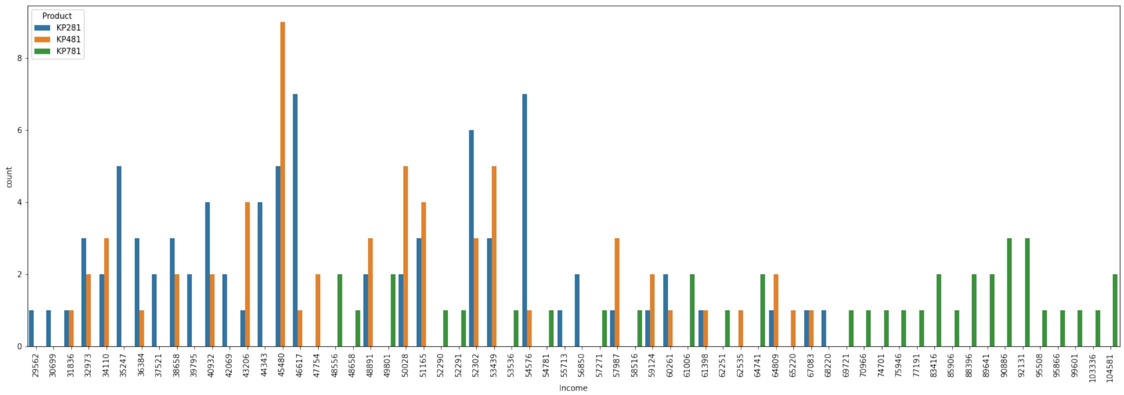
[109]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Fitness', data = df, hue = 'Product')
plt.show()
```



Above is the Relationship between Product and Fitness ratings for different Products

1. Self-rated fitness rating for the Product **KP281** is **3**
2. Self-rated fitness rating for the Product **KP481** is **3**
3. Self-rated fitness rating for the Product **KP781** is **5**

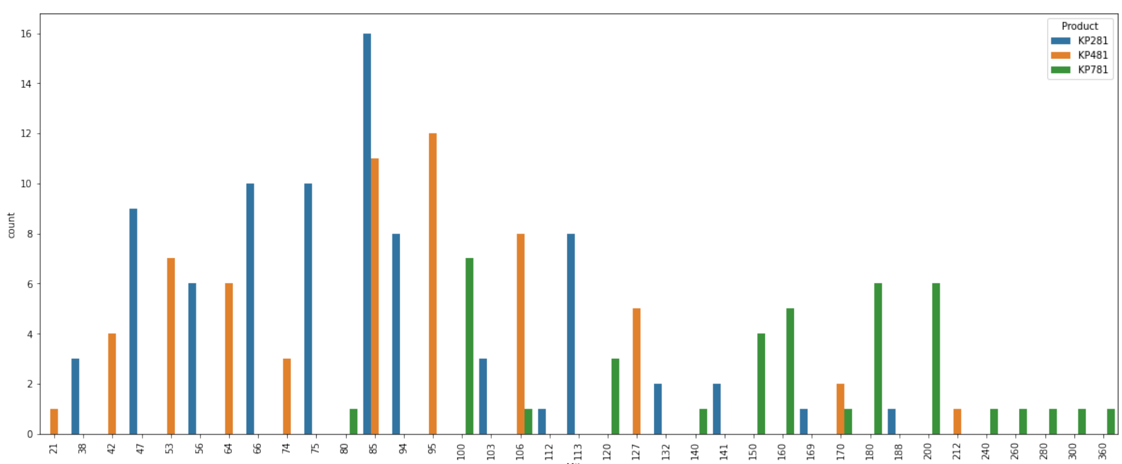
[110]:
```
plt.figure(figsize = (25, 8))
sns.countplot(x = 'Income', data = df, hue = 'Product')
plt.xticks(rotation = 90)
plt.show()
```



Above is the Relationship between Product and Income of the customer

1. The Product **KP281** Mostly bought by the customers whose Income is **Between 45480 and 46617**
2. The Product **KP481** Mostly bought by the customers whose Income is **Between 45480 and 46617**
3. The Product **KP781** Mostly bought by the customers whose Income is **Between 90886 and 95508**

[111]:
```
plt.figure(figsize = (20, 8))
sns.countplot(x = 'Miles', data = df, hue = 'Product')
plt.xticks(rotation = 90)
plt.show()
```

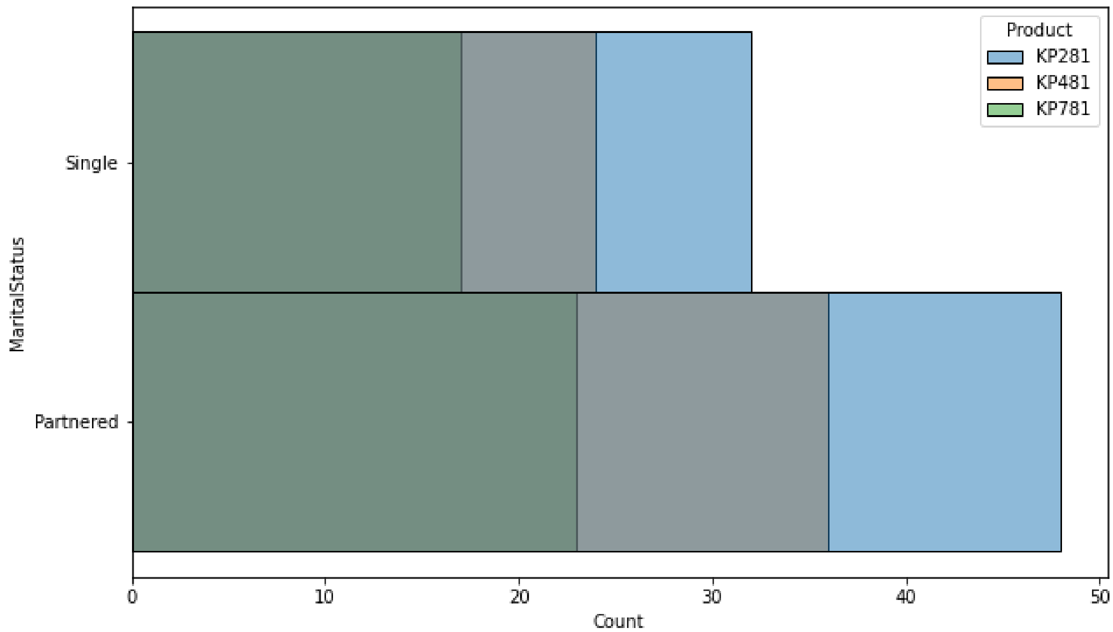


Above is the Relationship between Product and Average Number of miles the customer expected to walk each week

1. The customers who bought the Product **KP281** mostly ran about **85 miles/week**
2. The customers who bought the Product **KP481** mostly ran about **95 miles/week**

3. The customers who bought the Product **KP781** mostly ran about **(180-200) miles/week**

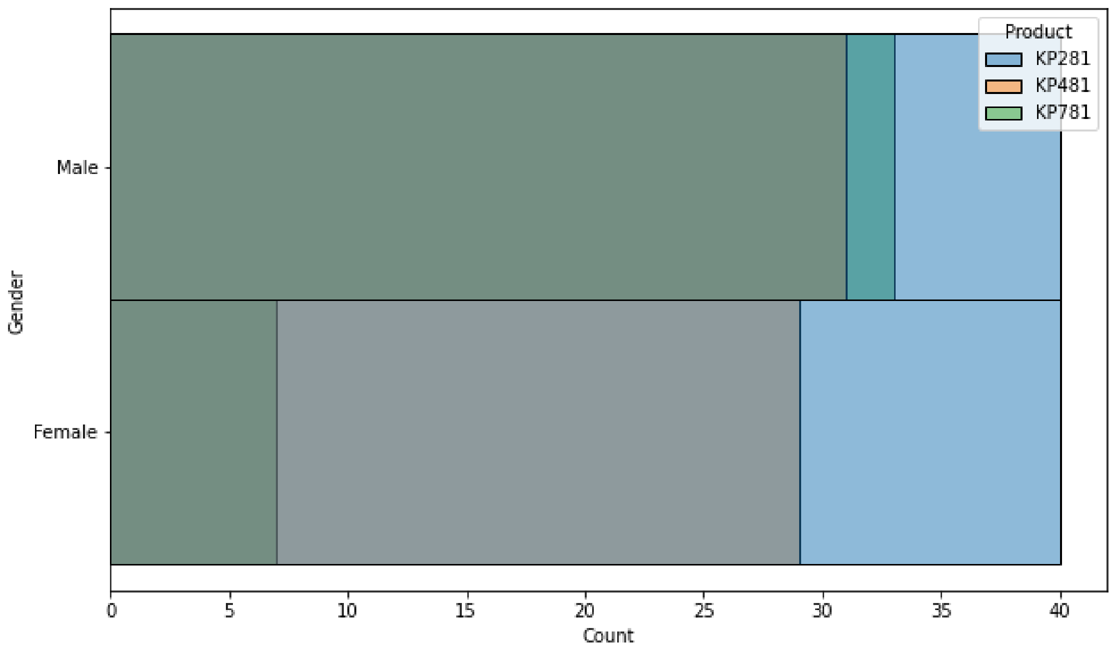
[112]:
```
plt.figure(figsize = (10, 6))
sns.histplot(data = df, y = 'MaritalStatus', hue = 'Product')
# plt.xticks(rotation = 90)
plt.show()
```



Above is the Relationship between Product and Marital Status

1. The customers who bought the Product **KP281** mostly were **Partnered**
2. The customers who bought the Product **KP481** mostly were **Partnered**
3. The customers who bought the Product **KP781** mostly were **Partnered**

[113]:
```
plt.figure(figsize = (10, 6))
sns.histplot(data = df, y = 'Gender', hue = 'Product')
# plt.xticks(rotation = 90)
plt.show()
```



Above is the Relationship between Product and Gender

1. The customers who bought the Product **KP281** mostly were **Male**
2. The customers who bought the Product **KP481** mostly were **Male**
3. The customers who bought the Product **KP781** mostly were **Male**

[114]:
```
data = []
for att in df.columns:
  if att == 'Product':
    continue
  for model in df['Product'].unique():
    obj = {}

    obj['Attributes'] = att
    obj['Model'] = model
    obj['Observations'] = df.loc[df['Product'] == model, att].value_counts().
 ↪index[0]

    data.append(obj)

pd.DataFrame(data)
```

[114]:

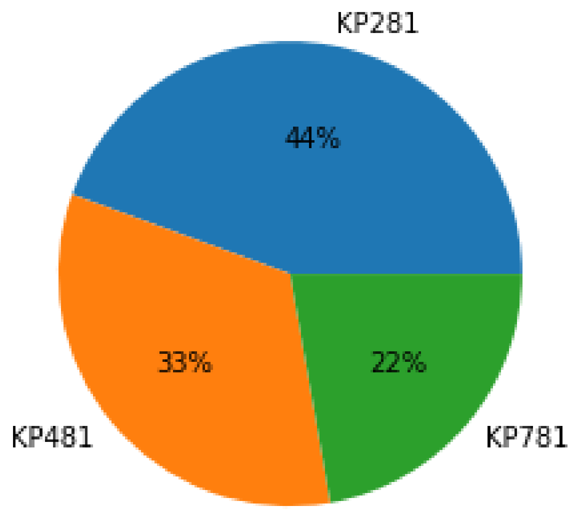
	Attributes	Model	Observations
0	Age	KP281	23
1	Age	KP481	25
2	Age	KP781	25

```
3          Gender  KP281       Male
4          Gender  KP481       Male
5          Gender  KP781       Male
6       Education  KP281         16
7       Education  KP481         16
8       Education  KP781         18
9   MaritalStatus  KP281  Partnered
10  MaritalStatus  KP481  Partnered
11  MaritalStatus  KP781  Partnered
12          Usage  KP281          3
13          Usage  KP481          3
14          Usage  KP781          4
15        Fitness  KP281          3
16        Fitness  KP481          3
17        Fitness  KP781          5
18         Income  KP281      46617
19         Income  KP481      45480
20         Income  KP781      92131
21          Miles  KP281         85
22          Miles  KP481         95
23          Miles  KP781        100
```

7 Computing Marginal & Conditional Probabilities

[115]:

```
# PIE CHART for the percentage sales of Each Model

plt.pie(df['Product'].value_counts(), labels = df['Product'].value_counts().
 ↪index, autopct='%.0f%%')
plt.show()
```



[116]:
```
print('Probability of Male customer buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['Gender'] ==␣
↪'Male')]) / len(df['Gender'] == 'Male')*100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['Gender'] ==␣
↪'Male')]) / len(df['Gender'] == 'Male')*100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['Gender'] ==␣
↪'Male')]) / len(df['Gender'] == 'Male')*100)
print()
print('--------------')

print('Probability of Female customer buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['Gender'] ==␣
↪'Female')]) / len(df['Gender'] == 'Female')*100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['Gender'] ==␣
↪'Female')]) / len(df['Gender'] == 'Female')*100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['Gender'] ==␣
↪'Female')]) / len(df['Gender'] == 'Female')*100)
print()
print('--------------')

print('Probability of customer with status Single buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus']␣
↪== 'Single')]) / len(df['MaritalStatus'] == 'Single')*100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus']␣
↪== 'Single')]) / len(df['MaritalStatus'] == 'Single')*100)
```

```python
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Single')]) / len(df['MaritalStatus'] == 'Single')*100)
print()
print('-------------')

print('Probability of customer with status Partnered buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus'] == 'Partnered')]) / len(df['MaritalStatus'] == 'Partnered')*100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus'] == 'Partnered')]) / len(df['MaritalStatus'] == 'Partnered')*100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Partnered')]) / len(df['MaritalStatus'] == 'Partnered')*100)
print()
print('-------------')

print('Probability of customer with status Single and Male buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) * 100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) * 100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) * 100)
print()
print('-------------')


print('Probability of customer with status Single and Feale buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) * 100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) * 100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) * 100)
print()
print('-------------')

print('Probability of customer with status Partnered and Male buying treadmills')
```

```python
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Male')]) * 100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Male')]) * 100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Male')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Male')]) * 100)
print()
print('-------------')


print('Probability of customer with status Partnered and Feale buying treadmills')
print('KP781 ->', len(df.loc[(df['Product'] == 'KP781') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Female')]) * 100)
print('KP481 ->', len(df.loc[(df['Product'] == 'KP481') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Female')]) * 100)
print('KP281 ->', len(df.loc[(df['Product'] == 'KP281') & (df['MaritalStatus'] == 'Single') & (df['Gender'] == 'Female')]) / len(df.loc[(df['MaritalStatus'] == 'Partnered') & (df['Gender'] == 'Female')]) * 100)
print()
print('-------------')
```

```
Probability of Male customer buying treadmills
KP781 -> 18.333333333333332
KP481 -> 17.22222222222222
KP281 -> 22.22222222222222

-------------
Probability of Female customer buying treadmills
KP781 -> 3.888888888888889
KP481 -> 16.11111111111111
KP281 -> 22.22222222222222

-------------
Probability of customer with status Single buying treadmills
KP781 -> 9.444444444444445
KP481 -> 13.333333333333334
KP281 -> 17.77777777777778
```

```
-------------
Probability of customer with status Partnered buying treadmills
KP781 -> 12.777777777777777
KP481 -> 20.0
KP281 -> 26.666666666666668

-------------
Probability of customer with status Single and Male buying treadmills
KP781 -> 32.55813953488372
KP481 -> 23.25581395348837
KP281 -> 44.18604651162791

-------------
Probability of customer with status Single and Feale buying treadmills
KP781 -> 10.0
KP481 -> 46.666666666666664
KP281 -> 43.333333333333336

-------------
Probability of customer with status Partnered and Male buying treadmills
KP781 -> 22.950819672131146
KP481 -> 16.39344262295082
KP281 -> 31.147540983606557

-------------
Probability of customer with status Partnered and Feale buying treadmills
KP781 -> 6.521739130434782
KP481 -> 30.434782608695656
KP281 -> 28.26086956521739

-------------
```

8 Recommendations - Actionable items for business. No technical jargon. No complications. Simple action items that everyone can understand

For the Category of the Model KP281

1. Customer with Status Single has high priority both (Male and Female)
2. Customer with Average Income 46,418 prefered to buy this Model
3. Customer with Average Education of 16 years tends to buy this model
4. Customer with Average age of 23 buys this models
5. Custoemr with Self Rated 3 buys this type of Product
6. Customer who has habit of running Averagely about 85 miles/week buy this model

For the Category of the Model KP481

1. Customer with Status Single and Female has high priority

```
2.   Customer with Average Income 48,973 prefered to buy this Model
3.   Customer with Average Education of 16 years tends to buy this model
4.   Customer with Average age of 25 buys this models
5.   Custoemr with Self Rated 3 buys this type of Product
6.   Customer who has habit of running Averagely about 95 miles/week buy this model
```

For the Category of the Model KP781

```
1.   Customer with Status Partnered and Male has high priority
2.   Customer with Average Income 75,441 prefered to buy this Model
3.   Customer with Average Education of 18 years tends to buy this model
4.   Customer with Average age of 25 buys this models
5.   Custoemr with Self Rated 5 buys this type of Product
6.   Customer who has habit of running Averagely about 180-200 miles/week buy this model
```

SIMPLE ACTIONABLE ITEMS

1. If customer is Single and aged 23 yrs with 16 yrs of education earn about 47k on an average and need basic model to start with then push him/ her to go with KP281 model
2. If customer is Single and aged more than 25 with 16yrs of education earn about 49k on an average and need Intermediate model then push him/ her to go with KP481 model
3. If customer is Partnered and Male aged more than 25 with 18yrs of education earn about 76k on an average and need best model for better experience with then push him to go with KP781 model
4. If customer is Partnered and Female aged more than 25 with 18yrs of education earn about 76k on an average and need best model for better experience with then push her to go with either KP481 or KP781 model
5. Check even the Usage of customer If he/ she is beginner then suggest him/ her to go with KP281, If he/ she is Intermediate the suggest to go for KP481, If he/ she is Advanced then suggest to go for KP781