In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
1. Import the dataset and do usual data analysis steps like checking the structure &
characteristics of the dataset
```

In [2]:
```
df = pd.read_csv(r'D:\aerofit_treadmill.csv')
```

In [3]:
```
df
```

Out[3]:

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

In [4]:
```
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
```

Columns like Product, Gender & Maritalstatus are in string data (object) type and all other are interger typr data (int64)

In [5]:
```
Rows, Col = df.shape
```

In [6]:
```
print('Row =',Rows,' & Col = ', Col)
```

```
Row = 180  & Col =  9
```

There is no Nulls in any rows or col data.

In [7]:
```
df['Product'].unique()
```
Out[7]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [8]:
```
df['Gender'].unique()
```
Out[8]:
```
array(['Male', 'Female'], dtype=object)
```

In [9]:
```
df['MaritalStatus'].unique()
```
Out[9]:
```
array(['Single', 'Partnered'], dtype=object)
```

2. Detect Outliers (using boxplot, “describe” method by checking the difference between mean and median)

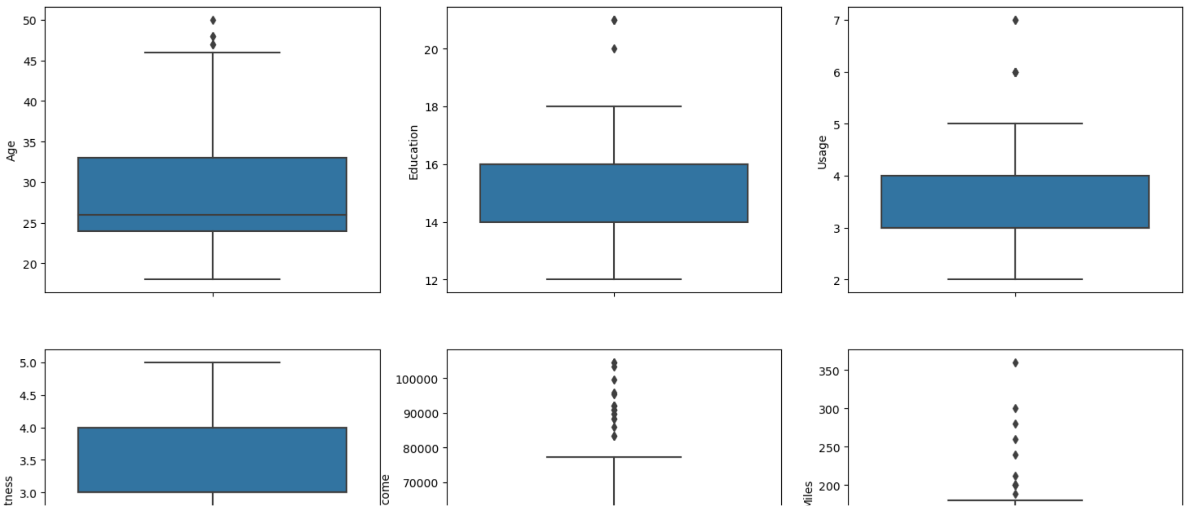
In [10]:
```
df.describe()
```
Out[10]:

	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

In [11]:
```
median_Age = df['Age'].median()
median_Education = df['Education'].median()
median_Usage = df['Usage'].median()
median_Fitness = df['Fitness'].median()
median_Income = df['Income'].median()
median_Miles = df['Miles'].median()
print('Median of Age',median_Age)
print('Median of Education',median_Education)
print('Median of Usage',median_Usage)
print('Median of Fitness',median_Fitness)
print('Median of Income',median_Income)
print('Median of Miles',median_Miles)
```
```
Median of Age 26.0
Median of Education 16.0
Median of Usage 3.0
Median of Fitness 3.0
Median of Income 50596.5
Median of Miles 94.0
```

In [12]:
```
plt.figure(figsize=(18,10))
plt.subplot(2,3,1)
sns.boxplot(y=df['Age'])

plt.subplot(2,3,2)
sns.boxplot(y=df['Education'])

plt.subplot(2,3,3)
sns.boxplot(y=df['Usage'])

plt.subplot(2,3,4)
sns.boxplot(y=df['Fitness'])

plt.subplot(2,3,5)
sns.boxplot(y=df['Income'])

plt.subplot(2,3,6)
sns.boxplot(y=df['Miles'])
```

Out[12]:
```
<AxesSubplot:ylabel='Miles'>
```

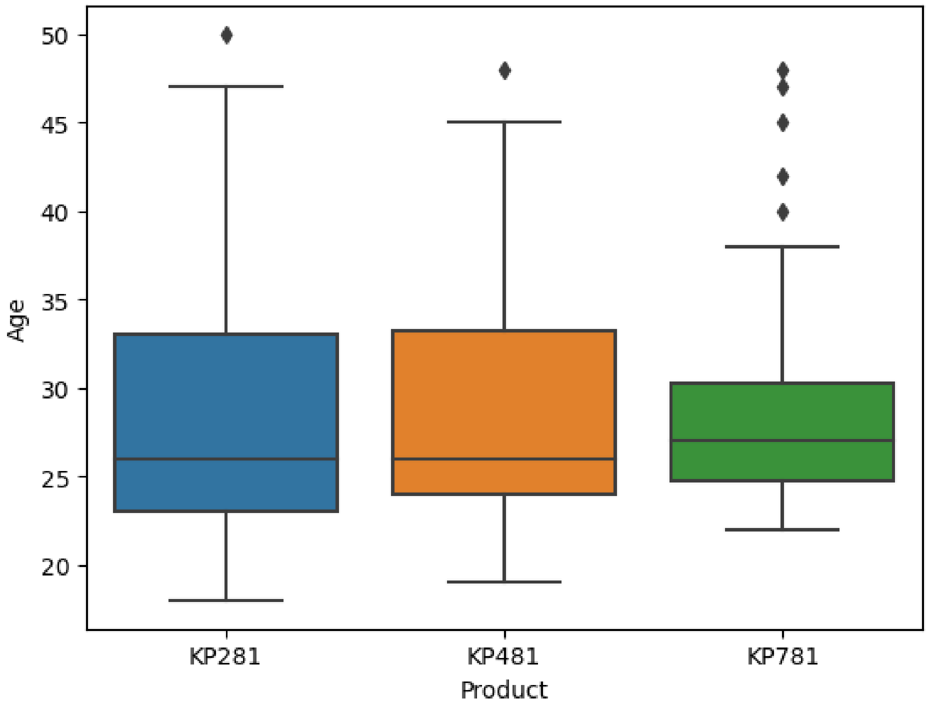


Almost all coloumn data have outlier which may affact my data analysis in term of Mean mode median.

Example -For Age: Q3 = 33 Upper outlier = Q3 + (1.5 * IQR) 33 + (1.5 * (33-24)) 46.5

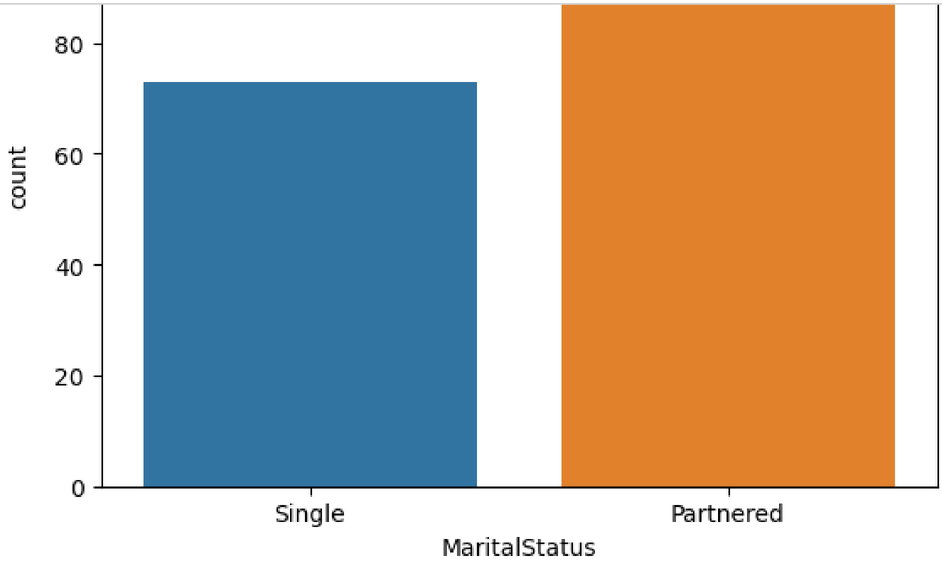
In [13]:
```
sns.boxplot(x=df['Product'], y=df['Age'])
```

Out[13]: <AxesSubplot:xlabel='Product', ylabel='Age'>



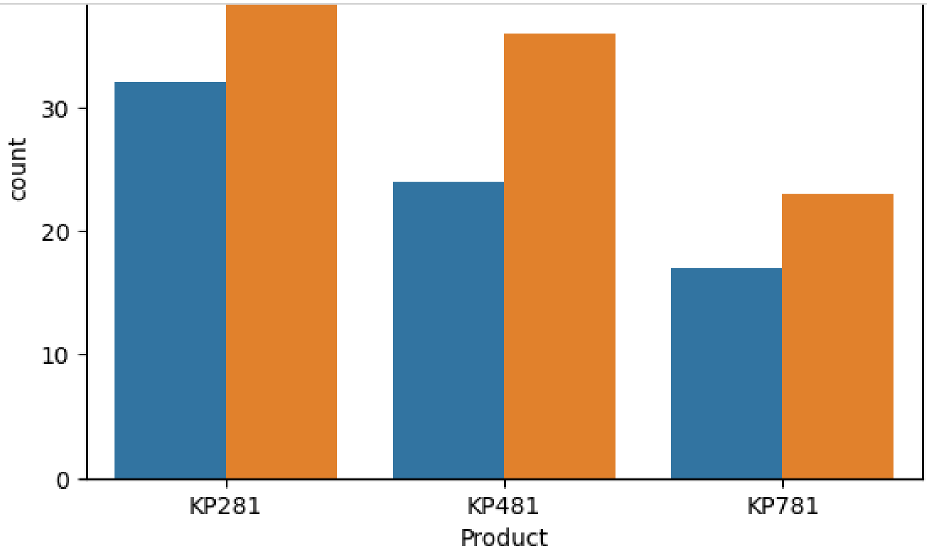
3. Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc)

In [14]:
```
sns.countplot(data=df, x = df['MaritalStatus'])
plt.show()
```



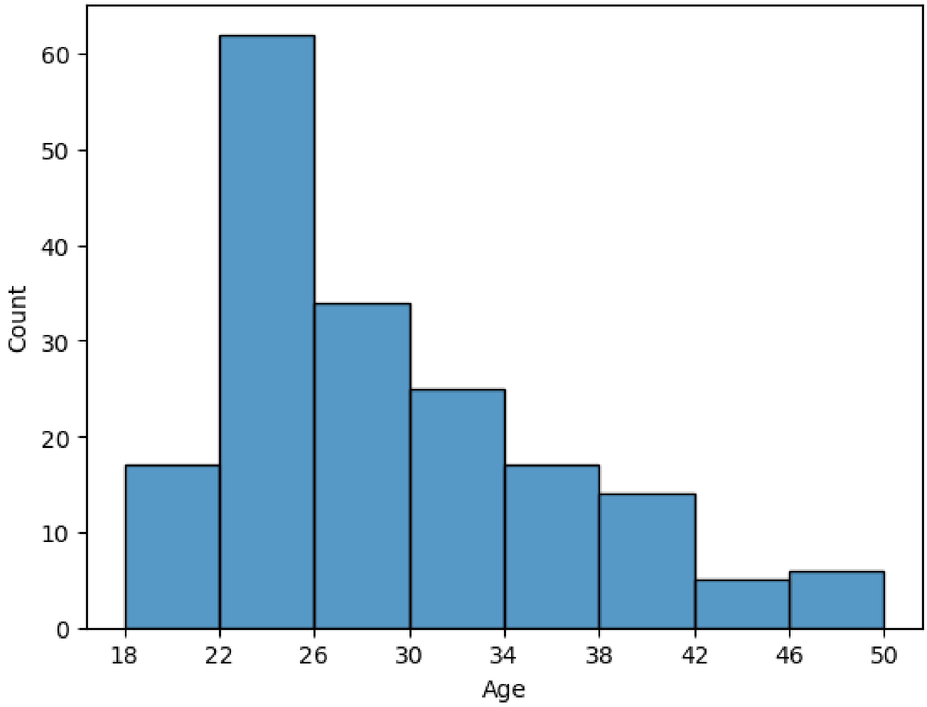
Partnered people are purchasing more of this machines.

In [15]:
```
sns.countplot(data=df, x = df['Product'], hue = df['MaritalStatus'])
plt.show()
```



Both singles & Partnered are purchasing KP281 mostly and Both singles & Partnered are purchasing KP781 less.

In [16]:
```
sns.histplot(df['Age'], bins = 8)
plt.xticks([18,22,26,30,34,38,42,46,50])
plt.show()
```



Peolpe between age 22 to 34 are purchasing more of this product.

4. Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)

In [17]:
```
pd.crosstab(df.Product, df.Product.count(), normalize = True)
```

Out[17]:

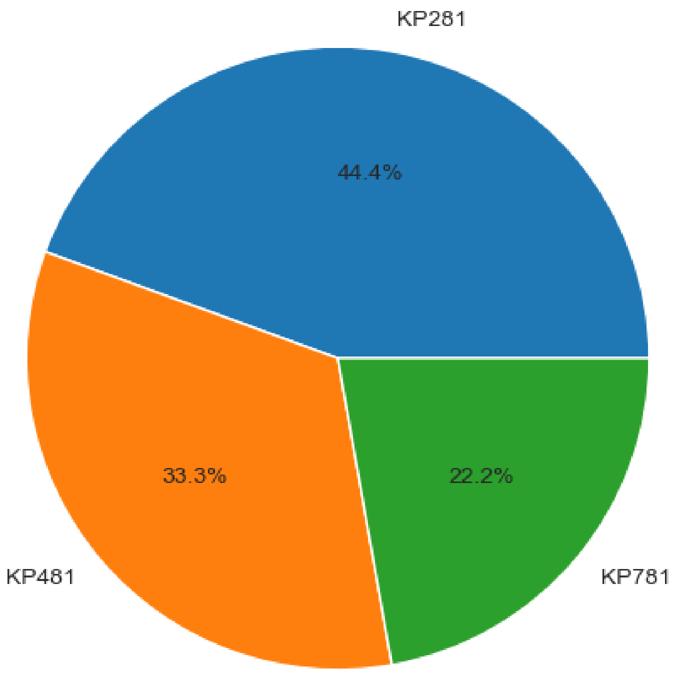
col_0	180
Product	
KP281	0.444444
KP481	0.333333
KP781	0.222222

So the chances of selling KP281 is more when ever a customer coming for purchase.

In [18]:
```
df['Product'].value_counts().index
```

Out[18]:
```
Index(['KP281', 'KP481', 'KP781'], dtype='object')
```

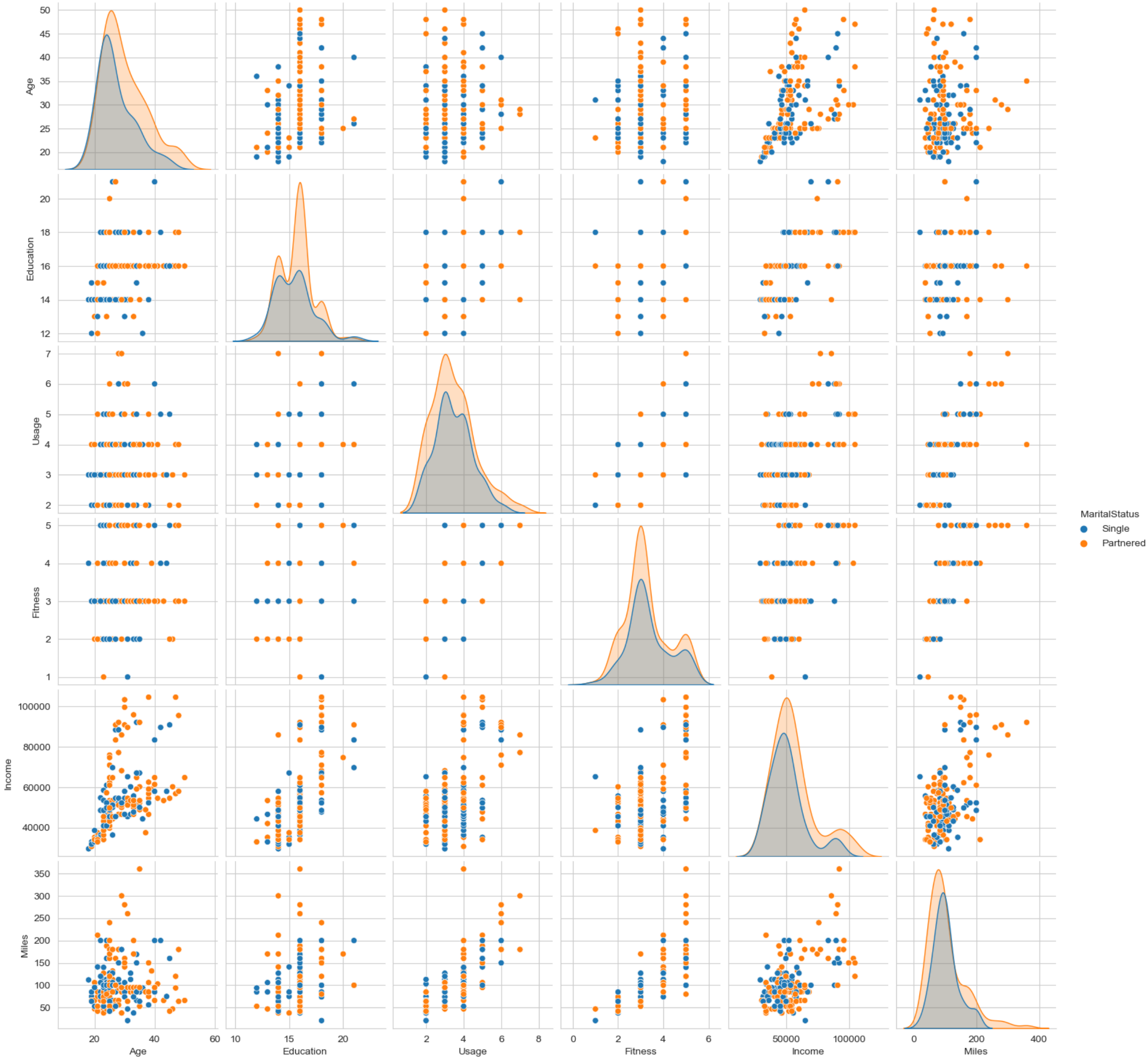
In [19]:
```
sns.set_style("whitegrid")
plt.figure(figsize=(6,6))
plt.pie(df['Product'].value_counts(), labels=df['Product'].value_counts().index, autopct='%1.1f
plt.show()
```



44.4% of peopel purchased KP281, 33.3% peolpe purchased KP481, 22.2% of people purchased KP781.

5. Check correlation among different factors using heat maps or pair plots.

In [22]:
```
sns.pairplot(data=df , hue = 'MaritalStatus')
plt.show()
```

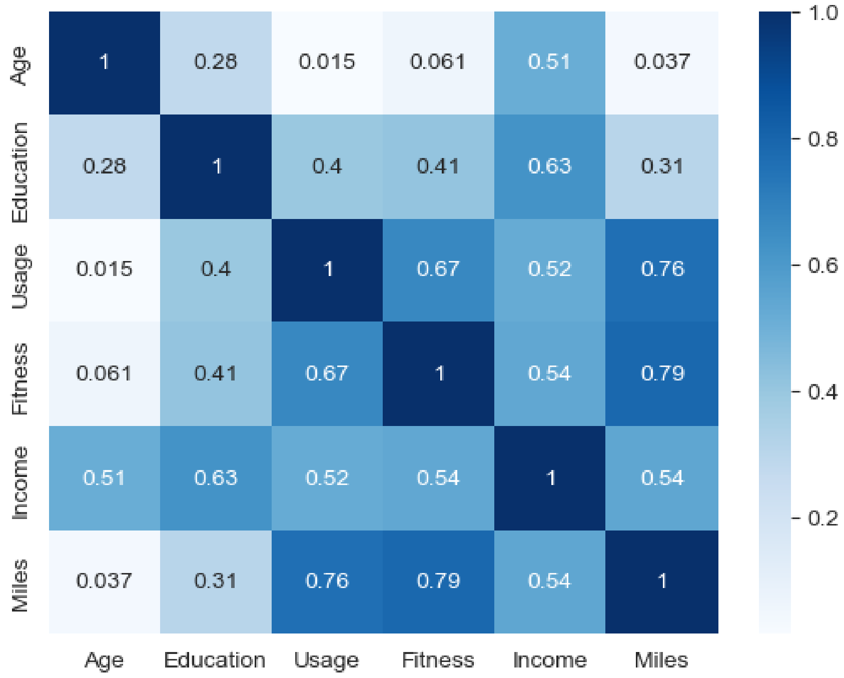


In [23]:
```
df.corr()
```

Out[23]:

	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

In [25]:
```
sns.heatmap(df.corr(), cmap='Blues', annot=True)
plt.show()
```



Miles Vs Fitness having highest positive correlation 0.78

This show that all are having positive correlation

6. With all the above steps you can answer questions like: What is the probability of a male customer buying a KP781 treadmill?

In [32]:
```
pd.crosstab(df.Gender, df.Product, normalize =True )
```

Out[32]:

Product Gender	KP281	KP481	KP781
Female	0.222222	0.161111	0.038889
Male	0.222222	0.172222	0.183333

```
Probability of male purchasing KP781 is 0.1833 i.e 18.3%
Same can be said for others also from this table.
```

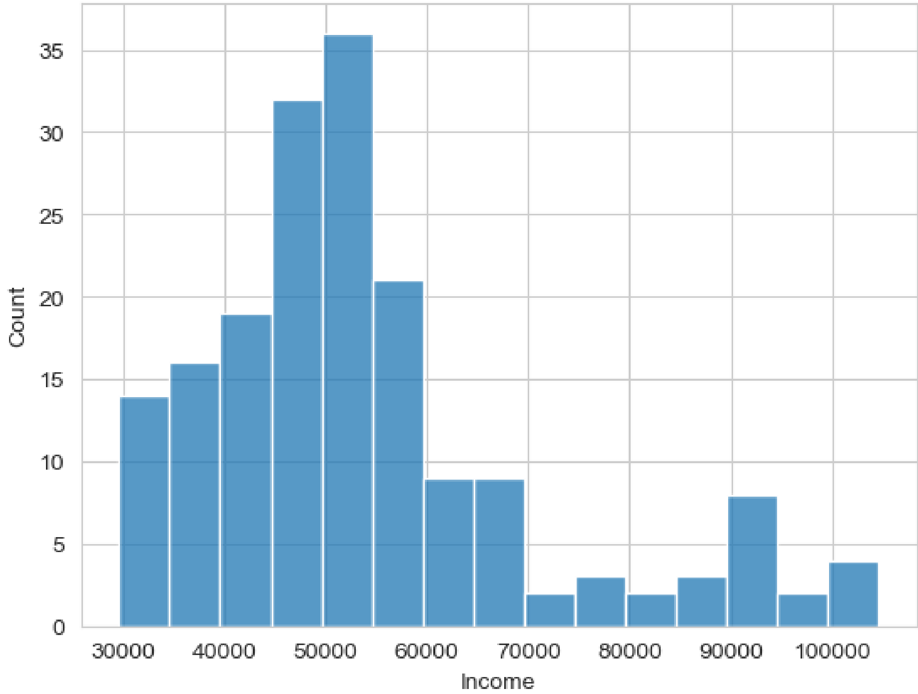
In [66]:
```
df['Gender'].value_counts(normalize=True)
```

Out[66]:
```
Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
```

Probalaity of Female purchasing is less than male

7. Customer Profiling - Categorization of users.

In [34]:
```
sns.histplot(df['Income'])
plt.show()
```



In [46]:
```
def profile(s):
  if s < 35000:
    return 'Low'
  elif s>=35000 and s<65000:
        return "Medium"
  else:
    return 'High'
```

In [47]:
```
df["Profile"] = df["Income"].apply(profile)
```

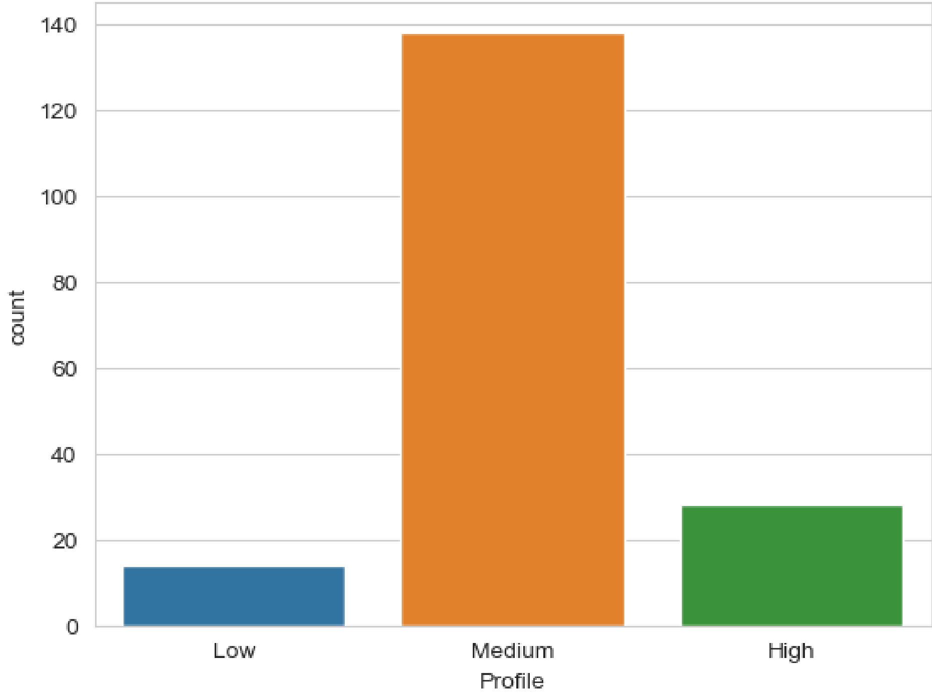
In [48]:
```
df.head()
```

Out[48]:

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

In [49]:
```
sns.countplot(df['Profile'])
plt.show()
```

```
C:\Users\Dhrubo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will result in an erro
r or misinterpretation.
  warnings.warn(
```



We categorise the cutomer as per their salary.
Low if <35000
Mededium if >=35000 & <65000
High if >=65000

We have observed that people with Medium profile are purchasing most.

Recommendations and actionable insights

1. We have seen that partnered people are purchasing more, People being in Medium profile purchasing more.
   So for them we can given some offers to increase the sells even better.

2. Because KP781 is least purchase comparitivly, we should do something to increse the sale.
   a. Recomending it to higher profile peolpe becuase it costly so they can only afford.
   b. Giving some proper demo of its feature to customer breifly for more sales.

3. From pairplot we have seen peolpe between the age of 20 to 40 have more usage. (Age VS usage)
   a. We can invite those age group people for some kind of physical trainig camping which will also promote our product and thus sales increase.

4. From probalaity we can see femal has less chance of purchasing this, we can target femal customer by encouragin them for health fitness, this will also increase sales.