Aerofit

FROM FIT-LESS TO FITNESS

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.

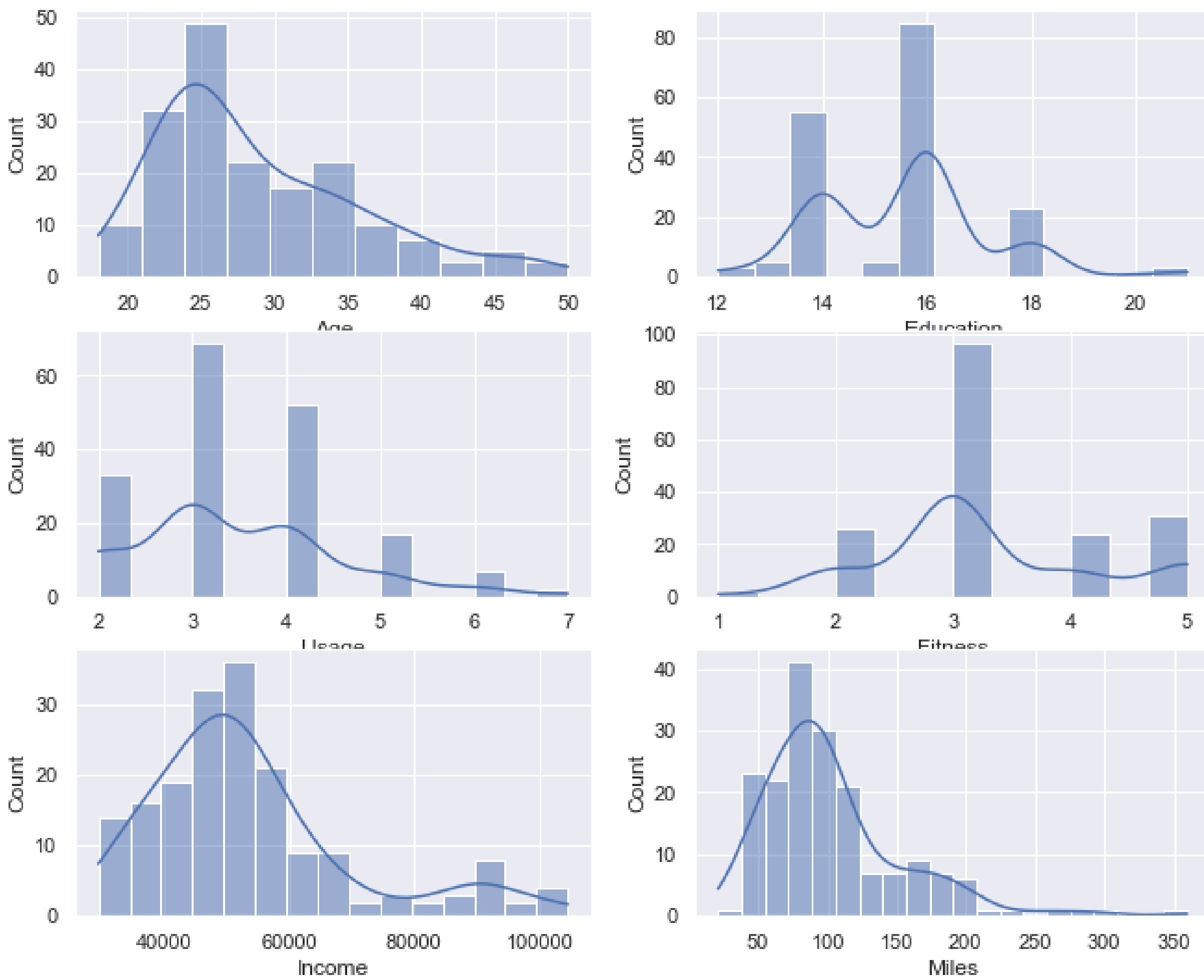
Business Problem:

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.

In [38]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
sns.set_theme(style="darkgrid")
```

In [32]:
```
df=pd.read_table('aerofit_treadmill.txt', delimiter=',')
```

In [5]:
```
fig, axis =plt.subplots(nrows=3 ,ncols=2 , figsize =(11,9))

sns.histplot(data=df,x='Age',kde=True,ax=axis[0,0])
sns.histplot(data=df,x='Education',kde=True,ax=axis[0,1])
sns.histplot(data=df,x='Usage',kde=True,ax=axis[1,0])
sns.histplot(data=df,x='Fitness',kde=True,ax=axis[1,1])
sns.histplot(data=df,x='Income',kde=True,ax=axis[2,0])
sns.histplot(data=df,x='Miles',kde=True,ax=axis[2,1])
plt.show()
```



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:

In [5]:
```
df.head()
```

Out[5]:

	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

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
```

The dataset contains 180 entries and no row has the null value in the dataset. The data type of each column is correctly defined so no need to change it. There are total of 9 columns.

```
In [5]: df.describe()
```

Out[5]:

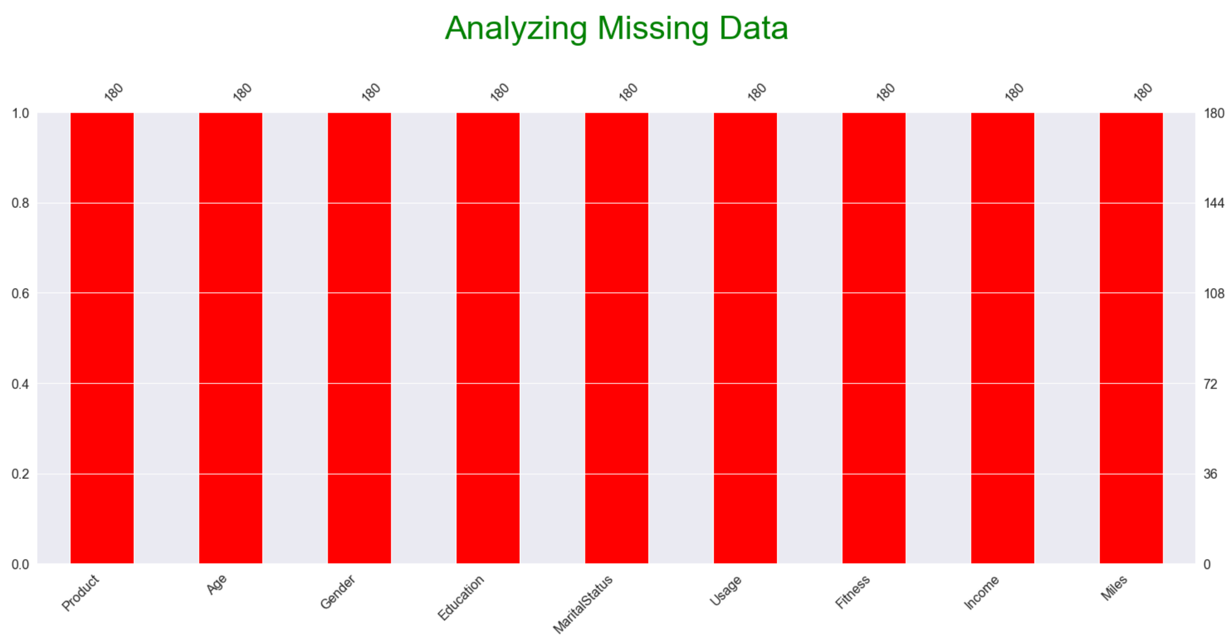
	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
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

Missing Value & Outlier Detection.

```
In [36]: df.isnull().sum()
```

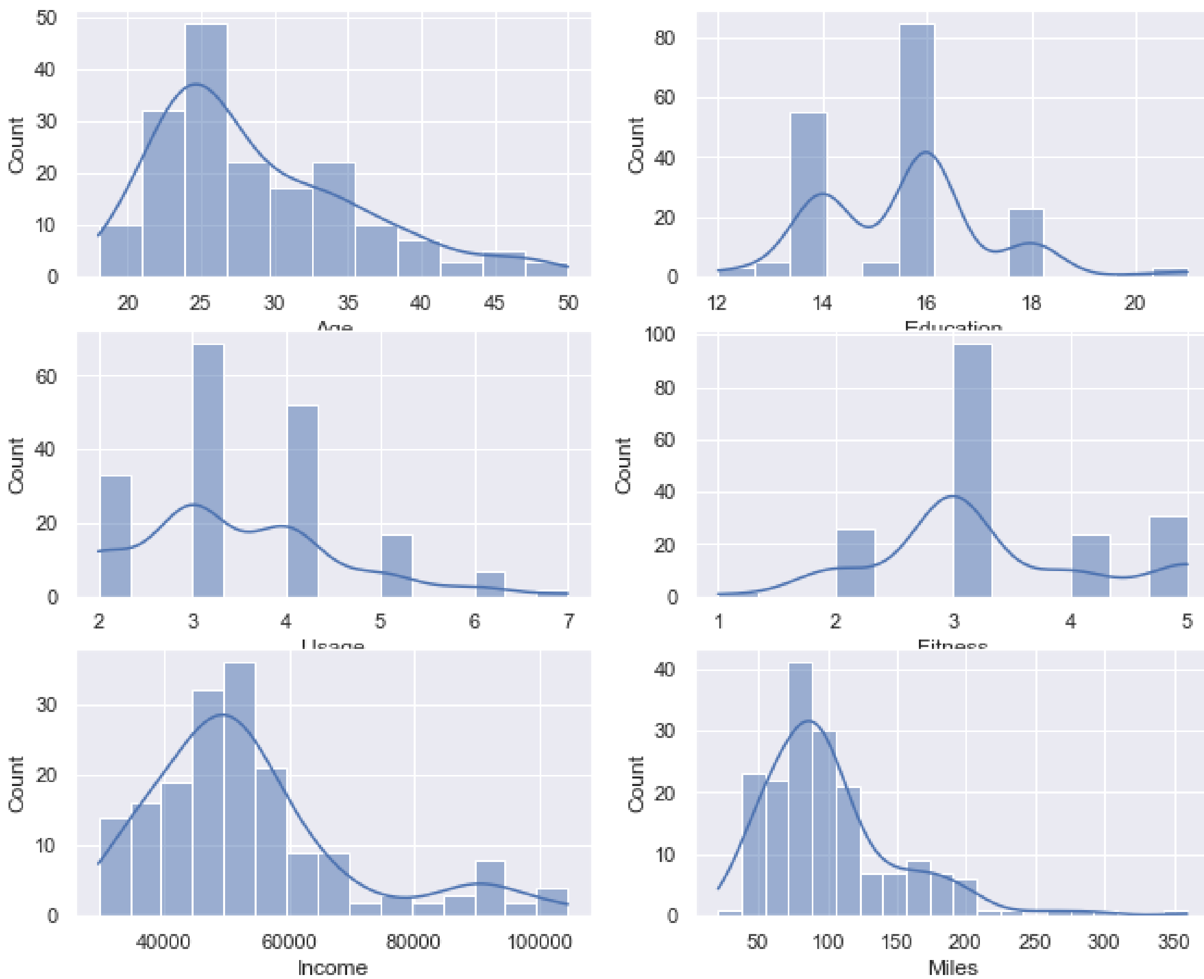
```
Out[36]: Product          0
         Age              0
         Gender           0
         Education        0
         MaritalStatus    0
         Usage            0
         Fitness          0
         Income           0
         Miles            0
         dtype: int64
```

In [39]:
```python
msno.bar(df, color='red')
plt.title("\nAnalyzing Missing Data\n", fontsize=40, color="green")
plt.show()
```

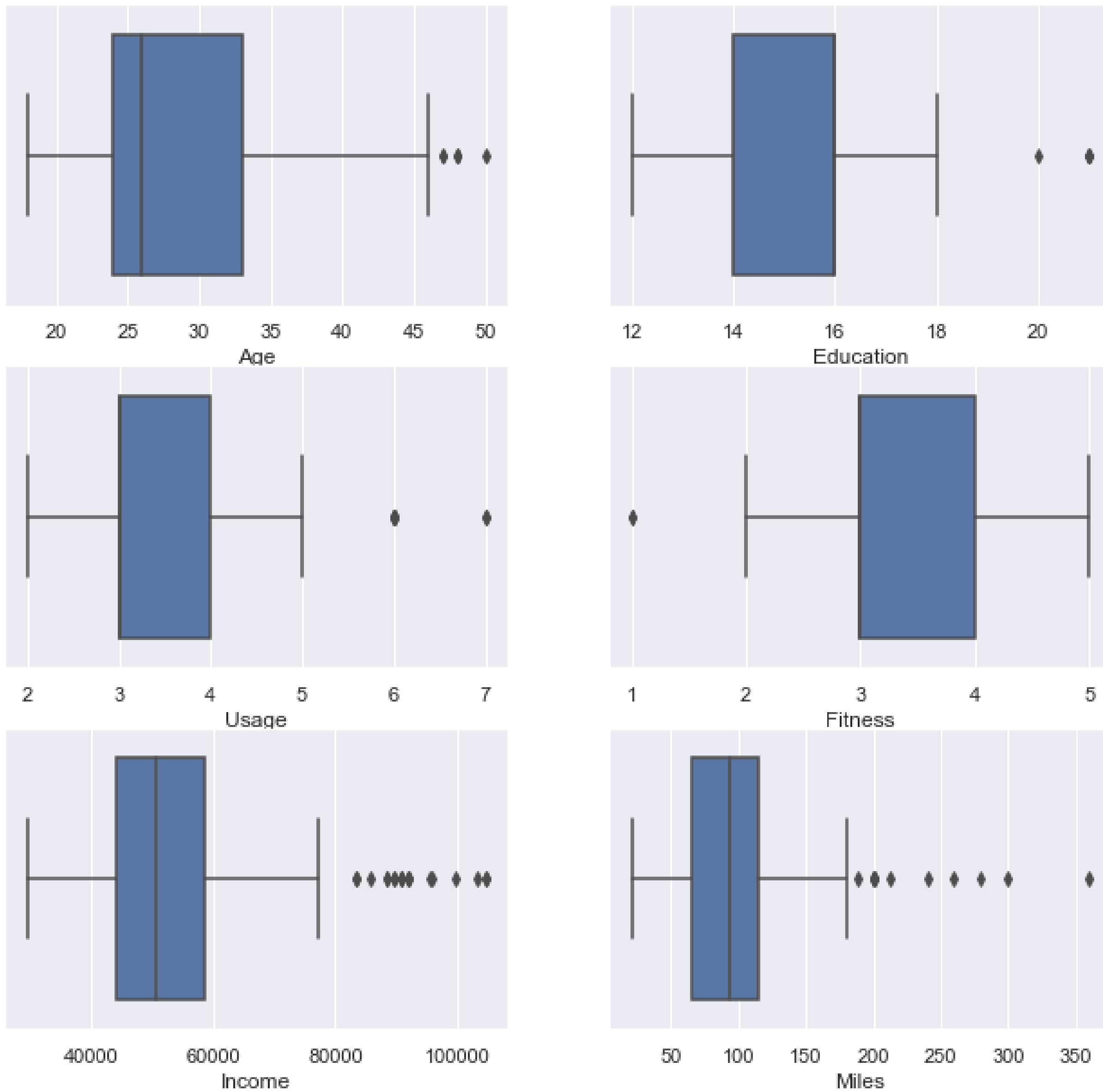


Detecting Outliers

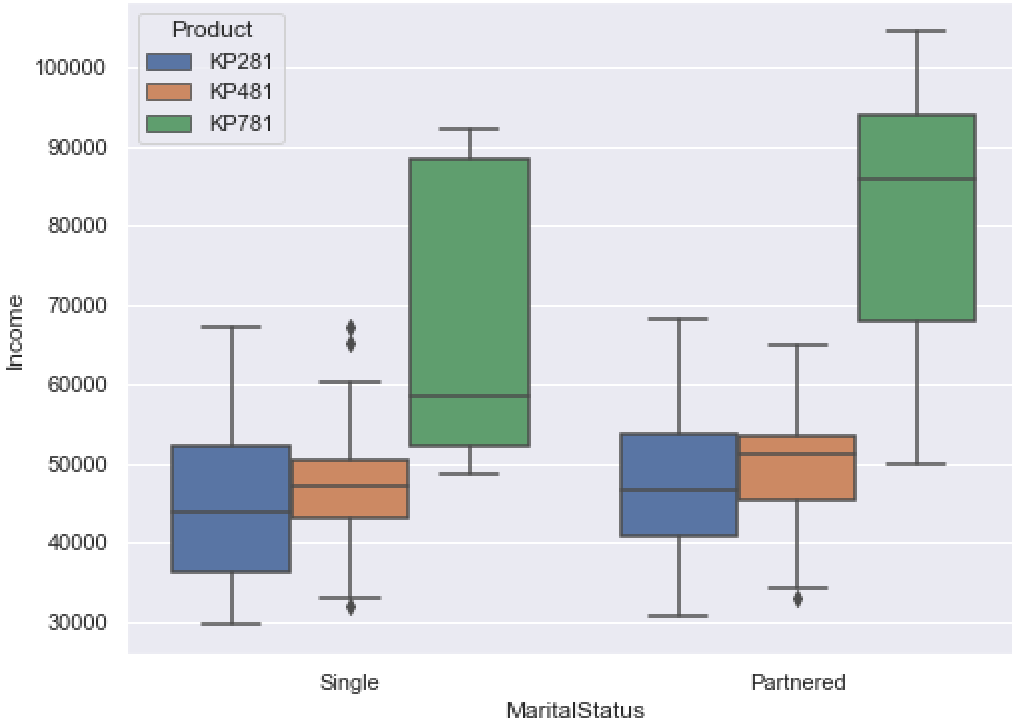
In [5]:
```
fig, axis =plt.subplots(nrows=3 ,ncols=2 , figsize =(11,9))

sns.histplot(data=df,x='Age',kde=True,ax=axis[0,0])
sns.histplot(data=df,x='Education',kde=True,ax=axis[0,1])
sns.histplot(data=df,x='Usage',kde=True,ax=axis[1,0])
sns.histplot(data=df,x='Fitness',kde=True,ax=axis[1,1])
sns.histplot(data=df,x='Income',kde=True,ax=axis[2,0])
sns.histplot(data=df,x='Miles',kde=True,ax=axis[2,1])
plt.show()
```



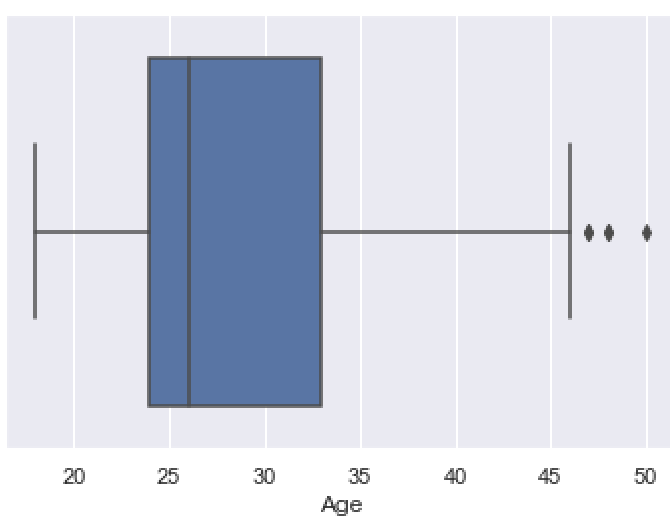
In [40]:
```
fig, axis =plt.subplots(nrows=3 ,ncols=2 , figsize =(11,9))
fig.subplots_adjust(top=1)

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()
```



In [6]:
```
plt.figure(figsize=(8,6))
sns.boxplot(x='MaritalStatus', y='Income',hue='Product', data=df)
plt.show()
```



In [7]:
```
sns.boxplot(data=df,x='Age')
plt.show()
```



In [7]:
```
IQR=np.percentile(df['Age'],75)-np.percentile(df['Age'],25)
print('IQR: ',IQR)
Lower_value=np.percentile(df['Age'],25)-1.5*IQR
print('Lower Inner Fence: ',Lower_value)
Higher_value=np.percentile(df['Age'],75)+1.5*IQR
print('Higher Inner Fence: ',Higher_value)
```

```
IQR:  9.0
Lower Inner Fence:  10.5
Higher Inner Fence:  46.5
```

In [8]:
```
df[df['Age']>46.5]
```

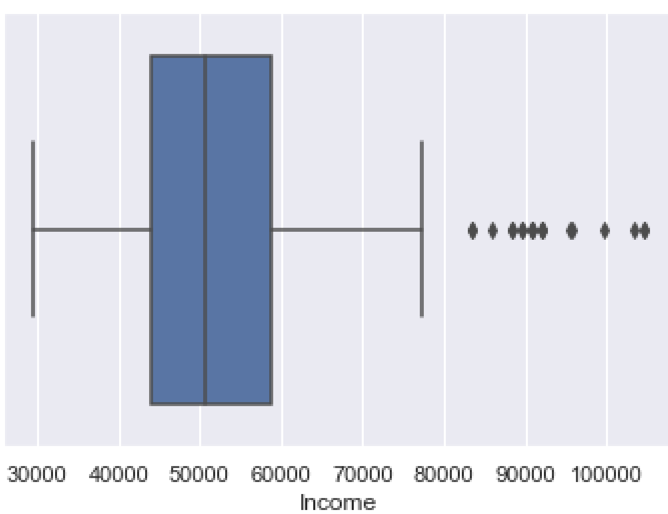
Out[8]:

	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

From the above tables, we can see that the outliers in the Age column are: 47,48,50

For Income:

In [8]:
```
sns.boxplot(data=df,x='Income')
plt.show()
```



In [10]:
```
IQR=np.percentile(df['Income'],75)-np.percentile(df['Income'],25)
print('IQR: ',IQR)
Lower_value=np.percentile(df['Income'],25)-1.5*IQR
print('Lower Inner Fence: ',Lower_value)
Higher_value=np.percentile(df['Income'],75)+1.5*IQR
print('Higher Inner Fence: ',Higher_value)
```

```
IQR:  14609.25
Lower Inner Fence:  22144.875
Higher Inner Fence:  80581.875
```

In [11]:
```
df[df['Income']>Higher_value]
```

Out[11]:

	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
169	KP781	30	Male	18	Partnered	5	5	99601	150
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
172	KP781	34	Male	16	Single	5	5	92131	150
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
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

All the outliers in the Income column is from the product category 'KP781' which is the most expensive treadmill and from the data it clearly shows that its buyer earn more money.

Since the product is divided into 3 categories:

The KP281 is an entry-level treadmill that sells for $1,500.

The KP481 is for mid-level runners that sell for $1,750.

The KP781 treadmill is having advanced features that sell for $2,500.

In [12]:
```
df['Product'].value_counts()
```

Out[12]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

Revenue Generated from the 3 products are:

KP281= 80*1500=120,000

KP481= 60*1750=105,000

KP781= 40*2500=100,000

Aerofit generates it's revenue more from the model KP281 as the buyers of this product is 33% more than average buyer of a single product.

In [197]:
```
df_KP281=df[df['Product']=='KP281']
df_KP481=df[df['Product']=='KP481']
df_KP781=df[df['Product']=='KP781']
```

In [42]:
```
df.head()
```

Out[42]:

	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

In [15]:
```
df['MaritalStatus'].value_counts()
```

Out[15]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

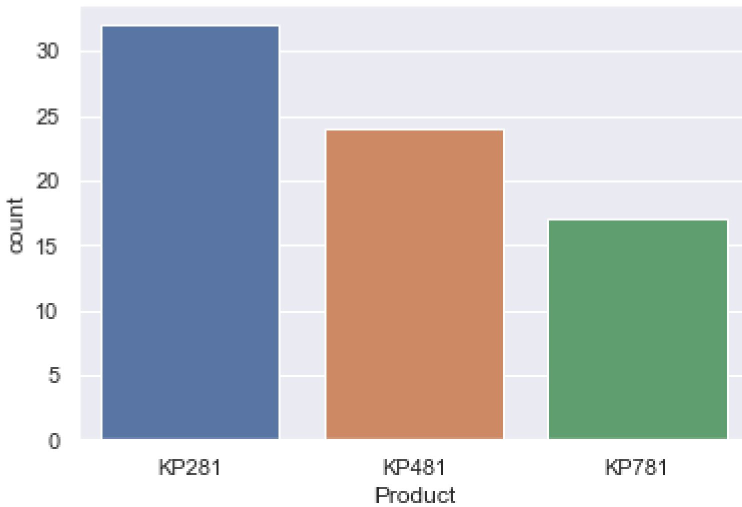
Marital Status: Single

In [10]:
```
df_Single=df[df['MaritalStatus']=='Single']
```

In [11]:
```
df_Single['Product'].value_counts()
```

Out[11]:
```
KP281    32
KP481    24
KP781    17
Name: Product, dtype: int64
```

In [12]:
```
sns.countplot(data=df_Single,x='Product')
plt.show()
```



Conditinal Probability of different product bought given that a person is Single

P(No. of particular product bought | buyer is Single)

Probability of purchasing a particular product by Customer:

Probability for KP281= 32/(32+24+17)=32/73= 43%
Probability for KP481= 24/73= 32.8%
Probability for KP781= 17/73= 23.3%

If the status of the customer is single, the probability to buy the product KP281 is higher among all the product.

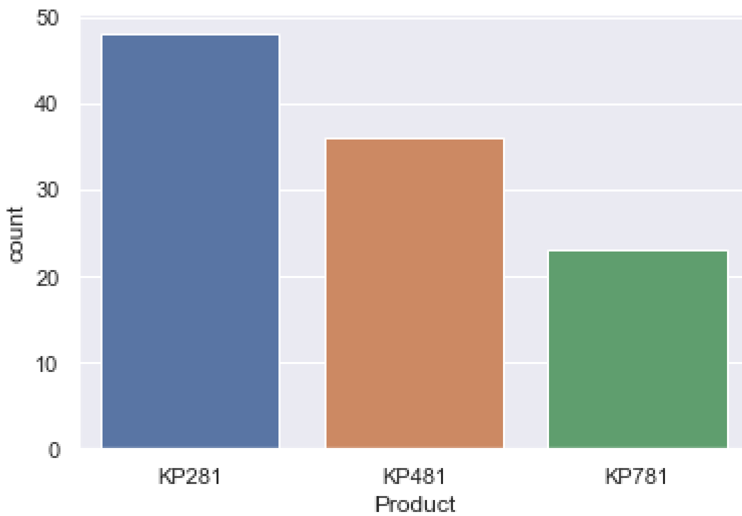
Marital Status: Partnered

In [13]:
```
df_Partnered=df[df['MaritalStatus']=='Partnered']
```

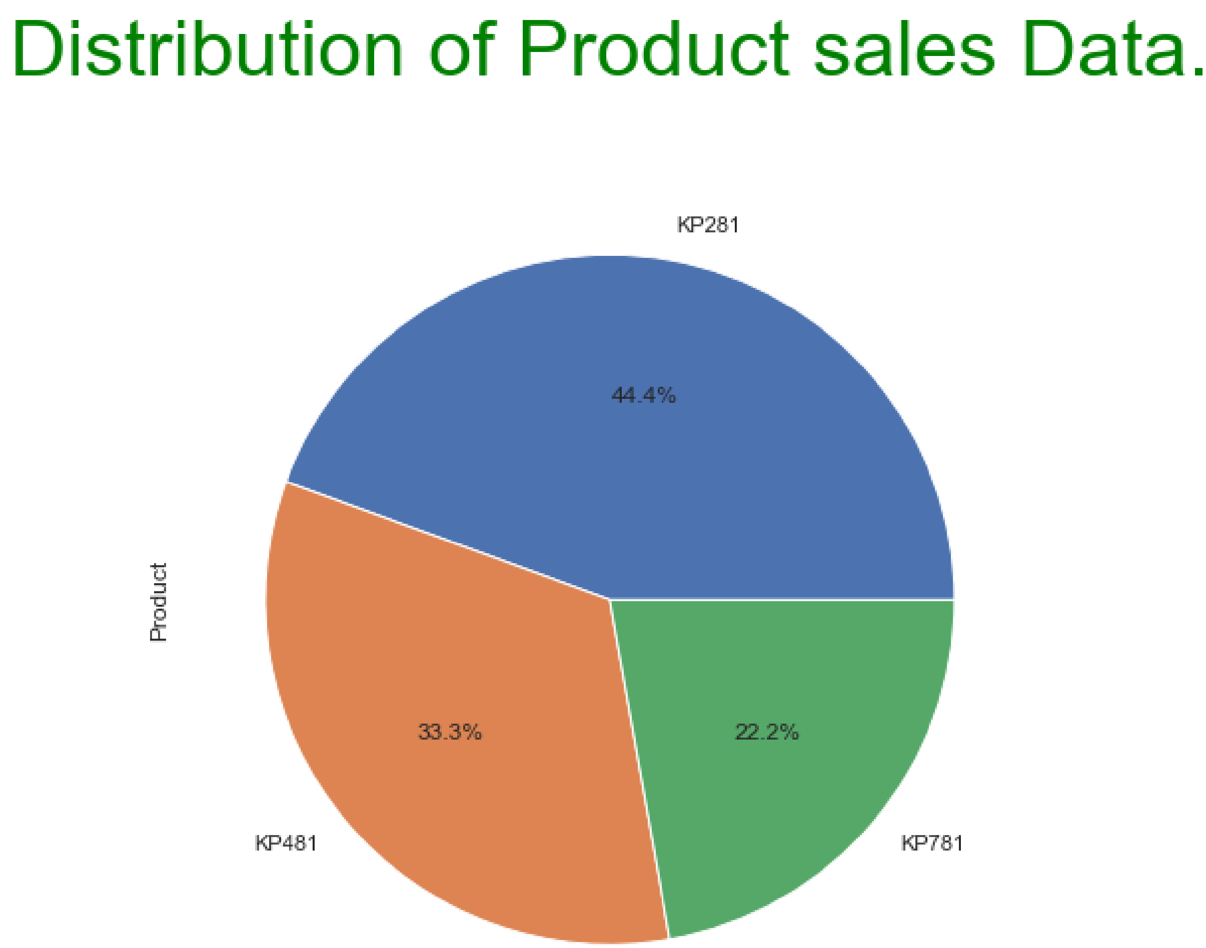
In [14]:
```
df_Partnered['Product'].value_counts()
```

Out[14]:
```
KP281    48
KP481    36
KP781    23
Name: Product, dtype: int64
```

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



In [35]:
```
plt.figure(figsize=(14,7))
df['Product'].value_counts().plot.pie(autopct='%1.1f%%',figsize=(8,8))
plt.title("\nDistribution of Product sales Data.\n", fontsize=40, color="green")
plt.show()
```



Conditinal Probability of different product bought given that a person is Partnered

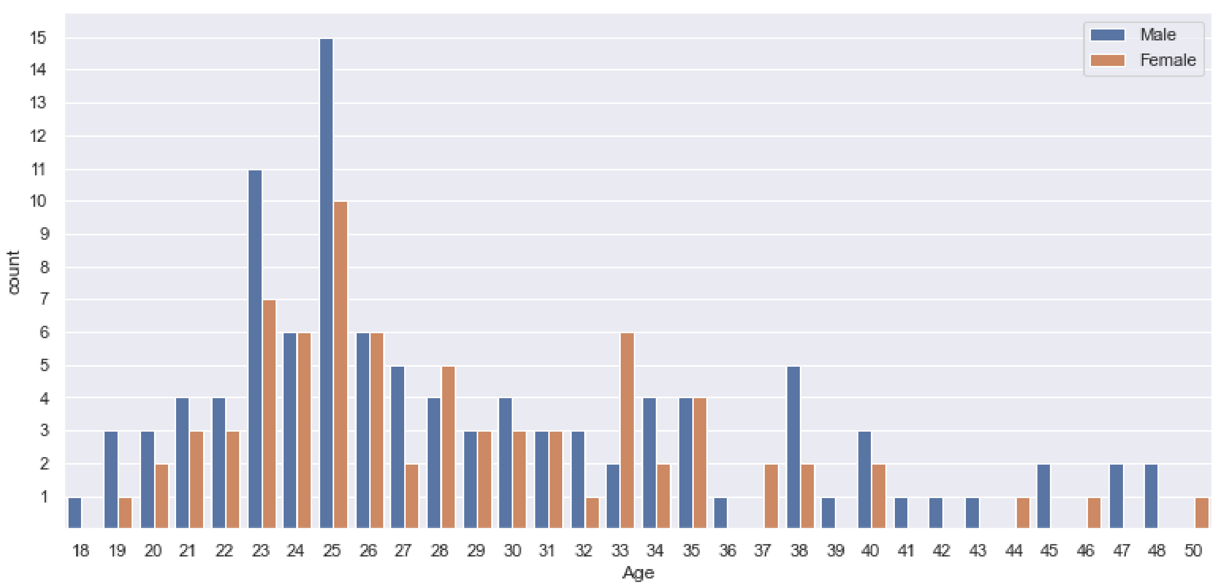
P(No. of particular product bought | buyer is Partnered)

Probability of purchasing a particular product by Partnered Customer:

Probability for KP281= 48/107= 44.85%
Probability for KP481= 36/107= 33.64%
Probability for KP781= 23/107= 21.5%

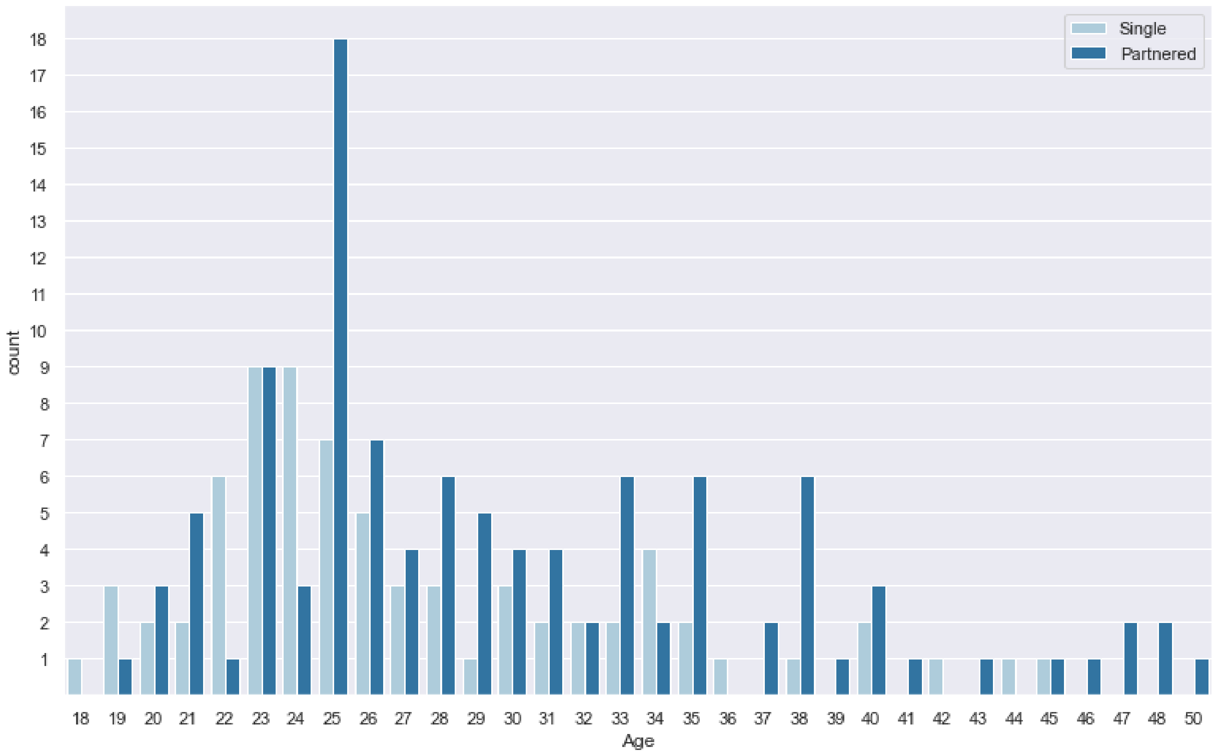
If the status of the customer is Partnered, the probability to buy the product KP281 is higher among all the product

In [16]:
```
plt.figure(figsize=(13,6))
plt.yticks(np.arange(1,26))
sns.countplot(x='Age',hue='Gender',data=df)
plt.legend(loc='upper right')
plt.show()
```

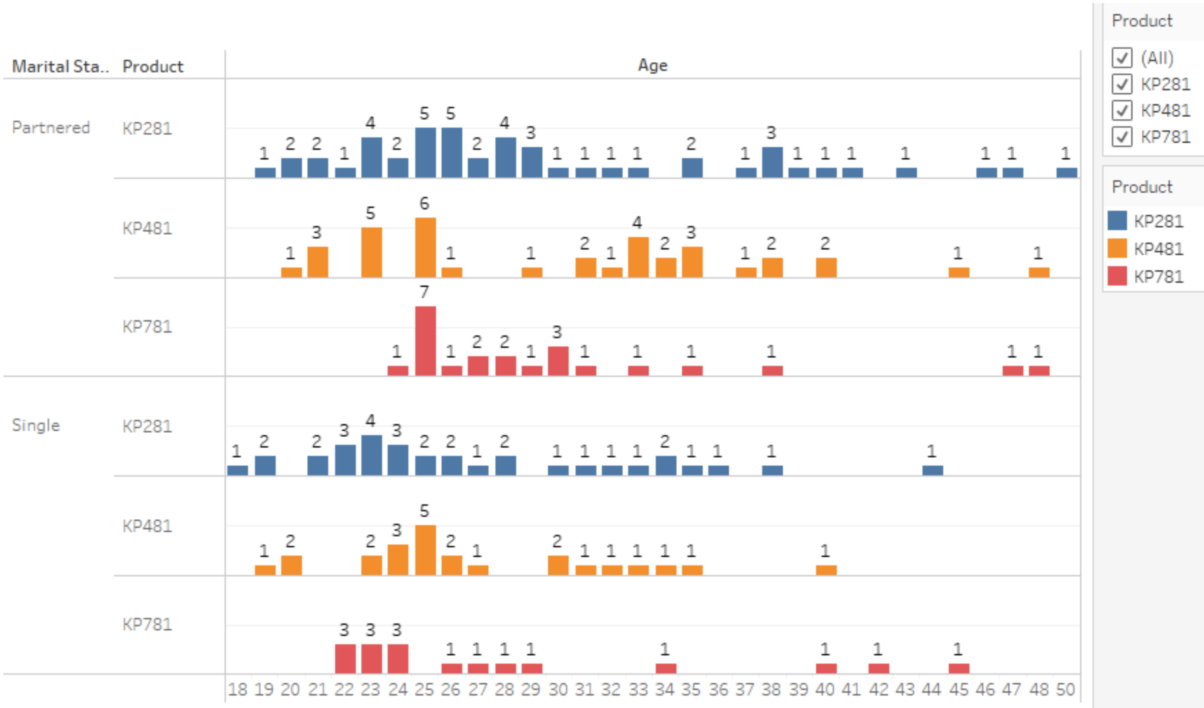


Prople in the age between 23 to 26 uses treadmill more often.
Age of 25 years seems to be more ideal for targetting both Male and Female.
After the age of 40 years, the probability of men buying treadmill is 9/12 and for female is 3/12.

In [17]:
```
plt.figure(figsize=(13,8))
plt.yticks(np.arange(1,26))
sns.countplot(x='Age',hue='MaritalStatus',data=df,color='green', palette='Paired'
plt.legend(loc='upper right')
plt.show()
```



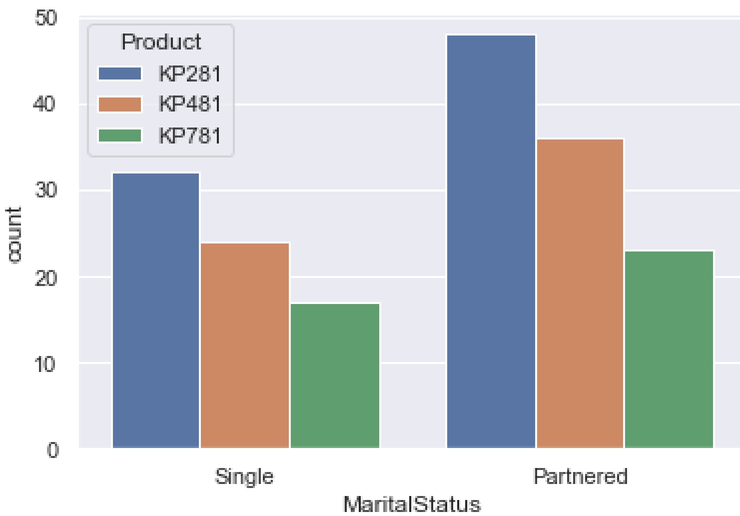
Following graph shows the count of people buying a product according to their age:



The probability of buying a product KP781 in the age between 22 to 30 is 77.5% of the total sale product KP781.

Marginal Probability

In [18]:
```
sns.countplot(x='MaritalStatus',hue='Product', data=df)
plt.show()
```



Marginal probability between Product and Marital Status of a customer:

In [66]:
```python
pd.crosstab(index=df['Product'], columns=df['MaritalStatus'], margins=True)
```

Out[66]:

MaritalStatus	Partnered	Single	All
Product			
KP281	48	32	80
KP481	36	24	60
KP781	23	17	40
All	107	73	180

Probability of Partnered Person bought the product KP281 = 48/180=26.6%
Probability of Single Person bought the product KP281 = 32/180=17.8%

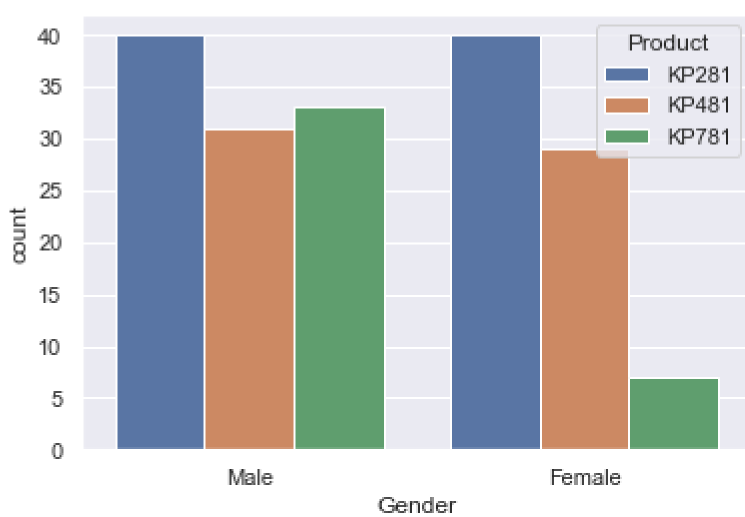
Probability of Partnered Person bought the product KP481 = 36/180=20%
Probability of Single Person bought the product KP481 = 24/180=13.3%

Probability of Partnered Person bought the product KP781 = 23/180=12.7%
Probability of Single Person bought the product KP781 = 17/180=9.4%

Probability of Partnered people bought any of the product is 107/180= 59.5%
Probability of Single people bought any of the product is 73/180= 40.5%

Marginal probability between Product and Gender of a customer:

In [19]:
```python
sns.countplot(x='Gender',hue='Product', data=df)
plt.show()
```



```
In [69]: pd.crosstab(index=df['Product'], columns=df['Gender'], margins=True)
```

Out[69]:

Gender	Female	Male	All
Product			
KP281	40	40	80
KP481	29	31	60
KP781	7	33	40
All	76	104	180

Probability of Male among total no. of Males buying KP281 is 40/104=38.5%
Probability of Male among total no. of Males buying KP481 is 31/104=29.8%
Probability of Male among total no. of Males buying KP781 is 33/104=31.7%

Probability of Female among total no. of Females buying KP281 is 40/76=52.6%
Probability of Female among total no. of Females buying KP481 is 29/76=38.15%
Probability of Female among total no. of Females buying KP781 is 7/76=9.2%

Marginal probability between Product, Gender and Marital Status of a customer:

```
In [78]: pd.crosstab(df['Product'], [df['MaritalStatus'],df['Gender']], margins=True)
```

Out[78]:

MaritalStatus	Partnered		Single		All
Gender	**Female**	**Male**	**Female**	**Male**	
Product					
KP281	27	21	13	19	80
KP481	15	21	14	10	60
KP781	4	19	3	14	40
All	46	61	30	43	180

Probability of buying a product KP281 by a Female whose Marital Status is partnered = 27/180= 15%
Probability of buying a product KP481 by a Female whose Marital Status is partnered = 15/180= 8.33%
Probability of buying a product KP781 by a Female whose Marital Status is partnered = 4/180= 2.22%

Probability of buying any product by Female whose Marital Status is partnered = 46/180= 25.55%

Probability of buying a product KP281 by a Female whose Marital Status is Single = 13/180= 7.22%
Probability of buying a product KP481 by a Female whose Marital Status is Single = 14/180=

7.77%
Probability of buying a product KP781 by a Female whose Marital Status is Single = 3/180= 1.66%

Probability of buying any product by Female whose Marital Status is Single = 30/180= 16.66%

Probability of buying a product KP281 by a male whose Marital Status is partnered = 21/180= 11.66%
Probability of buying a product KP481 by a male whose Marital Status is partnered = 21/180= 11.66%
Probability of buying a product KP781 by a male whose Marital Status is partnered = 19/180= 10.55%

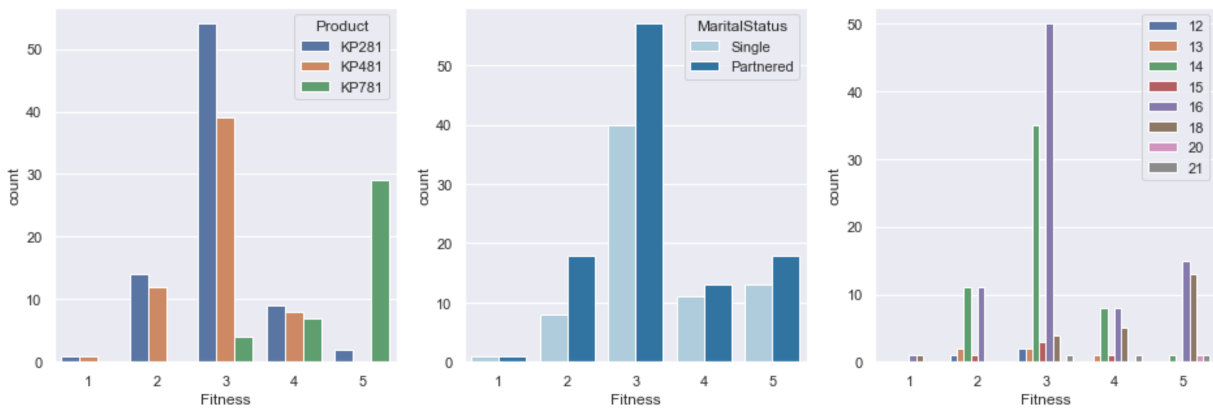
Probability of buying any product by male whose Marital Status is partnered = 61/180= 33.88%

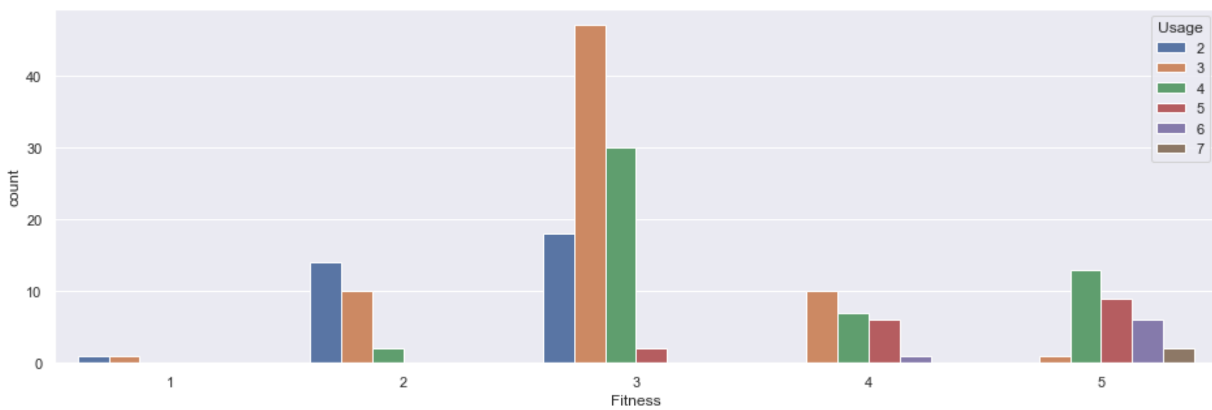
Probability of buying a product KP281 by a male whose Marital Status is Single = 19/180= 10.55%
Probability of buying a product KP481 by a male whose Marital Status is Single = 10/180= 5.55%
Probability of buying a product KP781 by a male whose Marital Status is Single = 14/180= 7.77%

Probability of buying any product by male whose Marital Status is Single = 43/180= 23.88%

Fitness and Usage

```
In [22]: fig, ax =plt.subplots(1,3,figsize=(16,5))

sns.countplot(x='Fitness',hue='Product', data=df,ax=ax[0])
sns.countplot(x='Fitness',hue='MaritalStatus', data=df,color='blue', palette='Pai
sns.countplot(x='Fitness', hue='Education', data=df, ax=ax[2])
plt.legend(loc='upper left')
plt.show()

plt.figure(figsize=(16,5))
sns.countplot(x='Fitness',hue='Usage', data=df)

plt.show()
```



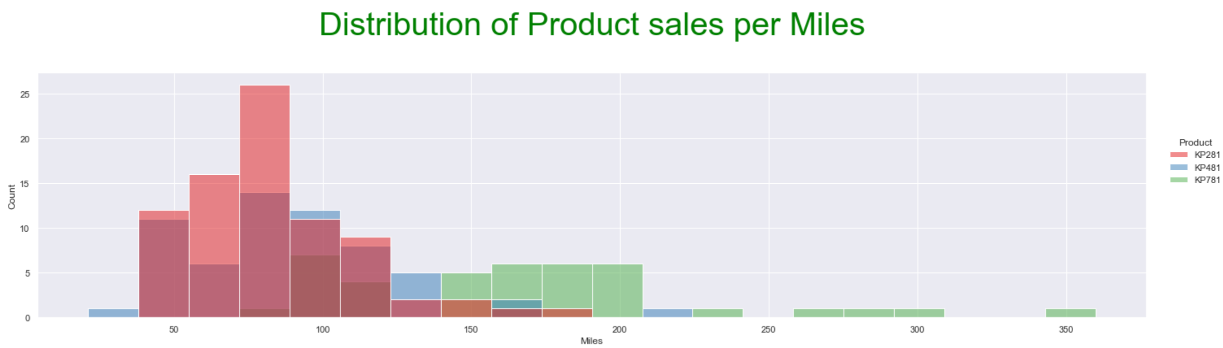


From the above plots, we can say that: 1.) If customer average usage of treadmill is more than 5 times a week, then he will buy KP781 only. i.e.

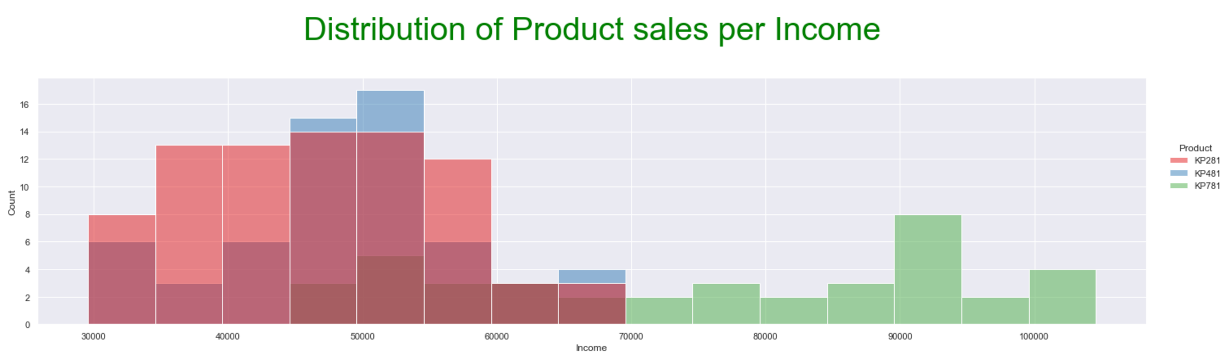
P['KP781'|Usage>5]= 100%

i.e. customer with usage>5 will not buy the product KP281 and KP481.

In [33]:
```
sns.displot(data=df, x='Miles', aspect=4, hue='Product', palette="Set1")
plt.title("\nDistribution of Product sales per Miles\n", fontsize=40, color="gree
plt.show()
```



In [34]:
```
sns.displot(data=df, x='Income', aspect=4, hue='Product', palette="Set1")
plt.title("\nDistribution of Product sales per Income\n", fontsize=40, color="gre
plt.show()
```



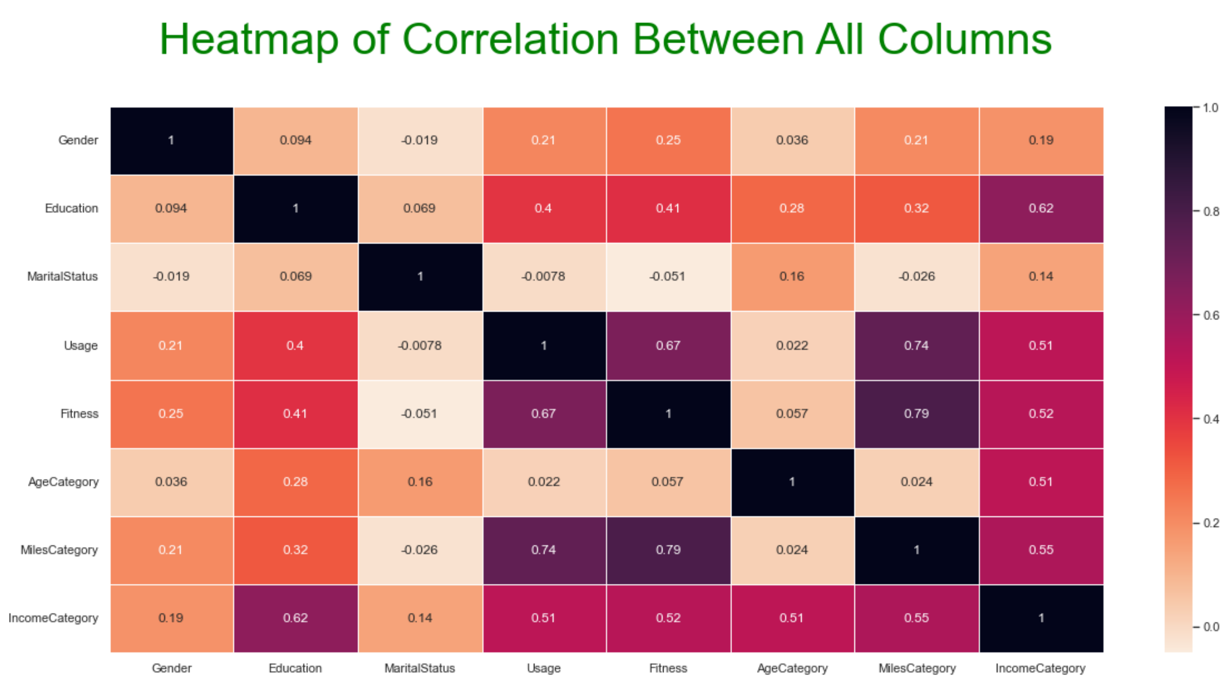
Correlation among different factors:

In [28]:
```
df['Gender'] = df['Gender'].apply(lambda x: 1 if str(x)=='Male' else 0)
df['MaritalStatus'] = df['MaritalStatus'].apply(lambda x: 1 if str(x)=='Partnerec
df['AgeCategory'] = df['Age'].apply(lambda x: int((int(x)-18)/4))
df['MilesCategory'] = df['Miles'].apply(lambda x: int(float(x)/50))
df['IncomeCategory'] = df['Income'].apply(lambda x: int((int(x)-30000)/5000))
df.drop(['Age', 'Miles', 'Income'], axis=1, inplace=True)
df.head()
```

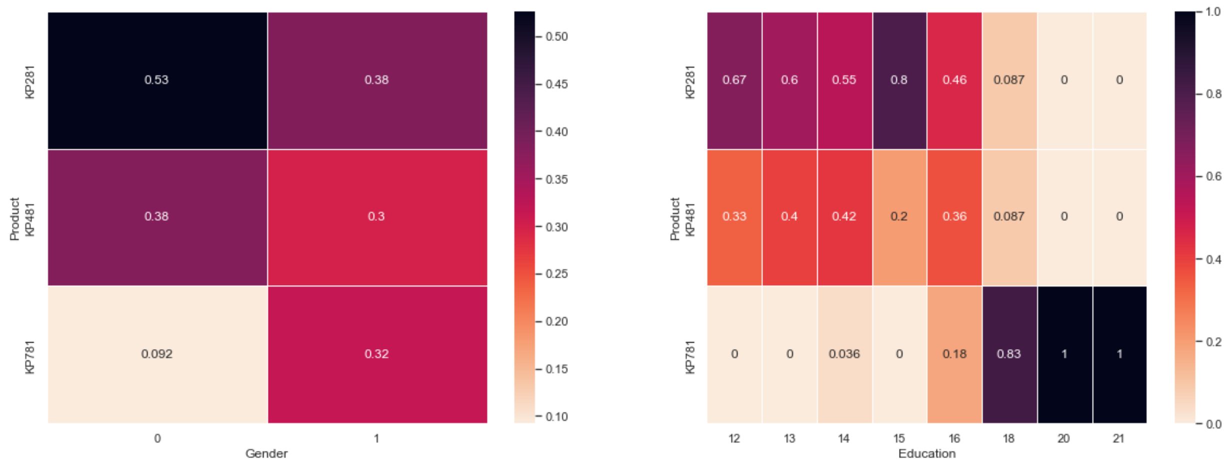
Out[28]:

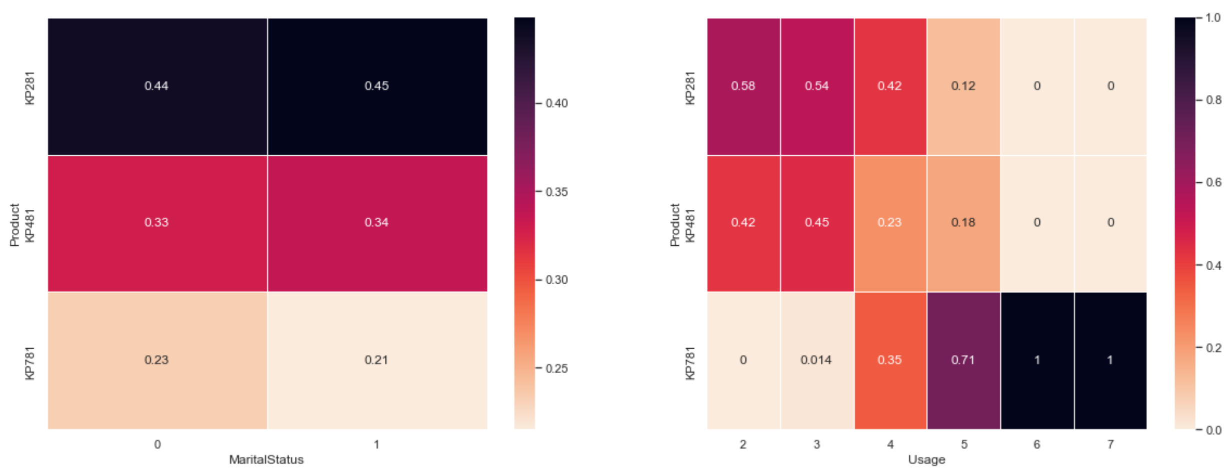
	Product	Gender	Education	MaritalStatus	Usage	Fitness	AgeCategory	MilesCategory	Incom
0	KP281	1	14	0	3	4	0	2	
1	KP281	1	15	0	2	3	0	1	
2	KP281	0	14	1	4	3	0	1	
3	KP281	1	12	0	3	3	0	1	
4	KP281	1	13	1	4	2	0	0	

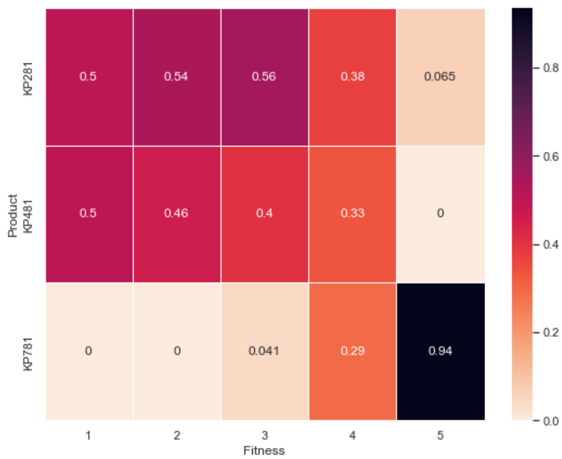
In [30]:
```
fig, ax = plt.subplots(figsize=(20,9))
sns.heatmap(df.corr(), linewidths=.5, cmap=sns.cm.rocket_r, annot=True, ax=ax)
plt.title("\nHeatmap of Correlation Between All Columns\n", fontsize=40, color="g
plt.show()
```

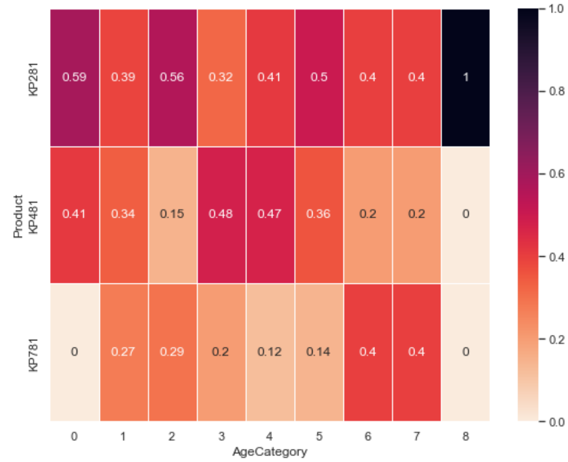


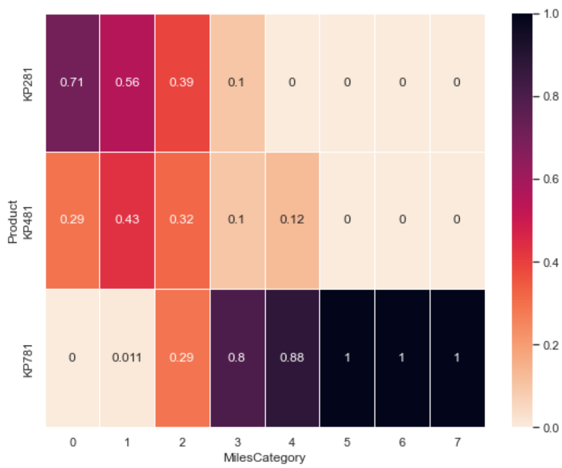
In [29]:
```
fig, ax = plt.subplots(1, 2, figsize=(20,7))
for i in range(1, len(df.columns)):
    y = (i-1)%2
    sns.heatmap(pd.crosstab(df.Product, df[df.columns[i]], normalize='columns'),
    if y == 1:
        plt.show()
        if i < len(df.columns)-1:
            fig, ax = plt.subplots(1, 2, figsize=(20,7))
```

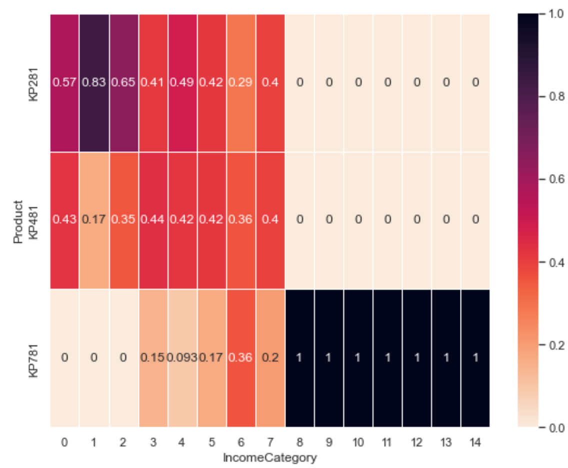





Product
KP281
KP481
KP781
0.5
0.54
0.56
0.38
0.065
0.5
0.46
0.4
0.33
0
0
0
0.041
0.29
0.94
Fitness


Product
KP281
KP481
KP781
0.59
0.39
0.56
0.32
0.41
0.5
0.4
0.4
1
0.41
0.34
0.15
0.48
0.47
0.36
0.2
0.2
0
0
0.27
0.29
0.2
0.12
0.14
0.4
0.4
0
AgeCategory


Product
KP281
KP481
KP781
0.71
0.56
0.39
0.1
0
0
0
0
0.29
0.43
0.32
0.1
0.12
0
0
0
0
0.011
0.29
0.8
0.88
1
1
1
MilesCategory


Product
KP281
KP481
KP781
IncomeCategory

PairPlot

```
In [24]: sns.pairplot(data=df, hue='Product')
plt.show()
```

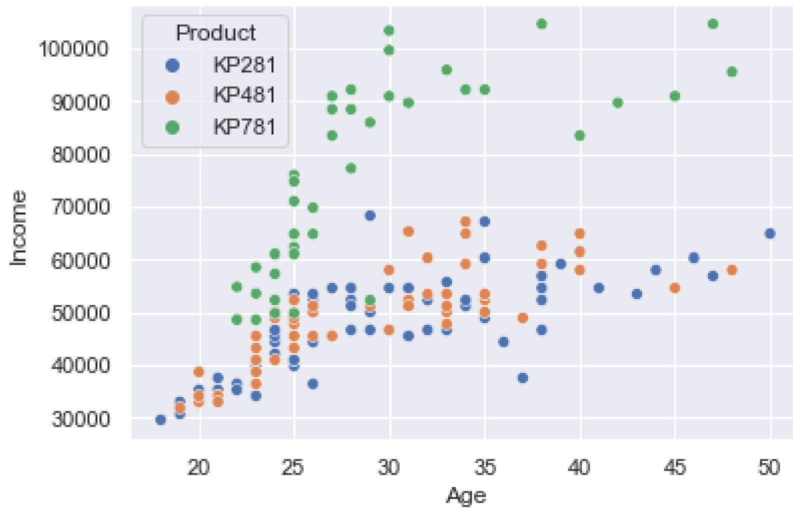
From the above Pair Plot, it is observed :

1. Observing the Income- Miles Graph, we can see that high Income people are most likely to walk/run for miles greater than 200 and their age lies between 20-30

Scatter Plot

Below plot showing the relation between age, Income and product

In [25]:
```
sns.scatterplot(data=df,x='Age',y='Income',hue='Product')
plt.show()
```



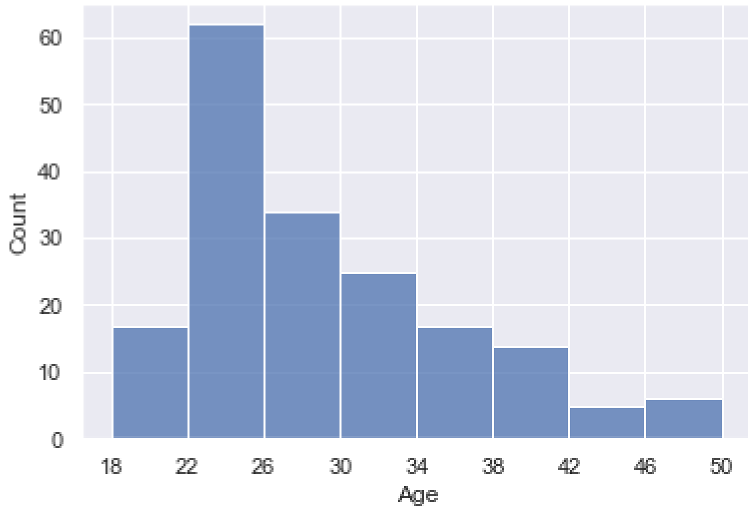
From the above scatter plot, it is clearly visible that the product KP781 is majorly purchased by the people having income>$70000 and this category of people didn't buy product KP281 and KP81. That means for high class people product KP781 is most common.

In [11]:
```
df.head()
```

Out[11]:

	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

In [26]:
```
plt.xticks(np.arange(18,51,4))
sns.histplot(df['Age'], bins=8)
plt.show()
```



In [176]:
```
df['Age'].value_counts(bins=8).sort_index()
```

Out[176]:
```
(17.967, 22.0]    24
(22.0, 26.0]      67
(26.0, 30.0]      29
(30.0, 34.0]      24
(34.0, 38.0]      18
(38.0, 42.0]       8
(42.0, 46.0]       5
(46.0, 50.0]       5
Name: Age, dtype: int64
```

The probability of buying any product between the age 22-26 is 67/180 i.e. 37%

In [186]:
```
df.head()
```

Out[186]:

	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

Some questions that can be answered from the above analysis:

1. What is the probability of a male customer buying a KP781 treadmill?
   Ans. 33/180 i.e. 18.33%

2. What is the probability of a female customer who is married and buying a KP481 treadmill?
   Ans. 15/180 i.e. 8.3%

3. What is the ideal duration of education for which the product are bought by the customer more often and what is their probability?
   Ans. Ideal duration of education is 16 where 85 customers buy treadmill out of which 39 buy KP281, 31 buy KP481 and 15 customers buy KP781.

4. What is the avearge Income of the customers buying the product KP781?
   Ans. 75441

5. Whic product is more likable for the customer whose age is above 40 years?
   Ans. KP281 and it's probability: P[KP281 | age>40] = 50%

6. Which product is more popular among the Age group of 22-26?
   Ans. KP281 and it's probability: P[KP281 | 21<Age<27]=31/74= 41.9%

7. What is the probability of a customer being single given that the customer buy the product KP281?
   Ans. 32/180 i.e. 17.77%

8. Which is the most common product among single male and single female?
   Ans. Single Man= KP281 and it's probability is P[KP281 | Single male]=19/43 i.e. 44.18%
   Single Female= KP481 and it's probsbility is P[KP481 | Single Female]= 14/30 i.e. 46.66%

9. What is the average Fitness of the customer buying KP281?
   Ans. 2.97

10. What is the probability of customers whose Marital Status is Partnered and Usage is less than 4 buying the product KP481?
    Ans. 27/180 i.e. 15%

Insights

1. The product KP281 is more likely to be purchased by the customers and it adds 120K to the revenue which is highest among all the 3 products.

2. Aerofit generates it's revenue more from the model KP281 as the buyers of this product is 33% more than average buyer of a single product.

3. Customers wose Marital Status is partnered are mre likely to buy a treadmill then Single ones.

4. Customers who are single buy the product KP281 with probability of 43%, KP481 with 33% and KP781 with 23%

5. Marital Customers also buy the product KP281 more than other products.

6. Customers with age 25 are the ones who buys more treadmill among all the other ages

7. The probability of buying a product KP781 in the age between 22 to 30 is 77.5% of the total sale product KP781.

8. The popularity of the product KP281 is equal among both the Genders

9. Probability of buying the product KP781 whose Usage is greater than 5 times a week on an average is 100%

10. High Income people are most likely to walk/run for miles greater than 200 and their age lies between 20-30.

11. The product KP781 is majorly purchased by the people having income>70000 and this category of people didn't buy product KP281 and KP81.

12. In the age between 22-26, large no. of people buy treadmills than any other age group.

Recommendations:

1. Since the product KP281 is more likely to be sold and it's market share is 45%, So the stocked should be maintained for KP281 first, then KP481 and then KP781 to avoid any shortage.

2. The Audience withing the age of 22-26 should be targetted more often as this range of age is crucial for the revenue generation.

3. The advertisement for KP281 should be more among the social media as the audience with the age 22-26 are easily available and active there.

4. To increase the sell of the most expensive product i.e. KP781, it should be advertised among the high class people as they are the targetted audience for that product. It should be advertised in Branded Gyms, Lavish Hotels, Airports where the footfall of the high income people is more often. This way, revenue and profit margin can also be increased

5. Product should be showcased according to the fitness level also which helps people in choosing the right product according to their usage and fitness which helps in increasing the credibility of the Aerofit.

6. A scheme should be introduced where if someone wants to upgrade the product, then he is eligible to get a discount of 30%-40% of total amount of the previous product under specified terms and condition. This way Aerofit can hold their customers for a longer time and spread their business among larger audience. This also develop faith among the customers towards Aerofit and ultimately the brand value increases.

Thanks

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