Aerofit Project

In [98]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv(r"D:\DSML class\Real world data assignments\Python\Aerofit\d2beiqkhq929
```

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

Basic Analysis and understanding the data

1. Observation of the data

In [4]:
```
df.shape
```

Out[4]:
```
(180, 9)
```

In [5]:
```
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
```

In [6]:
```
df.describe()
```

Out[6]:

	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 [7]:
```
df.describe(include=object)
```

Out[7]:

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

In [72]:
```
df.nunique()
```

Out[72]:
```
Product            3
Age               32
Gender             2
Education          8
MaritalStatus      2
Usage              6
Fitness            5
Income            62
Miles             37
Age_Group          3
Income_Group       4
dtype: int64
```

In [78]:
```
df['Product'].value_counts()
```

Out[78]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [91]:
```
df['Education'].value_counts()
```

Out[91]:
```
16    85
14    55
18    23
15     5
13     5
12     3
```

```
21      3
20      1
Name: Education, dtype: int64
```

Creating groups for analysis

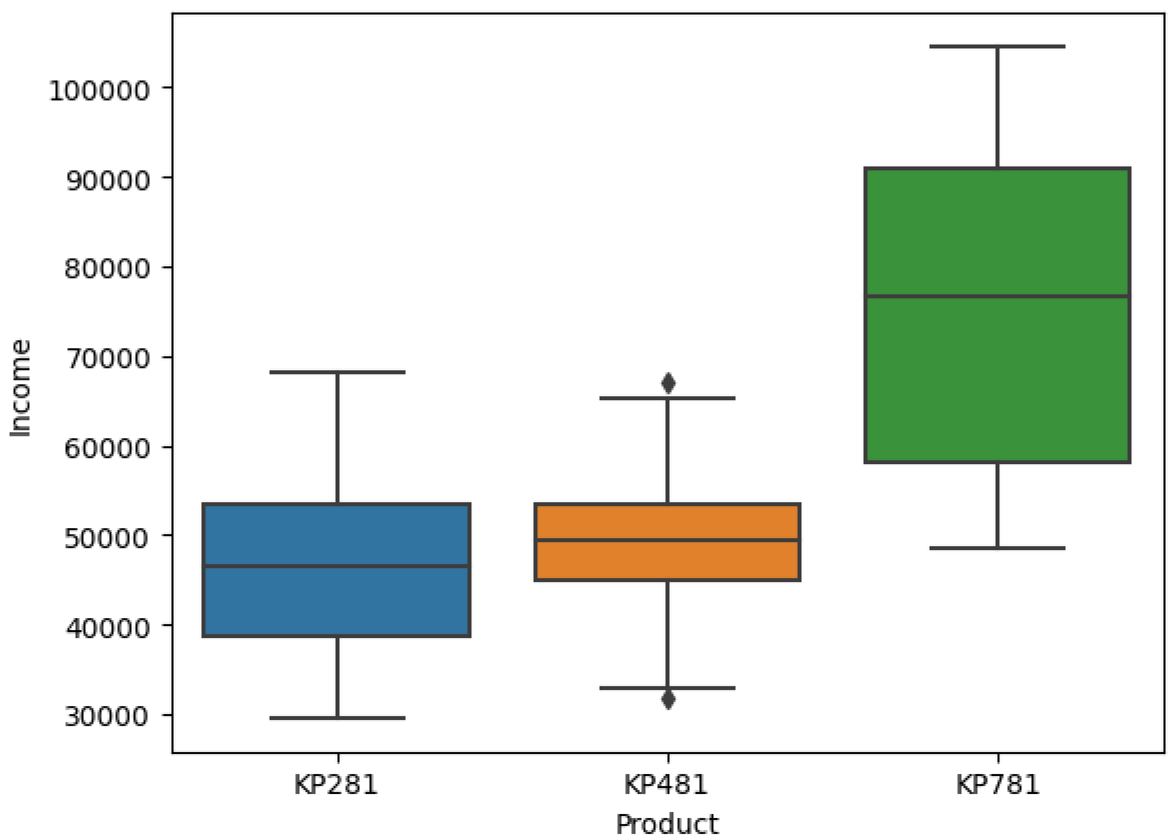
In [79]:
```python
df['Age_Group'] = pd.cut(df['Age'], bins = [0,24,34,50], labels = ['under 25', 'under 35
```

In [62]:
```python
df['Income_Group']  = pd.cut(df['Income'], bins = [29000,50000-1,60000-1,80000-1,105000]
```

2. Outliers

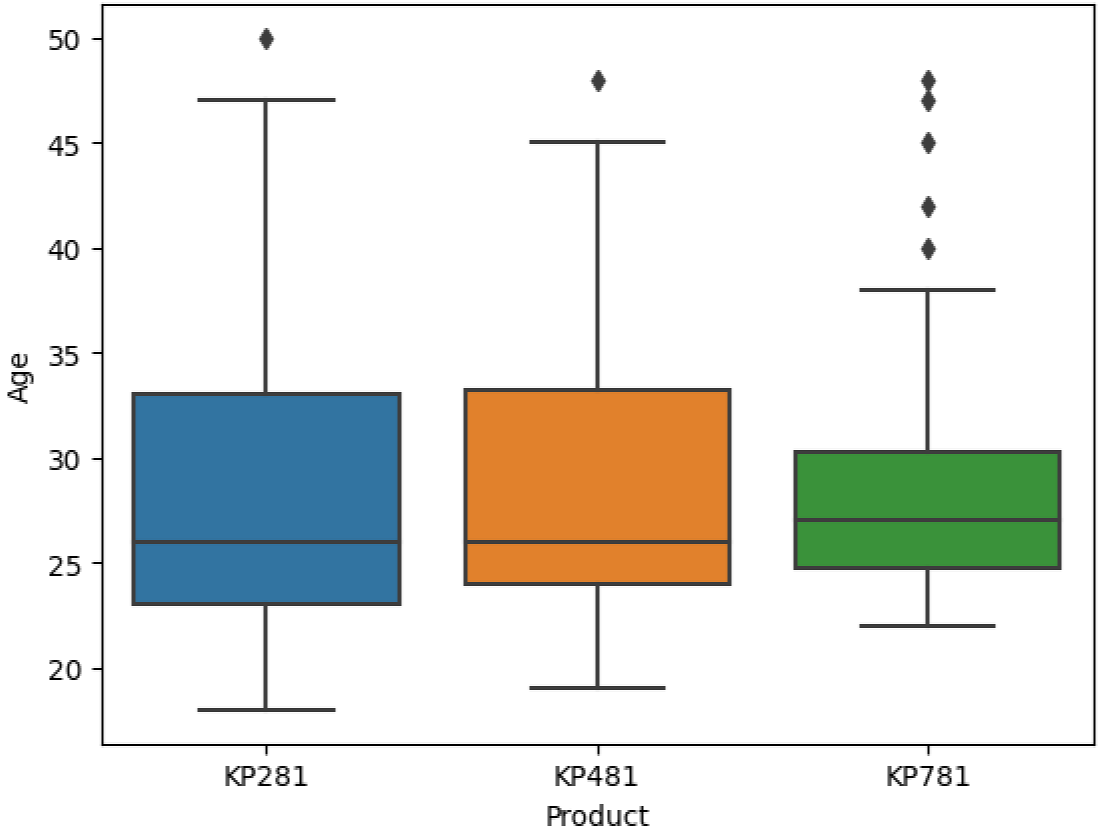
In [10]:
```python
sns.boxplot(data = df, x = 'Product', y = 'Income')
```

Out[10]:
```
<Axes: xlabel='Product', ylabel='Income'>
```



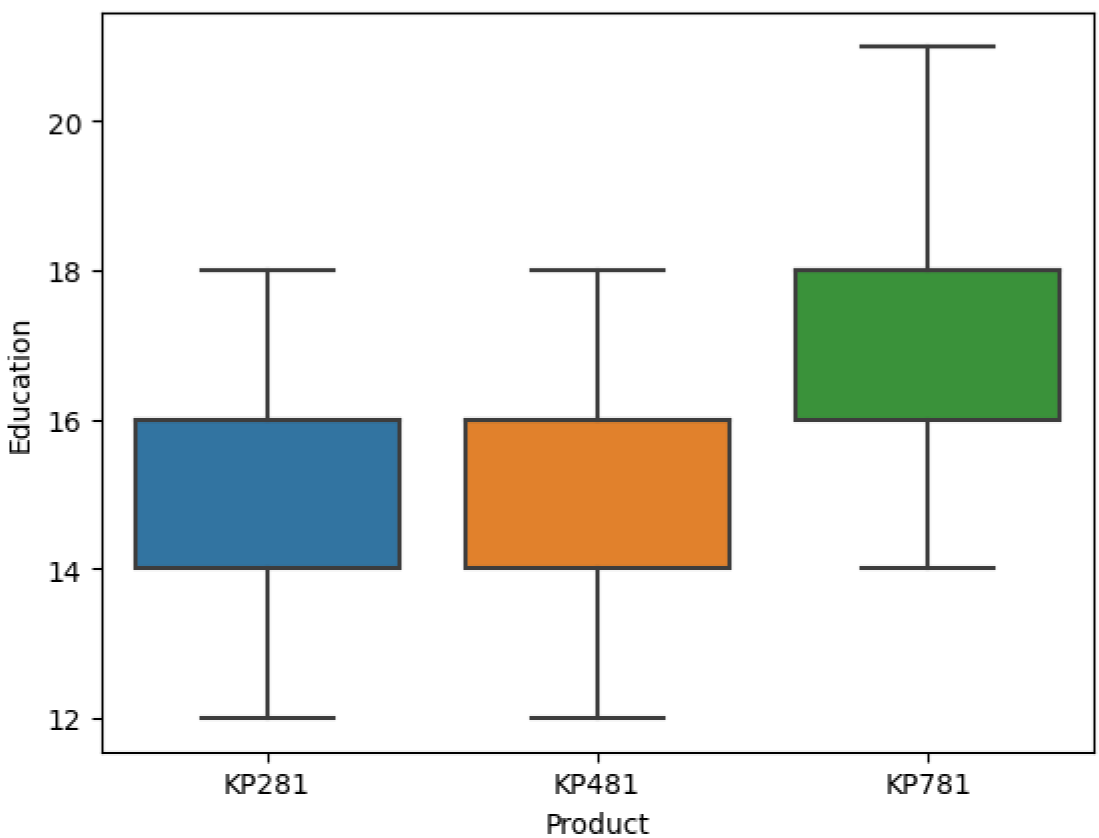
In [8]:
```python
sns.boxplot(data = df, x = 'Product', y = 'Age')
```

Out[8]:
```
<Axes: xlabel='Product', ylabel='Age'>
```




```
In [9]: sns.boxplot(data = df, x = 'Product', y = 'Education')
```

```
Out[9]: <Axes: xlabel='Product', ylabel='Education'>
```




```
In [11]: df.loc[df['Product']=='KP281'].describe()
```

Out[11]:

	Age	Education	Usage	Fitness	Income	Miles
count	80.000000	80.000000	80.000000	80.00000	80.00000	80.000000

mean	28.550000	15.037500	3.087500	2.96250	46418.02500	82.787500
std	7.221452	1.216383	0.782624	0.66454	9075.78319	28.874102
min	18.000000	12.000000	2.000000	1.00000	29562.00000	38.000000
25%	23.000000	14.000000	3.000000	3.00000	38658.00000	66.000000
50%	26.000000	16.000000	3.000000	3.00000	46617.00000	85.000000
75%	33.000000	16.000000	4.000000	3.00000	53439.00000	94.000000
max	50.000000	18.000000	5.000000	5.00000	68220.00000	188.000000

In [12]:

```
df.loc[df['Product']=='KP481'].describe()
```

Out[12]:

	Age	Education	Usage	Fitness	Income	Miles
count	60.000000	60.000000	60.000000	60.00000	60.000000	60.000000
mean	28.900000	15.116667	3.066667	2.90000	48973.650000	87.933333
std	6.645248	1.222552	0.799717	0.62977	8653.989388	33.263135
min	19.000000	12.000000	2.000000	1.00000	31836.000000	21.000000
25%	24.000000	14.000000	3.000000	3.00000	44911.500000	64.000000
50%	26.000000	16.000000	3.000000	3.00000	49459.500000	85.000000
75%	33.250000	16.000000	3.250000	3.00000	53439.000000	106.000000
max	48.000000	18.000000	5.000000	4.00000	67083.000000	212.000000

In [13]:

```
df.loc[df['Product']=='KP781'].describe()
```

Out[13]:

	Age	Education	Usage	Fitness	Income	Miles
count	40.000000	40.000000	40.000000	40.000000	40.00000	40.000000
mean	29.100000	17.325000	4.775000	4.625000	75441.57500	166.900000
std	6.971738	1.639066	0.946993	0.667467	18505.83672	60.066544
min	22.000000	14.000000	3.000000	3.000000	48556.00000	80.000000
25%	24.750000	16.000000	4.000000	4.000000	58204.75000	120.000000
50%	27.000000	18.000000	5.000000	5.000000	76568.50000	160.000000
75%	30.250000	18.000000	5.000000	5.000000	90886.00000	200.000000
max	48.000000	21.000000	7.000000	5.000000	104581.00000	360.000000

Observation

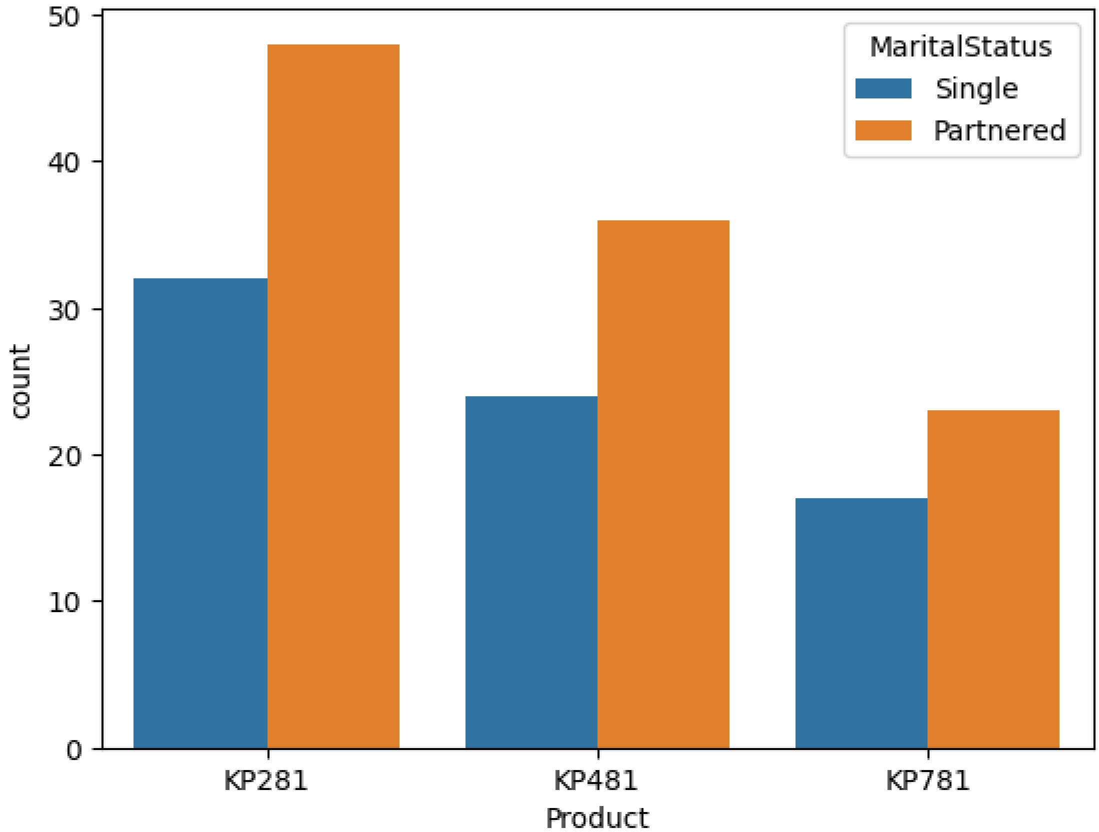
- With the observation from the box plot there isn't any considerable ouliers with respect to Income and Education.
- The Age has some outliers for all the three products.

3. Effect of Marital Status, Age on product purchase

In [14]:

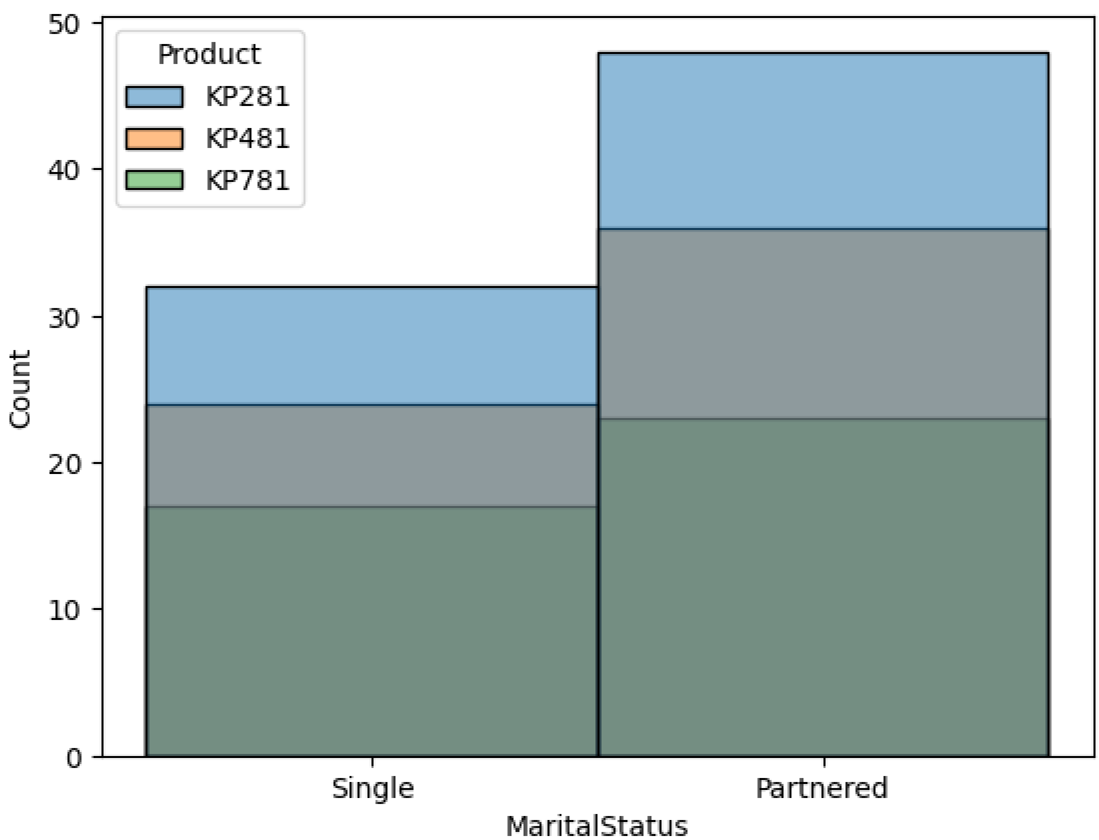
```
sns.countplot(data = df, x = 'Product', hue = 'MaritalStatus')
```

Out[14]: <Axes: xlabel='Product', ylabel='count'>



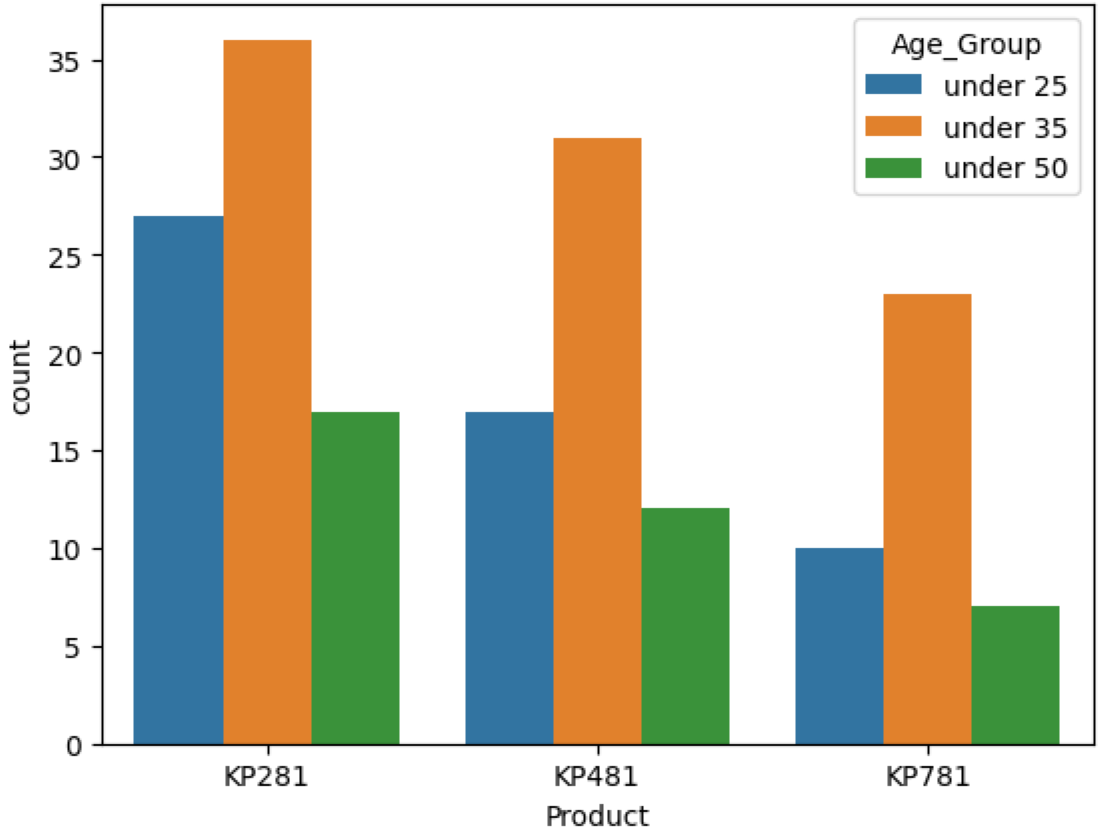
In [37]:
```
sns.histplot(data = df, x = 'MaritalStatus', hue = 'Product')
```

Out[37]: <Axes: xlabel='MaritalStatus', ylabel='Count'>



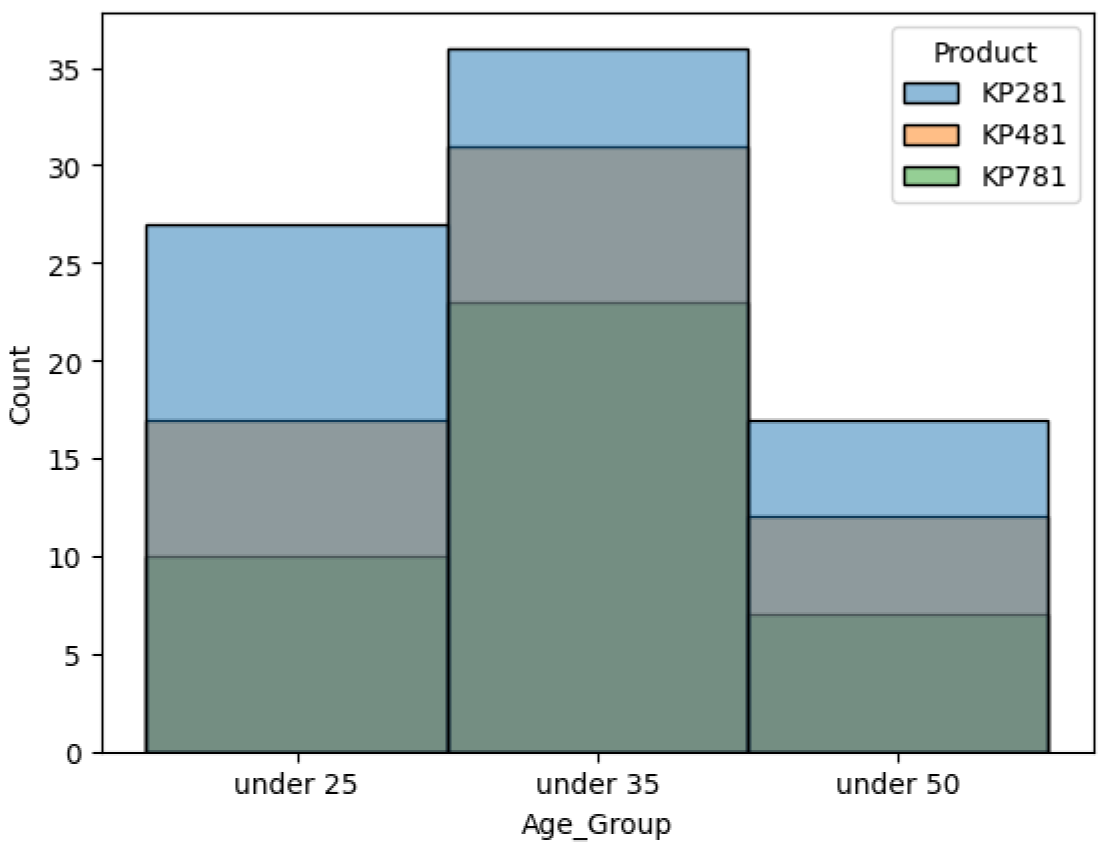
In [64]:
```
sns.countplot(data = df, x = 'Product', hue = 'Age_Group')
```

Out[64]: <Axes: xlabel='Product', ylabel='count'>



In [93]:
```
sns.histplot(data = df, x = 'Age_Group', hue = 'Product')
```

Out[93]:
```
<Axes: xlabel='Age_Group', ylabel='Count'>
```



Observation

- The marital status of the customer clearly impacts the purchase of all the three products. Married people are more prone to become customers.
- For better analysis Age has been divided into three categories such as less than 25 years, between 25 and 34 years and customers between 35 and 50 years old.
- Customers in the second group in the age abetween 25 and 34 tend to purchase a product from given three products compared to other age groups.
- More number of customers lie in the second category.

4. Marginal Probablity of Product purchase

Categorization by Age Groups

In [65]:
```
df1 = df.groupby(['Product', 'Age_Group']).agg({'Age': 'count'}).reset_index()
df1.rename(columns = {'Age': 'Count'}, inplace = True)
pd.crosstab(
    df1['Product'],
    df1['Age_Group'],
    values = df1['Count'],
    aggfunc= lambda x: round(x.sum()/df1['Count'].sum()*100,2),
    colnames = ['Purchase %'],
    margins = True,
    margins_name = 'Totals'
    )
```

Out[65]:

Purchase %	under 25	under 35	under 50	Totals
Product				
KP281	15.00	20.00	9.44	44.44
KP481	9.44	17.22	6.67	33.33
KP781	5.56	12.78	3.89	22.22
Totals	30.00	50.00	20.00	100.00

Observation

- Based on the analysis 50% of the customers belong to the age group between 25 and 34 yearr ans 30% belong to the age group under 25 years.
- 44.44% of the customers purchase the KP281 treadmill.
- The highest probablity of a customer to purchase KP781 treadmill which is the expensive in the given range of products is that the customer should belong to the age group between 25 and 34 years when compared to other age groups.

Categorization by Marital Status

In [66]:
```
df2 = df.groupby(['Product', 'MaritalStatus']).agg({'Age': 'count'}).reset_index()
df2.rename(columns = {'Age': 'Count'}, inplace = True)
pd.crosstab(
    df2['Product'],
    df2['MaritalStatus'],
    values = df2['Count'],
    aggfunc= lambda x: round(x.sum()/df2['Count'].sum()*100,2),
    colnames = ['Purchase %'],
    margins = True,
```

```
    margins_name = 'Totals'
    )
```

Out[66]:

Purchase %	Partnered	Single	Totals
Product			
KP281	26.67	17.78	44.44
KP481	20.00	13.33	33.33
KP781	12.78	9.44	22.22
Totals	59.44	40.56	100.00

Observation

- Almost 60% of the current customers are married, out of which 45% of the customers tend to purchase the product KP281.
- And 40% of the customers are single and out of which 43.8% of the customers choose the product KP281.
- No matter whether the customers are married or single the product KP281 is most likely to be chosen by the customers.

Categorization by Income Group

In [69]:

```
df3 = df.groupby(['Product', 'Income_Group']).agg({'Age': 'count'}).reset_index()
df3.rename(columns = {'Age': 'Count'}, inplace = True)
pd.crosstab(
    df3['Product'],
    df3['Income_Group'],
    values = df3['Count'],
    aggfunc= lambda x: round(x.sum()/df3['Count'].sum()*100,2),
    colnames = ['Purchase %'],
    margins = True,
    margins_name = 'Totals'
    )
```

Out[69]:

Purchase %	under 50k	under 60k	under 80k	under 105k	Totals
Product					
KP281	26.67	14.44	3.33	0.00	44.44
KP481	16.67	12.78	3.89	0.00	33.33
KP781	2.78	3.33	5.56	10.56	22.22
Totals	46.11	30.56	12.78	10.56	100.00

Observation

- From the given dataset 46.11% of the customers belong to the income category under 50k.
- 47.5% of the customers who purchased the most expensive product KP781 treadmill belongs to the income category between 80k and 105k.
- All the customers who belong to the highest income category has purchased the most expensive product.

- Only 6% of the customers from the lowest income group have chosen the most expensive product KP781.

Categorization by Gender

In [70]:
```
df4 = df.groupby(['Product', 'Gender']).agg({'Age': 'count'}).reset_index()
df4.rename(columns = {'Age': 'Count'}, inplace = True)
pd.crosstab(
    df4['Product'],
    df4['Gender'],
    values = df4['Count'],
    aggfunc= lambda x: round(x.sum()/df4['Count'].sum()*100,2),
    colnames = ['Purchase %'],
    margins = True,
    margins_name = 'Totals'
    )
```

Out[70]:

Purchase %	Female	Male	Totals
Product			
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
Totals	42.22	57.78	100.00

Observation

- The males dominate the customer count by accounting to 57.78% of the total customers.
- The probablity of male customer buying a KP781 treadmill is 0.32.
- The probablity of a female customer buying the expensive treadmill KP781 is just 0.09.

5. Correlation between factors

In [23]:
```
sns.pairplot(df)
```

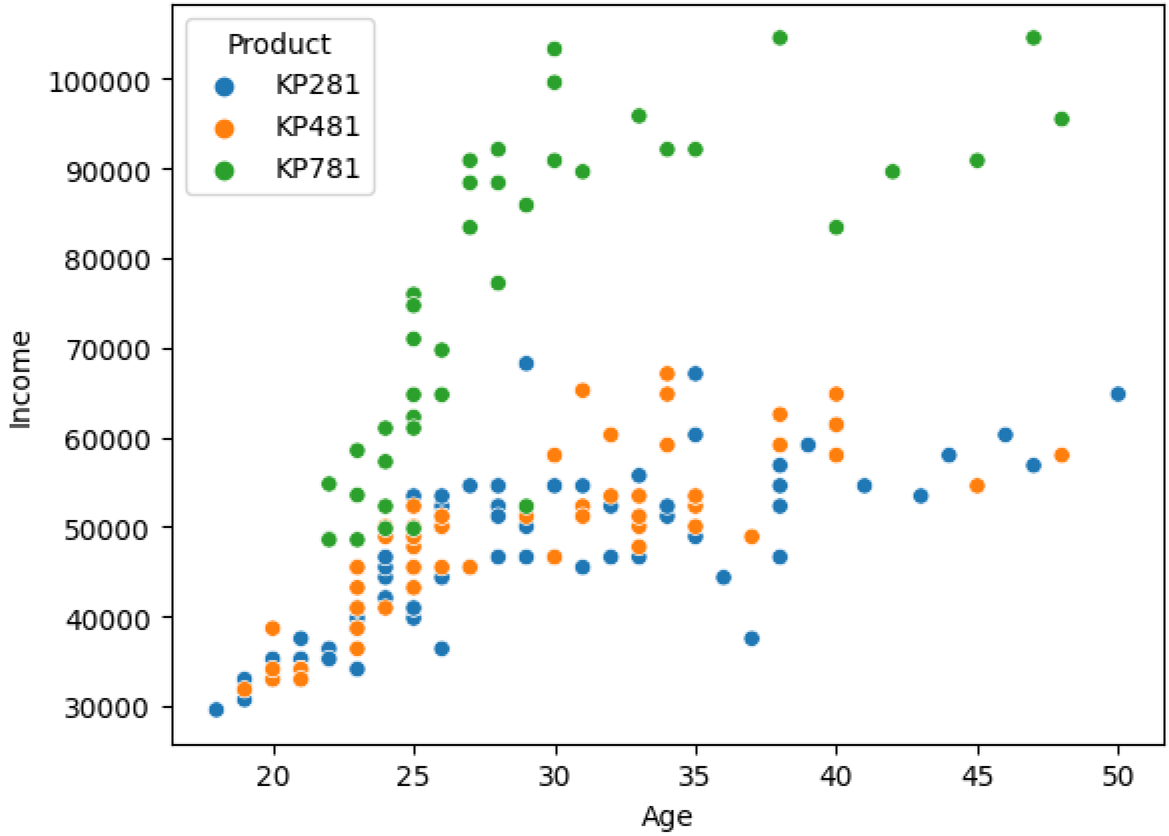
Out[23]:
```
<seaborn.axisgrid.PairGrid at 0x27f14ca27c0>
```

Observation

- From the pairplot we can find that there's a correlation between the age and income which can be plotted using a scatter plot to have a better understanding

In [96]:
```
sns.scatterplot(data = df, x = 'Age', y = 'Income', hue='Product')
```

Out[96]:
```
<Axes: xlabel='Age', ylabel='Income'>
```

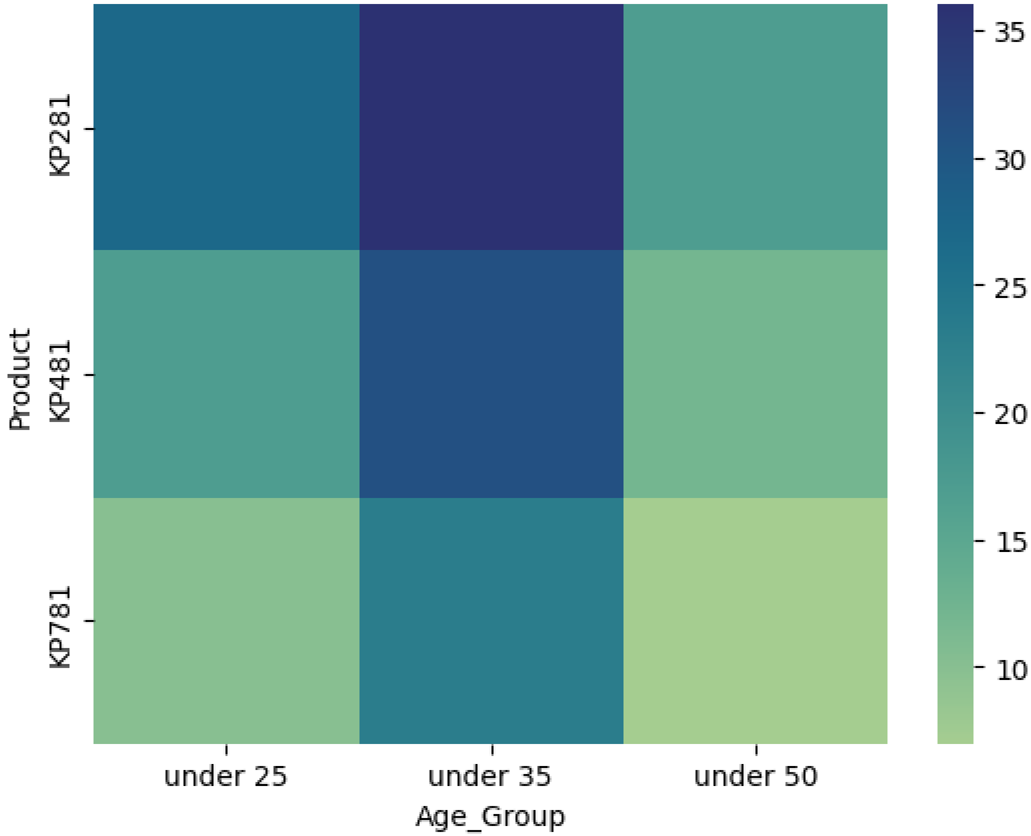


Observation

- It can be observed from the chart that as age increases the income has increased.
- Most of the customers who've purchased the expensive product KP781 belong to the income more than 50k.
- Most potential customers belong to the age group between 23 and 38.

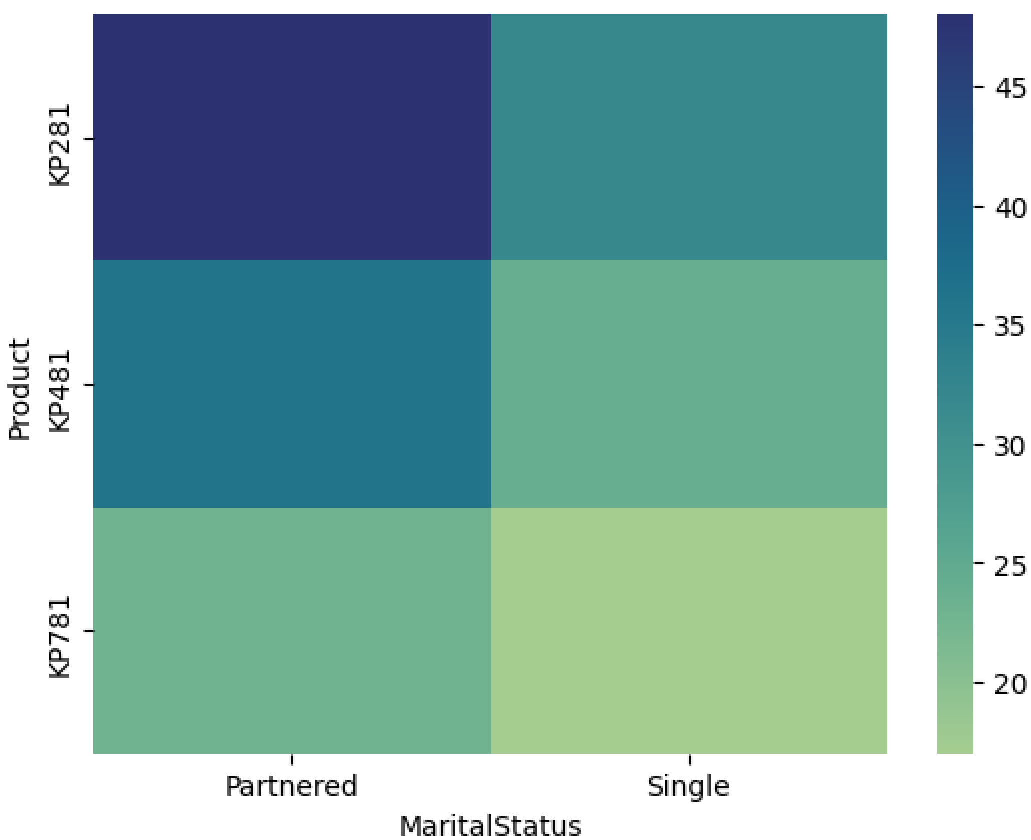
In [88]:
```
data1 = df1.pivot('Product', 'Age_Group', 'Count')
sns.heatmap(data1, cmap = 'crest')
```

Out[88]:
```
<Axes: xlabel='Age_Group', ylabel='Product'>
```



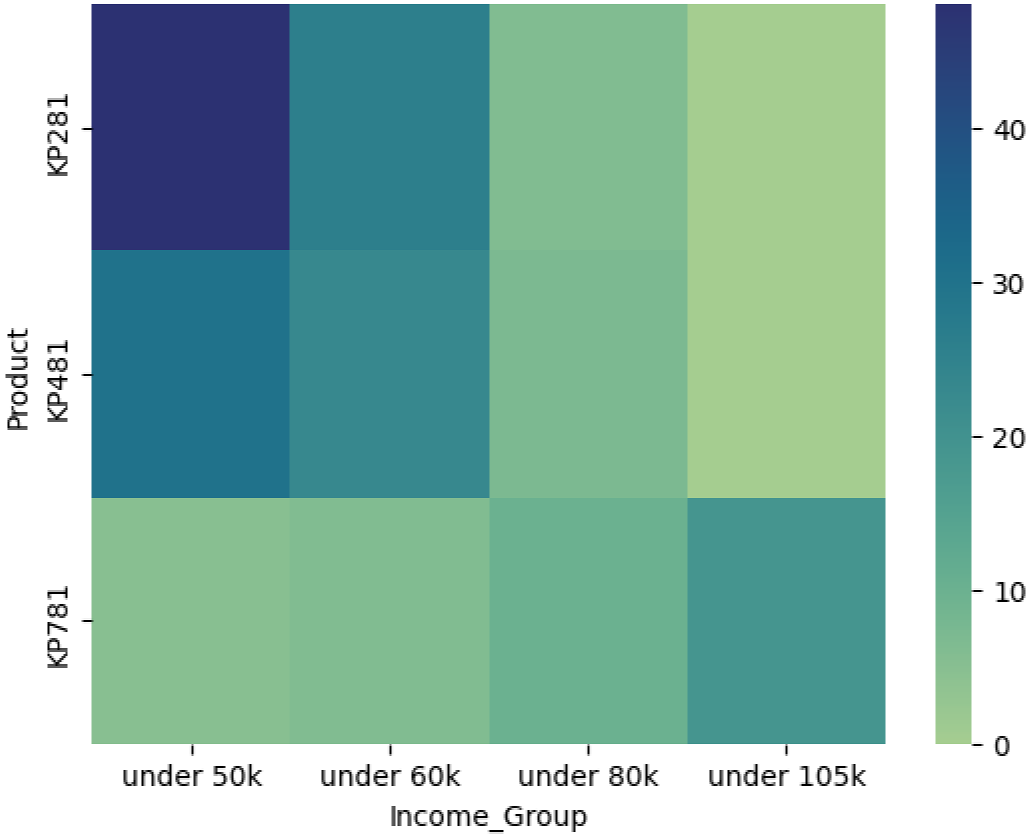
In [89]:
```
data2 = df2.pivot('Product', 'MaritalStatus', 'Count')
sns.heatmap(data2, cmap = 'crest')
```

Out[89]: <Axes: xlabel='MaritalStatus', ylabel='Product'>



In [90]:
```
data3 = df3.pivot('Product', 'Income_Group', 'Count')
sns.heatmap(data3, cmap = 'crest')
```

Out[90]: <Axes: xlabel='Income_Group', ylabel='Product'>



Observation

- Most famous product among the customers is KP281 treadmill.
- Most of the customers belong to the age group between 25 and 34 years old.
- Most of the customers are married.

Overall Insights and recommendations

Insights:

- The marital status of the customer clearly impacts the purchase of all the three products. Married people are more prone to become customers.
- For better analysis Age has been divided into three categories such as less than 25 years, between 25 and 34 years and customers between 35 and 50 years old.
- Customers in the second group in the age abetween 25 and 34 tend to purchase a product from given three products compared to other age groups. To be more precise the scatter plot shows that most of the customers afrom the age between 23 and 38.
- 44.44% of the customers purchase the KP281 treadmill which makes it the most famous product among the customers.
- Almost 60% of the current customers are married, out of which 45% of the customers tend to purchase the product KP281.
- And 40% of the customers are single and out of which 43.8% of the customers choose the product KP281.
- No matter whether the customers are married or single the product KP281 is most likely to be chosen by the customers.
- From the given dataset 46.11% of the customers belong to the income category under 50k.

- 47.5% of the customers who purchased the most expensive product KP781 treadmill belongs to the income category between 80k and 105k.
- All the customers who belong to the highest income category has purchased the most expensive product.
- Only 6% of the customers from the lowest income group have chosen the most expensive product KP781.
- The probablity of male customer buying a KP781 treadmill is 0.32 and the probablity of a female customer buying the expensive treadmill KP781 is just 0.09 which means female customers prefer less expensive treadmills.
- There is a correlation between age and the income, as age increases income has increased.
- Most of the customers who've purchased the expensive product KP781 belong to the income more than 50k.
- Most potential customers belong to the age group between 23 and 38.

Recommendations:

- Since most of the customers prefer the less expensive products, in case if there's a possibility to increase the range of prodcuts, the advice is to go for products in the price range of 1500 and 1750 dollars.
- The expensive product is purchased by the elder people and those who belong to the high income group and hence the budget to market the product should be spent to reach the high profile people with high income groups.
- As per the given dataset most of the customers belong to the age beween 23 and 38 who are more prone to be our customers. This should be communicated to the marketing team so that appropriate measures be taken to focus on this age group.