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

1.1 Defining Problem Statement and Analysing basic metrics

In [50]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv('aerofit.csv')
df2 =pd.read_csv('aerofit.csv')
```

In [4]:

```
df.head()
```

Out[4]:

	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 [5]:

```
df.shape
```

Out[5]:

```
(180, 9)
```

In [8]:

```
df.sample(20)
```

Out[8]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
27	KP281	25	Female	14	Partnered	3	3	48891	75
16	KP281	23	Female	14	Single	2	3	34110	103
126	KP481	34	Male	16	Partnered	3	4	59124	85
155	KP781	25	Male	18	Partnered	6	5	75946	240
44	KP281	28	Female	14	Partnered	2	3	46617	56
169	KP781	30	Male	18	Partnered	5	5	99601	150
120	KP481	33	Male	13	Partnered	4	4	53439	170
93	KP481	23	Male	16	Partnered	3	3	45480	64
176	KP781	42	Male	18	Single	5	4	89641	200
79	KP281	50	Female	16	Partnered	3	3	64809	66
110	KP481	26	Male	16	Single	4	3	51165	106
31	KP281	25	Male	16	Single	3	4	40932	113
86	KP481	21	Male	12	Partnered	2	2	32973	53
137	KP481	40	Male	16	Partnered	3	3	64809	95
170	KP781	31	Male	16	Partnered	6	5	89641	260
22	KP281	24	Female	16	Single	4	3	42069	94
68	KP281	38	Male	16	Partnered	3	3	46617	75
162	KP781	28	Female	18	Partnered	6	5	92131	180
125	KP481	34	Female	16	Partnered	4	3	64809	95
46	KP281	28	Male	14	Single	3	3	52302	103

Observation: there are 180 rows 9 columns and it does not seem like there are any nested data

In [6]:

```
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 [9]:

```
df.columns
```

Out[9]:

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

Observation: There are 9 columns and and we can see that there are no null values in any of the columns

In [11]:

```
df.describe()
```

Out[11]:

	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

Observation: All the relevant count , mean, std, min, 3 quartiles and max for each of the numeric fields. Usage can be treated as a categorical data between 1 and 7. Fitness is a categorical data between 1 to 5. Age, education, Income and miles are more continuous in nature.

In [12]:

```
df.describe(include=object)
```

Out[12]:

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

Observation: As can be seen above KP281 is the most popular model . more than 2/3rd (104) of the customers are Male . Most of the customer are Partnered. SO at first glance it seems like Male partnered customer is the most likely to buy a KP281, but that is not the full story.

2 Detect Outliers

In [13]:

```
df.head()
```

Out[13]:

	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

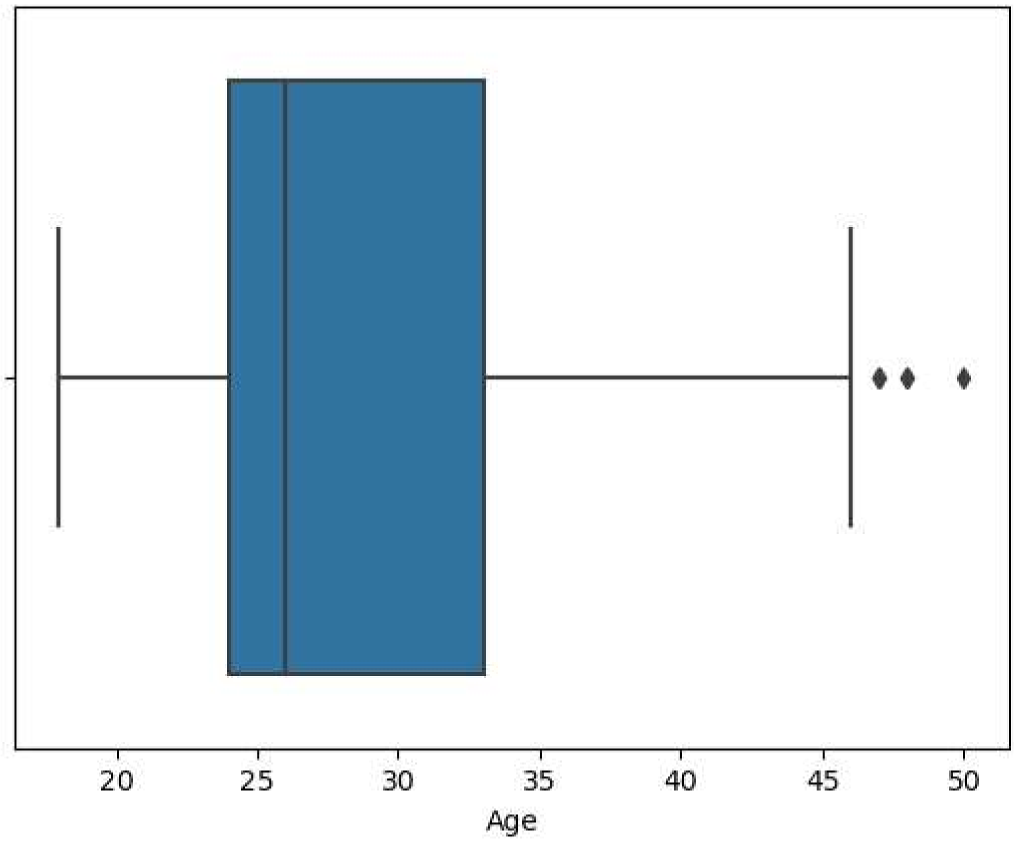
In [14]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[14]:

<AxesSubplot:xlabel='Age'>



Observation: As can be seen values roughly above 46 are outliers

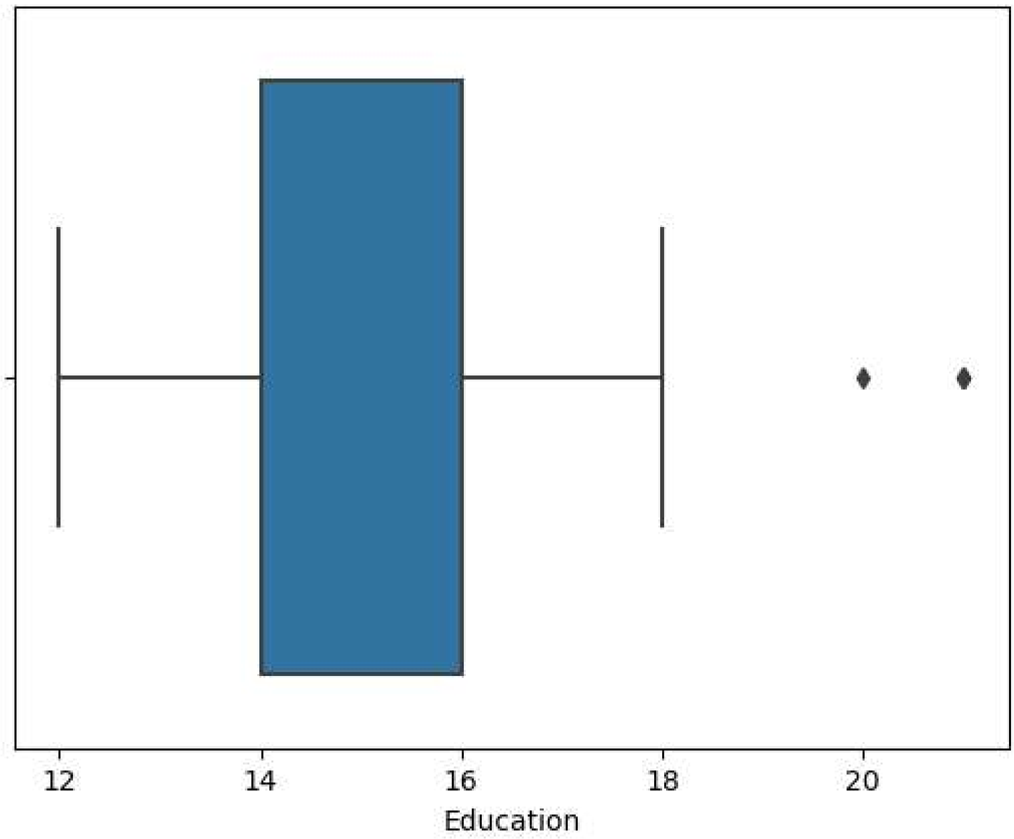
In [16]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[16]:

<AxesSubplot:xlabel='Education'>



Observation: Education roughly above 20 years can be considered as outliers

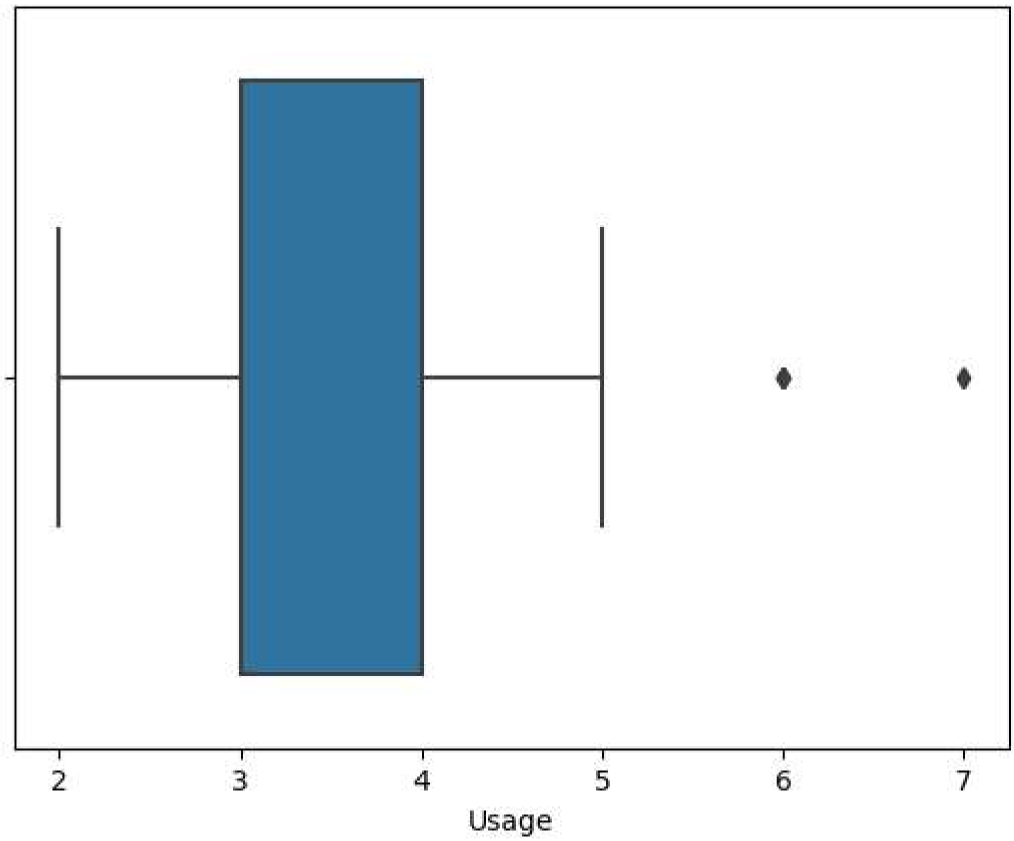
In [17]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[17]:

```
<AxesSubplot:xlabel='Usage'>
```



Observation: Usage above 5 can be considered an outlier

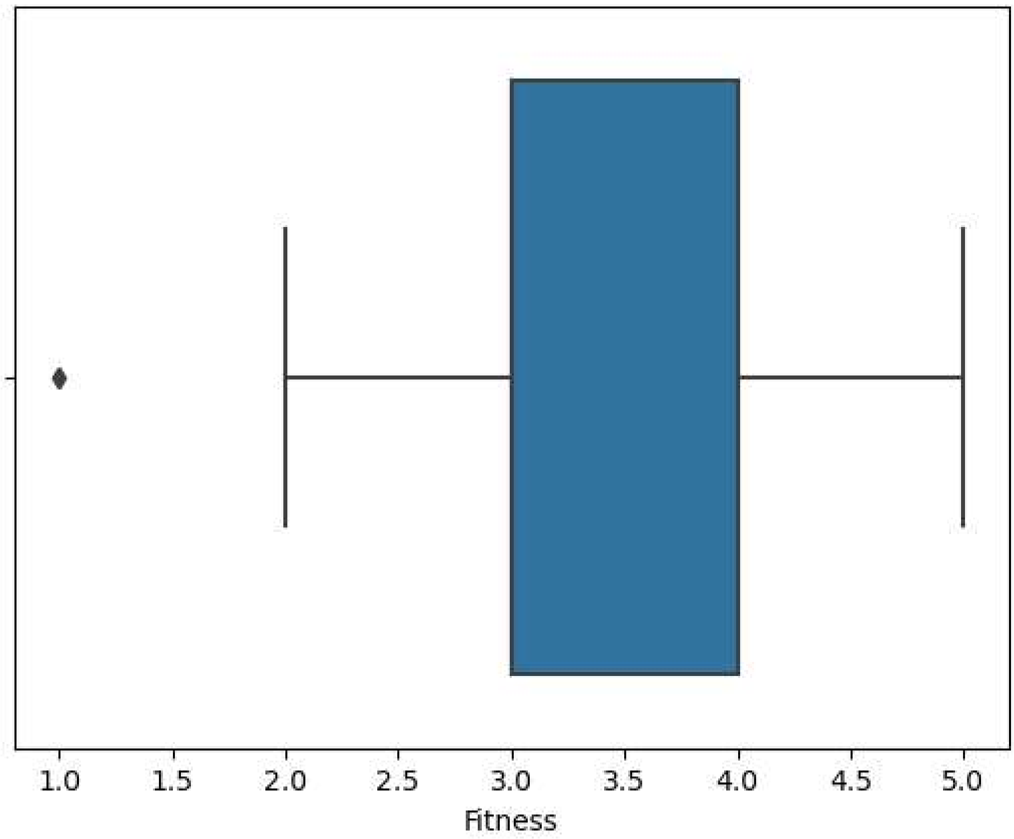
In [18]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[18]:

```
<AxesSubplot:xlabel='Fitness'>
```



Observation: Fitness lower than 2 can be considered as outlier

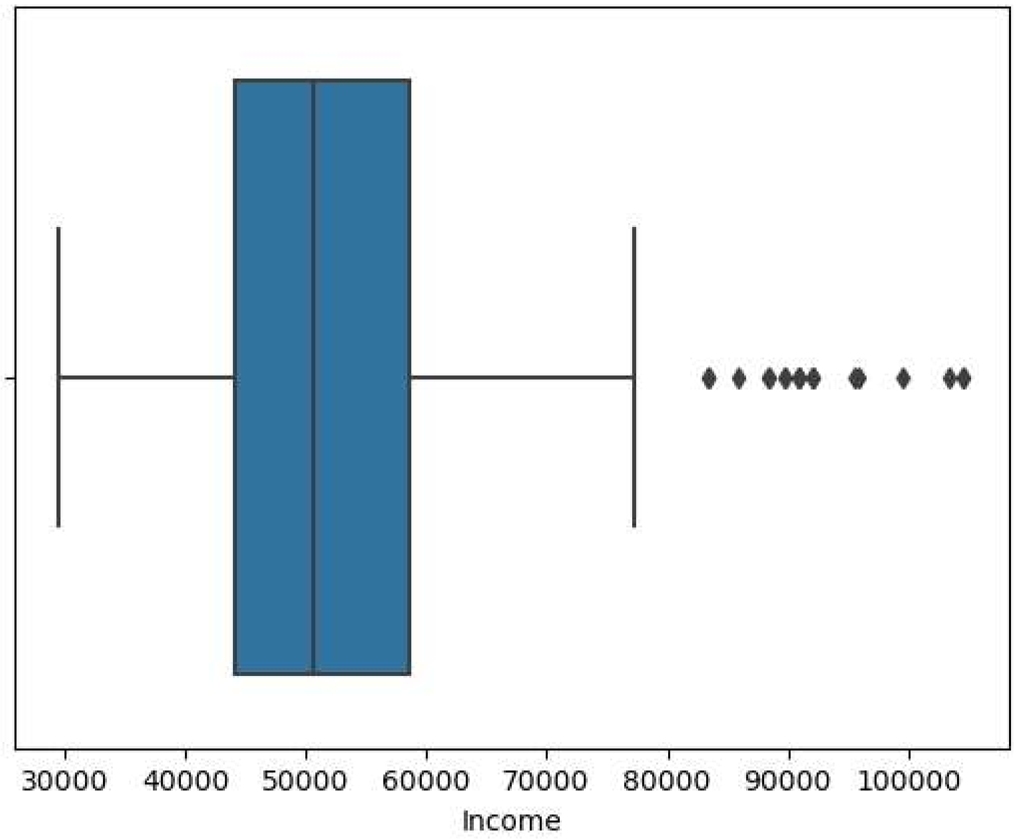
In [19]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[19]:

```
<AxesSubplot:xlabel='Income'>
```



Observation: Income more than 80000 can be considered as outlier

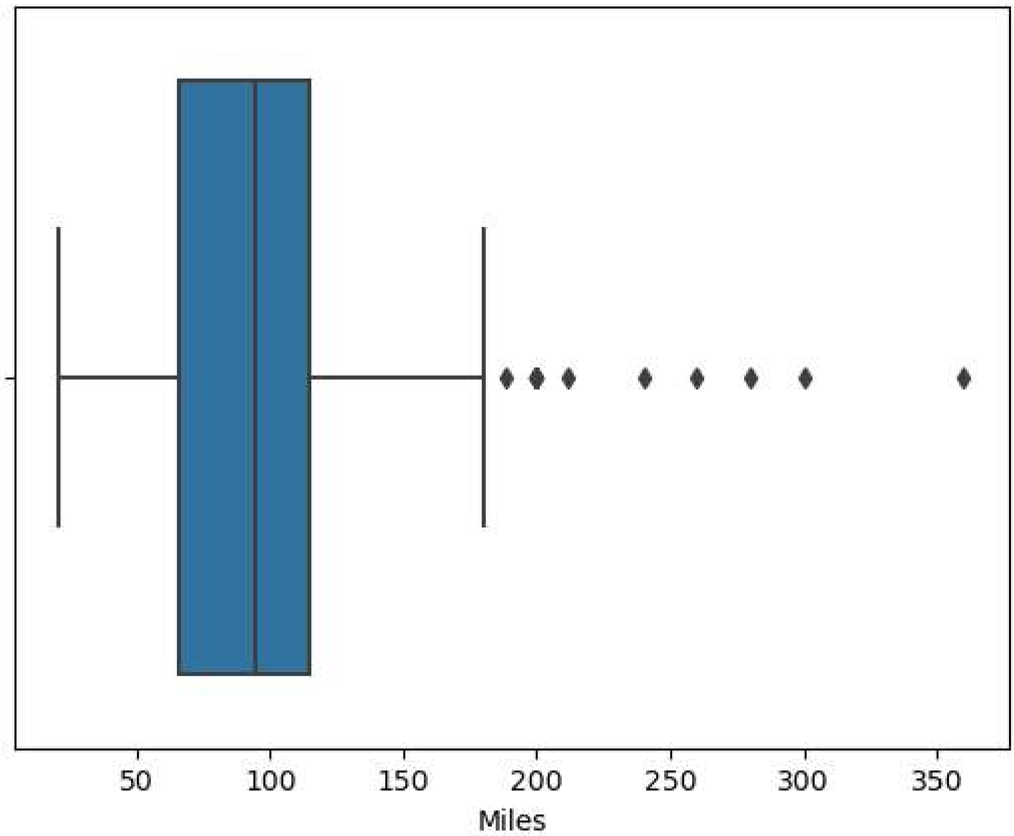
In [20]:

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

```
D:\anaconda_home\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[20]:

```
<AxesSubplot:xlabel='Miles'>
```



Observation: Expected miles roughly more than 180 can be considered as outlier

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

3.1 Visual Analysis - Univariate & Bivariate

In [3]:

```
df.head()
```

Out[3]:

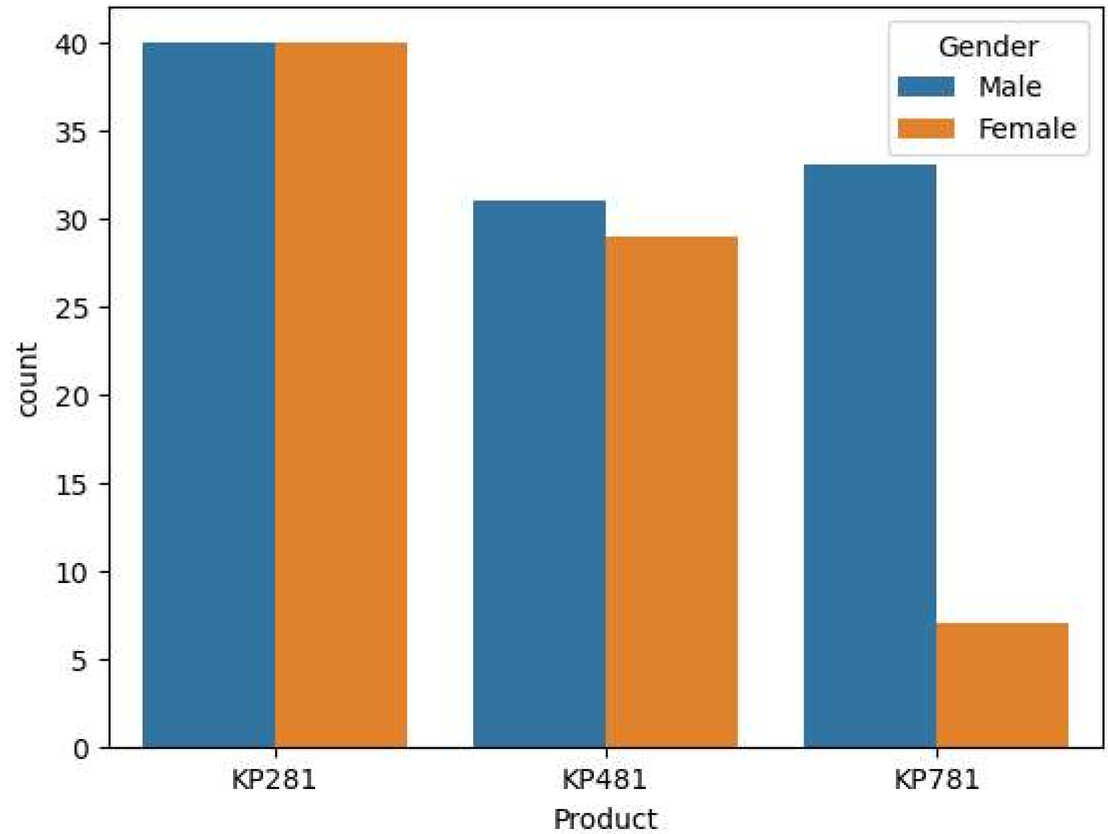
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

In [76]:

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

Out[76]:

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



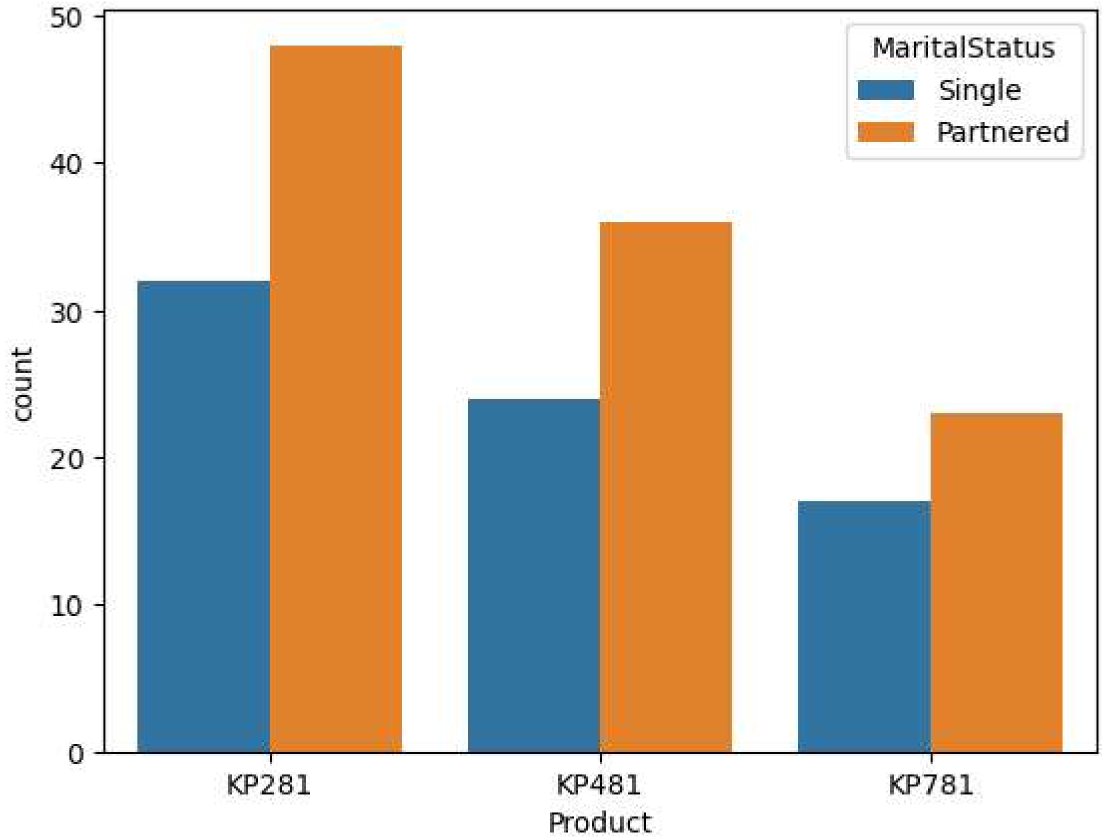
Observation: KP281 and KP481 are almost equaly popular among Male and Female whereas KP781 is significantly more popular among Male customers

In [6]:

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

Out[6]:

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



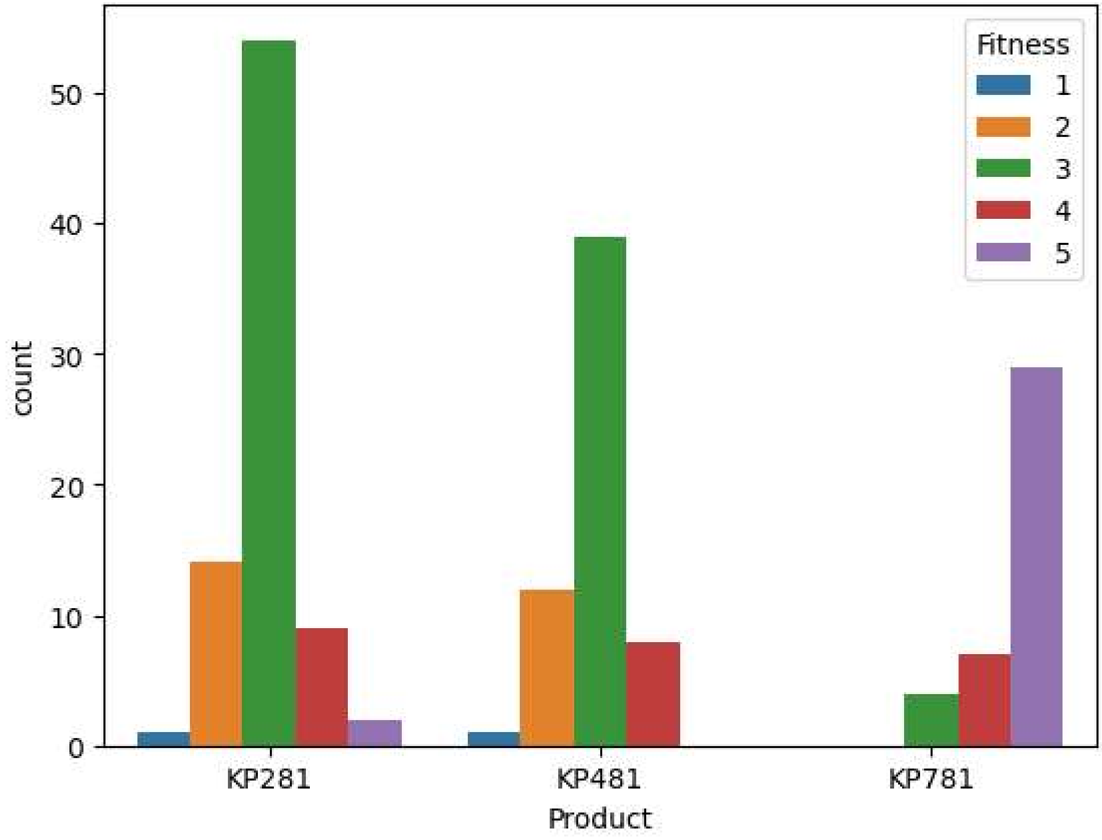
Observation: Partnered people are more likely to buy treadmills across all 3 products. But the difference between single and partnered people keeps decreasing from KP281 to KP481 to KP781

In [7]:

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

Out[7]:

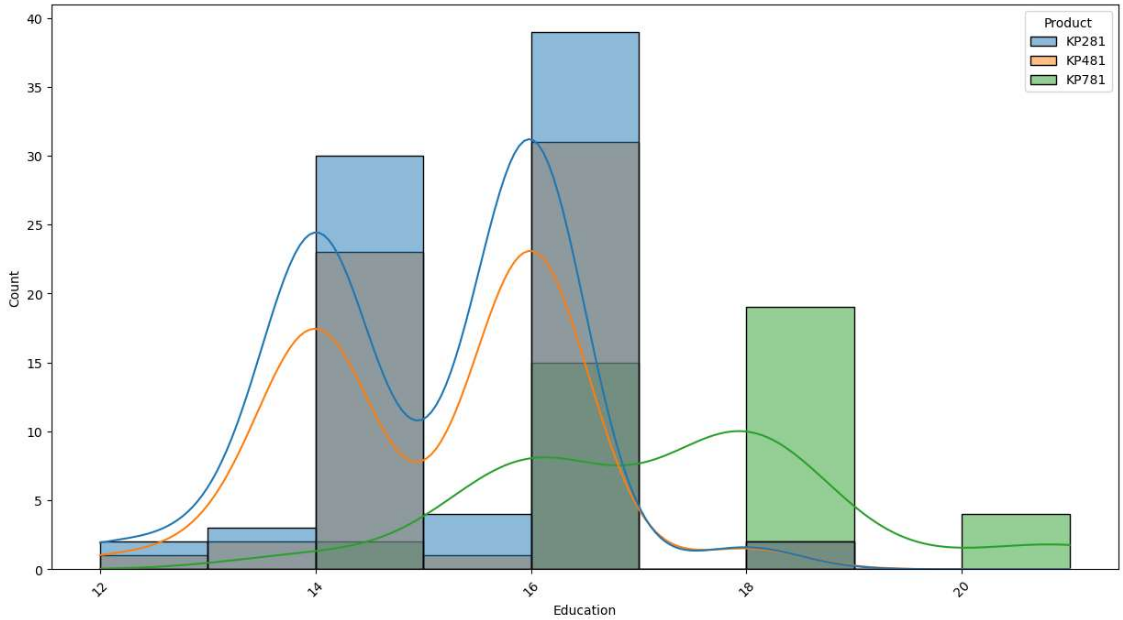
```
<AxesSubplot:xlabel='Product', ylabel='count'>
```



Observation: People who rate themselves as 2 and 3 are more likely to buy KP281 and KP481 where as people who rate themselves as 4 and 5 are more likely to buy KP781

In [78]:

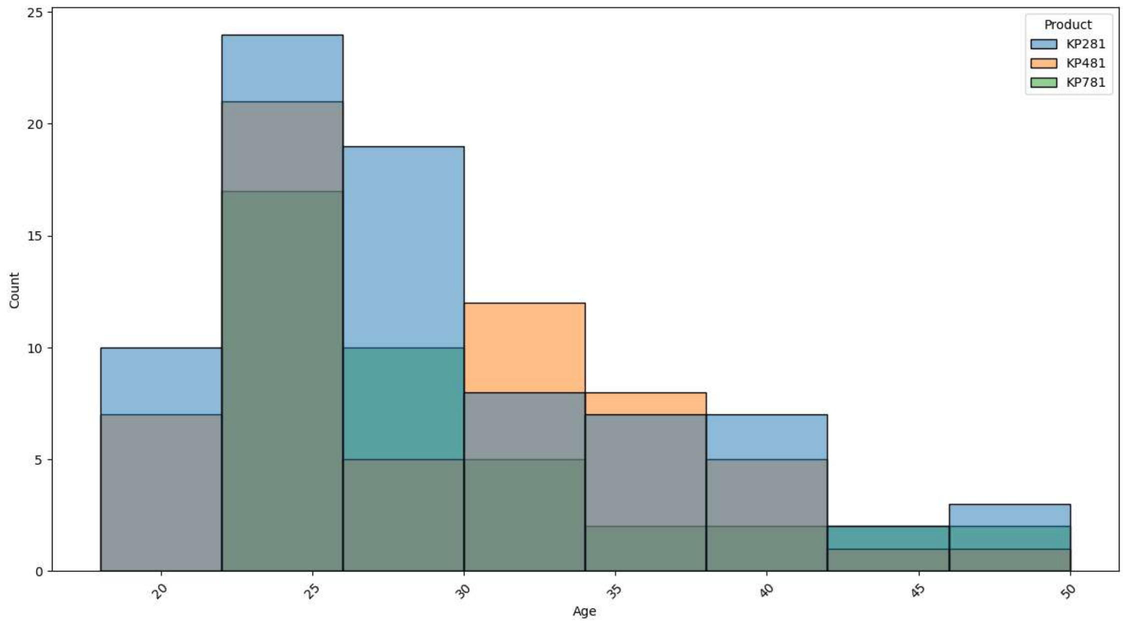
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(hue ='Product',x="Education", bins=9, data = df, kde=True)
plt.show()
```



Observation: People with 14 , 16 or 18 years of education are more likely to buy a treadmill. all three products are popular among people with education 16 or less. whereas people with education level 18 and above almost exclusively buy KP781

In [79]:

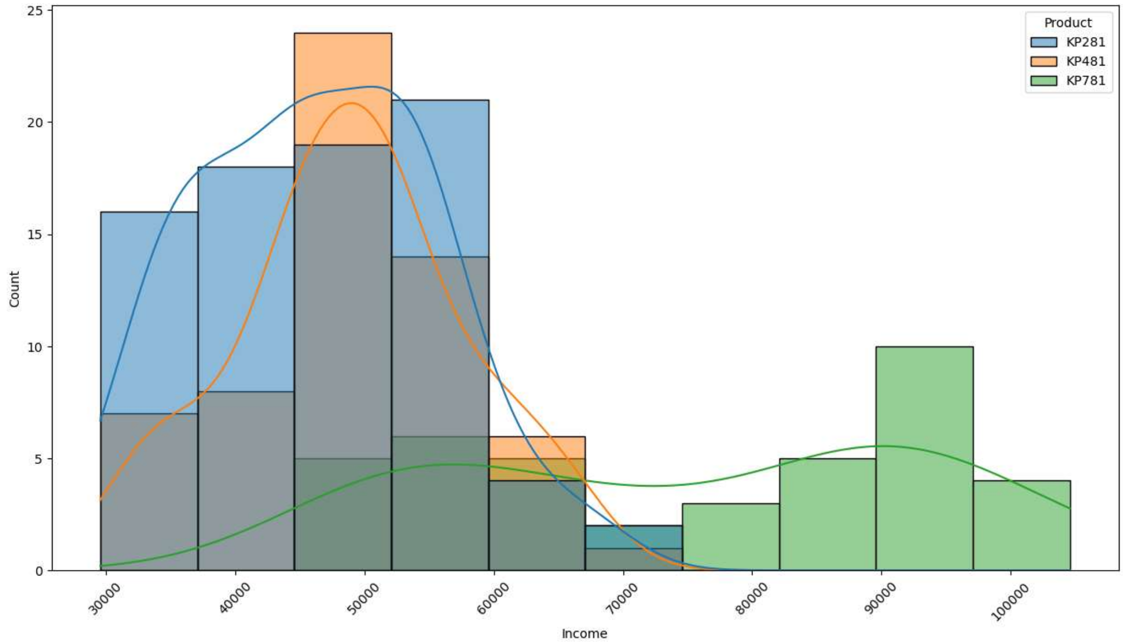
```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(hue ='Product',x="Age", bins=8, data = df)
plt.show()
```



Observation: Treadmills are mostly popular in the 22 to 34 years of Age range. the likelihood of buying a treadmill decreases with increase in age. KP781 is particularly popular in the 22 to 26 years of age range

In [23]:

```
plt.figure(figsize=(15,8))
plt.xticks(rotation=45)
sns.histplot(hue ='Product',x="Income", bins=10, data = df, kde=True)
plt.show()
```



Observation: People with income above 75000 almost exclusively buy KP781. People with income from 30000 to 59000 generally prefer KP281 and KP481. Popularity of treadmill is lowest in the 66000 to 74000 income range

4 Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table

4.1 Non-Graphical Analysis: Value counts and unique attributes

In [27]:

```
df.head()
```

Out[27]:

	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 [28]:

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

Out[28]:

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

Observation: the entry-level KP281 is the most popular product.

In [29]:

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

Out[29]:

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

Observation: Male buy more treadmill

In [30]:

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

Out[30]:

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

Observation: Partnered people are more likely to buy treadmill

In [31]:

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

Out[31]:

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

Observation: People rating themselves at fitness 3 is almost 3 time likely to buy a treadmill than the second most common rating of 5

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

In [41]:

```
sns.heatmap(df.corr(),annot=True, cmap="crest")
```

Out[41]:

```
<AxesSubplot:>
```

Observation: features that seem like most correlated are:

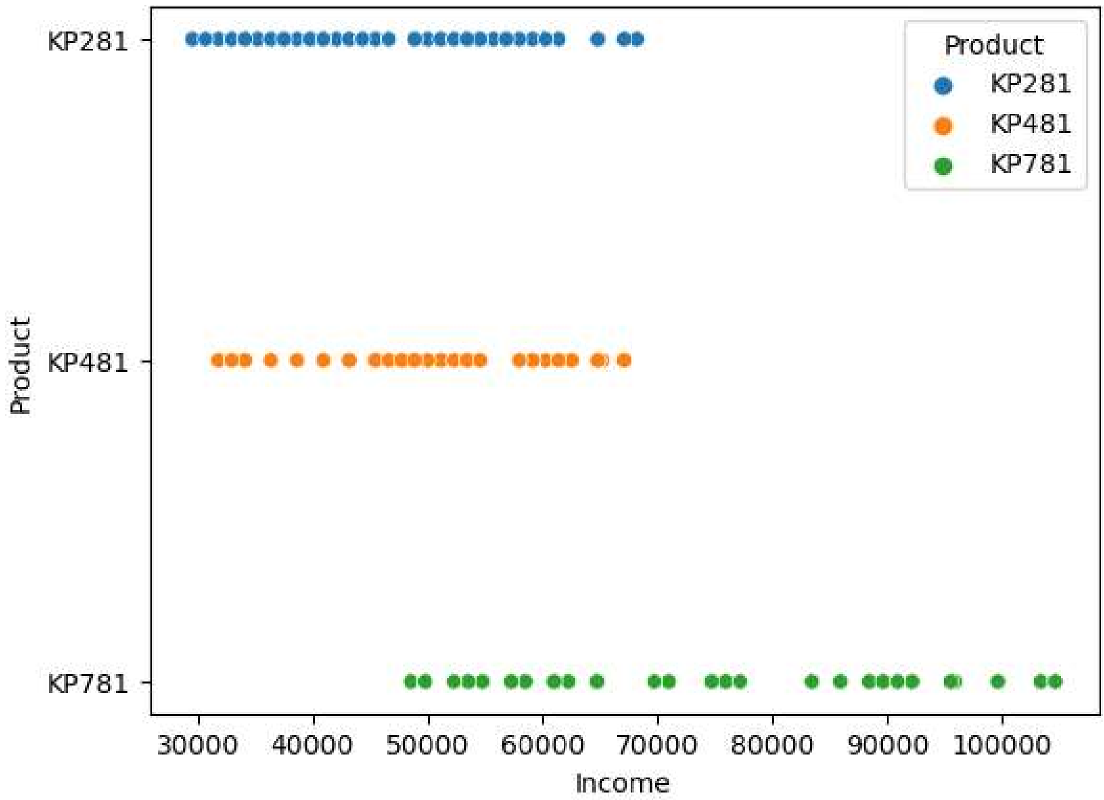
1. Age seems to have the least coorelation with other fields
2. Education correlated to Income
3. Income and Fitness are very highly correlated to most of the other fields. which means they are key determining factors while making a purchase decision

In [70]:

```
sns.scatterplot(x='Income',y='Product', hue="Product",data=df)
```

Out[70]:

```
<AxesSubplot:xlabel='Income', ylabel='Product'>
```



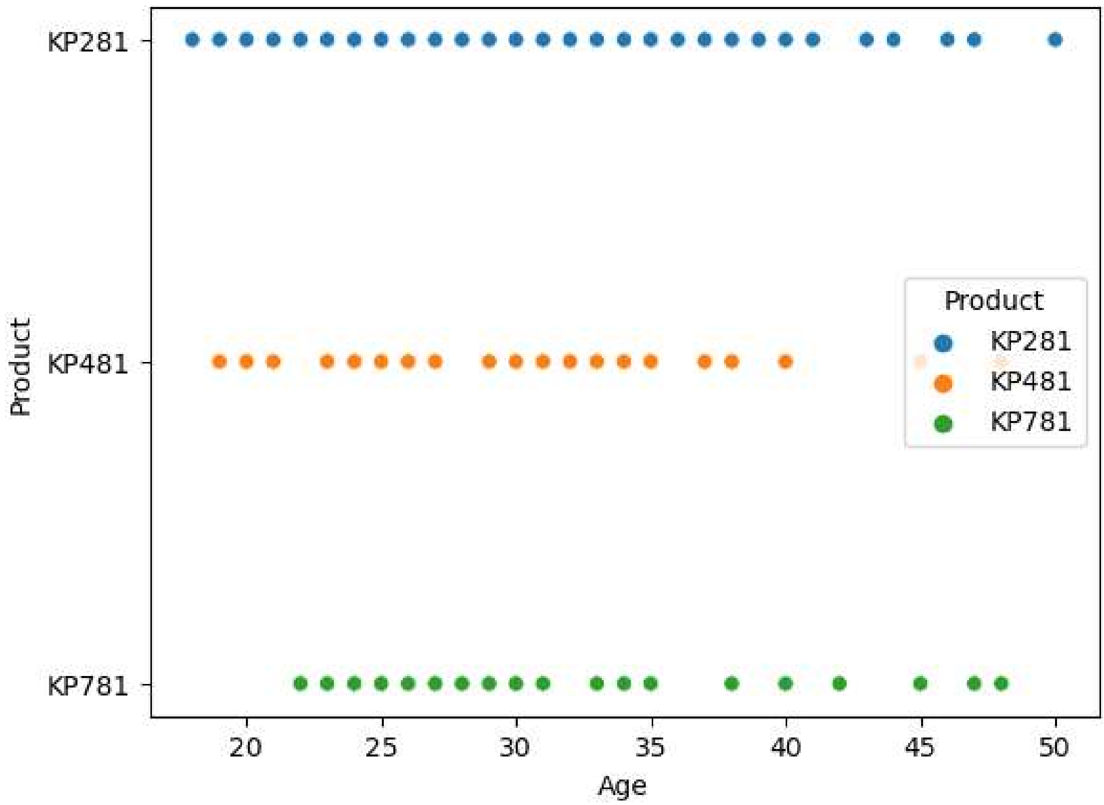
Observation: People with income above 75000 almost exclusively buy KP781. People with income from 30000 to 59000 generally prefer KP281 and KP481. Popularity of treadmill is lowest in the 66000 to 74000 income range

In [71]:

```
sns.scatterplot(x='Age',y='Product', hue="Product",data=df)
```

Out[71]:

<AxesSubplot:xlabel='Age', ylabel='Product'>



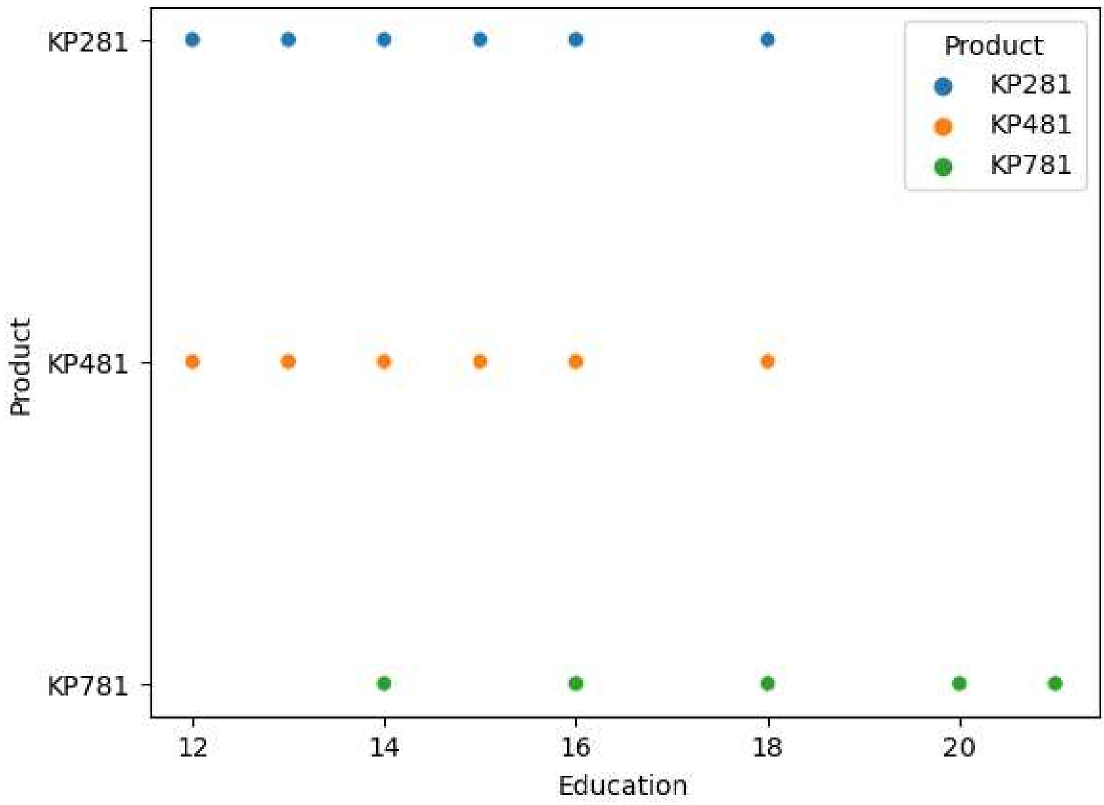
Observation: Treadmills are mostly popular in the 22 to 34 years of Age range. the likelihood of buying a treadmill decreases with increase in age.

In [72]:

```
sns.scatterplot(x='Education',y='Product', hue="Product",data=df)
```

Out[72]:

```
<AxesSubplot:xlabel='Education', ylabel='Product'>
```



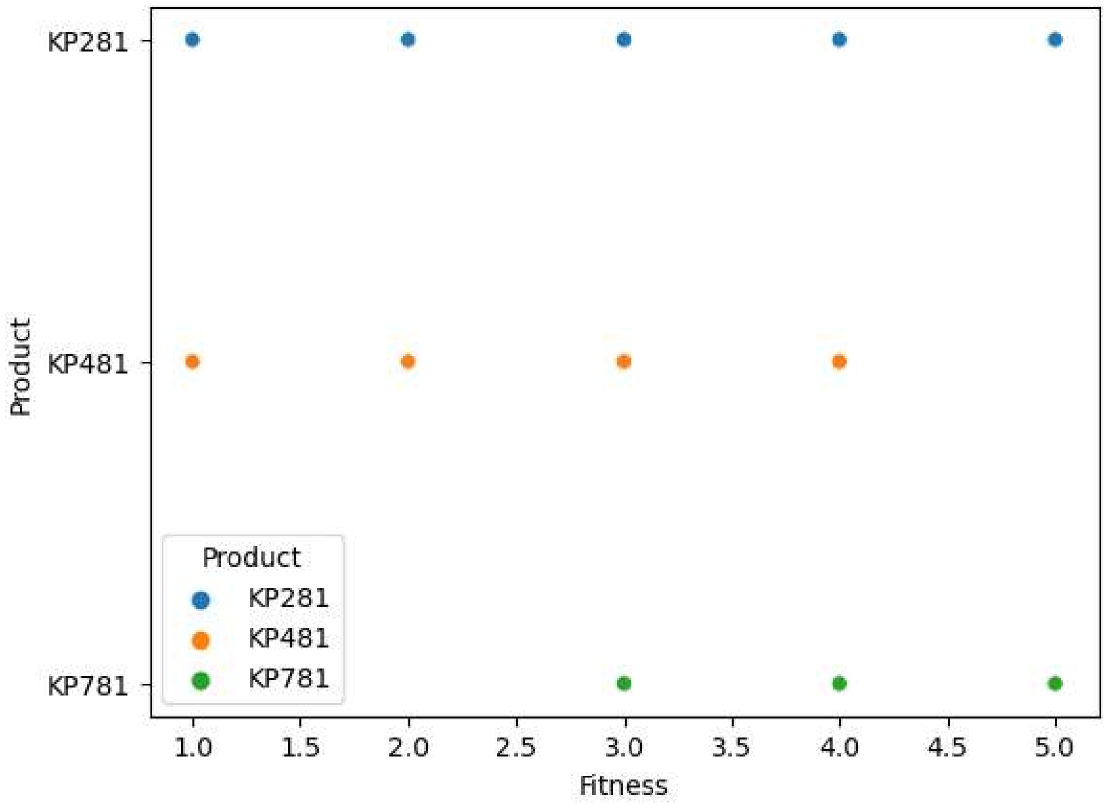
Observation: people with education level 18 and above almost exclusively buy KP781. people with education level lower than 14 prefer either KP281 or KP481

In [73]:

```
sns.scatterplot(x='Fitness',y='Product', hue="Product",data=df)
```

Out[73]:

```
<AxesSubplot:xlabel='Fitness', ylabel='Product'>
```



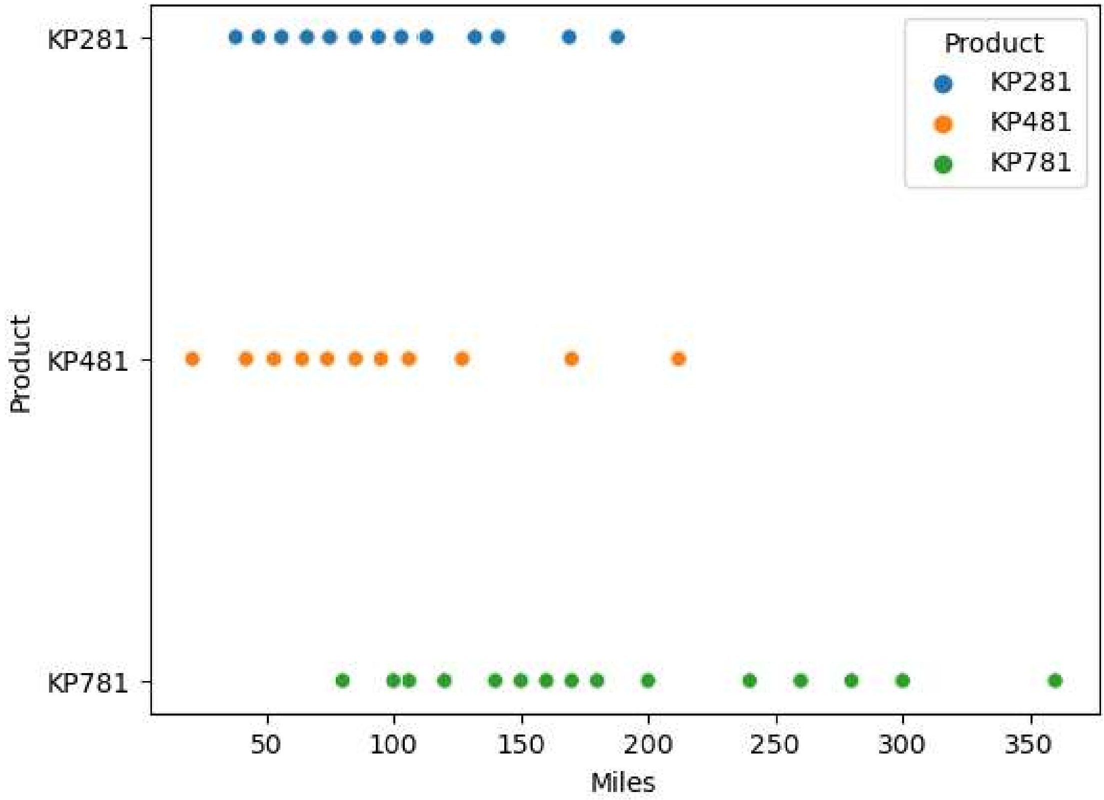
Observation: People who rate themselves as lower than 3 are more likely to buy KP281 and KP481 where as people who rate themselves as 4 and 5 are more likely to buy KP781

In [74]:

```
sns.scatterplot(x='Miles',y='Product', hue="Product",data=df)
```

Out[74]:

```
<AxesSubplot:xlabel='Miles', ylabel='Product'>
```



Observation: People who intend to run more than 240 Mile almost exclusively buy KP781. Whereas People who want to run less than 100 miles tend to prefer either of KP281 or KP481

In [42]:

```
plt.figure(figsize=(8,8))
sns.pairplot(data=df,hue="Product")
```

Out[42]:

<seaborn.axisgrid.PairGrid at 0x2063ff25d90>

<Figure size 800x800 with 0 Axes>

Observation:

6 Probability- marginal, conditional probability.

6.1 analyse data using pandas.crosstab to identify the relation between the different parameters

In [44]:

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

Out[44]:

Gender	Female		Male	
MaritalStatus	Partnered	Single	Partnered	Single
Product				
KP281	27	13	21	19
KP481	15	14	21	10
KP781	4	3	19	14

Observation: KP781 is more popular among Male. partnered people are more likely to buy treadmills. partnered female has a higher preference for KP281.

In [45]:

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

Out[45]:

Gender	Female						Male							
Education	13	14	15	16	18	21	12	13	14	15	16	18	20	21
Product														
KP281	0	18	2	19	1	0	2	3	12	2	20	1	0	0
KP481	1	12	0	14	2	0	1	1	11	1	17	0	0	0
KP781	0	0	0	2	4	1	0	0	2	0	13	15	1	2

Observation: KP281 and KP481 is mostly popular among male and female Education of 14 and 16. KP 781 is mostly popular among Male in the education of 16 and 18. Male 16 year Education in general has the highest chance of buying a treadmill across all 3 products.

In [46]:

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

Out[46]:

Gender	Female					Male				
Fitness	1	2	3	4	5	1	2	3	4	5
Product										
KP281	0	10	26	3	1	1	4	28	6	1
KP481	1	6	18	4	0	0	6	21	4	0
KP781	0	0	1	1	5	0	0	3	6	24

Observation: Male and female with a fitness score of 3 is more likely to buy KP281 or KP481/ Where as male of female with fitness rating 5 is more likely to buy KP781

In [80]:

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

Out[80]:

Gender	Female					Male					
Usage	2	3	4	5	6	2	3	4	5	6	7
Product											
KP281	13	19	7	1	0	6	18	15	1	0	0
KP481	7	14	5	3	0	7	17	7	0	0	0
KP781	0	0	2	3	2	0	1	16	9	5	2

Observation: Female with usage 2 and 3 is more likely to buy KP281 and KP 481. Male with usage 3 tend to buy KP281 or KP481 . Where as KP781 is preferred by Male with usage 4 or 5

In [49]:

```
pd.crosstab(df['Product'], [df['Gender'], df['MaritalStatus'],df['Fitness'],df['Educati
```

Out[49]:

			Product	KP281	KP481	KP781
Gender	**MaritalStatus**	**Fitness**	**Education**			
Female	**Partnered**	**2**	**14**	4	1	0
			15	1	0	0
			16	2	1	0
		3	**14**	9	4	0
			15	1	0	0
			16	8	8	0
		4	**14**	1	1	0
		5	**16**	1	0	1
			18	0	0	3
	Single	**1**	**18**	0	1	0
		2	**14**	1	3	0
			16	2	1	0
		3	**13**	0	1	0
			14	2	2	0
			16	5	3	0
			18	1	0	0
			21	0	0	1
		4	**14**	1	1	0
			16	1	1	0
			18	0	1	1
		5	**16**	0	0	1

			Product	KP281	KP481	KP781
Gender	**MaritalStatus**	**Fitness**	**Education**			
Male	**Partnered**	**1**	**16**	1	0	0
		2	**12**	0	1	0
			13	2	0	0
			14	1	0	0
			16	1	4	0
		3	**14**	2	3	0
			16	10	10	0
			18	1	0	1
		4	**13**	0	1	0
			14	1	1	0
			16	2	1	2
			18	0	0	2
			21	0	0	1
		5	**14**	0	0	1
			16	0	0	4
			18	0	0	7
			20	0	0	1
	Single	**2**	**14**	0	1	0
		3	**12**	2	0	0
			13	1	0	0
			14	7	5	1
			15	1	1	0
			16	4	2	0
			18	0	0	1
		4	**14**	1	1	0
			15	1	0	0
			16	1	0	0
			18	0	0	1
		5	**16**	1	0	7
			18	0	0	3
			21	0	0	1

Observation: Male , partnered , 3 fitness score, and 16 year education AND Female , partnered , 3 fitness score, and 16 year education are more likely to buy a KP281 or KP481 treadmill. where as Male, Partnered with fitness rating 4 or 5 is more likely to buy KP781.

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

In [43]:

```
df.head()
```

Out[43]:

	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

6.2.1 Marginal probability

In [51]:

```
df.groupby('Gender').size().div(len(df))
```

Out[51]:

```
Gender
Female    0.422222
Male      0.577778
dtype: float64
```

In [60]:

```
bins = [18, 20, 25, 30, 35, 40, 46] #removed outlier 50
groups = df.groupby(['Product', pd.cut(df['Age'], bins)])
groups.size().unstack()
```

Out[60]:

Age	(18, 20]	(20, 25]	(25, 30]	(30, 35]	(35, 40]	(40, 46]
Product						
KP281	5	28	21	11	8	4
KP481	4	24	7	17	6	1
KP781	0	17	13	4	2	2

In [59]:

```
groups.size().unstack().div(len(df))
```

Out[59]:

Age	(18, 20]	(20, 25]	(25, 30]	(30, 35]	(35, 40]	(40, 46]
Product						
KP281	0.027778	0.155556	0.116667	0.061111	0.044444	0.022222
KP481	0.022222	0.133333	0.038889	0.094444	0.033333	0.005556
KP781	0.000000	0.094444	0.072222	0.022222	0.011111	0.011111

Observation: Male have a higher probability to buy a treadmill. KP281 and KP781 is most popular in the age group of 20 to 30. Where as KP481 is popular in the age group 20 to 25 and 30 to 35.

In [57]:

```
df.groupby('MaritalStatus').size().div(len(df))
```

Out[57]:

```
MaritalStatus
Partnered    0.594444
Single       0.405556
dtype: float64
```

Observation: Partnered people has almost 60 % chance to buy a treadmill.

In [63]:

```
bins2 =[30000, 40000,50000,60000,70000, 80000]
groups2 = df.groupby(['Product', pd.cut(df['Income'], bins2)])
groups2.size().unstack()
```

Out[63]:

Income Product	(30000, 40000]	(40000, 50000]	(50000, 60000]	(60000, 70000]	(70000, 80000]
KP281	22	25	26	6	0
KP481	9	21	23	7	0
KP781	0	5	6	6	4

In [64]:

```
groups2.size().unstack().div(len(df))
```

Out[64]:

Income Product	(30000, 40000]	(40000, 50000]	(50000, 60000]	(60000, 70000]	(70000, 80000]
KP281	0.122222	0.138889	0.144444	0.033333	0.000000
KP481	0.050000	0.116667	0.127778	0.038889	0.000000
KP781	0.000000	0.027778	0.033333	0.033333	0.022222

Observation: people with income between 30k and 60k tend to buy KP281 or KP481. Where as people with income more than 70k almost exclusively buy KP781

6.2.2 Conditional Probability:

In [66]:

```
pd.crosstab(df['Product'], df['Gender'], margins=True, normalize="columns")
```

Out[66]:

Gender Product	Female	Male	All
KP281	0.526316	0.384615	0.444444
KP481	0.381579	0.298077	0.333333
KP781	0.092105	0.317308	0.222222

Observation:

In [67]:

```
pd.crosstab(df['Product'], df['MaritalStatus'], margins=True, normalize="columns")
```

Out[67]:

MaritalStatus Product	Partnered	Single	All
KP281	0.448598	0.438356	0.444444
KP481	0.336449	0.328767	0.333333
KP781	0.214953	0.232877	0.222222

Observation:

In [68]:

```
pd.crosstab(df['Product'], df['Fitness'], margins=True, normalize="columns")
```

Out[68]:

Fitness Product	1	2	3	4	5	All
KP281	0.5	0.538462	0.556701	0.375000	0.064516	0.444444
KP481	0.5	0.461538	0.402062	0.333333	0.000000	0.333333
KP781	0.0	0.000000	0.041237	0.291667	0.935484	0.222222

Observation: people with fitness rating 1 or 2 never buys KP781 . whereas people with fitness rating 5 never buys KP481

7 Customer Profiling - Categorization of users.

7.1 KP281

Customer Profile:

> 1. Age : 20 to 30
> 2. Gender : Female / Male
> 3. Education : 14 to 16
> 4. Marital Status : Partnered
> 5. Usage : 2 to 3
> 6. Fitness : 2/3
> 7. Income : 30000 to 59000
> 8. Miles : less than 150

7.2 KP481

Customer Profile:

> 1. Age : 20 to 25 or 30 to 35
> 2. Gender : Male / female
> 3. Education : 14 to 16
> 4. Marital Status: Partnered
> 5. Usage : 2 to 3
> 6. Fitness : 2/3
> 7. Income : 30000 to 59000
> 8. Miles: less than 150

7.3 KP781

Customer Profile:

> 1. Age : 22 to 26
> 2. Gender : Male
> 3. Education : greater than 16
> 4. Marital Status : Partnered
> 5. Usage: 4 to 5
> 6. Fitness : 4/5
> 7. Income : greater than 75000
> 8. Miles: greater than 200

8 Some recommendations and actionable insights, based on the inferences

8.1 Business Insights based on Non-Graphical and Visual Analysis

All the insights and observations are mentioned next to each cell after both graphical and non-graphical analysis is done. Marked as "Observation"

8.2 Recommendations

1. KP281 and KP481 has overlapping customer profile. SO they can be either clubbed into a single product or changes shoul be made to make them more different to appeal to different demographic
2. Single people are less likely to buy treadmills over all. so more effort needs to go in to attract more single customers.
3. People with education lower than 14 does not buy treadmills . So the efforts needs to be made to make the product more accessible to this demographic.
4. Lower priced entry level model needed for income group less than 30k