In [1]:

```
import pandas as pd
```

In [2]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [3]:

```
data=pd.read_csv(r"C://Users//aerofit_treadmill.csv")
```

In [4]:

```
data.columns
```

Out[4]:

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

BASIC OBSERVATIONS

In [5]:

```
data.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]:

```
data.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]:

```
data.shape
```

Out[7]:

```
(180, 9)
```

NON-GRAPHICAL ANALYSIS

In [8]:

```
data.isnull().sum()/len(data)*100
```

Out[8]:

```
Product          0.0
Age              0.0
Gender           0.0
Education        0.0
MaritalStatus    0.0
Usage            0.0
Fitness          0.0
Income           0.0
Miles            0.0
dtype: float64
```

In [9]:

```
data["Product"].value_counts()
```

Out[9]:

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

In [10]:

```
data["MaritalStatus"].value_counts()
```

Out[10]:

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

In [11]:

```
data["Usage"].value_counts().sort_values()
```

Out[11]:

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

In [12]:

```
data["Fitness"].value_counts().sort_values()
```

Out[12]:

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

In [13]:

```
data["Gender"].value_counts().sort_values()
```

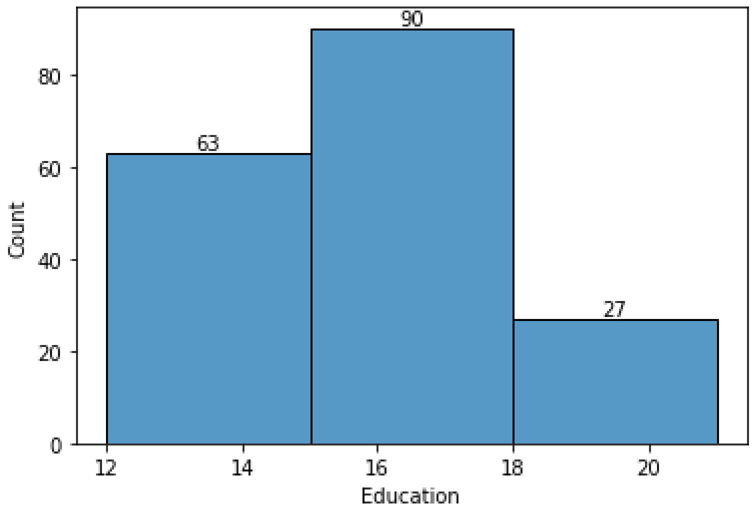
Out[13]:

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

UNIVARIATE ANALYSIS

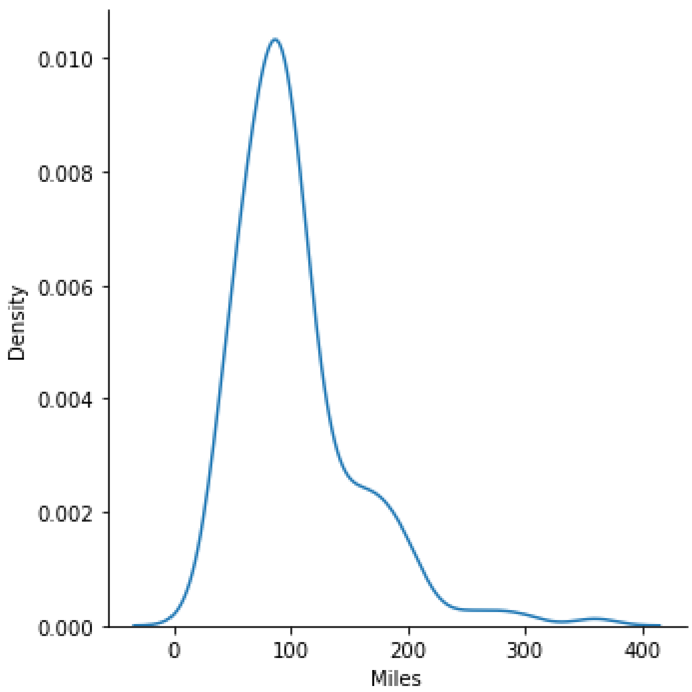
In [14]:

```
ax=sns.histplot(data=data["Education"],bins=[12,15,18,21])
ax.bar_label(ax.containers[0])
plt.show()
```



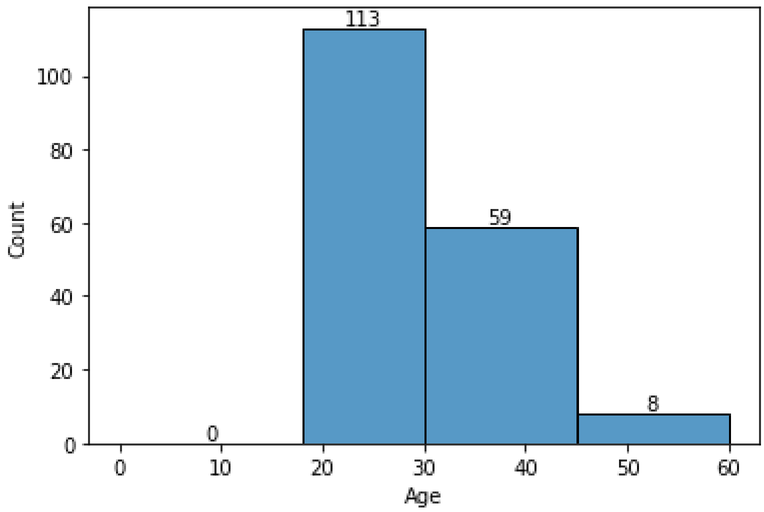
In [15]:

```
a=sns.displot(data=data,x=data["Miles"],kind="kde")
```



In [16]:

```
ax=sns.histplot(data=data["Age"],bins=[0,18,30,45,60])
ax.bar_label(ax.containers[0])
plt.show()
```

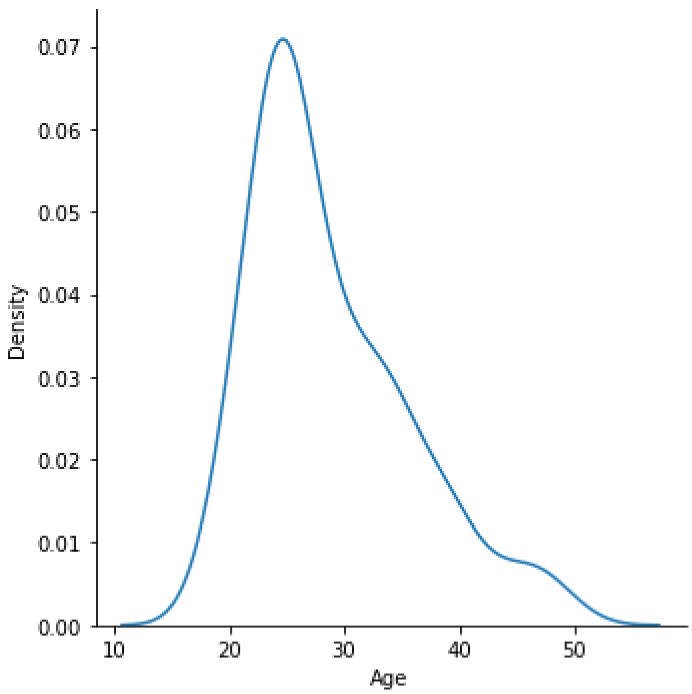


In [17]:

```
sns.displot(data=data,x="Age",kind="kde")
```

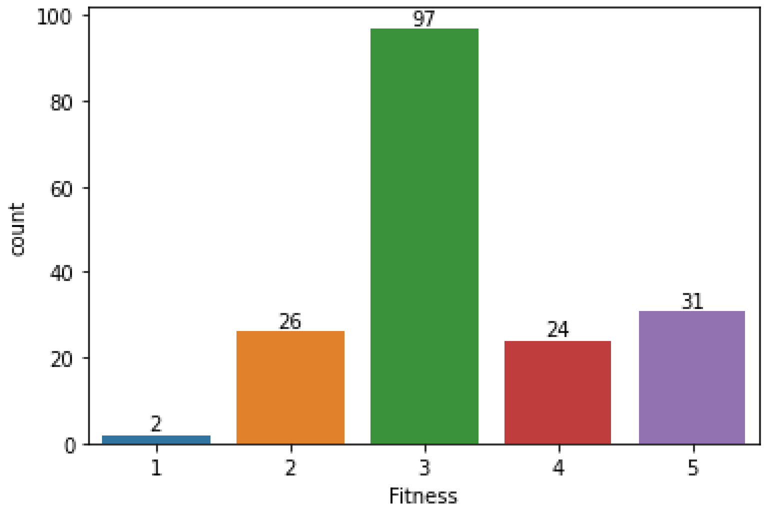
Out[17]:

```
<seaborn.axisgrid.FacetGrid at 0x202c352e490>
```



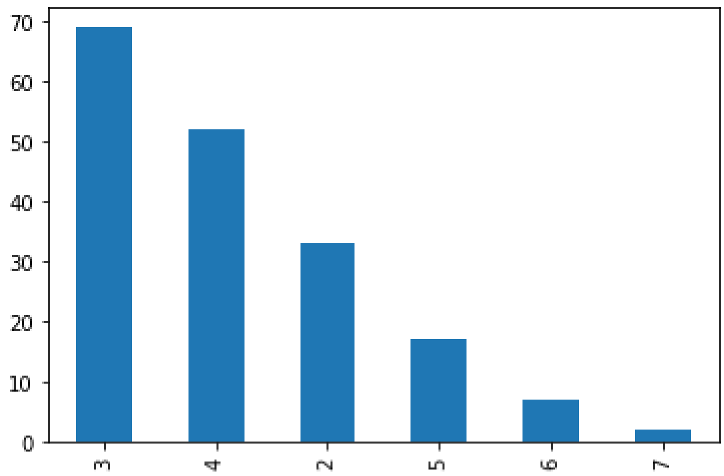
In [18]:

```
ax= sns.countplot(data=data,x="Fitness")
ax.bar_label(container=ax.containers[0])
plt.show()
```



In [19]:

```
data["Usage"].value_counts().plot(kind="bar")
plt.show()
```



BIVARIATE & MULTIVARIATE ANALYSIS

In [20]:

```
data.corr()
```

Out[20]:

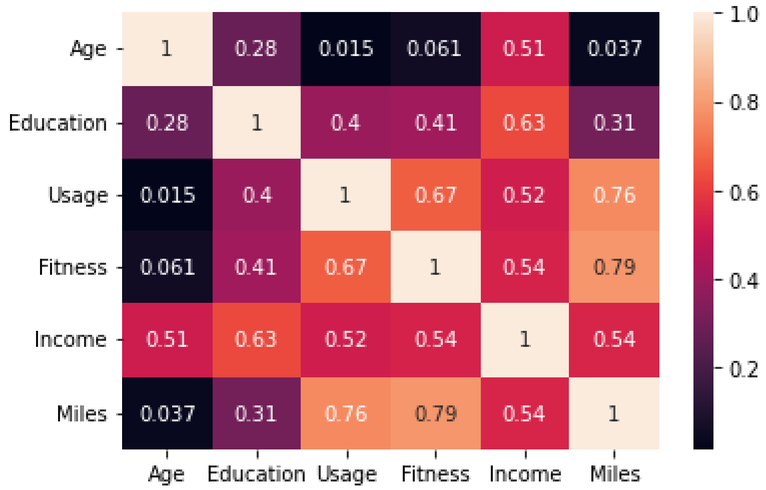
	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000

In [21]:

```
sns.heatmap(data.corr(), annot=True)
```

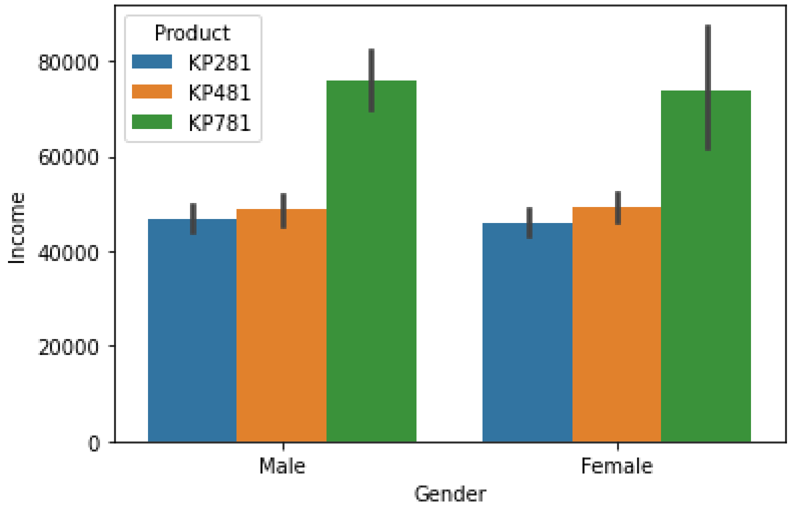
Out[21]:

<AxesSubplot:>



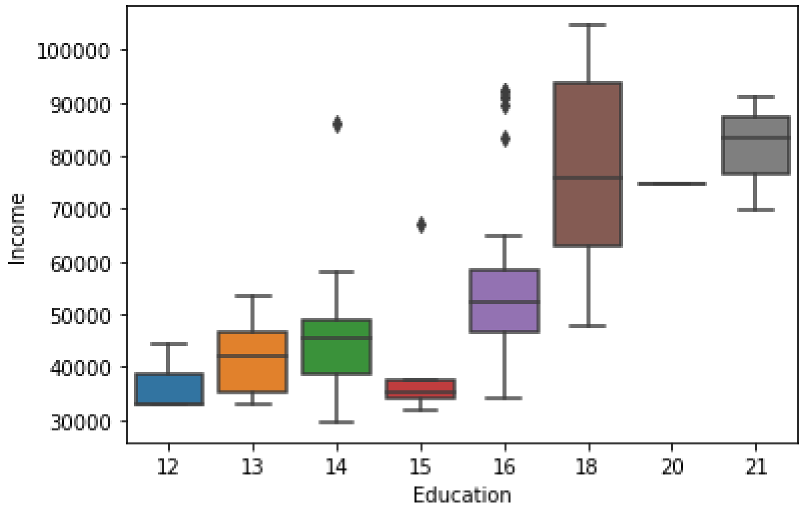
In [22]:

```
sns.barplot(x="Gender",y="Income",hue="Product",data=data)
plt.show()
```



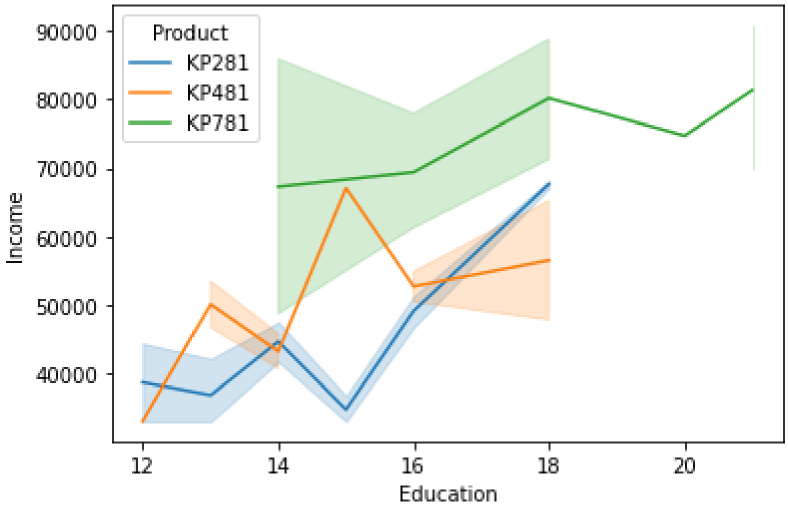
In [23]:

```
sns.boxplot(x="Education",y="Income",data=data)
plt.show()
```



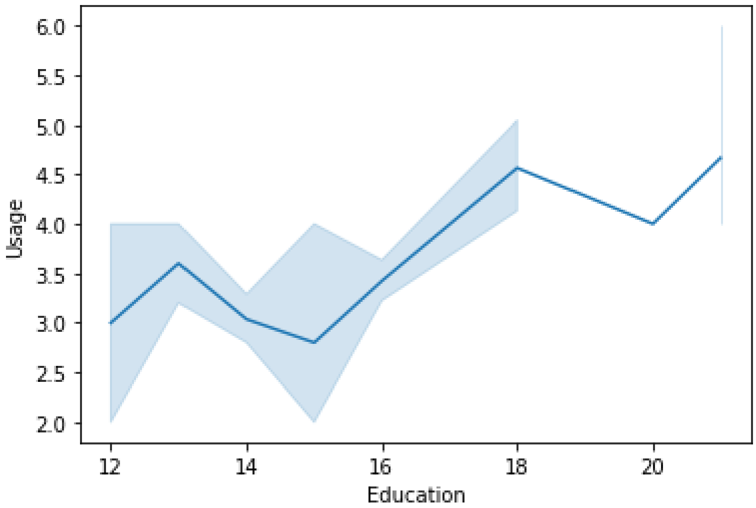
In [24]:

```
sns.lineplot(x="Education",y="Income",hue="Product",data=data)
plt.show()
```



In [25]:

```
sns.lineplot(x="Education",y="Usage",data=data)
plt.show()
```

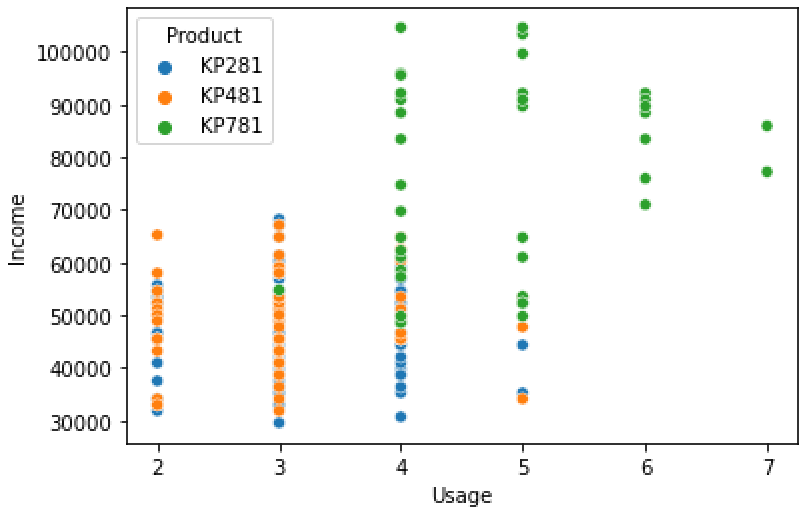


In [26]:

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

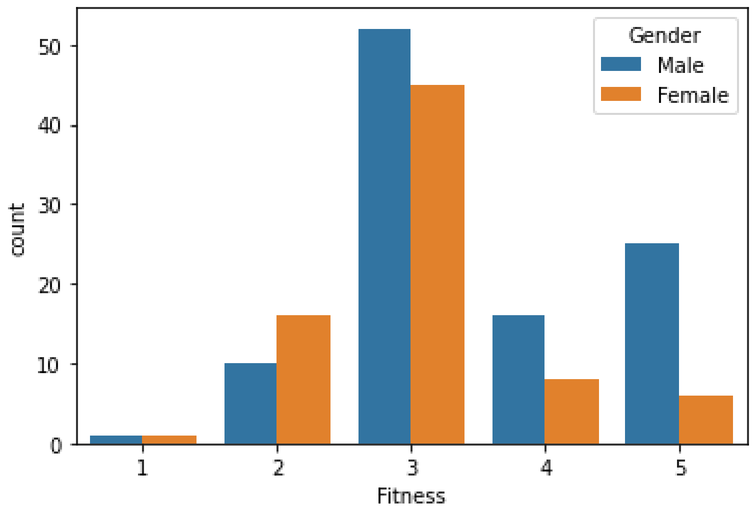
Out[26]:

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



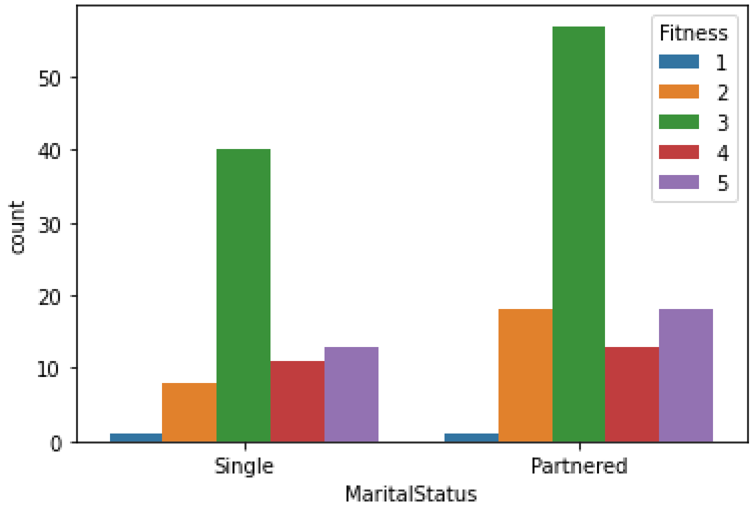
In [27]:

```
sns.countplot(x="Fitness",hue="Gender",data=data)
plt.show()
```



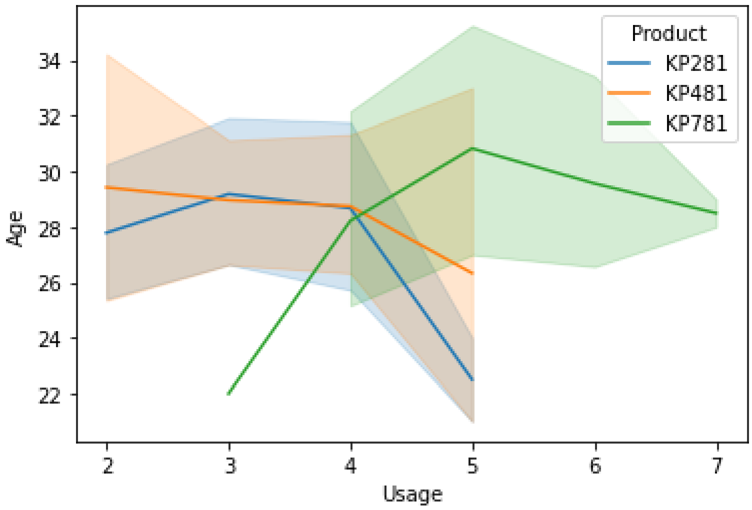
In [28]:

```
sns.countplot(x="MaritalStatus",hue="Fitness",data=data)
plt.show()
```



In [29]:

```
sns.lineplot(x="Usage",y="Age",data=data,hue="Product")
plt.show()
```

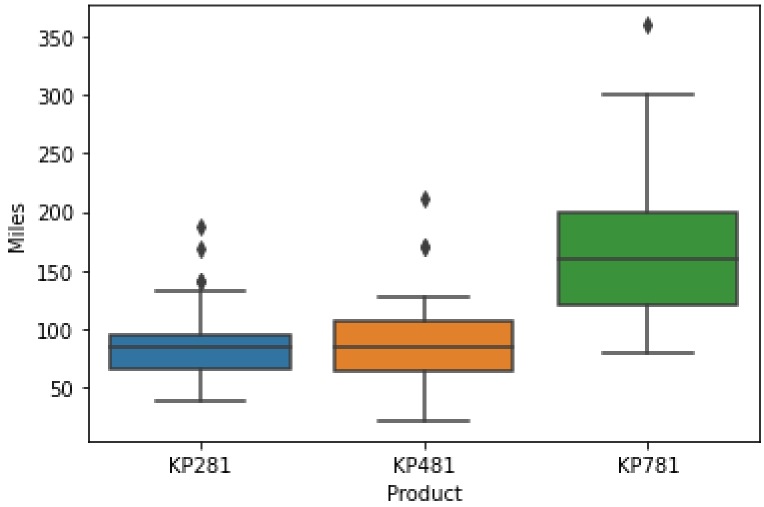


In [30]:

```
sns.boxplot(y="Miles",x="Product",data=data)
```

Out[30]:

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

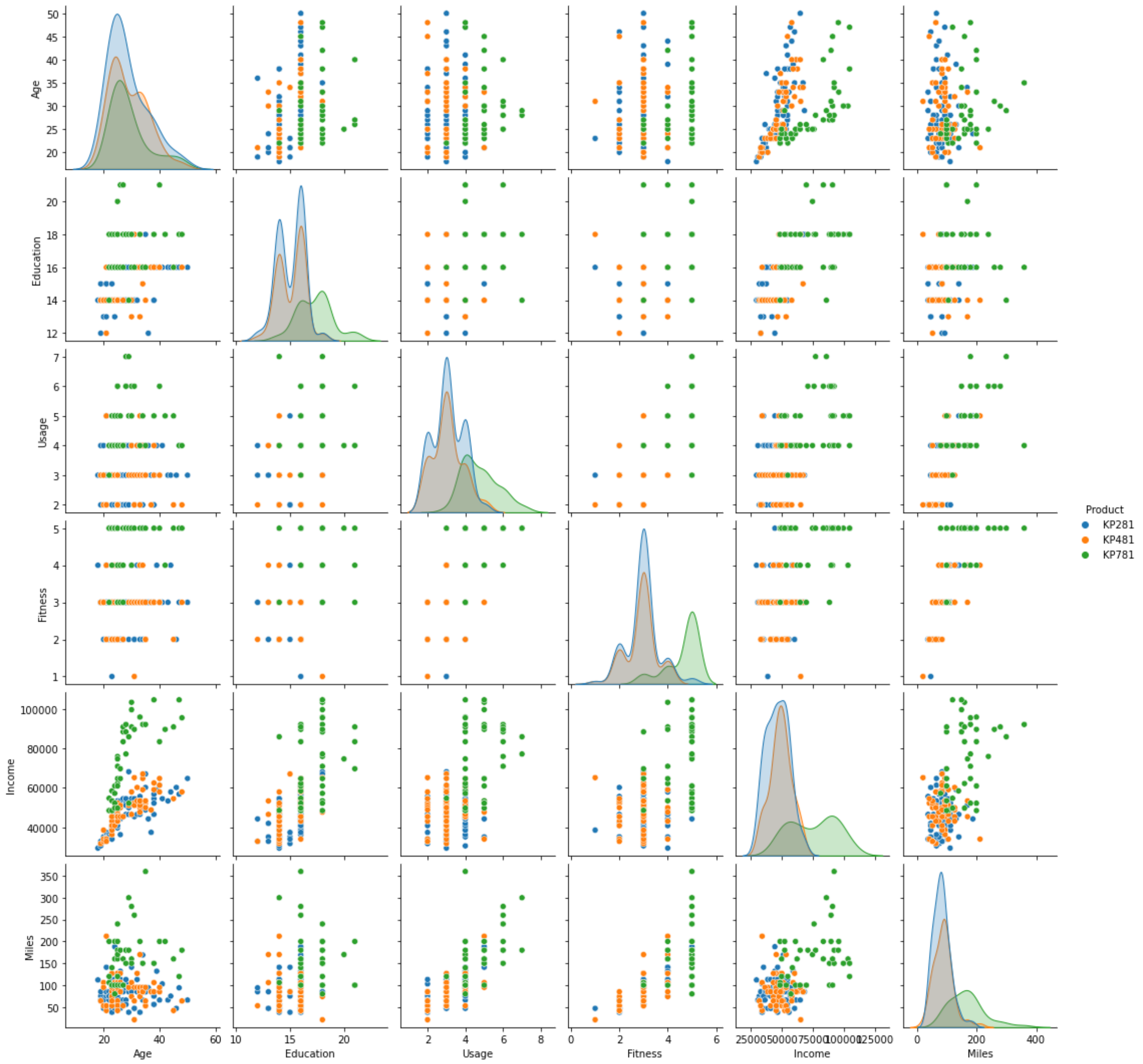


In [31]:

```
sns.pairplot(data=data,hue="Product")
```

Out[31]:

```
<seaborn.axisgrid.PairGrid at 0x202c49bbfd0>
```



In [32]:

```
data.groupby("Gender")["Product"].count()/len(data)*100
```

Out[32]:

```
Gender
Female    42.222222
Male      57.777778
Name: Product, dtype: float64
```

Prob(Gender|KP481)

In [33]:

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

Out[33]:

Product	KP281	KP481	KP781	All
Gender				
Female	0.5	0.483333	0.175	0.422222
Male	0.5	0.516667	0.825	0.577778

Prob(KP481|Gender)

In [34]:

```
pd.crosstab(index=data["Gender"],columns=data["Product"],normalize="index")
```

Out[34]:

Product	KP281	KP481	KP781
Gender			
Female	0.526316	0.381579	0.092105
Male	0.384615	0.298077	0.317308

In [35]:

```
data.groupby(["Product"])[["Miles"]].sum()
```

Out[35]:

	Miles
Product	
KP281	6623
KP481	5276
KP781	6676

Analysis Insights

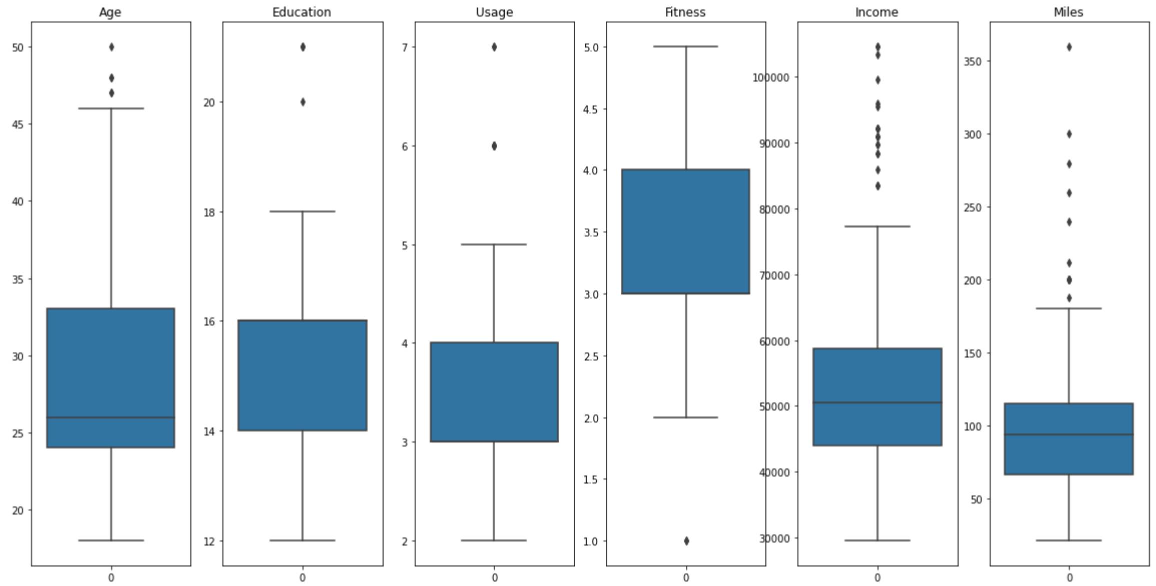
#Missing Value & Outlier Related Insights

1. There are no null values .

In [36]:

```
numeric_cols=['Age', 'Education',  'Usage',
       'Fitness', 'Income', 'Miles']
fig, axs = plt.subplots(ncols=6, figsize=(20, 10))
for i in range(len(numeric_cols)):
    sns.boxplot(data=data[numeric_cols[i]], ax=axs[i]).set(title=numeric_cols[i])

plt.show()
```



#Age Related Insights

1. Age has strong +ve correlation with Income levels
2. Age has low +ve correlation with Education Levels
3. Age has negligible correlation with **Usage, Fitness, Miles**

#Gender,Product & Income Related Insights

1. It is clearly visible in both the genders as income rises people with greater mean income , i.e greater than 40k tend to go for better products

#Education & Income Related Insights

1. people with more education have higher mean level of income

#MaritalStatus & Fitness Related Insights

1. We can clearly see that in all the categories(except 1): there are greater number of married people who are fit .

#Usage,Income & Product Related Insights

1. We can see that people with more Usage are the ones with higher income .
2. Myabe we can infer that those with higher income are more health conscious .
3. Also we can see that more the usage more is the demand for the better product i.e. tending towards KP|781 .

#Usage & Age Related Insights

1. there is negligible correlation b/w age and usage,
2. **BUT** we can see that b/w age 30-32 , the usage is limited to 5 times .
3. The most active age group is b/w 26 - 30 , with an average of 4-5 times .

#Gender & Fitness Related Insights

1. we can see that in both the genders , the distribtuion is more centered towards fitness lvels of 3.
2. count of Male category is more in **almost** all levels of fitness .

#Education Income & Product Related Insights

1. It is visible that as education increases income levels increases and so does the demand for the better product -
   - as between 12 and 14 years of Education , the income levels are low , therefore the demand for KP281 is there,
   - as we move to 14 anad 16 years of Education , the income levels further rise ,the demand for KP 281 takes a dip and Demand for KP 481 rises
   - as Education further rises ,the demand , along with income , the Demand for KP 281 vanishes , Demand for KP 481 slows down Demand for KP 781 takes a boost

#Miles & Product Related Insights

1. It is visible that people as people walk more miles, they opt fot the better product i.e gradually going from KP281 > KP481 > KP781.

Recommendations

1. Target the people with more income better products and people with low income less expensive products !!
2. Market a camapign of the benfits of fitness and walking , as more the people walk on an avergae more they tend to go for the better product .
3. To cater and maximize the sales for each product ,

```
a. target KP281 to young people and teens with education years b/w 12-14
b. target KP481 to people with education years b/w 14-16
c. target KP781 to people with education years of 18 above .
```

4. As we can see that male category is on avergae more fit, we can nudge competitions b/w both the genders which will boost demand for our products in all the categories .
5. We should target people with more income , and offer them discounts, as they are usually influential and more fitness conscious:-

```
 A. ALSO NOT TO FORGET , THEY WILL PUBLICIZE THE BRAND  BY MOUTH OF WORD, AL
SO THE RESULTS WOULD BE VISIBLE !!( AS
 ACTIONS SPEAK LOUDER THAN WORDS )
```

6. Target the products in the age group of 26-30, since they are the most active age hroup and they have an average use of 4-5 times .
7. If the customer is married , there are more chances of him being fit, so in married age group b/w 26-30

In [ ]: