Business Case: Aerofit - Descriptive Statistics & Probability

About Aerofit

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.

Submitted By :-

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1. Defining Problem Statement and Analysing basic metrics **.**
    1. Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import binom,norm,poisson
```

In [2]:
```
df = pd.read_csv("aerofit_treadmill.txt")
```

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.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.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.isna().sum()
#there are no values missing
```

Out[6]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [7]:
```
df.describe
#to check in basic characteristics
```

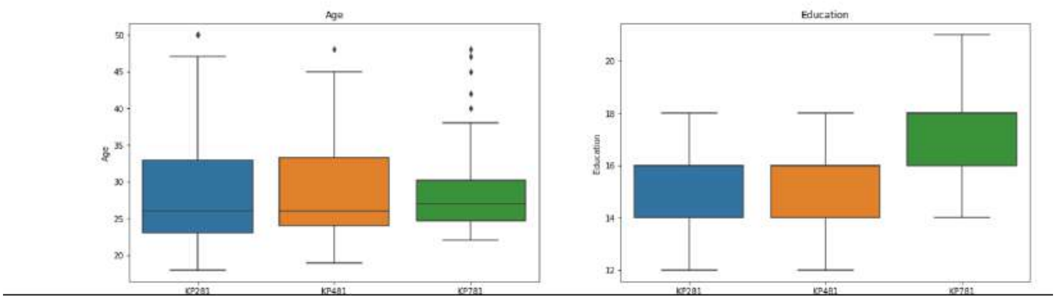
Out[7]:
```
<bound method NDFrame.describe of      Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0      KP281   18    Male         14        Single      3        4   29562
1      KP281   19    Male         15        Single      2        3   31836
2      KP281   19  Female         14     Partnered      4        3   30699
3      KP281   19    Male         12        Single      3        3   32973
4      KP281   20    Male         13     Partnered      4        2   35247
..       ...  ...     ...        ...           ...    ...      ...     ...
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641
177    KP781   45    Male         16        Single      5        5   90886
178    KP781   47    Male         18     Partnered      4        5  104581
179    KP781   48    Male         18     Partnered      4        5   95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     ...
175    200
```

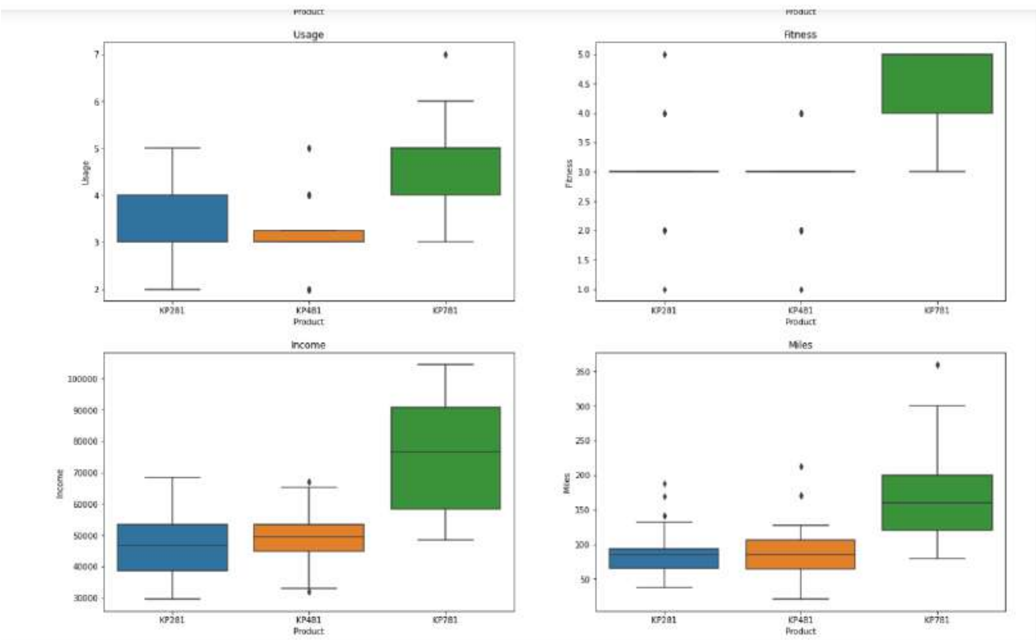
```
[180 rows x 9 columns]>
```

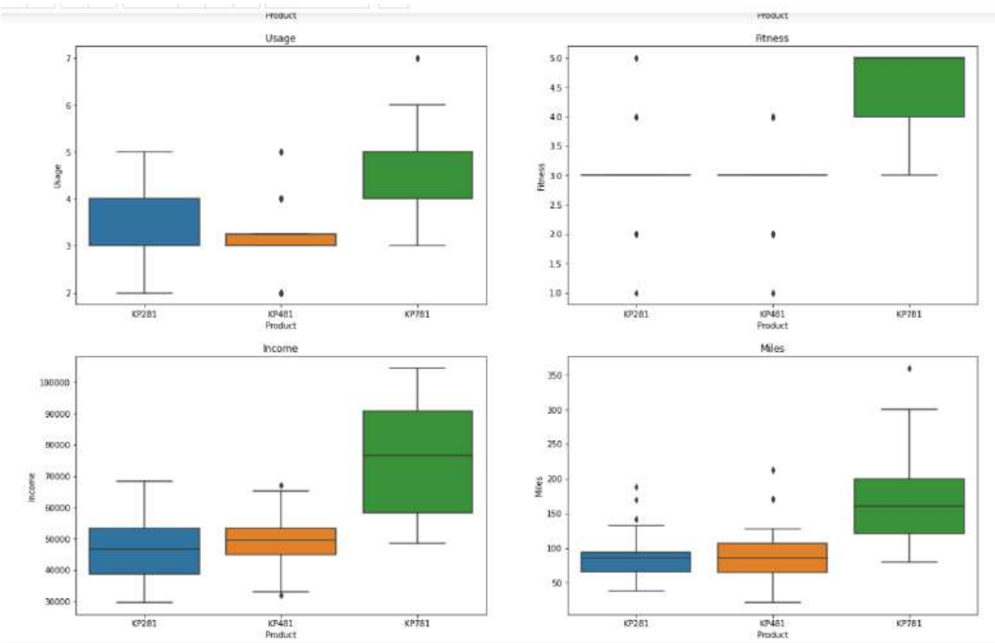
```
In [8]: df['Income(in K)']=round(df['Income']/1000,2)
```

```
In [9]: fig=plt.figure(figsize=(20,20))
        k=1
        for i in ['Age','Education','Usage','Fitness','Income','Miles']:
            plt.subplot(3,2,k)
            sns.boxplot(data=df,y=i,x='Product')
            plt.title(i)
            k=k+1
        fig.suptitle('Checkingthe Outliers',fontsize=25)
        plt.show()
```

Checkingthe Outliers







Now from this data we observe that for column Education,usages, and fitness are consistent data with negligible outliers

Product Purchased

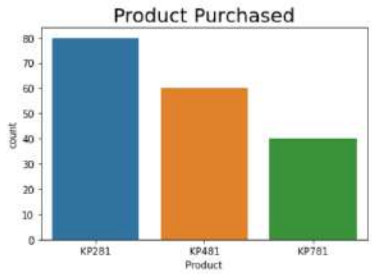
```
In [9]: Products=df['Product'].value_counts().reset_index()
        Products
        #Number of products purchased
```

Out[9]:

	index	Product
0	KP281	80
1	KP481	60
2	KP781	40

```
In [10]: sns.countplot(df['Product'])
         plt.title('Product Purchased',fontsize=20)
         plt.show()
```

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



```
In [11]: Products['PMF']=Products['Product']/180
         Products
         #Calculating the Marginal Probability of the different productsP
```

Out[11]:

	index	Product	PMF
0	KP281	80	0.444444
1	KP481	60	0.333333
2	KP781	40	0.222222

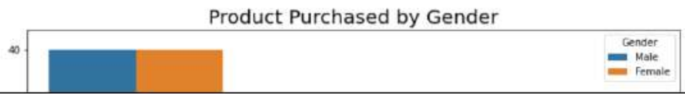
```
In [12]: Product_Gender=pd.crosstab(df['Product'],df['Gender'],margins=True)
         Product_Gender
```

Out[12]:

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

```
In [13]: #Plotting the countplot
         plt.figure(figsize=(12,8))
         sns.countplot(data=df,x='Product',hue='Gender')
         plt.title('Product Purchased by Gender',fontsize=20)
```

```
Out[13]: Text(0.5, 1.0, 'Product Purchased by Gender')
```



A. Observation- Purchased order is KP281>KP481>KP781

B. Proability of Purchasing:

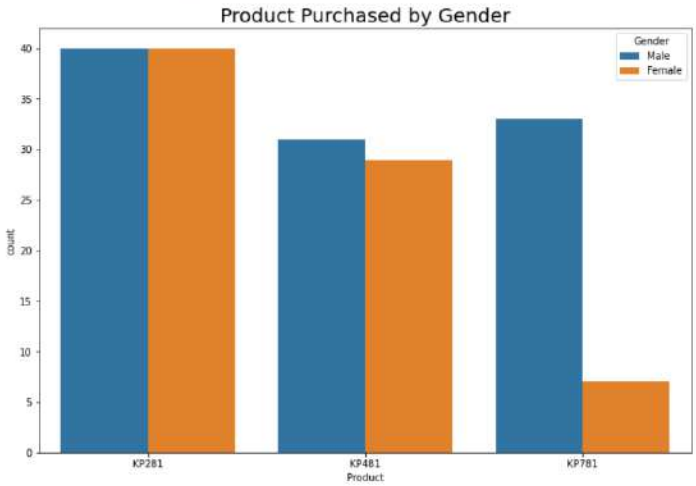
KP281=44.4%

KP481=33.3%

KP781=22.2%

Product Purchased by the Gender

```
In [13]: #Plotting the countplot
         plt.figure(figsize=(12,8))
         sns.countplot(data=df,x='Product',hue='Gender')
         plt.title('Product Purchased by Gender',fontsize=20)

Out[13]: Text(0.5, 1.0, 'Product Purchased by Gender')
```




```
In [14]: #Getting the conditional Probability
         Product_Gender['Product|Female']=round(Product_Gender['Female']*100/76,2)
         Product_Gender['Product|Male']=round(Product_Gender['Male']*100/104,2)
         Product_Gender
```

Out[14]:

Gender	Female	Male	All	Product|Female	Product|Male
Product					
KP281	40	40	80	52.63	38.46
KP481	29	31	60	38.16	29.81
KP781	7	33	40	9.21	31.73
All	76	104	180	100.00	100.00

```
In [15]: #Calculating the Marginal Probability
         Product_Gender['P(P^F)']=round(Product_Gender['Female']*100/180,2)
         Product_Gender['P(P^M)']=round(Product_Gender['Male']*100/180,2)
         Product_Gender
```

Out[15]:

Gender	Female	Male	All	Product|Female	Product|Male	P(P^F)	P(P^M)
Product							
KP281	40	40	80	52.63	38.46	22.22	22.22
KP481	29	31	60	38.16	29.81	16.11	17.22
KP781	7	33	40	9.21	31.73	3.89	18.33
All	76	104	180	100.00	100.00	42.22	57.78

```
In [16]: Product_Marital=pd.crosstab(df['Product'],df['MaritalStatus'],margins=True)
         Product_Marital

Out[16]:
```

Probability - F=Female, M=Male

P(KP281|F)=40/76 = 52.63% ---- P(KP281|M)=40/104 = 38.46%

P(KP481|F)=29/76 = 38.16% ---- P(KP481|M)=31/104 = 29.81%

P(KP781|F)=07/76 = 09.21% ---- P(KP781|M)=33/104 = 31.73%

Observation :- 1. KP281 is more purchased, But the chances with equal amount purchase:

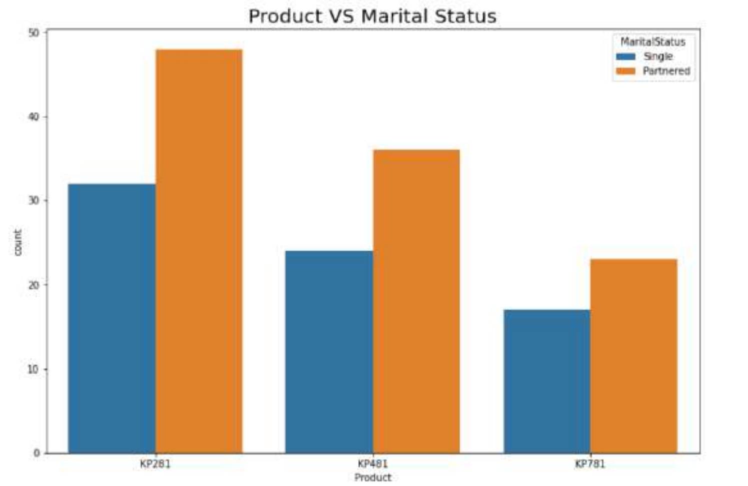
women Buying KP281(52.63%) >>> male buying KP281(38.46%)

2. KP481 is more purchased with almost equal number of man and women but chances:- women buying the KP481 (38.15%) >>> male Buying KP481(29.30%)

3. KP781 is least Purchased Predominately Purchased by the Males. chances of Male buying the KP781 >>>> Female Buying KP781

4. Chances of Buying KP781 in males are higher the Chances of Buying KP481 by males

In [18]:
```
# PLOTTING
plt.figure(figsize=(12,8))
sns.countplot(data=df,x='Product',hue='MaritalStatus')
plt.title('Product VS Marital Status', fontsize=20)
plt.show()
```



Probability - F=Female, M=Male

P(KP281|F)=40/76 = 52.63% ---- P(KP281|M)=40/104 = 38.46%

P(KP481|F)=29/76 = 38.16% ---- P(KP481|M)=31/104 = 29.81%

P(KP781|F)=07/76 = 09.21% ---- P(KP781|M)=33/104 = 31.73%

Observation :- 1. KP281 is more purchased, But the chances with equal amount purchase:

women Buying KP281(52.63%) >>> male buying KP281(38.46%)

2. KP481 is more purchased with almost equal number of man and women but chances:- --women buying the KP481 (38.15%) >>> male Buying KP481(29.30%)

3. KP781 is least Purchased Predominately Purchased by the Males. chances of Male buying the KP781 >>>> Female Buying KP781

4. Chances of Buying KP781 in males are higher the Chances of Buying KP481 by males

Product Purchased on the basis of Marital Status

In [17]:
```
# calculating the Conditional Probability
Product_Marital['Product|Partnered']=round(Product_Marital['Partnered']*100/107,2)
Product_Marital['Product|Single']=round(Product_Marital['Single']*100/73,2)
Product_Marital['P(P^P)']=round(Product_Marital['Partnered']*100/180,2)
Product_Marital['P(P^S)']=round(Product_Marital['Single']*100/180,2)
Product_Marital
```

Out[17]:

MaritalStatus	Partnered	Single	All	Product|Partnered	Product|Single	P(P^P)	P(P^S)
Product							
KP281	48	32	80	44.86	43.84	26.67	17.78
KP481	36	24	60	33.64	32.88	20.00	13.33
KP781	23	17	40	21.50	23.29	12.78	9.44
All	107	73	180	100.00	100.00	59.44	40.56

In [18]:
```
# Extracting age and product then Classification in age category
product_age=df[['Product','Age']]
product_age['Age_category']=pd.cut(product_age['Age'],bins=[0,20,26,30,35,40,45,50],labels=['<20','21-26','25-30','30-35','35-40'
```

```
C:\Users\anshu\AppData\Local\Temp\ipykernel_26396\2836058686.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy
  product_age['Age_category']=pd.cut(product_age['Age'],bins=[0,20,26,30,35,40,45,50],labels=['<20','21-26','25-30','30-35','35
-40','40-45','45-50'])
```

In [19]:
```
product_age
```

observation: KP281,KP481,KP781 is more Purchased by the Patterned customers

Probability - S=Single, P=Partnered

P(KP281|S) = 43.84% ---- P(KP281|P) = 44.86%

P(KP481|S) = 32.88% ---- P(KP481|P) = 33.64%

P(KP781|S) = 23.29% ---- P(KP781|P) = 21.50%

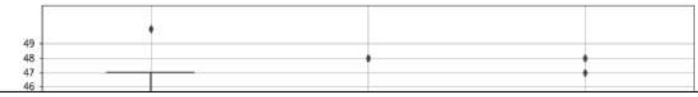
Observation :- Irrespective of Partnered or single there are higher chances that they will buy KP281 All the Product have similar chances with respect to buying by partnered or single

In [19]:
```
product_age
```
Out[19]:

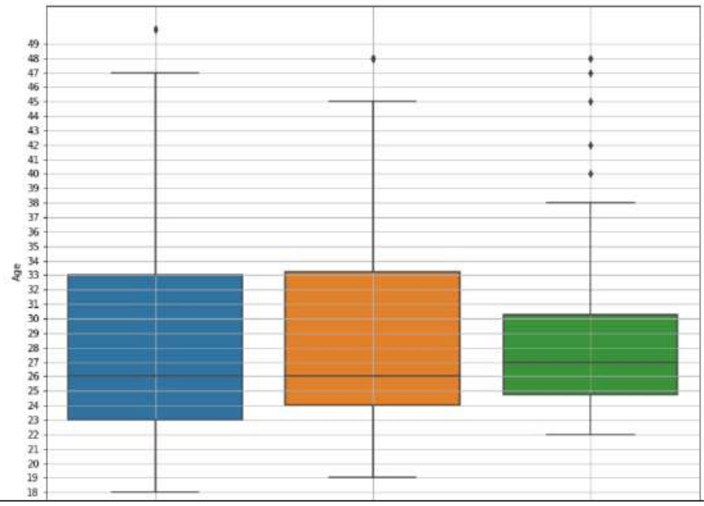
	Product	Age	Age_category
0	KP281	18	<20
1	KP281	19	<20
2	KP281	19	<20
3	KP281	19	<20
4	KP281	20	<20
...	...	...	...
175	KP781	40	35-40
176	KP781	42	40-45
177	KP781	45	40-45
178	KP781	47	45-50
179	KP781	48	45-50

180 rows × 3 columns

In [20]:
```
# Analyzing the Outliers of Age for each product
plt.figure(figsize=(12,10))
n=sns.boxplot(data=df,y=df['Age'],x='Product')
n.set_yticks(range(15,50,1))
plt.grid()
plt.show()
```



In [20]:
```
# Analyzing the Outliers of Age for each product
plt.figure(figsize=(12,10))
n=sns.boxplot(data=df,y=df['Age'],x='Product')
n.set_yticks(range(15,50,1))
plt.grid()
plt.show()
```

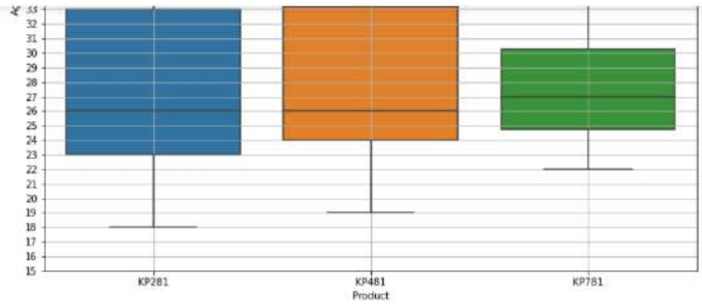
Outliers:-

KP281 - Age > 47

KP481 - Age > 45

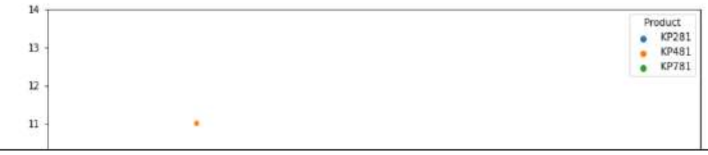
KP781 - Age > 38

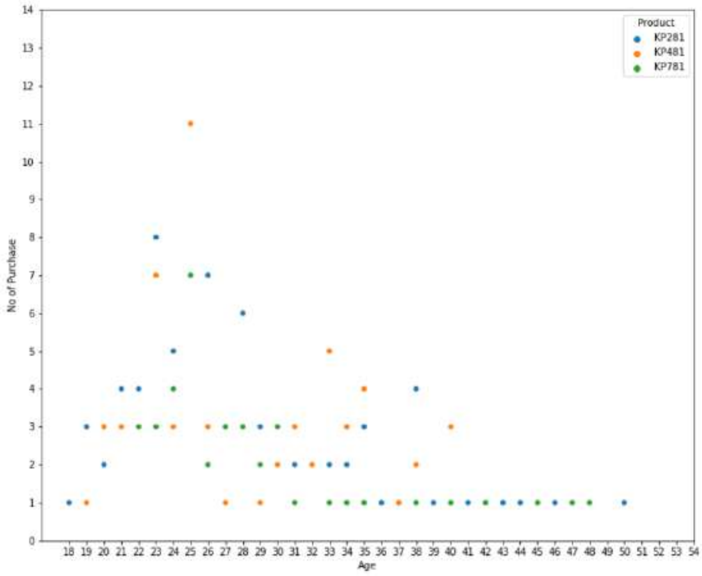
there are More outliers for KP781 Treadmill



In [27]:

```
# we groupby the age and product then count the frequency and plotted a scatterplot
plt.figure(figsize=(12,10))
k=sns.scatterplot(data=df.groupby(['Product','Age']).size().reset_index().rename(columns={0:'values'}),
 x='Age',y='values',hue='Product')
k.set_xticks(range(18,55,1))
k.set_yticks(range(0,15,1))
plt.ylabel('No of Purchase')
plt.show()
```





In [21]:

```
Product_age_table=pd.crosstab(product_age['Age_category'],product_age['Product'],margins=True)
Product_age_table
```

Out[21]:

Product Age_category	KP281	KP481	KP781	All
<20	6	4	0	10
21-26	35	27	19	81
25-30	14	4	11	29
30-35	11	17	4	32
35-40	8	6	2	16
40-45	3	1	2	6
45-50	3	1	2	6
All	80	60	40	180

In [22]:

```
# calculating the Conditional Probability
Product_age_table['KP281|Age']=round(Product_age_table['KP281']*100/Product_age_table['All'],2)
Product_age_table['KP481|Age']=round(Product_age_table['KP481']*100/Product_age_table['All'],2)
Product_age_table['KP781|Age']=round(Product_age_table['KP781']*100/Product_age_table['All'],2)
Product_age_table
```

Out[22]:

Product Age_category	KP281	KP481	KP781	All	KP281|Age	KP481|Age	KP781|Age
<20	6	4	0	10	60.00	40.00	0.00
21-26	35	27	19	81	43.21	33.33	23.46
25-30	14	4	11	29	48.28	13.79	37.93

In [22]:

```
# calculating the Conditional Probability
Product_age_table['KP281|Age']=round(Product_age_table['KP281']*100/Product_age_table['All'],2)
Product_age_table['KP481|Age']=round(Product_age_table['KP481']*100/Product_age_table['All'],2)
Product_age_table['KP781|Age']=round(Product_age_table['KP781']*100/Product_age_table['All'],2)
Product_age_table
```

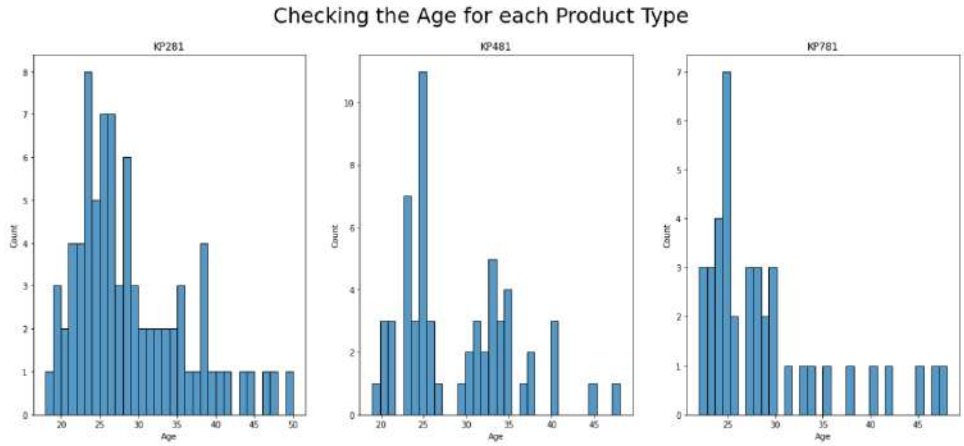
Out[22]:

Product	KP281	KP481	KP781	All	KP281|Age	KP481|Age	KP781|Age
Age_category							
<20	6	4	0	10	60.00	40.00	0.00
21-26	35	27	19	81	43.21	33.33	23.46
25-30	14	4	11	29	48.28	13.79	37.93
30-35	11	17	4	32	34.38	53.12	12.50
35-40	8	6	2	16	50.00	37.50	12.50
40-45	3	1	2	6	50.00	16.67	33.33
45-50	3	1	2	6	50.00	16.67	33.33
All	80	60	40	180	44.44	33.33	22.22

In [30]:

```
# plotting the histogram for each product WRT age
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
 plt.subplot(1,3,k)
 sns.histplot(df.loc[df['Product']==i]['Age'],bins=int(32))
 plt.title(i)
 k=k+1
fig.suptitle('Checking the Age for each Product Type',fontsize=25)
plt.show()
```

Checking the Age for each Product Type



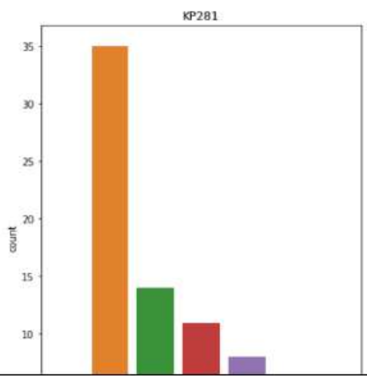
In [23]:

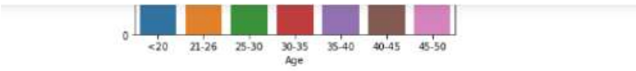
```
# plotting the Age category
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
    bin=[0,20,26,30,35,40,45,50]
    label=['<20','21-26','25-30','30-35','35-40','40-45','45-50']
```

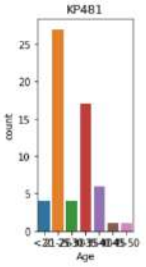

In [23]:

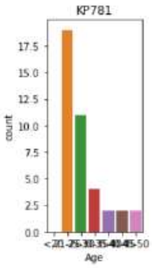
```
# plotting the Age category
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
    bin=[0,20,26,30,35,40,45,50]
    label=['<20','21-26','25-30','30-35','35-40','40-45','45-50']
    plt.subplot(1,3,k)
    sns.countplot(x=pd.cut(df.loc[df['Product']==i]['Age'],bins=bin,labels=label))
    plt.title(i)
    k=k+1
    fig.suptitle('Checking the Age for each Product Type',fontsize=25)
    plt.show()
```

Checking the Age for each Product Type

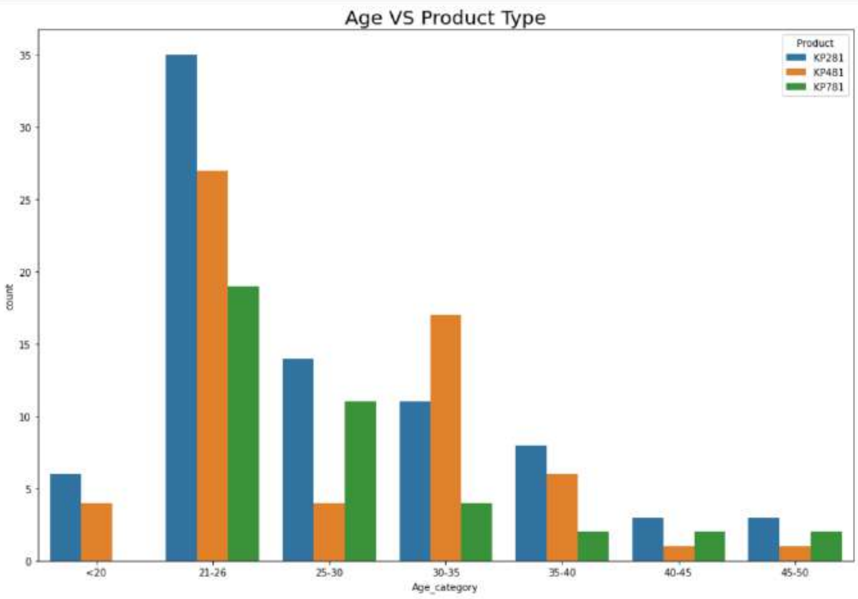









```
[33]: # Plotting the Count with age category
      plt.figure(figsize=(15,10))
      sns.countplot(data=product_age,x='Age_category',hue='Product')
      plt.title('Age VS Product Type',fontsize=20)
      plt.show()
```



Product analysis with Income

In [24]:
```
df
```
Out[24]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
2	KP281	19	Female	14	Partnered	4	3	30699	66	30.70
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42
176	KP781	42	Male	18	Single	5	4	89641	200	89.64
177	KP781	45	Male	16	Single	5	5	90886	160	90.89
178	KP781	47	Male	18	Partnered	4	5	104581	120	104.58
179	KP781	48	Male	18	Partnered	4	5	95508	180	95.51

180 rows × 10 columns

In [31]:
```
#Extracting the Income and product column and defining the category income
Product_income=df[['Product','Income(in K)']]
Product_income['Income_category']=pd.cut(Product_income['Income(in K)'],bins=[0,30,40,50,60,70,80,90,100,110],labels=['<30','30-4
```
```
C:\Users\anshu\AppData\Local\Temp\ipykernel_26396\2245561069.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy
  Product_income['Income_category']=pd.cut(Product_income['Income(in K)'],bins=[0,30,40,50,60,70,80,90,100,110],labels=['<3
0','30-40','40-50','50-60','60-70','70-80','80-90','90-100','100-110'])
```

In [32]:
```
Product_income
```
Out[32]:

	Product	Income(in K)	Income_category
0	KP281	29.56	<30
1	KP281	31.84	30-40
2	KP281	30.70	30-40
3	KP281	32.97	30-40
4	KP281	35.25	30-40
...	...	...	...
175	KP781	83.42	80-90
176	KP781	89.64	80-90
177	KP781	90.89	90-100
178	KP781	104.58	100-110
179	KP781	95.51	90-100

180 rows × 3 columns

In [33]:
```
#creating a table
Product_income_table=pd.crosstab(Product_income['Income_category'],Product_income['Product'],margins=True)
Product_income_table
```
Out[33]:

Product	KP281	KP481	KP781	All
Income_category				
<30	1	0	0	1
30-40	22	9	0	31
40-50	25	21	5	51
50-60	26	23	6	55

In [33]:
```
#creating a table
Product_income_table=pd.crosstab(Product_income['Income_category'],Product_income['Product'],margins=True)
Product_income_table
```

Out[33]:

Product	KP281	KP481	KP781	All
Income_category				
<30	1	0	0	1
30-40	22	9	0	31
40-50	25	21	5	51
50-60	26	23	6	55
60-70	6	7	6	19
70-80	0	0	4	4
80-90	0	0	7	7
90-100	0	0	9	9
100-110	0	0	3	3
All	80	60	40	180

In [34]:
```
# calculating the Conditional Probability
Product_income_table['KP281|Income']=round(Product_income_table['KP281']*100/Product_income_table['All'],2)
Product_income_table['KP481|Income']=round(Product_income_table['KP481']*100/Product_income_table['All'],2)
Product_income_table['KP781|Income']=round(Product_income_table['KP781']*100/Product_income_table['All'],2)
Product_income_table
```
Out[34]:

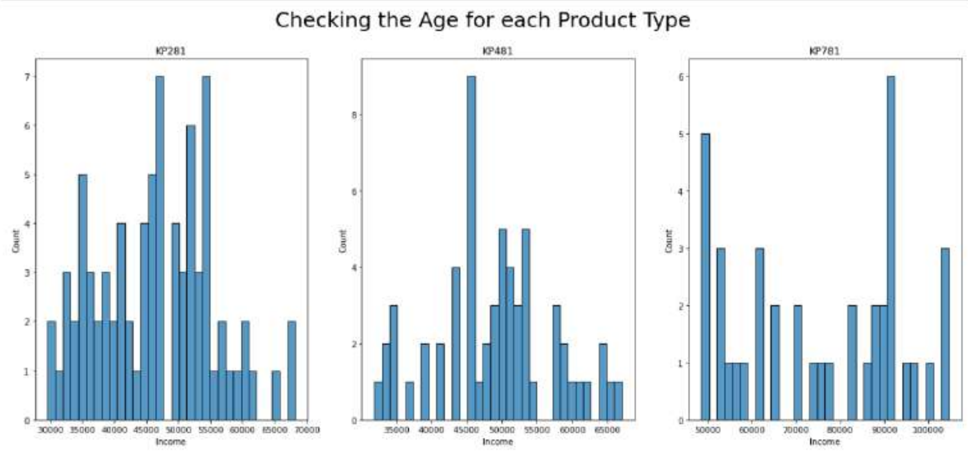
Product	KP281	KP481	KP781	All	KP281|Income	KP481|Income	KP781|Income
Income_category							
<30	1	0	0	1	100.00	0.00	0.00
30-40	22	9	0	31	70.97	29.03	0.00

In [34]:
```
# calculating the Conditional Probability
Product_income_table['KP281|Income']=round(Product_income_table['KP281']*100/Product_income_table['All'],2)
Product_income_table['KP481|Income']=round(Product_income_table['KP481']*100/Product_income_table['All'],2)
Product_income_table['KP781|Income']=round(Product_income_table['KP781']*100/Product_income_table['All'],2)
Product_income_table
```

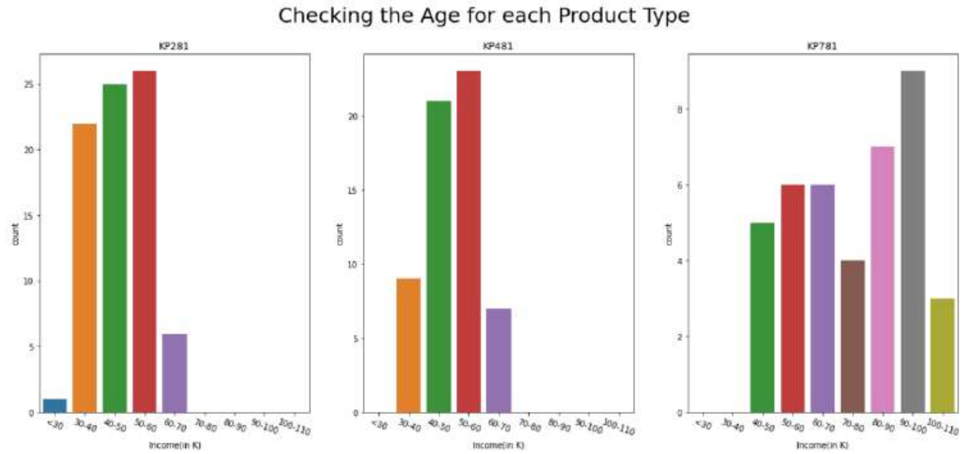
Out[34]:

Product	KP281	KP481	KP781	All	KP281|Income	KP481|Income	KP781|Income
Income_category							
<30	1	0	0	1	100.00	0.00	0.00
30-40	22	9	0	31	70.97	29.03	0.00
40-50	25	21	5	51	49.02	41.18	9.80
50-60	26	23	6	55	47.27	41.82	10.91
60-70	6	7	6	19	31.58	36.84	31.58
70-80	0	0	4	4	0.00	0.00	100.00
80-90	0	0	7	7	0.00	0.00	100.00
90-100	0	0	9	9	0.00	0.00	100.00
100-110	0	0	3	3	0.00	0.00	100.00
All	80	60	40	180	44.44	33.33	22.22

In [35]:
```
# plotting the histogram for each product for Income
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
 plt.subplot(1,3,k)
 sns.histplot(df.loc[df['Product']==i]['Income'],bins=int(32))
 plt.title(i)
 k=k+1
fig.suptitle('Checking the Age for each Product Type',fontsize=25)
plt.show()
```

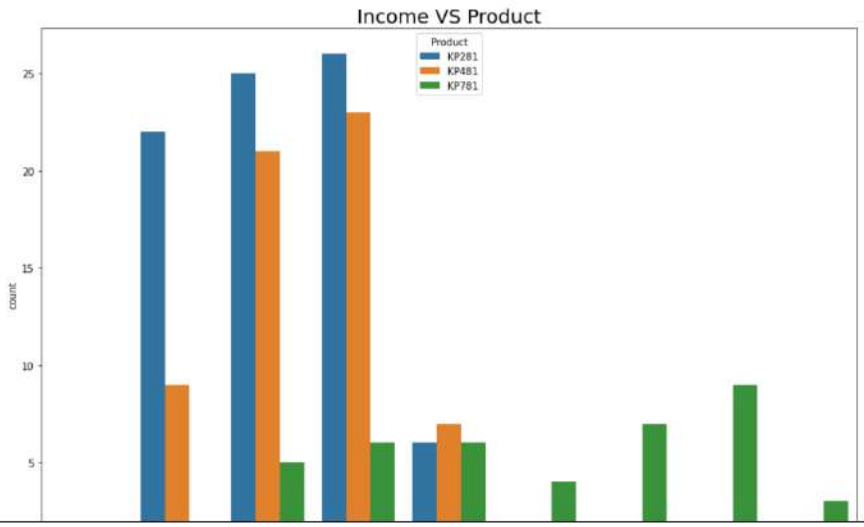


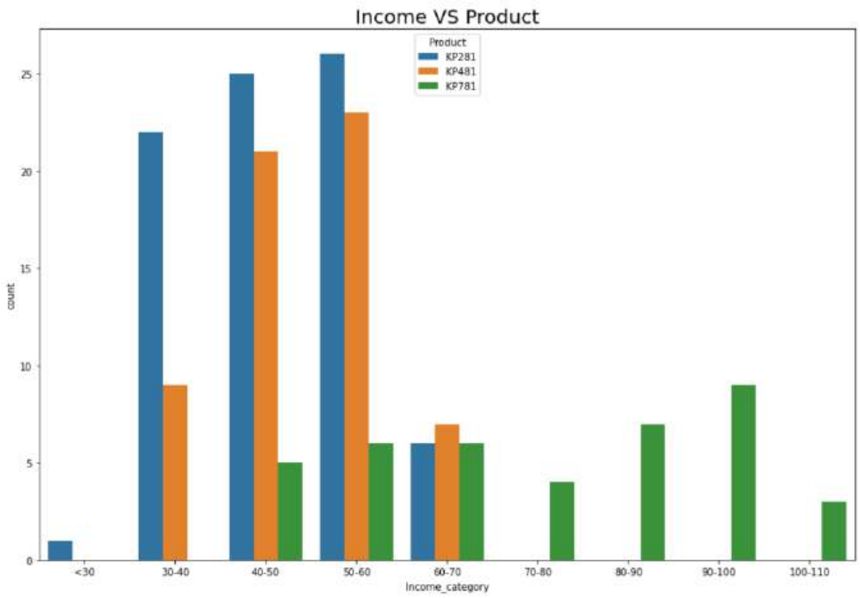
In [37]:
```
# plotting the Income Category
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
 bin=[0,30,40,50,60,70,80,90,100,110]
 label=['<30','30-40','40-50','50-60','60-70','70-80','80-90','90-100','100-110']
 plt.subplot(1,3,k)
 sns.countplot(x=pd.cut(df.loc[df['Product']==i]['Income(in K)'],bins=bin,labels=label))
 plt.title(i)
 plt.xticks(rotation=340)
 k=k+1
fig.suptitle('Checking the Age for each Product Type',fontsize=25)
plt.show()
```



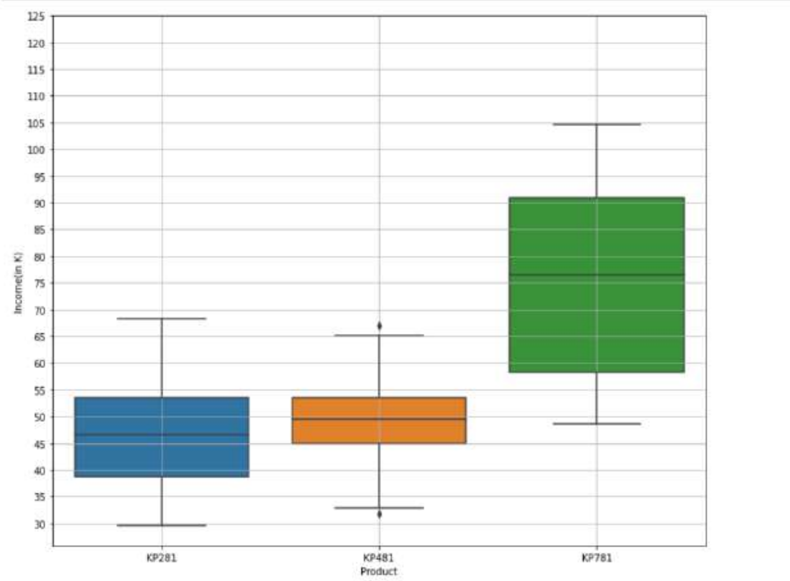
In [38]:
```
# Plotting the income category with the product
plt.figure(figsize=(15,10))
sns.countplot(data=Product_income,x='Income_category',hue='Product')
plt.title('Income VS Product',fontsize=20)
plt.show()
```


```
# Plotting the income category with the product
plt.figure(figsize=(15,10))
sns.countplot(data=Product_income,x='Income_category',hue='Product')
plt.title('Income VS Product',fontsize=20)
plt.show()
```

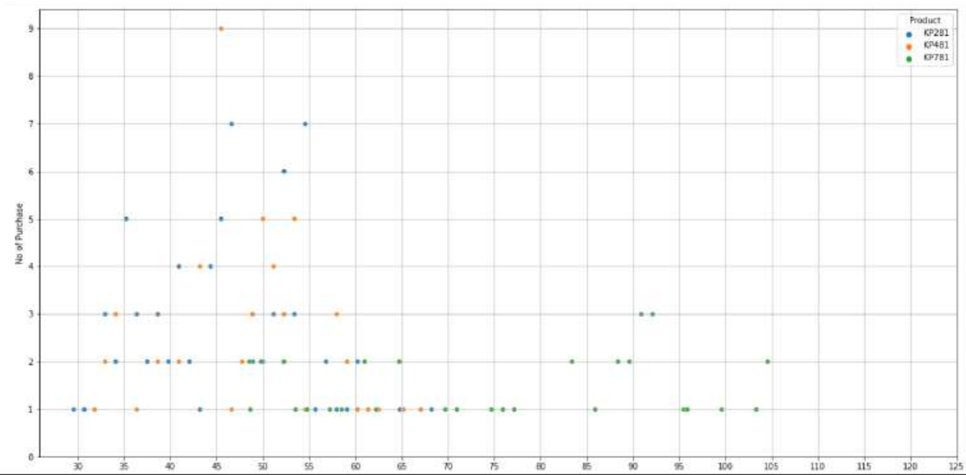





n [40]:
```
# Analyzing the Outliers of Income for each product
plt.figure(figsize=(12,10))
n=sns.boxplot(data=df,y=df['Income(in K)'],x='Product')
n.set_yticks(range(30,130,5))
plt.grid()
plt.show()
```




```
In [43]: # we groupby the age and product then count the frequency and plotted a scatterplot
         plt.figure(figsize=(20,10))
         k=sns.scatterplot(data=df.groupby(['Product','Income(in K)']).size().reset_index().rename(columns={0:'values'}),
          x='Income(in K)',y='values',hue='Product')
         k.set_xticks(range(30,130,5))
         k.set_yticks(range(0,10,1))
         plt.ylabel('No of Purchase')
         plt.grid()
         plt.show()
```



Observation

1. KP281- customer having Income in between 30k-60k

2. KP481- customer having Income in between 40k-60k

3. KP781- customer having Income in greater > 60k

Analyzation of Product with Education

In [44]:
```
Product_income_table
```

Out[44]:

Product Income_category	KP281	KP481	KP781	All	KP281|Income	KP481|Income	KP781|Income
<30	1	0	0	1	100.00	0.00	0.00
30-40	22	9	0	31	70.97	29.03	0.00
40-50	25	21	5	51	49.02	41.18	9.80
50-60	26	23	6	55	47.27	41.82	10.91
60-70	6	7	6	19	31.58	36.84	31.58
70-80	0	0	4	4	0.00	0.00	100.00
80-90	0	0	7	7	0.00	0.00	100.00
90-100	0	0	9	9	0.00	0.00	100.00
100-110	0	0	3	3	0.00	0.00	100.00
All	80	60	40	180	44.44	33.33	22.22

In [45]:
```
df
```

Out[45]:

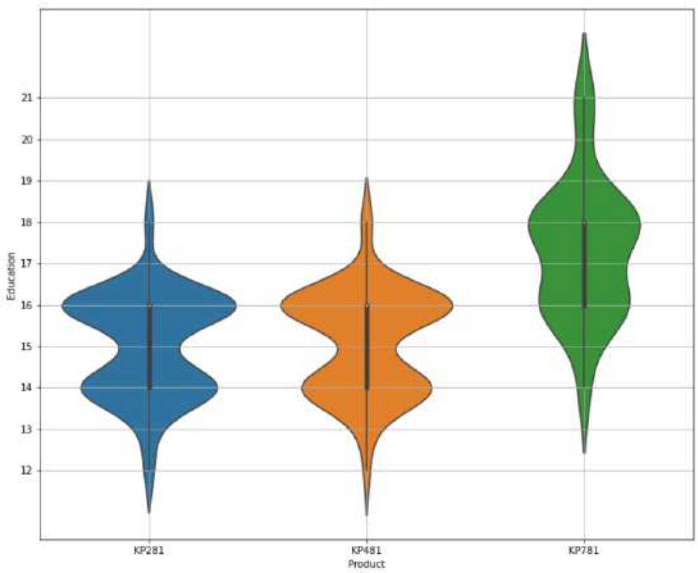
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
2	KP281	19	Female	14	Partnered	4	3	30699	66	30.70
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42

In [46]:
```
# Import the sum of values with Education and Product
Prodcut_education_table=pd.crosstab(df['Education'],df['Product'],margins=True)
Prodcut_education_table
```

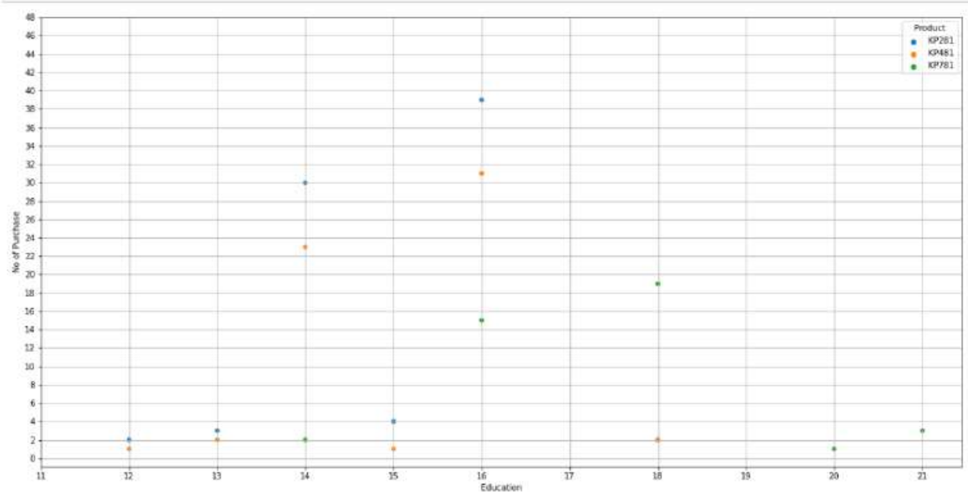
Out[46]:

Product Education	KP281	KP481	KP781	All
12	2	1	0	3
13	3	2	0	5
14	30	23	2	55
15	4	1	0	5
16	39	31	15	85
18	2	2	19	23
20	0	0	1	1
21	0	0	3	3
All	80	60	40	180

In [47]:
```
# Analyzing the Outliers of Education for each product
plt.figure(figsize=(12,10))
n=sns.violinplot(data=df,y=df['Education'],x='Product')
n.set_yticks(range(12,22,1))
plt.grid()
plt.show()
```




```
# we groupby the Education in years and product then count the frequency and plotted a scatterplot
plt.figure(figsize=(20,10))
k=sns.scatterplot(data=df.groupby(['Product','Education']).size().reset_index().rename(columns={0:'values'}),
 x='Education',y='values',hue='Product')
k.set_xticks(range(11,22))
k.set_yticks(range(0,50,2))
plt.ylabel('No of Purchase')
plt.grid()
plt.show()
```




```
In [49]: df['Education'].unique()
Out[49]: array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)
```

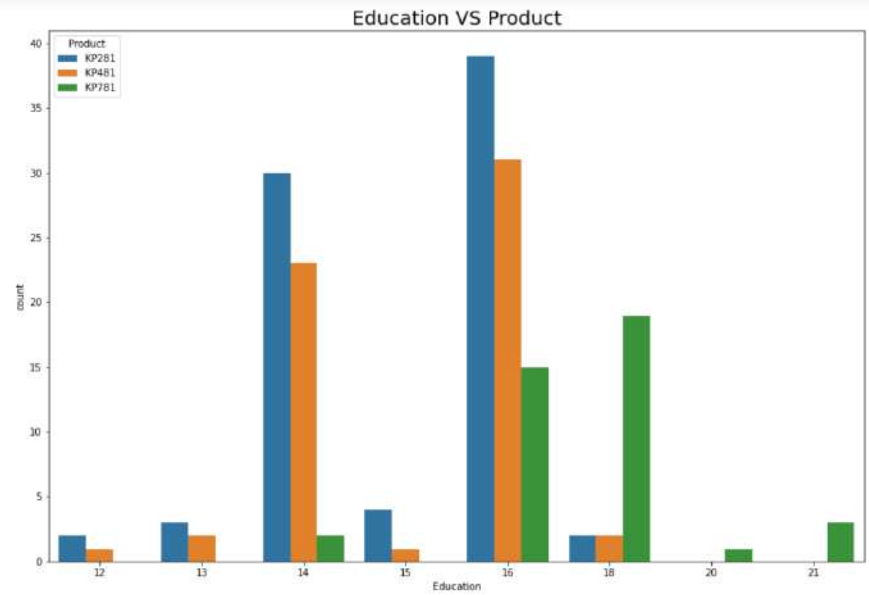

In [49]: df['Education'].unique()
Out[49]: array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)


```
In [50]: # calculating the Conditional Probability
Prodcut_education_table['KP281|Education']=round(Prodcut_education_table['KP281']*100/Prodcut_education_table['All'],2)
Prodcut_education_table['KP481|Education']=round(Prodcut_education_table['KP481']*100/Prodcut_education_table['All'],2)
Prodcut_education_table['KP781|Education']=round(Prodcut_education_table['KP781']*100/Prodcut_education_table['All'],2)
Prodcut_education_table
```

Out[50]:

Product Education	KP281	KP481	KP781	All	KP281|Education	KP481|Education	KP781|Education
12	2	1	0	3	66.67	33.33	0.00
13	3	2	0	5	60.00	40.00	0.00
14	30	23	2	55	54.55	41.82	3.64
15	4	1	0	5	80.00	20.00	0.00
16	39	31	15	85	45.88	36.47	17.65
18	2	2	19	23	8.70	8.70	82.61
20	0	0	1	1	0.00	0.00	100.00
21	0	0	3	3	0.00	0.00	100.00
All	80	60	40	180	44.44	33.33	22.22

```
In [51]: # Plotting the countplot with Education vs product
plt.figure(figsize=(15,10))
sns.countplot(x=df['Education'],hue=df['Product'])
plt.title('Education VS Product',fontsize=20)
plt.show()
```



Observations:

1. KP281= customer having Education of 14 and 16 years

2. KP281= customer having Education of 14 and 16 years

3. KP781= customer having Education of 18 and more years

Analyzation of Usages with the Product type

In [52]:
```
df
```

Out[52]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
2	KP281	19	Female	14	Partnered	4	3	30699	66	30.70
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42
176	KP781	42	Male	18	Single	5	4	89641	200	89.64
177	KP781	45	Male	16	Single	5	5	90886	160	90.89
178	KP781	47	Male	18	Partnered	4	5	104581	120	104.58
179	KP781	48	Male	18	Partnered	4	5	95508	180	95.51

180 rows × 10 columns

In [53]:
```
Product_Usage_table=pd.crosstab(df['Usage'],df['Product'],margins=True)
Product_Usage_table
```

Out[53]:

Product Usage	KP281	KP481	KP781	All
2	19	14	0	33
3	37	31	1	69
4	22	12	18	52
5	2	3	12	17

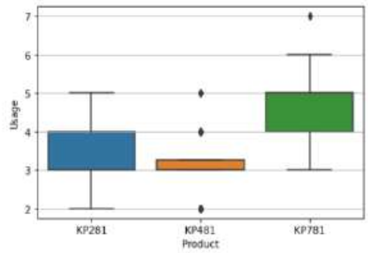
In [53]:

```
Product_Usage_table=pd.crosstab(df['Usage'],df['Product'],margins=True)
Product_Usage_table
```

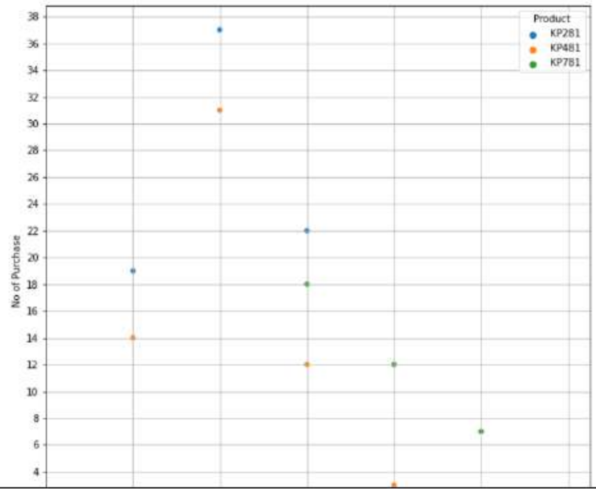

Out[53]:

Product Usage	KP281	KP481	KP781	All
2	19	14	0	33
3	37	31	1	69
4	22	12	18	52
5	2	3	12	17
6	0	0	7	7
7	0	0	2	2
All	80	60	40	180

In [54]:
```
sns.boxplot(data=df,y='Usage',x='Product')
plt.grid(axis='y')
```



```
In [56]: # we groupby the Education in years and product then count the frequency and plotted a scatterplot
         plt.figure(figsize=(10,10))
         k=sns.scatterplot(data=df.groupby(['Product','Usage']).size().reset_index().rename(columns={0:'values'}),
          x='Usage',y='values',hue='Product')
         k.set_xticks(range(1,8))
         k.set_yticks(range(0,40,2))
         plt.ylabel('No of Purchase')
         plt.grid()
```

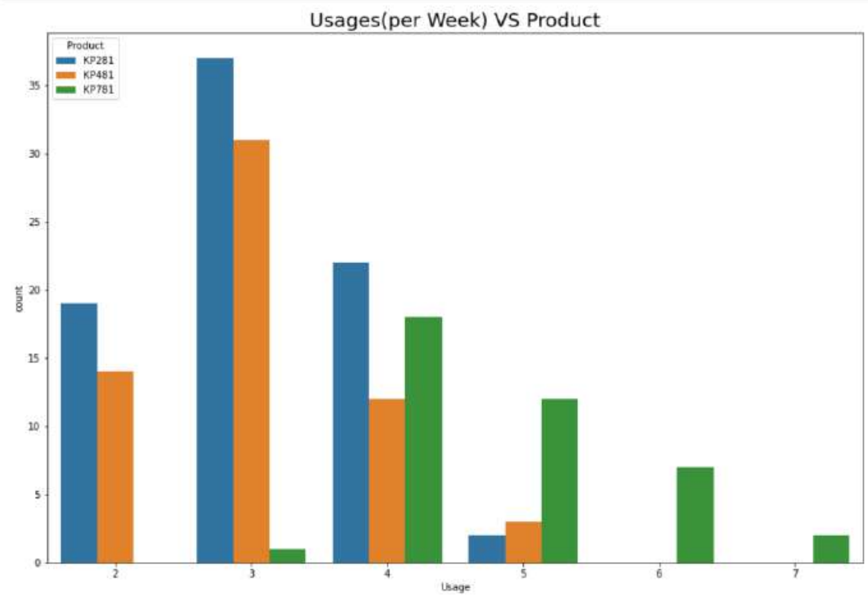



```
In [58]:
         # calculating the Conditional Probability
         Product_Usage_table['KP281|Usage']=round(Product_Usage_table['KP281']*100/Product_Usage_table['All'],2)
         Product_Usage_table['KP481|Usage']=round(Product_Usage_table['KP481']*100/Product_Usage_table['All'],2)
         Product_Usage_table['KP781|Usage']=round(Product_Usage_table['KP781']*100/Product_Usage_table['All'],2)
         Product_Usage_table
```

Out[58]:

Product	KP281	KP481	KP781	All	KP281|Usage	KP481|Usage	KP781|Usage
Usage							
2	19	14	0	33	57.58	42.42	0.00
3	37	31	1	69	53.62	44.93	1.45
4	22	12	18	52	42.31	23.08	34.62
5	2	3	12	17	11.76	17.65	70.59
6	0	0	7	7	0.00	0.00	100.00
7	0	0	2	2	0.00	0.00	100.00
All	80	60	40	180	44.44	33.33	22.22

```
In [59]: # Plotting the countplot of Usages(per week) with the Product type
         plt.figure(figsize=(15,10))
         sns.countplot(x=df['Usage'],hue=df['Product'])
         plt.title('Usages(per Week) VS Product',fontsize=20)
         plt.show()
```



Observation-:

1. KP281= more preferred for usage 2-4

2. KP481= more preferred for usage 2-3

3. KP781= more preferred for usage more than 4

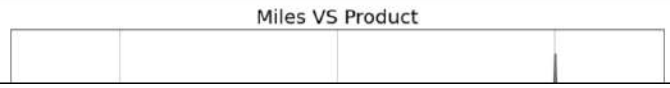
Analyzation of Miles with Product

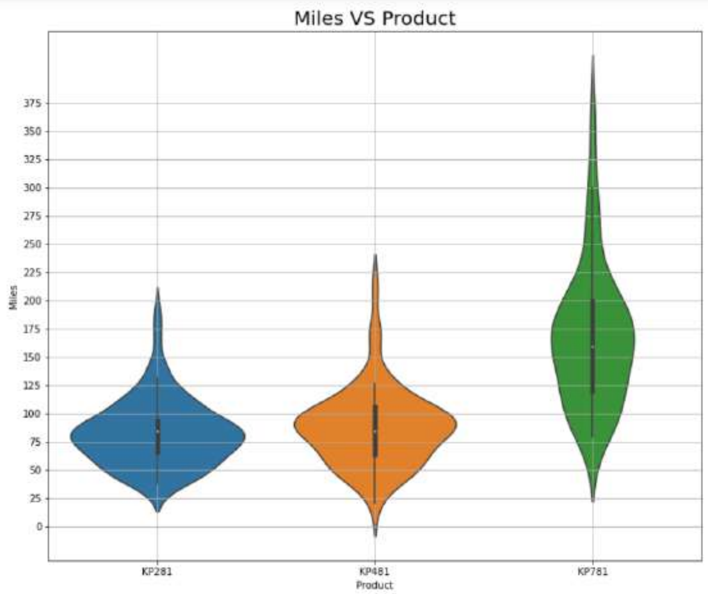
In [60]:
```
df
```
Out[60]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
2	KP281	19	Female	14	Partnered	4	3	30699	66	30.70
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42
176	KP781	42	Male	18	Single	5	4	89641	200	89.64
177	KP781	45	Male	16	Single	5	5	90886	160	90.89
178	KP781	47	Male	18	Partnered	4	5	104581	120	104.58
179	KP781	48	Male	18	Partnered	4	5	95508	180	95.51

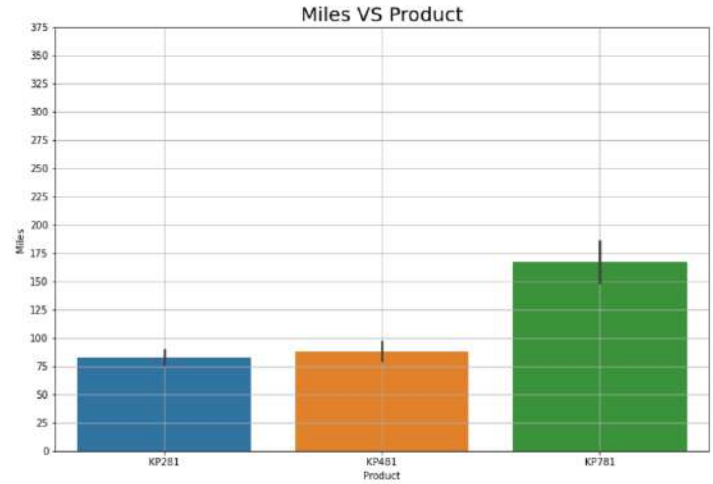
180 rows × 10 columns

In [61]:
```
# Checking the outliers
plt.figure(figsize=(12,10))
g=sns.violinplot(data=df,y='Miles',x='Product')
g.set_yticks(range(0,400,25))
plt.title('Miles VS Product',fontsize=20)
plt.grid()
plt.show()
```





```python
plt.figure(figsize=(12,8))
h=sns.barplot(data=df,y='Miles',x='Product')
h.set_yticks(range(0,400,25))
plt.title('Miles VS Product',fontsize=20)
plt.grid()
plt.show()
```



Outliers:

KP281 = miles more than 135 is outliers

KP481 = >125

KP781= >300

```python
In [63]: #Extracting the Miles and product column and defining the Miles categories
         Product_Miles=df[['Product','Miles']]
         a=[x for x in range(0,400,25)]
         b=[str(a[i])+"-"+str(a[i+1]) for i in range(0,len(a)-1)]
         Product_Miles['Miles_category']=pd.cut(Product_Miles['Miles'],bins=a,labels=b)
         Product_Miles
```

```
C:\Users\anshu\AppData\Local\Temp\ipykernel_26396\1078747982.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy
  Product_Miles['Miles_category']=pd.cut(Product_Miles['Miles'],bins=a,labels=b)
```

Out[63]:

	Product	Miles	Miles_category
0	KP281	112	100-125
1	KP281	75	50-75
2	KP281	66	50-75
3	KP281	85	75-100
4	KP281	47	25-50
...	...	...	...
175	KP781	200	175-200
176	KP781	200	175-200
177	KP781	160	150-175
178	KP781	120	100-125
179	KP781	180	175-200

180 rows × 3 columns

```python
In [64]: product_miles_table=pd.crosstab(Product_Miles['Miles_category'],Product_Miles['Product'],margins=True)
         product_miles_table
```

In [64]:
```python
product_miles_table=pd.crosstab(Product_Miles['Miles_category'],Product_Miles['Product'],margins=True)
product_miles_table
```

Out[64]:

Miles_category	KP281	KP481	KP781	All
0-25	0	1	0	1
25-50	12	4	0	16
50-75	26	16	0	42
75-100	24	23	8	55
100-125	12	8	4	24
125-150	4	5	5	14
150-175	1	2	6	9
175-200	1	0	12	13
200-225	0	1	0	1
225-250	0	0	1	1
250-275	0	0	1	1
275-300	0	0	2	2
350-375	0	0	1	1
All	80	60	40	180

In [65]:
```python
# calculating the Conditional Probability
product_miles_table['KP281|Miles']=round(product_miles_table['KP281']*100/product_miles_table['All'],2)
product_miles_table['KP481|Miles']=round(product_miles_table['KP481']*100/product_miles_table['All'],2)
product_miles_table['KP781|Miles']=round(product_miles_table['KP781']*100/product_miles_table['All'],2)
product_miles_table
```

Out[65]:

Miles_category	KP281	KP481	KP781	All	KP281|Miles	KP481|Miles	KP781|Miles
0-25	0	1	0	1	0.00	100.00	0.00
25-50	12	4	0	16	75.00	25.00	0.00
50-75	26	16	0	42	61.90	38.10	0.00
75-100	24	23	8	55	43.64	41.82	14.55
100-125	12	8	4	24	50.00	33.33	16.67
125-150	4	5	5	14	28.57	35.71	35.71
150-175	1	2	6	9	11.11	22.22	66.67
175-200	1	0	12	13	7.69	0.00	92.31
200-225	0	1	0	1	0.00	100.00	0.00
225-250	0	0	1	1	0.00	0.00	100.00
250-275	0	0	1	1	0.00	0.00	100.00
275-300	0	0	2	2	0.00	0.00	100.00
350-375	0	0	1	1	0.00	0.00	100.00
All	80	60	40	180	44.44	33.33	22.22

In [66]:
```python
df.describe()
```

Out[66]:

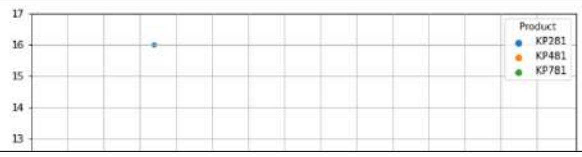
	Age	Education	Usage	Fitness	Income	Miles	Income(in K)
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444	53.720000
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605	16.507097
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000	29.560000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000	44.057500

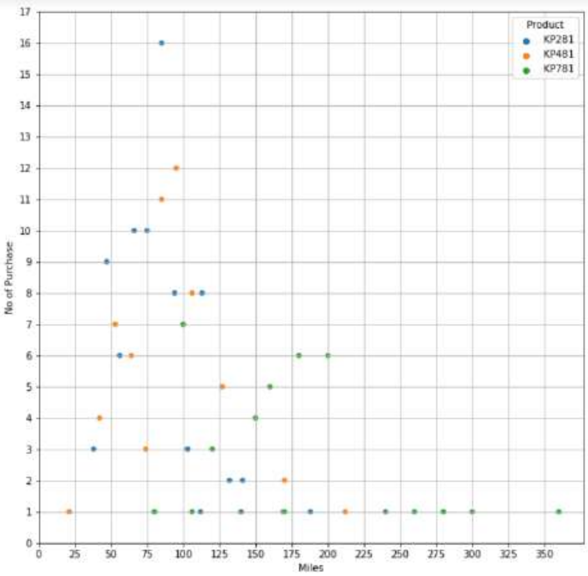
In [66]:
```python
df.describe()
```

Out[66]:

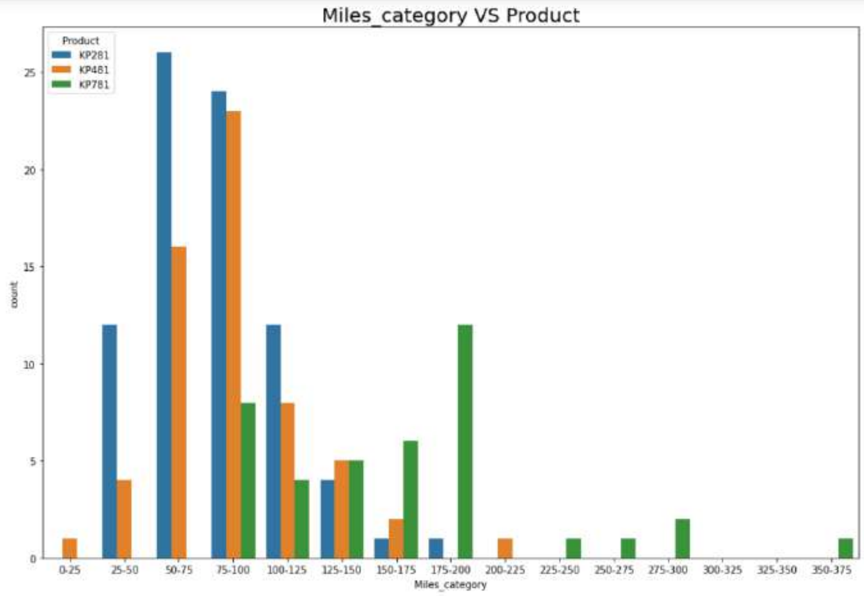
	Age	Education	Usage	Fitness	Income	Miles	Income(in K)
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444	53.720000
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605	16.507097
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000	29.560000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000	44.057500
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000	50.595000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000	58.670000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000	104.580000

In [67]:
```python
# we groupby the Miles and product then count the frequency and plotted a scatterplot
plt.figure(figsize=(10,10))
k=sns.scatterplot(data=df.groupby(['Product','Miles']).size().reset_index().rename(columns={0:'values'}),
 x='Miles',y='values',hue='Product')
k.set_xticks(range(0,375,25))
k.set_yticks(range(0,18,1))
plt.ylabel('No of Purchase')
plt.grid()
plt.show()
```



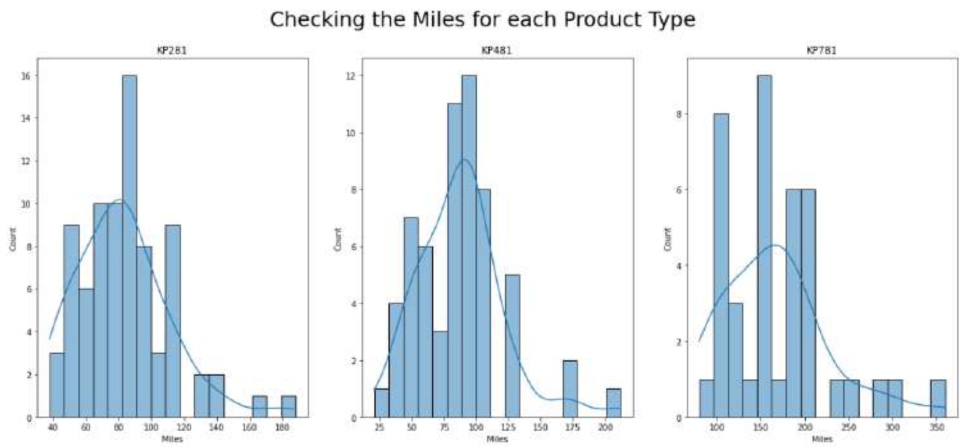


In [68]:
```
plt.figure(figsize=(15,10))
sns.countplot(data=Product_Miles,x='Miles_category',hue='Product')
plt.title('Miles_category VS Product',fontsize=20)
plt.show()
```



In [73]:

In [73]:
```
# plotting the histogram for each product for Miles
fig=plt.figure(figsize=(20,8))
k=1
for i in ['KP281','KP481','KP781']:
 plt.subplot(1,3,k)
 sns.histplot(df.loc[df['Product']==i]['Miles'],bins=int(17),kde=True)
 plt.title(i)
 k=k+1
fig.suptitle('Checking the Miles for each Product Type',fontsize=25)
plt.show()
```



In [72]:
```
product_fitness_table=pd.crosstab(df['Fitness'],df['Product'],margins=True)
product_fitness_table
```
Out[72]:

Observation –

1)KP 481 is preferred by customer expected to running miles in between(60-100) less tha but it depends upon the income also

2) KP281 is also purchased in between(80-100)

3)KP781 as it is an advance version so customer who are willing to running > 125 miles use this

Analyzation of Fitness with product

In [72]:
```
product_fitness_table=pd.crosstab(df['Fitness'],df['Product'],margins=True)
product_fitness_table
```

Out[72]:

Product Fitness	KP281	KP481	KP781	All
1	1	1	0	2
2	14	12	0	26
3	54	39	4	97
4	9	8	7	24
5	2	0	29	31
All	80	60	40	180

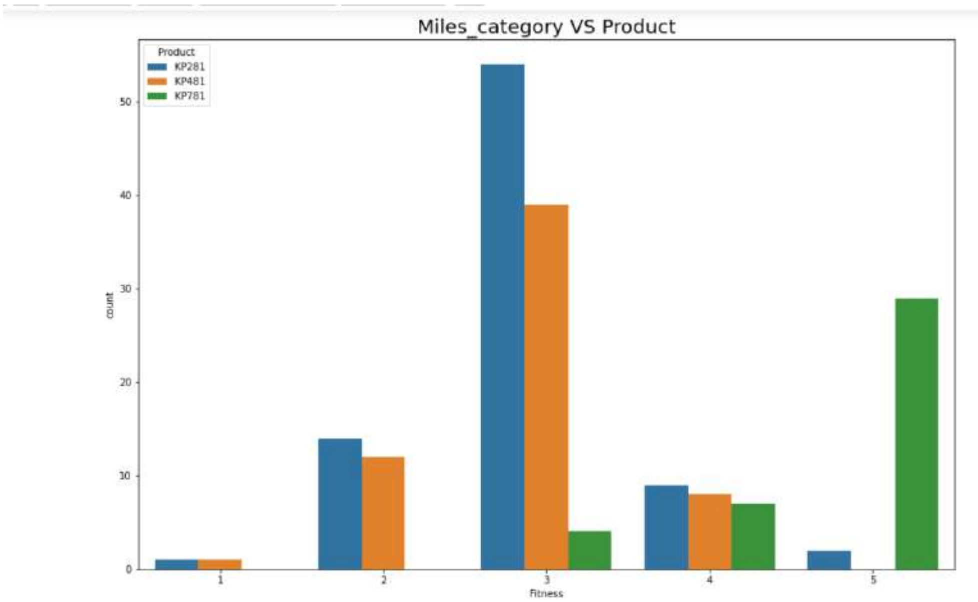
In [74]:
```
# calculating the Conditional Probability
product_fitness_table['KP281|Fitness']=round(product_fitness_table['KP281']*100/product_fitness_table['All'],2)
product_fitness_table['KP481|Fitness']=round(product_fitness_table['KP481']*100/product_fitness_table['All'],2)
product_fitness_table['KP781|Fitness']=round(product_fitness_table['KP781']*100/product_fitness_table['All'],2)
product_fitness_table
```


In [74]:
```
# calculating the Conditional Probability
product_fitness_table['KP281|Fitness']=round(product_fitness_table['KP281']*100/product_fitness_table['All'],2)
product_fitness_table['KP481|Fitness']=round(product_fitness_table['KP481']*100/product_fitness_table['All'],2)
product_fitness_table['KP781|Fitness']=round(product_fitness_table['KP781']*100/product_fitness_table['All'],2)
product_fitness_table
```

Out[74]:

Product Fitness	KP281	KP481	KP781	All	KP281|Fitness	KP481|Fitness	KP781|Fitness
1	1	1	0	2	50.00	50.00	0.00
2	14	12	0	26	53.85	46.15	0.00
3	54	39	4	97	55.67	40.21	4.12
4	9	8	7	24	37.50	33.33	29.17
5	2	0	29	31	6.45	0.00	93.55
All	80	60	40	180	44.44	33.33	22.22

In [75]:
```
plt.figure(figsize=(15,10))
sns.countplot(data=df,x='Fitness',hue='Product')
plt.title('Miles_category VS Product',fontsize=20)
plt.show()
```



Observations:

1. customer having fitness score of 3 are tend to buy the KP281,KP481

2. customer having fitness score of 5 are tend to buy the KP781

CCN Analysis

```
In [76]: df
```

Out[76]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
2	KP281	19	Female	14	Partnered	4	3	30699	66	30.70
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42
176	KP781	42	Male	18	Single	5	4	89641	200	89.64
177	KP781	45	Male	16	Single	5	5	90886	160	90.89
178	KP781	47	Male	18	Partnered	4	5	104581	120	104.58
179	KP781	48	Male	18	Partnered	4	5	95508	180	95.51

180 rows × 10 columns

```
In [77]: male_df=df.loc[df['Gender']=="Male"]
         male_df
```

Out[77]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
7	KP281	21	Male	13	Single	3	3	32973	85	32.97

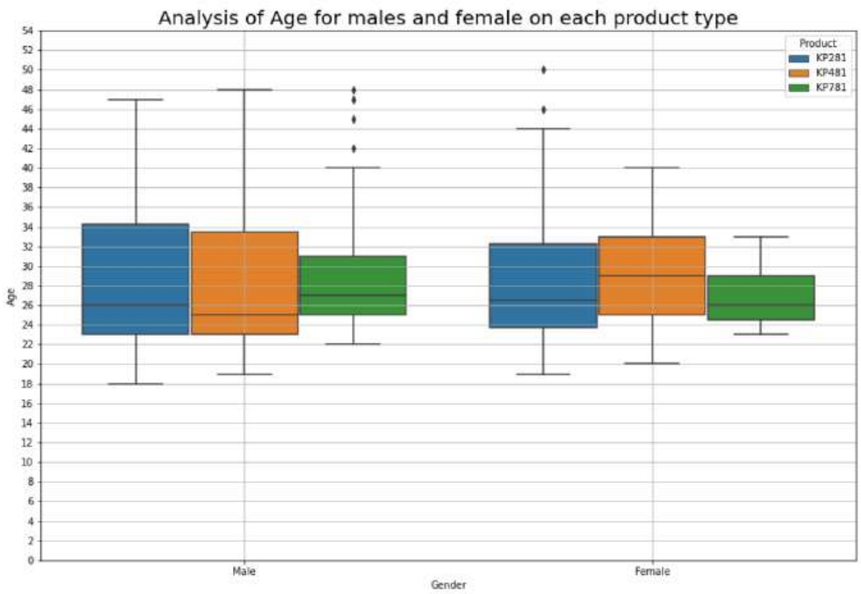
In [77]:
```
male_df=df.loc[df['Gender']=="Male"]
male_df
```

Out[77]:

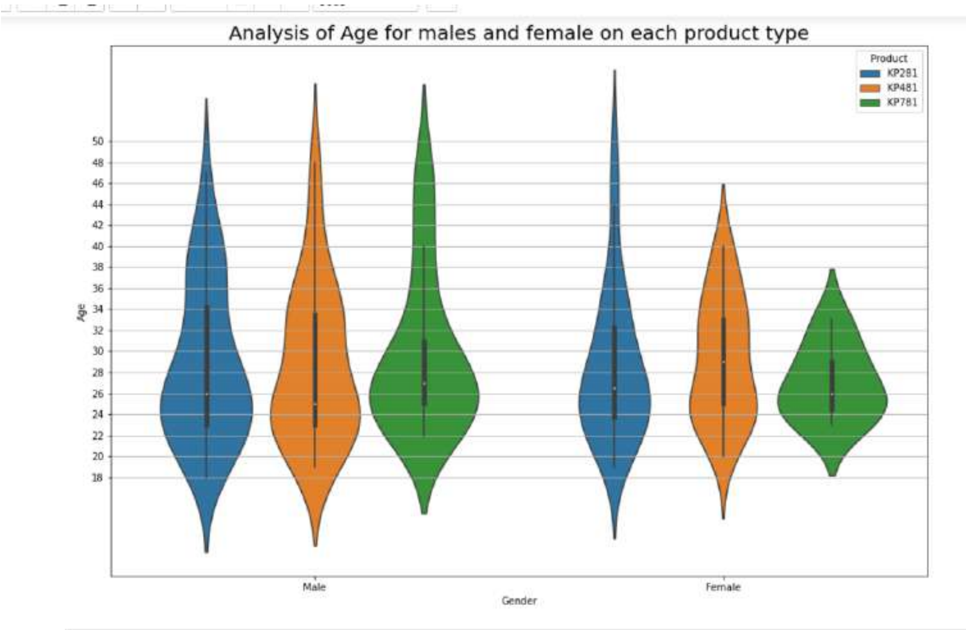
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income(in K)
0	KP281	18	Male	14	Single	3	4	29562	112	29.56
1	KP281	19	Male	15	Single	2	3	31836	75	31.84
3	KP281	19	Male	12	Single	3	3	32973	85	32.97
4	KP281	20	Male	13	Partnered	4	2	35247	47	35.25
7	KP281	21	Male	13	Single	3	3	32973	85	32.97
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	83.42
176	KP781	42	Male	18	Single	5	4	89641	200	89.64
177	KP781	45	Male	16	Single	5	5	90886	160	90.89
178	KP781	47	Male	18	Partnered	4	5	104581	120	104.58
179	KP781	48	Male	18	Partnered	4	5	95508	180	95.51

104 rows × 10 columns

In [78]:
```
# Plotting the violin plot for Age with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.boxplot(data=df,y='Age',x='Gender',hue='Product')
q.set_yticks(range(0,55,2))
plt.title('Analysis of Age for males and female on each product type',fontsize=20)
plt.grid()
plt.show()
```



In [80]:
```
# Plotting the violin plot for Age with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Age',x='Gender',hue='Product')
q.set_yticks(range(18,52,2))
plt.title('Analysis of Age for males and female on each product type',fontsize=20)
plt.grid(axis='y')
plt.show()
```



Observations:

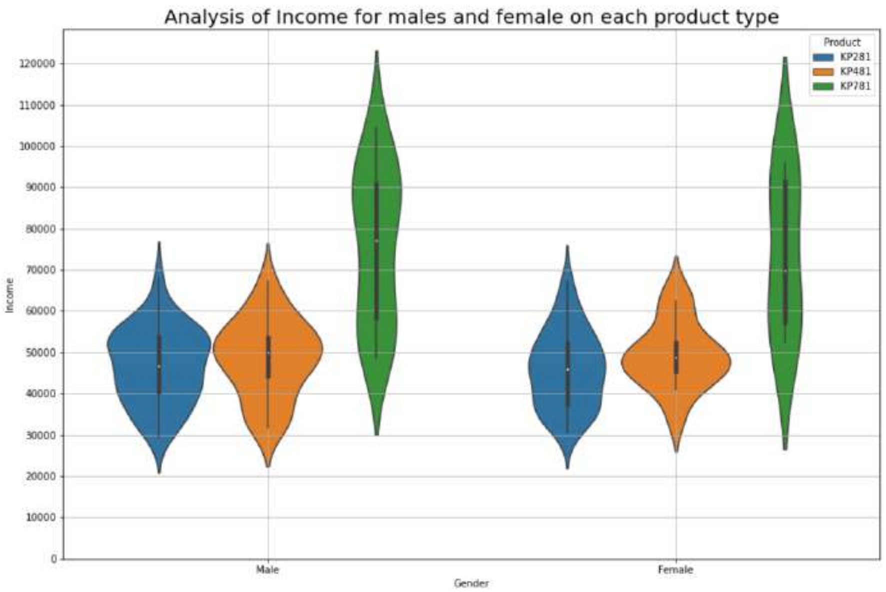
1. Age 20-30: Males= 24-26 has the higher chances for KP781 Females= 24-26 has the higher chances for KP781

2. 30-35: Males,Females = has the higher chances for KP481

3. >40 there are higher chances of buying KP781,KP481 by males than females

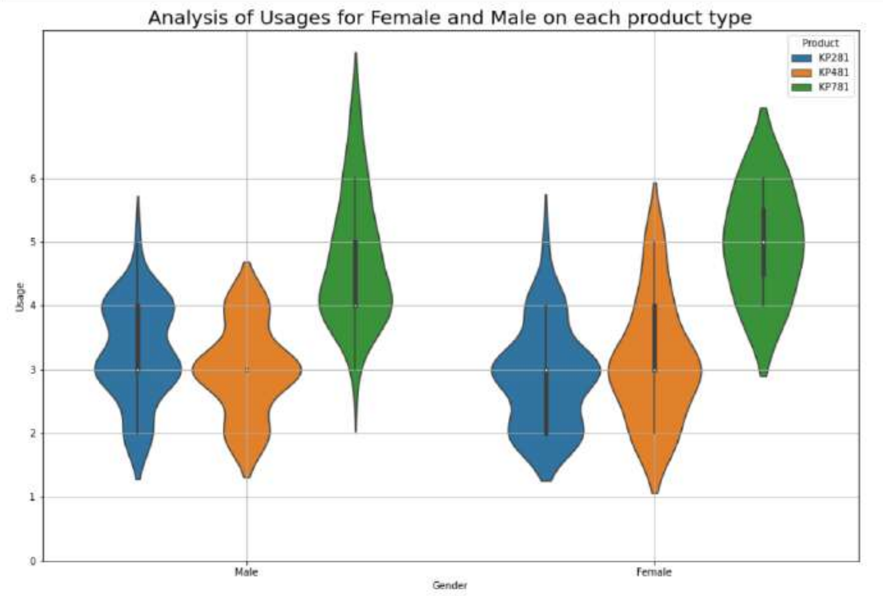
4. Median age of males buying KP481 is less than Median age of female buying KP481

In [81]:
```
# Plotting the violin plot for Income with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Income',x='Gender',hue='Product')
q.set_yticks(range(0,130000,10000))
plt.title('Analysis of Income for males and female on each product type',fontsize=20)
plt.grid()
plt.show()
```

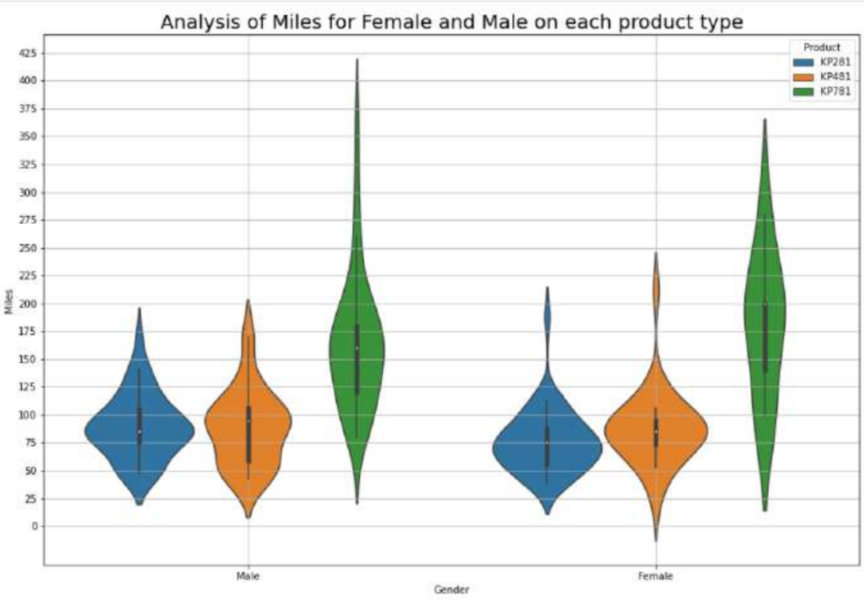


```
In [82]: # Plotting the violin plot for IUsage with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Usage',x='Gender',hue='Product')
q.set_yticks(range(0,7,1))
plt.title('Analysis of Usages for Female and Male on each product type',fontsize=20)
plt.grid()
plt.show()
```

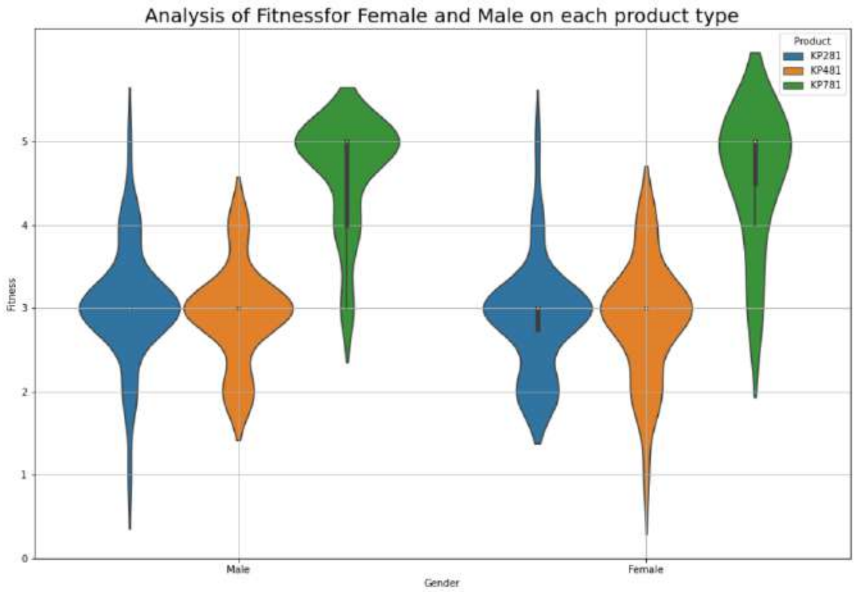
Analysis of Usages for Female and Male on each product type



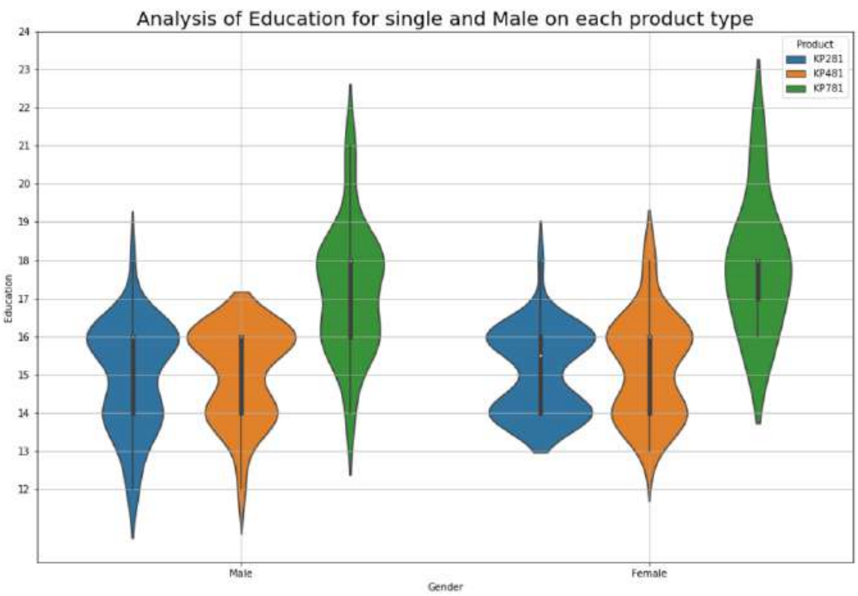

```
: # Plotting the violin plot for Miles(Expected to run) with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Miles',x='Gender',hue='Product')
q.set_yticks(range(0,450,25))
plt.title('Analysis of Miles for Female and Male on each product type',fontsize=20)
plt.grid()
plt.show()
```



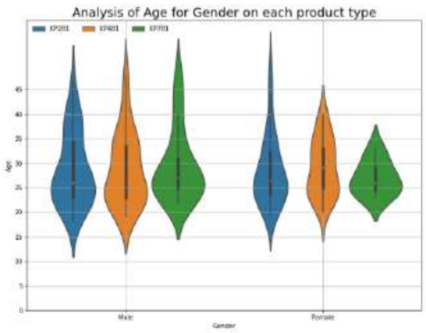

```
: # Plotting the violin plot for IFitness with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Fitness',x='Gender',hue='Product')
q.set_yticks(range(0,6))
plt.title('Analysis of Fitnessfor Female and Male on each product type',fontsize=20)
plt.grid()
plt.show()
```

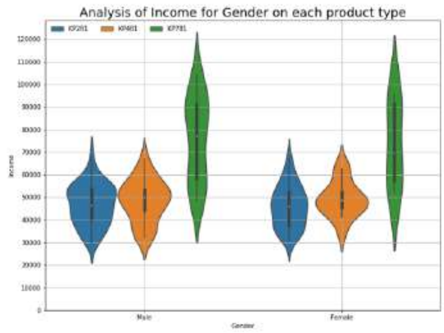


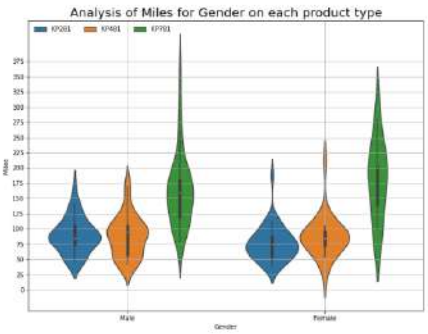
In [87]:
```python
# Plotting the violin plot for Education with Product type and Gender category
plt.figure(figsize=(15,10))
q=sns.violinplot(data=df,y='Education',x='Gender',hue='Product')
q.set_yticks(range(12,25))
plt.title('Analysis of Education for single and Male on each product type',fontsize=20)
plt.grid()
plt.show()
```

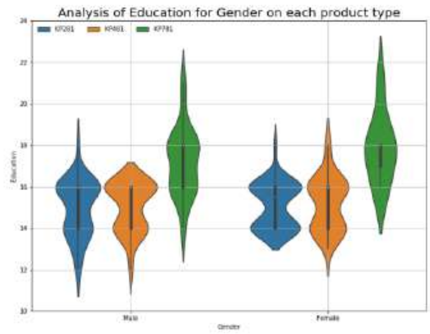


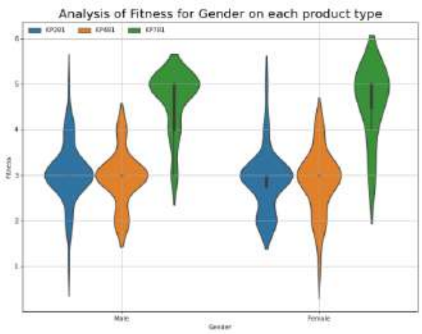
In [90]:
```python
# Plotting the violin plots of each Numerical column i.e. ['Age','Income','Miles','Education','Fitness','Usage']
# with Gender, Marital Status Status and Product Type
fig=plt.figure(figsize=(25,60))
k=1
for m in ['Gender','MaritalStatus']:
    for i in ['Age','Income','Miles','Education','Fitness','Usage']:
        plt.subplot(6,2,k)
        q=sns.violinplot(data=df,y=i,x=m,hue='Product')
        plt.title(f'Analysis of {i} for {m} on each product type',fontsize=20)
        plt.legend(loc='upper left',frameon=False,ncol=3)
        k=k+1
        if i=='Age':
            q.set_yticks(range(0,50,5))
        elif i=='Income':
            q.set_yticks(range(0,130000,10000))
        elif i=='Miles':
            q.set_yticks(range(0,400,25))
        elif i=='Education':
            q.set_yticks(range(10,26,2))
        plt.grid()
plt.show()
```

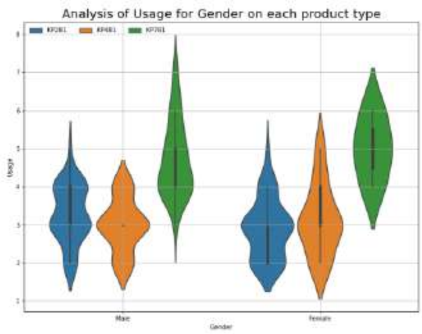

Analysis of Age for Gender on each product type
KP281
KP481
KP781
Age
Male
Female
Gender

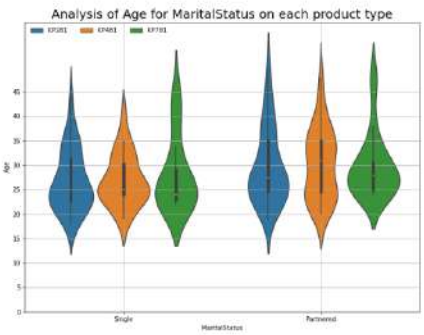

Analysis of Income for Gender on each product type
KP281
KP481
KP781
Income
Male
Female
Gender

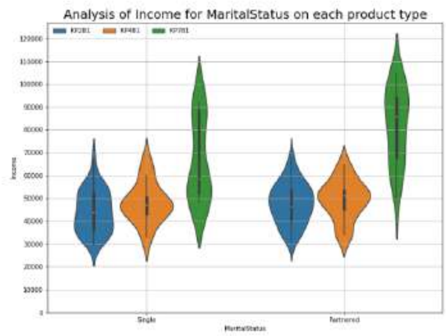

Analysis of Miles for Gender on each product type
KP281
KP481
KP781
Miles
Male
Female
Gender

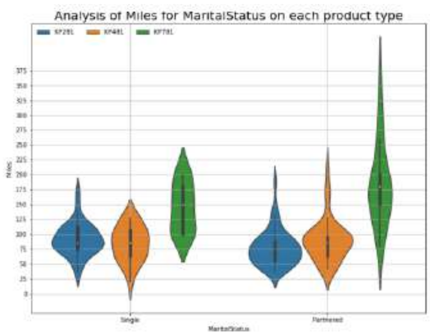

Analysis of Education for Gender on each product type
KP281
KP481
KP781
Education
Male
Female
Gender

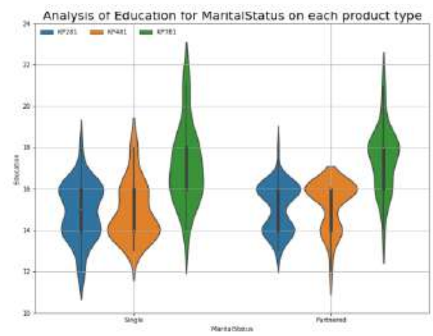

Analysis of Fitness for Gender on each product type
KP281
KP481
KP781
Fitness
Male
Female
Gender

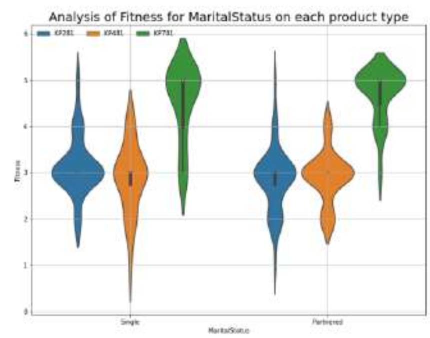

Analysis of Usage for Gender on each product type
KP281
KP481
KP781
Usage
Male
Female
Gender

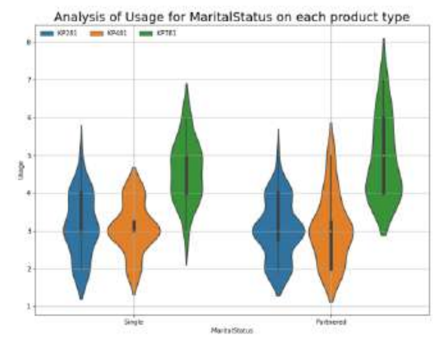

Analysis of Age for MaritalStatus on each product type
KP281
KP481
KP781
Age
Single
Partnered
MaritalStatus


Analysis of Income for MaritalStatus on each product type
KP281
KP481
KP781
Income
Single
Partnered
MaritalStatus

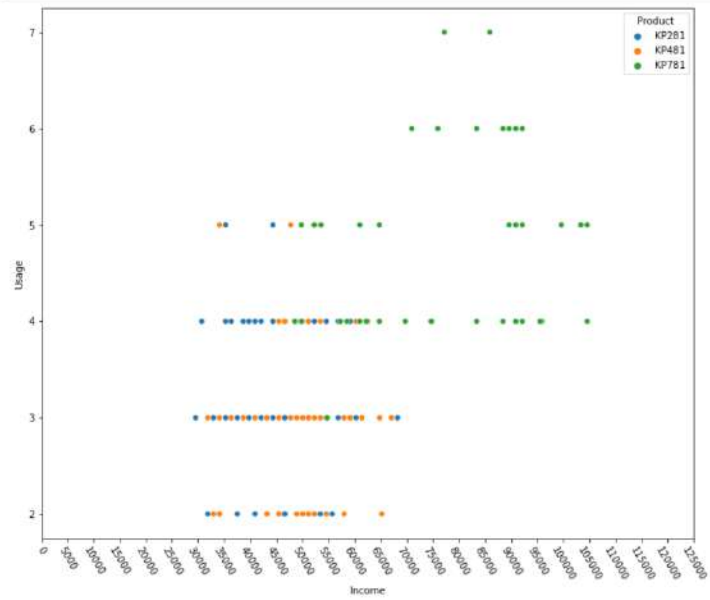

Analysis of Miles for MaritalStatus on each product type
KP281
KP481
KP781
Miles
Single
Partnered
MaritalStatus


Analysis of Education for MaritalStatus on each product type
KP281
KP481
KP781
Education
Single
Partnered
MaritalStatus

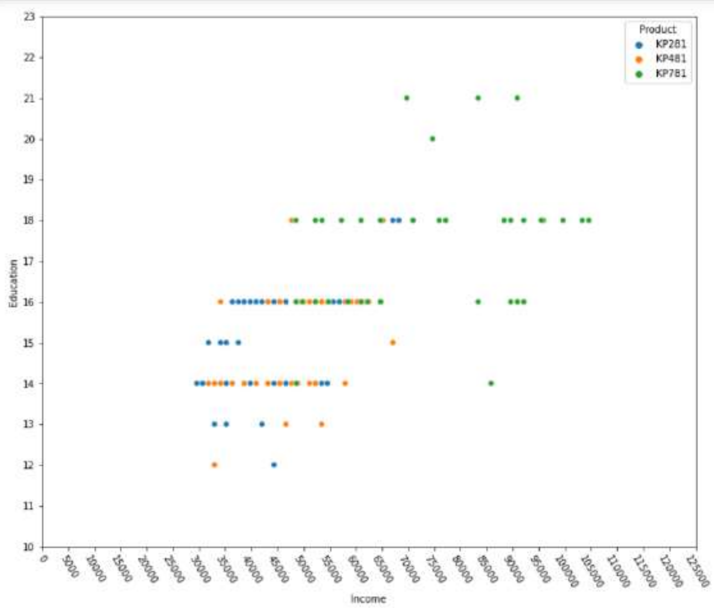

Analysis of Fitness for MaritalStatus on each product type
KP281
KP481
KP781
Fitness
Single
Partnered
MaritalStatus


Analysis of Usage for MaritalStatus on each product type
KP281
KP481
KP781
Usage
Single
Partnered
MaritalStatus

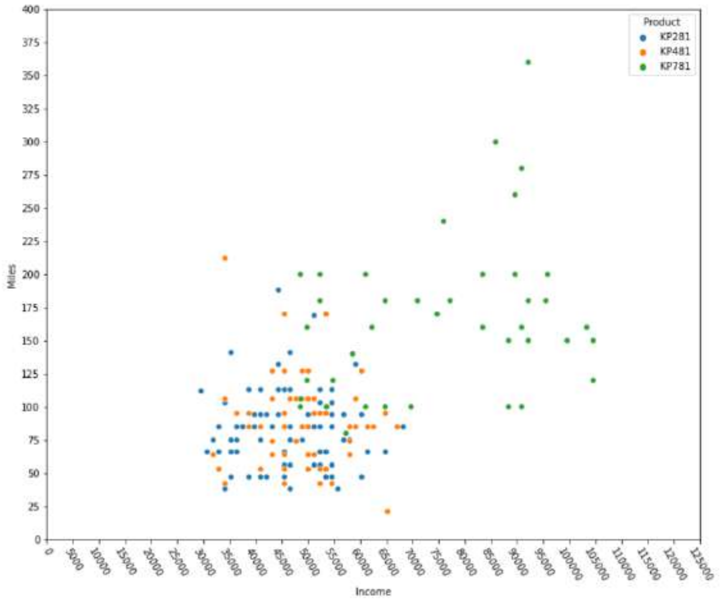
[91]:
```
# plotting the scatter plot for customer usages with customer income with each product type
plt.figure(figsize=(12,10))
t=sns.scatterplot(data=df,y='Usage',x='Income',hue='Product')
t.set_xticks(range(0,130000,5000))
plt.xticks(rotation=300)
plt.show()
```



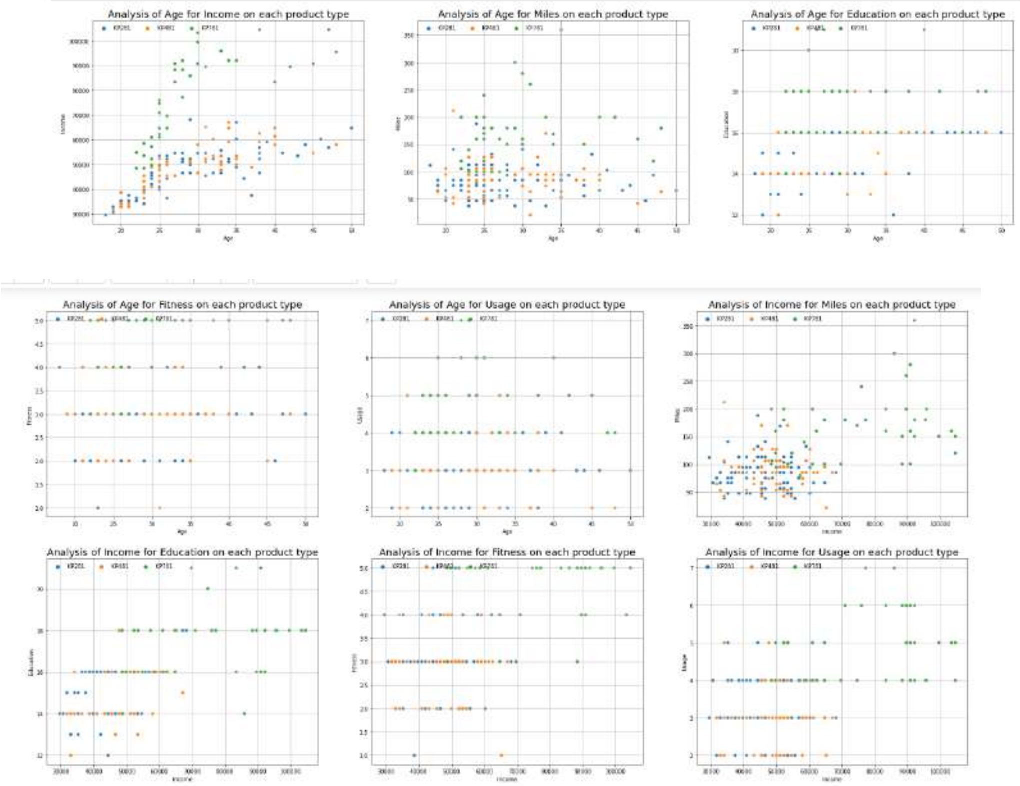
In [92]:
```
# plotting the scatter plot for customer Education with customer income with each product type
plt.figure(figsize=(12,10))
t=sns.scatterplot(data=df,y='Education',x='Income',hue='Product')
t.set_xticks(range(0,130000,5000))
t.set_yticks(range(10,24))
plt.xticks(rotation=300)
plt.show()
```

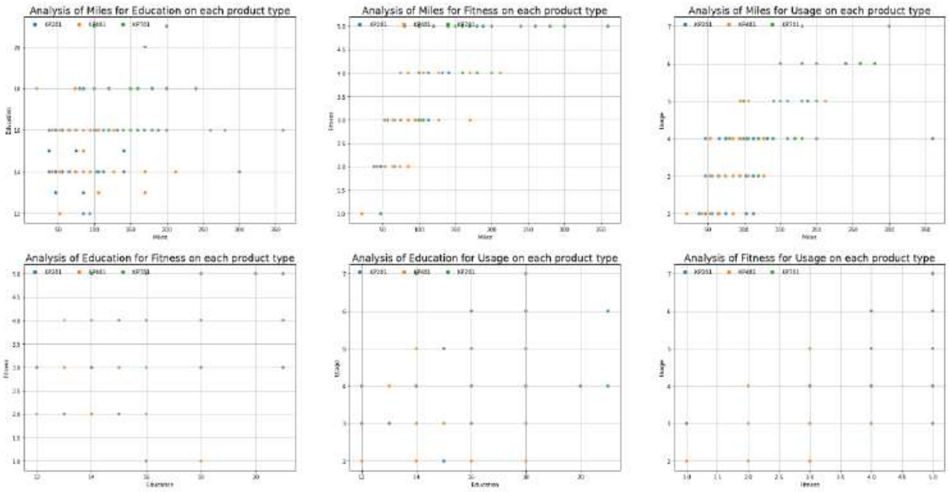


In [93]:
```
# plotting the scatter plot for customer Expectation of miles running with customer income with each product type
plt.figure(figsize=(12,10))
t=sns.scatterplot(data=df,y='Miles',x='Income',hue='Product')
t.set_xticks(range(0,130000,5000))
t.set_yticks(range(0,425,25))
plt.xticks(rotation=300)
plt.show()
```




```
[95]: # Plotting the scatter plot of all numerical column with each other for each product type
      fig=plt.figure(figsize=(30,40))
      k=1
      numlist=['Age','Income','Miles','Education','Fitness','Usage']
      for i in range(0,6):
          for j in range(i+1,len(numlist)):
              plt.subplot(5,3,k)
              q=sns.scatterplot(data=df,x=numlist[i],y=numlist[j],hue='Product')
              plt.title(f'Analysis of {numlist[i]} for {numlist[j]} on each product type',fontsize=18)
              plt.legend(loc='upper left',frameon=False,ncol=3)
              k=k+1
              if (i) =='Age':
                  q.set_xticks(range(0,50,5))
              plt.grid()
      plt.show()
```





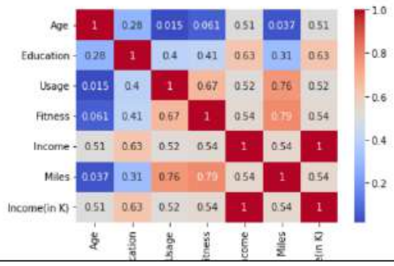

```
# getting the correlation with each numerical with each other
df.corr()
```

Out[96]:

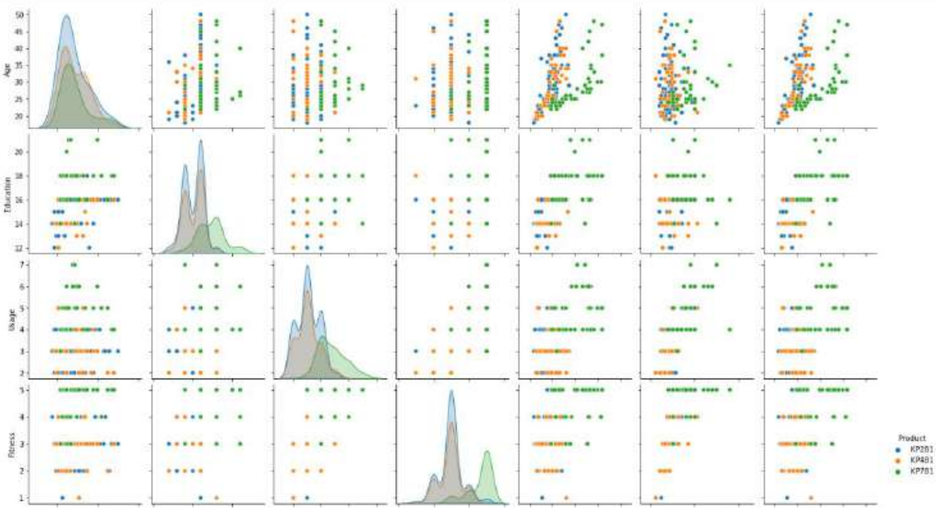
	Age	Education	Usage	Fitness	Income	Miles	Income(in K)
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618	0.513406
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284	0.625823
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130	0.519548
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702	0.535007
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473	1.000000
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000	0.543476
Income(in K)	0.513406	0.625823	0.519548	0.535007	1.000000	0.543476	1.000000

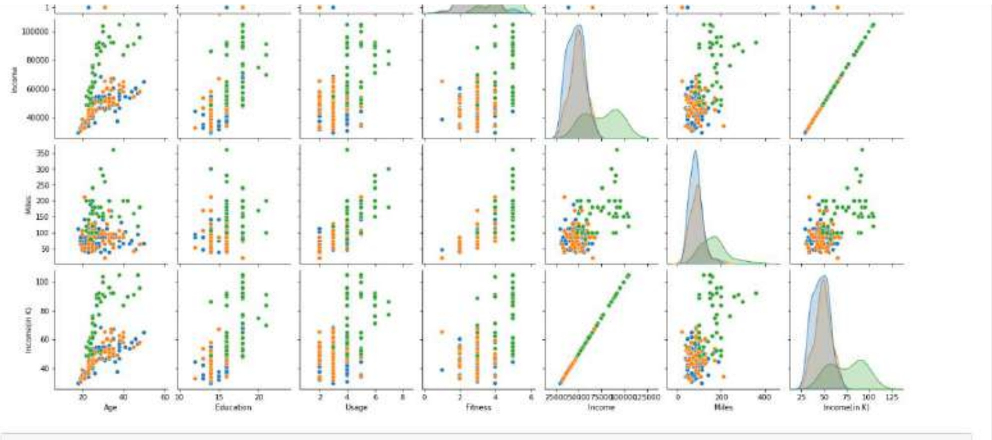
In [97]:
```
# Plotting the heatmap
sns.heatmap(df.corr(),cmap='coolwarm',annot=True)
```

Out[97]: <AxesSubplot:>



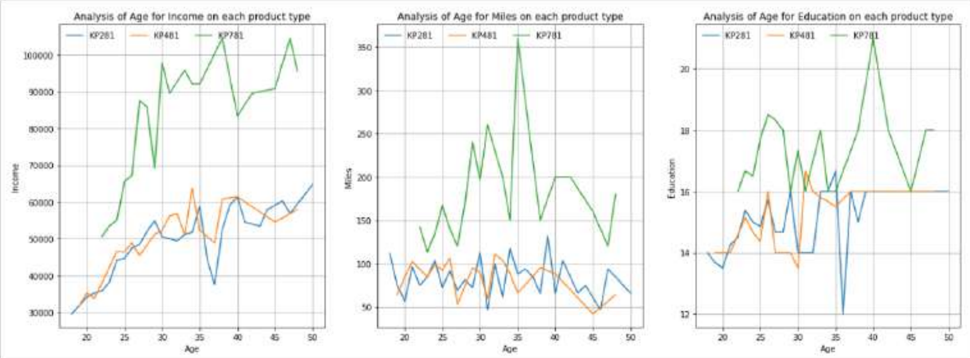
In [98]:
```
# Plotting the pair plot
sns.pairplot(df,hue='Product')
plt.show()
```

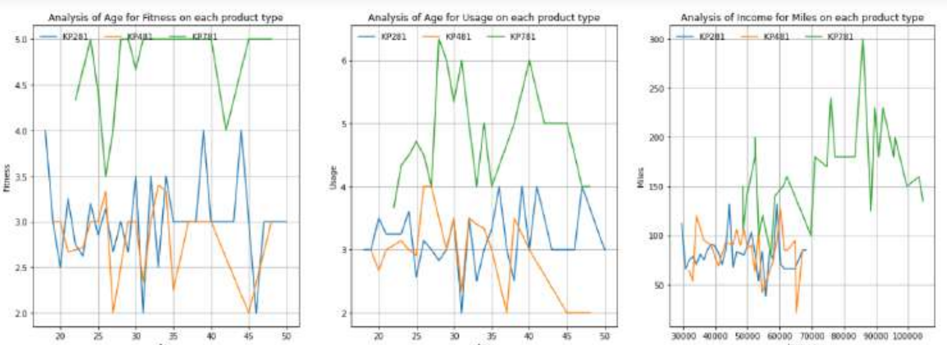


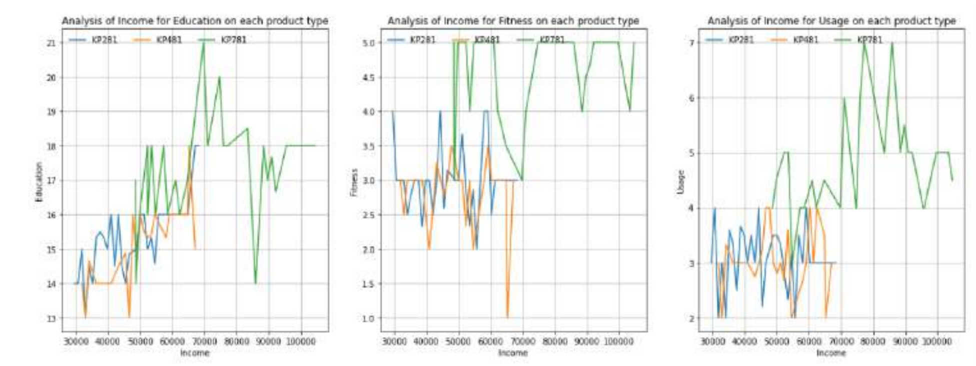


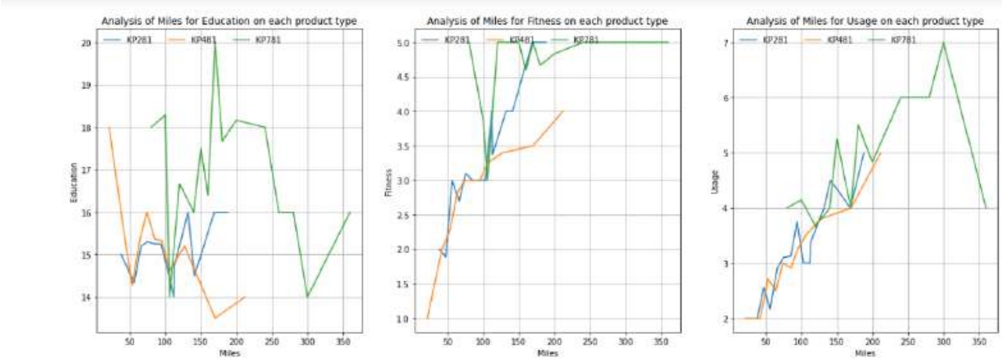
In [101]:

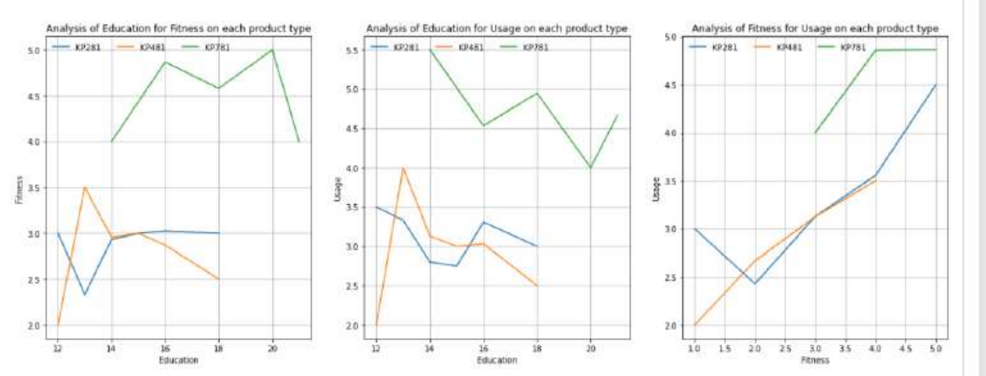
```
# Plotting the Lineplot of all numerical column with each other for each product type
fig=plt.figure(figsize=(20,40))
k=1
numlist=['Age','Income','Miles','Education','Fitness','Usage']
for i in range(0,6):
    for j in range(i+1,len(numlist)):
        plt.subplot(5,3,k)
        q=sns.lineplot(data=df,x=numlist[i],y=numlist[j],hue='Product',ci=False)
        plt.title(f'Analysis of {numlist[i]} for {numlist[j]} on each product type',fontsize=12)
        plt.legend(loc='upper left',frameon=False,ncol=3)
        k=k+1
        if (i) =='Age':
            q.set_xticks(range(0,50,5))
        plt.grid()
plt.show()
```











Observations:- 1. Age

KP281 - Customer having age in between 20-30

KP481 - Customer having age in between 30-35

KP781 - Customer having age in between >40(outliers),25-30

2 Income
KP281- customer having Income in between 30k-60k
KP481- customer having Income in between 40k-60k
KP781- customer having Income in greater > 60k

3. Education
KP281= customer having Education of 14 and 16 years
KP281= customer having Education of 14 and 16 years
KP781= customer having Education of 18 and more year

4. Usages
KP281= more preferred for usage 2-4
KP481= more preferred for usage 2-3
KP781= more preferred for usage more than 4

5. Miles
KP 481 is preferred by customer expected to running miles in between(60-100) less than but it depends upon the income also
KP281 is also purchased in between(80-100)
KP781 as it is an advance version so customer who are willing to running > 125 miles use this

6. Fitness
customer having fitness score of 3 are tend to buy the KP281,
KP481 customer having fitness score of 5 are tend to buy the KP781.

7. Age_Gender –
Age 20-30:
Males= 24-26 has the higher chances for KP781
Females= 24-26 has the higher chances for KP781
Age 30-35:
Males,Females = has the higher chances for KP481
>40 there are higher chances of buying KP781,KP481 by males than females
Median age of males buying KP481 is less than Median age of female buying KP481

8. Usages-Gender:-
   There are more chances of Female having usage between 2-3 buying KP281,KP781 than males: Males and Females having higher income and more than 4 usage are tend to buy KP781 Median use of Female is Higher than median use of males for KP781
9. Age_Income:-
   KP281= Age(20-25), income(30k-50k)
   KP481= Age(30-35), Income(45k-60k)
   KP781 =Age(20-70)- Income(>60k)
10. Age_Miles:-
   KP281= Age(20-30), 50-100 Miles More preferred
   KP481= Age(30-35), 50-100 Miles
   KP781 =Age(25-30)- >125 miles Age the age Increase people are tend to buy less KP781

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 Le. 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.