Problem Statement/Aim-

Identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers.

In [1]:

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

In [2]:

```
raw_df=pd.read_csv('aerofit_treadmill.csv')
raw_df.head()
```

Out[2]:

	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 [3]:

```
raw_df.shape
```

Out[3]:

```
(180, 9)
```

In [4]:

```
raw_df.dtypes
```

Out[4]:

```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

In [5]:

```
raw_df.nunique()
```

Out[5]:

```
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

In [6]:

```
raw_df.describe(include='all')
```

Out[6]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

Observations:

- There are no missing values
- There are 3 unique products where KP281 is the most frequent product.
- Minimum & Maximum age of the person is 18 & 50, and 75% of persons have age less than or equal to 33.
- 75% of persons are having education <= 16 years.
- Out of 180 data points, 104's gender is Male and rest are the female.
- Standard deviation for Income & Miles is very high and also mean and median have lot of difference. These variables might have the outliers in it.
- 3 cols are categorical- Product, Gender, Marital Status and rest are numeric/quantative cols

Unique attributes and Value counts

In [7]:

```
raw_df['Product'].unique()
```

Out[7]:

```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [8]:

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

Out[8]:

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

```
Given the Product Portfolio:

- The KP281 is an entry-level treadmill that sells for 1500dollars :the highest sales.
- The KP481 is for mid-level runners that sell for 1750dollars : 2nd highest sales
- The KP781 treadmill is having advanced features that sell for 2500dollars : it makes sense that expensive one was sold the least
```

In [9]:

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

Out[9]:

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

In [10]:

```
104*100/180
```

Out[10]:

```
57.77777777777778
```

57.7% of males bought AeroFit treadmill product

In [11]:

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

Out[11]:

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

In [12]:

```
107*100/180
```

Out[12]:

```
59.44444444444444
```

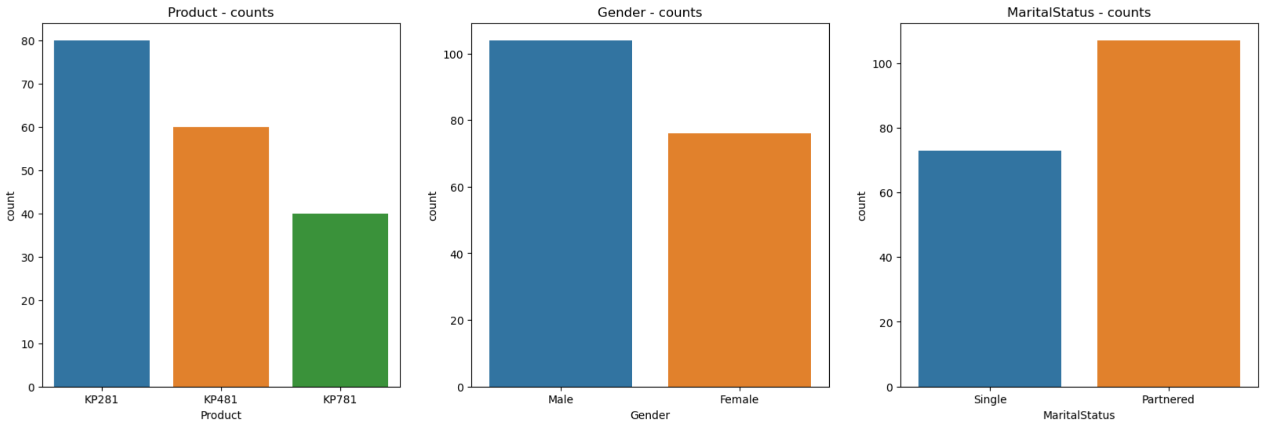
Almost 60% of partnered people bought AeroFit treadmill product

Visual Analysis

1. For categorical variables

In [13]:

```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 6))
sns.countplot(data=raw_df, x='Product', ax=axs[0])
sns.countplot(data=raw_df, x='Gender', ax=axs[1])
sns.countplot(data=raw_df, x='MaritalStatus', ax=axs[2])

axs[0].set_title("Product - counts")
axs[1].set_title("Gender - counts")
axs[2].set_title("MaritalStatus - counts")
plt.show()
```



2. For finding outliers

In [14]:

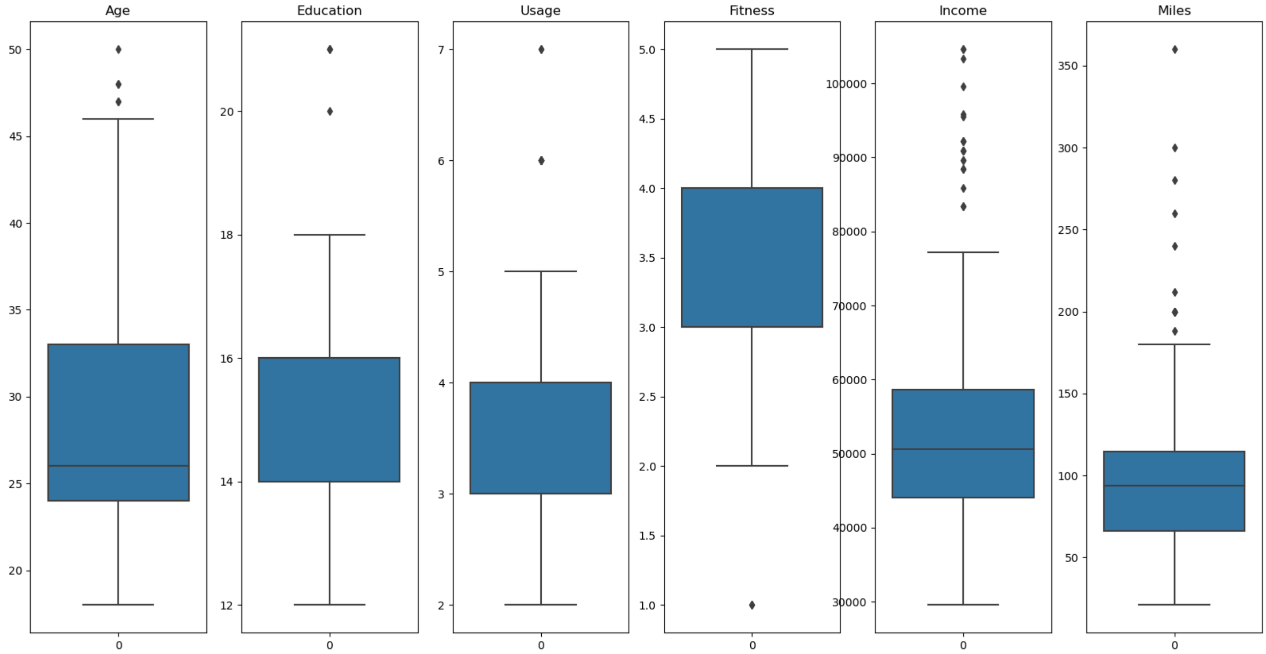
```
raw_df.columns
```

Out[14]:

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

In [15]:

```
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=raw_df[numeric_cols[i]], ax=axs[i]).set(title=numeric_cols[i])

plt.show()
```

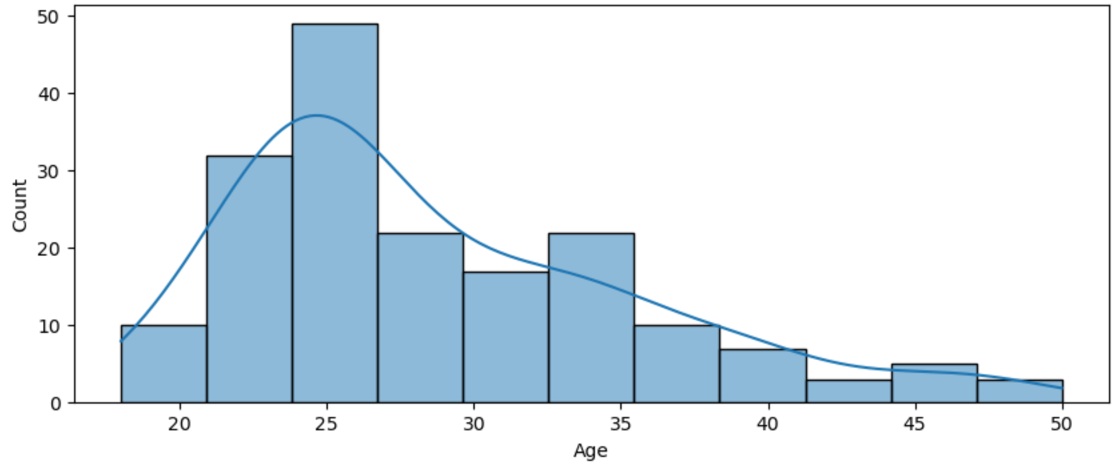


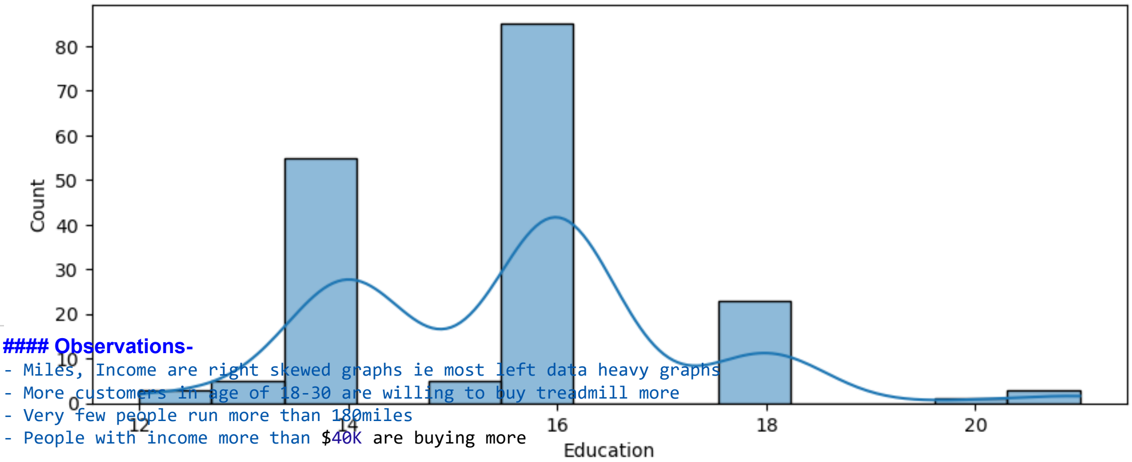
Observation - Age, Education and Usage are having very few outliers. While Income and Miles are having more outliers.

3. Check data distribution for numeric/quantative cols

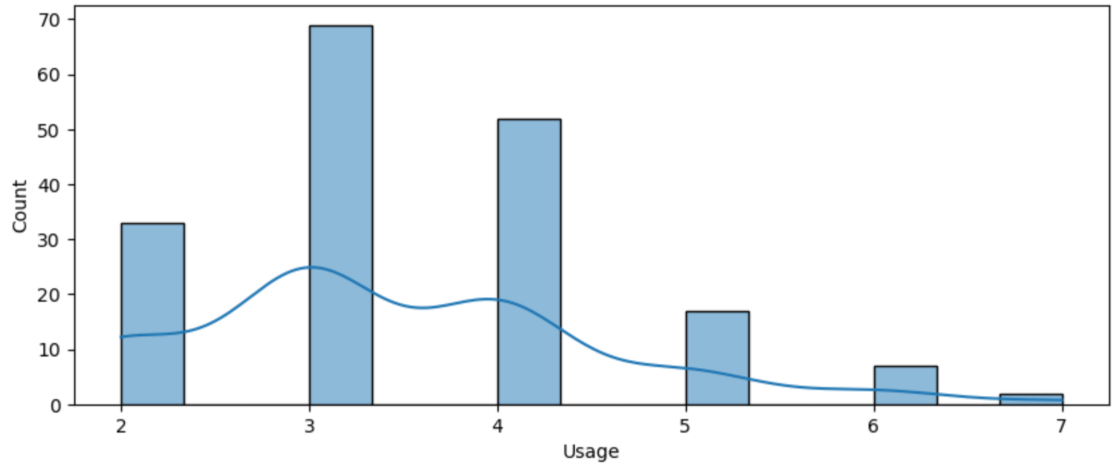
In [16]:

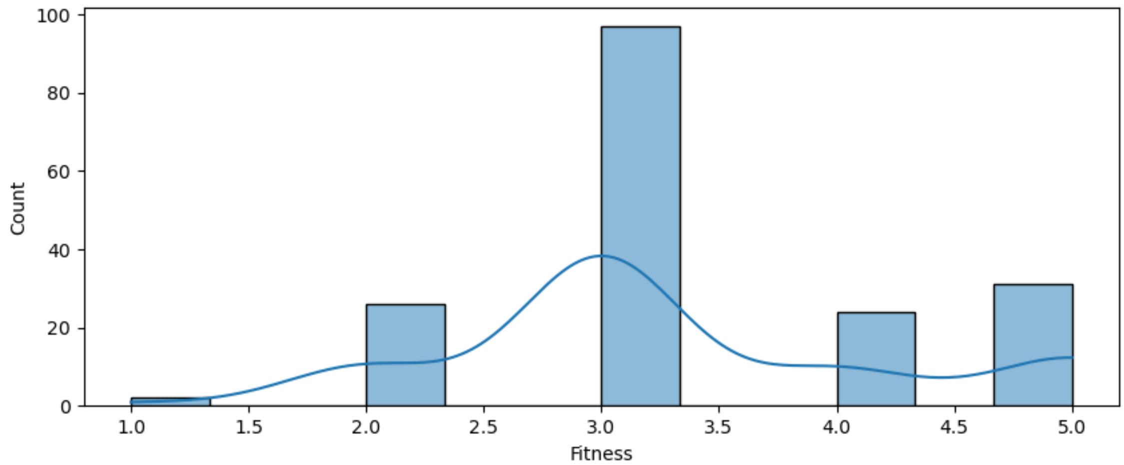
```
numeric_cols=['Age', 'Education',  'Usage',
       'Fitness', 'Income', 'Miles']
fig, axs = plt.subplots(nrows=6, figsize=(10, 10))
fig.subplots_adjust(top=2.2)
for i in range(len(numeric_cols)):
    sns.histplot(data=raw_df[numeric_cols[i]], ax=axs[i],kde=True)

plt.show()
```

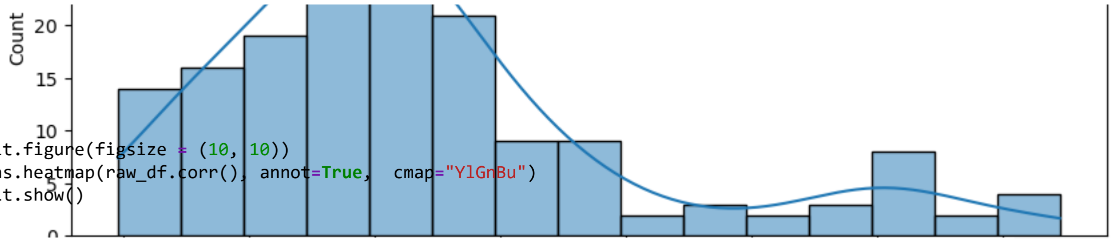




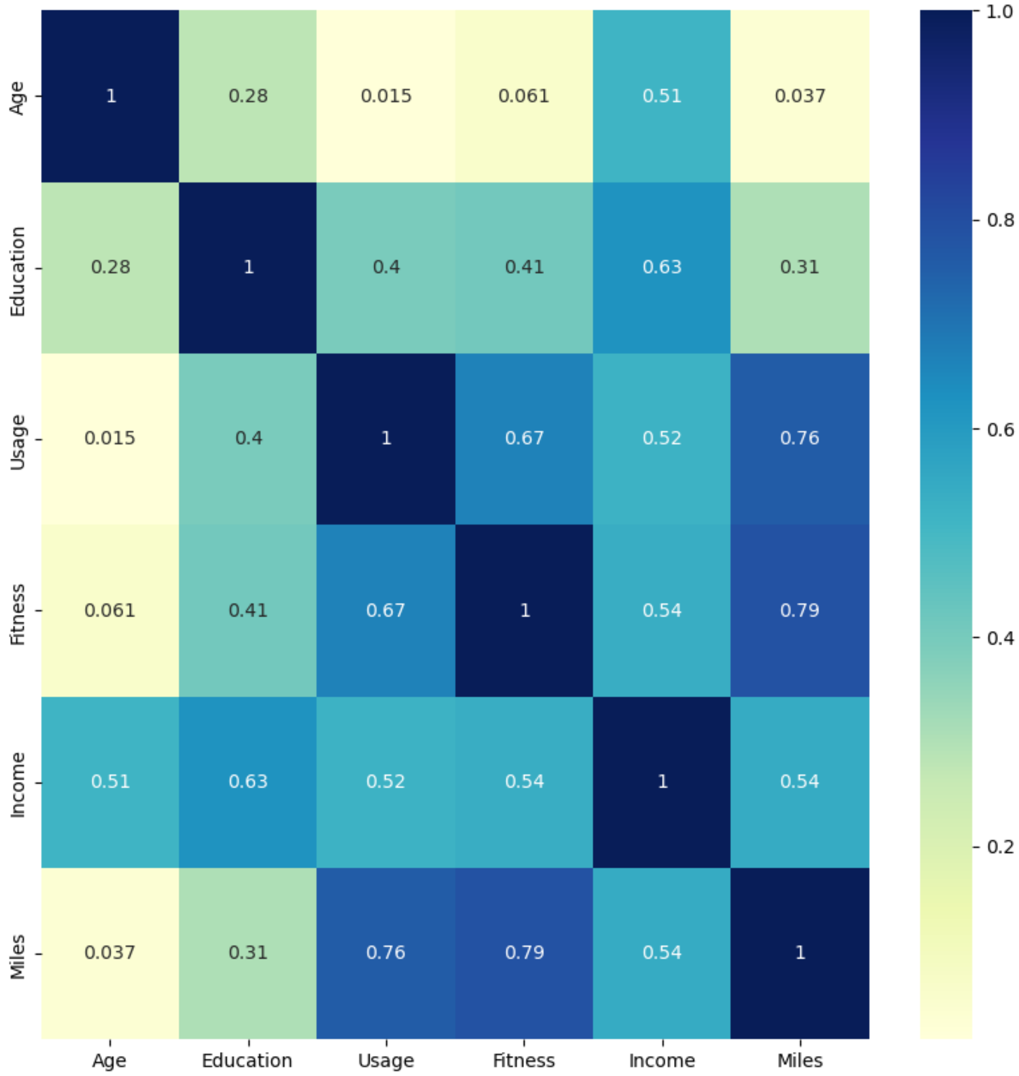
Observations-
- Miles, Income are right skewed graphs ie most left data heavy graphs
- More customers in age of 18-30 are willing to buy treadmill more
- Very few people run more than 180miles
- People with income more than $40K are buying more








```
plt.figure(figsize = (10, 10))
sns.heatmap(raw_df.corr(), annot=True,  cmap="YlGnBu")
plt.show()
```



Observation-

- Miles and Fitness are highly correlated. This makes sense as if customer fitness is high more treadmill they would want to use
- Hence high correlation is with 'Fitness and Usage' and 'Usage and fitness' that customer usage is higher when fitness is high and more people tend to buy
- Education and income have high correlation which means higher yrs of education have resulted them to get better jobs

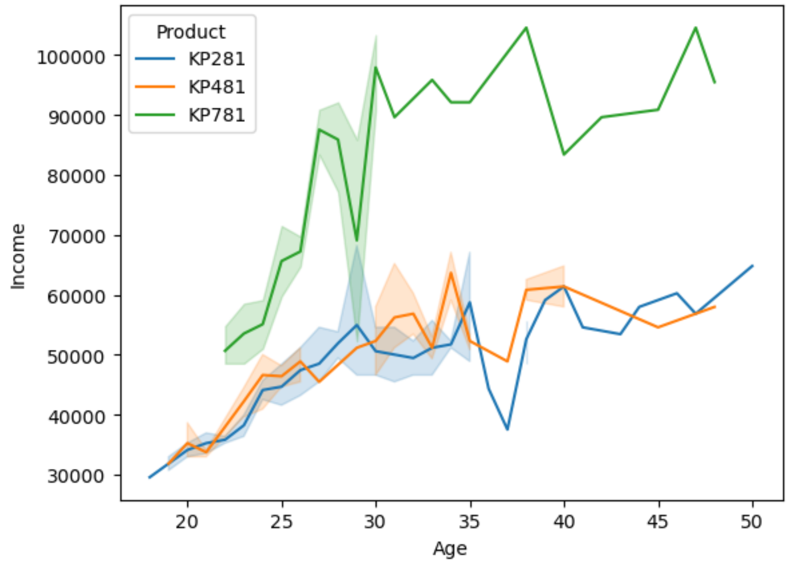
Analysis based for each product type

In [18]:

```
sns.lineplot(x='Age',y='Income',data=raw_df,hue='Product')
```

Out[18]:

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

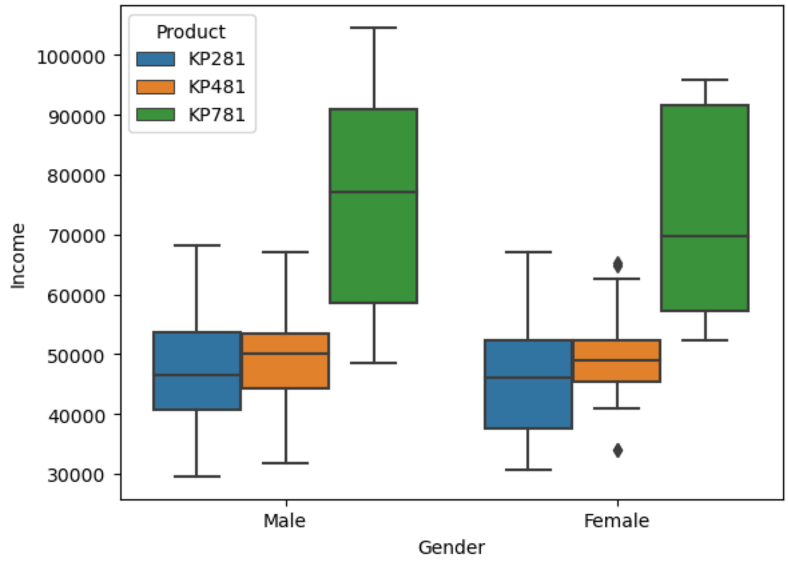


In [19]:

```
sns.boxplot(x='Gender',y='Income',data=raw_df,hue='Product')
```

Out[19]:

<AxesSubplot:xlabel='Gender', ylabel='Income'>



Convert numerical to categorical column

1. Age- Derive into Age_groups
2. Income- Derive into Income groups

In [20]:

```
raw_df['age_group']=pd.cut(x=raw_df['Age'],
                           bins=[0,18,28,38,48,58,68,100],
                           labels=['0-18','19-28','29-38','39-48','49-58','59-68','69-100'])
raw_df['age_group'].value_counts()
```

Out[20]:

```
19-28     106
29-38      55
39-48      17
0-18        1
49-58       1
59-68       0
69-100      0
Name: age_group, dtype: int64
```

In [21]:

```
raw_df['age_group'].value_counts().sum()
```

Out[21]:

```
180
```

In [25]:

```
raw_df['income_group']=pd.cut(x=raw_df['Income'],
                           bins=[10000,30000,60000,80000,105000],
                           labels=['Lower income','Lower Middle income','Upper Middle income','Higher income'])
raw_df['income_group'].value_counts()
```

Out[25]:

```
Lower Middle income    137
Upper Middle income     23
Higher income           19
Lower income             1
Name: income_group, dtype: int64
```

In [27]:

```
raw_df['income_group'].value_counts().sum()
```

Out[27]:

```
180
```

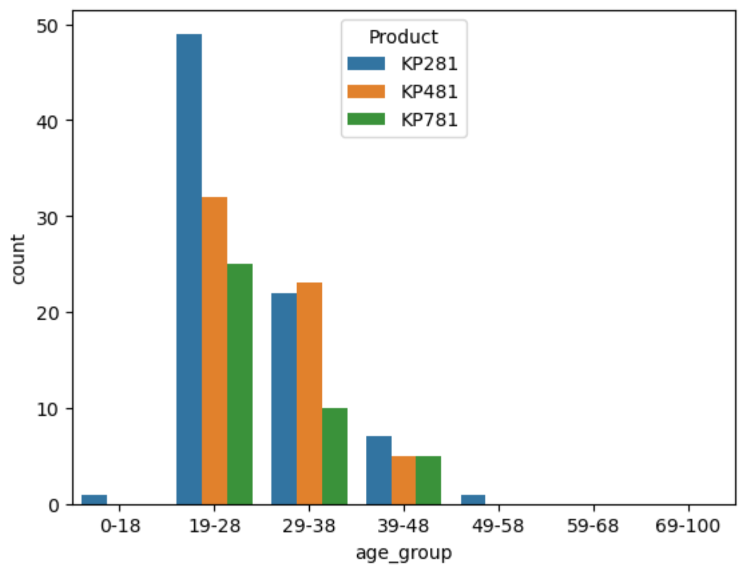
Distribution across Age and income groups for each product type

In [28]:

```
sns.countplot(data=raw_df,x='age_group', hue='Product')
```

Out[28]:

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

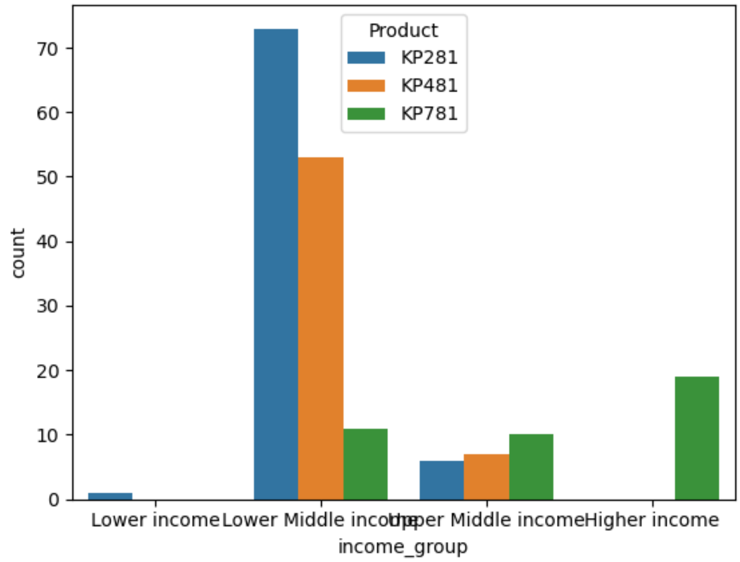


In [29]:

```
sns.countplot(data=raw_df,x='income_group', hue='Product')
```

Out[29]:

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

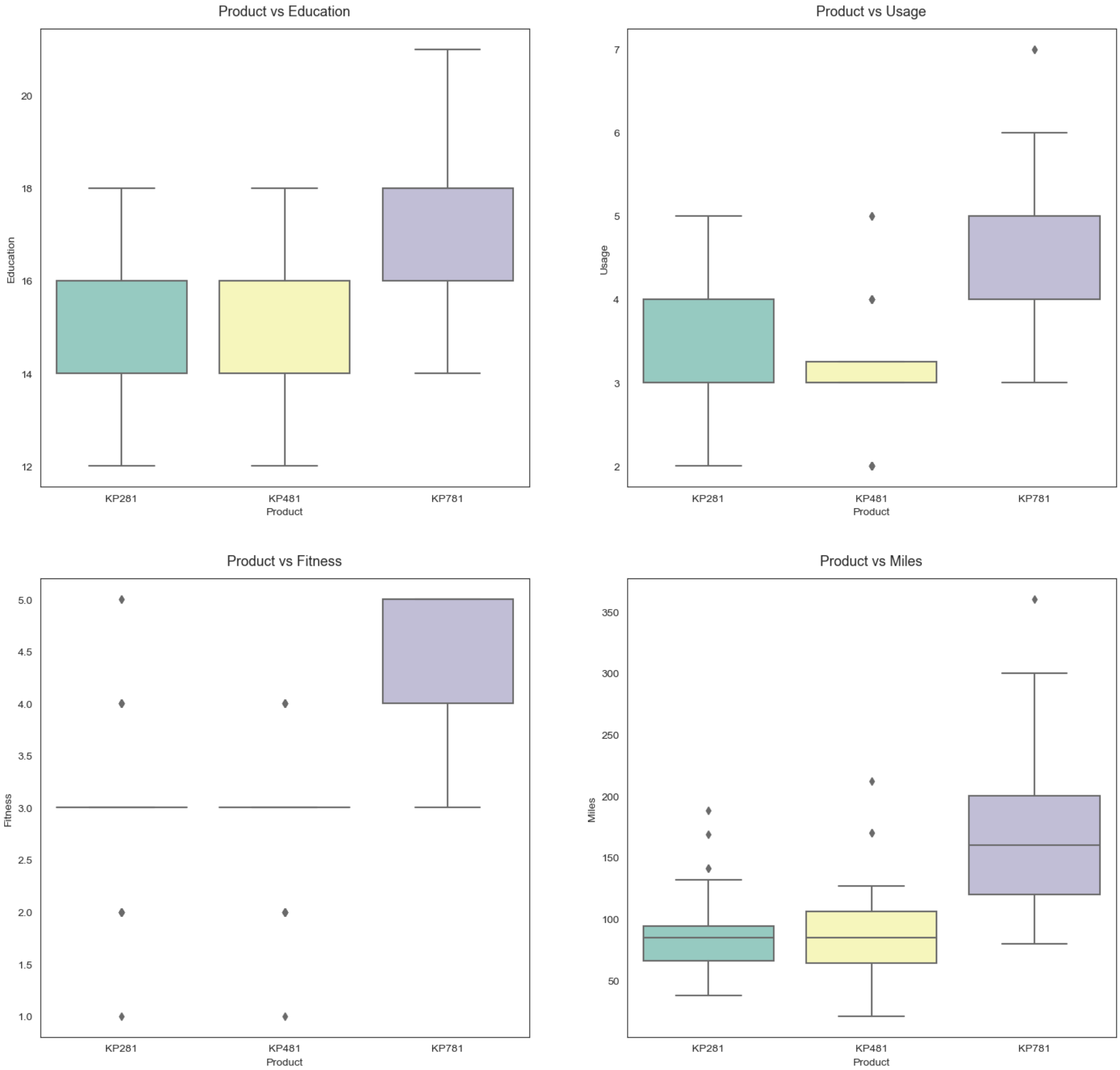


Observation-

1. Customers in the age group of 39 to 40 tend to buy higher end product 'KP781', but fewer in number. Also upper middle or higher income customers tend to buy higher end product. So business can target these segment people to sell these more.
2. Lower Middle income customers tend to buy KP281 product more and mostly they tend to be in age group of 19-28.

In [30]:

```
attrs = [ 'Education', 'Usage', 'Fitness', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(18, 12))
fig.subplots_adjust(top=1.2)
count = 0
for i in range(2):
    for j in range(2):
        sns.boxplot(data=raw_df, x='Product', y=attrs[count], ax=axs[i,j], palette='Set3')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
```



Observations-

1. Product vs Education Customers whose Education is greater than 16, have more chances to purchase the KP781 product. While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481.
2. Customers who are planning to use the treadmill greater than 4 times a week, are more likely to buy the KP781 product. While the other customers are likely to purchasing KP281 or KP481
3. Chances of buying higher end product like KP781 if customers are more fit
4. Customers who run/plan to more miles are likely to buy KP781, than the ones who don't.

Analysis using Contingency Tables to Calculate Probabilities (Marginal Probabilities, Conditional Probabilities)

- Product - Income group
- Product - Gender
- Product - Marital Status

In [31]:

```
raw_df.head()
```

Out[31]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age_group	income_group
0	KP281	18	Male	14	Single	3	4	29562	112	0-18	Lower income
1	KP281	19	Male	15	Single	2	3	31836	75	19-28	Lower Middle income
2	KP281	19	Female	14	Partnered	4	3	30699	66	19-28	Lower Middle income
3	KP281	19	Male	12	Single	3	3	32973	85	19-28	Lower Middle income
4	KP281	20	Male	13	Partnered	4	2	35247	47	19-28	Lower Middle income

In [40]:

```
ct_income_prod=pd.crosstab( raw_df.Product,raw_df.income_group)
ct_income_prod
```

Out[40]:

income_group	Lower income	Lower Middle income	Upper Middle income	Higher income
Product				
KP281	1	73	6	0
KP481	0	53	7	0
KP781	0	11	10	19

In [49]:

```
ct_gender_prod=pd.crosstab( raw_df.Product,raw_df.Gender)
ct_gender_prod
```

Out[49]:

Gender	Female	Male
Product		
KP281	40	40
KP481	29	31
KP781	7	33

In [50]:

```
ct_maritalstatus_prod=pd.crosstab( raw_df.Product,raw_df.MaritalStatus)
ct_maritalstatus_prod
```

Out[50]:

MaritalStatus	Partnered	Single
Product		
KP281	48	32
KP481	36	24
KP781	23	17

-> Marginal probability

In [45]:

```
## What is the probability of a each income group customer buying a treadmill?
for col in ct_income_prod.columns:
    print("P(",col,"):", ct_income_prod[col].sum()*100/sum(ct_income_prod.sum()))
```

```
P( Lower income ): 0.5555555555555556
P( Lower Middle income ): 76.11111111111111
P( Upper Middle income ): 12.777777777777779
P( Higher income ): 10.555555555555555
```

In [52]:

```
## What is the probability of each gender customer buying a treadmill?
for col in ct_gender_prod.columns:
    print("P(",col,"):", ct_gender_prod[col].sum()*100/sum(ct_gender_prod.sum()))
```

```
P( Female ): 42.22222222222222
P( Male ): 57.77777777777778
```

In [54]:

```
## What is the probability based on maritalstatus of customer of buying a treadmill?
for col in ct_maritalstatus_prod.columns:
    print("P(",col,"):", ct_maritalstatus_prod[col].sum()*100/sum(ct_maritalstatus_prod.sum()))
```

```
P( Partnered ): 59.44444444444444
P( Single ): 40.55555555555556
```

Conditional probability - what is the probability of each customer segment to buy certain product given its that product

In [66]:

```
for i in raw_df.Product.unique():
    for j in raw_df.income_group.unique():
        print('P(',j,'|',i,'):',len(raw_df[(raw_df['income_group']==j) & (raw_df['Product']==i)])/len(raw_df[raw_df['Product']==i]))
```

```
P( Lower income | KP281 ): 0.0125
P( Lower Middle income | KP281 ): 0.9125
P( Upper Middle income | KP281 ): 0.075
P( Higher income | KP281 ): 0.0
P( Lower income | KP481 ): 0.0
P( Lower Middle income | KP481 ): 0.8833333333333333
P( Upper Middle income | KP481 ): 0.11666666666666667
P( Higher income | KP481 ): 0.0
P( Lower income | KP781 ): 0.0
P( Lower Middle income | KP781 ): 0.275
P( Upper Middle income | KP781 ): 0.25
P( Higher income | KP781 ): 0.475
```

Observation-

- 91% and 88% of Lower middle class income customers buy KP281 and KP481 treadmill models respectively
- Around 50% of Higher income class customers have probability to buy KP781 treadmill

In [64]:

```
## What is the probability of a male customer buying a KP781 treadmill?
for i in raw_df.Product.unique():
    for j in raw_df.Gender.unique():
        print('P(',j,'|',i,'):',len(raw_df[(raw_df['Gender']==j) & (raw_df['Product']==i)])/len(raw_df[raw_df['Product']==i]))
```

```
P( Male | KP281 ): 0.5
P( Female | KP281 ): 0.5
P( Male | KP481 ): 0.5166666666666667
P( Female | KP481 ): 0.48333333333333334
P( Male | KP781 ): 0.825
P( Female | KP781 ): 0.175
```

Observation-

- There is equal probability of male and female customers to buy KP281, while slightly higher chances of male customers buying KP481 treadmill models
- 82% of male customers has chances to buy KP781 treadmill

In [67]:

```
for i in raw_df.Product.unique():
    for j in raw_df.MaritalStatus.unique():
        print('P(',j,'|',i,'):',len(raw_df[(raw_df['MaritalStatus']==j) & (raw_df['Product']==i)])/len(raw_df[raw_df['Product']==i]))
```

```
P( Single | KP281 ): 0.4
P( Partnered | KP281 ): 0.6
P( Single | KP481 ): 0.4
P( Partnered | KP481 ): 0.6
P( Single | KP781 ): 0.425
P( Partnered | KP781 ): 0.575
```

Observation-

- There is 60% higher probability of Partnered customers to buy KP281 and KP481 treadmill models
- 57% of Partnered customers has higher chances to buy KP781 treadmill model

Recommendations

- KP281 model is sold the most so Aerofit should focus on targetting customers buying these. These people include in age group of 18-28 and those who have lower middle income(People with income more than $40K)
- For KP481 model, we should focus on Lower middle class income customers who are partnered
- For KP781 model, we should focus on higher income group male customers(i.e earning more than $80K) and people with good fitness levels
- Also be it any product, we should try selling more treadmills to FIT people who self-rate themselves greater than 3, as we see a correlation that more fit a person is higher number of miles they would want to run on treadmill

In [ ]: