AEROFIT TREADMIL

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

#To wrap title in graph
from textwrap import wrap
```

Importing Dataset

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

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
...	...	...	...	...	...	...	...	...	...
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

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Problem Statement & Anaysis

> **Problem Statements**
>
> > We have to check how gender,income education is affecting the choice of customer to purchase a particular Treadmills. We have to find the relationship between them.
>
> > We want to recommend the Treadmills to the new customer according to the ustomer characteristics.
>
> > By calculating the above relationship we want to increase our Sales for Treadmills

2.Analysis of DataSets

1.Checking for shape

In [3]:
```
df.shape
```

Out[3]:
```
(180, 9)
```

2.Checing information & datatype for data set

In [4]:
```
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 [5]:
```
#Checking of data types of columns
df.dtypes
```

Out[5]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

3.Conversion of DataTypes to Category

In [6]:
```
#Converting Product from object to Category
df['Product'] = df['Product'].astype('category')

#Converting Gender from object to Category
df['Gender'] = df['Gender'].astype('category')

#Converting MaritalStatus from object to Category
```

```
df['MaritalStatus'] = df['MaritalStatus'].astype('category')

#Converting Fitness from int to Categorical value
df['Fitness'] =  df['Fitness'].astype('category')
```

In [7]:
```
df.dtypes
```

Out[7]:
```
Product          category
Age                 int64
Gender           category
Education           int64
MaritalStatus    category
Usage               int64
Fitness          category
Income              int64
Miles               int64
dtype: object
```

4.Checking for Null Values

In [8]:
```
df.isna().sum()
```

Out[8]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

5. Statistical summary

In [9]:
```
df.describe(include = 'all')
```

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Out[9]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.0	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	5.0	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	3.0	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	97.0	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	NaN	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	NaN	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	NaN	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	NaN	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	NaN	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	NaN	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	NaN	104581.000000	360.000000

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Non-Graphical Analysis

1.Value Counts

1 . Value counts for different Products

In [10]:
```
df['Product'].value_counts()
```

Out[10]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

2 . Value counts for different Gender

In [11]:
```
df['Gender'].value_counts()
```

Out[11]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

3 . Value counts for MaritalStatus

In [12]:
```
df['MaritalStatus'].value_counts()
```

Out[12]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

4 . Value counts for MaritalStatus

In [13]:
```
df['Fitness'].value_counts()
```

Out[13]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

2.Unique Values

1. Unique Values for Ages

In [14]:
```
df['Age'].unique()
```

Out[14]:
```
array([18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
       35, 36, 37, 38, 39, 40, 41, 43, 44, 46, 47, 50, 45, 48, 42],
      dtype=int64)
```

2. Unique values for Education

In [15]:
```python
df['Education'].unique()
```

Out[15]:
```
array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)
```

3. Unique Values for Usage

In [16]:
```python
df['Usage'].unique()
```

Out[16]:
```
array([3, 2, 4, 5, 6, 7], dtype=int64)
```

4. Unique Values for Miles

In [17]:
```python
df['Miles'].unique()
```

Out[17]:
```
array([112,  75,  66,  85,  47, 141, 103,  94, 113,  38, 188,  56, 132,
       169,  64,  53, 106,  95, 212,  42, 127,  74, 170,  21, 120, 200,
       140, 100,  80, 160, 180, 240, 150, 300, 280, 260, 360], dtype=int64)
```

5. Unique Values of Income

In [18]:
```python
df['Income'].unique()
```

Out[18]:
```
array([ 29562,  31836,  30699,  32973,  35247,  37521,  36384,  38658,
        40932,  34110,  39795,  42069,  44343,  45480,  46617,  48891,
        53439,  43206,  52302,  51165,  50028,  54576,  68220,  55713,
        60261,  67083,  56850,  59124,  61398,  57987,  64809,  47754,
        65220,  62535,  48658,  54781,  48556,  58516,  53536,  61006,
        57271,  52291,  49801,  62251,  64741,  70966,  75946,  74701,
        69721,  83416,  88396,  90886,  92131,  77191,  52290,  85906,
       103336,  99601,  89641,  95866, 104581,  95508], dtype=int64)
```

Visual Analysis

1.Univariate Analysis

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Count plot

In [19]:
```
figure, axes = plt.subplots(1, 3,
                            figsize=(15, 5))
figure.suptitle('NO OF PRODUCT PURCHASE ACCORDING TO GENDER,FITNESS & MARITAL STATUS DISTRIBUTION')
axes[0].set_title("No of customers buying acc to Gender")
axes[1].set_title("No of customers buying acc to MaritalStatus wise")
axes[2].set_title("No of customers buying acc to Fitnese")

plt.subplot(1,3,1)
sns.countplot(data=df,x='Gender')

plt.subplot(1,3,2)
sns.countplot(data=df,x='MaritalStatus')

plt.subplot(1,3,3)
sns.countplot(data=df,x='Fitness',hue='Product')

plt.show()
```

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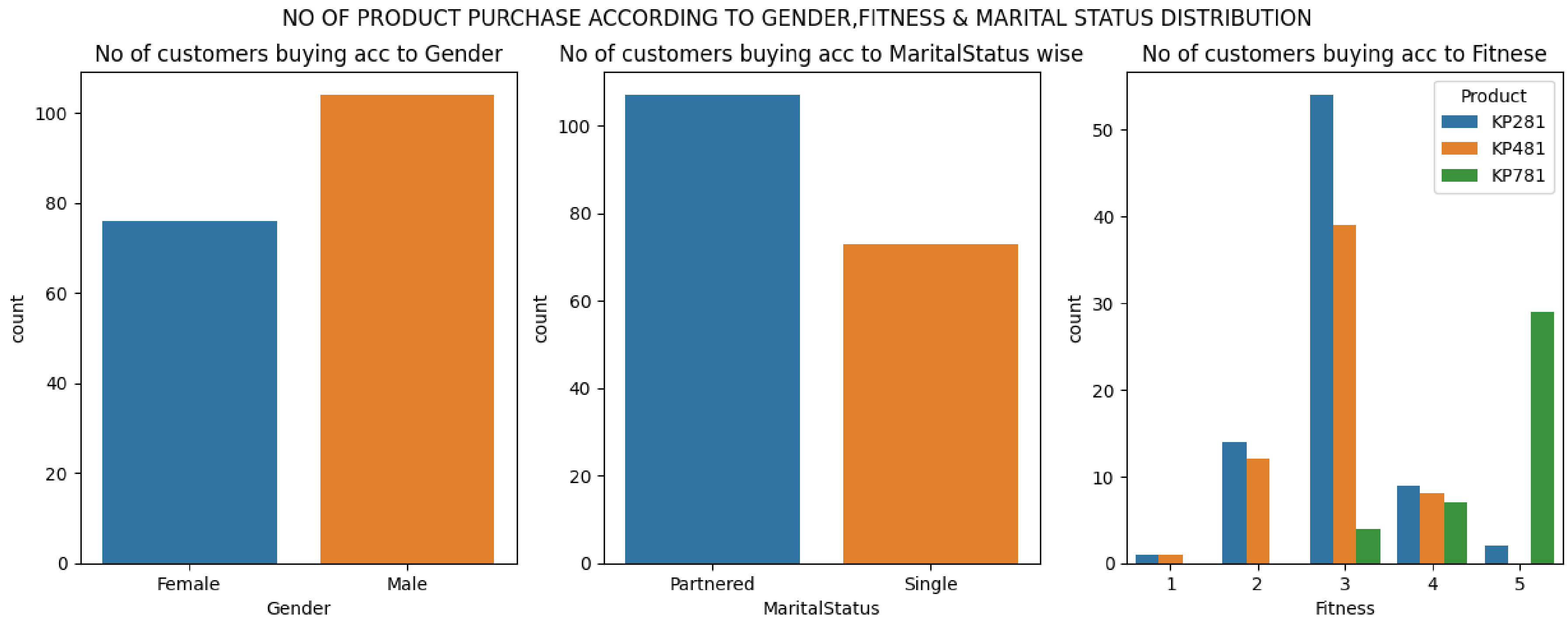

2.Bivariate Analysis

In [20]:
```
figure, axes = plt.subplots(1, 4,
                            figsize=(25, 5))
figure.suptitle('PRODUCT  PURCHASE  ACCORDING  TO  AGE,EDUCATION,USAGE,INCOME,MILES')
axes[0].set_title("Product  Purchased  VS  Education")
axes[1].set_title("Product Purchased VS Usage")
axes[2].set_title("Product  Purchased  VS  Income")
axes[3].set_title("Product  Purchased  VS  Miles")


plt.subplot(1,4,1)
sns.countplot(data=df,hue='Product',x  =  'Education')

plt.subplot(1,4,2)
sns.barplot(data=df,x='Product',y  =  'Usage')
```

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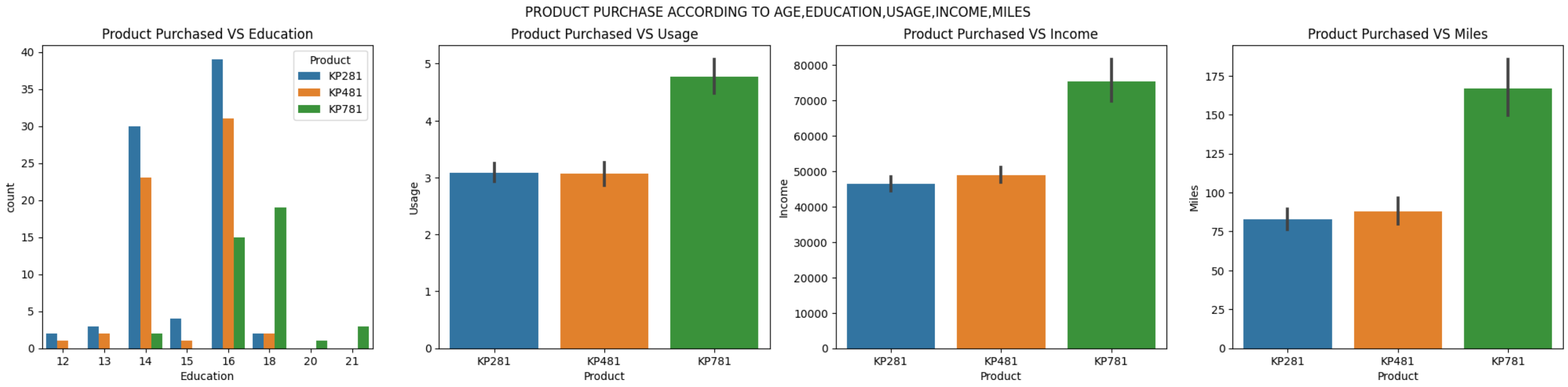
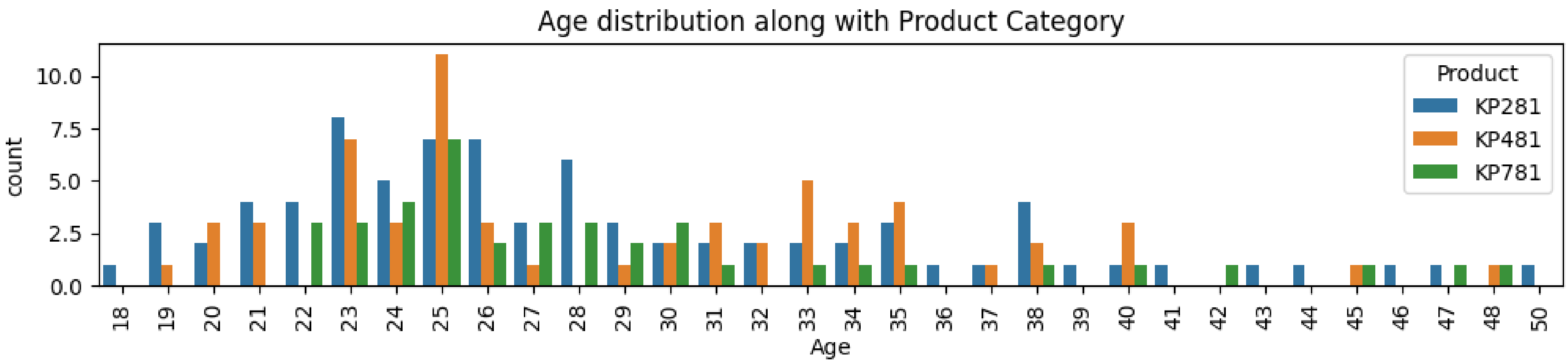
```
plt.subplot(1,4,3)
sns.barplot(data=df,x='Product',y  =  'Income')

plt.subplot(1,4,4)
sns.barplot(data=df,x='Product',y  =  'Miles')

plt.show()

plt.figure(figsize=(12,2))
sns.countplot(data=df,hue='Product',x='Age')
plt.xticks(rotation=90)
plt.title('Age distribution along with Product Category')
plt.show()
```





Histogram

In [21]:
```
plt.figure(figsize=(12,5))
sns.histplot(data=df,x='Age',bins=7,kde=True,hue='Product')
plt.title('Age distribution along with Product Category with binsize of 5yrs')
plt.show()
```

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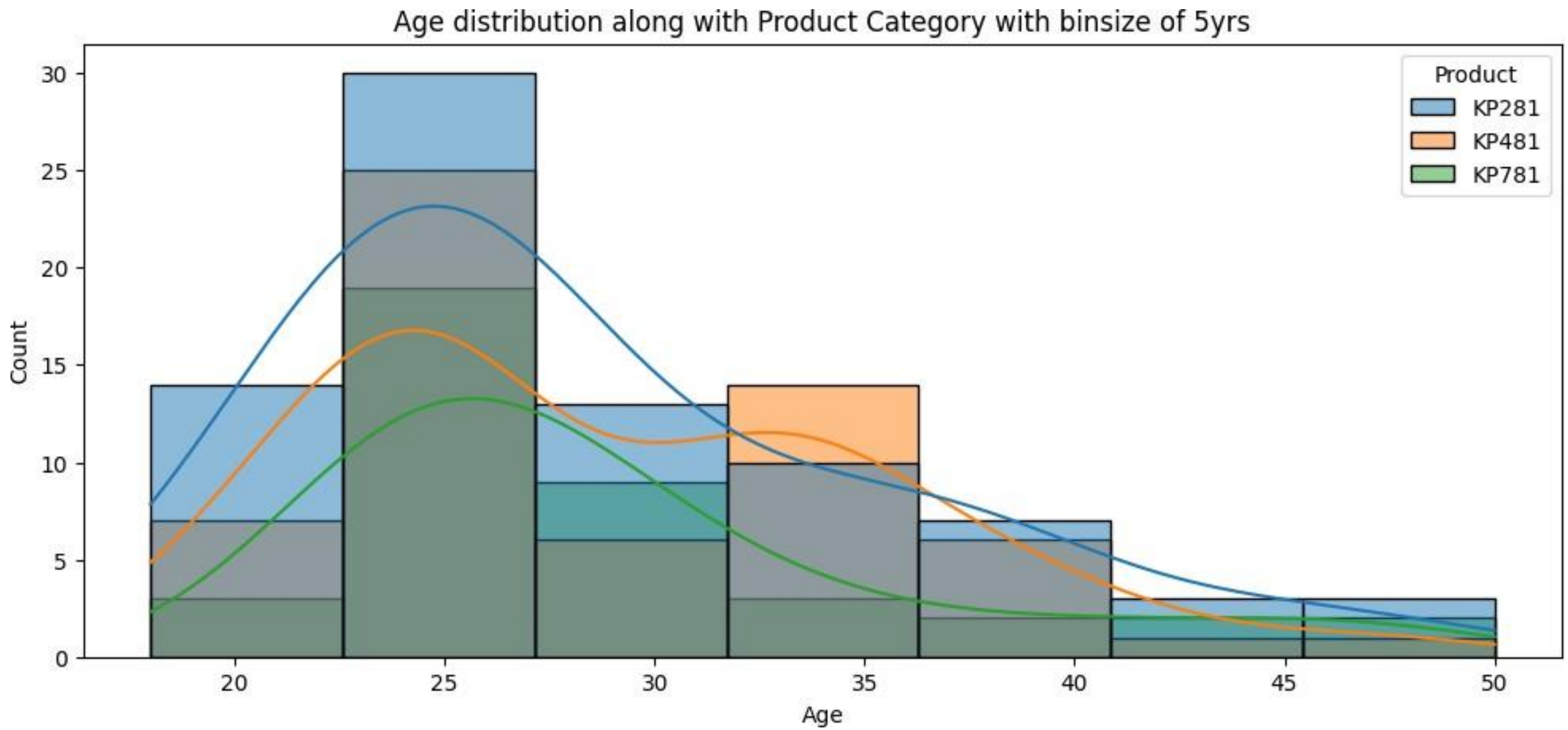
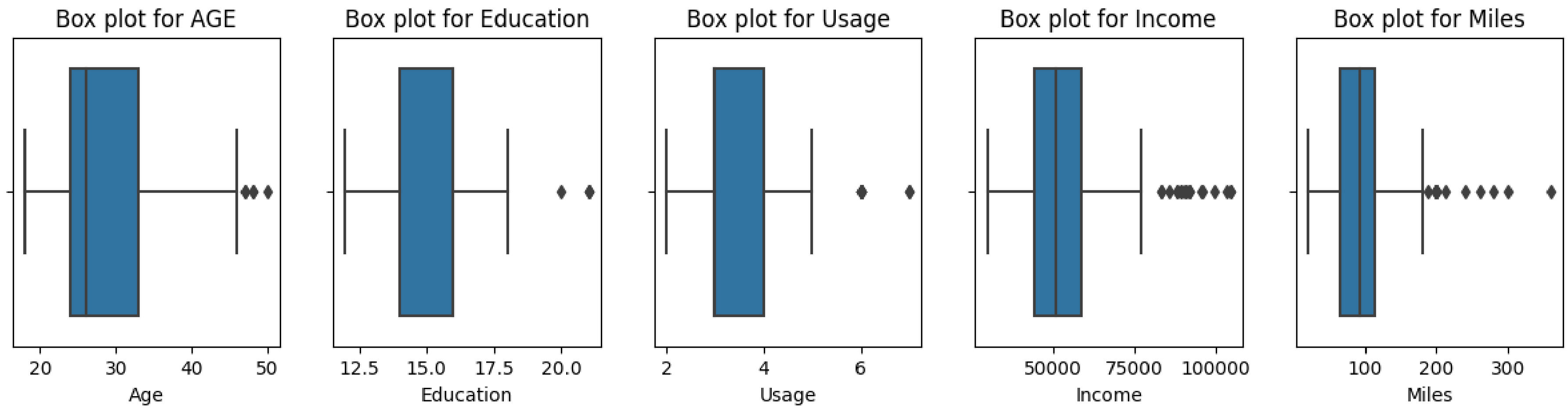


Box PLots

In [22]:
```
plt.figure(figsize=(15,3))
plt.subplot(1,5,1)
sns.boxplot(data=df,x='Age')
plt.title('Box plot for AGE')

plt.subplot(1,5,2)
sns.boxplot(data=df,x='Education')
plt.title('Box plot for Education')

plt.subplot(1,5,3)
sns.boxplot(data=df,x='Usage')
plt.title('Box plot for Usage')
```

```
plt.subplot(1,5,4)
sns.boxplot(data=df,x='Income')
plt.title('Box plot for Income')

plt.subplot(1,5,5)
sns.boxplot(data=df,x='Miles')
plt.title('Box plot for Miles')
```

Out[22]: Text(0.5, 1.0, 'Box plot for Miles')



Correlation Detection

In [23]:
```
sns.pairplot(data=df)
plt.show()
```

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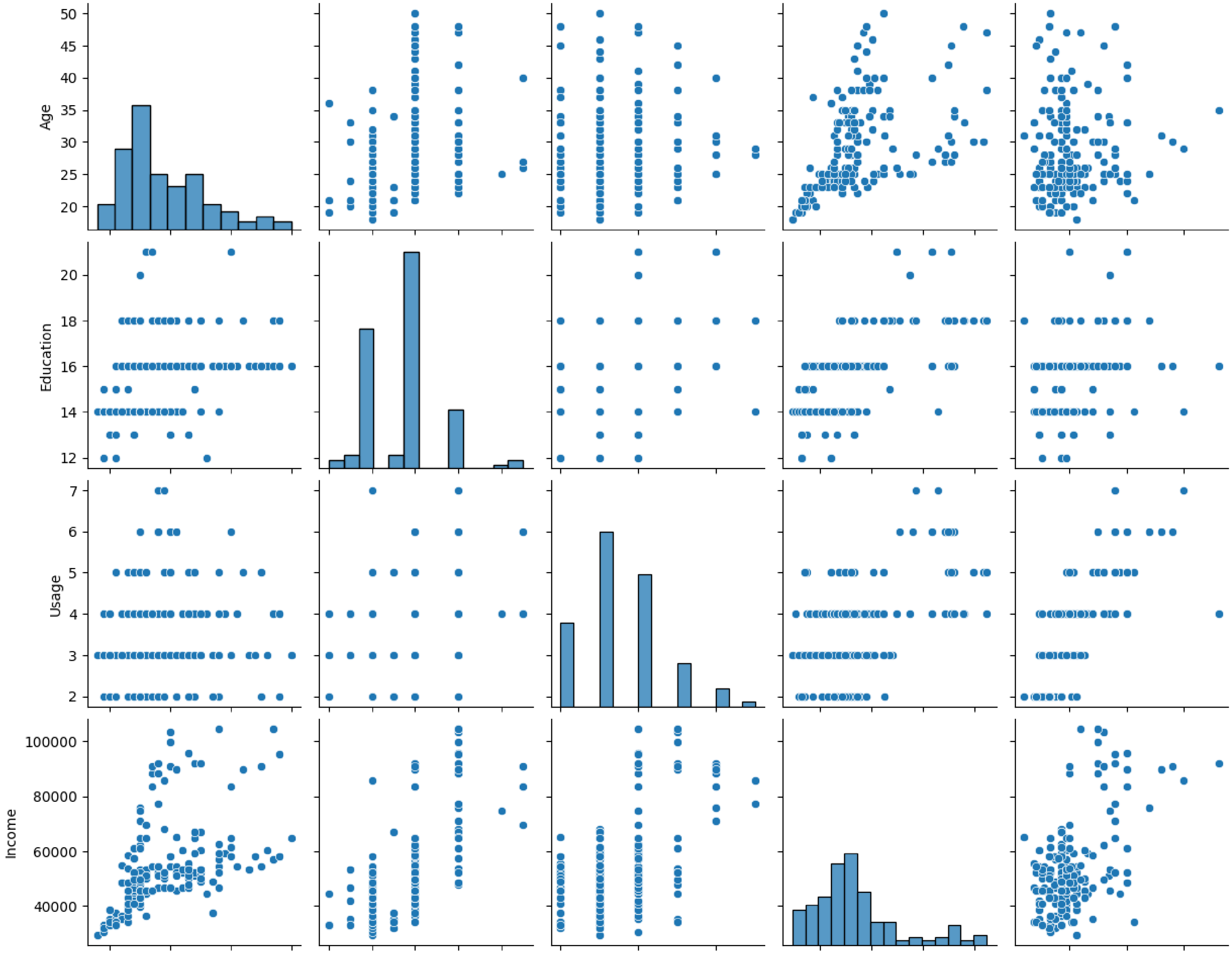

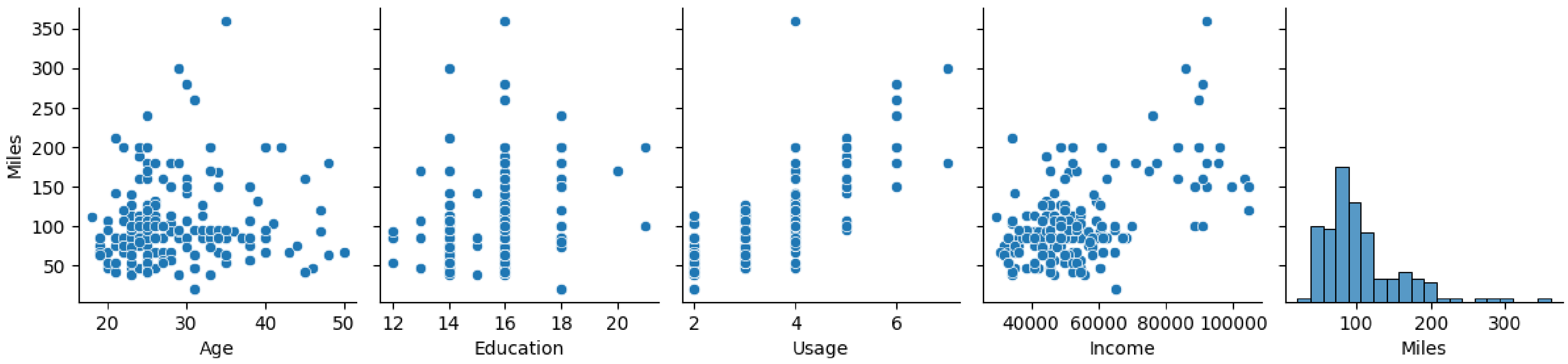

Heat Map

In [24]:

```
plt.figure(figsize=(15,3))
plt.subplot(1,2,1)
a  =  df.groupby('Product').Age.value_counts().unstack().fillna(0)
sns.heatmap(a)
plt.title('No of People in age group VS Product type')

plt.subplot(1,2,2)
b = df.groupby('Product')[['Education']].value_counts().unstack().fillna(0)
sns.heatmap(b)
plt.title('No of People Educational basis VS Product type')
plt.show()

plt.figure(figsize=(15,3))
plt.subplot(1,2,1)
a  =  df.groupby('Product').Usage.value_counts().unstack().fillna(0)
sns.heatmap(a)
plt.title('No of People on Usage VS Product type')

plt.subplot(1,2,2)
b = df.groupby('Product')[['MaritalStatus']].value_counts().unstack().fillna(0)
sns.heatmap(b)
plt.title('No of People Educational basis VS Product type')
plt.show()

plt.figure(figsize=(15,3))
```

```
plt.subplot(1,2,1)
a1  =  pd.crosstab(df.Product,columns=[df.Fitness])
sns.heatmap(a1)
plt.title('Fitness VS Product type')

plt.figure(figsize=(15,3))
plt.subplot(1,4,1)
a1  =  pd.crosstab(df.Product,columns=[df.Fitness])
sns.heatmap(a1)
plt.title('Fitness VS Product type')

plt.subplot(1,4,2)
a1  =  pd.crosstab(df.Product,columns=[df.Income])
sns.heatmap(a1)
plt.title('Income VS Product type')

plt.subplot(1,4,3)
a1  =  pd.crosstab(df.Product,columns=[df.Gender])
sns.heatmap(a1)
plt.title('Gender VS Product type')

plt.subplot(1,4,4)
a1  =  pd.crosstab(df.Product,columns=[df.Miles])
sns.heatmap(a1)
plt.title('Miles VS Product type')
plt.show()
```

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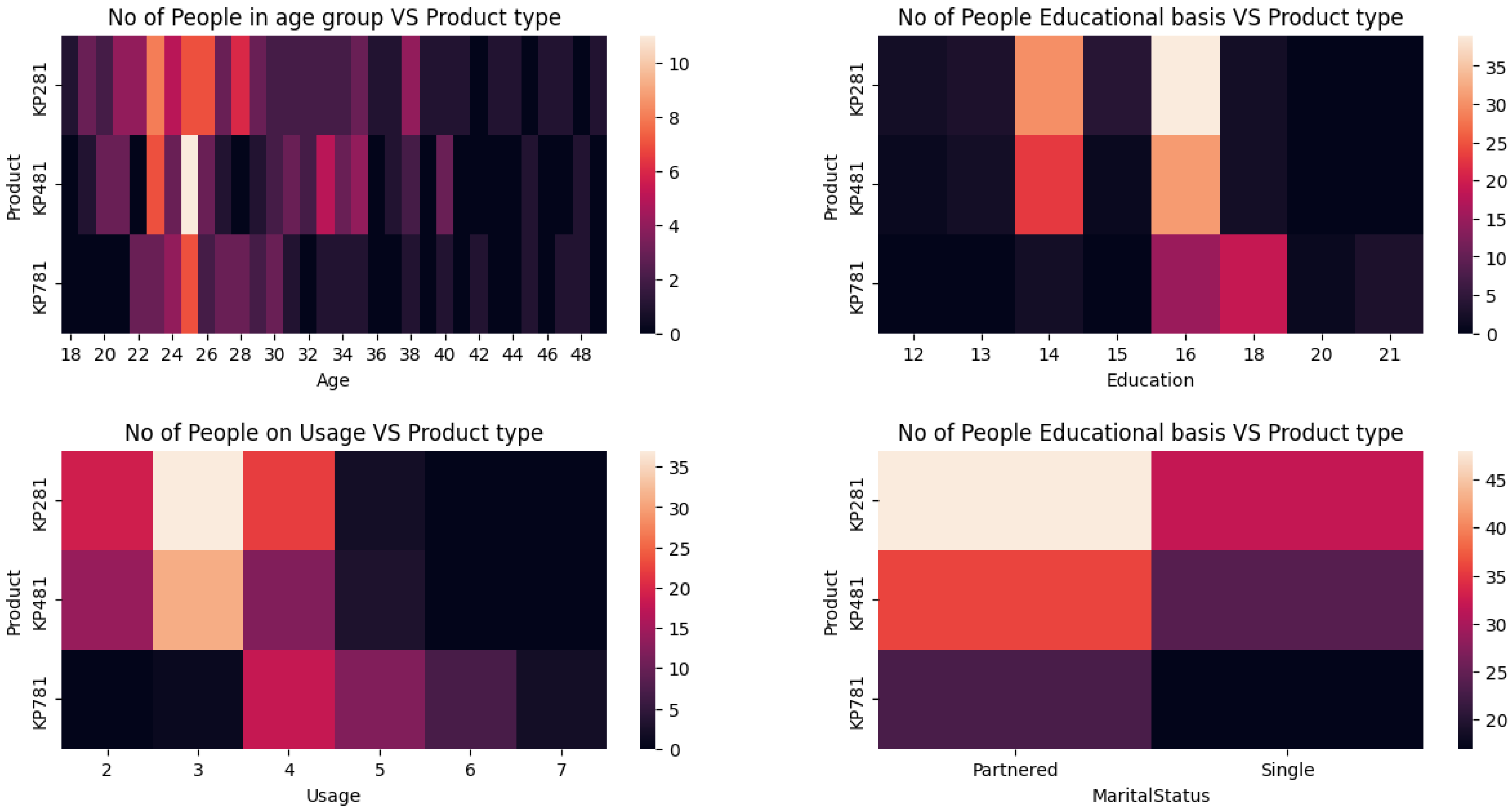

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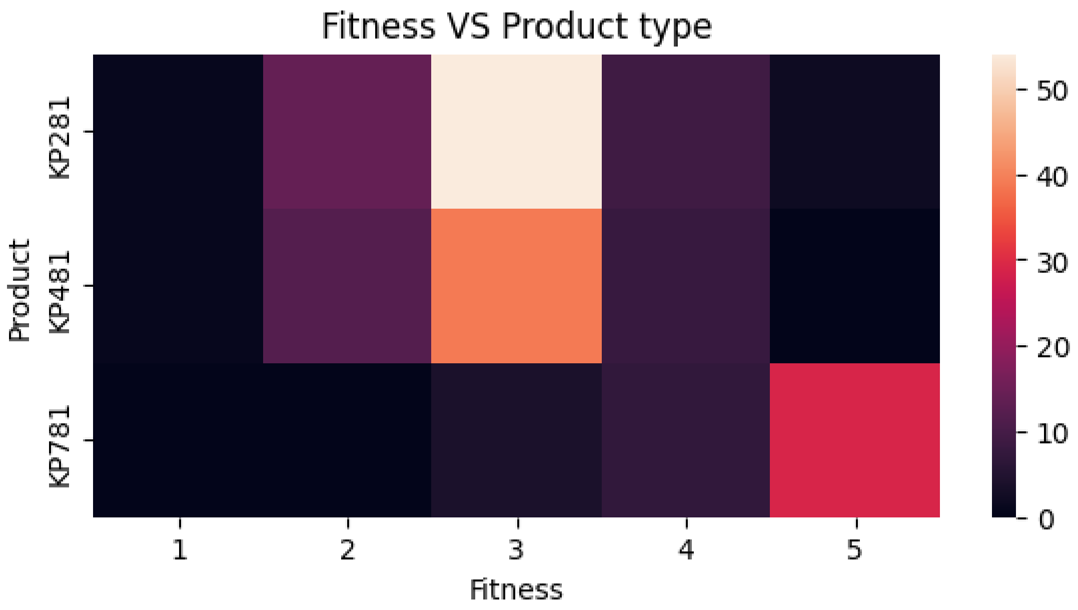
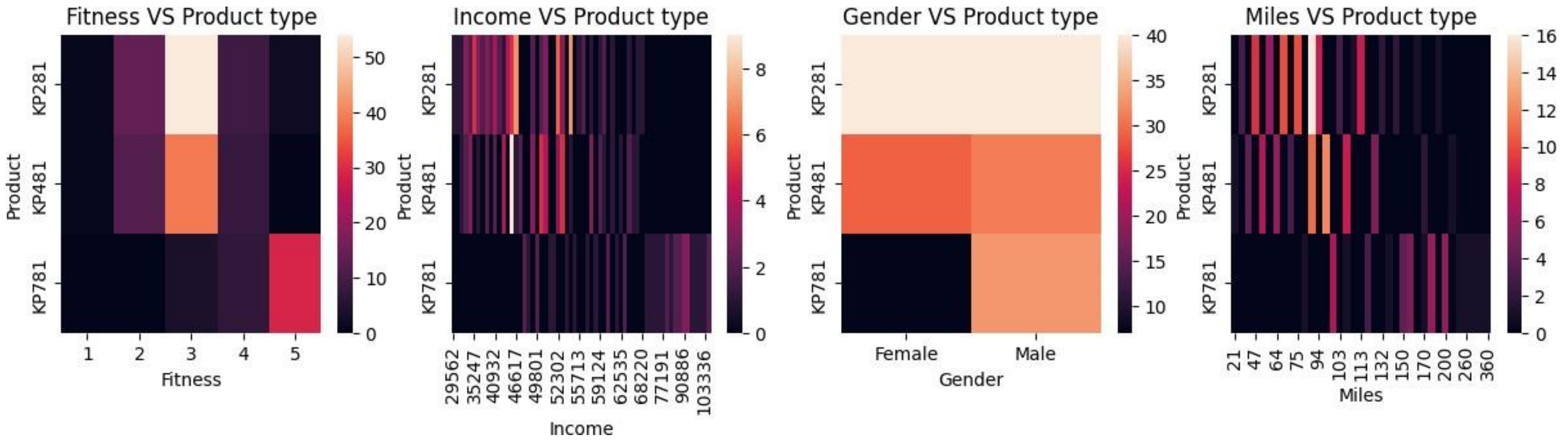
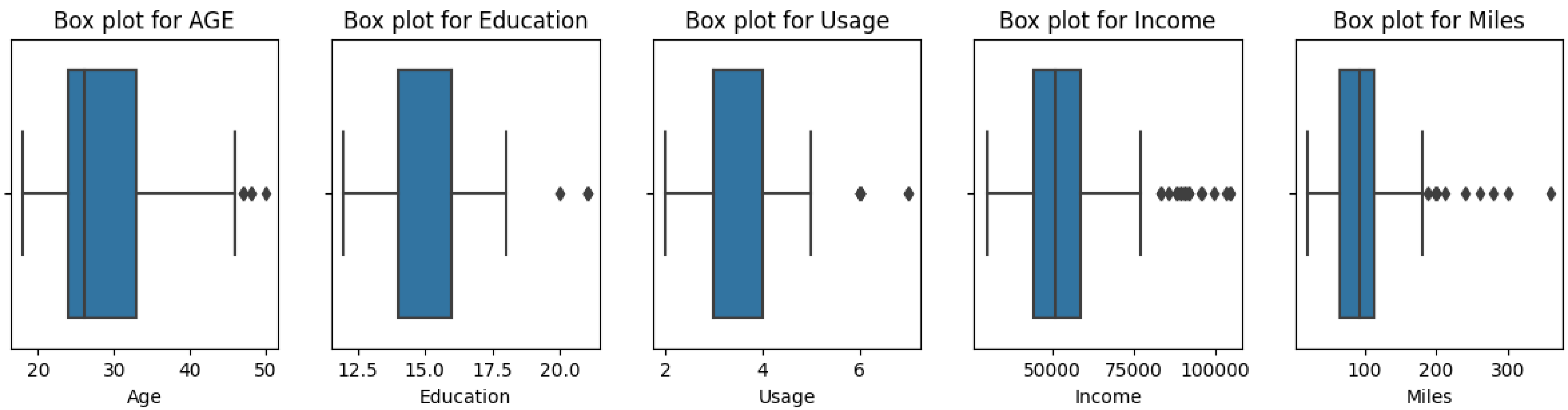




Outliers Detections: The values with black dot in box plots are the outliers . We have to remove this outliers

Missing Values & Outliers Detection

Outliers Detection



> **Outliers** : This are the Black dots in BOX plot shown above

In [25]:
```
#Use 25% & 75% to calculate IQR= 75% - 25%
# outliers > 75% + 1.5 * IQR
df.describe()
```

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Out[25]:

	Age	Education	Usage	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	53719.577778	103.194444
std	6.943498	1.617055	1.084797	16506.684226	51.863605
min	18.000000	12.000000	2.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	104581.000000	360.000000

In [26]:

```
# Outliers for Age
df.loc[df['Age']>47,'Age']
```

Out[26]:

```
79     50
139    48
179    48
Name: Age, dtype: int64
```

In [27]:

```
# Outliers for Education
df.loc[df['Education']>19,'Education']
```

Out[27]:

```
156    20
157    21
161    21
175    21
Name: Education, dtype: int64
```

In [28]:

```
# Outliers for Usage
df.loc[df['Usage']>5.5,'Usage']
```

Out[28]:
```
154    6
155    6
162    6
163    7
164    6
166    7
167    6
170    6
175    6
Name: Usage, dtype: int64
```

In [29]:
```
# Outliers for Miles
df.loc[df['Miles']>187.875,'Miles']
```

Out[29]:
```
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
170    260
171    200
173    360
175    200
176    200
Name: Miles, dtype: int64
```

Missing Values Detection

In [30]:
```
df.isna().sum()
```

Out[30]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Probability Calculations

Category wise Product Probability

In [31]:
```
S = df.shape[0]
a1  =  df.loc[df['Product']=='KP281','Product'].shape[0]
print('Probability of TreadMill to be KP281 is {}'.format(round(a1/S,4)))

a2  =  df.loc[df['Product']=='KP481','Product'].shape[0]
print('Probability of TreadMill to be KP481 is {}'.format(round(a2/S,4)))

a3  =  df.loc[df['Product']=='KP781','Product'].shape[0]
print('Probability of TreadMill to be KP781 is {}'.format(round(a3/S,4)))
```

```
Probability of TreadMill to be KP281 is 0.4444
Probability of TreadMill to be KP481 is 0.3333
Probability of TreadMill to be KP781 is 0.2222
```

1.Gender Vs Product

In [32]:
```
pd.crosstab(df.Product,df.Gender,margins=True)
```

Out[32]:

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

In [33]:

```
print()
print('__'*40)
###################   Buying of **KP281** on Basis of Gender Calculation ################
print("Buying of **KP281** on Basis of Gender Calculation")

#Probability that a person buy KP281 irrespective of gender
print('Probability that a person buy KP281 irrespective of gender is {}'.format(round(80/180,2)))

#Probability that a person buy KP281 given Male
print('Probability that a person buy KP281 given Male is {}'.format(round(40/80,2)))

#Probability that a person buy KP281 given Female
print('Probability that a person buy KP281 given Female is {}'.format(round(40/80,2)))
print()
print('__'*40)



############################ Buying of **KP481** on Basis of Gender Calculation ########################################
print("Buying of **KP481** on Basis of Gender Calculation")

#Probability that a person buy KP481 irrespective of gender
print('Probability that a person buy KP481 irrespective of gender is {}'.format(round(60/180,2)))

#Probability that a person buy KP481 given Male
print('Probability that a person buy KP481 given Male is {}'.format(round(31/60,2)))

#Probability that a person buy KP481 given Female
print('Probability that a person buy KP481 given Female is {}'.format(round(29/60,2)))
```

```
print()
print('__'*40)



############################  Buying of **KP781** on Basis of Gender Calculation ##################
print("Buying of **KP781** on Basis of Gender Calculation")

#Probability that a person buy KP781 irrespective of gender
print('Probability that a person buy KP781 irrespective of gender is {}'.format(round(40/180,2)))

#Probability that a person buy KP781 given Male
print('Probability that a person buy KP781 given Male is {}'.format(round(33/40,2)))

#Probability that a person buy KP781 given Female
print('Probability that a person buy KP781 given Female is {}'.format(round(7/40,2)))
print()
print('__'*40)
```

```
________________________________________________________________________________
Buying of **KP281** on Basis of Gender Calculation
Probability that a person buy KP281 irrespective of gender is 0.44
Probability that a person buy KP281 given Male is 0.5
Probability that a person buy KP281 given Female is 0.5

________________________________________________________________________________
Buying of **KP481** on Basis of Gender Calculation
Probability that a person buy KP481 irrespective of gender is 0.33
Probability that a person buy KP481 given Male is 0.52
Probability that a person buy KP481 given Female is 0.48

________________________________________________________________________________
Buying of **KP781** on Basis of Gender Calculation
Probability that a person buy KP781 irrespective of gender is 0.22
Probability that a person buy KP781 given Male is 0.82
Probability that a person buy KP781 given Female is 0.17

________________________________________________________________________________
```

2.MaritalStatus Vs Product

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In [34]:
```
pd.crosstab(df.Product,df.MaritalStatus,margins=True)
```

Out[34]:

MaritalStatus	Partnered	Single	All
Product			
KP281	48	32	80
KP481	36	24	60
KP781	23	17	40
All	107	73	180

In [35]:
```
print()
print('__'*40)
###################   Buying of **KP281** on Basis of MaritalStatus ################
print("Buying of **KP281** on Basis of MaritalStatus")

#Probability that a person buy KP281 irrespective of MaritalStatus
print('Probability that a person buy KP281 irrespective of MaritalStatus is {}'.format(round(80/180,2)))

#Probability that a person buy KP281 given Married/Parterned
print('Probability that a person buy KP281 given Married/Parterned is {}'.format(round(48/80,2)))

#Probability that a person buy KP281 given Unmarried/Single
print('Probability that a person buy KP281 given Unmarried/Single is {}'.format(round(32/80,2)))
print()
print('__'*40)



########################### Buying of **KP481** on Basis of MaritalStatus ###########################################
print("Buying of **KP481** on Basis of MaritalStatus")

#Probability that a person buy KP481 irrespective of MaritalStatus
print('Probability that a person buy KP481 irrespective of MaritalStatus is {}'.format(round(60/180,2)))

#Probability that a person buy KP481 given Married/parterned
print('Probability that a person buy KP481 given Married/parterned is {}'.format(round(36/60,2)))
```

```
#Probability that a person buy KP481 given Unmarried/Single
print('Probability that a person buy KP481 given Unmarried/Single is {}'.format(round(24/60,2)))
print()
print('__'*40)



############################## Buying of **KP781** on Basis of MaritalStatus ###################
print("Buying of **KP781** on Basis of MaritalStatus")

#Probability that a person buy KP781 irrespective of MaritalStatus
print('Probability that a person buy KP781 irrespective of MaritalStatus is {}'.format(round(40/180,2)))

#Probability that a person buy KP781 given Married/parterned
print('Probability that a person buy KP781 given Married/parterned is {}'.format(round(23/40,2)))

#Probability that a person buy KP781 given Unmarried/Single
print('Probability that a person buy KP781 given Unmarried/Single is {}'.format(round(17/40,2)))
print()
print('__'*40)
```

```
________________________________________________________________________________
Buying of **KP281** on Basis of MaritalStatus
Probability that a person buy KP281 irrespective of MaritalStatus is 0.44
Probability that a person buy KP281 given Married/Parterned is 0.6
Probability that a person buy KP281 given Unmarried/Single is 0.4


________________________________________________________________________________
Buying of **KP481** on Basis of MaritalStatus
Probability that a person buy KP481 irrespective of MaritalStatus is 0.33
Probability that a person buy KP481 given Married/parterned is 0.6
Probability that a person buy KP481 given Unmarried/Single is 0.4


________________________________________________________________________________
Buying of **KP781** on Basis of MaritalStatus
Probability that a person buy KP781 irrespective of MaritalStatus is 0.22
Probability that a person buy KP781 given Married/parterned is 0.57
Probability that a person buy KP781 given Unmarried/Single is 0.42


________________________________________________________________________________
```

AEROFIT TREADMIL

Business Insights based on Non-Graphical and Visual Analysis

Insight baased on Visual Analysis

> **1 :** It can be seen from Graph that higly Educated people(>= 18yrs) tend to buy **KP781** more frequently compared to people with less year of Education buys **KP281** and also some people buy **KP481**

> **2 :** People with Higher Average Usage no of Hours(i.e. Hours >= 3) a week uses **KP781** and remaining people choses **KP281** or **KP481** as per their requirements

> **3 :** People with Highest Income prefer(income >= 48000) **KP781** as they can afford the price

> **4 :** People with the higher average number of miles choses **KP781** followed by **KP481** and then least by **KP281**

> **5 :** from Heatmap we can say that People using **KP781** are lying in Age group of **22 to 30** , People using **KP481** are lying in Age group of **20 to 42** ,People using **KP281** are lying in Age group of **19 to 38**
>
> **:** People in the age range of **22-28** Uses Treadmill more compared to people of other Ages

> **6 :** From Count plot. The no of people having a Fitness score of **5(i.e. best shape)** prefer **KP781** more.

People with fitness Score lying between **2.5-4** prefer **KP481** & people with **score < 2.5** were using **KP281**

> **: KP781** having an additional impact on the Fitness Score

> **7 : Observation from Scatterplots & Pair plots :**

> > **:** People with **age > 25**, People with **Education in Years >= 18** were having **Income higher** as compared to other people **7.2 :** People with **age < 35** , People with **Education < 18**,People with **Income <60000** were walking **More miles**

Insight based on Non Graphical Analysis

> **8 :** No of People buyings **KP281**(i.e. 44.4 %) is more followed by **KP481**(i.e. 33.33 %) & Then **KP781**(i.e. 22.22 %). The above figure in bracket indicate Probability of People buying Treadmill w/o any criteria

> **9 :** for **KP281 & KP481** Gender effect is not much effect but for **KP781** Male Prefer more compared to Female as shown below
>
> > **:** Probability that a person buy **KP281 given Male is 0.5** & & person buy **KP281 given Female is 0.5**. No effect of Gender **9.2 :** Probability that a person buy **KP481 given Male is 0.52** & & person buy **KP481 given Female is 0.48** No effect of Gender **9.3 :** Probability that a person buy **KP781 given Male is 0.82** & & person buy **KP781 given Female is 0.17**.There is an effect of Gender

> **10 :** Probability of Married/Partnered buying Treadmill is more compared to Unmarried/Single
>
> > **:** Probability that a person buy **KP281** given Married/Parterned is 0.6 & person buy **KP281** given Unmarried/Single is 0.4 **10.2 :** Probability that a person buy **KP481** given Married/Parterned is 0.6 & person buy **KP481** given Unmarried/Single is 0.4 **10.3 :** Probability that a person buy **KP781** given Married/Parterned is 0.57 & person buy **KP781** given Unmarried/Single is 0.42

Recommendations

> **1 :** People with Higher Education will have higer Salary/Income and they often buy **KP781** more compared to other. So its better to reccomend them this product

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> **2 :** People having a **Fitness Score of 5** .Mostly Prefer **KP781** so we can say for a Person who is willing to having a good fitness we should recommend **KP781**.

> **3 :** People who are Married/Partnered buy Treadmill more so its better to give discount on price to increase Sales

> **4 :** People at Younger **Age < 20** buys **KP281** more frequently. So its better to recomend this kind of Treadmill to younger People

> **5 : Male** having a higer chance of buying **KP781** Compared to Female. So its better to recommend this Treadmills to **Males**.If we want to increase Sales then we can provide Discount on Price