tzr2muv0k

April 28, 2025

0.1 Aerofit?

Aerofit, a dynamic player in the fitness industry, traces its origins to M/s. Sachdev Sports Co, established in 1928 by Ram Ratan Sachdev. From its modest beginnings in Hyderabad, India, the company evolved into a leading sports equipment supplier across Andhra Pradesh and Telangana. Recognizing the growing need for fitness solutions, M/s. Sachdev Overseas emerged to import quality fitness equipment under the "Aerofit" brand, ensuring affordability and post-sales excellence.

Driven by a dedication to innovation, Nityasach Fitness Pvt Ltd was founded, spearheaded by director Nityesh Sachdev. With the brand "Aerofit" at its core, the company aimed to bridge the gap between international fitness technology and the Indian market. By importing advanced fitness equipment at accessible price points, Aerofit sought to redefine the industry landscape, prioritizing health and vitality while staying true to its legacy of passion and customer focus.

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.

##Objective

- The market research team at AeroFit wants to 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. The team decides to investigate whether there are differences across the product with respect to customer characteristics.
- Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts. For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

0.2 About Data

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during `three months`.The data is available in a single csv file

Product Portfolio

- The `KP281` is an `entry-level` treadmill that sells for `USD 1,500`.
- The `KP481` is for `mid-level` runners that sell for `USD 1,750`.
- The `KP781` treadmill is having `advanced features` that sell for `USD 2,500`.

0.3 Features of the dataset:

Feature	Description
Product	Product Purchased: KP281, KP481, or KP781
Age	Age of buyer in years
Gender	Gender of buyer (Male/Female)
Education	Education of buyer in years
MaritalStatus	MaritalStatus of buyer (Single or partnered)
Usage	The average number of times the buyer plans to use the treadmill each week
Income	Annual income of the buyer (in $)
Fitness	Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape
Miles	The average number of miles the buyer expects to walk/run each week

---

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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

[3]:
```
df
```

[3]:
```
    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
```

```
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[4]:
```python
df.head()
```

[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

[5]:
```python
af=df.copy()
```

[6]:
```python
af.head()
```

[6]:

	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

[7]:
```python
af.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
```

[8]:
```python
af.describe()
```

[8]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

[9]:
```python
af.shape
```

[9]: (180, 9)

0.4 Changing the data types of the columns.

[10]:
```python
for col in af.columns:
  if af[col].dtype=='object':
    af[col]=af[col].astype('category')

af.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    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 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: category(3), int64(6)
```

```
memory usage: 9.5 KB
```

[11]:
```python
af.head()
```

[11]:
```
  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
```

[12]:
```python
af.describe().T
```

[12]:
```
           count          mean           std      min       25%      50%  \
Age        180.0     28.788889      6.943498     18.0     24.00     26.0
Education  180.0     15.572222      1.617055     12.0     14.00     16.0
Usage      180.0      3.455556      1.084797      2.0      3.00      3.0
Fitness    180.0      3.311111      0.958869      1.0      3.00      3.0
Income     180.0  53719.577778  16506.684226  29562.0  44058.75  50596.5
Miles      180.0    103.194444     51.863605     21.0     66.00     94.0

                75%       max
Age           33.00      50.0
Education     16.00      21.0
Usage          4.00       7.0
Fitness        4.00       5.0
Income     58668.00  104581.0
Miles        114.75     360.0
```

0.5 Insights

1. Age - The age range of customers spans from 18 to 50 year, with an average age of 29 years.
2. Education - Customer education levels vary between 12 and 21 years, with an average education duration of 16 years.
3. Usage - Customers intend to utilize the product anywhere from 2 to 7 times per week, with an average usage frequency of 3 times per week.
4. Fitness - On average, customers have rated their fitness at 3 on a 5-point scale, reflecting a moderate level of fitness.
5. Income - The annual income of customers falls within the range of USD 30,000 to USD 100,000, with an average income of approximately USD 54,000.
6. Miles - Customers' weekly running goals range from 21 to 360 miles, with an average target of 103 miles per week.

[13]:
```python
af.describe(include='category').T
```

[13]:
```
              count unique        top freq
Product         180      3      KP281   80
Gender          180      2       Male  104
MaritalStatus   180      2  Partnered  107
```

1. Product - Over the past three months, the KP281 product demonstrated the highest sales performance among the three products
2. Gender - Based on the data of last 3 months, around 58% of the buyers were Male and 42% were female
3. Marital Status - Based on the data of last 3 months, around 60% of the buyers were Married and 40% were single

[14]:
```python
af.duplicated().sum()
```

[14]:
```
np.int64(0)
```

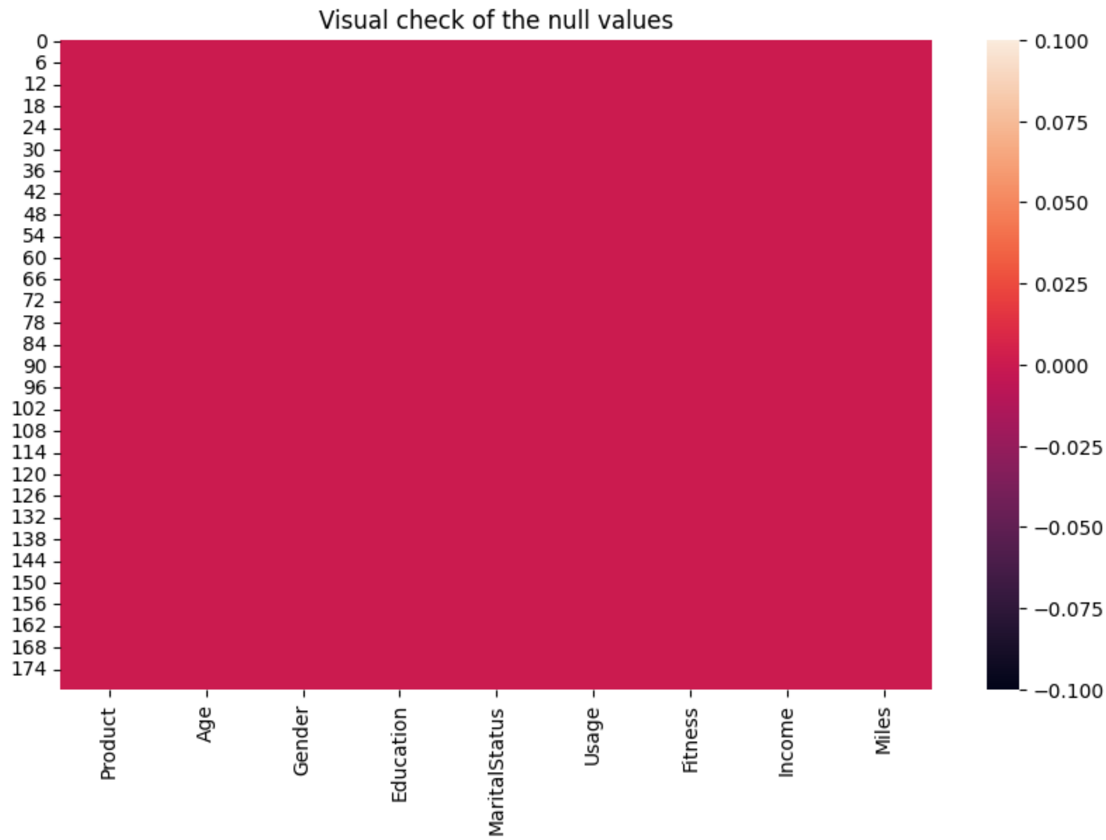
There are no duplicate values

0.6 Checking for null values.

[15]:
```python
af.isnull().sum()
```

[15]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

[16]:
```python
plt.figure(figsize=(10,6))
sns.heatmap(af.isnull())
plt.title('Visual check of the null values')
plt.show()
```



1 Checking for unique values

[17]:
```
af.nunique()
```

[17]:
```
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

[18]:
```
for col in af.columns:
    print()
    print('Total Unique Values in',col,'column are :-',af[col].nunique())
    print('Unique Values in',col,'column are :-\n',af[col].unique())
```

```
    print()
    print('-'*100)
```

```
Total Unique Values in Product column are :- 3
Unique Values in Product column are :-
 ['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']

--------------------------------------------------------------------------------
--------------------

Total Unique Values in Age column are :- 32
Unique Values in Age column are :-
 [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]

--------------------------------------------------------------------------------
--------------------

Total Unique Values in Gender column are :- 2
Unique Values in Gender column are :-
 ['Male', 'Female']
Categories (2, object): ['Female', 'Male']

--------------------------------------------------------------------------------
--------------------

Total Unique Values in Education column are :- 8
Unique Values in Education column are :-
 [14 15 12 13 16 18 20 21]

--------------------------------------------------------------------------------
--------------------

Total Unique Values in MaritalStatus column are :- 2
Unique Values in MaritalStatus column are :-
 ['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']

--------------------------------------------------------------------------------
--------------------

Total Unique Values in Usage column are :- 6
Unique Values in Usage column are :-
 [3 2 4 5 6 7]
```

```
----------------------------------------------------------------------------------------------------
```

```
Total Unique Values in Fitness column are :- 5
Unique Values in Fitness column are :-
 [4 3 2 1 5]

----------------------------------------------------------------------------------------------------

Total Unique Values in Income column are :- 62
Unique Values in Income column are :-
 [ 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]

----------------------------------------------------------------------------------------------------

Total Unique Values in Miles column are :- 37
Unique Values in Miles column are :-
 [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]

----------------------------------------------------------------------------------------------------
```

[19]:
```python
for col in af.columns:
  if af[col].dtype!='category':
    print(f"Value counts for {col} are:- \n{af[col].value_counts().to_frame().
 ↪reset_index()}")
    print()
    print("-"*100)
```

```
Value counts for Age are:-
    Age  count
0    25     25
1    23     18
2    24     12
3    26     12
4    28      9
5    33      8
6    35      8
```

```
7    22      7
8    30      7
9    27      7
10   38      7
11   21      7
12   31      6
13   34      6
14   29      6
15   20      5
16   40      5
17   19      4
18   32      4
19   37      2
20   45      2
21   48      2
22   47      2
23   18      1
24   41      1
25   39      1
26   36      1
27   43      1
28   46      1
29   44      1
30   50      1
31   42      1

--------------------------------------------------------------------------------
--------------------
Value counts for Education are:-
   Education  count
0         16     85
1         14     55
2         18     23
3         15      5
4         13      5
5         12      3
6         21      3
7         20      1

--------------------------------------------------------------------------------
--------------------
Value counts for Usage are:-
   Usage  count
0      3     69
1      4     52
2      2     33
3      5     17
4      6      7
```

```
5      7      2

--------------------------------------------------------------------------------
--------------------
Value counts for Fitness are:-
   Fitness  count
0        3     97
1        5     31
2        2     26
3        4     24
4        1      2

--------------------------------------------------------------------------------
--------------------
Value counts for Income are:-
    Income  count
0    45480     14
1    52302      9
2    53439      8
3    54576      8
4    46617      8
..     …    …
57   85906      1
58   99601      1
59  103336      1
60   95866      1
61   95508      1

[62 rows x 2 columns]

--------------------------------------------------------------------------------
--------------------
Value counts for Miles are:-
    Miles  count
0      85     27
1      95     12
2      66     10
3      75     10
4      47      9
5     106      9
6     113      8
7      94      8
8      53      7
9     100      7
10    200      6
11     56      6
12     64      6
13    180      6
```

```
14      160       5
15      127       5
16       42       4
17      150       4
18       74       3
19       38       3
20      103       3
21      170       3
22      120       3
23      132       2
24      141       2
25      112       1
26      212       1
27      188       1
28      169       1
29       80       1
30      140       1
31       21       1
32      240       1
33      300       1
34      280       1
35      260       1
36      360       1

--------------------------------------------------------------------------------
--------------------
```

1.1 Insights

- There are 180 rows and 3 columns. -No missing values. -There are 3 unique products ['KP281', 'KP481', 'KP781']

1.2 EDA- Exploratory data analysis

[20]:
```
af.sample()
```

[20]:
```
   Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
13   KP281   22  Female         14        Single      3        3   35247

    Miles
13     75
```

[21]:
```
af['Product'].value_counts()
```

[21]:
```
Product
KP281    80
KP481    60
KP781    40
```

```
Name: count, dtype: int64
```

[22]:
```
fp=af['Product'].value_counts(normalize=True)
fp=fp.to_frame().reset_index()
```

[23]:
```
fp
```

[23]:

	Product	proportion
0	KP281	0.444444
1	KP481	0.333333
2	KP781	0.222222

[24]:
```
fp['proportion']=round(fp.proportion*100,2)
fp
```

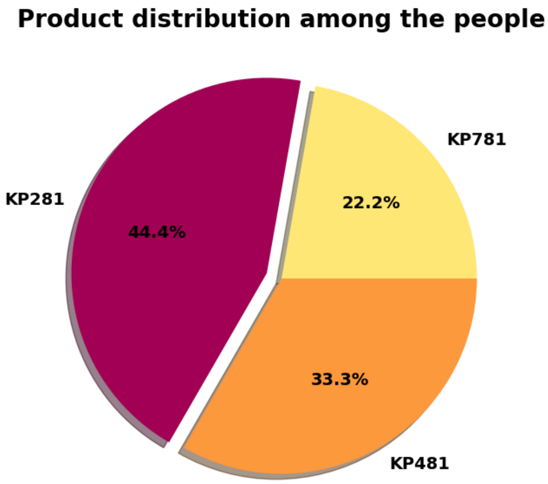
[24]:

	Product	proportion
0	KP281	44.44
1	KP481	33.33
2	KP781	22.22

[25]:
```
cp = ['#A10054','#FC993C','#FFE775','#BD4682','#8C2057']
cp1 = ['#D25380','#E7CBCB','#EE8972','#790252']
cp2 = ['#F7D695','#EE8972','#D15A7C']
cp3 = ['#4F8A8B','#FBD46D','#E7CBCB']
cp4 = ['#A10054','#FC993C','#EE8972','#D15A7C','#FFE775','#BD4682','#8C2057']
product_count=af['Product'].value_counts()
```

[26]:
```
plt.figure(figsize=(16,8))
plt.subplot(1,2,1)
plt.pie(product_count,labels=product_count.index,startangle=80,
        autopct="%1.
 ↪1f%%",colors=['#A10054','#FC993C','#FFE775'],shadow=True,explode=(0.
 ↪08,0,0),textprops={'fontsize': 14, 'color': 'black','fontweight': 'bold'})

plt.title("Product distribution among the people",fontsize=20,fontweight='bold')



plt.subplot(1,2,2)
product_portfolio =␣
 ↪[['KP281','$1500','$120k'],['KP481','$1750','$105k'],['KP781','$2500','$100k']]
color_2d =␣
 ↪[[cp[0],'#FFFFFF','#FFFFFF'],[cp[1],'#FFFFFF','#FFFFFF'],[cp[2],'#FFFFFF','#FFFFFF']]

table = plt.table(cellText = product_portfolio, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Product','Price','Sales'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])
plt.axis('off')
```

```
plt.show()

plt.show()
```



Product	Price	Sales
KP281	$1500	$120k
KP481	$1750	$105k
KP781	$2500	$100k

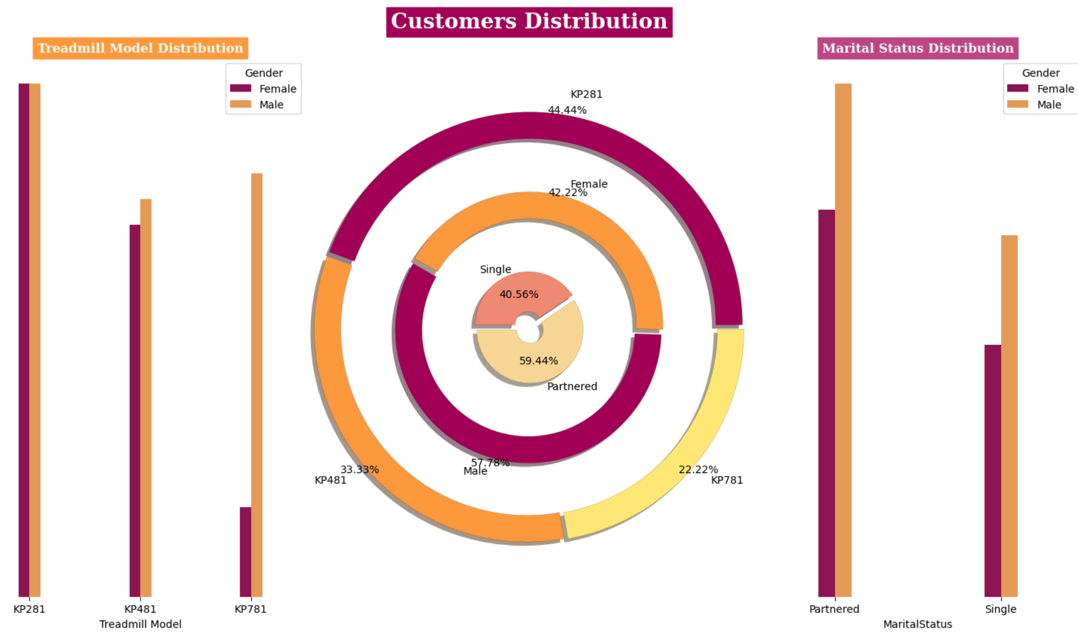
1.3 Insights :-

- Most of the customers bought KP281.
- **33.3%** of the customeres bought KP481.
- **22.2%** of the customers bought KP781

```
[27]: plt.figure(figsize=(15,8.5))
plt.suptitle('Customers␣
↪Distribution',fontfamily='serif',fontweight='bold',fontsize=20,
             backgroundcolor=cp[0],color='w')
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

plt.subplot(1,3,1)
plt.title('Treadmill Model␣
↪Distribution',fontfamily='serif',fontweight='bold',fontsize=12,
          backgroundcolor=cp[1],color='w')
a = sns.countplot(data=af,x='Product',hue='Gender',palette=cp,width=0.2)
plt.xlabel('Treadmill Model')
plt.ylabel('')
plt.yticks([])

plt.subplot(1,3,3)
```

```
a = sns.countplot(data=af,x='MaritalStatus',hue='Gender',palette=cp,width=0.2)
plt.title('Marital Status␣
↪Distribution',fontfamily='serif',fontweight='bold',fontsize=12,
          backgroundcolor=cp[3],color='w')
plt.yticks([])
plt.ylabel('')
sns.despine(left=True,bottom=True,trim=True)

plt.subplot(1,3,2)
plt.pie(af.Product.value_counts(), labels=af.Product.value_counts().index,
       counterclock=True , explode=(0.02,0.02,0.02) , autopct='%.2f%%',␣
↪pctdistance=1.025,
       colors=cp , textprops={'color':'k','fontsize':10} , shadow=True,␣
↪radius=1.6,
       wedgeprops=dict(edgecolor='k',linewidth=0.1,width=0.2))

plt.pie(af.Gender.value_counts(), labels=af.Gender.value_counts().index,
       startangle=150 , explode=(0.02,0.02) , autopct='%.2f%%',pctdistance=1.
↪035,
       colors=cp , textprops={'color':'k','fontsize':10} , shadow=True,radius=1,
       wedgeprops=dict(edgecolor='k',linewidth=0.1,antialiased=True,width=0.2))

plt.pie(af.MaritalStatus.value_counts(), labels=af.MaritalStatus.value_counts().
↪index,
       startangle=180 , explode=(0.02,0.02) , autopct='%.2f%%',
       colors=cp2 , textprops={'color':'k','fontsize':10} , shadow=True,␣
↪radius=0.4,
       wedgeprops=dict(edgecolor='k',linewidth=0.1,antialiased=True,width=0.3))
plt.tight_layout()
plt.show()
```

```
<ipython-input-27-0baa72be9123>:10: UserWarning: The palette list has more
values (5) than needed (2), which may not be intended.
  a = sns.countplot(data=af,x='Product',hue='Gender',palette=cp,width=0.2)
<ipython-input-27-0baa72be9123>:16: UserWarning: The palette list has more
values (5) than needed (2), which may not be intended.
  a = sns.countplot(data=af,x='MaritalStatus',hue='Gender',palette=cp,width=0.2)
```



#Insights:-

- Partnered customers bought the most od the products.
- **57.7%** of male bought the products.
- And most of male custoners bought the KP281.

[28]:
```python
af.sample()
```

[28]:
```
     Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
146    KP781   24   Male         16        Single      4        5   61006

     Miles
146    100
```

[29]:
```python
af.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    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 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: category(3), int64(6)
memory usage: 9.5 KB
```

[30]:
```
af_usage=af.Usage.value_counts(normalize=True).reset_index()
af_usage['proportion']=round(af_usage.proportion*100,2)

af_usage
```

[30]:

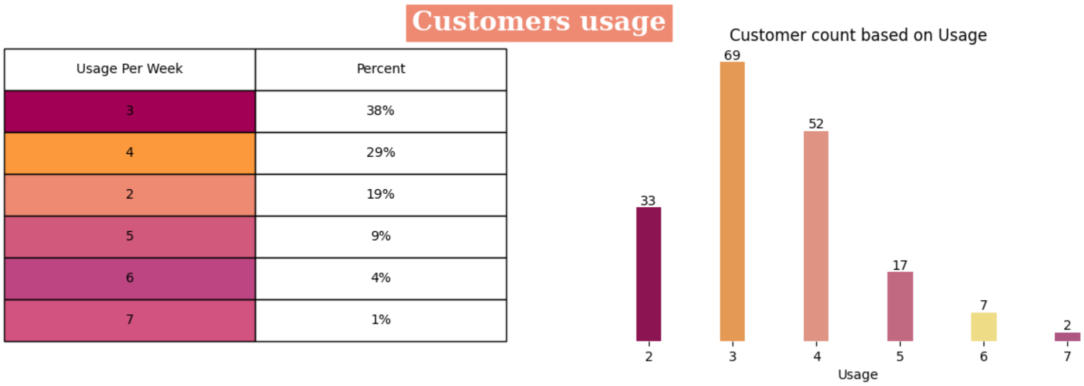
	Usage	proportion
0	3	38.33
1	4	28.89
2	2	18.33
3	5	9.44
4	6	3.89
5	7	1.11

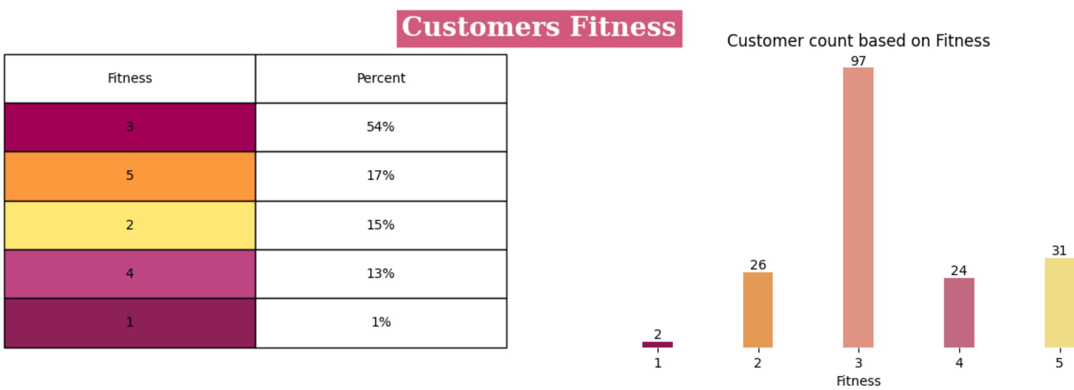
[31]:
```
plt.figure(figsize=(15,4))
plt.suptitle('Customers usage',fontfamily='serif',fontweight='bold',fontsize=20,
             backgroundcolor=cp2[1],color='w')
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

plt.subplot(1,2,1)
usage_info =␣
 ↪[['3','38%'],['4','29%'],['2','19%'],['5','9%'],['6','4%'],['7','1%']]
color_2d =␣
 ↪[[cp4[0],'#FFFFFF'],[cp4[1],'#FFFFFF'],[cp4[2],'#FFFFFF'],[cp4[3],'#FFFFFF'],[cp4[5],'#FFFF
           [cp1[0],'#FFFFFF']]

plt.table(cellText = usage_info, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Usage Per Week','Percent'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])
plt.axis('off')

plt.subplot(1,2,2)
u = af['Usage'].value_counts()
a = sns.barplot(x=u.index,y = u.values,palette=cp4,width=0.3)
for i in a.containers:
  a.bar_label(i,label_type='edge')
plt.title('Customer count based on Usage')
sns.despine(left=True,bottom=True)
#plt.xticks([])
plt.yticks([])
plt.ylabel('')
```

```
plt.figure(figsize=(15,4))
plt.suptitle('Customers␣
↪Fitness',fontfamily='serif',fontweight='bold',fontsize=20,
             backgroundcolor=cp2[2],color='w')
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

plt.subplot(1,2,1)
fitness_info = [['3','54%'],['5','17%'],['2','15%'],['4','13%'],['1','1%']]
color_2d =␣
↪[[cp[0],'#FFFFFF'],[cp[1],'#FFFFFF'],[cp[2],'#FFFFFF'],[cp[3],'#FFFFFF'],[cp[4],'#FFFFFF']]

plt.table(cellText = fitness_info, cellColours=color_2d,␣
↪cellLoc='center',colLabels =['Fitness','Percent'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])
plt.axis('off')

plt.subplot(1,2,2)
f = af['Fitness'].value_counts()
b = sns.barplot(x=f.index,y = f.values,palette=cp4,width=0.3)
for i in b.containers:
  b.bar_label(i,label_type='edge')
plt.title('Customer count based on Fitness')
sns.despine(left=True,bottom=True)
plt.yticks([])
#plt.xticks([])
plt.ylabel('')
plt.show()
```

```
<ipython-input-31-caedf824f076>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  a = sns.barplot(x=u.index,y = u.values,palette=cp4,width=0.3)
<ipython-input-31-caedf824f076>:18: UserWarning: The palette list has more
values (7) than needed (6), which may not be intended.
  a = sns.barplot(x=u.index,y = u.values,palette=cp4,width=0.3)
<ipython-input-31-caedf824f076>:43: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  b = sns.barplot(x=f.index,y = f.values,palette=cp4,width=0.3)
<ipython-input-31-caedf824f076>:43: UserWarning: The palette list has more
```

```
values (7) than needed (5), which may not be intended.
  b = sns.barplot(x=f.index,y = f.values,palette=cp4,width=0.3)
```





#Insights:-

- **38%** customers use the product 3 times a week. -**58%** of customers have fitness level of 3

[32]:
```python
#Gender stats

fg=af['Gender'].value_counts(normalize=True)
fg=fg.map(lambda z: round(z*100,2))
fg
#
```

[32]:
```
Gender
Male      57.78
Female    42.22
Name: proportion, dtype: float64
```

#Insights:-

- 57% of male
- 42% of female

[33]:
```
#Martial stats

ms=af['MaritalStatus'].value_counts(normalize=True)
ms=ms.map(lambda z: round(z*100,2))
ms
#
```

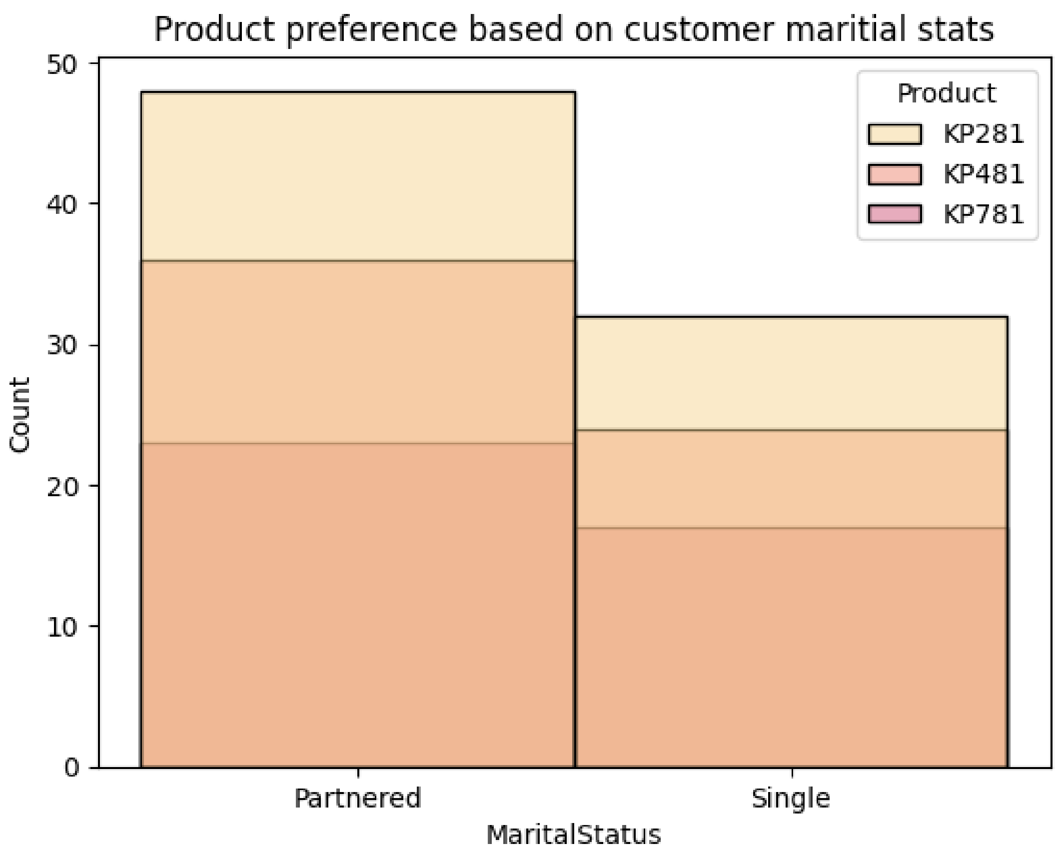
[33]:
```
MaritalStatus
Partnered    59.44
Single       40.56
Name: proportion, dtype: float64
```

#Insights:

59.44% of customers are Married/Partnered

40.56% of customers are Single

[34]:
```
sns.histplot(data=af, x="MaritalStatus", hue="Product" , palette=cp2)
plt.title('Product preference based on customer maritial stats')
plt.show()
```



[35]:
```
af.sample()
```

[35]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
39	KP281	26	Male	16	Partnered	4	4	44343	132

[36]:
```
ffc = af['Fitness'].value_counts(normalize=True)
fc=ffc.map(lambda z: round(z*100,2)).reset_index().sort_values(by='Fitness')
od=['Poor shape','Bad shape','Average shape','Good shape','Excellent shape']
fc['Fitness']=od
fc=fc.reset_index(drop=True)
fc
```

[36]:

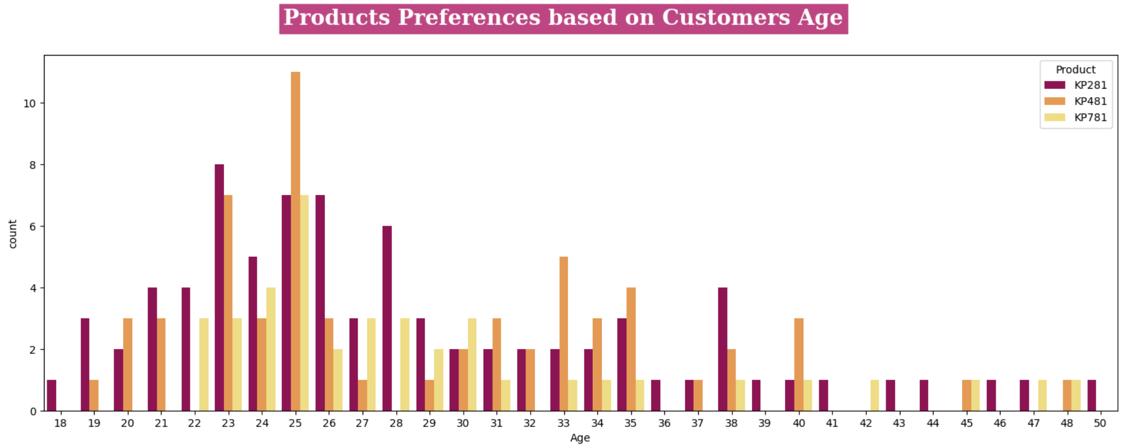
	Fitness	proportion
0	Poor shape	1.11
1	Bad shape	14.44
2	Average shape	53.89
3	Good shape	13.33
4	Excellent shape	17.22

#Insights:

- Approx 54% of customers have rated themselves as they are in Average Shape
- Little close to 14% of customers have rated their fitness less than average
- Over 17% of customers have Peak fitness ratings

[37]:
```
plt.figure(figsize = (18,6))
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')
sns.countplot(data=af, x='Age',hue="Product",palette=cp)
plt.suptitle('Products Preferences based on Customers␣
↪Age',fontfamily='serif',fontweight='bold',fontsize=20,
             backgroundcolor=cp4[5],color='w')

plt.show()
```

```
<ipython-input-37-4a68ea9832e6>:4: UserWarning: The palette list has more values
(5) than needed (3), which may not be intended.
  sns.countplot(data=af, x='Age',hue="Product",palette=cp)
```



[38]:
```
af['age_category'] = af.Age
af['age_category'] = pd.cut(af.age_category,bins=[0,20,35,45,60],labels=['Teenage','Adults','Middle Aged','Elderly'])
af.sample(2)
```

[38]:
```
    Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
72    KP281   39   Male         16     Partnered      4        4   59124
137   KP481   40   Male         16     Partnered      3        3   64809

     Miles age_category
72     132  Middle Aged
137     95  Middle Aged
```

[39]:
```
af['Fitness_comment'] = af.Fitness
af['Fitness_comment'] = af.Fitness_comment.replace({
                            1:"Poor Shape",
                            2:"Bad Shape",
                            3:"Average Shape",
                            4:"Good Shape",
                            5:"Excellent Shape"})
af.tail()
```

[39]:
```
    Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
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 age_category  Fitness_comment
```

```
175    200  Middle Aged  Excellent Shape
176    200  Middle Aged       Good Shape
177    160  Middle Aged  Excellent Shape
178    120      Elderly  Excellent Shape
179    180      Elderly  Excellent Shape
```

[40]:
```
af['income_grp'] = pd.cut(af.Income , bins=[25000,50000,75000,150000] ,␣
 ↪labels=['middle_class','upper_middle_class','high_class'])
```

[41]:
```
af.sample(4)
```

[41]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
4     KP281   20    Male         13     Partnered      4        2   35247
74    KP281   41    Male         16     Partnered      4        3   54576
118   KP481   32    Male         16        Single      4        3   60261
18    KP281   23  Female         16        Single      4        3   38658

     Miles age_category Fitness_comment          income_grp
4       47      Teenage       Bad Shape        middle_class
74     103  Middle Aged   Average Shape  upper_middle_class
118    127       Adults   Average Shape  upper_middle_class
18     113       Adults   Average Shape        middle_class
```

[42]:
```
af.sample(4)
```

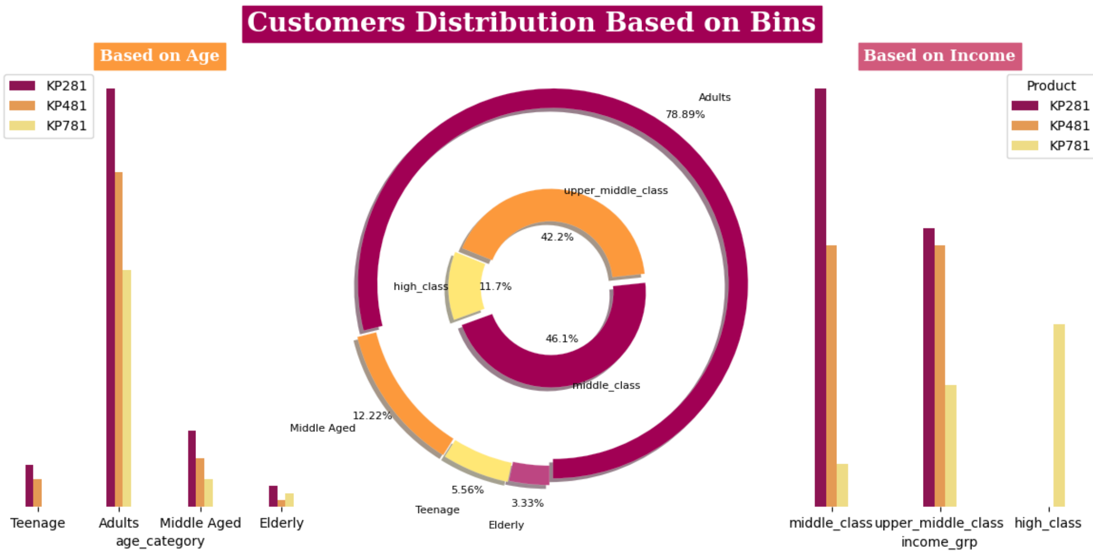
[42]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
143   KP781   23    Male         16        Single      4        5   58516
30    KP281   25  Female         14     Partnered      3        3   39795
70    KP281   38    Male         14        Single      2        3   52302
150   KP781   25    Male         16     Partnered      4        5   49801

     Miles age_category  Fitness_comment          income_grp
143    140       Adults  Excellent Shape  upper_middle_class
30      85       Adults    Average Shape        middle_class
70      56  Middle Aged    Average Shape  upper_middle_class
150    120       Adults  Excellent Shape        middle_class
```

[43]:
```
af.to_csv('aerofit_final.csv',sep=',',index=False)
```

[44]:
```
plt.figure(figsize=(15,6))
plt.suptitle('Customers Distribution Based on␣
 ↪Bins',fontfamily='serif',fontweight='bold',fontsize=20,
            backgroundcolor=cp4[0],color='w')
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

plt.subplot(1,3,1)
```

```
sns.countplot(af,x='age_category',hue='Product',palette=cp,width=0.3)
plt.title('Based on␣
 ↪Age',fontfamily='serif',fontweight='bold',fontsize=12,backgroundcolor=cp4[1],color='w')
plt.yticks([])
plt.legend(loc='upper left')
plt.ylabel('')

plt.subplot(1,3,2)
plt.pie(af.age_category.value_counts(), labels=af.age_category.value_counts().
 ↪index,
       explode=(0.04,0.03,0.03,0.02) , autopct='%.2f%%', pctdistance=1.
 ↪1,startangle=270,
       colors=cp , textprops={'color':'k','fontsize':8} , shadow=True,␣
 ↪labeldistance=1.21,
       wedgeprops=dict(edgecolor='w',linewidth=0.1,width=0.15), radius=1.5)

plt.pie(af.income_grp.value_counts(), labels=af.income_grp.value_counts().
 ↪index, counterclock=True,
       startangle=200 , explode=(0.04,0.03,0.05) , autopct='%.1f%%',␣
 ↪pctdistance=0.5,
       colors=cp , textprops={'color':'k','fontsize':8} , shadow=True,␣
 ↪labeldistance=1,
       wedgeprops=dict(edgecolor='w',linewidth=0.1,width=0.25), radius=0.73)

plt.subplot(1,3,3)
sns.countplot(af,x='income_grp',hue='Product',palette=cp,width=0.3)
plt.title('Based on␣
 ↪Income',fontfamily='serif',fontweight='bold',fontsize=12,backgroundcolor=cp4[3],color='w')
sns.despine(left=True,bottom=True,trim=True)
plt.yticks([])
plt.ylabel('')

plt.show()
```

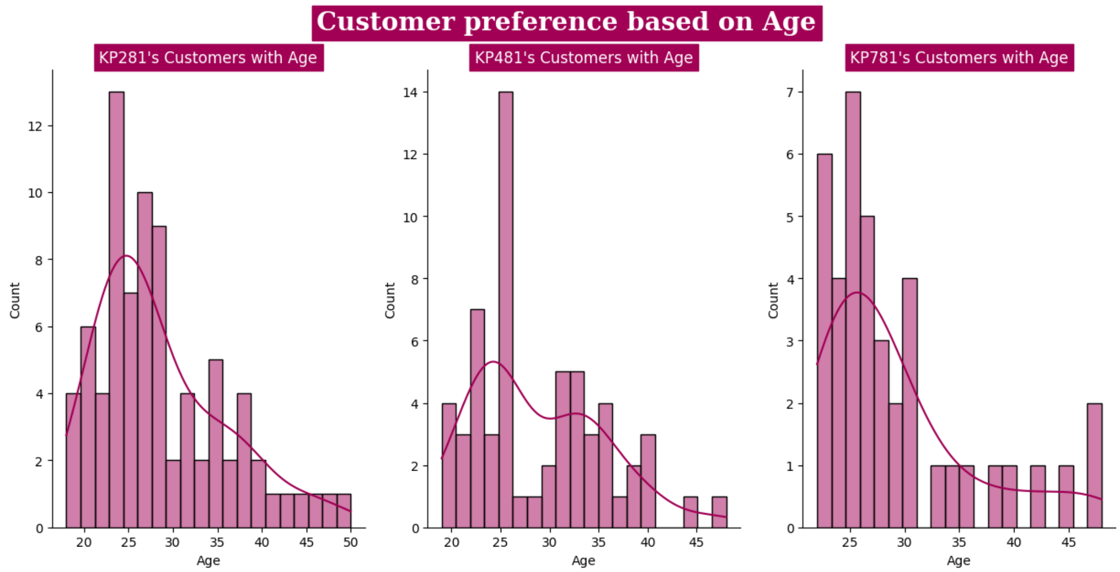
```
<ipython-input-44-a65446be3f4b>:8: UserWarning: The palette list has more values
(5) than needed (3), which may not be intended.
  sns.countplot(af,x='age_category',hue='Product',palette=cp,width=0.3)
<ipython-input-44-a65446be3f4b>:26: UserWarning: The palette list has more
values (5) than needed (3), which may not be intended.
  sns.countplot(af,x='income_grp',hue='Product',palette=cp,width=0.3)
```



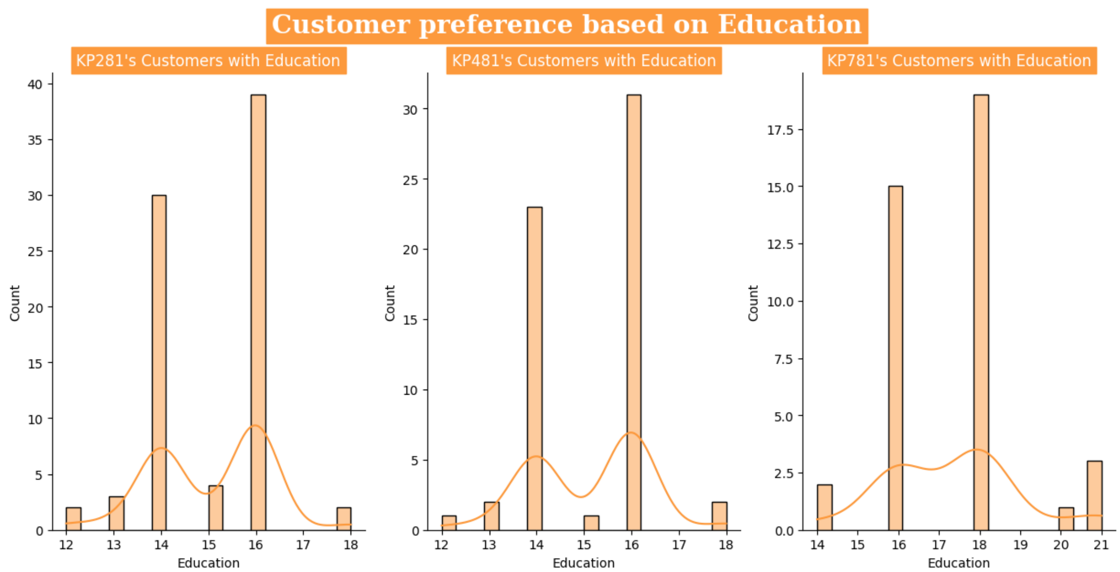
[45]:
```
af.sample()
```

[45]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
116    KP481   31  Female         16     Partnered      2        3   51165

     Miles age_category Fitness_comment          income_grp
116     64       Adults   Average Shape  upper_middle_class
```

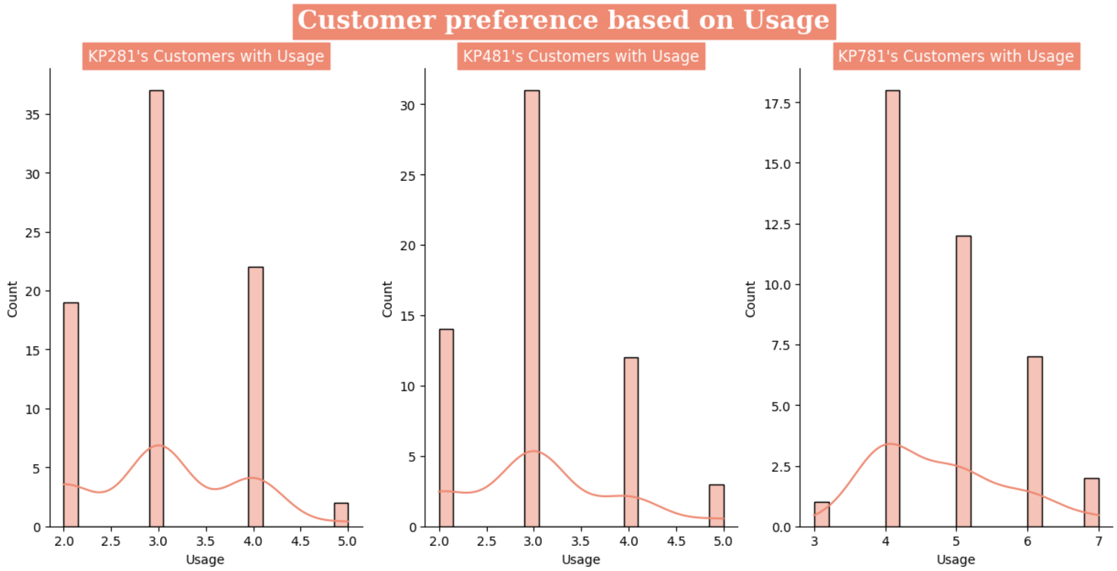
[46]:
```
p=af['Product'].unique()
cols=['Age','Education','Usage','Fitness','Income','Miles']

for i in range(len(cols)):
  fig,ax = plt.subplots(nrows=1, ncols=3, figsize=(15,6.5))
  plt.suptitle(f"Customer preference based on␣
 ↪{cols[i]}",fontsize=20,fontweight='bold',fontfamily='serif',backgroundcolor=cp4[i],color='w

  for j in range(len(p)):
    prd=af[af.Product==p[j]]
    sns.histplot(prd,x=cols[i],bins=20,kde=True, ax=ax[j], color=cp4[i])
    sns.despine()
    ax[j].set_title(f"{p[j]}'s Customers with␣
 ↪{cols[i]}",backgroundcolor=cp4[i],color='w')
```

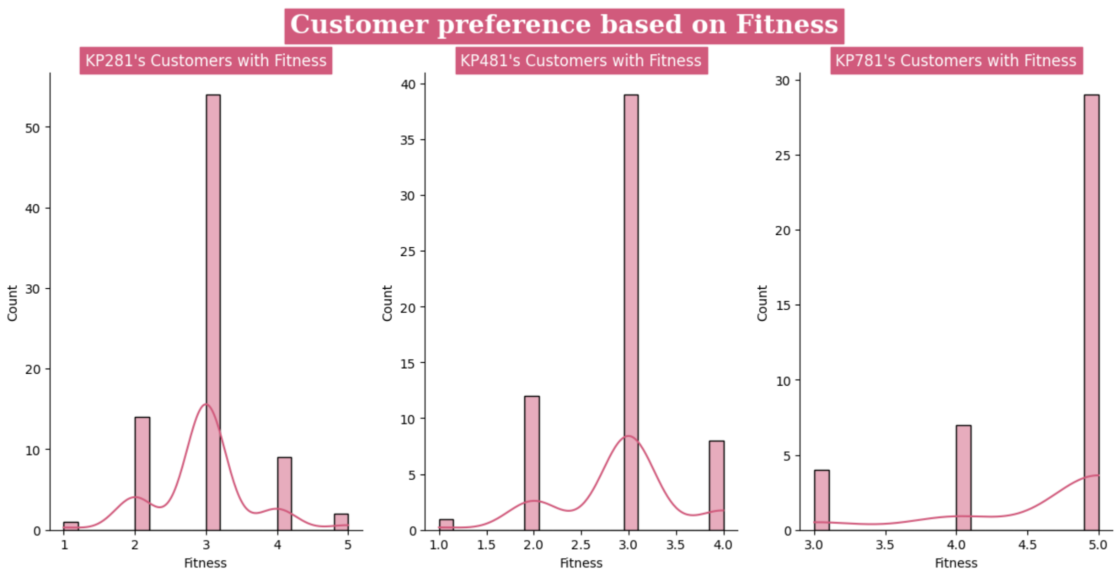


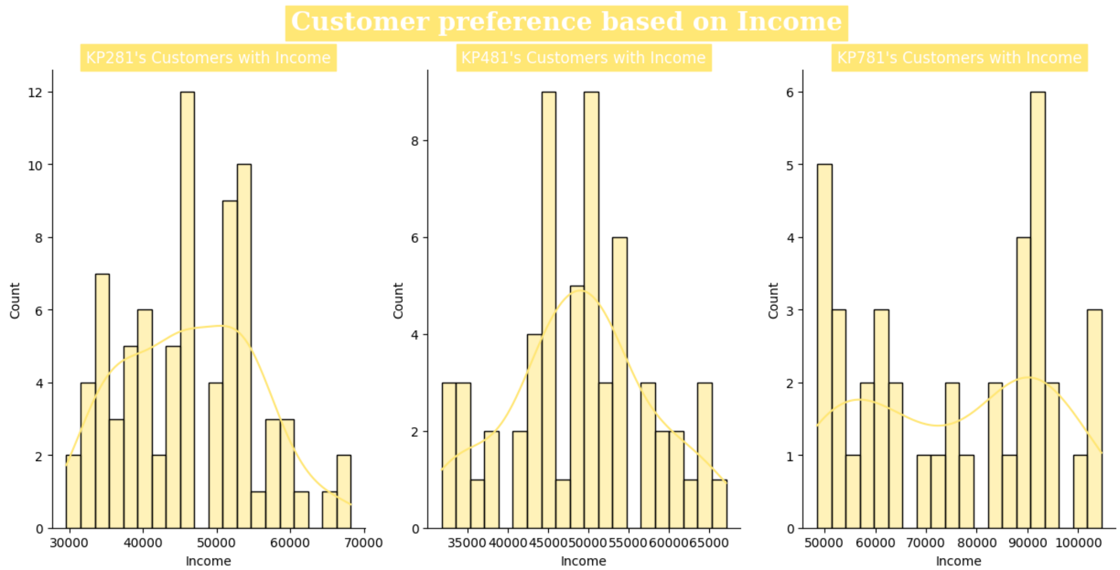
Customer preference based on Age
KP281's Customers with Age
KP481's Customers with Age
KP781's Customers with Age
Count
Age

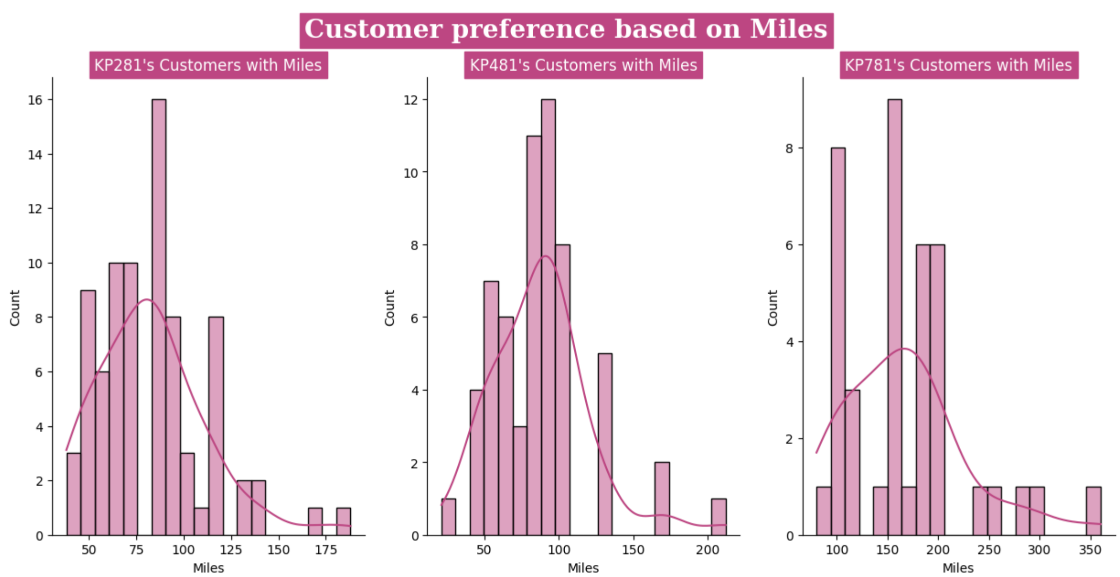


Customer preference based on Education
KP281's Customers with Education
KP481's Customers with Education
KP781's Customers with Education
Count
Education


Customer preference based on Usage
KP281's Customers with Usage
KP481's Customers with Usage
KP781's Customers with Usage
Count
Usage


Customer preference based on Fitness
KP281's Customers with Fitness
KP481's Customers with Fitness
KP781's Customers with Fitness
Count
Fitness





[47]:
```
af.sample()
```

[47]:
```
    Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
179   KP781   48   Male         18     Partnered      4        5   95508

     Miles age_category  Fitness_comment  income_grp
179    180      Elderly  Excellent Shape  high_class
```

1.4 Probability:-

Based on the above analysis:

- Probalility of selecting KP281 is 44%
- Probalility of selecting KP481 is 33%
- Probalility of selecting KP&81 is 22%

[48]:
```
kp281_d=af[af['Product']=='KP281']
kp481_d=af[af['Product']=='KP481']
kp781_d=af[af['Product']=='KP781']
```

[49]:
```
af.shape
```

[49]:
```
(180, 12)
```

Conditional Probability :-

- Male and Single

[50]:
```
pms = af[(af['Gender']=='Male') & (af['MaritalStatus']=='Single')]
v1=round(len(pms[pms['Product']=='KP281'])/(len(pms))*100,2)
v2=round(len(pms[pms['Product']=='KP481'])/(len(pms))*100,2)
v3=round(len(pms[pms['Product']=='KP781'])/(len(pms))*100,2)
print('Probability of Male and Single for buying')
print(f'- KP281 is {v1}%\n- KP481 is {v2}%\n- KP781 is {v3}%')
```

```
Probability of Male and Single for buying
- KP281 is 44.19%
- KP481 is 23.26%
- KP781 is 32.56%
```

- Male and Partnered :

[51]:
```
pmp = af[(af['Gender']=='Male') & (af['MaritalStatus']=='Partnered')]
v1=round(len(pmp[pmp['Product']=='KP281'])/(len(pmp))*100,2)
v2=round(len(pmp[pmp['Product']=='KP481'])/(len(pmp))*100,2)
v3=round(len(pmp[pmp['Product']=='KP781'])/(len(pmp))*100,2)
print('Probability of Male and Partnered for buying')
print(f'- KP281 is {v1}%\n- KP481 is {v2}%\n- KP781 is {v3}%')
```

```
Probability of Male and Partnered for buying
- KP281 is 34.43%
- KP481 is 34.43%
- KP781 is 31.15%
```

- Female and Single :

[52]:
```
pfs = af[(af['Gender']=='Female') & (af['MaritalStatus']=='Single')]
v1=round(len(pfs[pfs['Product']=='KP281'])/(len(pfs))*100,2)
v2=round(len(pfs[pfs['Product']=='KP481'])/(len(pfs))*100,2)
```

```
v3=round(len(pfs[pfs['Product']=='KP781'])/(len(pfs))*100,2)
print('Probability of Female and Single for buying')
print(f'- KP281 is {v1}%\n- KP481 is {v2}%\n- KP781 is {v3}%')
```

```
Probability of Female and Single for buying
- KP281 is 43.33%
- KP481 is 46.67%
- KP781 is 10.0%
```

- Female and Partnered :

[53]:
```
pfp = af[(af['Gender']=='Female') & (af['MaritalStatus']=='Partnered')]
v1=round(len(pfp[pfp['Product']=='KP281'])/(len(pfp))*100,2)
v2=round(len(pfp[pfp['Product']=='KP481'])/(len(pfp))*100,2)
v3=round(len(pfp[pfp['Product']=='KP781'])/(len(pfp))*100,2)
print('Probability of Female and Partnered for buying')
print(f'- KP281 is {v1}%\n- KP481 is {v2}%\n- KP781 is {v3}%')
```

```
Probability of Female and Partnered for buying
- KP281 is 58.7%
- KP481 is 32.61%
- KP781 is 8.7%
```

Probability of Buying KP281 increased from 44.44% to 58.7%, if the customer is Female and Partnered.

Probability of Buying KP481 increased from 33.33% to 46.67%, if the customer is Female and Single.

Probability of Buying KP781 increased from 22.22% to 32.56%, if the customer is Male and Single.

Probability of Buying KP481 & KP781 increased from 33.33% & 22.22% to 34.43%, if the customer is Male and Single.

Probability of Buying KP781 decreased from 22.22% to 8.7%, if the customer is Female and Partnered.

1.5 Probability of Product purchase with respect to gender

[57]:
```
gct=round(pd.crosstab(af.Product,af.Gender,normalize=True,margins=True)*100,2)
gct
```

[57]:

Gender Product	Female	Male	All
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

1.6 Insights

The Probability of a treadmill being purchased by a female is 42%.

The conditional probability of purchasing the treadmill model given that the customer is Female is

For Treadmill model KP281 - 22%

For Treadmill model KP481 - 16%

For Treadmill model KP781 - 4%

The Probability of a treadmill being purchased by a male is 58%.

The conditional probability of purchasing the treadmill model given that the customer is Male is -

For Treadmill model KP281 - 22%

For Treadmill model KP481 - 17%

For Treadmill model KP781 - 18%

[58]:
```
gcct = round(pd.crosstab(index=af.Product,columns=af.
 ↪Gender,normalize='columns')*100,2)
gcct
```

[58]:
```
Gender   Female   Male
Product
KP281     52.63  38.46
KP481     38.16  29.81
KP781      9.21  31.73
```

1.7 Insights:-

he Probability of Customer purchasing the Product Genderwise (only males or only females)

P(KP281 | Female) = 52.63 %

P(KP481 | Female) = 38.16 %

P(KP781 | Female) = 9.21 %

P(KP281 | male) = 38.46 %

P(KP481 | male) = 29.81 %

P(KP781 | male) = 31.73 %

Probability of Female customer buying KP281(52.63%) which is more than male(38.46%).

we can say that KP281 is more preferred by Female customers.

Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).

Probability of Female customer buying Product KP481(38.15%) is significantly higher than male (29.80%).

```
[59]: (pd.crosstab(index =af['Product'],columns = af['MaritalStatus'],margins =␣
       ↪True,normalize = True)*100).round(2)
      # round(pd.crosstab(af.Product,af.
       ↪MaritalStatus,margins=True,normalize=True)*100,2)
```

```
[59]: MaritalStatus  Partnered  Single     All
      Product
      KP281              26.67   17.78   44.44
      KP481              20.00   13.33   33.33
      KP781              12.78    9.44   22.22
      All                59.44   40.56  100.00
```

1.8 Insights:-

The Probability of a treadmill being purchased by a Married/partnered Customer is 59%.

The conditional probability of purchasing the treadmill model given that the customer is Married/partnered is

For Treadmill model KP281 - 27%

For Treadmill model KP481 - 20%

For Treadmill model KP781 - 13%

The Probability of a treadmill being purchased by a Single Customer is 41%.

The conditional probability of purchasing the treadmill model given that the customer is Single is -

For Treadmill model KP281 - 18%

For Treadmill model KP481 - 13%

For Treadmill model KP781 - 9%

```
[60]: (pd.crosstab(index =af['Product'],columns = af['MaritalStatus'],normalize =␣
       ↪'columns')*100).round(2)
```

```
[60]: MaritalStatus  Partnered  Single
      Product
      KP281              44.86   43.84
      KP481              33.64   32.88
      KP781              21.50   23.29
```

```
[61]: uct = round(pd.crosstab(af.Product,af.Usage,margins=True,normalize=True)*100,2)
      uct
```

```
[61]: Usage        2      3      4     5     6     7     All
      Product
      KP281    10.56  20.56  12.22  1.11  0.00  0.00   44.44
      KP481     7.78  17.22   6.67  1.67  0.00  0.00   33.33
```

KP781	0.00	0.56	10.00	6.67	3.89	1.11	22.22
All	18.33	38.33	28.89	9.44	3.89	1.11	100.00

Insights :-

The Probability of a treadmill being purchased by a customer with Usage 3 per week is 38%.

The conditional probability of purchasing the treadmill model given that the customer has Usage 3 per week is -

For Treadmill model KP281 - 21%

For Treadmill model KP481 - 17%

For Treadmill model KP781 - 1%

The Probability of a treadmill being purchased by a customer with Usage 4 per week is 29%.

The conditional probability of purchasing the treadmill model given that the customer has Usage 4 per week is -

For Treadmill model KP281 - 12%

For Treadmill model KP481 - 7%

For Treadmill model KP781 - 10%

The Probability of a treadmill being purchased by a customer with Usage 2 per week is 18%

The conditional probability of purchasing the treadmill model given that the customer has Usage 2 per week is -

For Treadmill model KP281 - 11%

For Treadmill model KP481 - 8%

For Treadmill model KP781 - 0%

[62]:
```
fcct = np.round(pd.crosstab(af.Product,af.
 ↪Fitness_comment,margins=True,normalize=True)*100,2)
fcct.T
```

[62]:

Product	KP281	KP481	KP781	All
Fitness_comment				
Average Shape	30.00	21.67	2.22	53.89
Bad Shape	7.78	6.67	0.00	14.44
Excellent Shape	1.11	0.00	16.11	17.22
Good Shape	5.00	4.44	3.89	13.33
Poor Shape	0.56	0.56	0.00	1.11
All	44.44	33.33	22.22	100.00

1.9 Insights :-

The Probability of a treadmill being purchased by a customer with Average(3) Fitness is 54%.

The conditional probability of purchasing the treadmill model given that the customer has Average Fitness is -

For Treadmill model KP281 - 30%

For Treadmill model KP481 - 22%

For Treadmill model KP781 - 2%

The Probability of a treadmill being purchased by a customer with Fitness of 2,4,5 is almost 15%.

The Probability of a treadmill being purchased by a customer with very low(1) Fitness is only 1%.

[63]:
```
np.round(pd.crosstab(index=[af.Product,af.Fitness_comment],columns=af.
↪Gender,normalize='columns')*100,2).T
```

[63]:
```
Product              KP281                                                  \
Fitness_comment Average Shape Bad Shape Excellent Shape Good Shape Poor Shape
Gender
Female                34.21     13.16            1.32       3.95       0.00
Male                  26.92      3.85            0.96       5.77       0.96

Product              KP481                                    KP781  \
Fitness_comment Average Shape Bad Shape Good Shape Poor Shape Average Shape
Gender
Female                23.68      7.89       5.26       1.32          1.32
Male                  20.19      5.77       3.85       0.00          2.88

Product
Fitness_comment Excellent Shape Good Shape
Gender
Female                    6.58       1.32
Male                     23.08       5.77
```

Probability of Product purchase with respect to Age:

[67]:
```
round(pd.crosstab(af.Product,af.age_category,normalize='columns')*100,2).T
```

[67]:
```
Product       KP281  KP481  KP781
age_category
Teenage       60.00  40.00   0.00
Adults        42.25  33.80  23.94
Middle Aged   50.00  31.82  18.18
Elderly       50.00  16.67  33.33
```

[68]:
```
round(pd.crosstab(af.Product,af.
↪age_category,margins=True,normalize=True)*100,2).T
```

[68]:
```
Product       KP281  KP481  KP781    All
age_category
```

```
Teenage          3.33   2.22   0.00    5.56
Adults          33.33  26.67  18.89   78.89
Middle Aged      6.11   3.89   2.22   12.22
Elderly          1.67   0.56   1.11    3.33
All             44.44  33.33  22.22  100.00
```

1.10 Insights :-

The Probability of a treadmill being purchased by a Teens(0-20) is 6%.

The conditional probability of purchasing the treadmill model given that the customer is Teens is

For Treadmill model KP281 - 3%

For Treadmill model KP481 - 2%

For Treadmill model KP781 - 0%

The Probability of a treadmill being purchased by a Adults(20-35) is 79%.

The conditional probability of purchasing the treadmill model given that the customer is Adult is -

For Treadmill model KP281 - 33%

For Treadmill model KP481 - 26%

For Treadmill model KP781 - 19%

The Probability of a treadmill being purchased by a Middle Aged(36-45) is 12%. The Probability of a treadmill being purchased by a Elder(Above 45) is only 3%.

[69]:
```
np.round(pd.crosstab(index=af.Product , columns=af.income_grp ,␣
 ↪normalize='columns')*100,2).T
```

[69]:
```
Product             KP281  KP481   KP781
income_grp
middle_class        57.83  36.14    6.02
upper_middle_class  42.11  39.47   18.42
high_class           0.00   0.00  100.00
```

[70]:
```
np.round(pd.crosstab(index=af.Product , columns=af.income_grp , margins=True ,␣
 ↪normalize=True)*100,2).T
```

[70]:
```
Product             KP281  KP481  KP781     All
income_grp
middle_class        26.67  16.67   2.78   46.11
upper_middle_class  17.78  16.67   7.78   42.22
high_class           0.00   0.00  11.67   11.67
All                 44.44  33.33  22.22  100.00
```

[71]:
```
num_cols = ['Age','Education','Usage','Fitness','Income','Miles']
```

```
for i in range(len(num_cols)):
    data = af[num_cols[i]].tolist()
    mini = np.min(data)
    Q1 = np.percentile(data, 25)
    Q2 = np.median(data)
    Q3 = np.percentile(data, 75)
    maxi = np.max(data)
    IQR = Q3 - Q1

    lo = Q1 - (1.5 * IQR)
    ho = Q3 + (1.5 * IQR)

    lower_outliers=[]
    upper_outliers=[]
    for k in data:
        if k < lo:
            lower_outliers.append(k)

        elif k > ho:
            upper_outliers.append(k)

    uo_pct = round((len(upper_outliers)*100/af.shape[0]),2)
    lo_pct = round((len(lower_outliers)*100/af.shape[0]),2)

    print()
    print(f"Outlier detection of {num_cols[i]}")
    print('.'*30)
    print("Minimum:", mini)
    print("Maximum:", maxi)
    print(f'Initial Range (with outlier) : {(maxi-mini)}')
    print("Q1:", Q1)
    print("Q2:", Q2)
    print("Q3:", Q3)
    print("IQR:", IQR)
    print(f'Final Range (without outlier) : {(ho-lo)}')
    print("Lower outliers are:", lower_outliers)
    print("Upper outliers are:", upper_outliers)
    print(f'Lower Outlier Percentage is {lo_pct}%')
    print(f'Upper Outlier Percentage is {uo_pct}%')
    print(f'Overall Outlier Percentage is {(lo_pct+uo_pct)}%')

    if len(set(lower_outliers)):
        print(f'Outlier points towards left of boxplot :␣
↪{len(set(lower_outliers))} and they are {(set(lower_outliers))}')
    else:
        print(f'Outlier points towards left of boxplot :␣
↪{len(set(lower_outliers))}')
```

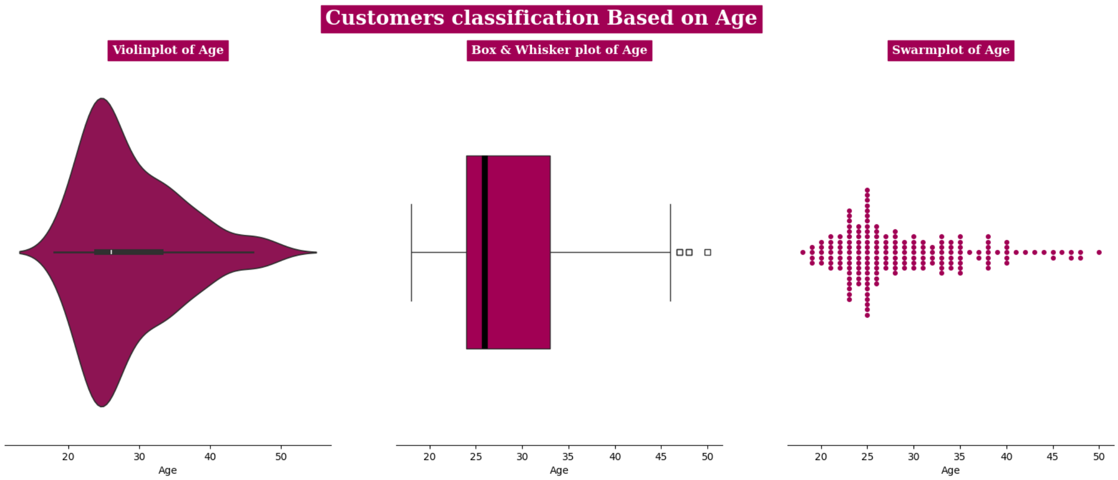
```
    if len(set(upper_outliers)):
        print(f'Outlier points towards right of boxplot :␣
↪{len(set(upper_outliers))} and they are {(set(upper_outliers))}')
    else:
        print(f'Outlier points towards right of boxplot :␣
↪{len(set(upper_outliers))}')
    print()

    plt.figure(figsize=(20,7))
    plt.style.use('default')
    plt.style.use('seaborn-v0_8-bright')
    plt.suptitle(f'Customers classification Based on␣
↪{num_cols[i]}',fontfamily='serif',fontweight='bold',fontsize=20,
                backgroundcolor=cp4[i],color='w')


    plt.subplot(1,3,1)
    sns.violinplot(af,x=num_cols[i],color=cp4[i])
    plt.title(f'Violinplot of␣
↪{num_cols[i]}',fontfamily='serif',fontweight='bold',fontsize=12,
                loc='center',backgroundcolor=cp4[i],color='w')
    plt.yticks([])

    plt.subplot(1,3,2)
    bxp = sns.boxplot(af,x=num_cols[i],color=cp4[i],width=0.
↪5,saturation=97,flierprops={"marker":"s"},
                        medianprops={"color": "k", "linewidth":␣
↪6})#,boxprops={"facecolor": (.3, .5, .7, .5)})
    plt.title(f'Box & Whisker plot of␣
↪{num_cols[i]}',fontfamily='serif',fontweight='bold',fontsize=12,
                loc='center',backgroundcolor=cp4[i],color='w')
    sns.despine(left=True)
    plt.yticks([])

    plt.subplot(1,3,3)
    sns.swarmplot(af,x=num_cols[i],color=cp4[i])
    plt.title(f'Swarmplot of␣
↪{num_cols[i]}',fontfamily='serif',fontweight='bold',fontsize=12,
                loc='center',backgroundcolor=cp4[i],color='w')
    sns.despine(left=True)
    plt.yticks([])
    print('-'*127)
```

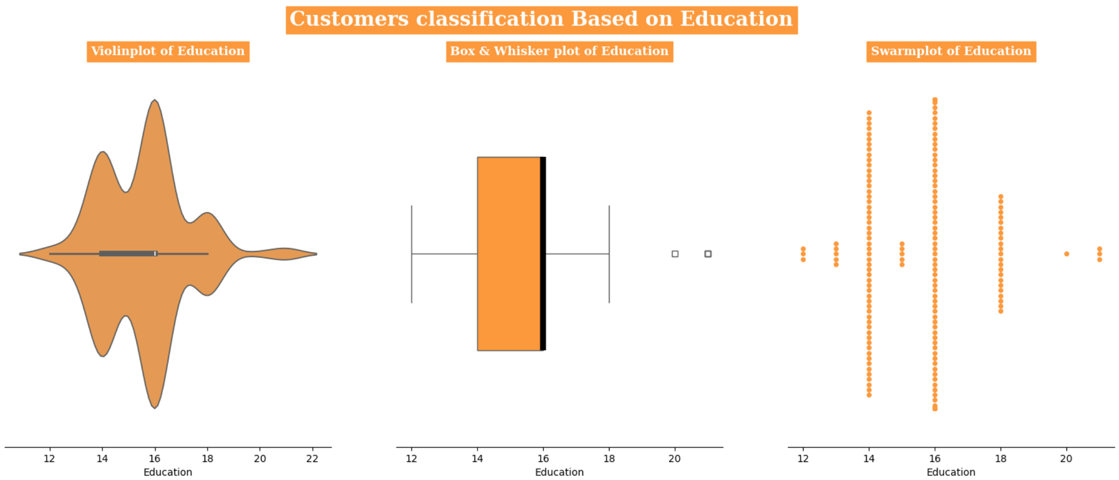
```
Outlier detection of Age
…
Minimum: 18
```

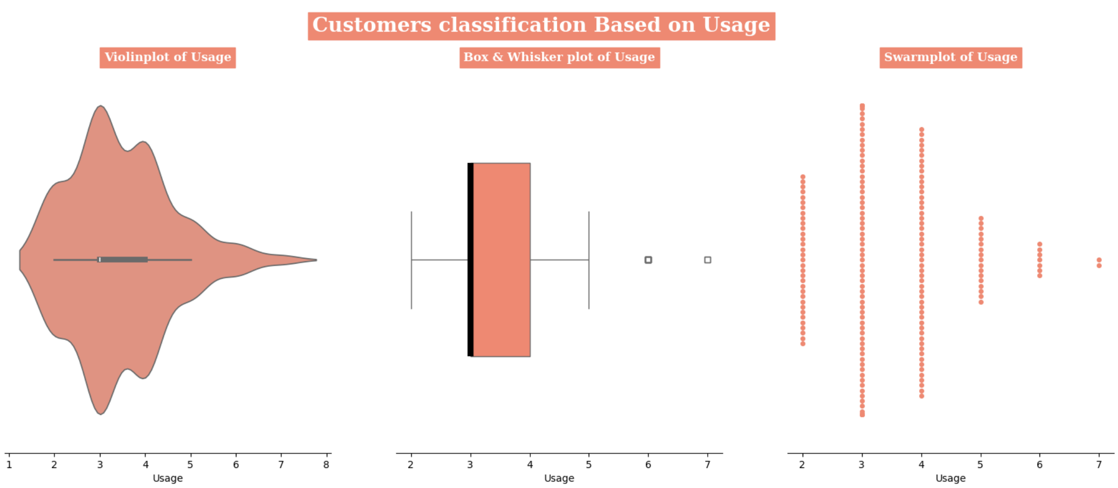
```
Maximum: 50
Initial Range (with outlier) : 32
Q1: 24.0
Q2: 26.0
Q3: 33.0
IQR: 9.0
Final Range (without outlier) : 36.0
Lower outliers are: []
Upper outliers are: [47, 50, 48, 47, 48]
Lower Outlier Percentage is 0.0%
Upper Outlier Percentage is 2.78%
Overall Outlier Percentage is 2.78%
Outlier points towards left of boxplot : 0
Outlier points towards right of boxplot : 3 and they are {48, 50, 47}

--------------------------------------------------------------------------------
-----------------------------------------------

Outlier detection of Education
…
Minimum: 12
Maximum: 21
Initial Range (with outlier) : 9
Q1: 14.0
Q2: 16.0
Q3: 16.0
IQR: 2.0
Final Range (without outlier) : 8.0
Lower outliers are: []
Upper outliers are: [20, 21, 21, 21]
Lower Outlier Percentage is 0.0%
Upper Outlier Percentage is 2.22%
Overall Outlier Percentage is 2.22%
Outlier points towards left of boxplot : 0
Outlier points towards right of boxplot : 2 and they are {20, 21}

--------------------------------------------------------------------------------
-----------------------------------------------

Outlier detection of Usage
…
Minimum: 2
Maximum: 7
Initial Range (with outlier) : 5
Q1: 3.0
Q2: 3.0
Q3: 4.0
IQR: 1.0
```

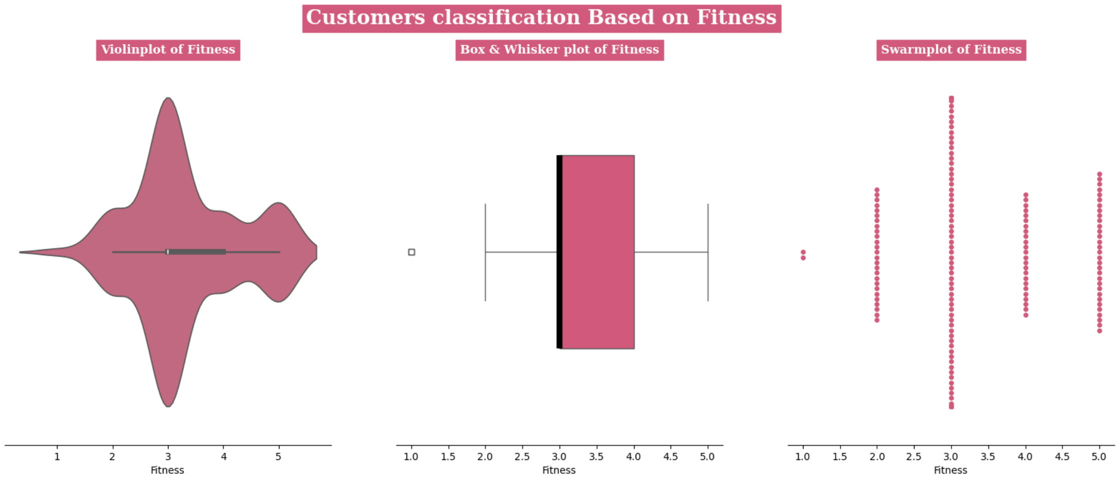
```
Final Range (without outlier) : 4.0
Lower outliers are: []
Upper outliers are: [6, 6, 6, 7, 6, 7, 6, 6, 6]
Lower Outlier Percentage is 0.0%
Upper Outlier Percentage is 5.0%
Overall Outlier Percentage is 5.0%
Outlier points towards left of boxplot : 0
Outlier points towards right of boxplot : 2 and they are {6, 7}

--------------------------------------------------------------------------------
-----------------------------------------------

Outlier detection of Fitness
…
Minimum: 1
Maximum: 5
Initial Range (with outlier) : 4
Q1: 3.0
Q2: 3.0
Q3: 4.0
IQR: 1.0
Final Range (without outlier) : 4.0
Lower outliers are: [1, 1]
Upper outliers are: []
Lower Outlier Percentage is 1.11%
Upper Outlier Percentage is 0.0%
Overall Outlier Percentage is 1.11%
Outlier points towards left of boxplot : 1 and they are {1}
Outlier points towards right of boxplot : 0

--------------------------------------------------------------------------------
-----------------------------------------------

Outlier detection of Income
…
Minimum: 29562
Maximum: 104581
Initial Range (with outlier) : 75019
Q1: 44058.75
Q2: 50596.5
Q3: 58668.0
IQR: 14609.25
Final Range (without outlier) : 58437.0
Lower outliers are: []
Upper outliers are: [83416, 88396, 90886, 92131, 88396, 85906, 90886, 103336,
99601, 89641, 95866, 92131, 92131, 104581, 83416, 89641, 90886, 104581, 95508]
Lower Outlier Percentage is 0.0%
Upper Outlier Percentage is 10.56%
```

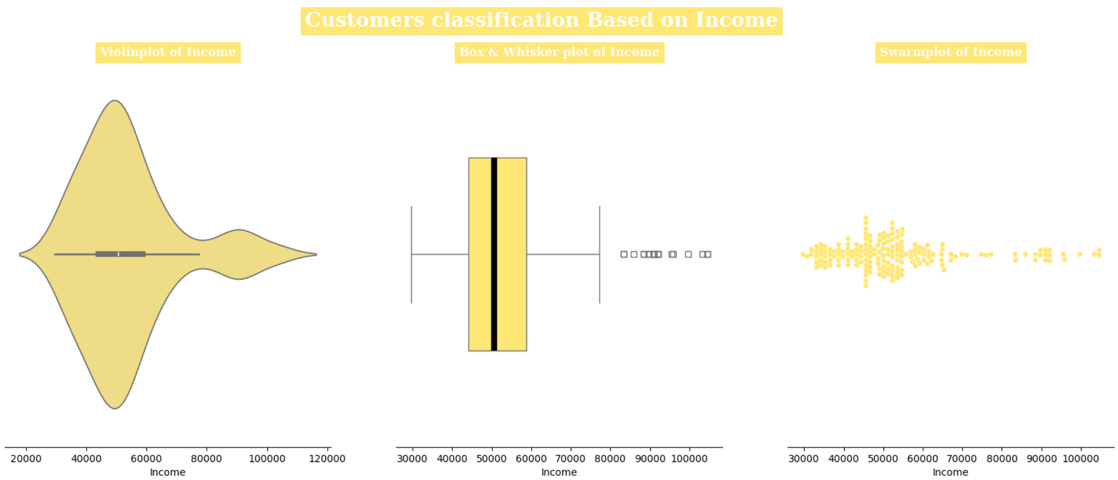
```
Overall Outlier Percentage is 10.56%
Outlier points towards left of boxplot : 0
Outlier points towards right of boxplot : 11 and they are {92131, 104581, 90886,
103336, 89641, 88396, 99601, 85906, 95508, 83416, 95866}

--------------------------------------------------------------------------------
-----------------------------------------------

Outlier detection of Miles
…
Minimum: 21
Maximum: 360
Initial Range (with outlier) : 339
Q1: 66.0
Q2: 94.0
Q3: 114.75
IQR: 48.75
Final Range (without outlier) : 195.0
Lower outliers are: []
Upper outliers are: [188, 212, 200, 200, 200, 240, 300, 280, 260, 200, 360, 200,
200]
Lower Outlier Percentage is 0.0%
Upper Outlier Percentage is 7.22%
Overall Outlier Percentage is 7.22%
Outlier points towards left of boxplot : 0
Outlier points towards right of boxplot : 8 and they are {260, 200, 360, 300,
240, 212, 280, 188}

--------------------------------------------------------------------------------
-----------------------------------------------

/usr/local/lib/python3.11/dist-packages/seaborn/categorical.py:3399:
UserWarning: 14.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.11/dist-packages/seaborn/categorical.py:3399:
UserWarning: 5.6% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.11/dist-packages/seaborn/categorical.py:3399:
UserWarning: 21.1% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
```


Customers classification Based on Age
Violinplot of Age
Box & Whisker plot of Age
Swarmplot of Age
Age
Age
Age


Customers classification Based on Education
Violinplot of Education
Box & Whisker plot of Education
Swarmplot of Education
Education
Education
Education


Customers classification Based on Usage
Violinplot of Usage
Box & Whisker plot of Usage
Swarmplot of Usage
Usage
Usage
Usage


Customers classification Based on Fitness
Violinplot of Fitness
Box & Whisker plot of Fitness
Swarmplot of Fitness
Fitness
Fitness
Fitness


Customers classification Based on Income
Violinplot of Income
Box & Whisker plot of Income
Swarmplot of Income
Income
Income
Income

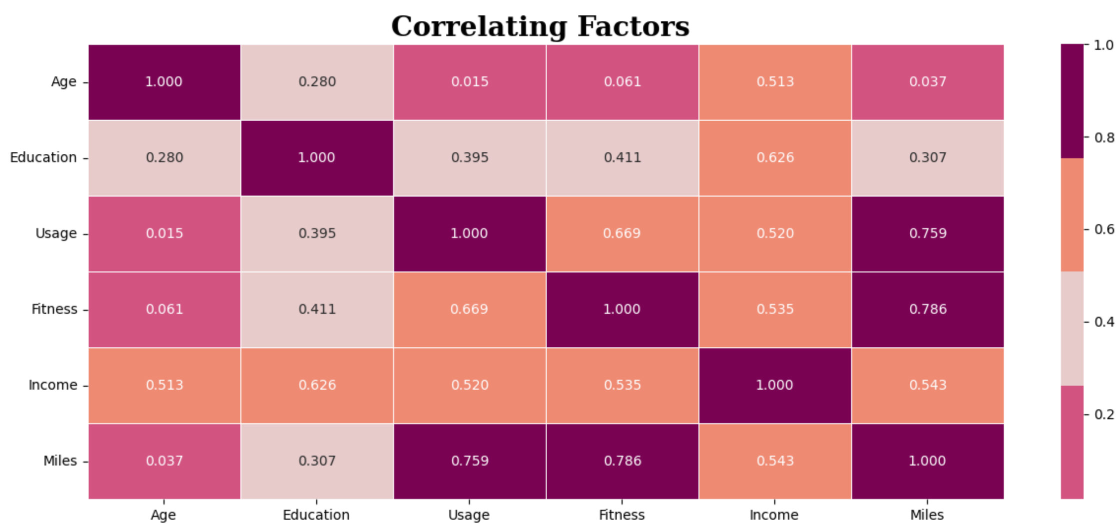

Customers classification Based on Miles
Violinplot of Miles
Box & Whisker plot of Miles
Swarmplot of Miles
Miles
Miles
Miles

[72]:
```python
afcorr = af[['Age','Education','Usage','Fitness','Income','Miles']].corr()
afcorr
```

[72]:

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

[73]:
```python
plt.figure(figsize=(15,6))
ax = sns.heatmap(afcorr,annot=True,fmt='.3f',linewidths=.5,cmap=cp1)
plt.title('Correlating Factors␣
↪',fontfamily='serif',fontweight='bold',fontsize=20)
plt.yticks(rotation=0)
plt.show()
```



1.11 Insights :-

From the pair plot we can see Age and Income are positively correlated and heatmap also suggests a strong correlation betwwen them Eductaion and Income are highly correlated as its obvious. Eductation also has significatnt correlation between Fitness rating and Usage of the treadmill. Usage is highly correlated with Fitness and Miles as more the usage more the fitness and mileage.

Based on all the above analysis

`-> Probability of purchase of KP281 = 44%`

```
-> Probability of purchase of KP481 = 33%
-> Probability of purchase of KP781 = 22%
```

- `Customer Profile` for **`KP281`** Treadmill:
  - Most preferred by entry level
  - Age of customer mainly between 18 to 35 years with few between 35 to 50 years
  - Education level of customer 13 years and above
  - Annual Income of customer ranges from 35k USD 55k USD
  - Weekly Usage - 3 to 4 times
  - Fitness Scale - 2 to 4
  - Weekly Running Mileage - 50 to 100 miles
  -

1.12 Mostly Single Female and Partnered Male prefer this product

- `Customer Profile` for **`KP481`** Treadmill:
  - This is an Intermediate level Product.
  - Age of customer mainly between 18 to 35 years with few between 35 to 50 years
  - Education level of customer 13 years and above
  - Annual Income of customer between 40k-80k USD
  - Weekly Usage - 2 to 4 times
  - Fitness Scale - 2 to 4
  - Weekly Running Mileage - 50 to 200 miles
  - Probability of Female customer buying KP481 is significantly higher than male.

- `Customer Profile` for **`KP781`** Treadmill:
  - Due to the High Price & being the advanced type, customer prefers less of this product.
  - Age of customer between 18 to 35 years
  - Education level of customer 15 years and above
  - Annual Income of customer 80k USD and above
  - Weekly Usage - 4 to 7 times
  - Fitness Scale - 3 to 5
  - Weekly Running Mileage is >100 miles and above
  - Partnered Female bought KP781 treadmill compared to Partnered Male.
  - This product is preferred by the customer where the correlation between Education and Income is High.

[ ]:

```

```