Aerofit - Descriptive Statistics & Probability

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1 Business Case: Aerofit - Descriptive Statistics & Probability

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- Aerofit Data_Set
- Aerofit Project Sebmision Link

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

     import math
     from scipy.stats import norm, binom, geom, zscore, ttest_1samp, ttest_ind

     sns.set_theme(style="darkgrid")
```

```
[ ]: aerofit = pd.read_csv("./aerofit_treadmill.csv")
     aerofit.head(5)
```

```
[ ]:   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
```

1.1 Provided Inputs

```
[ ]: price = pd.DataFrame([["KP281", 1500], ["KP481", 1750], ["KP781",␣
       ↪2500]],columns=["Product", "Price"])
     price
```

```
[ ]:   Product  Price
     0   KP281   1500
     1   KP481   1750
     2   KP781   2500
```

1.2 Exploring The Data Set

```
[ ]: aerofit.shape
```

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

```
[ ]: aerofit.size
```

```
[ ]: 1620
```

```
[ ]: aerofit = aerofit[['Product', 'Gender', 'MaritalStatus', 'Age', 'Income',␣
       ↪'Miles', 'Education', 'Fitness', 'Usage']]
```

```
[ ]: aerofit.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   Gender         180 non-null    object
 2   MaritalStatus  180 non-null    object
 3   Age            180 non-null    int64
 4   Income         180 non-null    int64
 5   Miles          180 non-null    int64
 6   Education      180 non-null    int64
 7   Fitness        180 non-null    int64
 8   Usage          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

1.2.1 Missing value detection & fill with relevent data.

```
[ ]: aerofit.isnull().sum()
```

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

1.2.2 Check for Outliers

[ ]:

```
def check_outlier(df, x):
    Q1 = df[x].quantile(0.25)
    Q3 = df[x].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5*IQR
    upper = Q3 + 1.5*IQR
    lower_outlier = df[x][df[x] < lower]
    upper_outlier = df[x][df[x] > upper]

    return {
        'lower': {
            'list': lower_outlier,
            'length': len(lower_outlier)
        },
        'upper': {
            'list': upper_outlier,
            'length': len(upper_outlier)
        }}
```

[ ]:

```
for i in aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].
  ↪columns:
    # print(i)
    outlier = check_outlier(aerofit, i)
    print("{} : ({}, {})".format(i, outlier['lower']['length'],␣
  ↪outlier['upper']['length']))
```

```
Age : (0, 5)
Income : (0, 19)
Miles : (0, 13)
Education : (0, 4)
Fitness : (2, 0)
Usage : (0, 9)
```

1.2.3 Conversion of categorical attributes to 'category'.

[ ]:

```
aerofit['Product'] = aerofit['Product'].astype('category')
aerofit['Gender'] = aerofit['Gender'].astype('category')
aerofit['MaritalStatus'] = aerofit['MaritalStatus'].astype('category')
aerofit.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   Gender         180 non-null    category
 2   MaritalStatus  180 non-null    category
 3   Age            180 non-null    int64
 4   Income         180 non-null    int64
 5   Miles          180 non-null    int64
 6   Education      180 non-null    int64
 7   Fitness        180 non-null    int64
 8   Usage          180 non-null    int64
dtypes: category(3), int64(6)
memory usage: 9.5 KB
```

Insight * ‘Product’, ‘Gender’, ‘MaritalStatus’ are Converted as Type Category.

1.2.4 ****Consolidated Data****

[ ]:

```
def aerofit_categorise(df):
    df["age_group"] = pd.cut(x=df['Age'], bins=[0,15,20,25,30,35,40,45,50],
                    labels=["0-15", "15-20", "20-25", "25-30", "30-35",␣
 ↪"35-40", "40-45", "45-50"])
    df['age_group'] = df['age_group'].astype('category')

    df["income_group"] = pd.cut(x=df['Income'],␣
 ↪bins=[0,25000,35000,45000,55000,65000,75000,85000,95000,105000],
                    labels=["0-25K", "25K-35K", "35K-45K", "45K-55K",␣
 ↪"55K-65K", "65K-75K", "75K-85K", "85K-95K", "95K-105K"])
    df['income_group'] = df['income_group'].astype('category')

    df["miles_group"] = pd.cut(x=df['Miles'],␣
 ↪bins=[0,20,50,80,110,140,170,200,230,260,290,320,350,380],
                    labels=["0-20", "20-50", "50-80", "80-110", "110-140",␣
 ↪"140-170", "170-200", "200-230", "230-260", "260-290", "290-320", "320-350",␣
 ↪"350-380"])
    df['miles_group'] = df['miles_group'].astype('category')

    df['education_group'] = df['Education'].astype('category')
    df['fitness_group'] = df['Fitness'].astype('category')
    df['usage_group'] = df['Usage'].astype('category')

    return df

aerofit = aerofit_categorise(aerofit)
aerofit.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Product          180 non-null    category
 1   Gender           180 non-null    category
 2   MaritalStatus    180 non-null    category
 3   Age              180 non-null    int64
 4   Income           180 non-null    int64
 5   Miles            180 non-null    int64
 6   Education        180 non-null    int64
 7   Fitness          180 non-null    int64
 8   Usage            180 non-null    int64
 9   age_group        180 non-null    category
 10  income_group     180 non-null    category
 11  miles_group      180 non-null    category
 12  education_group  180 non-null    category
 13  fitness_group    180 non-null    category
 14  usage_group      180 non-null    category
dtypes: category(9), int64(6)
memory usage: 12.7 KB
```

1.2.5 Statistical Summary

Descriptive Statistits

```
[ ]: aerofit[['Product', 'Gender', 'MaritalStatus']].describe()
```

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

```
[ ]: aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
```

```
[ ]:               Age         Income       Miles   Education     Fitness  \
     count  180.000000     180.000000  180.000000  180.000000  180.000000
     mean    28.788889   53719.577778  103.194444   15.572222    3.311111
     std      6.943498   16506.684226   51.863605    1.617055    0.958869
     min     18.000000   29562.000000   21.000000   12.000000    1.000000
     25%     24.000000   44058.750000   66.000000   14.000000    3.000000
     50%     26.000000   50596.500000   94.000000   16.000000    3.000000
     75%     33.000000   58668.000000  114.750000   16.000000    4.000000
     max     50.000000  104581.000000  360.000000   21.000000    5.000000

                 Usage
     count  180.000000
     mean     3.455556
     std      1.084797
     min      2.000000
     25%      3.000000
     50%      3.000000
     75%      4.000000
```

```
max      7.000000
```

```
[ ]: aerofit[['age_group', 'income_group', 'miles_group', 'education_group',␣
      ↪'usage_group', 'fitness_group']].describe()
```

```
[ ]:        age_group income_group miles_group  education_group  usage_group  \
     count        180          180         180              180          180
     unique         7            8          11                8            6
     top        20-25      45K-55K      80-110               16            3
     freq          69           77          66               85           69

             fitness_group
     count             180
     unique              5
     top                 3
     freq               97
```

Unique Count

```
[ ]: aerofit.nunique()
```

```
[ ]: Product             3
     Gender              2
     MaritalStatus       2
     Age                32
     Income             62
     Miles              37
     Education           8
     Fitness             5
     Usage               6
     age_group           7
     income_group        8
     miles_group        11
     education_group     8
     fitness_group       5
     usage_group         6
     dtype: int64
```

Mean

```
[ ]: aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].mean()
```

```
[ ]: Age             28.788889
     Income       53719.577778
     Miles          103.194444
     Education       15.572222
     Fitness          3.311111
     Usage            3.455556
     dtype: float64
```

Median

[ ]:
```
aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
```

[ ]:
```
Age              26.0
Income        50596.5
Miles            94.0
Education        16.0
Fitness           3.0
Usage             3.0
dtype: float64
```

Mode

[ ]:
```
for i in aerofit.columns:
  print(i,':',aerofit[i].mode()[0])
```

```
Product : KP281
Gender : Male
MaritalStatus : Partnered
Age : 25
Income : 45480
Miles : 85
Education : 16
Fitness : 3
Usage : 3
age_group : 20-25
income_group : 45K-55K
miles_group : 80-110
education_group : 16
fitness_group : 3
usage_group : 3
```

1.3 Uni Variate Analysis

1.3.1 Product

[ ]:
```
aerofit['Product'].unique()
```

[ ]:
```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

[ ]:
```
aerofit['Product'].value_counts()
```

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

Statitical Analysis

```
[ ]: aerofit['Product'].describe()
```

```
[ ]: count       180
     unique        3
     top       KP281
     freq         80
     Name: Product, dtype: object
```

```
[ ]: aerofit['Product'].mode()[0]
```

```
[ ]: 'KP281'
```

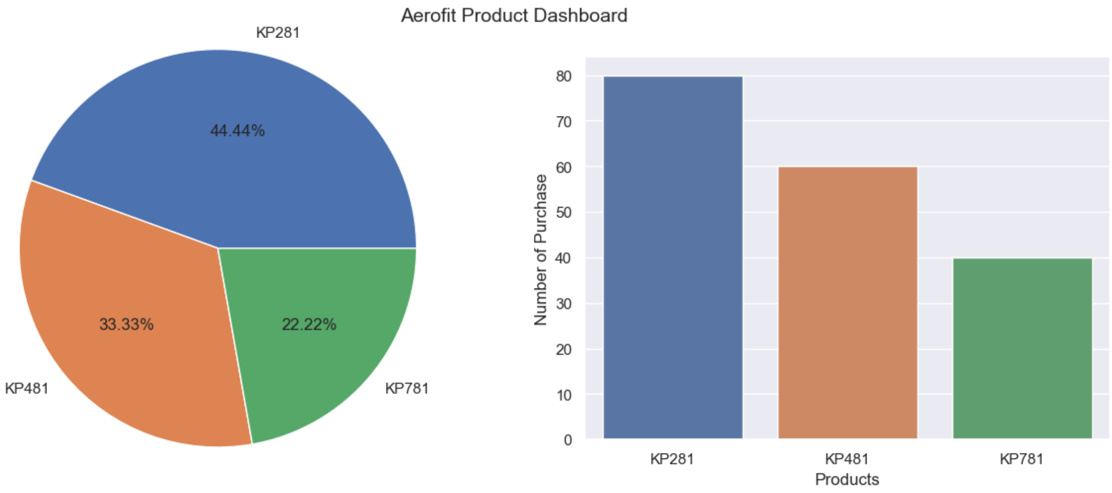
Find Probability

```
[ ]: aerofit['Product'].value_counts(normalize=True)*100
```

```
[ ]: KP281    44.444444
     KP481    33.333333
     KP781    22.222222
     Name: Product, dtype: float64
```

Plot the Graph

```
[ ]: plt.figure(figsize=(15,5)).suptitle("Aerofit Product Dashboard",fontsize=14)

     plt.subplot(1, 2, 1)
     plt.pie(aerofit['Product'].value_counts().values,labels = aerofit['Product'].
       ↪value_counts().index,radius = 1.3,autopct = '%1.2f%%',) # type: ignore

     plt.subplot(1, 2, 2)
     sns.countplot(aerofit, x='Product')
     plt.xlabel('Products', fontsize=12)
     plt.ylabel('Number of Purchase', fontsize=12)

     plt.show()
```



Insight * There is only 3 type of Product. which are `KP281`, `KP481` & `KP781`. * There are 80 `KP281` which is equivalent to 44.44%. * There are 60 `KP481` which is equivalent to 33.33%. * There are 40 `KP781` which is equivalent to 22.22%.

1.3.2 Gender

```
[ ]: aerofit['Gender'].unique()
```

```
[ ]: ['Male', 'Female']
     Categories (2, object): ['Female', 'Male']
```

```
[ ]: aerofit['Gender'].value_counts()
```

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

```
[ ]: aerofit['Gender'].value_counts(normalize=True)*100
```

```
[ ]: Male      57.777778
     Female    42.222222
     Name: Gender, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Gender'].describe()
```

```
[ ]: count      180
     unique       2
     top       Male
```

```
freq       104
Name: Gender, dtype: object
```

```
[ ]: aerofit['Gender'].mode()[0]
```

```
[ ]: 'Male'
```

```
[ ]: aerofit.groupby('Product')["Gender"].describe()
```

```
[ ]:         count unique     top freq
     Product
     KP281      80      2  Female   40
     KP481      60      2    Male   31
     KP781      40      2    Male   33
```

Find Probability

Probability of a `Product` & `Gender` across all Combination *"Product   Gender"*

```
[ ]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481      KP781         All
     Gender
     Female   22.222222  16.111111   3.888889   42.222222
     Male     22.222222  17.222222  18.333333   57.777778
     All      44.444444  33.333333  22.222222  100.000000
```

Probability of `Product's` for given `Gender` *"Product | Gender"*

```
[ ]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize='index',␣
      ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481      KP781
     Gender
     Female   52.631579  38.157895   9.210526
     Male     38.461538  29.807692  31.730769
     All      44.444444  33.333333  22.222222
```

Probability of `Gender` for given `Product` *"Gender | Product"*

```
[ ]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize='columns',␣
      ↪margins=True)*100
```

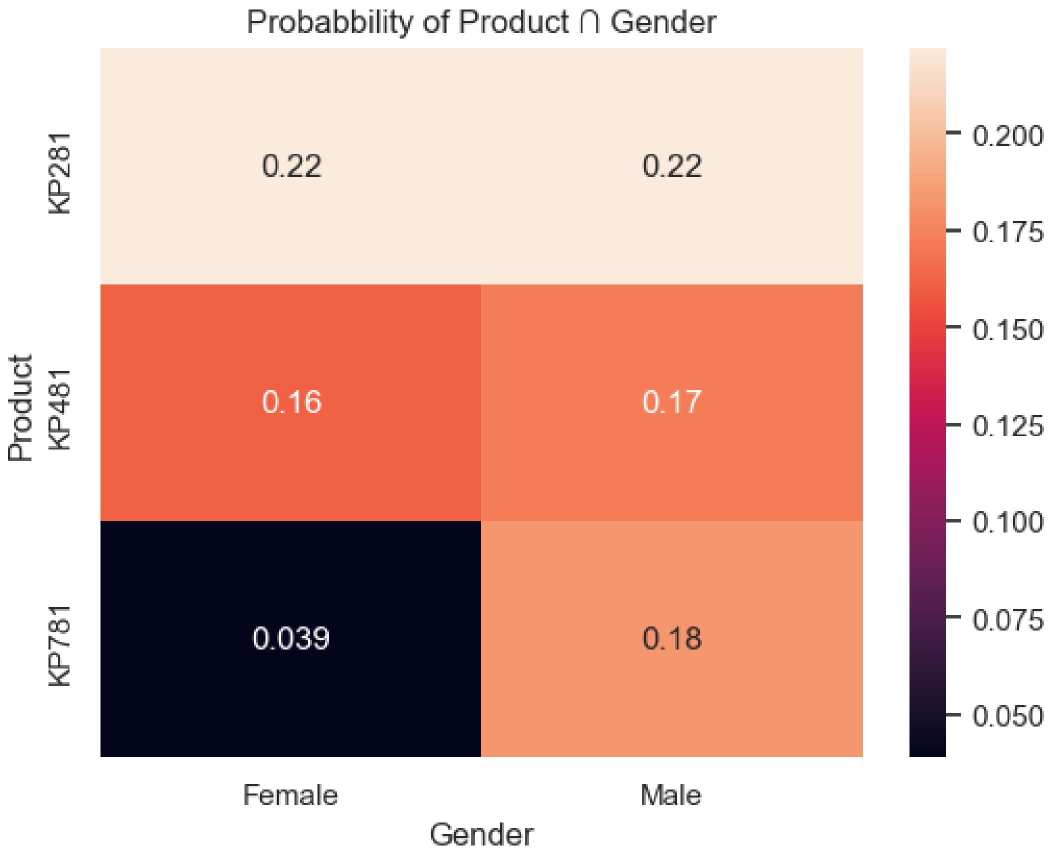
```
[ ]: Product  KP281      KP481  KP781        All
     Gender
     Female    50.0  48.333333   17.5  42.222222
     Male      50.0  51.666667   82.5  57.777778
```

Plot the Graph

Heat Map

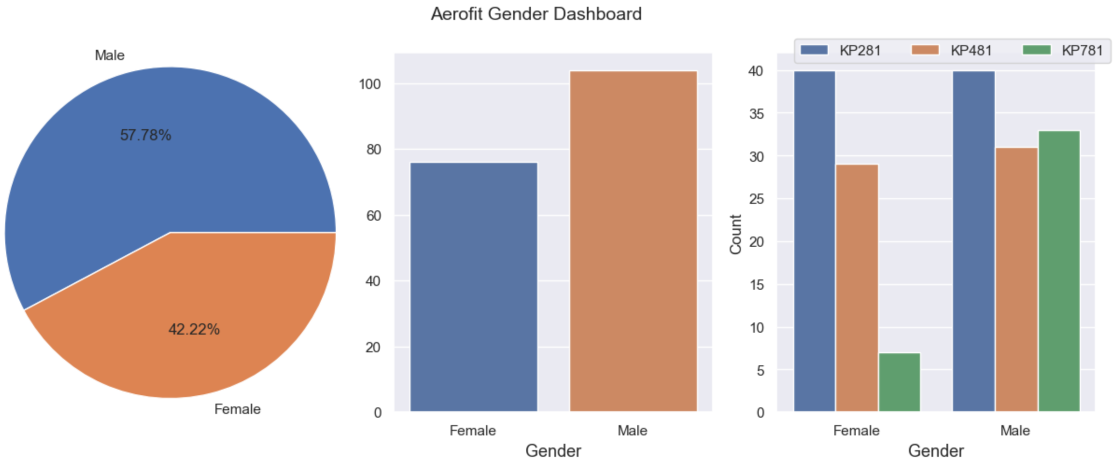
```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Gender'],␣
      ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product   Gender', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product   Gender')
```



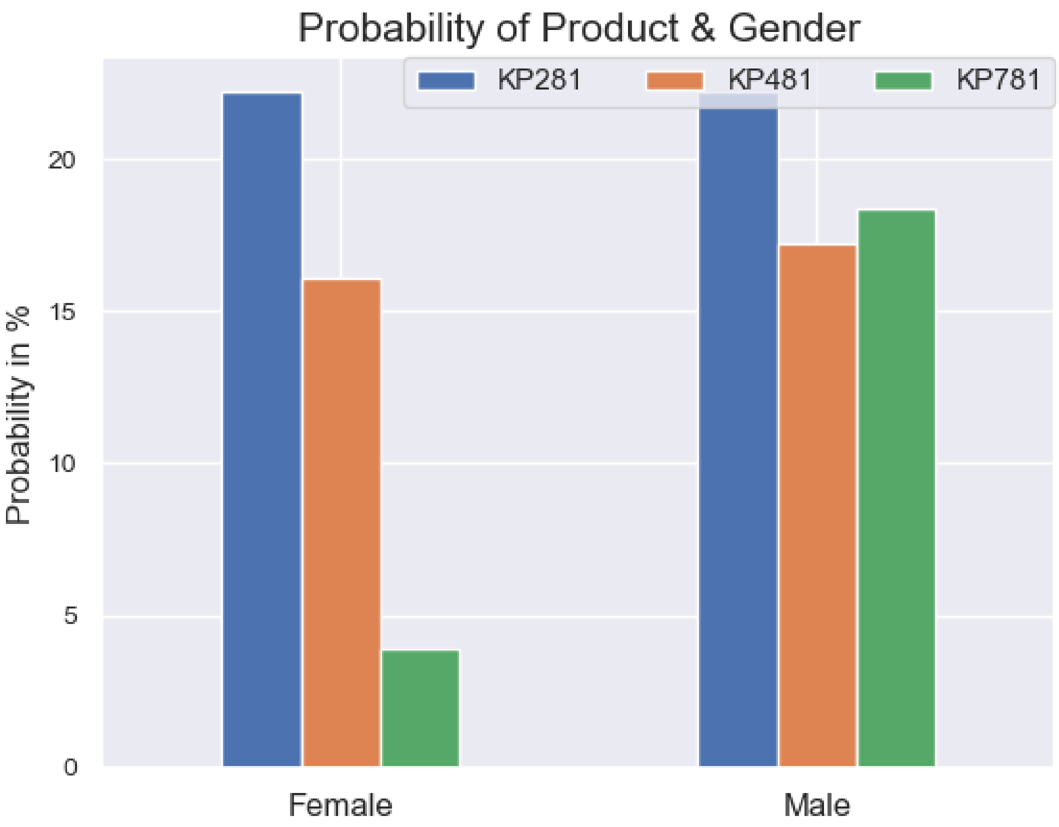
Descriptive Plot

```
[ ]: plt.figure(figsize=(15,5)).suptitle("Aerofit Gender Dashboard",fontsize=14)

     plt.subplot(1, 3, 1)
     plt.pie(aerofit['Gender'].value_counts().values,labels = aerofit['Gender'].
      ↪value_counts().index,radius = 1.3,autopct = '%1.2f%%',) # type: ignore

     plt.subplot(1, 3, 2)
     sns.countplot(aerofit, x='Gender')
     plt.ylabel('', fontsize=12)
     plt.xlabel('Gender', fontsize=13)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)

     plt.subplot(1, 3, 3)
     sns.countplot(aerofit, x='Gender', hue='Product')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('Gender', fontsize=13)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.legend(borderaxespad=-1, ncol=3)

     plt.show()
```



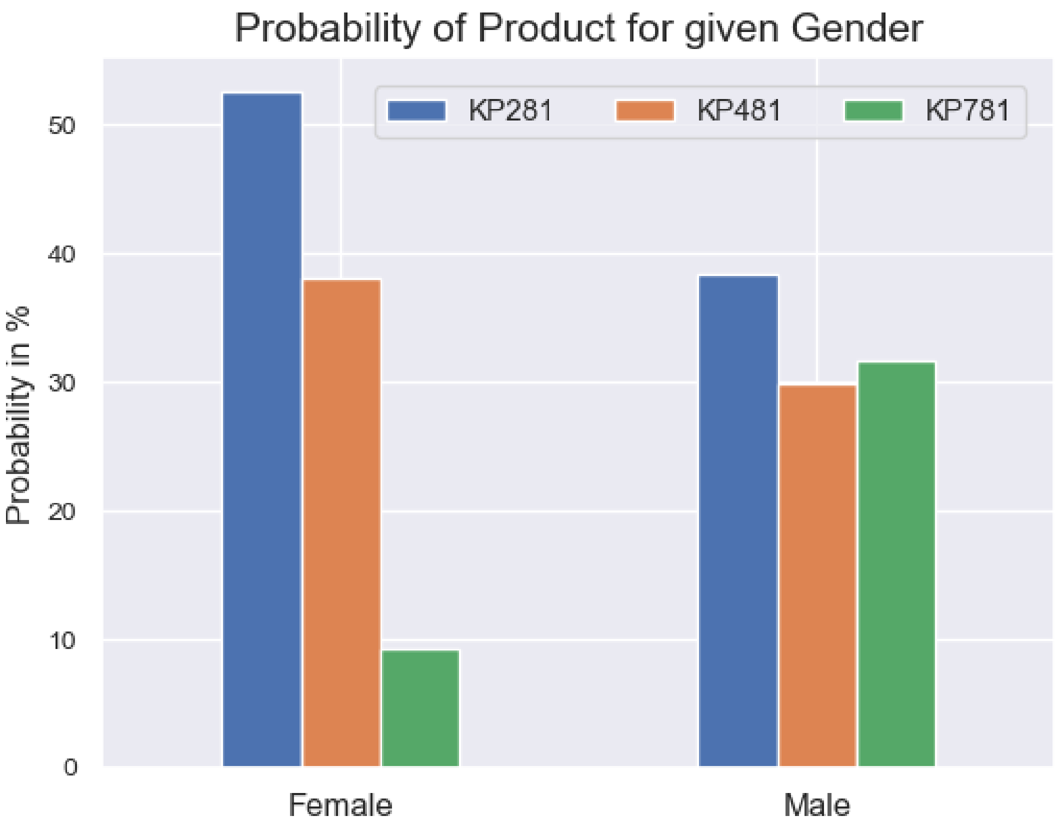
Probability Plot

```
[ ]: (pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product & Gender', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(borderaxespad=0, ncol=3)
     plt.show()
```

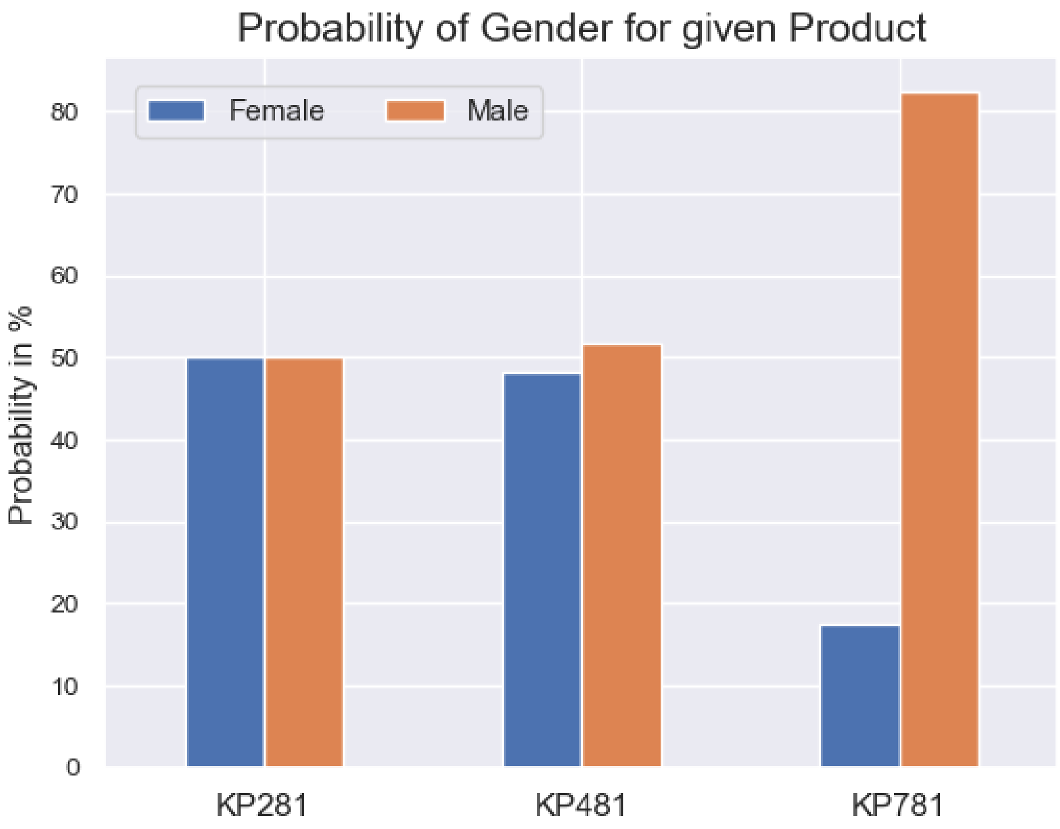


[ ]:

```
(pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize="index")*100).
  ↪plot(kind='bar')
plt.title('Probability of Product for given Gender', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(borderaxespad=1, ncol=3)
plt.show()
```

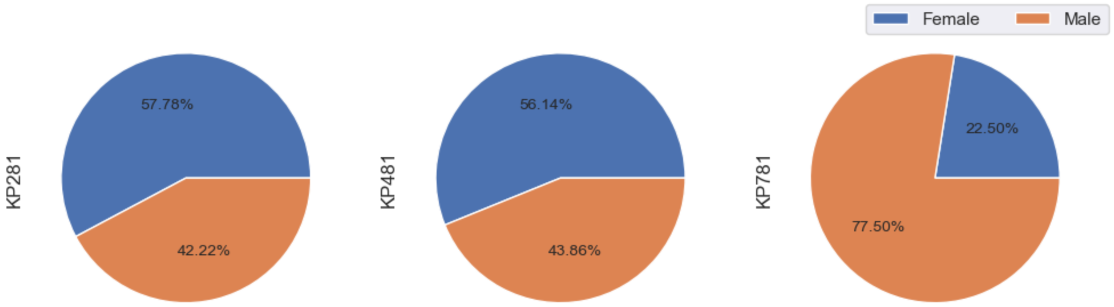


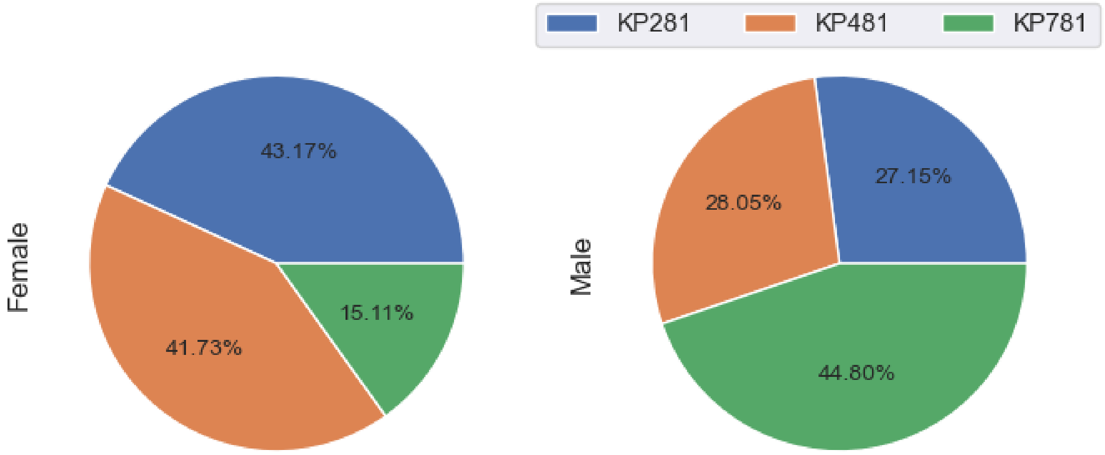
```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['Gender'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Gender for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(borderaxespad=1, ncol=2)
     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize="index").
      ↪plot(kind='pie', subplots=True, figsize=(12,4), labeldistance=None,␣
      ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=3)
     plt.show()
     pd.crosstab(aerofit['Product'], aerofit['Gender'], normalize="index").
      ↪plot(kind='pie', subplots=True, figsize=(8,4), labeldistance=None,␣
      ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=3)
     plt.show()
```





Insight * There are 104 `Male` which is equivalent to 57.78%. * There are 76 `Female` which is equivalent to 42.22%.

1.3.3 Marital Status

```
[ ]: aerofit['MaritalStatus'].unique()
```

```
[ ]: ['Single', 'Partnered']
     Categories (2, object): ['Partnered', 'Single']
```

```
[ ]: aerofit['MaritalStatus'].value_counts()
```

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

```
[ ]: aerofit['MaritalStatus'].value_counts(normalize=True)*100
```

```
[ ]: Partnered    59.444444
     Single       40.555556
     Name: MaritalStatus, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['MaritalStatus'].describe()
```

```
[ ]: count           180
     unique            2
     top       Partnered
     freq            107
     Name: MaritalStatus, dtype: object
```

```
[ ]: aerofit['MaritalStatus'].mode()[0]
```

```
[ ]: 'Partnered'
```

```
[ ]: aerofit.groupby('Product')["MaritalStatus"].describe()
```

```
[ ]:         count unique        top freq
     Product
     KP281      80      2  Partnered   48
     KP481      60      2  Partnered   36
     KP781      40      2  Partnered   23
```

Find Probability

Probability of a Product & Marital Status across all Combination *“Product Marital Status”*

```
[ ]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize=True, margins=True)*100
```

```
[ ]: Product            KP281      KP481      KP781         All
     MaritalStatus
     Partnered      26.666667  20.000000  12.777778   59.444444
     Single         17.777778  13.333333   9.444444   40.555556
     All            44.444444  33.333333  22.222222  100.000000
```

Probability of Product's for given Marital Status *“Product | Marital Status”*

```
[ ]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize='index', margins=True)*100
```

```
[ ]: Product            KP281      KP481      KP781
     MaritalStatus
     Partnered      44.859813  33.644860  21.495327
```

```
Single          43.835616  32.876712  23.287671
All             44.444444  33.333333  22.222222
```

Probability of `Marital Status` for given `Product` *“Marital Status / Product”*

```
[ ]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize='columns',␣
       ↪margins=True)*100
```

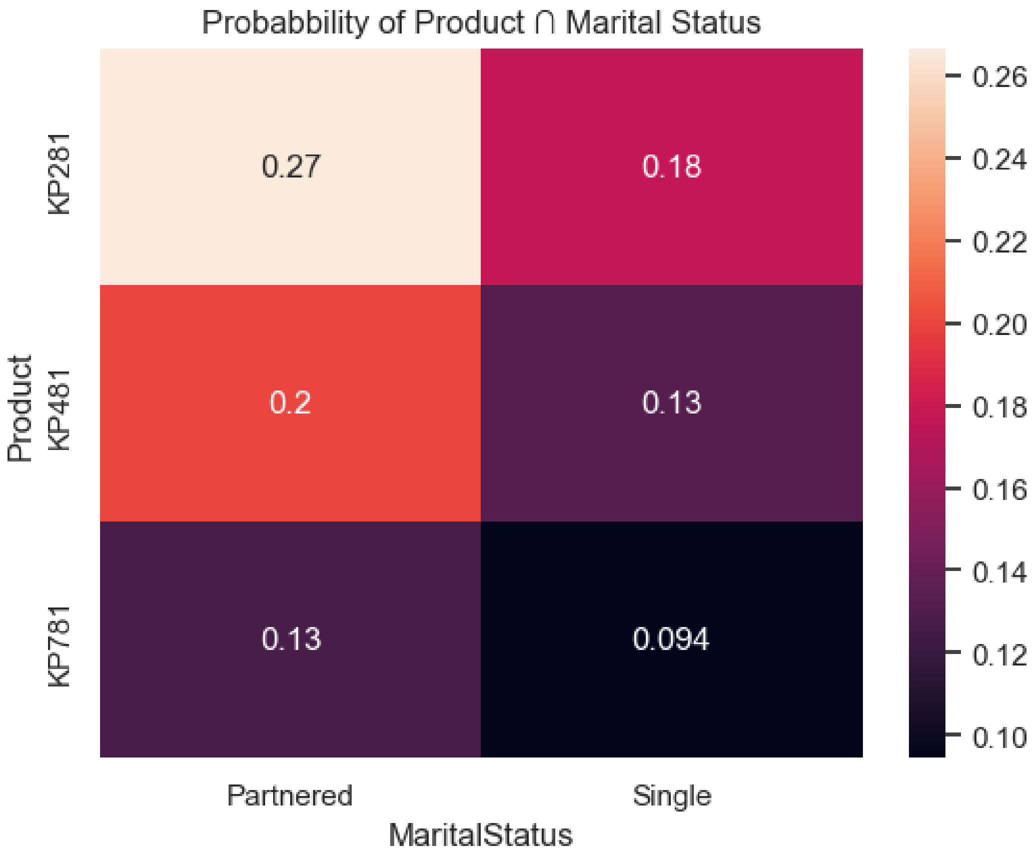
```
[ ]: Product        KP281  KP481  KP781        All
     MaritalStatus
     Partnered       60.0   60.0   57.5  59.444444
     Single          40.0   40.0   42.5  40.555556
```

Plot the Graph

`Heat Map`

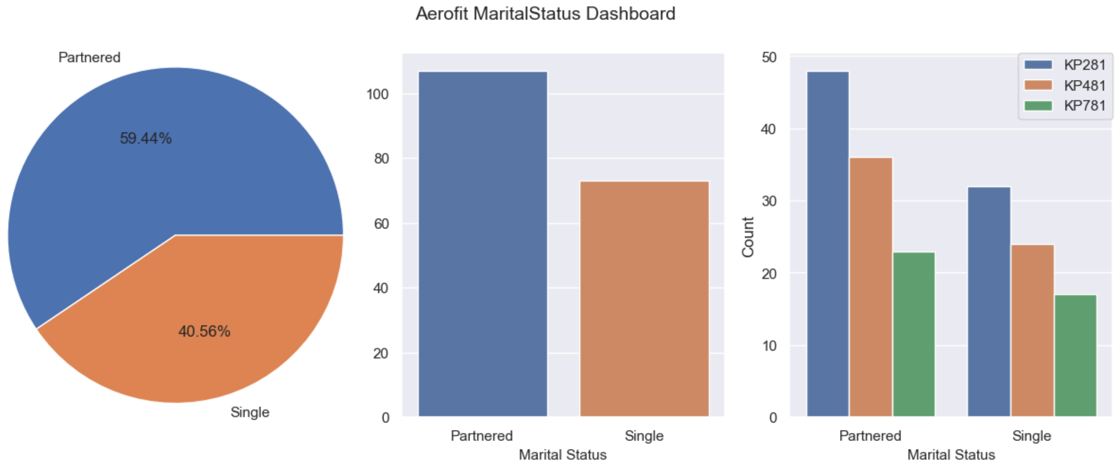
```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'],␣
       ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product  Marital Status', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product  Marital Status')
```



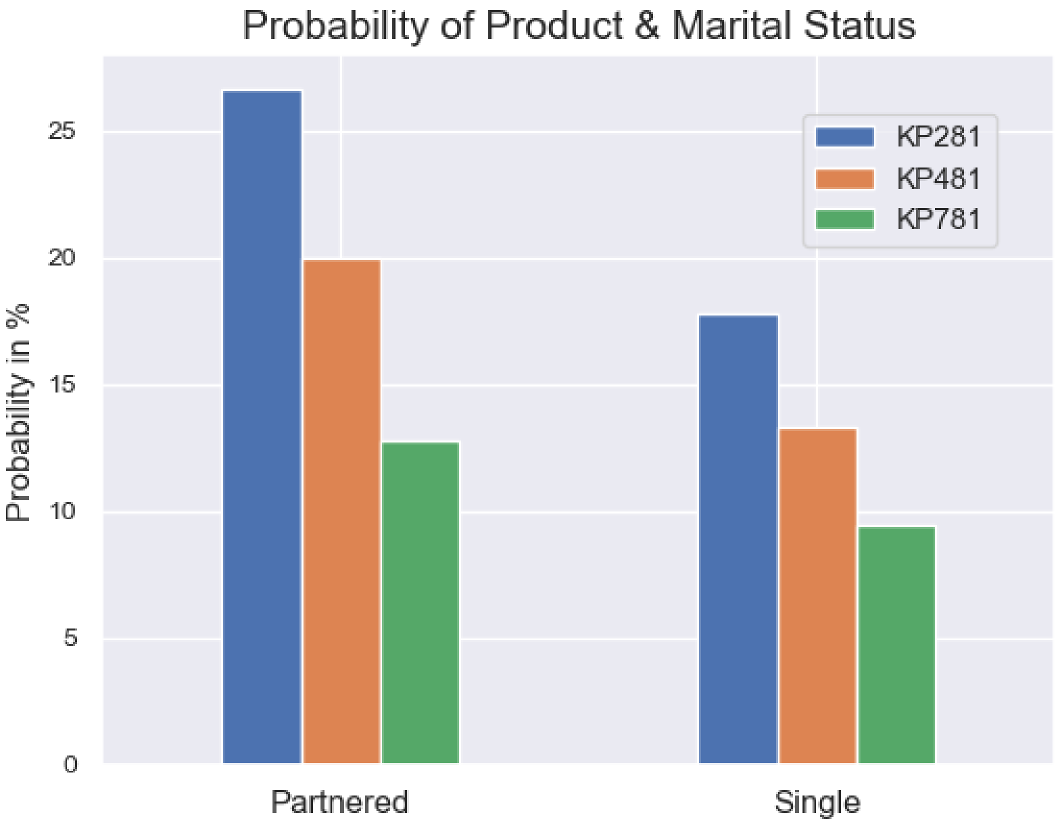
Descriptive Plot

[ ]:
```
plt.figure(figsize=(15,5)).suptitle("Aerofit MaritalStatus␣
 ↪Dashboard",fontsize=14)

plt.subplot(1, 3, 1)
plt.pie(aerofit['MaritalStatus'].value_counts().values,labels =␣
 ↪aerofit['MaritalStatus'].value_counts().index,radius = 1.3,autopct = '%1.
 ↪2f%%',) # type: ignore

plt.subplot(1, 3, 2)
sns.countplot(aerofit, x='MaritalStatus')
plt.ylabel('', fontsize=12)
plt.xlabel('Marital Status', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(1, 3, 3)
sns.countplot(aerofit, x='MaritalStatus', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Marital Status', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=0, ncol=1)

plt.show()
```

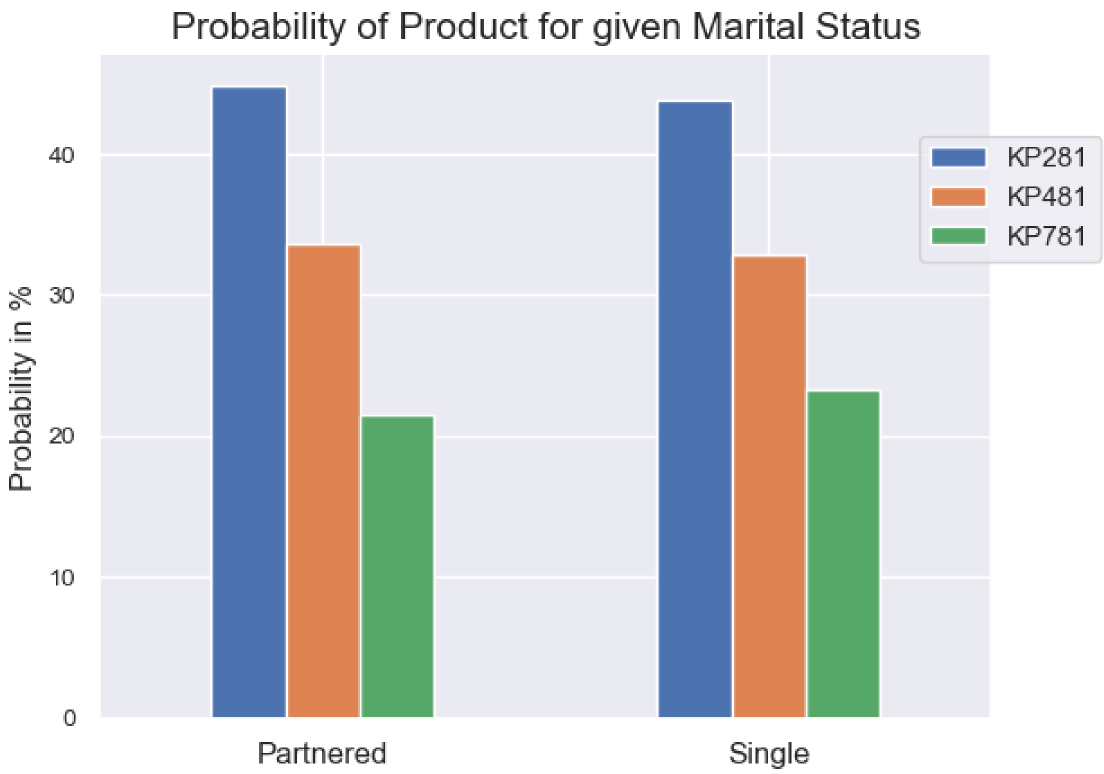


Probability Plot

```
[ ]: (pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product & Marital Status', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(borderaxespad=2, ncol=1)
     plt.show()
```

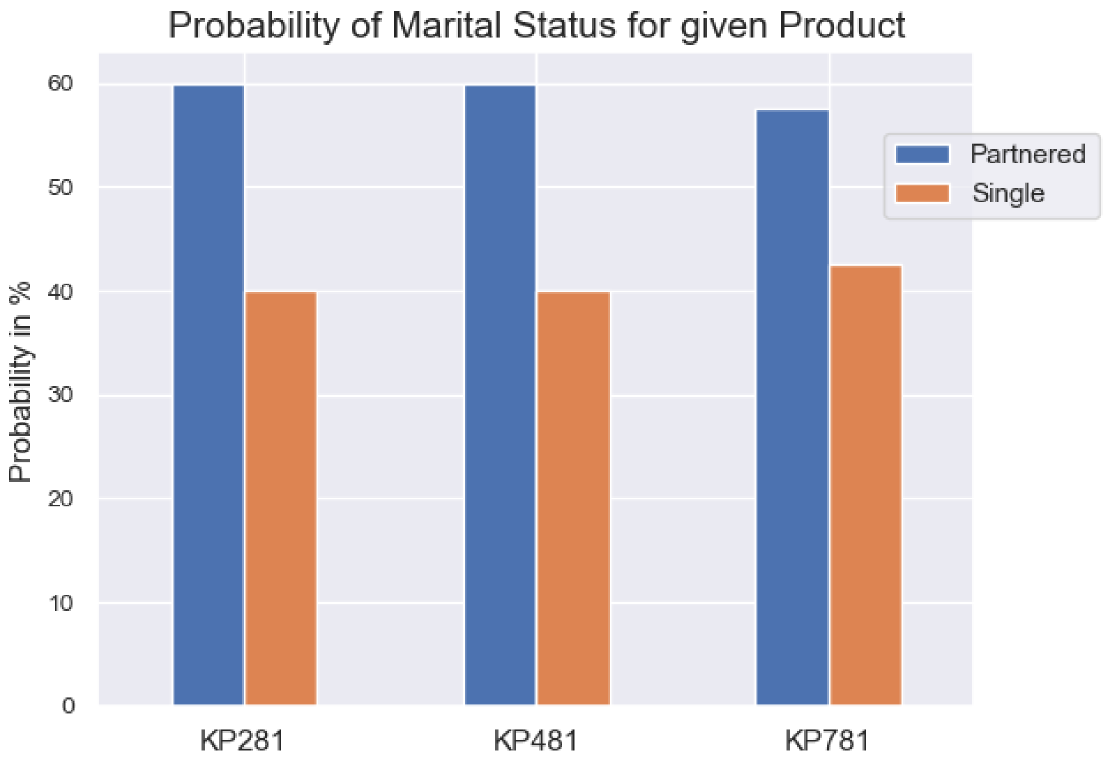


```
[ ]: (pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'],␣
      ↪normalize="index")*100).plot(kind='bar')
     plt.title('Probability of Product for given Marital Status', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=3)
     plt.show()
```



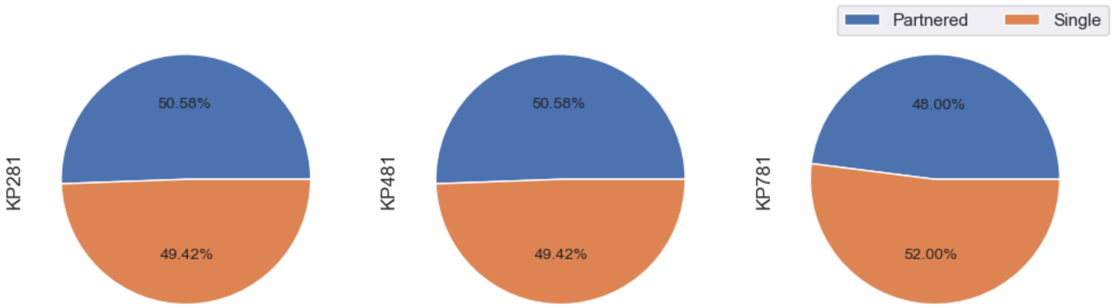
[ ]:

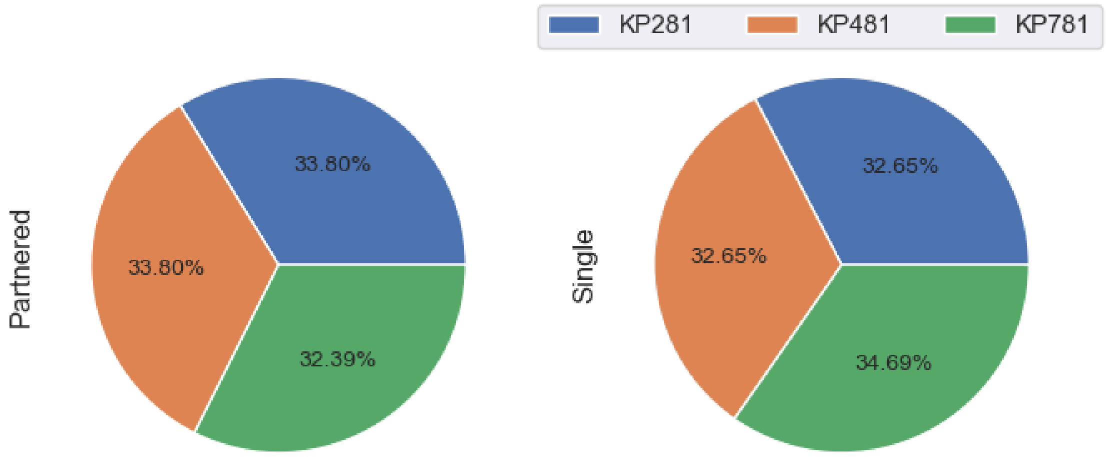
```
(pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'], normalize="index")*100).plot(kind='bar')
plt.title('Probability of Marital Status for given Product', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=3)
plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize="index").
       ↪plot(kind='pie', subplots=True, figsize=(12,4), labeldistance=None,␣
       ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=3)
     plt.show()
     pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'], normalize="index").
       ↪plot(kind='pie', subplots=True, figsize=(8,4), labeldistance=None,␣
       ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=3)
     plt.show()
```





Insight * There are 107 `Partnered` which is equivalent to 59.44%. * There are 73 `Single` which is equivalent to 40.56%.

1.3.4 Age

Age value Count

```
[ ]: aerofit['Age'].unique()
```

```
[ ]: 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)
```

```
[ ]: aerofit['Age'].value_counts()[:5]
```

```
[ ]: 25    25
     23    18
     24    12
     26    12
     28     9
     Name: Age, dtype: int64
```

```
[ ]: aerofit['Age'].value_counts(normalize=True)[:5]*100
```

```
[ ]: 25    13.888889
     23    10.000000
     24     6.666667
```

```
26     6.666667
28     5.000000
Name: Age, dtype: float64
```

Age Group Value Count

```
[ ]: aerofit['age_group'].unique()
```

```
[ ]: ['15-20', '20-25', '25-30', '30-35', '35-40', '40-45', '45-50']
     Categories (8, object): ['0-15' < '15-20' < '20-25' < '25-30' < '30-35' <
     '35-40' < '40-45' < '45-50']
```

```
[ ]: aerofit['age_group'].value_counts()[:5]
```

```
[ ]: 20-25    69
     25-30    41
     30-35    32
     35-40    16
     15-20    10
     Name: age_group, dtype: int64
```

```
[ ]: aerofit['age_group'].value_counts(normalize=True)[:5]*100
```

```
[ ]: 20-25    38.333333
     25-30    22.777778
     30-35    17.777778
     35-40     8.888889
     15-20     5.555556
     Name: age_group, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Age'].describe()
```

```
[ ]: count    180.000000
     mean      28.788889
     std        6.943498
     min       18.000000
     25%       24.000000
     50%       26.000000
     75%       33.000000
     max       50.000000
     Name: Age, dtype: float64
```

```
[ ]: aerofit['age_group'].describe()
```

```
[ ]: count       180
     unique        7
     top       20-25
```

```
freq          69
Name: age_group, dtype: object
```

```
[ ]: aerofit['Age'].mean()
```

```
[ ]: 28.788888888888888
```

```
[ ]: aerofit['Age'].median()
```

```
[ ]: 26.0
```

```
[ ]: aerofit['Age'].mode()[0]
```

```
[ ]: 25
```

```
[ ]: aerofit.groupby('Product')["Age"].describe()
```

```
[ ]:          count   mean       std   min    25%   50%    75%   max
     Product
     KP281     80.0  28.55  7.221452  18.0  23.00  26.0  33.00  50.0
     KP481     60.0  28.90  6.645248  19.0  24.00  26.0  33.25  48.0
     KP781     40.0  29.10  6.971738  22.0  24.75  27.0  30.25  48.0
```

```
[ ]: aerofit.groupby('Product')["age_group"].describe()
```

```
[ ]:         count unique    top freq
     Product
     KP281      80      7  20-25   28
     KP481      60      7  20-25   24
     KP781      40      6  20-25   17
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Age')['upper']
```

```
[ ]: {'list': 78     47
      79     50
      139    48
      178    47
      179    48
      Name: Age, dtype: int64,
      'length': 5}
```

```
[ ]: check_outlier(aerofit, 'Age')['lower']
```

```
[ ]: {'list': Series([], Name: Age, dtype: int64), 'length': 0}
```

Find Probability

Probability of a Product & Age Group across all Combination *“Product Age Group”*

```
[ ]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: Product        KP281      KP481      KP781         All
     age_group
     15-20       3.333333   2.222222   0.000000    5.555556
     20-25      15.555556  13.333333   9.444444   38.333333
     25-30      11.666667   3.888889   7.222222   22.777778
     30-35       6.111111   9.444444   2.222222   17.777778
     35-40       4.444444   3.333333   1.111111    8.888889
     40-45       1.666667   0.555556   1.111111    3.333333
     45-50       1.666667   0.555556   1.111111    3.333333
     All        44.444444  33.333333  22.222222  100.000000
```

Probability of Product's for given Age Group *“Product | Age Group”*

```
[ ]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize='index',␣
      ↪margins=True)*100
```

```
[ ]: Product        KP281      KP481      KP781
     age_group
     15-20      60.000000  40.000000   0.000000
     20-25      40.579710  34.782609  24.637681
     25-30      51.219512  17.073171  31.707317
     30-35      34.375000  53.125000  12.500000
     35-40      50.000000  37.500000  12.500000
     40-45      50.000000  16.666667  33.333333
     45-50      50.000000  16.666667  33.333333
     All        44.444444  33.333333  22.222222
```

Probability of Age Group for given Product *“Age Group | Product”*

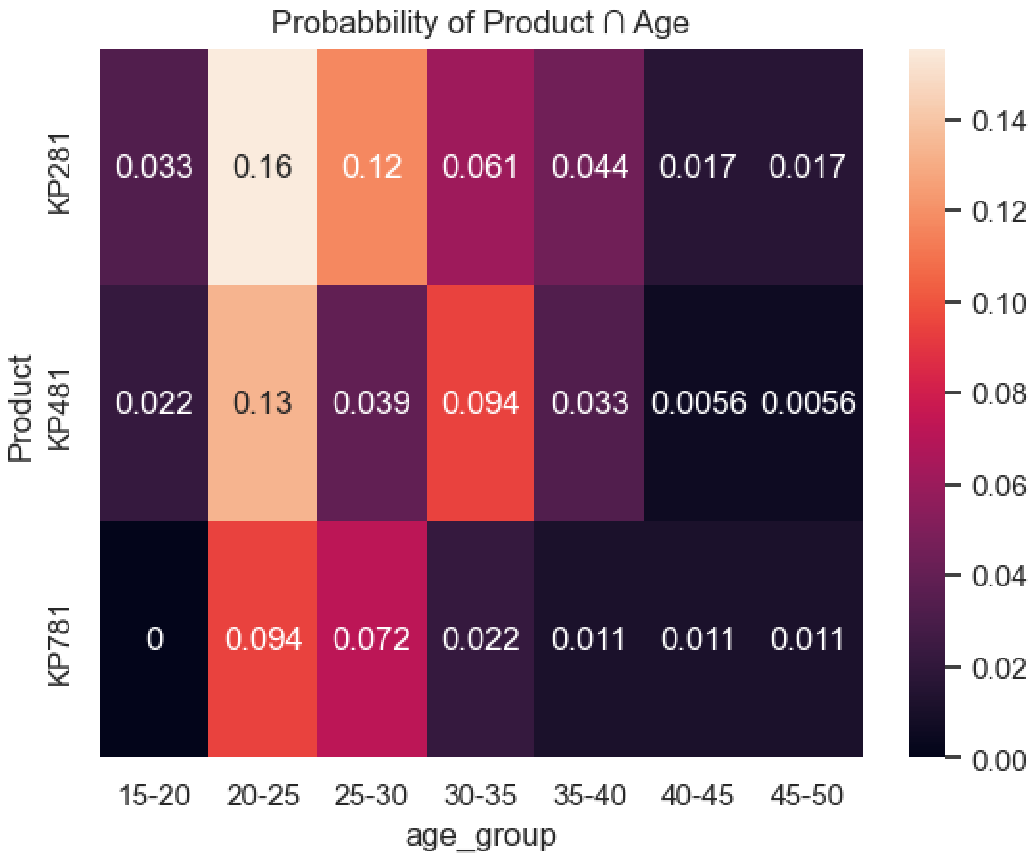
```
[ ]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize='columns',␣
      ↪margins=True)*100
```

```
[ ]: Product    KP281      KP481  KP781        All
     age_group
     15-20       7.50   6.666667    0.0   5.555556
     20-25      35.00  40.000000   42.5  38.333333
     25-30      26.25  11.666667   32.5  22.777778
     30-35      13.75  28.333333   10.0  17.777778
     35-40      10.00  10.000000    5.0   8.888889
     40-45       3.75   1.666667    5.0   3.333333
     45-50       3.75   1.666667    5.0   3.333333
```

Plot the Graph

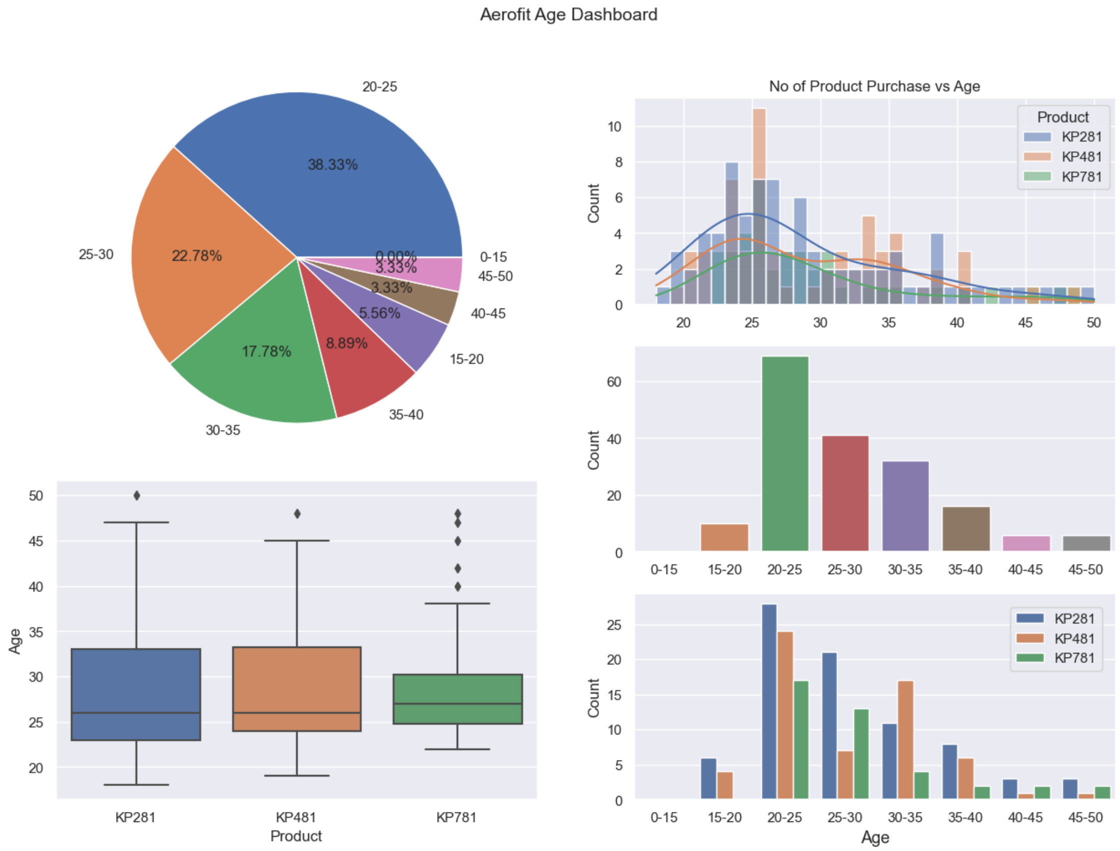
Heat Map

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['age_group'],␣
      ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product   Age', fontsize=12)
     plt.show()
```



Descriptive Plot

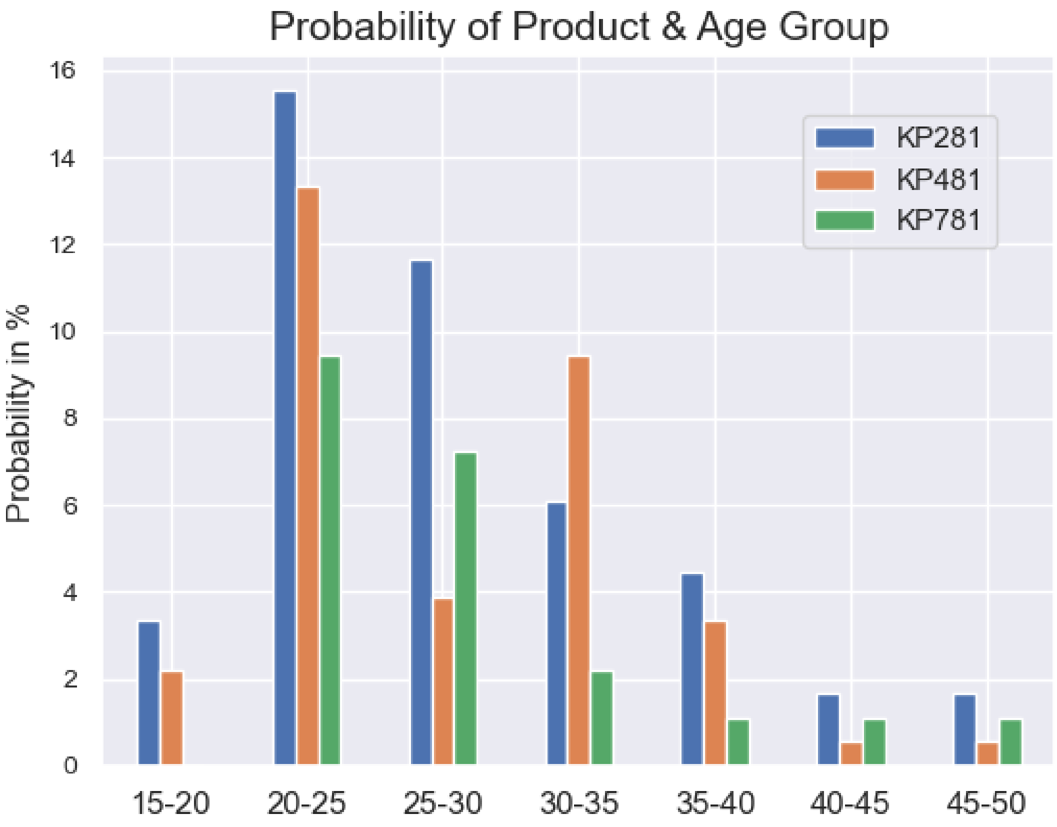
```
[ ]: plt.figure(figsize=(15,10)).suptitle("Aerofit Age Dashboard",fontsize=14)

     plt.subplot(2, 2, 1)
     plt.pie(aerofit['age_group'].value_counts().values,labels =␣
      ↪aerofit['age_group'].value_counts().index,radius = 1.3,autopct = '%1.2f%%')␣
      ↪# type: ignore

     plt.subplot(2, 2, 3)
     sns.boxplot(aerofit, y="Age", x='Product')

     plt.subplot(3, 2, 2)
     sns.histplot(aerofit, x='Age', binwidth=1, kde=True, hue='Product')
     plt.title('No of Product Purchase vs Age', fontsize=12)
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)

     plt.subplot(3, 2, 4)
     sns.countplot(aerofit, x='age_group')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)

     plt.subplot(3, 2, 6)
     sns.countplot(aerofit, x='age_group', hue='Product')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('Age', fontsize=13)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.legend(borderaxespad=1, ncol=1)

     plt.show()
```



Probability Plot

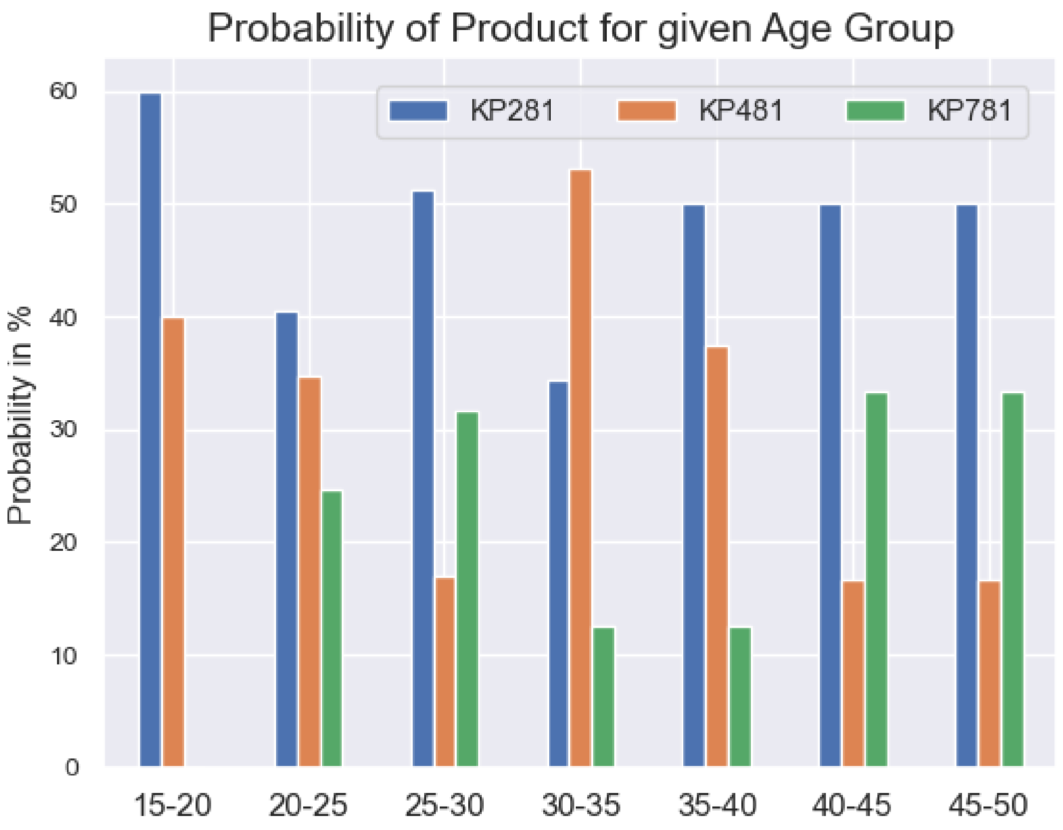
[ ]:

```
(pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize=True)*100).
  ↪plot(kind='bar')
plt.title('Probability of Product & Age Group', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(borderaxespad=2, ncol=1)
plt.show()
```

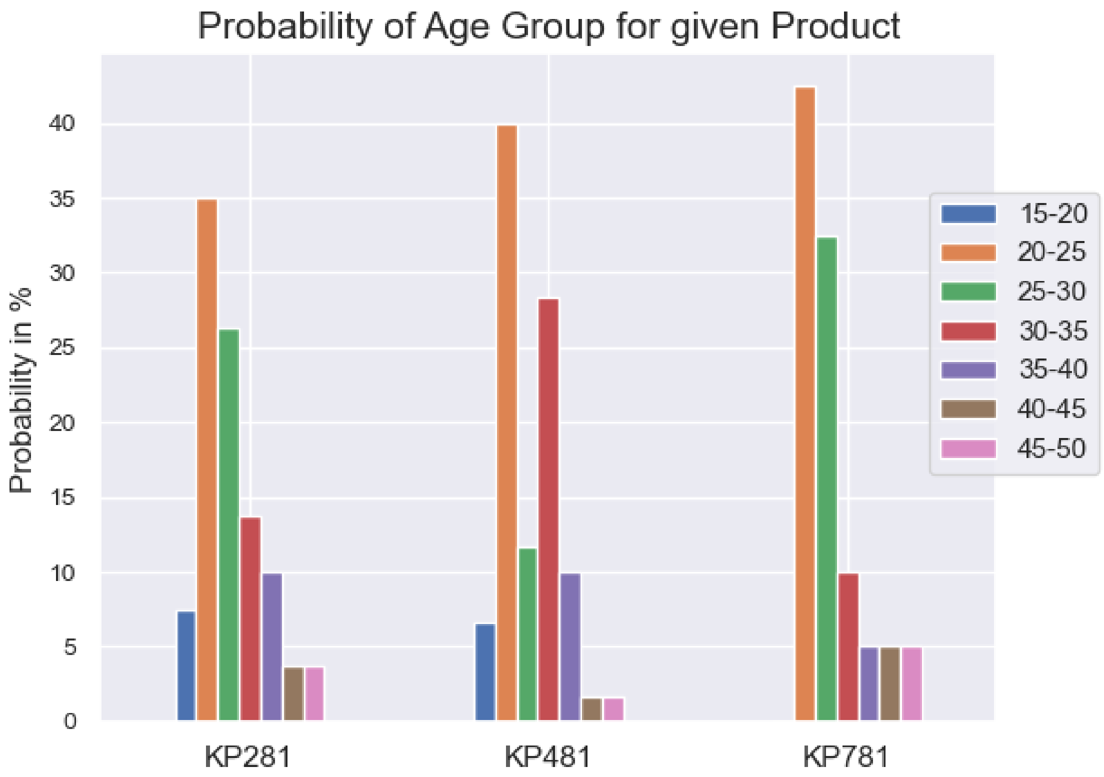


[ ]:

```
(pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize="index")*100).
  ↪plot(kind='bar')
plt.title('Probability of Product for given Age Group', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(borderaxespad=1, ncol=3)
plt.show()
```

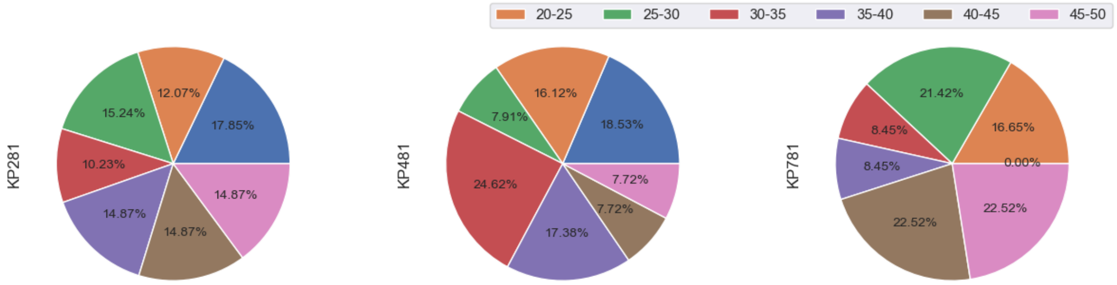


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['age_group'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Age Group for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize="index").
       ↪plot(kind='pie', subplots=True, figsize=(15,4), labeldistance=None,␣
       ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=6)
     plt.show()
```



1.3.5 Income

Income value Count

```
[ ]: aerofit['Income'].unique()
```

```
[ ]: 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)
```

```
[ ]: aerofit['Income'].value_counts()[:5]
```

```
[ ]: 45480    14
     52302     9
     46617     8
     54576     8
     53439     8
     Name: Income, dtype: int64
```

```
[ ]: aerofit['Income'].value_counts(normalize=True)[:5]*100
```

```
[ ]: 45480    7.777778
     52302    5.000000
     46617    4.444444
     54576    4.444444
     53439    4.444444
     Name: Income, dtype: float64
```

Income Group Value Count

```
[ ]: aerofit['income_group'].unique()
```

```
[ ]: ['25K-35K', '35K-45K', '45K-55K', '65K-75K', '55K-65K', '75K-85K', '85K-95K',
     '95K-105K']
     Categories (9, object): ['0-25K' < '25K-35K' < '35K-45K' < '45K-55K' …
     '65K-75K' < '75K-85K' < '85K-95K' < '95K-105K']
```

```
[ ]: aerofit['income_group'].value_counts()[:5]
```

```
[ ]: 45K-55K    77
     35K-45K    35
     55K-65K    26
     25K-35K    14
     85K-95K    11
     Name: income_group, dtype: int64
```

```
[ ]: aerofit['income_group'].value_counts(normalize=True)[:5]*100
[ ]: 45K-55K    42.777778
     35K-45K    19.444444
     55K-65K    14.444444
     25K-35K     7.777778
     85K-95K     6.111111
     Name: income_group, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Income'].describe()
```

```
[ ]: count       180.000000
     mean      53719.577778
     std       16506.684226
     min       29562.000000
     25%       44058.750000
     50%       50596.500000
     75%       58668.000000
     max      104581.000000
     Name: Income, dtype: float64
```

```
[ ]: aerofit['income_group'].describe()
```

```
[ ]: count         180
     unique          8
     top       45K-55K
     freq           77
     Name: income_group, dtype: object
```

```
[ ]: aerofit['Income'].mean()
```

```
[ ]: 53719.57777777778
```

```
[ ]: aerofit['Income'].median()
```

```
[ ]: 50596.5
```

```
[ ]: aerofit['Income'].mode()[0]
```

```
[ ]: 45480
```

```
[ ]: aerofit.groupby('Product')["Income"].describe()
```

```
[ ]:          count       mean           std      min       25%      50%      75%  \
     Product
     KP281     80.0  46418.025   9075.783190  29562.0  38658.00  46617.0  53439.0
     KP481     60.0  48973.650   8653.989388  31836.0  44911.50  49459.5  53439.0
     KP781     40.0  75441.575  18505.836720  48556.0  58204.75  76568.5  90886.0
```

```
              max
Product
KP281     68220.0
KP481     67083.0
KP781    104581.0
```

```
[ ]: aerofit.groupby('Product')["income_group"].describe()
```

```
[ ]:         count unique      top freq
     Product
     KP281      80      5  45K-55K   35
     KP481      60      5  45K-55K   33
     KP781      40      6  85K-95K   11
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Income')['upper']
```

```
[ ]: {'list': 159     83416
      160     88396
      161     90886
      162     92131
      164     88396
      166     85906
      167     90886
      168    103336
      169     99601
      170     89641
      171     95866
      172     92131
      173     92131
      174    104581
      175     83416
      176     89641
      177     90886
      178    104581
      179     95508
      Name: Income, dtype: int64,
      'length': 19}
```

```
[ ]: check_outlier(aerofit, 'Income')['lower']
```

```
[ ]: {'list': Series([], Name: Income, dtype: int64), 'length': 0}
```

Find Probability

Probability of a `Product` & `Income Group` across all Combination *“Product Income Group”*

```
[ ]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: Product           KP281      KP481      KP781         All
     income_group
     25K-35K        4.444444   3.333333   0.000000    7.777778
     35K-45K       14.444444   5.000000   0.000000   19.444444
     45K-55K       19.444444  18.333333   5.000000   42.777778
     55K-65K        5.000000   5.555556   3.888889   14.444444
     65K-75K        1.111111   1.111111   1.666667    3.888889
     75K-85K        0.000000   0.000000   2.222222    2.222222
     85K-95K        0.000000   0.000000   6.111111    6.111111
     95K-105K       0.000000   0.000000   3.333333    3.333333
     All           44.444444  33.333333  22.222222  100.000000
```

Probability of `Product's` for given `Income Group` *“Product / Income Group”*

```
[ ]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize='index',␣
      ↪margins=True)*100
```

```
[ ]: Product           KP281      KP481       KP781
     income_group
     25K-35K       57.142857  42.857143    0.000000
     35K-45K       74.285714  25.714286    0.000000
     45K-55K       45.454545  42.857143   11.688312
     55K-65K       34.615385  38.461538   26.923077
     65K-75K       28.571429  28.571429   42.857143
     75K-85K        0.000000   0.000000  100.000000
     85K-95K        0.000000   0.000000  100.000000
     95K-105K       0.000000   0.000000  100.000000
     All           44.444444  33.333333   22.222222
```

Probability of `Income Group` for given `Product` *“Income Group / Product”*

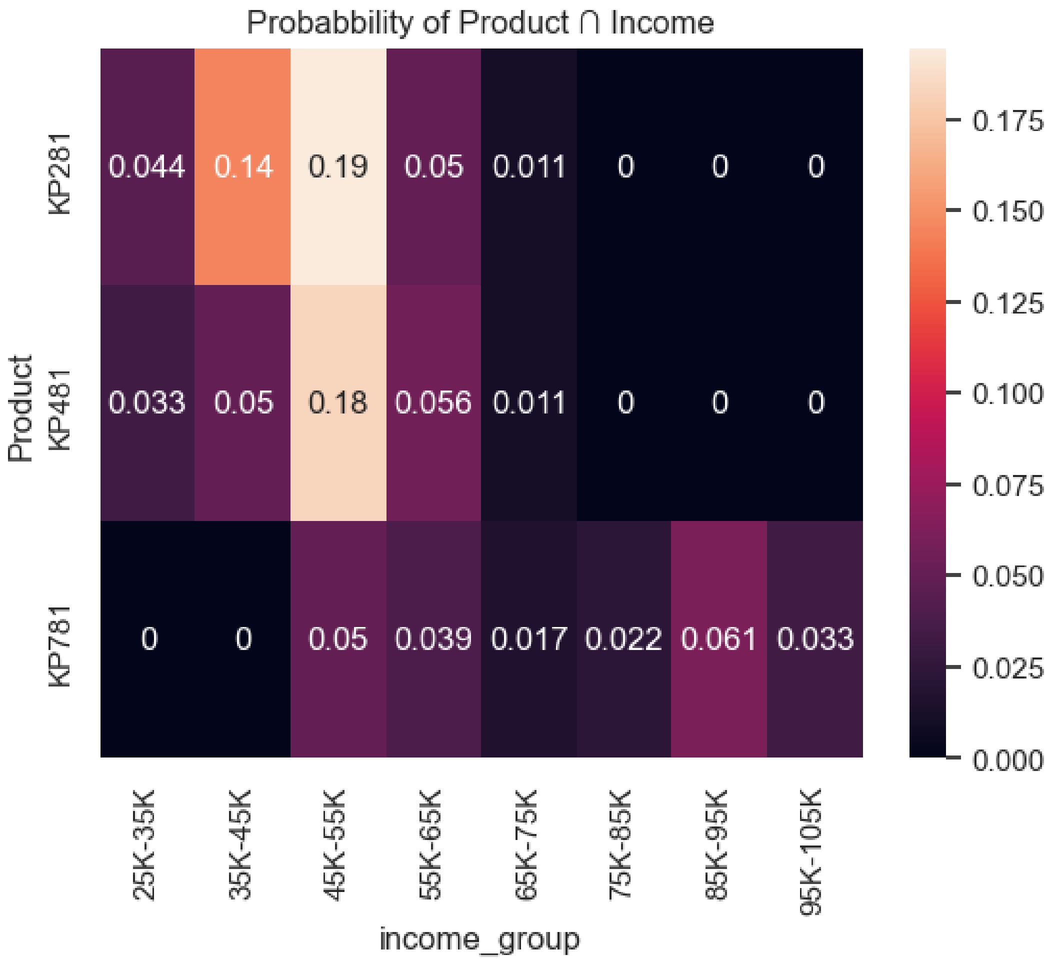
```
[ ]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize='columns',␣
      ↪margins=True)*100
```

```
[ ]: Product       KP281      KP481  KP781        All
     income_group
     25K-35K       10.00  10.000000    0.0   7.777778
     35K-45K       32.50  15.000000    0.0  19.444444
     45K-55K       43.75  55.000000   22.5  42.777778
     55K-65K       11.25  16.666667   17.5  14.444444
     65K-75K        2.50   3.333333    7.5   3.888889
     75K-85K        0.00   0.000000   10.0   2.222222
     85K-95K        0.00   0.000000   27.5   6.111111
     95K-105K       0.00   0.000000   15.0   3.333333
```

Plot the Graph

Heat Map

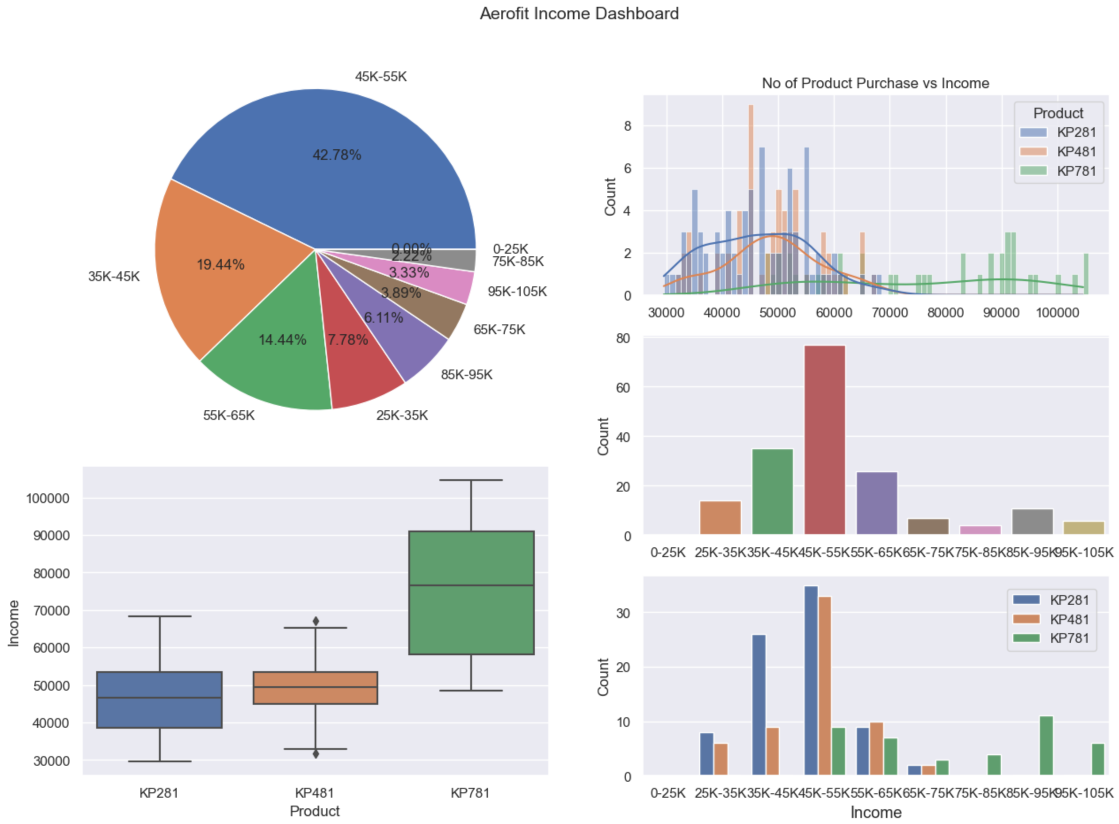
[ ]:
```
sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['income_group'],␣
 ↪normalize='all'),annot=True)
plt.title('Probabbility of Product   Income', fontsize=12)
plt.show()
```



Descriptive Plot

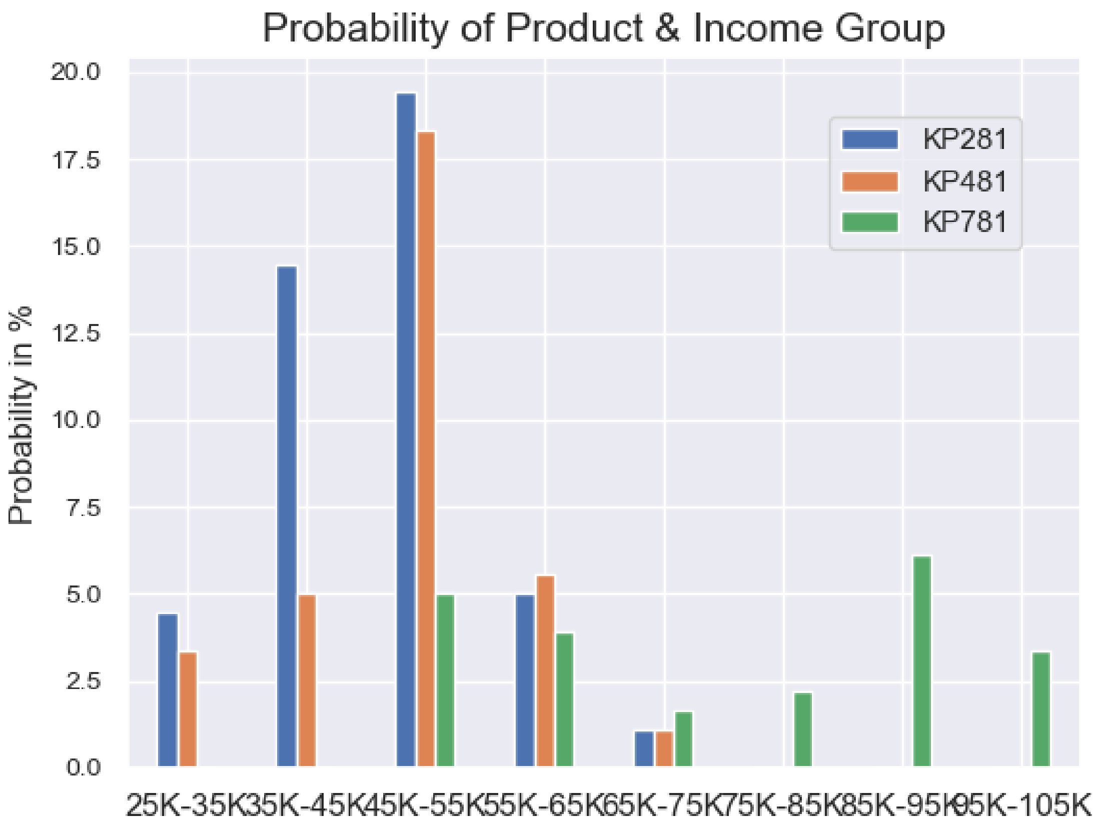
[ ]:
```
plt.figure(figsize=(15,10)).suptitle("Aerofit Income Dashboard",fontsize=14)

plt.subplot(2, 2, 1)
plt.pie(aerofit['income_group'].value_counts().values,labels =␣
 ↪aerofit['income_group'].value_counts().index,radius = 1.3,autopct = '%1.
 ↪2f%%') # type: ignore

plt.subplot(2, 2, 3)
sns.boxplot(aerofit, y="Income", x='Product')
```

```
plt.subplot(3, 2, 2)
sns.histplot(aerofit, x='Income', binwidth=1000, kde=True, hue='Product')
plt.title('No of Product Purchase vs Income', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='income_group')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='income_group', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Income', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)

plt.show()
```

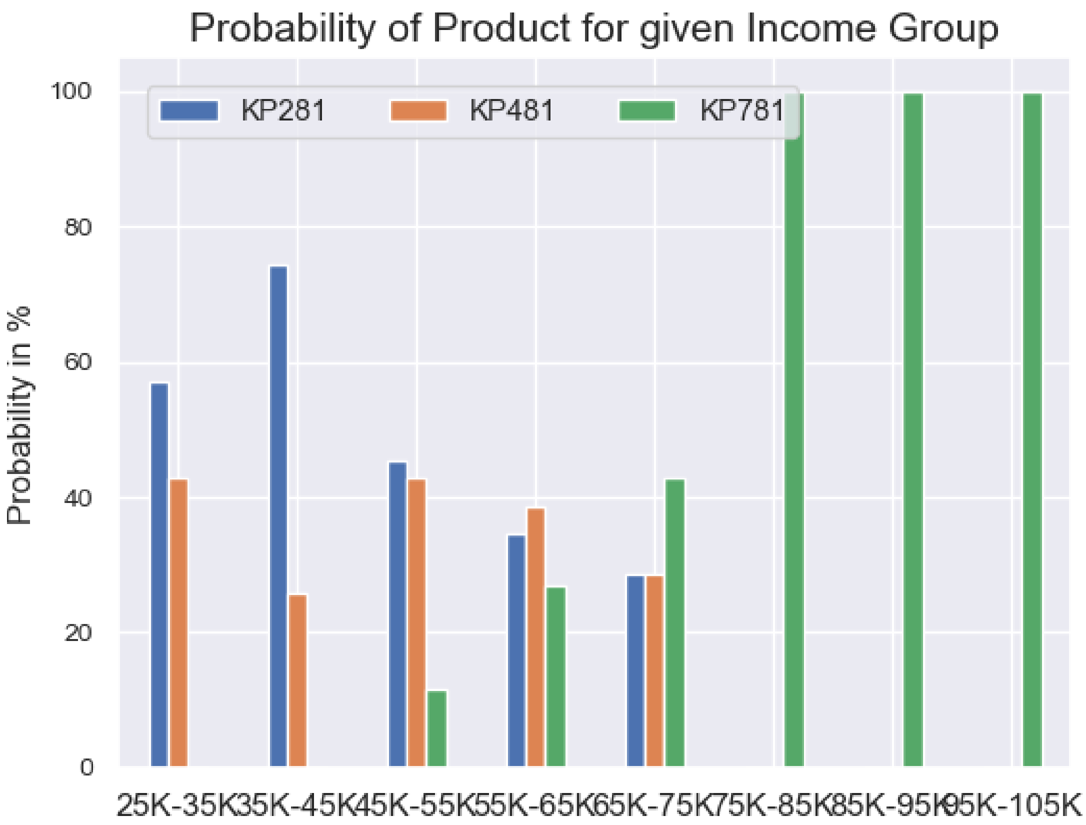


Probability Plot

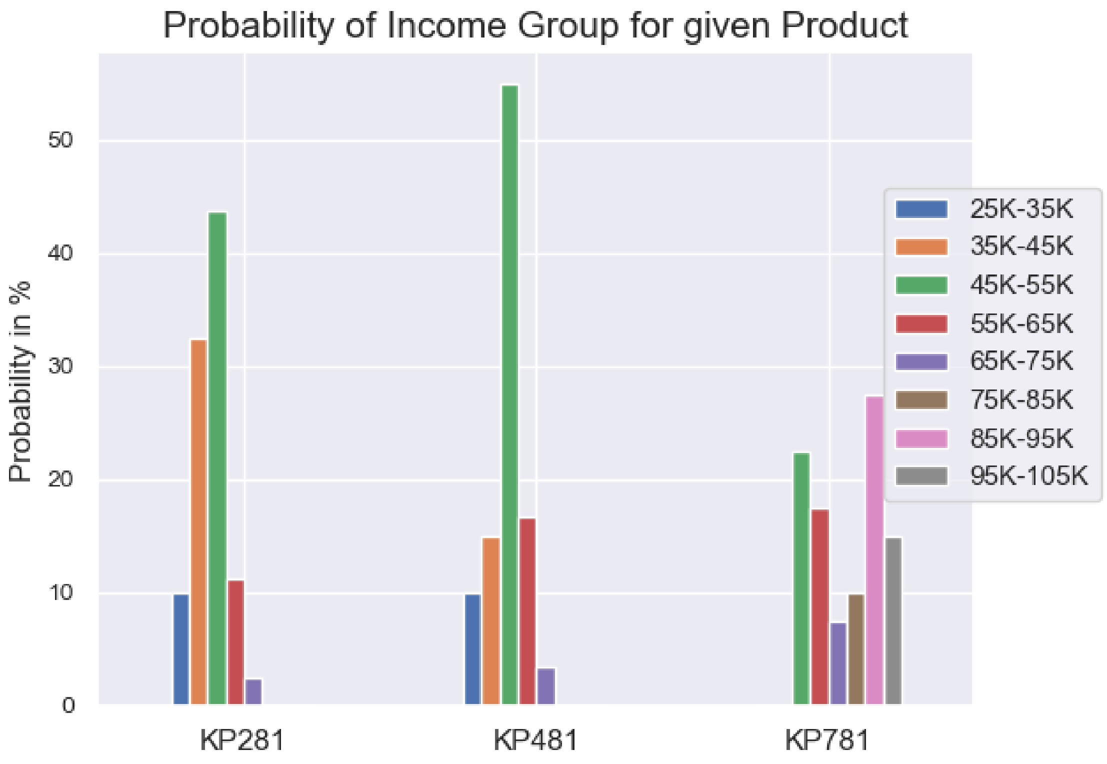
```
[ ]: (pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product & Income Group', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(borderaxespad=2, ncol=1)
     plt.show()
```



```
[ ]: (pd.crosstab(aerofit['income_group'], aerofit['Product'],␣
      ↪normalize="index")*100).plot(kind='bar')
     plt.title('Probability of Product for given Income Group', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(borderaxespad=1, ncol=3)
     plt.show()
```

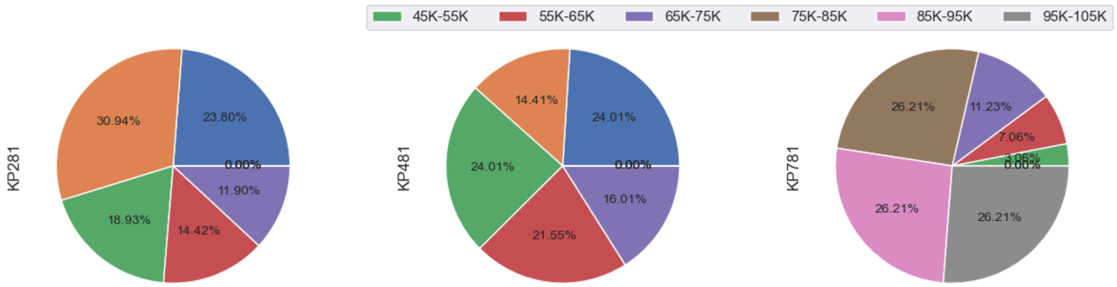


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['income_group'],␣
      ↪normalize="index")*100).plot(kind='bar')
     plt.title('Probability of Income Group for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize="index").
       ↪plot(kind='pie', subplots=True, figsize=(15,4), labeldistance=None,␣
       ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=6)
     plt.show()
```



1.3.6 Miles

Miles value Count

```
[ ]: aerofit['Miles'].unique()
```

```
[ ]: 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)
```

```
[ ]: aerofit['Miles'].value_counts()[:5]
```

```
[ ]: 85     27
     95     12
     66     10
     75     10
     47      9
     Name: Miles, dtype: int64
```

```
[ ]: aerofit['Miles'].value_counts(normalize=True)[:5]*100
```

```
[ ]: 85     15.000000
     95      6.666667
     66      5.555556
     75      5.555556
     47      5.000000
     Name: Miles, dtype: float64
```

Miles Group Value Count

```
[ ]: aerofit['miles_group'].unique()
```

```
[ ]: ['110-140', '50-80', '80-110', '20-50', '140-170', …, '200-230', '230-260',
     '290-320', '260-290', '350-380']
     Length: 11
     Categories (13, object): ['0-20' < '20-50' < '50-80' < '80-110' … '260-290' <
     '290-320' < '320-350' < '350-380']
```

```
[ ]: aerofit['miles_group'].value_counts()[:5]
```

```
[ ]: 80-110     66
     50-80      43
     110-140    20
     20-50      17
     140-170    15
     Name: miles_group, dtype: int64
```

```
[ ]: aerofit['miles_group'].value_counts(normalize=True)[:5]*100
```

```
[ ]: 80-110     36.666667
     50-80      23.888889
     110-140    11.111111
     20-50       9.444444
```

```
140-170     8.333333
Name: miles_group, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Miles'].describe()
```

```
[ ]: count    180.000000
     mean     103.194444
     std       51.863605
     min       21.000000
     25%       66.000000
     50%       94.000000
     75%      114.750000
     max      360.000000
     Name: Miles, dtype: float64
```

```
[ ]: aerofit['miles_group'].describe()
```

```
[ ]: count        180
     unique        11
     top       80-110
     freq          66
     Name: miles_group, dtype: object
```

```
[ ]: aerofit['Miles'].mean()
```

```
[ ]: 103.19444444444444
```

```
[ ]: aerofit['Miles'].median()
```

```
[ ]: 94.0
```

```
[ ]: aerofit['Miles'].mode()[0]
```

```
[ ]: 85
```

```
[ ]: aerofit.groupby('Product')["Miles"].describe()
```

```
[ ]:          count        mean        std   min    25%    50%    75%    max
     Product
     KP281     80.0   82.787500  28.874102  38.0   66.0   85.0   94.0  188.0
     KP481     60.0   87.933333  33.263135  21.0   64.0   85.0  106.0  212.0
     KP781     40.0  166.900000  60.066544  80.0  120.0  160.0  200.0  360.0
```

```
[ ]: aerofit.groupby('Product')["miles_group"].describe()
```

```
[ ]:        count unique      top freq
     Product
```

```
KP281      80      6   80-110   27
KP481      60      6   80-110   31
KP781      40      9  170-200   12
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Miles')['upper']
```

```
[ ]: {'list': 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,
      'length': 13}
```

```
[ ]: check_outlier(aerofit, 'Miles')['lower']
```

```
[ ]: {'list': Series([], Name: Miles, dtype: int64), 'length': 0}
```

Find Probability

Probability of a Product & Miles Group across all Combination *“Product Miles Group”*

```
[ ]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize=True,␣
       ↪margins=True)*100
```

```
[ ]: Product          KP281      KP481      KP781         All
     miles_group
     20-50         6.666667   2.777778   0.000000    9.444444
     50-80        14.444444   8.888889   0.555556   23.888889
     80-110       15.000000  17.222222   4.444444   36.666667
     110-140       6.111111   2.777778   2.222222   11.111111
     140-170       1.666667   1.111111   5.555556    8.333333
     170-200       0.555556   0.000000   6.666667    7.222222
     200-230       0.000000   0.555556   0.000000    0.555556
     230-260       0.000000   0.000000   1.111111    1.111111
     260-290       0.000000   0.000000   0.555556    0.555556
     290-320       0.000000   0.000000   0.555556    0.555556
     350-380       0.000000   0.000000   0.555556    0.555556
     All          44.444444  33.333333  22.222222  100.000000
```

Probability of `Product's` for given `Miles Group` *“Product | Miles Group”*

```
[ ]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize='index',␣
       ↪margins=True)*100
```

```
[ ]: Product          KP281       KP481       KP781
     miles_group
     20-50        70.588235   29.411765    0.000000
     50-80        60.465116   37.209302    2.325581
     80-110       40.909091   46.969697   12.121212
     110-140      55.000000   25.000000   20.000000
     140-170      20.000000   13.333333   66.666667
     170-200       7.692308    0.000000   92.307692
     200-230       0.000000  100.000000    0.000000
     230-260       0.000000    0.000000  100.000000
     260-290       0.000000    0.000000  100.000000
     290-320       0.000000    0.000000  100.000000
     350-380       0.000000    0.000000  100.000000
     All          44.444444   33.333333   22.222222
```

Probability of `Miles Group` for given `Product` *“Miles Group | Product”*

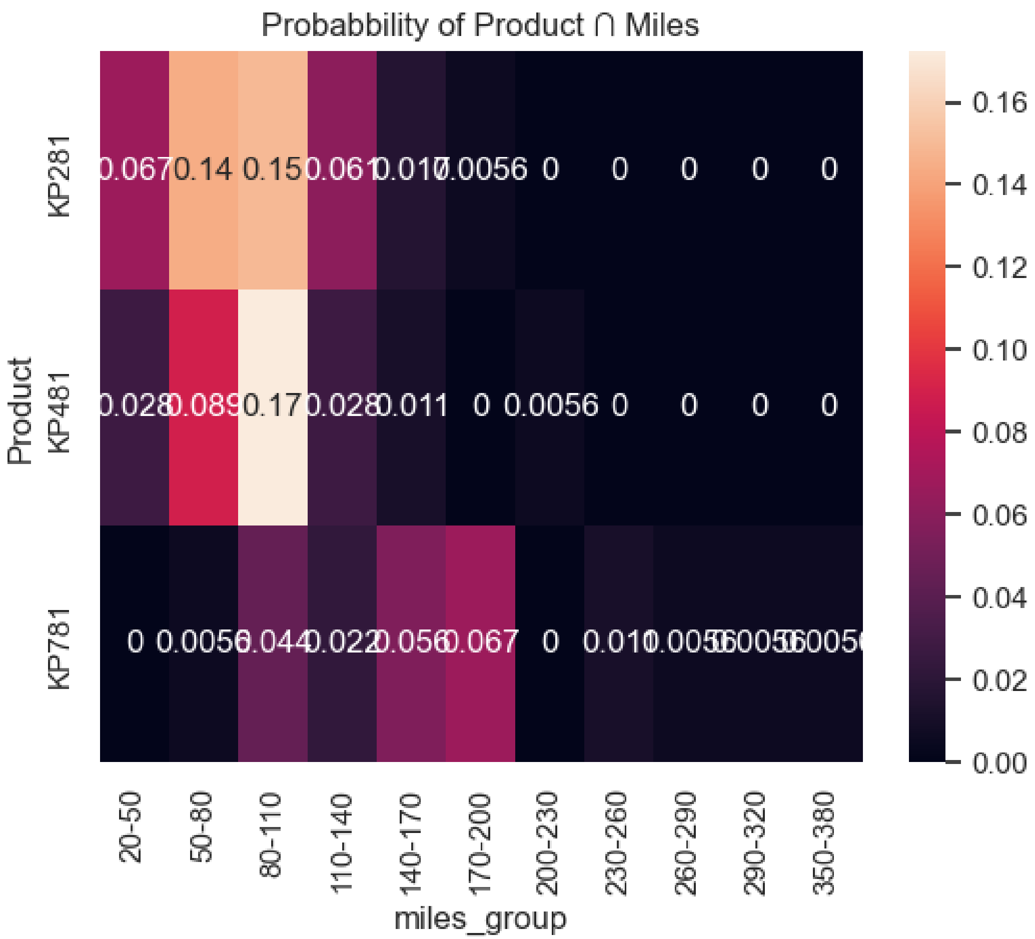
```
[ ]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize='columns',␣
       ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481  KP781        All
     miles_group
     20-50        15.00   8.333333    0.0   9.444444
     50-80        32.50  26.666667    2.5  23.888889
     80-110       33.75  51.666667   20.0  36.666667
     110-140      13.75   8.333333   10.0  11.111111
     140-170       3.75   3.333333   25.0   8.333333
     170-200       1.25   0.000000   30.0   7.222222
     200-230       0.00   1.666667    0.0   0.555556
     230-260       0.00   0.000000    5.0   1.111111
     260-290       0.00   0.000000    2.5   0.555556
     290-320       0.00   0.000000    2.5   0.555556
     350-380       0.00   0.000000    2.5   0.555556
```

Plot the Graph

`Heat Map`

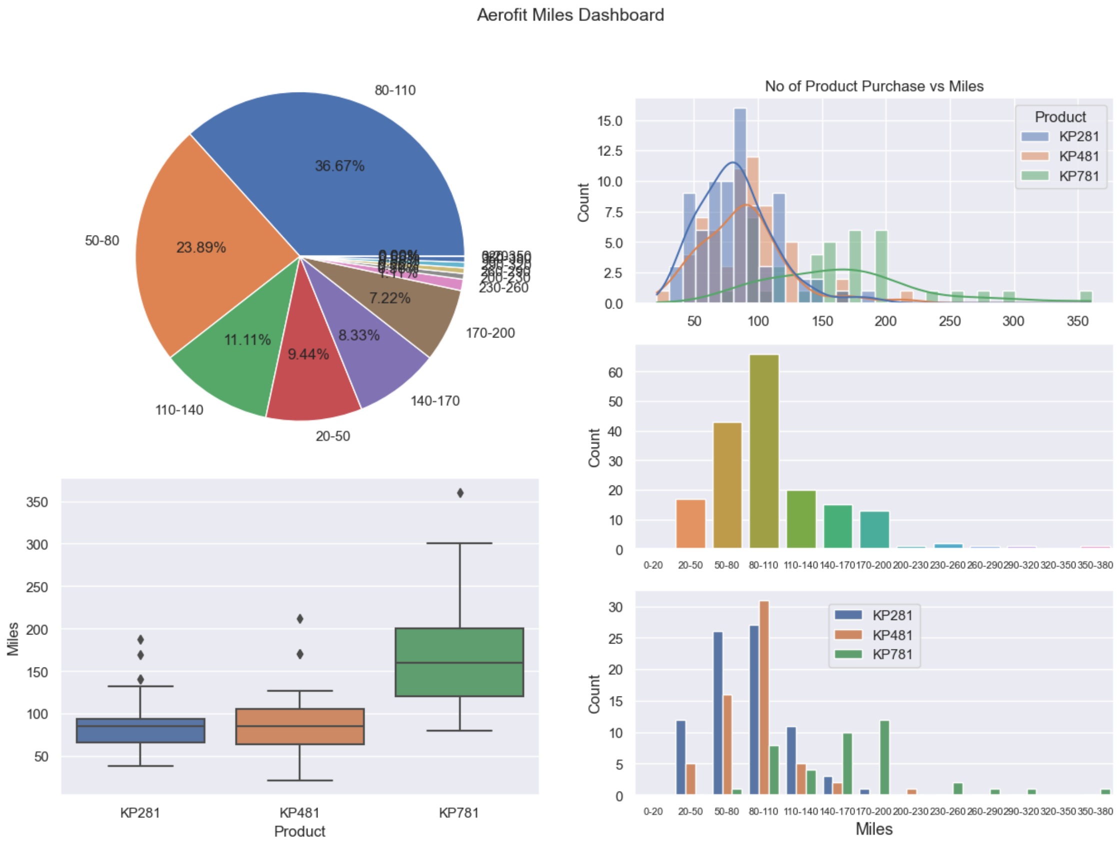
```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['miles_group'],␣
       ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product   Miles', fontsize=12)
     plt.show()
```



Descriptive Plot

[ ]:

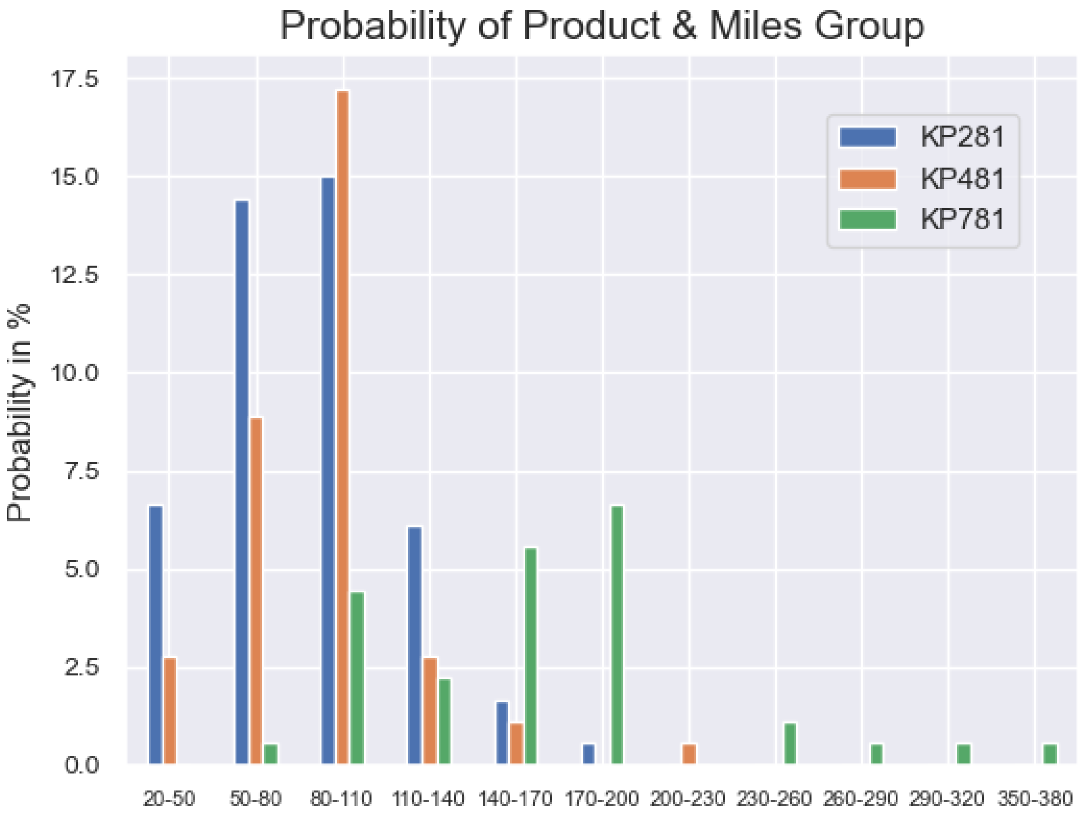
```
plt.figure(figsize=(15,10)).suptitle("Aerofit Miles Dashboard",fontsize=14)

plt.subplot(2, 2, 1)
plt.pie(aerofit['miles_group'].value_counts().values,labels =␣
 ↪aerofit['miles_group'].value_counts().index,radius = 1.3,autopct = '%1.
 ↪2f%%') # type: ignore

plt.subplot(2, 2, 3)
sns.boxplot(aerofit, y="Miles", x='Product')

plt.subplot(3, 2, 2)
sns.histplot(aerofit, x='Miles', binwidth=10, kde=True, hue='Product')
plt.title('No of Product Purchase vs Miles', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='miles_group')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=8)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='miles_group', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Miles', fontsize=13)
plt.xticks(fontsize=8)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)

plt.show()
```



Probability Plot

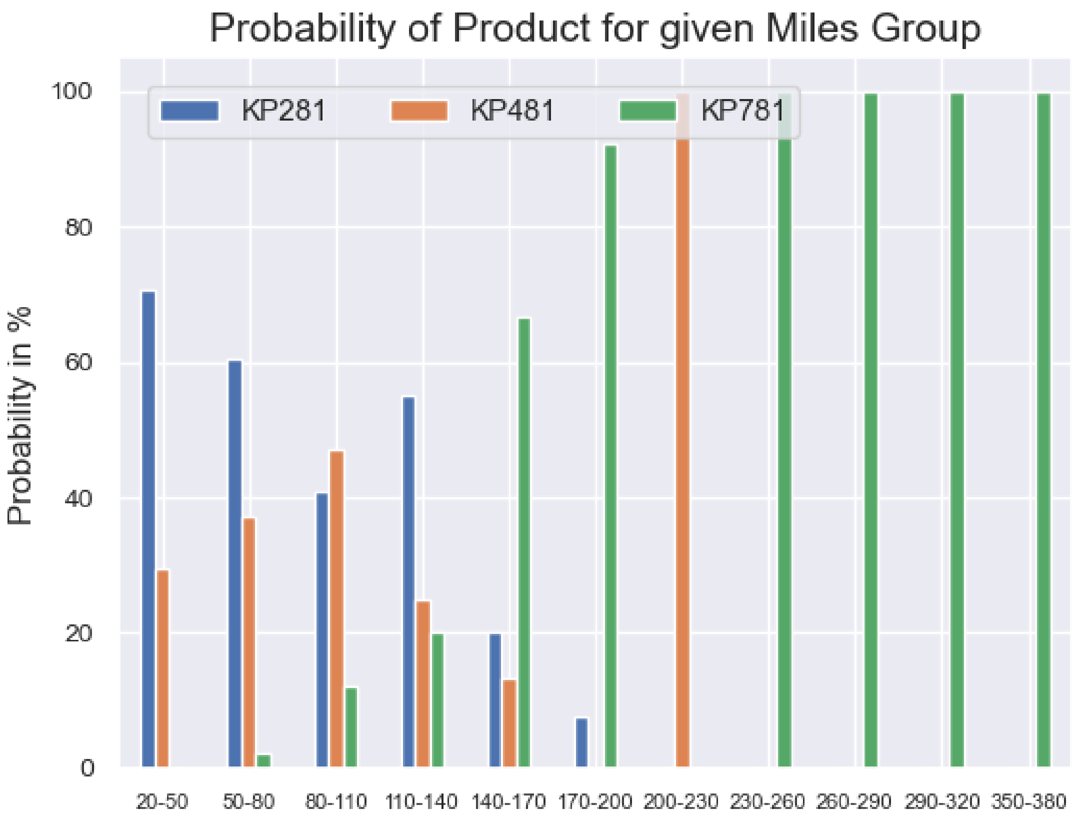
[ ]:

```
(pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize=True)*100).
 ↪plot(kind='bar')
plt.title('Probability of Product & Miles Group', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=8)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(borderaxespad=2, ncol=1)
plt.show()
```

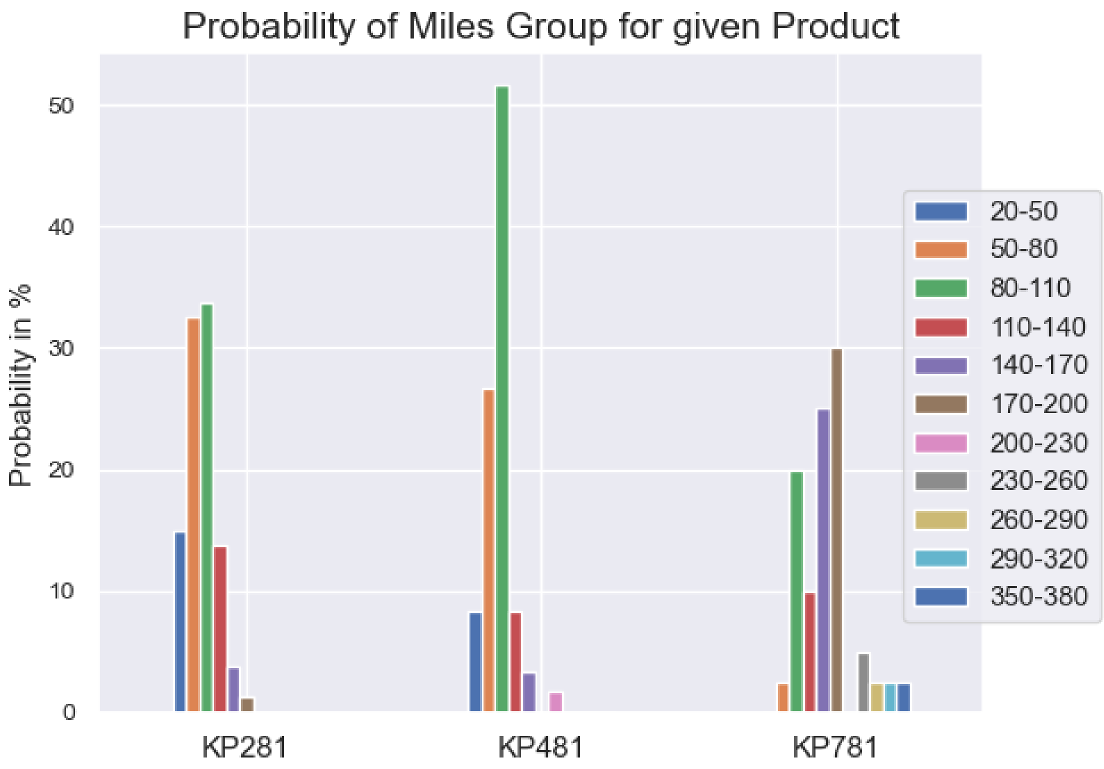


[ ]:

```
(pd.crosstab(aerofit['miles_group'], aerofit['Product'],␣
 ↪normalize="index")*100).plot(kind='bar')
plt.title('Probability of Product for given Miles Group', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=8)
plt.yticks(rotation= 0, fontsize=10)
plt.legend(borderaxespad=1, ncol=3)
plt.show()
```

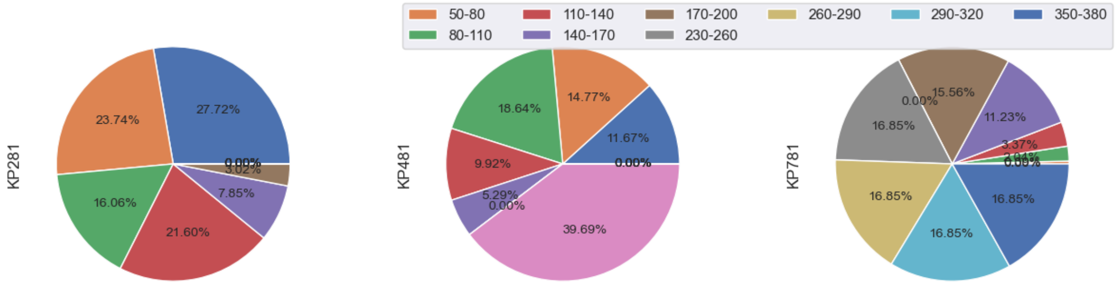


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['miles_group'],␣
      ↪normalize="index")*100).plot(kind='bar')
     plt.title('Probability of Miles Group for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=10)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize="index").
       ↪plot(kind='pie', subplots=True, figsize=(15,4), labeldistance=None,␣
       ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=6)
     plt.show()
```



1.3.7 Education

```
[ ]: aerofit['Education'].unique()
```

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

```
[ ]: aerofit['Education'].value_counts()
```

```
[ ]: 16    85
     14    55
     18    23
     15     5
     13     5
     12     3
     21     3
     20     1
     Name: Education, dtype: int64
```

```
[ ]: aerofit['Education'].value_counts(normalize=True)*100
```

```
[ ]: 16    47.222222
     14    30.555556
     18    12.777778
     15     2.777778
     13     2.777778
     12     1.666667
     21     1.666667
     20     0.555556
     Name: Education, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Education'].describe()
```

```
[ ]: count    180.000000
     mean      15.572222
     std        1.617055
     min       12.000000
     25%       14.000000
     50%       16.000000
     75%       16.000000
     max       21.000000
     Name: Education, dtype: float64
```

```
[ ]: aerofit['Education'].mean()
```

```
[ ]: 15.572222222222223
```

```
[ ]: aerofit['Education'].median()
[ ]: 16.0
```

```
[ ]: aerofit['Education'].mode()[0]
```

```
[ ]: 16
```

```
[ ]: aerofit.groupby('Product')["Education"].describe()
```

```
[ ]:          count       mean       std   min   25%   50%   75%   max
     Product
     KP281     80.0  15.037500  1.216383  12.0  14.0  16.0  16.0  18.0
     KP481     60.0  15.116667  1.222552  12.0  14.0  16.0  16.0  18.0
     KP781     40.0  17.325000  1.639066  14.0  16.0  18.0  18.0  21.0
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Education')['upper']
```

```
[ ]: {'list': 156    20
      157    21
      161    21
      175    21
      Name: Education, dtype: int64,
      'length': 4}
```

```
[ ]: check_outlier(aerofit, 'Education')['lower']
```

```
[ ]: {'list': Series([], Name: Education, dtype: int64), 'length': 0}
```

Find Probability

Probability of a `Product` & `Education` across all Combination *“Product Education”*

```
[ ]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize=True,␣
       ↪margins=True)*100
```

```
[ ]: Product        KP281      KP481      KP781         All
     Education
     12          1.111111   0.555556   0.000000    1.666667
     13          1.666667   1.111111   0.000000    2.777778
     14         16.666667  12.777778   1.111111   30.555556
     15          2.222222   0.555556   0.000000    2.777778
     16         21.666667  17.222222   8.333333   47.222222
     18          1.111111   1.111111  10.555556   12.777778
     20          0.000000   0.000000   0.555556    0.555556
     21          0.000000   0.000000   1.666667    1.666667
     All        44.444444  33.333333  22.222222  100.000000
```

Probability of `Product's` for given `Education` *“Product | Education”*

```
[ ]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize='index',␣
       ↪margins=True)*100
```

```
[ ]: Product        KP281      KP481       KP781
     Education
     12         66.666667  33.333333    0.000000
     13         60.000000  40.000000    0.000000
     14         54.545455  41.818182    3.636364
     15         80.000000  20.000000    0.000000
     16         45.882353  36.470588   17.647059
     18          8.695652   8.695652   82.608696
     20          0.000000   0.000000  100.000000
     21          0.000000   0.000000  100.000000
     All        44.444444  33.333333   22.222222
```

Probability of `Education` for given `Product` *"Education | Product"*

```
[ ]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize='columns',␣
       ↪margins=True)*100
```

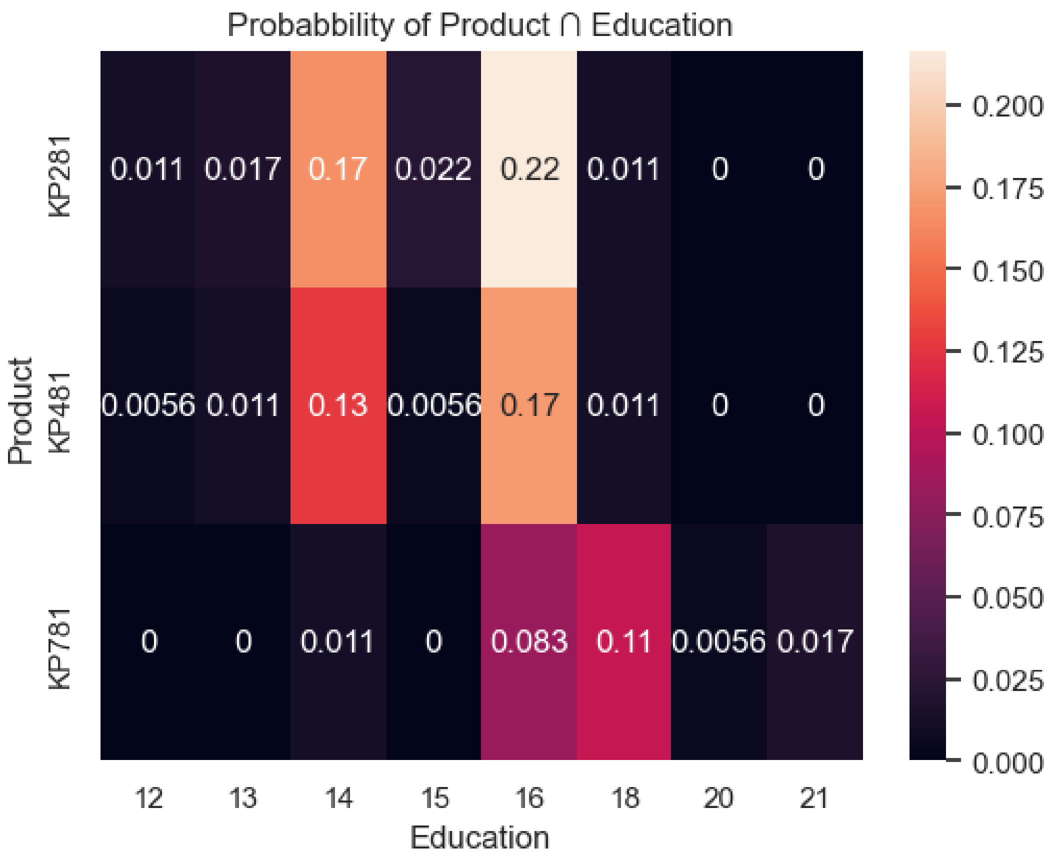
```
[ ]: Product    KP281      KP481  KP781        All
     Education
     12          2.50   1.666667    0.0   1.666667
     13          3.75   3.333333    0.0   2.777778
     14         37.50  38.333333    5.0  30.555556
     15          5.00   1.666667    0.0   2.777778
     16         48.75  51.666667   37.5  47.222222
     18          2.50   3.333333   47.5  12.777778
     20          0.00   0.000000    2.5   0.555556
     21          0.00   0.000000    7.5   1.666667
```

Plot the Graph

`Heat Map`

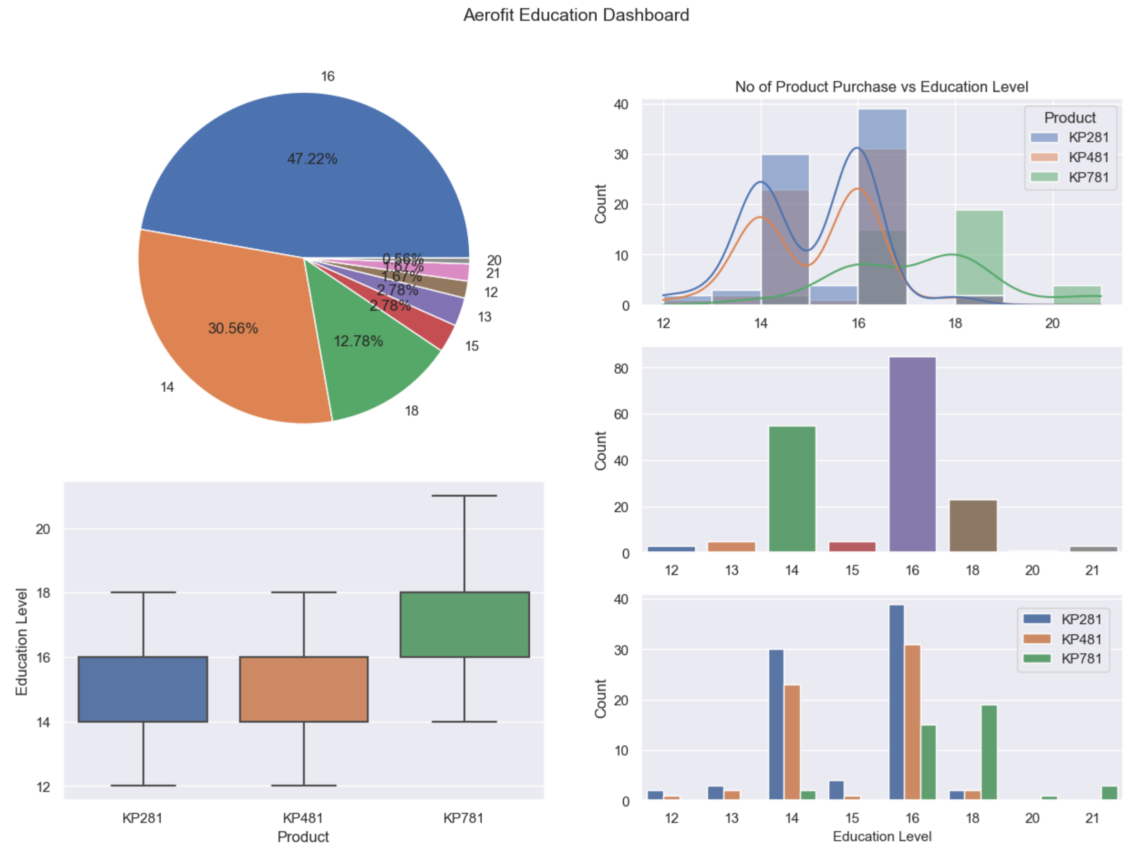
```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Education'],␣
       ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product  Education', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product  Education')
```



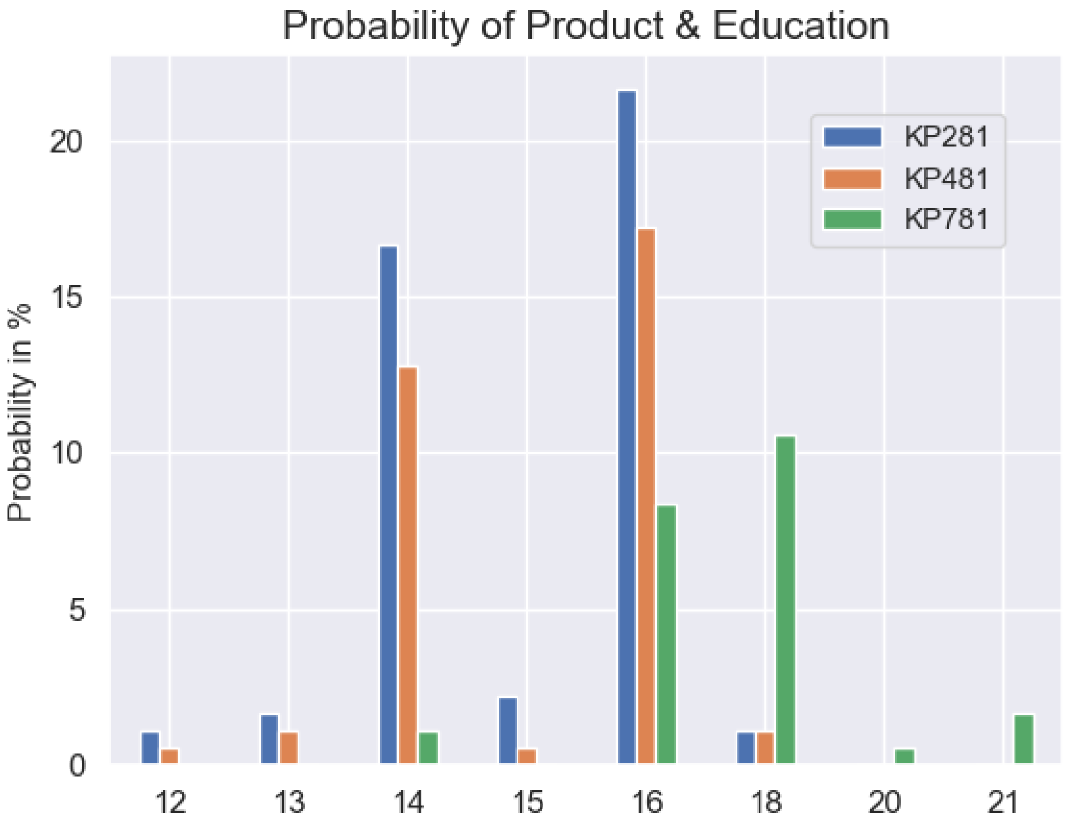
Descriptive Plot

```
[ ]: plt.figure(figsize=(15,10)).suptitle("Aerofit Education Dashboard",fontsize=14)

     plt.subplot(2, 2, 1)
     plt.pie(aerofit['Education'].value_counts().values,labels =␣
      ↪aerofit['Education'].value_counts().index,radius = 1.3,autopct = '%1.2f%%')␣
      ↪# type: ignore

     plt.subplot(2, 2, 3)
     sns.boxplot(aerofit, y="Education", x='Product')
     plt.ylabel('Education Level', fontsize=12)

     plt.subplot(3, 2, 2)
     sns.histplot(aerofit, x='Education', binwidth=1, kde=True, hue="Product")
     plt.title('No of Product Purchase vs Education Level', fontsize=12)
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.subplot(3, 2, 4)
     sns.countplot(aerofit, x='Education')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)

     plt.subplot(3, 2, 6)
     sns.countplot(aerofit, x='Education', hue='Product')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('Education Level', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.legend(borderaxespad=1, ncol=1)

     plt.show()
```

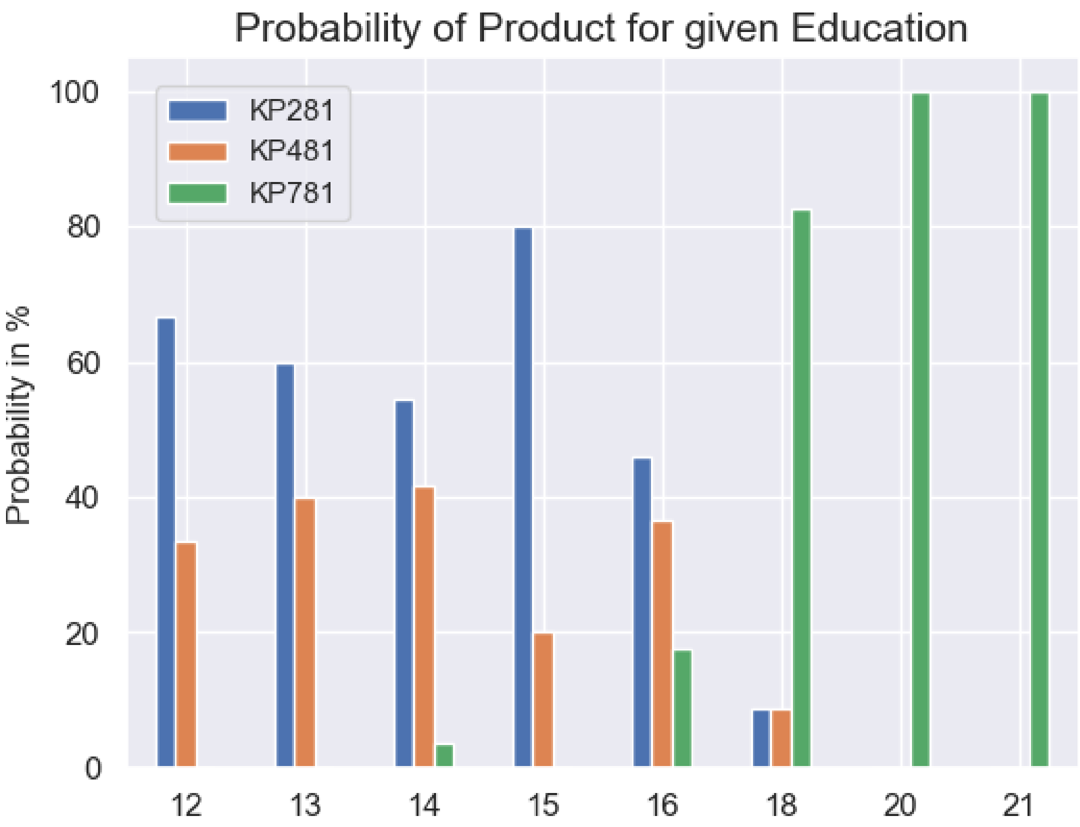


Probability Plot

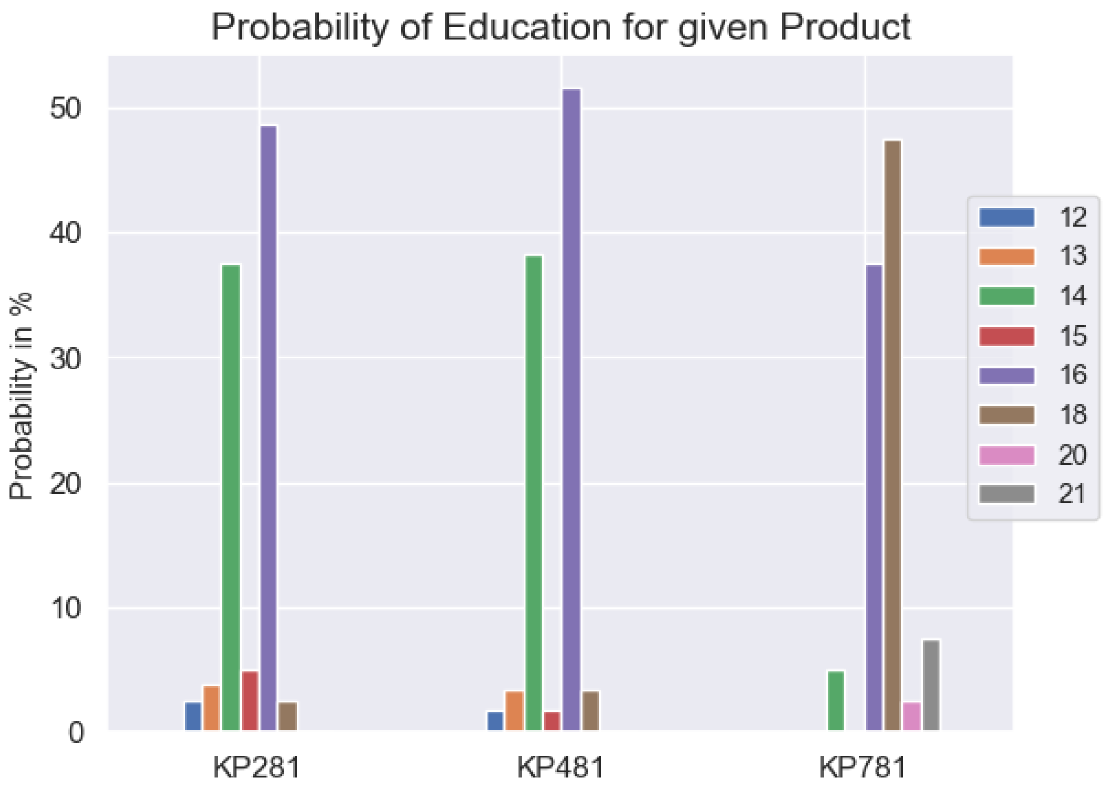
```
[ ]: (pd.crosstab(aerofit['Education'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product & Education', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=2, ncol=1)
     plt.show()
```



```
[ ]: (pd.crosstab(aerofit['Education'], aerofit['Product'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product for given Education', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=1, ncol=1)
     plt.show()
```

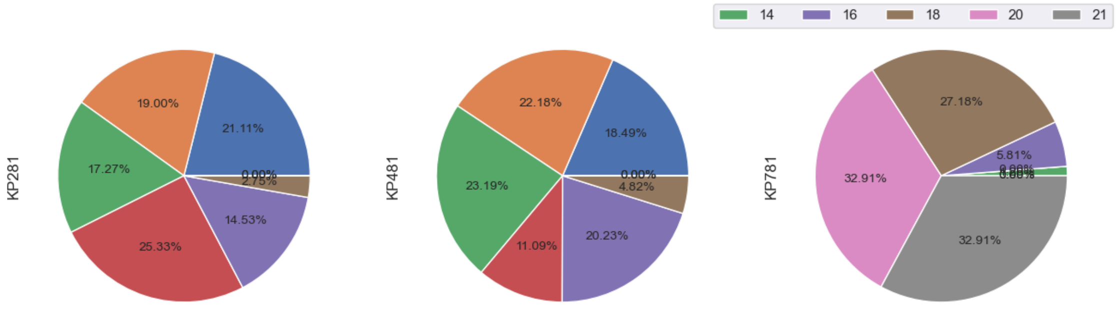


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['Education'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Education for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize="index").
      ↪plot(kind='pie', subplots=True, figsize=(15,5), labeldistance=None,␣
      ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=5)
     plt.show()
```



1.3.8 Fitness

```
[ ]: aerofit['Fitness'].unique()
```

```
[ ]: array([4, 3, 2, 1, 5], dtype=int64)
```

```
[ ]: aerofit['Fitness'].value_counts()
```

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

```
[ ]: aerofit['Fitness'].value_counts(normalize=True)*100
```

```
[ ]: 3    53.888889
     5    17.222222
     2    14.444444
     4    13.333333
     1     1.111111
     Name: Fitness, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Fitness'].describe()
```

```
[ ]: count    180.000000
     mean       3.311111
     std        0.958869
     min        1.000000
     25%        3.000000
     50%        3.000000
     75%        4.000000
     max        5.000000
     Name: Fitness, dtype: float64
```

```
[ ]: aerofit['Fitness'].mean()
```

```
[ ]: 3.311111111111111
```

```
[ ]: aerofit['Fitness'].median()
```

```
[ ]: 3.0
```

```
[ ]: aerofit['Fitness'].mode()[0]
```

```
[ ]: 3
[ ]: aerofit.groupby('Product')["Fitness"].describe()
```

```
[ ]:          count    mean       std  min  25%  50%  75%  max
     Product
     KP281     80.0  2.9625  0.664540  1.0  3.0  3.0  3.0  5.0
     KP481     60.0  2.9000  0.629770  1.0  3.0  3.0  3.0  4.0
     KP781     40.0  4.6250  0.667467  3.0  4.0  5.0  5.0  5.0
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Fitness')['upper']
```

```
[ ]: {'list': Series([], Name: Fitness, dtype: int64), 'length': 0}
```

```
[ ]: check_outlier(aerofit, 'Fitness')['lower']
```

```
[ ]: {'list': 14     1
      117    1
      Name: Fitness, dtype: int64,
      'length': 2}
```

Find Probability

Probability of a Product & Fitness across all Combination *"Product Fitness"*

```
[ ]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize=True,␣
       ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481      KP781         All
     Fitness
     1         0.555556   0.555556   0.000000    1.111111
     2         7.777778   6.666667   0.000000   14.444444
     3        30.000000  21.666667   2.222222   53.888889
     4         5.000000   4.444444   3.888889   13.333333
     5         1.111111   0.000000  16.111111   17.222222
     All      44.444444  33.333333  22.222222  100.000000
```

Probability of Product's for given Fitness *"Product | Fitness"*

```
[ ]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize='index',␣
       ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481      KP781
     Fitness
     1        50.000000  50.000000   0.000000
     2        53.846154  46.153846   0.000000
     3        55.670103  40.206186   4.123711
     4        37.500000  33.333333  29.166667
     5         6.451613   0.000000  93.548387
     All      44.444444  33.333333  22.222222
```

Probability of Fitness for given Product *“Fitness / Product”*

```
[ ]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize='columns',␣
       ↪margins=True)*100
```

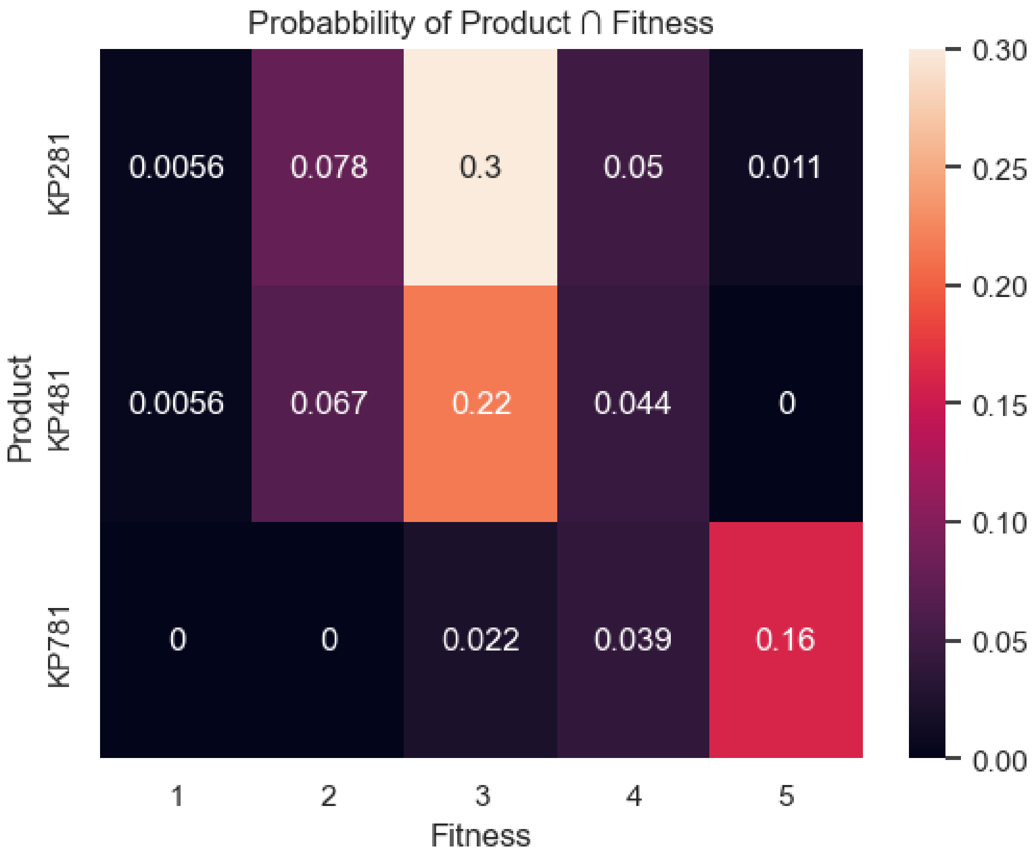
```
[ ]: Product  KP281      KP481  KP781        All
     Fitness
     1         1.25   1.666667    0.0   1.111111
     2        17.50  20.000000    0.0  14.444444
     3        67.50  65.000000   10.0  53.888889
     4        11.25  13.333333   17.5  13.333333
     5         2.50   0.000000   72.5  17.222222
```

Plot the Graph

Heat Map

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Fitness'],␣
       ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product  Fitness', fontsize=12)
```

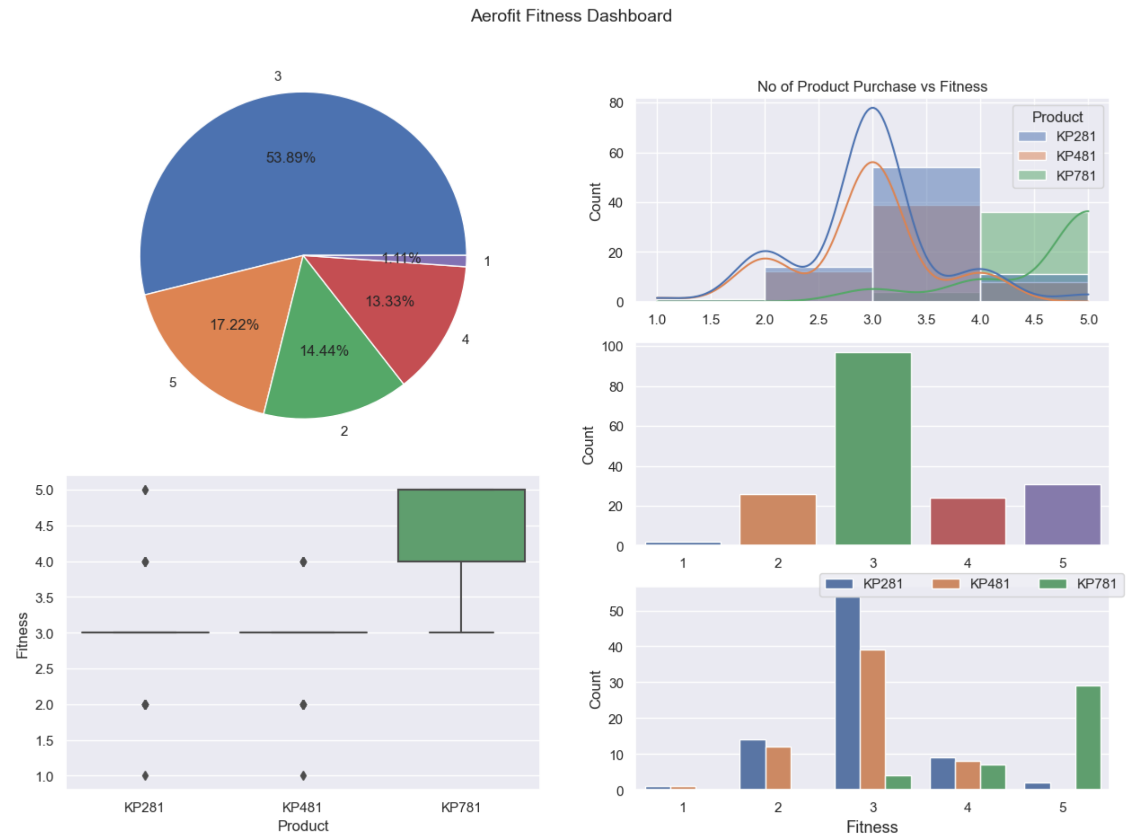
```
[ ]: Text(0.5, 1.0, 'Probabbility of Product  Fitness')
```



Descriptive Plot

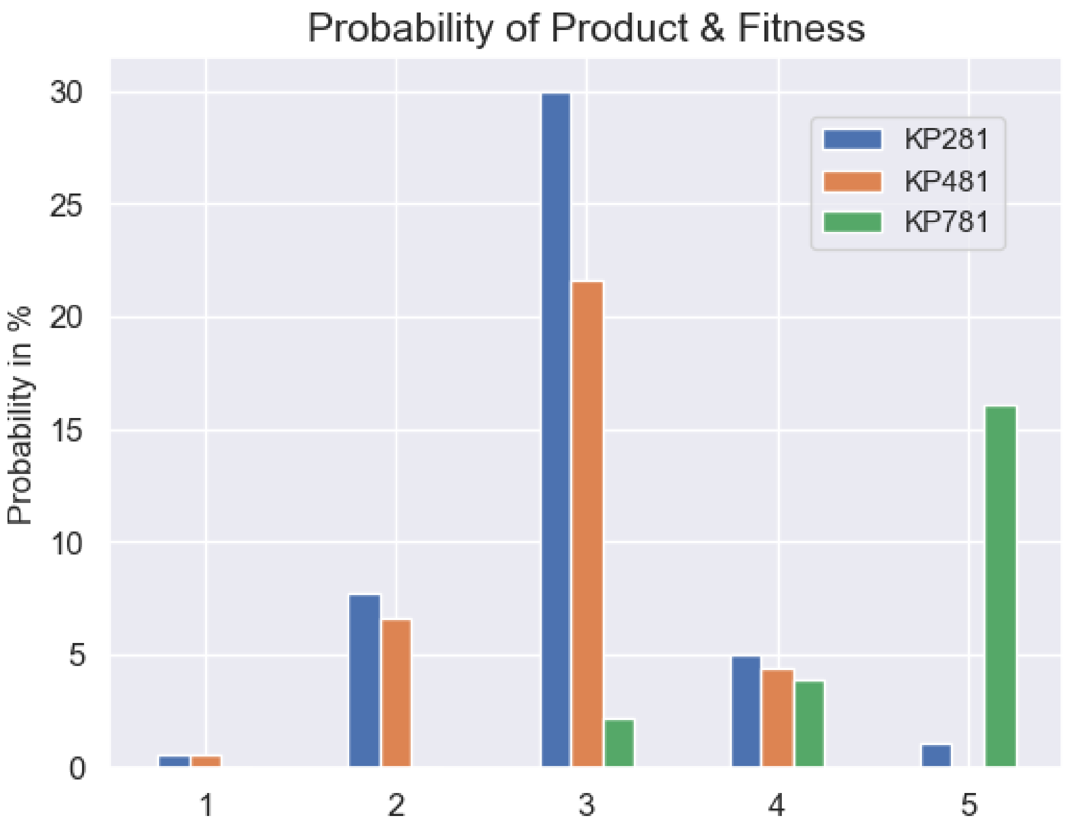
[ ]:

```
plt.figure(figsize=(15,10)).suptitle("Aerofit Fitness Dashboard",fontsize=14)

plt.subplot(2, 2, 1)
plt.pie(aerofit['Fitness'].value_counts().values,labels = aerofit['Fitness'].
  ↪value_counts().index,radius = 1.3,autopct = '%1.2f%%') # type: ignore

plt.subplot(2, 2, 3)
sns.boxplot(aerofit, y="Fitness", x='Product')

plt.subplot(3, 2, 2)
sns.histplot(aerofit, x='Fitness', binwidth=1, kde=True, hue="Product")
plt.title('No of Product Purchase vs Fitness', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='Fitness')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='Fitness', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Fitness', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=-1, ncol=3)
plt.show()
```

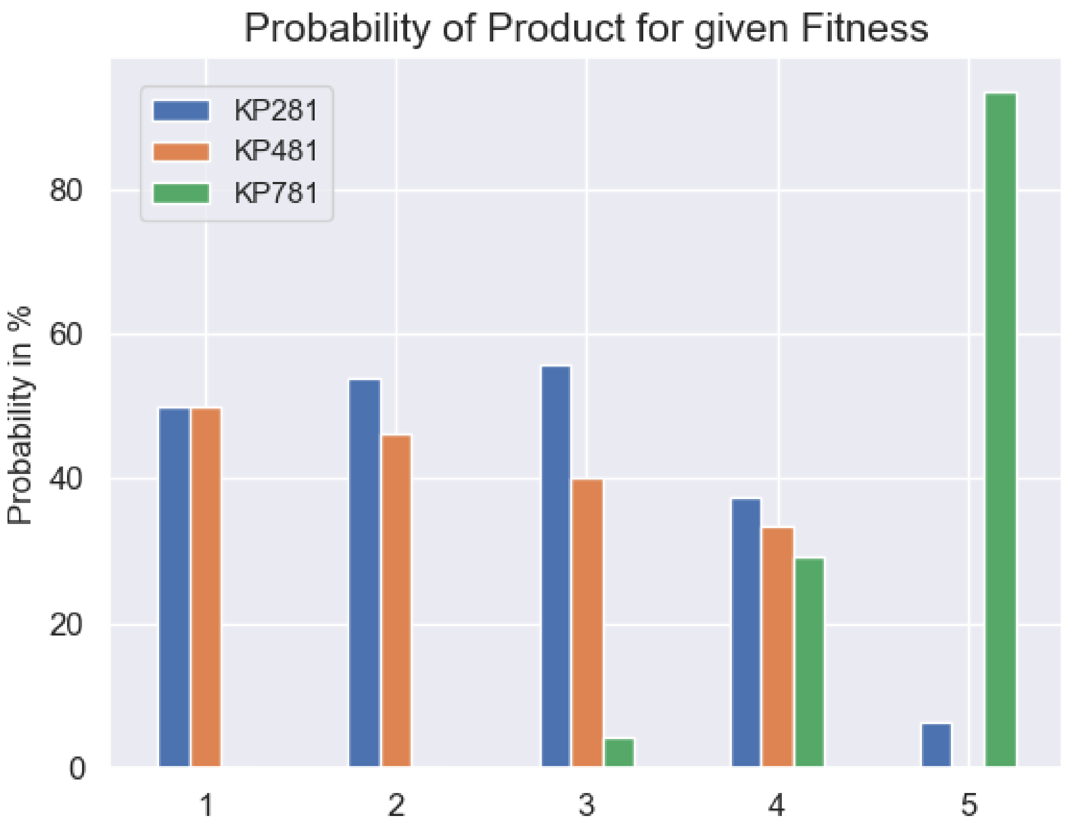


Probability Plot

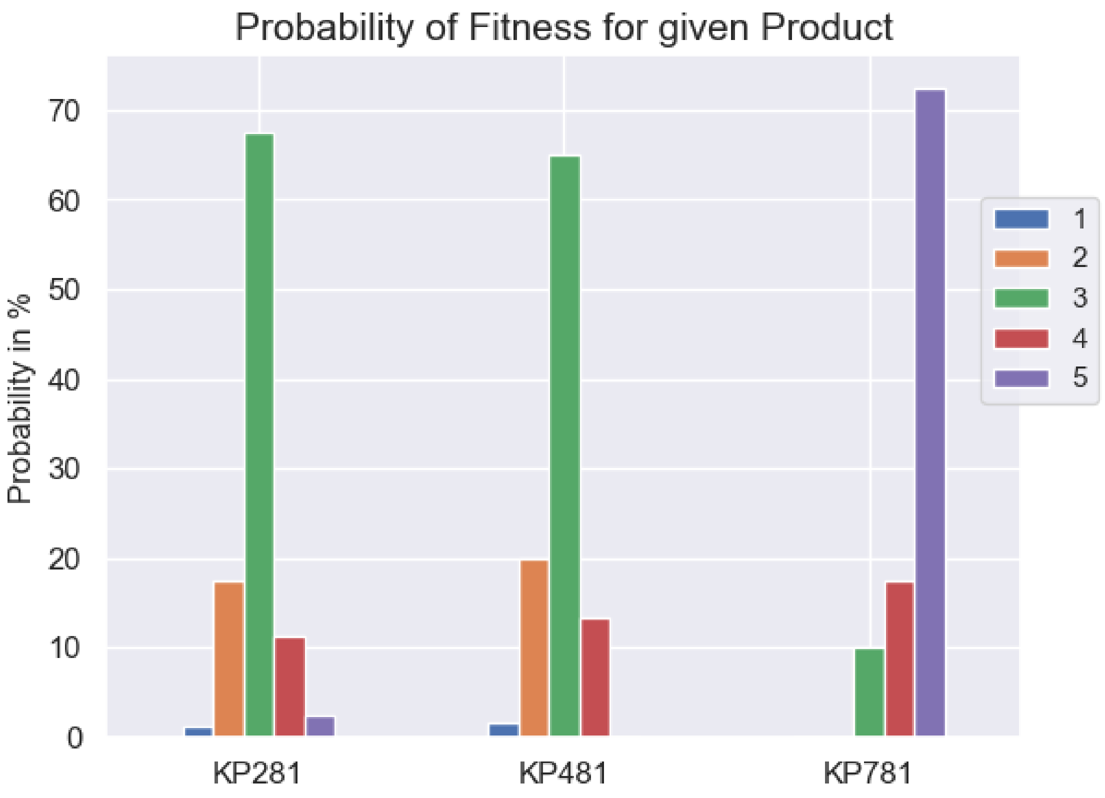
```
[ ]: (pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product & Fitness', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=2, ncol=1)
     plt.show()
```



```
[ ]: (pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product for given Fitness', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=1, ncol=1)
     plt.show()
```

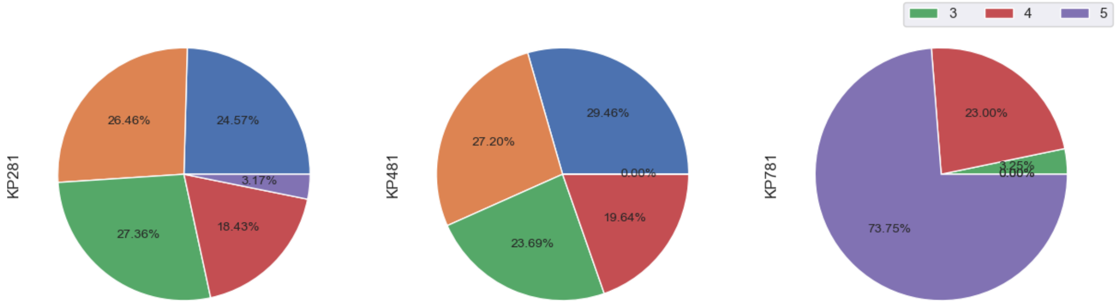


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['Fitness'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Fitness for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize="index").
      ↪plot(kind='pie', subplots=True, figsize=(15,5), labeldistance=None,␣
      ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=5)
     plt.show()
```



1.3.9 Usage

```
[ ]: aerofit['Usage'].unique()
```

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

```
[ ]: aerofit['Usage'].value_counts()
```

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

```
[ ]: aerofit['Usage'].value_counts(normalize=True)*100
```

```
[ ]: 3    38.333333
     4    28.888889
     2    18.333333
     5     9.444444
     6     3.888889
     7     1.111111
     Name: Usage, dtype: float64
```

Statitical Analysis

```
[ ]: aerofit['Usage'].describe()
```

```
[ ]: count    180.000000
     mean       3.455556
     std        1.084797
     min        2.000000
     25%        3.000000
     50%        3.000000
     75%        4.000000
     max        7.000000
     Name: Usage, dtype: float64
```

```
[ ]: aerofit['Usage'].mean()
```

```
[ ]: 3.4555555555555557
```

```
[ ]: aerofit['Usage'].median()
```

```
[ ]: 3.0
```

```
[ ]: aerofit['Usage'].mode()[0]
[ ]: 3
```

```
[ ]: aerofit.groupby('Product')["Usage"].describe()
```

```
[ ]:          count      mean       std  min  25%  50%   75%  max
     Product
     KP281     80.0  3.087500  0.782624  2.0  3.0  3.0  4.00  5.0
     KP481     60.0  3.066667  0.799717  2.0  3.0  3.0  3.25  5.0
     KP781     40.0  4.775000  0.946993  3.0  4.0  5.0  5.00  7.0
```

Check for Outliers

```
[ ]: check_outlier(aerofit, 'Usage')['upper']
```

```
[ ]: {'list': 154    6
      155    6
      162    6
      163    7
      164    6
      166    7
      167    6
      170    6
      175    6
      Name: Usage, dtype: int64,
      'length': 9}
```

```
[ ]: check_outlier(aerofit, 'Usage')['lower']
```

```
[ ]: {'list': Series([], Name: Usage, dtype: int64), 'length': 0}
```

Find Probability

Probability of a Product & Usage across all Combination “*Product Usage*”

```
[ ]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481      KP781         All
     Usage
     2        10.555556   7.777778   0.000000   18.333333
     3        20.555556  17.222222   0.555556   38.333333
     4        12.222222   6.666667  10.000000   28.888889
     5         1.111111   1.666667   6.666667    9.444444
     6         0.000000   0.000000   3.888889    3.888889
     7         0.000000   0.000000   1.111111    1.111111
     All      44.444444  33.333333  22.222222  100.000000
```

Probability of Product's for given Usage “*Product* | *Usage*”

```
[ ]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize='index',␣
      ↪margins=True)*100
```

```
[ ]: Product      KP281      KP481       KP781
     Usage
     2        57.575758  42.424242    0.000000
     3        53.623188  44.927536    1.449275
     4        42.307692  23.076923   34.615385
     5        11.764706  17.647059   70.588235
     6         0.000000   0.000000  100.000000
     7         0.000000   0.000000  100.000000
     All      44.444444  33.333333   22.222222
```

Probability of Usage for given Product *“Fitness | Product”*

```
[ ]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize='columns',␣
      ↪margins=True)*100
```

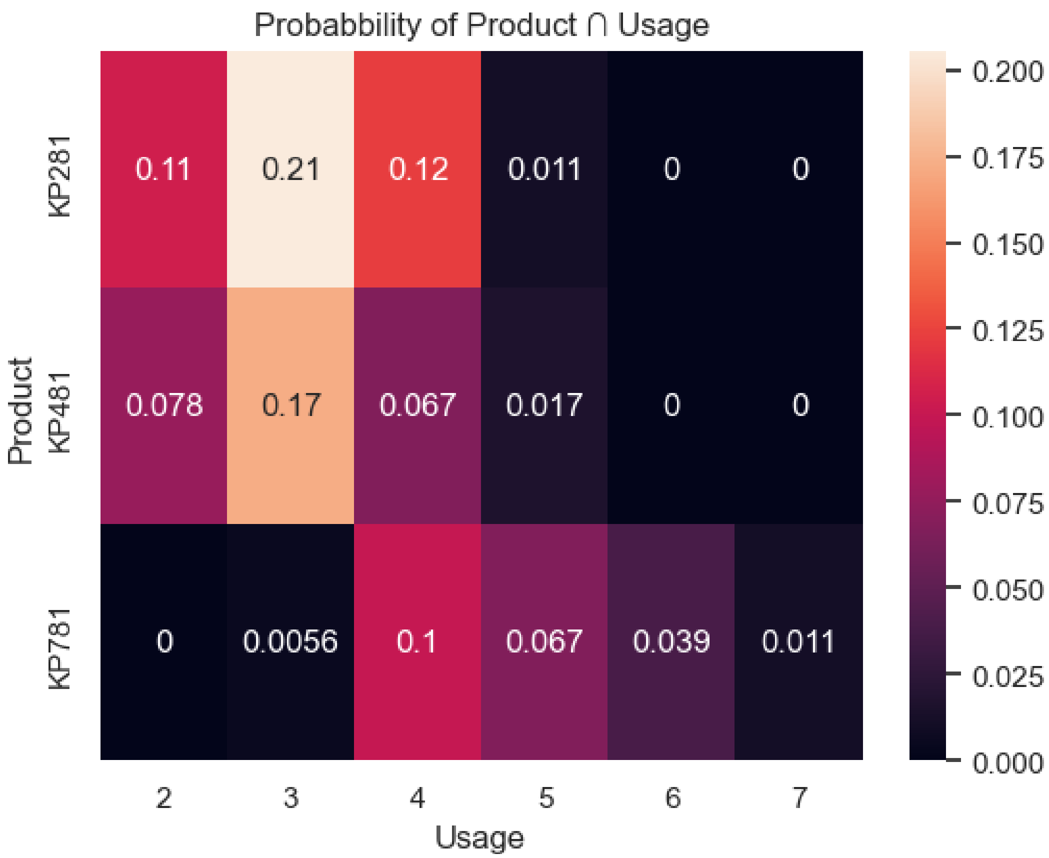
```
[ ]: Product  KP281      KP481  KP781        All
     Usage
     2        23.75  23.333333    0.0  18.333333
     3        46.25  51.666667    2.5  38.333333
     4        27.50  20.000000   45.0  28.888889
     5         2.50   5.000000   30.0   9.444444
     6         0.00   0.000000   17.5   3.888889
     7         0.00   0.000000    5.0   1.111111
```

Plot the Graph

Heat Map

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Usage'],␣
      ↪normalize='all'),annot=True)
     plt.title('Probabbility of Product  Usage', fontsize=12)
```

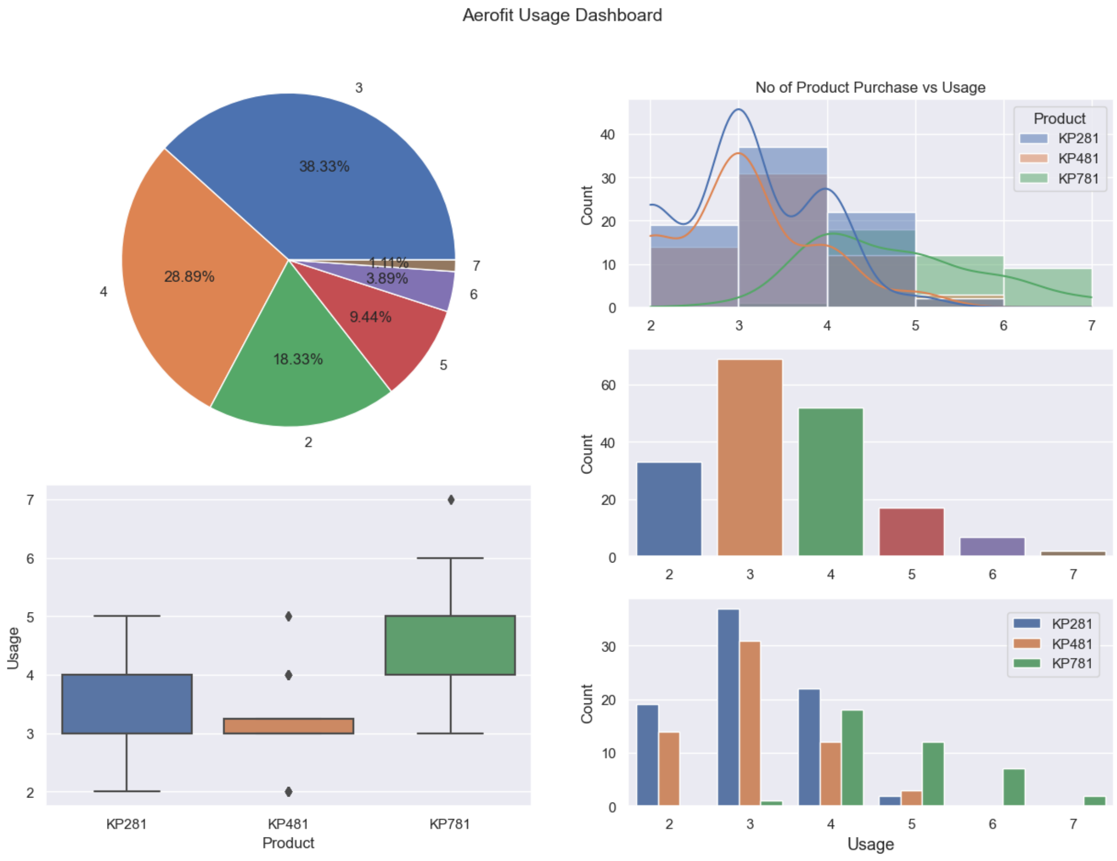
```
[ ]: Text(0.5, 1.0, 'Probabbility of Product  Usage')
```



Descriptive Plot

```
[ ]: plt.figure(figsize=(15,10)).suptitle("Aerofit Usage Dashboard",fontsize=14)

     plt.subplot(2, 2, 1)
     plt.pie(aerofit['Usage'].value_counts().values,labels = aerofit['Usage'].
      ↪value_counts().index,radius = 1.3,autopct = '%1.2f%%') # type: ignore

     plt.subplot(2, 2, 3)
     sns.boxplot(aerofit, y="Usage", x='Product')

     plt.subplot(3, 2, 2)
     sns.histplot(aerofit, x='Usage', binwidth=1, kde=True, hue="Product")
     plt.title('No of Product Purchase vs Usage', fontsize=12)
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)

     plt.subplot(3, 2, 4)
```

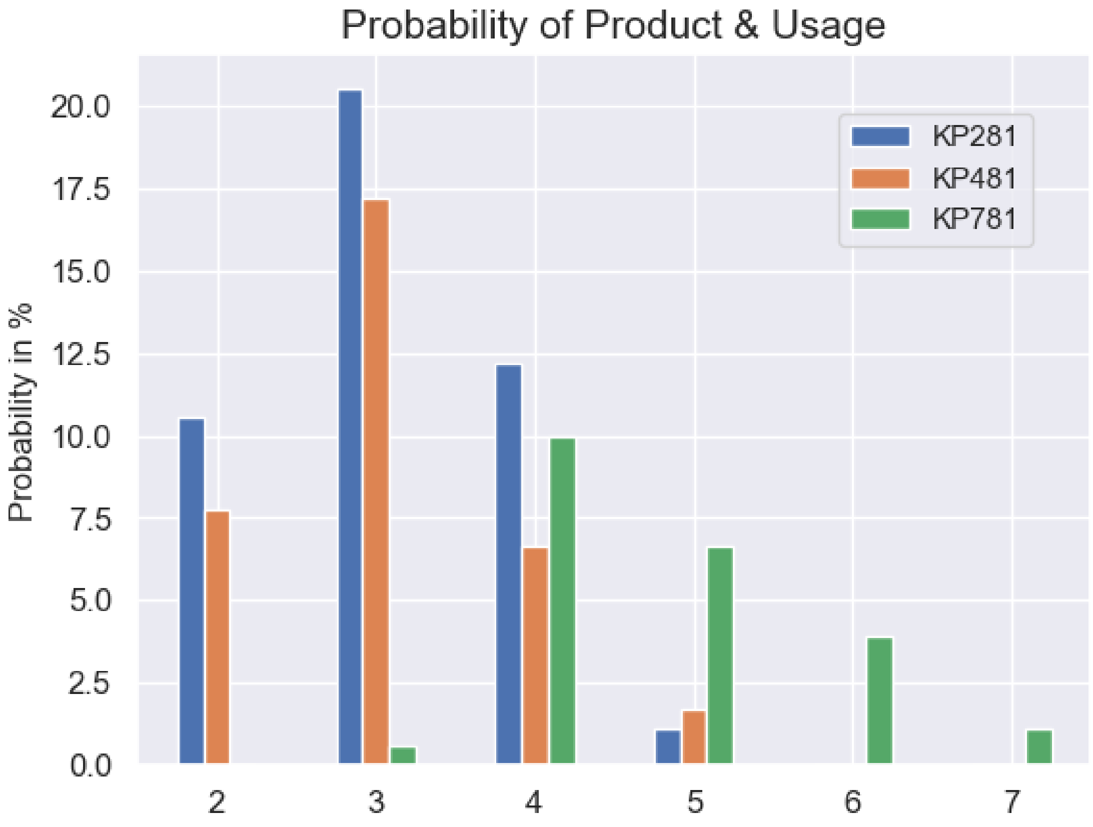
```
sns.countplot(aerofit, x='Usage')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='Usage', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Usage', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)

plt.show()
```



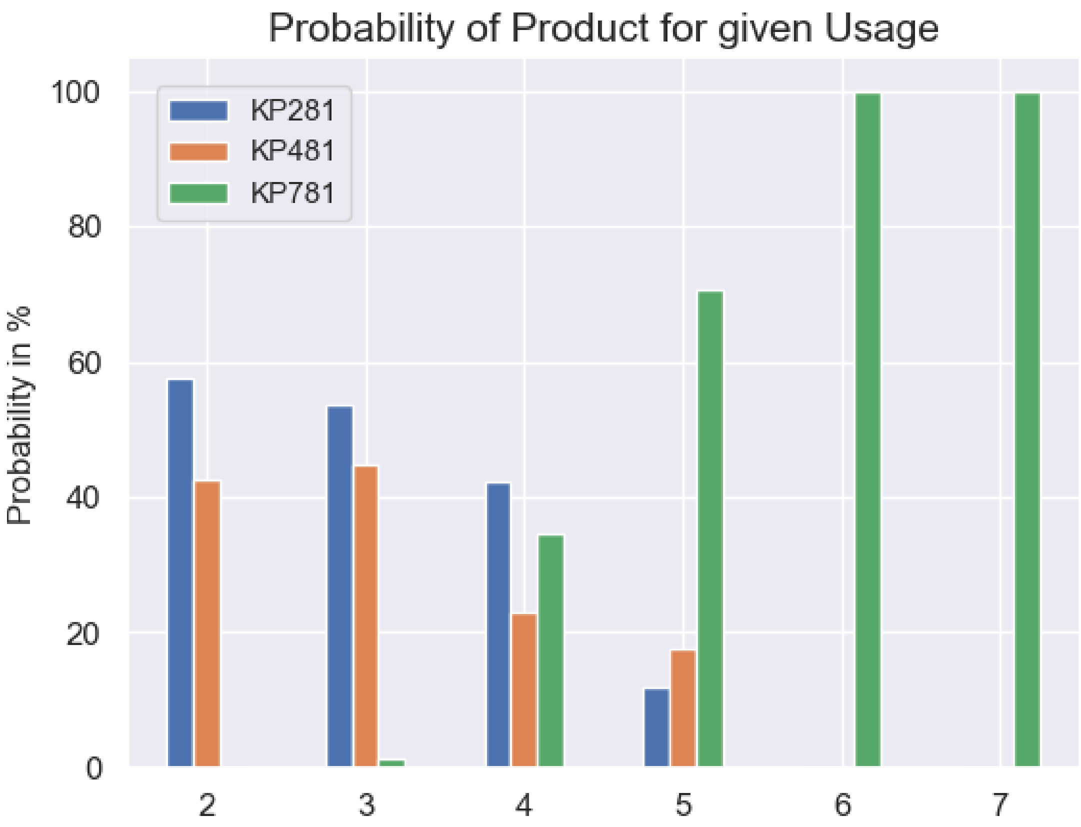
Probability Plot

```
[ ]: (pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize=True)*100).
      ↪plot(kind='bar')
```

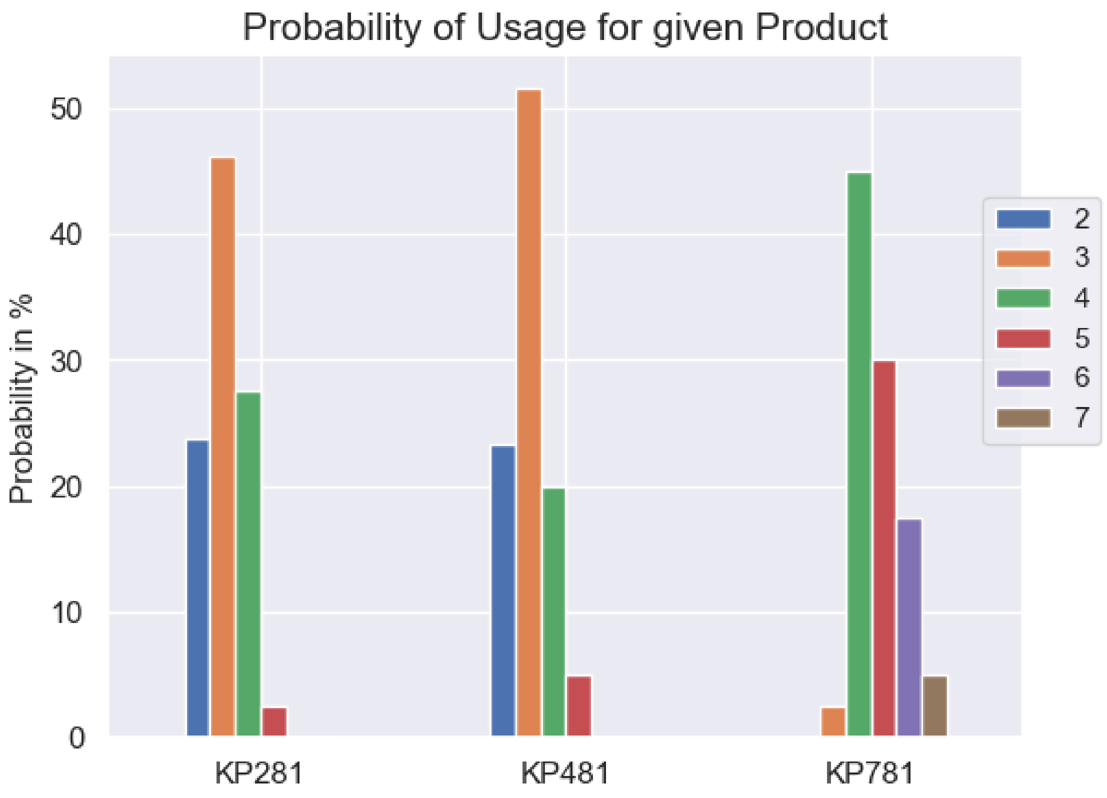
```
plt.title('Probability of Product & Usage', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=12)
plt.legend(borderaxespad=2, ncol=1)
plt.show()
```



```
[ ]: (pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Product for given Usage', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=1, ncol=1)
     plt.show()
```

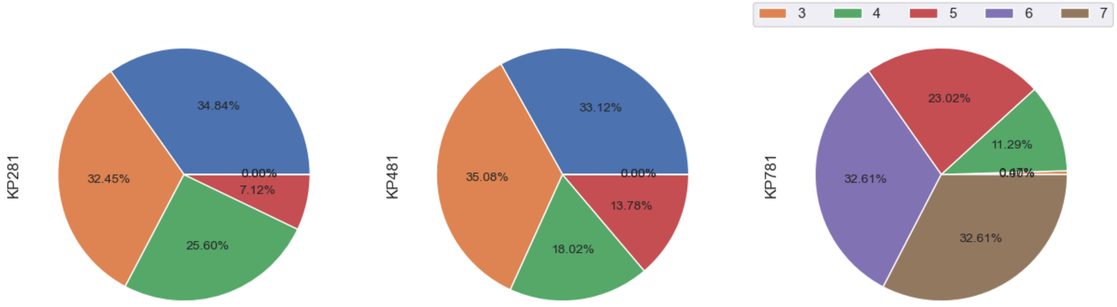


```
[ ]: (pd.crosstab(aerofit['Product'], aerofit['Usage'], normalize="index")*100).
      ↪plot(kind='bar')
     plt.title('Probability of Usage for given Product', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
     plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(bbox_to_anchor=(1.02, 1), loc='upper center', borderaxespad=5)

     plt.show()
```



Population Plot

```
[ ]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize="index").
     ↪plot(kind='pie', subplots=True, figsize=(15,5), labeldistance=None,␣
     ↪fontsize=10, legend=None, autopct = '%1.2f%%')
     plt.legend(borderaxespad=-1, ncol=5)
     plt.show()
```



1.4 Customer Profile of Different Product

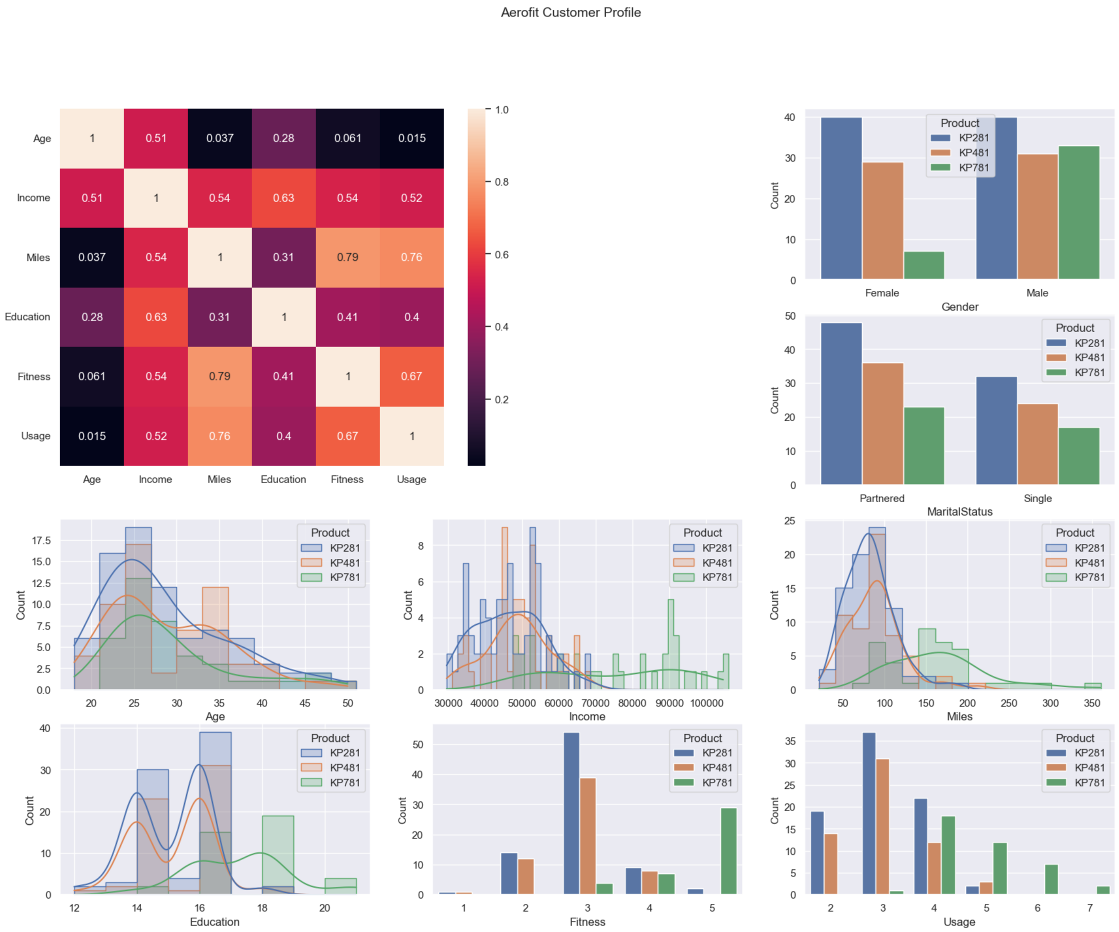
[ ]:

```
KP281 = aerofit.copy().loc[aerofit['Product']=='KP281']
KP481 = aerofit.copy().loc[aerofit['Product']=='KP481']
KP781 = aerofit.copy().loc[aerofit['Product']=='KP781']
```

1.4.1 Cummulative Profile

[ ]:

```
plt.figure(figsize=(20,15)).suptitle("Aerofit Customer Profile",fontsize=14)

plt.subplot(2, 2, 1)
sns.heatmap(aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness',␣
 ↪'Usage']].corr(), annot=True)
plt.yticks(rotation= 0, fontsize=11)
plt.xticks(fontsize=11)

plt.subplot(4, 3, 3)
sns.countplot(aerofit, x='Gender', hue="Product")
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 6)
sns.countplot(aerofit, x='MaritalStatus', hue="Product")
plt.ylabel("Count", fontsize=11)

plt.subplot(4, 3, 7)
sns.histplot(aerofit, x="Age", binwidth=3, kde=True, hue="Product",␣
 ↪element="step")
plt.subplot(4, 3, 8)
sns.histplot(aerofit, x="Income", binwidth=1500, kde=True, hue="Product",␣
 ↪element="step")
plt.subplot(4, 3, 9)
sns.histplot(aerofit, x="Miles", binwidth=20, kde=True, hue="Product",␣
 ↪element="step")

plt.subplot(4, 3, 10)
sns.histplot(aerofit, x="Education", binwidth=1, kde=True, hue="Product",␣
 ↪element="step")
plt.subplot(4, 3, 11)
sns.countplot(aerofit, x='Fitness', hue="Product")
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(aerofit, x='Usage', hue="Product")
plt.ylabel("Count", fontsize=11)

plt.show()
```



1.4.2 Profile of *KP281*

```
[ ]: KP281[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].
      ↪value_counts(normalize=True)[:5]*100
```

```
[ ]: Gender  MaritalStatus  Fitness  Usage  Age
     Female  Partnered      2        2      25     2.5
     Male    Partnered      3        3      38     2.5
     Female  Single         3        4      24     2.5
             Partnered      3        2      28     2.5
     Male    Single         3        4      23     2.5
     dtype: float64
```

Statitical Analysis

```
[ ]: KP281[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group',␣
      ↪'education_group', 'fitness_group', 'usage_group' ]].describe()
```

```
[ ]:        Gender MaritalStatus age_group income_group miles_group  \
     count      80            80        80           80          80
     unique      2             2         7            5           6
     top    Female     Partnered     20-25      45K-55K      80-110
     freq       40            48        28           35          27

            education_group  fitness_group  usage_group
     count               80             80           80
     unique               6              5            4
     top                 16              3            3
     freq                39             54           37
```

```
[ ]: KP281[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
```

```
[ ]:              Age        Income       Miles  Education   Fitness      Usage
     count  80.000000     80.00000   80.000000  80.000000  80.00000  80.000000
     mean   28.550000  46418.02500   82.787500  15.037500   2.96250   3.087500
     std     7.221452   9075.78319   28.874102   1.216383   0.66454   0.782624
     min    18.000000  29562.00000   38.000000  12.000000   1.00000   2.000000
     25%    23.000000  38658.00000   66.000000  14.000000   3.00000   3.000000
     50%    26.000000  46617.00000   85.000000  16.000000   3.00000   3.000000
     75%    33.000000  53439.00000   94.000000  16.000000   3.00000   4.000000
     max    50.000000  68220.00000  188.000000  18.000000   5.00000   5.000000
```

```
[ ]: KP281[['Age', 'Income', 'Miles', 'Education', 'Usage', 'Fitness']].median()
```

```
[ ]: Age              26.0
     Income        46617.0
     Miles            85.0
     Education        16.0
     Usage             3.0
     Fitness           3.0
     dtype: float64
```

Find Probability

```
[ ]: pd.crosstab([KP281.income_group], [KP281.age_group], normalize=True,␣
       ↪margins=True)*100
```

```
[ ]: age_group     15-20  20-25  25-30  30-35  35-40  40-45  45-50     All
     income_group
     25K-35K        6.25   3.75   0.00   0.00   0.00   0.00   0.00   10.00
     35K-45K        1.25  25.00   3.75   0.00   2.50   0.00   0.00   32.50
     45K-55K        0.00   6.25  21.25  10.00   3.75   2.50   0.00   43.75
     55K-65K        0.00   0.00   0.00   2.50   3.75   1.25   3.75   11.25
     65K-75K        0.00   0.00   1.25   1.25   0.00   0.00   0.00    2.50
     All            7.50  35.00  26.25  13.75  10.00   3.75   3.75  100.00
```

```
[ ]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281.
      ↪miles_group], normalize=True, margins=True)*100
```

```
[ ]: miles_group                    20-50  50-80  80-110  110-140  140-170  170-200  \
     Fitness Gender MaritalStatus
     1       Male   Partnered        1.25   0.00    0.00     0.00     0.00     0.00
     2       Female Partnered        6.25   2.50    0.00     0.00     0.00     0.00
                    Single           2.50   1.25    0.00     0.00     0.00     0.00
             Male   Partnered        5.00   0.00    0.00     0.00     0.00     0.00
     3       Female Partnered        0.00  12.50    8.75     1.25     0.00     0.00
                    Single           0.00   5.00    3.75     1.25     0.00     0.00
             Male   Partnered        0.00   7.50    8.75     0.00     0.00     0.00
                    Single           0.00   2.50   12.50     3.75     0.00     0.00
     4       Female Partnered        0.00   0.00    0.00     1.25     0.00     0.00
                    Single           0.00   1.25    0.00     1.25     0.00     0.00
             Male   Partnered        0.00   0.00    0.00     2.50     1.25     0.00
                    Single           0.00   0.00    0.00     2.50     1.25     0.00
     5       Female Partnered        0.00   0.00    0.00     0.00     0.00     1.25
             Male   Single           0.00   0.00    0.00     0.00     1.25     0.00
     All                            15.00  32.50   33.75    13.75     3.75     1.25

     miles_group                       All
     Fitness Gender MaritalStatus
     1       Male   Partnered         1.25
     2       Female Partnered         8.75
                    Single            3.75
             Male   Partnered         5.00
     3       Female Partnered        22.50
                    Single           10.00
             Male   Partnered        16.25
                    Single           18.75
     4       Female Partnered         1.25
                    Single            2.50
             Male   Partnered         3.75
                    Single            3.75
     5       Female Partnered         1.25
             Male   Single            1.25
     All                            100.00
```

```
[ ]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281.
      ↪age_group], normalize=True, margins=True)*100
```

```
[ ]: age_group                      15-20  20-25  25-30  30-35  35-40  40-45  45-50  \
     Fitness Gender MaritalStatus
     1       Male   Partnered        0.00   1.25   0.00   0.00   0.00   0.00   0.00
     2       Female Partnered        0.00   5.00   2.50   0.00   0.00   0.00   1.25
                    Single           0.00   0.00   0.00   3.75   0.00   0.00   0.00
```

```
        Male   Partnered       1.25   1.25   1.25   1.25   0.00   0.00   0.00
3       Female Partnered       2.50   5.00   8.75   2.50   2.50   0.00   1.25
               Single          0.00   7.50   1.25   1.25   0.00   0.00   0.00
        Male   Partnered       0.00   3.75   2.50   2.50   3.75   2.50   1.25
               Single          2.50   7.50   6.25   0.00   2.50   0.00   0.00
4       Female Partnered       0.00   0.00   1.25   0.00   0.00   0.00   0.00
               Single          0.00   0.00   0.00   1.25   0.00   1.25   0.00
        Male   Partnered       0.00   0.00   2.50   0.00   1.25   0.00   0.00
               Single          1.25   2.50   0.00   0.00   0.00   0.00   0.00
5       Female Partnered       0.00   1.25   0.00   0.00   0.00   0.00   0.00
        Male   Single          0.00   0.00   0.00   1.25   0.00   0.00   0.00
All                            7.50  35.00  26.25  13.75  10.00   3.75   3.75

age_group                        All
Fitness Gender MaritalStatus
1       Male   Partnered        1.25
2       Female Partnered        8.75
               Single           3.75
        Male   Partnered        5.00
3       Female Partnered       22.50
               Single          10.00
        Male   Partnered       16.25
               Single          18.75
4       Female Partnered        1.25
               Single           2.50
        Male   Partnered        3.75
               Single           3.75
5       Female Partnered        1.25
        Male   Single           1.25
All                           100.00
```

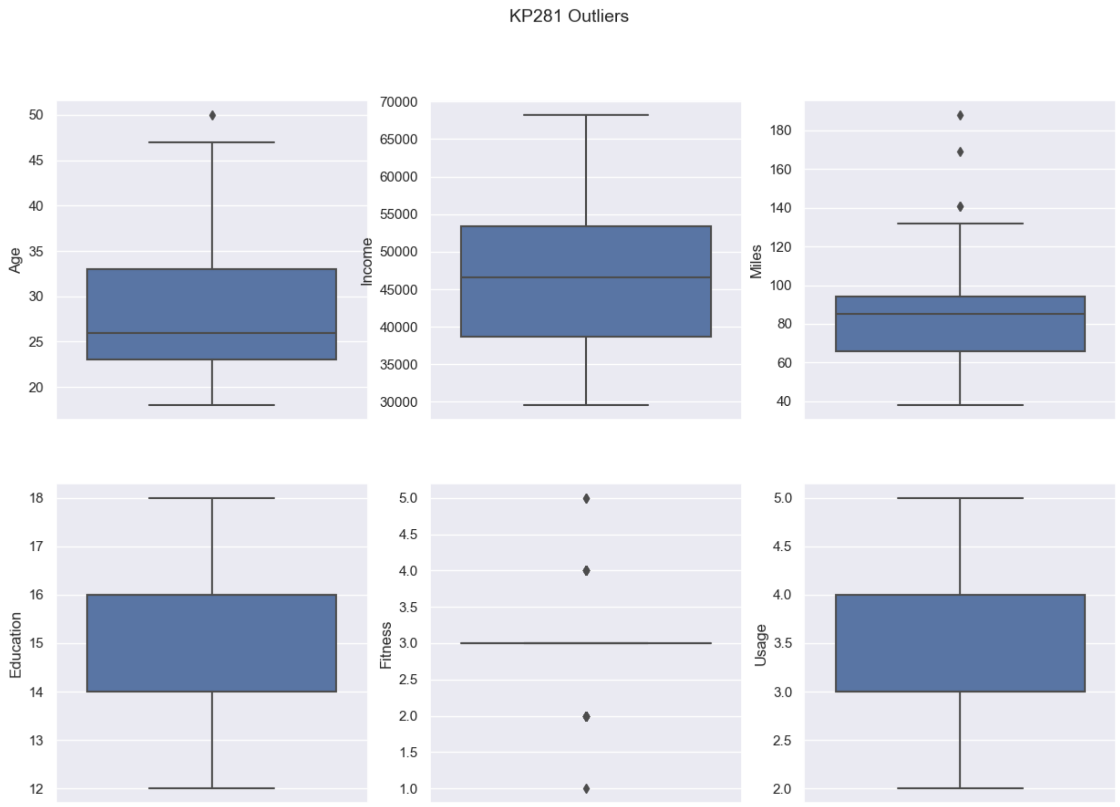
```
[ ]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281.
       ↪income_group], normalize=True, margins=True)*100
```

```
[ ]: income_group                  25K-35K  35K-45K  45K-55K  55K-65K  65K-75K  \
     Fitness Gender MaritalStatus
     1       Male   Partnered         0.00     1.25     0.00     0.00     0.00
     2       Female Partnered         1.25     2.50     3.75     1.25     0.00
                    Single            0.00     0.00     2.50     1.25     0.00
             Male   Partnered         0.00     2.50     2.50     0.00     0.00
     3       Female Partnered         2.50     5.00    12.50     2.50     0.00
                    Single            1.25     6.25     1.25     0.00     1.25
             Male   Partnered         0.00     2.50     8.75     3.75     1.25
                    Single            3.75     6.25     8.75     0.00     0.00
     4       Female Partnered         0.00     1.25     0.00     0.00     0.00
                    Single            0.00     0.00     1.25     1.25     0.00
             Male   Partnered         0.00     1.25     1.25     1.25     0.00
```

```
                  Single          1.25     2.50     0.00     0.00     0.00
5       Female Partnered          0.00     1.25     0.00     0.00     0.00
        Male   Single             0.00     0.00     1.25     0.00     0.00
All                              10.00    32.50    43.75    11.25     2.50

income_group                       All
Fitness Gender MaritalStatus
1       Male   Partnered          1.25
2       Female Partnered          8.75
               Single             3.75
        Male   Partnered          5.00
3       Female Partnered         22.50
               Single            10.00
        Male   Partnered         16.25
               Single            18.75
4       Female Partnered          1.25
               Single             2.50
        Male   Partnered          3.75
               Single             3.75
5       Female Partnered          1.25
        Male   Single             1.25
All                             100.00
```

Check for Outliers

[ ]:
```
plt.figure(figsize=(15,10)).suptitle("KP281 Outliers",fontsize=14)

plt.subplot(2, 3, 1)
sns.boxplot(KP281, y="Age")
plt.subplot(2, 3, 2)
sns.boxplot(KP281, y="Income")

plt.subplot(2, 3, 3)
sns.boxplot(KP281, y="Miles")
plt.subplot(2, 3, 4)
sns.boxplot(KP281, y="Education")

plt.subplot(2, 3, 5)
sns.boxplot(KP281, y='Fitness')
plt.subplot(2, 3, 6)
sns.boxplot(KP281, y='Usage')

plt.show()
```

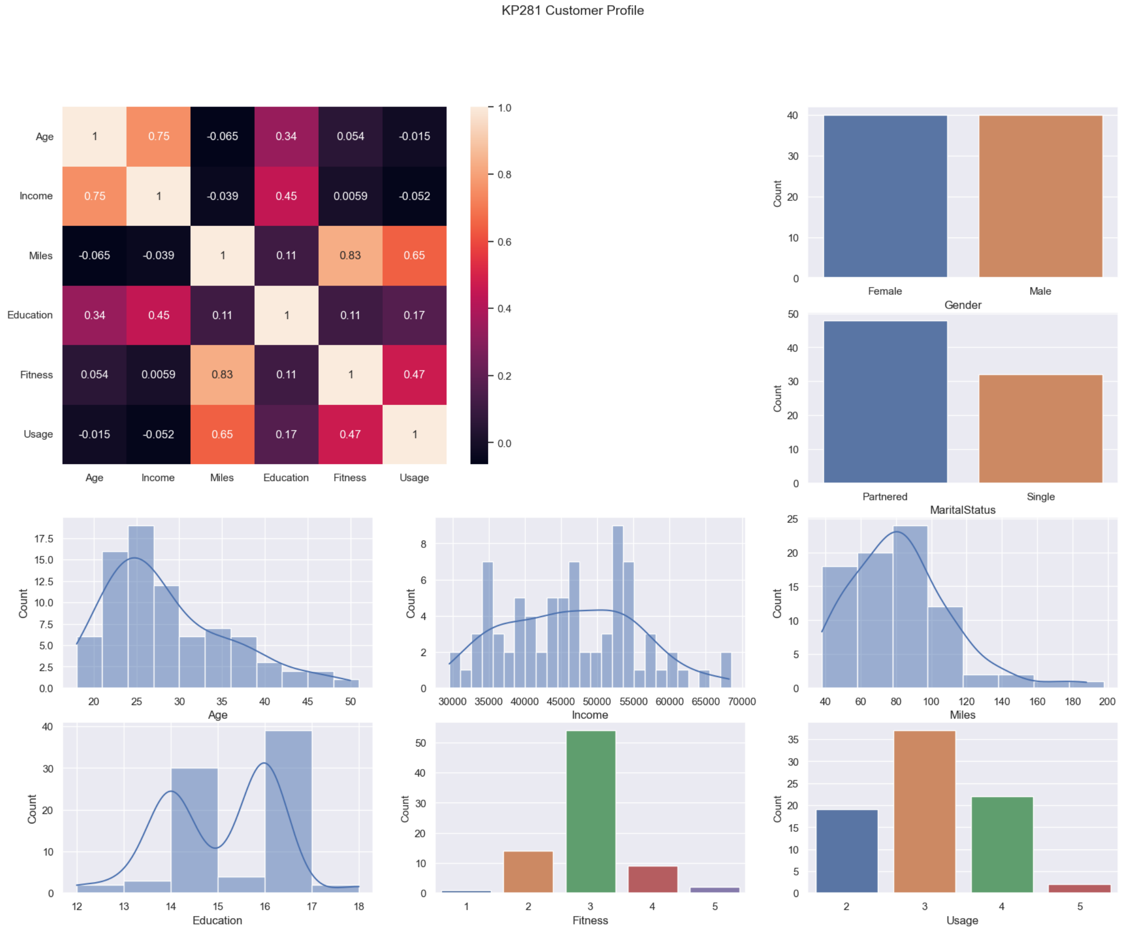


Plot the Graph

[ ]:

```
plt.figure(figsize=(20,15)).suptitle("KP281 Customer Profile",fontsize=14)

plt.subplot(2, 2, 1)
sns.heatmap(KP281[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].corr(), annot=True)
plt.yticks(rotation= 0, fontsize=11)
plt.xticks(fontsize=11)

plt.subplot(4, 3, 3)
sns.countplot(KP281, x='Gender')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 6)
sns.countplot(KP281, x='MaritalStatus')
plt.ylabel("Count", fontsize=11)

plt.subplot(4, 3, 7)
sns.histplot(KP281, x="Age", binwidth=3, kde=True)
plt.subplot(4, 3, 8)
sns.histplot(KP281, x="Income", binwidth=1500, kde=True)
plt.subplot(4, 3, 9)
```

```
sns.histplot(KP281, x="Miles", binwidth=20, kde=True)

plt.subplot(4, 3, 10)
sns.histplot(KP281, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP281, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP281, x='Usage')
plt.ylabel("Count", fontsize=11)

plt.show()
```



	Age	Income	Miles	Education	Fitness	Usage
Age	1	0.75	-0.065	0.34	0.054	-0.015
Income	0.75	1	-0.039	0.45	0.0059	-0.052
Miles	-0.065	-0.039	1	0.11	0.83	0.65
Education	0.34	0.45	0.11	1	0.11	0.17
Fitness	0.054	0.0059	0.83	0.11	1	0.47
Usage	-0.015	-0.052	0.65	0.17	0.47	1

Insight * There are highest number of customer have covered `70 miles`.

1.4.3 Profile of *KP481*

```
[ ]: KP481[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].
      ↪value_counts(normalize=True)[:5]*100
```

```
[ ]: Gender  MaritalStatus  Fitness  Usage  Age
     Male    Partnered      3        3      23     5.000000
                            2        2      21     3.333333
     Female  Partnered      2        3      23     1.666667
     Male    Partnered      2        2      45     1.666667
                                     3      35     1.666667
     dtype: float64
```

Statitical Analysis

```
[ ]: KP481[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group',␣
      ↪'education_group', 'fitness_group', 'usage_group' ]].describe()
```

```
[ ]:        Gender MaritalStatus age_group income_group miles_group  \
     count      60            60        60           60          60
     unique      2             2         7            5           6
     top      Male     Partnered     20-25      45K-55K      80-110
     freq       31            36        24           33          31

            education_group  fitness_group  usage_group
     count               60             60           60
     unique               6              4            4
     top                 16              3            3
     freq                31             39           31
```

```
[ ]: KP481[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
```

```
[ ]:              Age        Income       Miles  Education   Fitness      Usage
     count  60.000000     60.000000   60.000000  60.000000  60.00000  60.000000
     mean   28.900000  48973.650000   87.933333  15.116667   2.90000   3.066667
     std     6.645248   8653.989388   33.263135   1.222552   0.62977   0.799717
     min    19.000000  31836.000000   21.000000  12.000000   1.00000   2.000000
     25%    24.000000  44911.500000   64.000000  14.000000   3.00000   3.000000
     50%    26.000000  49459.500000   85.000000  16.000000   3.00000   3.000000
     75%    33.250000  53439.000000  106.000000  16.000000   3.00000   3.250000
     max    48.000000  67083.000000  212.000000  18.000000   4.00000   5.000000
```

```
[ ]: KP481[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
```

```
[ ]: Age             26.0
     Income       49459.5
     Miles           85.0
     Education       16.0
     Fitness          3.0
```

```
Usage              3.0
dtype: float64
```

Find Probability

```
[ ]: pd.crosstab([KP481.income_group], [KP481.age_group], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: age_group        15-20      20-25      25-30      30-35      35-40     40-45  \
     income_group
     25K-35K       5.000000   5.000000   0.000000   0.000000   0.000000  0.000000
     35K-45K       1.666667  13.333333   0.000000   0.000000   0.000000  0.000000
     45K-55K       0.000000  21.666667  10.000000  20.000000   1.666667  1.666667
     55K-65K       0.000000   0.000000   1.666667   5.000000   8.333333  0.000000
     65K-75K       0.000000   0.000000   0.000000   3.333333   0.000000  0.000000
     All           6.666667  40.000000  11.666667  28.333333  10.000000  1.666667

     age_group        45-50         All
     income_group
     25K-35K       0.000000   10.000000
     35K-45K       0.000000   15.000000
     45K-55K       0.000000   55.000000
     55K-65K       1.666667   16.666667
     65K-75K       0.000000    3.333333
     All           1.666667  100.000000
```

```
[ ]: pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.
      ↪miles_group], normalize=True, margins=True)*100
```

```
[ ]: miles_group                      20-50      50-80     80-110    110-140  \
     Fitness Gender MaritalStatus
     1       Female Single         1.666667   0.000000   0.000000   0.000000
     2       Female Partnered      0.000000   3.333333   0.000000   0.000000
                    Single         1.666667   3.333333   1.666667   0.000000
             Male   Partnered      5.000000   3.333333   0.000000   0.000000
                    Single         0.000000   1.666667   0.000000   0.000000
     3       Female Partnered      0.000000   1.666667  18.333333   0.000000
                    Single         0.000000   3.333333   6.666667   0.000000
             Male   Partnered      0.000000   5.000000  13.333333   1.666667
                    Single         0.000000   3.333333   6.666667   3.333333
     4       Female Partnered      0.000000   0.000000   0.000000   0.000000
                    Single         0.000000   1.666667   0.000000   3.333333
             Male   Partnered      0.000000   0.000000   3.333333   0.000000
                    Single         0.000000   0.000000   1.666667   0.000000
     All                           8.333333  26.666667  51.666667   8.333333

     miles_group                     140-170   200-230         All
     Fitness Gender MaritalStatus
```

```
1       Female Single         0.000000  0.000000    1.666667
2       Female Partnered      0.000000  0.000000    3.333333
               Single         0.000000  0.000000    6.666667
        Male   Partnered      0.000000  0.000000    8.333333
               Single         0.000000  0.000000    1.666667
3       Female Partnered      0.000000  0.000000   20.000000
               Single         0.000000  0.000000   10.000000
        Male   Partnered      1.666667  0.000000   21.666667
               Single         0.000000  0.000000   13.333333
4       Female Partnered      0.000000  1.666667    1.666667
               Single         0.000000  0.000000    5.000000
        Male   Partnered      1.666667  0.000000    5.000000
               Single         0.000000  0.000000    1.666667
All                           3.333333  1.666667  100.000000
```

[ ]:

```
pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.
 ↪age_group], normalize=True, margins=True)*100
```

[ ]:

```
age_group                        15-20      20-25      25-30      30-35  \
Fitness Gender MaritalStatus
1       Female Single         0.000000   0.000000   0.000000   1.666667
2       Female Partnered      0.000000   1.666667   0.000000   1.666667
               Single         0.000000   5.000000   0.000000   1.666667
        Male   Partnered      0.000000   5.000000   0.000000   1.666667
               Single         0.000000   0.000000   1.666667   0.000000
3       Female Partnered      1.666667   3.333333   3.333333   6.666667
               Single         0.000000   5.000000   3.333333   0.000000
        Male   Partnered      0.000000  10.000000   0.000000   6.666667
               Single         5.000000   3.333333   1.666667   3.333333
4       Female Partnered      0.000000   1.666667   0.000000   0.000000
               Single         0.000000   1.666667   1.666667   1.666667
        Male   Partnered      0.000000   1.666667   0.000000   3.333333
               Single         0.000000   1.666667   0.000000   0.000000
All                           6.666667  40.000000  11.666667  28.333333

age_group                         35-40     40-45     45-50        All
Fitness Gender MaritalStatus
1       Female Single          0.000000  0.000000  0.000000   1.666667
2       Female Partnered       0.000000  0.000000  0.000000   3.333333
               Single          0.000000  0.000000  0.000000   6.666667
        Male   Partnered       0.000000  1.666667  0.000000   8.333333
               Single          0.000000  0.000000  0.000000   1.666667
3       Female Partnered       5.000000  0.000000  0.000000  20.000000
               Single          1.666667  0.000000  0.000000  10.000000
        Male   Partnered       3.333333  0.000000  1.666667  21.666667
               Single          0.000000  0.000000  0.000000  13.333333
4       Female Partnered       0.000000  0.000000  0.000000   1.666667
```

```
               Single           0.000000  0.000000  0.000000    5.000000
        Male   Partnered        0.000000  0.000000  0.000000    5.000000
               Single           0.000000  0.000000  0.000000    1.666667
All                            10.000000  1.666667  1.666667  100.000000
```

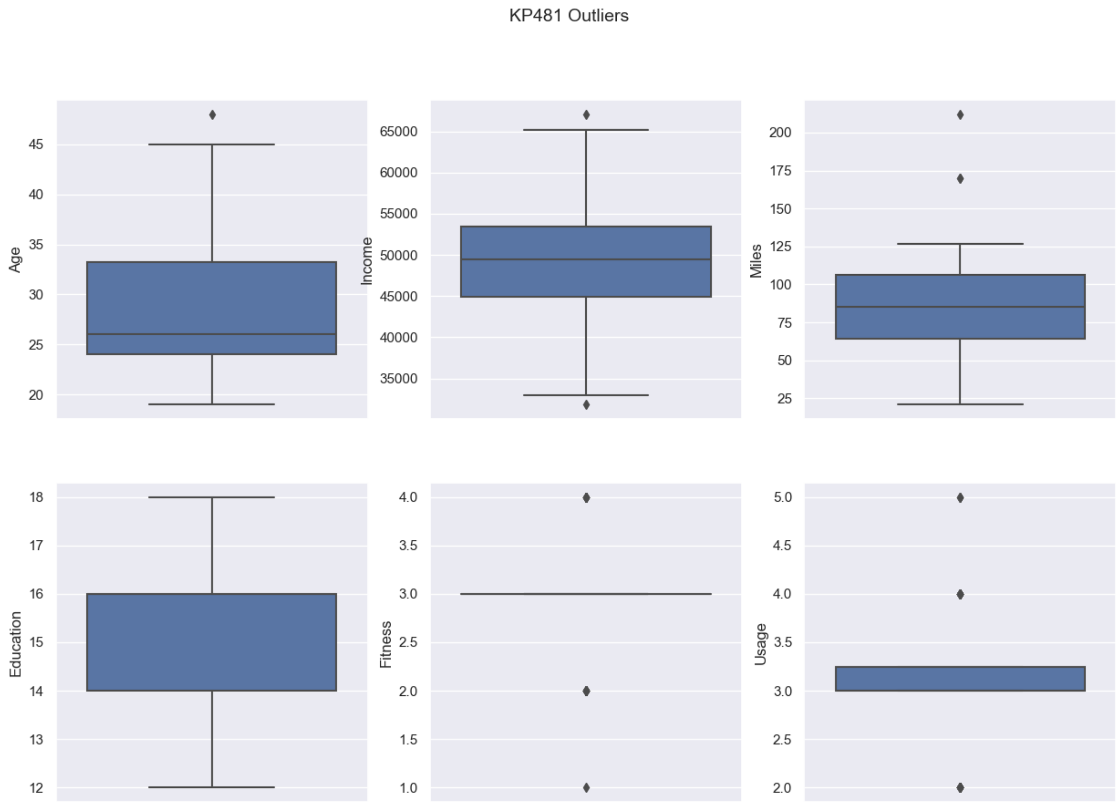
```
[ ]: pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.
      ↪income_group], normalize=True, margins=True)*100
```

```
[ ]: income_group                    25K-35K    35K-45K    45K-55K    55K-65K  \
     Fitness Gender MaritalStatus
     1       Female Single          0.000000   0.000000   0.000000   0.000000
     2       Female Partnered       0.000000   1.666667   1.666667   0.000000
                    Single          0.000000   3.333333   3.333333   0.000000
             Male   Partnered       3.333333   0.000000   5.000000   0.000000
                    Single          0.000000   0.000000   1.666667   0.000000
     3       Female Partnered       1.666667   0.000000  13.333333   5.000000
                    Single          0.000000   1.666667   5.000000   3.333333
             Male   Partnered       0.000000   3.333333  13.333333   5.000000
                    Single          3.333333   1.666667   5.000000   1.666667
     4       Female Partnered       1.666667   0.000000   0.000000   0.000000
                    Single          0.000000   1.666667   3.333333   0.000000
             Male   Partnered       0.000000   1.666667   1.666667   1.666667
                    Single          0.000000   0.000000   1.666667   0.000000
     All                           10.000000  15.000000  55.000000  16.666667

     income_group                   65K-75K         All
     Fitness Gender MaritalStatus
     1       Female Single         1.666667    1.666667
     2       Female Partnered      0.000000    3.333333
                    Single         0.000000    6.666667
             Male   Partnered      0.000000    8.333333
                    Single         0.000000    1.666667
     3       Female Partnered      0.000000   20.000000
                    Single         0.000000   10.000000
             Male   Partnered      0.000000   21.666667
                    Single         1.666667   13.333333
     4       Female Partnered      0.000000    1.666667
                    Single         0.000000    5.000000
             Male   Partnered      0.000000    5.000000
                    Single         0.000000    1.666667
     All                           3.333333  100.000000
```

Check for Outliers

```
[ ]: plt.figure(figsize=(15,10)).suptitle("KP481 Outliers",fontsize=14)

     plt.subplot(2, 3, 1)
     sns.boxplot(KP481, y="Age")
```

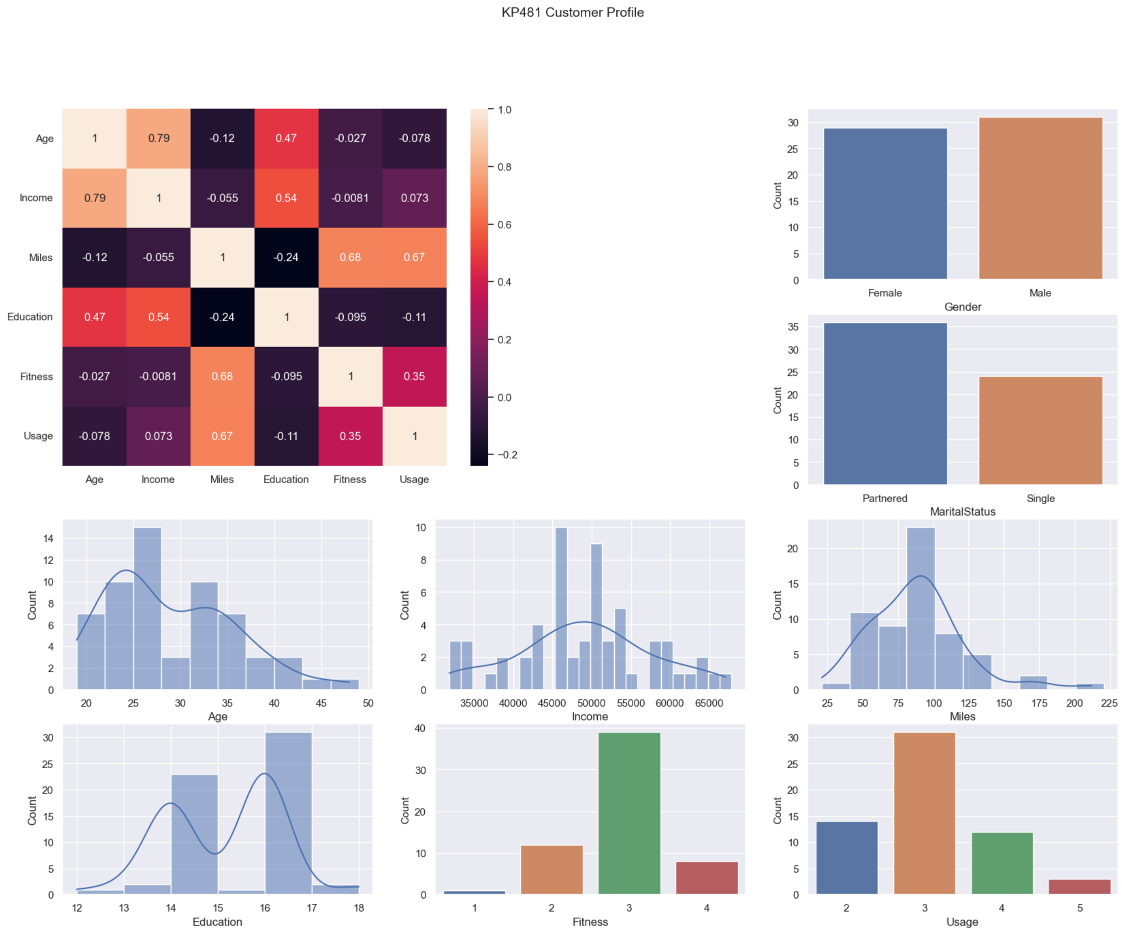
```
plt.subplot(2, 3, 2)
sns.boxplot(KP481, y="Income")

plt.subplot(2, 3, 3)
sns.boxplot(KP481, y="Miles")
plt.subplot(2, 3, 4)
sns.boxplot(KP481, y="Education")

plt.subplot(2, 3, 5)
sns.boxplot(KP481, y='Fitness')
plt.subplot(2, 3, 6)
sns.boxplot(KP481, y='Usage')

plt.show()
```



Plot the Graph

```
[ ]: plt.figure(figsize=(20,15)).suptitle("KP481 Customer Profile",fontsize=14)

plt.subplot(2, 2, 1)
sns.heatmap(KP481[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].corr(), annot=True)
```

```
plt.yticks(rotation= 0, fontsize=11)
plt.xticks(fontsize=11)

plt.subplot(4, 3, 3)
sns.countplot(KP481, x='Gender')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 6)
sns.countplot(KP481, x='MaritalStatus')
plt.ylabel("Count", fontsize=11)

plt.subplot(4, 3, 7)
sns.histplot(KP481, x="Age", binwidth=3, kde=True)
plt.subplot(4, 3, 8)
sns.histplot(KP481, x="Income", binwidth=1500, kde=True)
plt.subplot(4, 3, 9)
sns.histplot(KP481, x="Miles", binwidth=20, kde=True)

plt.subplot(4, 3, 10)
sns.histplot(KP481, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP481, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP481, x='Usage')
plt.ylabel("Count", fontsize=11)

plt.show()
```



Insight * There are highest number of customer have covered `70 miles`.

1.4.4 Profile of *KP781*

```
[ ]: KP781[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].
      ↪value_counts(normalize=True)[:5]*100
```

```
[ ]: Gender  MaritalStatus  Fitness  Usage  Age
     Male    Partnered      5        4      25     5.0
             Single         5        4      23     5.0
     Female  Partnered      5        4      33     2.5
     Male    Single         5        3      22     2.5
             Partnered      5        6      31     2.5
     dtype: float64
```

Statitical Analysis

```
[ ]: KP781[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group',␣
      ↪'education_group', 'fitness_group', 'usage_group' ]].describe()
```

```
[ ]:        Gender MaritalStatus age_group income_group miles_group  \
     count      40            40        40           40          40
     unique      2             2         6            6           9
     top      Male     Partnered     20-25      85K-95K     170-200
     freq       33            23        17           11          12

             education_group  fitness_group  usage_group
     count                40             40           40
     unique                5              3            5
     top                  18              5            4
     freq                 19             29           18
```

```
[ ]: KP781[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
```

```
[ ]:              Age         Income       Miles  Education    Fitness      Usage
     count  40.000000       40.00000   40.000000  40.000000  40.000000  40.000000
     mean   29.100000    75441.57500  166.900000  17.325000   4.625000   4.775000
     std     6.971738    18505.83672   60.066544   1.639066   0.667467   0.946993
     min    22.000000    48556.00000   80.000000  14.000000   3.000000   3.000000
     25%    24.750000    58204.75000  120.000000  16.000000   4.000000   4.000000
     50%    27.000000    76568.50000  160.000000  18.000000   5.000000   5.000000
     75%    30.250000    90886.00000  200.000000  18.000000   5.000000   5.000000
     max    48.000000   104581.00000  360.000000  21.000000   5.000000   7.000000
```

```
[ ]: KP781[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
```

```
[ ]: Age             27.0
     Income       76568.5
     Miles          160.0
     Education       18.0
     Fitness          5.0
     Usage            5.0
     dtype: float64
```

Find Probability

```
[ ]: pd.crosstab([KP781.income_group], [KP781.age_group], normalize=True,␣
      ↪margins=True)*100
```

```
[ ]: age_group     20-25  25-30  30-35  35-40  40-45  45-50   All
     income_group
     45K-55K        20.0    2.5    0.0    0.0    0.0    0.0  22.5
     55K-65K        15.0    2.5    0.0    0.0    0.0    0.0  17.5
     65K-75K         5.0    2.5    0.0    0.0    0.0    0.0   7.5
     75K-85K         2.5    5.0    0.0    2.5    0.0    0.0  10.0
```

```
85K-95K          0.0   15.0    7.5    0.0    5.0    0.0   27.5
95K-105K         0.0    5.0    2.5    2.5    0.0    5.0   15.0
All             42.5   32.5   10.0    5.0    5.0    5.0  100.0
```

[ ]:
```
pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781.
 ↪miles_group], normalize=True, margins=True)*100
```

[ ]:
```
miles_group                    50-80  80-110  110-140  140-170  170-200  \
Fitness Gender MaritalStatus
3       Female Single            0.0     2.5      0.0      0.0      0.0
        Male   Partnered         0.0     2.5      0.0      0.0      0.0
               Single            0.0     5.0      0.0      0.0      0.0
4       Female Single            0.0     2.5      0.0      0.0      0.0
        Male   Partnered         0.0     2.5      0.0      5.0      5.0
               Single            0.0     0.0      0.0      0.0      2.5
5       Female Partnered         0.0     0.0      0.0      0.0      7.5
               Single            0.0     0.0      0.0      0.0      2.5
        Male   Partnered         2.5     0.0      5.0     10.0      5.0
               Single            0.0     5.0      5.0     10.0      7.5
All                              2.5    20.0     10.0     25.0     30.0

miles_group                    230-260  260-290  290-320  350-380    All
Fitness Gender MaritalStatus
3       Female Single              0.0      0.0      0.0      0.0    2.5
        Male   Partnered           0.0      0.0      0.0      0.0    2.5
               Single              0.0      0.0      0.0      0.0    5.0
4       Female Single              0.0      0.0      0.0      0.0    2.5
        Male   Partnered           0.0      0.0      0.0      0.0   12.5
               Single              0.0      0.0      0.0      0.0    2.5
5       Female Partnered           0.0      2.5      0.0      0.0   10.0
               Single              0.0      0.0      0.0      0.0    2.5
        Male   Partnered           5.0      0.0      2.5      2.5   32.5
               Single              0.0      0.0      0.0      0.0   27.5
All                                5.0      2.5      2.5      2.5  100.0
```

[ ]:
```
pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781.
 ↪age_group], normalize=True, margins=True)*100
```

[ ]:
```
age_group                      20-25  25-30  30-35  35-40  40-45  45-50    All
Fitness Gender MaritalStatus
3       Female Single            0.0    2.5    0.0    0.0    0.0    0.0    2.5
        Male   Partnered         2.5    0.0    0.0    0.0    0.0    0.0    2.5
               Single            2.5    2.5    0.0    0.0    0.0    0.0    5.0
4       Female Single            2.5    0.0    0.0    0.0    0.0    0.0    2.5
        Male   Partnered         5.0    7.5    0.0    0.0    0.0    0.0   12.5
               Single            0.0    0.0    0.0    0.0    2.5    0.0    2.5
5       Female Partnered         2.5    5.0    2.5    0.0    0.0    0.0   10.0
```

```
                Single           2.5     0.0     0.0     0.0     0.0     0.0     2.5
        Male    Partnered       10.0    10.0     5.0     2.5     0.0     5.0    32.5
                Single          15.0     5.0     2.5     2.5     2.5     0.0    27.5
All                             42.5    32.5    10.0     5.0     5.0     5.0   100.0
```

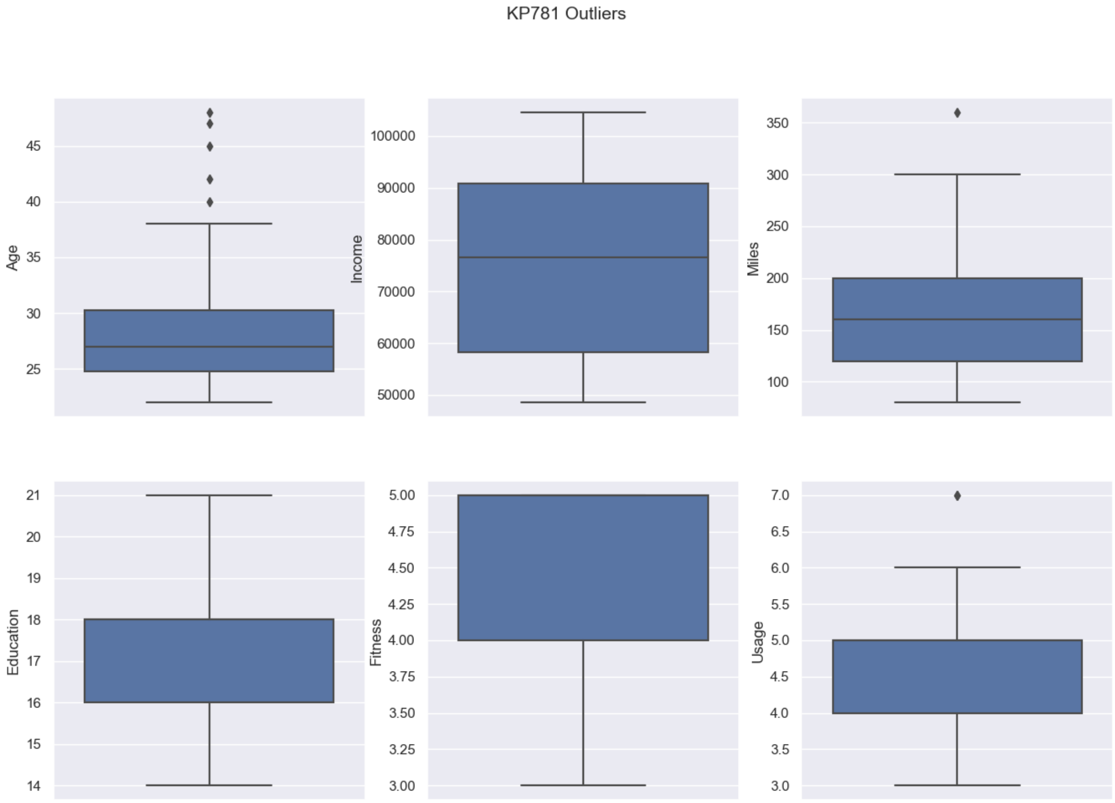
```
[ ]: pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781.
      ↪income_group], normalize=True, margins=True)*100
```

```
[ ]: income_group                  45K-55K  55K-65K  65K-75K  75K-85K  85K-95K  \
     Fitness Gender MaritalStatus
     3       Female Single             0.0      0.0      2.5      0.0      0.0
             Male   Partnered          0.0      2.5      0.0      0.0      0.0
                    Single             2.5      0.0      0.0      0.0      2.5
     4       Female Single             2.5      0.0      0.0      0.0      0.0
             Male   Partnered          0.0      5.0      2.5      0.0      2.5
                    Single             0.0      0.0      0.0      0.0      2.5
     5       Female Partnered          0.0      2.5      0.0      0.0      5.0
                    Single             2.5      0.0      0.0      0.0      0.0
             Male   Partnered          2.5      2.5      2.5      7.5      7.5
                    Single            12.5      5.0      0.0      2.5      7.5
     All                              22.5     17.5      7.5     10.0     27.5

     income_group                  95K-105K    All
     Fitness Gender MaritalStatus
     3       Female Single              0.0    2.5
             Male   Partnered           0.0    2.5
                    Single              0.0    5.0
     4       Female Single              0.0    2.5
             Male   Partnered           2.5   12.5
                    Single              0.0    2.5
     5       Female Partnered           2.5   10.0
                    Single              0.0    2.5
             Male   Partnered          10.0   32.5
                    Single              0.0   27.5
     All                               15.0  100.0
```

Check for Outliers

```
[ ]: plt.figure(figsize=(15,10)).suptitle("KP781 Outliers",fontsize=14)

     plt.subplot(2, 3, 1)
     sns.boxplot(KP781, y="Age")
     plt.subplot(2, 3, 2)
     sns.boxplot(KP781, y="Income")

     plt.subplot(2, 3, 3)
     sns.boxplot(KP781, y="Miles")
     plt.subplot(2, 3, 4)
```

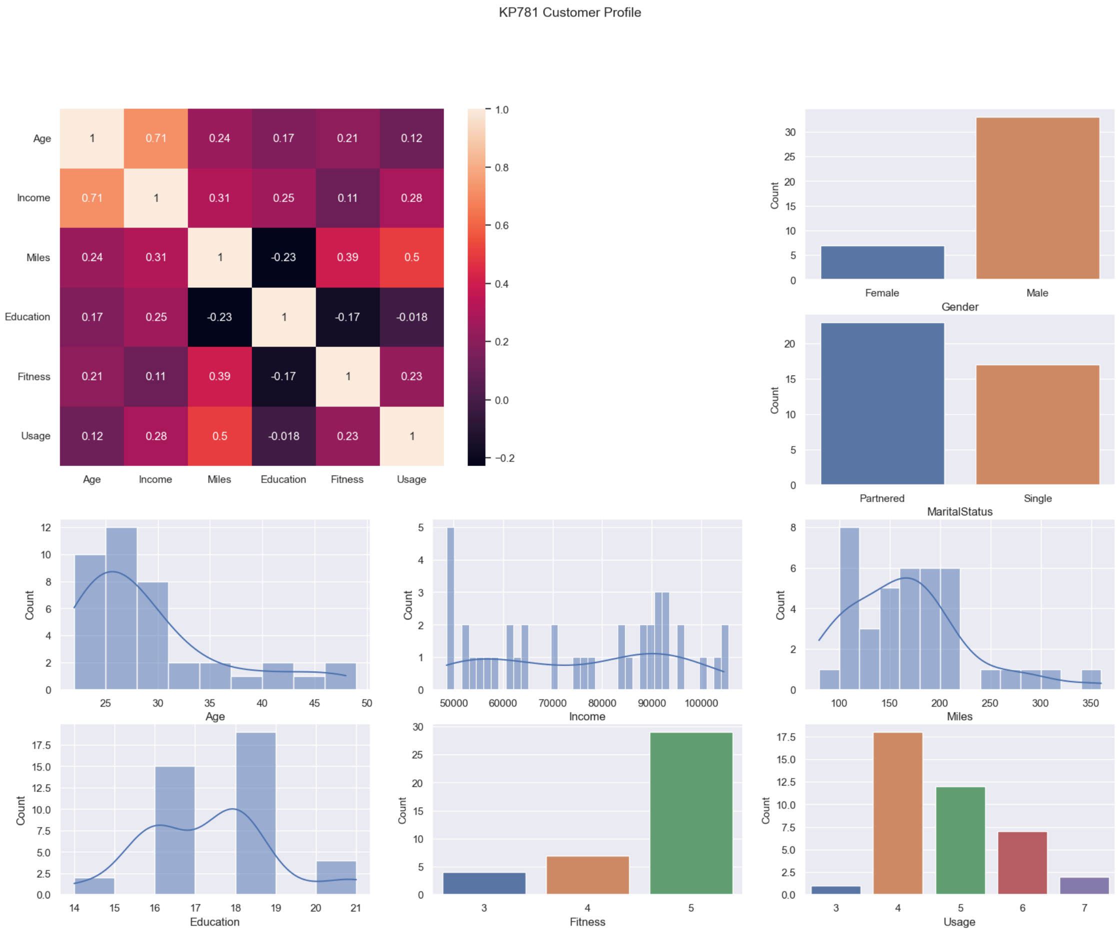
```
sns.boxplot(KP781, y="Education")

plt.subplot(2, 3, 5)
sns.boxplot(KP781, y='Fitness')
plt.subplot(2, 3, 6)
sns.boxplot(KP781, y='Usage')

plt.show()
```



Plot the Graph

```
[ ]: plt.figure(figsize=(20,15)).suptitle("KP781 Customer Profile",fontsize=14)

plt.subplot(2, 2, 1)
sns.heatmap(KP781[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].
 ↪corr(), annot=True)
plt.yticks(rotation= 0, fontsize=11)
plt.xticks(fontsize=11)

plt.subplot(4, 3, 3)
sns.countplot(KP781, x='Gender')
plt.ylabel("Count", fontsize=11)
```

```python
plt.subplot(4, 3, 6)
sns.countplot(KP781, x='MaritalStatus')
plt.ylabel("Count", fontsize=11)

plt.subplot(4, 3, 7)
sns.histplot(KP781, x="Age", binwidth=3, kde=True)
plt.subplot(4, 3, 8)
sns.histplot(KP781, x="Income", binwidth=1500, kde=True)
plt.subplot(4, 3, 9)
sns.histplot(KP781, x="Miles", binwidth=20, kde=True)

plt.subplot(4, 3, 10)
sns.histplot(KP781, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP781, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP781, x='Usage')
plt.ylabel("Count", fontsize=11)

plt.show()
```



Insight * There are highest number of customer have covered 70 miles.

1.5 Questions

1.5.1 Q0. What is the probability of a male customer buying a KP781 treadmill?

[ ]:
```
product_gender = pd.crosstab(aerofit['Gender'], aerofit['Product'],␣
  ↪normalize='index', margins=True)*100
product_gender
```

[ ]:
```
Product      KP281      KP481      KP781
Gender
Female   52.631579  38.157895   9.210526
Male     38.461538  29.807692  31.730769
All      44.444444  33.333333  22.222222
```

[ ]:
```
product_gender['KP781']['Male']
```

```
[ ]: 31.73076923076923
```

Insight * There is 31.73% chance a male customer will purchase KP781

1.5.2 Q1. What is the total count of each product present in the dataset?

```
[ ]: Products = aerofit.groupby("Product")["Age"].describe().T
```

```
[ ]: Products[:1]
```

```
[ ]: Product  KP281  KP481  KP781
     count     80.0   60.0   40.0
```

```
[ ]: Products[:1]/1.8
```

```
[ ]: Product      KP281      KP481      KP781
     count    44.444444  33.333333  22.222222
```

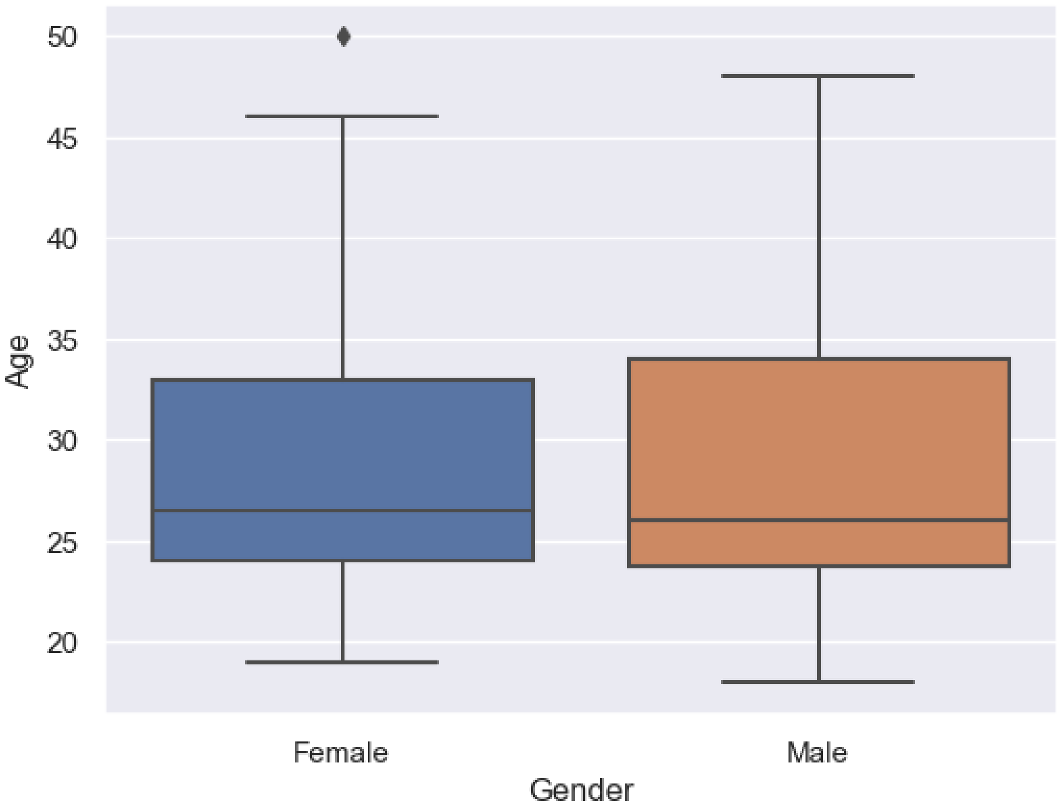
Insight * KP781 40 with 22.22% probability. * KP781 60 with 33.33% probability. * KP781 80 with 44.44% probability.

1.5.3 Q2. Describe the Age & Gender distribution of all the customers?

```
[ ]: aerofit.groupby("Gender")["Age"].describe()
```

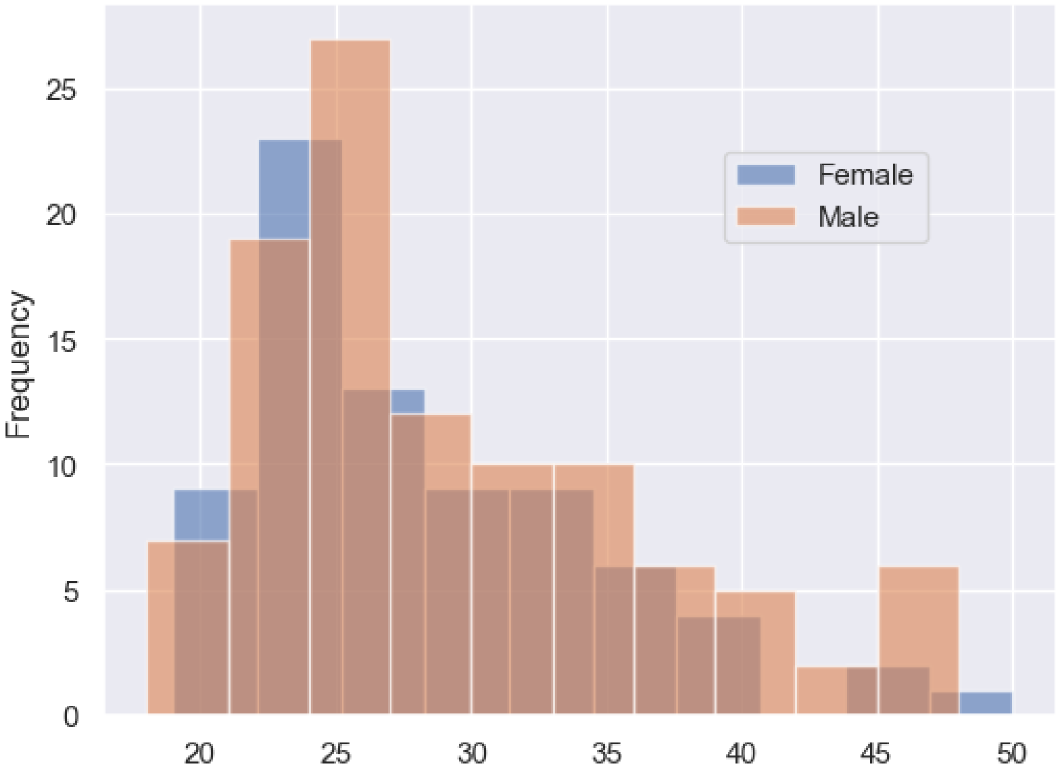
```
[ ]:         count       mean       std   min    25%   50%   75%   max
     Gender
     Female   76.0  28.565789  6.342104  19.0  24.00  26.5  33.0  50.0
     Male    104.0  28.951923  7.377978  18.0  23.75  26.0  34.0  48.0
```

```
[ ]: sns.boxplot(aerofit, x='Gender', y='Age')
     plt.show()
```



[ ]:

```
aerofit.groupby('Gender').Age.plot(kind='hist', alpha=0.6)
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper right', borderaxespad=5)
plt.show()
```



```
[ ]: aerofit.groupby('Gender')['Age'].mean()
```

```
[ ]: Gender
     Female    28.565789
     Male      28.951923
     Name: Age, dtype: float64
```

```
[ ]: male_age = aerofit.loc[aerofit['Gender']=='Male']['Age']
     female_age = aerofit.loc[aerofit['Gender']=='Female']['Age']
```

```
[ ]: t,p = ttest_ind(male_age, female_age, alternative='greater')
     p
```

```
[ ]: 0.3567980420783239
```

Insight * Their is a small differance between mean Age of Male & Female. * also, p-vale of T-Test of the 2 Group come out to be 35% (considering Male age is higher) * when following 95% Confidence Interval. So, we failed to prove that Male age are Higher then Female Age. amoung Customers.

1.5.4 Q3. Top 3 features having the highest coorelatios with the Product column. and Why?

[ ]:

```python
top_corr = aerofit.copy()
def add_product_as_column(x):
    return 1 if(x == 'KP281') else (2 if(x == 'KP481') else (3 if(x == 'KP781') else 0))
top_corr['product'] = top_corr.apply(lambda row: add_product_as_column(row['Product']),axis=1)

def add_product_columns(x):
    x['KP281'] = np.where((x['Product'] == 'KP281'), 1, 0)
    x['KP481'] = np.where((x['Product'] == 'KP481'), 1, 0)
    x['KP781'] = np.where((x['Product'] == 'KP781'), 1, 0)
    return x
top_corr = add_product_columns(top_corr)
```

[ ]:

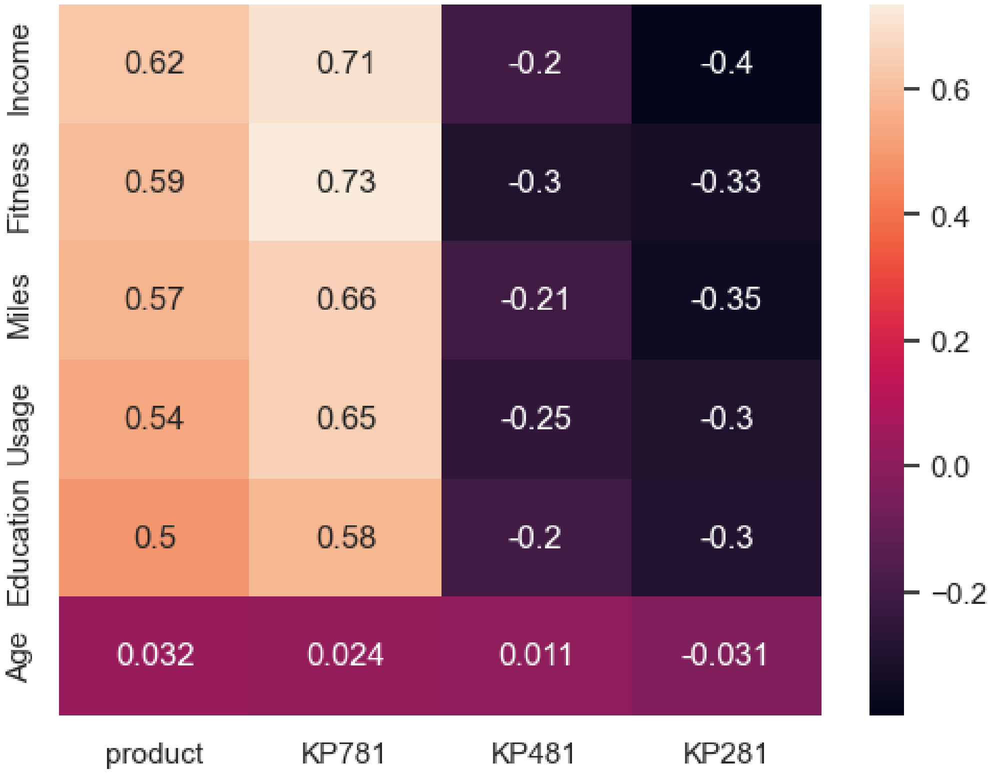
```python
top3_correlations = top_corr[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage', 'product', 'KP281', 'KP481', 'KP781']].corr()[['product', 'KP781', 'KP481', 'KP281']][:6]
```

[ ]:

```python
top3_correlations.sort_values('product', ascending=False, inplace=True)
```

[ ]:

```python
sns.heatmap(top3_correlations, annot=True)
plt.show()
```



> Insight * Product Have higher co-relation with `Income`, `Fitness` & `Miles`. * For **`KP781`** we have observed same co-relation. * But, for **`KP481`** Top 3 co-relation are `Age`, `Education` & `Income`. * But, for **`KP281`** Top 3 co-relation are `Age`, `Education` & `Usage`.

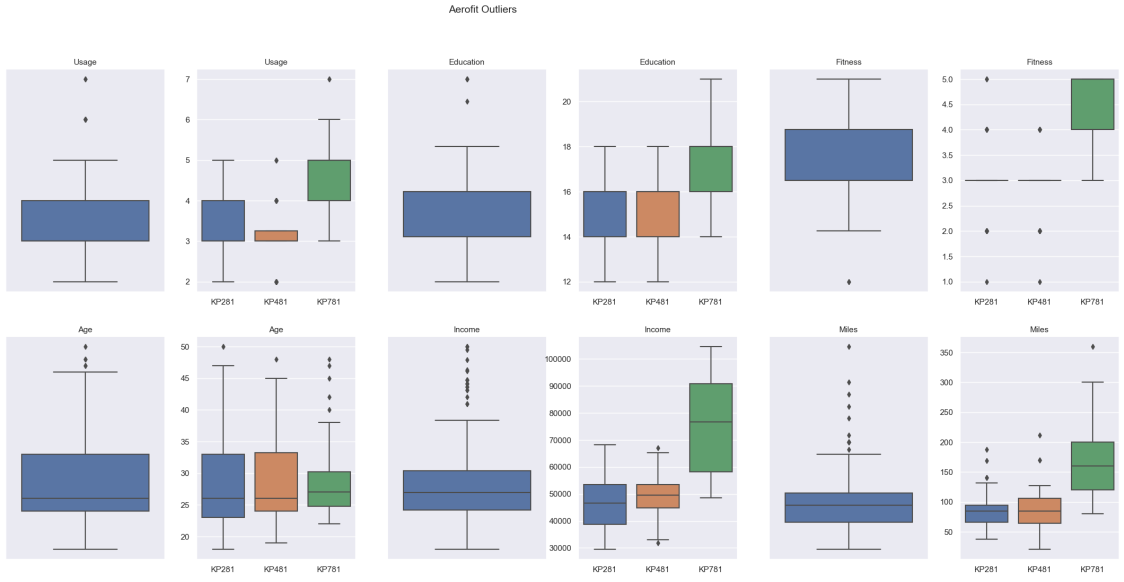
As, we know **`KP781`** is the expansive & better one, mostly prefered by Athletes or Fitness enthusiast, whos also have higher Income. But, for **`KP481`**, **`KP281`** people with good Education, who are health consious, want to have a Treadmill but can't efford a expansive one.

1.5.5 Q4. Were there any outliers present in the Data? If yes, suggest suitable method for their treatment?

[ ]:

```
plt.figure(figsize=(24,12)).suptitle("Aerofit Outliers",fontsize=14)
plt.subplots_adjust(right=1)



plt.subplot(2, 6, 1)
sns.boxplot(aerofit, y='Usage')
plt.title('Usage', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 2)
sns.boxplot(aerofit, y='Usage', x='Product')
plt.title('Usage', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.subplot(2, 6, 3)
sns.boxplot(aerofit, y="Education")
plt.title('Education', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 4)
sns.boxplot(aerofit, y="Education", x='Product')
plt.title('Education', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.subplot(2, 6, 5)
sns.boxplot(aerofit, y='Fitness')
plt.title('Fitness', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 6)
```

```python
sns.boxplot(aerofit, y='Fitness', x='Product')
plt.title('Fitness', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.subplot(2, 6, 7)
sns.boxplot(aerofit, y="Age")
plt.title('Age', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 8)
sns.boxplot(aerofit, y="Age", x='Product')
plt.title('Age', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.subplot(2, 6, 9)
sns.boxplot(aerofit, y="Income")
plt.title('Income', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 10)
sns.boxplot(aerofit, y="Income", x='Product')
plt.title('Income', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.subplot(2, 6, 11)
sns.boxplot(aerofit, y="Miles")
plt.title('Miles', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 12)
sns.boxplot(aerofit, y="Miles", x='Product')
plt.title('Miles', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)

plt.show()
```



Using Z-Score

```
[ ]: aerofit[np.abs(zscore(aerofit['Age']))>2]
```

```
[ ]:     Product  Gender MaritalStatus  Age  Income  Miles  Education  Fitness  \
     75    KP281    Male     Partnered   43   53439     66         16        3
     76    KP281  Female        Single   44   57987     75         16        4
     77    KP281  Female     Partnered   46   60261     47         16        2
     78    KP281    Male     Partnered   47   56850     94         16        3
     79    KP281  Female     Partnered   50   64809     66         16        3
     138   KP481    Male     Partnered   45   54576     42         16        2
     139   KP481    Male     Partnered   48   57987     64         16        3
     177   KP781    Male        Single   45   90886    160         16        5
     178   KP781    Male     Partnered   47  104581    120         18        5
     179   KP781    Male     Partnered   48   95508    180         18        5

          Usage age_group income_group miles_group education_group fitness_group  \
     75       3     40-45      45K-55K       50-80              16             3
     76       3     40-45      55K-65K       50-80              16             4
     77       3     45-50      55K-65K       20-50              16             2
     78       4     45-50      55K-65K      80-110              16             3
     79       3     45-50      55K-65K       50-80              16             3
     138      2     40-45      45K-55K       20-50              16             2
     139      2     45-50      55K-65K       50-80              16             3
     177      5     40-45      85K-95K     140-170              16             5
     178      4     45-50     95K-105K     110-140              18             5
     179      4     45-50     95K-105K     170-200              18             5
```

```
    usage_group
75            3
76            3
77            3
78            4
79            3
138           2
139           2
177           5
178           4
179           4
```

Using IQR (Inner Quartile Range)

```
[ ]: age_outlier = check_outlier(aerofit, 'Age')
     income_outlier = check_outlier(aerofit, 'Income')
     miles_outlier = check_outlier(aerofit, 'Miles')
     education_outlier = check_outlier(aerofit, 'Education')
     fitness_outlier = check_outlier(aerofit, 'Fitness')
     usage_outlier = check_outlier(aerofit, 'Usage')
```

```
[ ]: print("Age: \t\t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(age_outlier['lower']['length'], age_outlier['upper']['length']))
     print("Income: \t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(income_outlier['lower']['length'], income_outlier['upper']['length']))
     print("Miles: \t\t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(miles_outlier['lower']['length'], miles_outlier['upper']['length']))
     print("Education: \t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(education_outlier['lower']['length'],␣
       ↪education_outlier['upper']['length']))
     print("Fitness: \t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(fitness_outlier['lower']['length'],␣
       ↪fitness_outlier['upper']['length']))
     print("Usage: \t\t => Lower outlier: {}  => Upper outlier: {}" .
       ↪format(usage_outlier['lower']['length'], usage_outlier['upper']['length']))
     # print("%d, %d" %(age_outlier['lower']['length'],␣
       ↪age_outlier['upper']['length']))
```

```
Age:             => Lower outlier: 0  => Upper outlier: 5
Income:          => Lower outlier: 0  => Upper outlier: 19
Miles:           => Lower outlier: 0  => Upper outlier: 13
Education:       => Lower outlier: 0  => Upper outlier: 4
Fitness:         => Lower outlier: 2  => Upper outlier: 0
Usage:           => Lower outlier: 0  => Upper outlier: 9
```

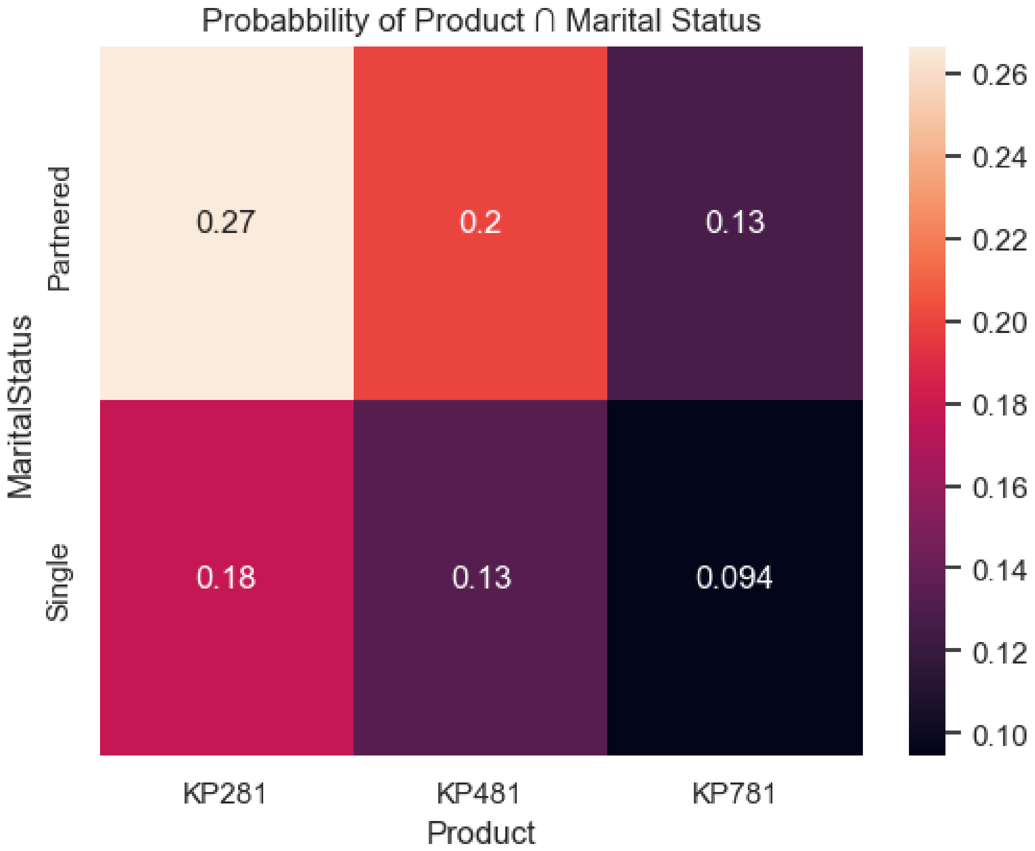
Insight * Yes, There is Outlier Present in DataSet for All of the Continuous Values, like

* Age: => Lower outlier: 0 => Upper outlier: 5 * Income: => Lower outlier: 0 => Upper outlier: 19 * Miles: => Lower outlier: 0 => Upper outlier: 13 * Education: => Lower outlier: 0 => Upper outlier: 4 * Fitness: => Lower outlier: 2 => Upper outlier: 0 * Usage: => Lower outlier: 0 => Upper outlier: 9

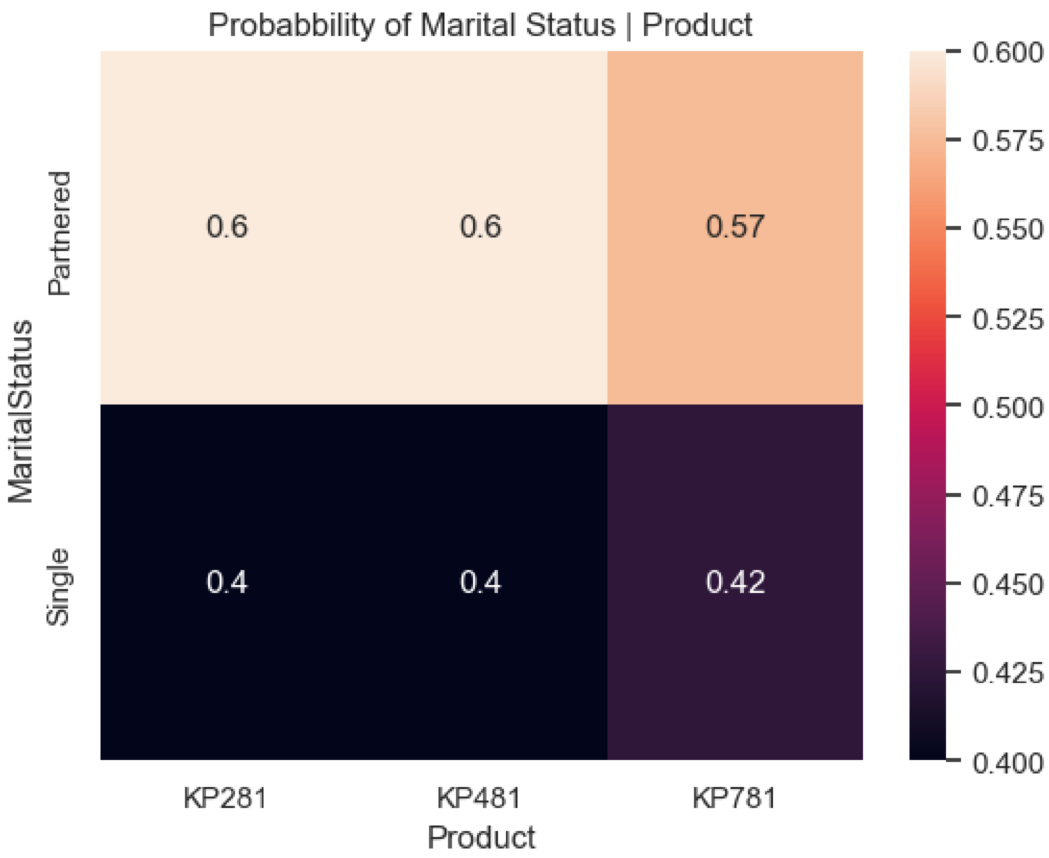
When, we remove these outliers it might effect credebility of `Product` specific analysis. Because Some of the product dependent on the datas.

1.5.6 Q5. Marital Status Implies no significant information on the usages of different TreadMills? (T/F)

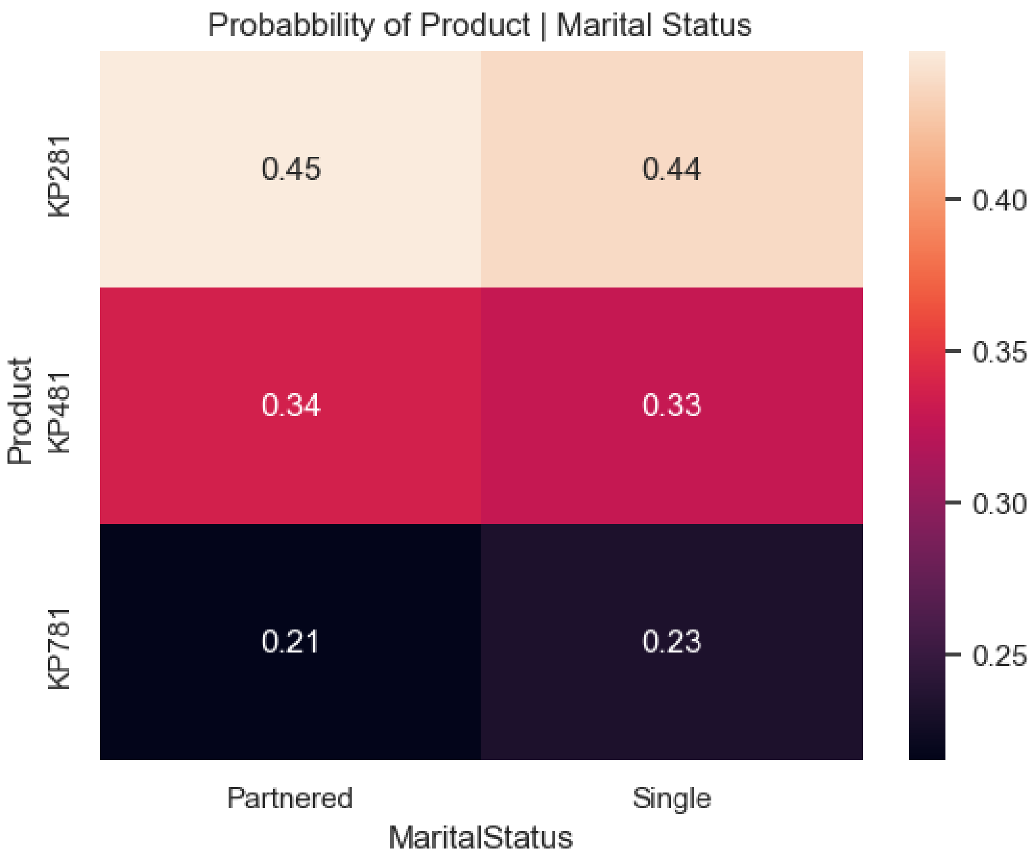
```
[ ]: sns.heatmap(pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'],␣
      ↪normalize=True),annot=True)
     plt.title('Probabbility of Product   Marital Status', fontsize=12)
     plt.show()
```



```
[ ]: sns.heatmap(pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'],␣
      ↪normalize='columns'),annot=True)
     plt.title('Probabbility of Marital Status | Product', fontsize=12)
     plt.show()
```



```
[ ]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'],␣
      ↪normalize='columns'),annot=True)
     plt.title('Probabbility of Product | Marital Status', fontsize=12)
     plt.show()
```



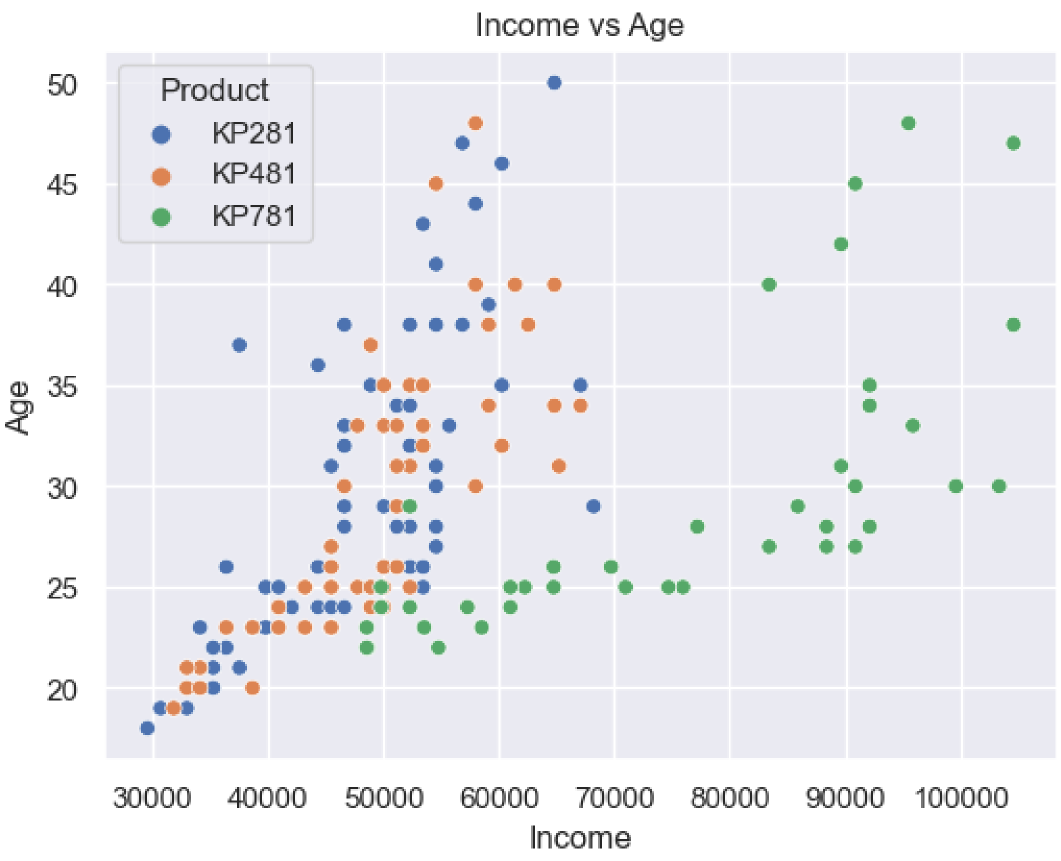
Insight * From Above Probability Heatmap, observed that for each product given marital status have nearly same probability.

Thus, Statement is True

1.5.7 Q6. The variance of Income in lower ages is smaller as compare to the variance in higher ages. *In Statistics , this is known as*

```
[ ]: low_income_age = aerofit.copy().loc[aerofit['Age']<aerofit['Age'].
       ↪mean()][['Income', "Age"]]
     high_income_age = aerofit.copy().loc[aerofit['Age']>aerofit['Age'].
       ↪mean()][['Income', "Age"]]
```

```
[ ]: sns.scatterplot(aerofit, x='Income', y='Age', hue='Product')
     plt.title("Income vs Age", fontsize=12)
     plt.show()
```



```
[ ]: low_income_age['Income'].var() < high_income_age['Income'].var()
```

```
[ ]: True
```

```
[ ]: low_income_age['Income'].std() < high_income_age['Income'].std()
```

```
[ ]: True
```

Insight * Here Variance & Standard Daviation in low Age Income Group is less then Higher Age Income Group. * Thus, It results a funnel shape & It's known as **Heteroscedasticity**

1.5.8 Q7. What proportion of woman have brought the KP781 TreadMill? Provide reson of Answar.

```
[ ]: product_gender = pd.crosstab(aerofit['Gender'], aerofit['Product'],␣
      ↪normalize='index', margins=True)*100
     product_gender
```

```
[ ]: Product      KP281      KP481      KP781
     Gender
     Female   52.631579  38.157895   9.210526
     Male     38.461538  29.807692  31.730769
     All      44.444444  33.333333  22.222222
```

```
[ ]: product_gender['KP781']['Female']
```

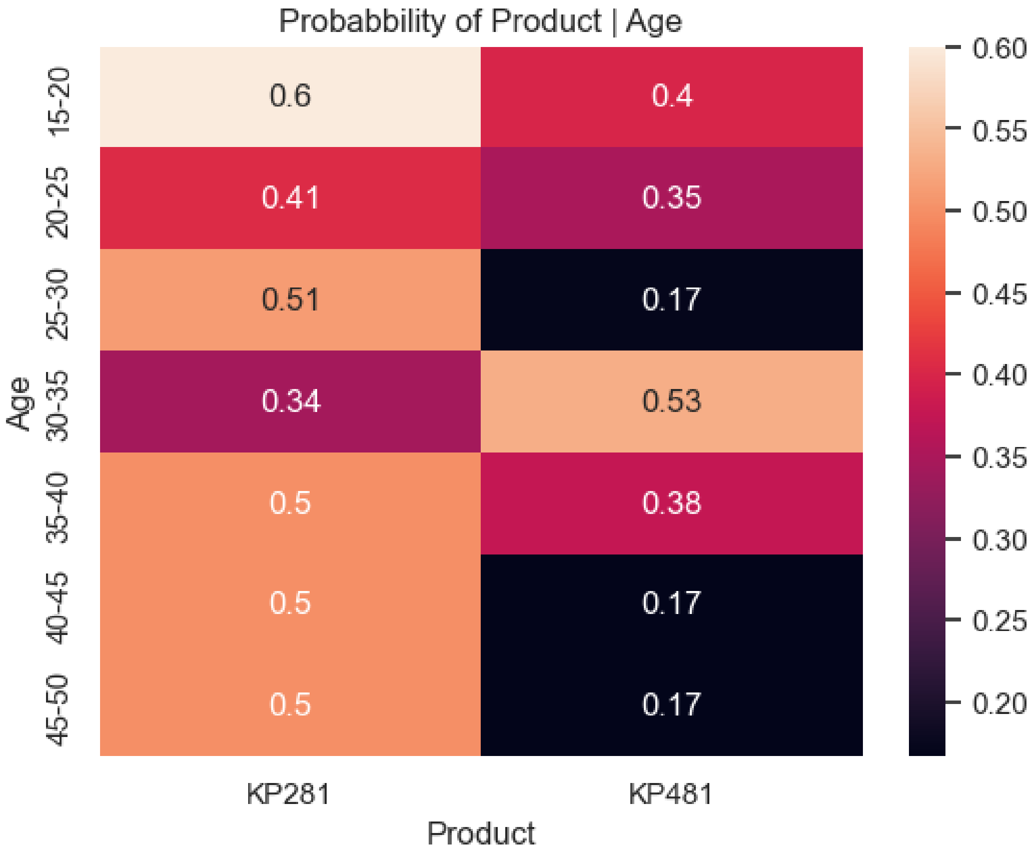
```
[ ]: 9.210526315789473
```

Insight * There is `9.21%` chance a male customer will purchase `KP781`

1.5.9 Q8. Distinguish between Customer Profiles for KP281 and KP481 TreadMill.

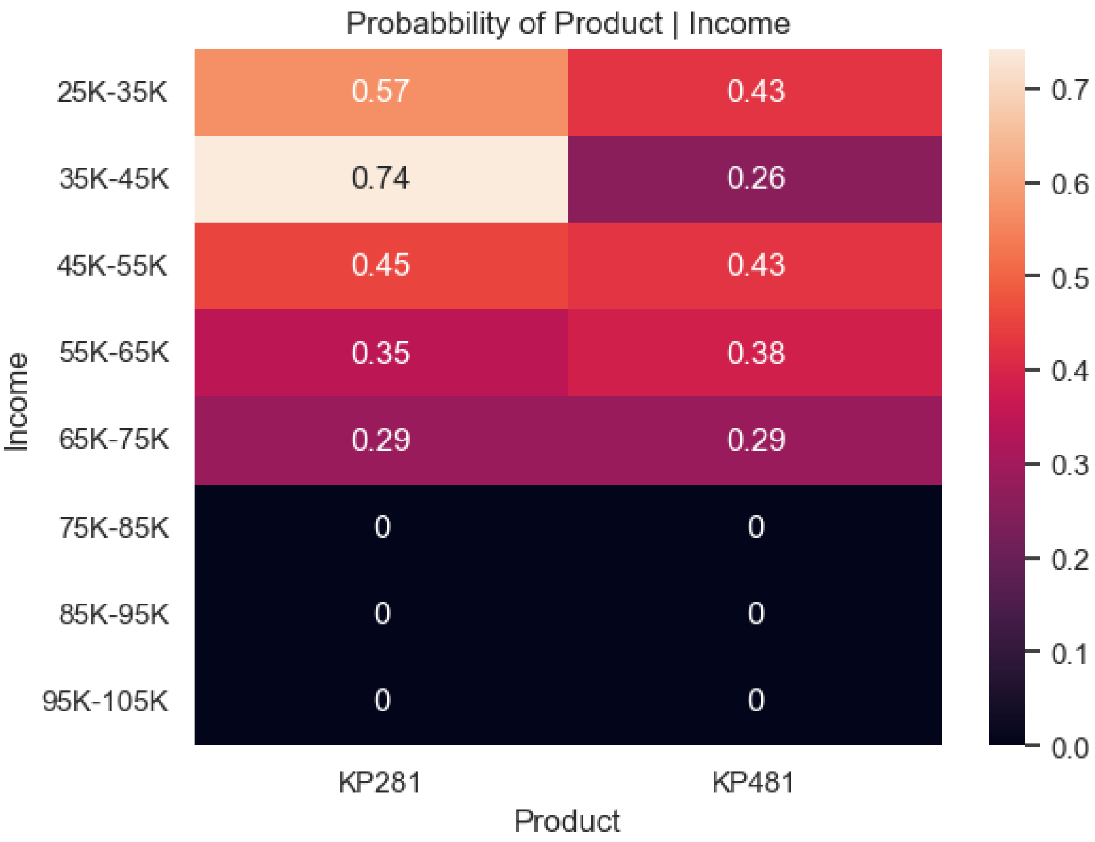
Probability of `Product's` for given `Age` *"Product | Age"*

```
[ ]: sns.heatmap(pd.crosstab(aerofit['age_group'], aerofit['Product'],␣
      ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Age', fontsize=12)
     plt.ylabel('Age')
     plt.show()
```



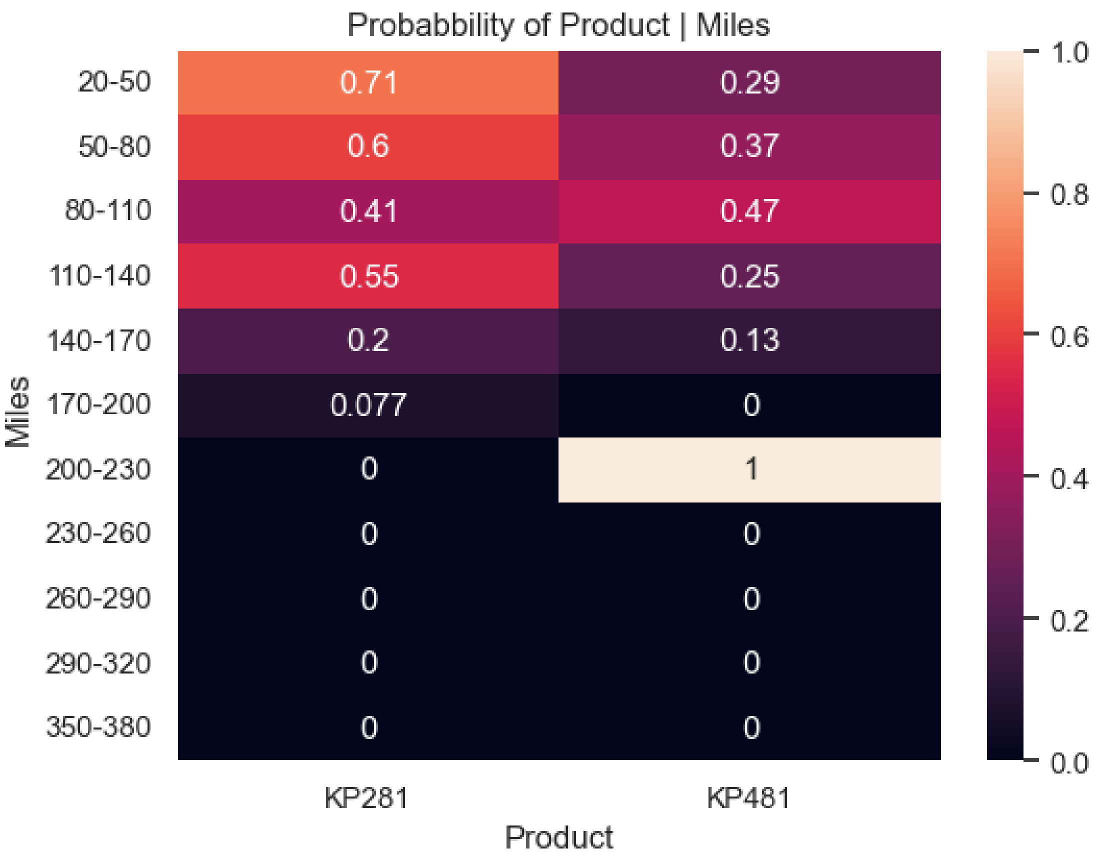
Probability of `Product's` **for given** `Income` ***"Product | Income"***

```
[ ]: sns.heatmap(pd.crosstab(aerofit['income_group'], aerofit['Product'],␣
      ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Income', fontsize=12)
     plt.ylabel('Income')
     plt.show()
```



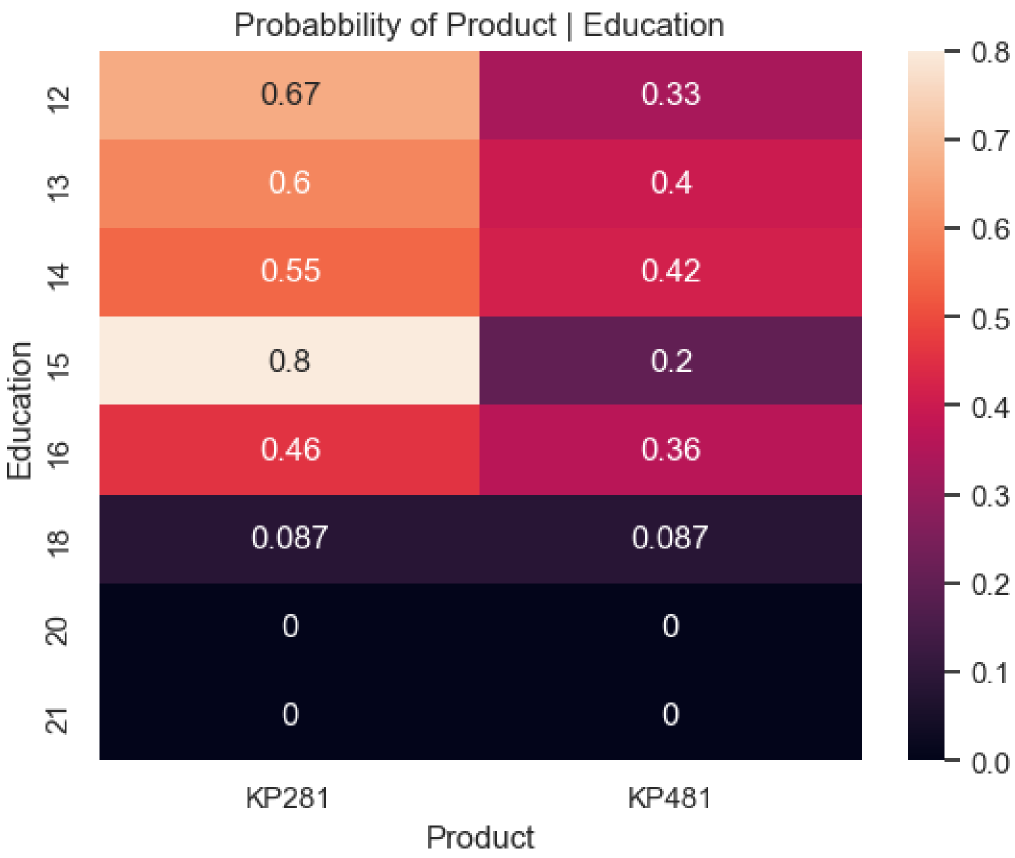
Probability of `Product's` **for given** `Miles` ***"Product | Miles"***

```
[ ]: sns.heatmap(pd.crosstab(aerofit['miles_group'], aerofit['Product'],␣
      ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Miles', fontsize=12)
     plt.ylabel('Miles')
     plt.show()
```



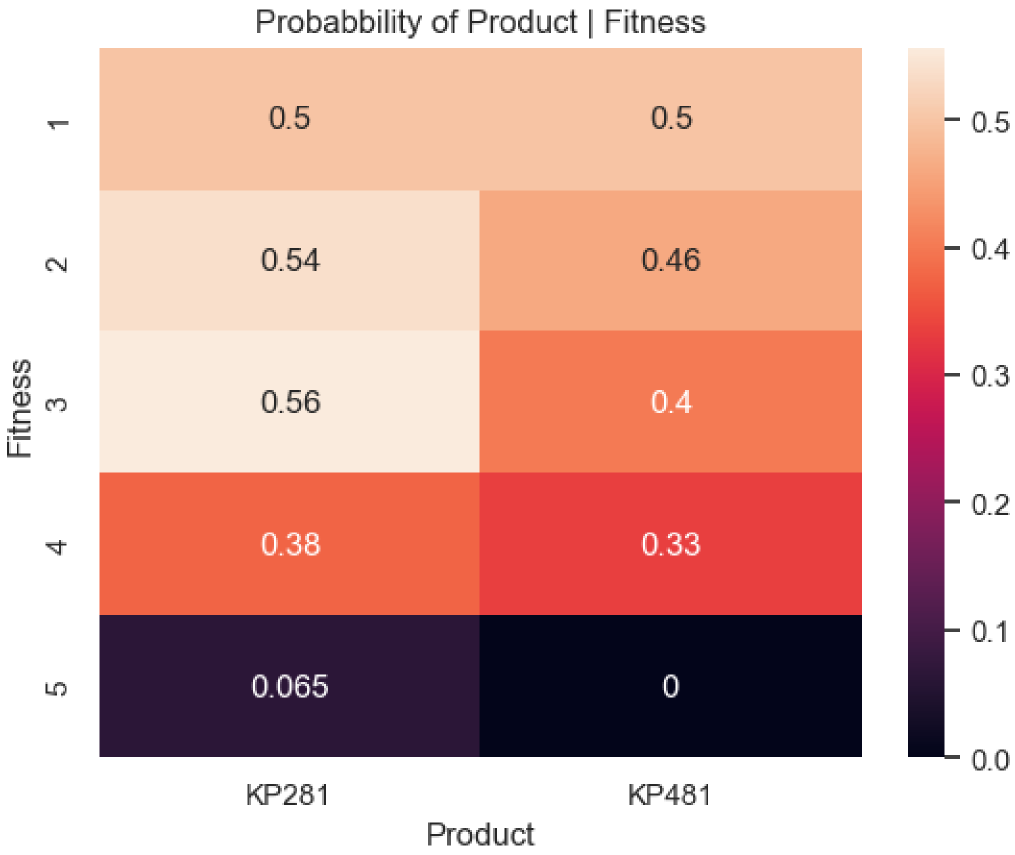
Probability of `Product's` for given `Education` ***"Product | Education"***

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Education'], aerofit['Product'],␣
       ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Education', fontsize=12)
     plt.show()
```



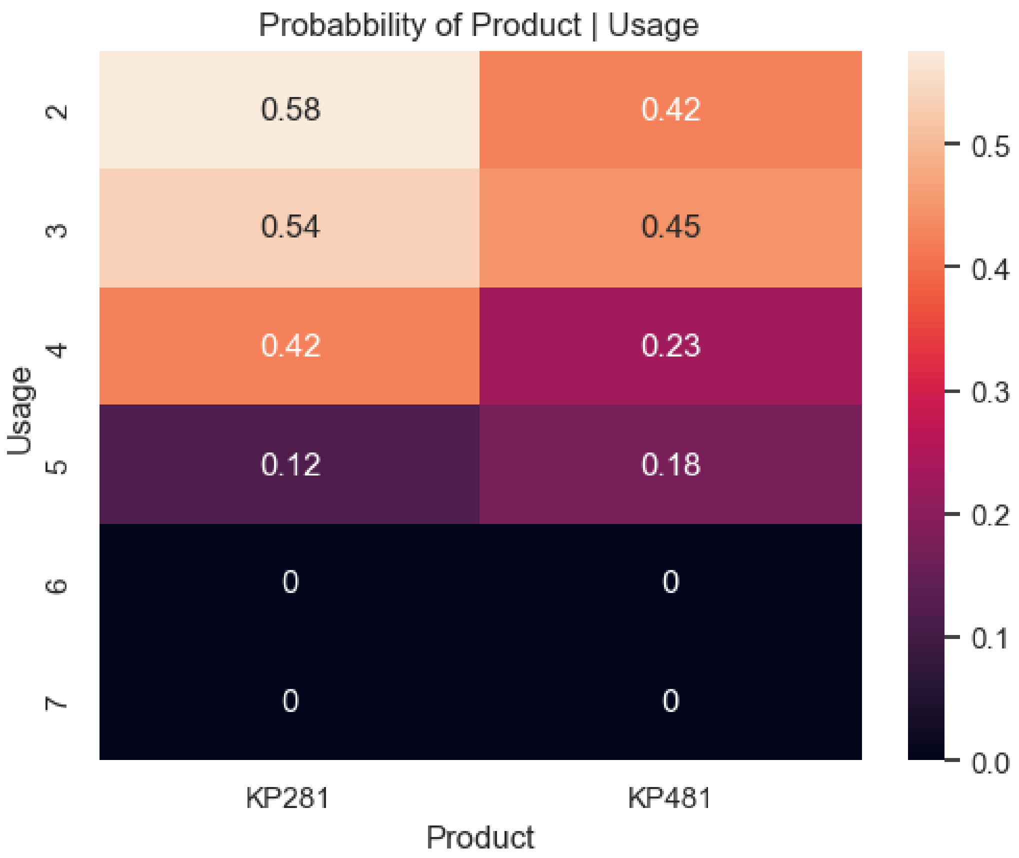
Probability of `Product's` for given `Fitness` *"Product | Fitness"*

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Fitness'], aerofit['Product'],␣
      ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Fitness', fontsize=12)
     plt.show()
```



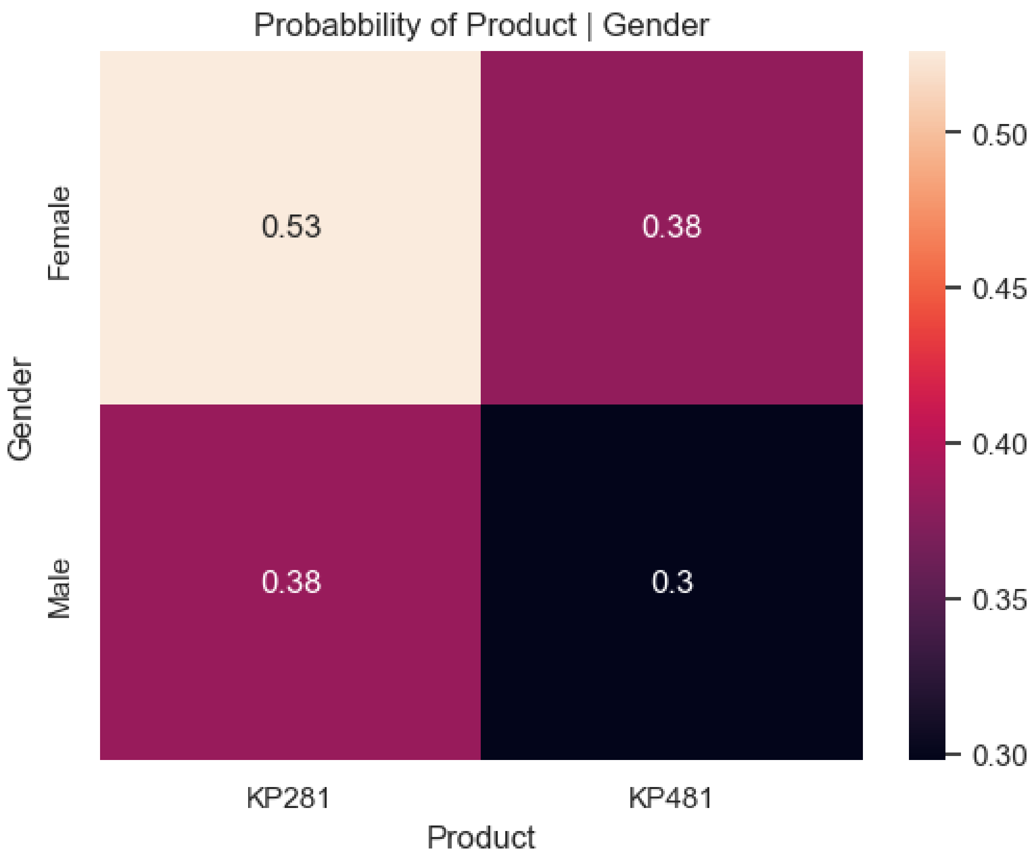
Probability of `Product's` for given `Usage` *“Product | Usage”*

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Usage'], aerofit['Product'],␣
       ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Usage', fontsize=12)
     plt.show()
```



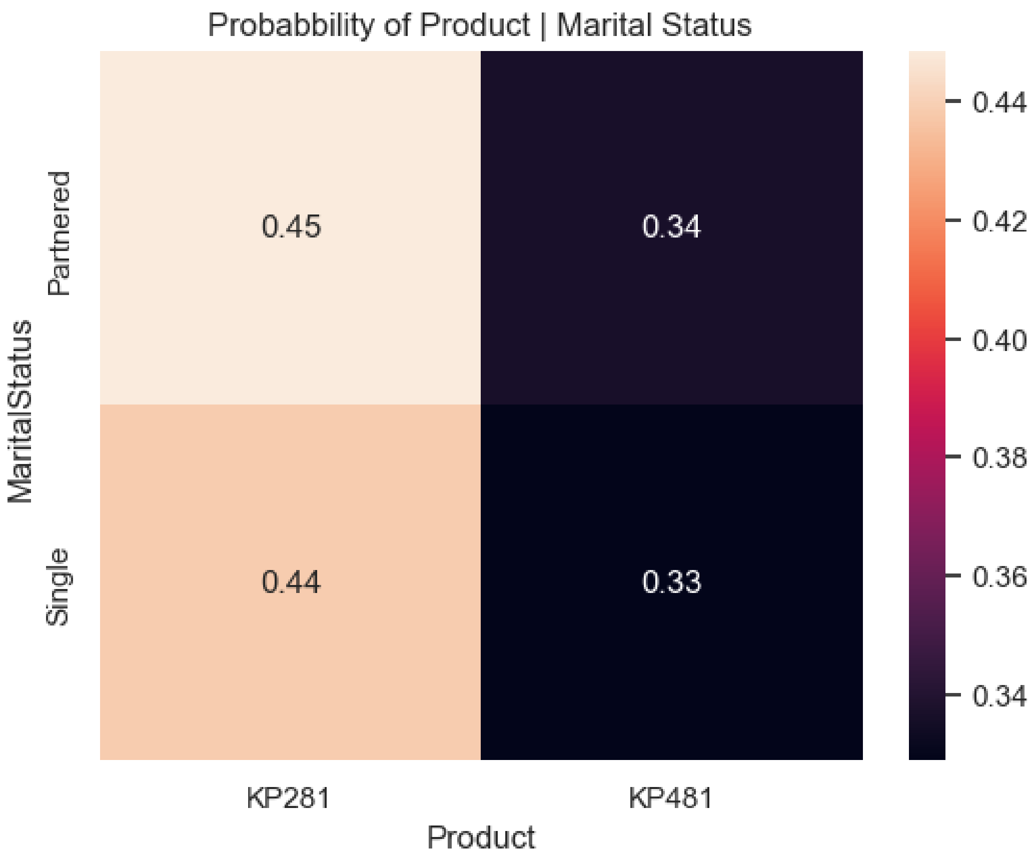
Probability of `Product`'s for given `Gender` *"Product | Gender"*

```
[ ]: sns.heatmap(pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Gender', fontsize=12)
     plt.show()
```



Probability of `Product's` for given `MaritalStatus` *"Product | Marital Status"*

```
[ ]: sns.heatmap(pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'],␣
      ↪normalize='index')[['KP281', 'KP481']], annot=True)
     plt.title('Probabbility of Product | Marital Status', fontsize=12)
     plt.show()
```



1.5.10 **Q9. The overall Probability of purchase for KP281, KP481 & KP781 TreadMill is ___ , _____ , _____.**

```
[ ]: aerofit.groupby('Product')['Product'].count()/1.80
```

```
[ ]: Product
     KP281    44.444444
     KP481    33.333333
     KP781    22.222222
     Name: Product, dtype: float64
```

1.5.11 Q10. Give conditions when you will and when you 'll not recomended KP781 TreadMill to a Customer?

When to recomend KP781 * Male's * Age between 20-30. * Income with 90K. * Who inteded or alredy covered 150-200 Miles. * Have Education between 16-19. * Have Fitness of level5. * Have Usages level of 4-5.

When not to recomend KP781 * Females's * Age above 35. * Income below 75K. * Have Fitness level less than 3. * Have Usages level less than 4.

1.6 Multi Variate Analysis

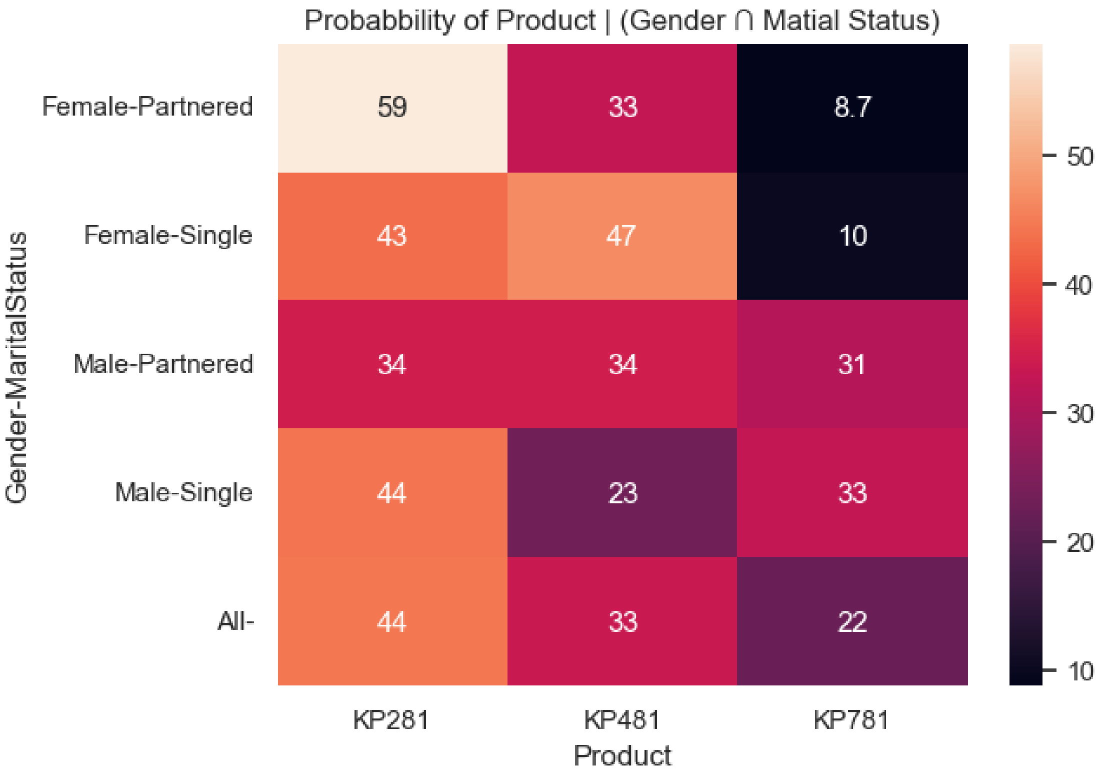
Find Probability & Coorelation

Probability of Product's for given Gender & Marital Status *"Product | (Gender Matial Status)"*

```
[ ]: p_pord_gend_marital= pd.crosstab([aerofit['Gender'], aerofit['MaritalStatus']],␣
      ↪aerofit['Product'], normalize='index', margins=True)*100
     # p_pord_gend_marital
```

```
[ ]: sns.heatmap(p_pord_gend_marital, annot=True)
     plt.title('Probabbility of Product | (Gender  Matial Status)', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product | (Gender  Matial Status)')
```

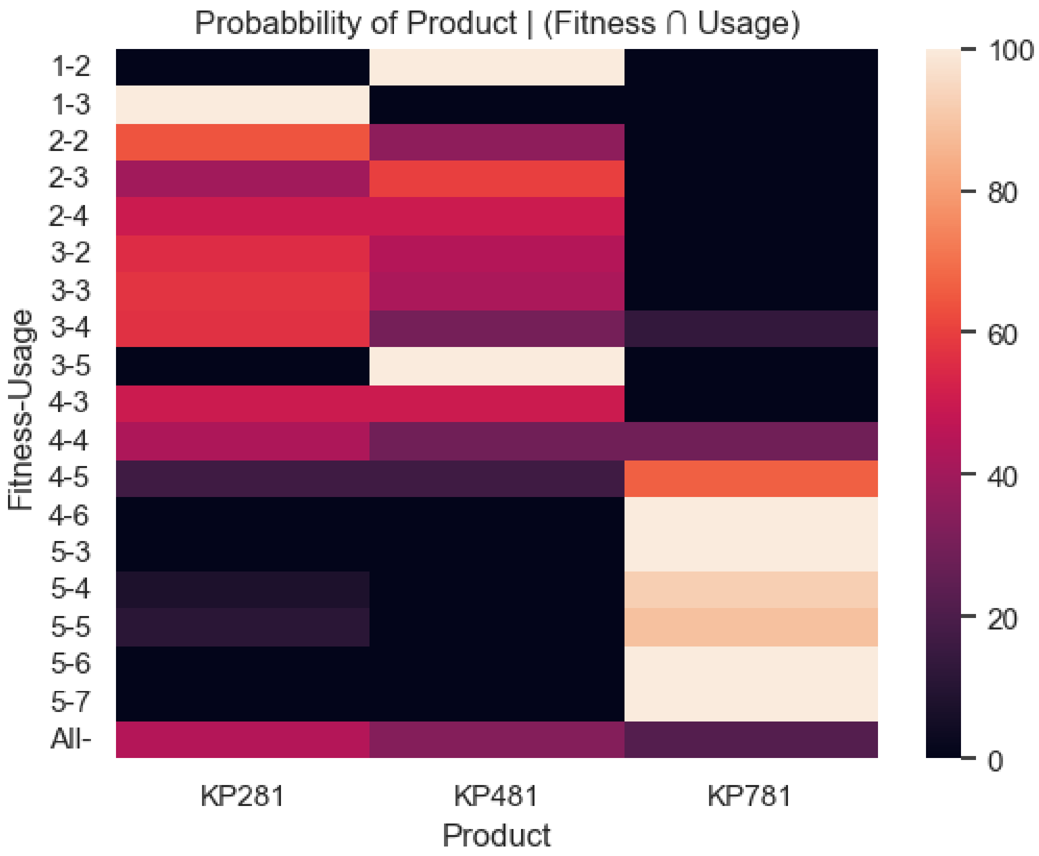


Probability of Product's for given Fitness & Usage *"Product | (Fitness Usage)"*

```
[ ]: p_pord_fit_usag= pd.crosstab([aerofit['Fitness'], aerofit['Usage']],␣
      ↪aerofit['Product'], normalize='index', margins=True)*100
     # p_pord_fit_usag
```

```
[ ]: sns.heatmap(p_pord_fit_usag)
     plt.title('Probabbility of Product | (Fitness   Usage)', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness   Usage)')
```

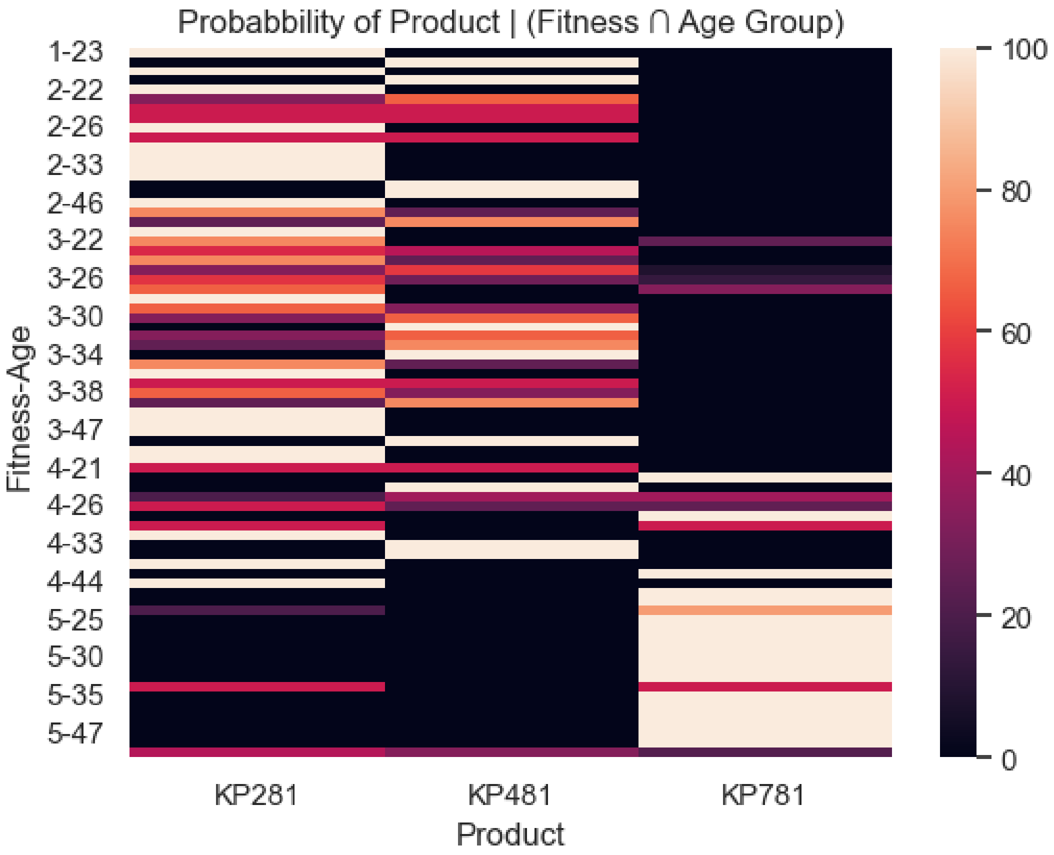


Probability of Product's for given Fitness & Age Group *“Product | (Fitness   Miles)”*

```
[ ]: p_pord_fit_age_group= pd.crosstab([aerofit['Fitness'], aerofit['Age']],␣
      ↪aerofit['Product'], normalize='index', margins=True)*100
     # p_pord_fit_age_group
```

```
[ ]: sns.heatmap(p_pord_fit_age_group)
     plt.title('Probabbility of Product | (Fitness   Age Group)', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness   Age Group)')
```

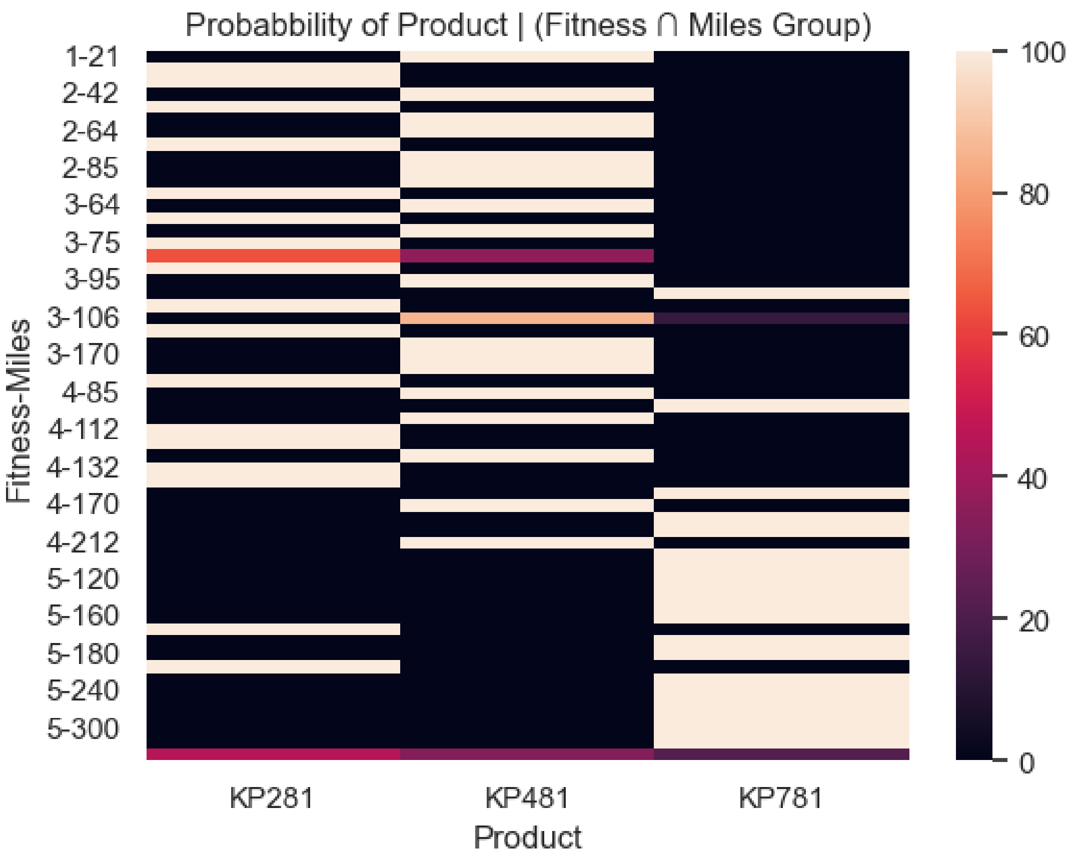


Probability of Product's for given Fitness & Mile Group ***“Product | (Fitness   Mile Group)”***

```
[ ]: p_pord_fit_mile_group= pd.crosstab([aerofit['Fitness'], aerofit['Miles']], aerofit['Product'], normalize='index', margins=True)*100
     # p_pord_fit_mile_group
```

```
[ ]: sns.heatmap(p_pord_fit_mile_group)
     plt.title('Probabbility of Product | (Fitness   Miles Group)', fontsize=12)
```

```
[ ]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness   Miles Group)')
```

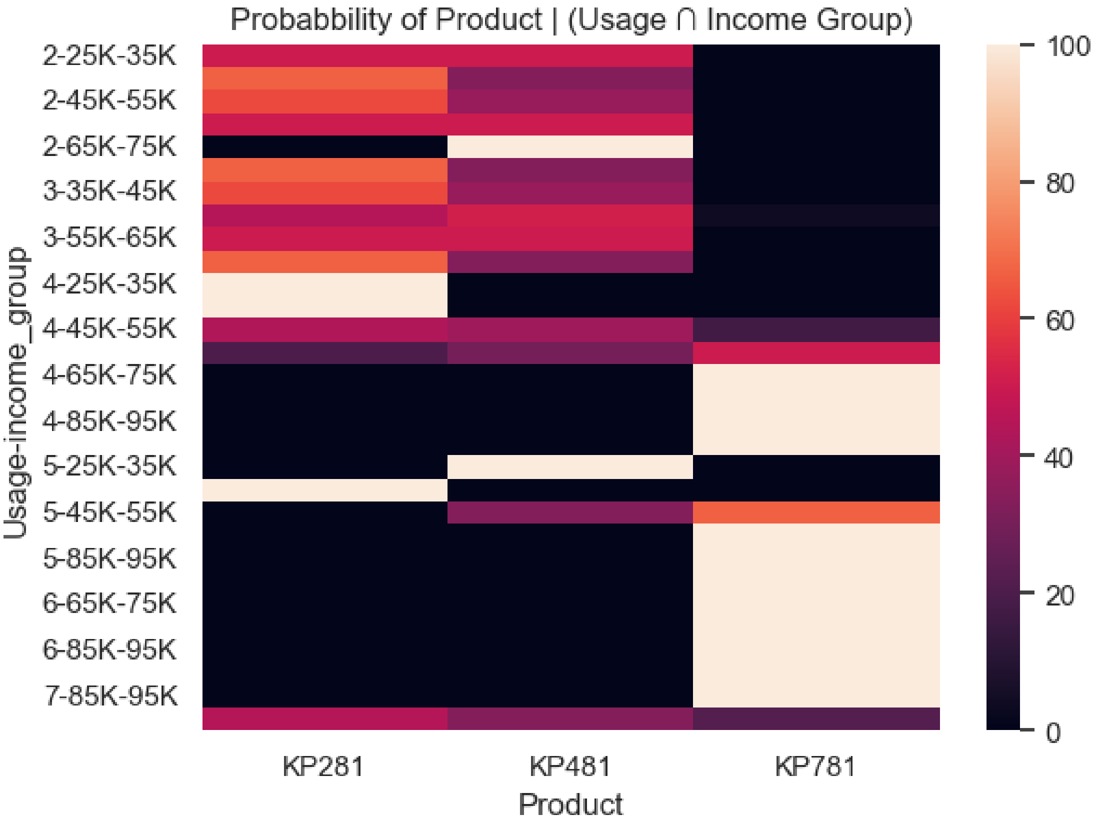


Probability of `Product's` **for given** `Usage & Income Group` ***“Product | (Fitness Mile Group)”***

```
[ ]: p_pord_usage_income_group= pd.crosstab([aerofit['Usage'],␣
       ↪aerofit['income_group']], aerofit['Product'], normalize='index',␣
       ↪margins=True)*100
     # p_pord_usage_income_group
```

```
[ ]: sns.heatmap(p_pord_usage_income_group)
     plt.title('Probabbility of Product | (Usage   Income Group)', fontsize=12)
```

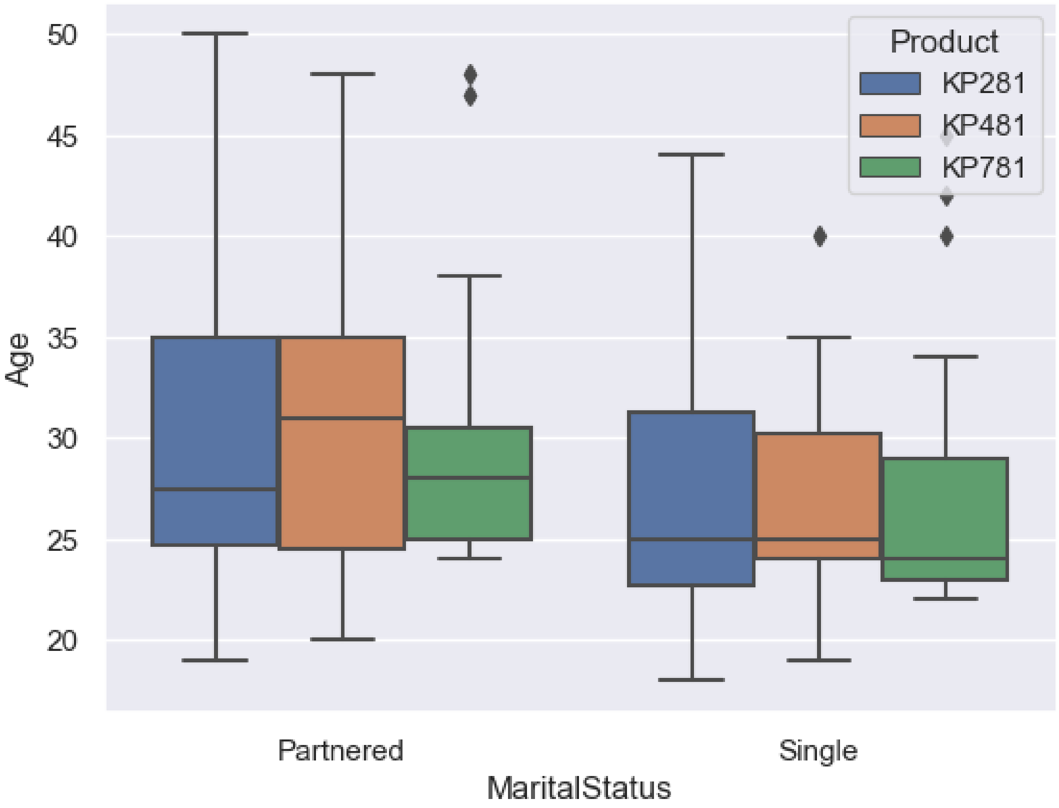
```
[ ]: Text(0.5, 1.0, 'Probabbility of Product | (Usage   Income Group)')
```



Find Correlation

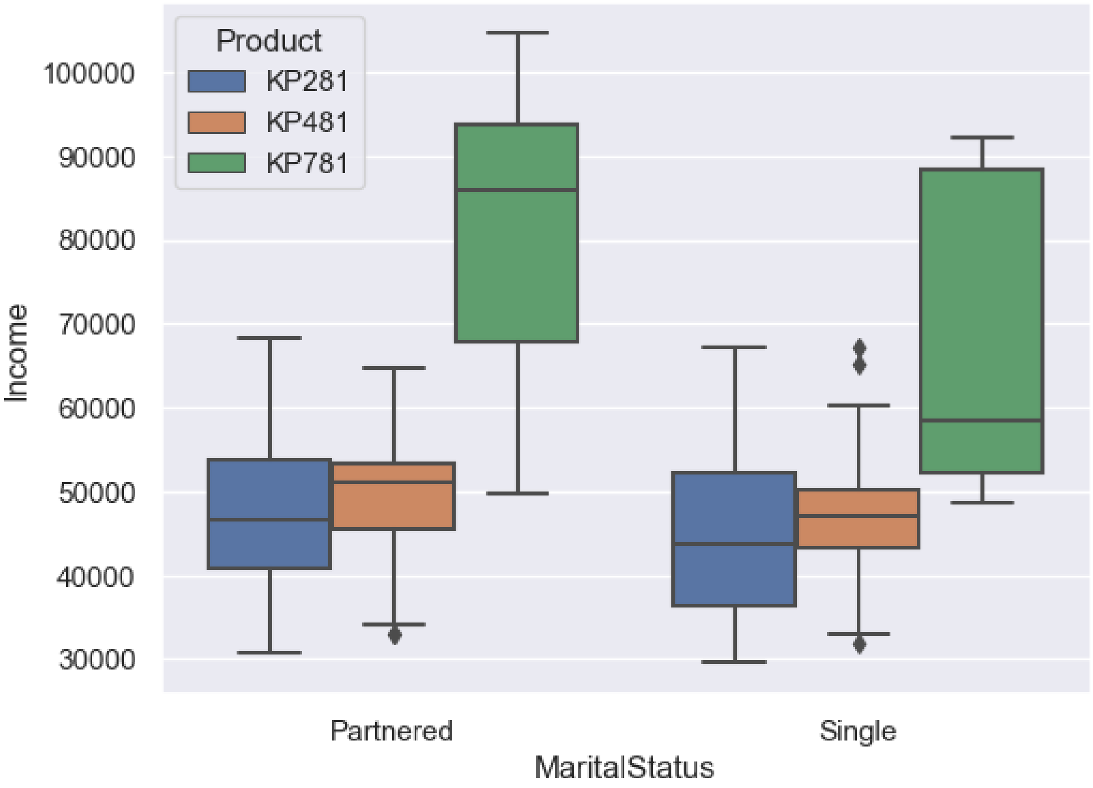
```
[ ]: sns.boxplot(x="MaritalStatus", y="Age", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='MaritalStatus', ylabel='Age'>
```



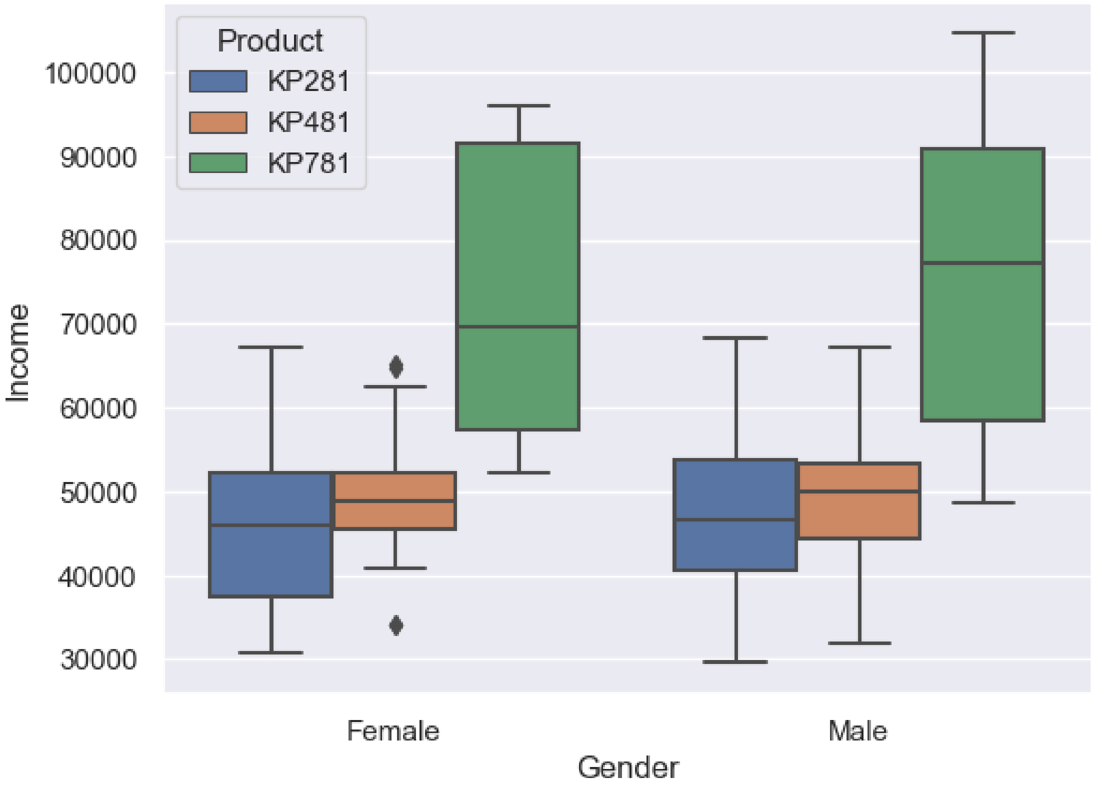
```
[ ]: sns.boxplot(x="MaritalStatus", y="Income", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='MaritalStatus', ylabel='Income'>
```



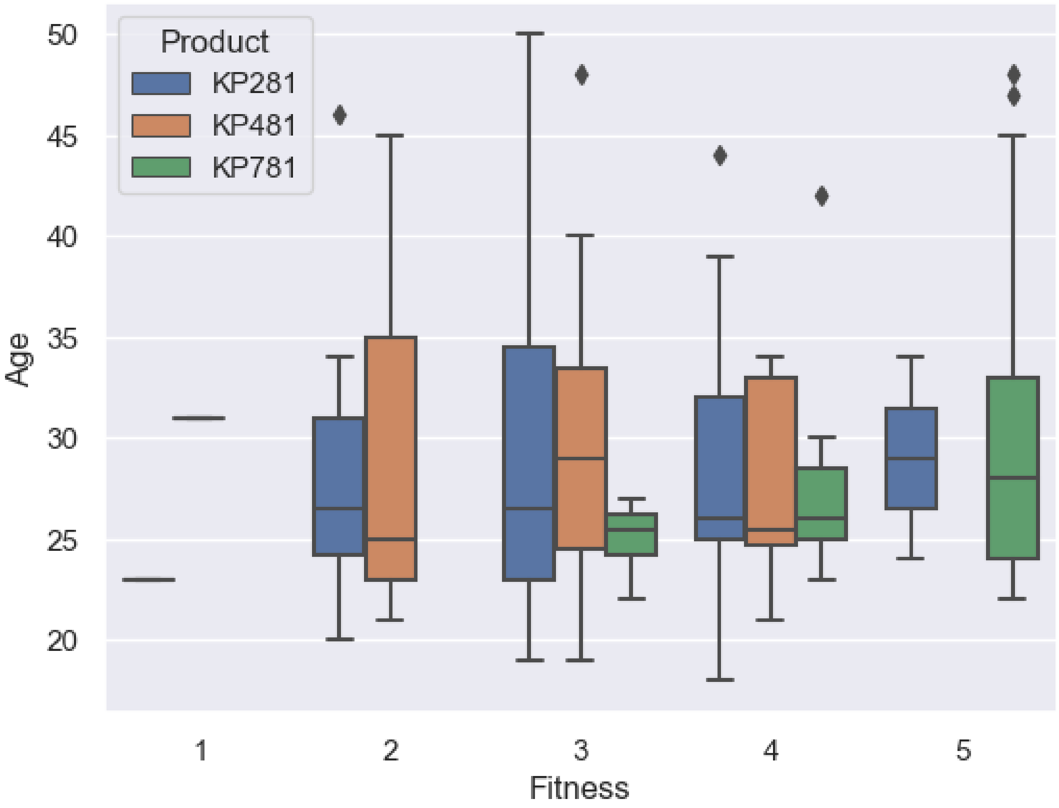
```
[ ]: sns.boxplot(x="Gender", y="Income", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='Gender', ylabel='Income'>
```



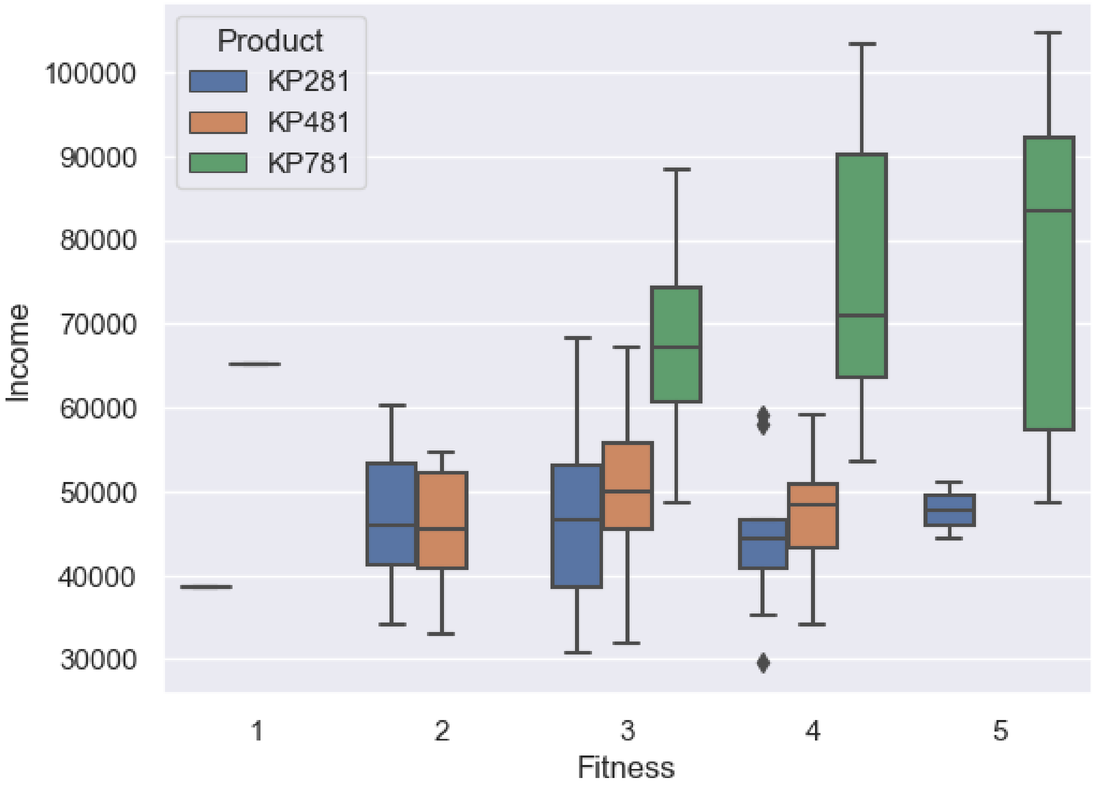
```
[ ]: sns.boxplot(x="Fitness", y="Age", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='Fitness', ylabel='Age'>
```



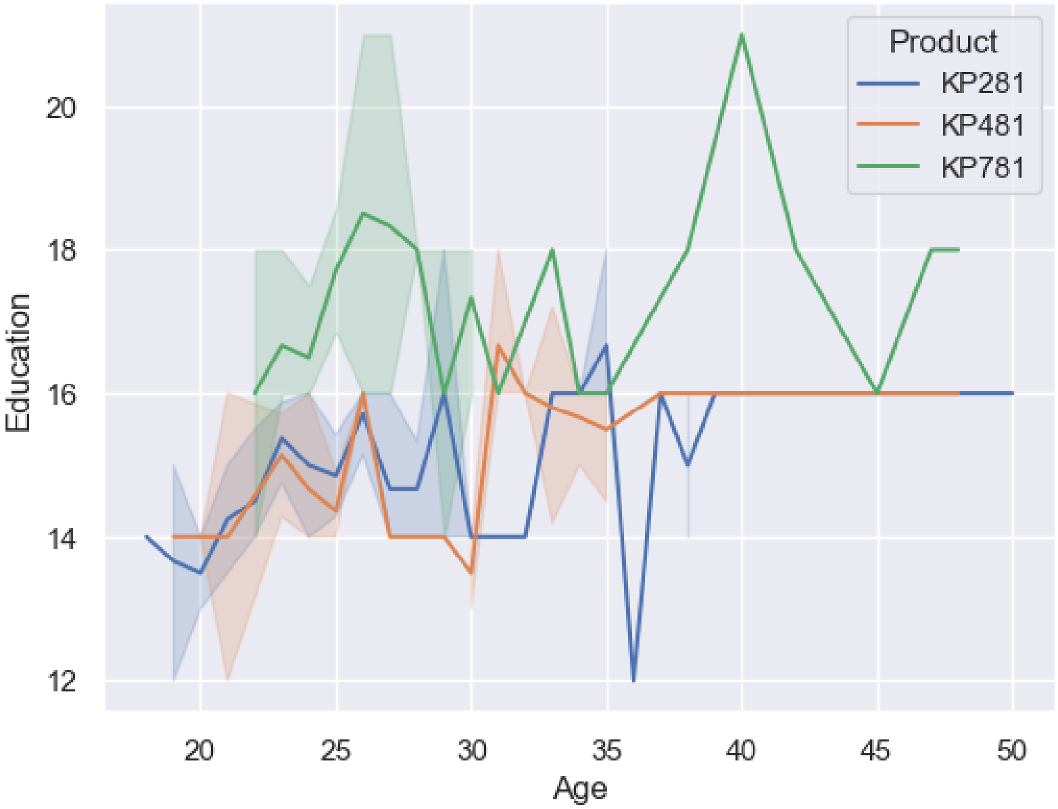
```
[ ]: sns.boxplot(x="Fitness", y="Income", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='Fitness', ylabel='Income'>
```



```
[ ]: sns.lineplot(x="Age", y="Education", hue="Product", data=aerofit)
```

```
[ ]: <Axes: xlabel='Age', ylabel='Education'>
```


Product
KP281
KP481
KP781
Education
20
18
16
14
12
20
25
30
35
40
45
50
Age

2 END