Aerofit - Descriptive Statistics & Probability

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

Importing aerofit csv file

```
aerofit_data = pd.read_csv('aerofit.csv')
```

Seggregating categorical and numerical variables

```
aerofit_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

```
aerofit_data
```

```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness
Income  \
0     KP281   18    Male         14        Single      3        4
29562
1     KP281   19    Male         15        Single      2        3
31836
2     KP281   19  Female         14     Partnered      4        3
30699
```

```
3      KP281   19    Male          12       Single      3        3
32973
4      KP281   20    Male          13    Partnered      4        2
35247
..       ...  ...     ...         ...          ...    ...      ...
...
175    KP781   40    Male          21       Single      6        5
83416
176    KP781   42    Male          18       Single      5        4
89641
177    KP781   45    Male          16       Single      5        5
90886
178    KP781   47    Male          18    Partnered      4        5
104581
179    KP781   48    Male          18    Partnered      4        5
95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     ...
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

The raw data set 'aerofit_data' has 9 columns out of which 4(Product, Gender, MaritalStatus,Fitness) are categorical variables and 5(Age, Education, Usage, Income, Miles) are numerical variables, 180 rows.

Checking for duplicates

```
aerofit_data.duplicated().sum()
```

```
0
```

No duplicate values found.

Checking for null values

```
aerofit_data.isna().sum()
```

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

No null values found.

There are no columns to split or explode. The data is clean and neat for analysis.

Creating a copy of original data

```
aerofit_data_temp = aerofit_data.copy()

aerofit_data_temp

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

     Miles
0      112
1       75
```

```
2        66
3        85
4        47
..      ...
175     200
176     200
177     160
178     120
179     180

[180 rows x 9 columns]
```

Exploring Categorical variables

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

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

There are three categories in Product Column - KP281, KP481, KP781.

```
aerofit_data_temp['Gender'].unique()

array(['Male', 'Female'], dtype=object)
```

There are two categories in Gender Column - Male, Female.

```
aerofit_data_temp['MaritalStatus'].unique()

array(['Single', 'Partnered'], dtype=object)
```

There are two categories in MaritalStatus column - Single, Partnered .

```
aerofit_data_temp['Fitness'].unique()

array([4, 3, 2, 1, 5])
```

There are five categories in Fitness column - 1, 2, 3, 4, 5 .

Adding fitness_category and age_group as categories for categorization of users

```
#Fitness 1:'Poor',2: 'Below Average',3: 'Above Average', 4: 'Good', 5: 
'Excellet'
aerofit_data_temp['fitness_category']=
aerofit_data_temp['Fitness'].replace(
```

```
                                                    {1:'Poor',2: 'Below
Average',3: 'Above Average', 4: 'Good', 5: 'Excellet'})

aerofit_data_temp['age_group'] = aerofit_data_temp['Age']

#Age group 0-20: Teen , 21-35: Adult, 35-45: Middle Aged, 45-60: Elder
aerofit_data_temp['age_group']= pd.cut(aerofit_data_temp.age_group,

bins=[0,21,35,45,60],labels=['Teen','Adult','Middle Aged','Elder'])

aerofit_data_temp

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

     Miles fitness_category    age_group
0      112              Good         Teen
1       75     Above Average         Teen
2       66     Above Average         Teen
3       85     Above Average         Teen
4       47     Below Average         Teen
..     ...               ...          ...
175    200          Excellet  Middle Aged
176    200              Good  Middle Aged
177    160          Excellet  Middle Aged
178    120          Excellet        Elder
179    180          Excellet        Elder
```

```
[180 rows x 11 columns]
```

Value counts of Categorical Variables

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

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

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

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

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

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

```
aerofit_data_temp['Fitness'].value_counts()
```

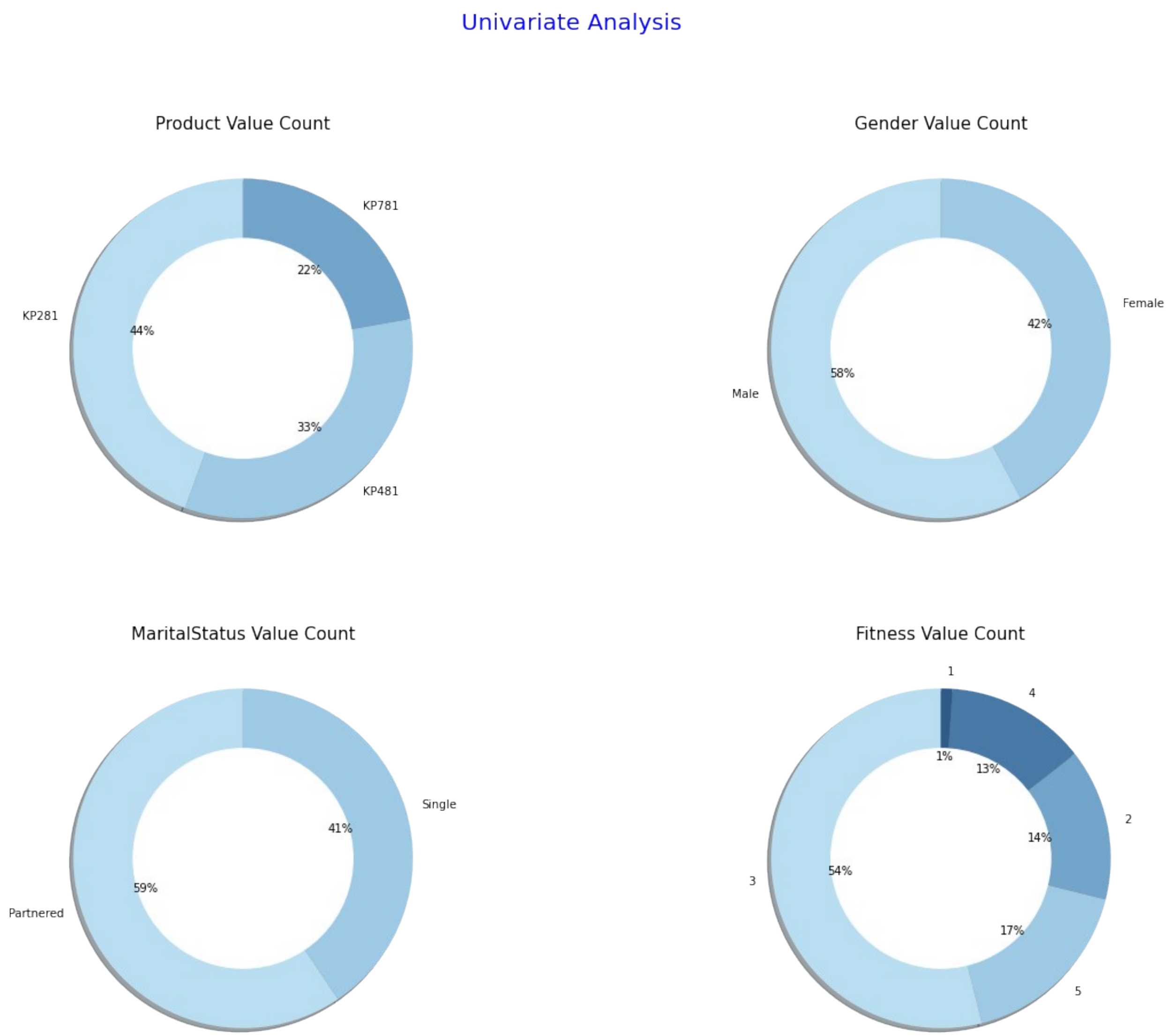
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

UniVariate Analysis

```
palette_color = ["#B9DDF1", "#9FCAE6", "#73A4CA", "#497AA7",
"#2E5B88"]

figure = plt.figure(figsize=(20,15))
plt.subplot(2,2,2)

plt.subplot(2,2,1)
plt.pie(list(aerofit_data_temp['Product'].value_counts().values),
        labels =
list(aerofit_data_temp['Product'].value_counts().index),
        colors= palette_color, autopct='%.0f%%',  shadow = True,
startangle=90)
hole = plt.Circle((0, 0), 0.65, facecolor='white')
```

```
plt.gcf().gca().add_artist(hole)
plt.title("Product Value Count", fontsize=15)

plt.subplot(2,2,2)
plt.pie(list(aerofit_data_temp['Gender'].value_counts().values),
        labels =
list(aerofit_data_temp['Gender'].value_counts().index),
        colors=palette_color, autopct='%.0f%%',  shadow = True,
startangle=90)
hole = plt.Circle((0, 0), 0.65, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title("Gender Value Count", fontsize=15)

plt.subplot(2,2,3)
plt.pie(list(aerofit_data_temp['MaritalStatus'].value_counts().values)
,
        labels =
list(aerofit_data_temp['MaritalStatus'].value_counts().index),
        colors=palette_color, autopct='%.0f%%',  shadow = True,
startangle=90)
hole = plt.Circle((0, 0), 0.65, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title("MaritalStatus Value Count", fontsize=15)

plt.subplot(2,2,4)
plt.pie(list(aerofit_data_temp['Fitness'].value_counts().values),
        labels =
list(aerofit_data_temp['Fitness'].value_counts().index),
        colors=palette_color, autopct='%.0f%%',  shadow = True,
startangle=90)
hole = plt.Circle((0, 0), 0.65, facecolor='white')
plt.gcf().gca().add_artist(hole)
plt.title("Fitness Value Count", fontsize=15)

plt.suptitle("Univariate Analysis", fontsize=20, color= 'Blue')
plt.show()
```

```
<ipython-input-22-a389faaff0e1>:14: MatplotlibDeprecationWarning:
Adding an axes using the same arguments as a previous axes currently
reuses the earlier instance.  In a future version, a new instance will
always be created and returned.  Meanwhile, this warning can be
suppressed, and the future behavior ensured, by passing a unique label
to each axes instance.
  plt.subplot(2,2,2)
```



Insight: From the above plot it can be observed that:

```
- KP281 has the heighest overall count in Product category.

- Males having heightest percentage in overall Gender category.

- Partnered has heighest count in MaritalStatus Category

- People with Fitness level 3 having the heighest overall count in
Fitness category.
```

Describing continuous variables

```
aerofit_data_temp.describe()
```

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

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

Descriptive Analysis:

Total count of all columns is 180.

Age: Mean age of the customer is 28 years, half of the customer's mean age is 26.

Education: Mean Education is 15 with maximum as 21 and minimum as 12.

Usage: Mean Usage per week is 3.4, with maximum as 7 and minimum as 2.

Fitness: Average rating is 3.3 on a scale of 1 to 5.

Miles: Average number of miles the customer walks is 103 with maximum distance travelled by most people is almost 115 and minimum is 21.

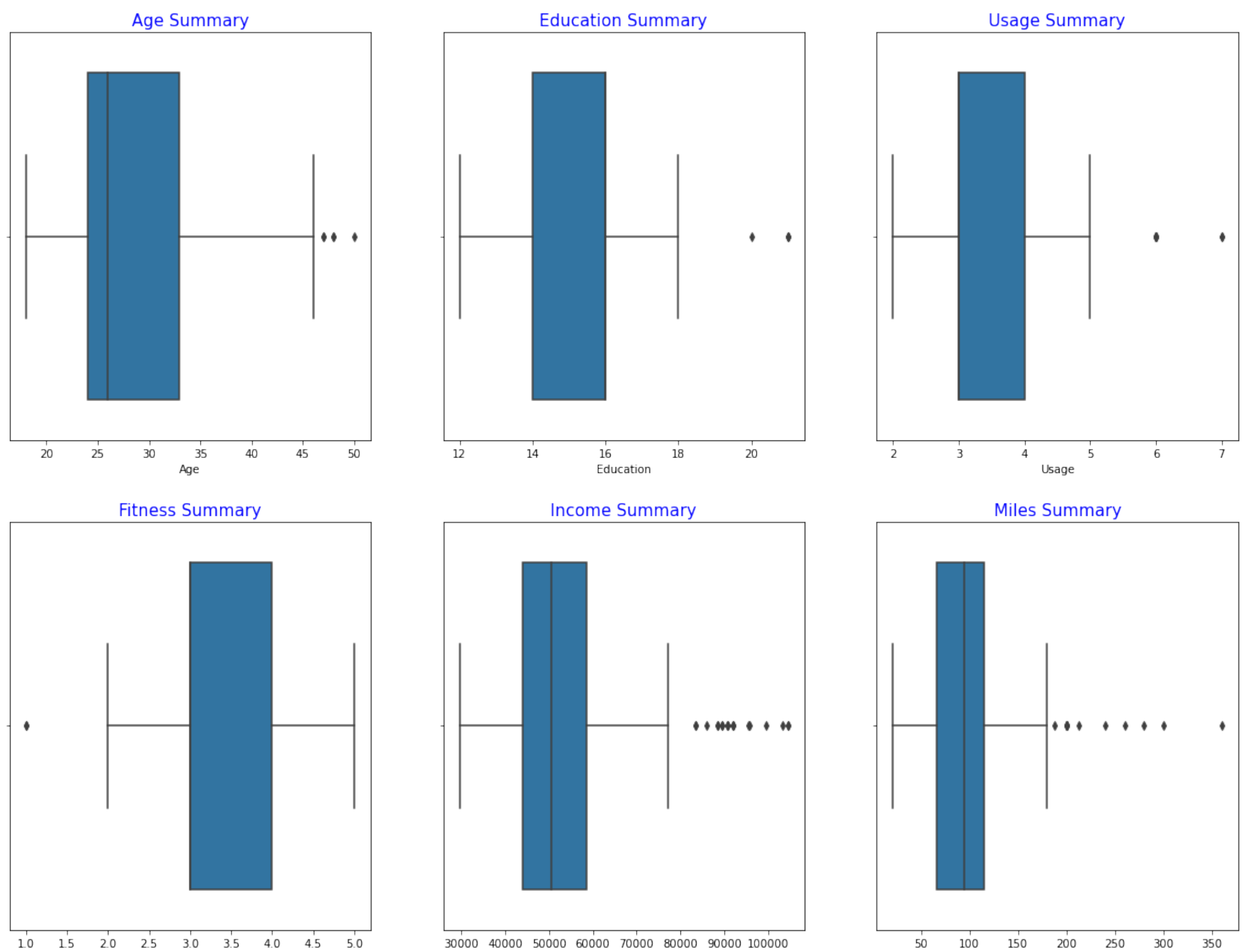
Income: Most customer earns around 58K annually, with maximum of 104K and minimum almost 30K.

Outlier detection

```
palette_color = ['blue','red','yellow','grey','green']
figure = plt.figure(figsize=(20,15))
#plt.subplot(2,3,2)

plt.subplot(2,3,1)
sns.boxplot(aerofit_data_temp.Age)
plt.title("Age Summary", fontsize = 15, color = 'blue')

plt.subplot(2,3,2)
sns.boxplot(aerofit_data_temp.Education)
plt.title("Education Summary", fontsize = 15, color = 'blue')

plt.subplot(2,3,3)
sns.boxplot(aerofit_data_temp.Usage)
plt.title("Usage Summary", fontsize = 15, color = 'blue')

plt.subplot(2,3,4)
sns.boxplot(aerofit_data_temp.Fitness)
plt.title("Fitness Summary", fontsize = 15, color = 'blue')

plt.subplot(2,3,5)
sns.boxplot(aerofit_data_temp.Income)
plt.title("Income Summary", fontsize = 15, color = 'blue')

plt.subplot(2,3,6)
sns.boxplot(aerofit_data_temp.Miles)
plt.title("Miles Summary", fontsize = 15, color = 'blue')

plt.show()
```

```
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```

```
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
/Users/manimahesh/opt/anaconda3/lib/python3.8/site-packages/seaborn/
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```



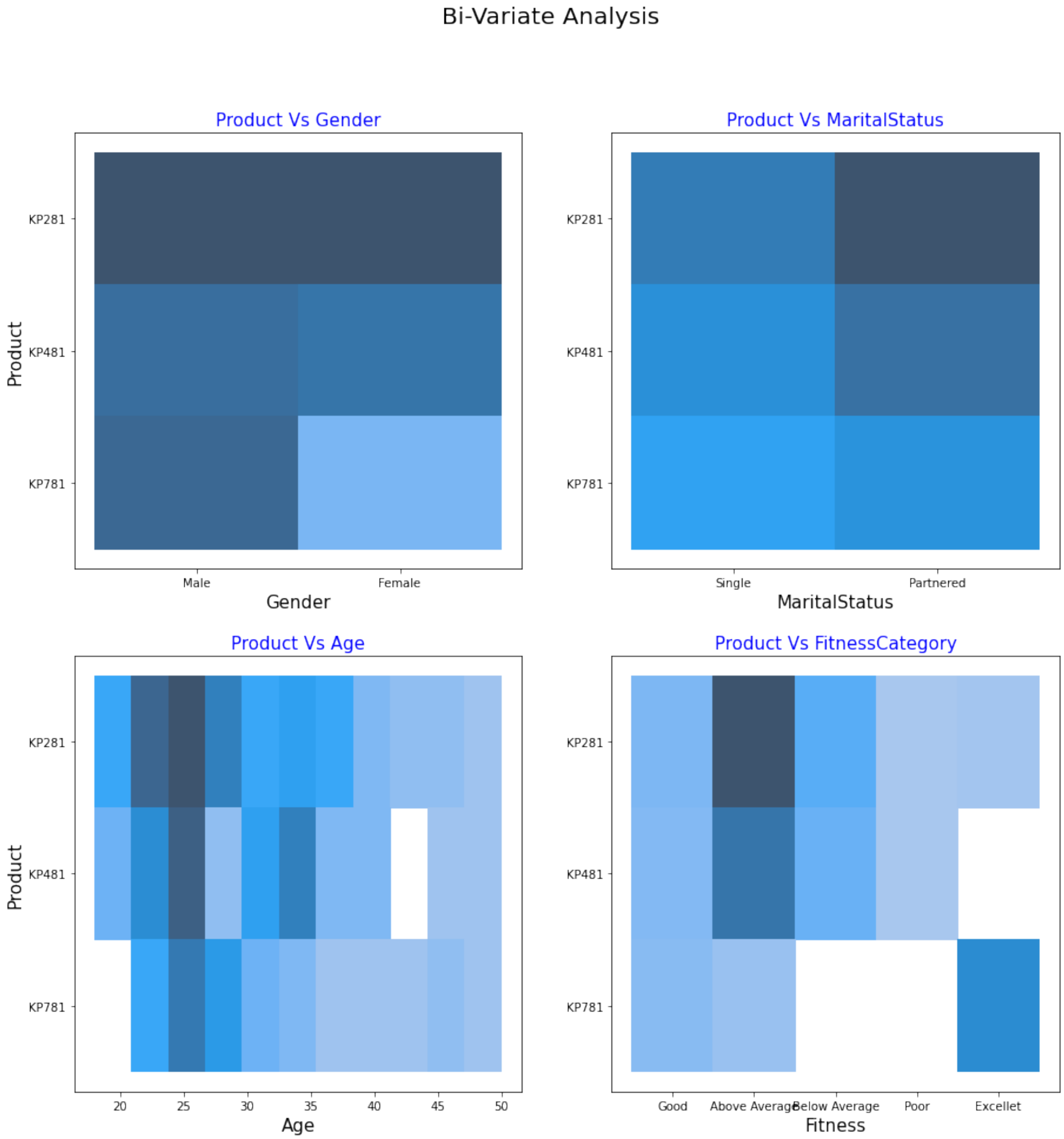
Insight: From the above box plots, it is observed that:

- Maximum number of aerofit customers are adults between 23-33 and some outliers observed between age 45-50.
- Maximum number of aerofit customers have an education summary between 14-16 years and some outliers are observed above 20 years.
- Maximum number of aerofit customers use the treadmill 3-4 times a week on average and there are some outliers observed whose use 6-7 times a week on average.
- Maximum number of aerofit customers has a fitness of 3-4 on a scale of 5 and there are some outliers minimum fitness level of 1.
- Maximum number of aerofit customers have an income summary raninging from 45k-60k and outliers are observed above 85k.
- Maximum number of aerofit customers have an average mile summary between 75-125 miles per week and some outliers are observed who has a record aove 200 miles average run/walk in a week.

Checking if features like marital status, age have any effect on the product purchased

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

plt.subplot(2,2,1)
sns.histplot(x= aerofit_data_temp.Gender, y =
aerofit_data_temp.Product, bins = 5)
plt.title("Product Vs Gender", fontsize=15, color = 'Blue')
plt.xlabel("Gender", size=15, color='Black')
plt.ylabel("Product",size=15, color='Black')

plt.subplot(2,2,2)
sns.histplot(x= aerofit_data_temp.MaritalStatus, y =
aerofit_data_temp.Product)
plt.title("Product Vs MaritalStatus", fontsize=15, color = 'Blue')
plt.xlabel("MaritalStatus", size=15, color='Black')
plt.ylabel("")

plt.subplot(2,2,3)
sns.histplot(x= aerofit_data_temp.Age, y = aerofit_data_temp.Product)
plt.title("Product Vs Age", fontsize=15, color = 'Blue')
plt.xlabel("Age", size=15, color='Black')
plt.ylabel("Product", size=15, color='Black')

plt.subplot(2,2,4)
sns.histplot(x= aerofit_data_temp.fitness_category, y =
```

```
aerofit_data_temp.Product)
plt.title("Product Vs FitnessCategory", fontsize=15, color = 'Blue')
plt.xlabel("Fitness", size=15, color='Black')
plt.ylabel("")

plt.suptitle('Bi-Variate Analysis', fontsize=20, color='Black')
plt.show()
```

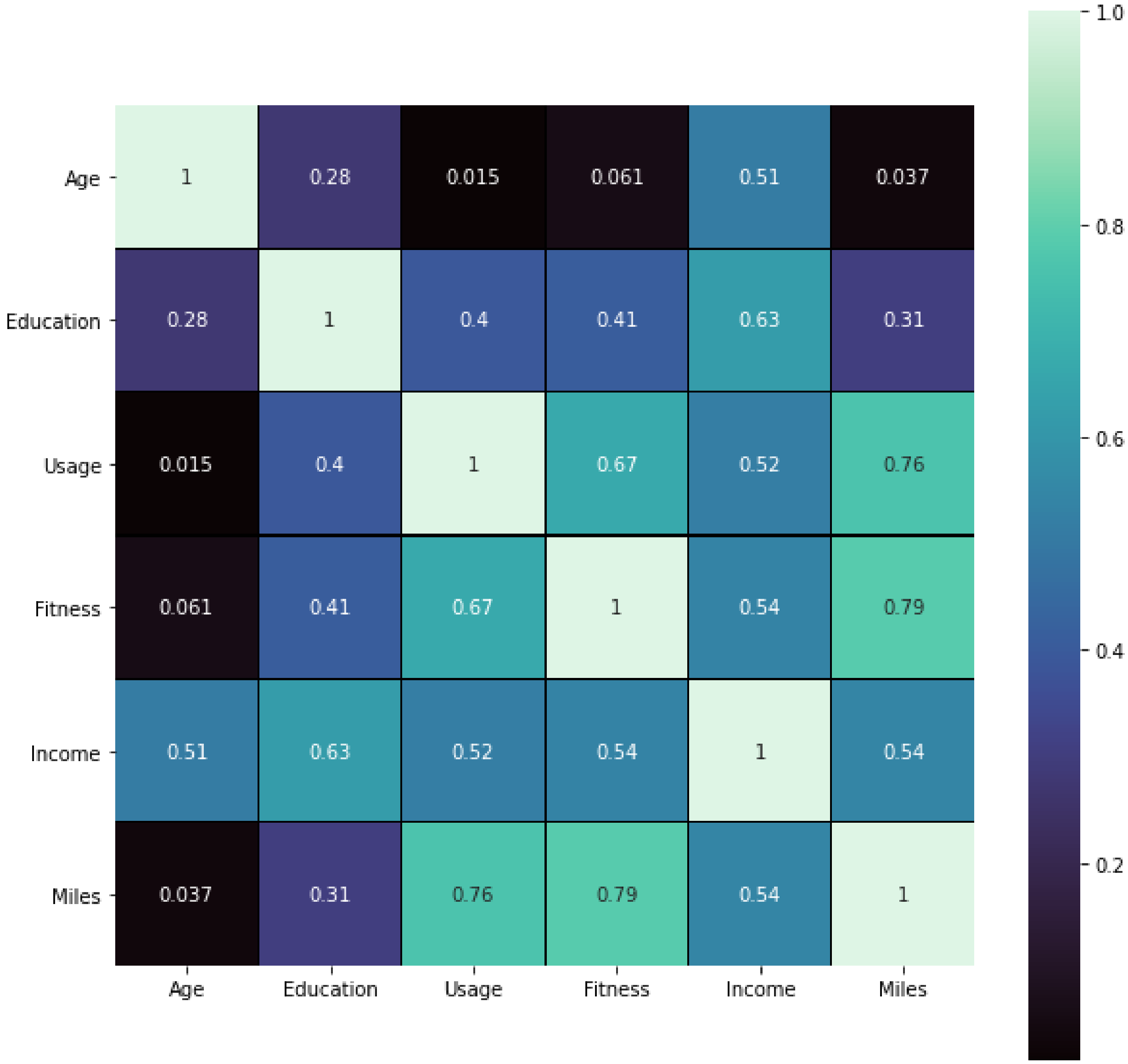


Insights:

```
K281 is bought by both Male and Female equally, where as KP481 and
KP781 are bought more by Male than Female.

All the products are bought more by Parenered than Single customers
where as KP281 is the best baught product both by siggle and partnered
customers next comes KP481 and KP781.

All the products are mostly baught by customers aged between 20-
30.Amongst the three products KP281 is baught by all age group, KP481
has no sales in the age group 40-45 and KP7821 is not baught by Teen
customers.

Only customers with Excellent, good and above average fitness
leve(3,4,5) tends to buy KP781. AboveAverage fitness(3) customers has
most percentage of KP481. KP281 is mostly used by customers with above
average fitnesslevel(3).
```

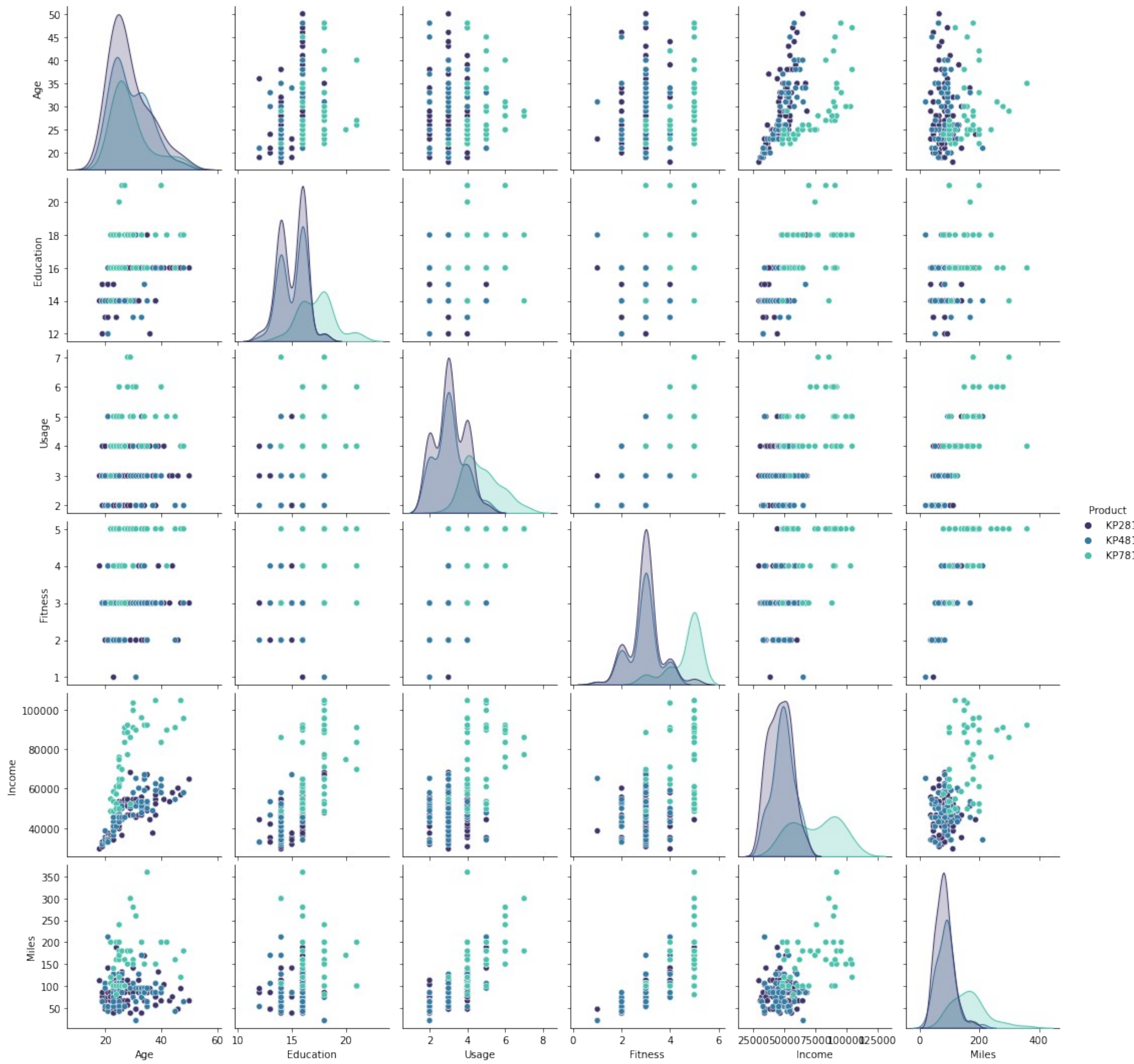
Checking correlation among different factors using heat maps and pair plots.

```
plt.figure(figsize=(10,10))
sns.heatmap(aerofit_data_temp.corr(),annot=True, cmap =
'mako',linewidths=0.1,
            square= True, linecolor= 'Black')
plt.yticks(rotation=0)
plt.show()
```

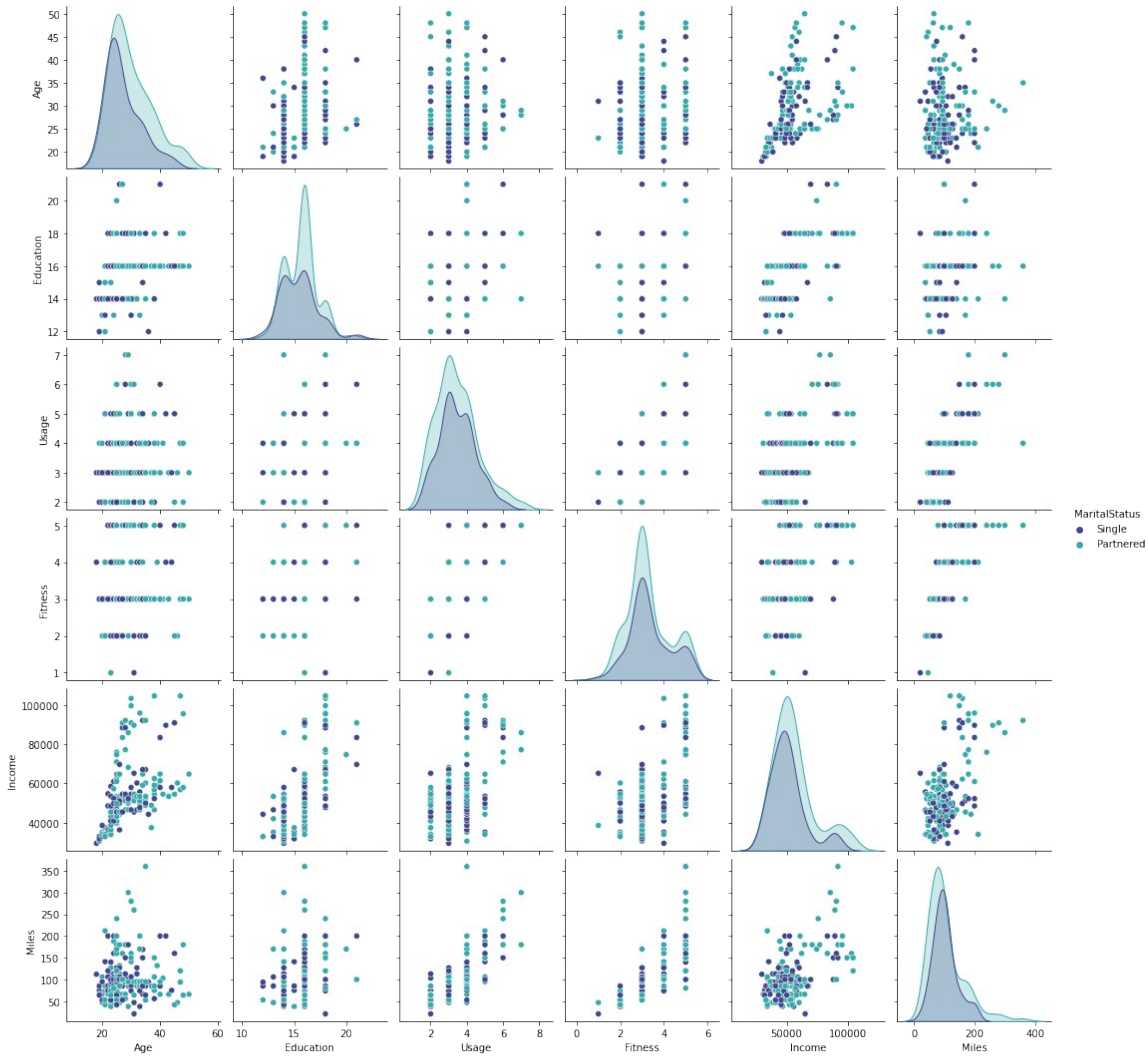


Insights: There is more correlation between Fitness-Miles (0.79), Usage-Miles (0.76), Usage-Fitness(0.67), Fitness-Income(0.54),Usage-Income (0.52).

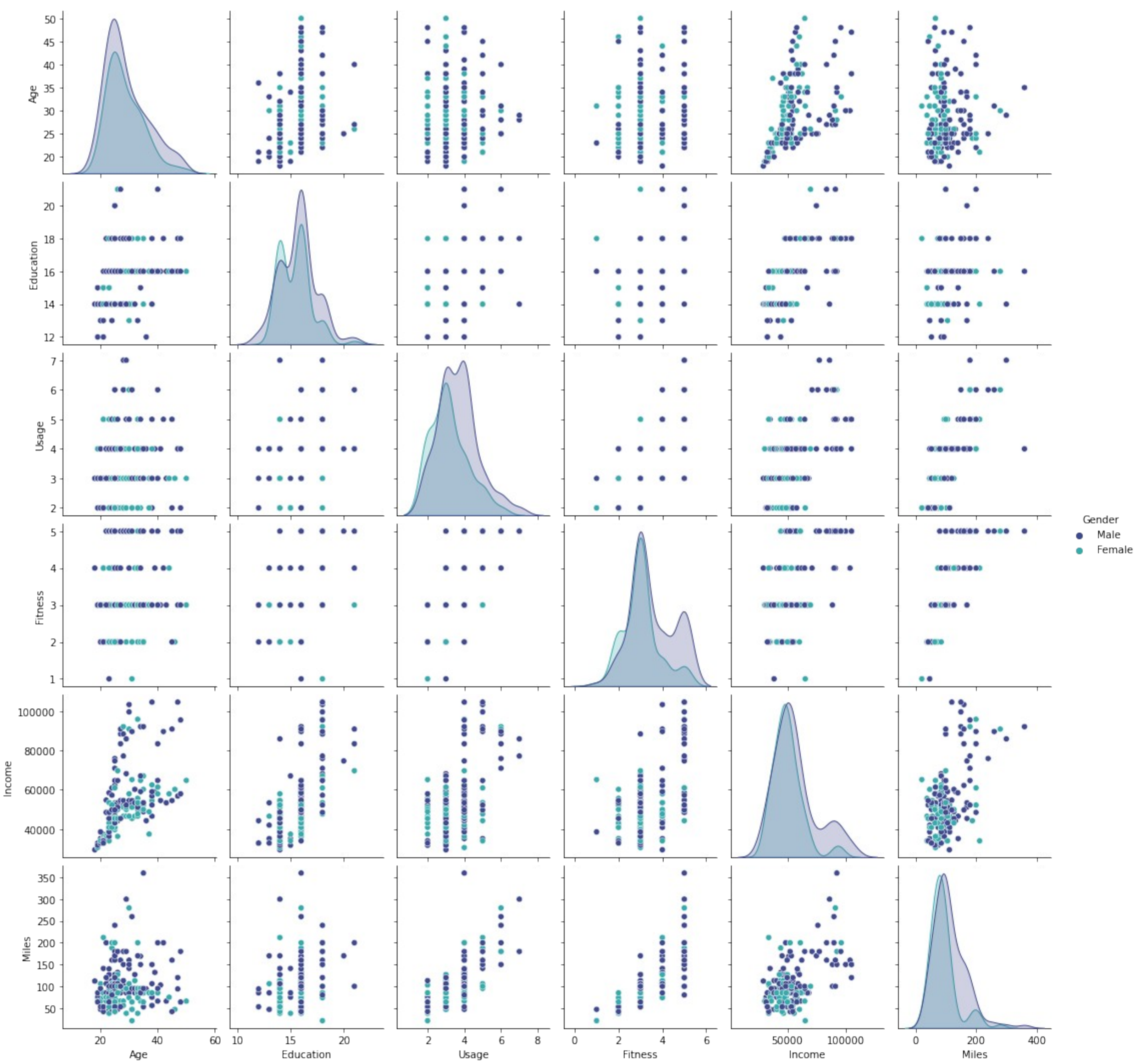
```
plt.figure(figsize=(10,10))
sns.pairplot(aerofit_data_temp, hue = 'Product', palette='mako')
plt.show()

<Figure size 720x720 with 0 Axes>
```




```
plt.figure(figsize=(10,10))
sns.pairplot(aerofit_data_temp, hue = 'MaritalStatus', palette='mako')
plt.show()

<Figure size 720x720 with 0 Axes>
```




```
plt.figure(figsize=(10,10))
sns.pairplot(aerofit_data_temp, hue = 'Gender', palette='mako')
plt.show()

<Figure size 720x720 with 0 Axes>
```



Customer Profiling - Categorization of users.

```
(aerofit_data_temp.fitness_category.value_counts()/
len(aerofit_data_temp)).round(2)

Above Average    0.54
Excellet         0.17
Below Average    0.14
Good             0.13
Poor             0.01
Name: fitness_category, dtype: float64

(aerofit_data_temp.age_group.value_counts()/
len(aerofit_data_temp)).round(2)
```

```
Adult          0.75
Middle Aged    0.12
Teen           0.09
Elder          0.03
Name: age_group, dtype: float64

aerofit_melt =
aerofit_data_temp[['Gender','MaritalStatus','Product']].melt()
(aerofit_melt.groupby(['variable','value'])['value'].count()/len(aerof
it_data_temp)).round(2)

variable       value
Gender         Female       0.42
               Male         0.58
MaritalStatus  Partnered    0.59
               Single       0.41
Product        KP281        0.44
               KP481        0.33
               KP781        0.22
Name: value, dtype: float64
```

Insights: Male adult customers with an above-average fitness level who are partnered and using KP281 are in the majority.

Marginal and Conditional Probabilities

```
#Marginal Probability Gender and product

pd.crosstab(aerofit_data_temp.Product, aerofit_data_temp.Gender,
normalize= True,margins= True,
            margins_name = 'Total').round(2)

Gender   Female  Male  Total
Product
KP281      0.22  0.22   0.44
KP481      0.16  0.17   0.33
KP781      0.04  0.18   0.22
Total      0.42  0.58   1.00
```

Probability of Female aerofit customers using any product P(Female) = 0.42

Probability of Male aerofit customers using any product P(Male) = 0.58

Probability of aerofit customers buying product KP281 P(KP281) = 0.44

Probability of aerofit customers buying product KP481 P(KP481) = 0.33

Probability of aerofit customers buying product KP781 P(KP781) = 0.22

Insights: From the above information it is known that there are more number male customers and customers using KP281 are high than the other models, where are Female to Male ratio who are using KP281 model are is equal. KP781 model is less used over all and Female to Male ratio using this model is almost 1 : 4.5. Model KP481 is moderatley used gy customers and Female to Male ratio is almost equal.

```
#Conditional Probability of a product for a given Gender

pd.crosstab(aerofit_data_temp.Product,
aerofit_data_temp.Gender,margins=True,normalize= 'columns',
            margins_name = 'Fraction_of_Product').round(2)
```

Gender	Female	Male	Fraction_of_Product
Product			
KP281	0.53	0.38	0.44
KP481	0.38	0.30	0.33
KP781	0.09	0.32	0.22

Probabilty of customers using KP281 who are Female: P(KP281|Female) = 0.53

Probabilty of customers using KP281 who are Male: P(KP281|Male) = 0.38

Probabilty of customers using KP481 who are Female: P(KP481|Female) = 0.38

Probabilty of customers using KP481 who are Male: P(KP481|Male) = 0.30

Probabilty of customers using KP781 who are Female: P(KP781|Female) = 0.09

Probabilty of customers using KP781 who are Male: P(KP781|Male) = 0.32

Insights: Taking Gender into consideration the over all female customers are giving highest preference to use model KP281 and least preference to use model KP781. Even male customers prefer model KP281 over other models.

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

```
P(KP781|Male) = 0.32

# Marginal probability age_group and product
pd.crosstab(aerofit_data_temp.Product, aerofit_data_temp.age_group,
normalize=True,margins= True,
            margins_name = 'Total').round(2)
```

age_group	Teen	Adult	Middle Aged	Elder	Total
Product					
KP281	0.06	0.31	0.06	0.02	0.44
KP481	0.04	0.25	0.04	0.01	0.33
KP781	0.00	0.19	0.02	0.01	0.22
Total	0.09	0.75	0.12	0.03	1.00

Probability of aerofit customers who are teen agers: P(Teen) = 0.09

Probability of aerofit customers who are adults: P(Adult) = 0.75

Probability of aerofit customers who are middle aged: P(Middle_age) = 0.12

Probability of aerofit customers who are elders: P(Elder) = 0.03

Insights: Over all aerofit customers are adults followed by middle-aged group.

```
#Conditional probability of using a product for a given age_group
pd.crosstab(aerofit_data_temp.Product, aerofit_data_temp.age_group,
normalize= 'columns',margins= True,
            margins_name = 'Fraction_of_Product').round(2)

age_group  Teen  Adult  Middle Aged  Elder  Fraction_of_Product
Product
KP281      0.59   0.41         0.50   0.50                 0.44
KP481      0.41   0.33         0.32   0.17                 0.33
KP781      0.00   0.25         0.18   0.33                 0.22
```

Insights: All the age_groups prefer using KP281 are more compared to other models. KP481 is moderately bought buy customers of all age groups where as KP781 is the least bought model Teens using KP781 is almost zero.

```
# Marginal Probability of fitness_category
pd.crosstab(aerofit_data_temp.Product,
aerofit_data_temp.fitness_category, normalize=True, margins = True,
           margins_name='Total').round(2)

fitness_category  Above Average  Below Average  Excellet  Good  Poor
Total
Product

KP281                      0.30           0.08      0.01  0.05  0.01
0.44
KP481                      0.22           0.07      0.00  0.04  0.01
0.33
KP781                      0.02           0.00      0.16  0.04  0.00
0.22
Total                      0.54           0.14      0.17  0.13  0.01
1.00
```

Probability of aerofit customers with Poor fitness: P(Poor)= 0.01

Probability of aerofit customers with Poor fitness: P(BelowAverage)= 0.14

Probability of aerofit customers with Poor fitness: P(AboveAverage)= 0.54

Probability of aerofit customers with Poor fitness: P(Good)= 0.13

Probability of aerofit customers with Poor fitness: P(Excellent)= 0.17

Insights: From the above information we can say that maximum aerofit customers are with AboveAverage fitness(3), where as minimum customers are with Poor Fitness(1).

```
#Conditional probability of fitness_category for a given product
pd.crosstab(aerofit_data_temp.Product,
aerofit_data_temp.fitness_category, normalize='columns', margins =
True,
           margins_name='Fraction_of_Product').round(2)

fitness_category  Above Average  Below Average  Excellet  Good
Poor  \
Product

KP281                      0.56           0.54      0.06  0.38   0.5

KP481                      0.40           0.46      0.00  0.33   0.5

KP781                      0.04           0.00      0.94  0.29   0.0


fitness_category  Fraction_of_Product
Product
KP281                            0.44
KP481                            0.33
KP781                            0.22
```

Insights:

```
      Maximum AboveAverage,BelowAverage,Good,Poor fitnesslevel
customers tend to buy KP281(Beginner Model).

      Minimum AboveAverage,BelowAverage,Good,Poor fitness level
customers tend to buy KP781(Advanced Model).

      Maximum Excellent Fitness level customers are contributing to
the sales of KP781(Advanced Model).

      A moderate number of customers with good fitness level are
contributing to the sales of KP781.

      A moderate number of customers are all fitness level except
Excellent are contributing to the sales of KP481.

#Marginal Probability MaritalStatus and product

pd.crosstab(aerofit_data_temp.Product,
aerofit_data_temp.MaritalStatus, normalize= True,margins= True,
            margins_name = 'Total').round(2)
```

```
MaritalStatus  Partnered  Single  Total
Product
KP281               0.27    0.18   0.44
KP481               0.20    0.13   0.33
KP781               0.13    0.09   0.22
Total               0.59    0.41   1.00
```

Probability of Parterend customers: P(Partnered)= 0.59

Probability of Single customers: P(Single)= 0.41

Insights: Partnered customers are a bit more compared to single customers.

```python
#Conditional probability of using a product for a given MaritalStatus
pd.crosstab(aerofit_data_temp.Product,
aerofit_data_temp.MaritalStatus, normalize= 'columns',margins= True,
            margins_name = 'Fraction_of_Product').round(2)
```

```
MaritalStatus  Partnered  Single  Fraction_of_Product
Product
KP281               0.45    0.44                 0.44
KP481               0.34    0.33                 0.33
KP781               0.21    0.23                 0.22
```

Probability of Partnered customers buying KP281: P(KP281|Partnered)=0.45

Probability of Single customers buying KP281: P(KP281|Single)=0.44

Probability of Partnered customers buying KP481: P(KP481|Partnered)=0.34

Probability of Single customers buying KP481: P(KP481|Partnered)=0.33

Probability of Partnered customers buying KP781: P(KP781|Partnered)=0.21

Probability of Single customers buying KP781: P(KP781|Partnered)=0.23

Insights: Chances of Partnered customers buying KP281,KP481,KP781 is a bit more than single customers where as maximum Partnered customers bought KP281