Aerofit-Descriptive-Statistics Probability

Aerofit

- Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

Objective/ Purpose of analyzing Aerofit data

- Creating comprehensive customer profiles AeroFit treadmill product through descriptive analysis and Data Visualization.
- Analayzing data given to reach with the help of two-way contingency tables. Fiding out onditional and marginal probabilities to focus on customer characteristics, enhancing product marketing skills and facilitating improved product recommendations and informed business decisions.

Product Portfolio

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

Importing Libraries

In [ ]:

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

In [ ]:

```
%pip install seaborn
```

```
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.1
)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /usr/local/lib/python3.10/dist-pac
kages (from seaborn) (1.23.5)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (fr
om seaborn) (1.5.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/local/lib/python3.10/dist-
packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-package
s (from matplotlib!=3.6.1,>=3.4->seaborn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (f
rom matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packag
```

```
es (from matplotlib!=3.6.1,>=3.4->seaborn) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packag
es (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages
(from matplotlib!=3.6.1,>=3.4->seaborn) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (
from matplotlib!=3.6.1,>=3.4->seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-package
s (from matplotlib!=3.6.1,>=3.4->seaborn) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-pac
kages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (f
rom pandas>=1.2->seaborn) (2023.3.post1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from
python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
```

In [ ]:

```
import seaborn as sns
```

Importing Dataset

In [ ]:

```
#Reading the CSV file data for Aerofit
aerofit_data = pd.read_csv('aerofit_treadmill.csv')
```

1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset

In [ ]:

```
aerofit_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 12 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
 9   age_group      180 non-null    category
 10  Income_Range   180 non-null    category
 11  miles_group    180 non-null    category
dtypes: category(3), int64(6), object(3)
memory usage: 13.9+ KB
```

Displaying data types of each column

In [ ]:

```
aerofit_data.dtypes
```

Out[ ]:

```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
```

```
Miles              int64
dtype: object
```

Finding the number of rows and columns given in the dataset

In [ ]:

```
print(f"'Number of Rows' : {aerofit_data.shape[0]}\n'Number of Columns' : {aerofit_data.shape[1]}")
```

```
'Number of Rows' : 180
'Number of Columns' : 9
```

Check for the missing values and find the number of missing values in each column

In [ ]:

```
aerofit_data.isnull().any()
```

Out[ ]:

```
Product          False
Age              False
Gender           False
Education        False
MaritalStatus    False
Usage            False
Fitness          False
Income           False
Miles            False
dtype: bool
```

Checking Duplicate values in the dataset

In [ ]:

```
aerofit_data.duplicated().value_counts()
```

Out[ ]:

```
False    180
dtype: int64
```

Viewing and understanding first 5 rows of the dataframe

In [ ]:

```
aerofit_data.head()
```

Out[ ]:

	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

INSIGHTS & OBSERVATIONS - From the above analysis, the observation is :

1. **Total number of rows and columns are 180 and 9 respectively.**
2. **Product, Gender and Marital Status columns have object datatype**
3. **Age, Education, Usage, Miles, Fitness, Income have Integer datatype**
4. **we can see there are no duplicate entries in the dataset**

5. Number of Unique Values in

- **Product - 3**
- **Age - 32**
- **Gender - 2**
- **Education - 8**
- **Marital Status - 2**
- **Usage - 6**
- **Fitness - 5**
- **Income - 62**
- **Miles - 37 iles column : 37**

Statistical summary of All columns

In [ ]:

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

Out[ ]:

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

2. Detect Outliers

Finding the outliers for every continuous variable in the dataset

In [ ]:

```
continuous_var = ['Age', 'Income', 'Usage', 'Fitness', 'Miles']
```

In [ ]:

```
arr = {'5th percentile': 5, '25th percentile or Q1': 25, '50th percentile or Q2': 50, '7
5th percentile or Q3': 75,
'95th percentile': 95}
```

In [ ]:

```
for key, value in arr.items():
  for var in continuous_var:
    print(f'{var} -> {key} : {np.percentile(aerofit_data[var], value):.2f}')
```

```
Age -> 5th percentile : 20.00
Income -> 5th percentile : 34053.15
Usage -> 5th percentile : 2.00
Fitness -> 5th percentile : 2.00
Miles -> 5th percentile : 47.00
Age -> 25th percentile or Q1 : 24.00
Income -> 25th percentile or Q1 : 44058.75
Usage -> 25th percentile or Q1 : 3.00
```

```
Fitness -> 25th percentile or Q1 : 3.00
Miles -> 25th percentile or Q1 : 66.00
Age -> 50th percentile or Q2 : 26.00
Income -> 50th percentile or Q2 : 50596.50
Usage -> 50th percentile or Q2 : 3.00
Fitness -> 50th percentile or Q2 : 3.00
Miles -> 50th percentile or Q2 : 94.00
Age -> 75th percentile or Q3 : 33.00
Income -> 75th percentile or Q3 : 58668.00
Usage -> 75th percentile or Q3 : 4.00
Fitness -> 75th percentile or Q3 : 4.00
Miles -> 75th percentile or Q3 : 114.75
Age -> 95th percentile : 43.05
Income -> 95th percentile : 90948.25
Usage -> 95th percentile : 5.05
Fitness -> 95th percentile : 5.00
Miles -> 95th percentile : 200.00
```

In [ ]:

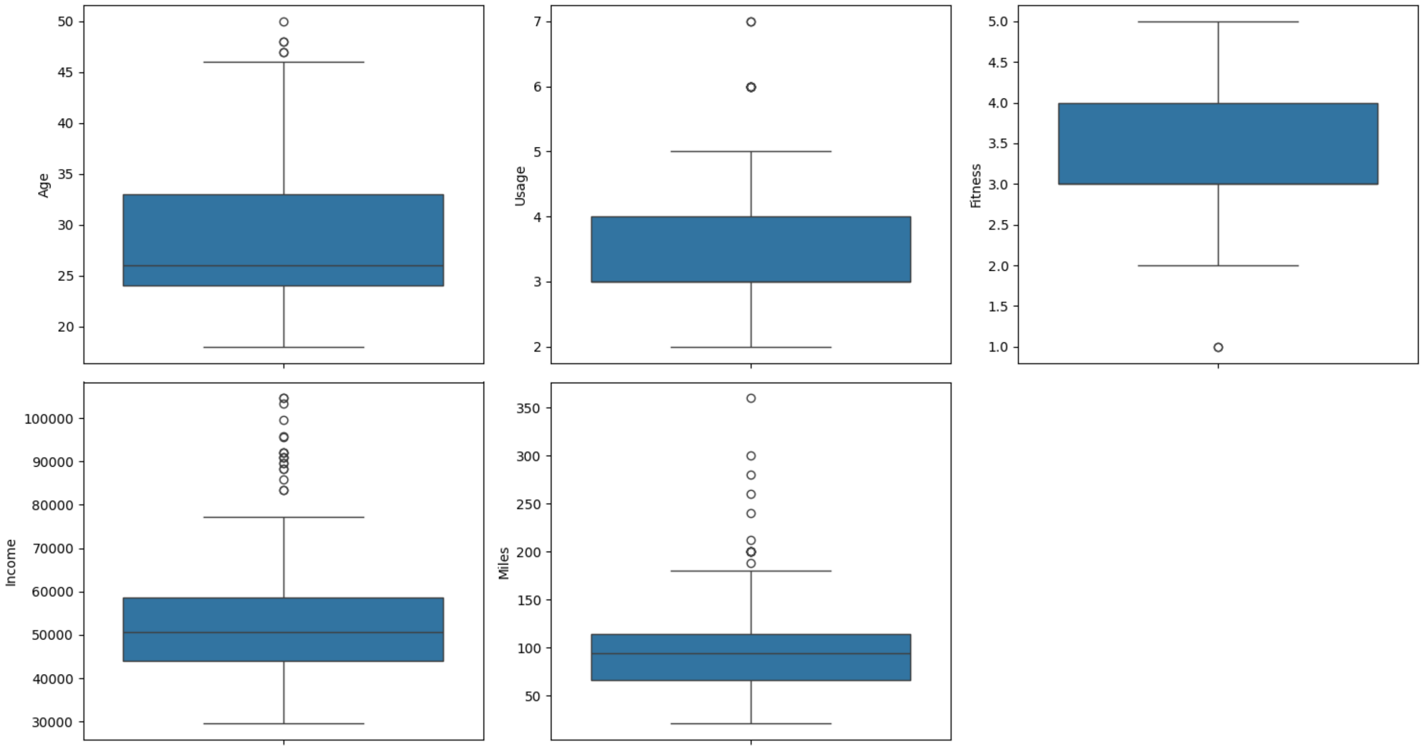
```
for var in continuous_var:
  Q1 = np.percentile(aerofit_data[var], arr['25th percentile or Q1'])
  Q3 = np.percentile(aerofit_data[var], arr['75th percentile or Q3'])
  percentile_95 = np.percentile(aerofit_data[var], arr['95th percentile'])
  IQR = Q3 - Q1
  lower_threshold = Q1 - 1.5 * IQR
  upper_threshold = Q3 + 1.5 * IQR
  outliers = aerofit_data[(aerofit_data[var] < lower_threshold) |(aerofit_data[var] > up
per_threshold)]
  outlier_percentage = round(len(outliers) / len(aerofit_data[var]) * 100, 2 )
  print(f"IQR for {var}: {IQR}")
  print(f"Outlier above this Q3 {var} : {upper_threshold}")
  print(f"Percentage of outliers for {var}: {outlier_percentage}% \n")
```

```
IQR for Age: 9.0
Outlier above this Q3 Age : 46.5
Percentage of outliers for Age: 2.78%

IQR for Income: 14609.25
Outlier above this Q3 Income : 80581.875
Percentage of outliers for Income: 10.56%

IQR for Usage: 1.0
Outlier above this Q3 Usage : 5.5
Percentage of outliers for Usage: 5.0%

IQR for Fitness: 1.0
Outlier above this Q3 Fitness : 5.5
Percentage of outliers for Fitness: 1.11%

IQR for Miles: 48.75
Outlier above this Q3 Miles : 187.875
Percentage of outliers for Miles: 7.22%
```

In [ ]:

```
plt.figure(figsize=(15,8))
# Box Plot for Age
plt.subplot(2,3,1)
sns.boxplot(aerofit_data['Age'])
# Box Plot for Usage
plt.subplot(2,3,2)
sns.boxplot(aerofit_data['Usage'])
#Box Plot for Fitness
plt.subplot(2,3,3)
sns.boxplot(aerofit_data['Fitness'])
#Box Plot for Income
plt.subplot(2,3,4)
sns.boxplot(aerofit_data['Income'])
#Box Plot for Miles
```

```
plt.subplot(2,3,5)
sns.boxplot(aerofit_data['Miles'])
plt.tight_layout()
plt.show()
```



INSIGHTS & OBSERVATIONS - Based on this graphical representation, it is evident that both Income and Miles have a huge number of outliers. In contrast, the remaining variables display only a minor presence of outliers as compared to them.

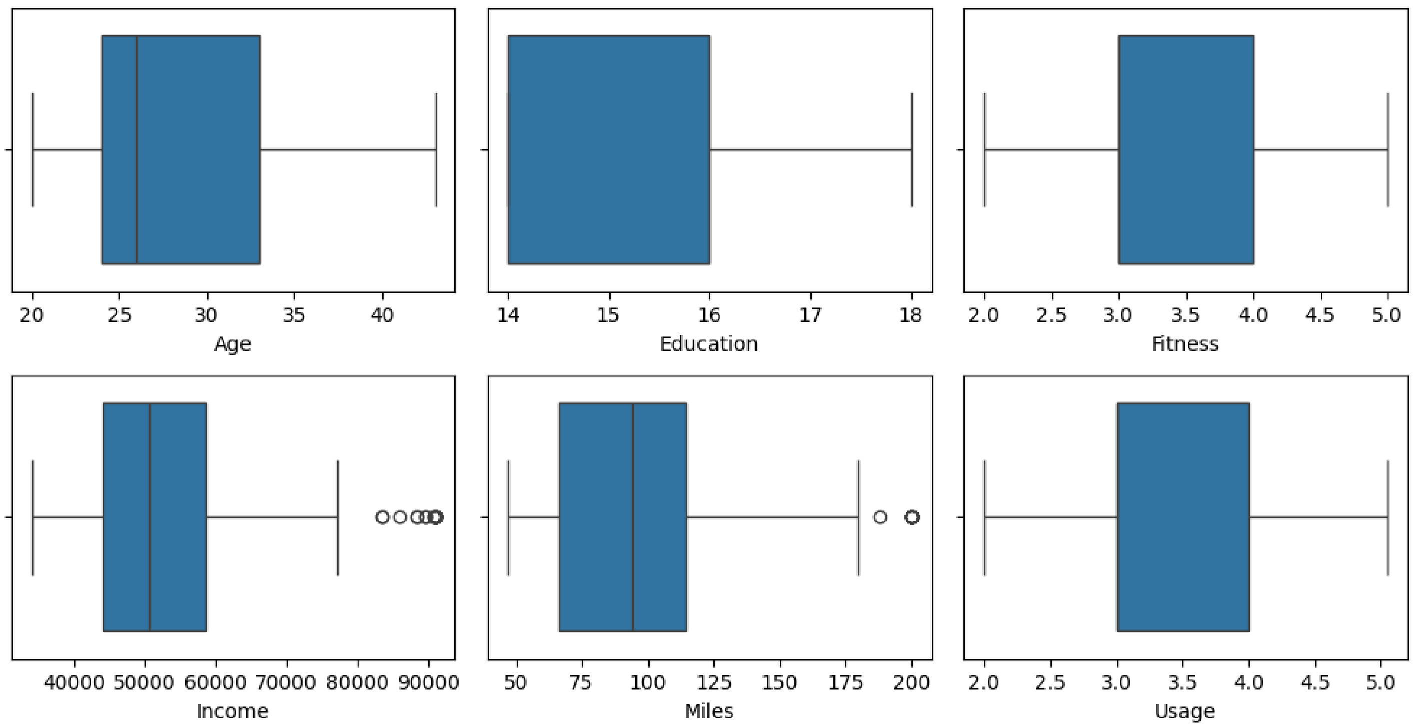
- **Least percentage of outliers are in Age with 2.78%**
- **Large percentage of outliers are in Income with 10.56%**

Remove/clip the data between the 5 percentile and 95 percentile

In [ ]:

```
clipped_age = np.clip(aerofit_data['Age'], np.percentile(aerofit_data['Age'],5), np.percentile(aerofit_data['Age'], 95))
clipped_education = np.clip(aerofit_data['Education'], np.percentile(aerofit_data['Education'], 5), np.percentile(aerofit_data['Education'], 95))
clipped_income = np.clip(aerofit_data['Income'], np.percentile(aerofit_data['Income'], 5), np.percentile(aerofit_data['Income'],95))
clipped_usage = np.clip(aerofit_data['Usage'], np.percentile(aerofit_data['Usage'], 5), np.percentile(aerofit_data['Usage'],95))
clipped_miles = np.clip(aerofit_data['Miles'], np.percentile(aerofit_data['Miles'], 5), np.percentile(aerofit_data['Miles'],95))
clipped_fitness = np.clip(aerofit_data['Fitness'], np.percentile(aerofit_data['Fitness'], 5), np.percentile(aerofit_data['Fitness'], 95))
fig,ax=plt.subplots(2,3,figsize=(10,6))
fig.suptitle("\nClipped Outliers\n")
plt.subplot(2,3,1)
sns.boxplot(data=aerofit_data,x=clipped_age)
plt.subplot(2,3,2)
sns.boxplot(data=aerofit_data,x=clipped_education)
plt.subplot(2,3,3)
sns.boxplot(data=aerofit_data,x=clipped_fitness)
plt.subplot(2,3,4)
sns.boxplot(data=aerofit_data,x=clipped_income)
plt.subplot(2,3,5)
sns.boxplot(data=aerofit_data,x=clipped_miles)
plt.subplot(2,3,6)
sns.boxplot(data=aerofit_data,x=clipped_usage)
plt.tight_layout()
plt.show()
```

Clipped Outliers



Non-Graphical Analysis: Value counts and unique attributes along with Gaphical : Univariate & Bivariate analysis

- **For Non-Graphical Analysis:**

In [ ]:

```
categorical_columns= ['Product', 'Gender', 'MaritalStatus']
```

In [ ]:

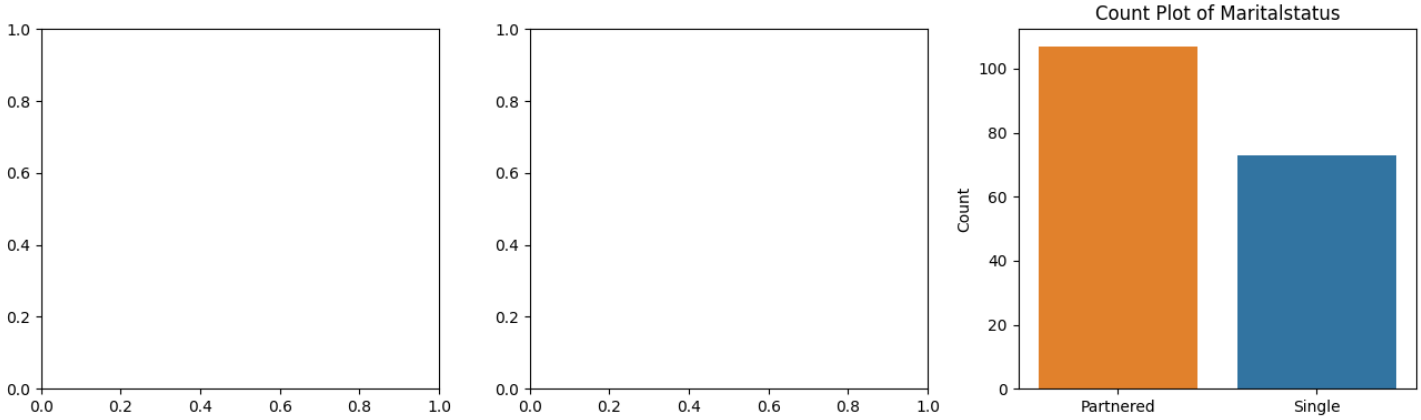
```
#Non-graphical analysis: Value counts for each categorical variable
for column in categorical_columns:
  print(f"{aerofit_data[column].value_counts()}\n")
```

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

Male      104
Female     76
Name: Gender, dtype: int64

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

In [ ]:

```
# Countplots for each categorical variable
fig,axes = plt.subplots(1, 3,figsize=(13, 4))
for i, column in enumerate(categorical_columns):
  order = aerofit_data[column].value_counts().index[:10]
sns.countplot(x=column, data=aerofit_data, order=order, ax=axes[i],hue=column)
axes[i].set_title(f'Count Plot of {column.capitalize()}')
axes[i].set_xlabel('')
axes[i].set_ylabel('Count')
axes[i].tick_params(axis='y',labelsize=10)
axes[i].tick_params(axis='x',labelsize=10)
```

```
plt.tight_layout()
plt.show()
```



Checking the unique values for columns

In [ ]:

```
for i in aerofit_data.columns:
  print(f'Unique Values in {i} column are :-\n {aerofit_data[i].unique()}\n')
  print('.'*80)
```

```
Unique Values in Product column are :-
 ['KP281' 'KP481' 'KP781']

................................................................................
Unique Values in Age column are :-
 [18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 43 44 46 47 50 45 48 42]

................................................................................
Unique Values in Gender column are :-
 ['Male' 'Female']

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

................................................................................
Unique Values in MaritalStatus column are :-
 ['Single' 'Partnered']

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

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

................................................................................
Unique Values in Income column are :-
 [ 29562  31836  30699  32973  35247  37521  36384  38658  40932  34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]

................................................................................
Unique Values in Miles column are :-
 [112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]

................................................................................
```

Checking the number of unique values for columns

In [ ]:

```
for i in aerofit_data.columns:
  print('Number of Unique Values in',i,'column :', aerofit_data[i].nunique())
  print('-'*70)
```

```
Number of Unique Values in Product column : 3
----------------------------------------------------------------------
Number of Unique Values in Age column : 32
----------------------------------------------------------------------
Number of Unique Values in Gender column : 2
----------------------------------------------------------------------
Number of Unique Values in Education column : 8
----------------------------------------------------------------------
Number of Unique Values in MaritalStatus column : 2
----------------------------------------------------------------------
Number of Unique Values in Usage column : 6
----------------------------------------------------------------------
Number of Unique Values in Fitness column : 5
----------------------------------------------------------------------
Number of Unique Values in Income column : 62
----------------------------------------------------------------------
Number of Unique Values in Miles column : 37
----------------------------------------------------------------------
```

In [ ]:

```
continuous_var = ['Age', 'Education', 'Income', 'Usage', 'Fitness', 'Miles']
```

In [ ]:

```
for column in continuous_var:
  print(f"{column}\n{aerofit_data[column].value_counts().sort_values(ascending=False)}")
```

```
Age
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
38     7
21     7
22     7
27     7
31     6
34     6
29     6
40     5
20     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
43     1
41     1
39     1
36     1
42     1
Name: Age, dtype: int64
Education
```

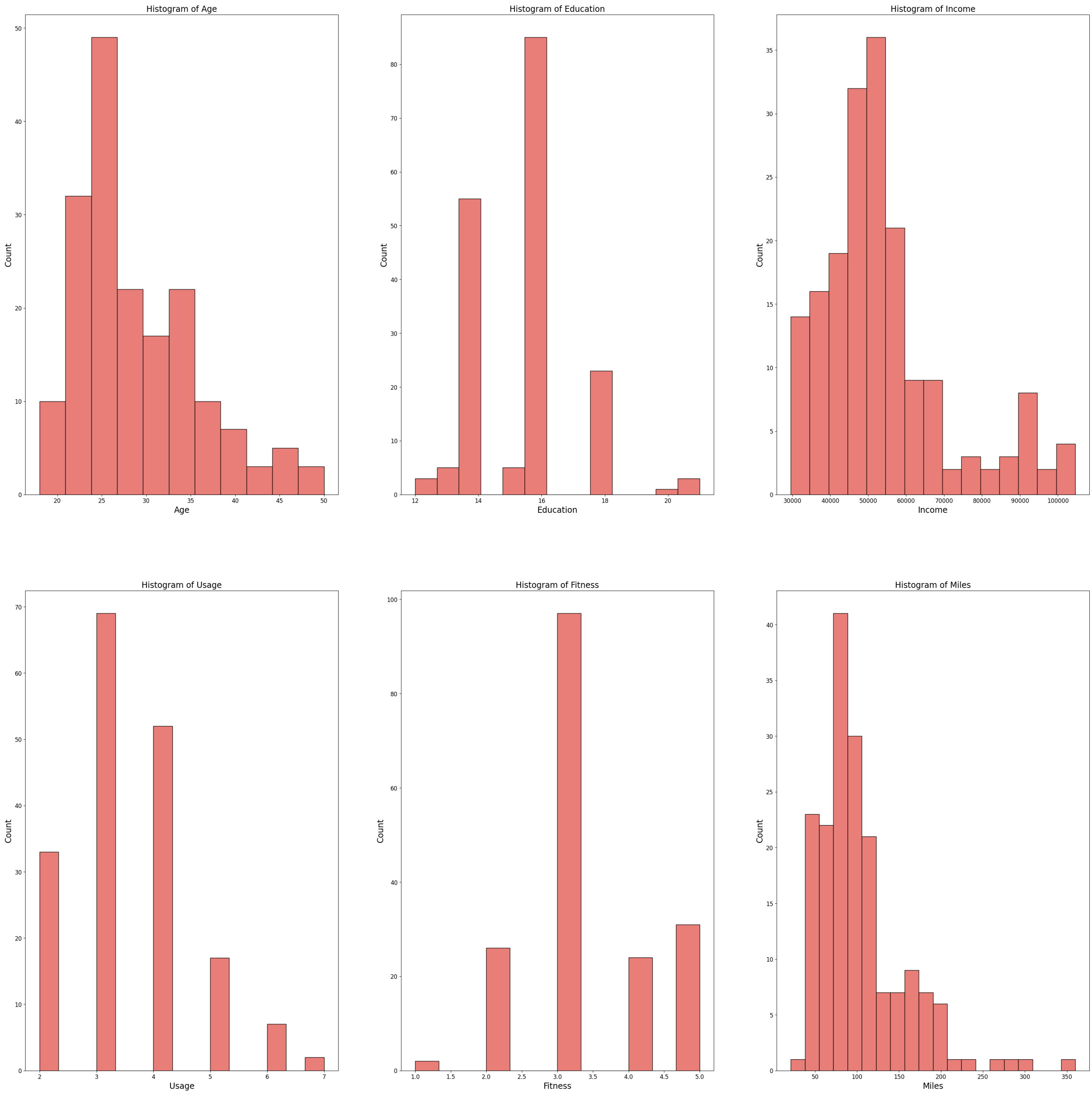
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
Income
45480     14
52302      9
46617      8
54576      8
53439      8
          ..
52290      1
85906      1
103336     1
99601      1
95508      1
Name: Income, Length: 62, dtype: int64
Usage
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
Fitness
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
Miles
85     27
95     12
66     10
75     10
47      9
106     9
94      8
113     8
53      7
100     7
56      6
64      6
180     6
200     6
127     5
160     5
42      4
150     4
120     3
103     3
38      3
170     3
74      3
132     2
141     2
280     1
260     1
300     1
240     1
112     1
212     1
80      1
140     1
21      1
```

```
169      1
188      1
360      1
Name: Miles, dtype: int64
```

- **For Graphical Analysis**

In [ ]:

```python
# Hisplot for Continuous Variable
sns.set_palette('Spectral')
fig, axes = plt.subplots(2,3, figsize=(40, 40))
axes = axes.flatten()
for i, column in enumerate(continuous_var):
  sns.histplot(aerofit_data[column], ax=axes[i])
  axes[i].set_title(f'Histogram of {column.capitalize()}', fontsize= 17)
  axes[i].set_ylabel('Count', fontsize=17)
  axes[i].set_xlabel(column.capitalize(), fontsize=17 )
  axes[i].tick_params(axis='both', labelsize=12)
plt.show()
```



INSIGHTS & OBSERVATIONS - From the Graphical and Non-graphical Univariate analysis, we can see that there

are highest number of customers are male customers compared to female customers. Moreover, partnered customers are more prevalent. We can also conclude that product KP281 is the most frequently purchased by customers whose self-rated fitness is 3 which means they are moderate - fitness individuals.

1. **Check if features like marital status, Gender, and age have any effect on the product purchased**

Finding if there is any relationship between the categorical variables and the output variable in the data.

In [ ]:

```
aerofit_data.groupby('MaritalStatus')['Product'].value_counts()
aerofit_data.groupby('Gender')['Product'].value_counts()
aerofit_data.groupby('Age')['Product'].value_counts()
```

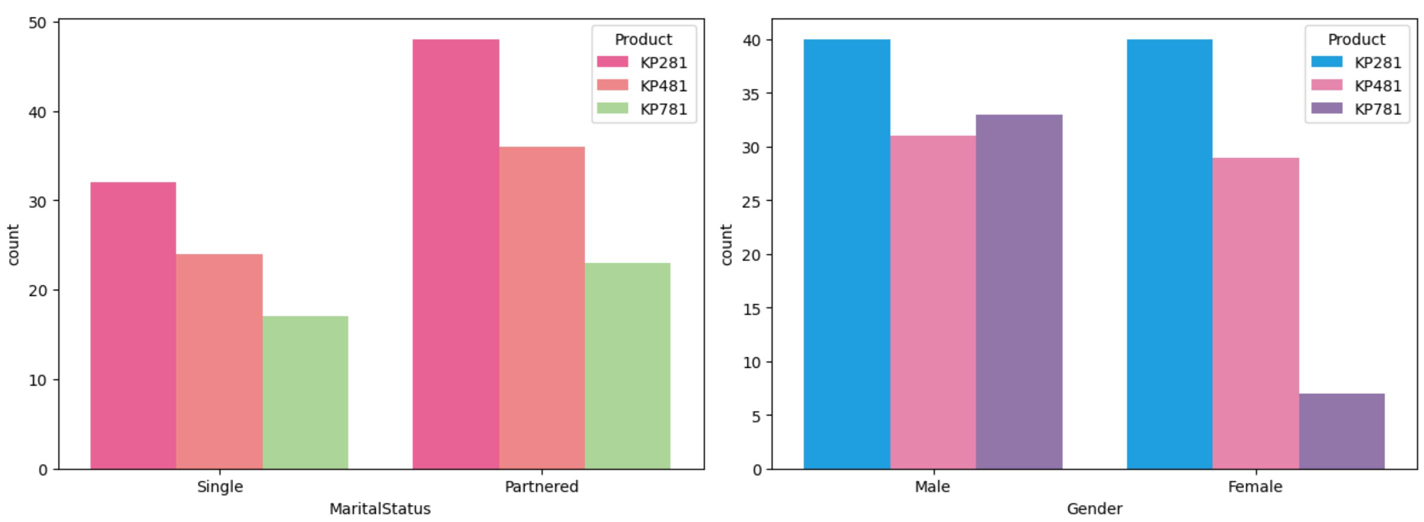
Out[ ]:

```
Age  Product
18   KP281      1
19   KP281      3
     KP481      1
20   KP481      3
     KP281      2
               ..
47   KP281      1
     KP781      1
48   KP481      1
     KP781      1
50   KP281      1
Name: Product, Length: 68, dtype: int64
```

In [ ]:

```
plt.figure(figsize =(13,10))
plt.suptitle('Product distribution on gender and Marital status\n\n',fontsize=17)
plt.subplot(2,2,1)
sns.countplot(data = aerofit_data, x='MaritalStatus', hue='Product',palette=['#FF4B91',
'#FF7676', '#A8DF8E'])
plt.subplot(2,2,2)
sns.countplot(data = aerofit_data, x='Gender', hue='Product',palette=['#00A9FF', '#F875AA
', '#916DB3'])
plt.tight_layout()
plt.show()
```

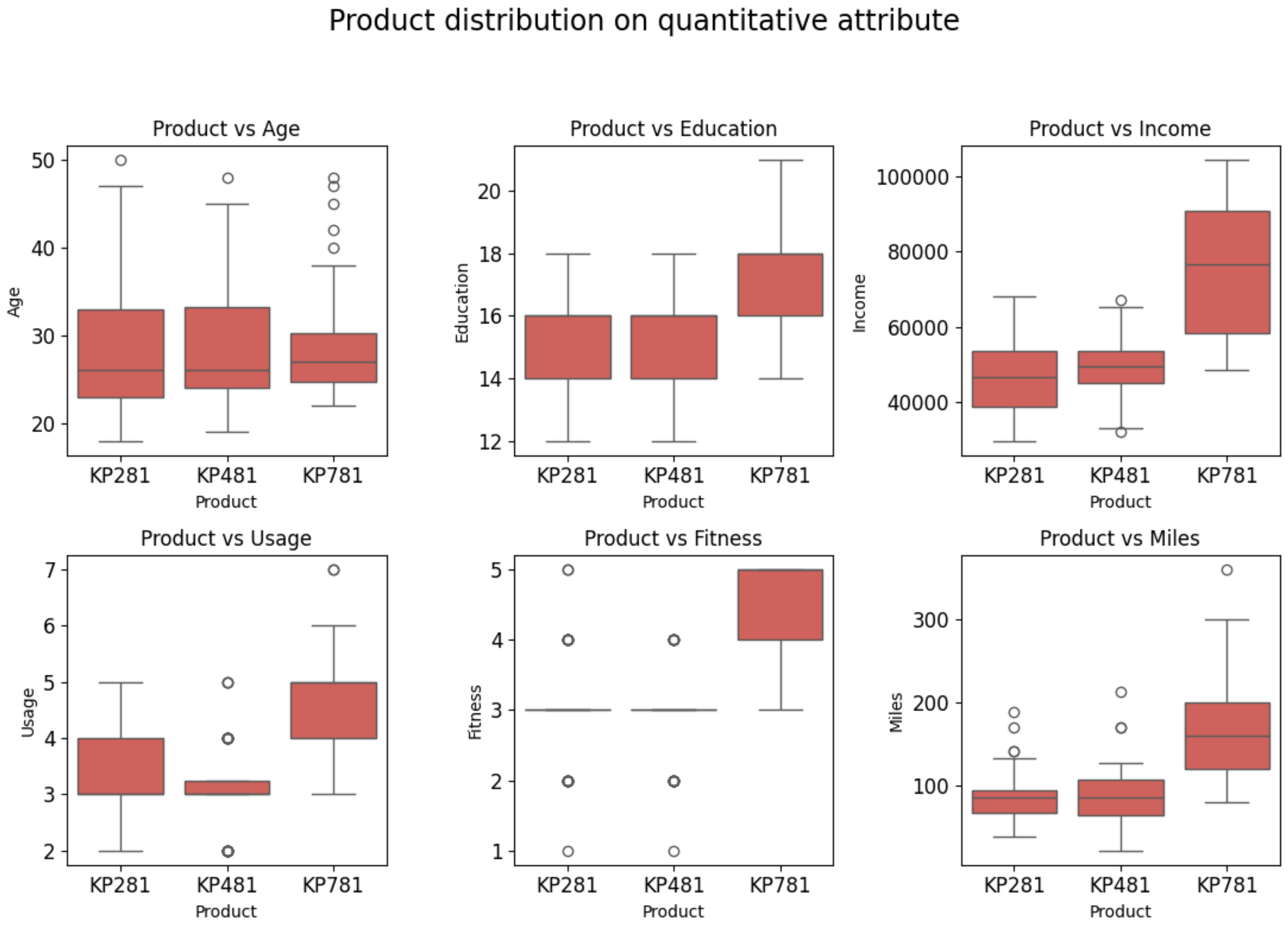
Product distribution on gender and Marital status



In [ ]:

```
# Product distribution on quantitative attribute
fig,axes = plt.subplots(2,3,figsize=(11,8))
plt.suptitle('Product distribution on quantitative attribute\n\n', fontsize=17)
axes = axes.flatten()
```

```
for i, column in enumerate(continuous_var):
  sns.boxplot(y=aerofit_data[column], x =aerofit_data['Product'],ax=axes[i])
  axes[i].set_title(f'Product vs {column.capitalize()}')
  axes[i].tick_params(axis='y',labelsize=12)
  axes[i].tick_params(axis='x',labelsize=12)
  plt.tight_layout()
plt.show()
```



INSIGHTS & OBSERVATIONS -

Product vs Age

- **Customers purchasing products KP281 & KP481 are having same Age median value.**
- **Customers whose age lies between 25-30, are more likely to buy KP781 product.**

Product vs Education

- **Customers whose Education is greater than 16, have more chances to purchase the KP781 product.**
- **While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481.**

Product vs Usage

- **Customers who plan to use the treadmill more than 4 times a week are more likely to purchase the KP781 product.**

Product vs Fitness

- **Customers who are more fit (fitness level of 3 or higher) have a higher chance of purchasing the KP781 product.**

Product vs Income

- **Customers with a higher income (income of $60,000 or more) are more likely to purchase the KP781 product.**

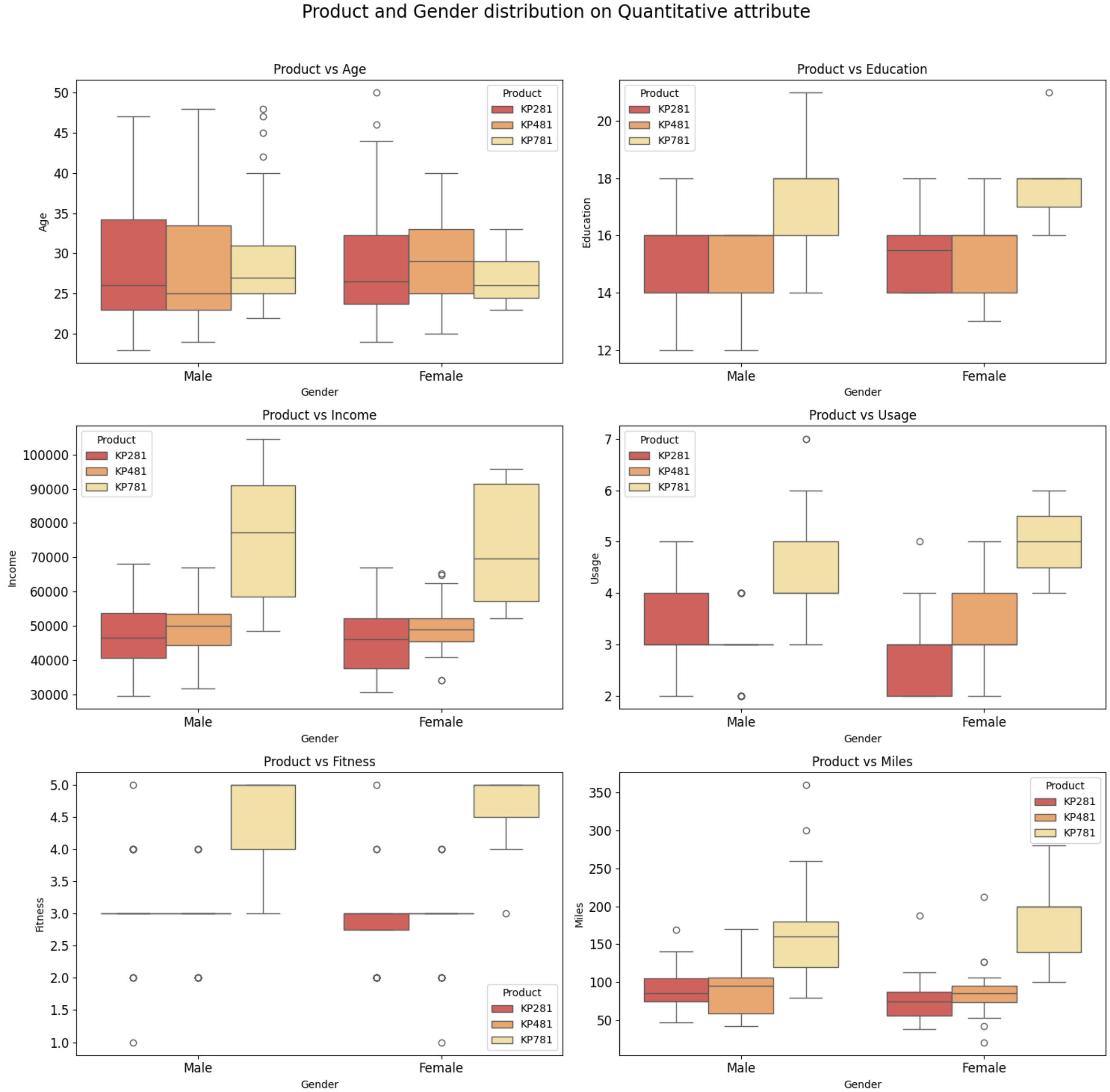
Product vs Miles

- **Customers who expect to walk or run more than 120 miles per week are more likely to buy the KP781 product.**

Multivariate Analysis

In [ ]:

```
fig,axes = plt.subplots(3,2,figsize=(15,15))
plt.suptitle('Product and Gender distribution on Quantitative attribute\n\n',fontsize=17)
axes = axes.flatten()
for i, column in enumerate(continuous_var):
  sns.boxplot(y=aerofit_data[column], x =aerofit_data['Gender'],ax=axes[i],hue=aerofit_data['Product'])
  axes[i].set_title(f'Product vs {column.capitalize()}')
  axes[i].tick_params(axis='y',labelsize=12)
  axes[i].tick_params(axis='x',labelsize=12)
  plt.tight_layout()
plt.show()
```



INSIGHTS & OBSERVATIONS -

- **Females planning to use treadmill 3-4 times a week, are more likely to buy KP481 product.**

1. **Representing the Probability**

Find the marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

In [ ]:

```
#METHOD 1
marginal_probability = aerofit_data['Product'].value_counts() /len(aerofit_data['Product
'])*100
round(marginal_probability,2)
```

Out[ ]:

```
KP281    44.44
KP481    33.33
KP781    22.22
Name: Product, dtype: float64
```

In [ ]:

```
#METHOD 2
marginal_probability= aerofit_data['Product'].value_counts(normalize=True)*100
marginal_probability
```

Out[ ]:

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

In [ ]:

```
#METHOD 3
marginal_probability_crosstab = pd.crosstab(aerofit_data['Product'],'count')
# Calculating the total number of customers
total_customers = marginal_probability_crosstab.sum().iloc[0]
# Calculating the marginal probability for each product
marginal_probability = round((marginal_probability_crosstab / total_customers)* 100, 2)
marginal_probability
```

Out[ ]:

col_0	count
Product	
KP281	44.44
KP481	33.33
KP781	22.22

INSIGHTS & OBSERVATIONS -

- **Based on the provided data, it seems that the KP281 treadmill is the most popular, followed by the KP481 and then the KP781.**
- **Approximately 44.44% of customers prefer the KP281, 33.33% prefer the KP481, and 22.22% prefer the KP781.**
- **Customers who plan to use the treadmill more than 4 times a week may be more inclined to choose the KP781, as it has a higher likelihood of being purchased.**
- **Similarly, customers who have a higher fitness level (3 or above) may also be more likely to choose the KP781.**
- **A higher income (equal to or greater than $60,000) may also be a factor in customers choosing the KP781 over the other options.**
- **Additionally, customers who expect to walk or run more than 120 miles per week may also show a preference for the KP781.**
- **These insights can be useful for marketing and product positioning strategies, as they highlight potential**

target segments for each treadmill product.

Find the probability that the customer buys a product based on each column.

In [ ]:

```
#binning the age values into categories
age_bin = [17,25,35,45,float('inf')]
bin_labels = ['17-25', '25-35', '35-45', '45+']
aerofit_data['age_group'] = pd.cut(aerofit_data['Age'],bins = age_bin ,labels =bin_label
s)
# binning the income values into categories
income_bin = [0,40000,60000,80000,float('inf')]
income_bin_labels = ['Low Income','Moderate Income','High Income','Very HighIncome']
aerofit_data['Income_Range'] = pd.cut(aerofit_data['Income'],bins = income_bin,labels =
income_bin_labels)
# binning the miles values into categories
miles_range = [0,70,100,200,float('inf')]
miles_bin_label = ['Light', 'Moderate', 'Active', 'Fitness Enthusiast ']
aerofit_data['miles_group'] = pd.cut(aerofit_data['Miles'],bins =miles_range,labels = mi
les_bin_label)
```

In [ ]:

```
# Calculate the probability of buying a product based on each column
probability_of_buy = {}
for column in aerofit_data.columns:
  if column not in ( 'Product', 'Age', 'Income', 'Miles'):
    probability_of_buy[column] = pd.crosstab(index=aerofit_data['Product'],columns=aerof
it_data[column], margins =True, normalize=True).round(2)
  # Display the probabilities
for column, prob in probability_of_buy.items():
  print(f"\nProbability of buying a product based on {column}:")
  print('-' * 70)
  print(f'{prob}\n')
```

```
Probability of buying a product based on Gender:
----------------------------------------------------------------------
Gender   Female  Male   All
Product
KP281      0.22  0.22  0.44
KP481      0.16  0.17  0.33
KP781      0.04  0.18  0.22
All        0.42  0.58  1.00


Probability of buying a product based on Education:
----------------------------------------------------------------------
Education    12    13    14    15    16    18    20    21   All
Product
KP281      0.01  0.02  0.17  0.02  0.22  0.01  0.00  0.00  0.44
KP481      0.01  0.01  0.13  0.01  0.17  0.01  0.00  0.00  0.33
KP781      0.00  0.00  0.01  0.00  0.08  0.11  0.01  0.02  0.22
All        0.02  0.03  0.31  0.03  0.47  0.13  0.01  0.02  1.00


Probability of buying a product based on MaritalStatus:
----------------------------------------------------------------------
MaritalStatus  Partnered  Single   All
Product
KP281               0.27    0.18  0.44
KP481               0.20    0.13  0.33
KP781               0.13    0.09  0.22
All                 0.59    0.41  1.00


Probability of buying a product based on Usage:
----------------------------------------------------------------------
Usage        2     3     4     5     6     7   All
Product
KP281      0.11  0.21  0.12  0.01  0.00  0.00  0.44
```

KP281	0.11	0.21	0.12	0.01	0.00	0.00	0.44
KP481	0.08	0.17	0.07	0.02	0.00	0.00	0.33
KP781	0.00	0.01	0.10	0.07	0.04	0.01	0.22
All	0.18	0.38	0.29	0.09	0.04	0.01	1.00

Probability of buying a product based on Fitness:

Fitness	1	2	3	4	5	All
Product						
KP281	0.01	0.08	0.30	0.05	0.01	0.44
KP481	0.01	0.07	0.22	0.04	0.00	0.33
KP781	0.00	0.00	0.02	0.04	0.16	0.22
All	0.01	0.14	0.54	0.13	0.17	1.00

Probability of buying a product based on age_group:

----

age_group	17-25	25-35	35-45	45+	All
Product					
KP281	0.19	0.18	0.06	0.02	0.44
KP481	0.16	0.13	0.04	0.01	0.33
KP781	0.09	0.09	0.02	0.01	0.22
All	0.44	0.41	0.12	0.03	1.00

Probability of buying a product based on Income_Range:

Income_Range	Low Income	Moderate Income	High Income	Very HighIncome	All
Product					
KP281	0.13	0.28	0.03	0.00	0.44
KP481	0.05	0.24	0.04	0.00	0.33
KP781	0.00	0.06	0.06	0.11	0.22
All	0.18	0.59	0.13	0.11	1.00

Probability of buying a product based on miles_group:

----

miles_group	Light	Moderate	Active	Fitness Enthusiast	All
Product					
KP281	0.16	0.19	0.10	0.00	0.44
KP481	0.10	0.14	0.08	0.01	0.33
KP781	0.00	0.04	0.15	0.03	0.22
All	0.26	0.38	0.33	0.03	1.00

INSIGHTS & OBSERVATIONS -

- **Gender: Probability of purchasing a particular product based on gender, we can see that there are highest number of customers are male customers compared to female customers.**

Education: KP281

- **Customers with education level 14 (some college education) have the highest probability of purchasing the KP281 treadmill.**
- **Customers with education levels 16 (graduate degree) and 18 (professional degree) also show a relatively high probability of purchasing KP281.**

KP481:

- **Customers with education level 14 (some college education) have the highest probability of purchasing the KP481 treadmill.**
- **Customers with education level 16 (graduate degree) and 18 (professional degree) also show a relatively high probability of purchasing KP481.**

KP781:

- **Customers with education level 18 (professional degree) have the highest probability of purchasing the KP781 treadmill.**
- **Customers with education levels 15 (college degree) and 16 (graduate degree) also show a relatively high**

probability of purchasing KP781.

Overall, customers with higher education levels (such as graduate degrees and professional degrees) tend to have a higher probability of purchasing all three treadmill products. However, customers with some college education (education level 14) also show a significant probability for both KP281 and KP481.

- Marital Status: Partnered customers have a higher probability of purchasing all three treadmill products compared to single customers.
- Usage: Customers who plan to use the treadmill 3-4 times a week have a higher probability of purchasing the KP281 treadmill. Those who plan to use it 5+ times a week have a higher probability of purchasing the KP781 treadmill.
- Fitness: Customers with higher fitness levels (3-5) have a higher probability of purchasing the KP281 treadmill. Customers with lower fitness levels (1-2) have a higher probability of purchasing the KP781 treadmill. [0,70,100,200]

1. For customers with a lifestyle of Light Activity (0 to 70 miles per week), the overall probability of purchasing any treadmill is 26%. However, the conditional probabilities for specific models are as follows:

- KP281: 16%
- KP481: 10%
- KP781: 0%

1. For customers with a lifestyle of Moderate Activity (71 to 100 miles per week), the overall probability of purchasing any treadmill is 38%. The conditional probabilities for specific models are:

- KP281: 19%
- KP481: 14%
- KP781: 4%

1. For customers with an Active Lifestyle (100 to 200 miles per week), the overall probability of purchasing any treadmill is 33%. The conditional probabilities for specific models are:

- KP281: 10%
- KP481: 8%
- KP781: 15%

1. For customers who are Fitness Enthusiasts (more than 200 miles per week), the overall probability of purchasing any treadmill is only 3%, which is relatively low compared to other lifestyle categories.

In summary, the probabilities indicate how likely customers with different activity lifestyles are to purchase specific treadmill models.

- Age Group: Customers in the age group 17-25 have a higher probability of purchasing the KP281 treadmill. Other age groups show similar probabilities for all three products.
- Income Range: Moderate and high-income customers have a higher probability of purchasing the KP281 and KP481 treadmills, while low-income customers have a higher probability of purchasing the KP781 treadmill. Very high-income customers have a higher probability of purchasing the KP781 and KP481 treadmills.
- Miles Group: Customers who categorize themselves as fitness enthusiasts have a higher probability of purchasing the KP781 treadmill. Other miles groups show similar probabilities for all three products.
- These insights can be useful for targeted marketing strategies, product development, and pricing decisions.

Find the conditional probability that an event occurs given that another event has occurred. (Example: given that a customer is female, what is the probability she'll purchase a KP481)

In [ ]:

```
def p_prod_given_gender(gender, print_marginal=False):
  if gender != "Female" and gender != "Male":
    return "Invalid Gender value."
  df1 = pd.crosstab(aerofit_data['Gender'], columns=[aerofit_data['Product']])
  p_781 = df1['KP781'][gender] / df1.loc[gender].sum()
  p_481 = df1['KP481'][gender] / df1.loc[gender].sum()
  p_281 = df1['KP281'][gender] / df1.loc[gender].sum()
  if print_marginal:
```

```
    print(f"P(Male): {df1.loc['Male'].sum()/len(aerofit_data):.2f}")
    print(f"P(Female): {df1.loc['Female'].sum()/len(aerofit_data):.2f}\n")
  print(f"P(KP781/{gender}): {p_781:.2f}")
  print(f"P(KP481/{gender}): {p_481:.2f}")
  print(f"P(KP281/{gender}): {p_281:.2f}\n")

p_prod_given_gender('Male', True)
p_prod_given_gender('Female')
```

```
P(Male): 0.58
P(Female): 0.42

P(KP781/Male): 0.32
P(KP481/Male): 0.30
P(KP281/Male): 0.38

P(KP781/Female): 0.09
P(KP481/Female): 0.38
P(KP281/Female): 0.53
```

INSIGHTS & OBSERVATIONS -

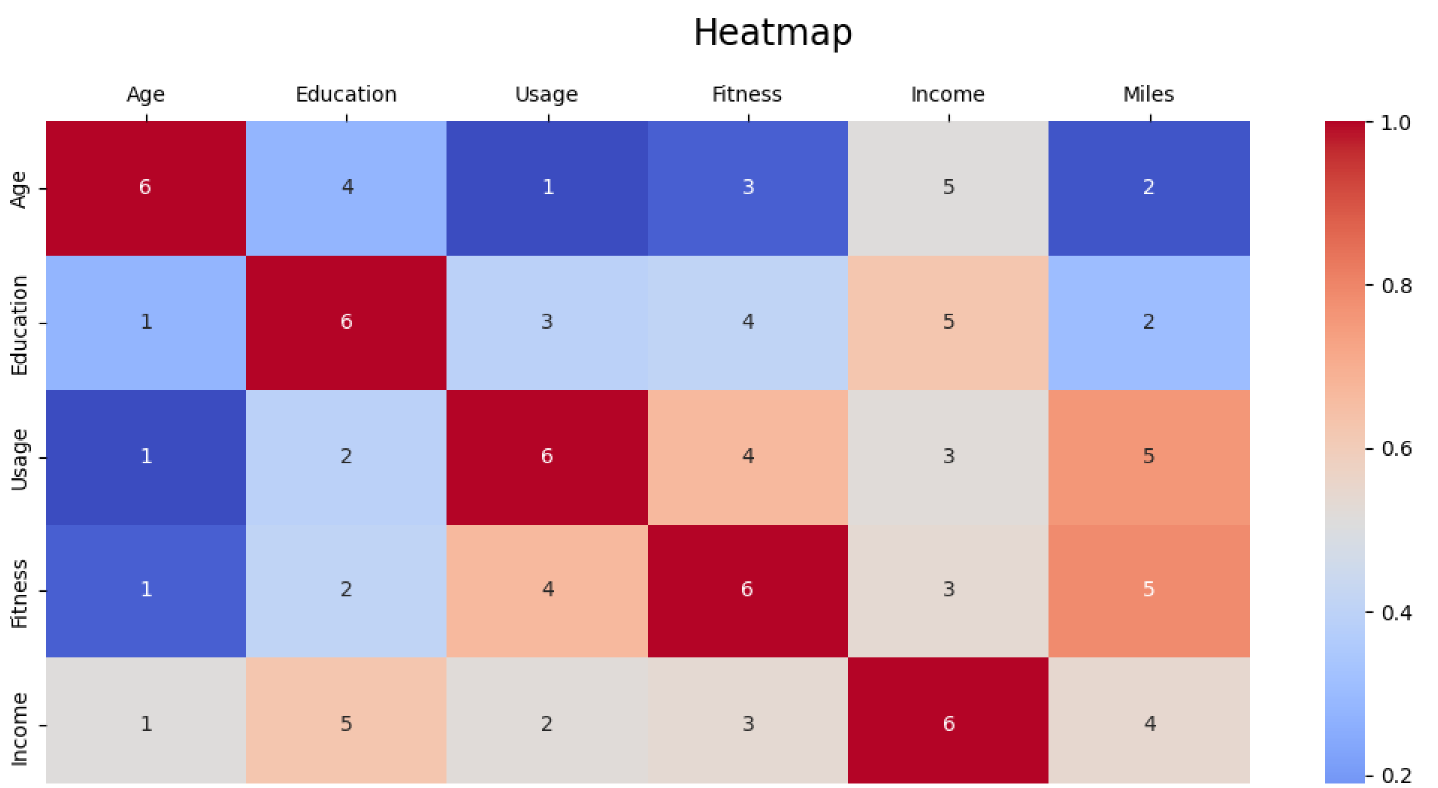
- **Among male customers, there is a higher probability of purchasing KP281 compared to KP781 or KP481.**
- **Among female customers, there is a higher probability of purchasing KP281 compared to KP481, but the probability of purchasing KP781 is the lowest.**
- **The conditional probabilities provide insights into the likelihood of customers purchasing specific products based on their gender.**

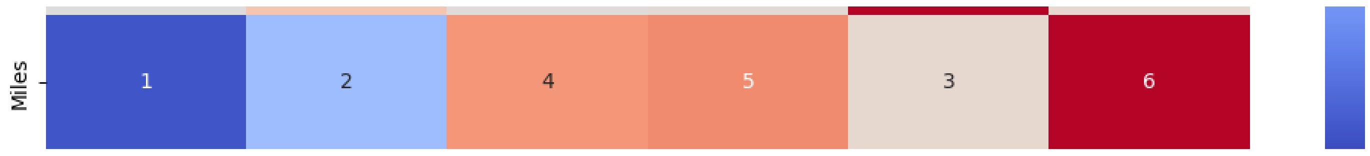
1. **Check the correlation among different factors**

Find the correlation between the given features in the table.

In [ ]:

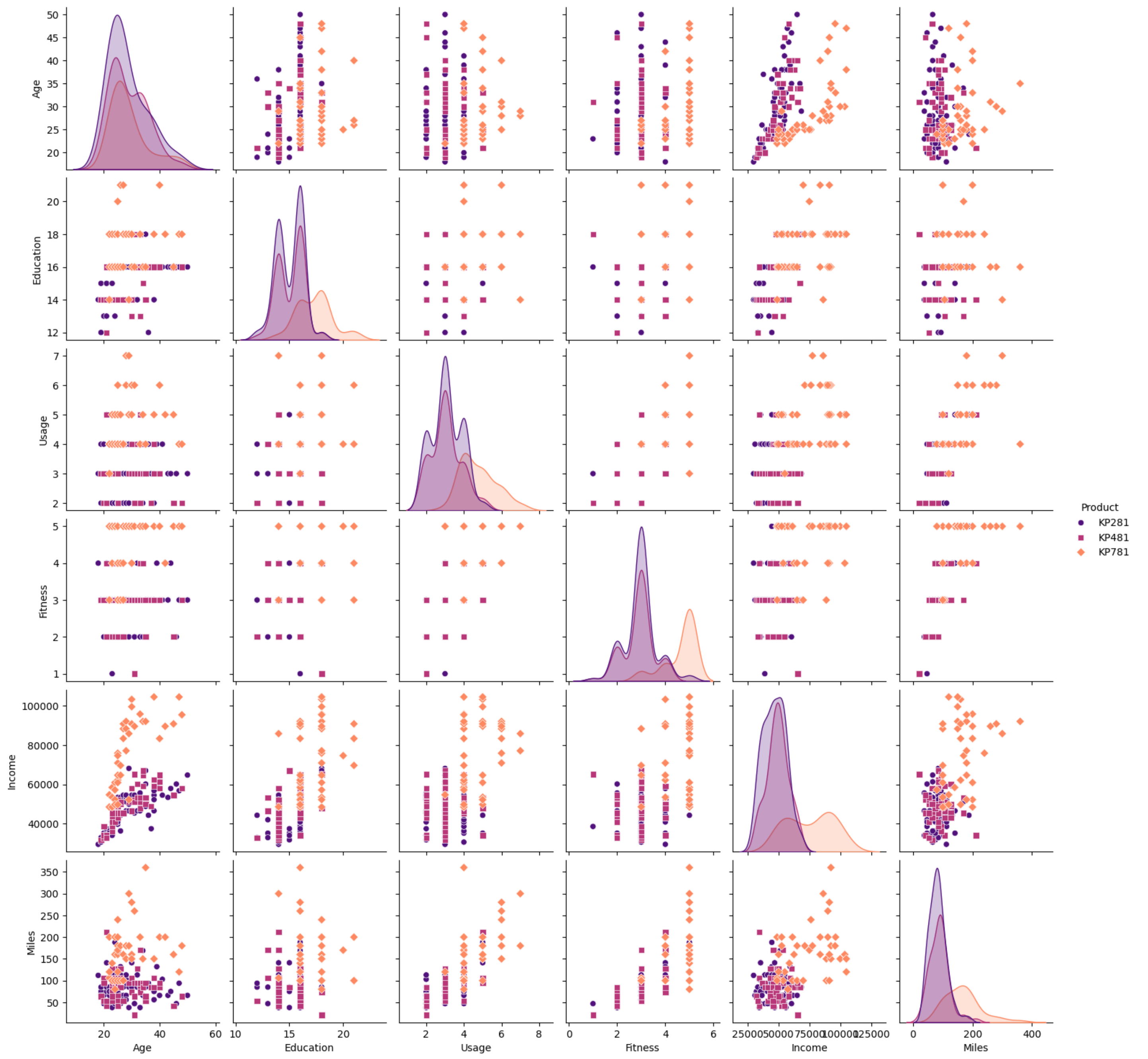
```
correlation_matrix = aerofit_data.corr(method='pearson', numeric_only = True)
# Display the heatmap of the correlation matrix:
plt.figure(figsize=(13,7))
plt.suptitle('Heatmap', fontsize= 17)
sns.heatmap(correlation_matrix, annot=correlation_matrix.rank(axis="columns"),cmap='coolwarm').xaxis.tick_top()
plt.show()
```





In [ ]:

```
# Display the Pairplot of the correlation matrix:
sns.pairplot(aerofit_data, hue ='Product', palette= 'magma', markers=["o", "s","D"])
plt.show()
```



INSIGHTS & OBSERVATIONS - From the pair plot and heatmap, it is evident that there is a positive correlation between Age and Income. This means that as Age increases, Income also tends to increase, and vice versa.

Similarly, Education and Income are also strongly correlated. This is expected, as higher levels of education often lead to higher income levels.

Furthermore, there is a significant correlation between Education and factors such as Fitness rating and Usage of the treadmill. This means that individuals with higher education levels tend to have better fitness ratings and use the treadmill more frequently

Additionally, the Usage of the treadmill shows a strong correlation with Fitness and Miles. This implies that the more someone uses the treadmill, the higher their fitness level tends to be, and they are likely to cover more distance in terms of miles.

In simple terms, these observations suggest that Age and Income, as well as Education and Income, are positively related. Moreover, Education has a considerable influence on Fitness rating and Usage of the treadmill. Lastly, more usage of the treadmill is associated with better fitness and covering more distance

The analysis reveals several important insights:

1. Usage and Fitness Connection: There is a strong positive correlation between usage of fitness equipment and fitness level. This means that individuals who use fitness equipment more frequently tend to have higher fitness levels. In other words, the more someone uses the treadmill, the fitter they are likely to be.
2. Income Influence: Income has notable associations with both education and miles covered. This implies that customers with higher incomes may have pursued more education and might prefer treadmills that offer longer mileage. In other words, higher-income individuals may be more likely to invest in higher-quality treadmills that allow them to cover more distance.
3. Age's Limited Influence: The analysis shows that age has relatively weak correlations with other variables. This suggests that age alone may not strongly influence factors like income, fitness level, or usage patterns. Other factors, such as income and education, may have a greater impact on these variables.
4. Education's Role: Education has a significant influence on several factors. It correlates positively with income, indicating that individuals with higher education levels may earn more. Additionally, education is moderately correlated with fitness level and usage. This suggests that individuals with higher education levels are more likely to engage in fitness activities and use fitness equipment regularly.

Overall, these findings highlight the importance of usage, income, and education in understanding fitness and purchasing patterns. Regular usage, higher income, and higher education levels are associated with higher fitness levels and potentially greater interest in advanced treadmill features.

1. **Customer profiling and recommendation**

   Customer Profilings

- Probability of purchase of KP281 = 44%
- Probability of purchase of KP481 = 33%
- Probability of purchase of KP781 = 22%

Customer Profile for KP281 Treadmill:

- Age of customer mainly between 18 to 35 years with few between 35 to 50 years
- Education level of customer 13 years and above
- Annual Income of customer below USD 60,000
- Weekly Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Mileage - 50 to 100 miles

Customer Profile for KP481 Treadmill:

- Age of customer mainly between 18 to 35 years with few between 35 to 50 years
- Education level of customer 13 years and above
- Annual Income of customer between USD 40,000 to USD 80,000
- Weekly Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Mileage - 50 to 200 miles

Customer Profile for KP781 Treadmill:

- Gender - Male
- Age of customer between 18 to 35 years
- Education level of customer 15 years and above
- Annual Income of customer USD 80,000 and above
- Weekly Usage - 4 to 7 times
- Fitness Scale - 3 to 5
- Weekly Running Mileage - 100 miles and above

Recommendations

Marketing Campaigns for KP781

- **The KP784 model exhibits a significant sales disparity in terms of gender, with only 18% of total sales attributed to female customers. To enhance this metric, it is recommended to implement targeted strategies such as offering special promotions and trials exclusively designed for the female customers.**

Affordable Pricing and Payment Plans

- **Given the target customer's age, education level, and income, it's important to offer the KP281 and KP481 Treadmill at an affordable price point. Additionally, consider providing flexible payment plans that allow customers to spread the cost over several months. This can make the treadmill more accessible to customers with varying budgets.**

User-Friendly App Integration

- **Create a user-friendly app that syncs with the treadmill. This app could track users' weekly running mileage, provide real-time feedback on their progress, and offer personalized recommendations for workouts based on their fitness scale and goals.This can enhance the overall treadmill experience and keep users engaged.**