AEROFIT - Exploratory Data Analysis

Problem Statement

Aerofit is India's leading fitness equipment brand that manufactures residential and commercial fitness machines including treadmills, elliptical trainers etc. Fitness accessories is the best way to engage in your daily fitness workouts, and to get the maximum out of it. It help you to be comfortable while exercising and improve the effectiveness of your workout. In this EDA, we will find out how good is the product used by different age , gender , Incomed persons. Also , this EDA will helpful to find out the usage of different products mentioned in data set

Following data analysis have been made in this notebook¶

1. Male Vs Female usage
2. Outliers for Age, Education , Income , Miles
3. Genderwise Product usage
4. Maritalstatus wise Product usage
5. usage of different products in dataset
6. Correlelation of different categories- age, gender, maritalstatus, income range
7. Probability of male and female usage of Products
8. Probability of products used by maritalstatus - single and partnered

In [31]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import matplotlib.pyplot as plt
import ipywidgets as w
from IPython.display import display
```

In [32]:

```
df=pd.read_csv("aerofit_treadmill.csv")
```

Finding dataset info

In [33]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
```

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

In [34]:

```
df.describe()
```

Out[34]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

In [35]:

```
df.head(5)
```

Out[35]:

	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

In [ ]:

Checking if ,there is any null values in data set

In [36]:

```
df.isna().sum()
```

Out[36]:

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

In [37]:

```
# total male and female ratio
```

Category wise data analysis

In [38]:
```
male_count=df[df['Gender']=='Male']
male_count=male_count.drop_duplicates(keep='last')
male_count= male_count.value_counts().value_counts()[1]
```

In [39]:
```
male_count
```

Out[39]:
```
104
```

In [40]:
```
female_count=df[df['Gender']=='Female']
female_count=female_count.drop_duplicates(keep='last')
female_count= female_count.value_counts().value_counts()[1]
```

In [41]:
```
female_count
```

Out[41]:
```
76
```

In [42]:
```
df_analysis = df[['Product', 'Gender', 'MaritalStatus']].melt()
df_analysis.groupby(['variable', 'value'])[['value']].count() / len(df)
```

Out[42]:

		value
variable	**value**	
Gender	**Female**	0.422222
	Male	0.577778
MaritalStatus	**Partnered**	0.594444
	Single	0.405556
Product	**KP281**	0.444444
	KP481	0.333333
	KP781	0.222222

Insight:

44% customers - purchased KP2821 product 33% customers - purchased KP481 product 22% customers - purchased KP781 product

Data Visualisation

In [ ]:
```

```

Male vs Female usage of Treadmill

In [43]:
```
#Category wise Usage
data_dict1 = {'Usage':[df[df['Gender']=='Male']['Usage'].sum(),
df[df['Gender']=='Female']['Usage'].sum()], 'Gender': ['Male','Female']}
df_b = pd.DataFrame(data=data_dict1, columns=['Gender','Usage'])
px.bar(data_frame=df_b, x="Gender", y="Usage", color="Gender",
barmode="group",title="Genderwise Usage of Treadmill in hours")
```

In [ ]:
```

```

In [ ]:
```

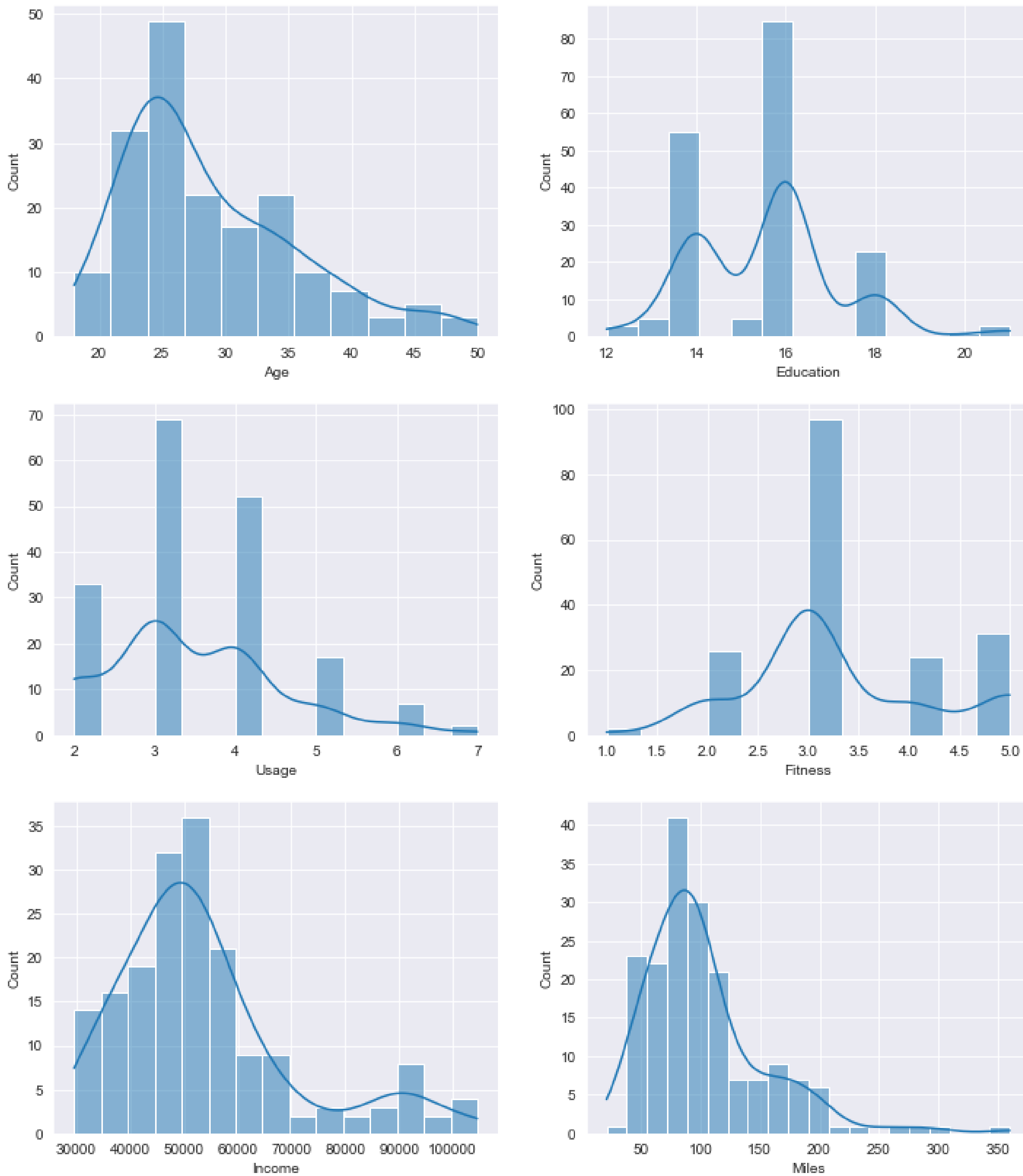
```

Analysing data for parameters like Age, Education, Usage, Fitness

In [44]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Education", kde=True, ax=axis[0,1])
sns.histplot(data=df, x="Usage", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Fitness", kde=True, ax=axis[1,1])
```

```
sns.histplot(data=df, x="Income", kde=True, ax=axis[2,0])
sns.histplot(data=df, x="Miles", kde=True, ax=axis[2,1])
plt.show()
```



In [ ]:

```
```

In [ ]:

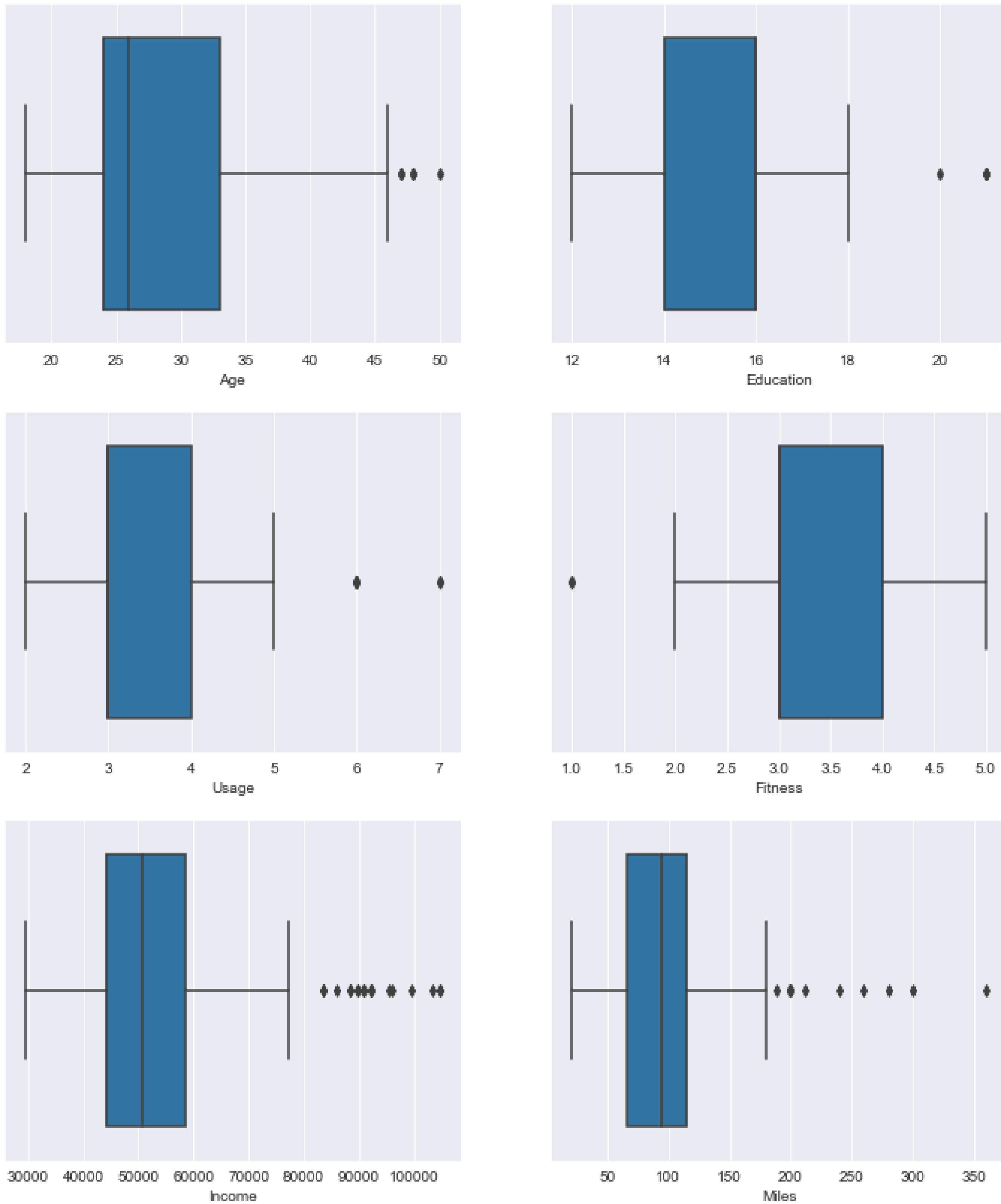
```
```

Finding Outliers of Age , Education , Income, Miles

In [45]:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.boxplot(data=df, x="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, x="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, x="Usage", orient='h', ax=axis[1,0])
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, x="Miles", orient='h', ax=axis[2,1])
plt.show()
```



In [ ]:

Insights:

Age, Education , Usage are having few outliers. Income and Miles are having more outliers. So we can use Age, Education ,Usage as our main parameters in data analysis

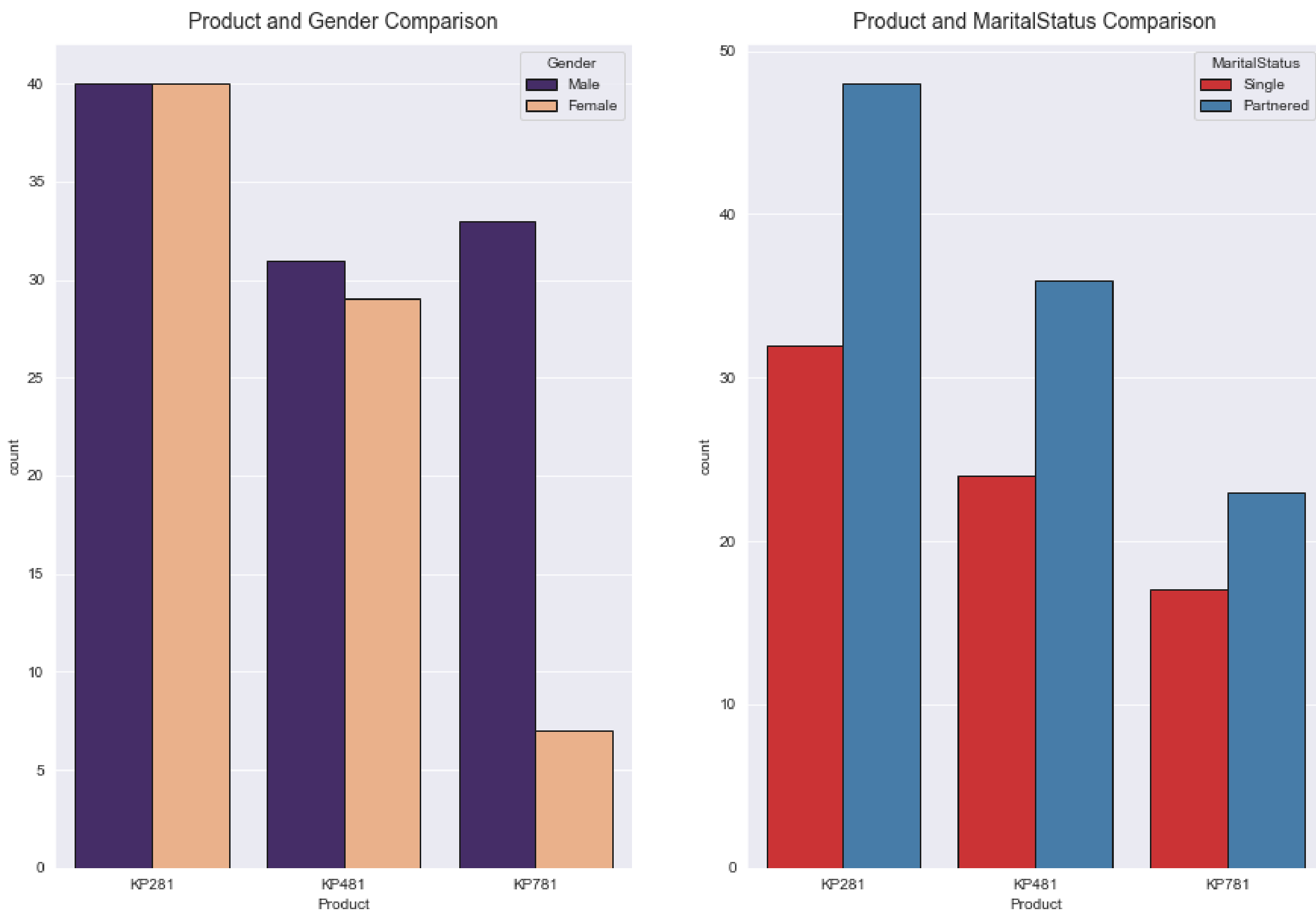
In [ ]:

In [ ]:

Comparison between Product and Gender, Product and Maritalstatus

In [46]:

```
sns.set_style(style='darkgrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(15, 10))
sns.countplot(data=df, x='Product', hue='Gender', edgecolor="0.10", palette=
['#432371',"#FAAE7B"], ax=axs[0])
sns.countplot(data=df, x='Product', hue='MaritalStatus', edgecolor="0.1",
palette='Set1', ax=axs[1])
axs[0].set_title("Product and Gender Comparison", pad=10, fontsize=14)
axs[1].set_title("Product and MaritalStatus Comparison", pad=10, fontsize=14)
plt.show()
```



In [47]:

```
# Finding Probability
```

Finding the Probability for using products by single and Married person

In [48]:

```
    df1 = pd.crosstab(index=df['MaritalStatus'], columns=[df['Product']])
    p_781 = df1['KP781']['Single'] / df1.loc['Single'].sum()
    p_481 = df1['KP481']['Single'] / df1.loc['Single'].sum()
    p_281 = df1['KP281']['Single'] / df1.loc['Single'].sum()
    print(f"Probaility(Single): {df1.loc['Single'].sum()/len(df):.2f}")
```

```
    print(f"Probaility(Partnered):
{df1.loc['Partnered'].sum()/len(df):.2f}\n")

    print(f"Probability of product p_781 used by Single: {p_781:.2f}")
    print(f"Probability of product p_481 used by Single): {p_481:.2f}")
    print(f"Probability of product p_281 used by Single): {p_281:.2f}\n")

    p_781 = df1['KP781']['Partnered'] / df1.loc['Partnered'].sum()
    p_481 = df1['KP481']['Partnered'] / df1.loc['Partnered'].sum()
    p_281 = df1['KP281']['Partnered'] / df1.loc['Partnered'].sum()

    print(f"Probability of product p_781 used by married person:
{p_781:.2f}")
    print(f"Probability of product p_481 used by married person):
{p_481:.2f}")
    print(f"Probability of product p_281 used by married person):
{p_281:.2f}\n")
```

```
Probaility(Single): 0.41
Probaility(Partnered): 0.59

Probability of product p_781 used by Single: 0.23
Probability of product p_481 used by Single): 0.33
Probability of product p_281 used by Single): 0.44

Probability of product p_781 used by married person: 0.21
Probability of product p_481 used by married person): 0.34
Probability of product p_281 used by married person): 0.45
```

In [ ]:

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In [ ]:

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```

Heatmap showing the correlation between different parameters

In [49]:

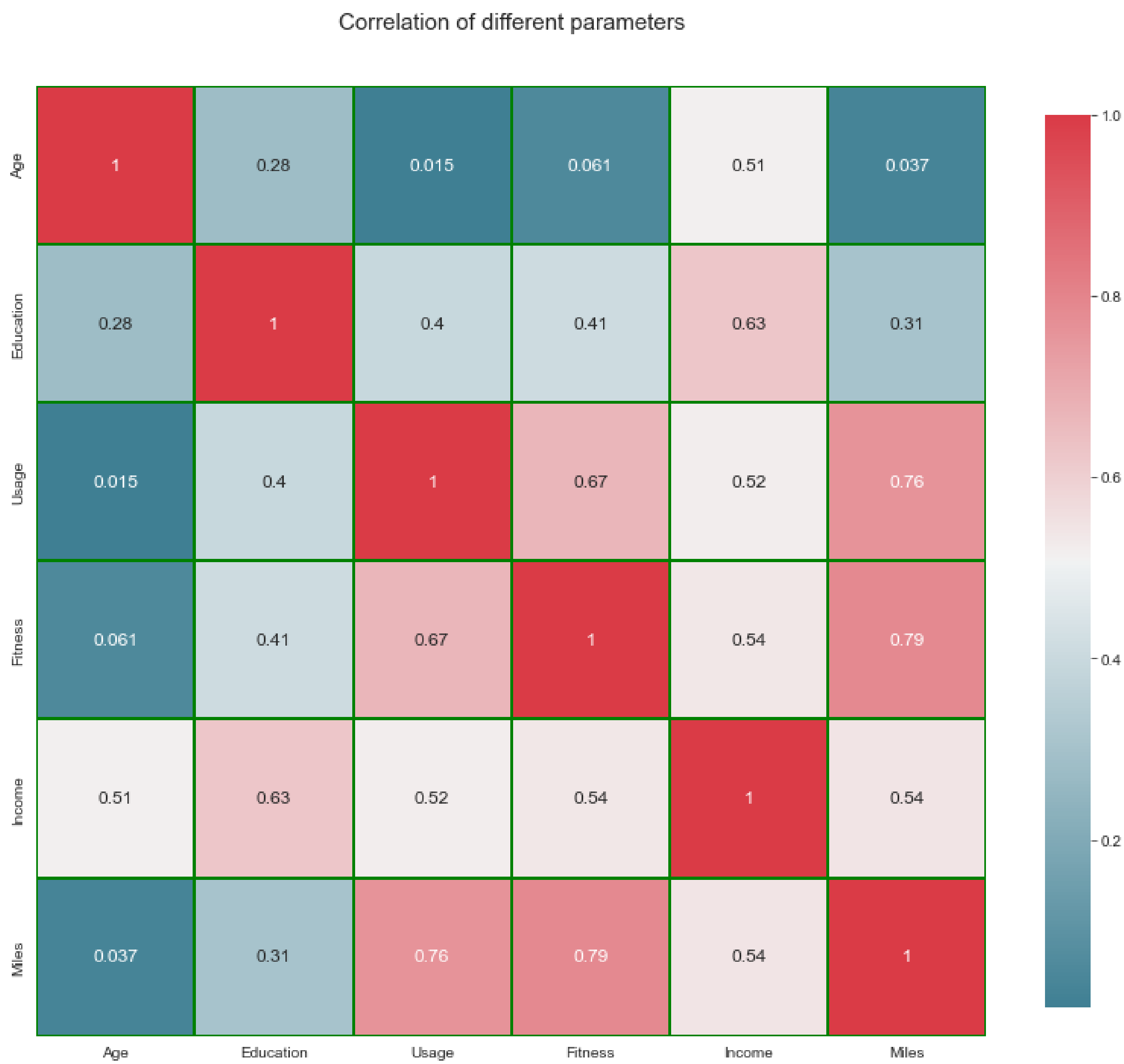
```
def heatmapp(df):
    _ , ax = plt.subplots(figsize =(14, 12))
    colormap = sns.diverging_palette(220, 10, as_cmap = True)

    _ = sns.heatmap(
        df.corr(),
        cmap = colormap,
        square=True,
        cbar_kws={'shrink':.9 },
        ax=ax,
```

```
        annot=True,
        linewidths=0.1,vmax=1.0, linecolor='green',
        annot_kws={'fontsize':12 }
    )

    plt.title('Correlation of different parameters', y=1.05, size=15)

heatmapp(df)
```



In [ ]:

```

```

Business Insights

1. Customers buying products KP281 & KP481 are of same age groups mostly
2. Customers whose age lies between 25-30, are more likely to buy KP781 product

3. Customers whose Education is greater than 16, have more chances to purchase the KP781 product,this depicts Kp781, is mostly choosed product by more incomed person and price is costlier than other two
4. While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481. This depicts that , these products are average priced ones

5. fitness> 3 persons have chances of the customer to purchase the KP781 product. 6.If the customer walk/run greater than 120 Miles, then the customer prefers buying KP781 product.

In [ ]:

In [ ]:

Recommendations

1. KP281 is the most frequent brought product, and mostly brought by average salary incomed person, so other products can be launched at this price segment will be most preferable among average salery customers

2. Thare are more Males in the data than Females.And this predicts that, male usage of fitness equipments is more than female. So more fitness equipments can be sold for female customers

3. Customer who is Partnered, is more likely to purchase the product. More Partnered persons are there in the data than single. And the age category for above 20 are likely to keep body fit. So more unisex fitness equipments can be sold

4.Equal number of males and females have purchased KP281 product and Almost same for the product KP481 product too, so unisex fitness equipments are brought more

1. Most of the Male customers have purchased the KP781 product. This shows that the features in KP781 is most liked by male, the same feature can be implemented in other new products going to launch in future.

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