RECOMMENDATION SYSTEM FOR DIFFERENT TRADEMILL OPTIONS FOR AEROFIT | PYTHON USING DATA STRUCTURES, PANDAS, NUMPY AND MATPLOTLIB/SEABORN LIBRARIES

This market research for AeroFit will be help identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers. This study will investigate whether there are differences across the product with respect to customer characteristics.

Importing Libraries, Loding of Aerofit dataset into Colab

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


path = '/content/drive/MyDrive/Dataset/aerofit.csv'

data = pd.read_csv(path)
```

1. Defining Problem Statement and Analysing basic metrics

```
data
```

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

```
data.shape
```

```
(180, 9)
```

```
print(f"Number of rows: {data.shape[0]}\nNumber of columns:{data.shape[1]}")
```

```
Number of rows: 180
Number of columns:9
```

```
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
```

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

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	
count	180	180.000000	180	180.000000	180	180.000000	180.000000	
unique	3	NaN	2	NaN	2	NaN	NaN	
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	
freq	80	NaN	104	NaN	107	NaN	NaN	
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	5
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	1
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	2
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	4
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	5
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	5
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	10

```
# Finding the missing values in the data
```

```
data.isnull().any()
```

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

2. Non-Graphical Analysis: Value counts and unique attributes

```
# Distribution of the data according to Gender of the customers
```

```
data.Gender.value_counts()
```

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

```
# Top 5 age for which the customers are divided.
```

```
data.Age.value_counts(ascending= False)[:5]
```

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

```
# Number of products available in dataset.
```

```
data.Product.nunique()
```

```
3
```

```
# Names of the products.
```

```
data.Product.unique()
```

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

```
# Distribution of the data according to Products

data.Product.value_counts()
```

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

```
# Distribution of the data according to Marital Status

data.MaritalStatus.value_counts()
```

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

```
# Distribution of the data according to Fitness Scale

data.Fitness.value_counts()
```

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

Insights from the attributes:

1. We can see here, that we do not have any null data.
2. We also have 3 unique products in the dataset.
3. The maximum age of the customer is 50 years where the minimum age of the same is 18 years. Also, the average age of the customer is 28.8 years.
4. The average income of the customers for the dataset is USD 53,719.58.
5. Minimum income for the customers USD 29,562 and maximum income is of USD 104,581
6. For the data provided, 104 customers are male and 76 customers are female.
7. For all the 3 products, KP281 has 80 records, KP481 has 60 records, and KP781 has 40 records.
8. According to the Fitness scale, 31 customers have excellent shape where 97 customers have an average shape and only 26 customers below average to poor shape.

Univariate Analysis:

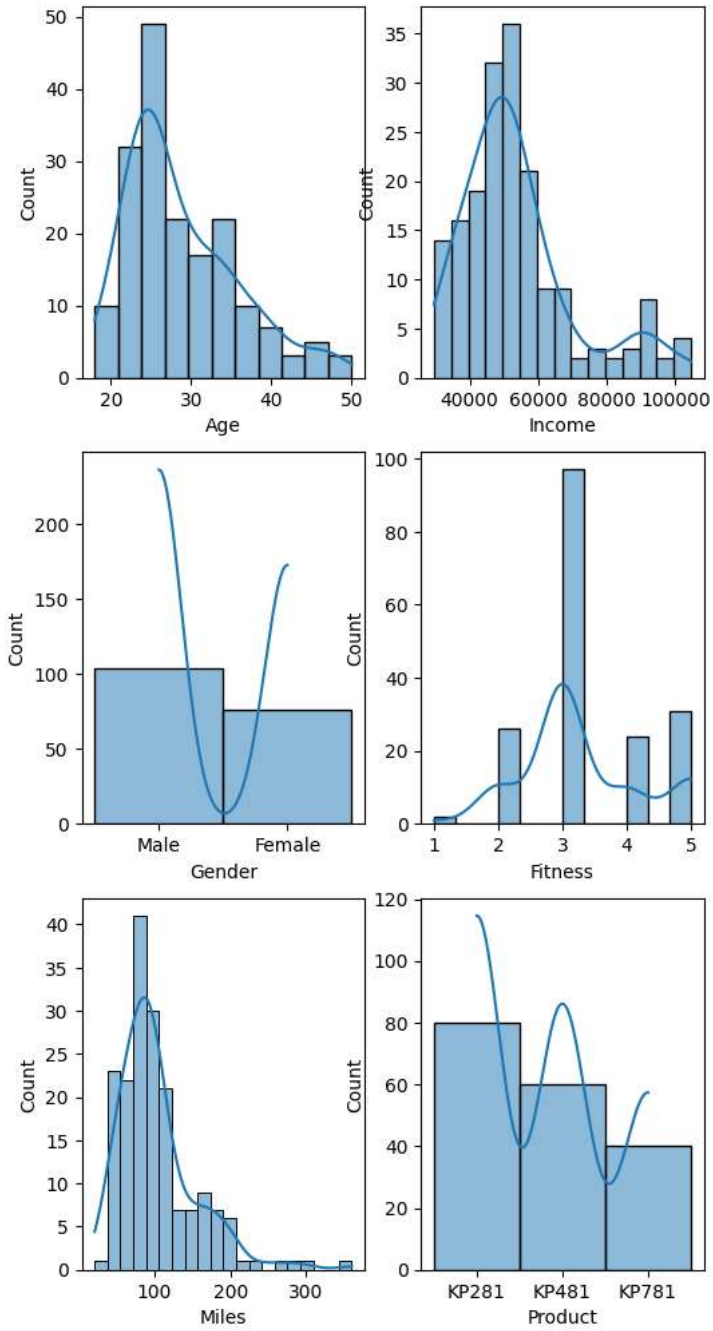
This analysis will provide us observations about all the columns like, age, income, gender, usage, fitness, miles, education of the data individually.

```
# The data will show the Histplots for the Age, Income, Gender, Fitness, Miles, and Products. This helps understand the trends of the each a

fig, axis = plt.subplots(nrows= 3, ncols= 2, figsize= (6,5))
fig.subplots_adjust(top= 2.0)

sns.histplot(data= data, x='Age', ax= axis[0,0], kde= True)
plt.xlabel('Age', fontsize = 10)
sns.histplot(data= data, x='Income', ax= axis[0,1], kde= True)
plt.xlabel('Income', fontsize = 10)
sns.histplot(data= data, x='Gender', ax= axis[1,0], kde= True)
plt.xlabel('Gender', fontsize = 10)
sns.histplot(data= data, x='Fitness', ax= axis[1,1], kde= True)
plt.xlabel('Fitness', fontsize = 10)
sns.histplot(data= data, x='Miles', ax= axis[2,0], kde= True)
plt.xlabel('Miles', fontsize = 10)
sns.histplot(data= data, x='Product', ax= axis[2,1], kde= True)
plt.xlabel('Product', fontsize = 10)

plt.show()
```

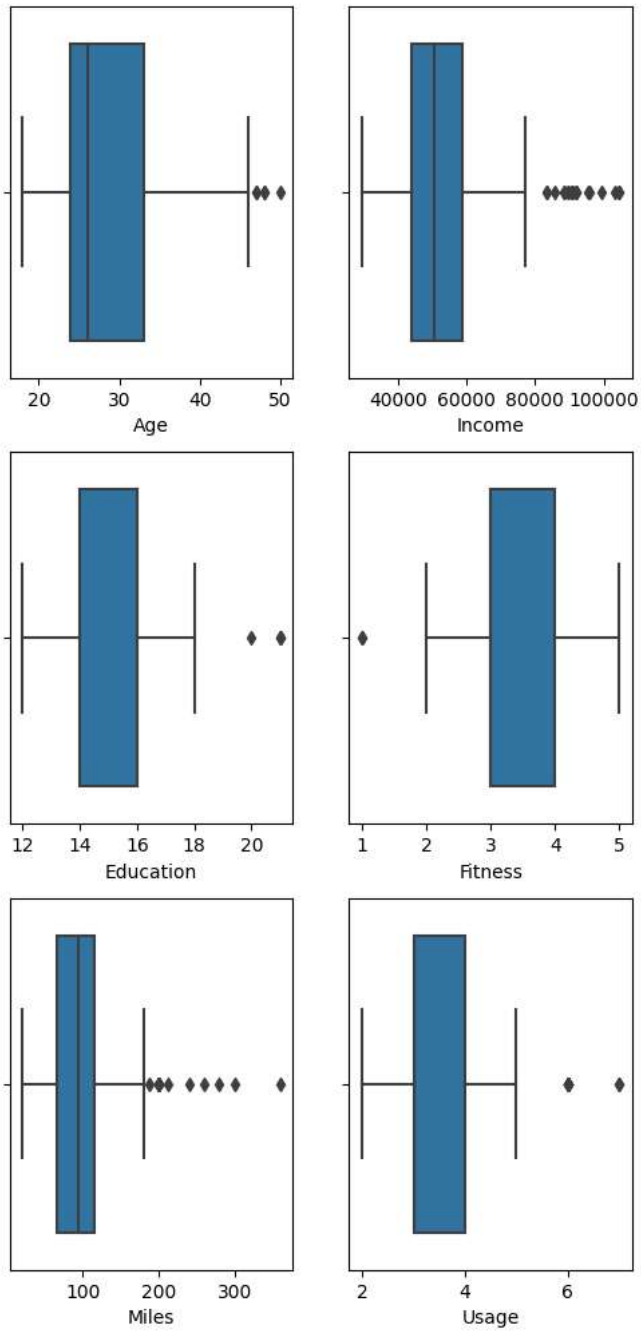



```
# Here we can use the boxplot to check for the outliers and also to check the correlation between the attributes

fig, axis = plt.subplots(nrows= 3, ncols= 2, figsize= (6,5))
fig.subplots_adjust(top= 2.0)

sns.boxplot(data= data, x='Age', ax= axis[0,0], orient= 'h')
plt.xlabel('Age', fontsize = 10)
sns.boxplot(data= data, x='Income', ax= axis[0,1], orient= 'h')
plt.xlabel('Income', fontsize = 10)
sns.boxplot(data= data, x='Education', ax= axis[1,0], orient= 'h')
plt.xlabel('Education', fontsize = 10)
sns.boxplot(data= data, x='Fitness', ax= axis[1,1], orient= 'h')
plt.xlabel('Fitness', fontsize = 10)
sns.boxplot(data= data, x='Miles', ax= axis[2,0], orient= 'h')
plt.xlabel('Miles', fontsize = 10)
sns.boxplot(data= data, x='Usage', ax= axis[2,1], orient= 'h')
plt.xlabel('Usage', fontsize = 10)

plt.show()
```



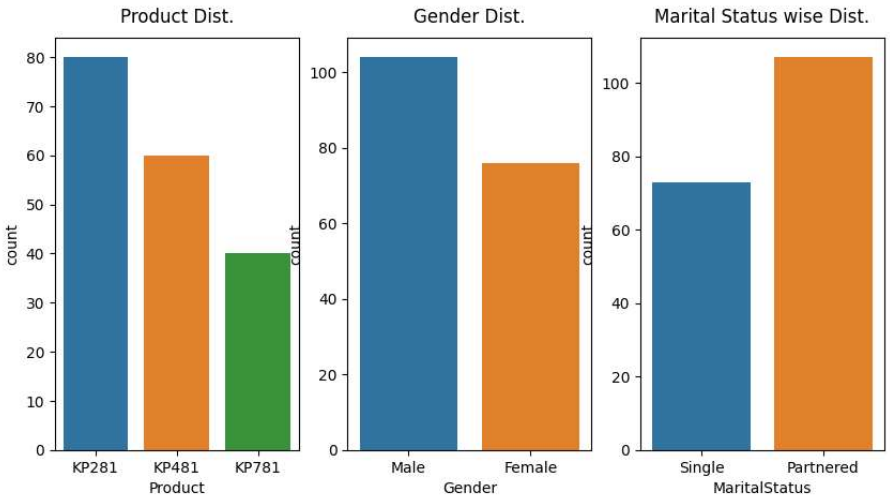

```
# The distribution of Product, Gender and Marital Status using countplots

fig, axis = plt.subplots(nrows= 1, ncols= 3, figsize= (10,5))

sns.countplot(data= data, x='Product', ax= axis[0])
sns.countplot(data= data, x='Gender', ax= axis[1])
sns.countplot(data= data, x='MaritalStatus', ax= axis[2])

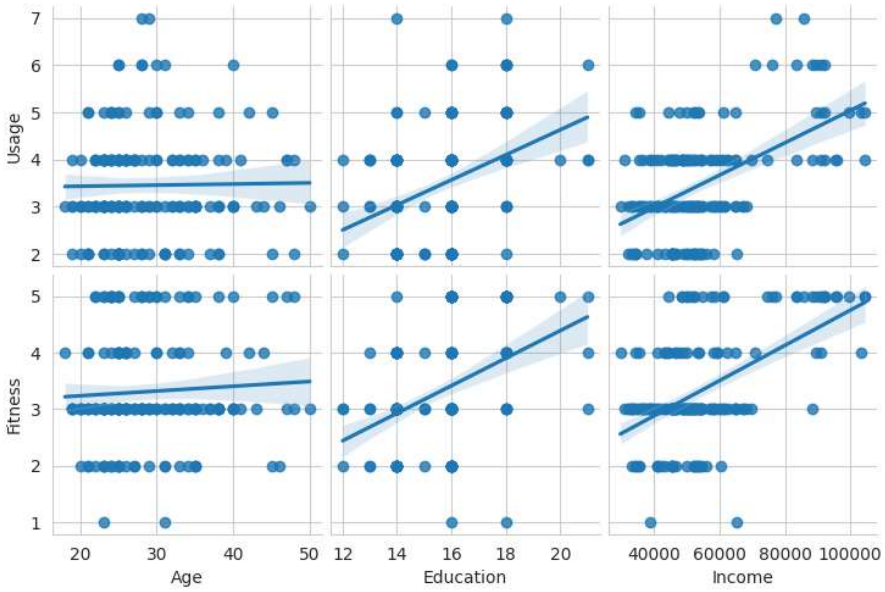
axis[0].set_title("Product Dist.", pad=10, fontsize=12)
axis[1].set_title("Gender Dist.", pad=10, fontsize=12)
axis[2].set_title("Marital Status wise Dist.", pad=10, fontsize=12)

plt.show()
```




```
# This is the pairplot which gives us an idea about a visual representation of the whole data and the co-relation between the any attributes

sns.pairplot(data,  x_vars= ['Age', 'Education', 'Income'], y_vars= ['Usage', 'Fitness'], kind= 'reg')
plt.show()
```




```
df1 = data[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count() / len(data)*100
```

		value
variable	value	
Gender	Female	42.222222
	Male	57.777778
MaritalStatus	Partnered	59.444444
	Single	40.555556
Product	KP281	44.444444
	KP481	33.333333
	KP781	22.222222

Insights from the Univariate plots:

1. From the Age histplot, we can observe that the prime users of the products are in the age group of 20 to 35 years.
2. Also, the income of the customers are in the range of USD 40,000 to USD 60,000.
3. From the Product distribution subplots, we can observe that the KP81 is the most popular product among customers, followed by KP481.
4. Also, Gender distribution chart gives the male customers are much higher than female customers.
5. Also, the marital status plot provides us with the information than partnered customers are much likely to purchase the product than the single customers.
6. From the above table, we can say that around 44% customers have purchased KP281, around 33% have purchased KP481 and he rest 22% have purchased the KP781.
7. 59% customers who purchased any product is partenered.
8. 57% of the customers are male.

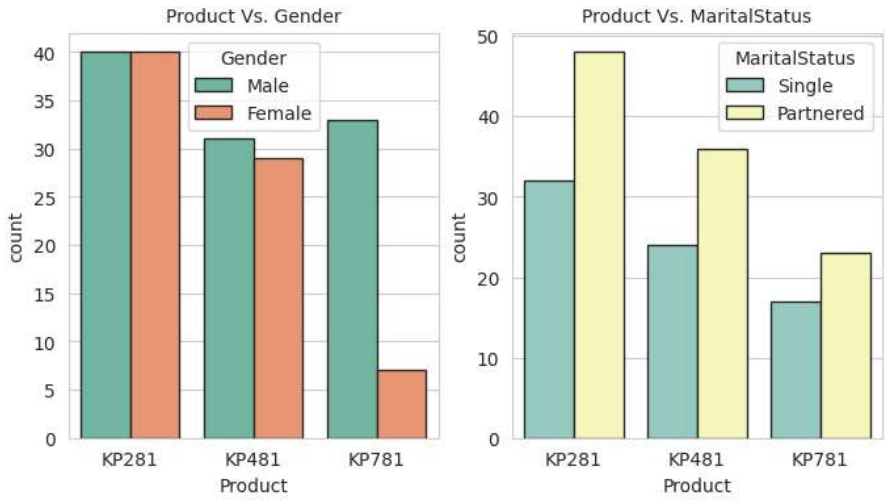
Bivariate Analysis:

```
# Countplot for Product vs Gender and Product vs. Marital Status
sns.set_style(style= 'whitegrid')
fig, axis = plt.subplots(nrows= 1, ncols= 2, figsize= (8,4))

sns.countplot(data= data, x= 'Product', hue= 'Gender', edgecolor= '0.15', palette= 'Set2', ax= axis[0])
sns.countplot(data= data, x= 'Product', hue= 'MaritalStatus', edgecolor= '0.15', palette= 'Set3', ax= axis[1])

axis[0].set_title('Product Vs. Gender', fontsize= 10)
axis[1].set_title('Product Vs. MaritalStatus', fontsize= 10)

plt.show()
```



```
# Boxplot for Product vs all the attributes

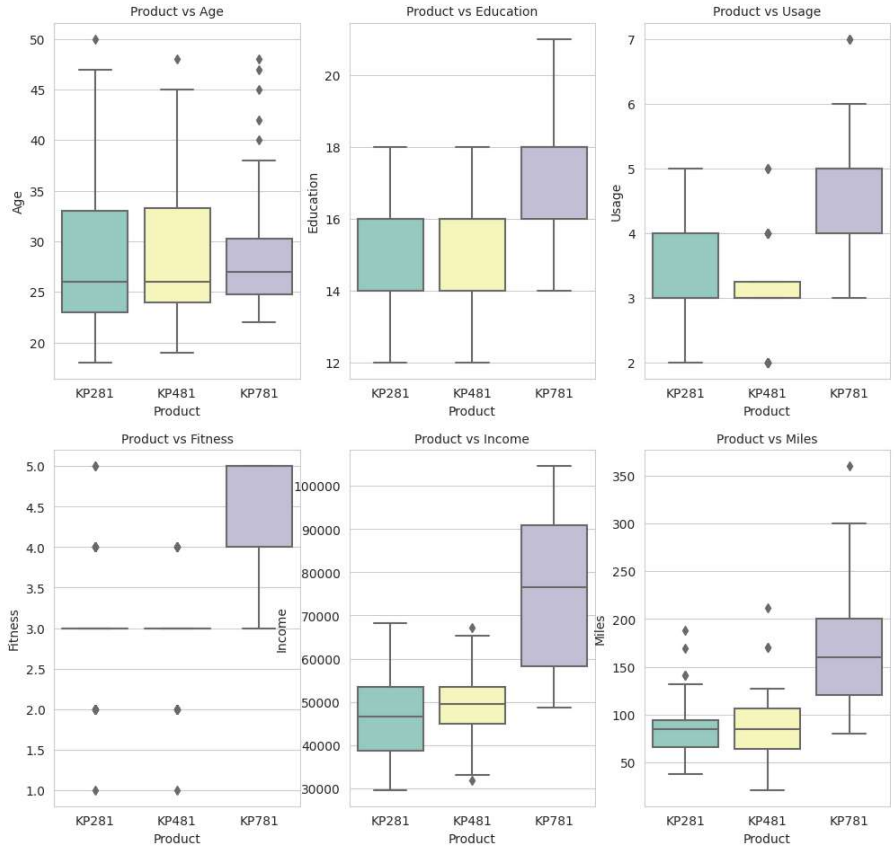
attr= ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

sns.set_style(style= 'whitegrid')
fig, axis = plt.subplots(nrows= 2, ncols= 3, figsize= (12,8))
fig.subplots_adjust(top= 1.2)

count= 0

for i in range(2):
  for j in range(3):
    sns.boxplot(data= data, x= 'Product', y= attr[count], palette= 'Set3', ax= axis[i,j])
    axis[i,j].set_title(f'Product vs {attr[count]}', fontsize= 10)
    count += 1

plt.show()
```



Insights from the bivariate plots:

1. From the first bivariate plot Product vs Gender, we can observe that for the purchase of products KP281 and KP481 is equal in number for male and female customers. Where male customers has largely purchased the KP781 than the female customers.
2. If we check for the Product vs Marital Status, as we observed before, here also the partnered customers have purchased more products than single customers.

3. From the boxplots, Median age of the customers purchasing KP281 and KP 481 are same. For all the purchased products, the customers are from the age group 20 to 40 years and in the age group of 25 to 30, customers are likely to purchase KP781.
4. From the Product vs Education plot, customers which are higher than 16 years in education are purchasing KP781 and the customers with education less than 16 years are purchasing KP281 and KP481.
5. Customers who use tradmills 3 to 4 times a week are purchasing KP281 while customers who are using trademills 4 to 5 times a week are purchasing KP781. KP481 customers are usually have 3 time a week usage.
6. Product vs Fitness plots suggests that customers with more than 4 fitness rating are purchasing KP781. Rest are purchasing KP281 and KP481.
7. From the Product vs Income plot we can observe, that customers with higher salaries (more than USD 60,000) are purchasing KP781 while customers with the salary range of USD 40,000 to USD 50,000 are purchasing KP281 and KP481 respectively.
8. The customers who runs 60 to 100 miles per week are purchasing the KP281 and KP481. The median run miles for these products are 90 miles per week. But the customers who runs more than 100 miles are purchasing KP781.

4. Missing values and Outlier detection

```
# Checking for missing data in the dataframe

data.isnull().any()
```

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

```
# Checking for the sum of missing values if any.

data.isnull().sum().sum()
```

```
0
```

Insight:

Here we can observe that we do not have any missing data in the dataframe.

Recommendations:

1. The data provided in the Aerofit dataset, clearely mentions few facts about the products KP281, KP481 and KP781.
2. For KP281, we can target the customers having any gender(male or female), customers having a partner, customers having age group is 20 to 33 years, who are having education between 14 to 16 years, customers having income ranging from USD 40 to 50,000, customers who runs 3 to 4 times per week for almost about 60 to 100 miles per week and who consider themselves having an average(3) customer rating.
3. For KP481, we can target the customers having any gender(male or female), customers having a partner, customers having age group is 25 to 35 years,who are having education between 14 to 16 years, customers having income ranging from USD 45 to 55,000, customers who runs 3 times per week for almost about 60 to 110 miles per week and who consider themselves having an average(3) customer rating.
4. For KP781, we can target the male customers, customers having a partner, customers having age group is 25 to 30 years,who are having education of more than 16 years, customers having income more than USD 60,000, customers who runs 4 to 5 times per week for almost about 130 to 200 miles per week and who consider themselves having highest (4 to 5) customer rating.

```
Start coding or generate with AI.
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