aerofit_casestudy

February 21, 2025

Exploratory Data Analysis

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

from google.colab import files
uploaded =files.upload()
```

```
&lt;IPython.core.display.HTML object&gt;
```

```
Saving aerofit_treadmill.txt to aerofit_treadmill.txt
```

[ ]:
```
df=pd.read_csv('aerofit_treadmill.txt')
df.head()
```

[ ]:

	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

[ ]:
```
df.tail()
```

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
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
175	200
176	200
177	160
178	120

```
179    180
```

[ ]:
```
df.shape
```

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

[ ]:
```
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
```

Insights:

- From the above analysis, its clear that, there are totally 9 columns and 180 rows with zero null values.

[ ]:
```
df.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
```

Insights:

- Standard deviation of Income and miles are high. They might have outliers in it.
- Minimum and maximum age of people are 18 and 50.
- 75 % of people are in age less than or equal to 33.

[ ]:
```
df.describe(include='object')
```

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

Insights:

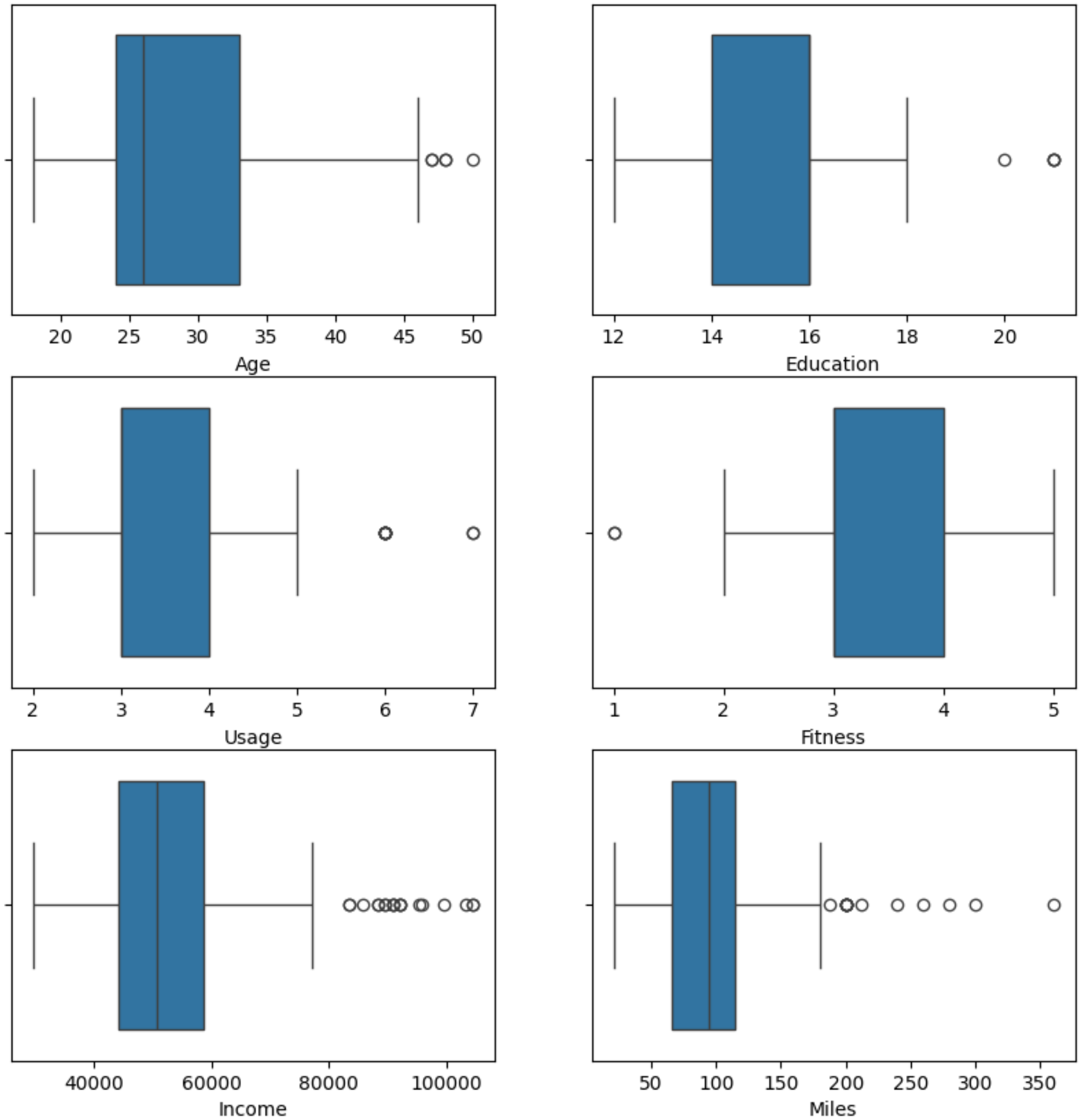
- There are three unique product in the dataset.
- KP281 is the most frequent product.
- There are totally 180 members in that, 104 are males and rest are females.

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
0
```

Outliers detection

[ ]:
```
figure,axis= plt.subplots(3,2, figsize=(10,10))
sns.boxplot(data=df, x='Age', ax=axis[0,0])
sns.boxplot(data=df,x='Education', ax=axis[0,1])
sns.boxplot(data=df,x='Usage', ax=axis[1,0])
sns.boxplot(data=df,x='Fitness', ax=axis[1,1])
sns.boxplot(data=df,x='Income', ax=axis[2,0])
sns.boxplot(data=df, x='Miles',ax=axis[2,1])
plt.show()
```



Insights:

- Income and Miles are showing more outliers.
- There are more outliers , therefore its important to find median of the attributes so that will get correct inference.

Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781

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

[ ]:
```
Product
KP281    80
```

```
KP481    60
KP781    40
Name: count, dtype: int64
```

[ ]:
```
df['Product'].value_counts(normalize=True)
```

[ ]:
```
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: proportion, dtype: float64
```

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

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

[ ]:
```
df['Gender'].value_counts(normalize=True)
```

[ ]:
```
Gender
Male      0.577778
Female    0.422222
Name: proportion, dtype: float64
```

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

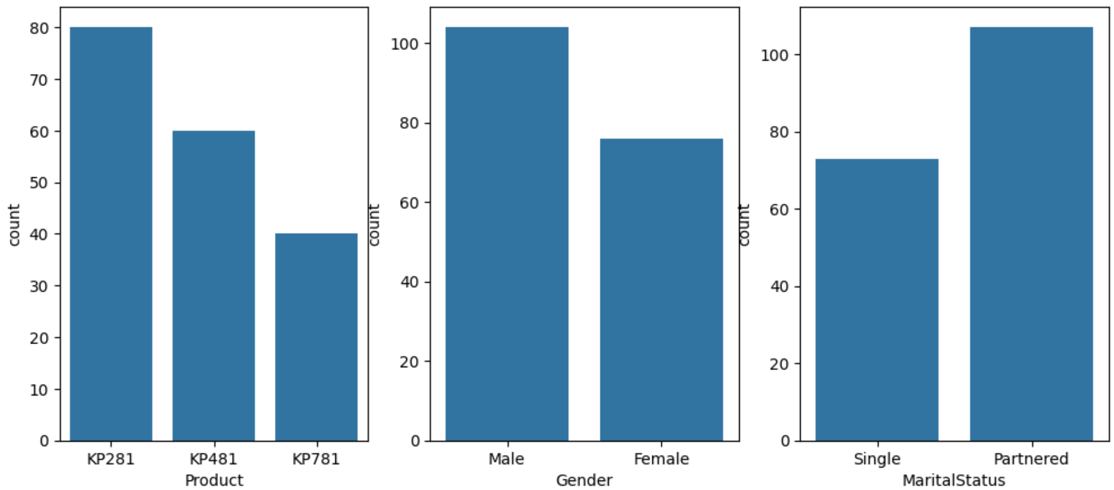
[ ]:
```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

[ ]:
```
df['MaritalStatus'].value_counts(normalize=True)
```

[ ]:
```
MaritalStatus
Partnered    0.594444
Single       0.405556
Name: proportion, dtype: float64
```

Univariate Analysis

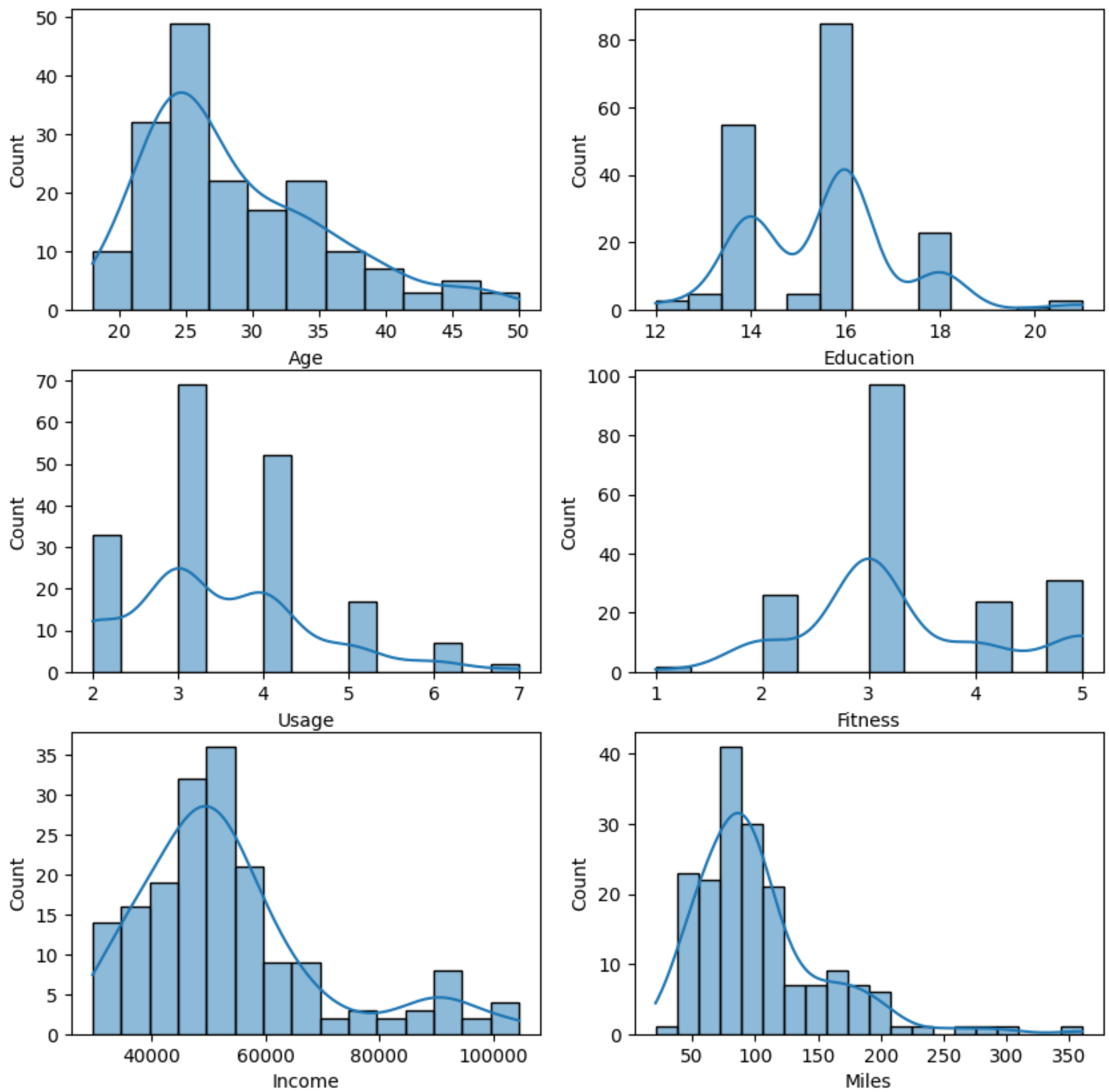
[ ]:
```
fig, axis = plt.subplots(nrows=1, ncols=3, figsize=(12, 5))
sns.countplot(data=df, x="Product",ax=axis[0])
sns.countplot(data=df, x="Gender", ax=axis[1])
sns.countplot(data=df,x='MaritalStatus',ax=axis[2])
plt.show()
```



Insights:

- KP281 is the most frequently sold product by customers with 44%, followed by KP281 of 33% and KP181 of 22%.
- Male share is 57 % which higher than female 42%.
- Married people (59%) perfer to buy treadmill than single(40%).

[ ]:
```
fig, axis = plt.subplots(3, 2, figsize=(10, 10))
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()
```



Insights:

- Most of the purchases are made my customer who fall under age a range of 23 and 26
- Customers who prefer to buy treadmill have moderate level of education.
- The usuage of treadmill by customers are mostly three to four times a week.
- The annual income of customers fall around 40000-60000 dollars.
- Customers perfered to walk around 70-80 miles in a week.

Check if features like marital status, age have any effect on the product purchased - Bivariate analysis.

[ ]:
```
#Distribution of gender and marital status of products in each category:
pd.crosstab(df['Gender'],df['Product'] )
```

[ ]:
```
Product  KP281  KP481  KP781
Gender
Female      40     29      7
Male        40     31     33
```

[ ]:
```
pd.crosstab(df['Gender'],df['Product'] ,normalize=True)
```

[ ]:
```
Product     KP281     KP481     KP781
Gender
Female   0.222222  0.161111  0.038889
Male     0.222222  0.172222  0.183333
```

[ ]:
```
pd.crosstab(df['MaritalStatus'], df['Product'])
```

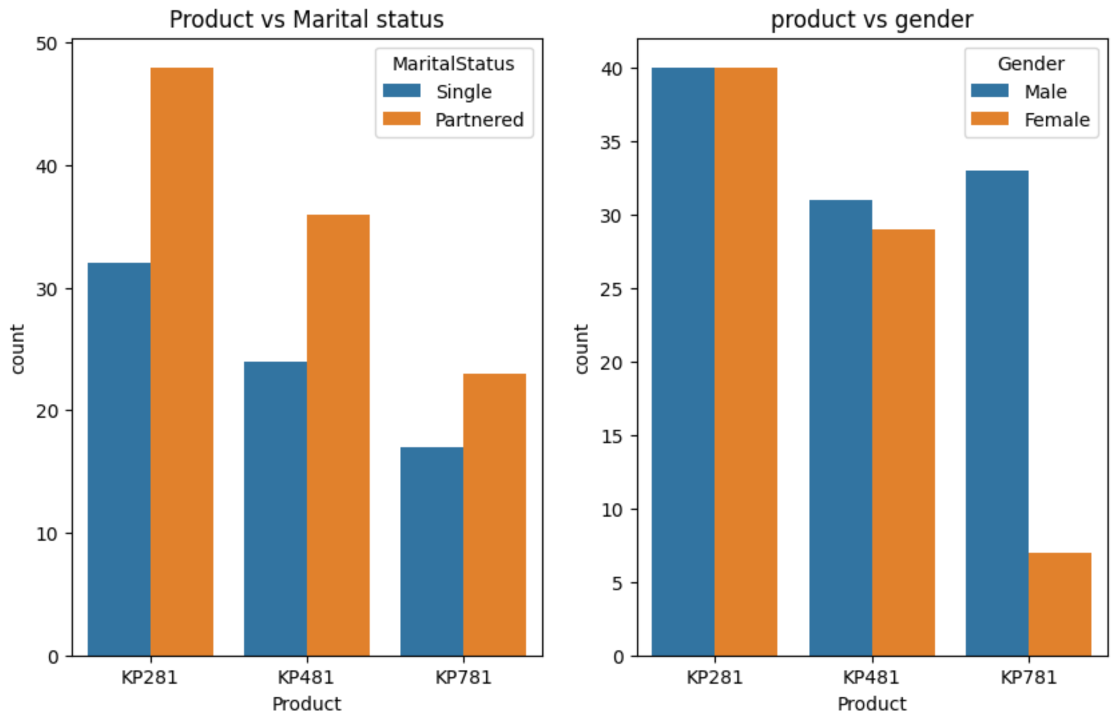
[ ]:
```
Product        KP281  KP481  KP781
MaritalStatus
Partnered         48     36     23
Single            32     24     17
```

[ ]:
```
pd.crosstab(df['MaritalStatus'], df['Product'],normalize=True)
```

[ ]:
```
Product           KP281     KP481     KP781
MaritalStatus
Partnered      0.266667  0.200000  0.127778
Single         0.177778  0.133333  0.094444
```

[ ]:
```
fig,axis= plt.subplots(1,2, figsize=(10,6))
sns.countplot(data=df, x='Product', hue='MaritalStatus', ax=axis[0])
sns.countplot(data=df, x="Product", hue="Gender", ax= axis[1])
axis[0].set_title('Product vs Marital status')
axis[1].set_title("product vs gender")
```

[ ]:
```
Text(0.5, 1.0, 'product vs gender')
```

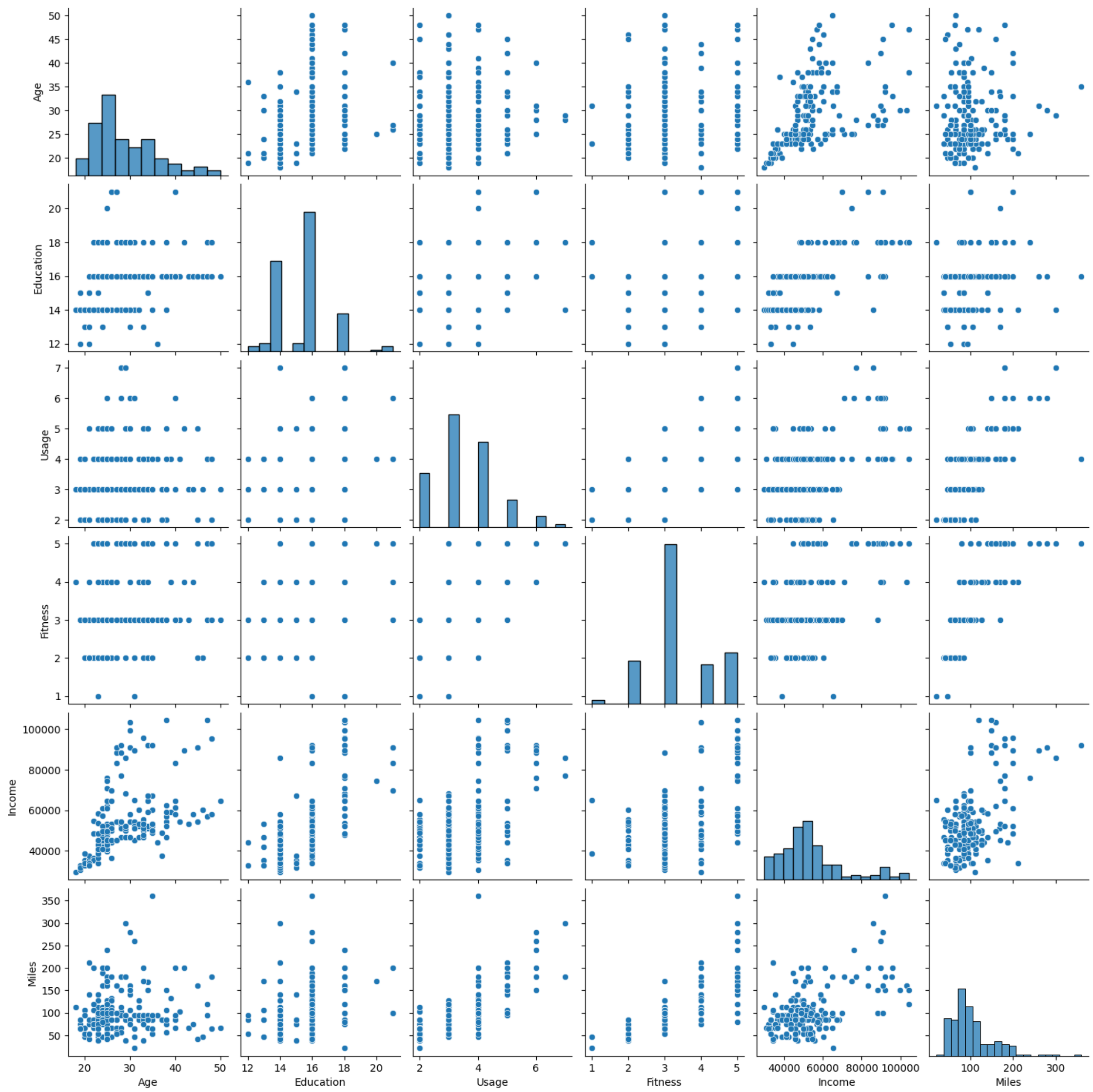


Insights:

- treadmill are mostly used by couples than singles , from that KP281 was highly used by them 48% and least used product is KP781 23%.
- Married and singles perfer buying the cheapest treadmill.
- Both male and female perfered to buy KP281 treadmill where as the highend model KP781 is mostly used by males and very less number of females buy KP781.

[ ]:
```
#Check correlation among different factors using heat maps or pair plots.
sns.pairplot(df)
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7f299a6ea7d0>



[ ]:

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 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
```

[3]:
```
df['Usage']=df['Usage'].astype('int')
df['Fitness']=df['Fitness'].astype('int')
df.info()
# Select only numerical features for correlation analysis
numerical_features = df.select_dtypes(include=['number'])
# Calculate the correlation matrix
corr_mat = numerical_features.corr()
# Plotting the heatmap
plt.figure(figsize=(15, 6))
sns.heatmap(corr_mat, annot=True)

plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
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 6   Fitness        180 non-null    int64
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 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
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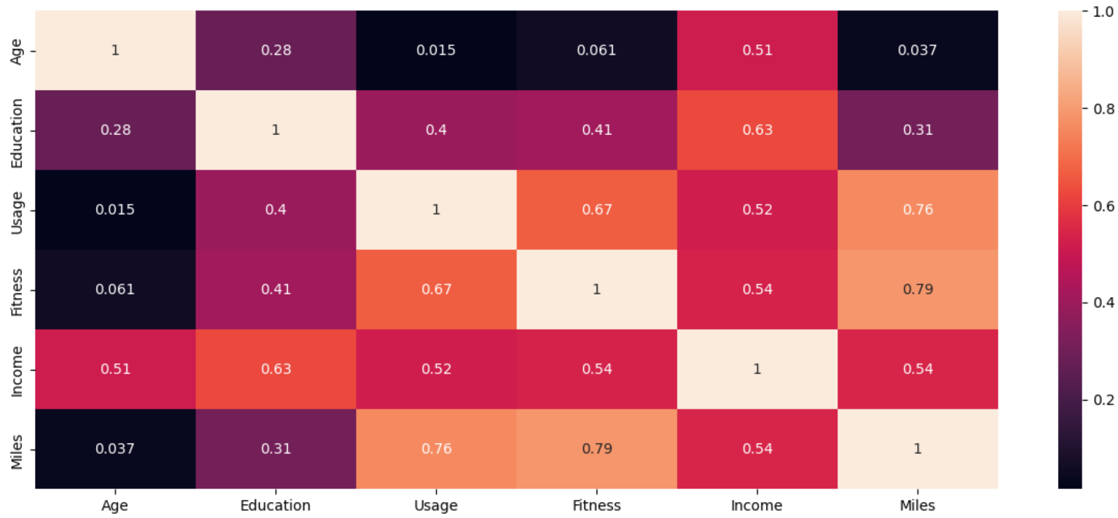
```



Insights:

- From this map, its clear that age and income are positively correlated, meaning age increases , income tend to increase as well.
- Usage is positively correlated with fitness and miles, means that regular exercises contributes to improved fitness and helps to use treadmill for longer duration.

Customer profiling:

youngsters [25-30] - people in this age group are more curious to start work out and buy KP281 and KP481 treadmill products.

We can introduce more products at this price range and cover these age groups by giving offers.

Educated people: These category tend to buy high end product (KP781) because they concentrate more in fitness and are economically manageable due to their stable income.

Therefore, we need to plan a marketing strategy by giving corporate offer schemes so that we can attract more professional customers.

Married/single: Its observed that single is mainly buying cheap product. They may be a student or a person who just started working. We can plan to visit colleges spread awareness and motivate them for their fitness and buy our economical Treadmills. We can introduce more models around this segment which will definitely help generate revenue ,although not much margin but volumes will be high. and if our quality is good he /she will be our future customer for our high end models.

Since many married people are buying our Treadmills mostly KP281. That infers that there is big scope of introducing more models around it since mane married and singles are buying low end Treadmills due to cost involved

Recommendation:

Based on the customer profiling and socio-economic factors, we can create targeted marketing strategies for each group.

There is a significant market for entry-level products, making up 78% of sales, providing a great opportunity to attract customers.

Once customers are on board and have a positive experience, we can introduce them to advanced treadmills.

We can use digital media, such as social media and YouTube, to reach these customers by using profiles from an agency.

Additionally, organizing fitness events in targeted areas will help promote our products.

With these strategies, we can increase market share and boost revenue.

[ ]:

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[ ]:

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[ ]:

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[ ]:

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