```
#1. Import the dataset and do usual data analysis steps like checking the structure &
#characteristics of the dataset
#o The data type of all columns in the “customers” table.


import pandas as pd
df= pd.read_csv('aerofit.csv')
print(df.dtypes)
```

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

```
#You can find the number of rows and columns given in the dataset

print(f"The dataset has {df.shape[0]} rows and {df.shape[1]} columns.")
```

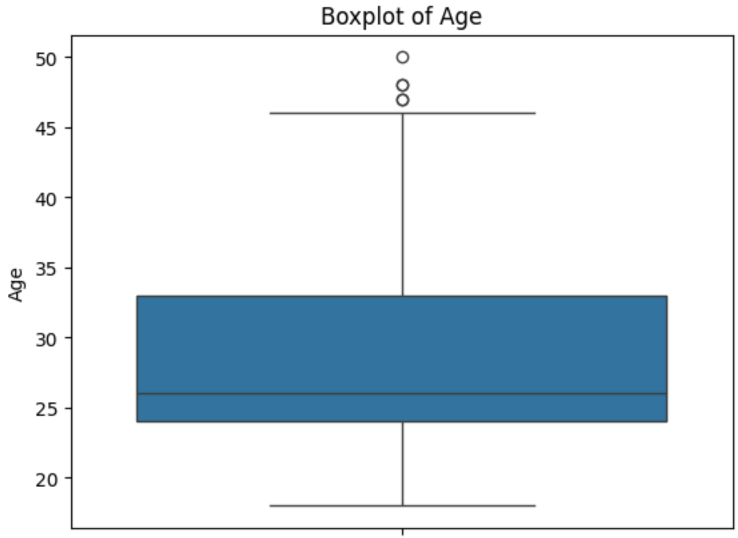
```
The dataset has 180 rows and 9 columns.
```

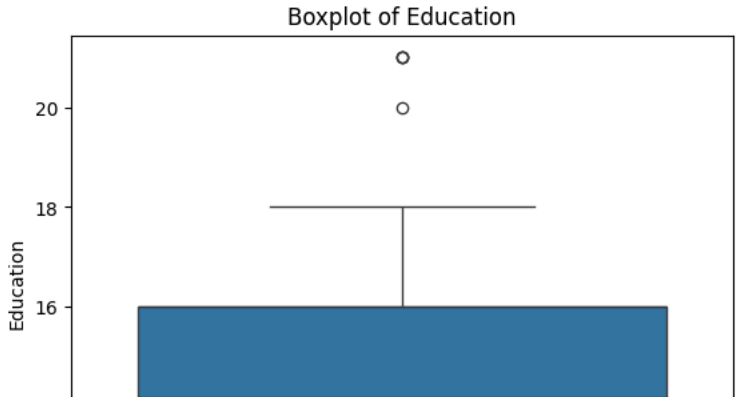
```
#o Check for the missing values and find the number of missing values in each column


df.isnull().sum()
```

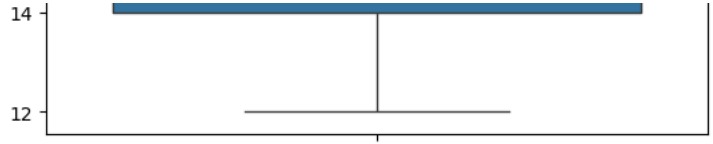
Show hidden output

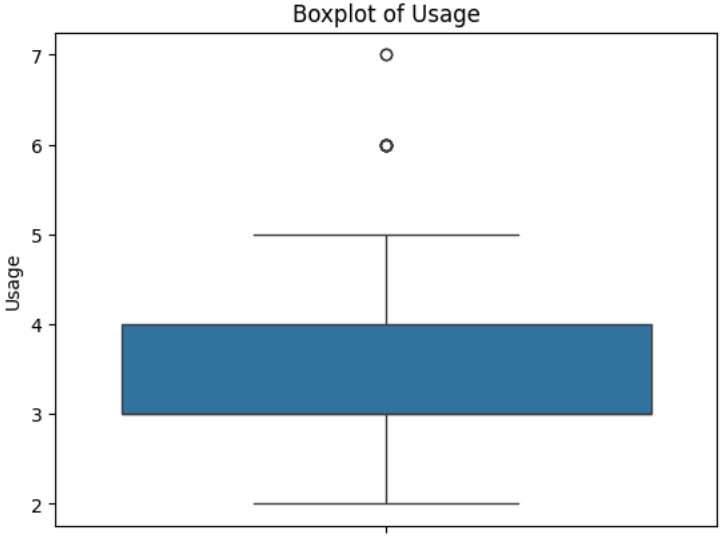
```
No null in any columns
```

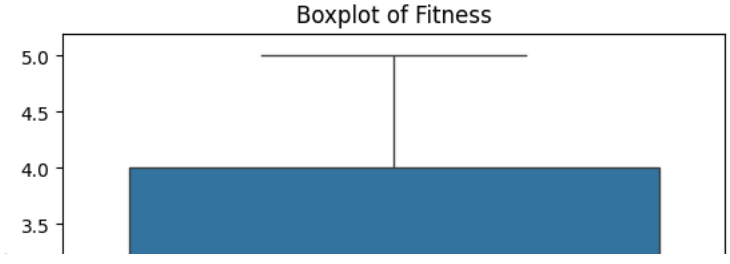
```
#2. Detect Outliers
#o Find the outliers for every continuous variable in the dataset


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

df_continuous_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Boxplots to visualize outliers
for column in df_continuous_columns:
    sns.boxplot(y=df[column])
    plt.title(f"Boxplot of {column}")
    plt.show()

# Function to find outliers using IQR
def find_outliers(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
    outliers = data[(data[column] < lower) | (data[column] > upper)]
    return outliers

# Print outliers for each column
print("\n Outliers found using IQR method:\n")
for column in df_continuous_columns:
    outliers = find_outliers(df, column)
    if not outliers.empty:
        print(f"{column}: {len(outliers)} outliers")
        print(outliers[column].values)
    else:
        print(f"{column}: No outliers")
```

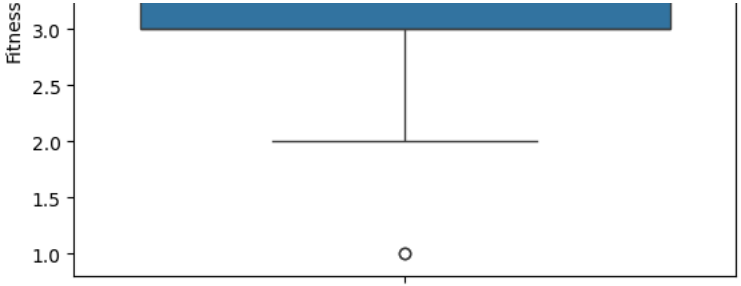

Boxplot of Age
Age
50
45
40
35
30
25
20

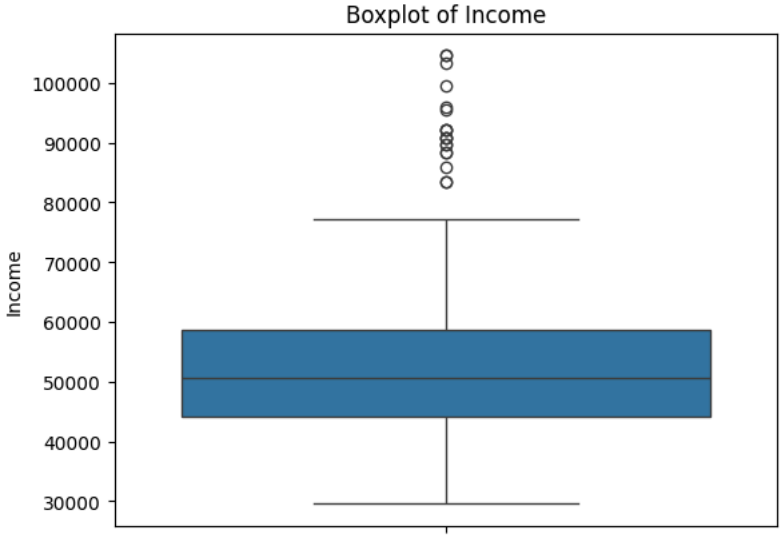

Boxplot of Education
Education
20
18
16

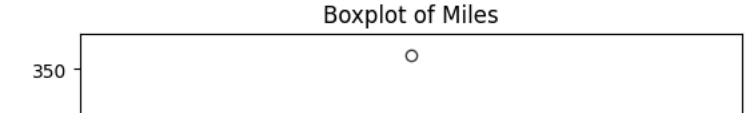

14
12

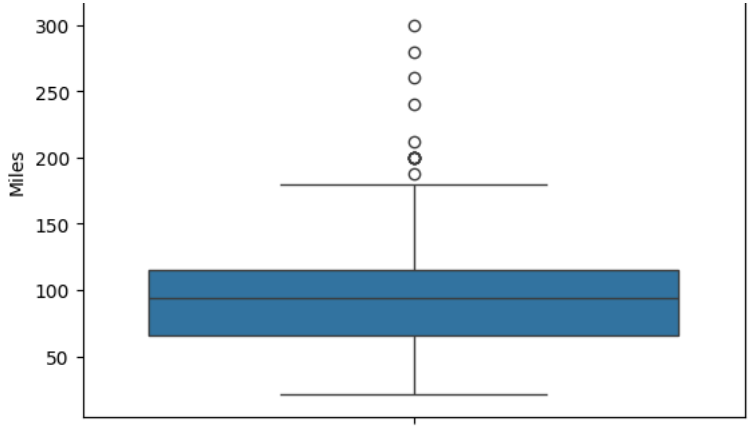

Boxplot of Usage
Usage
7
6
5
4
3
2


Boxplot of Fitness
5.0
4.5
4.0
3.5


Fitness
3.0
2.5
2.0
1.5
1.0


Boxplot of Income
Income
100000
90000
80000
70000
60000
50000
40000
30000


Boxplot of Miles
350




```
 Outliers found using IQR method:

Age: 5 outliers
[47 50 48 47 48]
Education: 4 outliers
[20 21 21 21]
Usage: 9 outliers
[6 6 6 7 6 7 6 6 6]
Fitness: 2 outliers
[1 1]
Income: 19 outliers
[ 83416  88396  90886  92131  88396  85906  90886 103336  99601  89641
  95866  92131  92131 104581  83416  89641  90886 104581  95508]
Miles: 13 outliers
[188 212 200 200 200 240 300 280 260 200 360 200 200]
```

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

```
import numpy as np
# Clipping each continuous column between its 5th and 95th percentiles
for column in df_continuous_columns:
    lower = df[column].quantile(0.05)
    upper = df[column].quantile(0.95)
    df[column] = np.clip(df[column], lower, upper)
    print(f" Clipped {column} between {round(lower, 2)} and {round(upper, 2)}")
```

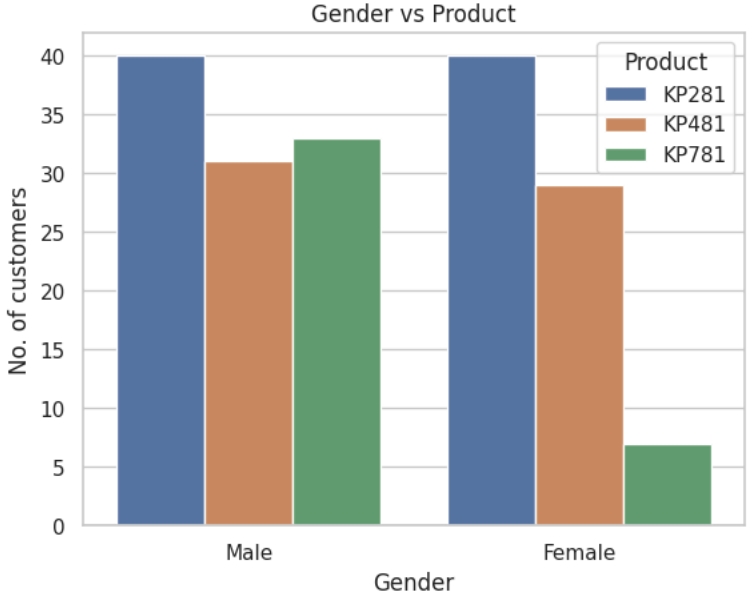
```
 Clipped Age between 20.0 and 43.0
 Clipped Education between 14.0 and 18.0
 Clipped Usage between 2.0 and 5.0
 Clipped Fitness between 2.0 and 5.0
 Clipped Income between 34107.16 and 90889.11
 Clipped Miles between 47.0 and 200.0
```

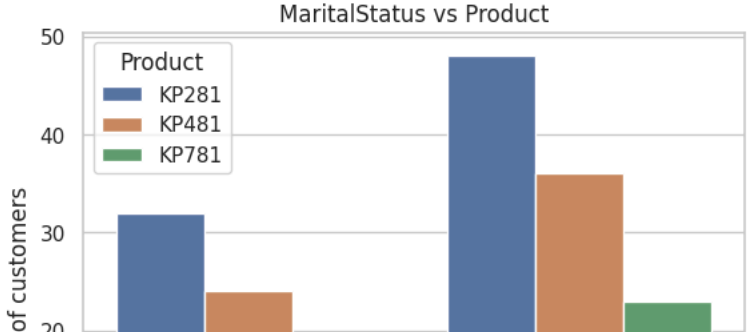
3. Check if features like marital status, Gender, and age have any effect on the product purchased
○ Find if there is any relationship between the categorical variables and the output variable in the data.

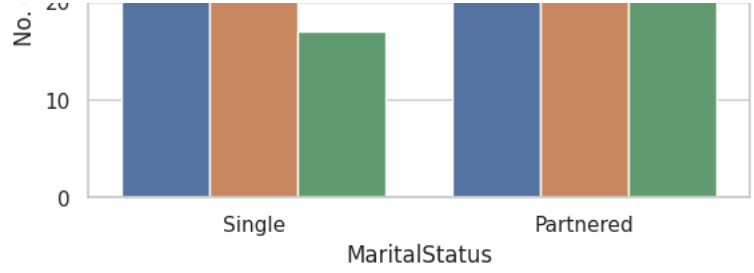
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
df=pd.read_csv('aerofit.csv')
df['AgeGroup']=pd.cut(df['Age'],bins=[0,25,35,45,55,100],labels=['<25','25-35','35-45','45-55','55+'])
features=['Gender','MaritalStatus','AgeGroup']
for feature in features:
  plt.figure()
  sns.countplot(x=feature,data=df, hue='Product')
  plt.title(f'{feature} vs Product')
  plt.xlabel(feature)
```

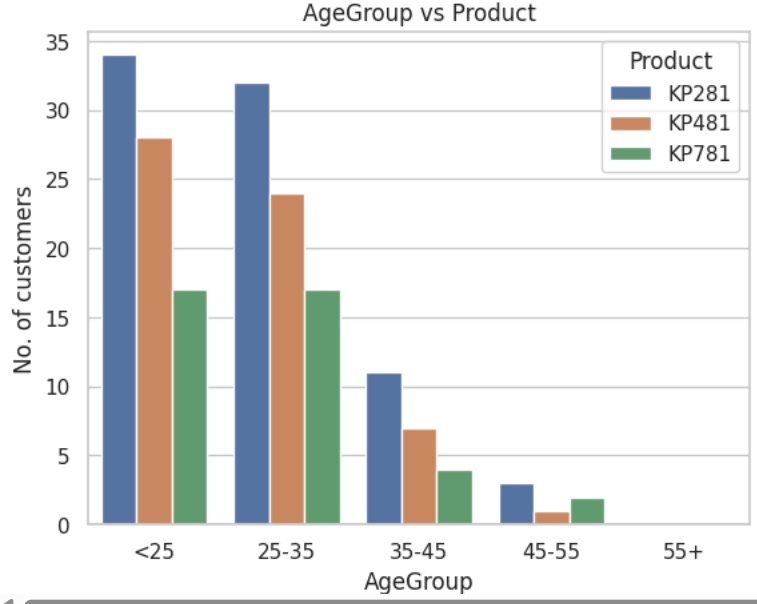
```
plt.ylabel('No. of customers')
plt.legend(title='Product')
plt.show()
```

[4]


Gender vs Product
Product
KP281
KP481
KP781
No. of customers
0
5
10
15
20
25
30
35
40
Male
Female
Gender


MaritalStatus vs Product
Product
KP281
KP481
KP781
of customers
30
40
50


No.
20
10
0
Single
Partnered
MaritalStatus


AgeGroup vs Product
Product
KP281
KP481
KP781
No. of customers
35
30
25
20
15
10
5
0
<25
25-35
35-45
45-55
55+
AgeGroup

kp281 is the most preferred by both male and female. kp781 is more preffered than kp481 by male, kp781 is preferred more by married peo
Customers with age below 25 are the ones who is using the products the most with kp281 being used the maximum

o Find if there is any relationship between the continuous variables and the output variable in the data.

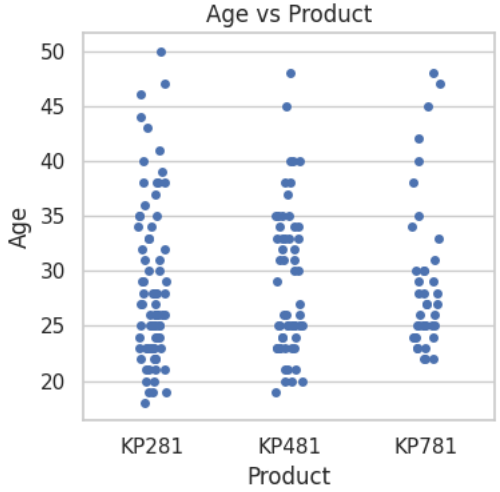
```
  File "<ipython-input-15-a35e6bd47598>", line 1
    o Find if there is any relationship between the continuous variables and the output variable in the data.
    ^
SyntaxError: invalid character 'o' (U+25CB)
```

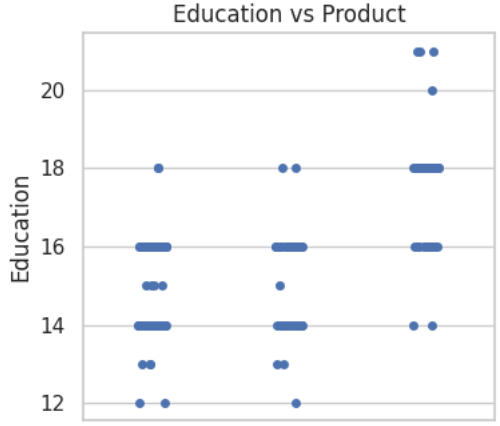
Next steps: Explain error

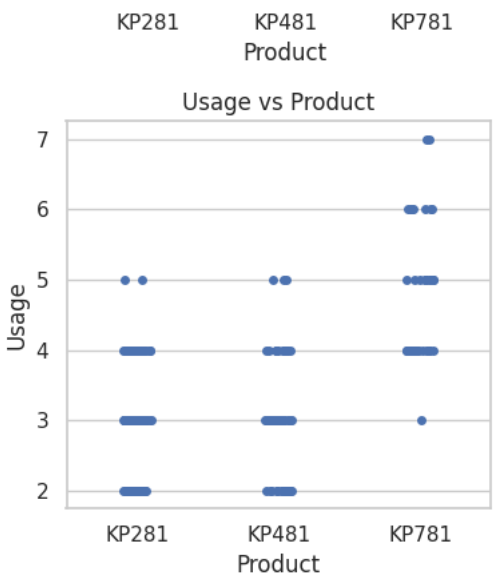
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load dataset
df = pd.read_csv("aerofit.csv")

# Identify continuous (numeric) variables
numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns

# Output variable
output_var = 'Product'

# Set up the plot style
sns.set(style="whitegrid")

# Loop through each numeric column and plot against Product
for col in numeric_cols:
    plt.figure(figsize=(4, 4))
    sns.stripplot(x=output_var, y=col, data=df, jitter=True)
    plt.title(f'{col} vs {output_var}')
    plt.xlabel('Product')
    plt.ylabel(col)
```

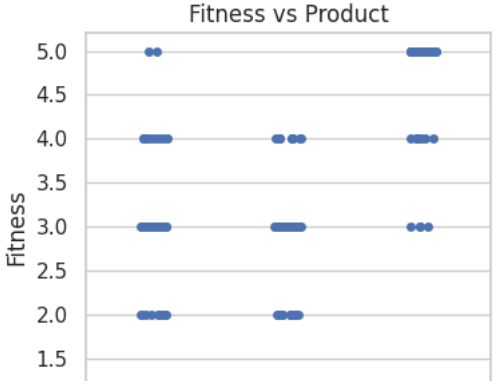
```
plt.ylabel(col)
plt.tight_layout()
plt.show()
```

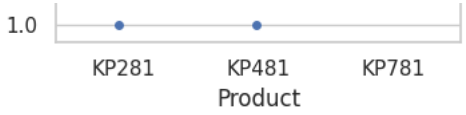
[+]

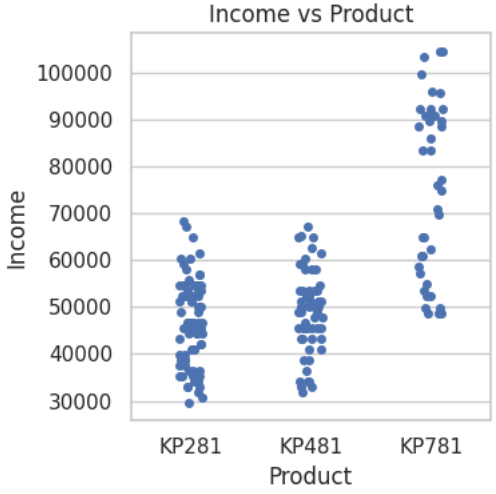

Age vs Product
Age
50
45
40
35
30
25
20
KP281
KP481
KP781
Product

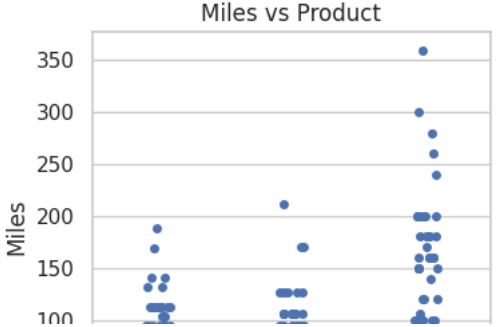

Education vs Product
Education
20
18
16
14
12


KP281
KP481
KP781
Product
Usage vs Product
7
6
5
4
3
2
Usage
KP281
KP481
KP781
Product


Fitness vs Product
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
Fitness


1.0
KP281
KP481
KP781
Product


Income vs Product
100000
90000
80000
70000
60000
50000
40000
30000
Income
KP281
KP481
KP781
Product


Miles vs Product
350
300
250
200
150
100
Miles


50
KP281
KP481
KP781
Product

This strip plot showing how the values are distributed across different products (KP281, KP481, KP781)
Helps you spot patterns, e.g., which product tends to be bought by younger people or higher-income customers
kp781 is preferred by high income people and all 3 products majorly getting preferred by young people. High education people preferring

4. Representing the Probability
○ Find the marginal probability (what percent of customers have purchased
KP281, KP481, or KP781)

```
import pandas as pd
df = pd.read_csv("aerofit.csv")

product_prob= pd.crosstab(index=df['Product'],columns='Count',normalize=True)*100
product_prob.round(2)
print("📊 Marginal Probability (Percentage of Customers by Product):")
print(product_prob)
```

```
📊 Marginal Probability (Percentage of Customers by Product):
col_0        Count
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

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

```
import pandas as pd
df = pd.read_csv("aerofit.csv")

feature_columns = []  # Create an empty list to store column names
for col in df.columns:
    if col != 'Product':  # If the column is not 'Product'
        feature_columns.append(col)

# Loop through each feature and compute conditional probability with respect to Product
for col in feature_columns:
```

```
print(f"\n Conditional Probability of Product given '{col}':\n")
prob_table = pd.crosstab(index=df[col], columns=df['Product'], normalize='index') * 100
print(prob_table.round(2))
```

```
 Conditional Probability of Product given 'Age':

Product   KP281  KP481   KP781
Age
18       100.00   0.00    0.00
19        75.00  25.00    0.00
20        40.00  60.00    0.00
21        57.14  42.86    0.00
22        57.14   0.00   42.86
23        44.44  38.89   16.67
24        41.67  25.00   33.33
25        28.00  44.00   28.00
26        58.33  25.00   16.67
27        42.86  14.29   42.86
28        66.67   0.00   33.33
29        50.00  16.67   33.33
30        28.57  28.57   42.86
31        33.33  50.00   16.67
32        50.00  50.00    0.00
33        25.00  62.50   12.50
34        33.33  50.00   16.67
35        37.50  50.00   12.50
36       100.00   0.00    0.00
37        50.00  50.00    0.00
38        57.14  28.57   14.29
39       100.00   0.00    0.00
40        20.00  60.00   20.00
41       100.00   0.00    0.00
42         0.00   0.00  100.00
43       100.00   0.00    0.00
44       100.00   0.00    0.00
45         0.00  50.00   50.00
46       100.00   0.00    0.00
47        50.00   0.00   50.00
48         0.00  50.00   50.00
50       100.00   0.00    0.00
```

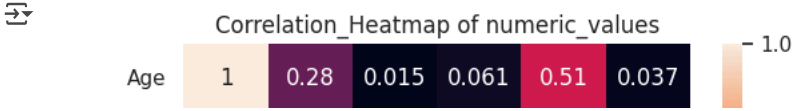
```
 Conditional Probability of Product given 'Gender':

Product  KP281  KP481  KP781
Gender
Female   52.63  38.16   9.21
Male     38.46  29.81  31.73

 Conditional Probability of Product given 'Education':

Product    KP281  KP481   KP781
Education
12         66.67  33.33    0.00
13         60.00  40.00    0.00
14         54.55  41.82    3.64
15         80.00  20.00    0.00
16         45.88  36.47   17.65
18          8.70   8.70   82.61
20          0.00   0.00  100.00
21          0.00   0.00  100.00
```

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)

```
import pandas as pd
df = pd.read_csv("aerofit.csv")

# Calculate conditional probability: P(Product | Gender)
gender_product_prob = pd.crosstab(index=df['Gender'], columns=df['Product'], normalize='index') * 100

# Display probabilities
print("📊 Conditional Probability of Product given Gender:\n")
print(gender_product_prob.round(2))

# Specific probability: P(KP481 | Female)
prob_kp481_given_female = gender_product_prob.loc['Female', 'KP481']
print(f"\n✅ Probability that a customer will purchase KP481 given they are Female: {prob_kp481_given_female:.2f}%")
```

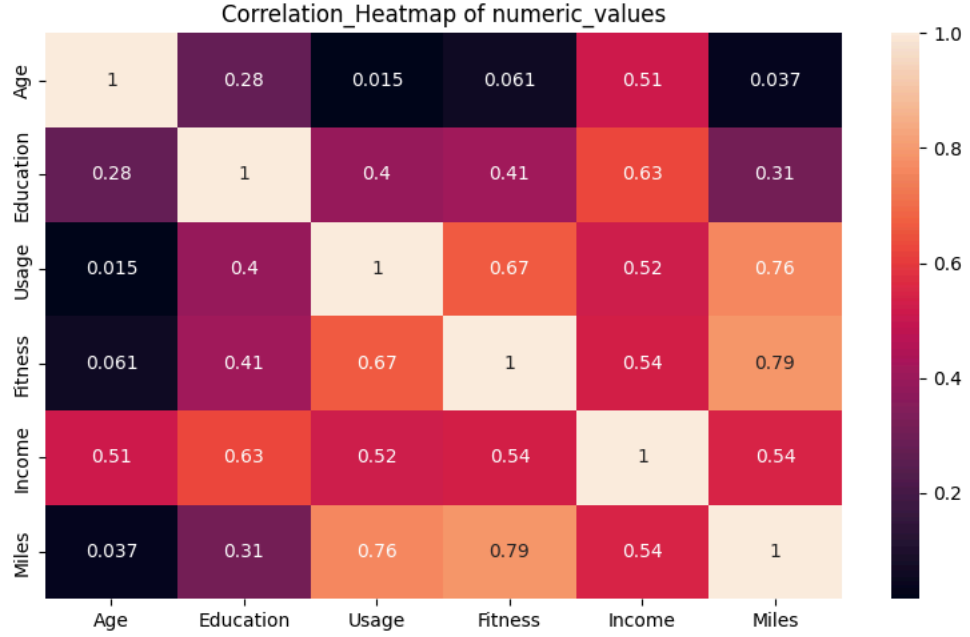
5. Check the correlation among different factors
o Find the correlation between the given features in the table

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv("aerofit.csv")

corr_mat = df.corr(numeric_only=True)
#heatmap
plt.figure(figsize=(6,4))
sns.heatmap(corr_mat, annot=True)
plt.title('Correlation_Heatmap of numeric_values')
plt.tight_layout()
plt.show()
```



5. Check the correlation among different factors
○ Find the correlation between the given features in the table

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

df=pd.read_csv("aerofit.csv")

corr_mat = df.corr(numeric_only=True)

#heatmap

plt.figure(figsize=(8,5))
sns.heatmap(corr_mat, annot=True)
plt.title('Correlation_Heatmap of numeric_values')
plt.tight_layout()
plt.show()
```



#Strong relationships

#Fitness and Miles (0.79) : People who rate themselves as more fit tend to accumulate more miles using the equipment – likely due to hig

#Usage and Miles (0.76) : The more frequently a customer uses the equipment, the more total miles they log – a direct and expected relat

#Usage and Fitness (0.67) : Increased usage of the product is strongly associated with higher self-rated fitness.

#Weak relationships-

#Usage and Age (0.015) : There’s no meaningful relationship between a customer’s age and how often they use the product.

#Miles and Age (0.037): Age doesn't influence total miles logged, suggesting older and younger customers use the equipment similarly in

#Age and Fitness (0.061) : No significant correlation between age and fitness level – possibly because fitness is influenced more by li

6. Customer profiling and recommendation
○ Make customer profilings for each and every product.

○ Write a detailed recommendation from the analysis that you have done.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv('aerofit.csv')

kp281_buyers=df[df['Product'] == 'KP281']
kp481_buyers=df[df['Product'] == 'KP481']
kp781_buyers=df[df['Product'] == 'KP781']

print("\n  KP281 Buyers - Age & Income ")
print(kp281_buyers[['Age','Income']].describe())

print("\n KP281 Buyers - Gender")
print(kp281_buyers['Gender'].value_counts(normalize=True)*100)

print(" \n KP281 Buyers - MaritalStatus")
print(kp281_buyers['MaritalStatus'].value_counts(normalize=True))

print("\n KP481 Buyers - Age & Income")
print(kp481_buyers[['Age','Income']].describe())

print(" \n KP481 Buyers - Gender")
print(kp481_buyers['Gender'].value_counts(normalize=True)*100)
```

```
print("\n  KP481 Buyers - MaritalStatus")
print(kp481_buyers['MaritalStatus'].value_counts(normalize=True))

print("\n KP781 Buyers - Age & Income")
print(kp781_buyers[['Age','Income']].describe())

print("\n KP781 Buyers - Gender")
print(kp781_buyers['Gender'].value_counts(normalize=True)*100)

print("\n  KP781 Buyers - MaritalStatus")
print(kp781_buyers['MaritalStatus'].value_counts(normalize=True))
```

```
   KP281 Buyers - Age & Income
              Age       Income
count  80.000000     80.00000
mean   28.550000  46418.02500
std     7.221452   9075.78319
min    18.000000  29562.00000
25%    23.000000  38658.00000
50%    26.000000  46617.00000
75%    33.000000  53439.00000
max    50.000000  68220.00000

 KP281 Buyers - Gender
Gender
Male      50.0
Female    50.0
Name: proportion, dtype: float64

 KP281 Buyers - MaritalStatus
MaritalStatus
Partnered    0.6
Single       0.4
Name: proportion, dtype: float64

 KP481 Buyers - Age & Income
```

```
             Age        Income
count  60.000000     60.000000
mean   28.900000  48973.650000
std     6.645248   8653.989388
min    19.000000  31836.000000
25%    24.000000  44911.500000
50%    26.000000  49459.500000
75%    33.250000  53439.000000
max    48.000000  67083.000000

 KP481 Buyers - Gender
Gender
Male      51.666667
Female    48.333333
Name: proportion, dtype: float64

  KP481 Buyers - MaritalStatus
MaritalStatus
Partnered    0.6
Single       0.4
Name: proportion, dtype: float64

 KP781 Buyers - Age & Income
             Age        Income
count  40.000000      40.00000
mean   29.100000   75441.57500
std     6.971738   18505.83672
min    22.000000   48556.00000
25%    24.750000   58204.75000
50%    27.000000   76568.50000
75%    30.250000   90886.00000
max    48.000000  104581.00000
```

#Findings – example- KP281 Customer Profile Summary:
#Most KP281 buyers are between 23 and 33 years old.

#Gender: Equal females and males buy KP281 (e.g., 50% Female, 50% Male).

#Income: Buyers typically fall in the $29,000–$55,000 income range.

#Marital Status: Majority are partnered (e.g., 60% Partnered, 40% Single)

#Similar analysis can be done for kp481 and kp781

recommendation-

kp281 is recommended for low income partnered people irrespective of gender(male/female equal)
kp481 is reommended for medium income partnered male
kp781 is recommended for high income partnered male

Start coding or generate with AI.