aerofit-final

July 27, 2025

AEROFIT BUSINESS CASE STUDY

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
data=pd.read_csv('aerofit_treadmill.csv')
```

1. Defining Problem Statement and Analysing basic metrics.

Business Problem

AeroFit aims to enhance its customer recommendation system by understanding the demographic and behavioral characteristics of buyers for each of its treadmill products. The market research team is tasked with identifying patterns and differences among customer segments (e.g., age, gender, fitness level, income) associated with each treadmill model. This analysis will support data-driven product recommendations and help tailor marketing strategies

[ ]:
```
#Observation: The data consists of information about the products, the age,␣
↪gender, education, marital status, usage, fitness, income about the clients
#along with the miles the equipment was used by the customers
data.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

[ ]:
```
#Observation: the dataset consists of 180 rows and 9 columns, with no missing␣
↪values. The categorical columns are in the object format in the dataset
#The numerical columns are in the integer format.
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
```

[ ]:
```
#Observation: Summary of the numerical columns shows that, customers range from␣
↪18 to 50 years of age, with an average age of 29 years.
#Majority are under 26 years, indicating a younger customer base. Most users␣
↪have 14-16 years of education, with a median of 16 years, suggesting␣
↪college-educated individuals.
#The average usage frequency is ~3.5 times per week. 50% of users use the␣
↪treadmill 3 times/week, with a few customers using it up to 7 times/week.
#Most customers rate their fitness between 3 and 4 (out of 5), with a median of␣
↪3 - suggesting moderately fit users.
#Income ranges from ~29,500 to  1,04,500, with a mean of  53,700. Mean>Median␣
↪in the income data suggesting a right-skewed distribution, with 25% earning␣
↪below  44,000.
#customers travel an average of 103 miles per week, with some high-activity␣
↪users going up to 360 miles. Most (75%) travel less than 115 miles weekly.
data.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
```

```
[ ]: #Observation: The dataset consists of 180 rows and 9 columns
     data.shape
```

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

```
[ ]: #Observation: There are no missing values
     data.isna().sum()
```

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

```
[ ]: #Obsevations: The Product, Gender, MaritalStatus and Fitness categorical␣
      ↪columns were converted to 'category' type.
     data['Product']=data['Product'].astype('category')
     data['Gender']=data['Gender'].astype('category')
     data['MaritalStatus']=data['MaritalStatus'].astype('category')
     data['Fitness']=data['Fitness'].astype('category')
     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    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    category
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: category(4), int64(5)
memory usage: 8.4 KB
```

```
[ ]:
```

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

```
[ ]: #Observations: Aerofit offers three product, KP281, KP481, KP781 to a wide␣
     ↪range of customers from young to middle aged. Since the customers are well␣
     ↪educated,
     #they could respond to tech/features. Some of the users use the device for 7␣
     ↪times a week which demands high performance/durability for the equipments.␣
     ↪Wide range of
     #income for the customers. High mileage users may prefer performance-focussed␣
     ↪models.
     for cols in data.columns:
       print(f"\nColumn: {cols},Unique: {data[cols].nunique()}")
       print(data[cols].unique())
```

```
Column: Product,Unique: 3
['KP281' 'KP481' 'KP781']

Column: Age,Unique: 32
[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]

Column: Gender,Unique: 2
['Male' 'Female']

Column: Education,Unique: 8
[14 15 12 13 16 18 20 21]

Column: MaritalStatus,Unique: 2
['Single' 'Partnered']

Column: Usage,Unique: 6
[3 2 4 5 6 7]

Column: Fitness,Unique: 5
[4 3 2 1 5]

Column: Income,Unique: 62
[ 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]

Column: Miles,Unique: 37
[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]

[ ]:
```
#Observations: The customer base leans slightly male.
data['Gender'].value_counts()
```

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

[ ]:
```
#Observations: Slightly more customers are partnered.
data['MaritalStatus'].value_counts()
```

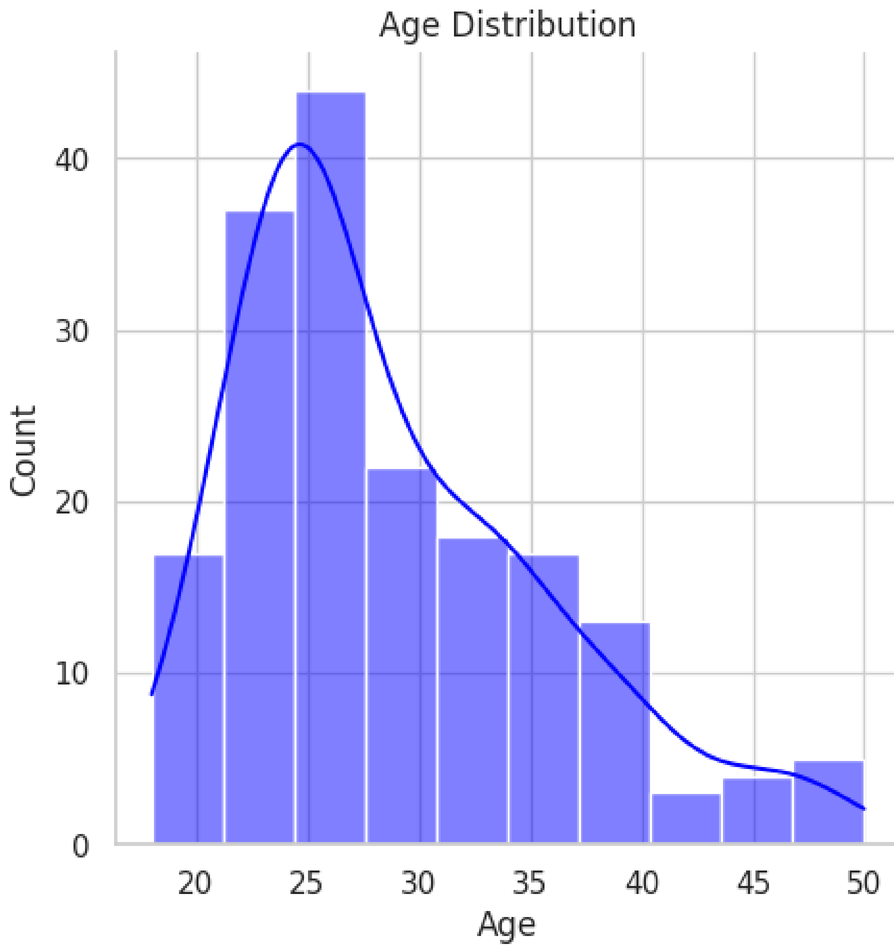
[ ]:
```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

[ ]:
```
#Observation: KP281 is the most popular model, possibly the best fit for a␣
↪broad audience.
data['Product'].value_counts()
```

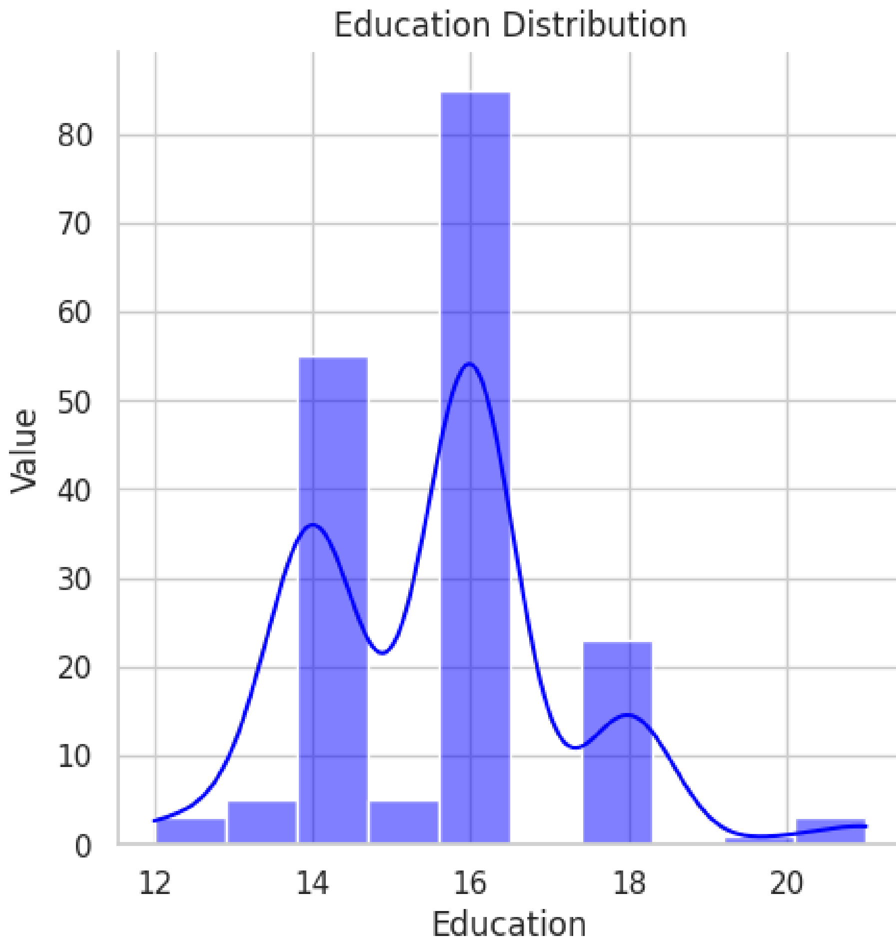
[ ]:
```
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
```

3. Visual Analysis - Univariate & Bivariate. For continuous variable(s): Distplot, countplot, histogram for univariate analysis For categorical variable(s): Boxplot For correlation: Heatmaps, Pairplots

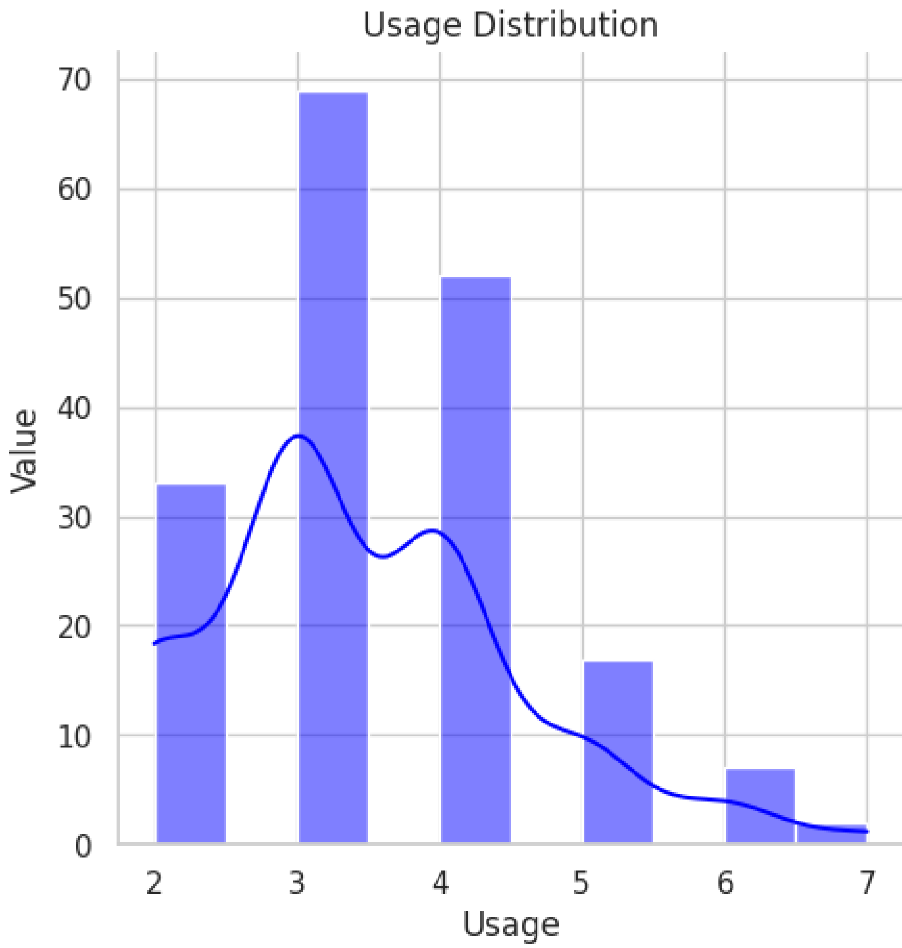
[ ]:
```
#Observation: Majority are young adults within the age range of 20-30
sns.set(style="whitegrid")
sns.displot(data['Age'],bins=10,kde=True,color='blue')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution')
plt.show()
```



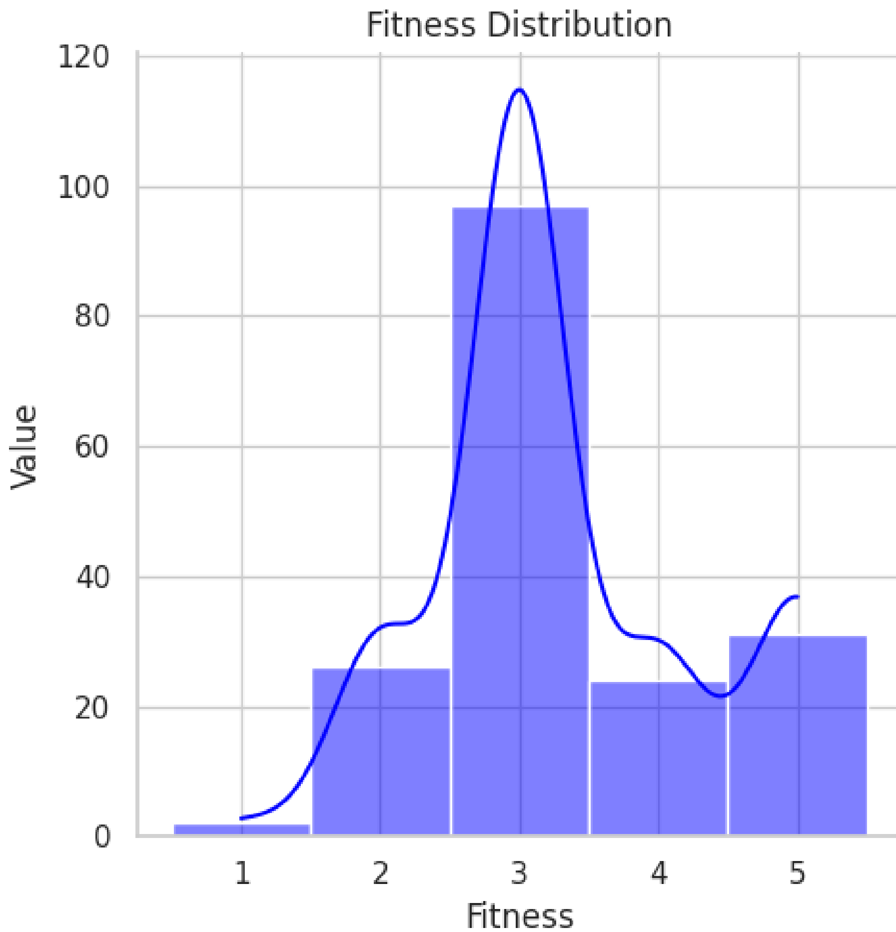

```
[ ]: #Observation: Most customers have 14-16 years of education, indicating they are
      ↪well-educated.
     sns.set(style="whitegrid")
     sns.displot(data['Education'],bins=10,kde=True,color='blue')
     plt.xlabel('Education')
     plt.ylabel('Value')
     plt.title('Education Distribution')
     plt.show()
```



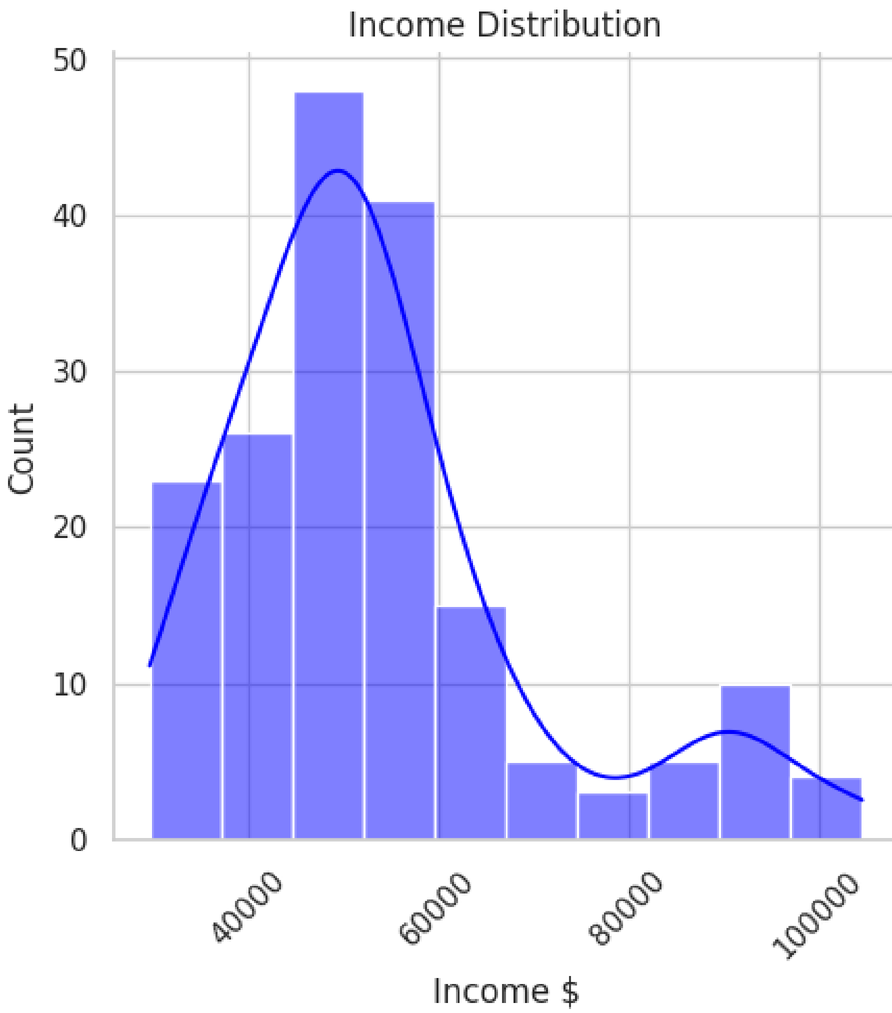
[ ]:
```
#Observation: Customers vary from light to heavy users, with most using␣
↪treadmills moderately
sns.set(style="whitegrid")
sns.displot(data['Usage'],bins=10,kde=True,color='blue')
plt.xlabel('Usage')
plt.ylabel('Value')
plt.title('Usage Distribution')
plt.show()
```



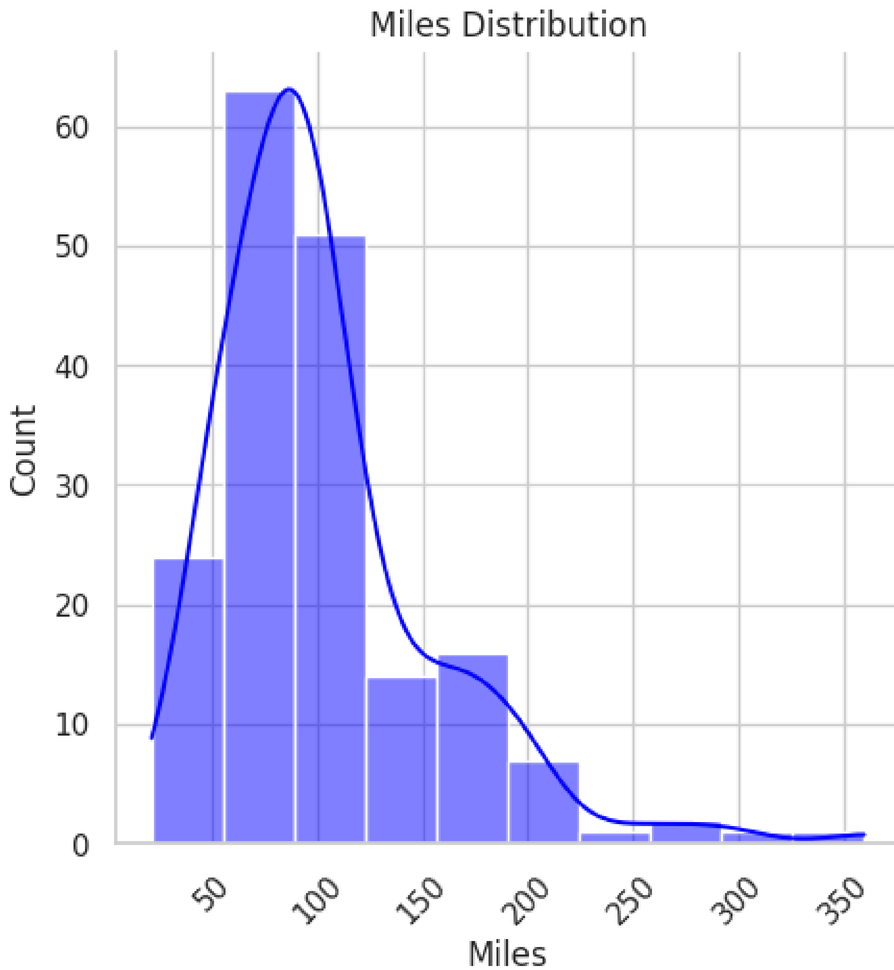

```
[ ]: #Observation: Most customers cluster around levels 3 and 4 (moderate to high
     ↪fitness)
     sns.set(style="whitegrid")
     sns.displot(data['Fitness'],bins=10,kde=True,color='blue')
     plt.xlabel('Fitness')
     plt.ylabel('Value')
     plt.title('Fitness Distribution')
     plt.show()
```



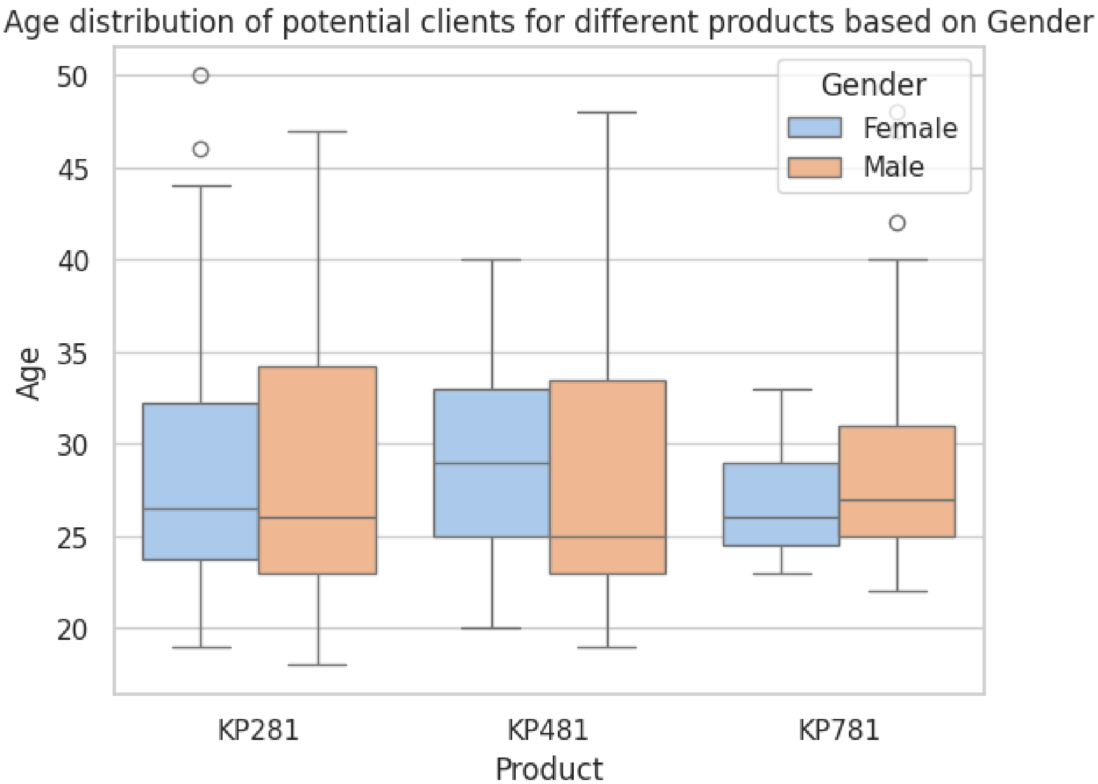

```
[ ]: #Observation: Wide spread from low to high income customers. The kde plot shows␣
     ↪a right skewed distribution.
     sns.set(style="whitegrid")
     sns.displot(data['Income'],bins=10,kde=True,color='blue')
     plt.xlabel('Income $')
     plt.ylabel('Count')
     plt.title('Income Distribution')
     plt.xticks(rotation=45)
     plt.show()
```



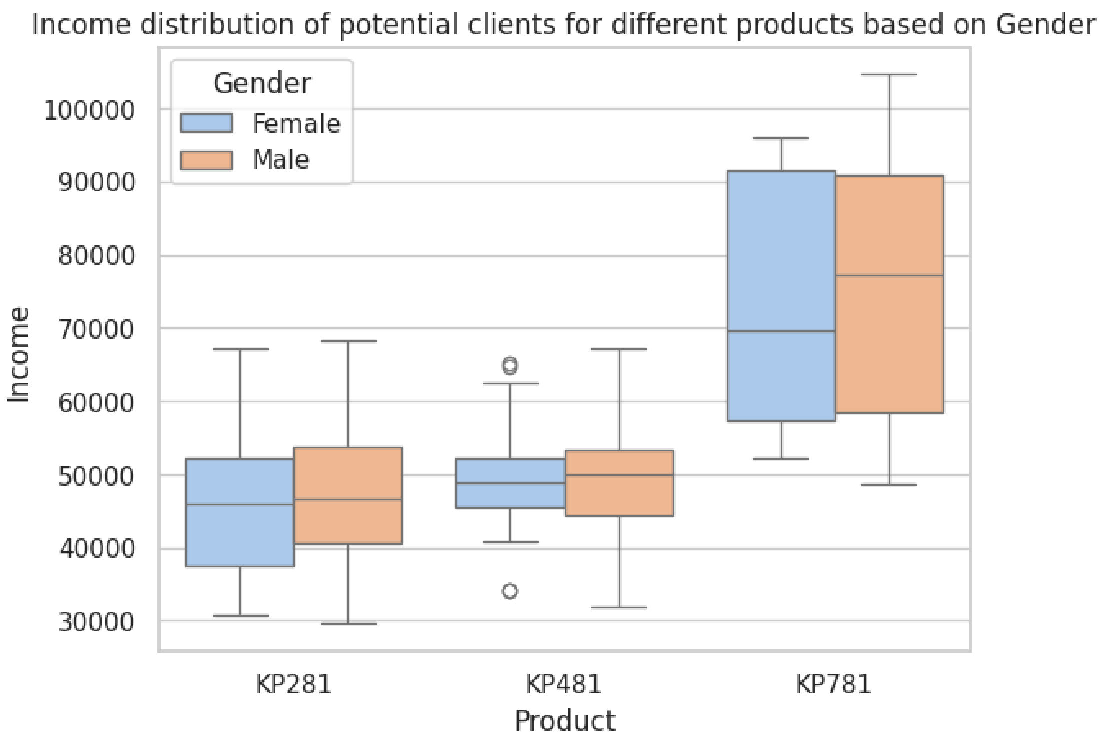
[ ]:
```
#Observation: The peak around 50-100 miles suggests moderate treadmill usage
sns.set(style="whitegrid")
sns.displot(data['Miles'],bins=10,kde=True,color='blue')
plt.xlabel('Miles')
plt.ylabel('Count')
plt.title('Miles Distribution')
plt.xticks(rotation=45)
plt.show()
```



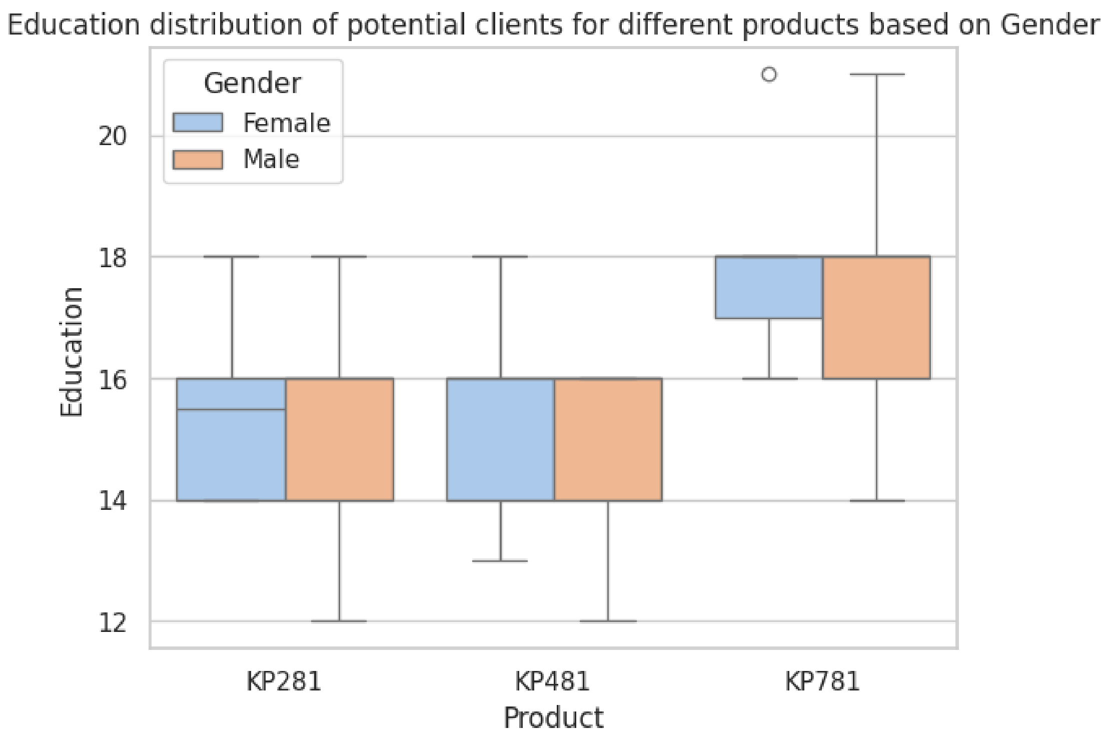

```
[ ]: #Observation: The boxplots shows that, KP281 and KP481 cater to a wider age␣
      ↪range. KP481 is preferred by female customers in the higher age range.
     sns.boxplot(x=data['Product'],y=data['Age'],hue=data['Gender'],palette='pastel')
     plt.xlabel('Product')
     plt.ylabel('Age')
     plt.title('Age distribution of potential clients for different products based␣
      ↪on Gender')
     plt.show()
```



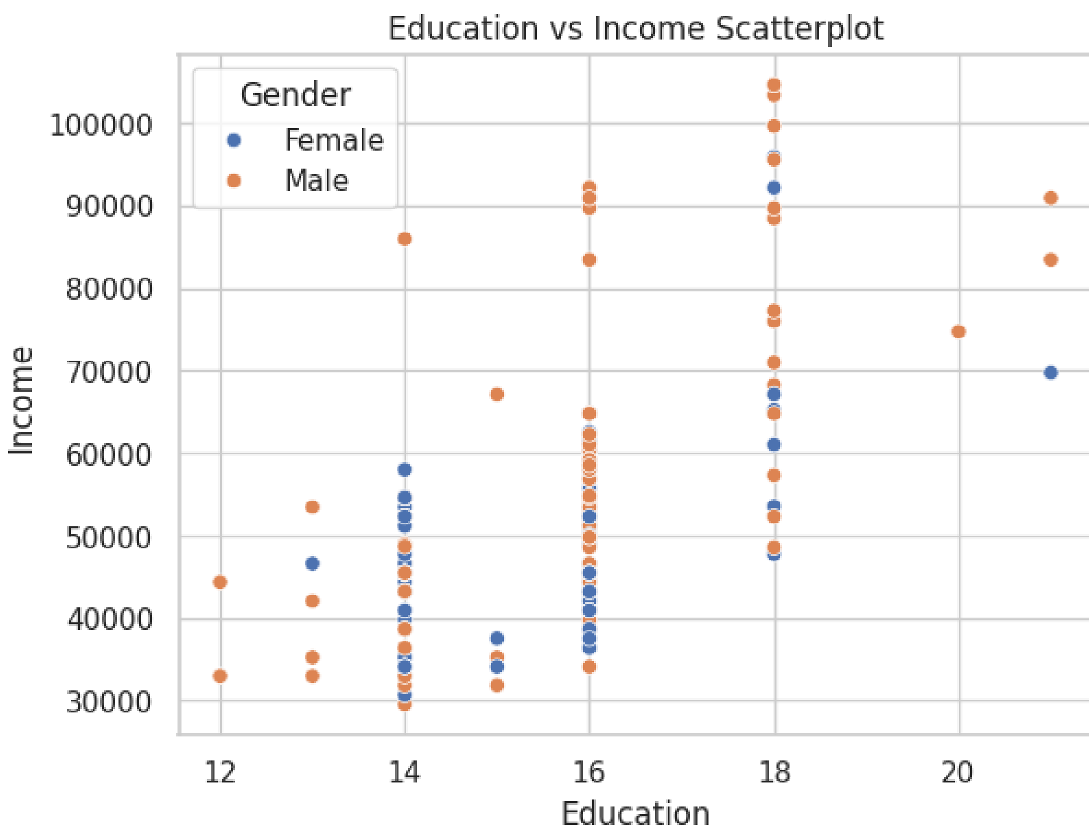

```
[ ]: #Observation: KP281/KP481 models are preferred by the relatively low/
      ↪moderate-income customers whereas the KP781 model is preferred by␣
      ↪high-income customers.
     sns.
      ↪boxplot(x=data['Product'],y=data['Income'],hue=data['Gender'],palette='pastel')
     plt.xlabel('Product')
     plt.ylabel('Income')
     plt.title('Income distribution of potential clients for different products␣
      ↪based on Gender')
     plt.show()
```



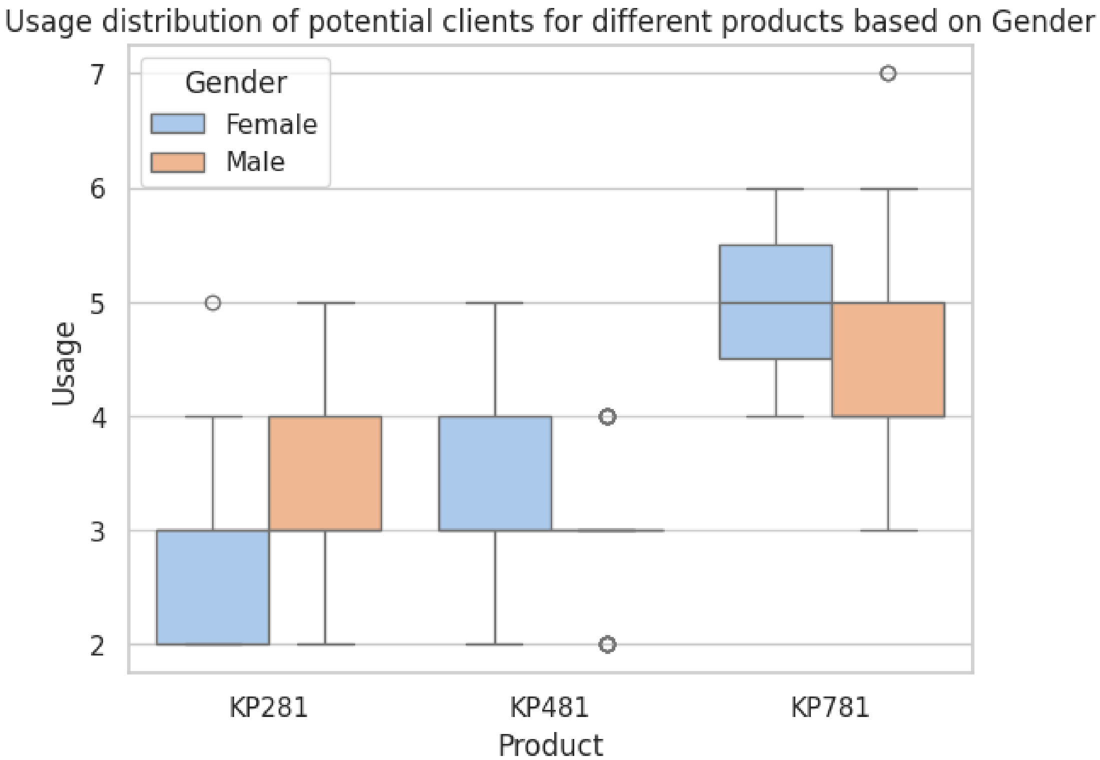
[ ]:
```
#Observation: Customers with high-school to bachelors degree prefer the KP281/
↪KP481 model whereas graduate and higher education customers prefer the KP781␣
↪model.
sns.
↪boxplot(x=data['Product'],y=data['Education'],hue=data['Gender'],palette='pastel')
plt.xlabel('Product')
plt.ylabel('Education')
plt.title('Education distribution of potential clients for different products␣
↪based on Gender')
plt.show()
```



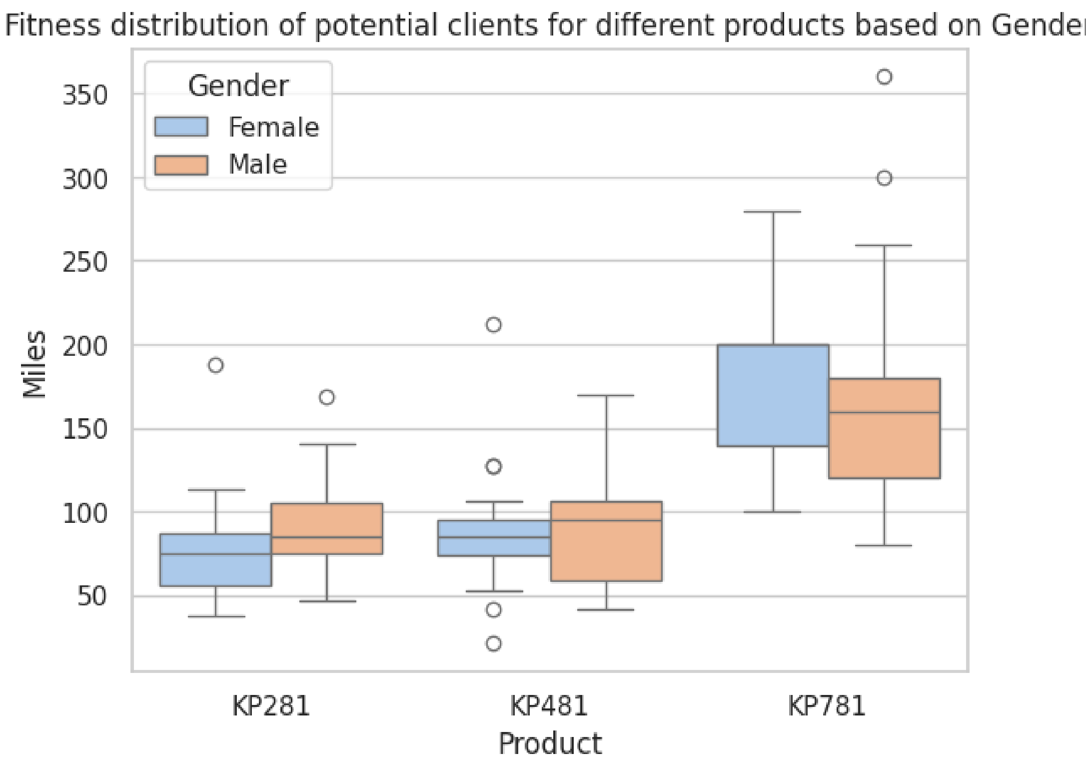

```
[ ]: #Observation: There is indeed a positive corelation between education and
      ↪income which could suggest the preference of the high-income/high-educated
      ↪customers towards
     #more technical and high priced model of KP781
     sns.scatterplot(data=data,x='Education',y='Income',hue='Gender')
     plt.xlabel('Education')
     plt.ylabel('Income')
     plt.title('Education vs Income Scatterplot')
     plt.show()
```



[ ]:
```
#Observation: Usage on the KP281 model is less compared to the KP781 which␣
 ↪suggests a need for more durability in the KP781 model for the high␣
 ↪performance customers
#while KP281 and KP481 caters more to a wider customers group
sns.
 ↪boxplot(x=data['Product'],y=data['Usage'],hue=data['Gender'],palette='pastel')
plt.xlabel('Product')
plt.ylabel('Usage')
plt.title('Usage distribution of potential clients for different products based␣
 ↪on Gender')
plt.show()
```

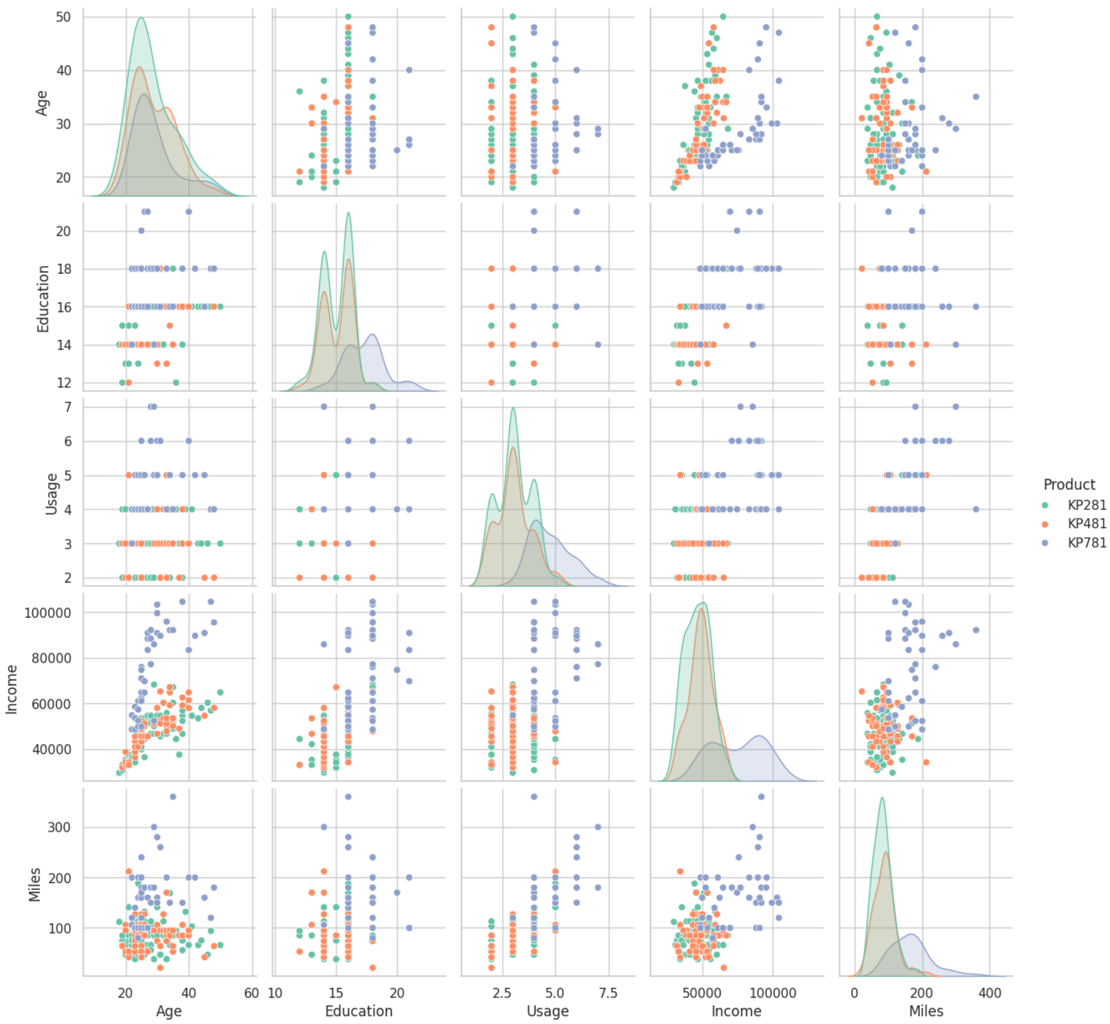


[ ]:
```
#Simialrly, the KP781 model is used more compared to the KP281 and KP481 models␣
↪demanding durability.
sns.
↪boxplot(x=data['Product'],y=data['Miles'],hue=data['Gender'],palette='pastel')
plt.xlabel('Product')
plt.ylabel('Miles')
plt.title('Fitness distribution of potential clients for different products␣
↪based on Gender')
plt.show()
```



Histogram and Pairplots

```
[ ]: #The pairplots show the scatterplots between different attributes. As expected␣
      ↪there is a positive relation between the education and income.
     #As expected, the KP781 product is preferred among the high income and high␣
      ↪education group, whereas KP481 and KP281 models are preferred by the wider␣
      ↪customer category.
     #In the diagnoal kde plots, a right shift is evident for the KP781 model for␣
      ↪the Education, Usage, Income, and miles category. But there is no age␣
      ↪associated
     #preference for the models. Higher usage and miles are observed among the KP781␣
      ↪users.
     sns.pairplot(data=data,hue='Product',palette='Set2')
     plt.show()
```



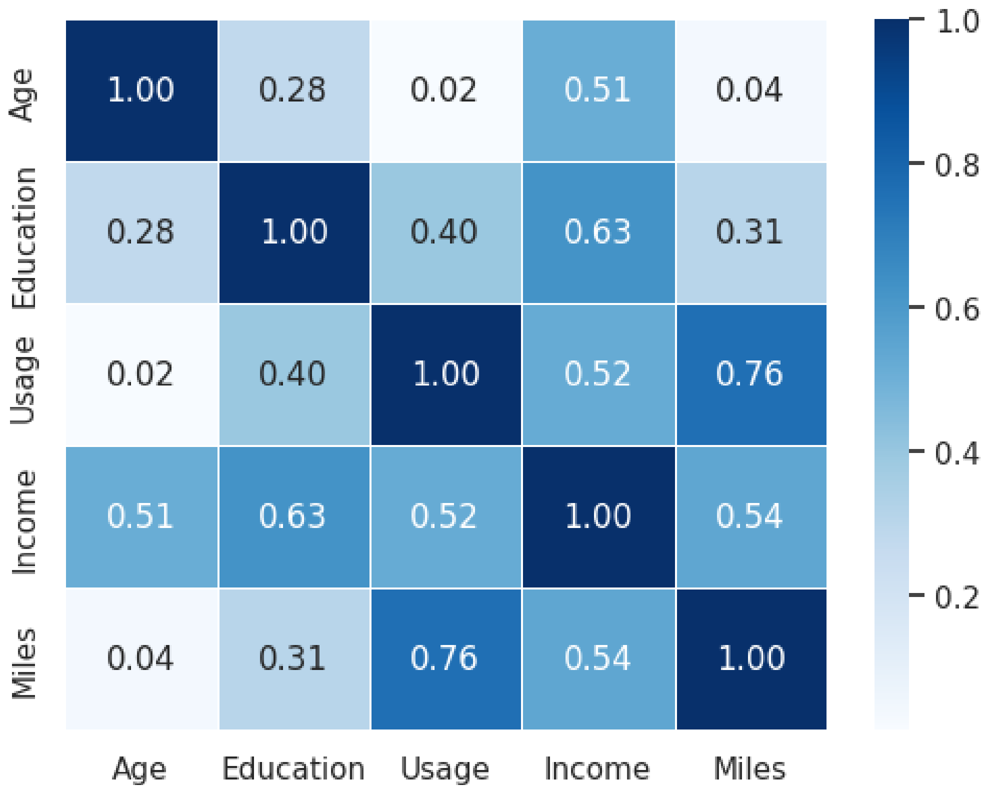
[ ]:
```
data_numerical=data[['Age','Education','Usage','Income','Miles']]
corr=data_numerical.corr()
corr
```

[ ]:

	Age	Education	Usage	Income	Miles
Age	1.000000	0.280496	0.015064	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.519537	0.759130
Income	0.513414	0.625827	0.519537	1.000000	0.543473
Miles	0.036618	0.307284	0.759130	0.543473	1.000000

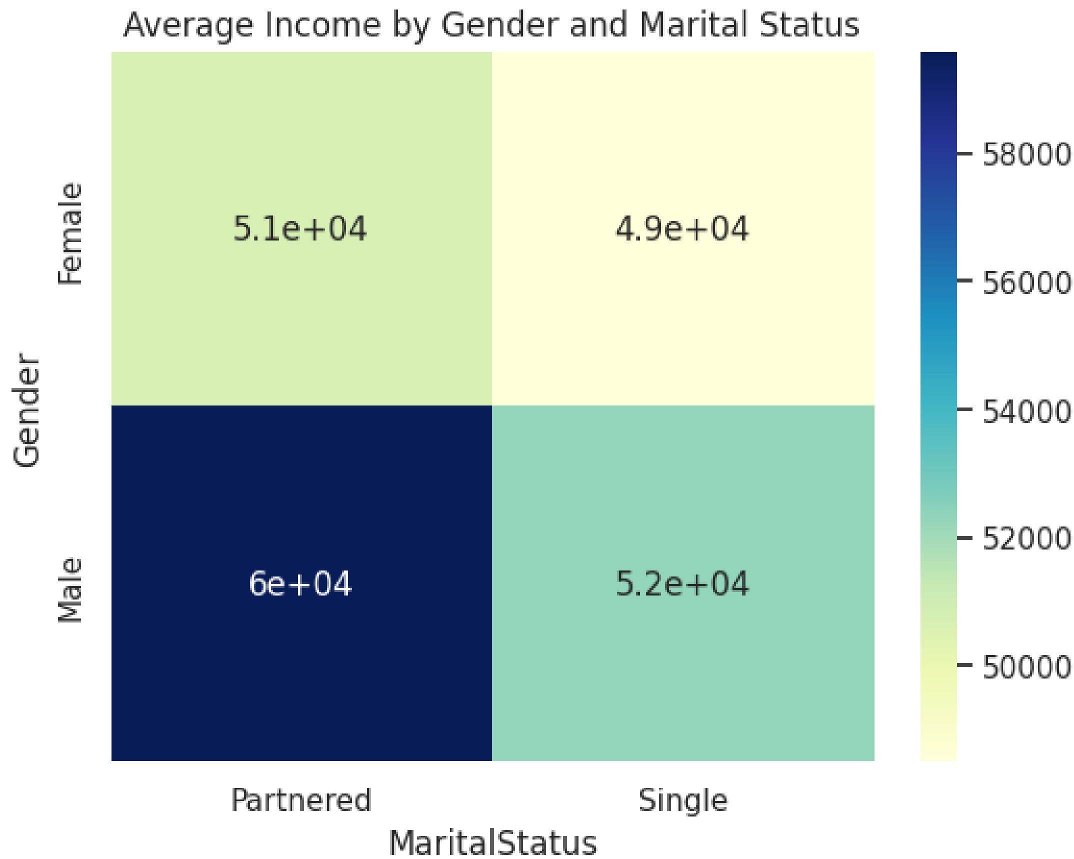
[ ]:
```
#Observation: Similar to the above observed findings, there is comparatively
↪higher corelation between (miles & usage), (income & miles), (income and
↪education),
```

```
#primarily arising from the preference of the KP781 by high performance␣
↪individuals.
sns.heatmap(corr,cmap='Blues',annot=True,fmt='.2f', linewidths=0.5)
plt.show()
```



[ ]:
```
#Observation: The below heatmap between maritalStatus and Gender show that, the␣
↪number of partnered male customers is higher, followed by single male␣
↪customers.
#This could provide clue towards targetted ads for customers based on Gender.
pivot = data.pivot_table(values='Income', index='Gender',␣
↪columns='MaritalStatus', aggfunc='mean')
pivot
sns.heatmap(pivot, annot=True, cmap='YlGnBu')
plt.title('Average Income by Gender and Marital Status')
plt.show()
```

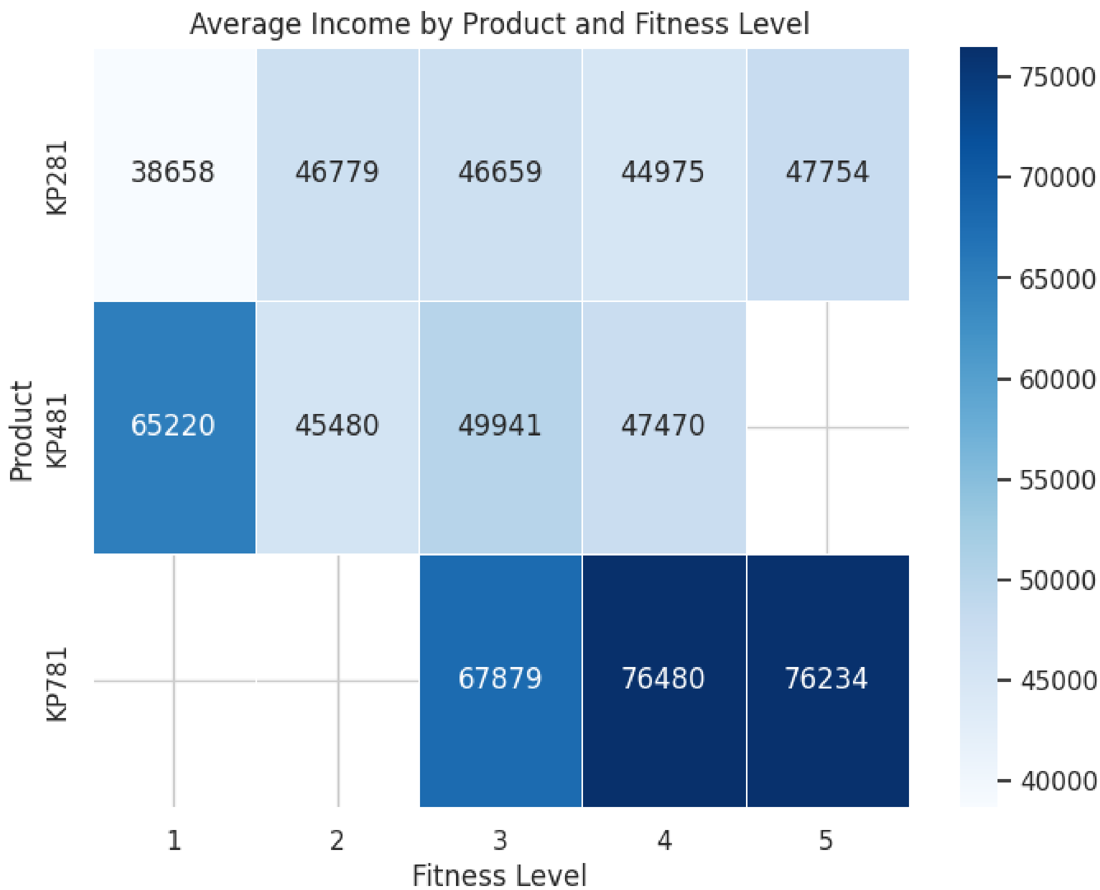
```
<ipython-input-109-cde30d0673e8>:1: FutureWarning: The default value of
observed=False is deprecated and will change to observed=True in a future
version of pandas. Specify observed=False to silence this warning and retain the
current behavior
  pivot = data.pivot_table(values='Income', index='Gender',
columns='MaritalStatus', aggfunc='mean')
```



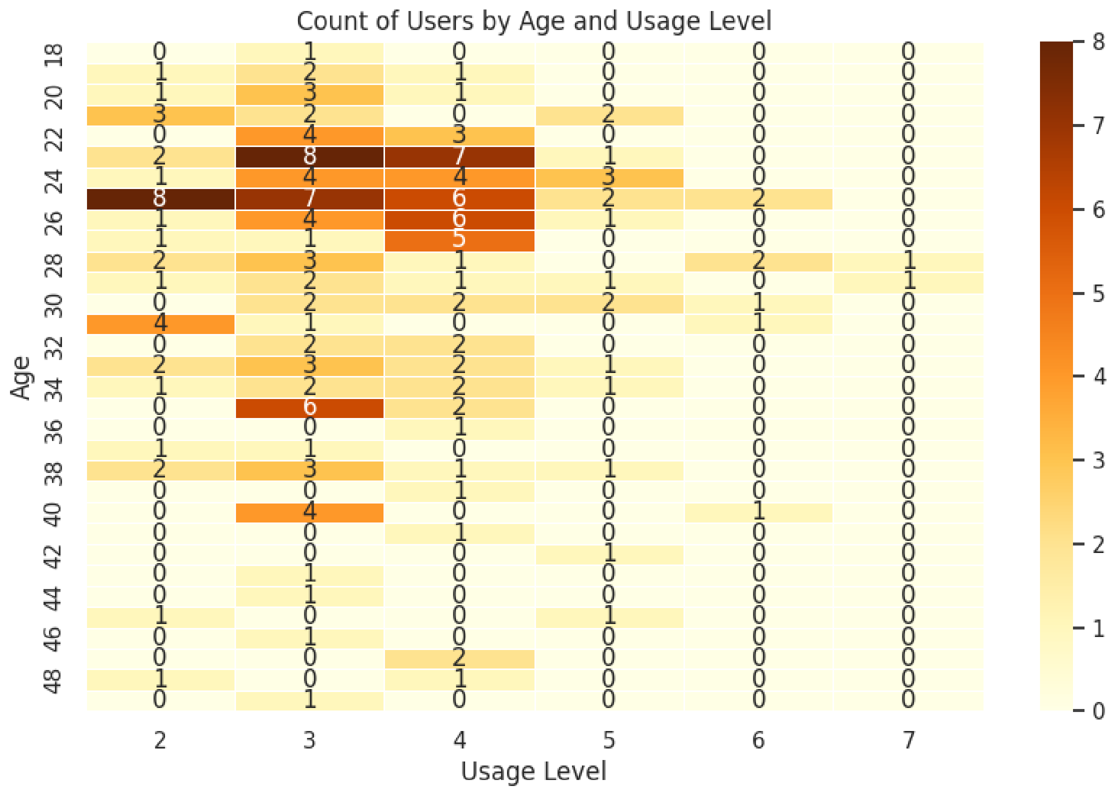

```
[ ]: #Observation: The heatmap shows that, the fitness and income of the KP781␣
     ↪customers is higher compared to the rest of the customer segment,
     #whereas for the KP481 model is preferred by relatively lower and medium income␣
     ↪customers. Interestingly, the KP281 model is preferred by the wider fitness␣
     ↪range customers
     #with lower to medium income segment.
     pivot_product_fitness = data.pivot_table(values='Income', index='Product',␣
     ↪columns='Fitness', aggfunc='mean')
     plt.figure(figsize=(8,6))
     sns.heatmap(pivot_product_fitness, annot=True, cmap='Blues', fmt='.0f',␣
     ↪linewidths=0.5)
     plt.title('Average Income by Product and Fitness Level')
     plt.xlabel('Fitness Level')
     plt.ylabel('Product')
     plt.show()
```

```
<ipython-input-111-8bcdbda0f19a>:1: FutureWarning: The default value of
observed=False is deprecated and will change to observed=True in a future
version of pandas. Specify observed=False to silence this warning and retain the
```

```
current behavior
  pivot_product_fitness = data.pivot_table(values='Income', index='Product',
columns='Fitness', aggfunc='mean')
```

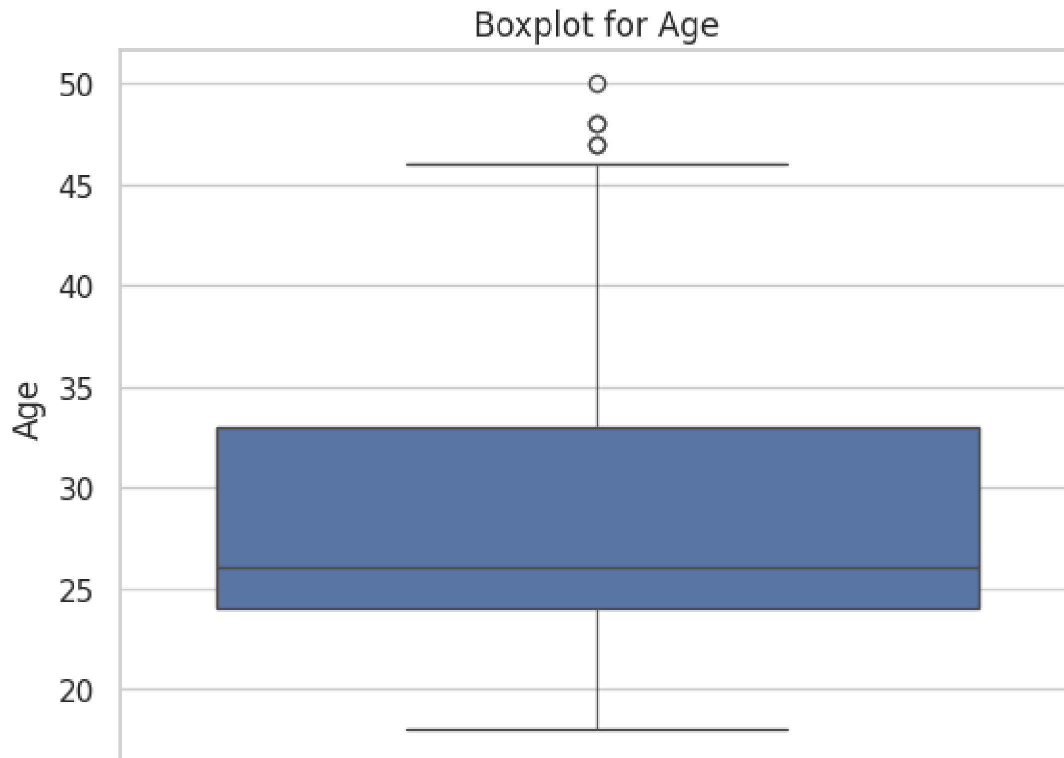


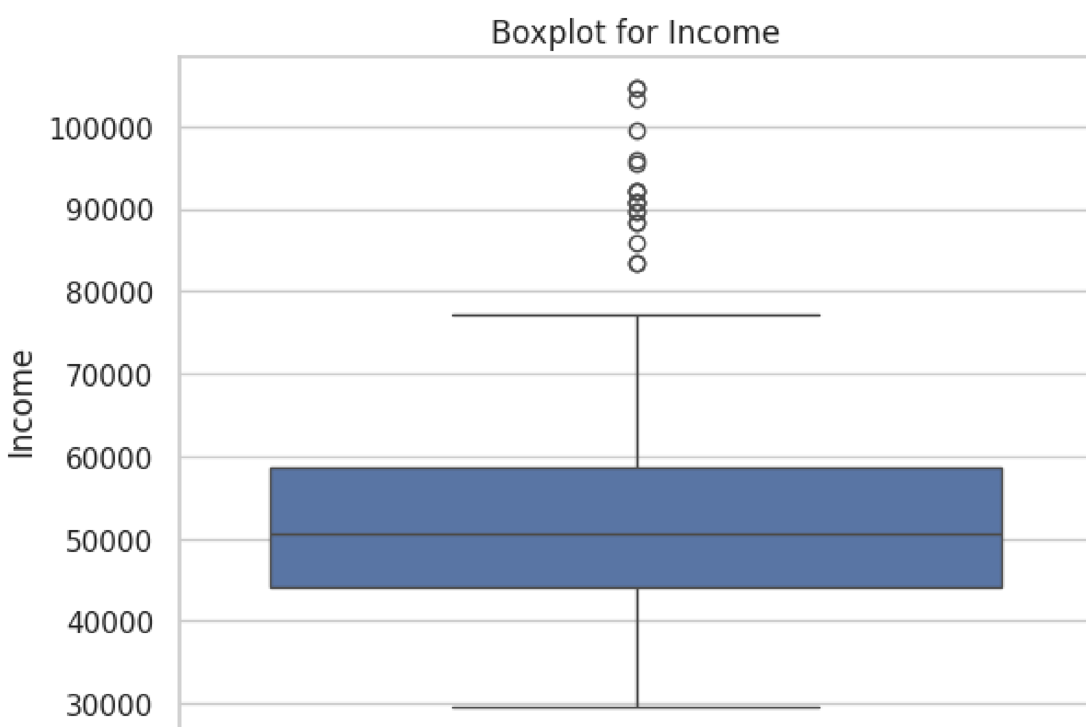

```
[ ]: #Observation: The heatmap shows that, the majority of the customers fall in␣
     ↪younger age category and the average usage of 3 times per week.
     pivot_age_usage = data.pivot_table(index='Age', columns='Usage',␣
     ↪aggfunc='size', fill_value=0)
     plt.figure(figsize=(10,6))
     sns.heatmap(pivot_age_usage, annot=True, cmap='YlOrBr', fmt='d', linewidths=0.5)
     plt.title('Count of Users by Age and Usage Level')
     plt.xlabel('Usage Level')
     plt.ylabel('Age')
     plt.show()
```

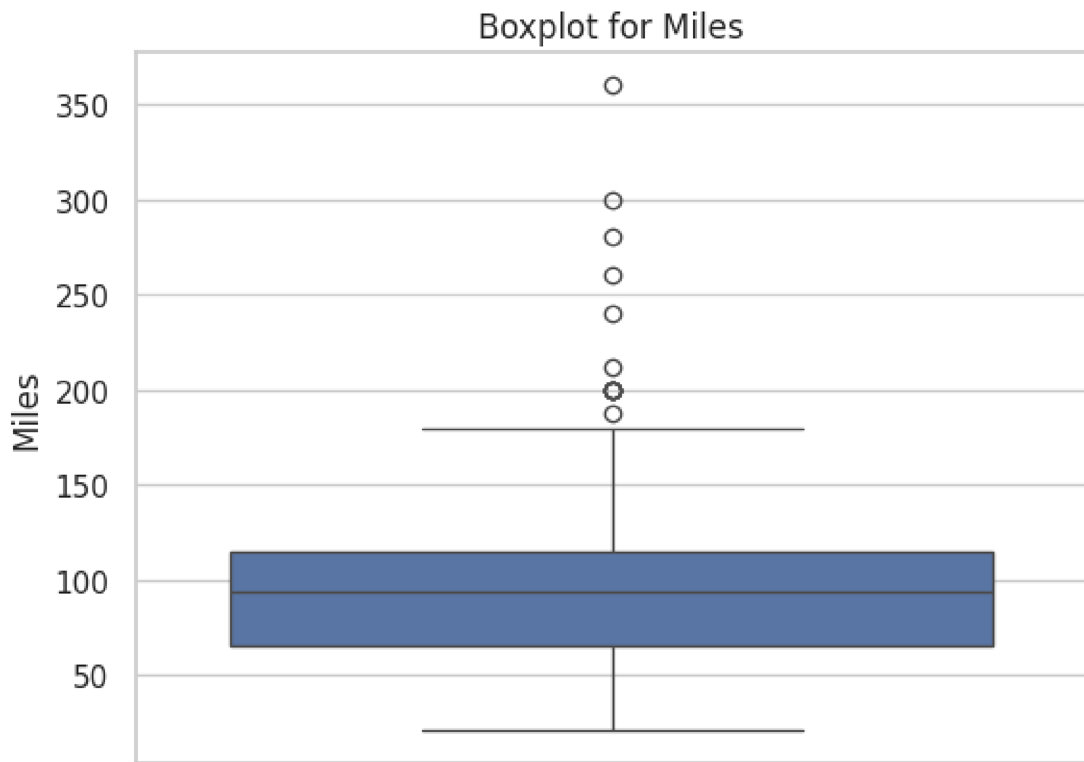


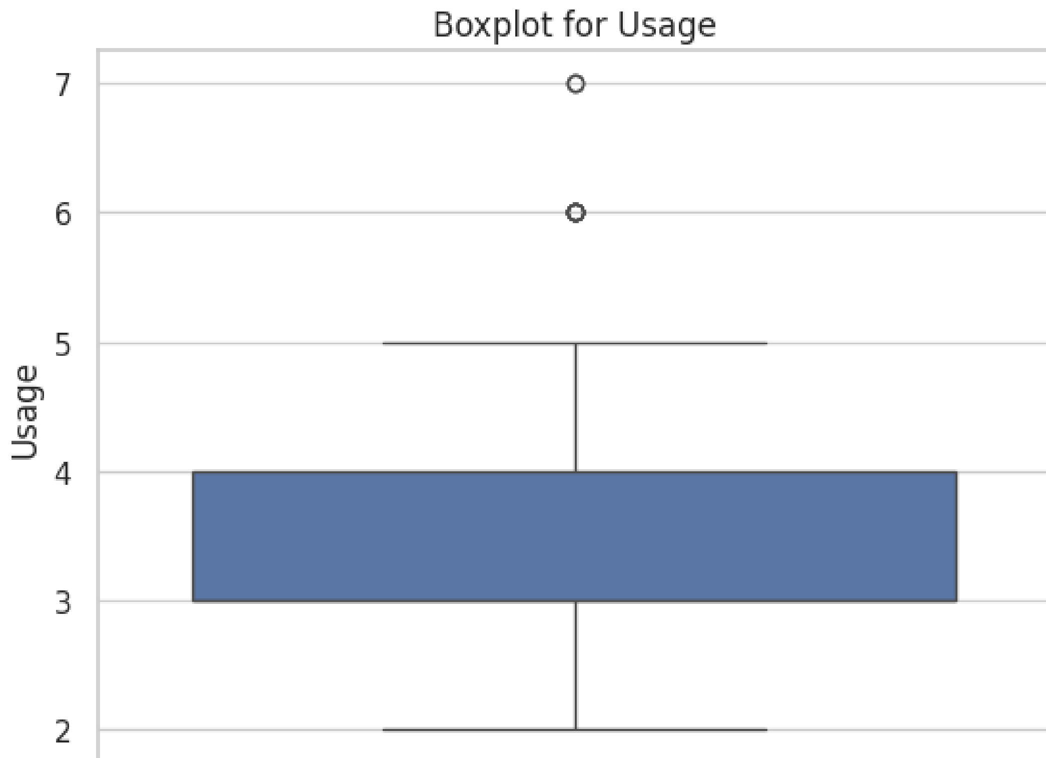
4. Outlier detection using boxplots

```
[ ]: #The boxplots show the number of outliers in the numerical columns.
for col in ['Age', 'Income', 'Miles', 'Usage', 'Fitness']:
    sns.boxplot(data[col])
    plt.title(f'Boxplot for {col}')
    plt.show()
```

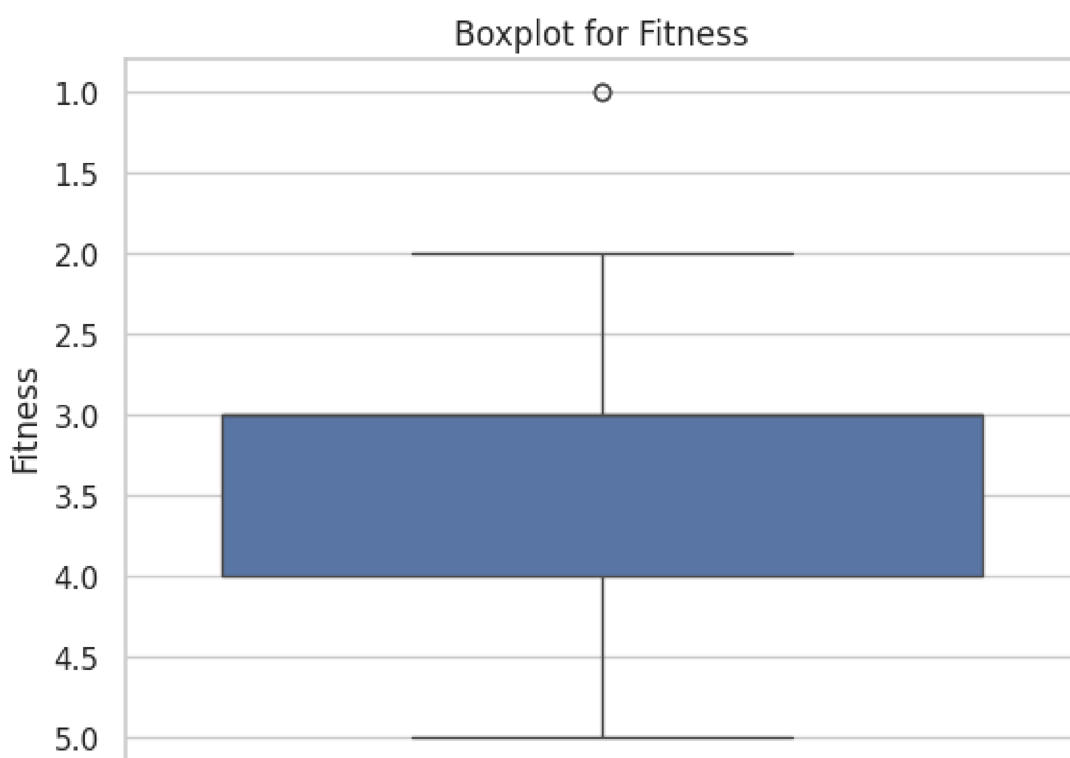

Boxplot for Age
Age
50
45
40
35
30
25
20


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


Boxplot for Miles
Miles
350
300
250
200
150
100
50



Boxplot for Usage
Usage
7
6
5
4
3
2



Boxplot for Fitness
Fitness
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

```
[ ]: #Observation: The number of outliers in the numerical values are shown below.␣
     ↪The ouliers in the income group are not removed because they indicate the␣
     ↪high income segment for the
     #customers of the high priced KP781 model. The outliers in the miles are also␣
     ↪not removed because they could represent the high performance athletes who␣
     ↪prefer the
     #high-end model of KP781. The rest of the outliers are few in number and they␣
     ↪do no show a high difference between the median and mean. Hence none of the␣
     ↪outliers are removed.
     for col in ['Age', 'Income', 'Miles', 'Usage','Education']:
         Q1 = data[col].quantile(0.25)
         Q3 = data[col].quantile(0.75)
         IQR = Q3 - Q1
         lower_bound = Q1 - 1.5 * IQR
         upper_bound = Q3 + 1.5 * IQR
         outliers = data[(data[col] < lower_bound) | (data[col] > upper_bound)]
         print(f"{col}: {len(outliers)} outliers")
```

```
Age: 5 outliers
Income: 19 outliers
Miles: 13 outliers
Usage: 9 outliers
Education: 4 outliers
```

```
[ ]: #Observation: The dfference between the mean and median for the miles and␣
     ↪income are expected due to the niche customer segment for the KP781 model.␣
     ↪The rest of the outliers do not
     #show a great difference between the mean and median
     ummary = data.describe()

     # Compute Mean vs Median difference
     num_cols=['Age','Education','Income','Miles','Usage']
     for col in num_cols:
         mean = summary.loc['mean', col]
         median = data[col].median()
         diff = mean - median
         print(f"{col}: Mean = {mean:.2f}, Median = {median}, Difference = {diff:.
     ↪2f}")
```

```
Age: Mean = 28.79, Median = 26.0, Difference = 2.79
Education: Mean = 15.57, Median = 16.0, Difference = -0.43
Income: Mean = 53719.58, Median = 50596.5, Difference = 3123.08
Miles: Mean = 103.19, Median = 94.0, Difference = 9.19
Usage: Mean = 3.46, Median = 3.0, Difference = 0.46
```

5. Marginal and Conditional Pribability for Customer Profiling

```
[ ]: age_bins = [0,15,20,25,30,35,40,45,50,55]
     age_labels =␣
      ↪['0-15','16-20','21-25','26-30','31-35','36-40','41-45','46-50','51-55']
     data['age_group']=pd.
      ↪cut(data['Age'],bins=age_bins,labels=age_labels,right=False)

     income_bins = [0, 30000, 50000, 70000, 100000, float('inf')]
     income_labels = ['<30k', '30k-50k', '50k-70k', '70k-100k', '100k+']
     data['income_group']=pd.
      ↪cut(data['Income'],bins=income_bins,labels=income_labels,right=False)

     miles_bins = [0, 50, 100, 150, 200, float('inf')]
     miles_labels = ['<50', '50-100', '100-150', '150-200', '200+']
     data['miles_group'] = pd.cut(data['Miles'], bins=miles_bins,␣
      ↪labels=miles_labels, right=False)
```

```
[ ]: attributes = ['Product', 'Gender', 'age_group', 'Education', 'MaritalStatus',␣
      ↪'Usage', 'Fitness', 'income_group', 'miles_group']
     marginal_tables = {}
     for col in attributes:
         counts = pd.crosstab(index=data[col], columns='Count')
         counts['Prob'] = np.round(counts['Count'] / counts['Count'].sum(), 2)
         marginal_tables[col] = counts

     print("Marginal probability for Product:")
     print(marginal_tables['Product'])

     print("\nMarginal probability for Gender:")
     print(marginal_tables['Gender'])

     print("\nMarginal probability for Age:")
     print(marginal_tables['age_group'])

     print("\nMarginal probability for Education:")
     print(marginal_tables['Education'])

     print("\nMarginal probability for MaritalStatus:")
     print(marginal_tables['MaritalStatus'])

     print("\nMarginal probability for Usage:")
     print(marginal_tables['Usage'])

     print("\nMarginal probability for Fitness:")
     print(marginal_tables['Fitness'])
```

```python
print("\nMarginal probability for Income:")
print(marginal_tables['income_group'])

print("\nMarginal probability for Miles:")
print(marginal_tables['miles_group'])
```

```
Marginal probability for Product:
col_0    Count  Prob
Product
KP281       80  0.44
KP481       60  0.33
KP781       40  0.22

Marginal probability for Gender:
col_0   Count  Prob
Gender
Female     76  0.42
Male      104  0.58

Marginal probability for Age:
col_0      Count  Prob
age_group
16-20          5  0.03
21-25         49  0.27
26-30         59  0.33
31-35         31  0.17
36-40         19  0.11
41-45          9  0.05
46-50          7  0.04
51-55          1  0.01

Marginal probability for Education:
col_0      Count  Prob
Education
12             3  0.02
13             5  0.03
14            55  0.31
15             5  0.03
16            85  0.47
18            23  0.13
20             1  0.01
21             3  0.02

Marginal probability for MaritalStatus:
col_0          Count  Prob
MaritalStatus
Partnered        107  0.59
```

```
Single            73  0.41

Marginal probability for Usage:
col_0  Count  Prob
Usage
2         33  0.18
3         69  0.38
4         52  0.29
5         17  0.09
6          7  0.04
7          2  0.01

Marginal probability for Fitness:
col_0    Count  Prob
Fitness
1            2  0.01
2           26  0.14
3           97  0.54
4           24  0.13
5           31  0.17

Marginal probability for Income:
col_0         Count  Prob
income_group
<30k              1  0.01
30k-50k          82  0.46
50k-70k          74  0.41
70k-100k         20  0.11
100k+             3  0.02

Marginal probability for Miles:
col_0        Count  Prob
miles_group
<50             17  0.09
50-100          90  0.50
100-150         41  0.23
150-200         20  0.11
200+            12  0.07
```

[ ]:
```
def conditional_prob(attribute):
  return pd.crosstab(data['Product'],data[attribute],normalize='index')

prob_gender_given_product=conditional_prob('Gender')
prob_age_given_product = conditional_prob('age_group')
prob_fitness_given_product = conditional_prob('Fitness')
prob_usage_given_product = conditional_prob('Usage')
prob_marital_given_product = conditional_prob('MaritalStatus')
```

```
prob_education_given_product = conditional_prob('Education')
prob_income_given_product = conditional_prob('income_group')
prob_miles_given_product = conditional_prob('miles_group')

print(f'P(Gender/Product):\n{prob_gender_given_product}')
print(f'\nP(Age/Product):\n{prob_age_given_product}')
print(f'\nP(Fitness/Product):\n{prob_fitness_given_product}')
print(f'\nP(Usage/Product):\n{prob_usage_given_product}')
print(f'\nP(Marital/Product):\n{prob_marital_given_product}')
print(f'\nP(Education/Product):\n{prob_education_given_product}')
print(f'\nP(Income/Product):\n{prob_income_given_product}')
print(f'\nP(Miles/Product):\n{prob_miles_given_product}')
```

```
P(Gender/Product):
Gender     Female      Male
Product
KP281    0.500000  0.500000
KP481    0.483333  0.516667
KP781    0.175000  0.825000

P(Age/Product):
age_group     16-20     21-25     26-30  31-35     36-40  41-45     46-50  \
Product
KP281      0.050000  0.287500  0.325000  0.125  0.125000   0.05  0.025000
KP481      0.016667  0.266667  0.266667  0.250  0.116667   0.05  0.033333
KP781      0.000000  0.250000  0.425000  0.150  0.050000   0.05  0.075000

age_group   51-55
Product
KP281      0.0125
KP481      0.0000
KP781      0.0000

P(Fitness/Product):
Fitness         1      2      3         4      5
Product
KP281    0.012500  0.175  0.675  0.112500  0.025
KP481    0.016667  0.200  0.650  0.133333  0.000
KP781    0.000000  0.000  0.100  0.175000  0.725

P(Usage/Product):
Usage           2         3      4      5      6     7
Product
KP281    0.237500  0.462500  0.275  0.025  0.000  0.00
KP481    0.233333  0.516667  0.200  0.050  0.000  0.00
KP781    0.000000  0.025000  0.450  0.300  0.175  0.05
```

```
P(Marital/Product):
MaritalStatus  Partnered  Single
Product
KP281              0.600   0.400
KP481              0.600   0.400
KP781              0.575   0.425

P(Education/Product):
Education        12        13        14        15        16        18     20  \
Product
KP281      0.025000  0.037500  0.375000  0.050000  0.487500  0.025000  0.000
KP481      0.016667  0.033333  0.383333  0.016667  0.516667  0.033333  0.000
KP781      0.000000  0.000000  0.050000  0.000000  0.375000  0.475000  0.025

Education     21
Product
KP281      0.000
KP481      0.000
KP781      0.075

P(Income/Product):
income_group    <30k  30k-50k  50k-70k  70k-100k  100k+
Product
KP281         0.0125   0.5875      0.4       0.0  0.000
KP481         0.0000   0.5000      0.5       0.0  0.000
KP781         0.0000   0.1250      0.3       0.5  0.075

P(Miles/Product):
miles_group       <50  50-100   100-150   150-200      200+
Product
KP281        0.150000   0.625  0.200000  0.025000  0.000000
KP481        0.083333   0.650  0.216667  0.033333  0.016667
KP781        0.000000   0.025  0.300000  0.400000  0.275000
```

[ ]:
```
def reverse_conditional_prob(attribute):
    return pd.crosstab(data[attribute], data['Product'], normalize='index')

prob_product_given_gender = reverse_conditional_prob('Gender')
prob_product_given_age = reverse_conditional_prob('age_group')
prob_product_given_fitness = reverse_conditional_prob('Fitness')
prob_product_given_marital = reverse_conditional_prob('MaritalStatus')
prob_product_given_income = reverse_conditional_prob('income_group')
prob_product_given_usage = reverse_conditional_prob('Usage')

print(f'P(Product/Gender):\n{prob_product_given_gender}')
print(f'\nP(Product/Age):\n{prob_product_given_age}')
print(f'\nP(Product/Fitness):\n{prob_product_given_fitness}')
```

```python
print(f'\nP(Product/Marital):\n{prob_product_given_marital}')
print(f'\nP(Product/Income):\n{prob_product_given_income}')
print(f'\nP(Product/Usage):\n{prob_product_given_usage}')
```

```
P(Product/Gender):
Product     KP281     KP481     KP781
Gender
Female   0.526316  0.381579  0.092105
Male     0.384615  0.298077  0.317308

P(Product/Age):
Product       KP281     KP481     KP781
age_group
16-20      0.800000  0.200000  0.000000
21-25      0.469388  0.326531  0.204082
26-30      0.440678  0.271186  0.288136
31-35      0.322581  0.483871  0.193548
36-40      0.526316  0.368421  0.105263
41-45      0.444444  0.333333  0.222222
46-50      0.285714  0.285714  0.428571
51-55      1.000000  0.000000  0.000000

P(Product/Fitness):
Product     KP281     KP481     KP781
Fitness
1        0.500000  0.500000  0.000000
2        0.538462  0.461538  0.000000
3        0.556701  0.402062  0.041237
4        0.375000  0.333333  0.291667
5        0.064516  0.000000  0.935484

P(Product/Marital):
Product           KP281     KP481     KP781
MaritalStatus
Partnered      0.448598  0.336449  0.214953
Single         0.438356  0.328767  0.232877

P(Product/Income):
Product          KP281     KP481     KP781
income_group
<30k          1.000000  0.000000  0.000000
30k-50k       0.573171  0.365854  0.060976
50k-70k       0.432432  0.405405  0.162162
70k-100k      0.000000  0.000000  1.000000
100k+         0.000000  0.000000  1.000000

P(Product/Usage):
```

Product	KP281	KP481	KP781
Usage			
2	0.575758	0.424242	0.000000
3	0.536232	0.449275	0.014493
4	0.423077	0.230769	0.346154
5	0.117647	0.176471	0.705882
6	0.000000	0.000000	1.000000
7	0.000000	0.000000	1.000000

Customer Profile: Product KP281 is the Popular Choice Gender: Evenly split (50% male, 50% female) Age: Mostly 26–30 (32.5%). Fitness: Mostly moderate (3) Usage: Primarily moderate (3–4 times per week) Education: Mostly 16 years (bachelor's degree) and 14 years Income: Mostly 30k–50k (58.75%) Miles: Predominantly 50–100 miles Marital Status: 60% Partnered

Product KP481 Gender: Slightly more male (51.7%) Age: Balanced spread across 21–40, especially 21–35 Fitness: Mostly 3 Usage: Mostly usage level 3 times per week Education: Predominantly 16 years (51.7%), then 14 years Income: Equal split between 30k–50k and 50k–70k Miles: Mostly 50–100 miles (65%) Marital Status: 60% Partnered

Product KP781 Gender: 82.5% male Age: Skews younger to mid-range. Fitness: Very high fitness (fitness = 5) Usage: Heavy users (Usage = 5, 6, or 7 = 52.5%) Education: More postgraduates (18–21 years of education) Income: High-income skew (70k+ = 57.5%) Miles: Higher use (>150 miles) Marital Status: Slightly more Partnered

Business Insights KP281 dominates has broader appeal, especially among young, middle-income, moderately fit users.

KP781 has strong appeal among high-end, fitness-focused male users, but its reach is limited — suggesting a niche market.

KP481 serves as a bridge product between KP281 and KP781, appealing to a wide but less loyal segment.

Fitness and usage intensity are highly correlated with product type — heavy users and fittest customers clearly prefer KP781.

Actionable Recommendations A. Segmentation and Personalization KP281: Maintain mass-market positioning. Consider bundling with basic fitness plans or student/young professional discounts. KP481: Target customers on the edge of moderate to high engagement. KP781: Market as a premium product. Use influencer marketing, performance athlete testimonials, and high-performance messaging.

B. Targeted Campaigns For KP781, target ads to high-income males in the 26–40 age bracket, using performance language and premium positioning. For KP281, use inclusive campaigns featuring both genders, highlighting reliability and value. For KP481, focus on versatility, customization, and adaptability — appeal to those still evaluating options.

C. Product Strategy Develop new features or training programs tied to KP781 to enhance loyalty among elite users. Offer a "fitness progression plan" where customers can upgrade from KP281 → KP481 → KP781 based on their progress or engagement level.

D. Channel & Distribution KP281 and KP481: Sell via general online marketplaces, gyms, and retail outlets. KP781: Position through exclusive fitness platforms or premium club memberships.

```
[ ]:
```