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

```
!gdown 1dKDbIRYiiohz9YCGeWJnIaVcROORupNM
```

```
Downloading...
From: https://drive.google.com/uc?id=1dKDbIRYiiohz9YCGeWJnIaVcROORupNM
To: /content/aerofit_treadmill.csv
100% 7.28k/7.28k [00:00<00:00, 17.5MB/s]
```

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

```
areofit_df = pd.DataFrame(areofit_df)
areofit_df.head(5)
```

	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

Next steps: Generate code with areofit_df View recommended plots New interactive sheet

Initial Analysis

```
areofit_df.shape
```

```
(180, 9)
```

Data Set has 180 rows and 9 coloumns

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

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

The Given Data has the below mentioned Features

- There are Three unique products of Aerofit
- Max Age is 50
- MAX income is 104581
- Highest miles is 360
- There are two marital status that is Partnered and Single
- top selling produyct is KP281 and the no of it sold are 80
- Most of the customers are Male who are 104 out of 180

```
areofit_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
```

The data types of the coloumns is as given above

```
areofit_df.isna().value_counts()
```

Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	count
False	**False**	**False**	**False**	**False**	**False**	**False**	**False**	**False**	180

dtype: int64

There is no null values present in any coloumns

```
areofit_df.duplicated().value_counts()
```

	count
False	180

dtype: int64

There is no duplicate data present in the given data set

```
areofit_df['Product'].unique()
```

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

We have mainly three types of product that are 'KP281', 'KP481' and 'KP781'

```
areofit_df['Gender'].value_counts()
```

Gender	count
Male	104
Female	76

dtype: int64

out of the total 180 customer 104 are males and 76 are females

```
areofit_df['MaritalStatus'].value_counts()
```

MaritalStatus	count
Partnered	107
Single	73

dtype: int64

out of the 180 customers 107 are Married and 73 are singles customers

```
areofit_df['Education'].value_counts()
```

Education	count
16	85
14	55
18	23
15	5
13	5
12	3
21	3
20	1

dtype: int64

unique Educations and its count

```
areofit_df['Fitness'].value_counts().sort_index()
```

Fitness	count
1	2
2	26
3	97
4	24
5	31

dtype: int64

We have five category of fitness and we can see that fitness of category 3 is highest

Converting the Fitness to a given category based on the fitness index

- 1=>Very Poor Fitness
- 2=>Poor Fitness
- 3=>Average Fitness
- 4=>Good Fitness
- 5=>Very Good Fitness

```
aerofittm_df=areofit_df
def fitnesscategorydriver(data):
  if(data==1):
    return "Very Poor"
  elif(data==2):
    return "Poor"
  elif(data==3):
    return "Average"
  elif(data==4):
    return "Good"
  elif(data==5):
    return "Very Good"

aerofittm_df['Fitness_category']=aerofittm_df['Fitness'].apply(fitnesscategorydriver)
aerofittm_df=pd.DataFrame(aerofittm_df)
aerofittm_df['Fitness_category'].value_counts()
```

Fitness_category	count
Average	97
Very Good	31
Poor	26
Good	24
Very Poor	2

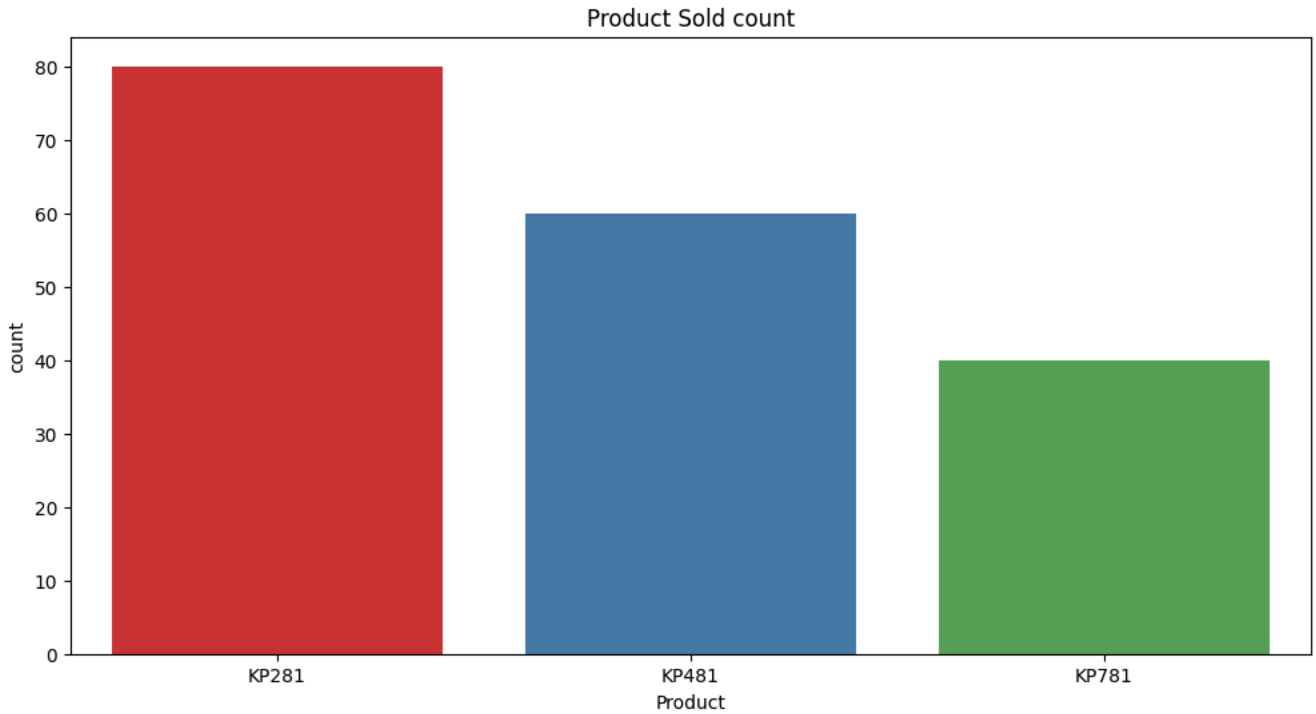
dtype: int64

Univariate Analysis

Product sold analysis of Aerofit

```
def productssoldcount(data):
  print("The count of unique product sold are as listed below")
  print(data['Product'].value_counts())
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Product', hue='Product', palette='Set1', legend=False)
  plt.title("Product Sold count")
  plt.xlabel("Product")
  plt.ylabel("count")
  plt.show()

productssoldcount(aerofittm_df)
```

```
The count of unique product sold are as listed below
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
```



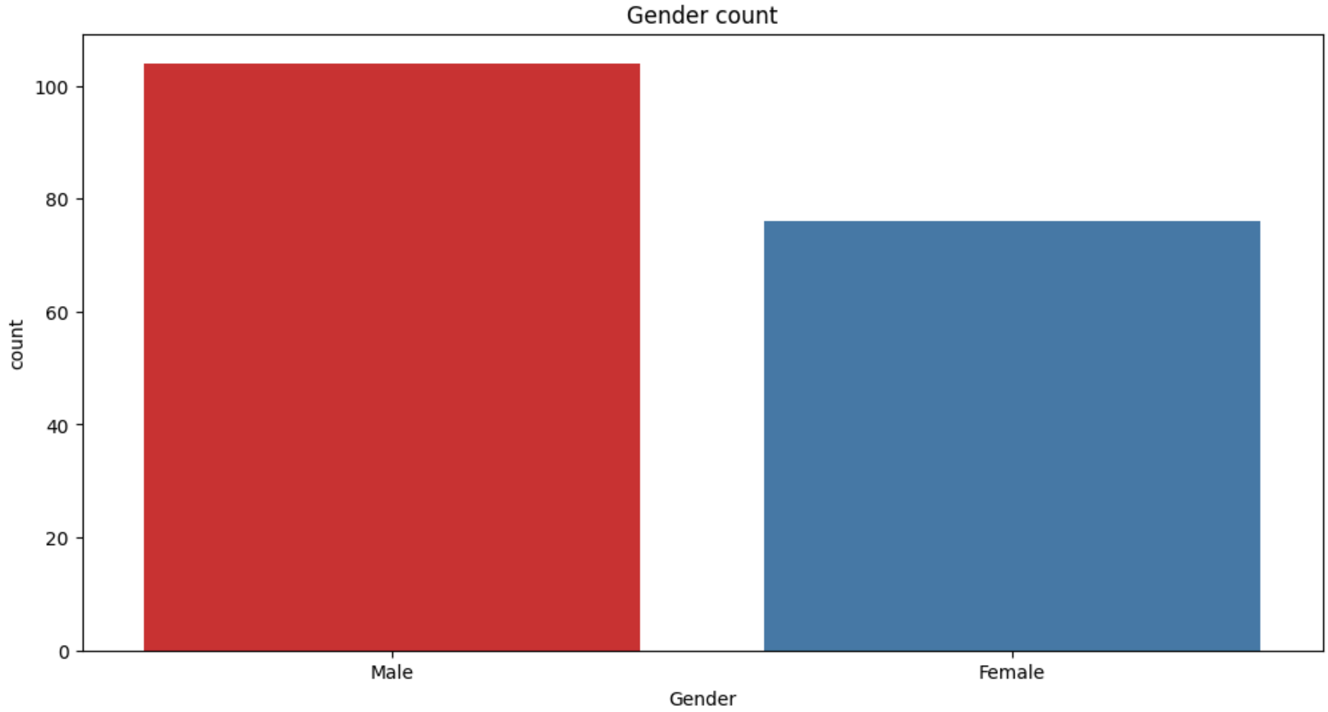
we can say that the highest no of products sold is KP281

Gender based analysis on the treadmills purchased

```
def genderspurchcount(data):
  print("Gender count of the customer who brought the product")
  print(data['Gender'].value_counts())
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Gender', hue='Gender', palette='Set1', legend=False)
  plt.title("Gender count")
```

```
  plt.xlabel("Gender")
  plt.ylabel("count")
  plt.show()

genderspurchcount(aerofittm_df)
```

```
Gender count of the customer who brought the product
Gender
Male      104
Female     76
Name: count, dtype: int64
```

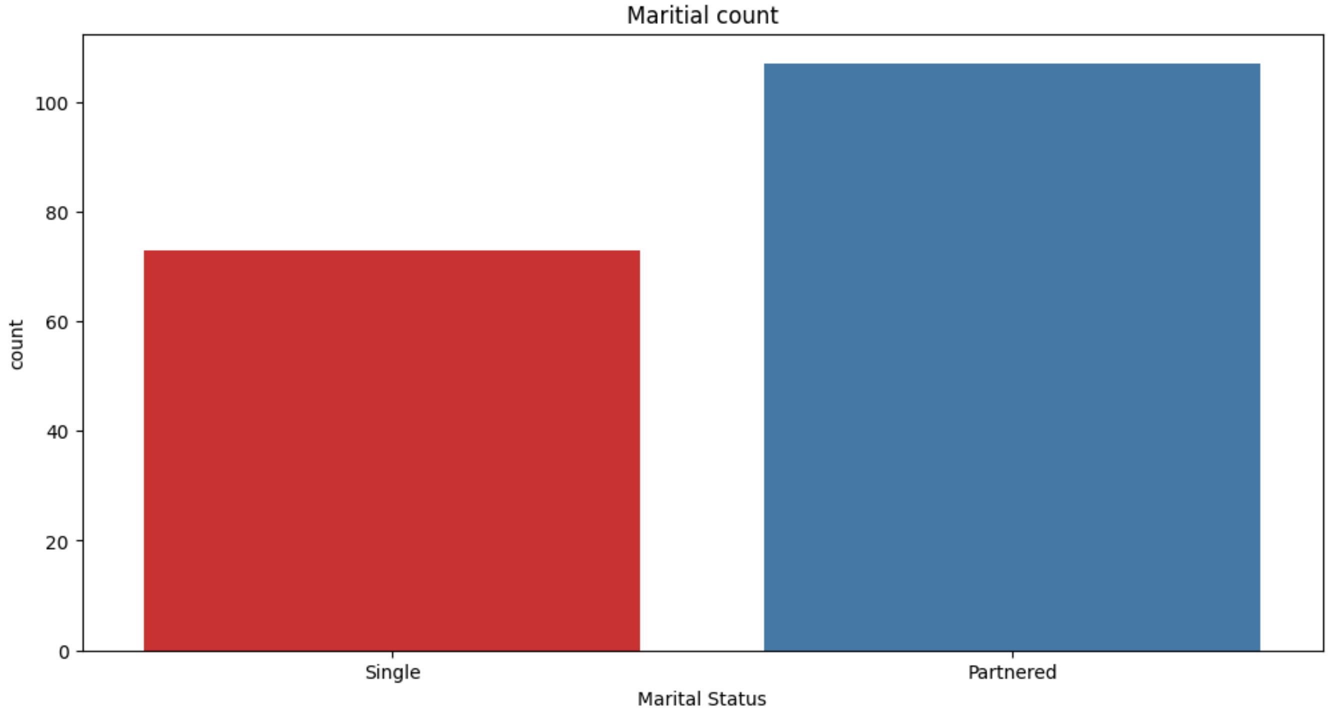


We have more male customer which accounts to about 104

Marital status based analysis on the treadmills purchased

```
def maritialbasedcount(data):
  print("Maritial count")
  print(data['MaritalStatus'].value_counts())
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='MaritalStatus', hue='MaritalStatus', palette='Set1', legend=False)
  plt.title("Maritial count")
  plt.xlabel("Marital Status")
  plt.ylabel("count")
  plt.show()

maritialbasedcount(aerofittm_df)
```

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

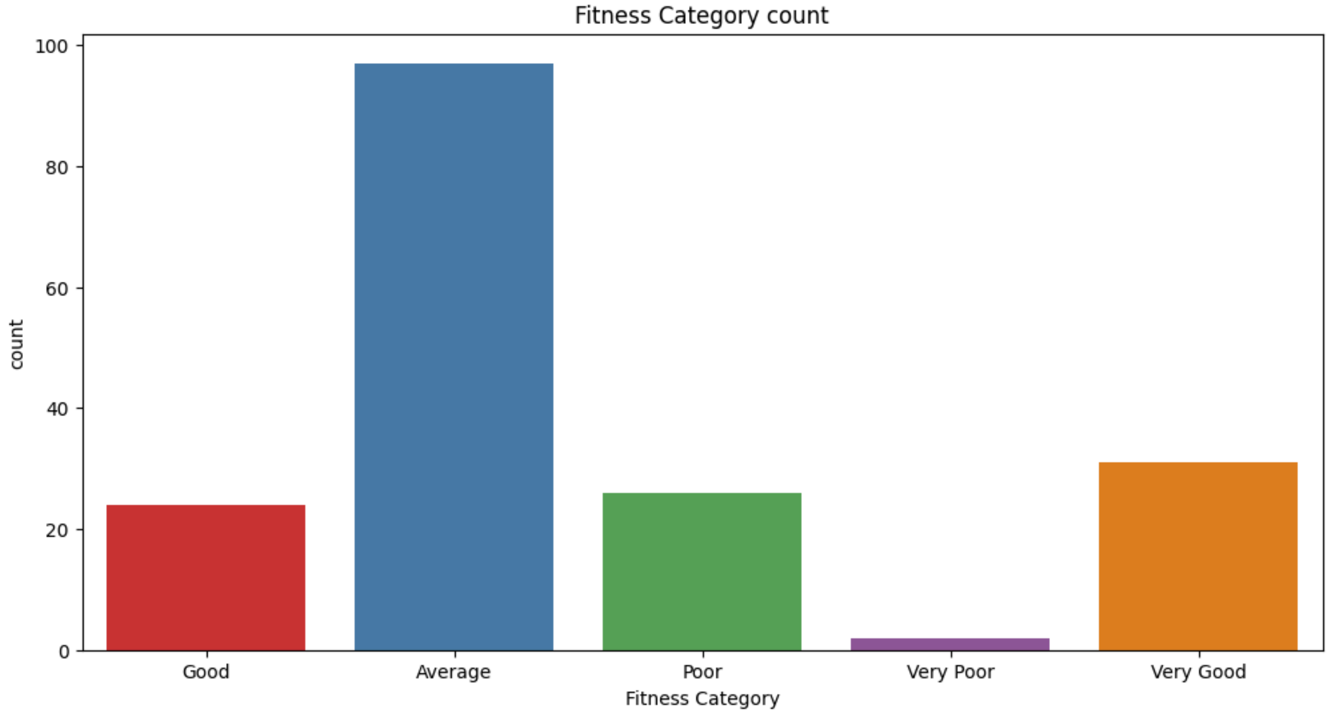


Most of the customers who have purchased the treadmill are married and account of 107 in total

Fitness category analysis

```
def fitnesscategorybasedcount(data):
  print("Count of Fitness category they belong to")
  print(data['Fitness_category'].value_counts())
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Fitness_category', hue='Fitness_category', palette='Set1', legend=False)
  plt.title("Fitness Category count")
  plt.xlabel("Fitness Category")
  plt.ylabel("count")
  plt.show()

fitnesscategorybasedcount(aerofittm_df)
```

```
Count of Fitness category they belong to
Fitness_category
Average      97
Very Good    31
Poor         26
Good         24
Very Poor     2
Name: count, dtype: int64
```

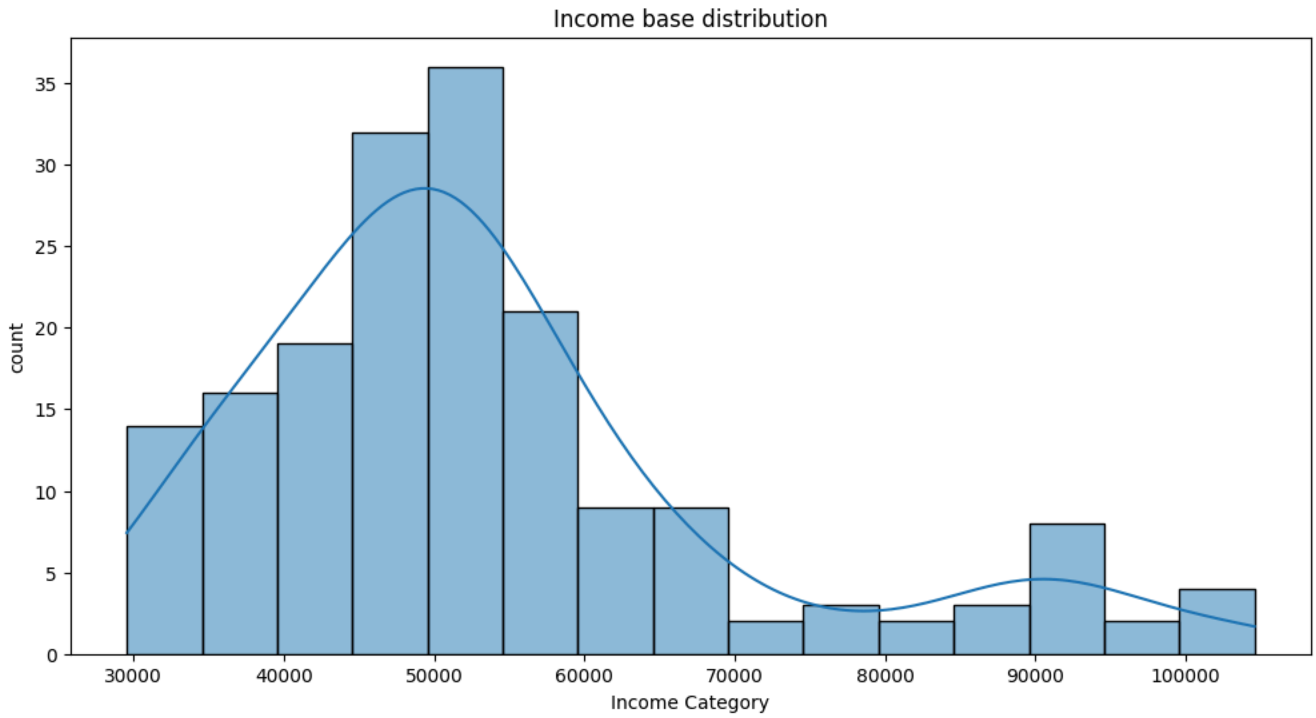


Most of the customer who bought the treadmill are of average fitness

Analysis on the Income

```
def fitnessincomecount(data):
  print("Income based distribution")
  print(data['Income'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Income', kde=True)
  plt.title("Income base distribution")
  plt.xlabel("Income Category")
  plt.ylabel("count")
  plt.show()

fitnessincomecount(aerofittm_df)
```

```
Income based distribution
Income
45480    14
52302     9
46617     8
54576     8
53439     8
         ..
65220     1
55713     1
68220     1
30699     1
95508     1
Name: count, Length: 62, dtype: int64
```



we can see that most of them have an income in the range of 45k to 50k.

```
aerofittm_df.head(4)
```

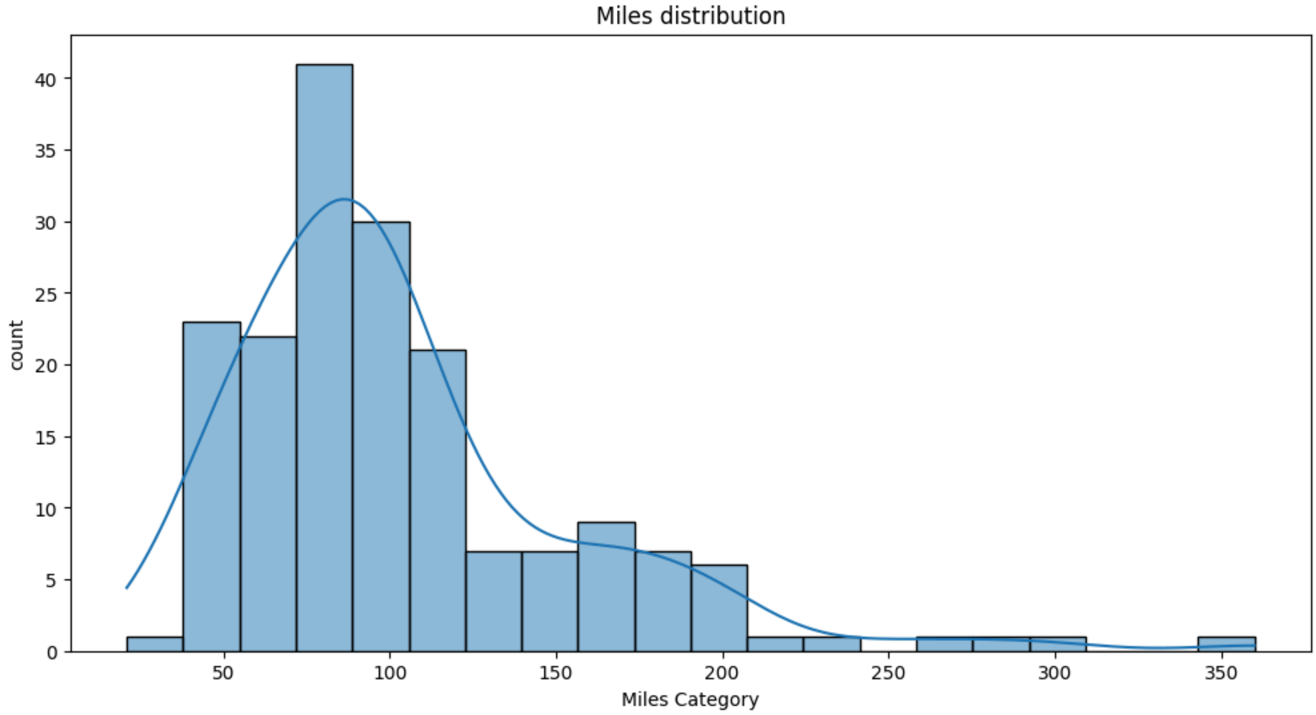
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fitness_category
0	KP281	18	Male	14	Single	3	4	29562	112	Good
1	KP281	19	Male	15	Single	2	3	31836	75	Average
2	KP281	19	Female	14	Partnered	4	3	30699	66	Average
3	KP281	19	Male	12	Single	3	3	32973	85	Average

Next steps: Generate code with aerofittm_df | View recommended plots | New interactive sheet

Analysis on Miles

```
def fitnessMilescount(data):
  print("Miles based distribution")
  print(data['Miles'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Miles', kde=True)
  plt.title("Miles distribution")
  plt.xlabel("Miles Category")
  plt.ylabel("count")
  plt.show()

fitnessMilescount(aerofittm_df)
```

```
Miles based distribution
Miles
85      27
95      12
66      10
75      10
47       9
106      9
94       8
113      8
53       7
100      7
180      6
200      6
56       6
64       6
127      5
160      5
42       4
150      4
38       3
74       3
170      3
120      3
103      3
132      2
141      2
280      1
260      1
300      1
240      1
112      1
212      1
80       1
140      1
21       1
169      1
188      1
360      1
Name: count, dtype: int64
```



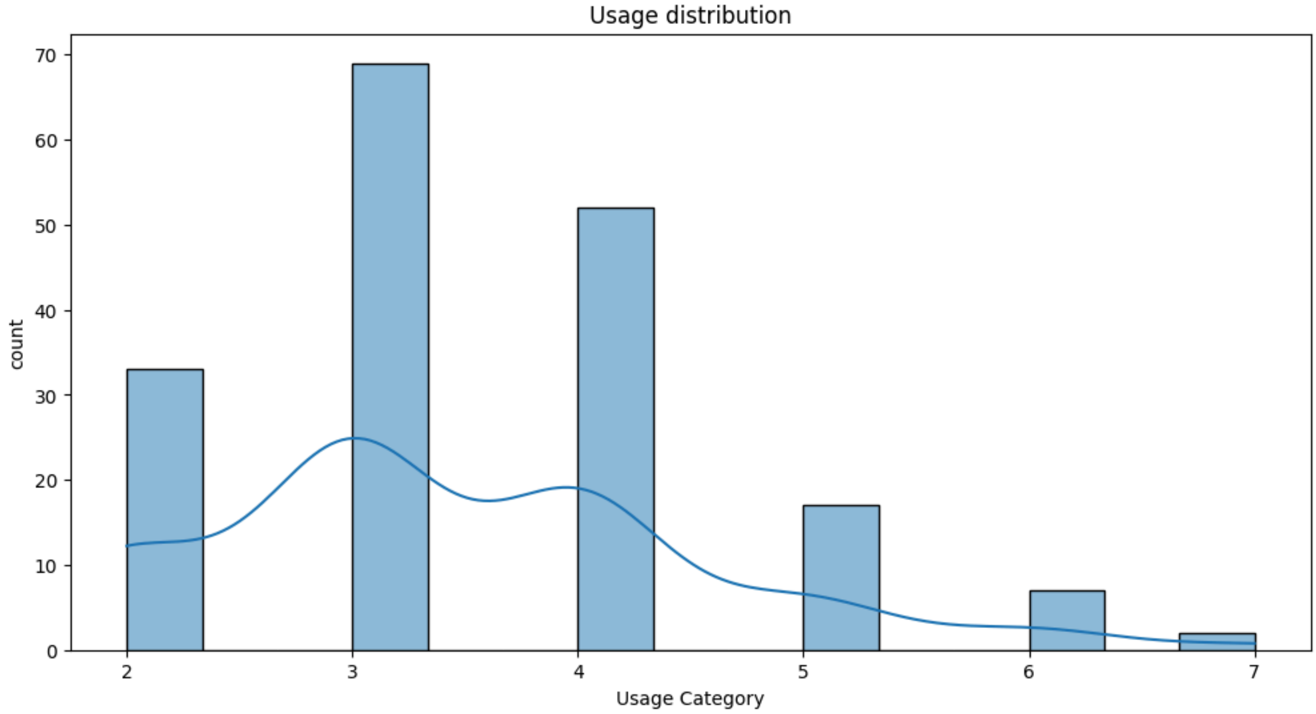
This is the miles ran distribution by the customers

Usage Analysis

```
def fitnessUsagecount(data):
  print("Usage based distribution")
  print(data['Usage'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Usage', kde=True)
  plt.title("Usage distribution")
  plt.xlabel("Usage Category")
  plt.ylabel("count")
  plt.show()
```

```
fitnessUsagecount(aerofittm_df)
```

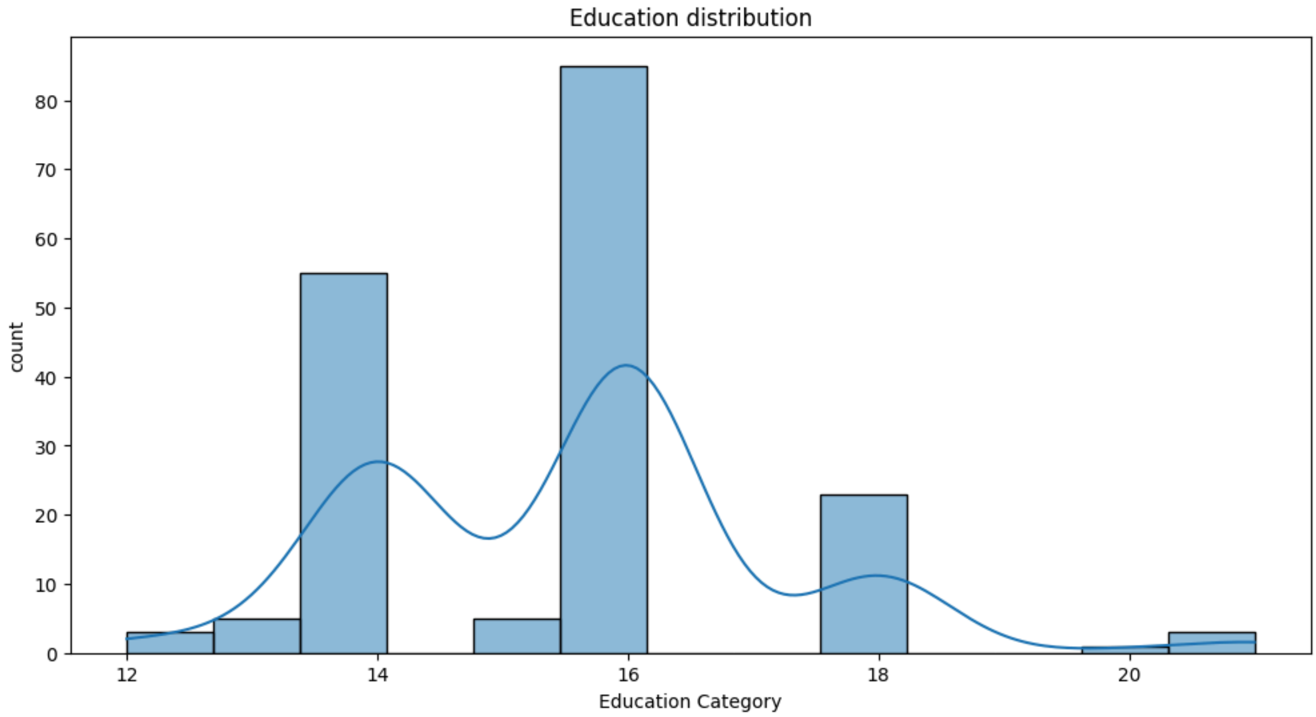
```
Usage based distribution
Usage
3    69
4    52
2    33
5    17
6     7
7     2
Name: count, dtype: int64
```



Education Analysis

```
def fitnessEducationcount(data):
  print("Education based distribution")
  print(data['Education'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Education', kde=True)
  plt.title("Education distribution")
  plt.xlabel("Education Category")
  plt.ylabel("count")
  plt.show()

fitnessEducationcount(aerofittm_df)
```

```
Education based distribution
Education
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: count, dtype: int64
```



Age Analysis

```
aerofittm_df['Age'].unique()
```

```
array([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])
```

Based ont he above result let us categorize

Age Categories

- Adolescent => 18-22
- Young Adult => 22-25
- Adult => 25-35
- Middle-Aged => 35-59
- Senior=> 60-100

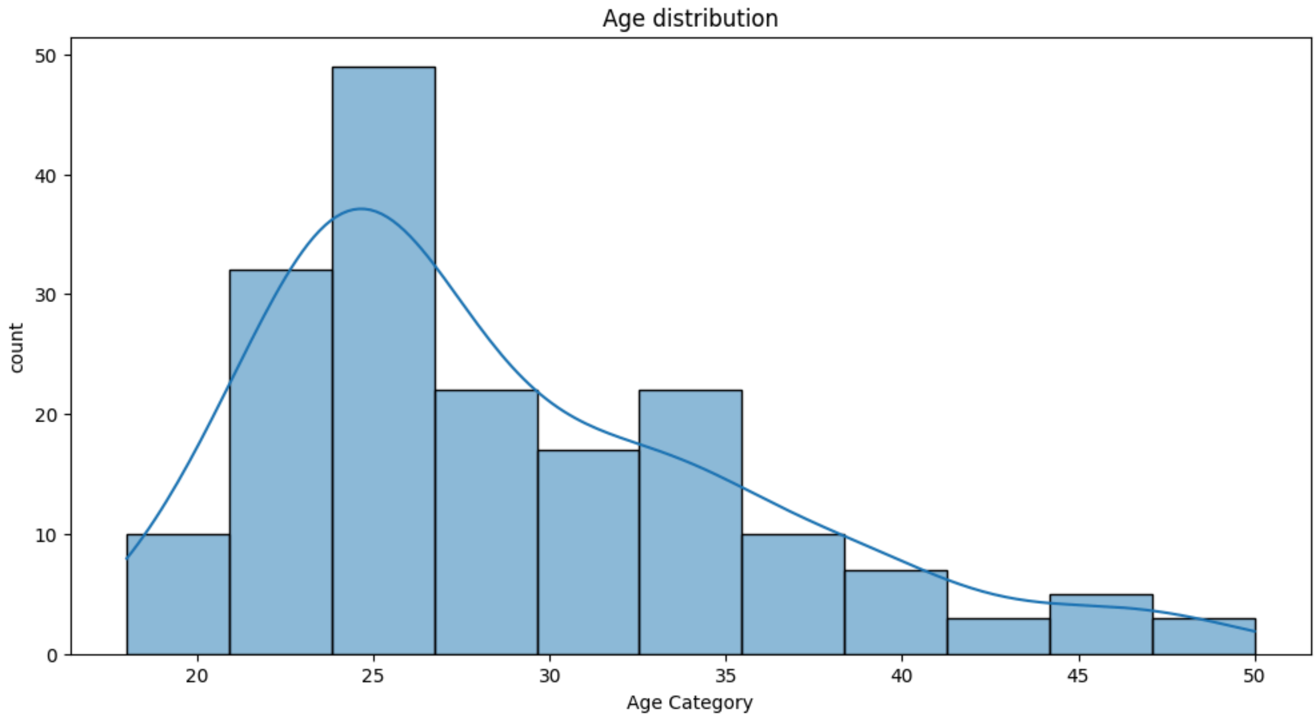
```
bins = [18, 22, 25, 35, 59, 100]
labels = ['Adolescent', 'Young Adult', 'Adult', 'Middle-Aged', 'Senior']

aerofittm_df['Age_Category'] = pd.cut(aerofittm_df['Age'], bins=bins, labels=labels, right=False)
print(aerofittm_df.head(10))
```

```
  Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0   KP281   18    Male         14        Single      3        4   29562
1   KP281   19    Male         15        Single      2        3   31836
2   KP281   19  Female         14     Partnered      4        3   30699
3   KP281   19    Male         12        Single      3        3   32973
4   KP281   20    Male         13     Partnered      4        2   35247
5   KP281   20  Female         14     Partnered      3        3   32973
6   KP281   21  Female         14     Partnered      3        3   35247
7   KP281   21    Male         13        Single      3        3   32973
8   KP281   21    Male         15        Single      5        4   35247
9   KP281   21  Female         15     Partnered      2        3   37521

   Miles Fitness_category Age_Category
0    112             Good   Adolescent
1     75          Average   Adolescent
2     66          Average   Adolescent
3     85          Average   Adolescent
```

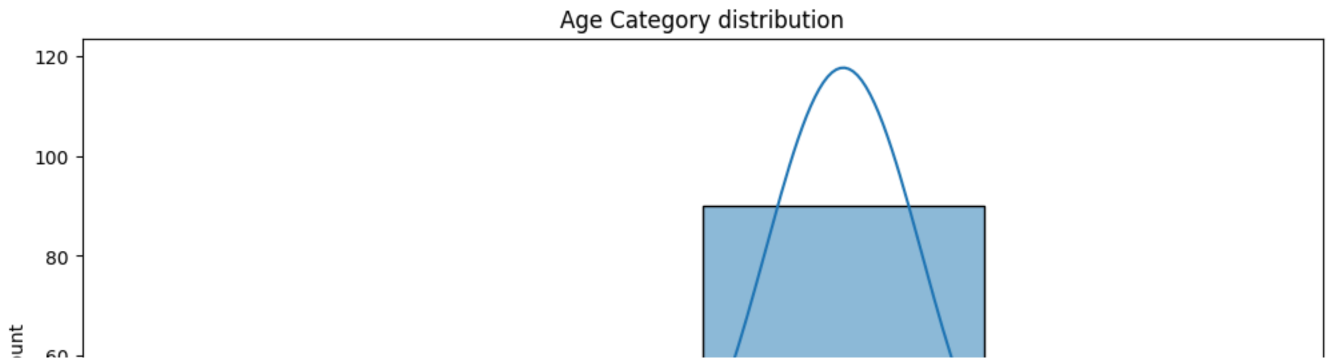
```
4    47        Poor   Adolescent
5    66     Average   Adolescent
6    75     Average   Adolescent
7    85     Average   Adolescent
8   141        Good   Adolescent
9    85     Average   Adolescent
```

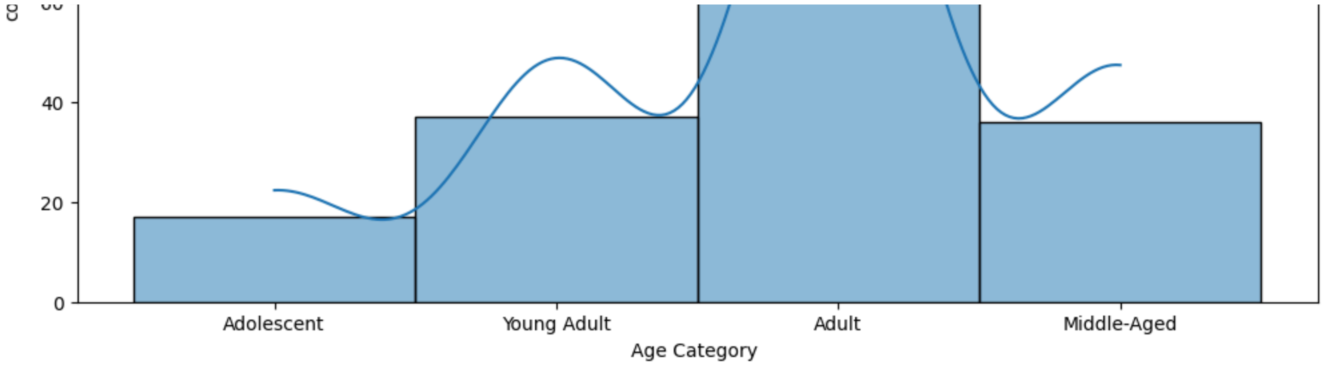
```
def fitnessagecount(data):
  print("Age distribution")
  print(data['Age'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Age', kde=True)
  plt.title("Age distribution")
  plt.xlabel("Age Category")
  plt.ylabel("count")
  plt.show()

  print("Age Category distribution")
  print(data['Age_Category'].value_counts())
  plt.figure(figsize=(12,6))
  sns.histplot(data=data, x='Age_Category', kde=True)
  plt.title("Age Category distribution")
  plt.xlabel("Age Category ")
  plt.ylabel("count")
  plt.show()


fitnessagecount(aerofittm_df)
```

```
Age distribution
Age
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
38     7
21     7
22     7
27     7
31     6
34     6
29     6
20     5
40     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
43     1
41     1
39     1
36     1
42     1
Name: count, dtype: int64
```




```
Age Category distribution
Age_Category
Adult          90
Young Adult    37
Middle-Aged    36
Adolescent     17
Senior          0
Name: count, dtype: int64
```

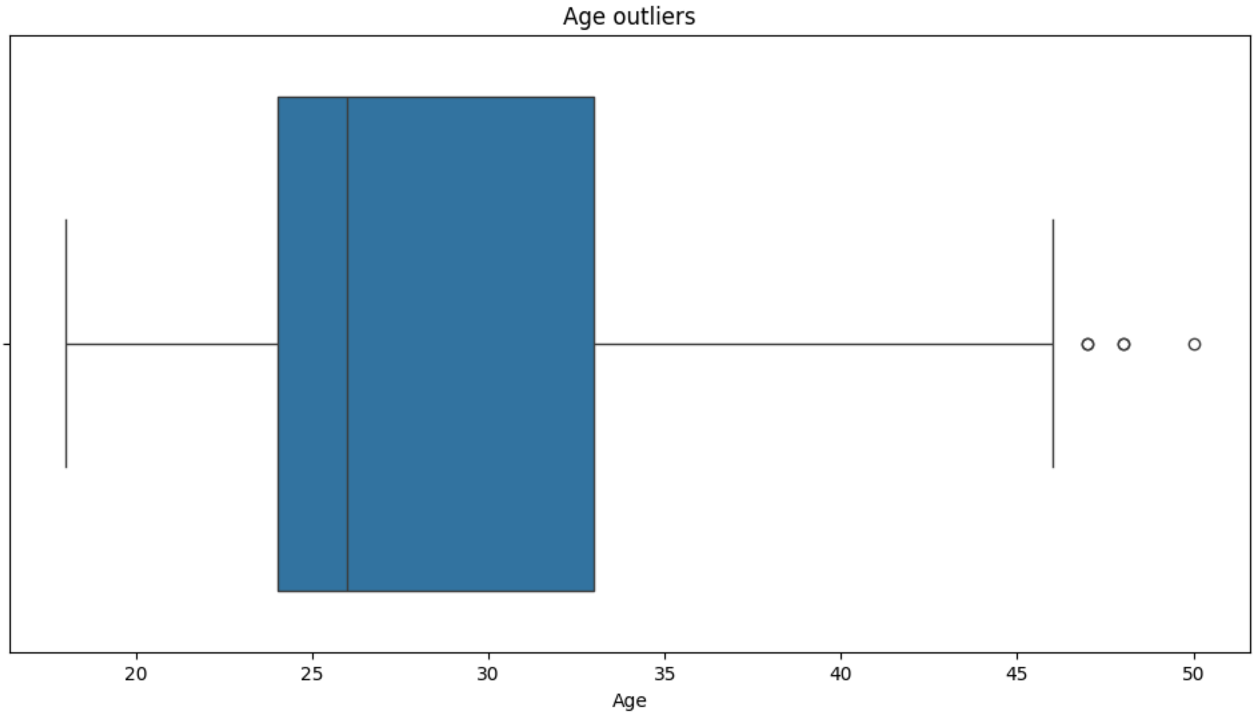


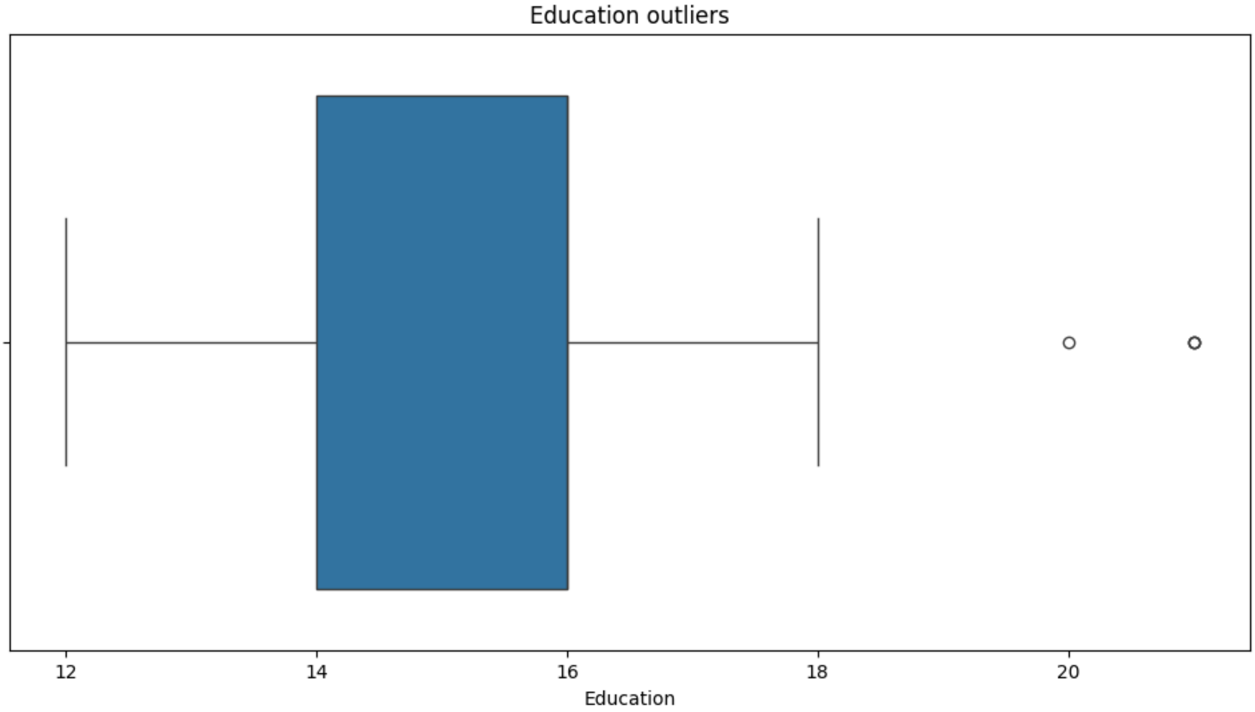


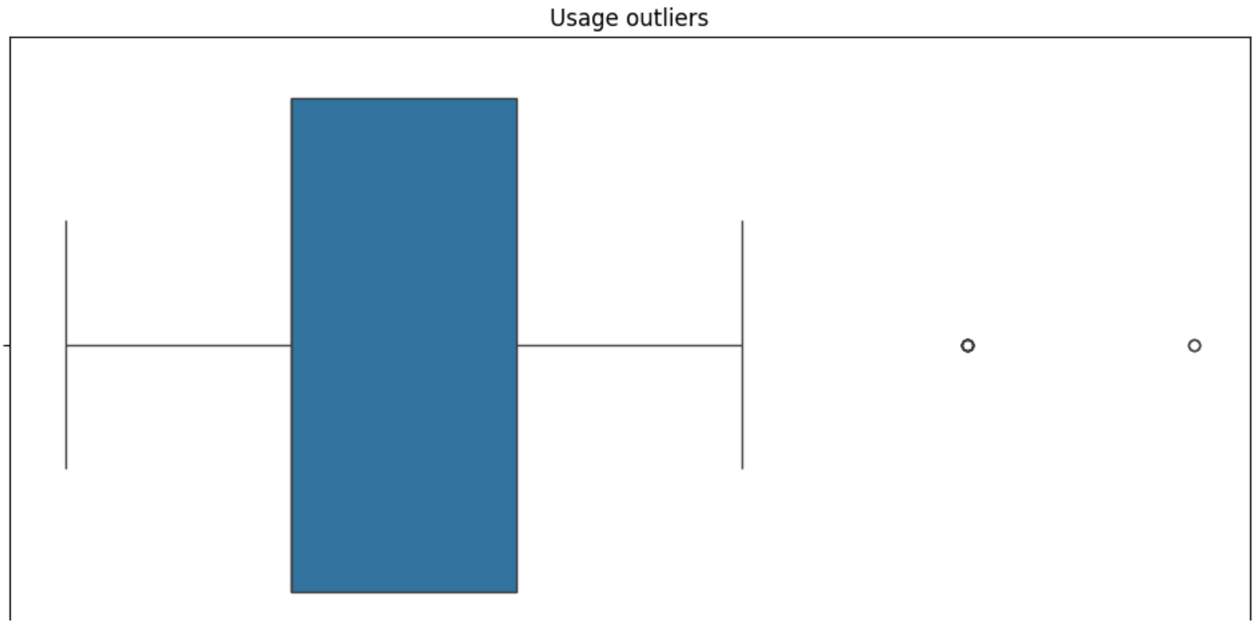
We can see from above most of them are of age 25 and belong to adult category

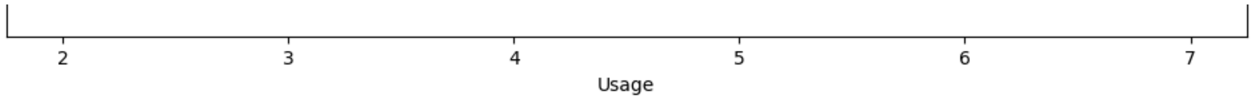
Outliers identification

```
def fitnessagecount(data,coloumn):
  for i in coloumn:
    plt.figure(figsize=(12,6))
    sns.boxplot(data=data, x=i)
    title=i+" outliers"
    plt.title(title)
    plt.xlabel(i)
    plt.show()

coloumn=['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
fitnessagecount(aerofittm_df,coloumn)
```

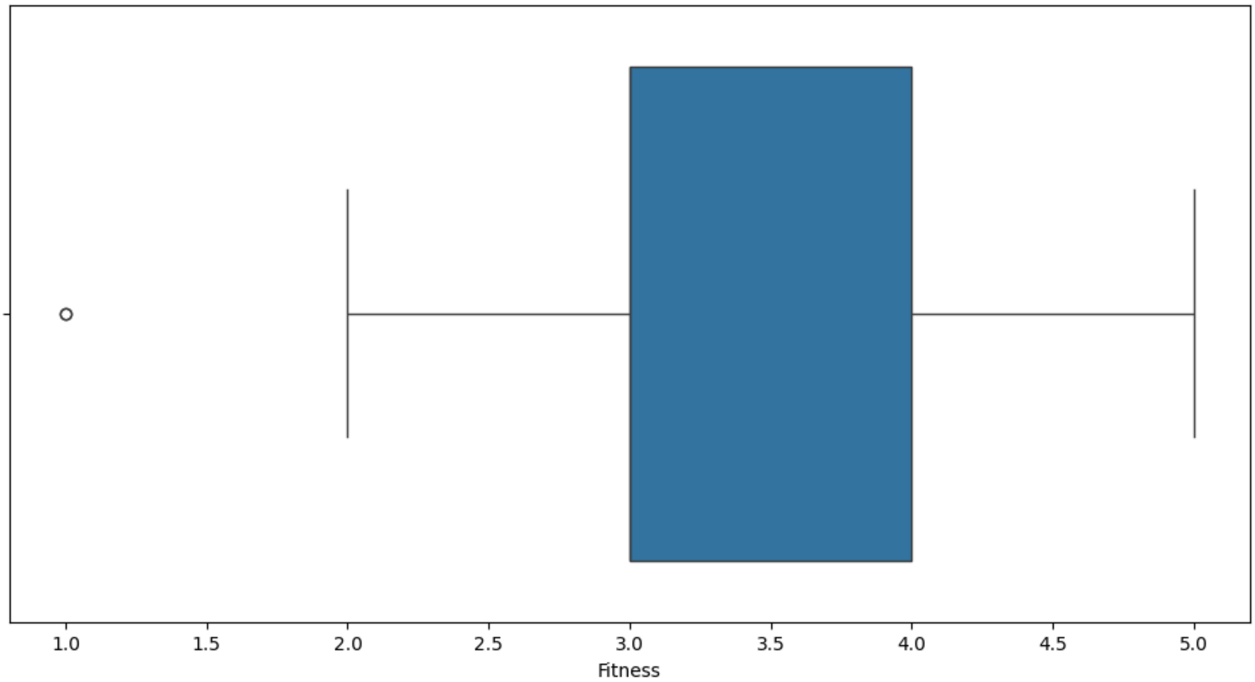

Age outliers
20
25
30
35
40
45
50
Age


Education outliers
12
14
16
18
20
Education

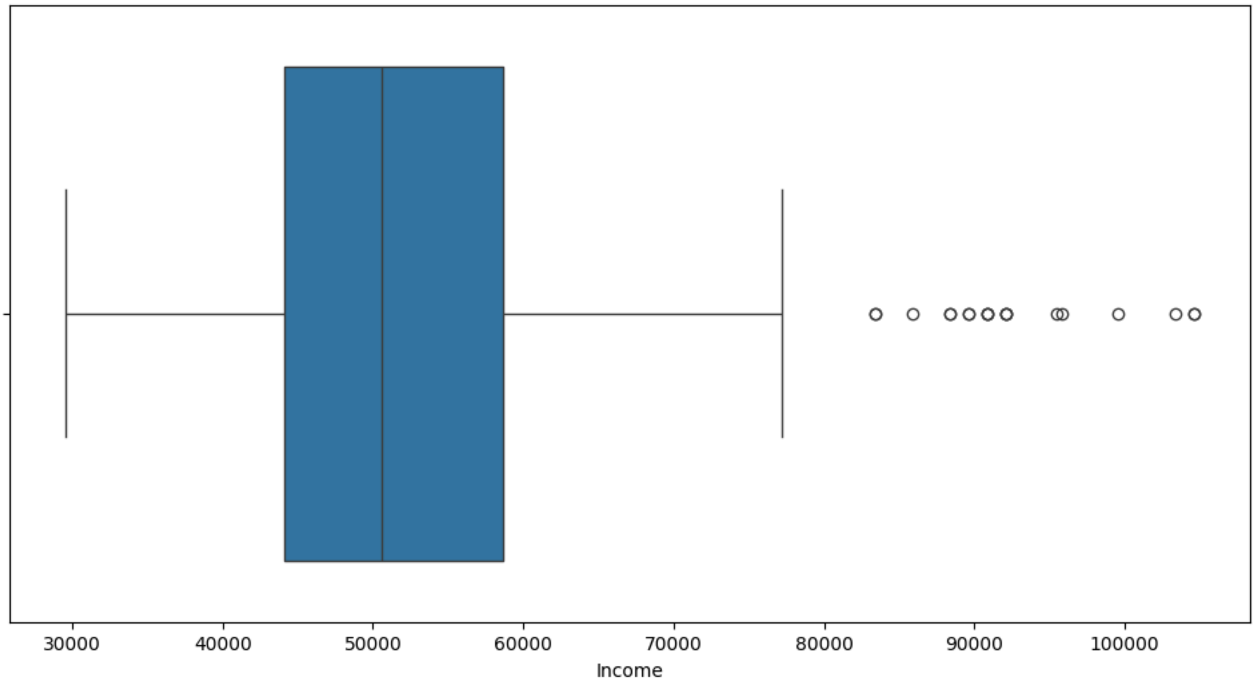

Usage outliers



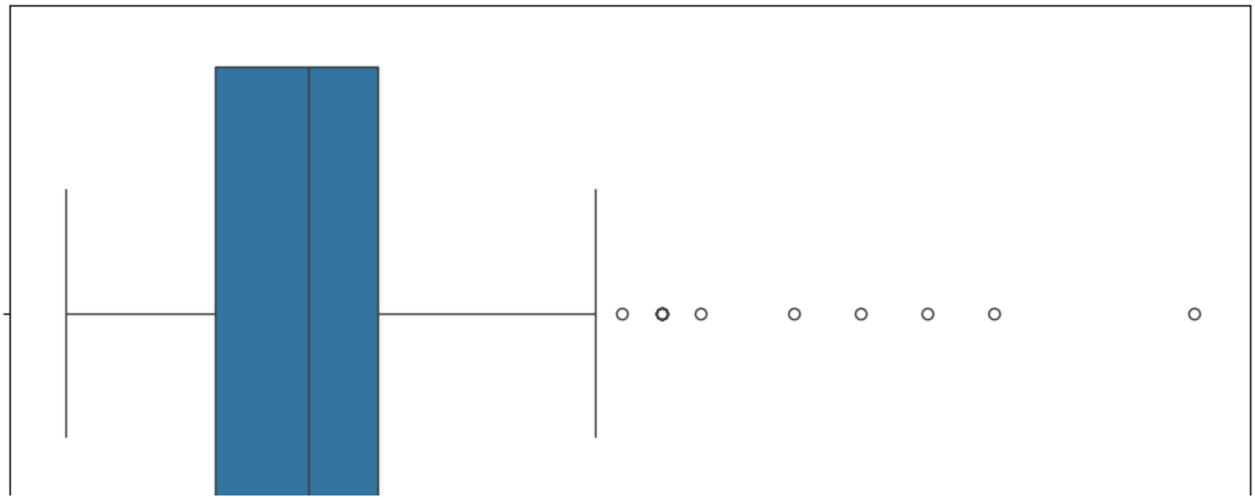
Fitness outliers

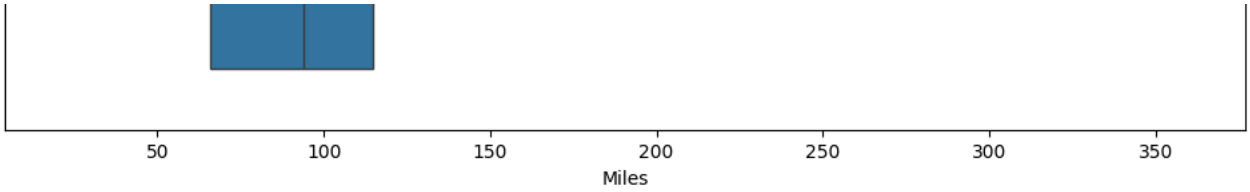


Income outliers



Miles outliers



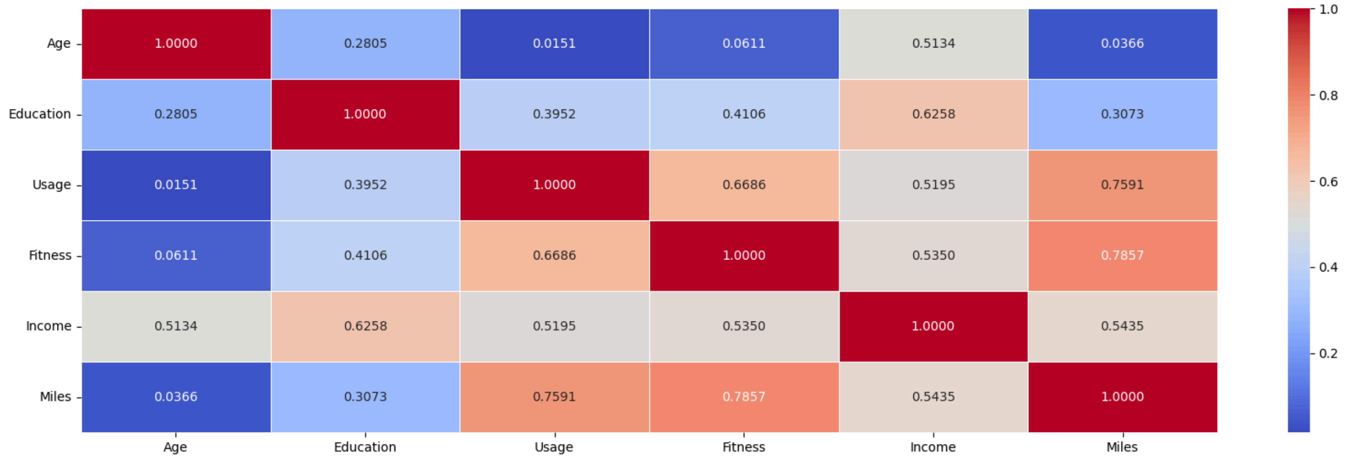

50
100
150
200
250
300
350
Miles

we do have outliers present in the given data mainly in the miles and income category where anything more than 200 miles is considered as an outlier. Where for the income anything more 80K is considered as an outlier

Age,Education and Usuage have very few outliers. Age anything above 45 is considered as an outlier and for Education anything above 20 is an outlier and usuage of 6 or above is considered as an outlier

HeatMaps for Correlation

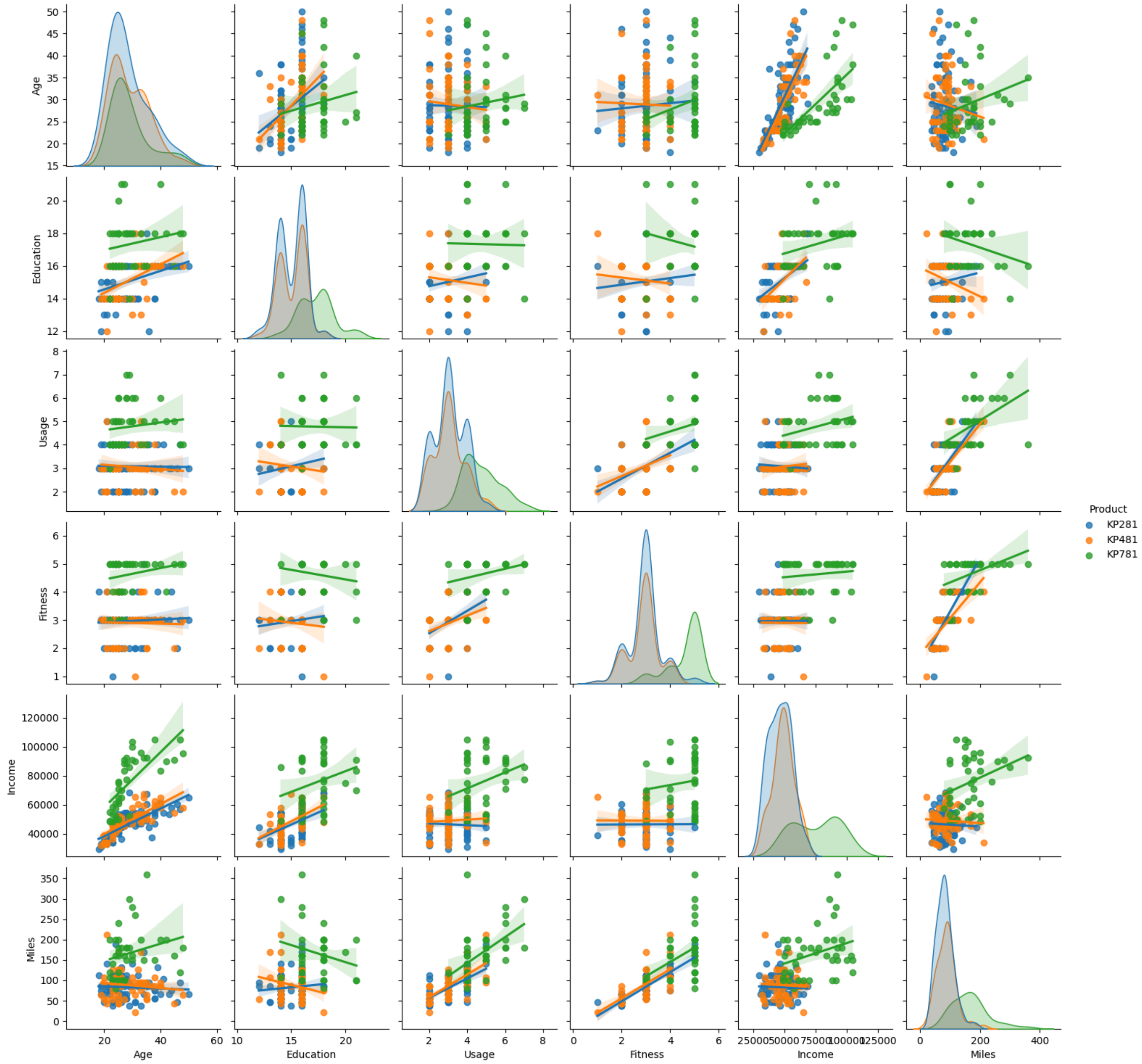
```
plt.figure(figsize=(20,6))
aerofittmf_df=aerofittm_df[['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']]
sns.heatmap(aerofittmf_df.corr(),annot=True,fmt='.4f',linewidths=.5,cmap='coolwarm')
plt.yticks(rotation=0)
plt.show()
```



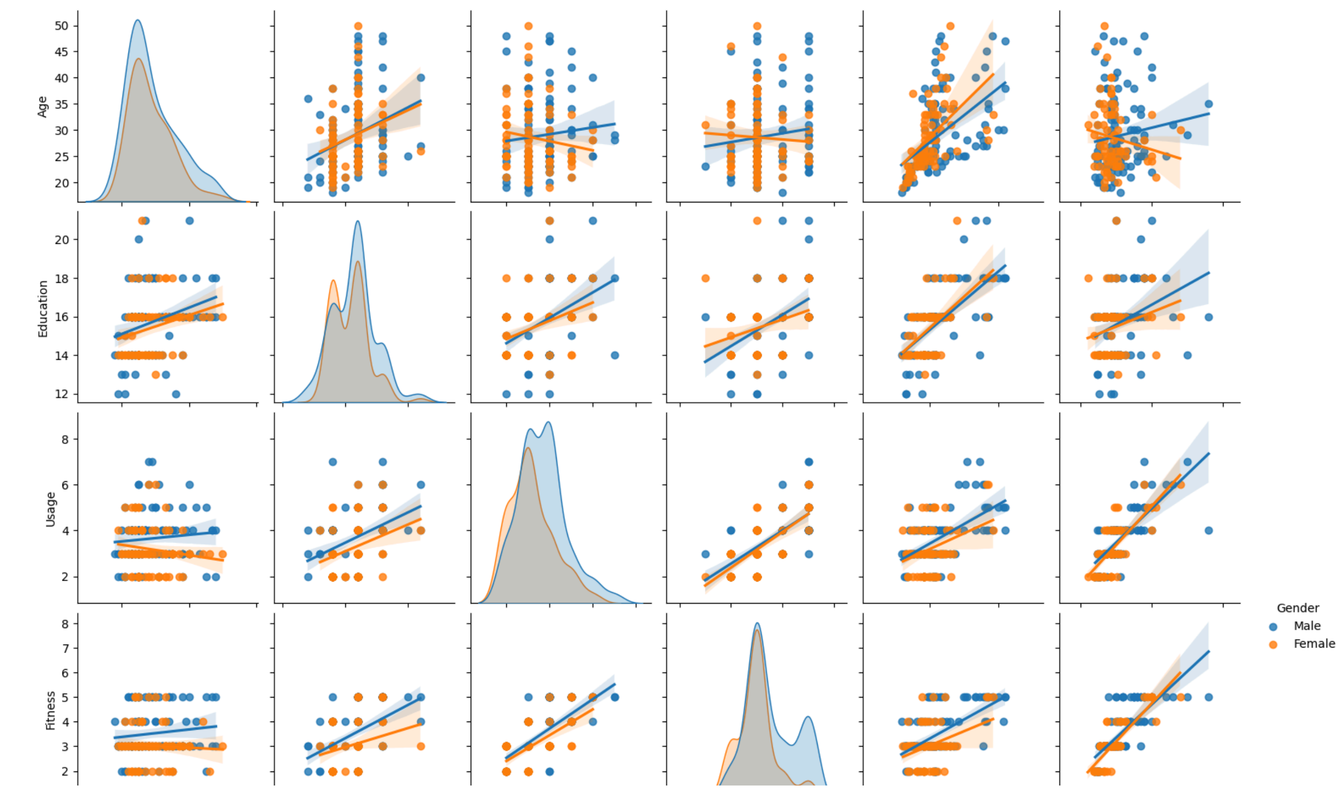
In the above heatmap Correlation between Age and Miles is 0.0366 Correlation between Education and Income is 0.6258 Correlation between Usage and Fitness is 0.6686 Correlation between Fitness and Age is 0.0611 Correlation between Income and Usage is 0.5195 Correlation between Miles and Age is 0.0366

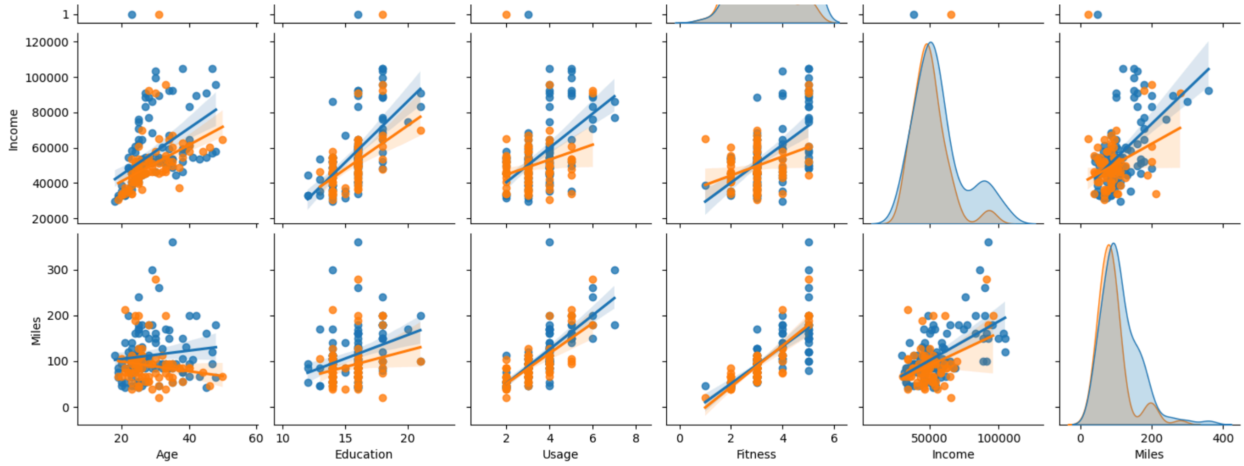
```
coloumn=['Product', 'Gender', 'MaritalStatus']
for i in coloumn:
  plt.figure(figsize=(20,6))
  sns.pairplot(aerofittm_df,hue=i ,kind='reg')
  plt.show()
```

<Figure size 2000x600 with 0 Axes>



<Figure size 2000x600 with 0 Axes>






```
<Figure size 2000x600 with 0 Axes>
```

Bivarent Analysis

Analysis with respect to product and Age,Education.usage,Fitness and Miles

```
coloumns = ['Age', 'Education', 'Usage', 'Fitness', 'Miles']
for i in coloumns:
  print("Analysis on "+i)
  print("")
  print(aerofittm_df.groupby('Product')[i].mean())
  print("")
```

```
Analysis on Age

Product
KP281    28.55
KP481    28.90
KP781    29.10
Name: Age, dtype: float64

Analysis on Education

Product
KP281    15.037500
KP481    15.116667
KP781    17.325000
Name: Education, dtype: float64

Analysis on Usage

Product
KP281    3.087500
KP481    3.066667
KP781    4.775000
Name: Usage, dtype: float64

Analysis on Fitness

Product
KP281    2.9625
KP481    2.9000
KP781    4.6250
Name: Fitness, dtype: float64

Analysis on Miles

Product
KP281     82.787500
KP481     87.933333
KP781    166.900000
Name: Miles, dtype: float64
```

Observation

Product and Age

- Mean Age of the customer who purchased product KP281 is 28.55
- Mean Age of the customer who purchased product KP481 is 28.90
- Mean Age of the customer who purchased product KP781 is 29.10

Product and Education

- Mean Education qualification of the customer who purchased product KP281 is 15.03
- Mean Education qualification of the customer who purchased product KP481 is 15.11
- Mean Education qualification of the customer who purchased product KP781 is 17.32

Product and Usage

- Customer usage mean for product KP281 is 3.08
- Customer usage mean for product KP481 is 3.06
- Customer usage mean for product KP781 is 4.77

Product and Fitness

- Customer fitness mean for product KP281 is 2.96
- Customer fitness mean for product KP481 is 2.90
- Customer fitness mean for product KP781 is 4.62

Product and Miles

- Customer miles mean for product KP281 is 82.78

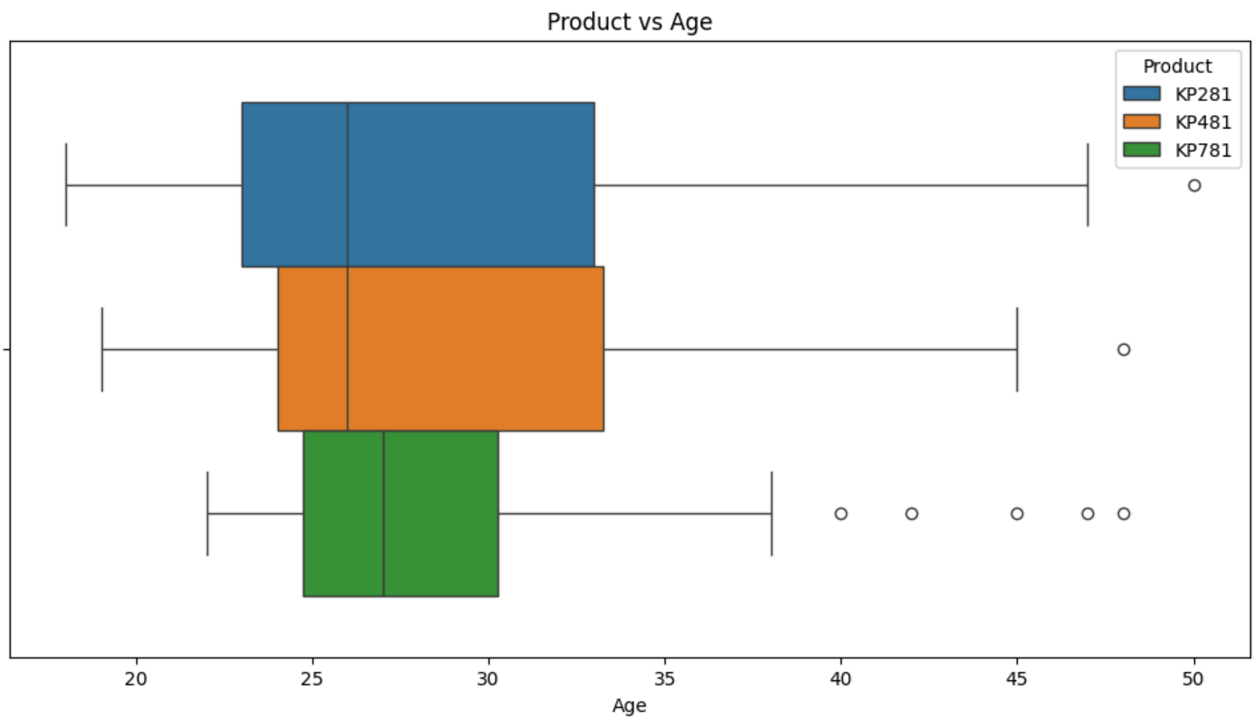
- Customer miles mean for product KP481 is 87.93
- Customer miles mean for product KP781 is 166.90

We will further analyze on product vs rest of the coloumns as mentioned below

- Product vs Age
- Product vs Gender
- Product vs Education
- Product vs Marital Status
- Product vs Usage
- Product vs Fitness
- Product vs Income
- Product vs Miles

Product Vs Age

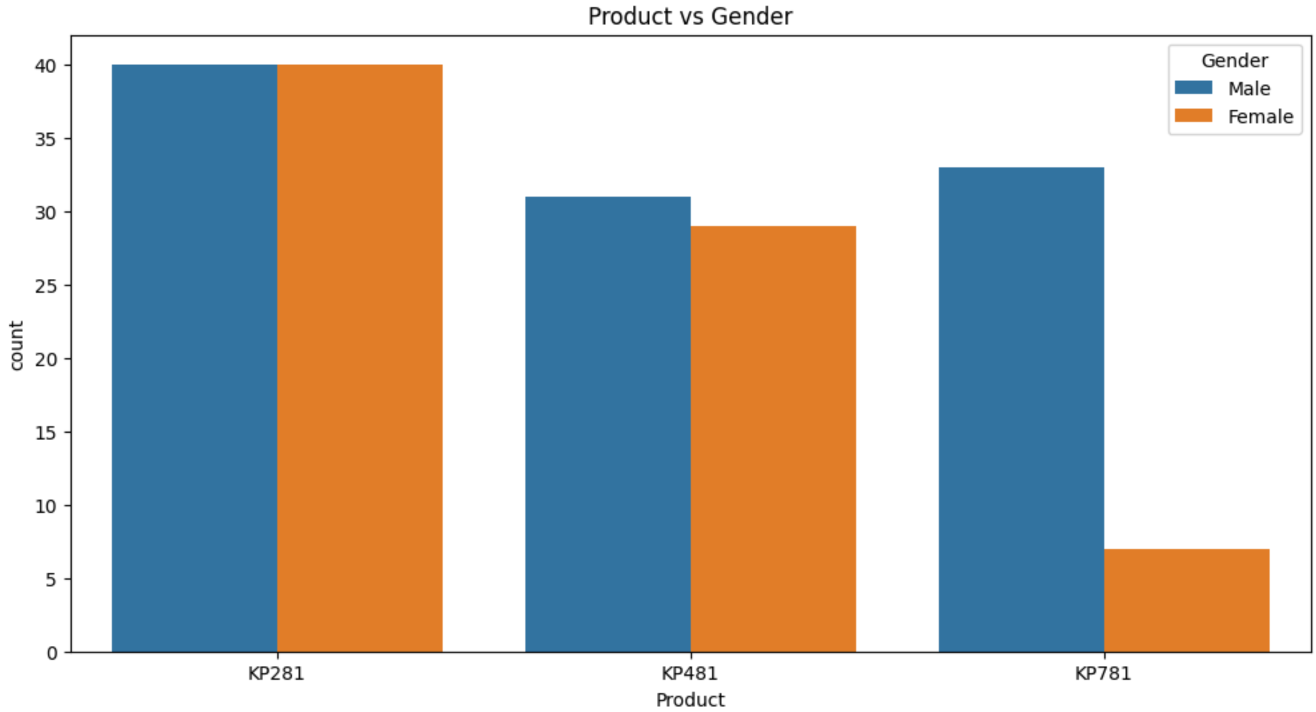
```
def productvsage(data):
  plt.figure(figsize=(12,6))
  sns.boxplot(data=data, x='Age', hue='Product')
  title="Product vs Age"
  plt.title(title)
  plt.xlabel("Age")
  plt.show()

productvsage(aerofittm_df)
```



Most of the people who brought KP281 are within the age of 20 to 48 and average age of 26 Most of the people who brought KP481 are within the age of 20 to 45 and average age of 26 Most of the people who brought KP481 are within the age of 22 to 38 and average age of 28

Product vs Gender

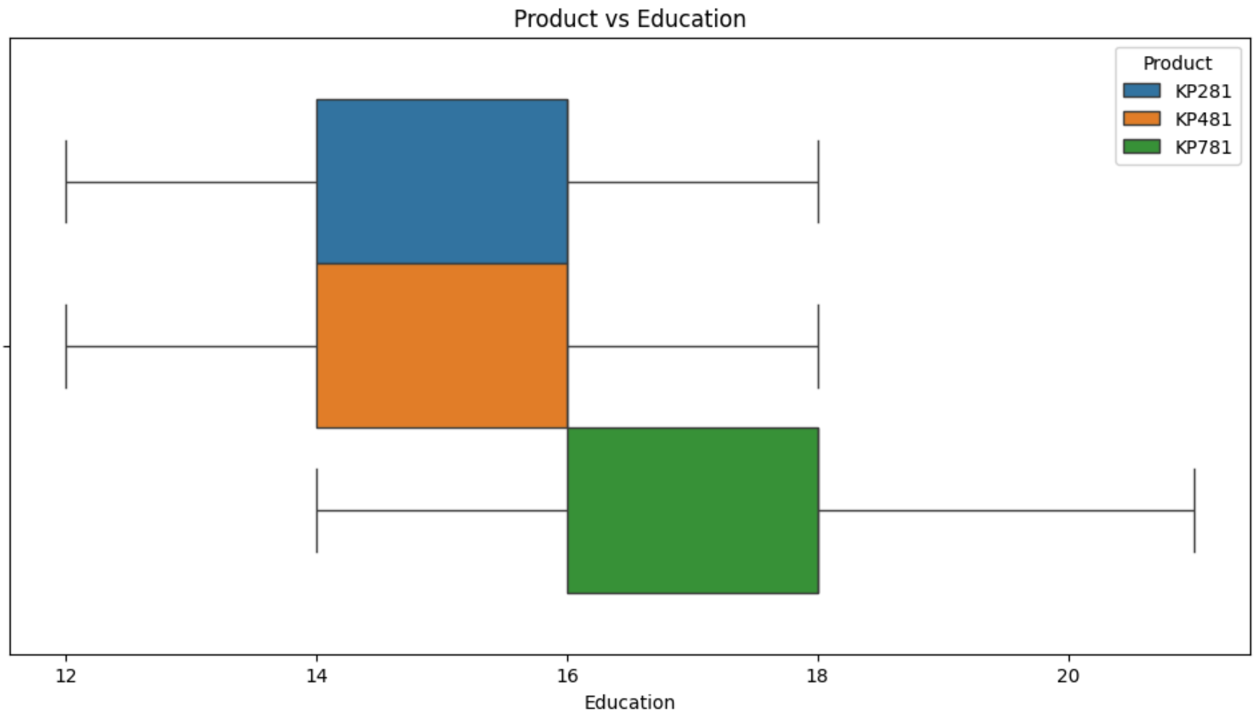
```
def productvsgender(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Product', hue='Gender')
  title="Product vs Gender"
  plt.title(title)
  plt.xlabel("Product")
  plt.show()

productvsgender(aerofittm_df)
```



Both male and female have purchased the product KP281 the same Male have purchased the product KP481 more Males have purchased the product KP781 significantly more

Product Vs Education

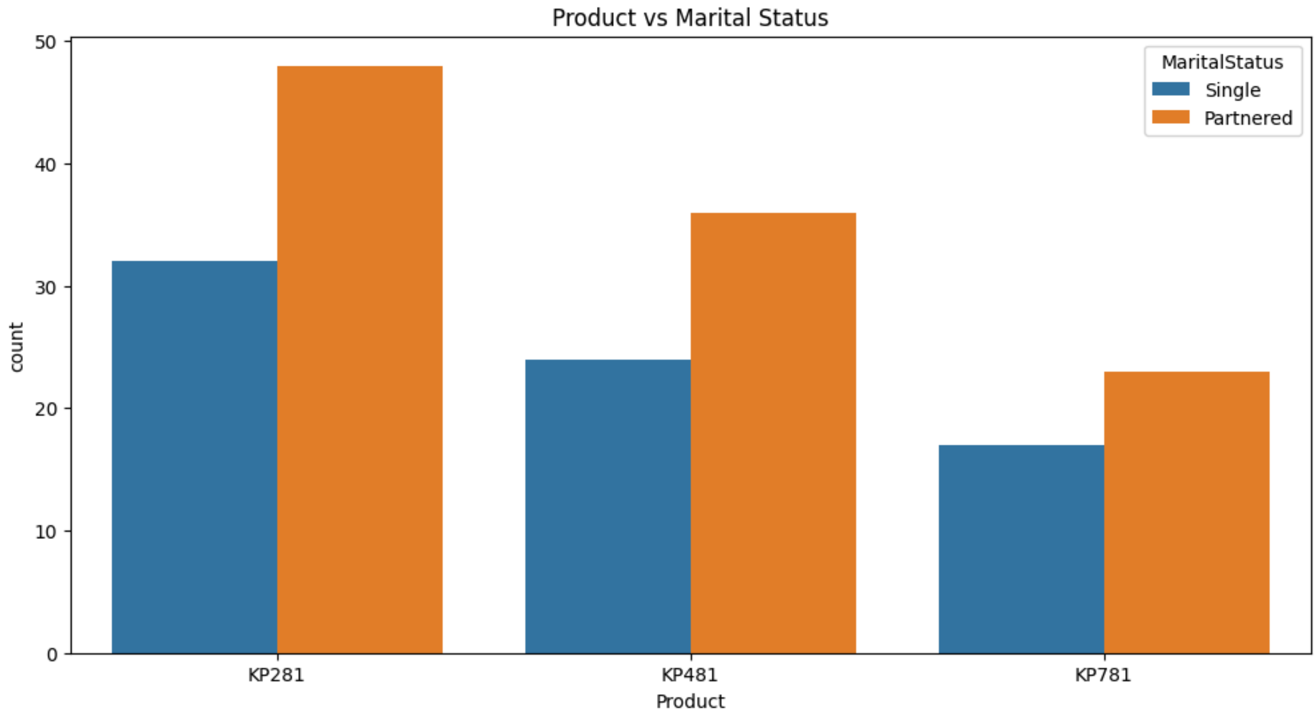
```
def productvsage(data):
  plt.figure(figsize=(12,6))
  sns.boxplot(data=data, x='Education', hue='Product')
  title="Product vs Education"
  plt.title(title)
  plt.xlabel("Education")
  plt.show()

productvsage(aerofittm_df)
```



People who have purchased the product KP281 and KP481 seems to have the same education trend People who have purchased the product KP781 seem to be on the higher educated background

Product Vs Marital Status

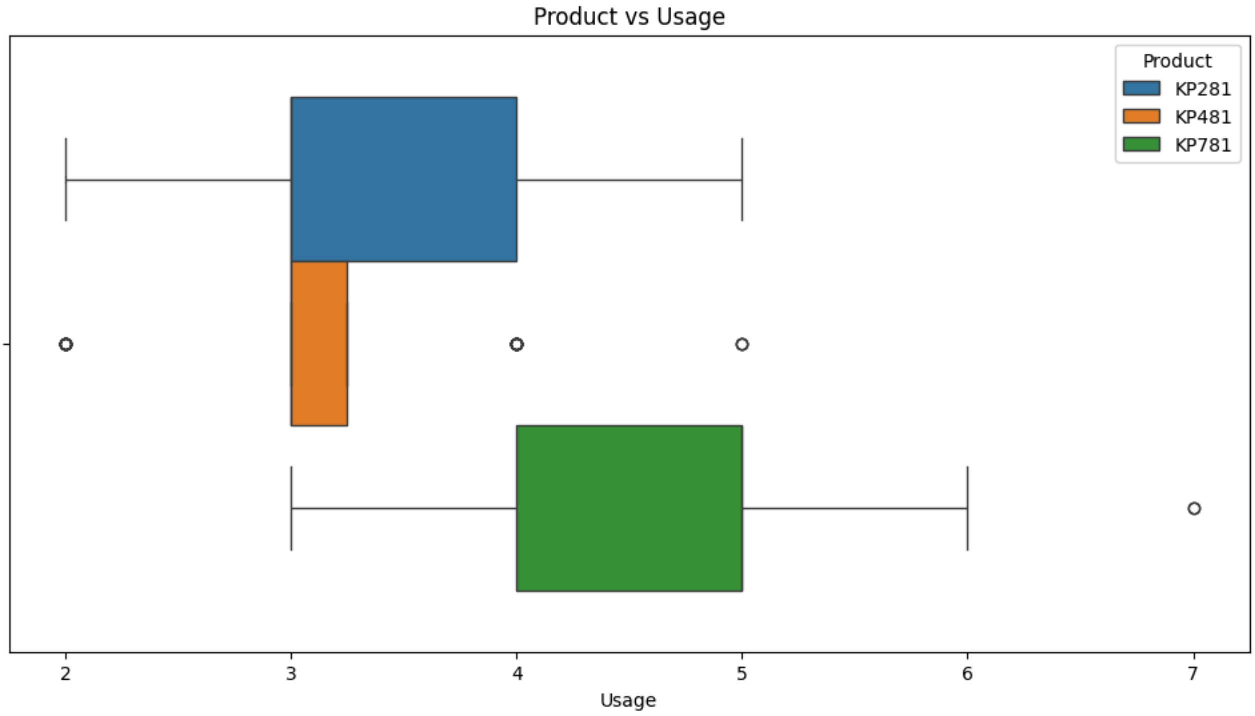
```
def productvsmarriage(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Product', hue='MaritalStatus')
  title="Product vs Marital Status"
  plt.title(title)
  plt.xlabel("Product")
  plt.show()

productvsmarriage(aerofittm_df)
```



The product KP281 is used by Married people more than that of the single ones and are significantly large compared to KP481 and KP781 as seen above

Product vs Usage

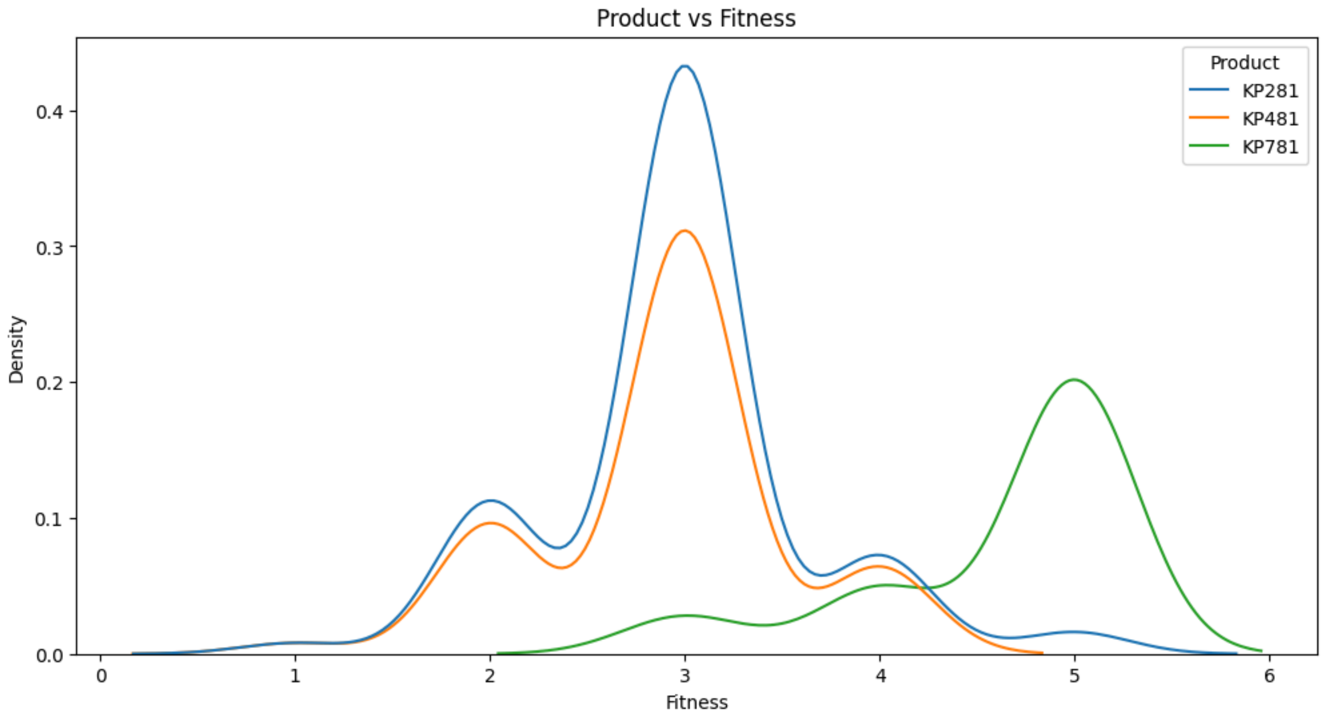
```
def productvsUsage(data):
  plt.figure(figsize=(12,6))
  sns.boxplot(data=data, x='Usage', hue='Product')
  title="Product vs Usage"
  plt.title(title)
  plt.xlabel("Usage")
  plt.show()

productvsUsage(aerofittm_df)
```



We have KP281 and KP781 usage as more compared to that of KP481

Product vs Fitness

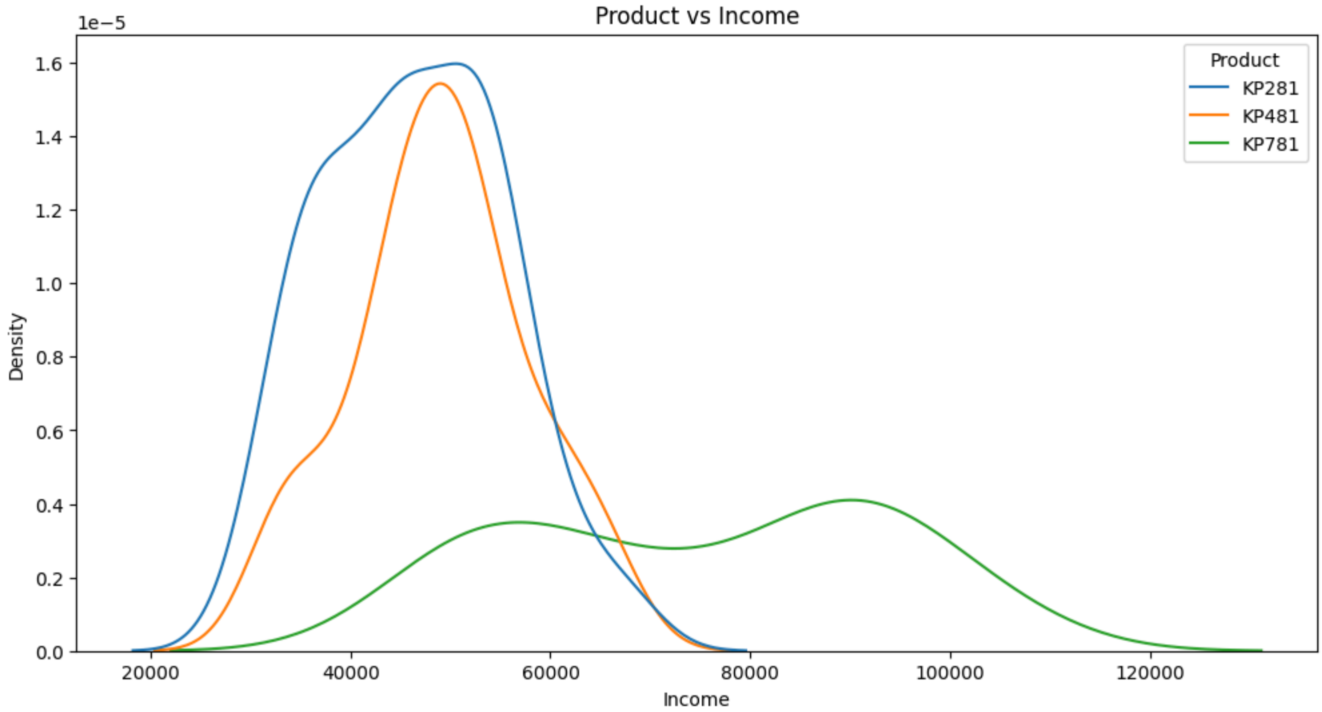
```
def productvsFitness(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Fitness', hue='Product')
  title="Product vs Fitness"
  plt.title(title)
  plt.xlabel("Fitness")
  plt.show()

productvsFitness(aerofittm_df)
```



We have the fitness of the product KP281 and KP481 more due to higher spike

Product vs Income

```
def productvsIncome(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Income', hue='Product')
  title="Product vs Income"
  plt.title(title)
  plt.xlabel("Income")
  plt.show()

productvsIncome(aerofittm_df)
```



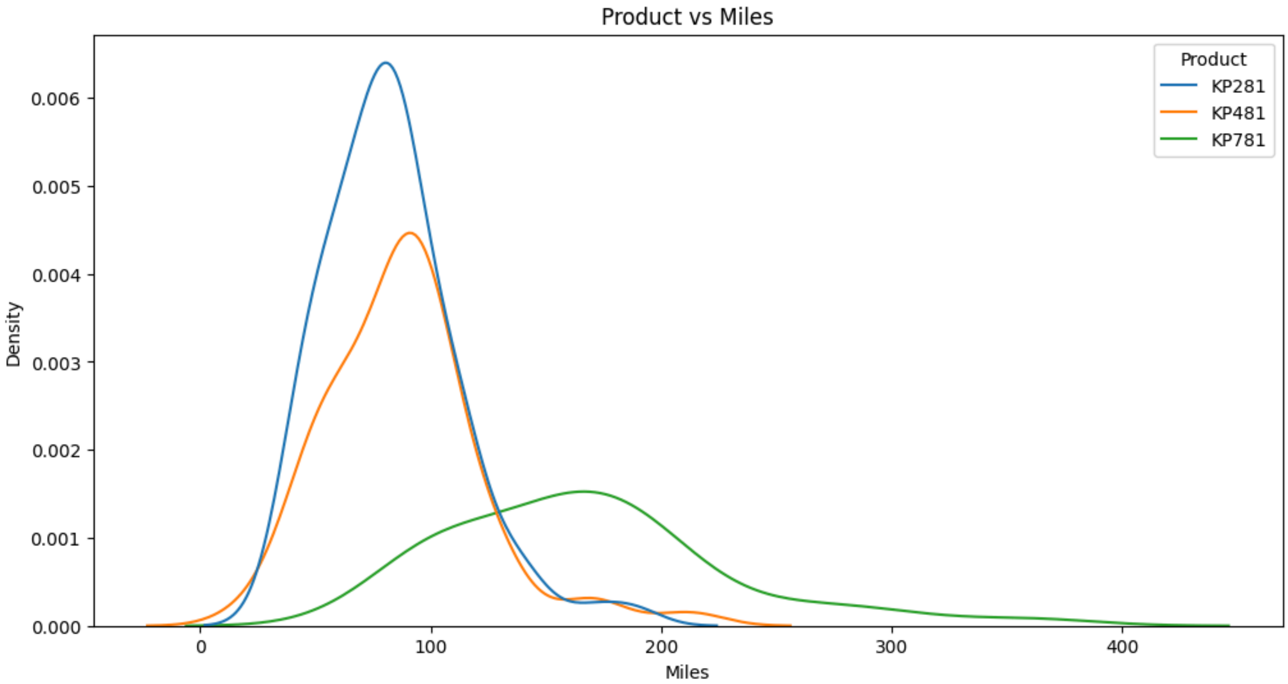
People who purchase the product KP281 and KP481 have higher spikes compared to KP781

Product vs Miles

```
def productvsMiles(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Miles', hue='Product')
  title="Product vs Miles"
  plt.title(title)
  plt.xlabel("Miles")
  plt.show()

productvsMiles(aerofittm_df)
```

Product vs Miles

```
def productvsMiles(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Miles', hue='Product')
  title="Product vs Miles"
  plt.title(title)
  plt.xlabel("Miles")
  plt.show()

productvsMiles(aerofittm_df)
```



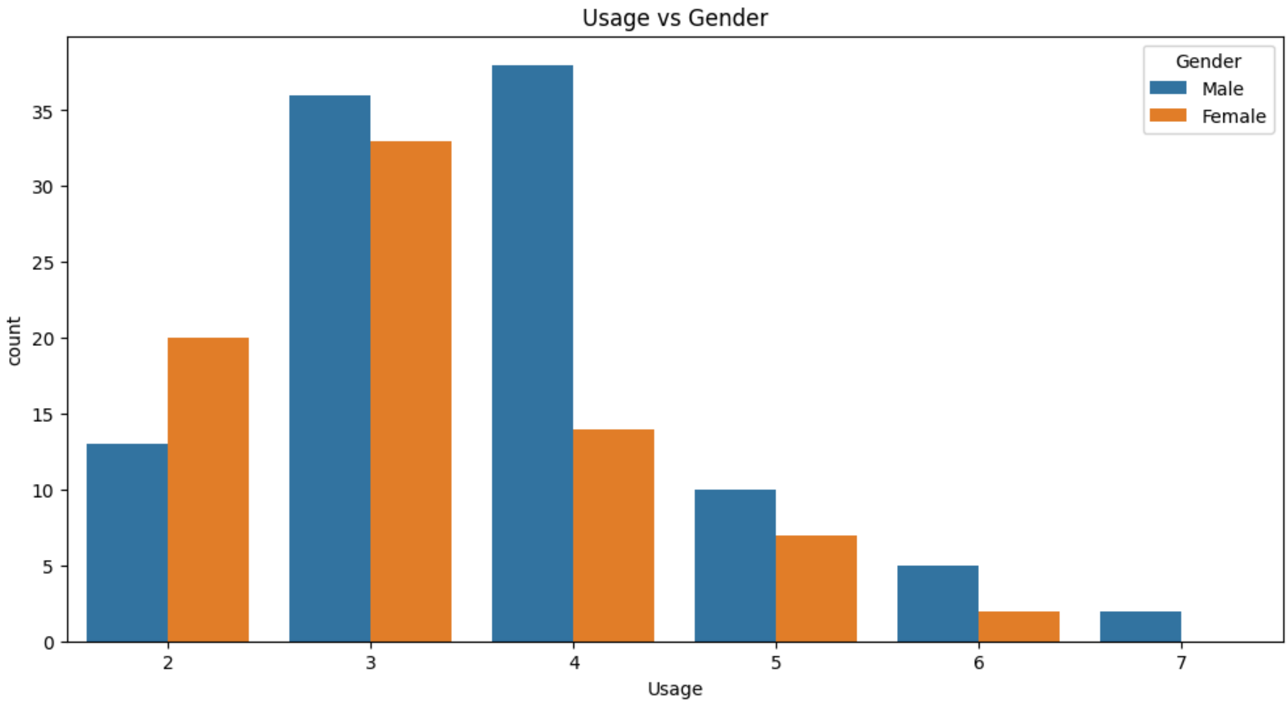
People who purchase the product KP281 and KP481 have higher spikes in miles compared to KP781

Gender analysis done on the rest of the fields as mentioned below

- Gender vs Usage
- Gender vs Fitness
- Gender vs Income

- Gender vs Miles

```
def Gendervsusage(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Usage', hue='Gender')
  title="Usage vs Gender"
  plt.title(title)
  plt.xlabel("Usage")
  plt.show()

Gendervsusage(aerofittm_df)
```

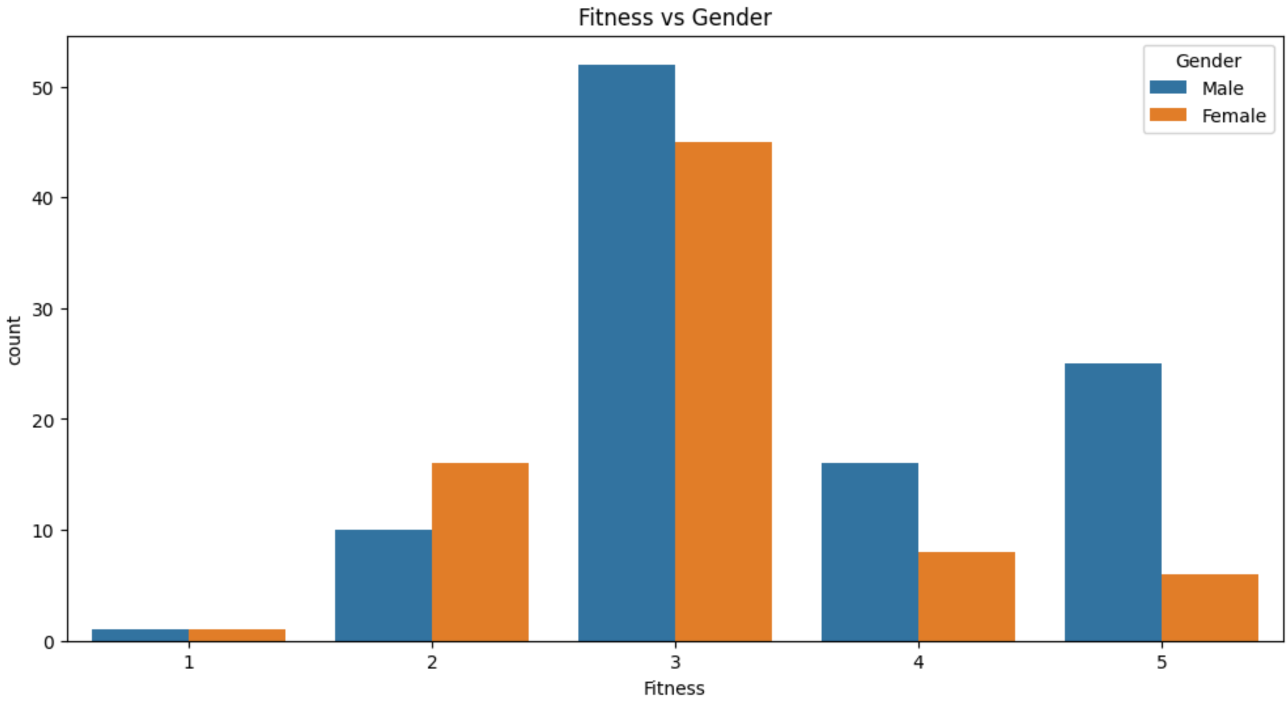


Among Male and Female Males usage higher in 4 days per week Female customers mostly use 3 days per week Only few Male customers use 7 days per week whereas female customers maximum usage is only 6 days per week

Gender vs Fitness

```
def GendervsFitness(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Fitness', hue='Gender')
```

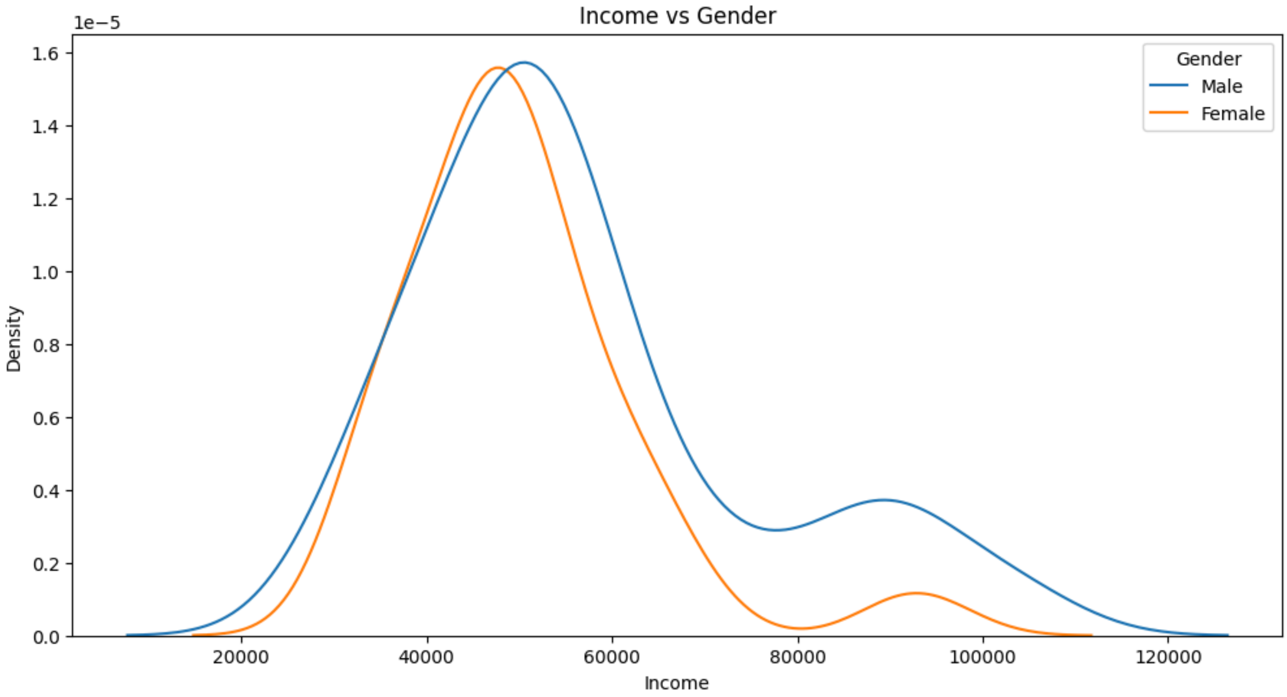
```
  title="Fitness vs Gender"
  plt.title(title)
  plt.xlabel("Fitness")
  plt.show()

GendervsFitness(aerofittm_df)
```



We can see that Among Males and females males have higher average fitness Even among the Average fitness that is 3 males are having higher than females

Gender vs Income

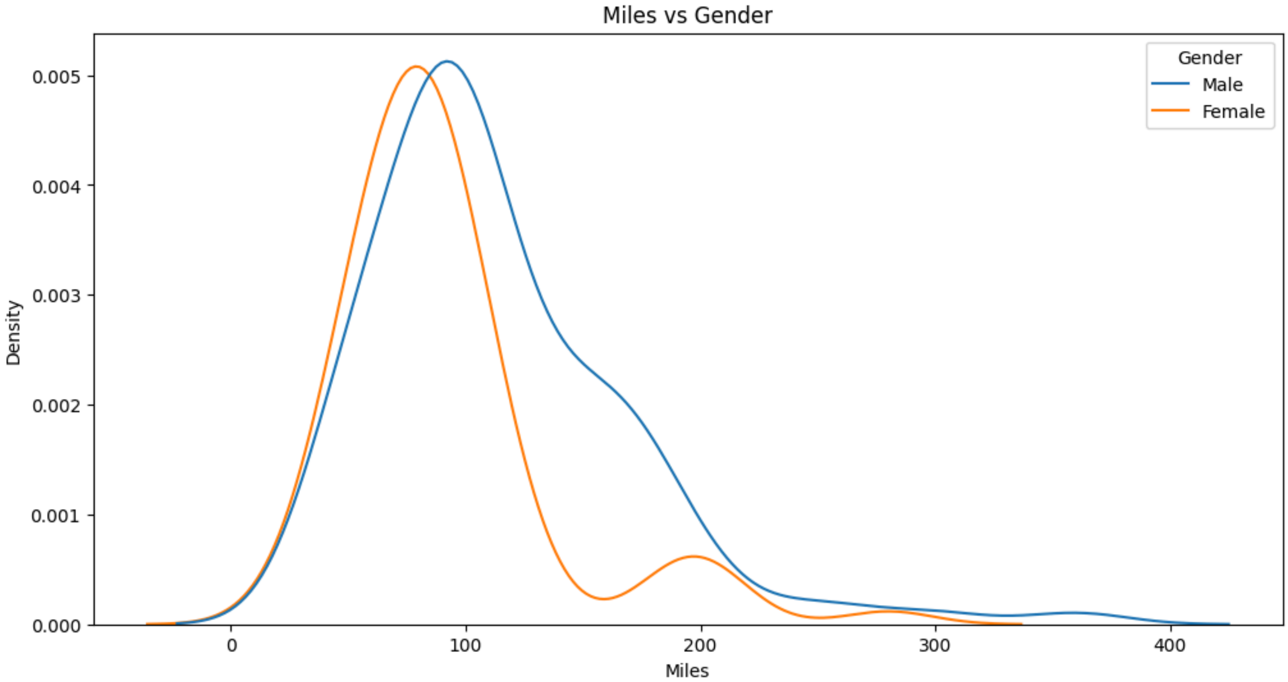
```
def GendervsIncome(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Income', hue='Gender')
  title="Income vs Gender"
  plt.title(title)
  plt.xlabel("Income")
  plt.show()

GendervsIncome(aerofittm_df)
```



We can see that both male and female have equal higher or peak income in the range of 20K to 80K and peak of about 40K

Gender vs Miles

```
def GendervsMiles(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Miles', hue='Gender')
  title="Miles vs Gender"
  plt.title(title)
  plt.xlabel("Miles")
  plt.show()

GendervsMiles(aerofittm_df)
```



Seems like over all males have a higher Mile range than female but they both peak at the same level

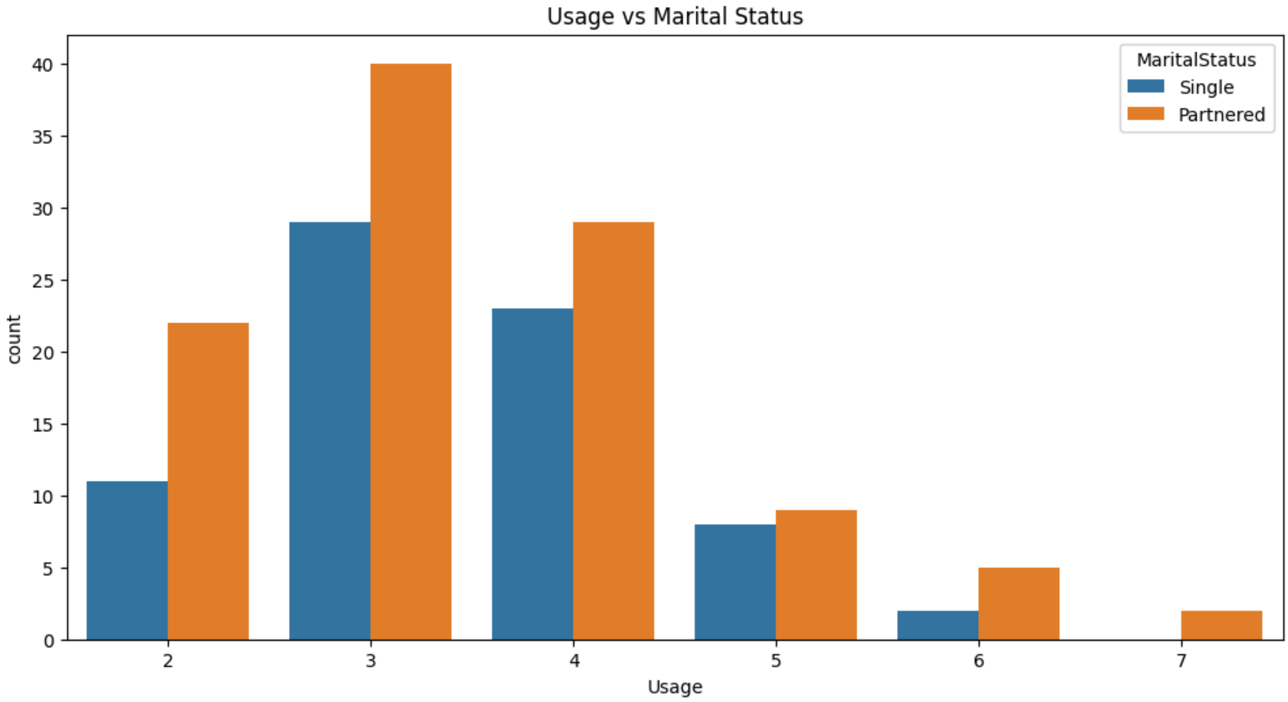
Analysis is on How Marital Status affects the rest of the values

- Marital vs Usage
- Marital vs Fitness
- Marital vs Income
- Marital vs Miles

Double-click (or enter) to edit

```
def Maritalvsusage(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Usage', hue='MaritalStatus')
  title="Usage vs Marital Status"
  plt.title(title)
  plt.xlabel("Usage")
  plt.show()
```

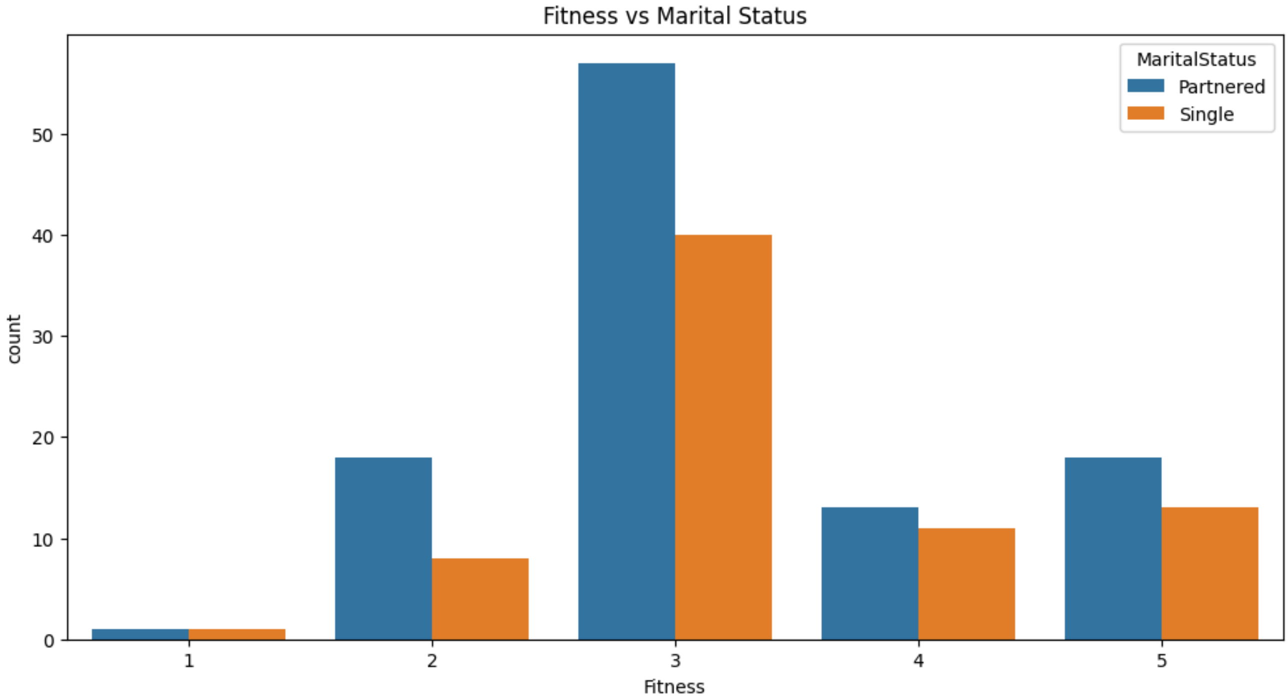
```
Maritalvsusage(aerofittm_df)
```



People who have married have an higher usage value in 3 and people who are single tend to stop of the usage value of 6

Marital vs Fitness

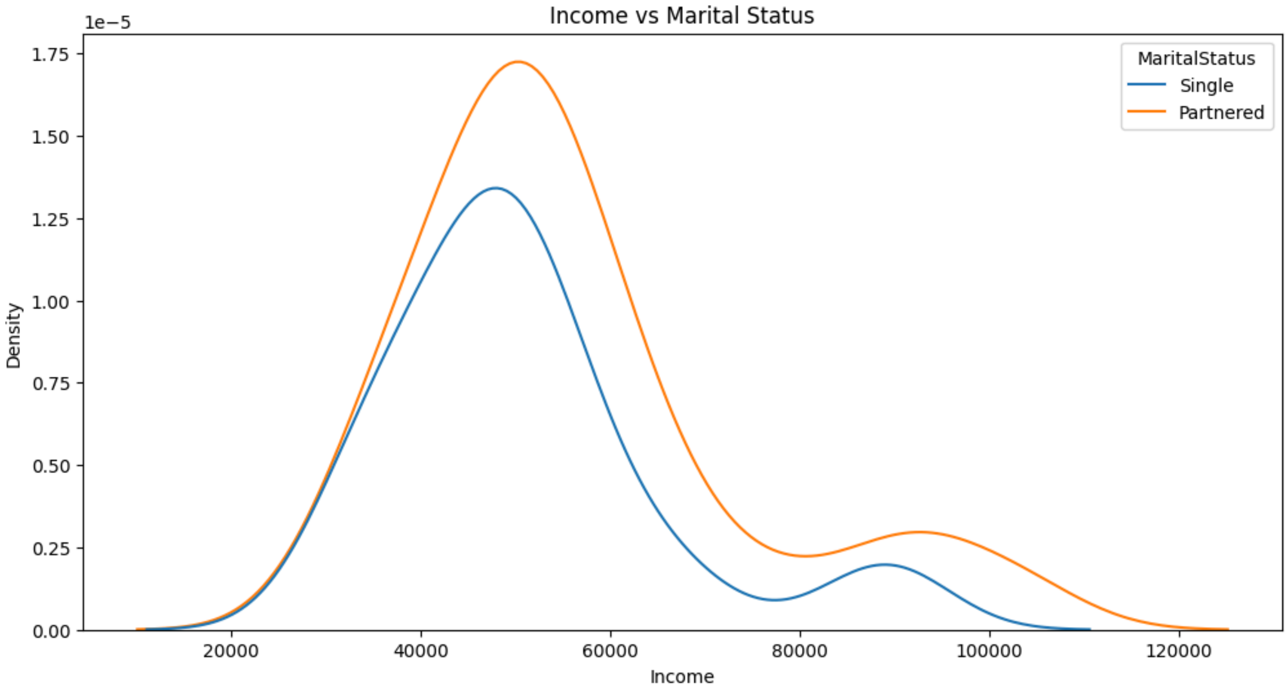
```
def MaritalvsFitness(data):
  plt.figure(figsize=(12,6))
  sns.countplot(data=data, x='Fitness', hue='MaritalStatus')
  title="Fitness vs Marital Status"
  plt.title(title)
  plt.xlabel("Fitness")
  plt.show()

MaritalvsFitness(aerofittm_df)
```



People who are single have a higher fitness in terms of average fitness that is 3

Marital vs Income

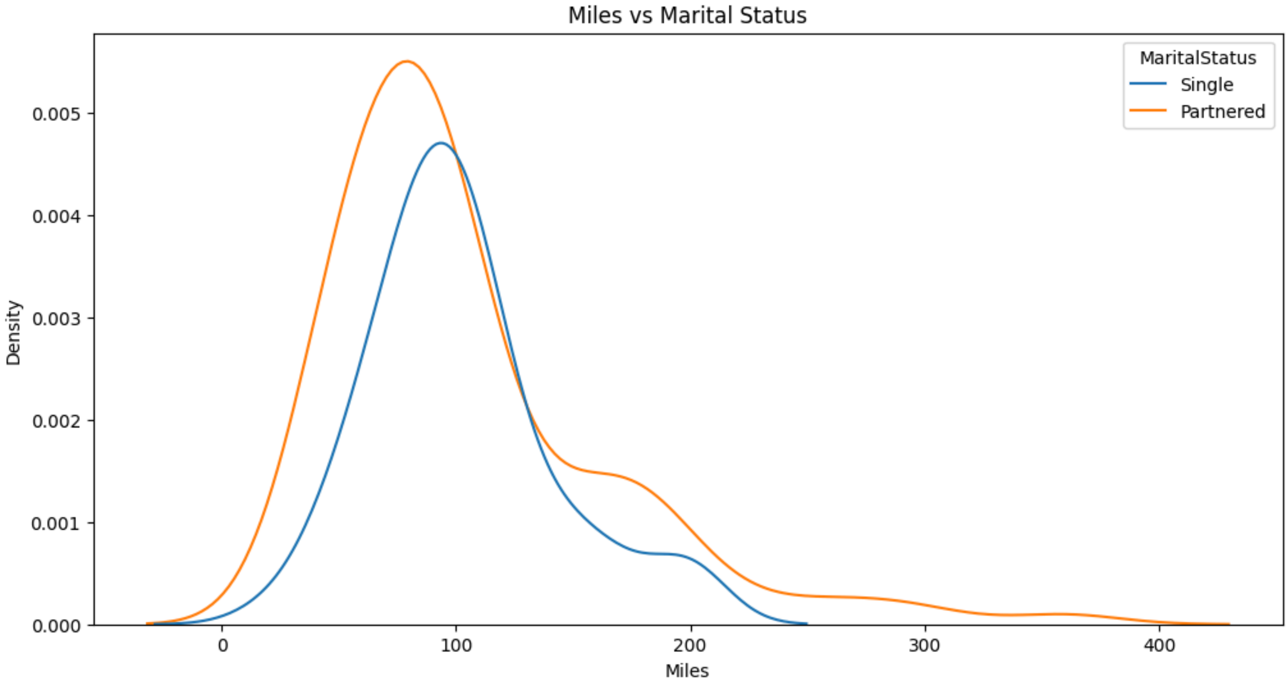
```
def MaritalvsIncome(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Income', hue='MaritalStatus')
  title="Income vs Marital Status"
  plt.title(title)
  plt.xlabel("Income")
  plt.show()

MaritalvsIncome(aerofittm_df)
```



Parterned people have higher income in the range of 20K to 80K and peak at 45K

Marital vs Miles

```
def MaritalvsMiles(data):
  plt.figure(figsize=(12,6))
  sns.kdeplot(data=data, x='Miles', hue='MaritalStatus')
  title="Miles vs Marital Status"
  plt.title(title)
  plt.xlabel("Miles")
  plt.show()

MaritalvsMiles(aerofittm_df)
```



Partnered people have higher Miles and peak at the value close to 90

Outlier Detection and probability

Inter Quartile Range

```
def interquartilerange(data , coloumn):
  for i in coloumn:
    q1=np.percentile(data[i], 25)
    q3=np.percentile(data[i], 75)
    quartile = q3-q1
    print("The Inter Quartile Range of "+i+" is",quartile)


coloumn=['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
interquartilerange(aerofittm_df,coloumn)
```

```
The Inter Quartile Range of Age is 9.0
The Inter Quartile Range of Education is 2.0
The Inter Quartile Range of Usage is 1.0
```

```
The Inter Quartile Range of Fitness is 1.0
The Inter Quartile Range of Income is 14609.25
The Inter Quartile Range of Miles is 48.75
```

Probability of Product for given gender

```
probabilityofp=pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Gender']]
print(probabilityofp)
np.round(((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Gender']],mar
```

```
Gender   Female  Male  All
Product
KP281        40    40   80
KP481        29    31   60
KP781         7    33   40
All          76   104  180
```

Gender Product	Female	Male	All
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

With the above data we can calculate the probability of each product with respect to the genders

Marginal Probability

Probability of Male Customer Purchasing product is 57.77

Probability of Female Customer Purchasing product is 42.22

Marginal Probability of any customer buying

product KP281 is : 44.44

product KP481 is : 33.33

product KP781 is : 22.22

```
np.round((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Gender']],marg
```

Gender	Female	Male	All
Product			
KP281	52.63	38.46	44.44
KP481	38.16	29.81	33.33
KP781	9.21	31.73	22.22

Probability of Selling Product

p(KP281|Female) = 52 p(KP481|Female) = 38 p(KP781|Female) = 10 p(KP281|male) = 38 p(KP481|male) = 30 p(KP781|male) = 32

Probability of product given MaritalStatus

```
probabilityofg=pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['MaritalSt
print(probabilityofg)
np.round(((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['MaritalStatus
```

```
MaritalStatus  Partnered  Single  All
Product
KP281                 48      32   80
KP481                 36      24   60
KP781                 23      17   40
All                  107      73  180
```

MaritalStatus	Partnered	Single	All
Product			
KP281	26.67	17.78	44.44
KP481	20.00	13.33	33.33
KP781	12.78	9.44	22.22
All	59.44	40.56	100.00

Marginal Probability

Probability of Married Customer Purchasingproduct is 59.44

Probability of Single Customer Purchasing product is 40.56

Marginal Probability of any customer buying

product KP281 is : 44.44

product KP481 is : 33.33

product KP781 is : 22.22

```
np.round((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['MaritalStatus'
```

MaritalStatus	Partnered	Single	All
Product			
KP281	44.86	43.84	44.44
KP481	33.64	32.88	33.33
KP781	21.50	23.29	22.22

Probability of Selling Product

p(KP281|Married) = 44.86 p(KP481|Married) = 33.64 p(KP781|Married) = 21.50 p(KP281|Single) = 43.84 p(KP481|Single) = 32.88 p(KP781|Single) = 23.29

Probability of a product given Fitness category

```
probabilityoffg=pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Fitness_
print(probabilityoffg)
np.round(((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Fitness_categ
```

```
Fitness_category  Average  Good  Poor  Very Good  Very Poor  All
Product
KP281                  54     9    14          2          1   80
KP481                  39     8    12          0          1   60
KP781                   4     7     0         29          0   40
All                    97    24    26         31          2  180
```

Fitness_category	Average	Good	Poor	Very Good	Very Poor	All
Product						
KP281	30.00	5.00	7.78	1.11	0.56	44.44
KP481	21.67	4.44	6.67	0.00	0.56	33.33
KP781	2.22	3.89	0.00	16.11	0.00	22.22
All	53.89	13.33	14.44	17.22	1.11	100.00

Marginal Probability

Probability of Fitness Customer of customer as average Purchasing product is 53.89 Probability of Fitness Customer of customer as Good Purchasing product is 13.33 Probability of Fitness Customer of customer as Poor Purchasing product is 14.44 Probability of Fitness Customer of customer as Very Good Purchasing product is 17.22 Probability of Fitness Customer of customer as Very Poor Purchasing product is 1.11

Marginal Probability of any customer buying

product KP281 is : 44.44 product KP481 is : 33.33 product KP781 is : 22.22

```
np.round((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Fitness_catego
```

Fitness_category Product	Average	Good	Poor	Very Good	Very Poor	All
KP281	55.67	37.50	53.85	6.45	50.0	44.44
KP481	40.21	33.33	46.15	0.00	50.0	33.33
KP781	4.12	29.17	0.00	93.55	0.0	22.22

Probability of Selling Product

p(KP281|Average) = 55.67 p(KP481|Average) = 40.21 p(KP781|Average) = 4.12 p(KP281|Good) = 37.50 p(KP481|Good) = 33.33 p(KP781|Good) = 29.17 p(KP281|Poor) = 53.85 p(KP481|Poor) = 46.15 p(KP781|Poor) = 0 p(KP281|Very Good) = 6.45 p(KP481|Very Good) = 0 p(KP781|Very Good) = 93.55 p(KP281|Very Poor) = 50 p(KP481|Very Poor) = 50 p(KP781|Very Poor) = 0

Probability of a product given Age category

```
probabilityoffg=pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Age_Cate
print(probabilityoffg)
np.round(((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Age_Category'
```

```
Age_Category  Adolescent  Young Adult  Adult  Middle-Aged  All
Product
KP281                 10           17     36           17   80
KP481                  7           10     31           12   60
KP781                  0           10     23            7   40
All                   17           37     90           36  180
```

Age_Category Product	Adolescent	Young Adult	Adult	Middle-Aged	All
KP281	5.56	9.44	20.00	9.44	44.44
KP481	3.89	5.56	17.22	6.67	33.33
KP781	0.00	5.56	12.78	3.89	22.22
All	9.44	20.56	50.00	20.00	100.00

Marginal Probability

Probability of Age of customer as Adolocent Purchasing product is 9.44 Probability of Age of customer as Young Adult Purchasing product is 20.56 Probability of Age of customer as Adult Purchasing product is 50 Probability of Age of customer as Middle Aged Purchasing product is 20

Marginal Probability of any customer buying

product KP281 is : 44.44 product KP481 is : 33.33 product KP781 is : 22.22

```
np.round((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Age_Category']
```

Age_Category Product	Adolescent	Young Adult	Adult	Middle-Aged	All
KP281	58.82	45.95	40.00	47.22	44.44
KP481	41.18	27.03	34.44	33.33	33.33
KP781	0.00	27.03	25.56	19.44	22.22

Probability of Selling Product

p(KP281|Adolescent) = 58.82 p(KP481|Adolescent) = 41.18 p(KP781|Adolescent) = 0 p(KP281|Young Adult) = 45.95 p(KP481|Young Adult) = 27.03 p(KP781|Young Adult) = 27.03 p(KP281|Adult) = 40.00 p(KP481|Adult) = 34.44 p(KP781|Adult) = 25.56 p(KP281|Middle Aged) = 47.22 p(KP481|Middle Aged) = 33.33 p(KP781|Middle Aged) = 19.44

Recommendations

Promote Customers to upgrade from lower versions to next level versions after consistent usages as there are very less people in the usage after 5 category so improvements can be pushed.

Married people prefer product KP281 more and this can be used as our advantage to have marketing done on these products for couples as exercise together to increase the sales.

```
np.round((pd.crosstab(index=aerofittm_df['Product'],columns=[aerofittm_df['Age_Category']],margins=True, normalize="columns"))*100,2)
```

Age_Category Product	Adolescent	Young Adult	Adult	Middle-Aged	All
KP281	58.82	45.95	40.00	47.22	44.44
KP481	41.18	27.03	34.44	33.33	33.33
KP781	0.00	27.03	25.56	19.44	22.22

Probability of Selling Product

p(KP281|Adolescent) = 58.82 p(KP481|Adolescent) = 41.18 p(KP781|Adolescent) = 0 p(KP281|Young Adult) = 45.95 p(KP481|Young Adult) = 27.03 p(KP781|Young Adult) = 27.03 p(KP281|Adult) = 40.00 p(KP481|Adult) = 34.44 p(KP781|Adult) = 25.56 p(KP281|Middle Aged) = 47.22 p(KP481|Middle Aged) = 33.33 p(KP781|Middle Aged) = 19.44

Recommendations

Promote Customers to upgrade from lower versions to next level versions after consistent usages as there are very less people in the usage after 5 category so improvements can be pushed.

Married people prefer product KP281 more and this can be used as our advantage to have marketing done on these products for couples as exercise together to increase the sales.

Female who prefer exercising is low here as compared to males. we should run a marketing campaign on to encourage women to exercise more

KP281 & KP481 treadmills are preferred by the customers as this is the most used and most of the people income lies around 45K so these models need to be put on offers or sales to increase the products.

As KP781 is better and advanced (based on the data that the male use this product more and is extensively used by higher fitness people) this treadmill should be marketed for professionals and athletes.

KP781 product should be promoted using influencers and other athletes.

KP781 can be recommended for Female customers who exercises extensively as this variant is preferred less.

Market the Adolescents to use the more of KP281 and provide its health benefits.

Target the Age group above 40 years to recommend Product KP781.