```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

About Case Study

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as **treadmills, exercise bikes, gym equipment, and fitness accessories** to cater to the needs of all categories of people.

Defining Problem Statement

Business Problem

The market research team at AeroFit wants **to identify the characteristics of the target audience for each type of treadmill** offered by the company, **to provide a better recommendation of the treadmills to the new customers**. The team decides to investigate whether there are differences across the product with respect to customer characteristics.

Objective

- Create a descriptive analytics **to create a customer profile for each AeroFit treadmill product** by developing appropriate tables and charts.
- For each AeroFit treadmill product, **construct two-way contingency tables and compute all conditional and marginal probabilities** along with their insights/impact on the business.

Analysing basic metrics

```
df = pd.read_csv('aerofit_treadmill.csv')
df.head()

  Product  Age  Gender  Education MaritalStatus  Usage  Fitness
Income  Miles
0   KP281   18    Male         14        Single      3        4
29562    112
1   KP281   19    Male         15        Single      2        3
31836     75
2   KP281   19  Female         14     Partnered      4        3
30699     66
3   KP281   19    Male         12        Single      3        3
32973     85
4   KP281   20    Male         13     Partnered      4        2
35247     47
```

Dataset Characteristics

Dataset contains following columns

- **Product Purchased**: KP281, KP481 and KP781, are the 3 different types of treadmills that are purchased by customers
- **Age** : In years, age of the customer who purchased
- **Gender**: Gender of the purchased customer
- **Education**: represented in years
- **Marital Status**: Single or partnered
- **Usage**: The average number of times the customer has planned to use the treadmill each week
- **Fitness**: Self rated fitness of the user rated from 1 (as poor shape) to 5 (as excellent shape)
- **Miles**: The average number of miles the customer expects to walk or run each week
- **Income**: Annual income of the user in Dollars $

```
df.shape
```

```
(180, 9)
```

Dataset contains 180 rows and 9 columns

```
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
```

- Product, Gender and Marital Status are **object(string)**
- Age, Education, Usage, Fitness, Income and Miles are in **int64(integer)**

```
df.describe()
```

```
              Age   Education       Usage     Fitness
Income  \
```

```
count  180.000000  180.000000  180.000000  180.000000    180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

Descriptive Analysis

- Total count of all columns is 180
- Age: Mean age of the customer is 28 years, half of the customer's mean age is 26.
- Education: Mean Education is 15 with maximum as 21 and minimum as 12.
- Usage: Mean Usage per week is 3.4, with maximum as 7 and minimum as 2.
- Fitness: Average rating is 3.3 on a scale of 1 to 5.
- Miles: Average number of miles the customer walks is 103 with maximum distance travelled by most people is almost 115 and minimum is 21.
- Income (in $): Most customer earns around 58K annually, with maximum of 104K and minimum almost 30K

Non-Graphical Analysis: Value counts and unique attributes

Numerical Summary

```
# Total number of unique Product ids
df['Product'].nunique()

3

# unique list of product ids
df['Product'].unique().tolist()
```

```
['KP281', 'KP481', 'KP781']

# Total number of unique ages
total_uniq_age = df['Age'].nunique()
total_uniq_age

32

# list of unique ages
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])

# Number of Male and Female customers
df['Gender'].value_counts()

Male      104
Female     76
Name: Gender, dtype: int64

# list of unique Educations
df['Education'].unique().tolist()

[14, 15, 12, 13, 16, 18, 20, 21]

# Number of customer againts the rating scale 1 to 5
df['Fitness'].value_counts().sort_index()

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

# Number of customers with 3 different product types
df['Product'].value_counts().sort_index()

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

# Number of customers counts on Usage
df['Usage'].value_counts().sort_index()

2    33
3    69
4    52
5    17
```

```
6     7
7     2
Name: Usage, dtype: int64

# Number of Single and Partnered customers
df['MaritalStatus'].value_counts()

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

Summary

- KP281, KP481, KP781 are the 3 different products
- Most commonly purchased treadmill product type is KP281
- There are 32 unique ages
- 104 Males and 76 Females are in the customers list
- 8 unique set of Educations (14, 15, 12, 13, 16, 18, 20, 21)
- Highest rated Fitness rating is 3
- Most customers usage treadmill atleast 3 days per week
- Majority of the customers who have purchased are Married/Partnered

conversion of categorical attributes to 'category'

```
# Converting Int data type of fitness rating to object data type
df_cat = df
df_cat['Fitness_category'] = df.Fitness
df_cat.head()

  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

   Miles  Fitness_category
0    112                 4
1     75                 3
2     66                 3
3     85                 3
4     47                 2
```

```
df_cat["Fitness_category"].replace({1:"Poor Shape",
                                    2:"Bad Shape",
                                    3:"Average Shape",
                                    4:"Good Shape",
                                    5:"Excellent Shape"},inplace=True)
df_cat.head()
```

```
  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

   Miles Fitness_category
0    112       Good Shape
1     75    Average Shape
2     66    Average Shape
3     85    Average Shape
4     47        Bad Shape
```

Categorization of **Fitness Rating** to following **descriptive categories**

1. Poor Shape
2. Bad Shape
3. Average Shape
4. Good Shape
5. Excellent Shape

```
df.describe()
```

```
              Age   Education       Usage     Fitness
Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000

mean    28.788889   15.572222    3.455556    3.311111   53719.577778

std      6.943498    1.617055    1.084797    0.958869   16506.684226

min     18.000000   12.000000    2.000000    1.000000   29562.000000

25%     24.000000   14.000000    3.000000    3.000000   44058.750000

50%     26.000000   16.000000    3.000000    3.000000   50596.500000
```

```
75%     33.000000   16.000000    4.000000    4.000000   58668.000000

max     50.000000   21.000000    7.000000    5.000000  104581.000000


            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

- Mean Age of the given customer dataset is 28.78
- Minimum Age of the customer starts from 18 and maximum age is 50
- 25% of the customers age is 24
- 75% of the customer age is 33
- Maximum Education qualification is 21, with most frequent education as 16
- Average usage per week for a customer is 3 days
- Average Fitness rating is 3 with most common fitness rating is 4
- Average Income of the purchased customer is around 54K per year
- Highest salary recorded for the customer is around 104K per year
- Maximum distance covered by the customer in treadmill is 360 miles
- Most of the customers cover a distance of 114 miles with an average of 103 miles
- Around 25% of the customer cover an average of 66 miles

Statistical Summary

```
# for unique list of products, listed in percentage
sr = df['Product'].value_counts(normalize=True)
stat = sr.map(lambda calc: round(100*calc,2))
stat

KP281    44.44
KP481    33.33
KP781    22.22
Name: Product, dtype: float64
```

- **44.44%** of customers bought **KP281** product type
- **33.33%** of customers bought **KP481** product type
- **22.22%** of customers bought **KP781** product type

```
# Customer Gender statistics (listed in %)
gender = df['Gender'].value_counts(normalize=True)
gender_res = gender.map(lambda calc: round(100*calc,2))
gender_res

Male      57.78
Female    42.22
Name: Gender, dtype: float64
```

- **57.78%** of customers are **Male** and **42.22%** customers are **Female**

```
# Customers Marital Status (listed in %)
marital_status = df['MaritalStatus'].value_counts(normalize=True)
marital_status_res = marital_status.map(lambda calc:round(100*calc,2))
marital_status_res

Partnered    59.44
Single       40.56
Name: MaritalStatus, dtype: float64
```

- **59.44%** of customers are **Married/Partnered**
- **40.56%** of customers are **Single**

```
# Usage: Number of days used per week (listed in %)
usage = df['Usage'].value_counts(normalize=True).map(lambda
calc:round(100*calc,2)).reset_index()
usage.rename(columns={'index':'DaysPerWeek'},inplace=True)
usage

   DaysPerWeek  Usage
0            3  38.33
1            4  28.89
2            2  18.33
3            5   9.44
4            6   3.89
5            7   1.11
```

- **Around 39%** of customers use **3 days per week**
- **Less than 2%** of customers use **7 days per week**

```
# Customer rating of their fitness (listed in %)
rating = df['Fitness'].value_counts(normalize=True).map(lambda
calc:round(100*calc,2)).reset_index()
rating.rename(columns={'index':'Rating'},inplace=True)
rating
```

```
   Rating  Fitness
0       3    53.89
1       5    17.22
2       2    14.44
3       4    13.33
4       1     1.11
```

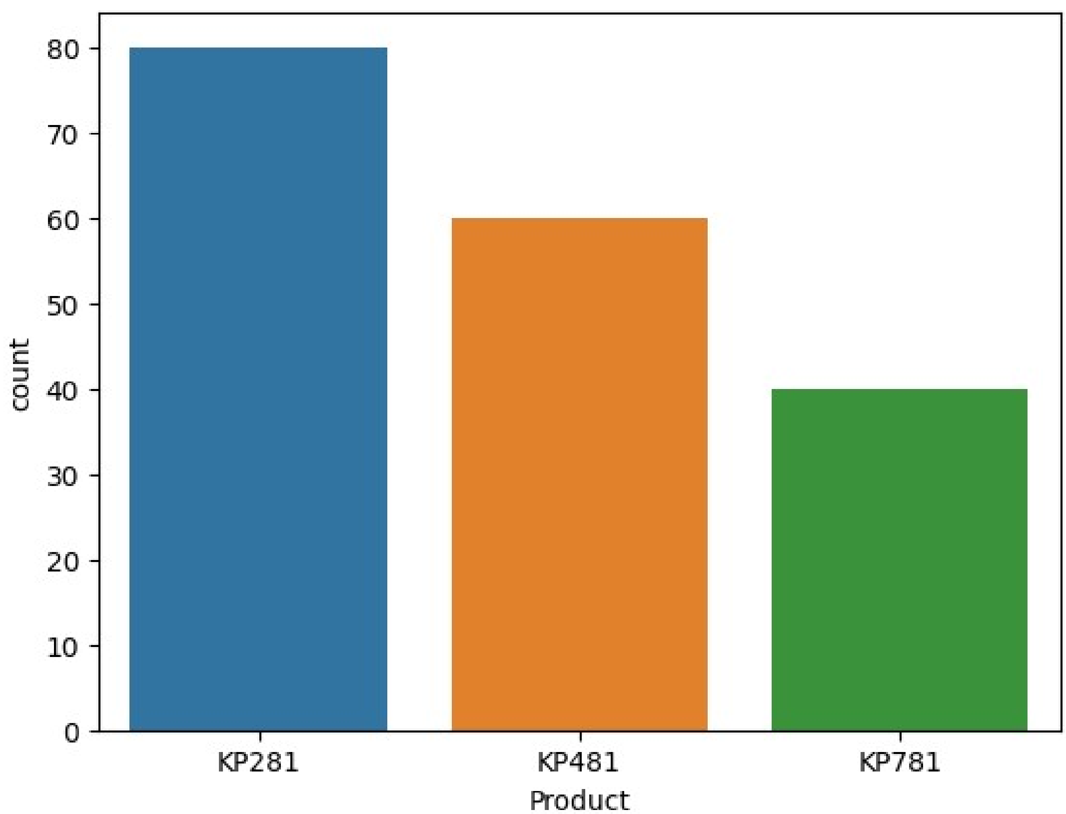
- **More than 53%** of customers have rated themselves as **average in fitness** (rated 3)
- **14%** of customers have rated their fitness less than average
- **Over 17%** of customers have **peak fitness ratings**

Visual Analysis - Univariate & Bivariate

Univariate Analysis

For Continous Variable(s):Distplot, countplot, histogram for univariate analysis

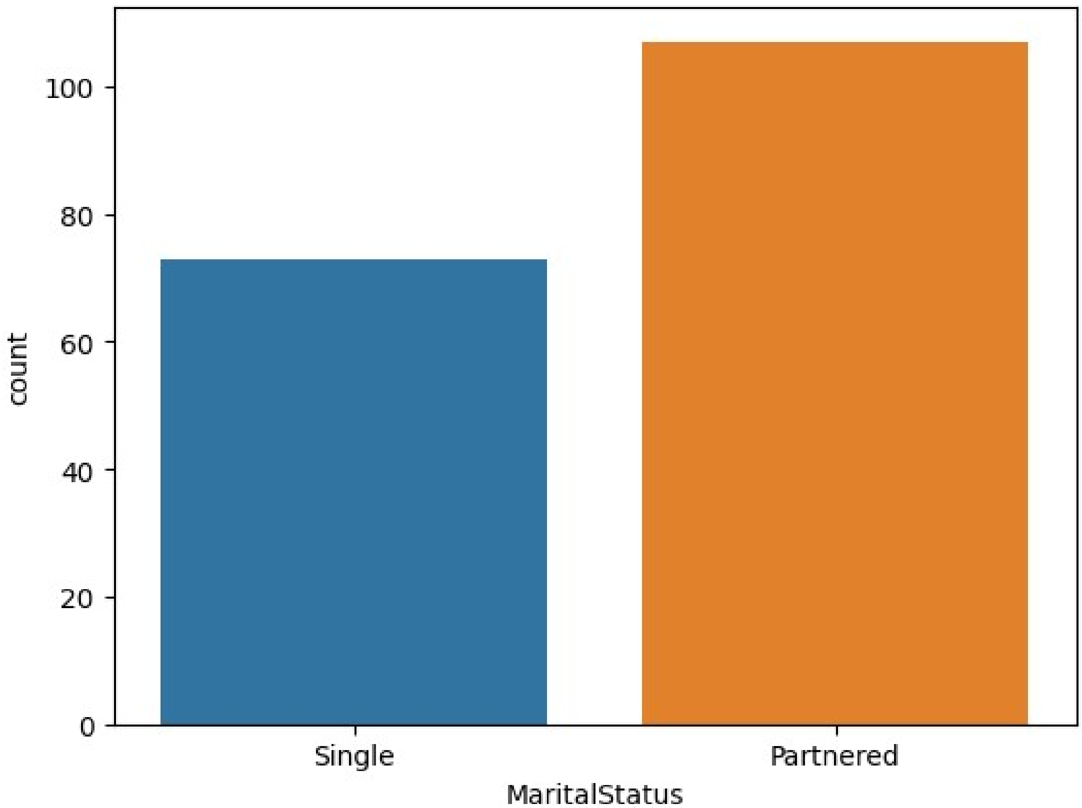
```
# Product Analysis - count plot
sns.countplot(data=df,x='Product')
plt.show

<function matplotlib.pyplot.show(close=None, block=None)>
```



- **KP281** is the most commonly purchase product type

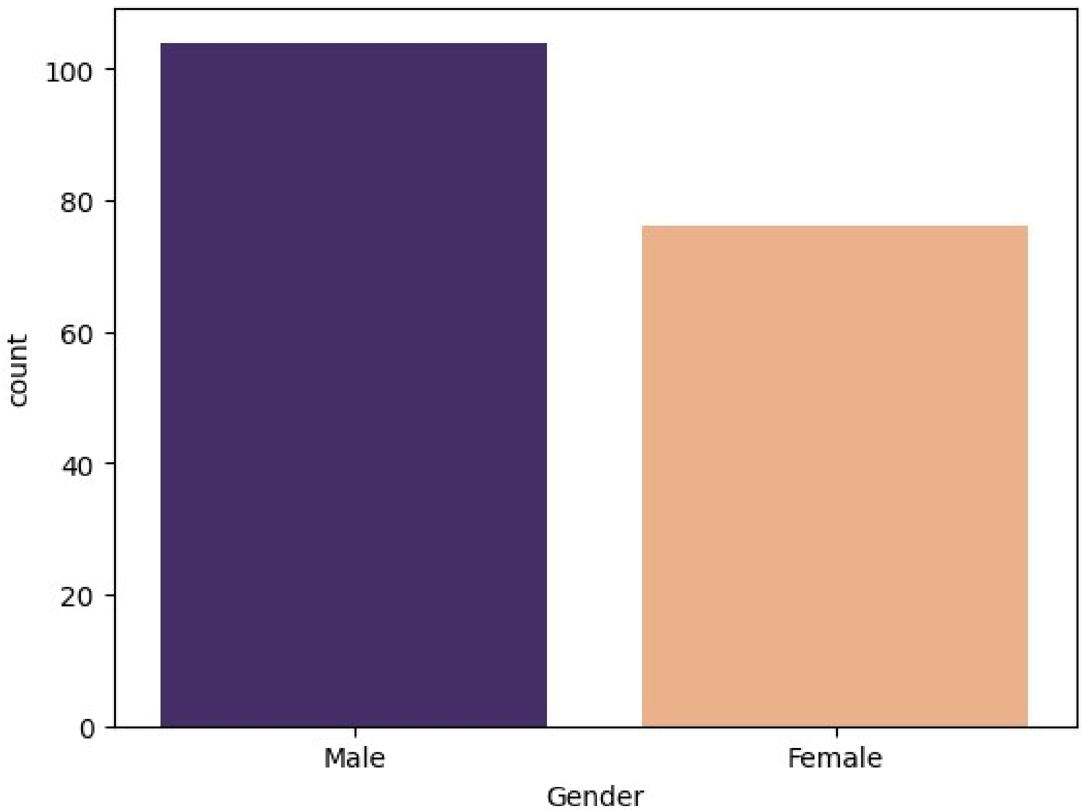
- **KP481** is the second most top product type purchased
- **KP781** is the least purchased product type

```
# Marital Status Analysis - Count plot
sns.countplot(data=df,x='MaritalStatus')
plt.show()
```



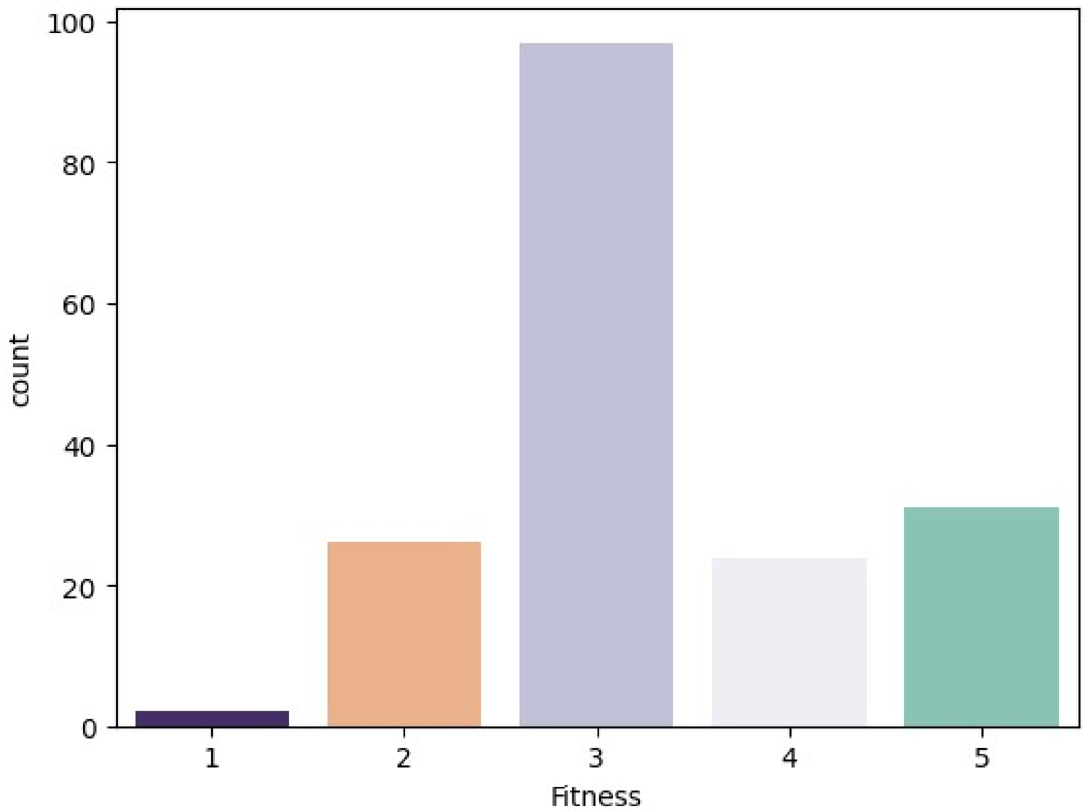
- Most products purchased by **couples/Married/Partnered** customer category

```
# Gender Analysis - Count Plot
sns.countplot(data=df,x='Gender',palette=['#432371',"#FAAE7B"])
plt.show

<function matplotlib.pyplot.show(close=None, block=None)>
```



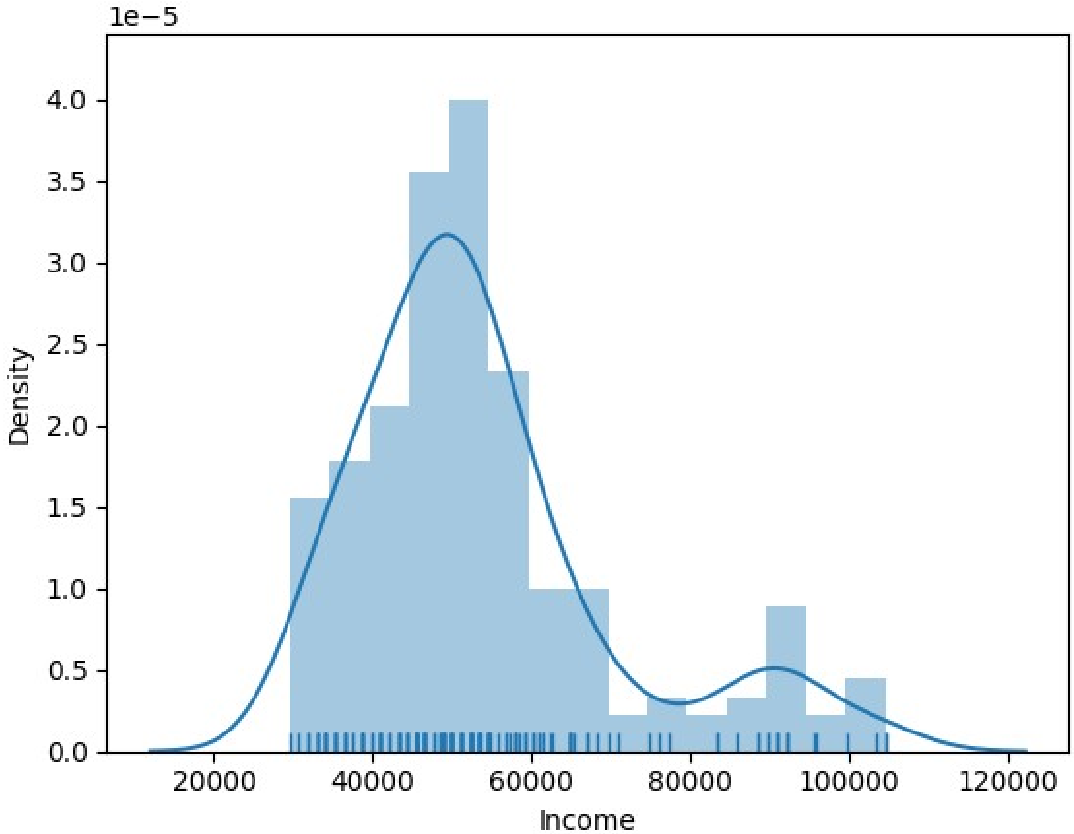
- Most products purchased by Males, females are less interested in the product compared to Males

```
# Fitness rating analysis - count plot
sns.countplot(data=df,x='Fitness',palette=['#432371',"#FAAE7B","#bcbddc", "#efedf5",'#7fcdbb'])
plt.show

<function matplotlib.pyplot.show(close=None, block=None)>
```



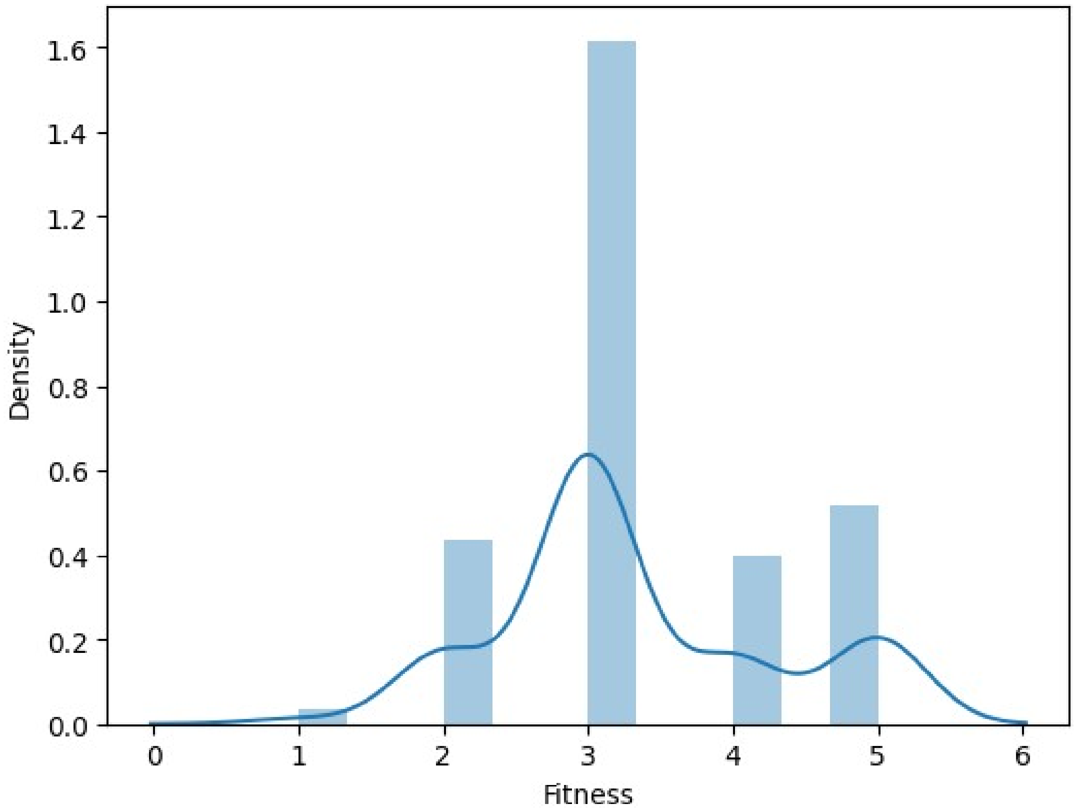
- More than 90 customers have rated their physical fitness rating as **Average**
- **Excellent shape is the second highest** rating provided by the customers

```
# Income Analysis - Distplot
sns.distplot(df.Income,rug=True)
plt.show()
```



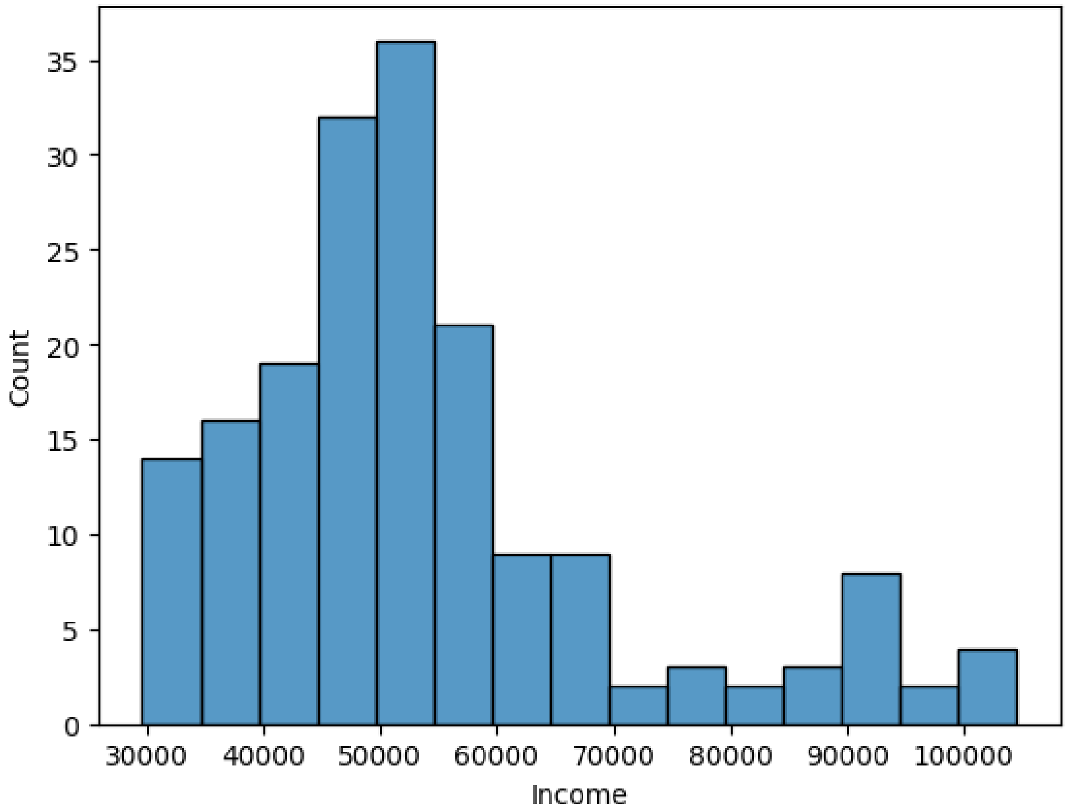
- Most of customers who have purchased the product have a **average income between 40K to 60K**
- Average Income density is over 3.0

```
# Fitness Rating Analysis - Distplot
sns.distplot(df.Fitness)
plt.show()
```



- Over 1.5 density customer population have rated their physical fitness rating as **Average**
- Second highest customer population density have rated Excellent shape as their fitness rating

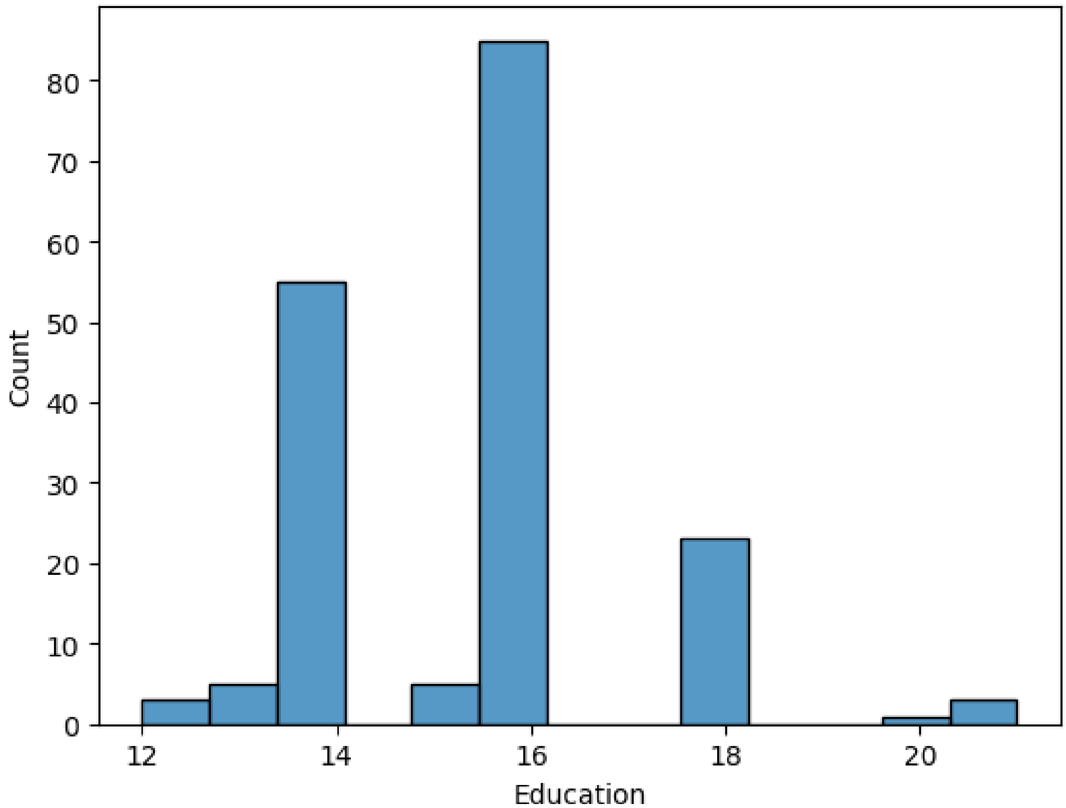
```
# Income Analysis - Histogram
sns.histplot(data=df,x='Income')

<Axes: xlabel='Income', ylabel='Count'>
```



- More than 35 customers earn 50-55K per year
- More than 30 customers earn 45-50K per year
- More than 20 customers earn 55-60K per year

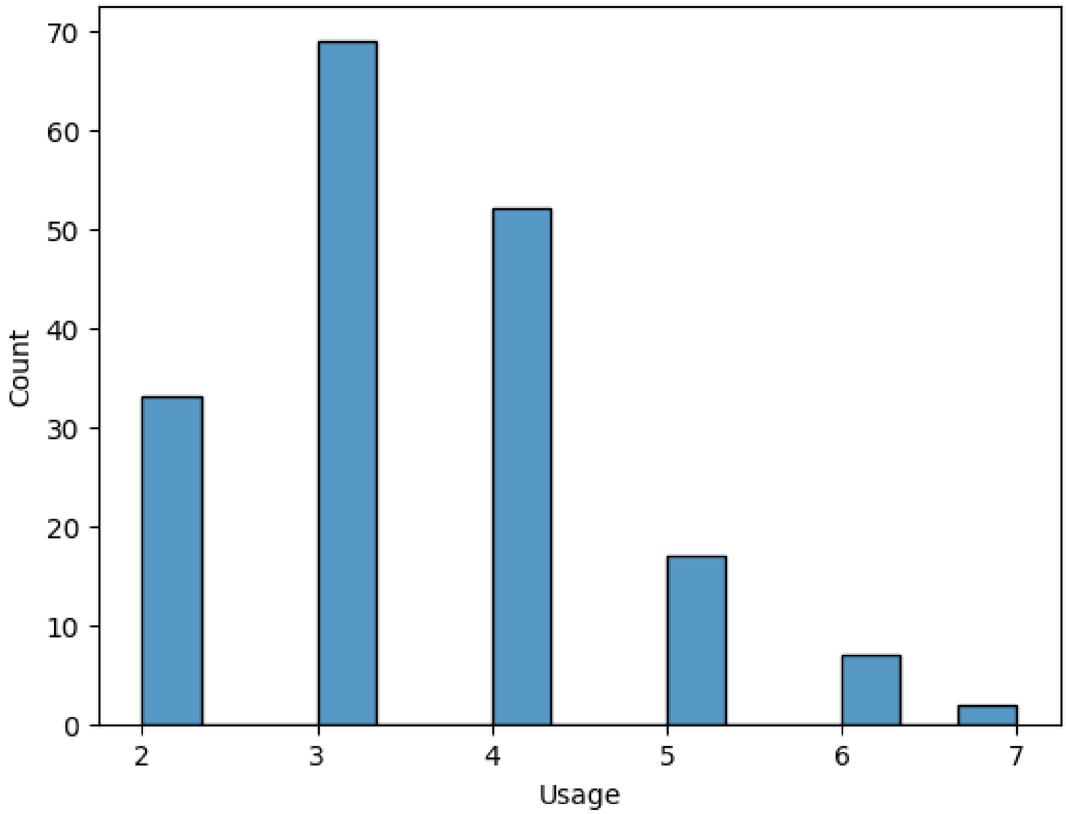
```
# Education Analysis - Histogram
sns.histplot(data=df,x='Education')
```

```
<Axes: xlabel='Education', ylabel='Count'>
```



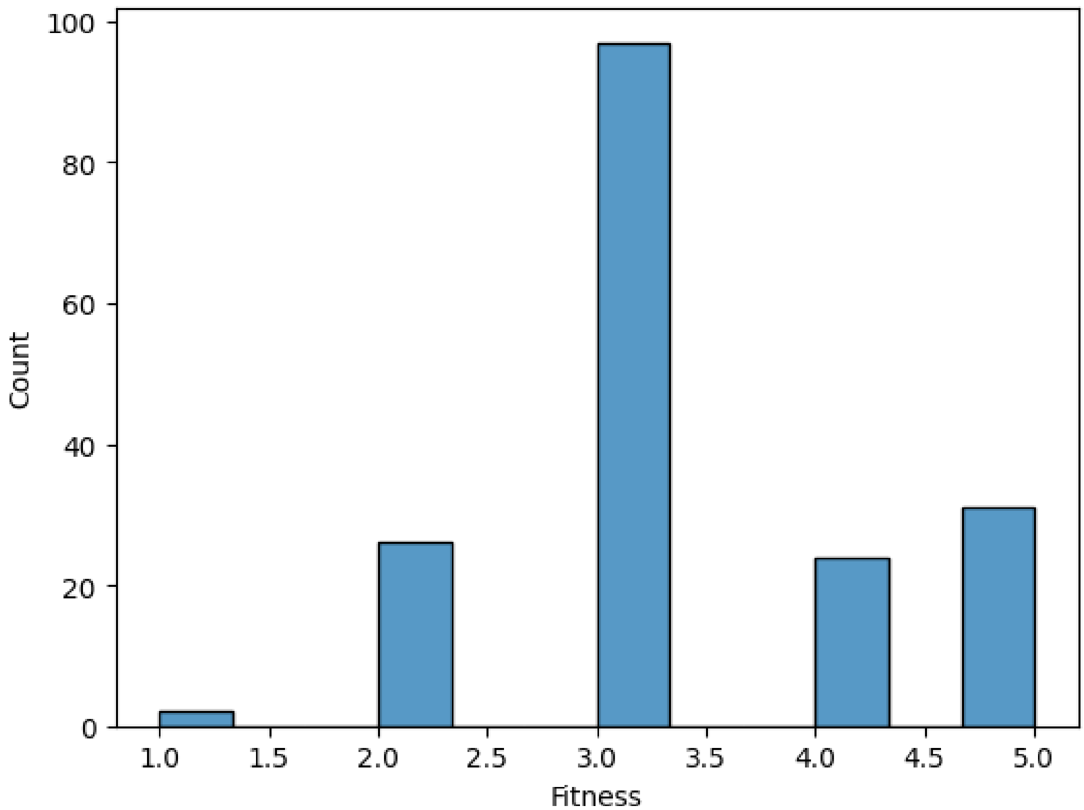
- Highest number of customers have 16 as their Education
- 14 is the second highest education among the customers
- 20 is the least education among the customers

```
# Usage Analysis - Histogram
sns.histplot(data=df,x='Usage')

<Axes: xlabel='Usage', ylabel='Count'>
```



- 3 days per week is the most common usage among the customers
- 4 days and 2 days per week is the second and third highest usage among the customers
- Very few customers use product 7 days per week

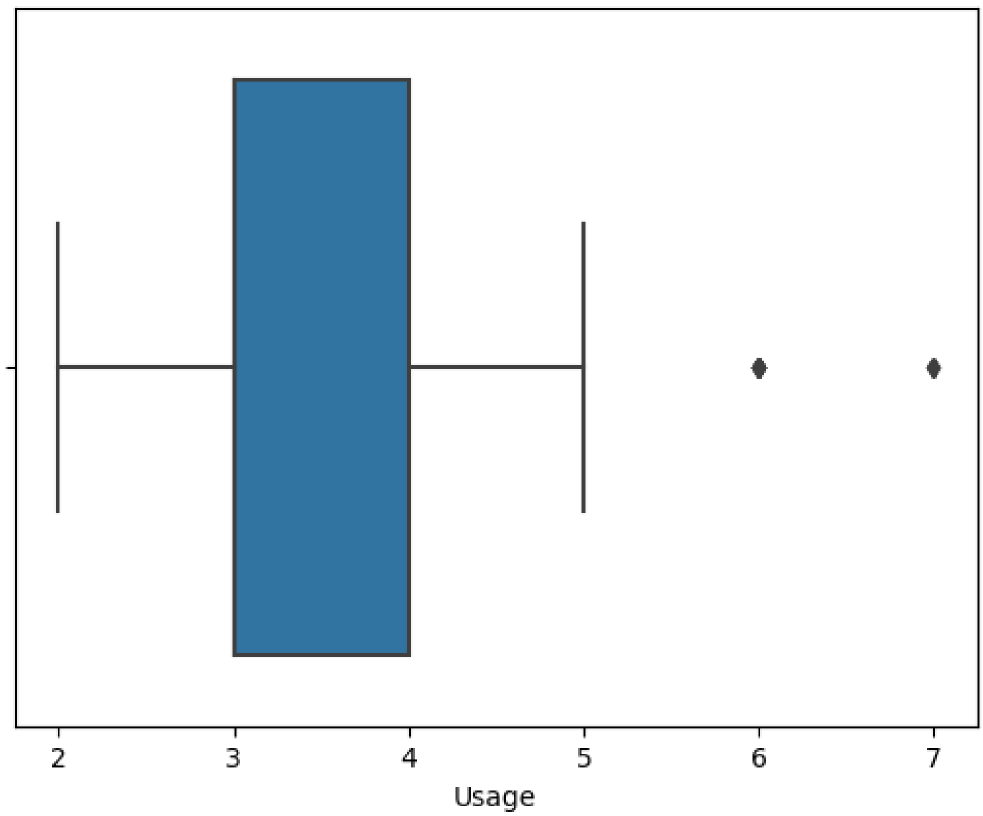
```
# Fitness Analysis - Histogram
sns.histplot(data=df,x='Fitness')

<Axes: xlabel='Fitness', ylabel='Count'>
```



- Average shape is the most rating customers have given for fitness rating
- Around 40 customers have stated Excelled Shape as fitness rating

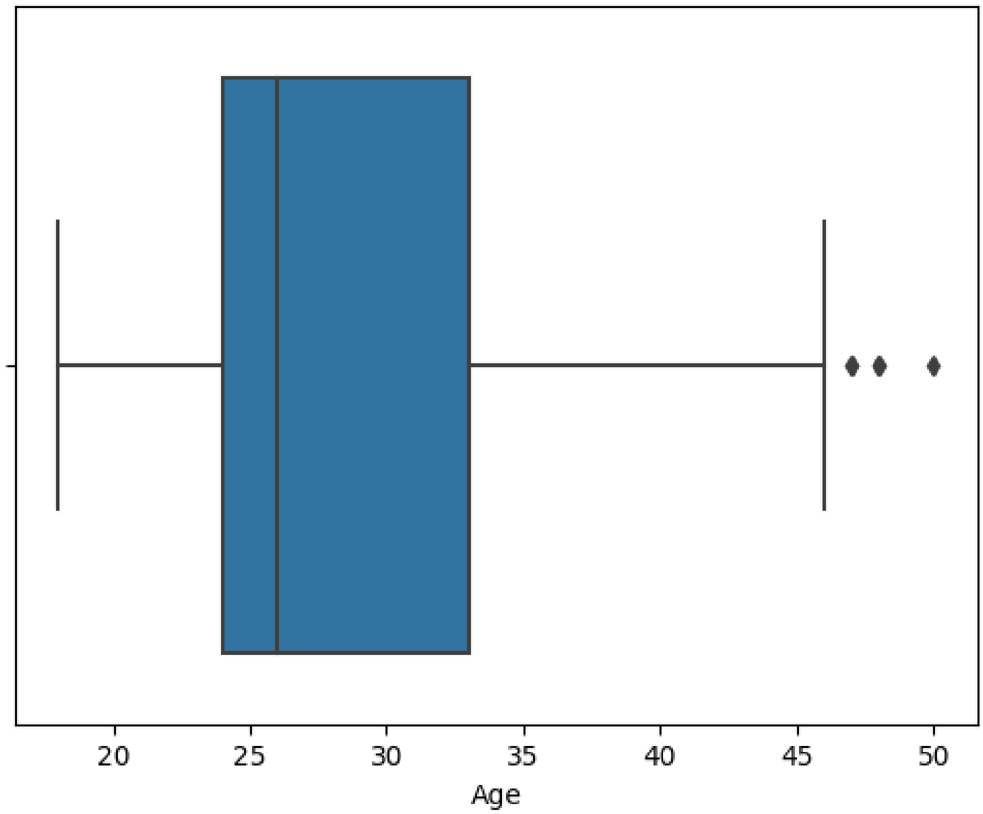
For categorical variable(s): Boxplot

```
# Usage Analysis - Box plot
sns.boxplot(data=df,x='Usage')
plt.show()
```



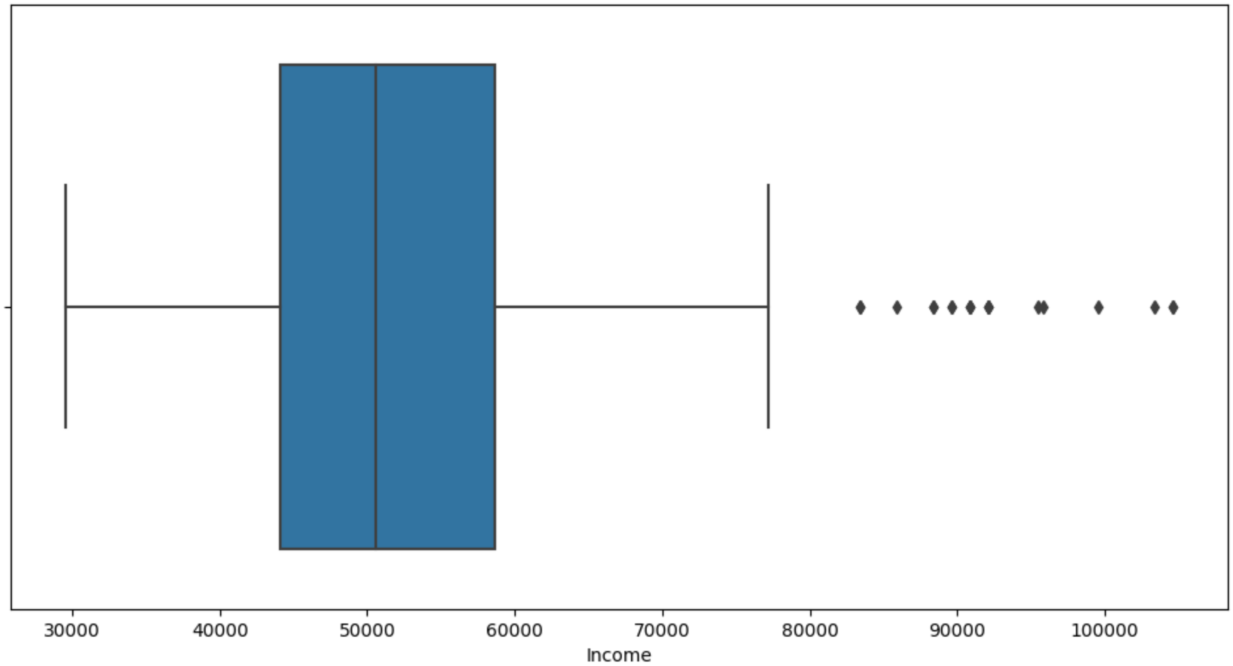
- 3 to 4 days is the most preferred usage days for customers
- 6 and 7 days per week is roughly the usage days for few customers (**Outliers**)

```
# Age Analysis - Box plot
sns.boxplot(data=df,x='Age')
plt.show()
```



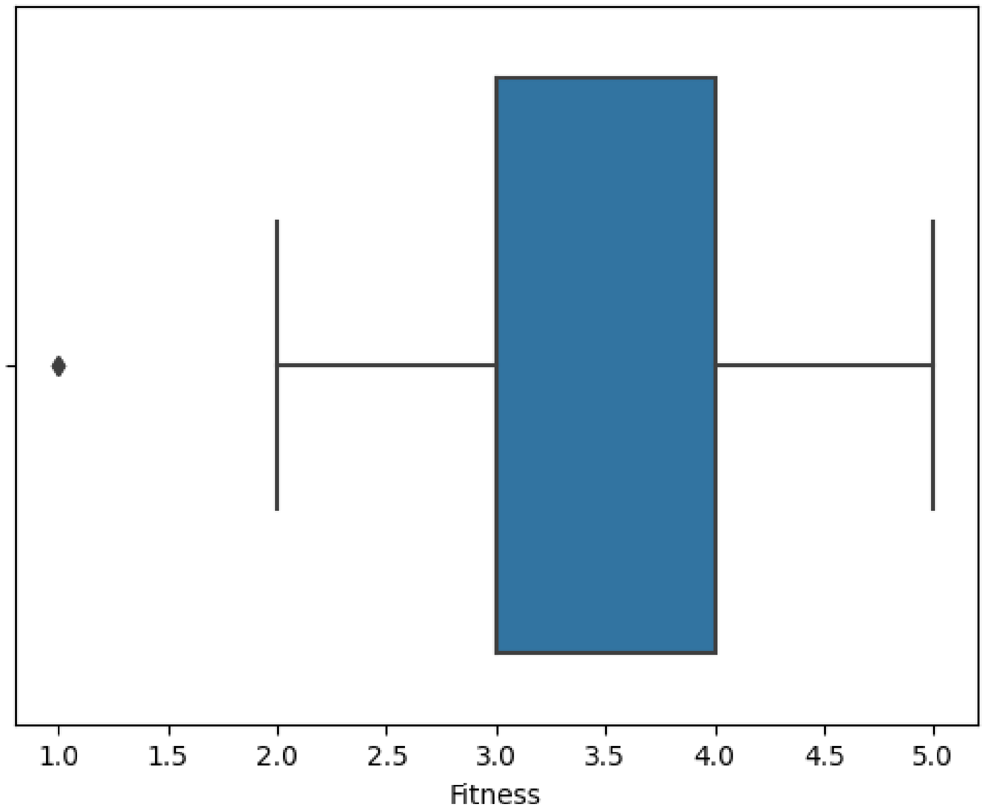
- 23 to 34 is the most common customer age group that has purchased the product
- Above 45 years old customers are very few compared to the young age group given in the dataset

```
# Income Analysis - Box plot
plt.figure(figsize=(12,6))
sns.boxplot(data=df,x='Income')
plt.show()
```



- Few customers have income above 80K per annum(Outliers)
- Most customers earn from 45K to around 60K per annum

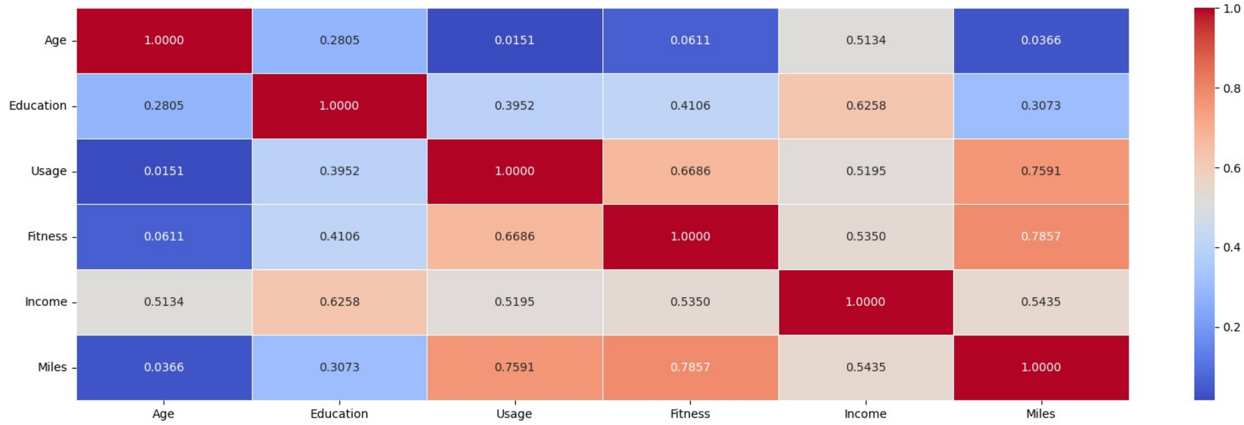
```
# Fitness Rating Analysis - Box plot
sns.boxplot(data=df,x='Fitness')
plt.show()
```



- Couple of customers have rated their fitness rating as 1 - Poor Shape
- Most customers have rated fitness rating as 3.0 to 4.0

For correlation: Heatmaps, Pairplots

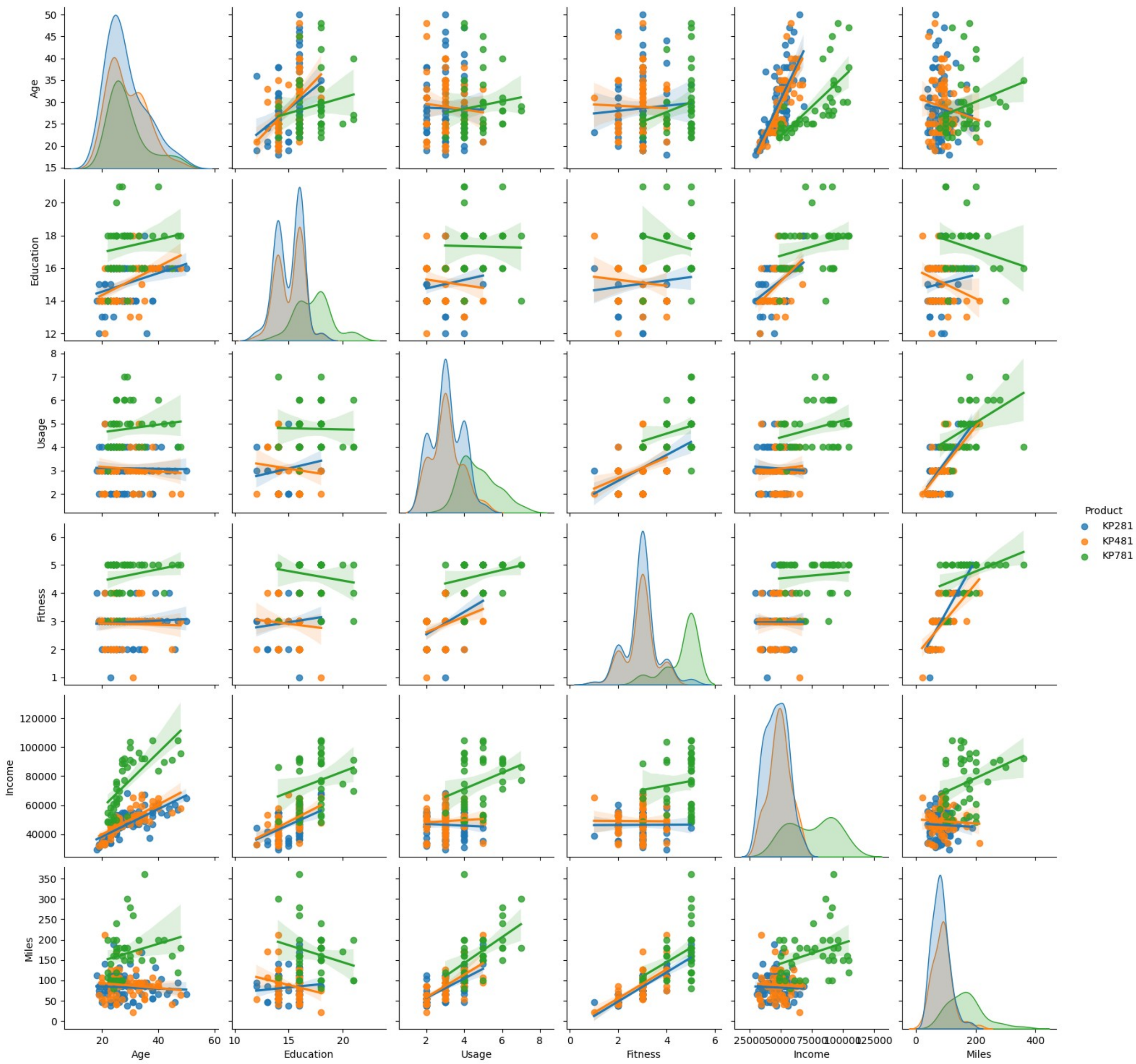
```
#Correlation HeatMap
plt.figure(figsize=(20,6))
ax =
sns.heatmap(df.corr(),annot=True,fmt='.4f',linewidths=.5,cmap='coolwar
m')
plt.yticks(rotation=0)
plt.show()
```



In the above heatmap linear relationship between data points is evaluated

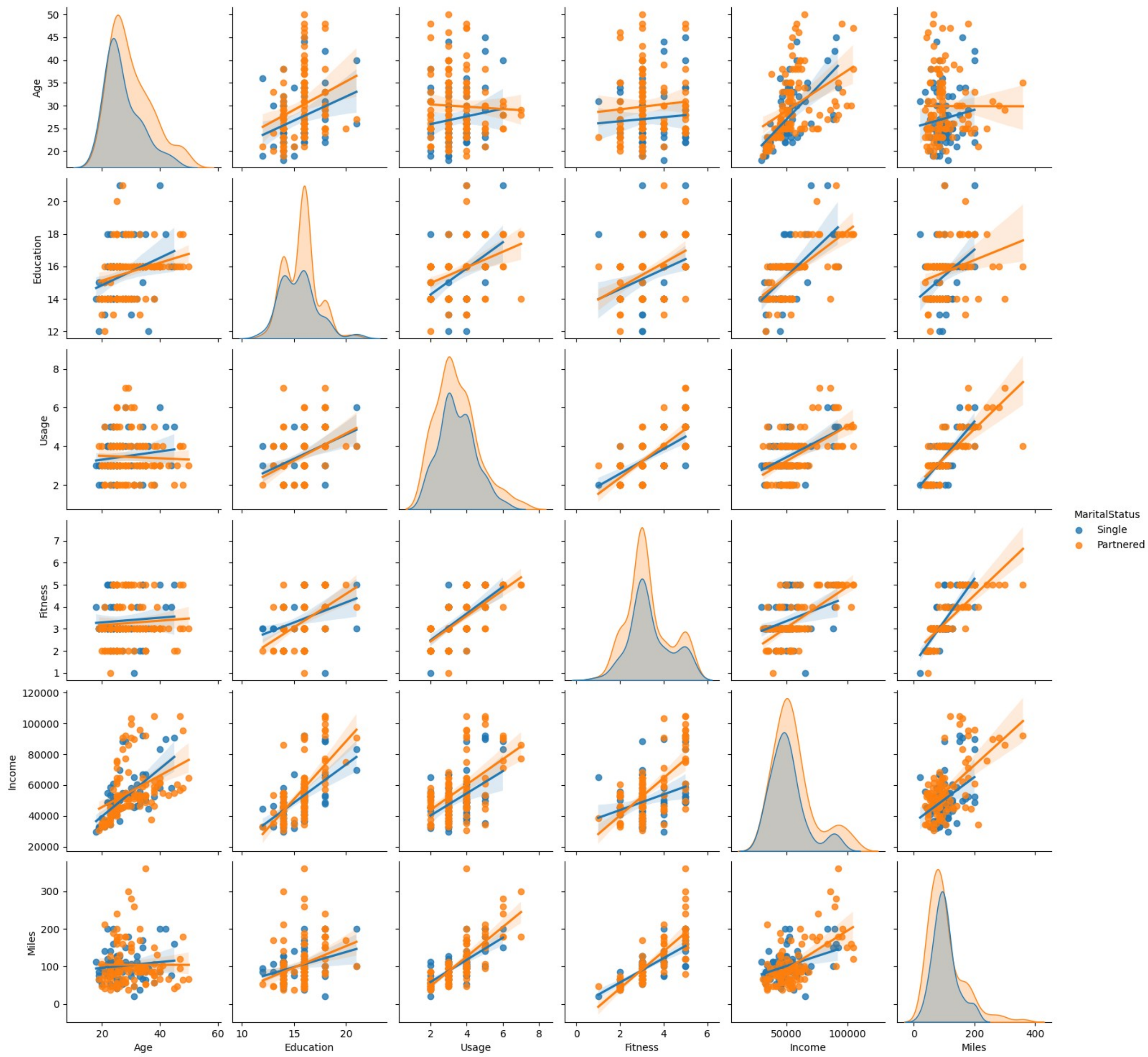
- Correlation between Age and Miles is 0.03
- Correlation between Education and Income is 0.62
- Correlation between Usage and Fitness is 0.66
- Correlation between Fitness and Age is 0.06
- Correlation between Income and Usage is 0.51
- Correlation between Miles and Age is 0.03

```
# Product Analysis - Pair Plot
sns.pairplot(df,hue='Product',kind='reg')
plt.show()
```



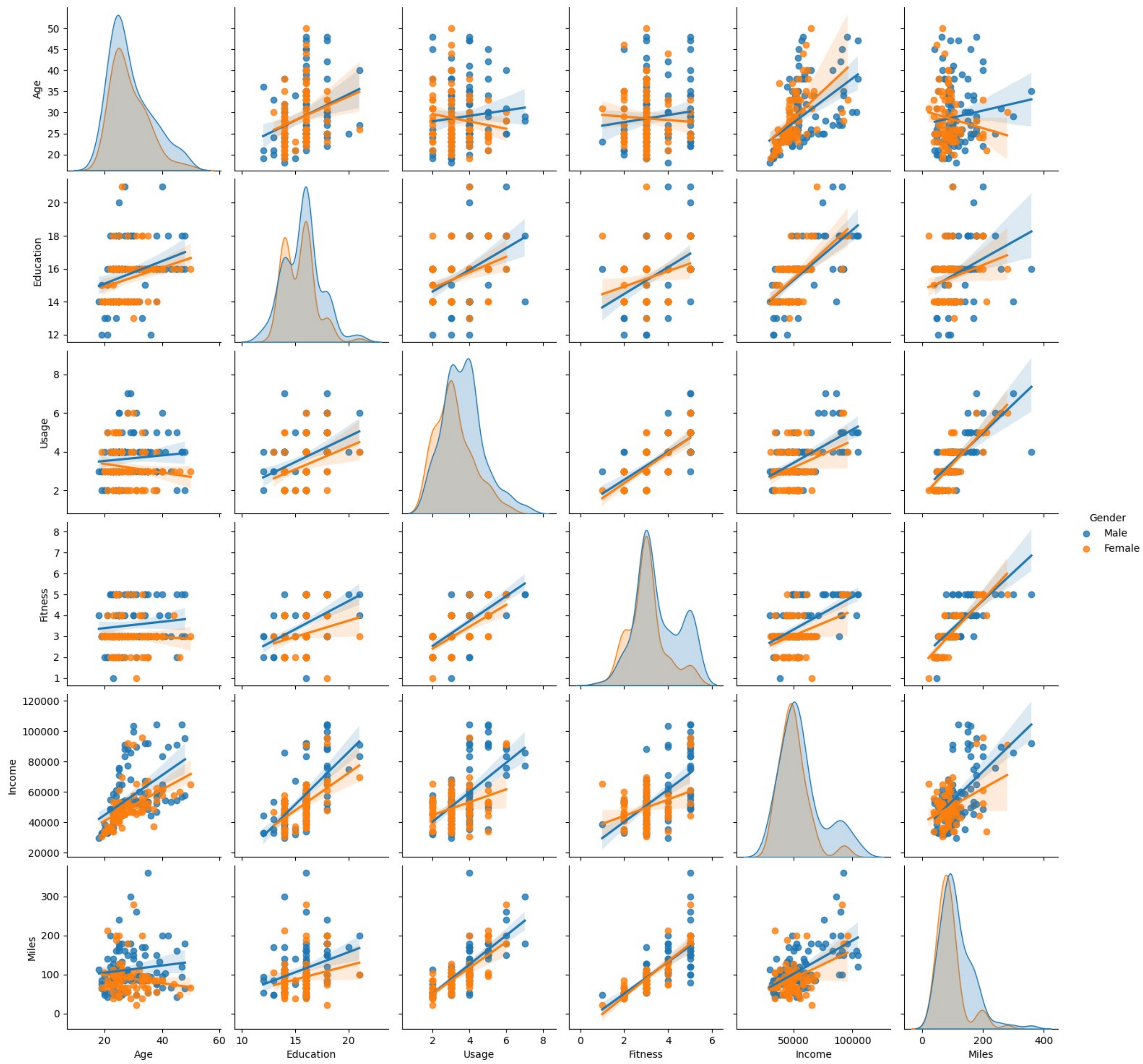
In the above pairplot the correlation with products and different attributes are as similar to previous observation

```
# Marital Status - pair plot
sns.pairplot(df,hue='MaritalStatus',kind='reg')
plt.show()
```



In the above pair plot the correlation with other attributes are pivotted around the marital status of the customer

```
# Gender Analysis - Pair Plot
sns.pairplot(df,hue='Gender',kind='reg')
plt.show()
```



Here the pair plot's correlation is same as the above mentioned heatmap

Bivariate Analysis

```
# Average usage of each product type by the customer
df.groupby('Product')['Usage'].mean()

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

- Mean usage for product KP281 is 3.08
- Mean usage for product KP481 is 3.06
- Mean usage for product KP781 is 4.77

```
# Average Age of customer using each product
df.groupby('Product')['Age'].mean()
```

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

- 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

```
# Average Education of customer using each product
df.groupby('Product')['Education'].mean()
```

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

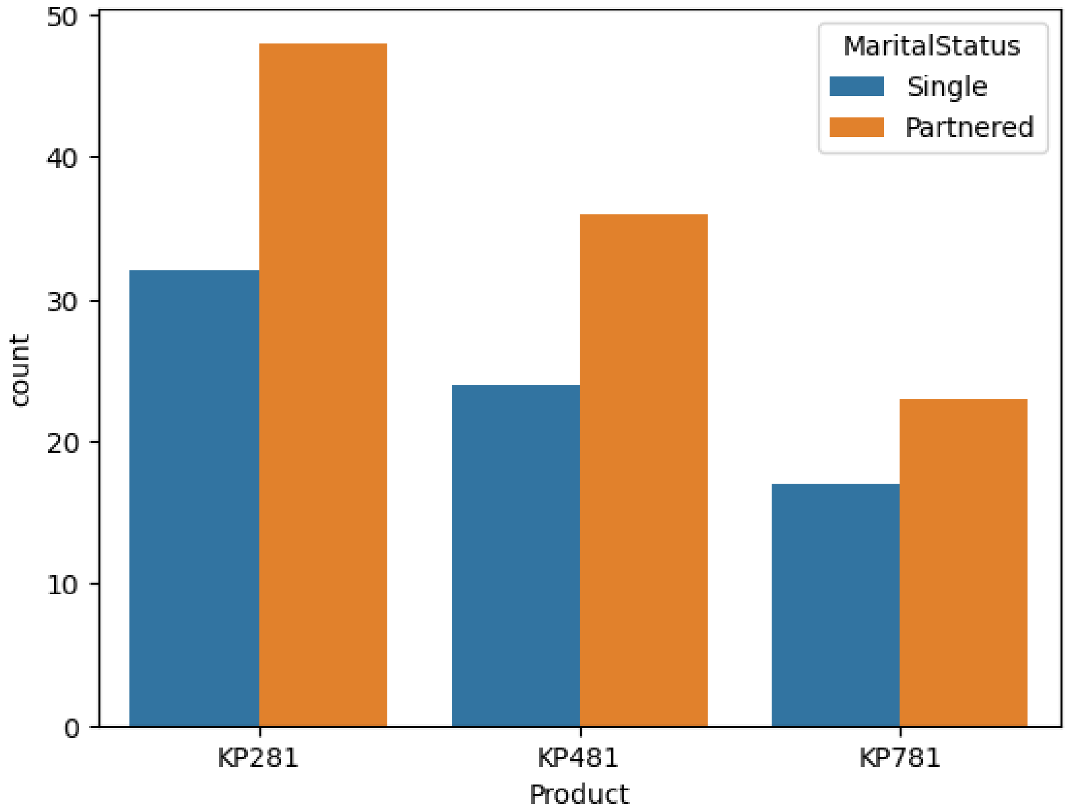
- Mean Education qualification of the customer who purchased product KP281 is 15.03
- Mean Education qualification of the customer who purchased product KP481 is 15.11
- Mean Education qualification of the customer who purchased product KP781 is 17.32

```
# Average customer fitness rating for each product type purchased
df.groupby('Product')['Fitness'].mean()
```

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

- 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

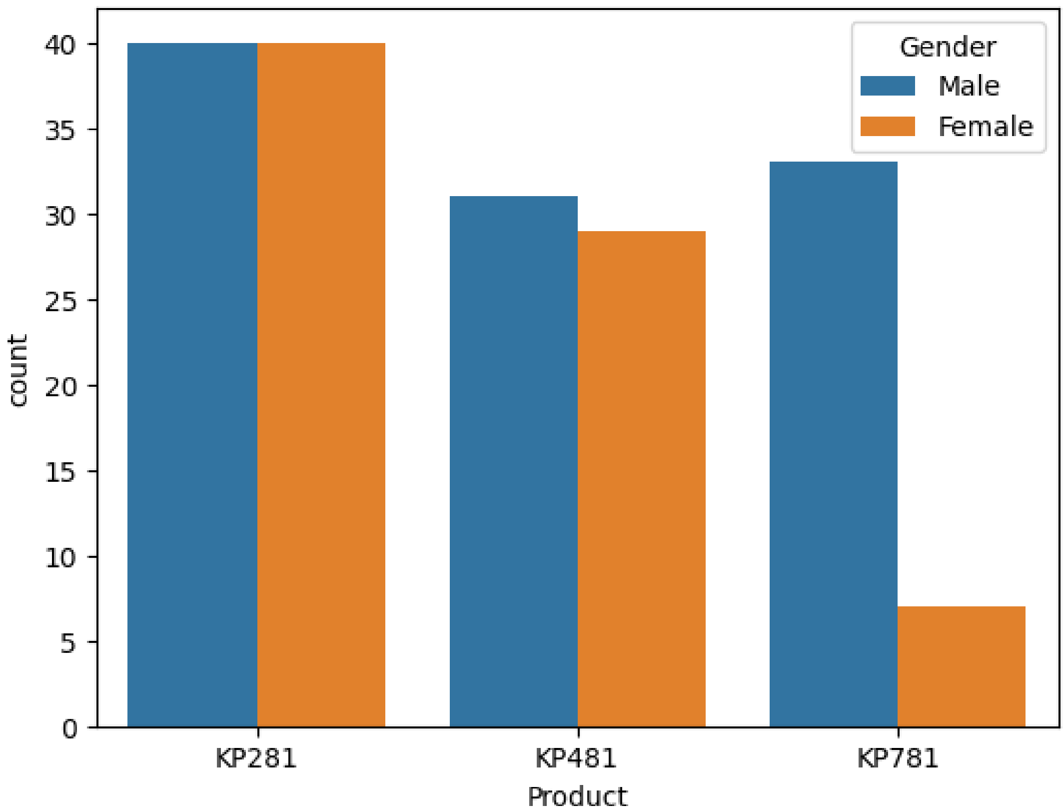
```
# Product purchased among Married/Partnered and Single
sns.countplot(data=df,x='Product',hue='MaritalStatus')
plt.show()
```



From the above countplot

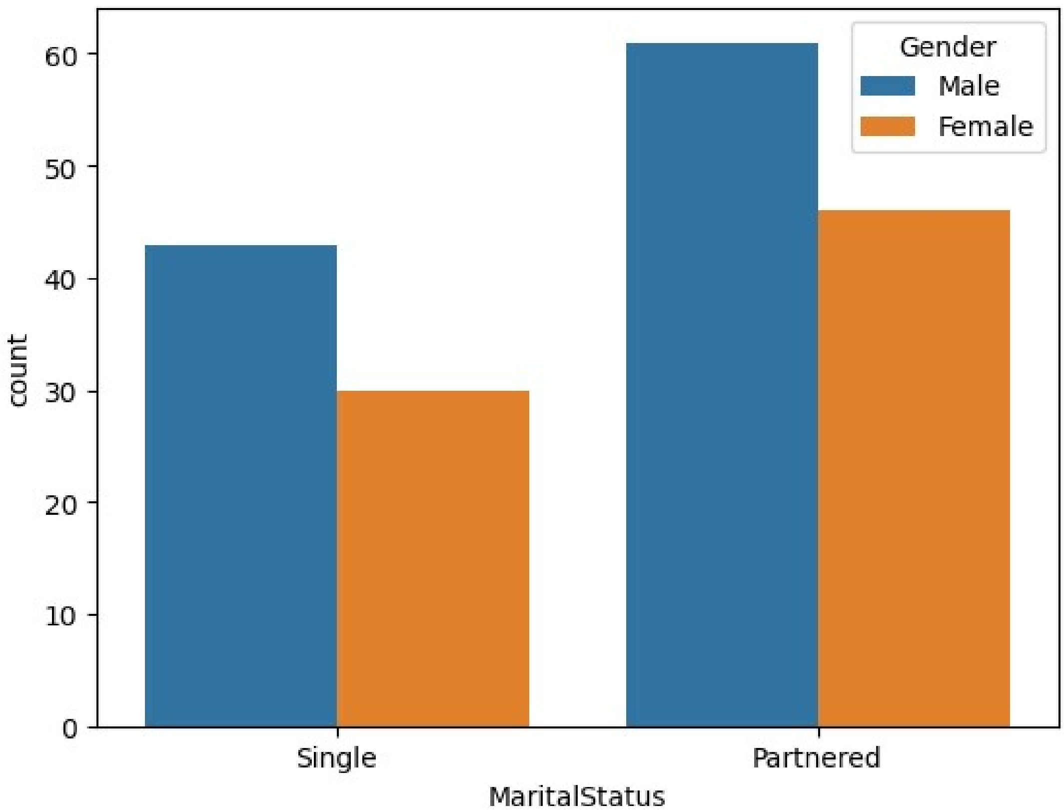
- KP281 is the most preferred product among customers
- KP481 is the second most preferred product among the customers
- Between Singles and Partnered, Partnered customers are the major product purchasers

```
# Product purchased among Male and Female
sns.countplot(data=df,x='Product',hue='Gender')
plt.show()
```



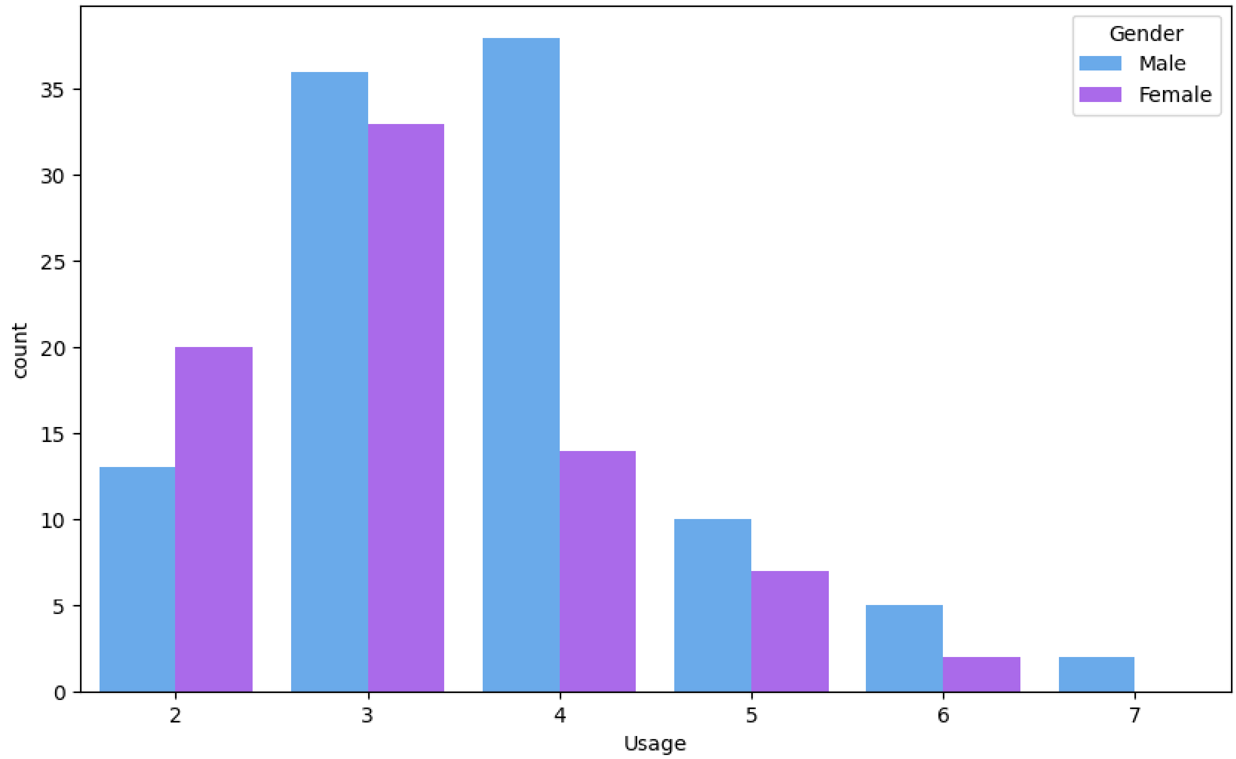
- KP281 Product is the equally preferred by both male and female genders
- KP781 Product is mostly preferred among the Male customers
- Overall Male customers are the highest product purchasers

```
# Count among Gender and their Marital Status
sns.countplot(data=df,x='MaritalStatus',hue='Gender')
plt.show()
```



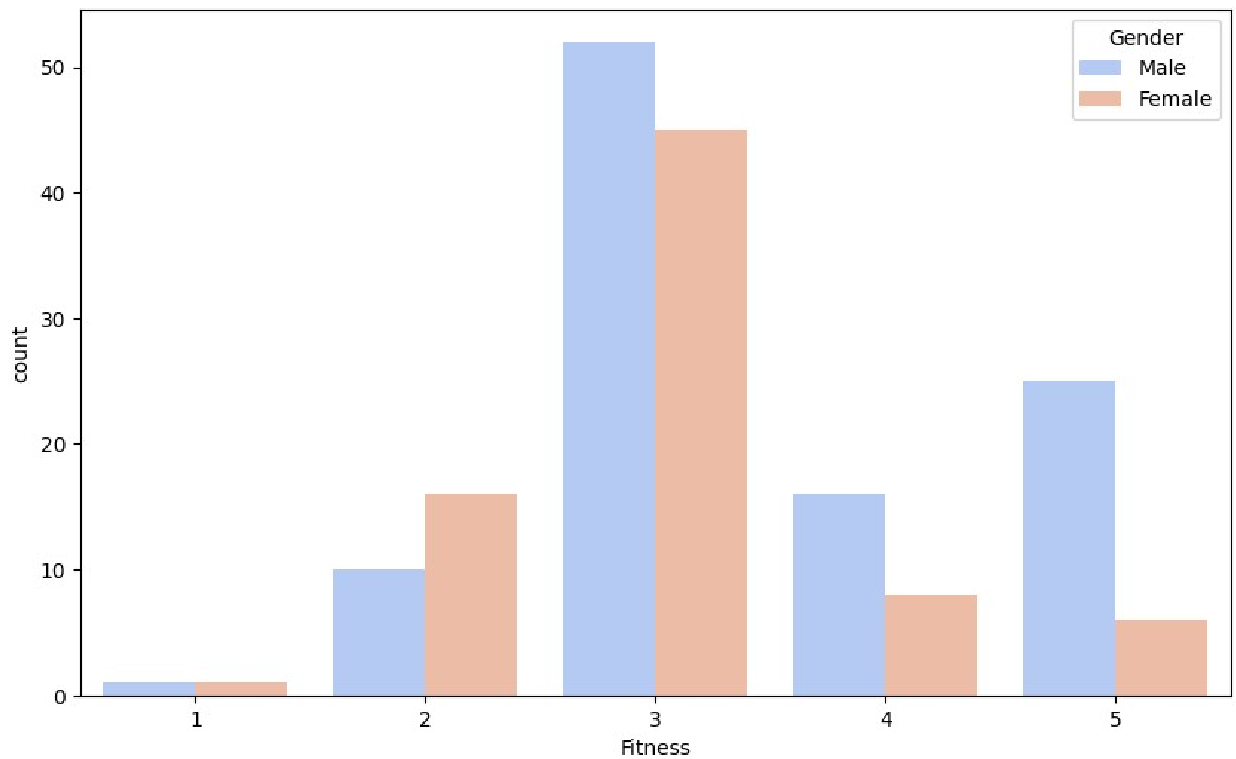
- Partnered customers are the most buyers of aerofit product
- Out of both Single and Partnered customers, Male customers are significantly high
- Female customers are considerably low compared to Male customers

```
# Purchased product usage among Gender
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='Usage',hue='Gender',palette='cool')
plt.show()
```



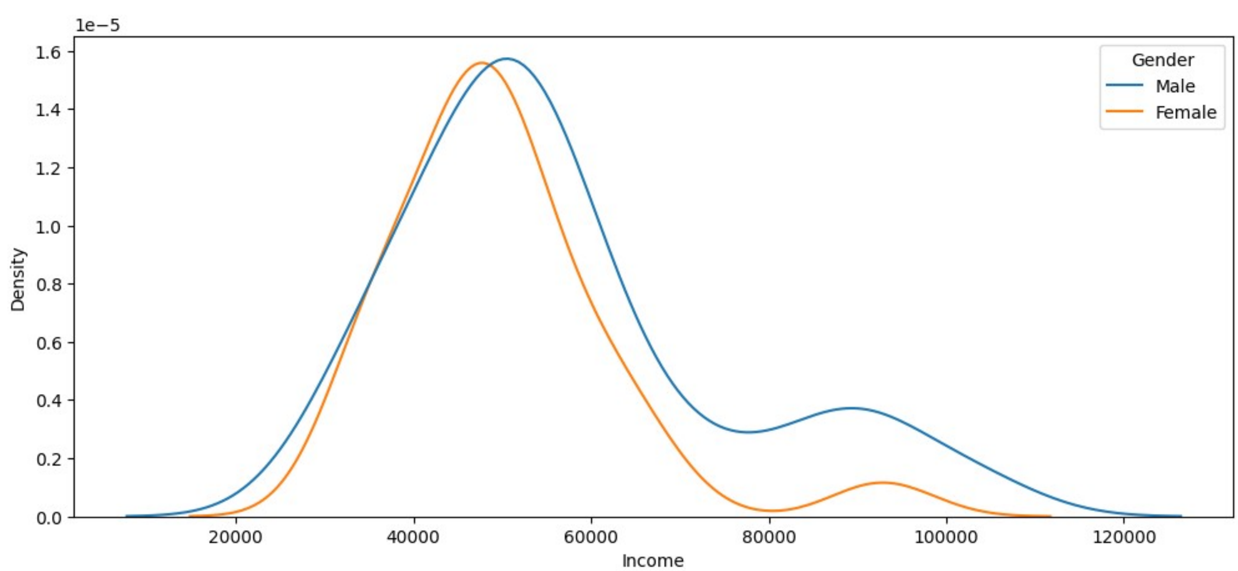
- Among Male and Female genders, Male's usage is 4 days per week
- Female customers mostly use 3 days per week
- Only few Male customers use 7 days per week whereas female customer's maximum usage is only 6 days per week

```
# Fitness rating among the customers categorised by Gender
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='Fitness',hue='Gender',palette='coolwarm')
plt.show()
```



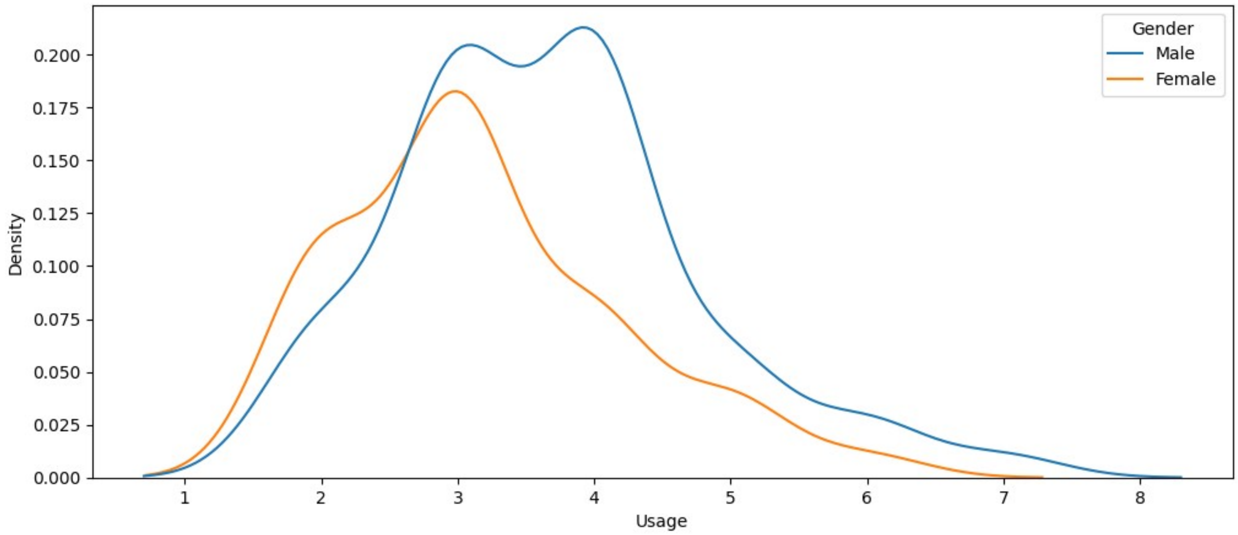
- Among the fitness rating both Male and Female most have rated as average
- Significant number of Male customers are at Excellent shape compared to Female customers

```
# Product purchased Customers Income and their Gender
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Income',hue='Gender')
plt.show()
```



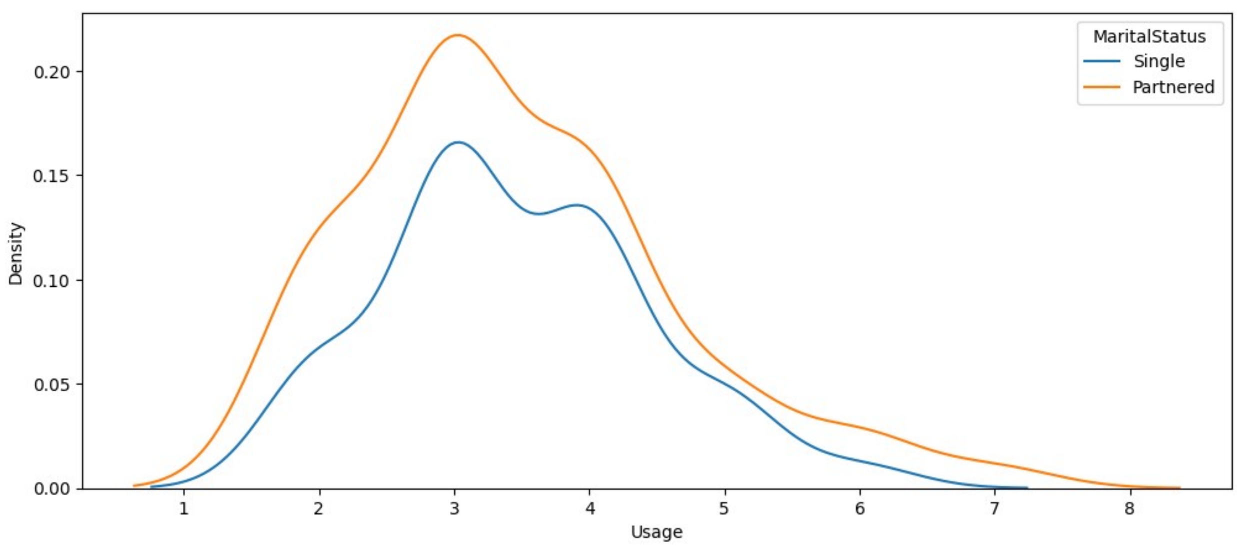
From the above diagram, we can conclude the spike from 40K to around 80K is the most common income per annum of the customers

```
# Product purchased Customers Usage per week and their Gender
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Usage',hue='Gender')
plt.show()
```



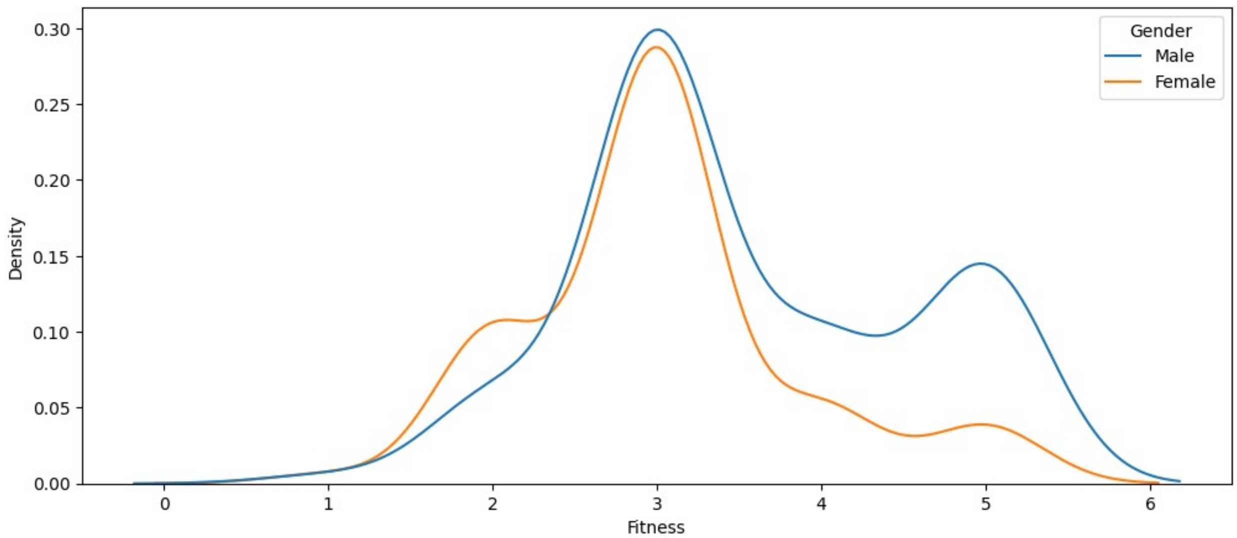
- Male customers usage is significantly higher the female customer
- Female customer's lack consistency after the 3 days per week

```
# Product purchased Customers Usage per week and their Marital Status
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Usage',hue='MaritalStatus')
plt.show()
```



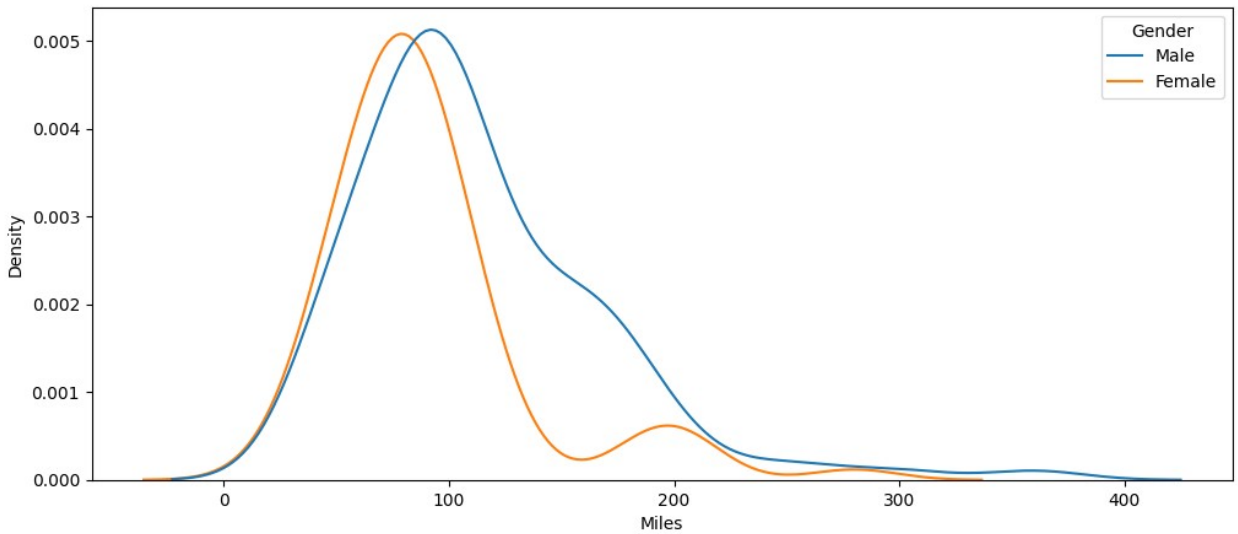
- Partnered customers usage is higher than single customers
- Partnered customers also have greater consistency per week of 7 days per week than single customers

```
# Product purchased Customers Fitness Rating and their Gender
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Fitness',hue='Gender')
plt.show()
```



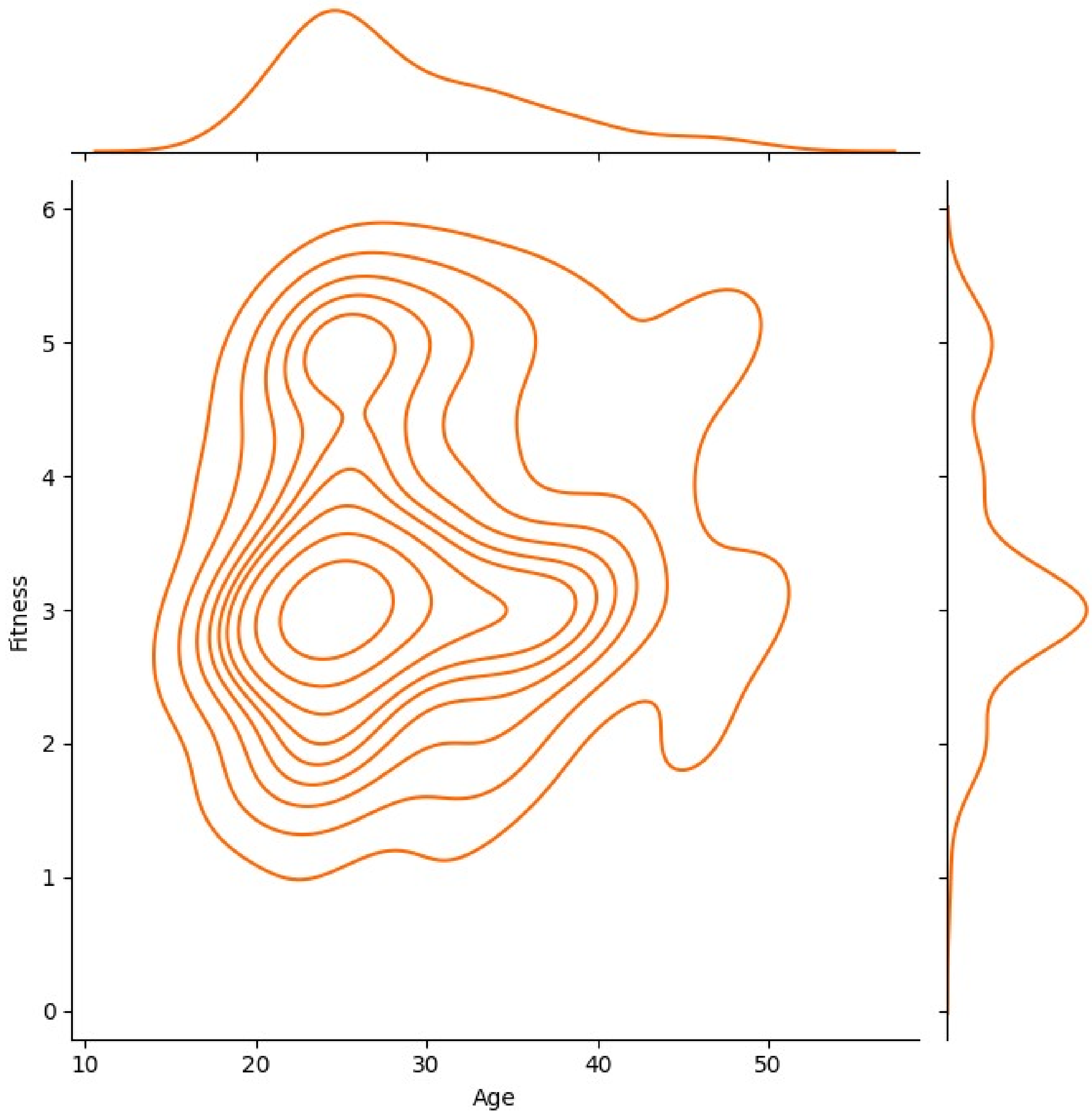
- Male customers are in better shape the female customers
- Though Female customers do not have poor shape, they are also not in excellent shape
- Some Male customers excellent body shape and few customers have poor shape as well

```
# Distance covered by each Gender among the customers
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Miles',hue='Gender')
plt.show()
```



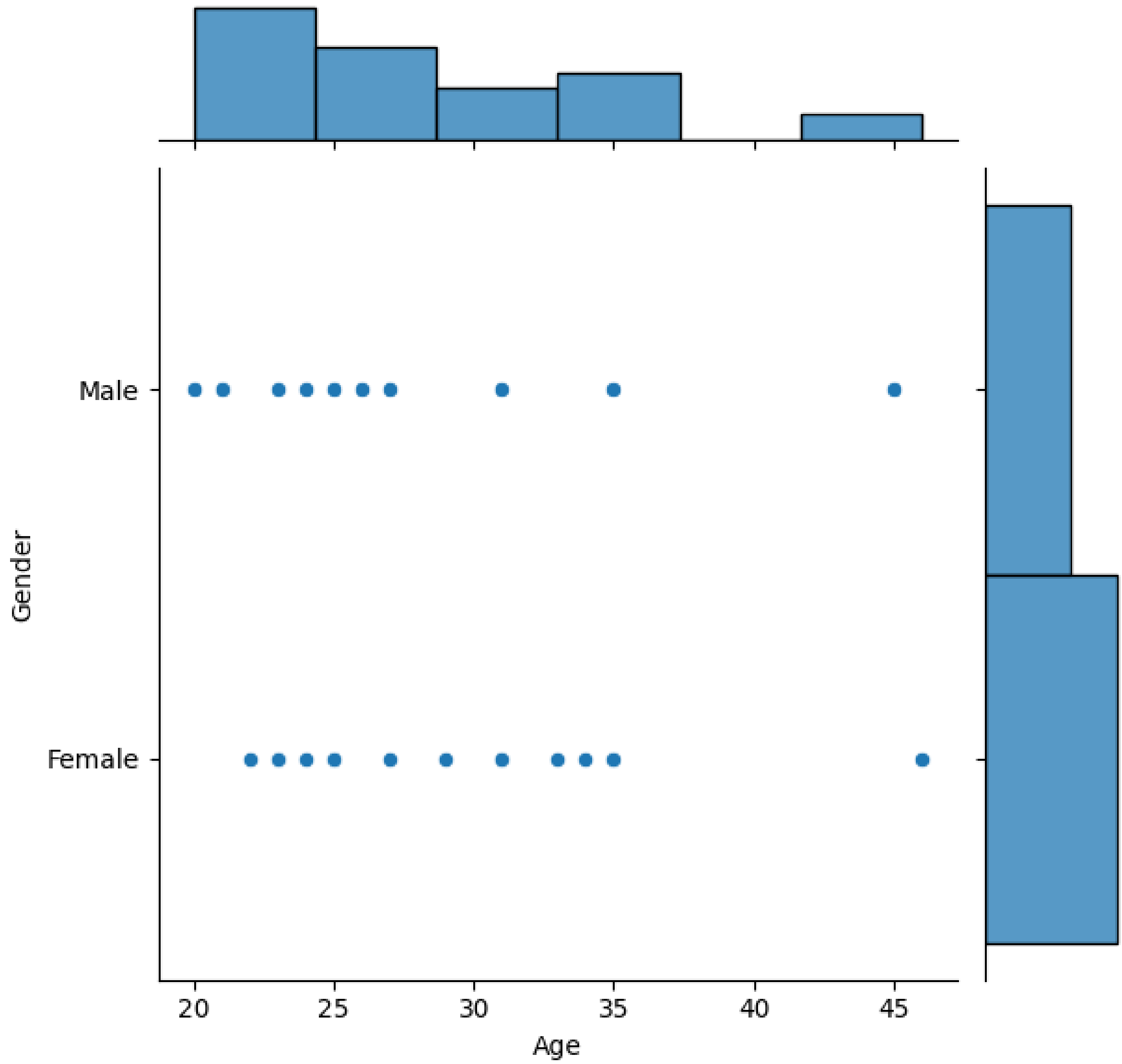
- Male customers have a consistent distance coverage than female customers
- Female customers have max distance covered as just over 300 miles

```
# Joint Histogram with KDE plot
sns.jointplot(x="Age", y="Fitness", data=df,height =
7,kind="kde",color="#FF6600")
plt.show()
```



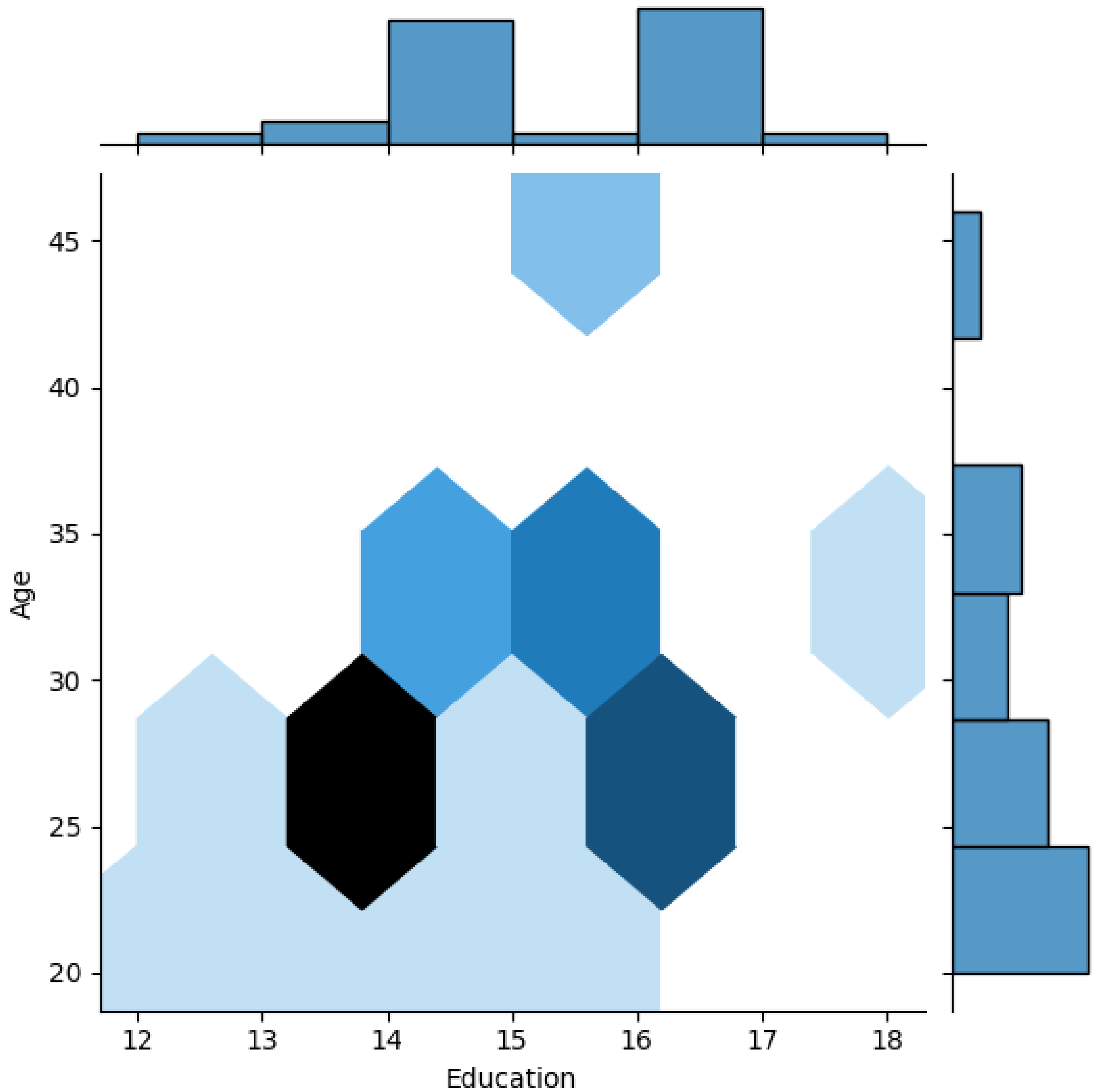
- Majority of the customer Age group is between 20 to mid 30s who have rated atleast average

```
# Scatterplot for customers Gender and Age who rated less than 2 in Fitness rating
sns.jointplot(x='Age',y='Gender',data=df[df.Fitness<3])
plt.show()
```



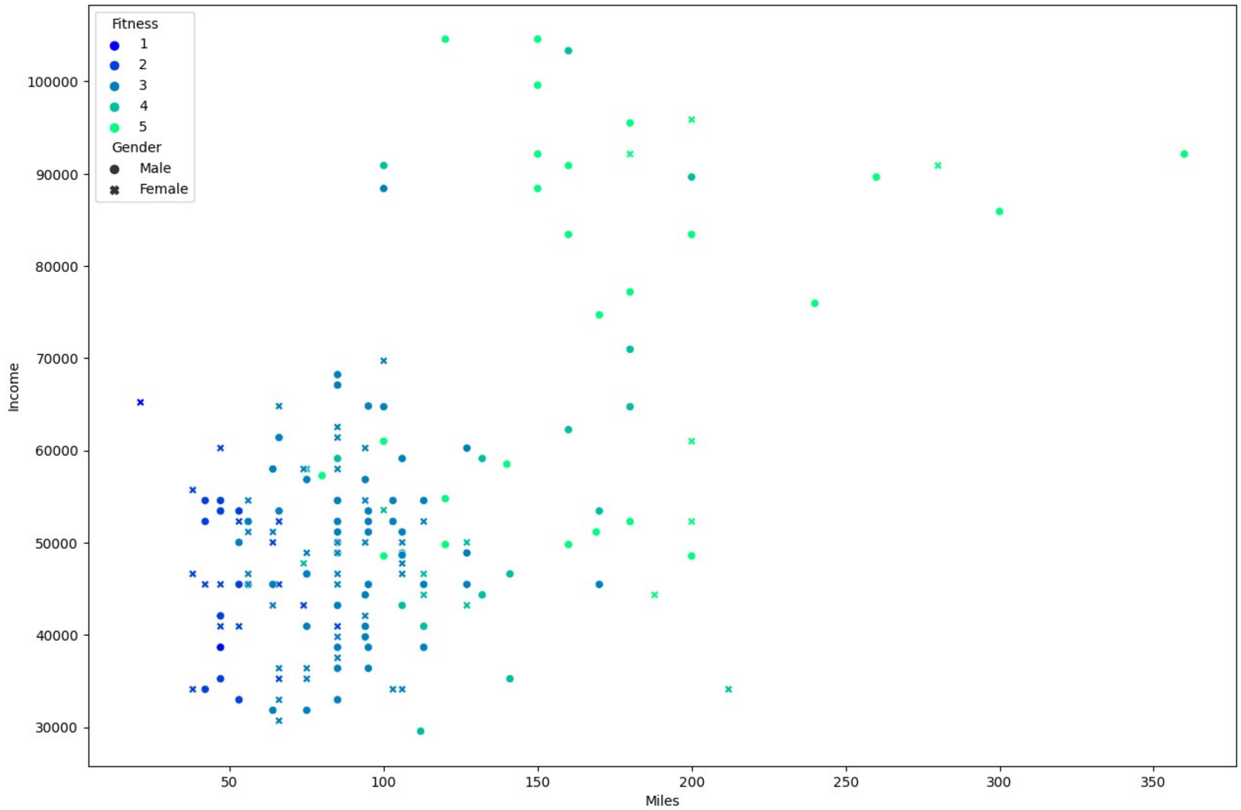
- Above Joint plot describes the relationship between the customer age and their gender grouping.
- Product is not familiar with older or middle age womens

```
# Hex Scatterplot for customers Education and Age who rated less than 2 in Fitness rating
sns.jointplot(x='Education',y='Age',kind='hex',data=df[df.Fitness<3])
plt.show()
```



- Majority of the age and education density falls on 25-30 age group and 13-14 education

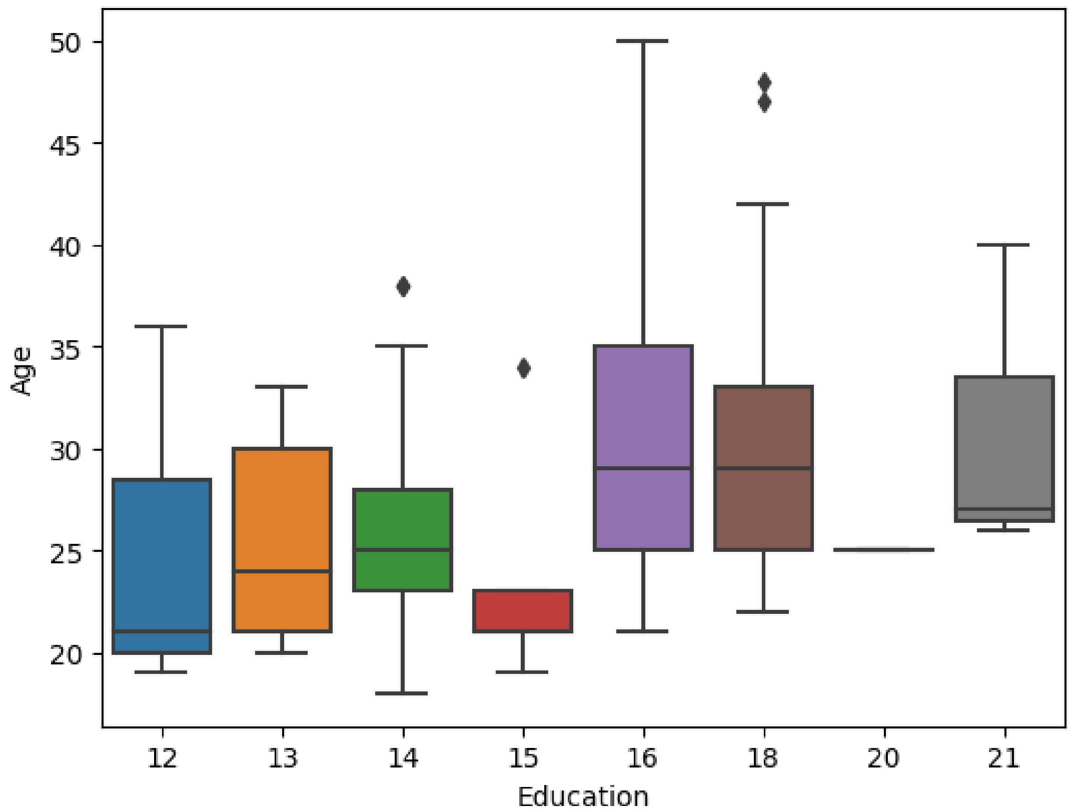
```
# Scatter Plot
plt.figure(figsize=(15,10))
sns.scatterplot(x='Miles',y='Income',data=df,hue='Fitness',style='Gend
er',palette='winter')

<Axes: xlabel='Miles', ylabel='Income'>
```



- Above scattered Plot shows the overall picture over customer's income, how much they exercise (run/walk miles) given their gender and their fitness level.
- Most of the customer's fitness level is around 3 to 4 . and it says people who run more miles are having good fitness level.
- Though there is a trend with income and miles. But there are very few customers who earn a lot and run more miles.

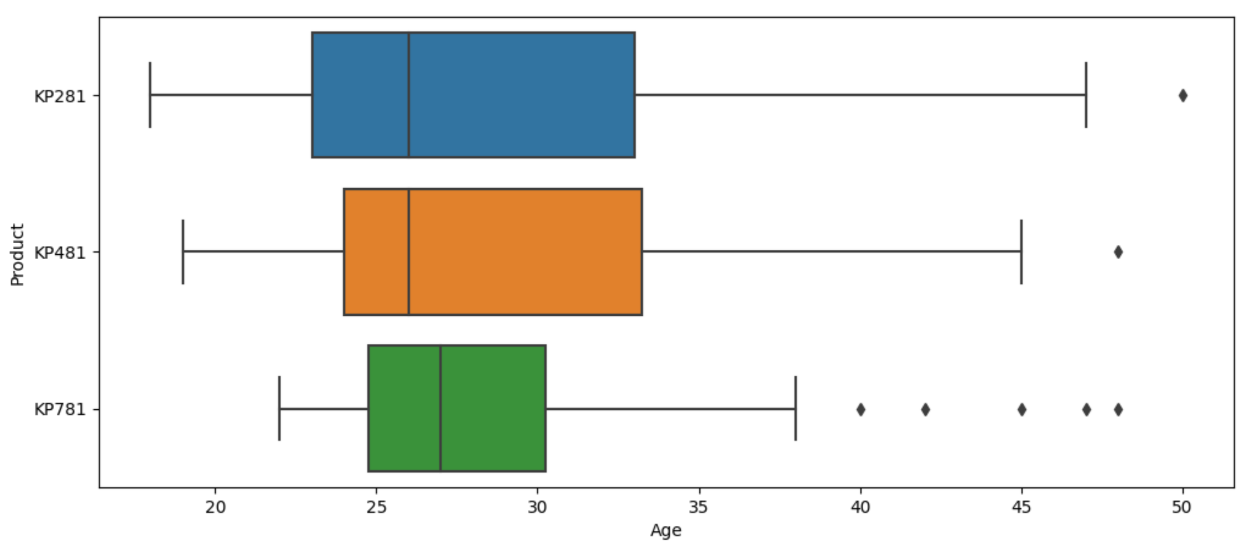
```
sns.boxplot(x='Education',y='Age',data=df)
```

```
<Axes: xlabel='Education', ylabel='Age'>
```



- Above box plot shows Education data against Age of the customer

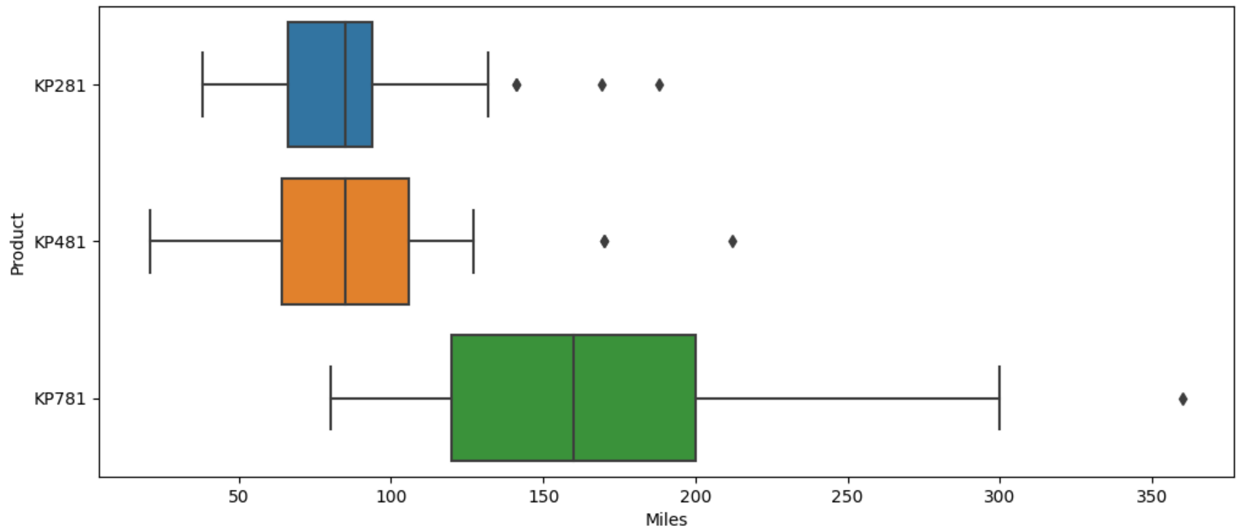
```
plt.figure(figsize=(12,5))
sns.boxplot(x='Age',y='Product',data=df)
plt.show()
```



- Roughly few customers with age above 40 use product KP781
- Most of the customers are comfortable with KP281 product type

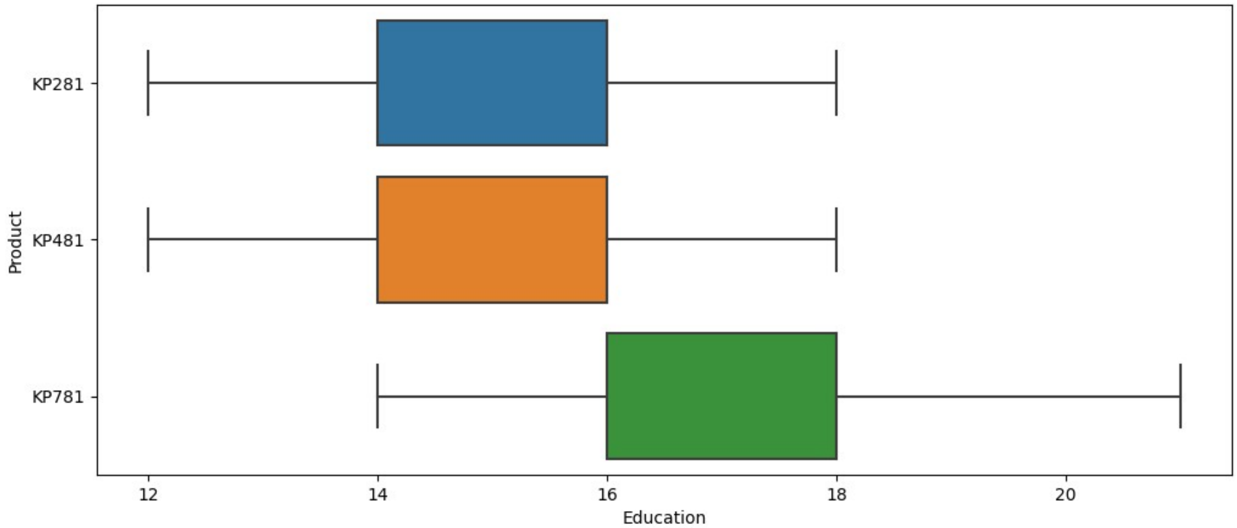
- KP481 is the second highest popular product among the younger side of the customer

```
# Miles with each product
plt.figure(figsize=(12,5))
sns.boxplot(x='Miles',y='Product',data=df)
plt.show()
```



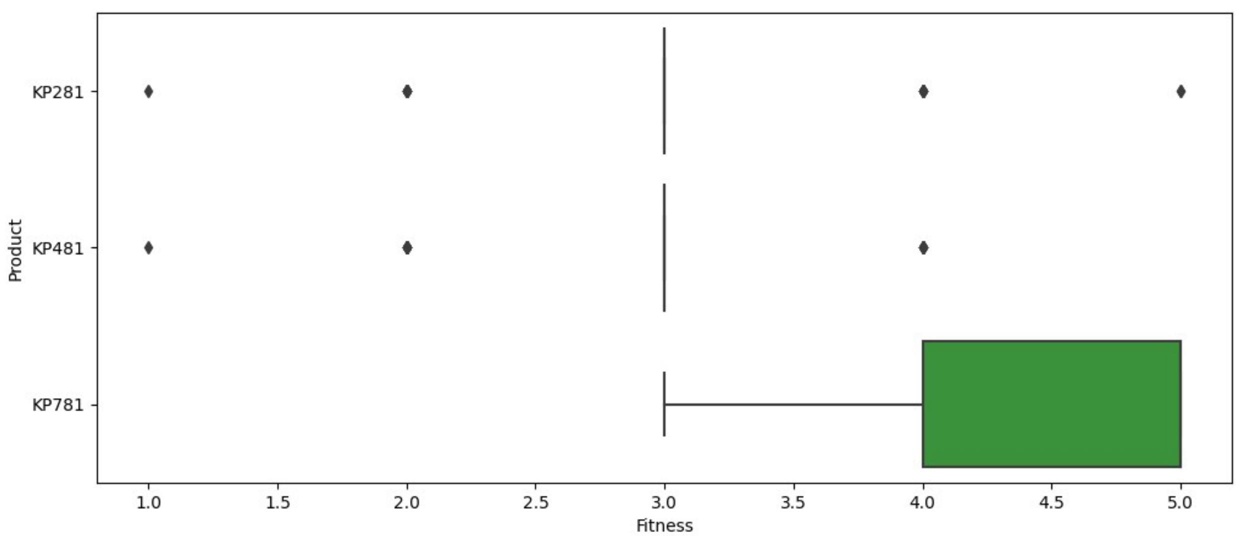
- Customers with product KP781, has been able to cover more miles than other two product types
- KP481 product is the second most highest miles covering product among the customers
- KP281 product customer had covered less distance compared with other two product types

```
# Education of customers with each product purchased
plt.figure(figsize=(12,5))
sns.boxplot(x='Education',y='Product',data=df)
plt.show()
```



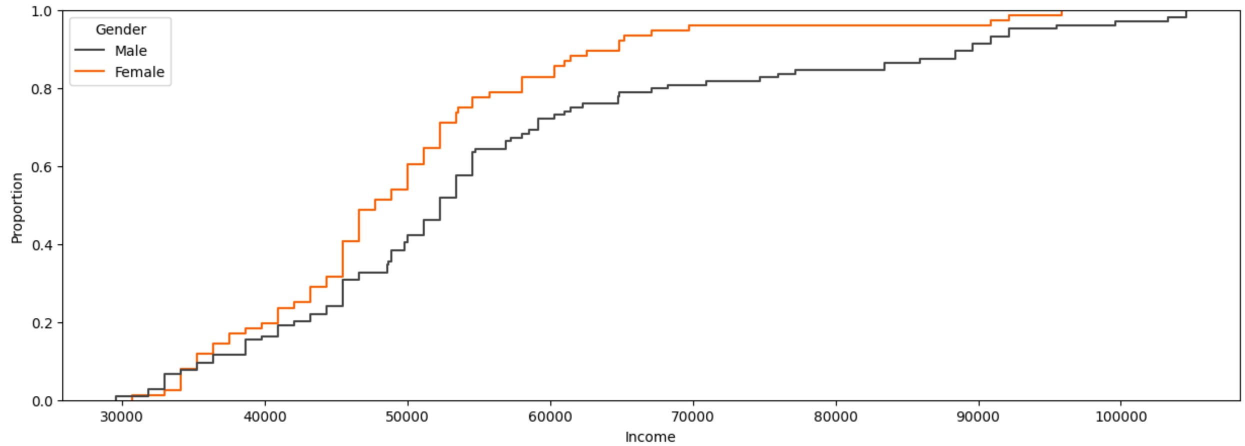
- Customers with Higher education of 16 to 18 have preferred mostly product type KP781
- Customers with education between 14 to 16 prefer KP281 and KP481 equally

```
# Fitness of customer with each product
plt.figure(figsize=(12,5))
sns.boxplot(x='Fitness',y='Product',data=df)
plt.show()
```



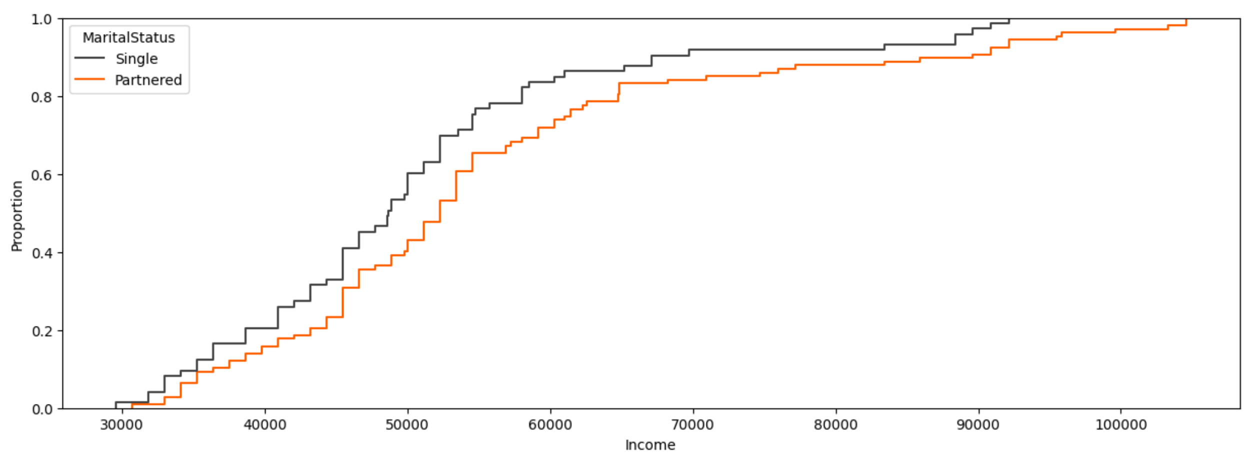
- Customers with excellent shape are significantly using KP781 product type
- KP481 and KP281 product type are scattered across the fitness rating

```
# Empirical Cumulative Distribution Function - proportional
distribution for Income of customers against their Gender
plt.figure(figsize=(15,5))
sns.ecdfplot(data=df,x='Income',hue='Gender',complementary=False,palet
te=['#454545','#FF6000'])
plt.show()
```



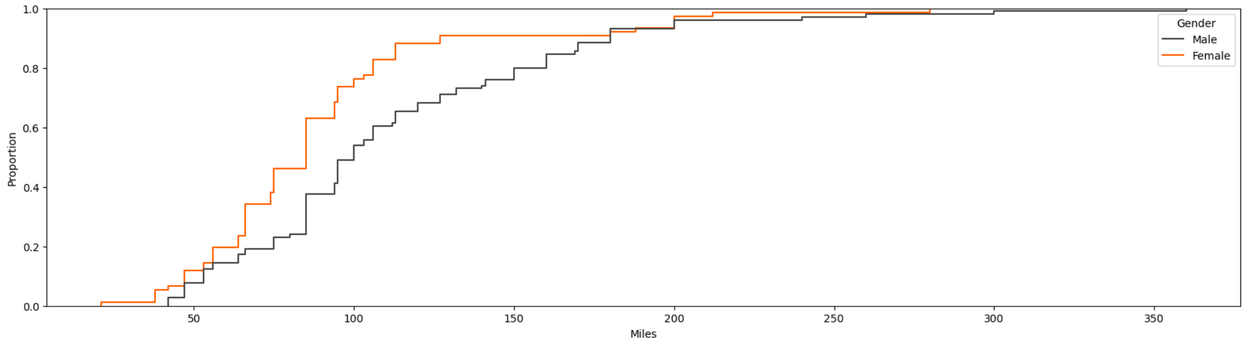
- Customers with minimum of 30K as annual income are the ones that are able to afford aerofit products
- Couple of Female customers less than 30K have also purchased aerofit product
- Male customers with Higher salaries are the most common purchasers of the product

```
# Empirical Cumulative Distribution Function - proportional distribution for Income of customers against their Marital Status
plt.figure(figsize=(15,5))
sns.ecdfplot(data=df,x='Income',hue='MaritalStatus',complementary=False,palette=['#454545','#FF6000'])
plt.show()
```



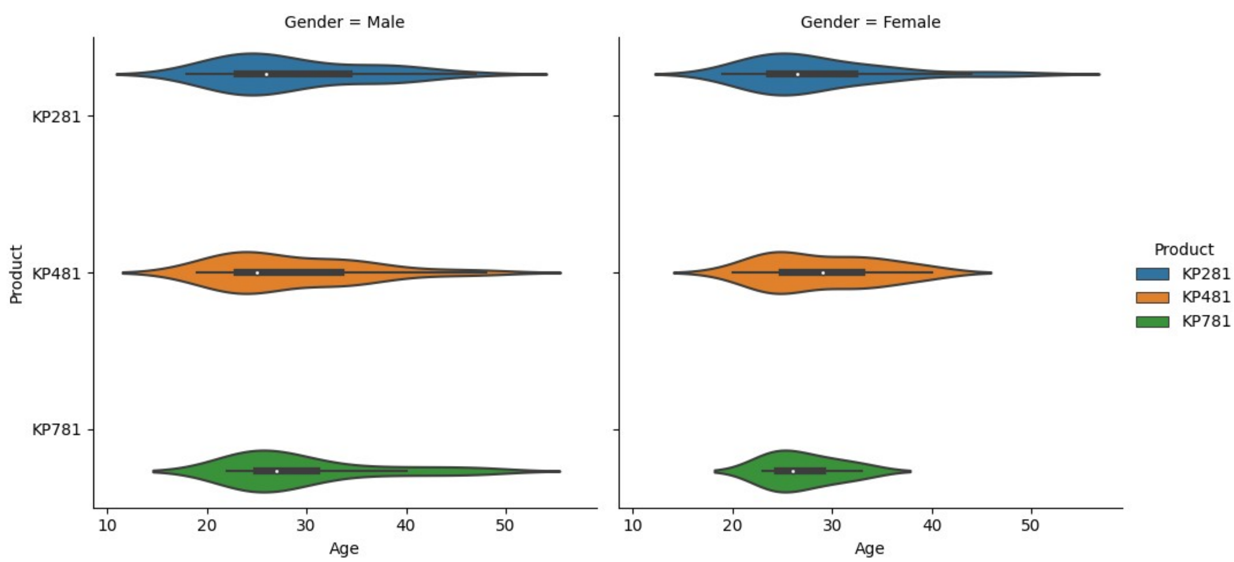
- Single customer have higher proportion than partnered customers
- Partnered customers are more than single customers and they also earn more than single customers

```
# Empirical Cumulative Distribution Function - proportional distribution for Miles of customers against their Gender
plt.figure(figsize=(20,5))
sns.ecdfplot(data=df,x='Miles',hue='Gender',complementary=False,palette=['#454545','#FF6000'])
plt.show()
```



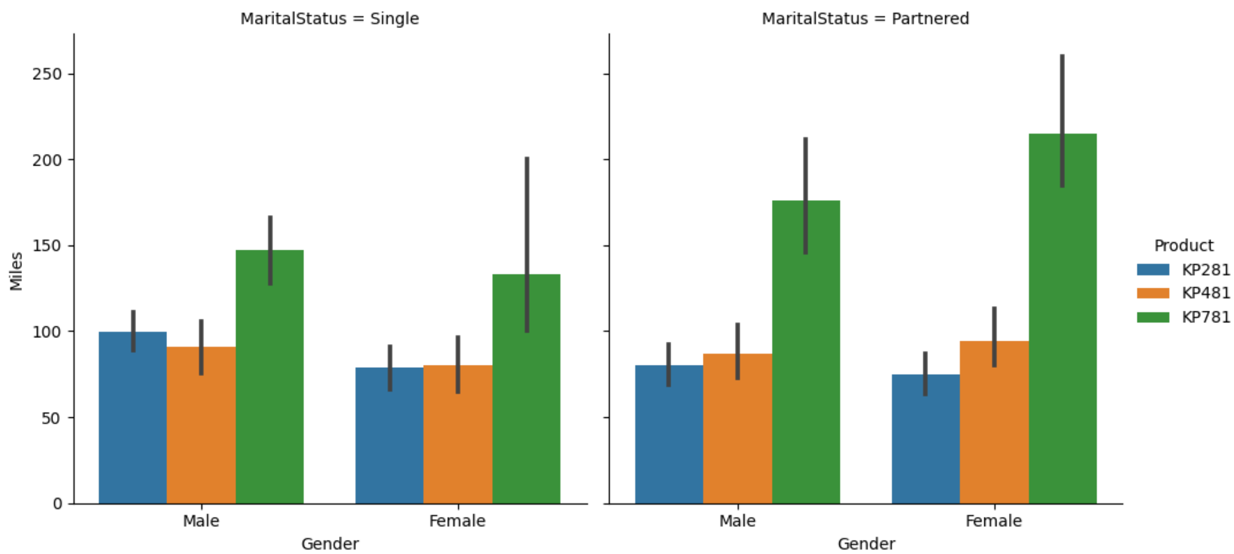
- Female customers proportion is higher than the male customers
- Male customers cover more miles than female customer with lower proportion than female customers

```
# Product used among age group seggregated by Gender
sns.catplot(x='Age',y='Product',hue='Product',col='Gender',data=df,kin
d='violin')
plt.show()
```



- From the above catplot, male customers are equally distributed among the three product types
- Female customers tend to use product KP281 and KP481 more than advanced KP781 product
- Female customers tend to prefer less complicated products than their male counterparts

```
# Miles covered in each product by gender and their marital status
sns.catplot(x='Gender',y='Miles',hue='Product',col='MaritalStatus',dat
a=df,kind='bar')
plt.show()
```



- KP781 is more populat among the single and Partnered customers
- Among the both marital statuses, Single female does not prefer much of the products.
- Partnered Female bought KP781 treadmill compared to Partnered Male.
- Single Female customers bought KP281 treadmill slightly more compared to Single Male customers.
- Partnered Male customers bought KP281 treadmill slightly more than Single Male customers.
- There are more single Males buying treadmill than single Females.
- Single Male customers bought KP781 treadmill compared to single Female.
- Partnered customers are more than Single customers.

Missing Value & Outlier Detection

```
df.isna().sum()

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

No Null values found in any columns

```
df.duplicated().sum()

0
```

No duplicates have been observed

Outliers

Outliers for other categorical data are mentioned inline with the respective analysis

```
# Outlier calculation for Miles using Inter Quartile Range
q_75, q_25 = np.percentile(df['Miles'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Miles is", miles_iqr)

Inter Quartile Range for Miles is 48.75
```

Business Insights based on Non-Graphical and Visual Analysis

```
df.Product.value_counts(normalize=True)

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

Probability of buying **KP281, KP481 & KP781** are **0.44, 0.33 & 0.22** respectively

```
df.Gender.value_counts(normalize=True)

Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
```

- Probability of Male customer is 0.57
- Probability of Female customer is 0.42

```
df.MaritalStatus.value_counts(normalize=True)

Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64
```

- Probability of Married/Partnered is 0.59
- Probability of Single is 0.40

Probability for each product for the both genders

```
def gender_Probability(gender,df):
    print(f"Prob P(KP781) for {gender}: {round(df['KP781']
[gender]/df.loc[gender].sum(),3)}")
    print(f"Prob P(KP481) for {gender}: {round(df['KP481']
[gender]/df.loc[gender].sum(),3)}")
    print(f"Prob P(KP281) for {gender}: {round(df['KP281']
```

```
[gender]/df.loc[gender].sum(),3)}")

df_temp = pd.crosstab(index=df['Gender'],columns=[df['Product']])
print("Prob of Male: ",round(df_temp.loc['Male'].sum()/len(df),3))
print("Prob of Female: ",round(df_temp.loc['Female'].sum()/len(df),3))
print()
gender_Probability('Male',df_temp)
print()
gender_Probability('Female',df_temp)
```

```
Prob of Male:  0.578
Prob of Female:  0.422

Prob P(KP781) for Male: 0.317
Prob P(KP481) for Male: 0.298
Prob P(KP281) for Male: 0.385

Prob P(KP781) for Female: 0.092
Prob P(KP481) for Female: 0.382
Prob P(KP281) for Female: 0.526
```

Probability of each product for given Marital Status

```
def MS_Probability(ms_status,df):
    print(f"Prob P(KP781) for {ms_status}: {round(df['KP781']
[ms_status]/df.loc[ms_status].sum(),3)}")
    print(f"Prob P(KP481) for {ms_status}: {round(df['KP481']
[ms_status]/df.loc[ms_status].sum(),3)}")
    print(f"Prob P(KP281) for {ms_status}: {round(df['KP281']
[ms_status]/df.loc[ms_status].sum(),3)}")

df_temp =
pd.crosstab(index=df['MaritalStatus'],columns=[df['Product']])
print("Prob of P(Single):
",round(df_temp.loc['Single'].sum()/len(df),3))
print("Prob of P(Married/Partnered):
",round(df_temp.loc['Partnered'].sum()/len(df),3))
print()
MS_Probability('Single',df_temp)
print()
MS_Probability('Partnered',df_temp)
```

```
Prob of P(Single):  0.406
Prob of P(Married/Partnered):  0.594

Prob P(KP781) for Single: 0.233
Prob P(KP481) for Single: 0.329
Prob P(KP281) for Single: 0.438

Prob P(KP781) for Partnered: 0.215
```

```
Prob P(KP481) for Partnered: 0.336
Prob P(KP281) for Partnered: 0.449
```

Customer Age Group Analysis

```
df_cat['age_group'] = df_cat.Age
df_cat.head()

  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

   Miles Fitness_category  age_group
0    112       Good Shape         18
1     75    Average Shape         19
2     66    Average Shape         19
3     85    Average Shape         19
4     47        Bad Shape         20

# 0-21 -> Teen
# 22-35 -> Adult
# 36-45 -> Middle Age
# 46-60 -> Elder Age
df_cat.age_group =
pd.cut(df.age_group,bins=[0,21,35,45,60],labels=['Teen','Adult','Middl
e Aged','Elder'])

df_cat.head()

  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
```

```
   Miles Fitness_category age_group
0    112        Good Shape      Teen
1     75     Average Shape      Teen
2     66     Average Shape      Teen
3     85     Average Shape      Teen
4     47         Bad Shape      Teen
```

```python
df_cat.age_group.value_counts()
```

```
Adult           135
Middle Aged      22
Teen             17
Elder             6
Name: age_group, dtype: int64
```

```python
df_cat.loc[df_cat.Product=='KP281']["age_group"].value_counts()
```

```
Adult           56
Middle Aged     11
Teen            10
Elder            3
Name: age_group, dtype: int64
```

```python
df_cat.loc[df_cat.Product=='KP481']["age_group"].value_counts()
```

```
Adult           45
Teen             7
Middle Aged      7
Elder            1
Name: age_group, dtype: int64
```

```python
df_cat.loc[df_cat.Product=='KP781']["age_group"].value_counts()
```

```
Adult           34
Middle Aged      4
Elder            2
Teen             0
Name: age_group, dtype: int64
```

```python
pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,margins=True
)
```

```
age_group  Teen  Adult  Middle Aged  Elder  All
Product
KP281        10     56           11      3   80
KP481         7     45            7      1   60
KP781         0     34            4      2   40
All          17    135           22      6  180
```

```python
# Conditional and Marginal Probabilities with product type and age
group
```

```
np.round(pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,normalize='columns',margins=True)*100,2)
```

```
age_group   Teen  Adult  Middle Aged  Elder    All
Product
KP281      58.82  41.48        50.00  50.00  44.44
KP481      41.18  33.33        31.82  16.67  33.33
KP781       0.00  25.19        18.18  33.33  22.22
```

```
# Conditional and Marginal Probabilities with product type and age group
np.round(pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,normalize=True,margins=True)*100,2)
```

```
age_group  Teen  Adult  Middle Aged  Elder     All
Product
KP281      5.56  31.11         6.11   1.67   44.44
KP481      3.89  25.00         3.89   0.56   33.33
KP781      0.00  18.89         2.22   1.11   22.22
All        9.44  75.00        12.22   3.33  100.00
```

```
pd.crosstab(columns=df_cat["Fitness_category"],index=df_cat["Product"])
```

```
Fitness_category  Average Shape  Bad Shape  Excellent Shape  Good Shape  \
Product

KP281                        54         14                2
9
KP481                        39         12                0
8
KP781                         4          0               29
7

Fitness_category  Poor Shape
Product
KP281                      1
KP481                      1
KP781                      0
```

```
round(pd.crosstab(index=df_cat["Product"],columns=df_cat["Fitness_category"],normalize="columns")*100,2)
```

```
Fitness_category  Average Shape  Bad Shape  Excellent Shape  Good Shape  \
Product

KP281                     55.67      53.85             6.45
37.50
KP481                     40.21      46.15             0.00
```

```
33.33
KP781                            4.12       0.00            93.55
29.17

Fitness_category  Poor Shape
Product
KP281                   50.0
KP481                   50.0
KP781                    0.0
```

```
pd.crosstab(index=[df_cat.Product,df_cat.Fitness_category],columns=df_
cat.Gender)
```

```
Gender                          Female  Male
Product Fitness_category
KP281   Average Shape               26    28
        Bad Shape                   10     4
        Excellent Shape              1     1
        Good Shape                   3     6
        Poor Shape                   0     1
KP481   Average Shape               18    21
        Bad Shape                    6     6
        Good Shape                   4     4
        Poor Shape                   1     0
KP781   Average Shape                1     3
        Excellent Shape              5    24
        Good Shape                   1     6
```

```
round(pd.crosstab(index=[df_cat.Product,df_cat.Fitness_category],colum
ns=df_cat.Gender,normalize=True)*100,2)
```

```
Gender                          Female   Male
Product Fitness_category
KP281   Average Shape            14.44  15.56
        Bad Shape                 5.56   2.22
        Excellent Shape           0.56   0.56
        Good Shape                1.67   3.33
        Poor Shape                0.00   0.56
KP481   Average Shape            10.00  11.67
        Bad Shape                 3.33   3.33
        Good Shape                2.22   2.22
        Poor Shape                0.56   0.00
KP781   Average Shape             0.56   1.67
        Excellent Shape           2.78  13.33
        Good Shape                0.56   3.33
```

```
round(pd.crosstab(index=[df_cat.Product,df_cat.MaritalStatus],columns=
df_cat.Gender,normalize=True),2)
```

```
Gender                       Female  Male
Product MaritalStatus
```

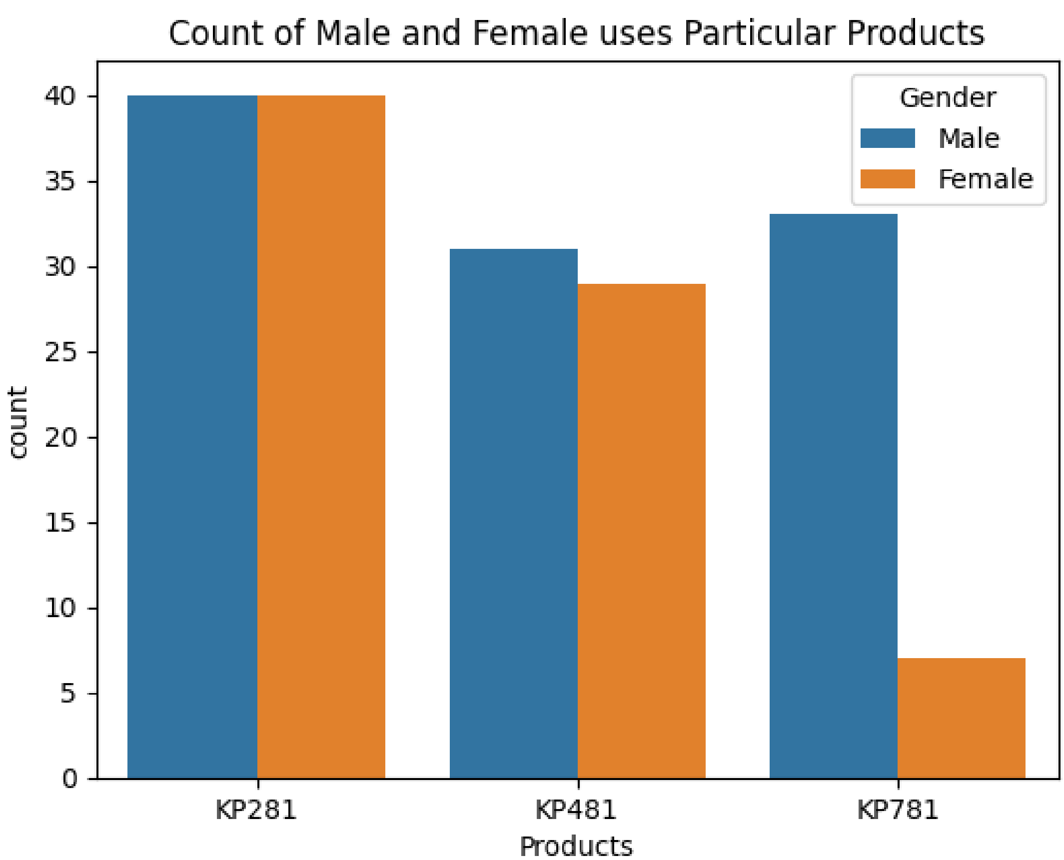
```
KP281    Partnered        0.15  0.12
         Single           0.07  0.11
KP481    Partnered        0.08  0.12
         Single           0.08  0.06
KP781    Partnered        0.02  0.11
         Single           0.02  0.08
```

Conditional and Marginal Probabilities

Two-Way Contingency Table

Marginal Probabilities

```
sns.countplot(x = "Product", data= df, hue = "Gender")
plt.xlabel("Products")
plt.title("Count of Male and Female uses Particular Products")
plt.show()
```




```
pd.crosstab([df.Product],df.Gender,margins=True)

Gender    Female  Male  All
Product
```

```
KP281         40    40   80
KP481         29    31   60
KP781          7    33   40
All           76   104  180
```

```
np.round(((pd.crosstab(df.Product,df.Gender,margins=True))/180)*100,2)
```

```
Gender    Female   Male      All
Product
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
```

Marginal Probability

- Probability of Male Customer Purchasing any product is : 57.77 %
- Probability of Female Customer Purchasing any product is : 42.22 %

Marginal Probability of any customer buying

- product KP281 is : 44.44 % (cheapest / entry level product)
- product KP481 is : 33.33 % (intermediate user level product)
- product KP781 is : 22.22 % (Advanced product with ease of use that help in covering longer distance)

Conditional Probabilities

```
np.round((pd.crosstab([df.Product],df.Gender,margins=True,normalize="c
olumns"))*100,2)
```

```
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

KP281 | Female = 52 %

KP481 | Female = 38 %

KP781 | Female = 10 %

KP281 | male = 38 %

KP481 | male = 30 %

KP781 | male = 32 %

Probability of Female customer buying KP281(52.63%) is more than male(38.46%).

KP281 is more recommended for female customers.

Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).

Probability of Female customer buying Product KP481(38.15%) is significantly higher than male (29.80%.)

KP481 product is specifically recommended for Female customers who are intermediate user.

Objective: Customer Profiling for Each Product

Customer profiling based on the 3 product categories provided

KP281

- Easily affordable entry level product, which is also the maximum selling product.
- KP281 is the most popular product among the entry level customers.
- This product is easily afforded by both Male and Female customers.
- Average distance covered in this model is around 70 to 90 miles.
- Product is used 3 to 4 times a week.
- Most of the customer who have purchased the product have rated Average shape as the fitness rating.
- Younger to Elder beginner level customers prefer this product.
- Single female & Partnered male customers bought this product more than single male customers.
- Income range between 39K to 53K have preferred this product.

KP481

- This is an Intermediate level Product.
- KP481 is the second most popular product among the customers.
- Fitness Level of this product users varies from Bad to Average Shape depending on their usage.
- Customers Prefer this product mostly to cover more miles than fitness.
- Average distance covered in this product is from 70 to 130 miles per week.
- More Female customers prefer this product than males.

- Probability of Female customer buying KP481 is significantly higher than male.
- KP481 product is specifically recommended for Female customers who are intermediate user.
- Three different age groups prefer this product - Teen, Adult and middle aged.
- Average Income of the customer who buys KP481 is 49K.
- Average Usage of this product is 3 days per week.
- More Partnered customers prefer this product.
- There are slightly more male buyers of the KP481.
- The distance travelled on the KP481 treadmill is roughly between 75 - 100 Miles. It is also the 2nd most distance travelled model.
- The buyers of KP481 in Single & Partnered, Male & Female are same.
- The age range of KP481 treadmill customers is roughly between 24-34 years.

KP781

- Due to the High Price & being the advanced type, customer prefers less of this product.
- Customers use this product mainly to cover more distance.
- Customers who use this product have rated excelled shape as fitness rating.
- Customer walk/run average 120 to 200 or more miles per week on his product.
- Customers use 4 to 5 times a week at least.
- Female Customers who are running average 180 miles (extensive exercise) , are using product KP781, which is higher than Male average using same product.
- Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).
- Probability of a single person buying KP781 is higher than Married customers. So , KP781 is also recommended for people who are single and exercises more.
- Middle aged to higher age customers tend to use this model to cover more distance.
- Average Income of KP781 buyers are over 75K per annum
- Partnered Female bought KP781 treadmill compared to Partnered Male.
- Customers who have more experience with previous aerofit products tend to buy this product

- This product is preferred by the customer where the correlation between Education and Income is High.

Recommendation

- Female who prefer exercising equipments are very low here. Hence, we should run a marketing campaign on to encourage women to exercise more
- KP281 & KP481 treadmills are preferred by the customers whose annual income lies in the range of 39K - 53K Dollars. These models should promoted as budget treadmills.
- As KP781 provides more features and functionalities, the treadmill should be marketed for professionals and athletes.
- KP781 product should be promotted using influencers and other international atheletes.
- Research required for expanding market beyond 50 years of age considering health pros and cons.
- Provide customer support and recommend users to upgrade from lower versions to next level versions after consistent usages.
- KP781 can be recommended for Female customers who exercises extensively along with easy usage guidance since this type is advanced.
- Target the Age group above 40 years to recommend Product KP781.