business-case-aerofit

May 28, 2024

1 About Aerofit

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.

1.1 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.

Perform 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.

1.2 Problem statement

To perform descriptive analytics to create a customer profile for each Aerofit Trademil products Constructing two way contingency tables & compute all conditional & marginal probability

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

[ ]:
```
    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
..      …   …       …           …             …      …        …       …
175   KP781   40    Male         21        Single      6        5   83416
176   KP781   42    Male         18        Single      5        4   89641
```

```
177   KP781   45    Male          16       Single       5          5    90886
178   KP781   47    Male          18    Partnered       4          5   104581
179   KP781   48    Male          18    Partnered       4          5    95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[ ]:
```
# Observations on shape of data
df.shape
# Given data set has 180 rows and 9 columns
```

[ ]: (180, 9)

[ ]:
```
# Checking Data type for all column
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
```

[ ]:
```
# Checking if there is any null/NaN value available
df.isna().sum()
```

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

[ ]:
```
# Checking Statistical summary about the data set.
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
```

2 Non-Graphical Analysis: Value counts and unique attributes

[ ]:
```
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
```

[ ]:
```
product_count = df['Product'].value_counts()
gender_count = df['Gender'].value_counts()
maritalStatus_count = df['MaritalStatus'].value_counts()
fitness_count = df['Fitness'].value_counts()
print("Product Value count \n",product_count)

# Product sold distribution -> Most bought product is KP281
```

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

[ ]:
```
print("Gender Value count \n",gender_count)
# Gender Distribution ->  More Male bought the product compare to Female
```

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

[ ]:
```
print("MaritalStatus Value count \n",maritalStatus_count)
# Marital Status Distribution -> Partnered people are more health concious and␣
↪using more tredmill.
```

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

[ ]:
```
print("Fitness Value count \n",fitness_count)
```

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

[ ]:
```

```

3 Visual Analysis - Univariate & Bivariate

[ ]:
```
df
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0     KP281   18    Male         14        Single      3        4   29562
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4     KP281   20    Male         13     Partnered      4        2   35247
..      …    …     …          …           …      …        …       …
175   KP781   40    Male         21        Single      6        5   83416
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     Miles
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177    160
178    120
179    180

[180 rows x 9 columns]
```
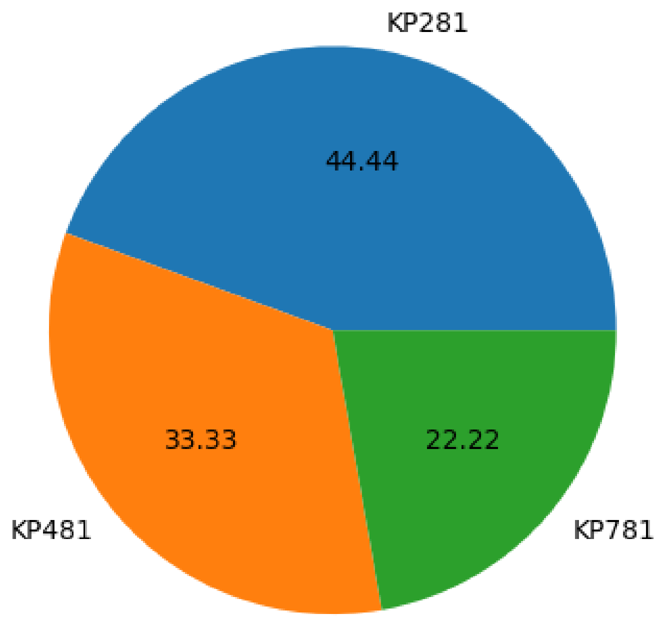
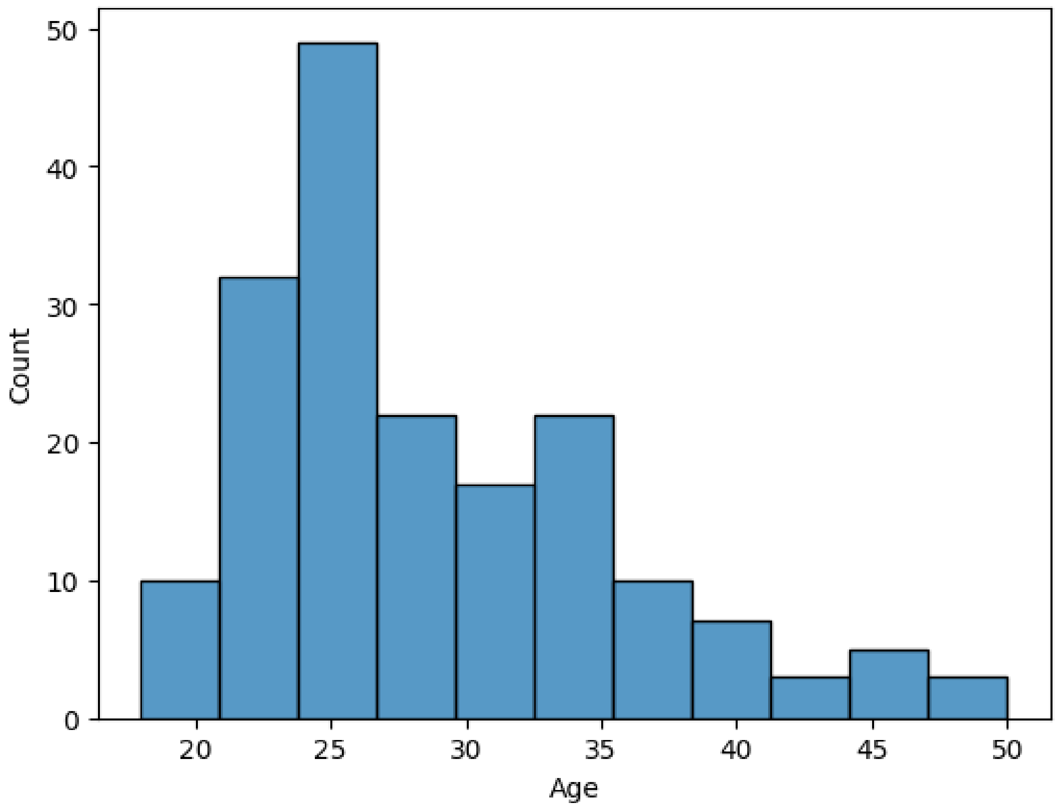
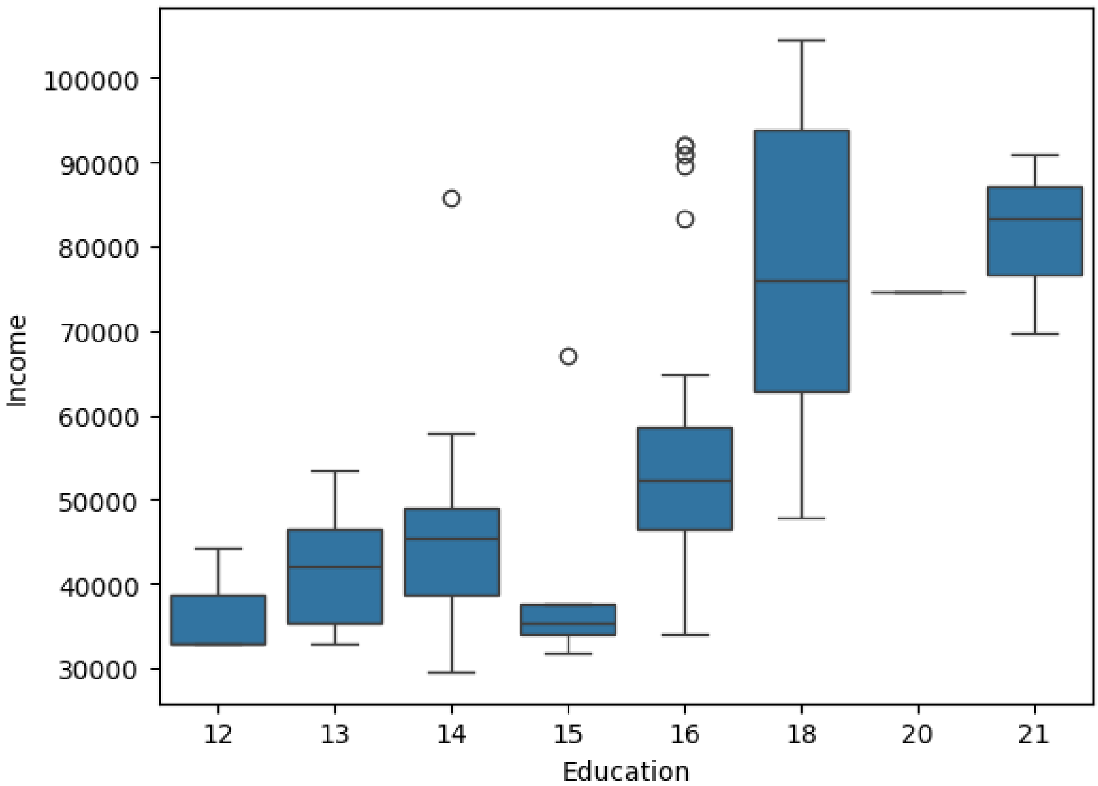

[ ]:
```
# Checking Product Percentage distribution
plt.pie(df['Product'].value_counts(),labels=df['Product'].value_counts().
 ↪index,autopct='%2.2f')
plt.show()

# Insights
 # 1. Most bought product is KP281 followed by KP481
 # 2. Least Bought product is KP781
```



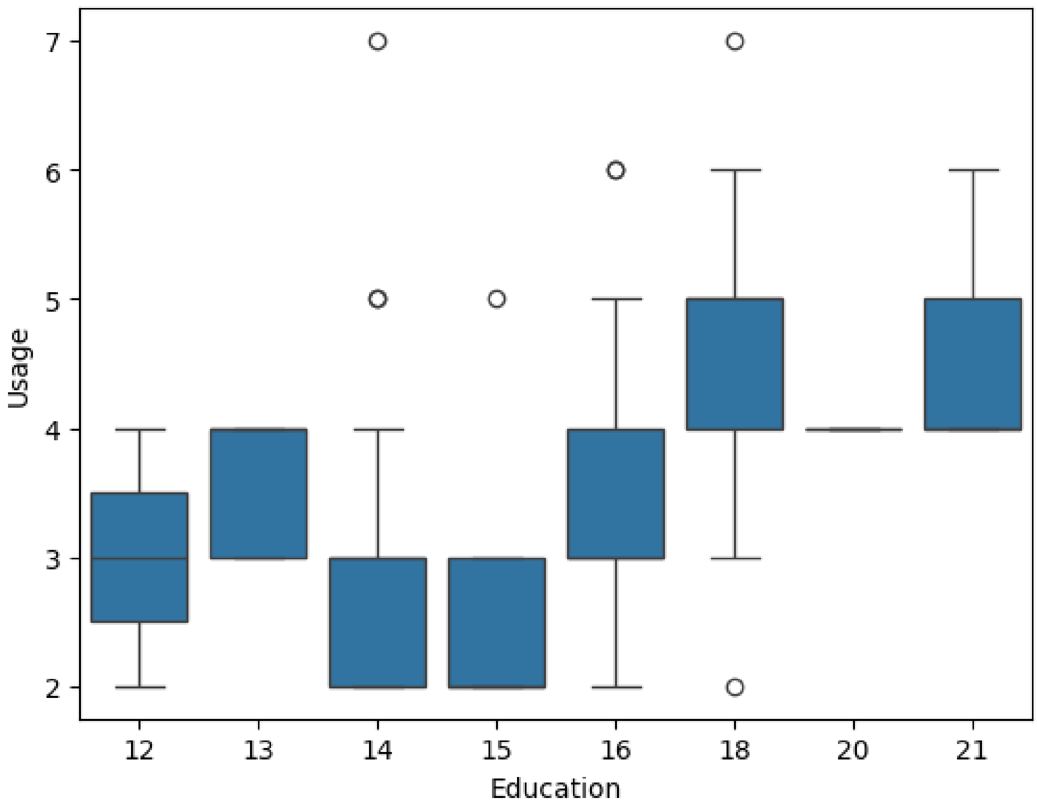
[ ]:
```
sns.histplot(df['Age'])
plt.show()
```



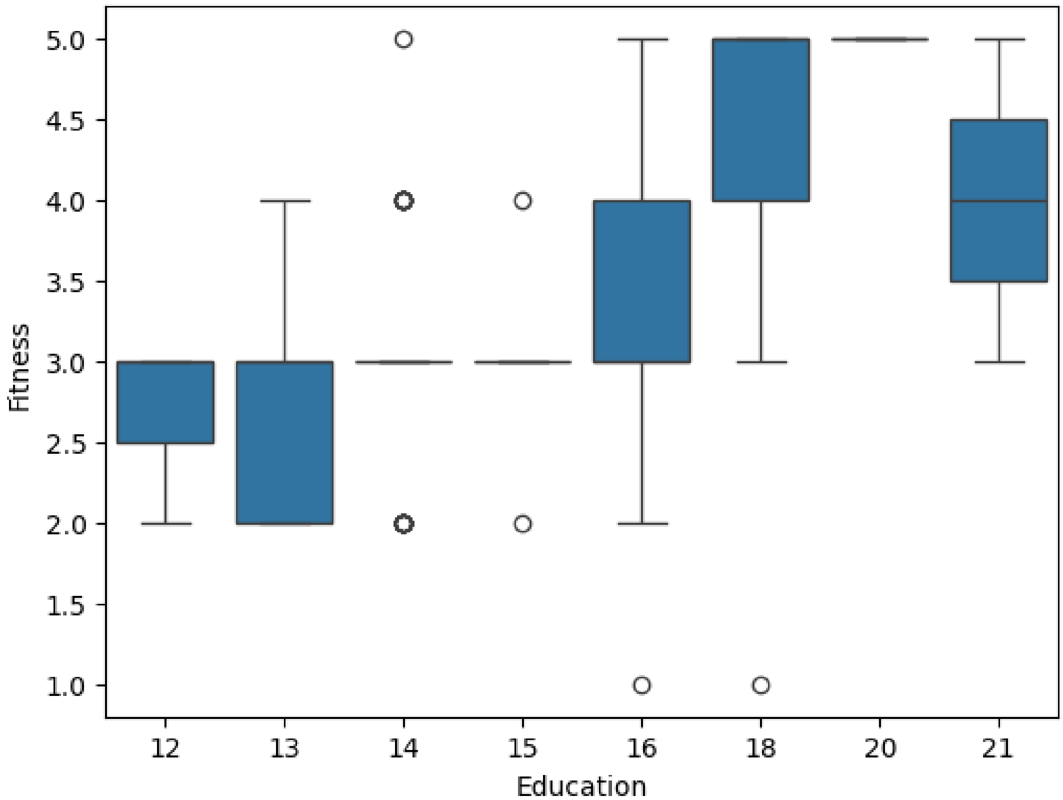
[ ]:
```
sns.boxplot(data=df, x= 'Education',y='Income')
plt.show()

# Insight More educated people have more income

# Oulier: Some Less educated people earning income similary they usage more␣
 ↪than some highly educated people.
```



[ ]:
```
sns.boxplot(data=df, x= 'Education',y='Usage')
plt.show()
# Insights
 # 1. More educating people have more usage
```



[ ]:
```
sns.boxplot(data=df, x= 'Education',y='Fitness')
plt.show()

# Insight
 # 1. More educated people has more fitness level
```



[ ]:
```
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
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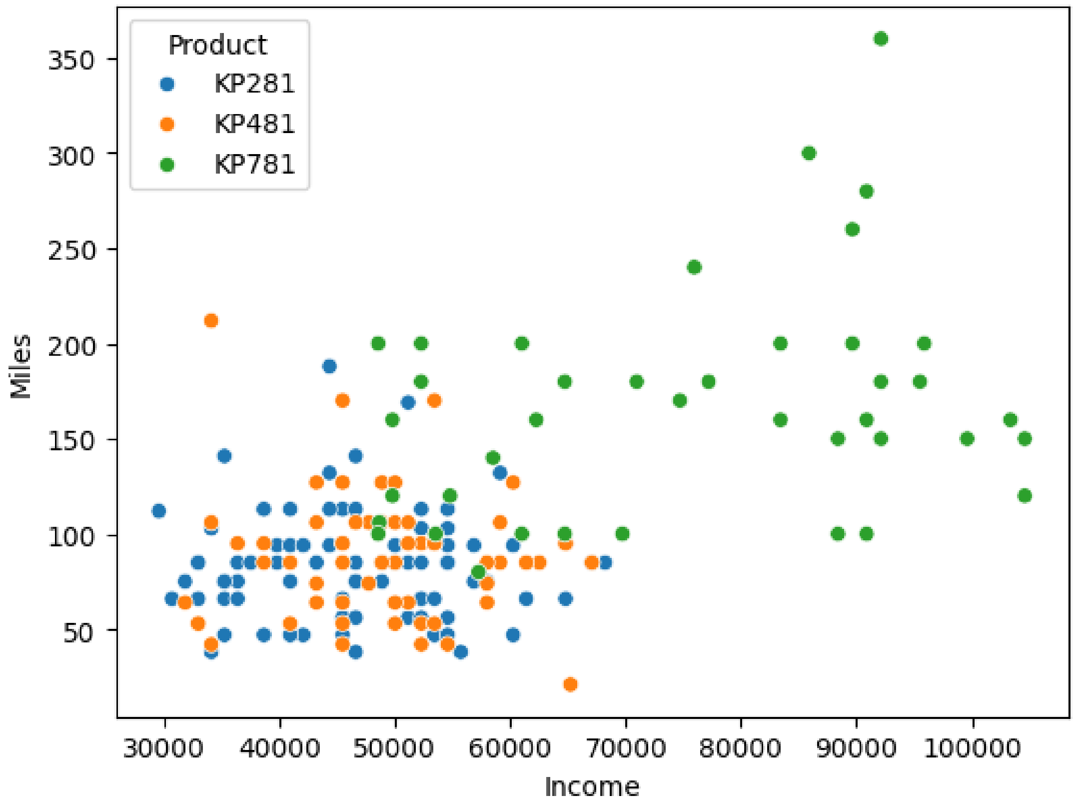
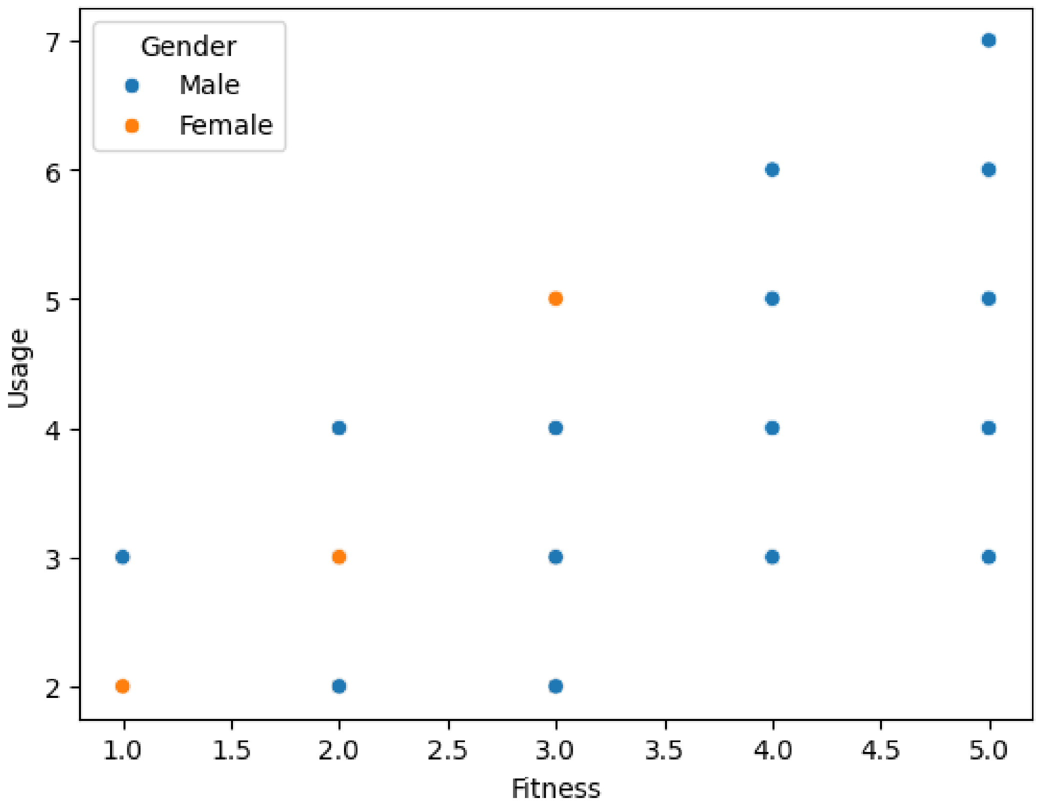
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

[ ]:
```
sns.scatterplot(data=df, x='Income',y='Miles',hue='Product')
plt.show()

# Insight
# 1. More income people are running more and buying product KP781
# 2. KP781 is mostly famous in rich people.
# 3. KP281 and KP481 have moderate relation of Income and no. of miles customer␣
↪ran.

# Recommendation
 # 1. Since only rich people is buying KP781, It needs to be fixed so that␣
↪moderate range income people can also buy to increase production of KP781.
```

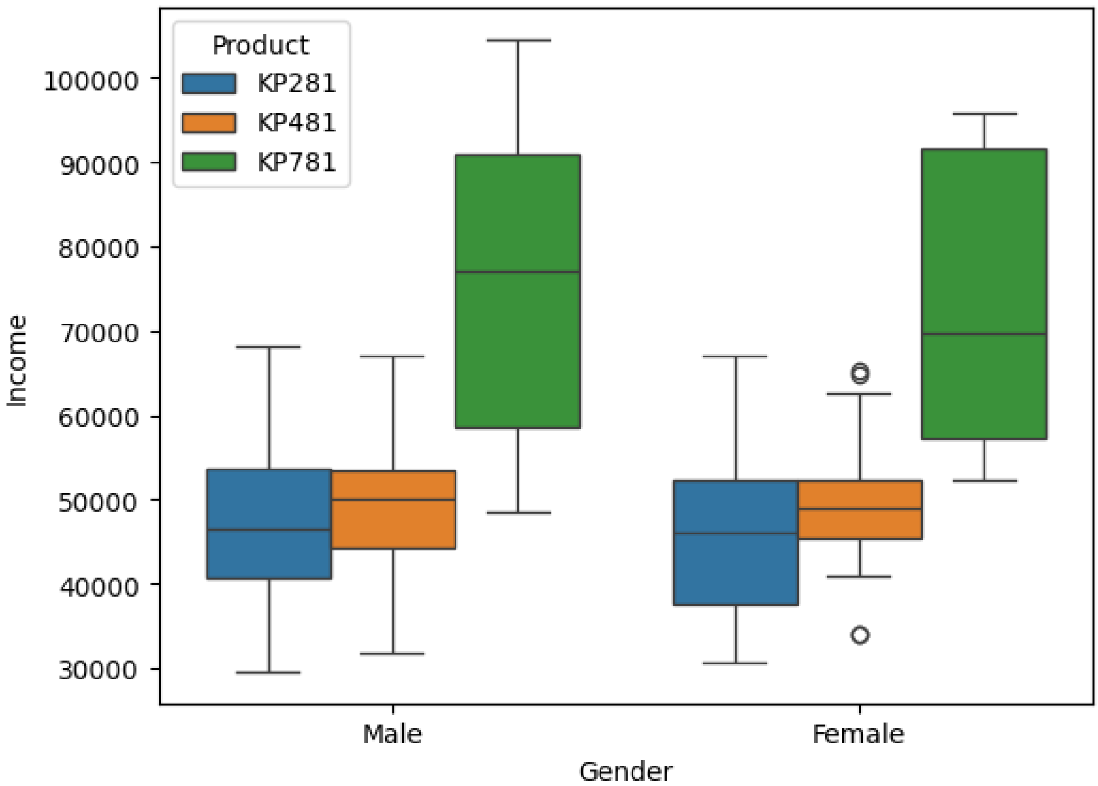
```
# 2. More Advertisement require to sell KP781 product.
```



[ ]:
```
sns.scatterplot(data=df, x='Fitness',y='Usage',hue='Gender')
plt.show()

# Insight
  # 1. Female is using tredmill very less hence their fitness level quite low.
# Recoomendation
  # 1.More Female advertisement and awareness content require to promote␣
 ↪product selling among females.
```



[ ]:
```
sns.boxplot(data=df,x='Gender',y='Income',hue='Product')
plt.show()
```



[ ]:
```
# Insight
# 1. KP781 most famous among both gender group
# 2. Less earn people buying mostly KP281 and KP481.
```

[ ]:
```
pd.crosstab(index=df['Gender'],␣
↪columns=df['Product'],margins=True,normalize='columns')*100

# Insight
  # 1. Only ~17.5% Female bought KP781, if company produced 1000 KP781 175 will␣
↪be buy by Female only.
  # 2. Males gonna buy more KP781
```

[ ]:

Product	KP281	KP481	KP781	All
Gender				
Female	50.0	48.333333	17.5	42.222222
Male	50.0	51.666667	82.5	57.777778

[ ]:
```
pd.crosstab(index=df['Gender'],␣
↪columns=df['Product'],margins=True,normalize=True)*100
# Insight
# 1. KP281 and KP481 are equally famous in both gender group
```

```
# Recommendation
# 1. KP781 need to be promoted or require more advertisement among both group.
```

[ ]:
```
Product       KP281      KP481      KP781         All
Gender
Female    22.222222  16.111111   3.888889   42.222222
Male      22.222222  17.222222  18.333333   57.777778
All       44.444444  33.333333  22.222222  100.000000
```

[ ]:
```

```

[ ]:
```
pd.crosstab(index=df['MaritalStatus'], columns=df['Product'],margins=True,␣
↪normalize='columns')
# Insight
# 1. ~60% Partnered people using more products.
```

[ ]:
```
Product        KP281  KP481  KP781       All
MaritalStatus
Partnered        0.6    0.6  0.575  0.594444
Single           0.4    0.4  0.425  0.405556
```