Aerofit-Dataset@Dhanureddy

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1 Aerofit - Descriptive Statistics and probability

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.

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.

[ ]:
```
import pandas as pd
import numpy as np
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]
```

Checking datatypes

```
[ ]: 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
```

Finding Unique values in each column

```
[ ]: for column in df.columns:
         unique_count = df[column].nunique()
         print(column, ":" , unique_count)
```

```
Product : 3
Age : 32
Gender : 2
Education : 8
```

```
MaritalStatus : 2
Usage : 6
Fitness : 5
Income : 62
Miles : 37
```

Ensuring we have no NaN values in the dataframe

```
[ ]: df.isna().isna().sum()
```

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

The overall shape and statistical summary of the dataframe

```
[ ]: df.shape
```

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

```
[ ]: summary = df.describe()
     summary
```

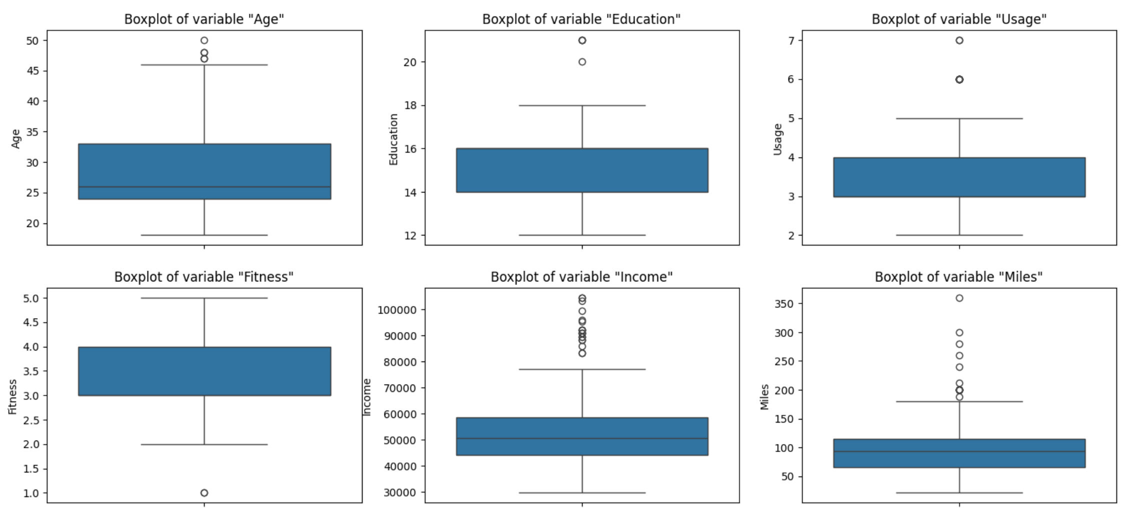
```
[ ]:               Age   Education       Usage     Fitness         Income  \
     count  180.000000  180.000000  180.000000  180.000000     180.000000
     mean    28.788889   15.572222    3.455556    3.311111   53719.577778
     std      6.943498    1.617055    1.084797    0.958869   16506.684226
     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
```

Graphical box plot representation of outliers in various columns

[ ]:
```
plt.figure(figsize =(18,8))
plt.subplot(2,3,1)
sns.boxplot(data = df.Age)
plt.title('Boxplot of variable "Age"')

plt.subplot(2,3,2)
sns.boxplot(data = df.Education)
plt.title('Boxplot of variable "Education"')

plt.subplot(2,3,3)
sns.boxplot(data = df.Usage)
plt.title('Boxplot of variable "Usage"')

plt.subplot(2,3,4)
sns.boxplot(data = df.Fitness)
plt.title('Boxplot of variable "Fitness"')

plt.subplot(2,3,5)
sns.boxplot(data = df.Income)
plt.title('Boxplot of variable "Income"')

plt.subplot(2,3,6)
sns.boxplot(data = df.Miles)
plt.title('Boxplot of variable "Miles"')
```

[ ]:
```
Text(0.5, 1.0, 'Boxplot of variable "Miles"')
```



Calculation of interquartile range

```
[ ]: Q1 = summary.loc["25%"]
     Q3 = summary.loc["75%"]
     IQR = Q3 - Q1
     print(IQR)
```

```
Age              9.00
Education        2.00
Usage            1.00
Fitness          1.00
Income       14609.25
Miles           48.75
dtype: float64
```

Calculation of Extreme boundaries

```
[ ]: Lower_bound = Q1 - 1.5*IQR
     Upper_bound = Q3 + 1.5*IQR

     bounds_df = pd.DataFrame({"LowerBound" :Lower_bound, "UpperBound" :Upper_bound})
     print(bounds_df)
```

```
           LowerBound  UpperBound
Age            10.500      46.500
Education      11.000      19.000
Usage           1.500       5.500
Fitness         1.500       5.500
Income      22144.875   80581.875
Miles          -7.125     187.875
```

DataFrame of Lowboundary outliers

(i) Fitness outliers

```
[ ]: fitness_outliers = (df['Fitness'] < Lower_bound['Fitness'])
     fitness_outliers_df = df[fitness_outliers]
     fitness_outliers_df
```

```
[ ]:    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
     14   KP281   23    Male         16     Partnered      3        1   38658
     117  KP481   31  Female         18        Single      2        1   65220

          Miles
     14      47
     117     21
```

DataFrames of Upperboundary outliers

(i) Age outliers

[ ]:
```
Age_outlier = (df['Age'] > Upper_bound['Age'])
Age_outlier_df = df[Age_outlier]
Age_outlier_df
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
78    KP281   47    Male         16     Partnered      4        3   56850
79    KP281   50  Female         16     Partnered      3        3   64809
139   KP481   48    Male         16     Partnered      2        3   57987
178   KP781   47    Male         18     Partnered      4        5  104581
179   KP781   48    Male         18     Partnered      4        5   95508

     Miles
78      94
79      66
139     64
178    120
179    180
```

(ii) Education outliers

[ ]:
```
Education_outlier = (df['Education'] > Upper_bound['Education'])
Education_outlier_df = df[Education_outlier]
Education_outlier_df
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
156   KP781   25    Male         20     Partnered      4        5   74701
157   KP781   26  Female         21        Single      4        3   69721
161   KP781   27    Male         21     Partnered      4        4   90886
175   KP781   40    Male         21        Single      6        5   83416

     Miles
156    170
157    100
161    100
175    200
```

(iii) Usage outliers

[ ]:
```
Usage_outlier = (df['Usage'] > Upper_bound['Usage'])
Usage_outlier_df = df[Usage_outlier]
Usage_outlier_df
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
154   KP781   25    Male         18     Partnered      6        4   70966
155   KP781   25    Male         18     Partnered      6        5   75946
162   KP781   28  Female         18     Partnered      6        5   92131
163   KP781   28    Male         18     Partnered      7        5   77191
164   KP781   28    Male         18        Single      6        5   88396
```

```
166  KP781   29    Male         14   Partnered      7        5   85906
167  KP781   30  Female         16   Partnered      6        5   90886
170  KP781   31    Male         16   Partnered      6        5   89641
175  KP781   40    Male         21      Single      6        5   83416

     Miles
154    180
155    240
162    180
163    180
164    150
166    300
167    280
170    260
175    200
```

(iv) Income outliers

```
[ ]: Income_outlier = (df['Income'] > Upper_bound['Income'])
     Income_outlier_df = df[Income_outlier]
     Income_outlier_df
```

```
[ ]:     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
     159   KP781   27    Male         16     Partnered      4        5   83416
     160   KP781   27    Male         18        Single      4        3   88396
     161   KP781   27    Male         21     Partnered      4        4   90886
     162   KP781   28  Female         18     Partnered      6        5   92131
     164   KP781   28    Male         18        Single      6        5   88396
     166   KP781   29    Male         14     Partnered      7        5   85906
     167   KP781   30  Female         16     Partnered      6        5   90886
     168   KP781   30    Male         18     Partnered      5        4  103336
     169   KP781   30    Male         18     Partnered      5        5   99601
     170   KP781   31    Male         16     Partnered      6        5   89641
     171   KP781   33  Female         18     Partnered      4        5   95866
     172   KP781   34    Male         16        Single      5        5   92131
     173   KP781   35    Male         16     Partnered      4        5   92131
     174   KP781   38    Male         18     Partnered      5        5  104581
     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
     159    160
     160    100
     161    100
```

```
162    180
164    150
166    300
167    280
168    160
169    150
170    260
171    200
172    150
173    360
174    150
175    200
176    200
177    160
178    120
179    180
```

(v) Miles outliers

[ ]:
```python
Miles_outlier = (df['Miles'] > Upper_bound['Miles'])
Miles_outlier_df = df[Miles_outlier]
Miles_outlier_df
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
23    KP281   24  Female         16     Partnered      5        5   44343
84    KP481   21  Female         14     Partnered      5        4   34110
142   KP781   22    Male         18        Single      4        5   48556
148   KP781   24  Female         16        Single      5        5   52291
152   KP781   25  Female         18     Partnered      5        5   61006
155   KP781   25    Male         18     Partnered      6        5   75946
166   KP781   29    Male         14     Partnered      7        5   85906
167   KP781   30  Female         16     Partnered      6        5   90886
170   KP781   31    Male         16     Partnered      6        5   89641
171   KP781   33  Female         18     Partnered      4        5   95866
173   KP781   35    Male         16     Partnered      4        5   92131
175   KP781   40    Male         21        Single      6        5   83416
176   KP781   42    Male         18        Single      5        4   89641

     Miles
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
```

```
170    260
171    200
173    360
175    200
176    200
```

DataFrame of both upperbounds and lowerbounds outliers combined

[ ]:
```
outliers = ((df < Lower_bound) | (df > Upper_bound)).any(axis=1)
potential_outliers = df[outliers]
potential_outliers
```

```
<ipython-input-70-93a8ff5e1b21>:1: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version. Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  outliers = ((df < Lower_bound) | (df > Upper_bound)).any(axis=1)
```

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
14	KP281	23	Male	16	Partnered	3	1	38658	
23	KP281	24	Female	16	Partnered	5	5	44343	
78	KP281	47	Male	16	Partnered	4	3	56850	
79	KP281	50	Female	16	Partnered	3	3	64809	
84	KP481	21	Female	14	Partnered	5	4	34110	
117	KP481	31	Female	18	Single	2	1	65220	
139	KP481	48	Male	16	Partnered	2	3	57987	
142	KP781	22	Male	18	Single	4	5	48556	
148	KP781	24	Female	16	Single	5	5	52291	
152	KP781	25	Female	18	Partnered	5	5	61006	
154	KP781	25	Male	18	Partnered	6	4	70966	
155	KP781	25	Male	18	Partnered	6	5	75946	
156	KP781	25	Male	20	Partnered	4	5	74701	
157	KP781	26	Female	21	Single	4	3	69721	
159	KP781	27	Male	16	Partnered	4	5	83416	
160	KP781	27	Male	18	Single	4	3	88396	
161	KP781	27	Male	21	Partnered	4	4	90886	
162	KP781	28	Female	18	Partnered	6	5	92131	
163	KP781	28	Male	18	Partnered	7	5	77191	
164	KP781	28	Male	18	Single	6	5	88396	
166	KP781	29	Male	14	Partnered	7	5	85906	
167	KP781	30	Female	16	Partnered	6	5	90886	
168	KP781	30	Male	18	Partnered	5	4	103336	
169	KP781	30	Male	18	Partnered	5	5	99601	
170	KP781	31	Male	16	Partnered	6	5	89641	
171	KP781	33	Female	18	Partnered	4	5	95866	
172	KP781	34	Male	16	Single	5	5	92131	
173	KP781	35	Male	16	Partnered	4	5	92131	

174	KP781	38	Male	18	Partnered	5	5	104581
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
14	47
23	188
78	94
79	66
84	212
117	21
139	64
142	200
148	200
152	200
154	180
155	240
156	170
157	100
159	160
160	100
161	100
162	180
163	180
164	150
166	300
167	280
168	160
169	150
170	260
171	200
172	150
173	360
174	150
175	200
176	200
177	160
178	120
179	180

Count of Upper bounds and Lower bounds outliers

[ ]:
```
outliers_lower = (df < Lower_bound).sum()
outliers_upper = (df > Upper_bound).sum()
```

```
total_outliers = outliers_lower  + outliers_upper

ouliers_count_df = pd.DataFrame({"LowerBound_outliers" :outliers_lower,␣
↪"UpperBound_outliers" :outliers_upper, "Total" : total_outliers})
print(ouliers_count_df)
```

```
               LowerBound_outliers  UpperBound_outliers  Total
Age                              0                    5      5
Education                        0                    4      4
Fitness                          2                    0      2
Gender                           0                    0      0
Income                           0                   19     19
MaritalStatus                    0                    0      0
Miles                            0                   13     13
Product                          0                    0      0
Usage                            0                    9      9
```

```
<ipython-input-71-e2fa83975e56>:1: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version. Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  outliers_lower = (df < Lower_bound).sum()
<ipython-input-71-e2fa83975e56>:2: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version. Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  outliers_upper = (df > Upper_bound).sum()
```

Calculation of difference between mean and median

If the result is positive, it means the mean is higher than the median, and if it's negative, it means the mean is lower than the median.

[ ]:
```
difference_between_Mean_and_Median = (summary.loc["mean"] - summary.loc["50%"])
difference_between_Mean_and_Median
```

[ ]:
```
Age             2.788889
Education      -0.427778
Usage           0.455556
Fitness         0.311111
Income       3123.077778
Miles           9.194444
dtype: float64
```

Insight : While checking the outliers in the datset, we can pretty much observe each and every column are affected by it; But suprisingly, we have only one outlier catering to "Fitness" coluumn falls below lower boundary level, however rest of all columns have outliers exceeding their upper boundary level.

Recommednation: The Outliers in income levels, miles and Usage columns are huge, hence no erroneous conclusions should be made by considering these outliers in general average estimates of the sales of treadmills.

«——————————————————————————————————»

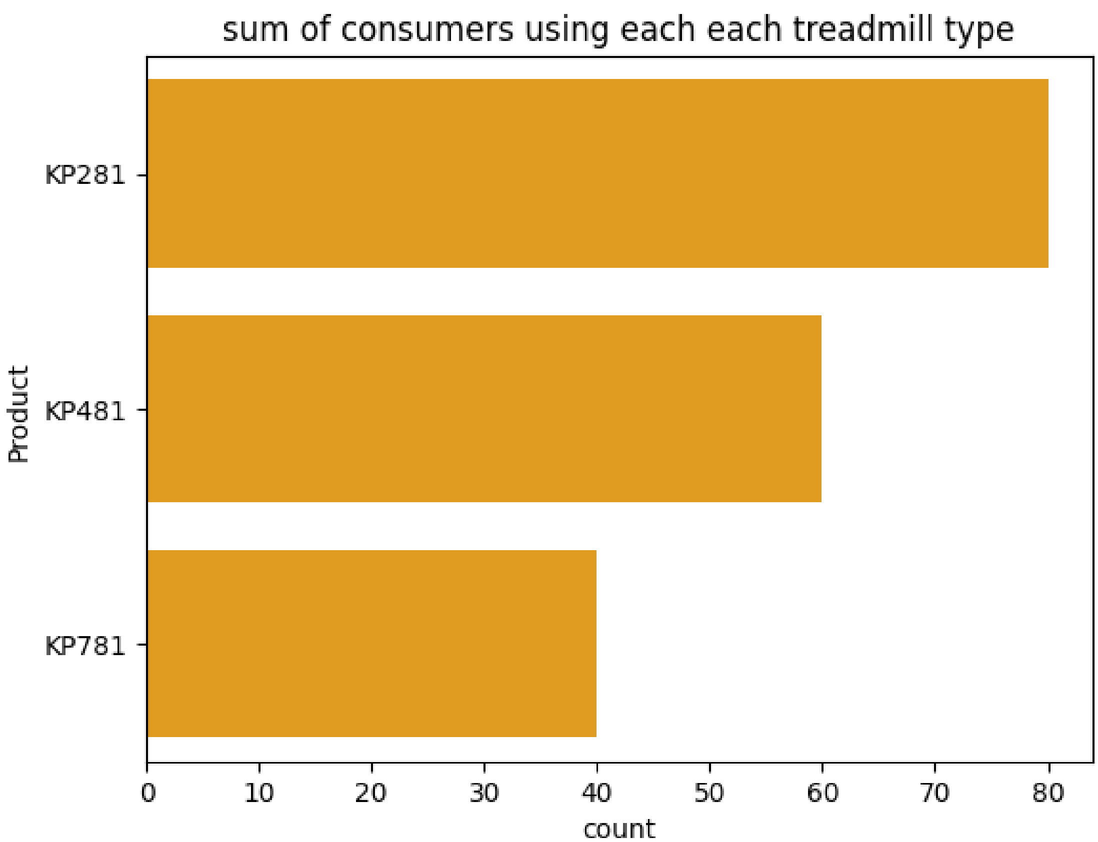
«——————————————————————————————————»

Analysis of the Dataset

1. Sum of Consumers using different treadmill types

[ ]:
```
sns.countplot(data = df.Product, color = 'orange')
plt.title("sum of consumers using each each treadmill type")
```

[ ]: Text(0.5, 1.0, 'sum of consumers using each each treadmill type')



Insight: As you can observe from the bar chart above that the KP281, The basic model have huge number of sales(double the sales of premium type) and there after demand for type2 and type3 decreases at a diminishing rate based on their usecase and cost.

Recommendation: Majority of consumers still purchase the basic model, hence focus should be made to leverage this opportunity for scaling the sales of basic model KP281.

«——————————————————————————————————»

2. Consumer segmentation based on multiple variables

KP281 Product - customer segmentation and analysis

(i) segmentation based on Gender and Maritalstatus

[ ]:
```
Count_of_KP281_products = df[df['Product'] == 'KP281'].groupby(['Gender',␣
↪'MaritalStatus'])['Product'].count()
Count_of_KP281_products = Count_of_KP281_products.sort_values(ascending =␣
↪False).reset_index()
Count_of_KP281_products
```

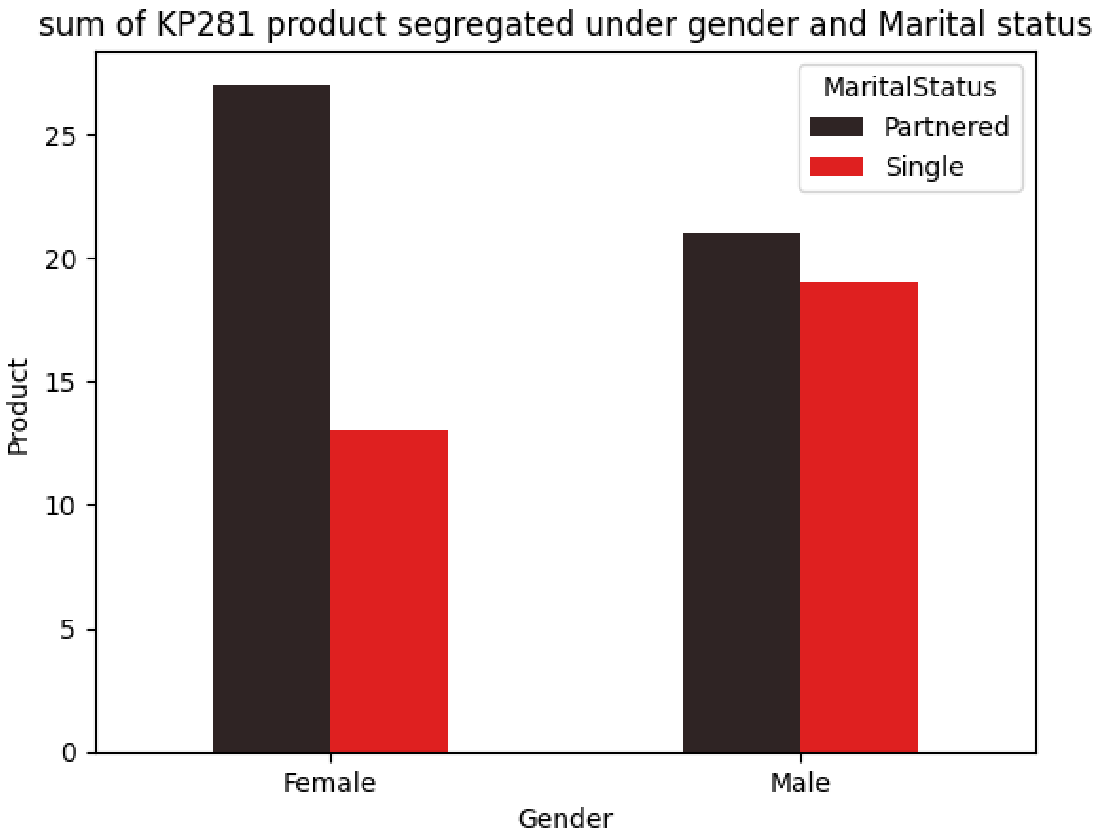
[ ]:

	Gender	MaritalStatus	Product
0	Female	Partnered	27
1	Male	Partnered	21
2	Male	Single	19
3	Female	Single	13

[ ]:
```
sns.barplot(data = Count_of_KP281_products, x = 'Gender' , y = 'Product', hue =␣
↪'MaritalStatus', color = 'r', width = 0.5)
plt.title("sum of KP281 product segregated under gender and Marital status")
```

```
<ipython-input-75-fe98eade0974>:1: FutureWarning:

Setting a gradient palette using color= is deprecated and will be removed in
v0.14.0. Set `palette='dark:r'` for the same effect.

  sns.barplot(data = Count_of_KP281_products, x = 'Gender' , y = 'Product', hue
= 'MaritalStatus', color = 'r', width = 0.5)
```

[ ]:
```
Text(0.5, 1.0, 'sum of KP281 product segregated under gender and Marital
status')
```



(ii) segmentation based on age

[ ]:
```
Count_of_KP281_products = df[df['Product'] == 'KP281'].
 ↪groupby(['Age'])['Product'].count()
Count_of_KP281_products = Count_of_KP281_products.sort_values(ascending =␣
 ↪False).reset_index()
Count_of_KP281_products
```

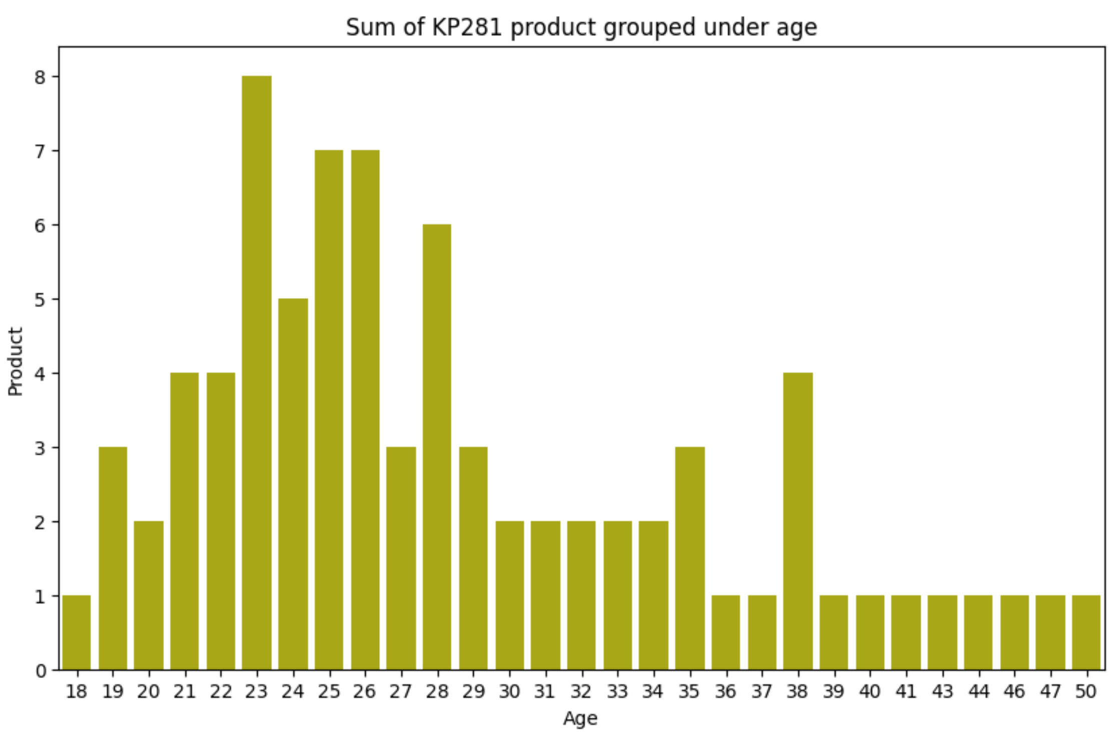
[ ]:

	Age	Product
0	23	8
1	25	7
2	26	7
3	28	6
4	24	5
5	38	4
6	21	4
7	22	4
8	29	3
9	19	3
10	27	3

11	35	3
12	34	2
13	33	2
14	32	2
15	31	2
16	30	2
17	20	2
18	41	1
19	47	1
20	46	1
21	44	1
22	43	1
23	18	1
24	40	1
25	39	1
26	37	1
27	36	1
28	50	1

[ ]:
```
plt.figure(figsize=(10,6))
sns.barplot(data = Count_of_KP281_products, x = 'Age', y = 'Product', color =␣
↪'y')
plt.title("Sum of KP281 product grouped under age")
```

[ ]: Text(0.5, 1.0, 'Sum of KP281 product grouped under age')



Insight: By observing the first graph we can infer that number of sales in the first model are equal for both male and female, and especially if we go into marital staus, for both cases we have partnered people dominating the singles in using the product KP281.

And from the second graph, we can infer that majority of the sales are from people who age between 21-29, and interestingly we also have a slight incremental demand from people who are 38 years old.

Recommednation: As this was a basic model with low cost and also caters to general fitness needs of young people who are between 20 -30, they will definitely show interest in purchasing it.

KP481 Product - customer segmentation and analysis

(i) Segmentation based on Gender and maritalstatus

[ ]:
```
Count_of_KP481_products = df[df['Product'] == 'KP481'].groupby(['Gender',␣
↪'MaritalStatus'])['Product'].count()
Count_of_KP481_products  = Count_of_KP481_products .sort_values(ascending =␣
↪False).reset_index()
Count_of_KP481_products
```

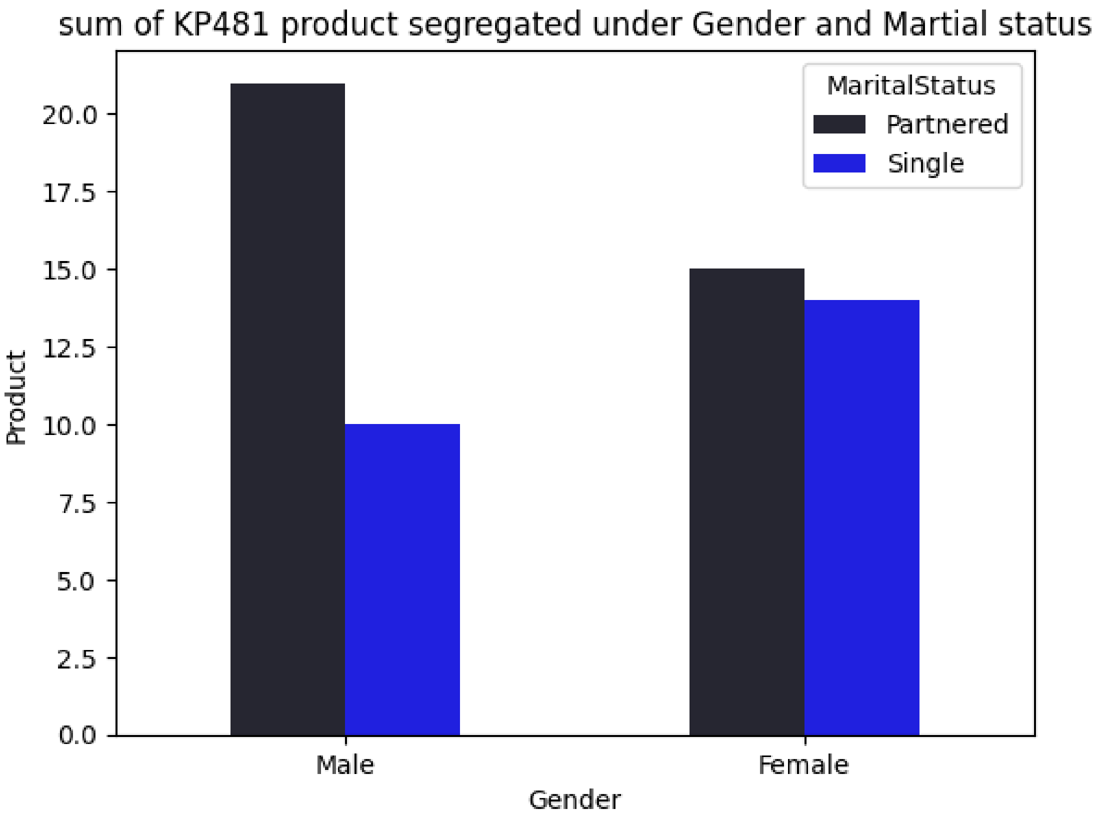
[ ]:

	Gender	MaritalStatus	Product
0	Male	Partnered	21
1	Female	Partnered	15
2	Female	Single	14
3	Male	Single	10

[ ]:
```
sns.barplot(data = Count_of_KP481_products, x = 'Gender', y = 'Product', hue =␣
↪'MaritalStatus', color = 'Blue', width = 0.5)
plt.title("sum of KP481 product segregated under Gender and Martial status")
```

```
<ipython-input-26-c799ce69d406>:1: FutureWarning:

Setting a gradient palette using color= is deprecated and will be removed in
v0.14.0. Set `palette='dark:Blue'` for the same effect.

  sns.barplot(data = Count_of_KP481_products, x = 'Gender', y = 'Product', hue =
'MaritalStatus', color = 'Blue', width = 0.5)
```

[ ]:
```
Text(0.5, 1.0, 'sum of KP481 product segregated under Gender and Martial
status')
```



(ii) segmentation based of Age

[ ]:
```
Count_of_KP481_products = df[df['Product'] == 'KP481'].
 ↪groupby(['Age'])['Product'].count()
Count_of_KP481_products = Count_of_KP481_products.sort_values(ascending =␣
 ↪False).reset_index()
Count_of_KP481_products
```

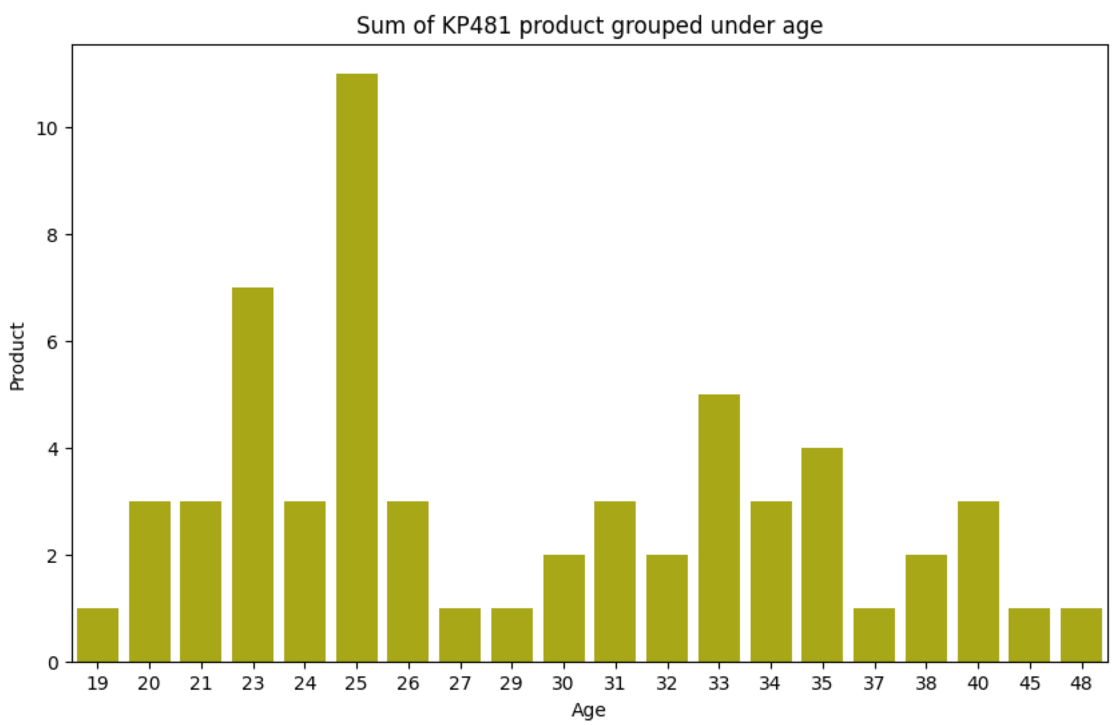
[ ]:

	Age	Product
0	25	11
1	23	7
2	33	5
3	35	4
4	31	3
5	21	3
6	24	3
7	26	3
8	40	3
9	20	3
10	34	3
11	38	2

```
12   30          2
13   32          2
14   45          1
15   19          1
16   37          1
17   29          1
18   27          1
19   48          1
```

[ ]:
```
plt.figure(figsize=(10,6))
sns.barplot(data = Count_of_KP481_products, x = 'Age', y = 'Product', color =␣
 ↪'y')
plt.title("Sum of KP481 product grouped under age")
```

[ ]:
```
Text(0.5, 1.0, 'Sum of KP481 product grouped under age')
```



Insight: By observing the first graph we can infer that number of sales from men are slightly more than female, and especially if we go into marital staus, for both male and female, we have partnered people dominating the singles in using the product KP481.

And from the second graph, we can infer that majority of the sales are from people who are 25 years old. But, interestingly here on an average the sales were distributed across all ages.

Recommednation: As this was a medium model, people and age groups who are demanding this should have good income and fitness levels; Thus, suggesting this model to those segment of people who have these two main traits will improve the sales of this model KP481.

KP781 Product - customer segmentation and analysis

(i) segmentation based on Gender and Maritalstatus

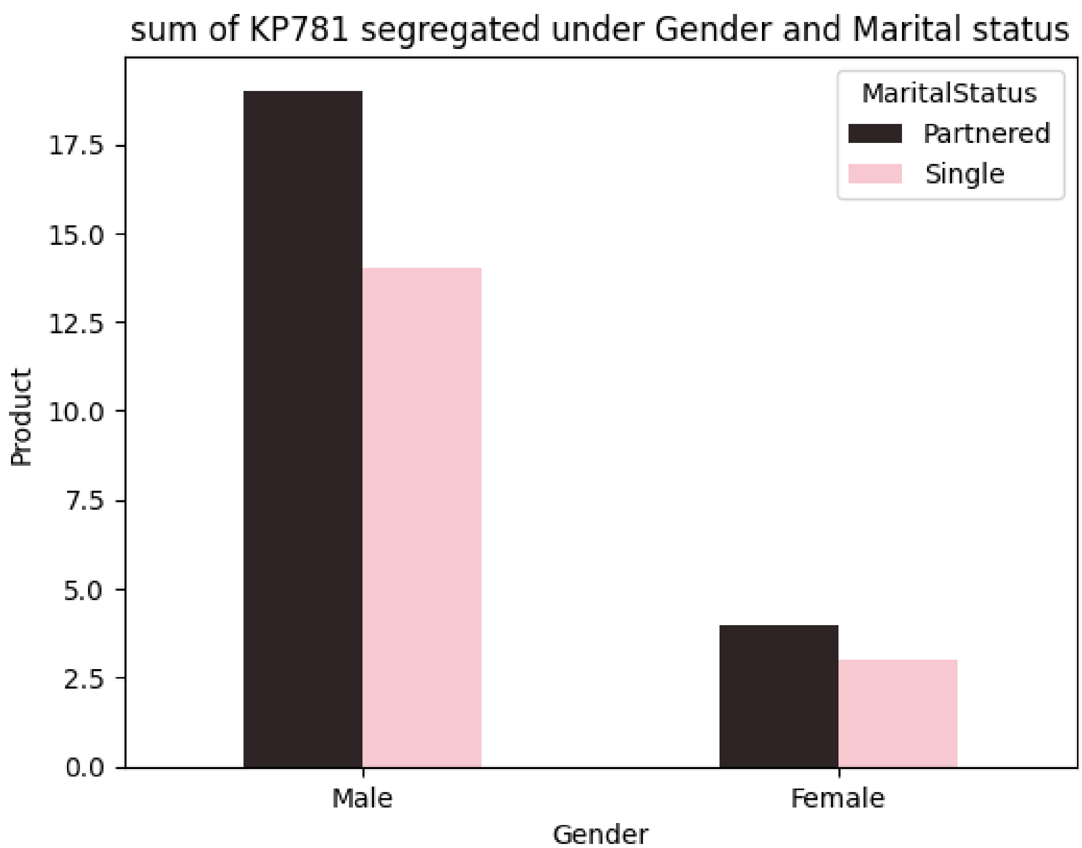
[ ]:
```
Count_of_KP781_products = df[df['Product'] == 'KP781'].groupby(['Gender',␣
↪'MaritalStatus'])['Product'].count()
Count_of_KP781_products  = Count_of_KP781_products .sort_values(ascending =␣
↪False).reset_index()
Count_of_KP781_products
```

[ ]:
```
   Gender MaritalStatus  Product
0    Male     Partnered       19
1    Male        Single       14
2  Female     Partnered        4
3  Female        Single        3
```

[ ]:
```
sns.barplot(data = Count_of_KP781_products, x = 'Gender', y = 'Product', hue =␣
↪'MaritalStatus', color = 'Pink', width = 0.5)
plt.title("sum of KP781 segregated under Gender and Marital status")
```

```
<ipython-input-78-6e420d315878>:1: FutureWarning:

Setting a gradient palette using color= is deprecated and will be removed in
v0.14.0. Set `palette='dark:Pink'` for the same effect.

  sns.barplot(data = Count_of_KP781_products, x = 'Gender', y = 'Product', hue =
'MaritalStatus', color = 'Pink', width = 0.5)
```

[ ]:
```
Text(0.5, 1.0, 'sum of KP781 segregated under Gender and Marital status')
```



Segmentation based on Age

```
[ ]: Count_of_KP781_products = df[df['Product'] == 'KP781'].
     ↪groupby(['Age'])['Product'].count()
     Count_of_KP781_products = Count_of_KP781_products.sort_values(ascending =␣
     ↪False).reset_index()
     Count_of_KP781_products
```

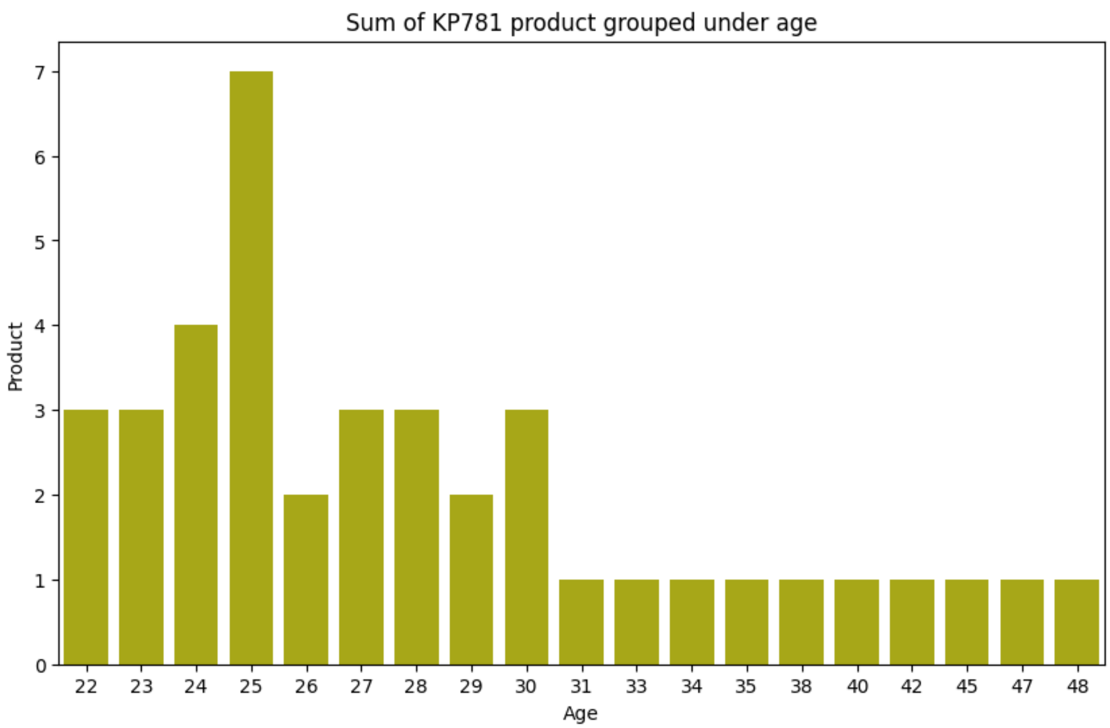
[ ]:

	Age	Product
0	25	7
1	24	4
2	22	3
3	27	3
4	28	3
5	30	3
6	23	3
7	26	2
8	29	2
9	40	1
10	47	1

11	45	1
12	42	1
13	31	1
14	38	1
15	35	1
16	34	1
17	33	1
18	48	1

[ ]:
```
plt.figure(figsize=(10,6))
sns.barplot(data = Count_of_KP781_products, x = 'Age', y = 'Product', color =␣
↪'y')
plt.title("Sum of KP781 product grouped under age")
```

[ ]: Text(0.5, 1.0, 'Sum of KP781 product grouped under age')



Insight: By observing the first graph we can infer that number of sales from men are significantly more than female, and especially if we go into marital staus, for both male and female, we have partnered people dominating the singles in using the product KP781.

And from the second graph, we can infer that majority of the sales are from people who are aged between 22 -30 years old. But, we also have a single machine demand form people who are aged between 31-48

Recommednation: As this was a Premium model, people and age groups who are demanding this should have excellent fitness levels and high end income levels; Thus, suggesting this model to those segment of people who have these two main traits will improve the sales of this model KP781.

«——————————————————————————————»

Creation of age and Income labels

```
[ ]: age_bins = [18,22,26,30,34,38,42,46,50]
age_labels = ['18-22', '23-26', '27-30', '31-34', '35-38', '39-42', '43-46',␣
 ↪'47-50']

df['Age_bracket'] = pd.cut(df['Age'], bins = age_bins, labels = age_labels,␣
 ↪right = False)
```

```
[ ]: income_bins = [29000, 39000, 49000, 59000, 69000, 79000, 89000, 99000, 109000]
income_labels = ['29000-39000', '39001-49000', '49001-59000', '59001-69000',␣
 ↪'69001-79000', '79001-89000', '89001-99000', '99001-109000']

df['Income_lables'] = pd.cut(df['Income'], bins = income_bins, labels =␣
 ↪income_labels, right = False)
```

3. Creation of Multi level contingency tables.

(i) Contingency table for columns like Gender and marital status to calculate marginal and conditional probability.

```
[ ]: contingency_table = pd.crosstab(index = [df['Product'], df['Gender'],␣
 ↪df['MaritalStatus']], columns = 'Count', normalize = True).reset_index()
contingency_table
```

```
[ ]: col_0 Product  Gender MaritalStatus     Count
0        KP281  Female     Partnered  0.150000
1        KP281  Female        Single  0.072222
2        KP281    Male     Partnered  0.116667
3        KP281    Male        Single  0.105556
4        KP481  Female     Partnered  0.083333
5        KP481  Female        Single  0.077778
6        KP481    Male     Partnered  0.116667
7        KP481    Male        Single  0.055556
8        KP781  Female     Partnered  0.022222
9        KP781  Female        Single  0.016667
10       KP781    Male     Partnered  0.105556
11       KP781    Male        Single  0.077778
```

Marginal probabilty for gender

```
[ ]: marginal_gender_probs = contingency_table.
 ↪groupby(['Product','Gender'])['Count'].sum() / contingency_table['Count'].
 ↪sum()
```

```
marginal_gender_probs
```

```
[ ]: Product  Gender
     KP281    Female    0.222222
              Male      0.222222
     KP481    Female    0.161111
              Male      0.172222
     KP781    Female    0.038889
              Male      0.183333
     Name: Count, dtype: float64
```

Conditional probability for gender

```
[ ]: conditional_gender_given_product = contingency_table.groupby(['Product',␣
      ↪'Gender'])['Count'].sum() / contingency_table.groupby('Product')['Count'].
      ↪sum()
     conditional_gender_given_product
```

```
[ ]: Product  Gender
     KP281    Female    0.500000
              Male      0.500000
     KP481    Female    0.483333
              Male      0.516667
     KP781    Female    0.175000
              Male      0.825000
     Name: Count, dtype: float64
```

Marginal probability for Maritalstatus

```
[ ]: marginal_MaritalStatus_probs = contingency_table.groupby(['Product',␣
      ↪'MaritalStatus'])['Count'].sum() / contingency_table['Count'].sum()
     marginal_MaritalStatus_probs
```

```
[ ]: Product  MaritalStatus
     KP281    Partnered        0.266667
              Single           0.177778
     KP481    Partnered        0.200000
              Single           0.133333
     KP781    Partnered        0.127778
              Single           0.094444
     Name: Count, dtype: float64
```

Conditional probability for Maritalstatus

```
[ ]: conditional_marital_given_product = contingency_table.groupby(['Product',␣
      ↪'MaritalStatus'])['Count'].sum() / contingency_table.
      ↪groupby('Product')['Count'].sum()
     conditional_marital_given_product
```

[ ]:
```
Product  MaritalStatus
KP281    Partnered        0.600
         Single           0.400
KP481    Partnered        0.600
         Single           0.400
KP781    Partnered        0.575
         Single           0.425
Name: Count, dtype: float64
```

Insight : If we check the marginal/conditional probability for products demand based on **gender and Maritalstatus**, we can conclude that male dominated the overall sales, but individually in type1, both male an female stood equal, However coming to marital status; partnered people demanded more than singles.

(ii) Contingency table for columns like Age_bracket and Income_labels to calculate marginal and conditional probability.

[ ]:
```
contingency_table = pd.crosstab(index = [df['Product'], df['Age_bracket'],␣
↪df['Income_lables']], columns = 'Count', normalize = True).reset_index()
contingency_table
```

[ ]:

col_0	Product	Age_bracket	Income_lables	Count
0	KP281	18-22	29000-39000	0.055866
1	KP281	23-26	29000-39000	0.050279
2	KP281	23-26	39001-49000	0.078212
3	KP281	23-26	49001-59000	0.005587
4	KP281	27-30	29000-39000	0.005587
5	KP281	27-30	39001-49000	0.033520
6	KP281	27-30	49001-59000	0.061453
7	KP281	27-30	59001-69000	0.005587
8	KP281	31-34	39001-49000	0.022346
9	KP281	31-34	49001-59000	0.022346
10	KP281	35-38	29000-39000	0.005587
11	KP281	35-38	39001-49000	0.011173
12	KP281	35-38	49001-59000	0.011173
13	KP281	35-38	59001-69000	0.011173
14	KP281	39-42	39001-49000	0.005587
15	KP281	39-42	49001-59000	0.022346
16	KP281	39-42	59001-69000	0.011173
17	KP281	43-46	49001-59000	0.011173
18	KP281	47-50	49001-59000	0.005587
19	KP281	47-50	59001-69000	0.005587
20	KP481	18-22	29000-39000	0.039106
21	KP481	23-26	29000-39000	0.011173
22	KP481	23-26	39001-49000	0.089385
23	KP481	23-26	49001-59000	0.016760
24	KP481	27-30	39001-49000	0.011173
25	KP481	27-30	49001-59000	0.016760

```
26      KP481       31-34   39001-49000  0.011173
27      KP481       31-34   49001-59000  0.044693
28      KP481       31-34   59001-69000  0.011173
29      KP481       35-38   39001-49000  0.005587
30      KP481       35-38   49001-59000  0.022346
31      KP481       35-38   59001-69000  0.016760
32      KP481       39-42   49001-59000  0.005587
33      KP481       39-42   59001-69000  0.022346
34      KP481       43-46   49001-59000  0.005587
35      KP481       47-50   49001-59000  0.005587
36      KP781       23-26   39001-49000  0.016760
37      KP781       23-26   49001-59000  0.039106
38      KP781       23-26   59001-69000  0.022346
39      KP781       23-26   69001-79000  0.016760
40      KP781       27-30   49001-59000  0.005587
41      KP781       27-30   59001-69000  0.005587
42      KP781       27-30   69001-79000  0.011173
43      KP781       27-30   79001-89000  0.022346
44      KP781       27-30   89001-99000  0.011173
45      KP781       31-34   89001-99000  0.016760
46      KP781       31-34  99001-109000  0.011173
47      KP781       35-38   89001-99000  0.011173
48      KP781       39-42   79001-89000  0.005587
49      KP781       39-42  99001-109000  0.005587
50      KP781       43-46   89001-99000  0.011173
51      KP781       47-50   89001-99000  0.005587
52      KP781       47-50  99001-109000  0.005587
```

Marginal probability for Age

[ ]:
```
marginal_Age_probs = contingency_table.
  ↪groupby(['Product','Age_bracket'])['Count'].sum() /␣
  ↪contingency_table['Count'].sum()
marginal_Age_probs
```

[ ]:
```
Product  Age_bracket
KP281    18-22          0.055866
         23-26          0.134078
         27-30          0.106145
         31-34          0.044693
         35-38          0.039106
         39-42          0.039106
         43-46          0.011173
         47-50          0.011173
KP481    18-22          0.039106
         23-26          0.117318
         27-30          0.027933
```

```
         31-34           0.067039
         35-38           0.044693
         39-42           0.027933
         43-46           0.005587
         47-50           0.005587
KP781    18-22           0.000000
         23-26           0.094972
         27-30           0.055866
         31-34           0.027933
         35-38           0.011173
         39-42           0.011173
         43-46           0.011173
         47-50           0.011173
Name: Count, dtype: float64
```

Conditional probability for Age

[ ]:
```
conditional_Age_given_product = contingency_table.groupby(['Product',␣
↪'Age_bracket'])['Count'].sum() / contingency_table.
↪groupby('Product')['Count'].sum()
conditional_Age_given_product
```

[ ]:
```
Product  Age_bracket
KP281    18-22           0.126582
         23-26           0.303797
         27-30           0.240506
         31-34           0.101266
         35-38           0.088608
         39-42           0.088608
         43-46           0.025316
         47-50           0.025316
KP481    18-22           0.116667
         23-26           0.350000
         27-30           0.083333
         31-34           0.200000
         35-38           0.133333
         39-42           0.083333
         43-46           0.016667
         47-50           0.016667
KP781    18-22           0.000000
         23-26           0.425000
         27-30           0.250000
         31-34           0.125000
         35-38           0.050000
         39-42           0.050000
         43-46           0.050000
         47-50           0.050000
```

```
Name: Count, dtype: float64
```

Marginal probabilty for Income

```
[ ]: marginal_Income_probs = contingency_table.
      ↪groupby(['Product','Income_lables'])['Count'].sum() /␣
      ↪contingency_table['Count'].sum()
     marginal_Income_probs
```

```
[ ]: Product  Income_lables
     KP281    29000-39000      0.117318
              39001-49000      0.150838
              49001-59000      0.139665
              59001-69000      0.033520
              69001-79000      0.000000
              79001-89000      0.000000
              89001-99000      0.000000
              99001-109000     0.000000
     KP481    29000-39000      0.050279
              39001-49000      0.117318
              49001-59000      0.117318
              59001-69000      0.050279
              69001-79000      0.000000
              79001-89000      0.000000
              89001-99000      0.000000
              99001-109000     0.000000
     KP781    29000-39000      0.000000
              39001-49000      0.016760
              49001-59000      0.044693
              59001-69000      0.027933
              69001-79000      0.027933
              79001-89000      0.027933
              89001-99000      0.055866
              99001-109000     0.022346
     Name: Count, dtype: float64
```

Conditional probablity for Income

```
[ ]: conditional_Income_given_product = contingency_table.groupby(['Product',␣
      ↪'Income_lables'])['Count'].sum() / contingency_table.
      ↪groupby('Product')['Count'].sum()
     conditional_Income_given_product
```

```
[ ]: Product  Income_lables
     KP281    29000-39000      0.265823
              39001-49000      0.341772
              49001-59000      0.316456
```

```
          59001-69000      0.075949
          69001-79000      0.000000
          79001-89000      0.000000
          89001-99000      0.000000
          99001-109000     0.000000
KP481     29000-39000      0.150000
          39001-49000      0.350000
          49001-59000      0.350000
          59001-69000      0.150000
          69001-79000      0.000000
          79001-89000      0.000000
          89001-99000      0.000000
          99001-109000     0.000000
KP781     29000-39000      0.000000
          39001-49000      0.075000
          49001-59000      0.200000
          59001-69000      0.125000
          69001-79000      0.125000
          79001-89000      0.125000
          89001-99000      0.250000
          99001-109000     0.100000
Name: Count, dtype: float64
```

Insight : If we check the marginal/conditional probability for products demand between diffrent age groups, then majority of sales had come from two blocks, i.e. 23-26, 27-30. And talking about income levels, majority of sales had come from people whose incomes range between 29000 - 59000.

«———————————————————————————»

4. Categorization of consumers based on Fitness and Usage

(i) Count of male consumers based on Usage and fitness levels

(Correlation between Usage and Fitness)

[ ]:

```python
Number_of_male = df[df['Gender'] == 'Male'].groupby(['Usage',
 'Fitness'])['Gender'].count().reset_index(name = 'count_of_male')
Number_of_male
```

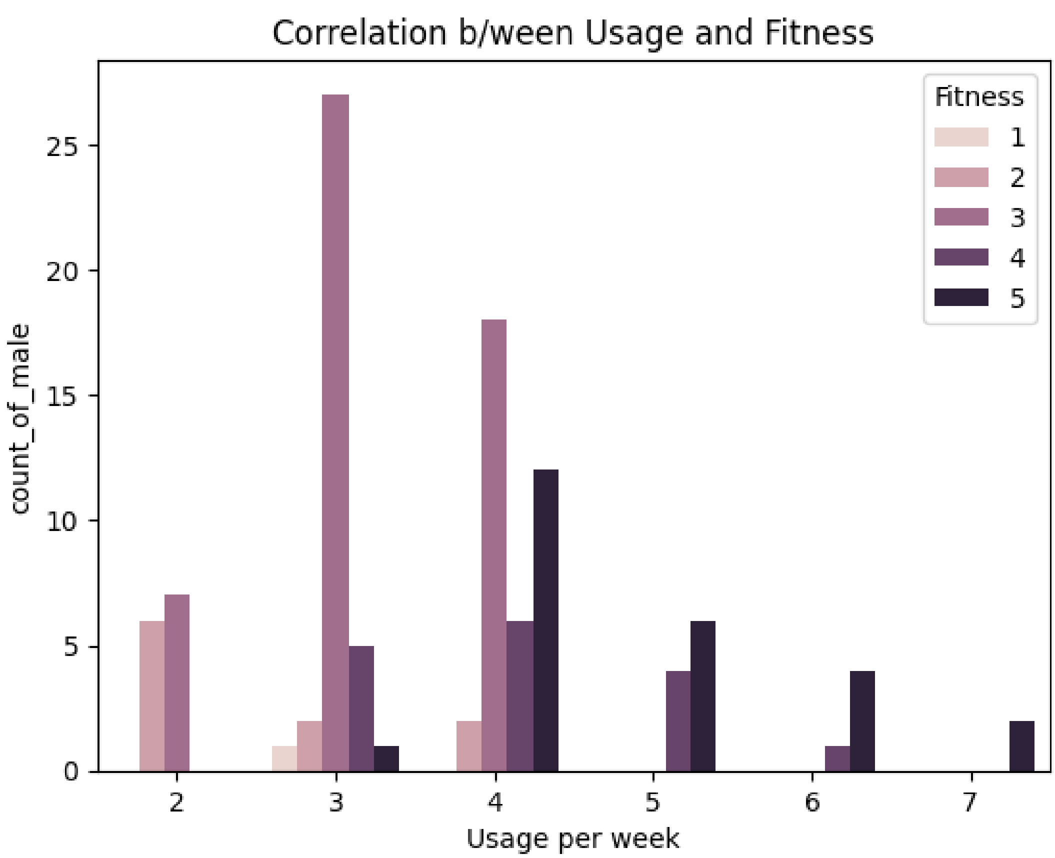
[ ]:

	Usage	Fitness	count_of_male
0	2	2	6
1	2	3	7
2	3	1	1
3	3	2	2
4	3	3	27
5	3	4	5
6	3	5	1
7	4	2	2
8	4	3	18

9	4	4	6
10	4	5	12
11	5	4	4
12	5	5	6
13	6	4	1
14	6	5	4
15	7	5	2

[ ]:
```
sns.barplot(data = Number_of_male, x = 'Usage', y = 'count_of_male', hue =␣
↪'Fitness')
plt.xlabel("Usage per week")
plt.title("Correlation b/ween Usage and Fitness")
```

[ ]:
```
Text(0.5, 1.0, 'Correlation b/ween Usage and Fitness')
```



(ii) Count of Female consumers based on Usage and fitness levels

(Correlation between Usage and Fitness)

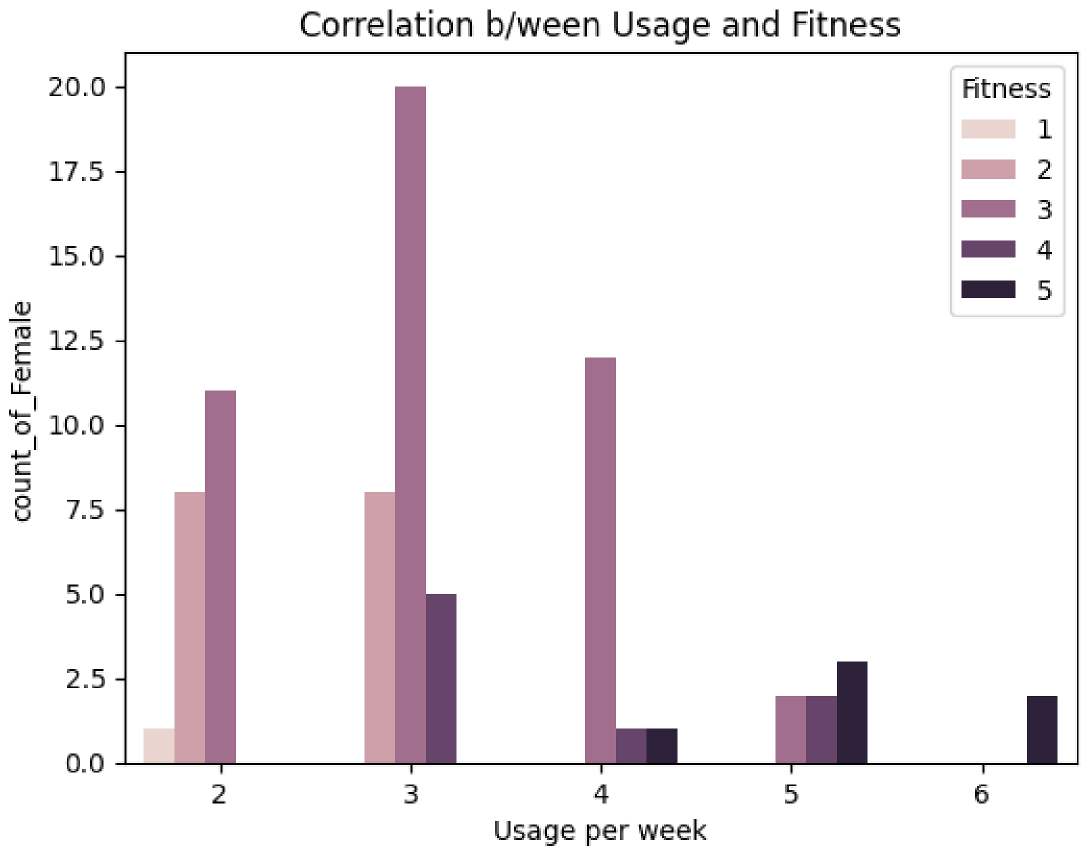
[ ]:
```python
Number_of_female = df[df['Gender'] == 'Female'].groupby(['Usage',
 ↪'Fitness'])['Gender'].count().reset_index(name = 'count_of_Female')
Number_of_female
```

[ ]:

	Usage	Fitness	count_of_Female
0	2	1	1
1	2	2	8
2	2	3	11
3	3	2	8
4	3	3	20
5	3	4	5
6	4	3	12
7	4	4	1
8	4	5	1
9	5	3	2
10	5	4	2
11	5	5	3
12	6	5	2

[ ]:
```python
sns.barplot(data = Number_of_female, x = 'Usage', y = 'count_of_Female', hue =
 ↪'Fitness')
plt.xlabel("Usage per week")
plt.title("Correlation b/ween Usage and Fitness")
```

[ ]: Text(0.5, 1.0, 'Correlation b/ween Usage and Fitness')



Insight : (Male) On an average most males are using the treadmills for approx 3 times a week, and among them a significant percent of people have a general fitness level of 3. But, interestingly the usage times for people who have high fitnes levels like 4 and 5 are distributed from 3 to 7. And in that majority of very fit people are just using the traeadmill for just four times per week.

(Female) On an average most Females are using the treadmills for approx 3 times a week, and among them a significant percent of ladies have a general fitness level of 3. And coming to high end fit people, they are on an average using tradmills 4 to 6 times per week.

Recommednation: If any customer enquires about the general usage limit per week, then we can suggest that for an averag fit individual, 3 times weekly usage is recommednatory and for ultra fit people, a usage of 5 to 6 times is recommended.

Categorization of consumers based on Fitness and Product

(i) Count of male consumers based on each Product type and fitness levels

(Correlation between Product and Fitness)

[ ]:
```
Number_of_Male = df[df['Gender'] == 'Male'].
↪groupby(['Product','Fitness'])['Gender'].count().reset_index(name =␣
↪'count_of_Male')
```

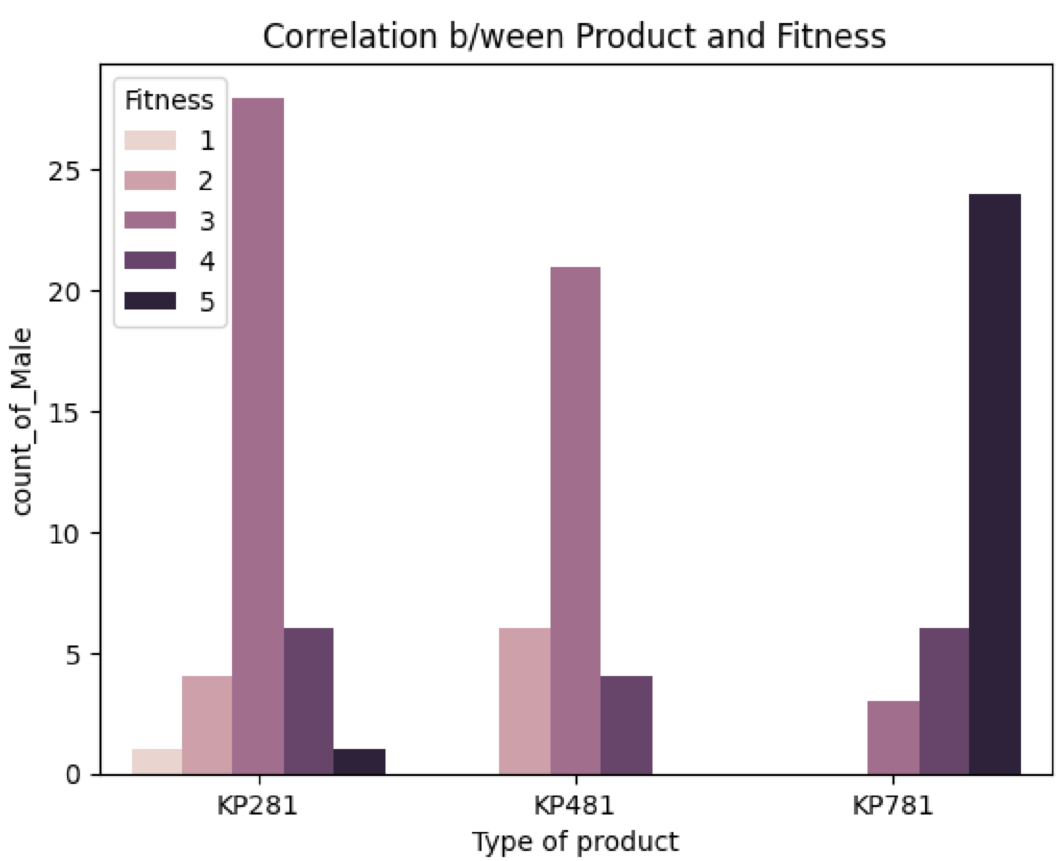
```
Number_of_Male
```

[ ]:

	Product	Fitness	count_of_Male
0	KP281	1	1
1	KP281	2	4
2	KP281	3	28
3	KP281	4	6
4	KP281	5	1
5	KP481	2	6
6	KP481	3	21
7	KP481	4	4
8	KP781	3	3
9	KP781	4	6
10	KP781	5	24

[ ]:
```
sns.barplot(data = Number_of_Male, x = 'Product', y = 'count_of_Male', hue =␣
    ↪'Fitness')
plt.xlabel("Type of product")
plt.title("Correlation b/ween Product and Fitness")
```

[ ]: Text(0.5, 1.0, 'Correlation b/ween Product and Fitness')



(ii) Count of Female consumers based on each Product type and fitness levels

(Correlation between Product and Fitness)

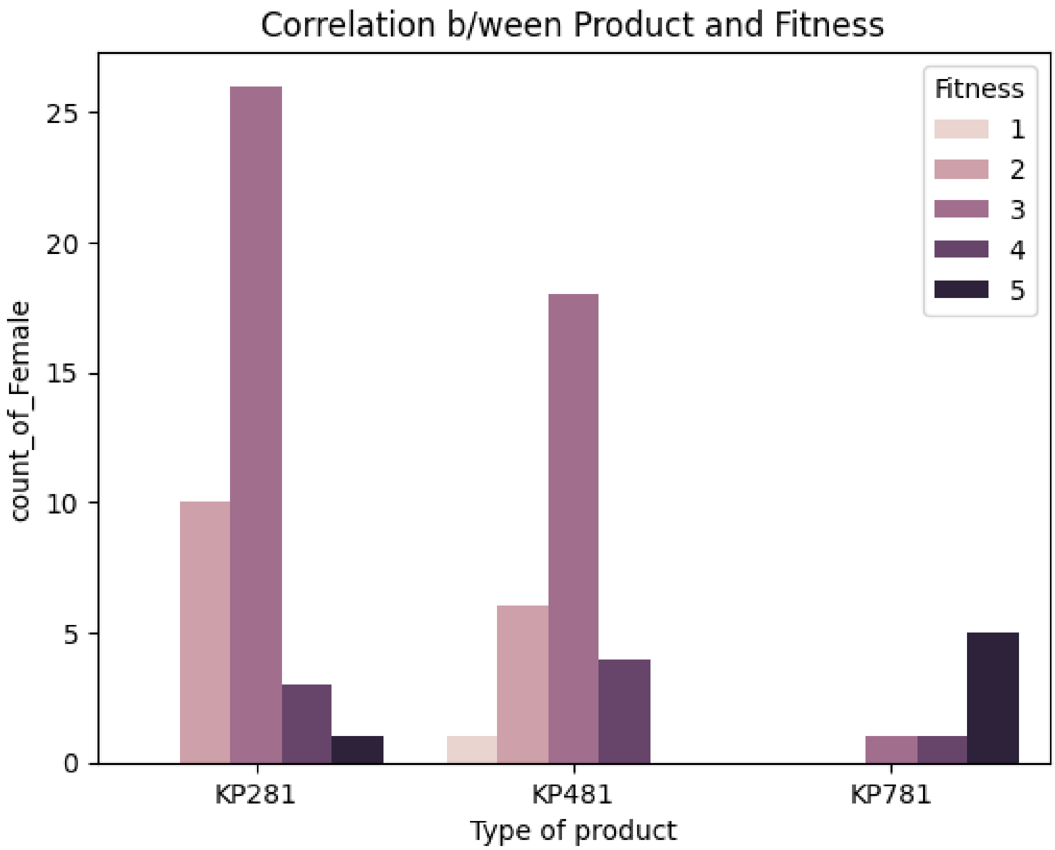
[ ]:
```
Number_of_Female = df[df['Gender'] == 'Female'].
 ↪groupby(['Product','Fitness'])['Gender'].count().reset_index(name =␣
 ↪'count_of_Female')
Number_of_Female
```

[ ]:

	Product	Fitness	count_of_Female
0	KP281	2	10
1	KP281	3	26
2	KP281	4	3
3	KP281	5	1
4	KP481	1	1
5	KP481	2	6
6	KP481	3	18
7	KP481	4	4
8	KP781	3	1
9	KP781	4	1
10	KP781	5	5

[ ]:
```
sns.barplot(data = Number_of_Female , x = 'Product', y = 'count_of_Female', hue␣
 ↪= 'Fitness')
plt.xlabel("Type of product")
plt.title("Correlation b/ween Product and Fitness")
```

[ ]:
```
Text(0.5, 1.0, 'Correlation b/ween Product and Fitness')
```



Insight : (Male) Most males who have a fitness levels of 3 using the KP281, KP481 treadmill models and people who have very high fitnes levels like 4 and 5 are using KP781 model. Some exceptions are always there and some people who are even ultra fit people are also using basic models.

(Female) Even same is happening with females, most female who have a fitness of 3, are using more KP281 & KP481 models and some ultra fit poeple in females too are using the basic models instead of KP781.

Recommednation: Suggestion of type of model is always an individual desire of consumer and their budget etc. However if asked, recommending the models based on their fitness levels will sound more logical. Thus, KP281 AND KP481 models are for medium fit people or young teenagers, whereas KP781 will be more suited to an advanced athelte.

«——————————————————————————————————»

5. Finding correlation between multiple variables

[ ]:
```
correlation_matrix = df.corr()
correlation_matrix
```

```
<ipython-input-53-f471181e404f>:1: FutureWarning: The default value of
```

```
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlation_matrix = df.corr()
```

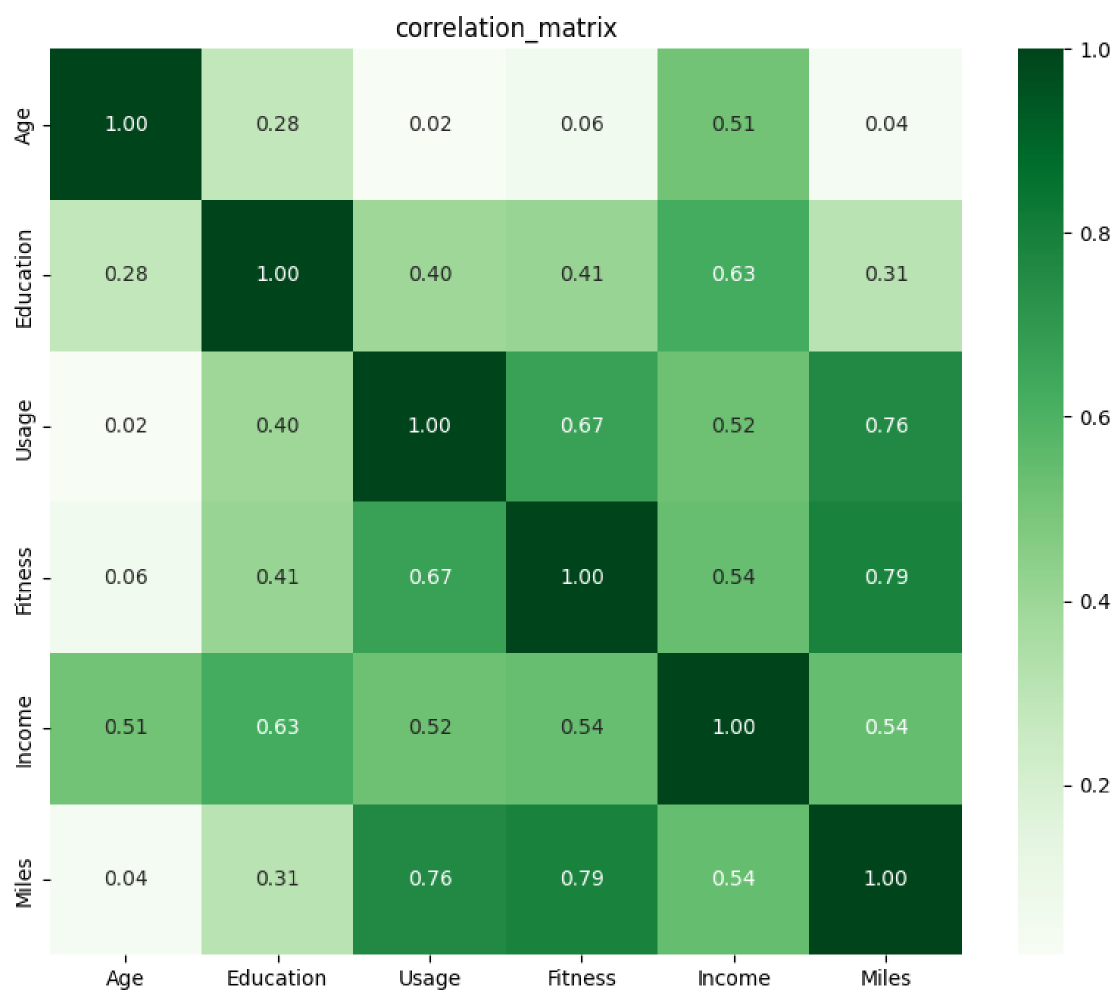
[ ]:

	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000

[ ]:

```python
plt.figure(figsize = (10,8))
sns.heatmap(data = correlation_matrix, annot = True, cmap = "Greens", fmt = ".
 ↪2f" )
plt.title("correlation_matrix")
```

[ ]: Text(0.5, 1.0, 'correlation_matrix')



Insight: (i) From the above heat map, we can infer lot of things but majorily by looking, we can observe that high correlation exists between variables like education-income, fitness-usage, usage/fitness - miles.

More education leads to more income and high fitness leads to more usage thus cultivating to more miles per week.

(ii) And low correlation exists for age/fitness - miles/usage

People who are aged and less fit will definitely use the machine low number of times and hence their miles run per week will also be the lowest.

«——————————————————————————————»

[1]:
```
!pip install nbconvert
```

```
Requirement already satisfied: nbconvert in /usr/local/lib/python3.10/dist-
packages (6.5.4)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (4.9.4)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (4.12.3)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (6.1.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (0.7.1)
Requirement already satisfied: entrypoints>=0.2.2 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.4)
Requirement already satisfied: jinja2>=3.0 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (3.1.3)
Requirement already satisfied: jupyter-core>=4.7 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (5.7.2)
Requirement already satisfied: jupyterlab-pygments in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (2.1.5)
Requirement already satisfied: mistune<2,>=0.8.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.8.4)
Requirement already satisfied: nbclient>=0.5.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.10.0)
Requirement already satisfied: nbformat>=5.1 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (5.10.3)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (24.0)
Requirement already satisfied: pandocfilters>=1.4.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (1.5.1)
Requirement already satisfied: pygments>=2.4.1 in
```