Business Case : Aerofit - Descriptive Statistics & Probability

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmi
```

Analysing Basic Metrics

Shape of data

In [3]:
```
df.shape
```

Out[3]:
```
(180, 9)
```

In [4]:
```
df.columns
```

Out[4]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

Datatypes of Columns

In [5]:
```
df.dtypes
```

Out[5]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

In [6]:
```
df.index
```

Out[6]:
```
RangeIndex(start=0, stop=180, step=1)
```

In [7]:
```
df.head(10)
```

Out[7]:

	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
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
9	KP281	21	Female	15	Partnered	2	3	37521	85

In [8]:
```
df.tail(10)
```

Out[8]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
172	KP781	34	Male	16	Single	5	5	92131	150
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

Missing Value Detection

In [9]:
```
np.any(df.isna())
```

Out[9]: False

In [10]:
```
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
```

- It can be clearly seen from the above that the DataFrame does not contain any missing value.

Statistical Summary

In [11]:
```
df.describe()
```

Out[11]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

In [12]:
```
df.describe(include = object)
```

Out[12]:

	Product	Gender	MaritalStatus
count	180	180	180
unique	3	2	2
top	KP281	Male	Partnered
freq	80	104	107

Value counts and unique attributes

In [13]:
```
prod_counts = df['Product'].value_counts()
prod_counts
```

Out[13]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [14]:
```
gender_counts = df['Gender'].value_counts()
gender_counts
```

Out[14]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [15]:
```
marital_status_counts = df['MaritalStatus'].value_counts()
marital_status_counts
```

Out[15]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

In [16]:
```
fitness_counts = df['Fitness'].value_counts()
fitness_counts
```

Out[16]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

In [17]:
```
usage_counts = df['Usage'].value_counts()
usage_counts
```

Out[17]:
```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

In [18]:
```
df['Education'].value_counts()
```

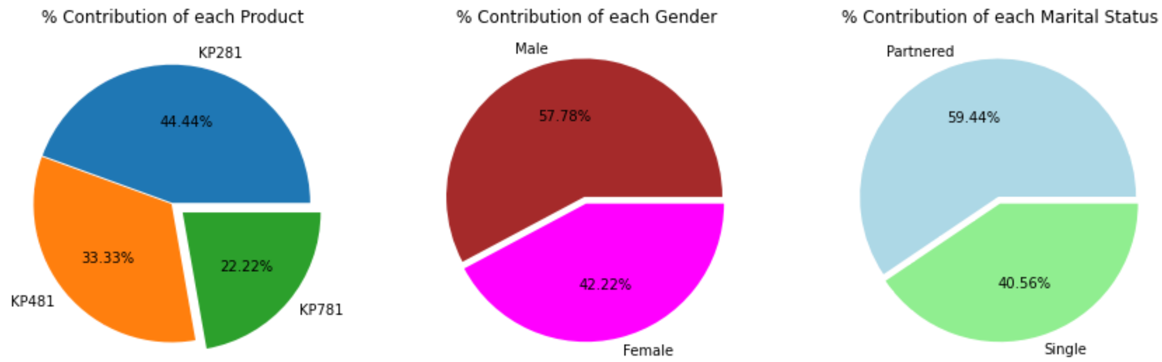
Out[18]:
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

In [19]:
```
prod_dist = np.round(df['Product'].value_counts(normalize = True) * 100, 2).to_frame()
plt.figure(figsize = (15, 30))
plt.subplot(1, 3, 1)
plt.title('% Contribution of each Product')
plt.pie(x = prod_dist['Product'], explode = [0.005, 0.005, 0.1], labels = prod_dist.index, autopct = '%.2f%%')


gender_dist = (np.round(df['Gender'].value_counts(normalize = True) * 100, 2)).to_frame()
plt.subplot(1, 3, 2)
plt.title('% Contribution of each Gender')
plt.pie(x = gender_dist['Gender'], explode = [0.05, 0],
        labels = gender_dist.index, autopct = '%.2f%%', colors = ['brown', 'magenta'])


marital_status_dist = (np.round(df['MaritalStatus'].value_counts(normalize = True) * 100, 2)).to_frame()
plt.subplot(1, 3, 3)
plt.title('% Contribution of each Marital Status')
plt.pie(x = marital_status_dist['MaritalStatus'], explode = [0.05, 0],
        labels = marital_status_dist.index, autopct = '%.2f%%', colors = ['lightblue', 'lightgreen'])
plt.plot()
```

Out[19]: []

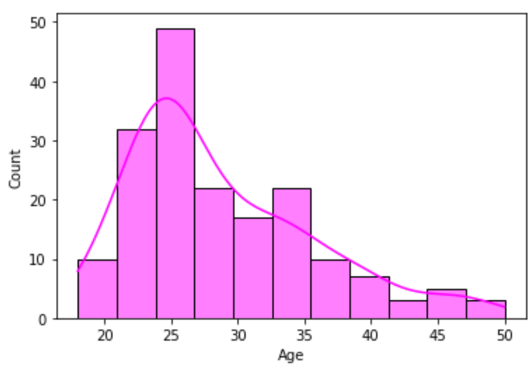


Univariate Analysis

How are the ages of the Aerofit Customers distributed ?

In [20]:
```
plt.figure()
sns.histplot(data = df, x = 'Age', kde = True, color = 'magenta')
plt.plot()
```

Out[20]: []

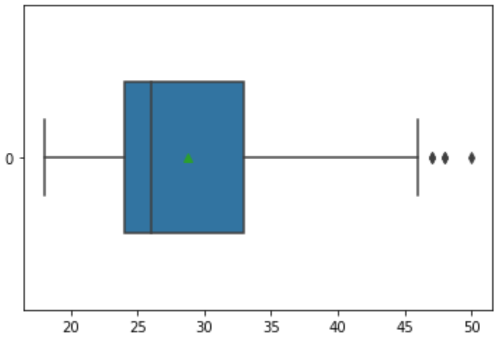


- Most of the customers (more than 80% of the total) are aged between 20 and 30 years.
- Less than 10% customers are aged 40 years and above.

Detecting outliers in age data for aerofit customers

In [21]:
```
sns.boxplot(data = df['Age'], width = 0.5, orient = 'h', showmeans = True)
plt.plot()
```

Out[21]: []



Sample Calculation

In [22]:
```
result = df[(df["Age"] >= 20) & (df['Age'] <= 35)]['Product'].count() / len(df) * 100
"%% of customers whose age is between 20 and 35 is %.2f%%"%(result)
```

Out[22]: '% of customers whose age is between 20 and 35 is 81.67%'

In [23]:
```
data = df['Age']
print('Mean : ', data.mean())
print('Median : ', data.median())
q1 = data.quantile(0.25)
q3 = data.quantile(0.75)
print("1st Quartile : ", q1)
print("3rd Quartile : ", q3)
iqr = q3 - q1
print('Innerquartile Range : ', iqr)
upper = q3 + 1.5 * iqr
lower = q1 - 1.5 * iqr
print("Upper Bound : ", upper)
print('Lower Bound : ', lower)
outliers = data[(data > upper) | (data < lower)]
print("Outliers : ", sorted(outliers))
len_outliers = len((data[(data > upper) | (data < lower)]))
print('No of Outliers : ', len_outliers)
```

```
Mean :  28.788888888888888
Median :  26.0
1st Quartile :  24.0
3rd Quartile :  33.0
Innerquartile Range :  9.0
Upper Bound :  46.5
Lower Bound :  10.5
Outliers :  [47, 47, 48, 48, 50]
No of Outliers :  5
```

Based on the above obtained values, converting age column into bins :

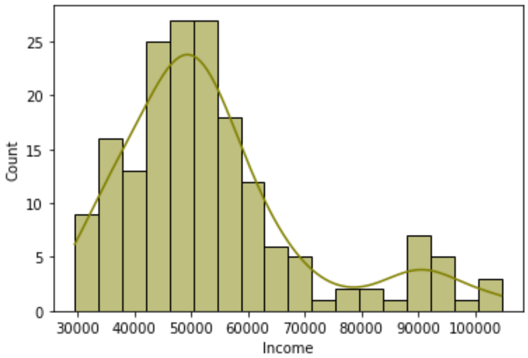
In [24]:
```
def age_partitions(x):
    if x <= 24:
        return '<= 24 '
    elif 25 < x <= 33:
        return '25 - 33'
    elif 34 < x <= 46:
        return '34 - 46'
    else:
        return '> 46'
df['age_bins'] = df['Age'].apply(age_partitions)
df['age_bins'].loc[np.random.randint(0, 180, 10)]
```

Out[24]:
```
157    25 - 33
6       <= 24
53     25 - 33
159    25 - 33
162    25 - 33
173    34 - 46
9       <= 24
27        > 46
41     25 - 33
124    25 - 33
Name: age_bins, dtype: object
```

How is the annual income of the Aerofit Customers distributed ?

In [25]:
```
plt.figure()
sns.histplot(data = df, x = 'Income', kde = True, bins = 18, color = 'olive')
plt.plot()
```

Out[25]: []

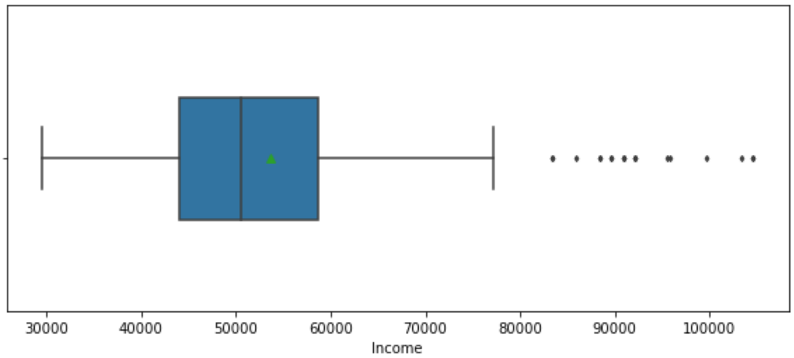


- Majority of the customers earn in between 35000 and 60000 dollars annually.
- 80 % of the customers annual salary is less than 65000$.

Detecting outliers in annual income data of aerofit customers

In [26]:
```
plt.figure(figsize = (10, 4))
sns.boxplot(data = df, x = 'Income', width = 0.4, orient = 'h', showmeans = True, fliersize = 3)
plt.plot()
```

Out[26]: []



Sample Calculation :

In [27]:
```
data = df['Income']
print('Mean : ', data.mean())
print('Median : ', data.median())
q1 = data.quantile(0.25)
q3 = data.quantile(0.75)
print("1st Quartile : ", q1)
print("3rd Quartile : ", q3)
iqr = q3 - q1
print('Innerquartile Range : ', iqr)
upper = q3 + 1.5 * iqr
lower = q1 - 1.5 * iqr
print("Upper Bound : ", upper)
print('Lower Bound : ', lower)
outliers = data[(data > upper) | (data < lower)]
print("Outliers : ", sorted(outliers))
len_outliers = len((data[(data > upper) | (data < lower)]))
print('No of Outliers : ', len_outliers)
```

```
Mean :  53719.57777777778
Median :  50596.5
1st Quartile :  44058.75
3rd Quartile :  58668.0
Innerquartile Range :  14609.25
Upper Bound :  80581.875
Lower Bound :  22144.875
Outliers :  [83416, 83416, 85906, 88396, 88396, 89641, 89641, 90886, 90886, 90886, 92131, 92131, 92131, 95508, 95
866, 99601, 103336, 104581, 104581]
No of Outliers :  19
```

Based on the above obtained values, converting age column into bins :

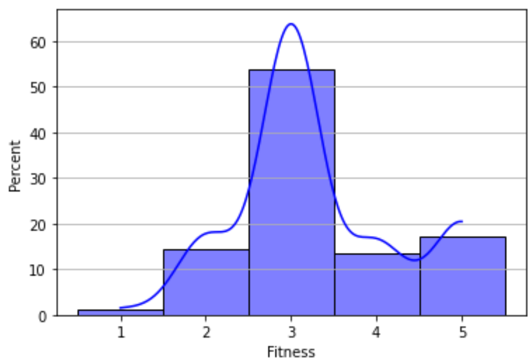
In [28]:
```
def income_partitions(x):
    if x < 45000:
        return '< 45k '
    elif 45000 <= x < 60000:
        return '45k - 60k'
    elif 60000 <= x < 80000:
        return '60k - 80k'
    else:
        return '> 80k'
df['income_bins'] = df['Income'].apply(income_partitions)
df['income_bins'].loc[np.random.randint(0, 180, 10)]
```

Out[28]:
```
125    60k - 80k
82         < 45k
143    45k - 60k
20         < 45k
140    45k - 60k
166        > 80k
112    45k - 60k
177        > 80k
128    45k - 60k
46     45k - 60k
Name: income_bins, dtype: object
```

How is the self rated fitness scale of Aerofit Treadmill customers distributed ?

In [29]:
```
plt.figure()
sns.histplot(data = df, x = 'Fitness', discrete = True, kde = True, stat = 'percent', color = 'blue')
plt.yticks(np.arange(0, 101, 10))
plt.grid(axis = 'y')
plt.plot()
```

Out[29]: []

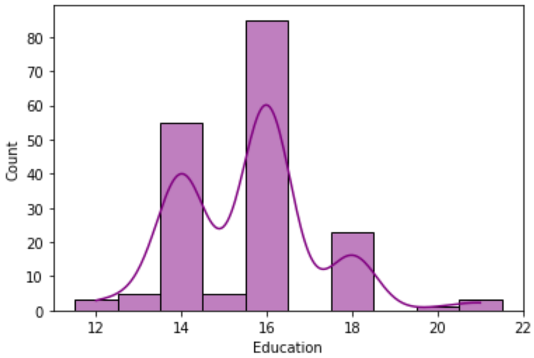


- More than 50% customers rate themselves 3 out of 5 in self rated fitness scale
- Around 30% of the total customers rate themselves 4 or above in the fitness scale.
- Around 70 % of the aerofit customers rate themselves 3 or less than 3 in fitness scale.
- Less than 20 % of aerofit customers have excellent shape.

How is the Education (in years) of Aerofit Treadmill customers distributed ?

In [30]:
```
sns.histplot(data = df, x = 'Education', discrete = True, kde = True, color = 'purple')
plt.plot()
```

Out[30]: []

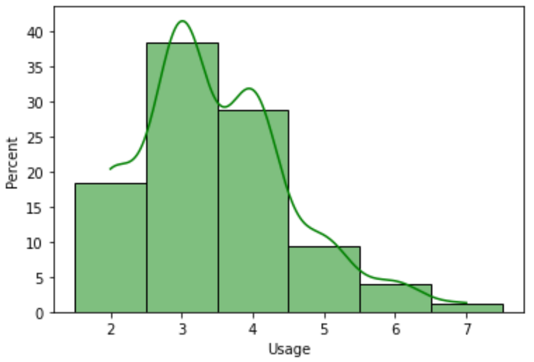


- It can be evidently observed in the above plot that most customers have 16 years of Education, followed by 14 years and 18 years.

How is the number of times the Aerofit Treadmill customers plan to use the treadmill each week distributed ?

In [31]:
```
sns.histplot(data = df, x = 'Usage', kde = True, stat = 'percent', discrete = True, color = 'green')
plt.plot()
```

Out[31]: []



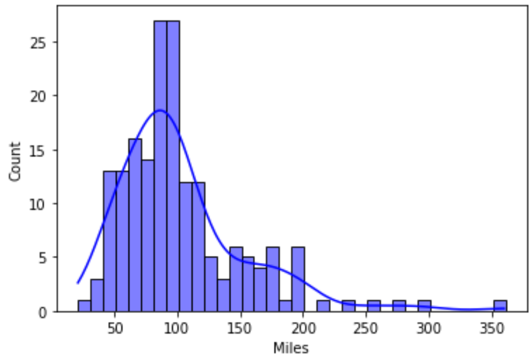
- Based on the above plot, it appears that most customers use treadmills on alternate days.

- There are about 40% of customers who use treadmills three days a week and about 30% who use them four days a week.

Count of customers vs the expected number of miles customers run / walk each week

In [32]:
```
plt.figure()
sns.histplot(data = df, x = 'Miles', kde = True, binwidth = 10, color = 'blue')
plt.plot()
```

Out[32]: []

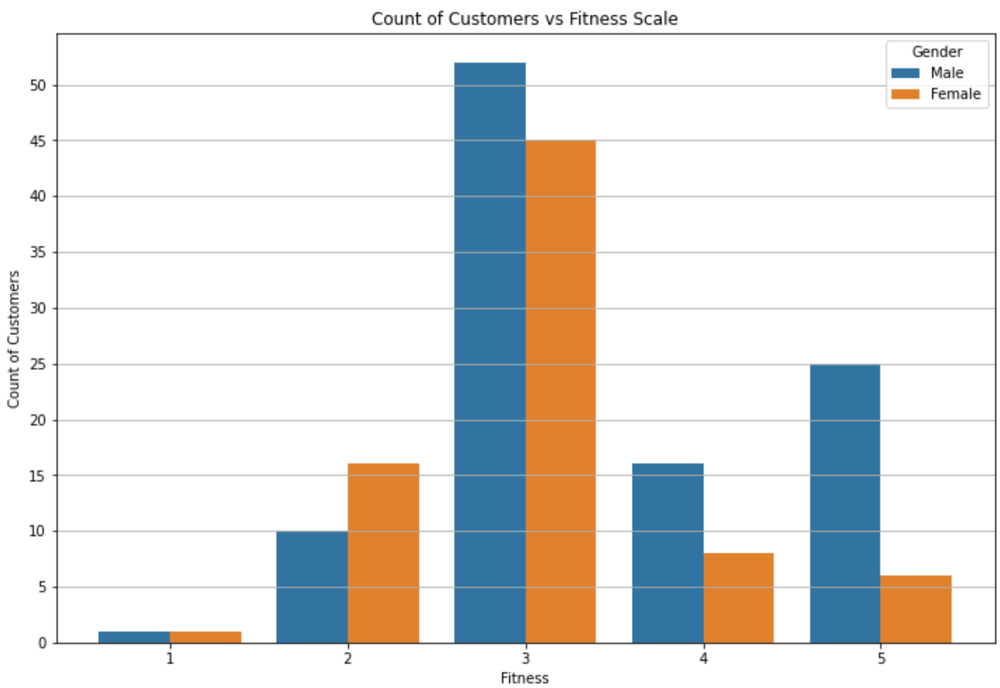


- On the above plot, we can see that most customers expect to walk or run between 40 and 120 miles a week.

Bivariate Analysis

In [33]:
```
plt.figure(figsize = (12, 8))
plt.title('Count of Customers vs Fitness Scale')
sns.countplot(data = df, x = 'Fitness', hue = 'Gender')
plt.grid(axis = 'y')
plt.yticks(np.arange(0, 60, 5))
plt.ylabel('Count of Customers')
plt.plot()
```

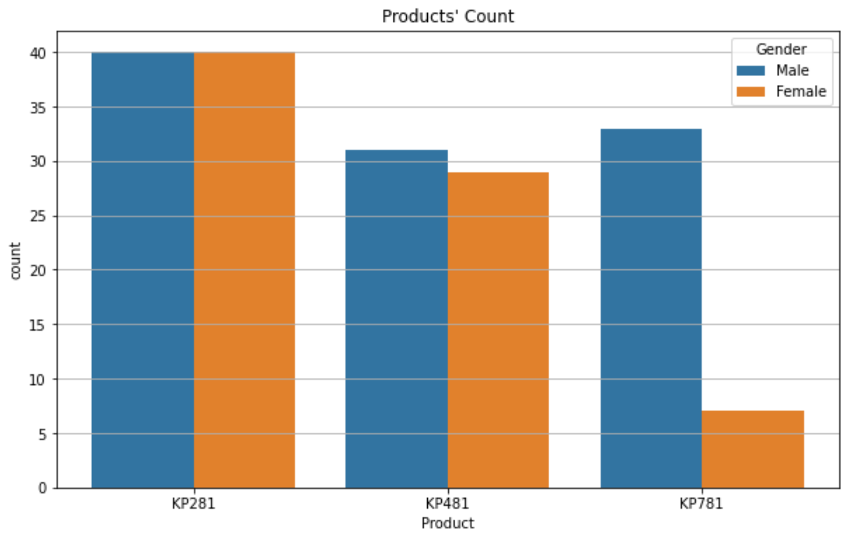
Out[33]: []



- Most of the males and females (more than 50% customers) find themselves in the fitness scale 3 .
- There is a slight difference in the number of males and females in all the fitness scales except for high fitness scales.
- For fitness scales 4 and 5, there are roughly 3 times more males than females.

```
In [34]: plt.figure(figsize = (10, 6))
         plt.title("Products' Count")
         sns.countplot(data = df, x = 'Product', hue = 'Gender')
         plt.grid(axis = 'y')
         plt.plot()
```

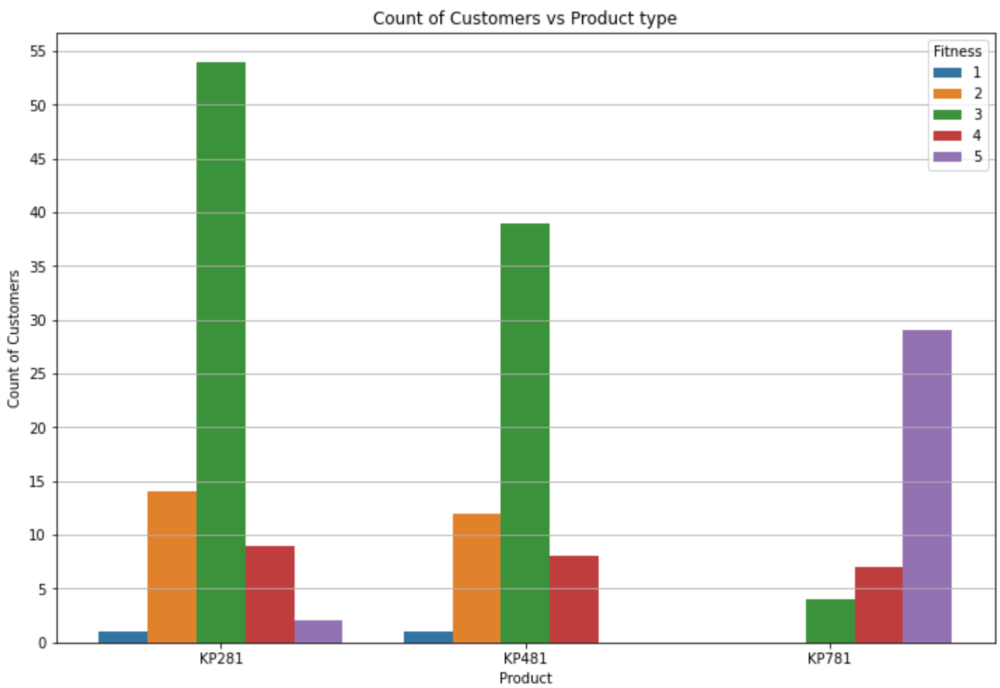
```
Out[34]: []
```



- It can be observed that most people buy the entry-level treadmills.
- The number of males buying the treadmills having advanced features is around 5 times the number of females buying the same.

```
In [35]: # For Male, different product categories and
         plt.figure(figsize = (12, 8))
         plt.title("Count of Customers vs Product type")
         plt.yticks(np.arange(0, 60, 5))
         sns.countplot(data = df, x = 'Product', hue = 'Fitness')
         plt.ylabel('Count of Customers')
         plt.grid(axis = 'y')
         plt.plot()
```

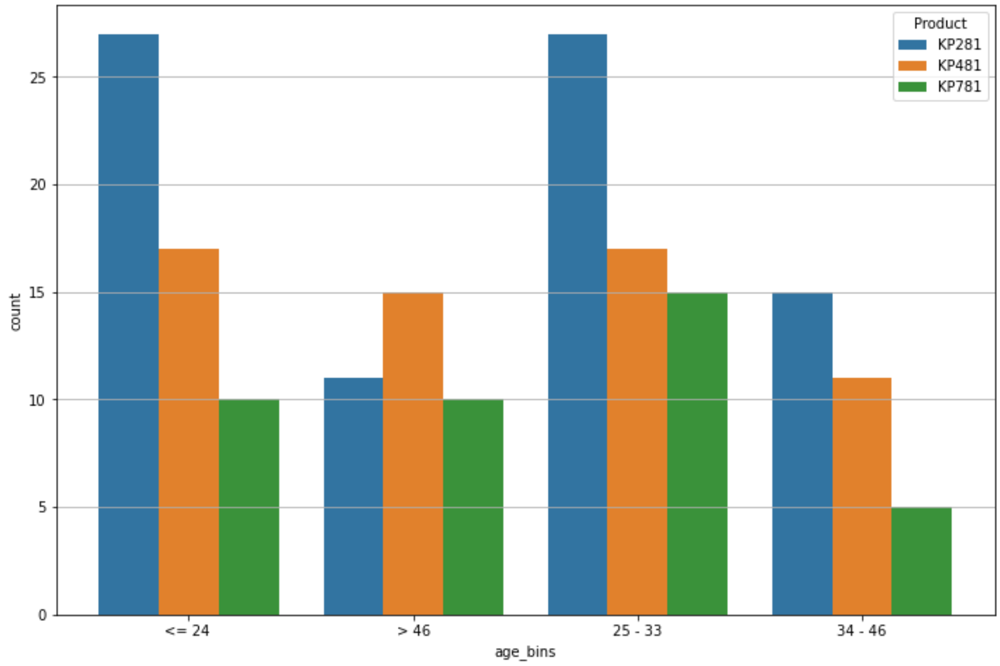
```
Out[35]: []
```



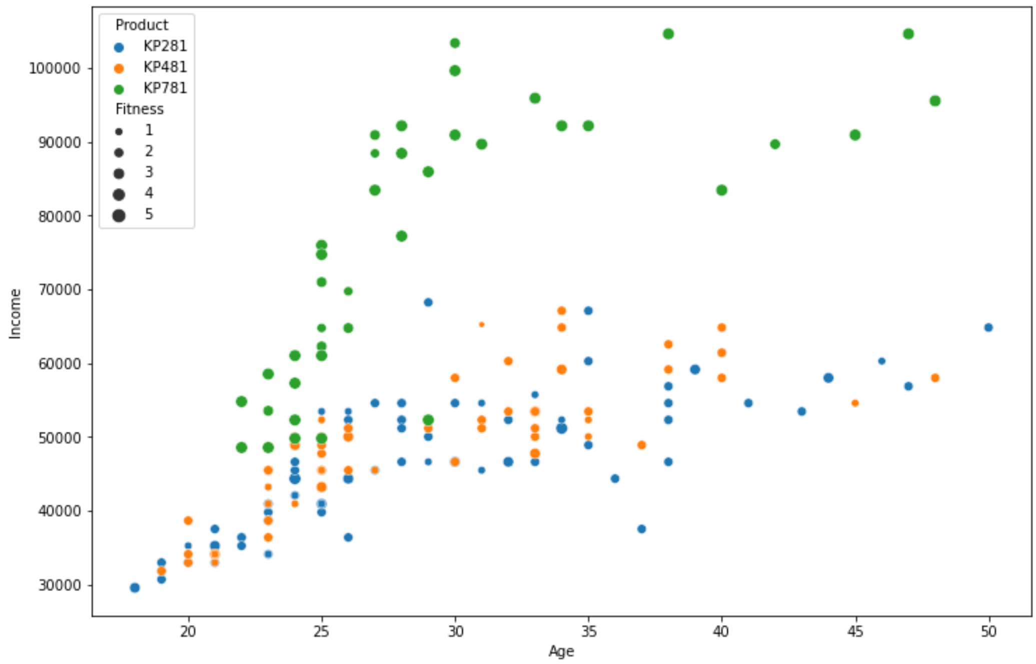
- The customers who rate themselses 3 out of 5 in self rated fitness scale are more likely to invest in the entry-level treadmills or treadmills for mid-level runners i.e., KP281 and KP481 respectively and they are more unlikey to buy the treadmill which has advanced features i.e., KP781.
- The treadmill having advanced features are mostly used by the people with high fitness levels.
- The customers who rate themselves 3 or below in the self-rated fitness scale do not buy KP781.

In [36]:
```
plt.figure(figsize = (12, 8))
sns.countplot(data = df, x = 'age_bins', hue = 'Product')
plt.grid(axis = 'y')
plt.plot()
```

Out[36]: []



In [37]:
```
plt.figure(figsize = (12, 8))
sns.scatterplot(data = df, x= 'Age', y = 'Income', hue = 'Product', size = 'Fitness')
plt.show()
```

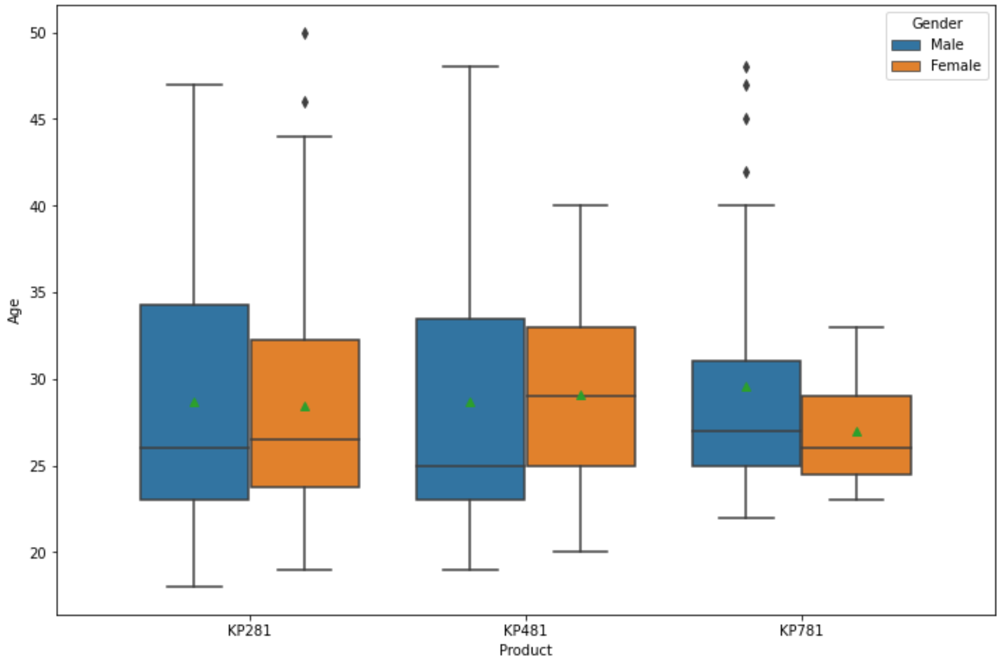


- The customers having high annual income and high fitness scale generally buys KP781.
- The customers having low fitness scale or low annual income generally buy KP281 and KP481.

What is the age range of the customers who purchase a specific type of product?

In [38]:
```
plt.figure(figsize = (12, 8))
sns.boxplot(data = df, x = 'Product', y = 'Age', hue = 'Gender', showmeans = True)
plt.plot()
```

Out[38]: []



- Most customers were in their 20s or 30s.
- The age range of KP781 customers is smaller than the age range of the customers who bought other two products.
- There is a significant difference in the median age of males and females who bought KP481.
- For any product, the age range for males is higher than that of female. The range difference is significant for the product KP781.

Sample calculation to detect outliers in the age of males who bought KP781

In [39]:
```
data = df.loc[(df['Product'] == 'KP781') & (df['Gender'] == 'Male'), 'Age']
print('Mean : ', data.mean())
print('Median : ', data.median())
q1 = data.quantile(0.25)
q3 = data.quantile(0.75)
print("Quartile 1 : ", q1)
print("Quartile 3 : ", q3)
iqr = q3 - q1
print('Inner Quartile Range : ', iqr)
upper = q3 + 1.5 * iqr
lower = q1 - 1.5 * iqr
print("Upper : ", upper)
print('Lower : ', lower)
outliers = data[(data > upper) | (data < lower)]
print("Outliers : ", list(outliers))
len_outliers = len((data[(data > upper) | (data < lower)]))
print('No of Outliers : ', len_outliers)
```

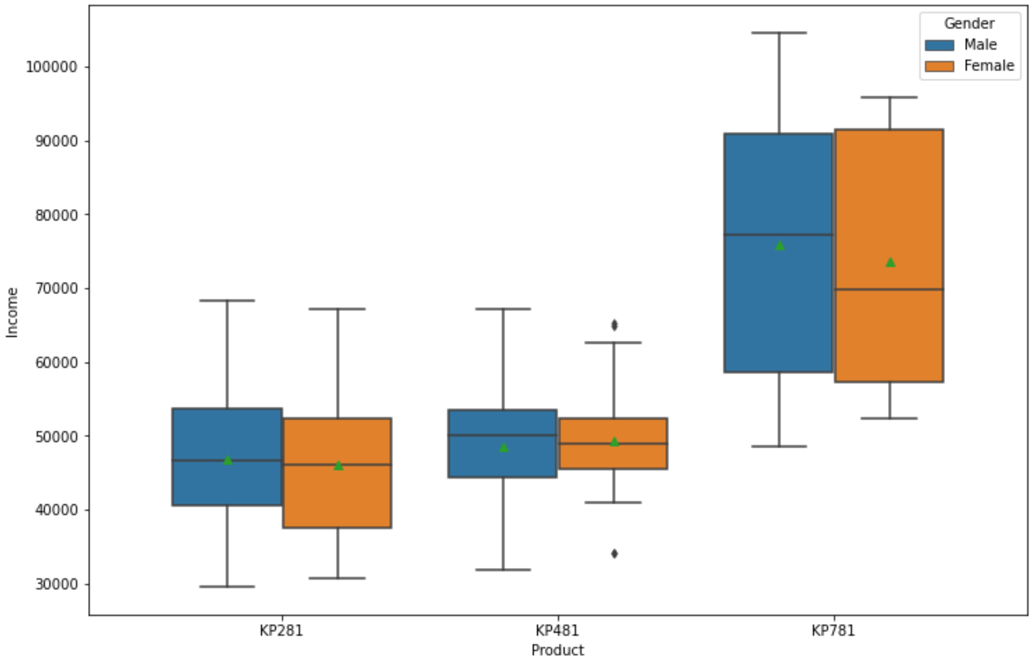
```
Mean :  29.545454545454547
Median :  27.0
Quartile 1 :  25.0
Quartile 3 :  31.0
Inner Quartile Range :  6.0
Upper :  40.0
Lower :  16.0
Outliers :  [42, 45, 47, 48]
No of Outliers :  4
```

- We can clearly see in the boxplot above the sample calculation that we have exactly 4 outliers in the data of age of the males who bought KP781 treadmill.

What is the income range of the customers who purchase a specific type of product?

In [40]:
```
plt.figure(figsize = (12, 8))
sns.boxplot(data = df, x = 'Product', y = 'Income', hue = 'Gender', showmeans = True, fliersize = 4)
plt.plot()
```

Out[40]: []



- The median income of customers who bought KP781 is much higher than that of the customers who bought other two products.
- The range of income for customers buying KP781 is much higher than the same for customers buying KP281 and KP481.

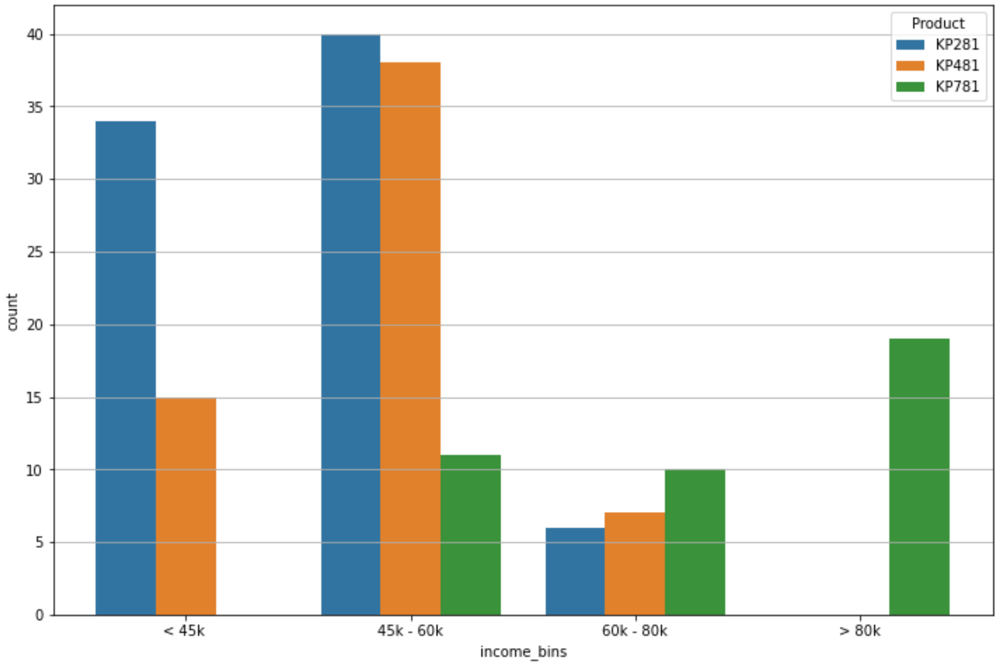
Sample calculation to detect outliers in the income of females who bought KP481

In [41]:
```
data = df.loc[(df['Product'] == 'KP481') & (df['Gender'] == 'Female'), 'Income']
print('Mean : ', data.mean())
print('Median : ', data.median())
q1 = data.quantile(0.25)
q3 = data.quantile(0.75)
print("Quartile 1 : ", q1)
print("Quartile 3 : ", q3)
iqr = q3 - q1
print('Inner Quartile Range : ', iqr)
upper = q3 + 1.5 * iqr
lower = q1 - 1.5 * iqr
print("Upper : ", upper)
print('Lower : ', lower)
outliers = data[(data > upper) | (data < lower)]
print("Outliers : ", list(outliers))
len_outliers = len((data[(data > upper) | (data < lower)]))
print('No of Outliers : ', len_outliers)
```

```
Mean :  49336.44827586207
Median :  48891.0
Quartile 1 :  45480.0
Quartile 3 :  52302.0
Inner Quartile Range :  6822.0
Upper :  62535.0
Lower :  35247.0
Outliers :  [34110, 34110, 65220, 64809]
No of Outliers :  4
```

In [42]:
```
plt.figure(figsize = (12, 8))
sns.countplot(data = df, x = 'income_bins', hue = 'Product')
plt.grid(axis = 'y')
plt.plot()
```

Out[42]: []

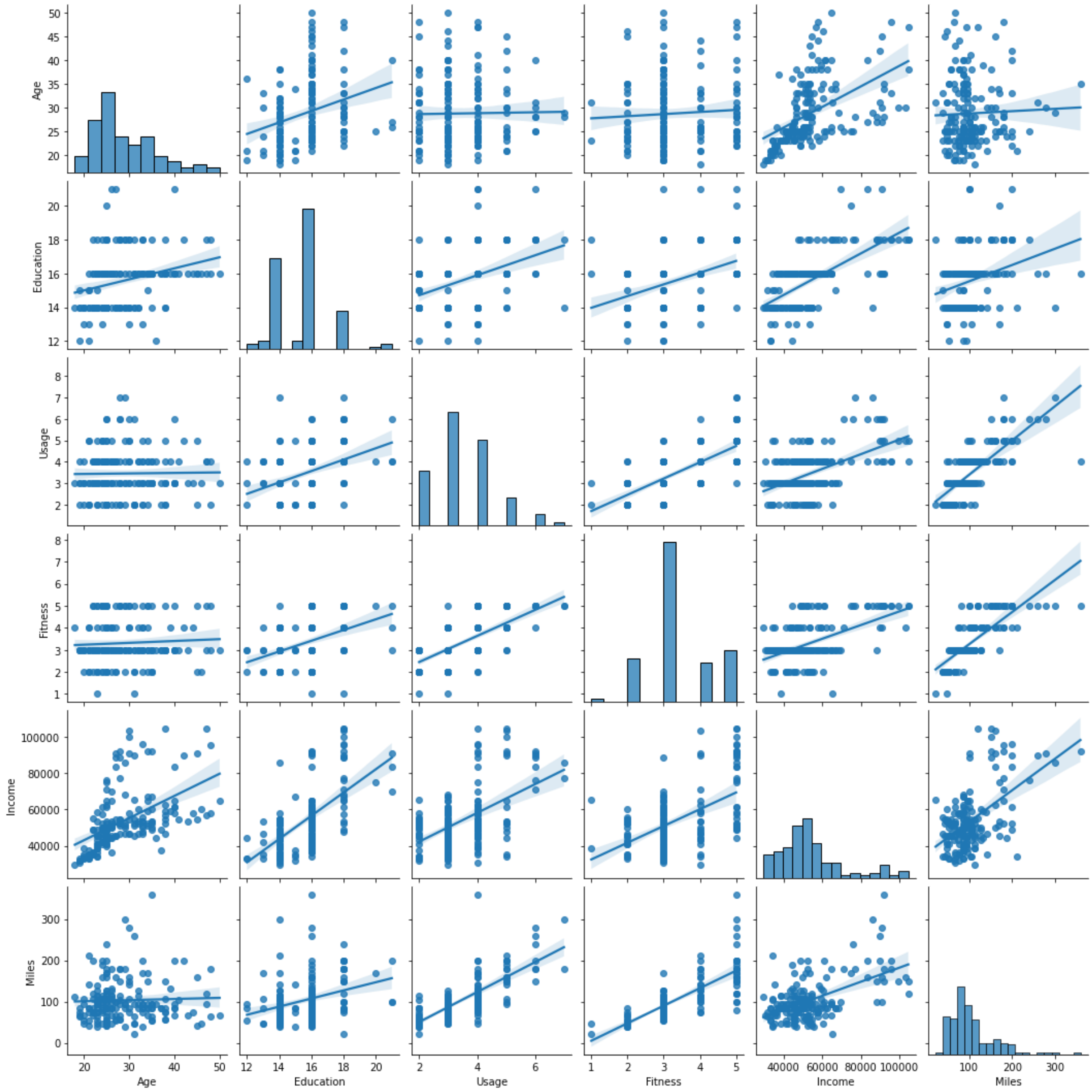


- The customers with high annual salary (60k and above) are more likely to buy KP781.
- The customers with annual salary < 60k are more likely to buy KP281 and KP481.

Coorelation between measurable quantities

In [43]:
```
sns.pairplot(data = df, kind = 'reg')
plt.plot()
```

Out[43]: []



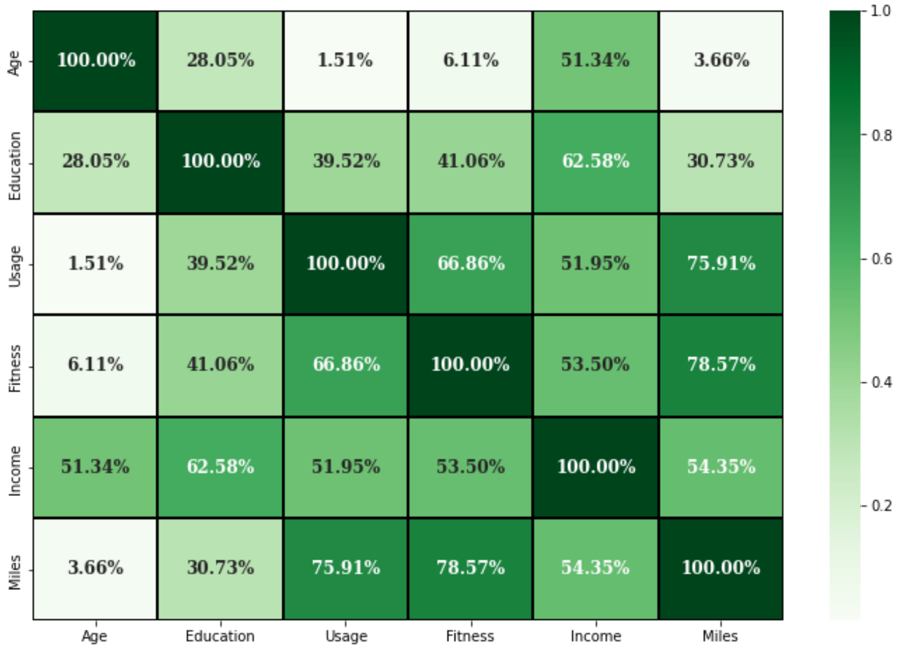
In [44]:
```
df_corr = df.corr()
df_corr
```

Out[44]:

	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

In [45]:
```python
plt.figure(figsize = (12, 8))
sns.heatmap(data = df_corr,
            annot = True,
            fmt = '.2%',
            cmap='Greens',
            linewidth = 2,
            linecolor = 'black',
            annot_kws = {'fontsize' : 'large',
                        'fontfamily' : 'serif',
                        'fontweight': 'bold'})
plt.plot()
```

Out[45]: []



- The customer with high fitness scale is more likely to run or walk more miles.
- The customer who expects to use the treadmill more times in a week generally expects to walk or run more miles in the week.
- The customer who have a high fitness scale generally uses the treadmill more frequently in a week.

What is the product buying behaviors of both the genders ?

In [84]:
```
print(pd.crosstab(index = df['Product'], columns = df['Gender'], margins = True))
print()
print('-' * 26)
print()
print("Product-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['Gender'], normalize = 'index') * 100, 2))
print()
print('-' * 23)
print()
print("Gender-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['Gender'], normalize = 'columns') * 100, 2))
```

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

--------------------------

Product-wise normalization :
Gender   Female   Male
Product
KP281     50.00  50.00
KP481     48.33  51.67
KP781     17.50  82.50

-----------------------

Gender-wise normalization :
Gender   Female   Male
Product
KP281     52.63  38.46
KP481     38.16  29.81
KP781      9.21  31.73
```

- Customers who bought KP781, 82.5% of them are males rest are females.
- Among all female customers, only 9.21 % buy KP781. Females mostly buy products KP281 or KP481.

What is the probability of buying a specific product provided the customer is of specific gender ?

In [47]:
```
products = df['Product'].unique()
genders = df['Gender'].unique()
for i in genders:
    for j in products:
        prob = len(df[(df['Gender'] == i) & (df['Product'] == j)]) / len(df[df['Gender'] == i])
        prob = np.round(prob * 100, 2)
        print("Probability of buying '{}' provided the customer is {} is {}% ".format(j, i, prob))
        print()
```

```
Probability of buying 'KP281' provided the customer is Male is 38.46%

Probability of buying 'KP481' provided the customer is Male is 29.81%

Probability of buying 'KP781' provided the customer is Male is 31.73%

Probability of buying 'KP281' provided the customer is Female is 52.63%

Probability of buying 'KP481' provided the customer is Female is 38.16%

Probability of buying 'KP781' provided the customer is Female is 9.21%
```

What is the probability of that the customer is of specific gender provided specific product is bought ?

In [48]:
```
products = df['Product'].unique()
genders = df['Gender'].unique()
for i in genders:
    for j in products:
        prob = len(df[(df['Gender'] == i) & (df['Product'] == j)]) / len(df[df['Product'] == j])
        prob = np.round(prob * 100, 2)
        print("Probability that the customer is {} provided {} was bought is {}% ".format(i, j, prob))
        print()
```

```
Probability that the customer is Male provided KP281 was bought is 50.0%

Probability that the customer is Male provided KP481 was bought is 51.67%

Probability that the customer is Male provided KP781 was bought is 82.5%

Probability that the customer is Female provided KP281 was bought is 50.0%

Probability that the customer is Female provided KP481 was bought is 48.33%

Probability that the customer is Female provided KP781 was bought is 17.5%
```

What is the product buying behaviors of both the Marital Statuses ?

In [85]:
```
print(pd.crosstab(index = df['Product'], columns = df['MaritalStatus'], margins = True))
print()
print('-' * 37)
print()
print("Product-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['MaritalStatus'], normalize = 'index') * 100, 2))
print()
print('-' * 33)
print()
print("Marital Status-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['MaritalStatus'], normalize = 'columns') * 100, 2))
```

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

-------------------------------------

Product-wise normalization :
MaritalStatus  Partnered  Single
Product
KP281               60.0    40.0
KP481               60.0    40.0
KP781               57.5    42.5

---------------------------------

Marital Status-wise normalization :
MaritalStatus  Partnered  Single
Product
KP281              44.86   43.84
KP481              33.64   32.88
KP781              21.50   23.29
```

What is the probability of buying a specific product provided the customer is of specific marital status ?

In [50]:
```python
products = df['Product'].unique()
statuses = df['MaritalStatus'].unique()
for i in statuses:
    if i != 'Single':
        print('-' * 76)
    for j in products:
        prob = len(df[(df['MaritalStatus'] == i) & (df['Product'] == j)]) / len(df[df['MaritalStatus'] == i])
        prob = np.round(prob * 100, 2)
        print("Probability of buying '{}' provided the customer is '{}' is {}% ".format(j, i, prob))
        print()
```

```
Probability of buying 'KP281' provided the customer is 'Single' is 43.84%

Probability of buying 'KP481' provided the customer is 'Single' is 32.88%

Probability of buying 'KP781' provided the customer is 'Single' is 23.29%

----------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer is 'Partnered' is 44.86%

Probability of buying 'KP481' provided the customer is 'Partnered' is 33.64%

Probability of buying 'KP781' provided the customer is 'Partnered' is 21.5%
```

What is the probability of that the customer is of specific Marital Status provided specific product is bought ?

In [51]:
```python
products = df['Product'].unique()
statuses = df['MaritalStatus'].unique()
for i in statuses:
    if i != 'Single':
        print('-' * 82)
    for j in products:
        prob = len(df[(df['MaritalStatus'] == i) & (df['Product'] == j)]) / len(df[df['Product'] == j])
        prob = np.round(prob * 100, 2)
        print("Probability that the customer is '{}' provided '{}' was bought is {}% ".format(i, j, prob))
        print()
```

```
Probability that the customer is 'Single' provided 'KP281' was bought is 40.0%

Probability that the customer is 'Single' provided 'KP481' was bought is 40.0%

Probability that the customer is 'Single' provided 'KP781' was bought is 42.5%

----------------------------------------------------------------------------------
Probability that the customer is 'Partnered' provided 'KP281' was bought is 60.0%

Probability that the customer is 'Partnered' provided 'KP481' was bought is 60.0%

Probability that the customer is 'Partnered' provided 'KP781' was bought is 57.5%
```

What is the product buying behaviors of customers with different fitness levels ?

In [86]:
```
print(pd.crosstab(index = df['Product'], columns = df['Fitness'], margins = True))
print()
print('-' * 40)
print()
print("Product-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['Fitness'], normalize = 'index') * 100, 2))
print()
print('-' * 40)
print()
print("Fitness Scale-wise normalization : ")
print(np.round(pd.crosstab(index = df['Product'], columns = df['Fitness'], normalize = 'columns') * 100, 2))
```

```
Fitness  1   2   3   4   5  All
Product
KP281    1  14  54   9   2   80
KP481    1  12  39   8   0   60
KP781    0   0   4   7  29   40
All      2  26  97  24  31  180

----------------------------------------

Product-wise normalization : 
Fitness     1     2     3      4     5
Product
KP281    1.25  17.5  67.5  11.25   2.5
KP481    1.67  20.0  65.0  13.33   0.0
KP781    0.00   0.0  10.0  17.50  72.5

----------------------------------------

Fitness Scale-wise normalization : 
Fitness     1      2      3      4      5
Product
KP281    50.0  53.85  55.67  37.50   6.45
KP481    50.0  46.15  40.21  33.33   0.00
KP781     0.0   0.00   4.12  29.17  93.55
```

- Number of customers who bought products KP281, KP481 and KP781 are in ratio 4 : 3 : 2. That means for every 9 customers, 4 customers bought KP281, 3 bought KP481 and 2 bought KP781.
- Among all the customers who bought KP281, 96.25 % of them had fitness scales of 2, 3 or 4. Only 2.5 % of them had excellent body shape.
- Among all the customers who bought KP781, 90 % of them had fitness scales 4 or 5. Only 10 % of them had average body shape.
- Among all the customers who had excellent body shape (fitness scale 5), 93.55 % of them bought product KP781 while the rest buy KP281.
- All the customers in each fitness levels 1 and 2 (i.e., customers having poor body shape) either bought product KP281 or KP481. None of them bought the treadmill having advanced features i.e., KP781.

What is the probability of buying a specific product provided the customer has specific fitness scale ?

In [53]:
```
products = df['Product'].unique()
scales = sorted(df['Fitness'].unique())
for i in scales:
    if i != 1:
        print('-' * 88)
    for j in products:
        prob = len(df[(df['Fitness'] == i) & (df['Product'] == j)]) / len(df[df['Fitness'] == i])
        prob = np.round(prob * 100, 2)
        print("Probability of buying '{}' provided the customer has the fitness scale '{}' is {}% ".format(j, i, pr
        print()
```

```
Probability of buying 'KP281' provided the customer has the fitness scale '1' is 50.0%

Probability of buying 'KP481' provided the customer has the fitness scale '1' is 50.0%

Probability of buying 'KP781' provided the customer has the fitness scale '1' is 0.0%

----------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the fitness scale '2' is 53.85%

Probability of buying 'KP481' provided the customer has the fitness scale '2' is 46.15%

Probability of buying 'KP781' provided the customer has the fitness scale '2' is 0.0%

----------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the fitness scale '3' is 55.67%

Probability of buying 'KP481' provided the customer has the fitness scale '3' is 40.21%

Probability of buying 'KP781' provided the customer has the fitness scale '3' is 4.12%

----------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the fitness scale '4' is 37.5%

Probability of buying 'KP481' provided the customer has the fitness scale '4' is 33.33%

Probability of buying 'KP781' provided the customer has the fitness scale '4' is 29.17%

----------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the fitness scale '5' is 6.45%

Probability of buying 'KP481' provided the customer has the fitness scale '5' is 0.0%

Probability of buying 'KP781' provided the customer has the fitness scale '5' is 93.55%
```

What is the probability of that the customer has a specific fitness scale provided specific product was bought ?

In [54]:
```
products = df['Product'].unique()
scales = sorted(df['Fitness'].unique())
for i in scales:
    if i != 1:
        print('-' * 94)
    for j in products:
        prob = len(df[(df['Fitness'] == i) & (df['Product'] == j)]) / len(df[df['Product'] == j])
        prob = np.round(prob * 100, 2)
        print("Probability that the customer has a fitness scale of '{}' provided '{}' was bought is {}% ".format(
        print()
```

```
Probability that the customer has a fitness scale of '1' provided 'KP281' was bought is 1.25%

Probability that the customer has a fitness scale of '1' provided 'KP481' was bought is 1.67%

Probability that the customer has a fitness scale of '1' provided 'KP781' was bought is 0.0%

----------------------------------------------------------------------------------------------
Probability that the customer has a fitness scale of '2' provided 'KP281' was bought is 17.5%

Probability that the customer has a fitness scale of '2' provided 'KP481' was bought is 20.0%

Probability that the customer has a fitness scale of '2' provided 'KP781' was bought is 0.0%

----------------------------------------------------------------------------------------------
Probability that the customer has a fitness scale of '3' provided 'KP281' was bought is 67.5%

Probability that the customer has a fitness scale of '3' provided 'KP481' was bought is 65.0%

Probability that the customer has a fitness scale of '3' provided 'KP781' was bought is 10.0%

----------------------------------------------------------------------------------------------
Probability that the customer has a fitness scale of '4' provided 'KP281' was bought is 11.25%

Probability that the customer has a fitness scale of '4' provided 'KP481' was bought is 13.33%

Probability that the customer has a fitness scale of '4' provided 'KP781' was bought is 17.5%

----------------------------------------------------------------------------------------------
Probability that the customer has a fitness scale of '5' provided 'KP281' was bought is 2.5%

Probability that the customer has a fitness scale of '5' provided 'KP481' was bought is 0.0%

Probability that the customer has a fitness scale of '5' provided 'KP781' was bought is 72.5%
```

What is the relation between Marital Statuses and fitness levels of the Aerofit Customers?

In [55]:
```
print(pd.crosstab(index = df['MaritalStatus'], columns = df['Fitness'], margins = True))
print()
print('-' * 48)
print('Marital Status wise normalization : ')
print()
print(np.round(pd.crosstab(index = df['MaritalStatus'], columns = df['Fitness'], normalize = 'index') * 100, 2))
print()
print("-" * 48)
print('Fitness levels wise normalization : ')
print()
print(np.round(pd.crosstab(index = df['MaritalStatus'], columns = df['Fitness'], normalize = 'columns') * 100, 2))
```

```
Fitness        1   2   3   4   5  All
MaritalStatus
Partnered      1  18  57  13  18  107
Single         1   8  40  11  13   73
All            2  26  97  24  31  180

------------------------------------------------
Marital Status wise normalization : 

Fitness           1      2      3      4      5
MaritalStatus
Partnered      0.93  16.82  53.27  12.15  16.82
Single         1.37  10.96  54.79  15.07  17.81

------------------------------------------------
Fitness levels wise normalization : 

Fitness           1      2      3      4      5
MaritalStatus
Partnered      50.0  69.23  58.76  54.17  58.06
Single         50.0  30.77  41.24  45.83  41.94
```

- Majority of customers (i.e., greater than 50%) in each marital statuses had fitness scale 3.
- Majority of customers (i.e., greater than 50%) in each of fitness scales 2, 3, 4 and 5 were partnered.(Since there are significantly higher number of customers who were partnered than single)

What is the relation between Incomes and Products bought by the Aerofit Customers?

In [56]:
```
print(pd.crosstab(index = df['Product'], columns = df['income_bins'], margins = True))
print()
print('-' * 54)
print('Product wise normalization : ')
print()
print(np.round(pd.crosstab(index = df['Product'], columns = df['income_bins'], normalize = 'index') * 100, 2))
print()
print("-" * 48)
print('Income-bins wise normalization :')
print()
print(np.round(pd.crosstab(index = df['Product'], columns = df['income_bins'], normalize = 'columns') * 100, 2))
```

```
income_bins  45k - 60k  60k - 80k  < 45k  > 80k  All
Product
KP281               40          6     34      0   80
KP481               38          7     15      0   60
KP781               11         10      0     19   40
All                 89         23     49     19  180

------------------------------------------------------
Product wise normalization : 

income_bins  45k - 60k  60k - 80k  < 45k  > 80k
Product
KP281            50.00       7.50   42.5    0.0
KP481            63.33      11.67   25.0    0.0
KP781            27.50      25.00    0.0   47.5

------------------------------------------------
Income-bins wise normalization :

income_bins  45k - 60k  60k - 80k  < 45k  > 80k
Product
KP281            44.94      26.09  69.39    0.0
KP481            42.70      30.43  30.61    0.0
KP781            12.36      43.48   0.00  100.0
```

What is the probability of buying a specific product provided the customer's annual income lies in a specific income range ?

In [57]:
```python
products = df['Product'].unique()
incomes = sorted(df['income_bins'].unique())
for i in incomes:
    if i != '45k - 60k':
        print('-' * 105)
    for j in products:
        prob = len(df[(df['income_bins'] == i) & (df['Product'] == j)]) / len(df[df['income_bins'] == i])
        prob = np.round(prob * 100, 2)
        print("Probability of buying '{}' provided the customer has the annual income in range '{}' is {}% ".forma
        print()
```

```
Probability of buying 'KP281' provided the customer has the annual income in range '45k - 60k' is 44.94%

Probability of buying 'KP481' provided the customer has the annual income in range '45k - 60k' is 42.7%

Probability of buying 'KP781' provided the customer has the annual income in range '45k - 60k' is 12.36%

---------------------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the annual income in range '60k - 80k' is 26.09%

Probability of buying 'KP481' provided the customer has the annual income in range '60k - 80k' is 30.43%

Probability of buying 'KP781' provided the customer has the annual income in range '60k - 80k' is 43.48%

---------------------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the annual income in range '< 45k ' is 69.39%

Probability of buying 'KP481' provided the customer has the annual income in range '< 45k ' is 30.61%

Probability of buying 'KP781' provided the customer has the annual income in range '< 45k ' is 0.0%

---------------------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer has the annual income in range '> 80k' is 0.0%

Probability of buying 'KP481' provided the customer has the annual income in range '> 80k' is 0.0%

Probability of buying 'KP781' provided the customer has the annual income in range '> 80k' is 100.0%
```

What is the probability of that the customer's annual income lies in a specific salary range provided specific product was bought ?

In [58]:
```python
products = df['Product'].unique()
incomes = sorted(df['income_bins'].unique())
for i in incomes:
    if i != '45k - 60k':
        print('-' * 105)
    for j in products:
        prob = len(df[(df['income_bins'] == i) & (df['Product'] == j)]) / len(df[df['Product'] == j])
        prob = np.round(prob * 100, 2)
        print("Probability that the customer's annual income lies in range '{}' provided '{}' was bought is {}% ".
        print()
```

```
Probability that the customer's annual income lies in range '45k - 60k' provided 'KP281' was bought is 50.0%

Probability that the customer's annual income lies in range '45k - 60k' provided 'KP481' was bought is 63.33%

Probability that the customer's annual income lies in range '45k - 60k' provided 'KP781' was bought is 27.5%

---------------------------------------------------------------------------------------------------------
Probability that the customer's annual income lies in range '60k - 80k' provided 'KP281' was bought is 7.5%

Probability that the customer's annual income lies in range '60k - 80k' provided 'KP481' was bought is 11.67%

Probability that the customer's annual income lies in range '60k - 80k' provided 'KP781' was bought is 25.0%

---------------------------------------------------------------------------------------------------------
Probability that the customer's annual income lies in range '< 45k ' provided 'KP281' was bought is 42.5%

Probability that the customer's annual income lies in range '< 45k ' provided 'KP481' was bought is 25.0%

Probability that the customer's annual income lies in range '< 45k ' provided 'KP781' was bought is 0.0%

---------------------------------------------------------------------------------------------------------
Probability that the customer's annual income lies in range '> 80k' provided 'KP281' was bought is 0.0%

Probability that the customer's annual income lies in range '> 80k' provided 'KP481' was bought is 0.0%

Probability that the customer's annual income lies in range '> 80k' provided 'KP781' was bought is 47.5%
```

What is the relation between Age Categories and Products bought by the Aerofit Customers?

In [59]:
```
print(pd.crosstab(index = df['Product'], columns = df['age_bins'], margins = True))
print()
print('-' * 45)
print('Product wise normalization : ')
print()
print(np.round(pd.crosstab(index = df['Product'], columns = df['age_bins'], normalize = 'index') * 100, 2))
print()
print("-" * 42)
print('Age-bins wise normalization : ')
print()
print(np.round(pd.crosstab(index = df['Product'], columns = df['age_bins'], normalize = 'columns') * 100, 2))
```

```
age_bins  25 - 33  34 - 46  <= 24   > 46  All
Product
KP281          27       15     27     11   80
KP481          17       11     17     15   60
KP781          15        5     10     10   40
All            59       31     54     36  180

---------------------------------------------
Product wise normalization : 

age_bins  25 - 33  34 - 46  <= 24   > 46
Product
KP281       33.75    18.75  33.75  13.75
KP481       28.33    18.33  28.33  25.00
KP781       37.50    12.50  25.00  25.00

------------------------------------------
Age-bins wise normalization : 

age_bins  25 - 33  34 - 46  <= 24   > 46
Product
KP281       45.76    48.39  50.00  30.56
KP481       28.81    35.48  31.48  41.67
KP781       25.42    16.13  18.52  27.78
```

What is the probability of buying a specific product provided the customer's age lies in a specific age range ?

In [60]:
```
products = df['Product'].unique()
ages = sorted(df['age_bins'].unique())
for i in ages:
    if i != '25 - 33':
        print('-' * 91)
    for j in products:
        prob = len(df[(df['age_bins'] == i) & (df['Product'] == j)]) / len(df[df['age_bins'] == i])
        prob = np.round(prob * 100, 2)
        print("Probability of buying '{}' provided the customer's age lies in range '{}' is {}% ".format(j, i, prol
        print()
```

```
Probability of buying 'KP281' provided the customer's age lies in range '25 - 33' is 45.76%

Probability of buying 'KP481' provided the customer's age lies in range '25 - 33' is 28.81%

Probability of buying 'KP781' provided the customer's age lies in range '25 - 33' is 25.42%

-------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer's age lies in range '34 - 46' is 48.39%

Probability of buying 'KP481' provided the customer's age lies in range '34 - 46' is 35.48%

Probability of buying 'KP781' provided the customer's age lies in range '34 - 46' is 16.13%

-------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer's age lies in range '<= 24 ' is 50.0%

Probability of buying 'KP481' provided the customer's age lies in range '<= 24 ' is 31.48%

Probability of buying 'KP781' provided the customer's age lies in range '<= 24 ' is 18.52%

-------------------------------------------------------------------------------------------
Probability of buying 'KP281' provided the customer's age lies in range '> 46' is 30.56%

Probability of buying 'KP481' provided the customer's age lies in range '> 46' is 41.67%

Probability of buying 'KP781' provided the customer's age lies in range '> 46' is 27.78%
```

What is the probability of that the customer's age lies in a specific age range provided specific product was bought ?

In [61]:
```python
products = df['Product'].unique()
ages = sorted(df['age_bins'].unique())
for i in ages:
    if i != '25 - 33':
        print('-' * 96)
    for j in products:
        prob = len(df[(df['age_bins'] == i) & (df['Product'] == j)]) / len(df[df['Product'] == j])
        prob = np.round(prob * 100, 2)
        print("Probability that the customer's age lies in range '{}' provided '{}' was bought is {}% ".format(i, 
        print()
```

```
Probability that the customer's age lies in range '25 - 33' provided 'KP281' was bought is 33.75%

Probability that the customer's age lies in range '25 - 33' provided 'KP481' was bought is 28.33%

Probability that the customer's age lies in range '25 - 33' provided 'KP781' was bought is 37.5%

------------------------------------------------------------------------------------------------
Probability that the customer's age lies in range '34 - 46' provided 'KP281' was bought is 18.75%

Probability that the customer's age lies in range '34 - 46' provided 'KP481' was bought is 18.33%

Probability that the customer's age lies in range '34 - 46' provided 'KP781' was bought is 12.5%

------------------------------------------------------------------------------------------------
Probability that the customer's age lies in range '<= 24 ' provided 'KP281' was bought is 33.75%

Probability that the customer's age lies in range '<= 24 ' provided 'KP481' was bought is 28.33%

Probability that the customer's age lies in range '<= 24 ' provided 'KP781' was bought is 25.0%

------------------------------------------------------------------------------------------------
Probability that the customer's age lies in range '> 46' provided 'KP281' was bought is 13.75%

Probability that the customer's age lies in range '> 46' provided 'KP481' was bought is 25.0%

Probability that the customer's age lies in range '> 46' provided 'KP781' was bought is 25.0%
```

Customer Profiling :

Product of buying a specific product based on gender, age, fitness scale, income :

In [76]:
```python
products = df['Product'].unique()
genders = df['Gender'].unique()
ages = df['age_bins'].unique()
fitnesses = sorted(df["Fitness"].unique())
statuses = df['MaritalStatus'].unique()
incomes = df['income_bins'].unique()
for i in products:
    for j in genders:
        for k in statuses:
            for l in ages:
                for m in fitnesses:
                    for n in incomes:
                        try :
                            count += 1
                            res = np.round(len(df[df['Product'] == i]) / len(df[(df['Gender'] == j) & (df['age_bin
                            print("P({} / ({}, {}, age {}, fitness scale = {}, income {})) = {}%".format(i, j, k, 
                        except:
                            print("No record for ({}, {}, age {}, fitness scale = {}, income {}) buying {}".format
```

```
No record for (Male, Single, age <= 24 , fitness scale = 1, income < 45k ) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 1, income 45k - 60k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 1, income 60k - 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 1, income > 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 2, income < 45k ) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 2, income 45k - 60k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 2, income 60k - 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 2, income > 80k) buying KP281
P(KP281 / (Male, Single, age <= 24 , fitness scale = 3, income < 45k )) = 8.89%
P(KP281 / (Male, Single, age <= 24 , fitness scale = 3, income 45k - 60k)) = 40.0%
No record for (Male, Single, age <= 24 , fitness scale = 3, income 60k - 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 3, income > 80k) buying KP281
P(KP281 / (Male, Single, age <= 24 , fitness scale = 4, income < 45k )) = 40.0%
P(KP281 / (Male, Single, age <= 24 , fitness scale = 4, income 45k - 60k)) = 80.0%
No record for (Male, Single, age <= 24 , fitness scale = 4, income 60k - 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 4, income > 80k) buying KP281
No record for (Male, Single, age <= 24 , fitness scale = 5, income < 45k ) buying KP281
P(KP281 / (Male, Single, age <= 24 , fitness scale = 5, income 45k - 60k)) = 16.0%
P(KP281 / (Male, Single, age <= 24 , fitness scale = 5, income 60k - 80k)) = 80.0%
```

Insights

- Number of customers who bought products KP281, KP481 and KP781 are in ratio 4 : 3 : 2. That means for every 9 customers, 4 customers bought KP281, 3 bought KP481 and 2 bought KP781.
- There are more male customers than females. Around 60% of the total customers are males.
- There are more customers who are partnered than single. Almost 60% of customers are partnered.
- Age of the customers varies between 18 and 50 years.
- More than 80% of the total customers are aged between 20 and 30 years.
- Annual income of the customers varies in the range of 29562 dollars to 104581 dollars.
- 80 % of the customers annual salary is less than 65000 dollars.
- Expected usage of treadmills lies in the range of 2 to 7 times in a week.
- Expected number of miles that the customer walks or runs vary between 21 miles to 360 miles per week.
- More than 50% customers rate themselves 3 out of 5 in self rated fitness scale
- Around 70 % of the aerofit customers rate themselves 3 or less in fitness scale.
- There are about 40% of customers who use treadmills three days a week and about 30% who use them four days a week.
- For fitness scales 4 and 5, there are 3 times more males than females.
- Among all the customers who bought KP781, 90 % of them had fitness scales 4 or 5. Only 10 % of them had average body shape.
- The number of males buying the treadmills having advanced features is around 5 times the number of females buying the same.
- The treadmill having advanced features are mostly bought by the people with high fitness levels.
- The customers having high annual income (> 60k dollars) and high fitness scales(> 4) generally buy KP781.
- The customers who rate themselves 1 or 2 in the self-rated fitness scale do not buy KP781.
- Customers who bought KP781, 82.5% of them are males rest are females.
- Among all female customers, only 9.21 % buy KP781. Females mostly buy products KP281 or KP481.
- Among all the customers who bought KP281, 96.25 % of them had fitness scales of 2, 3 or 4. Only 2.5 % of them had excellent body shape.
- Among all the customers who had excellent body shape (fitness scale 5), 93.55 % of them bought product KP781 while the rest buy KP281.
- All the customers in each fitness levels 1 and 2 (i.e., customers having poor body shape) either bought product KP281 or KP481. None of them bought the treadmill having advanced features i.e., KP781.
- Probability of buying 'KP781' provided the customer has the annual income in range '> 80k' is 100.0%.

Recommendations

```
 - Since the people of average fitness scale accounts for more than 50% of the total customers, such people who
have high annual income (> 50k dollars) can be the potential customers to buy KP781.

 - The number of customers buying KP281 and KP481 are roughly  in ratio 4 : 3. These people share common
characteristics. People planning to buy KP281 can be the potential customers to buy KP481.

 - Fitness challenges should be launched and people clearing more levels should be given special discounts in
the treadmills.

 - People can be offered special discounts on the product specific to the potential customer's profile on the
occasions of World Health Day(7th Apr), World Obesity Day(4th Mar), World Heart Day(29th Sep), International Day
of Yoga(21st June) etc.

 - Smartphone apps should be developed where the existing customers can track their fitness progress and can
share the milestones they have achieved in the social media so as to increase company's social media influence.

 - Advertisements should be based on diversed topics like sharing fitness tips, converting success stories into
motivational posts, listing common nutritional mistakes, busting fitness myths, showcasing body transformations
of existing customers etc.
```

In [ ]: