Importing all the necessary libraries

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

Reading the CSV data file

```
data = pd.read_csv("/content/Aerofit_treadmill.csv")
```

Getting the first 5 rows of the data using .head()

```
data.head()
```

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

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

Getting the number of rows and columns in the data

```
data.shape
```

```
(180, 9)
```

Getting the count of data points we have for each Product type using value_counts()

```
data["Product"].value_counts()
```

Product	count
KP281	80
KP481	60
KP781	40

dtype: int64

Getting the Non null count and the data types for all the columns in the data

```
data.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
```

Getting the statistical values for the numerical columns in the data

```
data.describe()
```

	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

Just from the .describe() function we will be able to detect where the possible outliers could be

By the differece between the mean and the median in each column we can know if there are ouliers or not

If the differance is high, it means that there are possible outliers

In this Aerofit dataset according to the above statistical values - Income and Miles columns can have the possible outliers

Checking if there are any Null values in the data

```
data.isnull().sum()
```

	0
Product	0
Age	0
Gender	0
Education	0
MaritalStatus	0
Usage	0
Fitness	0
Income	0
Miles	0

dtype: int64

```
data.isnull().sum() / len(data)
```

	0
Product	0.0
Age	0.0
Gender	0.0
Education	0.0
MaritalStatus	0.0
Usage	0.0
Fitness	0.0
Income	0.0
Miles	0.0

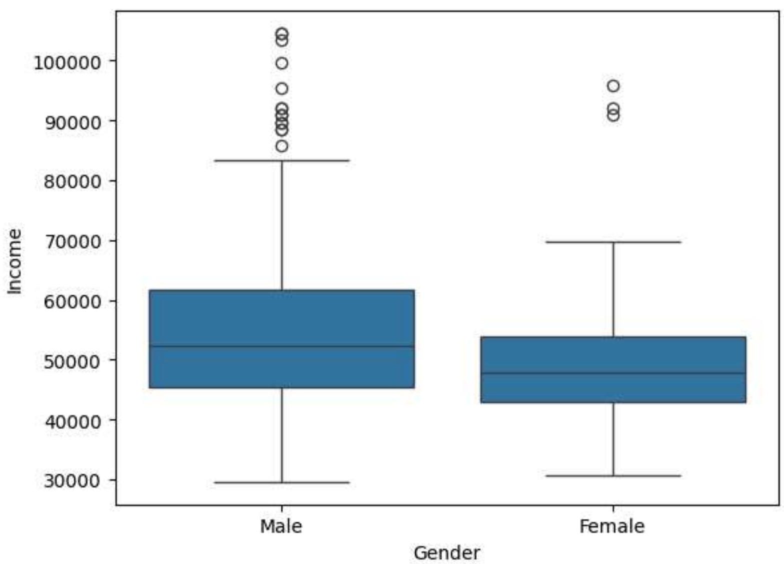
dtype: float64

From the above it is clear that there are no null values in the data

Using the Box plot on the "Gender" and "Income" columns to see if there are any possible outliers in the data

```
sns.boxplot(x = data["Gender"] , y = data["Income"])
```

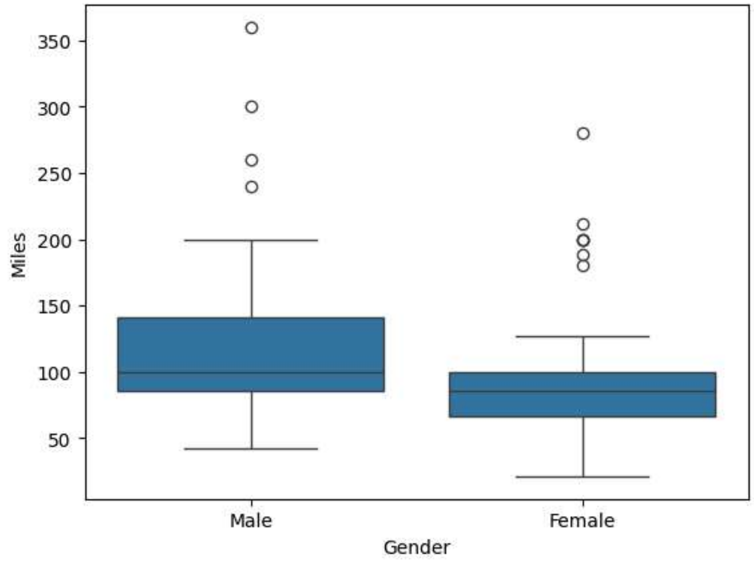
```
<Axes: xlabel='Gender', ylabel='Income'>
```



Using the Box plot on the "Gender" and "Miles" columns to see if there are any possible outliers in the data

```
sns.boxplot(x = data["Gender"] , y = data["Miles"])
```

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

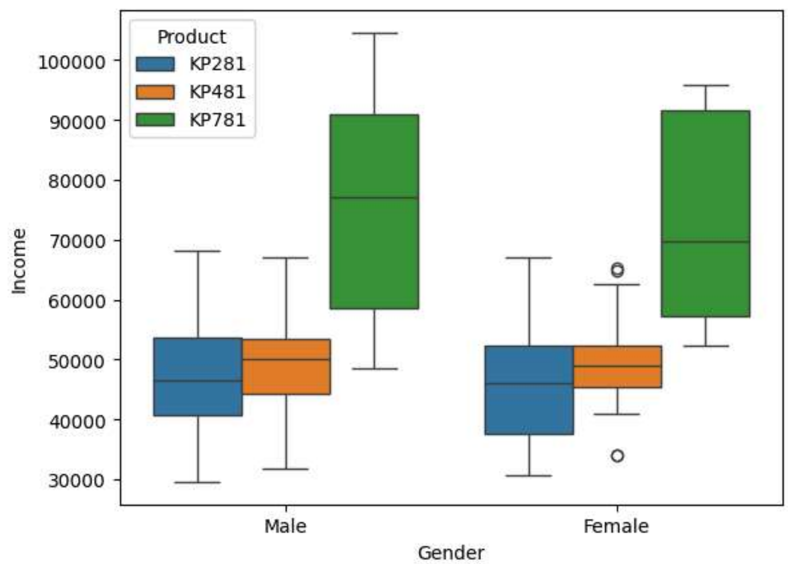


As there are only less number of data points skipping the removal of outluiers for this business case

Using the box plot on the "Gender" and "Income" columns with hue parameter applied to "Product" column

```
sns.boxplot(x = data["Gender"] , y = data["Income"] , hue = data["Product"])
```

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

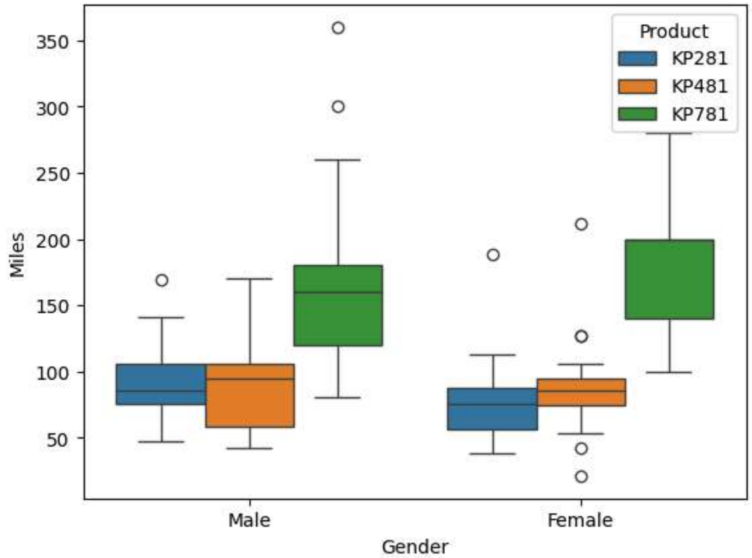


From the above it is clearly visible that people who are having high income tend to buy the "KP781" product

Using the box plot on the "Gender" and "Miles" columns with hue parameter applied to "Product" column

```
sns.boxplot(x = data["Gender"] , y = data["Miles"] , hue = data["Product"])
```

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

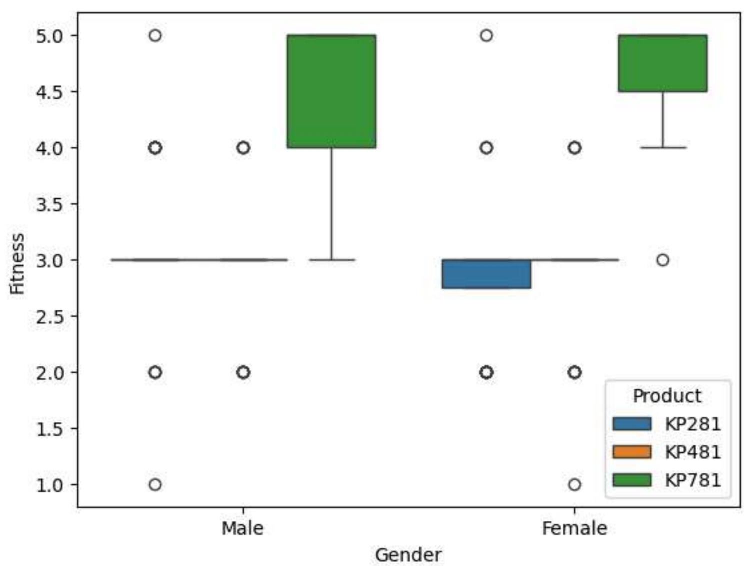


From the above it is clearly visible that people who tend to walk/run more likely to buy the "KP781" Product.

Using the box plot on the "Gender" and "Fitness" columns with hue parameter applied to "Product" column

```
sns.boxplot(x = data["Gender"] , y = data["Fitness"] , hue = data["Product"])
```

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

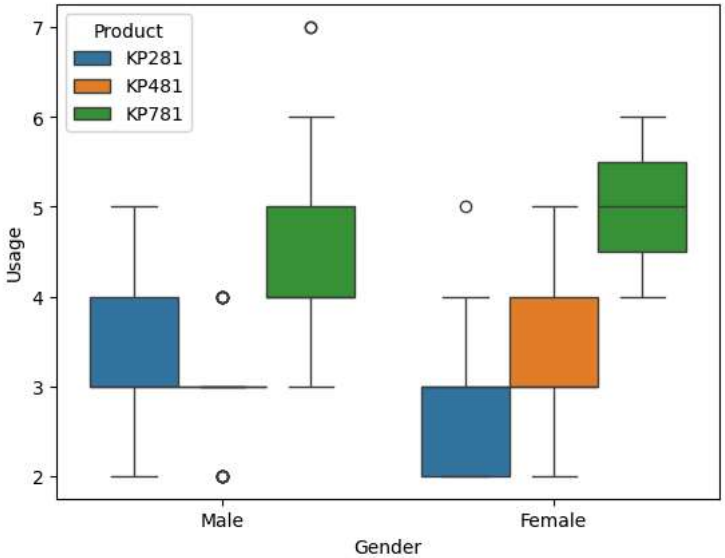


From the above it is clearly visible that the people who rated themselves highly fit are more likely to buy the "KP781" product.

Using the box plot on the "Gender" and "Usage" columns with hue parameter applied to "Product" column

```
sns.boxplot(x = data["Gender"] , y = data["Usage"] , hue = data["Product"])
```

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

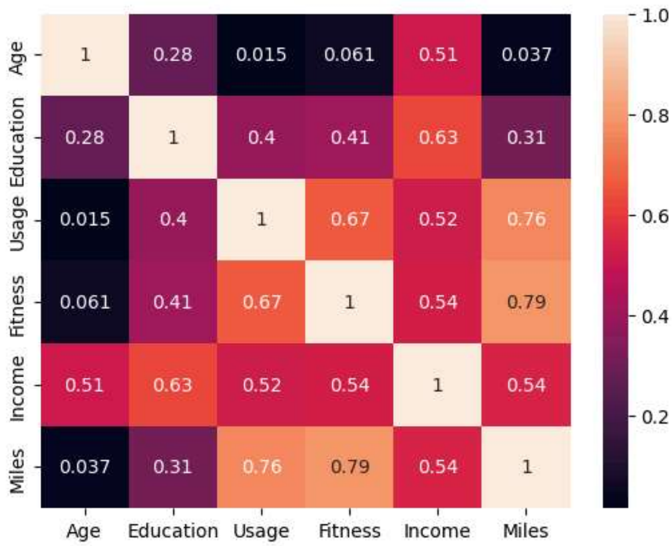


From the above it is clearly visible that people who are planning to use the equipment more often are likely to buy the "KP781" Product

Using heatmap to get the correlation between all the numerical metrics in the data

```
sns.heatmap(data.select_dtypes(include = ["number"]).corr() , annot = True)
```

```
<Axes: >
```



	Age	Education	Usage	Fitness	Income	Miles
Age	1	0.28	0.015	0.061	0.51	0.037
Education	0.28	1	0.4	0.41	0.63	0.31
Usage	0.015	0.4	1	0.67	0.52	0.76
Fitness	0.061	0.41	0.67	1	0.54	0.79
Income	0.51	0.63	0.52	0.54	1	0.54
Miles	0.037	0.31	0.76	0.79	0.54	1

Insights from the above

1. Fitness and Miles are having high correlation (People who tend to be more fit are more likely to walk/run more)

2. Usage and Miles are having high correlation (People who tend to walk/run more are more likely to use the fitness equipments

3. Income and Education are having high correlation (People who study more are more likely to recwive high income

4. Usage, Fitness, Miles with Age is having very low correlation

Starting off with the Statistical Data analysis with "Gender" and "Product" types

Using .crosstab() with "Gender" as the index and "Product" as the columns

```
pd.crosstab(index = data["Gender"] , columns = data["Product"])
```

Product	KP281	KP481	KP781
Gender			
Female	40	29	7
Male	40	31	33

Using .crosstab() with "Gender" as the index and "Product" as the columns and margins parameter as True

```
pd.crosstab(index = data["Gender"] , columns = data["Product"] , margins = True)
```

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

Marginal Probabilities

Probability of buying "KP281" - 80 / 180 = 0.44 (44%)

Probability of buying "KP481" - 60 / 180 = 0.33 (33%)

Probability of buying "KP781" - 40 / 180 = 0.22 (22%)

Joint Probabilities

Probability of women buying "KP281" - 40 / 180 = 0.22 (22%)

Probability of women buying "KP481" - 29 / 180 = 0.16 (16%)

Probability of women buying "KP781" - 7 / 180 = 0.038 (3.8%)

Probability of men buying "KP281" - 40 / 180 = 0.22 (22%)

Probability of men buying "KP481" - 31 / 180 = 0.17 (17%)

Probability of men buying "KP781" - 33 / 180 = 0.18 (18%)

Using .crosstab() with "Gender" as the index and "Product" as the columns and margins parameter as True, normalize as "index"

```
pd.crosstab(index = data["Gender"] , columns = data["Product"] , margins = True , normalize = "index").round(2)
```

Product	KP281	KP481	KP781
Gender			
Female	0.53	0.38	0.09
Male	0.38	0.30	0.32
All	0.44	0.33	0.22

Conditional probabilities

Probability of buying "KP281" given it is women - P(buy KP281 | women) = 40 / 76 = 53%

Probability of buying "KP481" given it is women - P(buy KP481 | women) = 29 / 76 = 38%

Probability of buying "KP781" given it is women - P(buy KP781 | women) = 7 / 76 = 9%

Probability of buying "KP281" given it is men - P(buy KP281 | men) = 40 / 104 = 38%

Probability of buying "KP481" given it is men - P(buy KP481 | men) = 31 / 104 = 30%

Probability of buying "KP781" given it is men - P(buy KP781 | men) = 33 / 104 = 32%

Using .crosstab() with "Gender" as the index and "Product" as the columns and margins parameter as True, normalize as "columns"

```
pd.crosstab(index = data["Gender"] , columns = data["Product"] , margins = True , normalize = "columns").round(2)
```

Product	KP281	KP481	KP781	All
Gender				
Female	0.5	0.48	0.18	0.42
Male	0.5	0.52	0.82	0.58

Conditional probabilities

Probability of women buying given it is "KP281" - P(women buy | KP281) - 40 / 80 = 50%

Probability of women buying given it is "KP481" - P(women buy | KP481) - 29 / 60 = 48%

Probability of women buying given it is "KP781" - P(women buy | KP781) - 7 / 40 = 18%

Probability of men buying given it is "KP281" - P(men buy | KP281) - 40 / 80 = 50%

Probability of men buying given it is "KP481" - P(men buy | KP481) - 31 / 60 = 52%

Probability of men buying given it is "KP781" - P(men buy | KP781) - 33 / 40 = 82%

Continuing the statistical analysis with "Marital status" and "Product" types

Using .crosstab() with "Marital Status" as the index and "Product" as the columns and margins parameter as True

```
pd.crosstab(index = data["MaritalStatus"] , columns = data["Product"] , margins = True)
```

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

Joint probabilities

Probability of "partenered people" buying "KP281" - 48 / 180 = 27%

Probability of "partenered people" buying "KP481" - 36 / 180 = 20%

Probability of "partenered people" buying "KP781" - 23 / 180 = 12.8%

Probability of "Single people" buying "KP281" - 32 / 180 = 18%

Probability of "Single people" buying "KP481" - 24 / 180 = 13%

Probability of "Single people" buying "KP781" - 17 / 180 = 9%

Using .crosstab() with "Marital Status" as the index and "Product" as the columns and margins parameter as True, normalize as "index"

```
pd.crosstab(index = data["MaritalStatus"] , columns = data["Product"] , margins = True)
```

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

```
pd.crosstab(index = data["MaritalStatus"] , columns = data["Product"] , margins = True , normalize = "index").round(2)
```

Product MaritalStatus	KP281	KP481	KP781
Partnered	0.45	0.34	0.21
Single	0.44	0.33	0.23
All	0.44	0.33	0.22

Conditional probabilities

Probability of buying "KP281" given "Partenered"- p(KP281 | Partenered) = 48 / 107 = 45%

Probability of buying "KP481" given "Partenered"- p(KP481 | Partenered) = 36 / 107 = 34%

Probability of buying "KP781" given "Partenered"- p(KP781 | Partenered) = 23 / 107 = 21%

Probability of buying "KP281" given "Single"- p(KP281 | Single) = 32 / 73 = 44%

Probability of buying "KP481" given "Single"- p(KP481 | Single) = 24 / 73 = 33%

Probability of buying "KP781" given "Single"- p(KP781 | Single) = 23 / 107 = 23%

Using .crosstab() with "Marital Status" as the index and "Product" as the columns and margins parameter as True, normalize as "columns"

```
pd.crosstab(index = data["MaritalStatus"] , columns = data["Product"] , margins = True)
```

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

```
pd.crosstab(index = data["MaritalStatus"] , columns = data["Product"] , margins = True , normalize = "columns").round(2)
```

Product MaritalStatus	KP281	KP481	KP781	All
Partnered	0.6	0.6	0.57	0.59
Single	0.4	0.4	0.42	0.41

Conditional probabilities

Probability of "Partenered" buying given it is "KP281" - P(Partenered buy| KP281) = 48 / 80 = 60%

Probability of "Partenered" buying given it is "KP481" - P(Partenered buy | KP481) = 36 / 60 = 60%

Probability of "Partenered" buying given it is "KP781" - P(Partenered buy | KP781) = 23 / 40 = 57%

Probability of "Singles" buying given it is "KP281" - P(Singles buy| KP281) = 32 / 80 = 40%

Probability of "Singles" buying given it is "KP481" - P(Singles buy | KP481) = 24 / 60 = 40%

Probability of "Singles" buying given it is "KP781" - P(Singles buy | KP781) = 17 / 40 = 42%

Continuing the statistical analysis with "Fitness" and "Product" types

Using .crosstab() with "Fitness" as the index and "Product" as the columns and margins parameter as True

```
pd.crosstab(index = data["Fitness"] , columns = data["Product"] , margins = True)
```

Product	KP281	KP481	KP781	All
Fitness				
1	1	1	0	2
2	14	12	0	26
3	54	39	4	97
5	2	0	29	[illegible]
All	80	60	40	[illegible]

```
pd.crosstab(index = data["Fitness"] , columns = data["Product"] , margins = True , normalize = "index").round(2)
```

Product	KP281	KP481	KP781
Fitness			
1	0.50	0.50	0.00
2	0.54	0.46	0.00
3	0.56	0.40	0.04
4	0.38	0.33	0.29
5	0.06	0.00	0.94
All	0.44	0.33	0.22

Conditional probabilities

Probability of "KP281" given the fitness rating is "1" - P(buy KP281 | Fitness is 1) = 1 / 2 = 50%

Probability of "KP481" given the fitness rating is "1" - P(buy KP481 | Fitness is 1) = 1 / 2 = 50%

Probability of "KP781" given the fitness rating is "1" - P(buy KP781 | Fitness is 1) = 0 / 2 = 0%

Probability of "KP281" given the fitness rating is "2" - P(buy KP281 | Fitness is 2) = 14 / 26 = 54%

Probability of "KP481" given the fitness rating is "2" - P(buy KP481 | Fitness is 2) = 12 / 26 = 46%

Probability of "KP781" given the fitness rating is "2" - P(buy KP781 | Fitness is 2) = 0 / 26 = 0%

Probability of "KP281" given the fitness rating is "3" - P(buy KP281 | Fitness is 3) = 54 / 97 = 56%

Probability of "KP481" given the fitness rating is "3" - P(buy KP481 | Fitness is 3) = 39 / 97 = 40%

Probability of "KP781" given the fitness rating is "3" - P(buy KP781 | Fitness is 3) = 4 / 97 = 4%

Probability of "KP281" given the fitness rating is "4" - P(buy KP281 | Fitness is 4) = 9 / 24 = 38%

Probability of "KP481" given the fitness rating is "4" - P(buy KP481 | Fitness is 4) = 8 / 24 = 33%

Probability of "KP781" given the fitness rating is "4" - P(buy KP781 | Fitness is 4) = 7 / 24 = 29%

Probability of "KP281" given the fitness rating is "5" - P(buy KP281 | Fitness is 5) = 2 / 31 = 6.45%

Probability of "KP481" given the fitness rating is "5" - P(buy KP481 | Fitness is 5) = 0 / 31 = 0%

Probability of "KP781" given the fitness rating is "5" - P(buy KP781 | Fitness is 5) = 29 / 31 = 94%

Recommendations

1. The probability of customers who rated themselves with low fitness score buying "KP781" is moslty 0 - To improve this please share the key features and easeness of using this equipment. Make sure the customers understand the importance of doing the workout with "KP781" so they can improve their fitness. Also may be provide them some extra warranty on this product if needed for this customer