Problem Statement

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.

1. Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
2. 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.

Dataset

Product Purchased: KP281, KP481, or KP781

Age: In years

Gender: Male/Female

Education: In years

MaritalStatus: Single or partnered

Usage: The average number of times the customer plans to use the treadmill each week.

Income: Annual income

Fitness: Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.

Miles: The average number of miles the customer expects to walk/run each week

Product Portfolio:

• The KP281 is an entry-level treadmill that sells for 1,500.

• The KP481 is for mid-level runners that sell for 1,750.

• The KP781 treadmill is having advanced features that sell for 2,500. all in dollars

What good looks like?

1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset

2. Detect Outliers (using boxplot, "describe" method by checking the difference between mean and median)
3. Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc)
4. Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)
5. Check correlation among different factors using heat maps or pair plots.
6. With all the above steps you can answer questions like: What is the probability of a male customer buying a KP781 treadmill?
7. Customer Profiling - Categorization of users.
8. Probability- marginal, conditional probability.
9. Some recommendations and actionable insights, based on the inferences.

In [8]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
```

In [10]:

```
!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/origi
```

```
Downloading...
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/origi
nal/aerofit_treadmill.csv?1639992749
To: /content/aerofit_treadmill.csv?1639992749
100% 7.28k/7.28k [00:00<00:00, 21.6MB/s]
```

Q1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset

In [11]:

```
data = pd.read_csv('aerofit_treadmill.csv?1639992749')
data
```

Out[11]:

	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
...	...	...	...	...	...	...	...	...	...
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

180 rows × 9 columns

In [12]:
```
data.shape
```

Out[12]:
```
(180, 9)
```

In [13]:
```
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
```

as from above observation we can see there no missing value and also the data type of columns are such as its need to be like for age,education(years),usage,fitness,income and miles are all integer type and the remaining are of string type so there is no requirement of changing data type of any column in the given data

In [14]:
```
data['Product'].unique()
```

Out[14]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

Q2. Checking outlier using describe and boxplot

In [15]:
```
data.loc[data['Product']=='KP281'].describe()
```

Out[15]:

	Age	Education	Usage	Fitness	Income	Miles
count	80.000000	80.000000	80.000000	80.00000	80.00000	80.000000
mean	28.550000	15.037500	3.087500	2.96250	46418.02500	82.787500
std	7.221452	1.216383	0.782624	0.66454	9075.78319	28.874102
min	18.000000	12.000000	2.000000	1.00000	29562.00000	38.000000
25%	23.000000	14.000000	3.000000	3.00000	38658.00000	66.000000
50%	26.000000	16.000000	3.000000	3.00000	46617.00000	85.000000
75%	33.000000	16.000000	4.000000	3.00000	53439.00000	94.000000
max	50.000000	18.000000	5.000000	5.00000	68220.00000	188.000000

In [16]:
```
data.loc[data['Product']=='KP481'].describe()
```

Out[16]:

	Age	Education	Usage	Fitness	Income	Miles
count	60.000000	60.000000	60.000000	60.00000	60.000000	60.000000
mean	28.900000	15.116667	3.066667	2.90000	48973.650000	87.933333
std	6.645248	1.222552	0.799717	0.62977	8653.989388	33.263135
min	19.000000	12.000000	2.000000	1.00000	31836.000000	21.000000
25%	24.000000	14.000000	3.000000	3.00000	44911.500000	64.000000
50%	26.000000	16.000000	3.000000	3.00000	49459.500000	85.000000
75%	33.250000	16.000000	3.250000	3.00000	53439.000000	106.000000
max	48.000000	18.000000	5.000000	4.00000	67083.000000	212.000000

In [17]:
```
data.loc[data['Product']=='KP781'].describe()
```

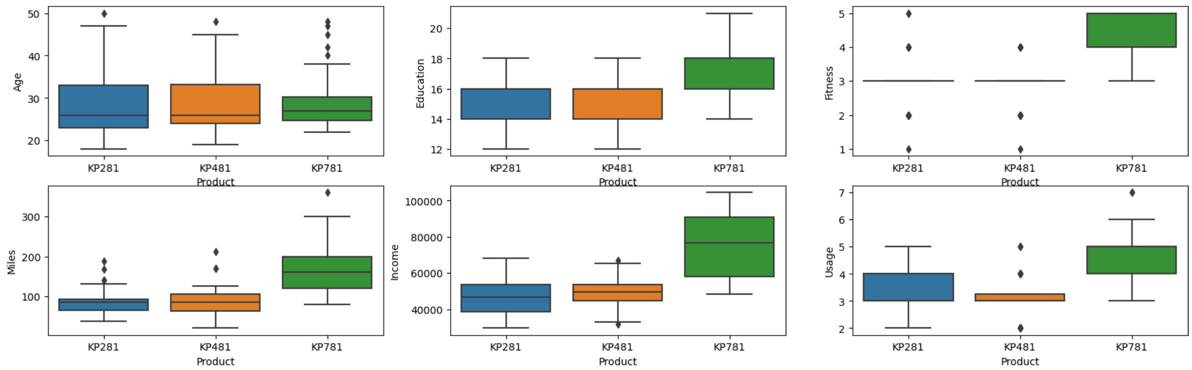
Out[17]:

	Age	Education	Usage	Fitness	Income	Miles
count	40.000000	40.000000	40.000000	40.000000	40.00000	40.000000
mean	29.100000	17.325000	4.775000	4.625000	75441.57500	166.900000
std	6.971738	1.639066	0.946993	0.667467	18505.83672	60.066544
min	22.000000	14.000000	3.000000	3.000000	48556.00000	80.000000
25%	24.750000	16.000000	4.000000	4.000000	58204.75000	120.000000
50%	27.000000	18.000000	5.000000	5.000000	76568.50000	160.000000
75%	30.250000	18.000000	5.000000	5.000000	90886.00000	200.000000
max	48.000000	21.000000	7.000000	5.000000	104581.00000	360.000000

Checking Outlier for age,usage,education,fitness,income,miles

In [18]:
```
plt.figure(figsize=(20,9))
plt.subplot(3,3,1)
sns.boxplot(data=data,x='Product',y='Age')
plt.subplot(3,3,2)
sns.boxplot(data=data,x='Product',y='Education')
plt.subplot(3,3,3)
sns.boxplot(data=data,x='Product',y='Fitness')
plt.subplot(3,3,4)
sns.boxplot(data=data,x='Product',y='Miles')
plt.subplot(3,3,5)
sns.boxplot(data=data,x='Product',y='Income')
plt.subplot(3,3,6)
sns.boxplot(data=data,x='Product',y='Usage')
```

Out[18]:
```
<Axes: xlabel='Product', ylabel='Usage'>
```



Insight: if we can see from above analysis for outliers detection we can say that for:

Figure which compare age and product -- have 1 outlier for each for KP281 and KP481 & 5 outliers for KP781 with age as a criteria

Education and Product- no Outliers detected

Fitness/Usage and Product: -- outlier detected in Fitness and Usage graph with products are found as such that product have discrete set of data which need to be analysed accordingly as it is given

Miles and Products: -- KP281 have 3 outlier KP481 have 2 and KP781 have 1 outliers in miles

Income and Products -- Only KP481 have 2 outliers with respect to income remaining product have no oultliers in it

we can do seperate check for outliers for Male and Female customer w.r.t Products but we have not enough data so it is better to consider them as single individuals and analyse accordingly

Q.3 Check if features like marital status, age have any effect on the product purchased

Approach:

In [19]:
```
data
```

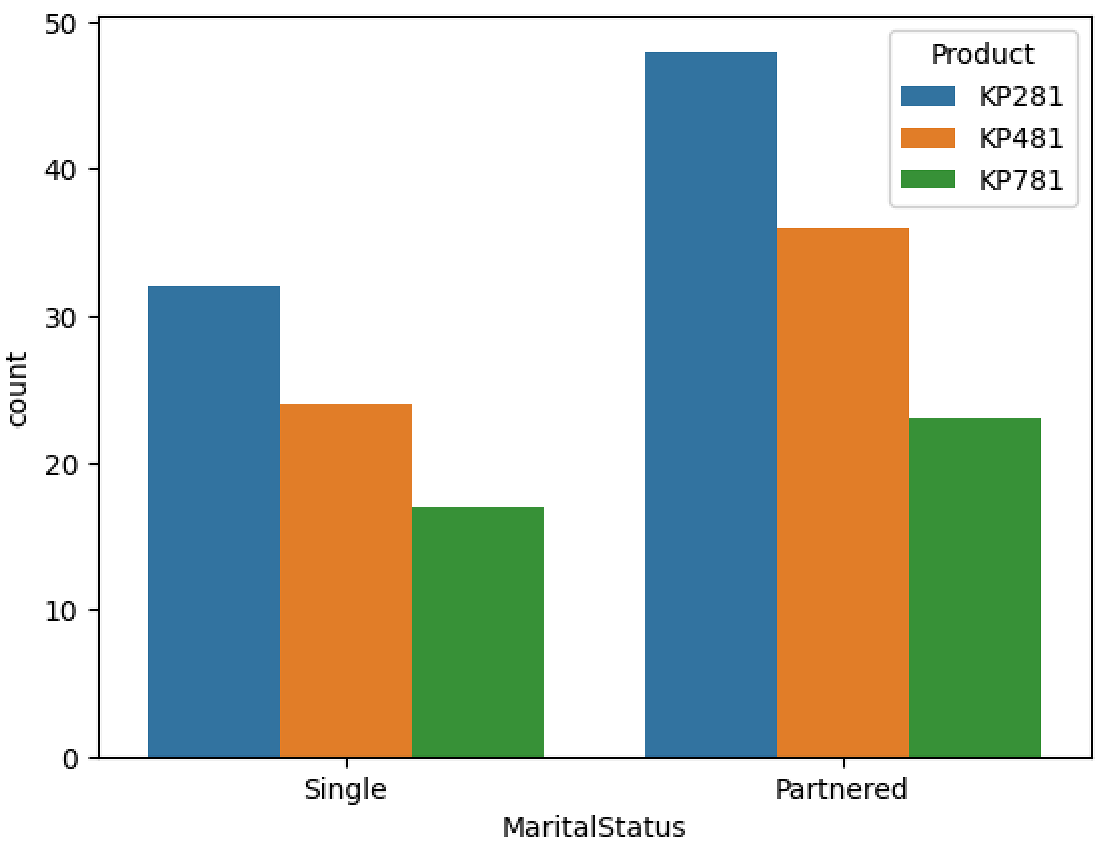
Out[19]:

	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
...	...	...	...	...	...	...	...	...	...
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

180 rows × 9 columns

In [20]:
```
sns.countplot(data=data,x='MaritalStatus',hue='Product')
```

Out[20]: <Axes: xlabel='MaritalStatus', ylabel='count'>



From the above graph we can infer that

Insights:

1. **KP281** is ***bought maximum*** among the **singles** and similar **KP281** is **bought in maximum number** by ***partnered*** as KP281 is an entry-level treadmill which is of least cost among treadmills furthermore KP781 treadmill is having advanced features with maximum costs is least purchased by people having Single and Partnered MaritalStatus

2.Partnered bought mostly the KP281 Treadmill

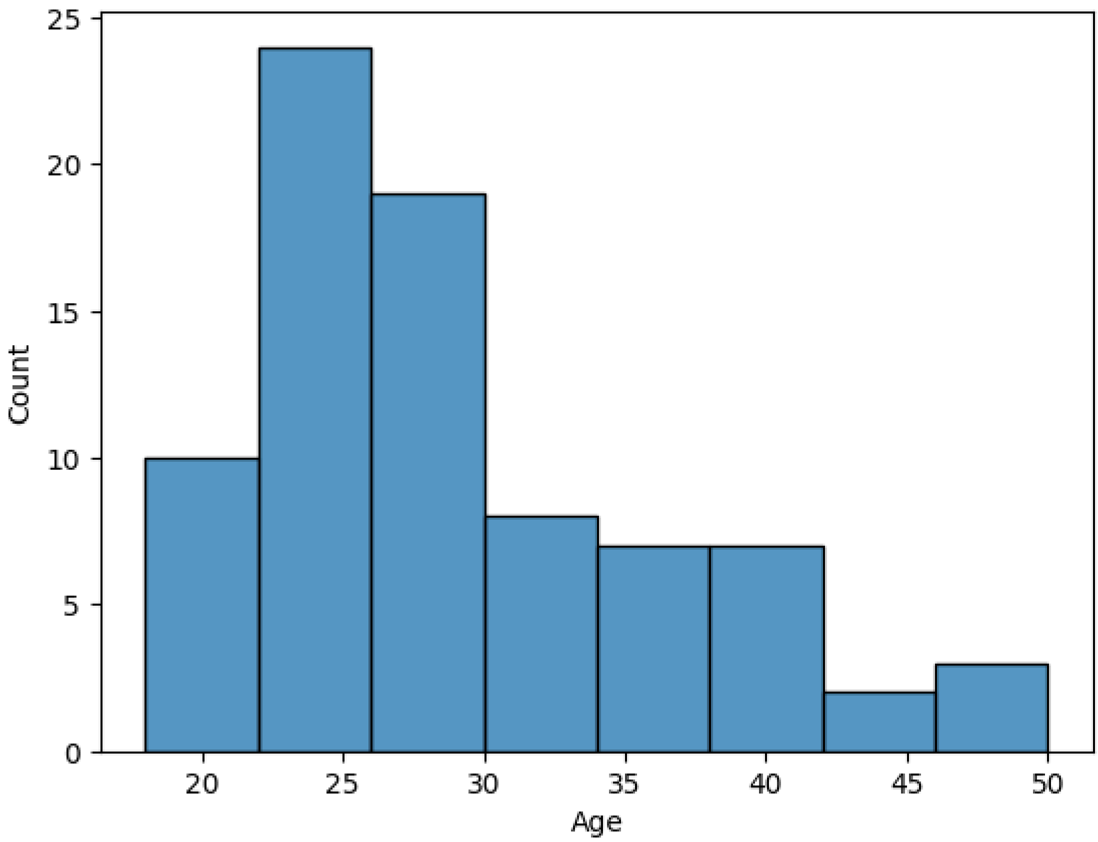
Recommendations:

since most KP281 is most bought among partner and single the firm should increase their inventroy of KP281 treadmill so as not to lag demands of customers also for other treadmill need to be added with offer so as to increase customemr interest consequently increasing the revenue of firm.

Person age and KP281 Trademill

In [21]:
```
sns.histplot(data=data.loc[data['Product']=='KP281'],x='Age')
```

Out[21]: <Axes: xlabel='Age', ylabel='Count'>

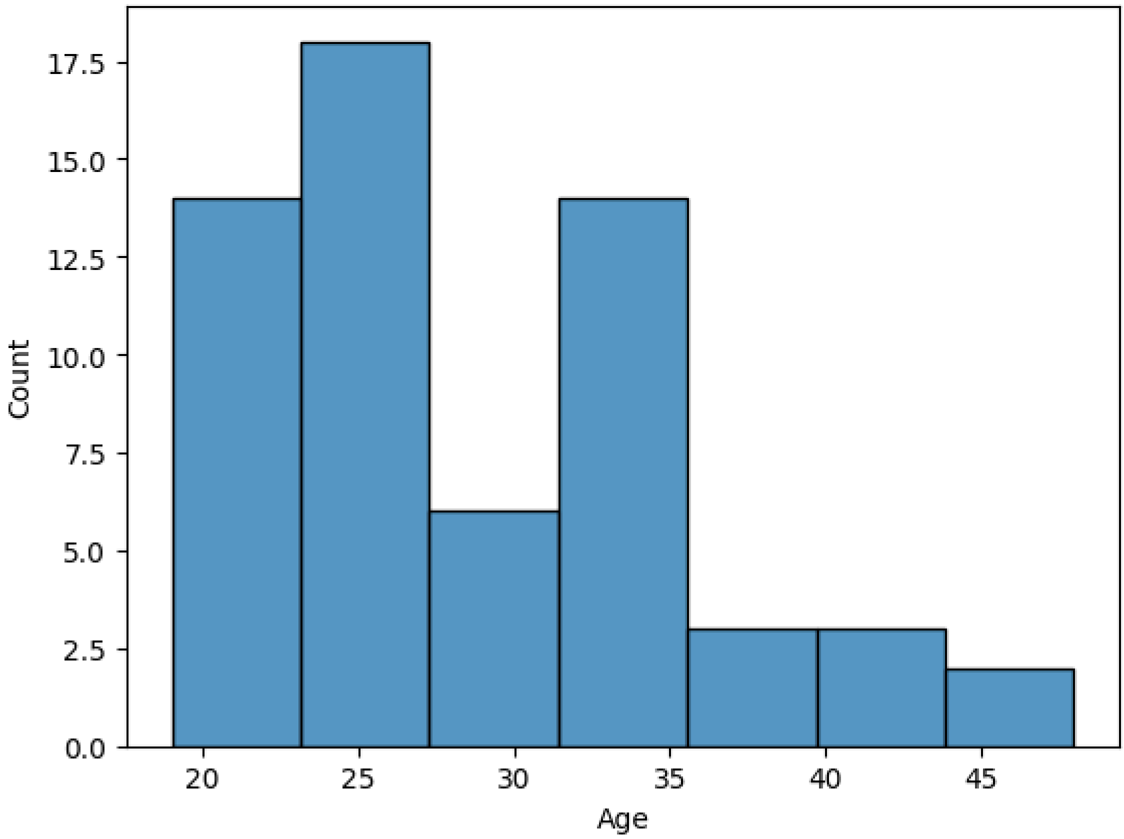


Insights: from above graph we can say KP281 is mostly preffered by the individuals in the age range close to 24-25 years old

Person age and KP481 Trademill

In [22]:
```
sns.histplot(data=data.loc[data['Product']=='KP481'],x='Age')
```

Out[22]: <Axes: xlabel='Age', ylabel='Count'>

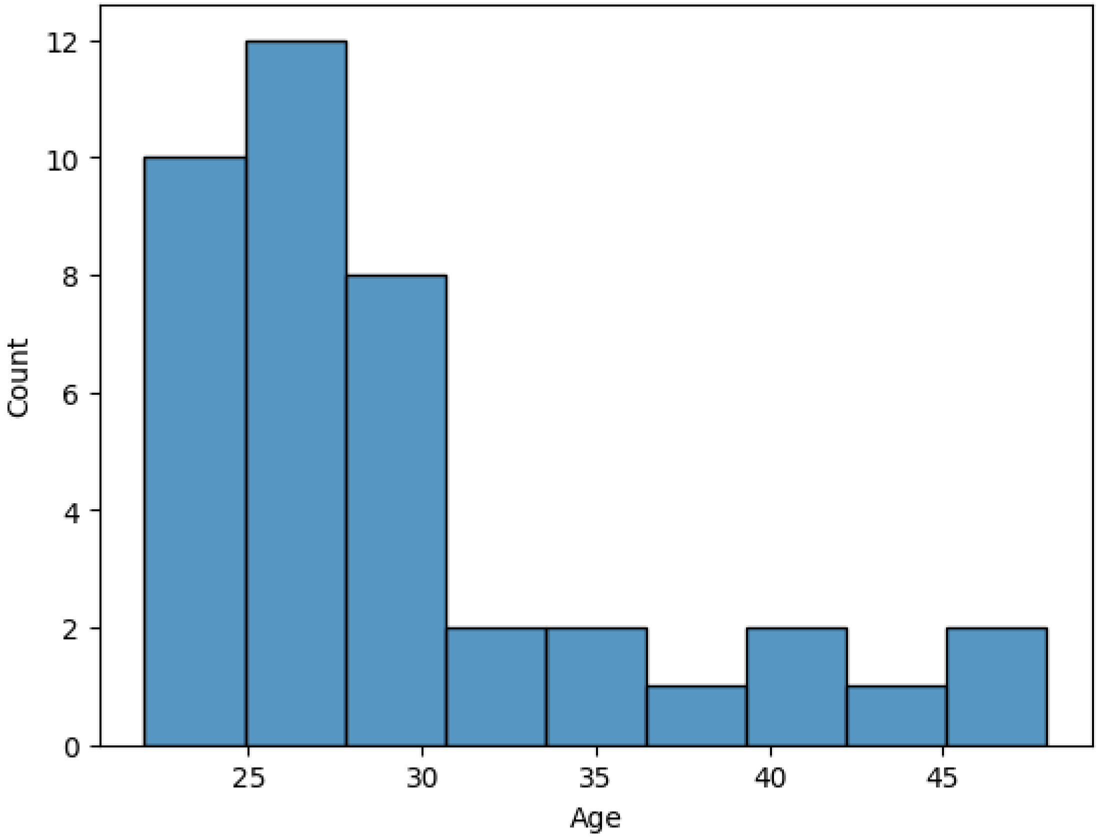


Insights: from above graph we can say KP481 is mostly preffered by the individuals in the age range close to around 25 years old

Person age and KP781 Treadmill

In [23]:
```
sns.histplot(data=data.loc[data['Product']=='KP781'],x='Age')
```

Out[23]: <Axes: xlabel='Age', ylabel='Count'>



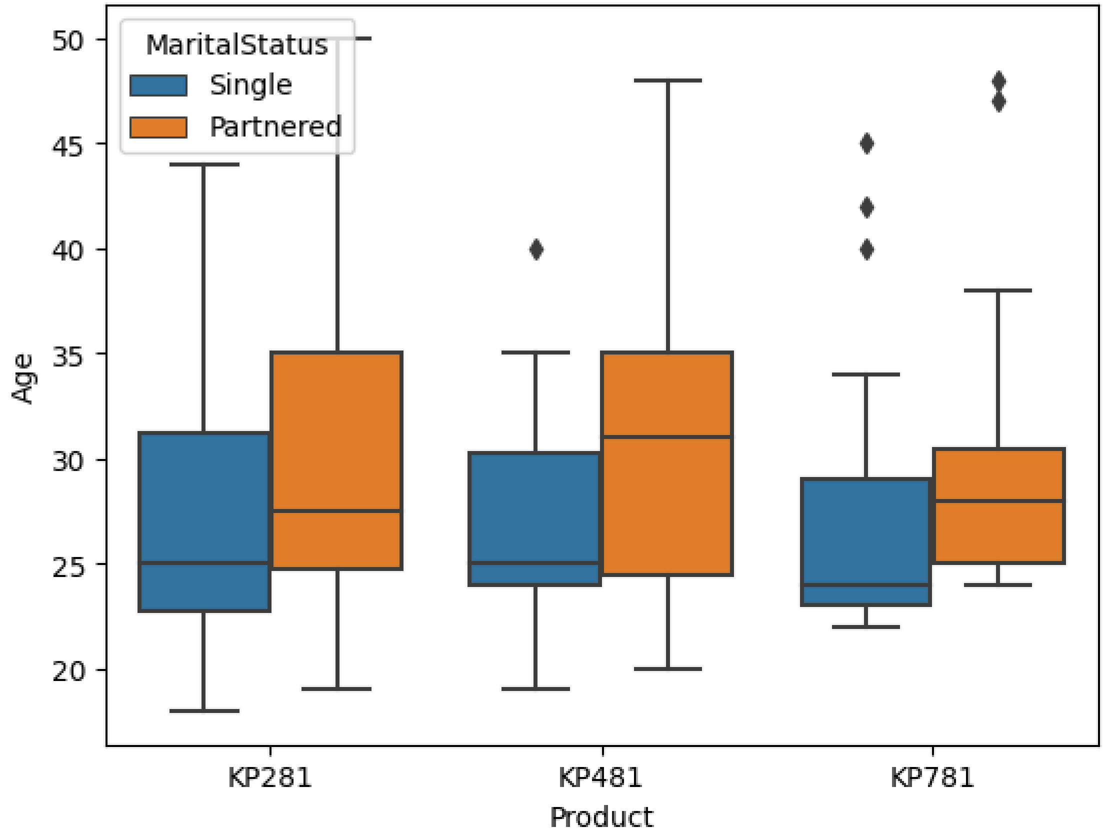
Insights: from above graph we can say KP781 is mostly preffered by the individuals in the age range close grater than 25 years old and less than 30 year old

Recommendations: it is clear from above three graphs if a person is close to age around 25 years of age it is for sure he/she is going to buy among these three treadmill , for their further choice we have to look over other parameter usage,fitness score, salary, marital status to recommend them the right treadmill for him/her for , the further analysis around such scenario has been done in below process

checking Marital status,age effect on product purchased

In [24]:
```
sns.boxplot(data=data,x='Product',y='Age',hue='MaritalStatus')
```

Out[24]:
```
<Axes: xlabel='Product', ylabel='Age'>
```



Insights: for all the partnered individuals whether male or female median age are more than single individuals either male/female , median age for singles male and female for all type of Treadmill is close to 25 years while partnered median age are more than 25 for kp281 , for kp481 it is 30 years and kp781 median age for partnered is in between 25 to 30 approx. 27 years.

Q.4 Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table

In [25]:
```
pd.crosstab(data['Product'],[data['Gender'],data['MaritalStatus']],margins=True)
```

Out[25]:

Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	27	13	21	19	80
KP481	15	14	21	10	60
KP781	4	3	19	14	40
All	46	30	61	43	180

Marginal probability distribution for calculation of percentages of people with their profiles

In [67]:
```
pd.crosstab(data['Product'],[data['Gender'],data['MaritalStatus']],normalize='all')
```

Out[67]:

Gender	Female		Male	
MaritalStatus	Partnered	Single	Partnered	Single
Product				
KP281	0.150000	0.072222	0.116667	0.105556
KP481	0.083333	0.077778	0.116667	0.055556
KP781	0.022222	0.016667	0.105556	0.077778

Insights:

1. if individual is Female and partnered most of them choose KP281 treadmill with highest probability as 0.15
2. if female is single there is a proximity in choosing either KP281 or KP481 but among them KP481 is highest preffered with probability 0.0777 3.Male+ Partnered : equal purchasing probability of KP281 and KP481 of treadmill
3. male+ single : KP281 is preffered most

Recommendations:

as according to the above analysis if a person or individuals follows the maritalstatus and gender criteria wee can suggest him/her the corresponding Treadmill keeping in mind the highest chance/probibility of buying a product with respect to their marital status and gender.e.g- if individual is **male+single : he should be recommended KP281 Treadmill**

Q5. Check correlation among different factors using heat maps or pair plots.

checking correlation

In [28]:
```
data.corr()
```

```
<ipython-input-28-c44ded798807>:1: FutureWarning: The default value of numeric_onl
y 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 war
ning.
  data.corr()
```

Out[28]:

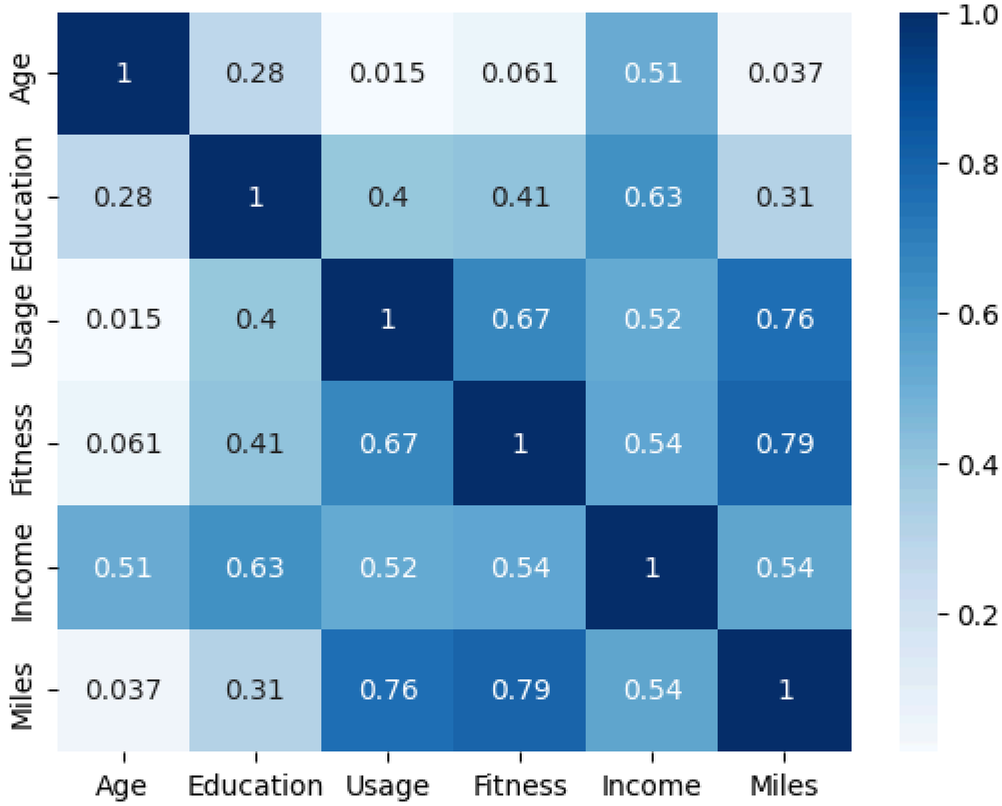
	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702
Income	0.513414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

Heatmap

In [29]:
```
sns.heatmap(data=data.corr(),annot=True,cmap='Blues')
```

```
<ipython-input-29-4744123c13fc>:1: FutureWarning: The default value of numeric_onl
y 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 war
ning.
  sns.heatmap(data=data.corr(),annot=True,cmap='Blues')
```

Out[29]:
```
<Axes: >
```



Insights: from above graph we can say

1. Fitness and miles are highly correlated 2.miles and usage are highly correlated 3.usage and fitness are highly correlated 4.income and age are hihly correlated

recommendation: analysis around these characteristics as mentioned in insights of an individuals would fetch a useful and insightful outcomes

Q6. What is the probability of a male customer buying a KP781 treadmill?

In [30]:
```
pd.crosstab(data['Product'],data['Gender'])
```

Out[30]:

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

to check probability of male customer buying KP781 we can use normalize in crosstab for finding probability as required as shown below

In [68]:
```
pd.crosstab(data['Product'],data['Gender'],normalize='columns')
```

Out[68]:

Gender	Female	Male
Product		
KP281	0.526316	0.384615
KP481	0.381579	0.298077
KP781	0.092105	0.317308

$$P(\mathrm{KP781}, \mathrm{male}) = 0.317$$

insights: as per above data the probability of *male customer buying KP781* would be ***0.3173***

Q7. Customer profiling

Categorization of users.

In [32]:
```
data
```

Out[32]:

	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
...	...	...	...	...	...	...	...	...	...
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

180 rows × 9 columns

A) Categorization of users for KP281 Trademill

In [33]:
```
T1 =data.loc[data['Product']=='KP281']
T1
```

Out[33]:

	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
...	...	...	...	...	...	...	...	...	...
75	KP281	43	Male	16	Partnered	3	3	53439	66
76	KP281	44	Female	16	Single	3	4	57987	75
77	KP281	46	Female	16	Partnered	3	2	60261	47
78	KP281	47	Male	16	Partnered	4	3	56850	94
79	KP281	50	Female	16	Partnered	3	3	64809	66

80 rows × 9 columns

Number of male and female users who opted KP281 treadmill

In [34]:
```
T1['Gender'].value_counts()
```

Out[34]:
```
Male      40
Female    40
Name: Gender, dtype: int64
```

Insights: from above analysis it is clear that there are 40 males and 40 females who considered KP281 treadmill

if we want to further analyse we can subcategorize customer on basis of male and female. lets start with male

Male(KP281)

1.income + usage : Considering this as a criteria we can profile the number of males who opted KP281

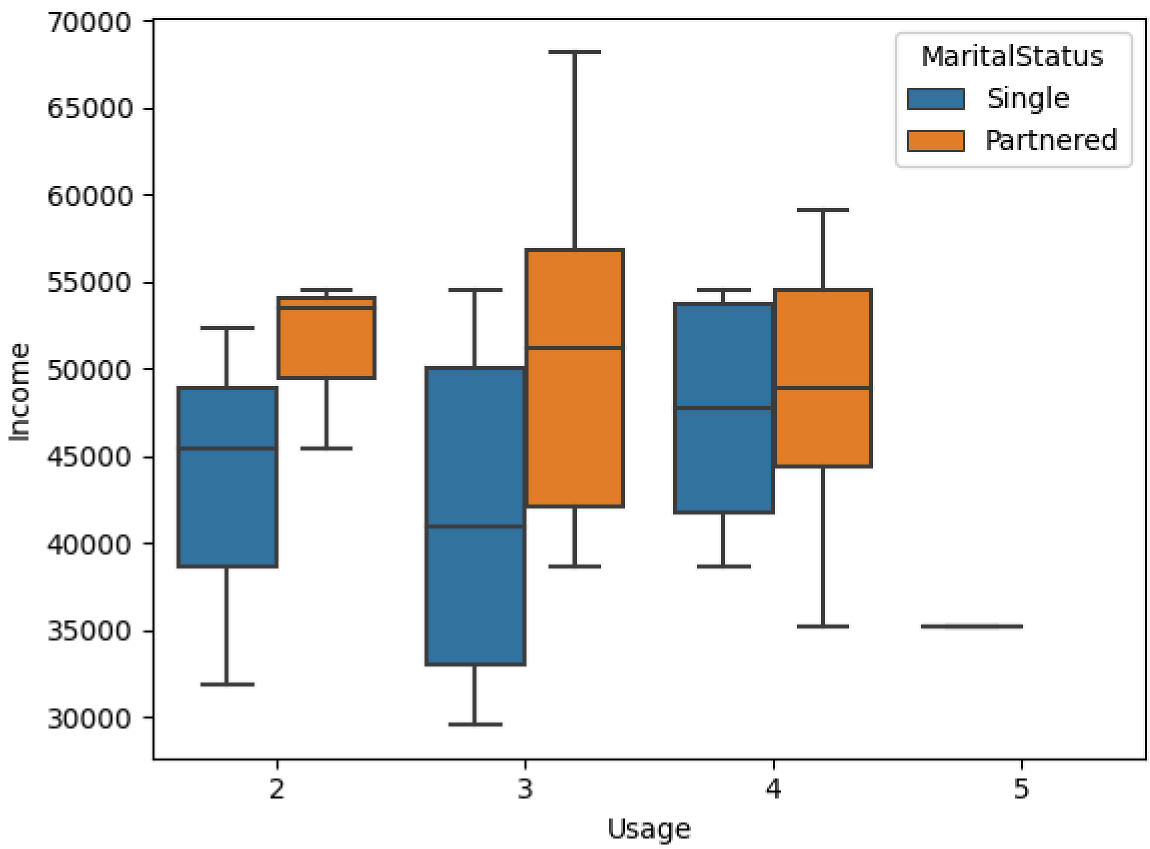
Usage: The average number of times the customer plans to use the treadmill each week.

income: Annual income(in $)

In [ ]:
```
T1_M = T1.loc[T1['Gender']=='Male']
T1_M
```

In [36]:
```
sns.boxplot(data=T1_M,x='Usage',y='Income',hue='MaritalStatus')
```

Out[36]: <Axes: xlabel='Usage', ylabel='Income'>



Insights:as per from above graph we can say

1. Mens who are single an who bought KP281 as per data have lower median salary overall as compared to partnered
2. single men with 2 time,3 time,4 time average usage of treadmill perweek have their median salary close to 45000,40000,47500 preffered KP281 treadmill
3. partnered men with 2 time,3 time,4 time average usage of treadmill perweek have their median salary close to 52500,51000,49000 preffered KP281 treadmill

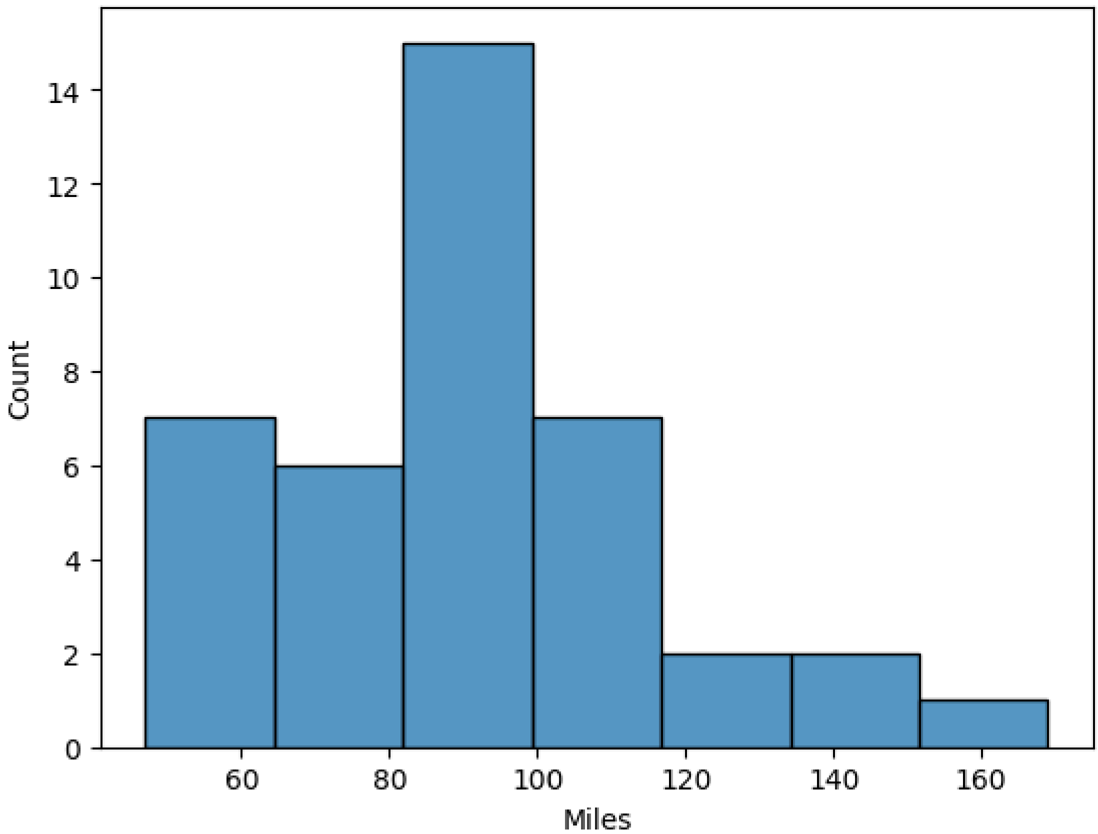
2. Fitness+Miles: Considering this as a criteria we can profile the number of males who opted KP281

Fitness: Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.

Miles: The average number of miles the customer expects to walk/run each week

In [37]:
```
T1_M
sns.histplot(data=T1_M,x='Miles')
```

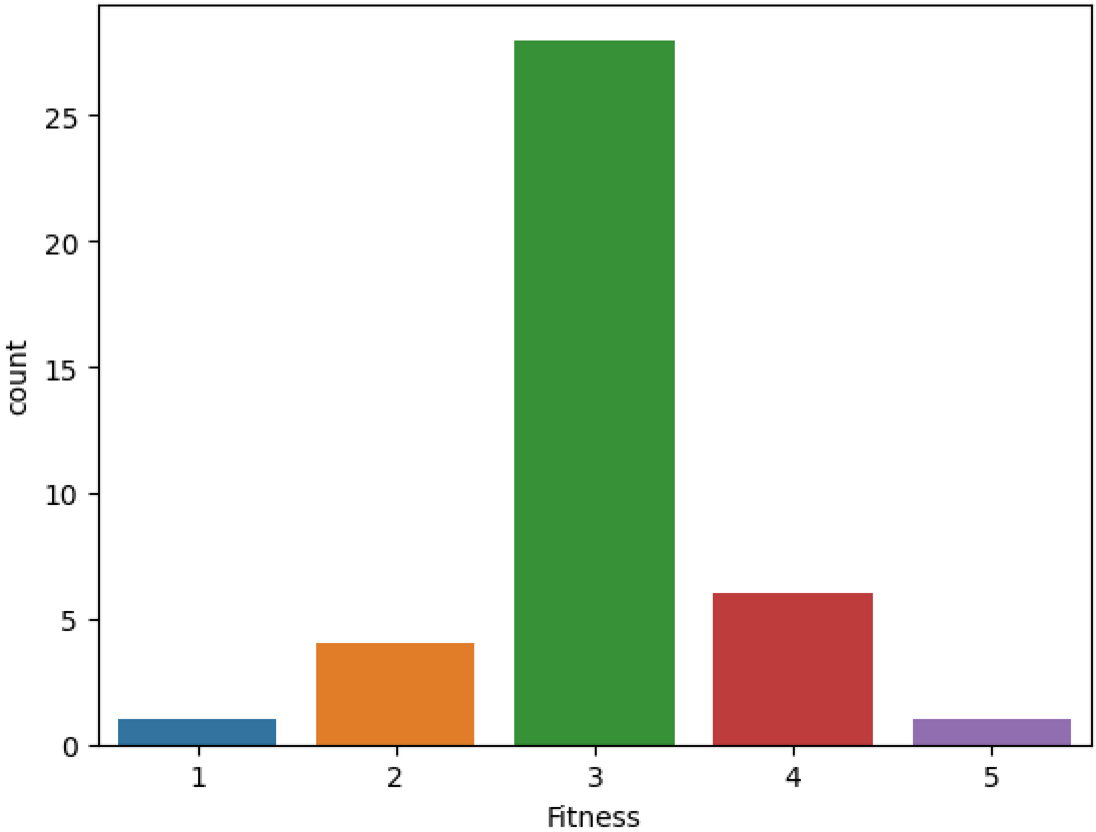
Out[37]:
```
<Axes: xlabel='Miles', ylabel='Count'>
```



Males who bought KP281 trademill most of them are from around who expects themselves to walk around 80-100 miles

In [38]:
```
sns.countplot(data=T1_M,x='Fitness')
```

Out[38]:
```
<Axes: xlabel='Fitness', ylabel='count'>
```



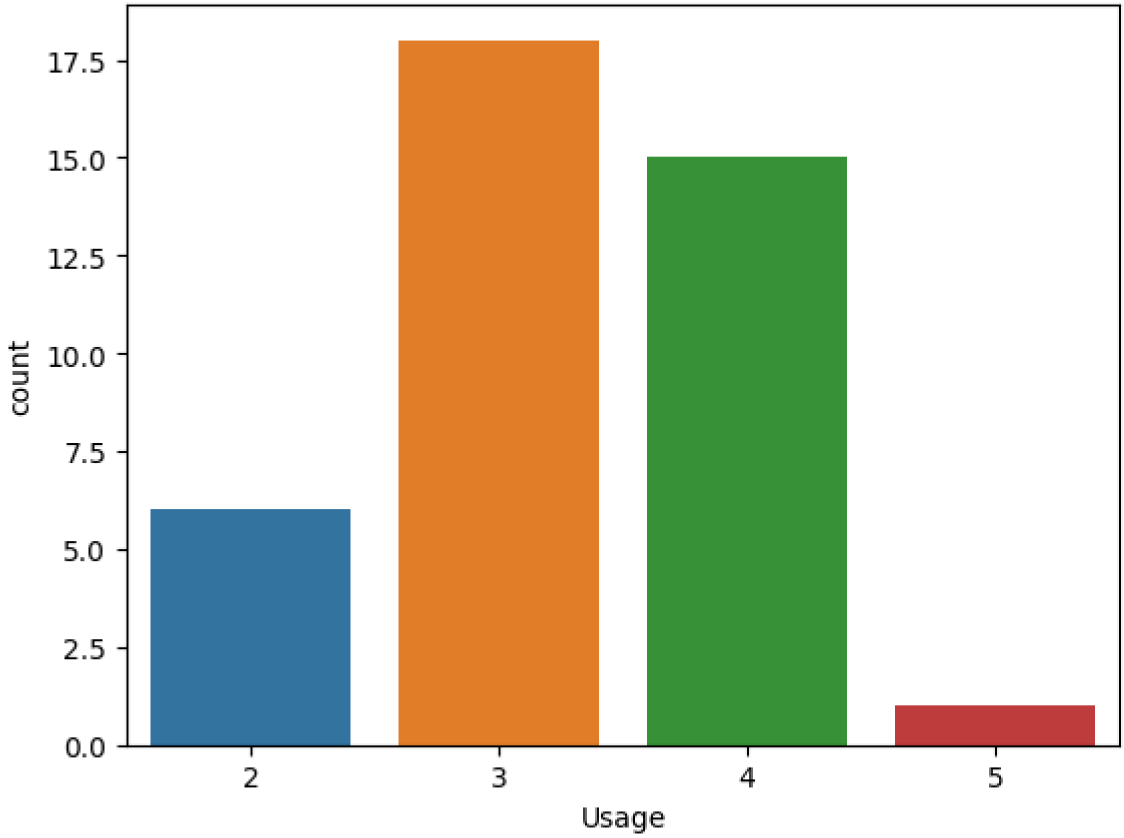
insight: males who preferred KP281 are most in number who rate their fitness score -3

3. Usage: Considering this as a criteria we can profile the number of males who opted KP281

Usage: The average number of times the customer plans to use the treadmill each week.

In [39]:
```
sns.countplot(data=T1_M,x='Usage')
```

Out[39]:
```
<Axes: xlabel='Usage', ylabel='count'>
```

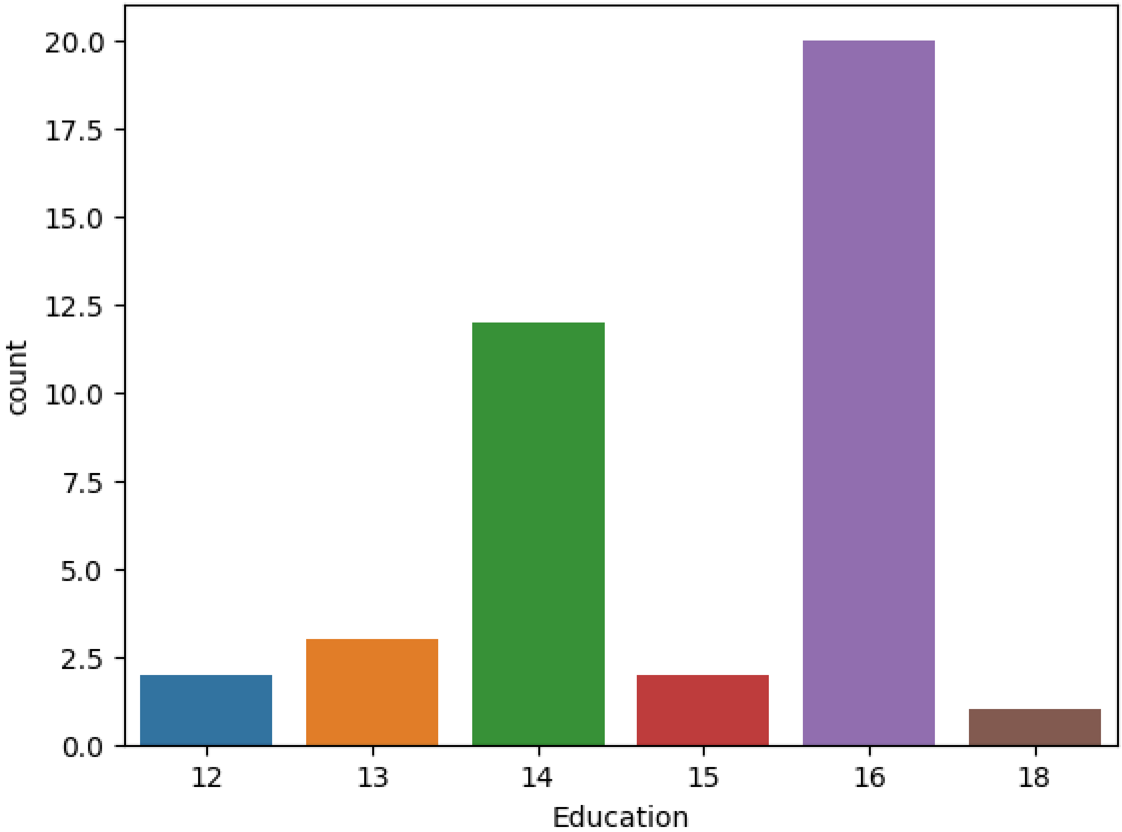


Insights: Males who bought KP281 are mostly those who plans **to use it 3 times in a week** on an average

4. Education: categorization customer consider this as parameter

In [40]:
```
sns.countplot(data=T1_M,x='Education')
```

Out[40]:
```
<Axes: xlabel='Education', ylabel='count'>
```



Insights: Graph depicts males who considered KP281 Treadmill most of them have education of 16 years

Female(KP281)

1.income + usage : Considering this as a criteria we can profile the number of females who opted KP281

Usage: The average number of times the customer plans to use the treadmill each week.

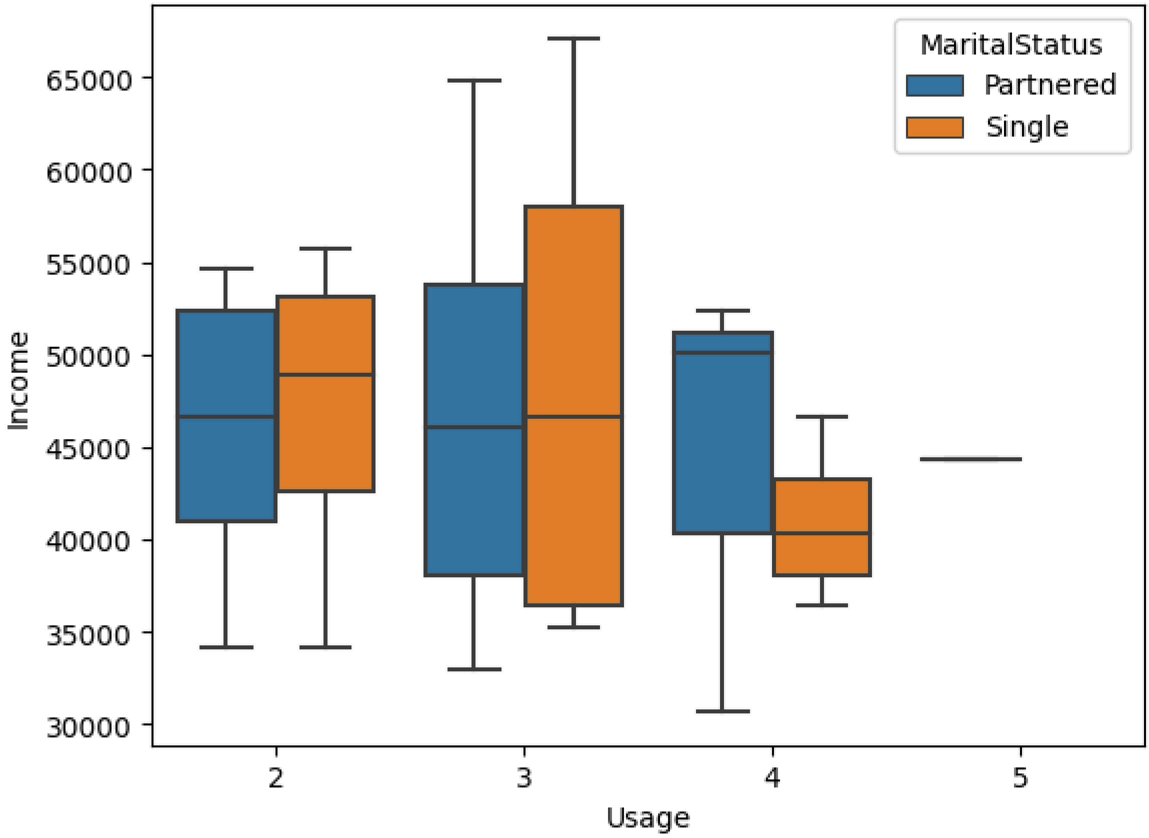
income: Annual income(in $)

In [41]:
```
T1_F = T1.loc[T1['Gender']=='Female']
T1_F.shape
```

Out[41]: (40, 9)

In [42]:
```
sns.boxplot(data=T1_F,x='Usage',y='Income',hue='MaritalStatus')
```

Out[42]: <Axes: xlabel='Usage', ylabel='Income'>



Insights:as per from above graph we can say

1. single Female who bought KP281 are planning to have **2,3 times** of average usage per week **have higher median salary** as compared to partnered female with same usage except female planning 4 time per week of average usage.
2. single Females with 2 time,3 time,4 time average usage of trademill perweek have their median salary close to 50000,45000,40000 preffered KP281 trademill
3. partnered Females with 2 time,3 time,4 time average usage of trademill perweek have their median salary close to 45000,45000,50000 preffered KP281 trademill

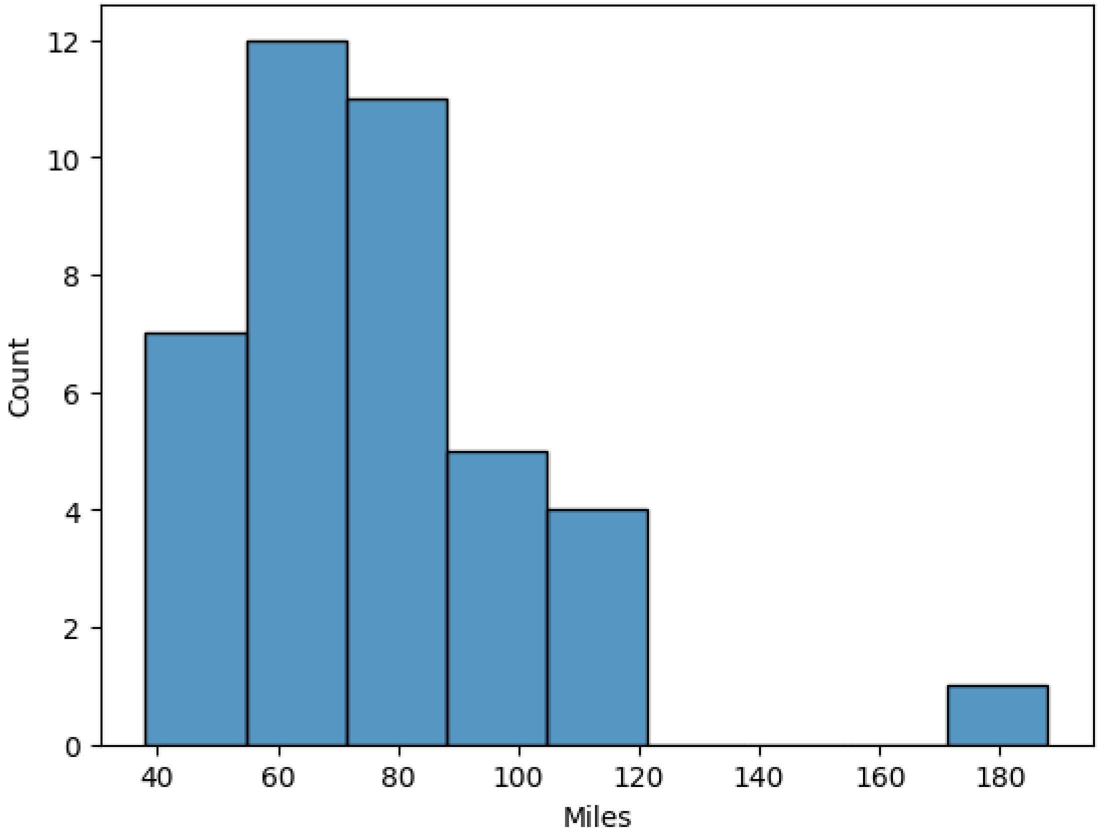
2. Fitness+Miles: Considering this as a criteria we can profile the number of Females who opted KP281

Fitness: Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.

Miles: The average number of miles the customer expects to walk/run each week

In [43]:
```
sns.histplot(data=T1_F,x='Miles')
```

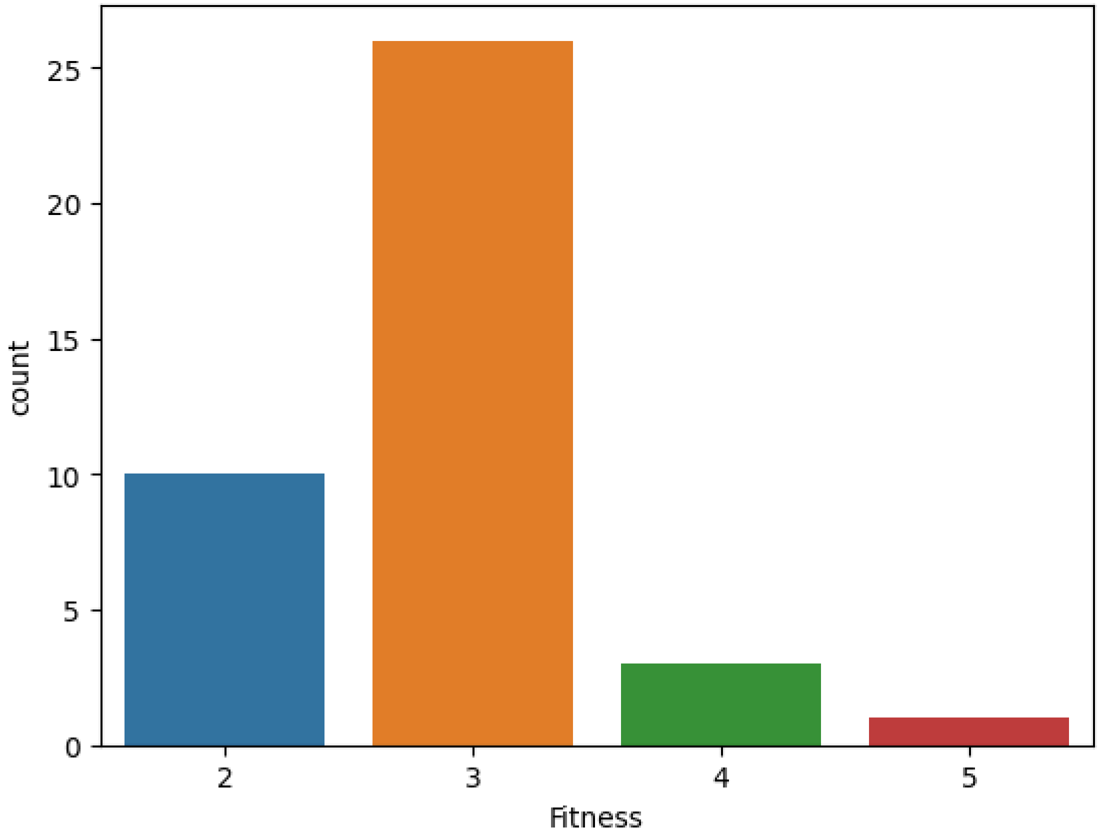
Out[43]:
```
<Axes: xlabel='Miles', ylabel='Count'>
```



Insights: Females who bought KP281 treadmill most of them are from around who expects themselves to walk around 60-80 miles

In [44]:
```
sns.countplot(data=T1_F,x='Fitness')
```

Out[44]: <Axes: xlabel='Fitness', ylabel='count'>



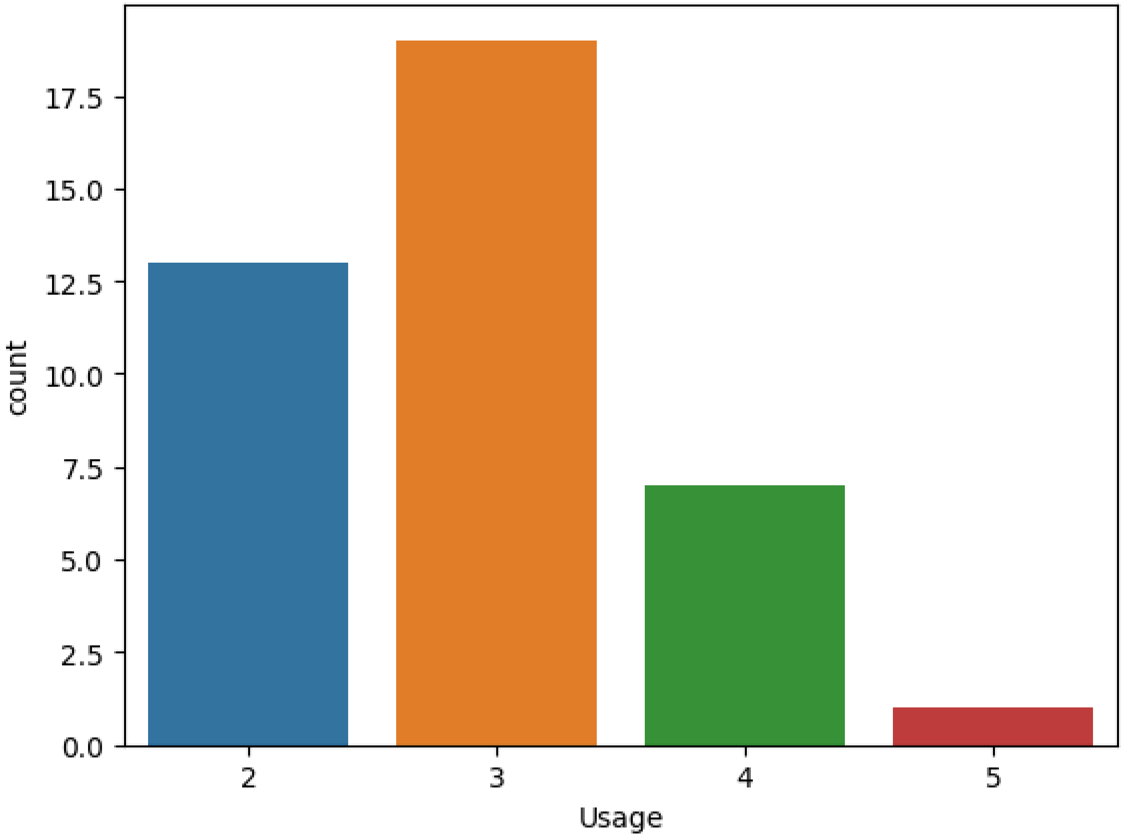
insight: Females who preferred KP281 are most in number who rate their fitness score -3

3. Usage: Considering this as a criteria we can profile the number of Females who opted KP281

Usage: The average number of times the customer plans to use the treadmill each week.

In [45]:
```
sns.countplot(data=T1_F,x='Usage')
```

Out[45]:
```
<Axes: xlabel='Usage', ylabel='count'>
```



Insights: Female who bought KP281 are mostly those who plans **to use it 3 times in a week** on an average

4. Education: categorization customer consider this as parameter

B) Categorization of users for KP481 Treadmill

In [46]:
```
T2 =data.loc[data['Product']=='KP481']
T2['Gender'].value_counts()
```

Out[46]:
```
Male      31
Female    29
Name: Gender, dtype: int64
```

SUBPLOT : for analyzing data around males/female who preffered KP481 Treadmill

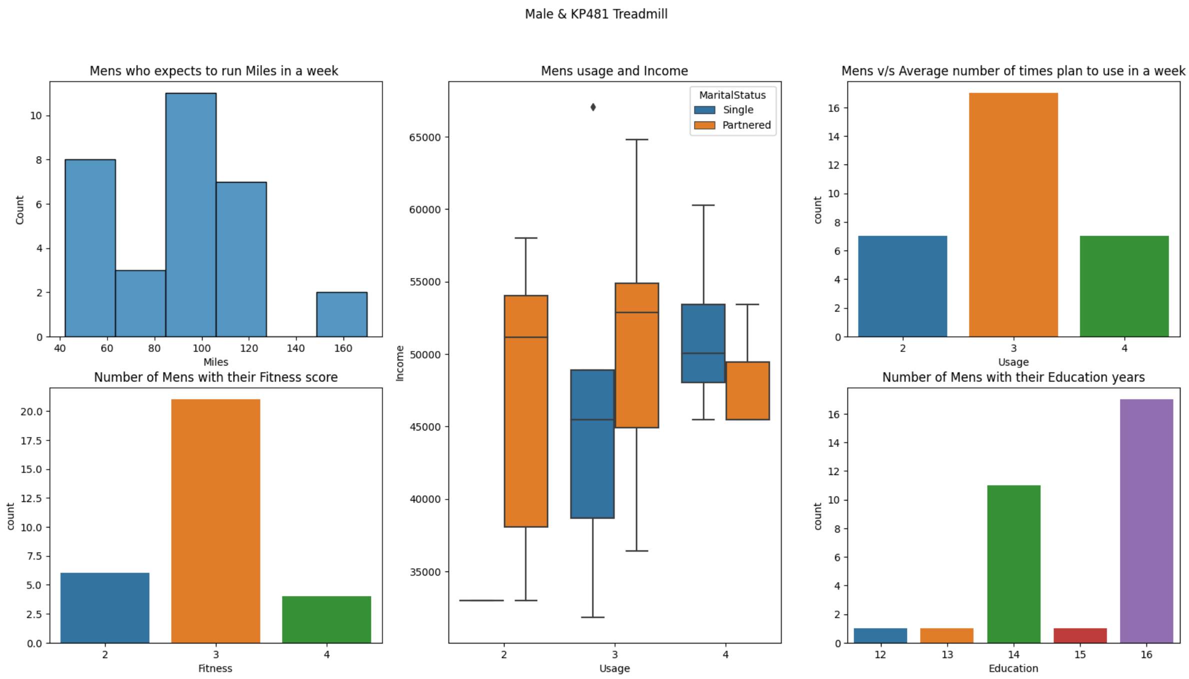
Males(KP481)

In [47]:
```
T2_M = T2.loc[T2['Gender']=='Male']
T2_M.shape
```

Out[47]:
```
(31, 9)
```

In [69]:
```
fig = plt.figure(figsize=(20,10))
fig.suptitle("Male & KP481 Treadmill")
plt.subplot(1,3,2)
sns.boxplot(data=T2_M,x='Usage',y='Income',hue='MaritalStatus')
plt.title('Mens usage and Income')
plt.subplot(2,3,1)
sns.histplot(data=T2_M,x='Miles')
plt.title('Mens who expects to run Miles in a week ')
plt.subplot(2,3,4)
sns.countplot(data=T2_M,x='Fitness')
plt.title('Number of Mens with their Fitness score')
plt.subplot(2,3,6)
sns.countplot(data=T2_M,x='Education')
plt.title('Number of Mens with their Education years')
plt.subplot(2,3,3)
sns.countplot(data=T2_M,x='Usage')
plt.title('Mens v/s Average number of times plan to use in a week')
```

Out[69]:
```
Text(0.5, 1.0, 'Mens v/s Average number of times plan to use in a week')
```



Insights:

1.Mens who opted KP481 most among them expects themselves to run around **100 miles**

2.Mens who opted KP481 most among them Scores themselves at **3 fitness scale**

3.Mens who opted KP481 **have highest median salary** who **were partnered** and expects**3 times** a week on average usage

4.Mens who opted KP481 maximum among them plans to **use 3 times a week**

5.Mens who opted KP481 maximum among them have **education of 16 years** in their life

Recommendation: from above insights we can profile mens who opted KP481 Treadmill

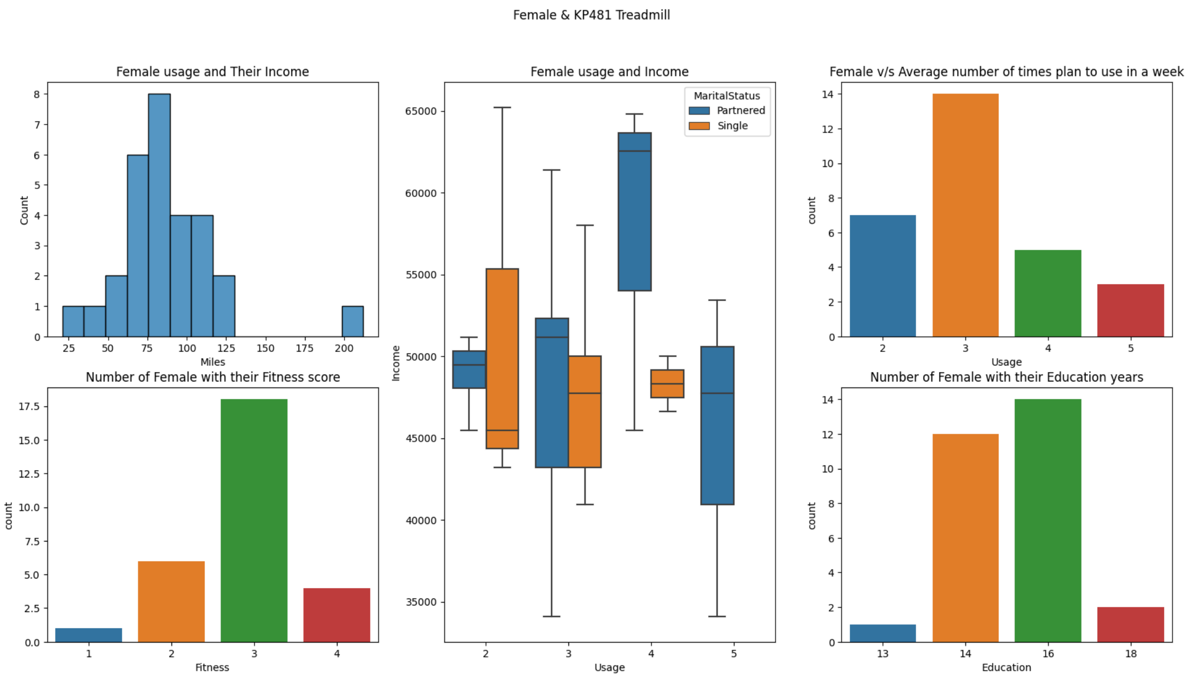
Female(KP481)

In [49]:
```
T2_F = T2.loc[T2['Gender']=='Female']
T2_F.shape
```

Out[49]: (29, 9)

In [50]:
```
fig = plt.figure(figsize=(20,10))
fig.suptitle("Female & KP481 Treadmill")
plt.subplot(1,3,2)
sns.boxplot(data=T2_F,x='Usage',y='Income',hue='MaritalStatus')
plt.title('Female usage and Income')
plt.subplot(2,3,1)
sns.histplot(data=T2_F,x='Miles')
plt.title('Female usage and Their Income')
plt.subplot(2,3,4)
sns.countplot(data=T2_F,x='Fitness')
plt.title('Number of Female with their Fitness score')
plt.subplot(2,3,6)
sns.countplot(data=T2_F,x='Education')
plt.title('Number of Female with their Education years')
plt.subplot(2,3,3)
sns.countplot(data=T2_F,x='Usage')
plt.title('Female v/s Average number of times plan to use in a week')
```

Out[50]: Text(0.5, 1.0, 'Female v/s Average number of times plan to use in a week')



Insights:

1.Female who opted KP481 most among them expects themselves to run around **75-80 miles**

2.Female who opted KP481 most among them Scores themselves at **3 fitness scale**

3.female who opted KP481 have **highest median salary** who **were partnered**

4.female who opted KP481 maximum among them plans to **use 3 times a week**

5.female who opted KP481 maximum among them have **education of 16 years** in their life

Recommendation: from above insights we can profile female who opted KP481 Treadmill

C) Categorization of users for KP781 Treadmill

In [51]:
```
T3 =data.loc[data['Product']=='KP781']
T3['Gender'].value_counts()
```

Out[51]:
```
Male      33
Female     7
Name: Gender, dtype: int64
```

SUBPLOT : for analyzing data around males/female who preffered KP781 Treadmill

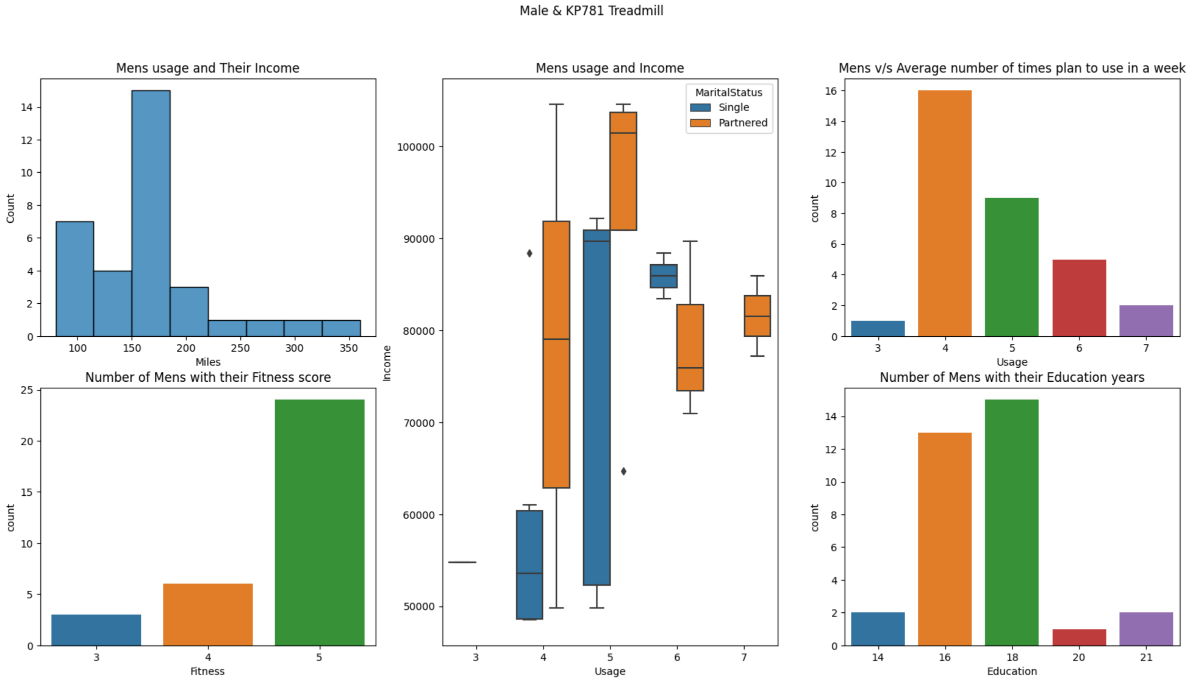
Male(KP781)

In [52]:
```
T3_M = T3.loc[T3['Gender']=='Male']
T3_M.shape
```

Out[52]:
```
(33, 9)
```

In [53]:
```
fig = plt.figure(figsize=(20,10))
fig.suptitle("Male & KP781 Treadmill")
plt.subplot(1,3,2)
sns.boxplot(data=T3_M,x='Usage',y='Income',hue='MaritalStatus')
plt.title('Mens usage and Income')
plt.subplot(2,3,1)
sns.histplot(data=T3_M,x='Miles')
plt.title('Mens usage and Their Income')
plt.subplot(2,3,4)
sns.countplot(data=T3_M,x='Fitness')
plt.title('Number of Mens with their Fitness score')
plt.subplot(2,3,6)
sns.countplot(data=T3_M,x='Education')
plt.title('Number of Mens with their Education years')
plt.subplot(2,3,3)
sns.countplot(data=T3_M,x='Usage')
plt.title('Mens v/s Average number of times plan to use in a week')
```

Out[53]:
```
Text(0.5, 1.0, 'Mens v/s Average number of times plan to use in a week')
```



Insights:

1.male who opted KP781 most among them expects themselves to run around `150` **-200 miles**

2.male who opted KP781 most among them Scores themselves at **5 fitness scale**

3.male who opted KP781 have **highest median salary** who **were partnered** with usage **5 times a week**

4.male who opted KP781 maximum among them usage plans is **4 times a week**

5.male who opted KP781 maximum among them have **education of 18 years** in their life

Recommendation: from above insights we can profile male who opted KP781 Treadmill

Female(KP781)

In [54]:
```
T3_F = T3.loc[T3['Gender']=='Female']
T3_F.shape
```

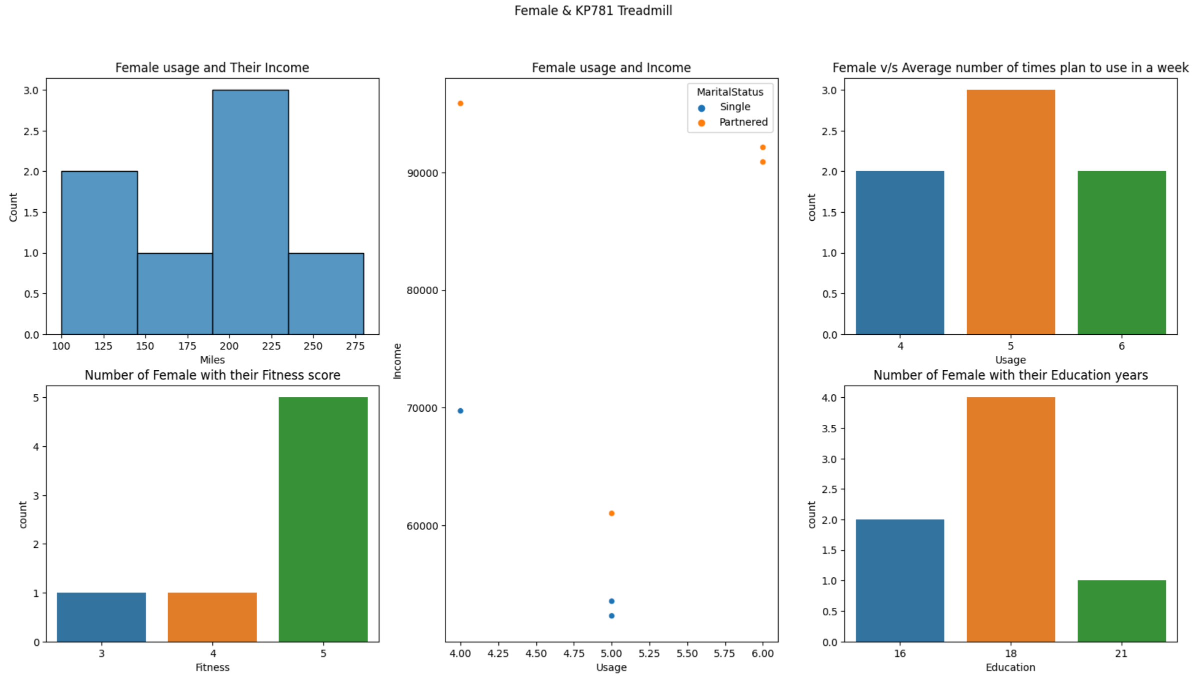
Out[54]:
```
(7, 9)
```

In [55]:
```
fig = plt.figure(figsize=(20,10))
fig.suptitle("Female & KP781 Treadmill")
plt.subplot(1,3,2)
sns.scatterplot(data=T3_F,x='Usage',y='Income',hue='MaritalStatus')
plt.title('Female usage and Income')
plt.subplot(2,3,1)
sns.histplot(data=T3_F,x='Miles')
plt.title('Female usage and Their Income')
plt.subplot(2,3,4)
sns.countplot(data=T3_F,x='Fitness')
plt.title('Number of Female with their Fitness score')
plt.subplot(2,3,6)
```

```
sns.countplot(data=T3_F,x='Education')
plt.title('Number of Female with their Education years')
plt.subplot(2,3,3)
sns.countplot(data=T3_F,x='Usage')
plt.title('Female v/s Average number of times plan to use in a week')
```

Out[55]:

```
Text(0.5, 1.0, 'Female v/s Average number of times plan to use in a week')
```



Insights:

1.female who opted KP781 most among them expects themselves to run in between **180-235 miles**

2.female who opted KP781 most among them Scores themselves at **5 fitness scale**

3.female who opted KP781 most of them have **high salary** greater than 90000

4.female who opted KP781 maximum among them usage plans is **5 times a week**

5.female who opted KP781 maximum among them have **education of 18 years** in their life

Recommendation: from above insights we can profile male who opted KP781 Treadmill

constructing-two-way-contingency-tables for each AeroFit treadmill product and compute all **conditional** and **marginal probabilities** along with their insights/impact on the business

Marginal probability: It refers to probability of occurence of simple event or Summation of Occurence of two or more event simultaniously **Conditional Probability:** probability of occurence of some event when an event already occured

Two way contingency table for KP281

In [56]:

```
d1 = data.loc[data['Product']=='KP281']
d1
```

Out[56]:

	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
...	...	...	...	...	...	...	...	...	...
75	KP281	43	Male	16	Partnered	3	3	53439	66
76	KP281	44	Female	16	Single	3	4	57987	75
77	KP281	46	Female	16	Partnered	3	2	60261	47
78	KP281	47	Male	16	Partnered	4	3	56850	94
79	KP281	50	Female	16	Partnered	3	3	64809	66

80 rows × 9 columns

Making Two-way contingency table around **[Usage]** vs **[Gender]** for KP281

In [57]:
```
pd.crosstab(index=d1['Usage'],columns= d1['Gender'],margins=True)
```

Out[57]:

Gender	Female	Male	All
Usage			
2	13	6	19
3	19	18	37
4	7	15	22
5	1	1	2
All	40	40	80

From above table we can say

$$MarginalProbability$$

$$P(\text{male})$$

Probability of male who bought KP281: = 40/80 =0.5

$$P(\text{female})$$

Probability of female who bought KP281: = 40/80 =0.5

To calculate each conditional probability, we simply divide the joint probability by the marginal probability

$$ConditionalProbability$$

Q1 - what is the probability that a user is male and his usage is 2 times a week

$$P(\text{usage-2}|\text{male}) = \frac{P(\text{usage-2}, \text{male})}{P(\text{male})}$$

= (6/80) /(40/80)

= 0.15

Q2 - what is the probability that a user is female and his usage is 2 times a week

$$P(\text{usage-2}|\text{male}) = \frac{P(\text{usage-2}, \text{male})}{P(\text{male})}$$

= (13/80)/(40/80)

=0.325

Instead of individually calculating by below process using crosstab function we can calculate probabilties normalizing along columns according to its **usage** and **provided they are male and female**

In [58]:
```
pd.crosstab(index=d1['Usage'],columns= d1['Gender'],margins=True,normalize='columns
```

Out[58]:

Gender Usage	Female	Male	All
2	0.325	0.150	0.2375
3	0.475	0.450	0.4625
4	0.175	0.375	0.2750
5	0.025	0.025	0.0250

Insights: there is highest probability which is 0.4625 that if an individual buy KP281 trademill he would have a usage of 3 times a week and female have higher probability than male with 3 time usage which is 0.475

From above insights we can see male and female preferences for KP281 however it is not sufficient to bring about useful insight for Treadmill recommendation in this way for that what we can do we can consider all Treadmill at once followed by consider male and femal then looking around the usage,fitness,education,MaritalStatus parameters for predicting choice prefrence

Two way contingency table considering

$$Gender + Treadmill$$

```
In [59]: pd.crosstab(index=data['Product'],columns=data['Gender'],margins='True')
```

Out[59]:

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

$$Insights$$

$$Conditional Probabilities$$

1. Probability a KP281 Trademill is bought given that she is female:

$$P(\text{KP281,Female})$$

= 40/76 = **0.5263**

$$P(\text{KP281,male})$$

for male it is: = 40/104 = **0.384**

2.Probability a KP481 Trademill is bought given that she is female:

$$P(\text{KP481,Female})$$

= 29/76 = **0.3815**

$$P(\text{KP481,male})$$

for male it is: = 31/104 = **0.298**

3.Probability a KP781 Trademill is bought given that she is female:

$$P(\text{KP781,Female})$$

= 7/76 = **0.092**

$$P(\text{KP781,male})$$

for male it is: = 33/104 = **0.317**

Insights: the above analysis shows insight as mentioned below

Female there is high probability which is 0.5263 she would go for KP281 treadmill and then for KP481 with 0.3815 probability and least preffered among female is KP781 with probability 0.092

(Female preference: KP281 > KP481 > KP781)

Male KP281 treadmill is most preffered by male with 0.384 followed by KP781 with probability 0.317 and least preffered among male is KP481 with 0.298 probability

(Male preference: KP281 > KP781 > KP481)

Recommendations : if individuals is male and female we can suggest according to their prefernce as from above insights furthermore firm need to have excess inventory to supply the most preferred treadmill by male and female as from above firm should have an inventory of KP281

Two Contingency Table considering:

$$Gender + Treadmill + Usage$$

In [60]:
```
pd.crosstab(index=data['Product'],columns=[data['Gender'],data['Usage']],margins='T
```

Out[60]:

Gender	Female					Male						All
Usage	2	3	4	5	6	2	3	4	5	6	7	
Product												
KP281	13	19	7	1	0	6	18	15	1	0	0	80
KP481	7	14	5	3	0	7	17	7	0	0	0	60
KP781	0	0	2	3	2	0	1	16	9	5	2	40
All	20	33	14	7	2	13	36	38	10	5	2	180

For simplifying the process and manually calculating it using it values we can calculate the probabilities along the Columns = 'Usage' & Gender using normalize in pd.crosstab() as shown below

In [61]:
```
pd.crosstab(index=data['Product'],columns=[data['Gender'],data['Usage']],normalize=
```

Out[61]:

Gender	Female					Male					
Usage	2	3	4	5	6	2	3	4	5	6	7
Product											
KP281	0.65	0.575758	0.500000	0.142857	0.0	0.461538	0.500000	0.394737	0.1	0.0	0.0
KP481	0.35	0.424242	0.357143	0.428571	0.0	0.538462	0.472222	0.184211	0.0	0.0	0.0
KP781	0.00	0.000000	0.142857	0.428571	1.0	0.000000	0.027778	0.421053	0.9	1.0	1.0

$$Insights$$

$$Conditional Probabilities$$

From above table we can say that if a Treadmill Purchaser is a

Female : if she propose to use Treadmill 2 times on average a week then it is high probability she will go for KP281 as from past data the probability is 0.65 which is highest among females for 2 times per week use , similarly female for 3 times use preffered KP281 Treadmill ,for 4 time KP281, 5 time per week use KP481 and 6 time KP781

Male: 2 time per week average usage the most preffered trademill is KP481 Wwith probability 0.5384

3 time usage mostly preffered KP281 with probability 0.5

4 time usage mostly preffered KP781 with probability 0.421

5,6,7 time usage mostly preffered KP781 with probability of 0.9,1,1

Recommendations: as from above Inferential analysis we can recommend the treadmill with highest probability to the male and female individuals according to their usage in a week

In [61]:

In [61]:

Two Contingency Table considering:

$$Gender + Treadmill + Age$$

To deal with this situation we can create bins for better insights for that we will use .cut() for creating separate columns for bins

In [62]:

```
d = data
bins= [10,20,30,40,50]
d['Age_bin']= pd.cut(d['Age'],bins)
d
```

Out[62]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_bin
0	KP281	18	Male	14	Single	3	4	29562	112	(10, 20]
1	KP281	19	Male	15	Single	2	3	31836	75	(10, 20]
2	KP281	19	Female	14	Partnered	4	3	30699	66	(10, 20]
3	KP281	19	Male	12	Single	3	3	32973	85	(10, 20]
4	KP281	20	Male	13	Partnered	4	2	35247	47	(10, 20]
...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	(30, 40]
176	KP781	42	Male	18	Single	5	4	89641	200	(40, 50]
177	KP781	45	Male	16	Single	5	5	90886	160	(40, 50]
178	KP781	47	Male	18	Partnered	4	5	104581	120	(40, 50]
179	KP781	48	Male	18	Partnered	4	5	95508	180	(40, 50]

180 rows × 10 columns

Generating two-way contingency tables for above table with Gender trademill and age as criteria

In [63]:
```
pd.crosstab(columns=d['Product'],index=[d['Gender'],d['Age_bin']],margins=True)
```

Out[63]:

	Product	**KP281**	**KP481**	**KP781**	**All**
Gender	**Age_bin**				
Female	**(10, 20]**	2	1	0	3
	(20, 30]	26	16	6	48
	(30, 40]	9	12	1	22
	(40, 50]	3	0	0	3
Male	**(10, 20]**	4	3	0	7
	(20, 30]	23	15	24	62
	(30, 40]	10	11	5	26
	(40, 50]	3	2	4	9
All		80	60	40	180

For simplifying the process and manually calculating it using it values we can calculate the probabilities along the index = 'Age_bin' & Gender using normalize in pd.crosstab() as shown below

In [64]:
```
pd.crosstab(columns=d['Product'],index=[d['Gender'],d['Age_bin']],normalize='index'
```

Out[64]:

Gender	Age_bin	KP281	KP481	KP781
Female	(10, 20]	0.666667	0.333333	0.000000
	(20, 30]	0.541667	0.333333	0.125000
	(30, 40]	0.409091	0.545455	0.045455
	(40, 50]	1.000000	0.000000	0.000000
Male	(10, 20]	0.571429	0.428571	0.000000
	(20, 30]	0.370968	0.241935	0.387097
	(30, 40]	0.384615	0.423077	0.192308
	(40, 50]	0.333333	0.222222	0.444444

$$Insights$$

$$Conditional Probabilities$$

From above table we can say that if a Treadmill Purchaser is a

Female :

1. if an individual is Female and her age comes in the range **[10,20]** years then highest probability is that she would choose **KP281 Treadmill** as its probability is **0.666**

2. If her age is in range **[20,30]** years with highest probability she would choose **KP281** with **probability in range 0.54**

3. if her age comes in range **[30,40]** years she would choose **KP481** treadmill with its highest probability **0.545**

1. if she is **above 40** years she would go for **KP281**

Male:

1. if an individual is male and his age comes in the range **[10,20]** years then highest probability is that he would choose **KP281 Treadmill** as its probability is **0.5714**

2. If his age is in range **[20,30]** years with highest probability he would choose **KP781** with **probability in range 0.387**

3. if his age comes in range **[30,40]** years he would choose **KP481** treadmill with its highest probability **0.423**

4. if he is **above 40** years he would go for **KP781**

Recommendations: as from above Inferential analysis we can recommend the treadmill with highest probability to the male and female individuals according to their age lying in respective ranges

Two Contingency Table considering:

$$Gender + Treadmill + Fitness$$

In [65]:
```
pd.crosstab(columns=data['Product'],index=[data['Gender'],data['Fitness']],margins=
```

Out[65]:

Gender	Fitness	KP281	KP481	KP781	All
Female	1	0	1	0	1
	2	10	6	0	16
	3	26	18	1	45
	4	3	4	1	8
	5	1	0	5	6
Male	1	1	0	0	1
	2	4	6	0	10
	3	28	21	3	52
	4	6	4	6	16
	5	1	0	24	25
All		80	60	40	180

For simplifying the process and manually calculating it using it values we can calculate the probabilities along the index = Fitness & Gender using normalize in pd.crosstab() as shown below

In [66]:
```
pd.crosstab(columns=data['Product'],index=[data['Gender'],data['Fitness']],normaliz
```

Out[66]:

Gender	Fitness	KP281	KP481	KP781
Female	1	0.000000	1.000000	0.000000
	2	0.625000	0.375000	0.000000
	3	0.577778	0.400000	0.022222
	4	0.375000	0.500000	0.125000
	5	0.166667	0.000000	0.833333
Male	1	1.000000	0.000000	0.000000
	2	0.400000	0.600000	0.000000
	3	0.538462	0.403846	0.057692
	4	0.375000	0.250000	0.375000
	5	0.040000	0.000000	0.960000

$$Insights$$

$$Conditional Probabilities$$

From above table we can say that if a Treadmill Purchaser is a

Female :

1. if an individual is Female and if she score herself at **1** at fitness scale then highest probability is that she would choose **KP481 Treadmill** as its probability is **1**
2. if she score herself at **2**at fitness scale with highest probability she would choose **KP281** with probability **0.54**
3. if she score herself at **3** at fitness scale she would choose **KP281** treadmill with its highest probability **0.5777**
4. if she score herself at **4** at fitness scale she would choose **KP481** treadmill with its highest probability **0.5**
5. if she score herself at **5** at fitness scale she would choose **KP781** treadmill with its highest probability **0.833**

Male:

1. if an individual is male and if he score himself at **1** at fitness scale then highest probability is that he would choose **KP281 Treadmill** as its probability is **1**
2. if he score himself at **2** at fitness scale with highest probability he would choose **KP481** with probability **0.60**

3. if he score himself at **3** at fitness scale he would choose **KP281** treadmill with its highest probability **0.538**

4. if he score himself at **4** at fitness scale he would choose **KP481** or **KP781** treadmill as their probability are same as **0.375**

5. if he score himself at **5** at fitness scale he would choose **KP781** treadmill with its highest probability **0.96**

Recommendations: as from above Inferential analysis we can recommend the treadmill with highest probability to the male and female individuals according to their Fitness score

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In [66]:
```