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.

Defining Problem statement and Analysing Basic Metrics

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.

Objective

- Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
- For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

Importing Libraries

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

```
import math
import warnings
warnings.filterwarnings('ignore')
```

Loading Dataset

In [2]:
```
df = pd.read_csv(r"C:\Users\SYEDA TAYABA\Downloads\Aerofit.csv")
df
```

Out[2]:

	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

shape of data

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

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

Data types of all attributes

In [4]:
```
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
```

Statistical Summary

In [5]:
```
df.describe()
```

Out[5]:

	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 [6]:
```
df.describe(include="all").T
```

Out[6]:

	count	unique	top	freq	mean	std	min	25%	5
Product	180	3	KP281	80	NaN	NaN	NaN	NaN	N
Age	180.0	NaN	NaN	NaN	28.788889	6.943498	18.0	24.0	2
Gender	180	2	Male	104	NaN	NaN	NaN	NaN	N
Education	180.0	NaN	NaN	NaN	15.572222	1.617055	12.0	14.0	1
MaritalStatus	180	2	Partnered	107	NaN	NaN	NaN	NaN	N
Usage	180.0	NaN	NaN	NaN	3.455556	1.084797	2.0	3.0	
Fitness	180.0	NaN	NaN	NaN	3.311111	0.958869	1.0	3.0	
Income	180.0	NaN	NaN	NaN	53719.577778	16506.684226	29562.0	44058.75	5059
Miles	180.0	NaN	NaN	NaN	103.194444	51.863605	21.0	66.0	9

Descriptive Analysis

- Total count of all columns is 180.
- Age: Mean age of customers is 28 years half of the customer's mean is 26.
- Education: Mean Education is 15 with maximum as 21 and minimum as 12.
- Usage: Mean usage per week is 3.4 with maximum as 7 and minimum as 2.
- Fitness: Average rating is 3.3 on a scale of 1 to 5.
- Miles: Average number of miles the customer walks is 103 with maximum distance travelled by most people is almost 115 and minimum is 21.
- Income(in $): Most customer earns around 58k annually with maximium almost 30k.

Non-Graphical Analysis: Value counts and unique attributes

Numerical Summary

In [7]:
```
# unique number of product ids
df['Product'].nunique()
```

Out[7]:
```
3
```

In [8]:
```
df['Product'].unique().tolist()
```

Out[8]:
```
['KP281', 'KP481', 'KP781']
```

In [9]:
```
# Total number of unique ages
total_uniq_age = df['Age'].nunique()
total_uniq_age
```

Out[9]:
```
32
```

In [10]:
```
# list of unique ages
df['Age'].unique()
```

Out[10]:
```
array([18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
       35, 36, 37, 38, 39, 40, 41, 43, 44, 46, 47, 50, 45, 48, 42],
      dtype=int64)
```

In [11]:
```
# Number of Male and Female customers
df['Gender'].value_counts()
```

Out[11]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [12]:
```
# list of unique Educations
df['Education'].unique().tolist()
```

Out[12]:
```
[14, 15, 12, 13, 16, 18, 20, 21]
```

In [13]:
```
# Number of customer againts the rating scale 1 to 5
df['Fitness'].value_counts().sort_index()
```

Out[13]:
```
1     2
2    26
3    97
4    24
5    31
Name: Fitness, dtype: int64
```

In [14]:
```
# Number of customers with 3 different product types
df['Product'].value_counts().sort_index()
```

Out[14]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [15]:
```
# Number of customers counts on Usage
df['Usage'].value_counts().sort_index()
```

Out[15]:
```
2    33
3    69
4    52
5    17
6     7
7     2
Name: Usage, dtype: int64
```

In [16]:
```
# Number of Single and Partnered customers
df['MaritalStatus'].value_counts()
```

Out[16]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

Summary

- KP281, KP481, KP781 are the 3 different products.
- Most commonly purchased treadmill product type is KP281.
- There are 32 unique ages.
- 104 Males and 76 Females are in the customers list.
- 8 unique set of Educations (14, 15, 12, 13, 16, 18, 20, 21).
- Highest rated Fitness rating is 3.
- Most customers usage treadmill atleast 3 days per week.
- Majority of the customers who have purchased are Married/Partnered.

conversion of categorical attributes to 'category'

In [17]:
```
# Converting Int data type of fitness rating to object data type
df_cat = df
df_cat['Fitness_category'] = df.Fitness
df_cat.head(10)
```

Out[17]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fitness_catego
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 [18]:
```
df_cat["Fitness_category"].replace({1:"Poor Shape",
                                    2:"Bad Shape",
                                    3:"Average Shape",
                                    4:"Good Shape",
                                    5:"Excellent Shape"},inplace=True)
df_cat.head()
```

Out[18]:

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

Categorization of Fitness Rating to following descriptive categories

- Poor Shape
- Bad Shape
- Average Shape
- Good Shape
- Excellent Shape

In [19]:
```
df.describe()
```

Out[19]:

	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

Summary

- Mean Age of the given customer dataset is 28.78.
- Minimum Age of the customer starts from 18 and maximum age is 50.
- 25% of the customers age is 24.
- 75% of the customer age is 33.
- Maximum Education qualification is 21, with most frequent education as 16.
- Average usage per week for a customer is 3 days.
- Average Fitness rating is 3 with most common fitness rating is 4.
- Average Income of the purchased customer is around 54K per year.
- Highest salary recorded for the customer is around 104K per year.

- Maximum distance covered by the customer in treadmill is 360 miles.
- Most of the customers cover a distance of 114 miles with an average of 103 miles.
- Around 25% of the customer cover an average of 66 miles.

Statistical Summary

In [20]:
```
# for unique list of products, listed in percentage

sr = df['Product'].value_counts(normalize=True)
stat = sr.map(lambda calc: round(100*calc,2))
stat
```

Out[20]:
```
KP281    44.44
KP481    33.33
KP781    22.22
Name: Product, dtype: float64
```

- 44.44% of customers bought KP281 product type.
- 33.33% of customers bought KP481 product type.
- 22.22% of customers bought KP781 product type.

In [21]:
```
# Customer Gender statistics (listed in %)

gender = df['Gender'].value_counts(normalize=True)
gender_res = gender.map(lambda calc: round(100*calc,2))
gender_res
```

Out[21]:
```
Male      57.78
Female    42.22
Name: Gender, dtype: float64
```

- 57.78% of customers are Male and 42.22% customers are Female.

In [22]:
```
# Customers Marital Status (listed in %)

marital_status = df['MaritalStatus'].value_counts(normalize=True)
marital_status_res = marital_status.map(lambda calc:round(100*calc,2))
marital_status_res
```

Out[22]:
```
Partnered    59.44
Single       40.56
Name: MaritalStatus, dtype: float64
```

- 59.44% of customers are Married/Partnered.
- 40.56% of customers are Single.

In [23]:
```
# Usage: Number of days used per week (listed in %)

usage = df['Usage'].value_counts(normalize=True).map(lambda calc:round(100*calc,2))
usage.rename(columns={'index':'DaysPerWeek'},inplace=True)
usage
```

Out[23]:

	DaysPerWeek	Usage
0	3	38.33
1	4	28.89
2	2	18.33
3	5	9.44
4	6	3.89
5	7	1.11

- Around 39% of customers use 3 days per week.
- Less than 2% of customers use 7 days per week.

In [24]:
```
# Customer rating of their fitness (listed in %)

rating = df['Fitness'].value_counts(normalize=True).map(lambda calc:round(100*calc,
rating.rename(columns={'index':'Rating'},inplace=True)
rating
```

Out[24]:

	Rating	Fitness
0	3	53.89
1	5	17.22
2	2	14.44
3	4	13.33
4	1	1.11

- More than 53% of customers have rated themselves as average in fitness (rated 3).
- 14% of customers have rated their fitness less than average.
- Over 17% of customers have peak fitness ratings.

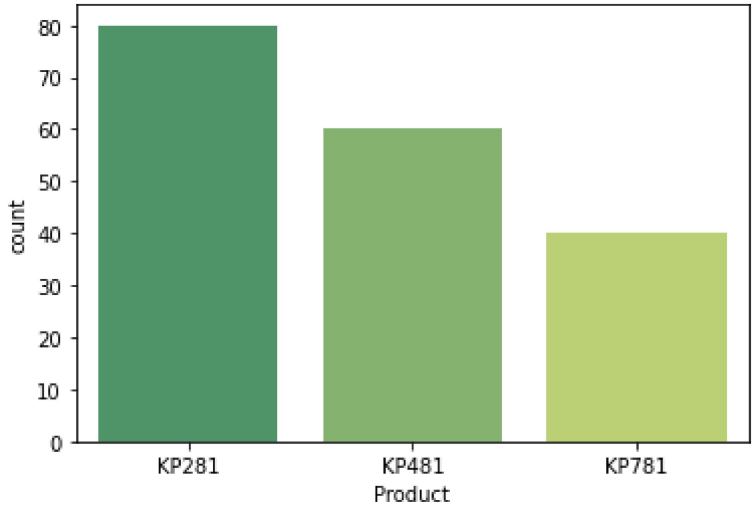
Visual Analysis - Univariate & Bivariate

Univariate Analysis

In [38]:
```
# Product Analysis - count plot

sns.countplot(data=df,x='Product', palette = "summer")
plt.show
```

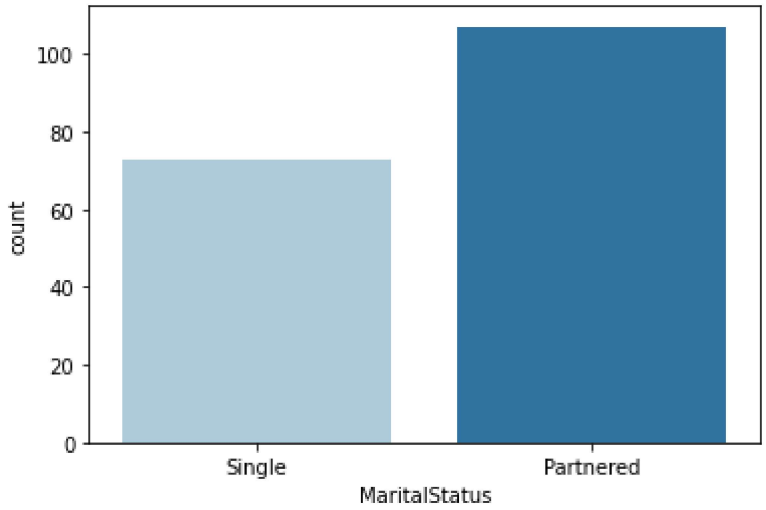
Out[38]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



- KP281 is the most commonly purchase product type.
- KP481 is the second most top product type purchased.
- KP781 is the least purchased product type.

In [26]:
```
# Marital Status Analysis - Count plot

sns.countplot(data=df,x='MaritalStatus', palette = "Paired")
plt.show()
```

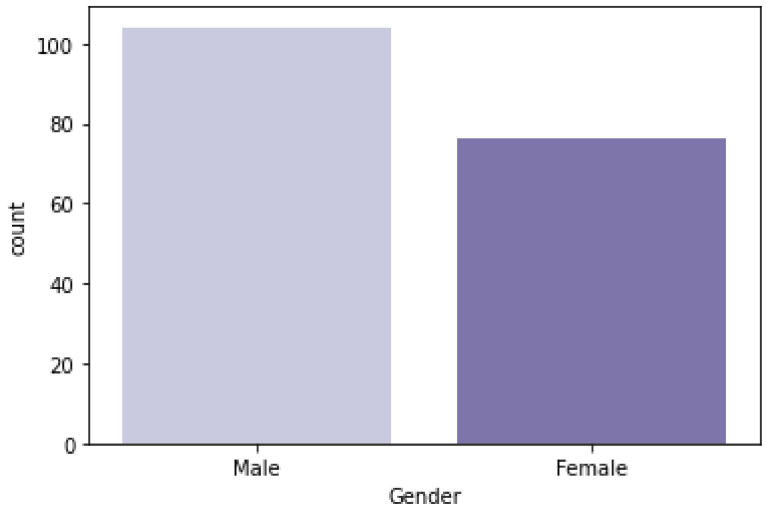


- Most products purchased by couples/Married/Partnered customer category.

In [32]:
```
# Gender Analysis - Count Plot

sns.countplot(data=df,x='Gender',palette="Purples")
plt.show
```

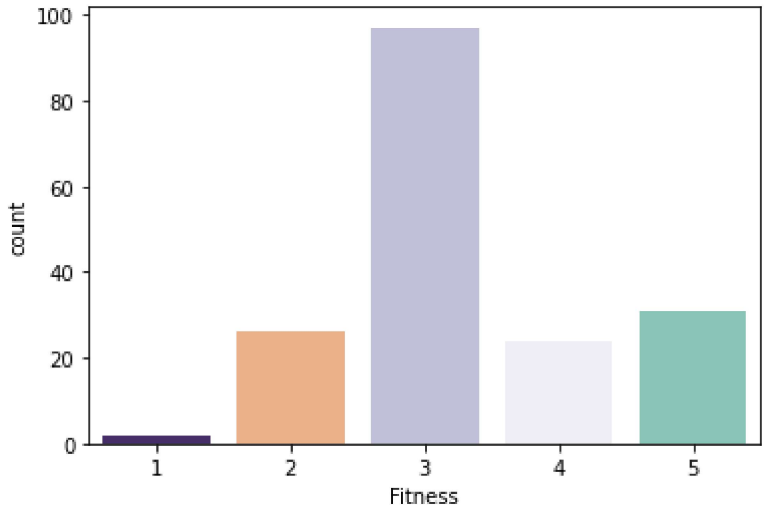
Out[32]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [33]:
```
# Fitness rating analysis - count plot

sns.countplot(data=df,x='Fitness',palette=['#432371',"#FAAE7B","#bcbddc", "#efedf5"
plt.show
```

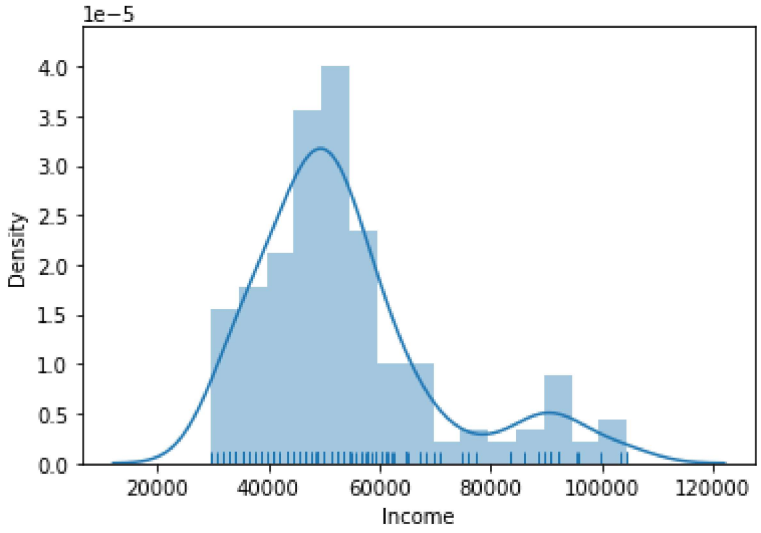
Out[33]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



- More than 90 customers have rated their physical fitness rating as Average.
- Excellent shape is the second highest rating provided by the customers.

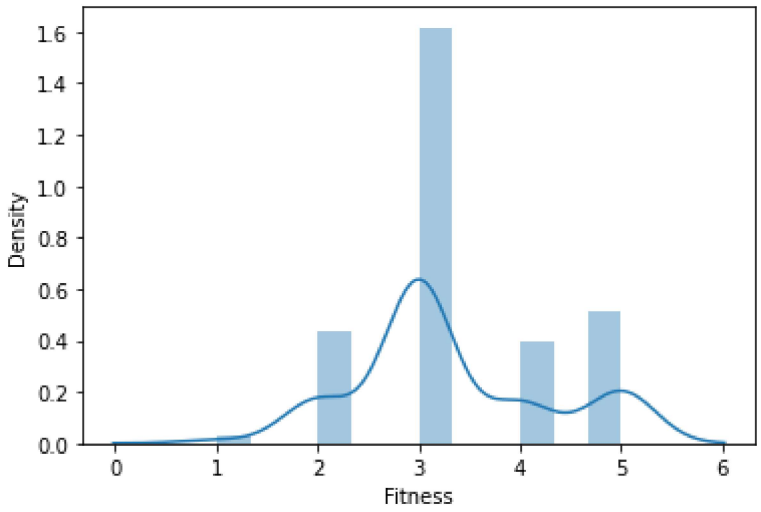
In [34]:
```
# Income Analysis - Distplot

sns.distplot(df.Income,rug=True)
plt.show()
```



In [39]:
```
# Fitness Rating Analysis - Distplot

sns.distplot(df.Fitness)
plt.show()
```

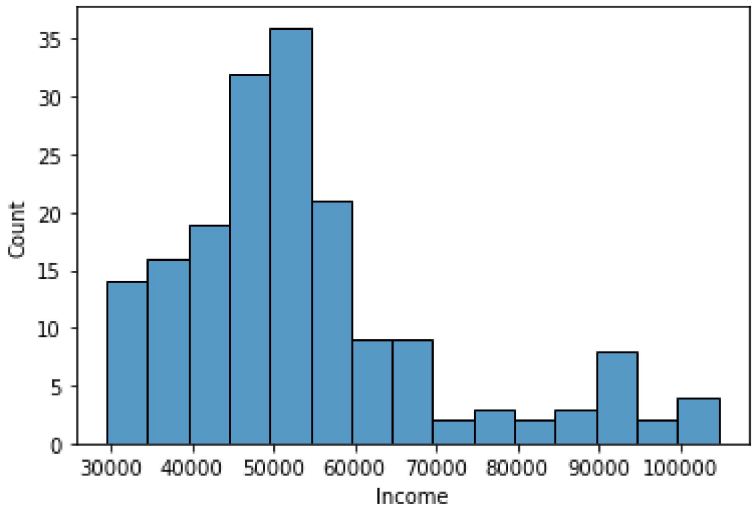


- Over 1.5 density customer population have rated their physical fitness rating as Average.
- Second highest customer population density have rated Excellent shape as their fitness rating.

In [45]:
```
# Income Analysis - Histogram

sns.histplot(data=df,x='Income', palette ="rainbow")
```

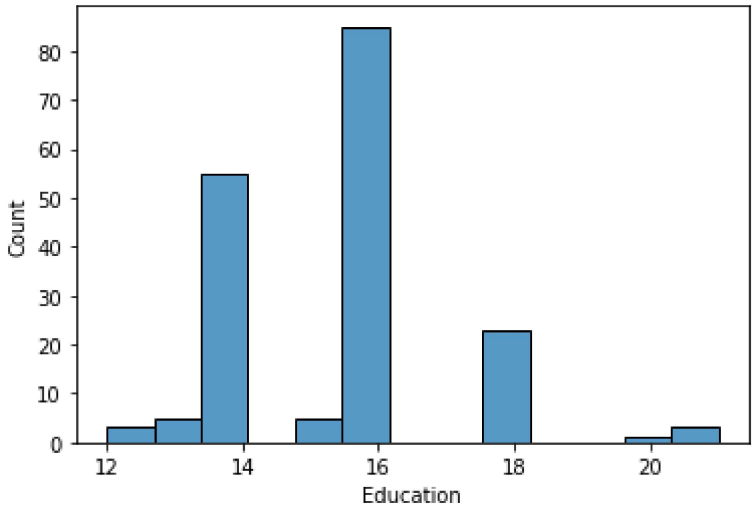
Out[45]:
```
<AxesSubplot:xlabel='Income', ylabel='Count'>
```



- More than 35 customers earn 50-55K per year.
- More than 30 customers earn 45-50K per year.
- More than 20 customers earn 55-60K per year.

In [46]:
```
# Education Analysis - Histogram
sns.histplot(data=df,x='Education')
```

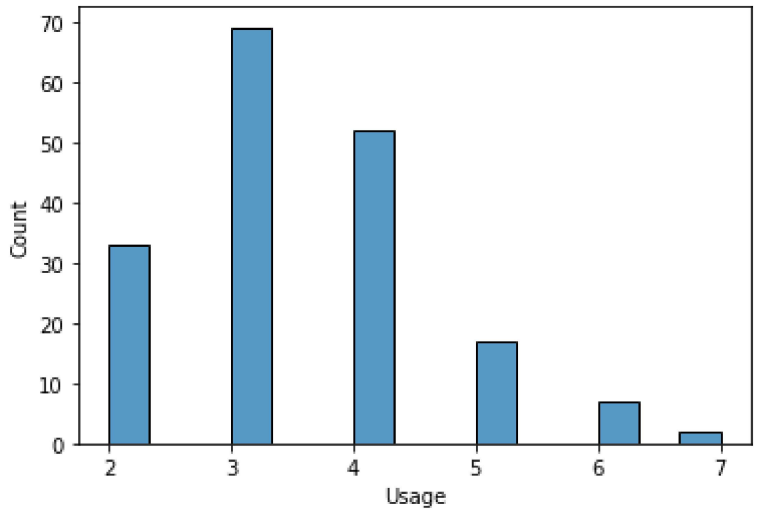
Out[46]:
```
<AxesSubplot:xlabel='Education', ylabel='Count'>
```



- Highest number of customers have 16 as their Education.
- 14 is the second highest education among the customers.
- 20 is the least education among the customers.

In [47]:
```
# Usage Analysis - Histogram
sns.histplot(data=df,x='Usage')
```

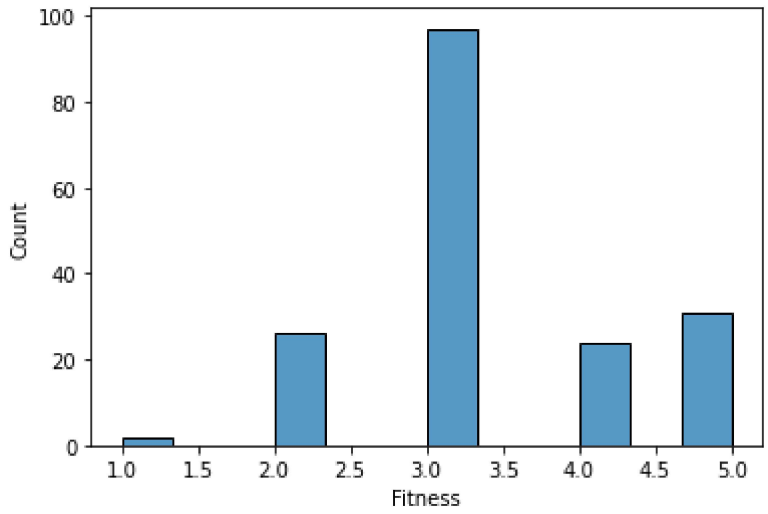
Out[47]:
```
<AxesSubplot:xlabel='Usage', ylabel='Count'>
```



- 3 days per week is the most common usage among the customers.
- 4 days and 2 days per week is the second and third highest usage among the customers.
- Very few customers use product 7 days per week.

In [48]:
```
# Fitness Analysis - Histogram
sns.histplot(data=df,x='Fitness')
```

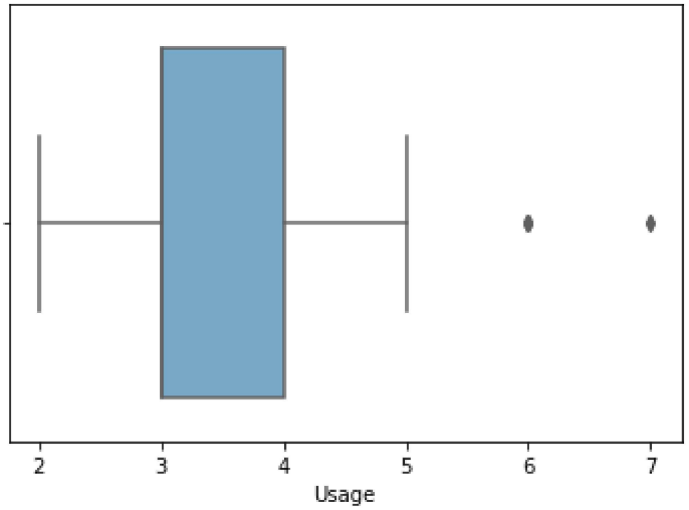
Out[48]:
```
<AxesSubplot:xlabel='Fitness', ylabel='Count'>
```



- Average shape is the most rating customers have given for fitness rating.
- Around 40 customers have stated Excelled Shape as fitness rating.

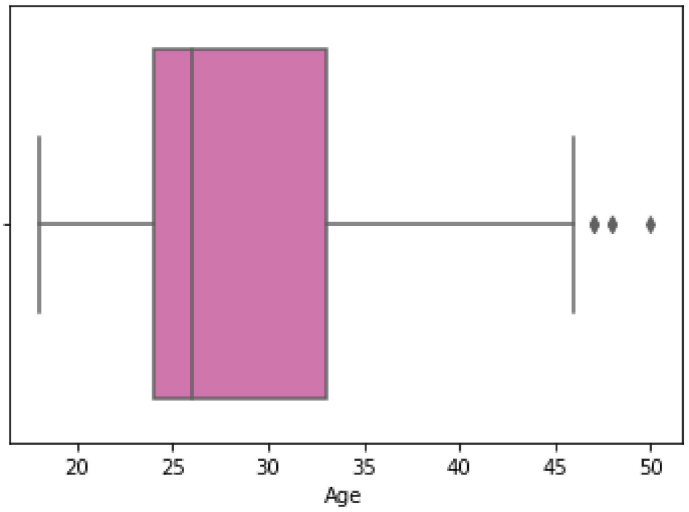
For categorical variable(s): Boxplot

In [50]:
```
# Usage Analysis - Box plot
sns.boxplot(data=df,x='Usage', palette ="Blues")
plt.show()
```



- 3 to 4 days is the most preferred usage days for customers.
- 6 and 7 days per week is roughly the usage days for few customers (Outliers).

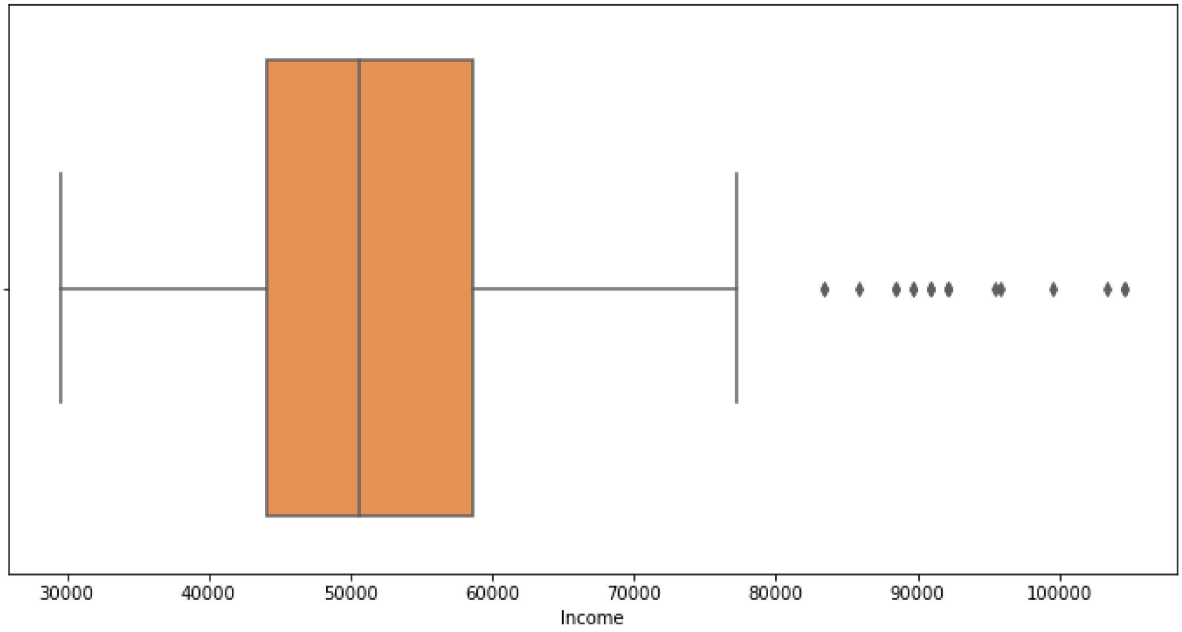
In [57]:
```
# Age Analysis - Box plot
sns.boxplot(data=df,x='Age', palette ="PuRd_r")
plt.show()
```



- 23 to 34 is the most common customer age group that has purchased the product.
- Above 45 years old customers are very few compared to the young age group given in the dataset.

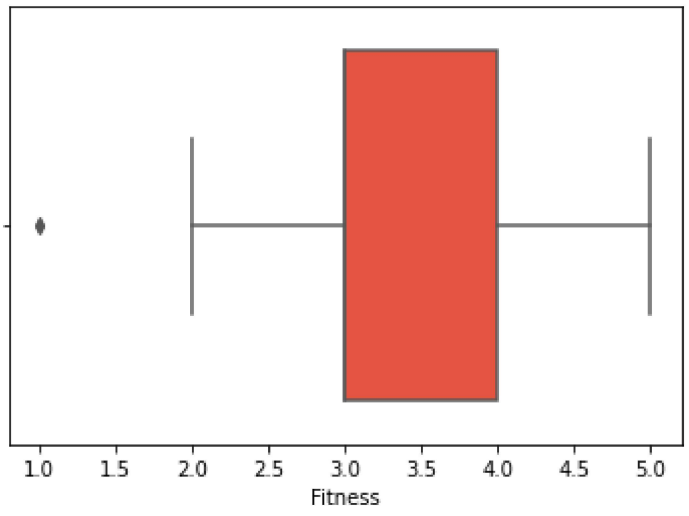
In [54]:
```
# Income Analysis - Box plot

plt.figure(figsize=(12,6))
sns.boxplot(data=df,x='Income', palette = "Oranges")
plt.show()
```



- Few customers have income above 80K per annum(Outliers).
- Most customers earn from 45K to around 60K per annum.

In [66]:
```
# Fitness Rating Analysis - Box plot
sns.boxplot(data=df,x='Fitness', palette ="CMRmap")
plt.show()
```

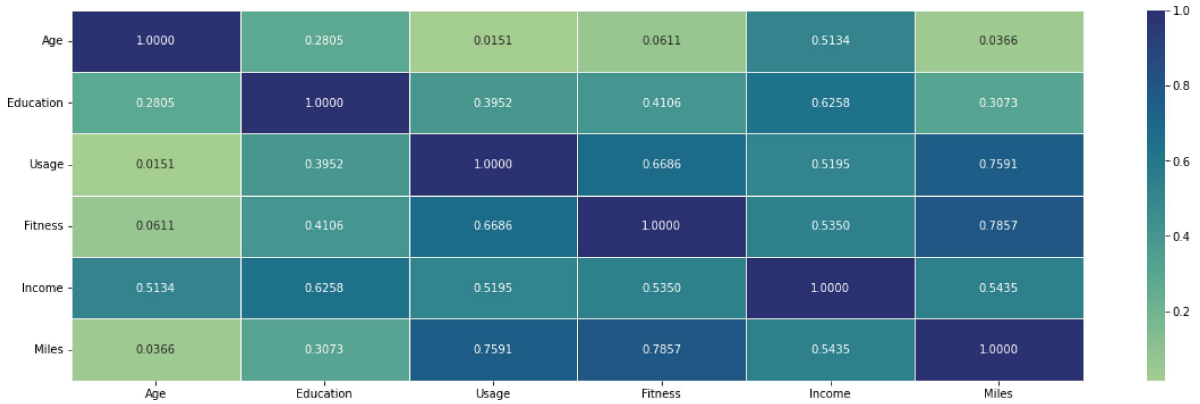


- Couple of customers have rated their fitness rating as 1 - Poor Shape.
- Most customers have rated fitness rating as 3.0 to 4.0.

For correlation: Heatmaps, Pairplots

In [68]:
```
#Correlation HeatMap
plt.figure(figsize=(20,6))
ax = sns.heatmap(df.corr(),annot=True,fmt='.4f',linewidths=.5,cmap="crest")
```

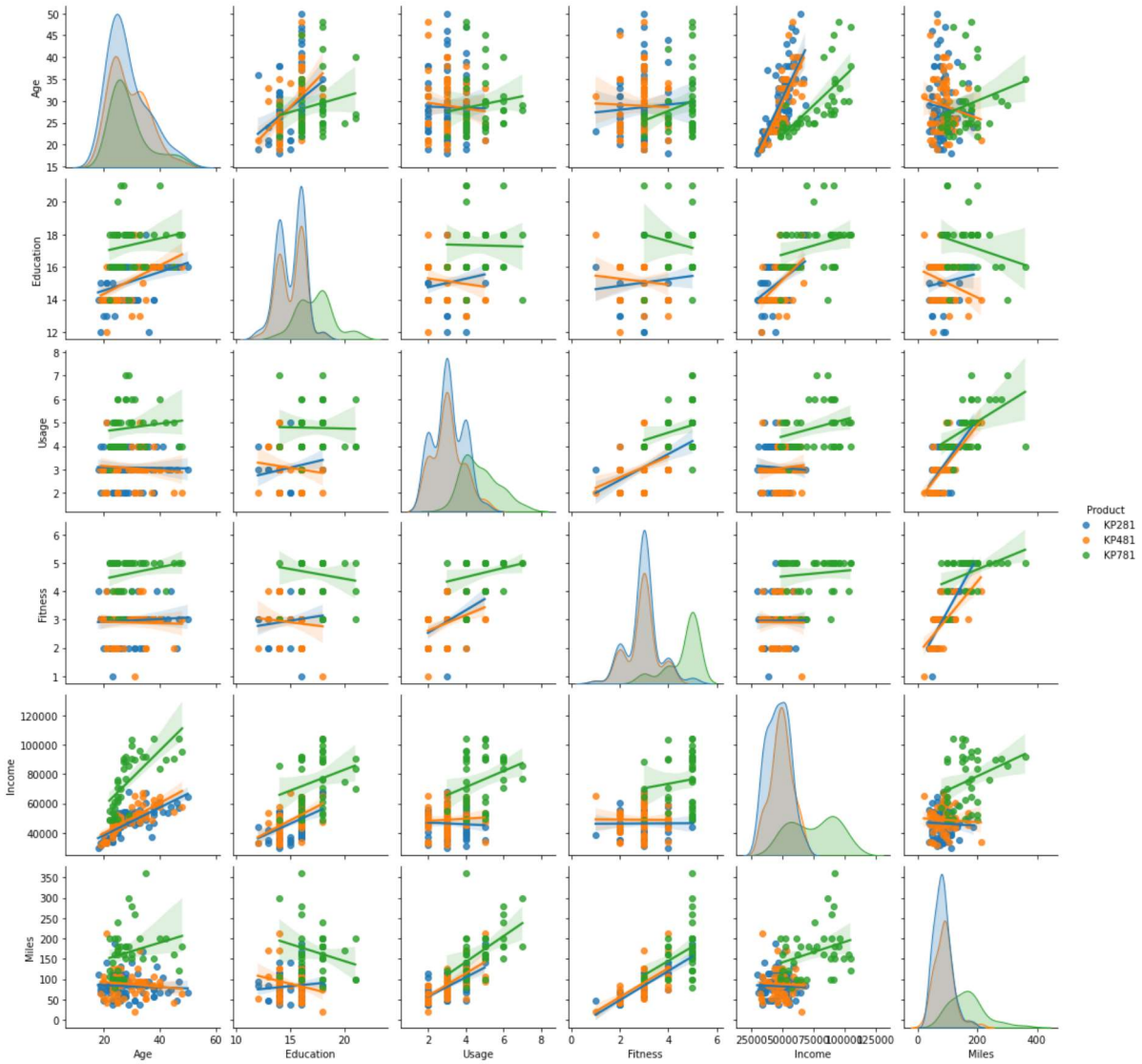
```
plt.yticks(rotation=0)
plt.show()
```



In the above heatmap linear relationship between data points is evaluated

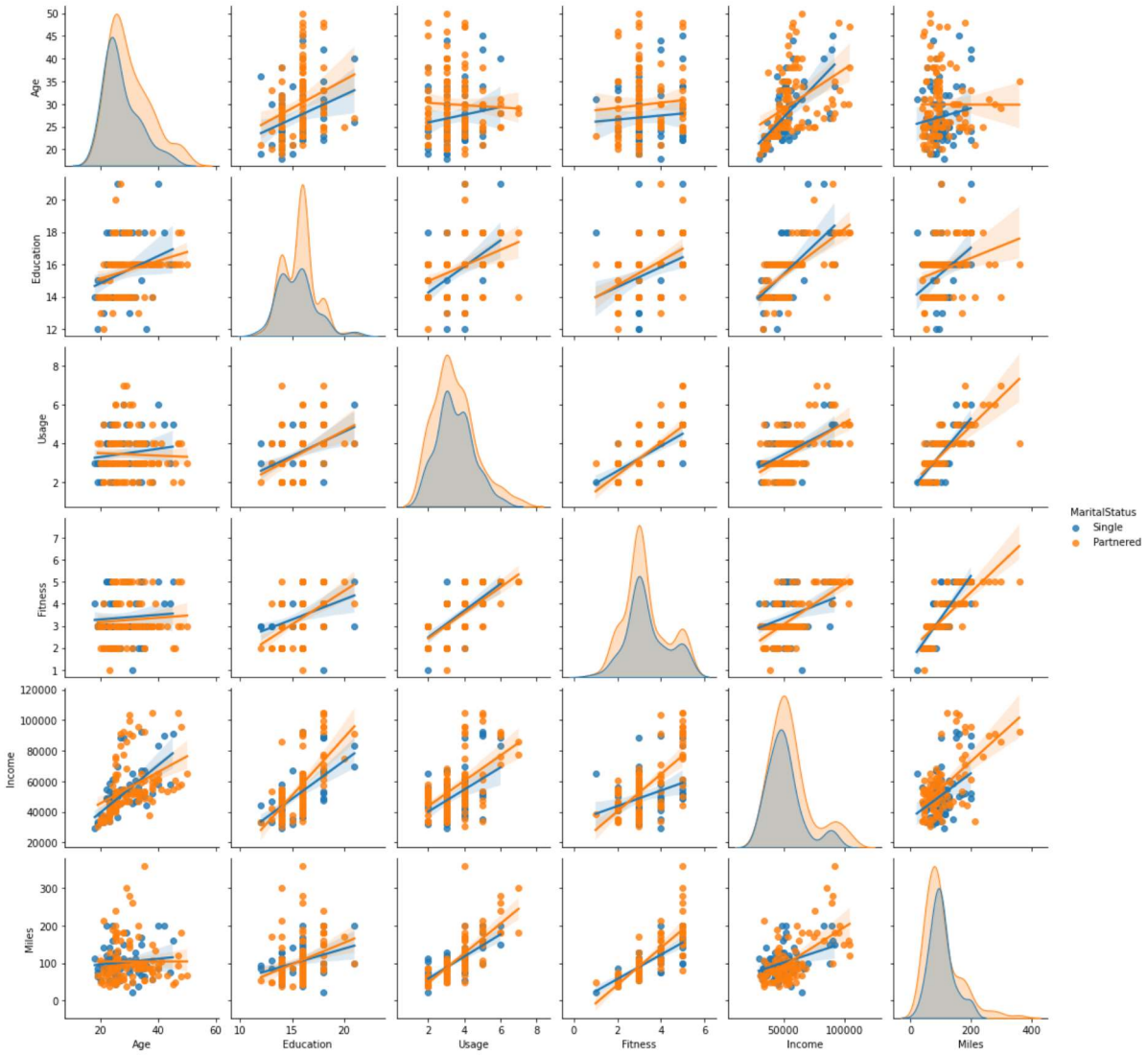
- Correlation between Age and Miles is 0.03
- Correlation between Education and Income is 0.62
- Correlation between Usage and Fitness is 0.66
- Correlation between Fitness and Age is 0.06
- Correlation between Income and Usage is 0.51
- Correlation between Miles and Age is 0.03

In [69]:
```
# Product Analysis - Pair Plot
sns.pairplot(df,hue='Product',kind='reg')
plt.show()
```



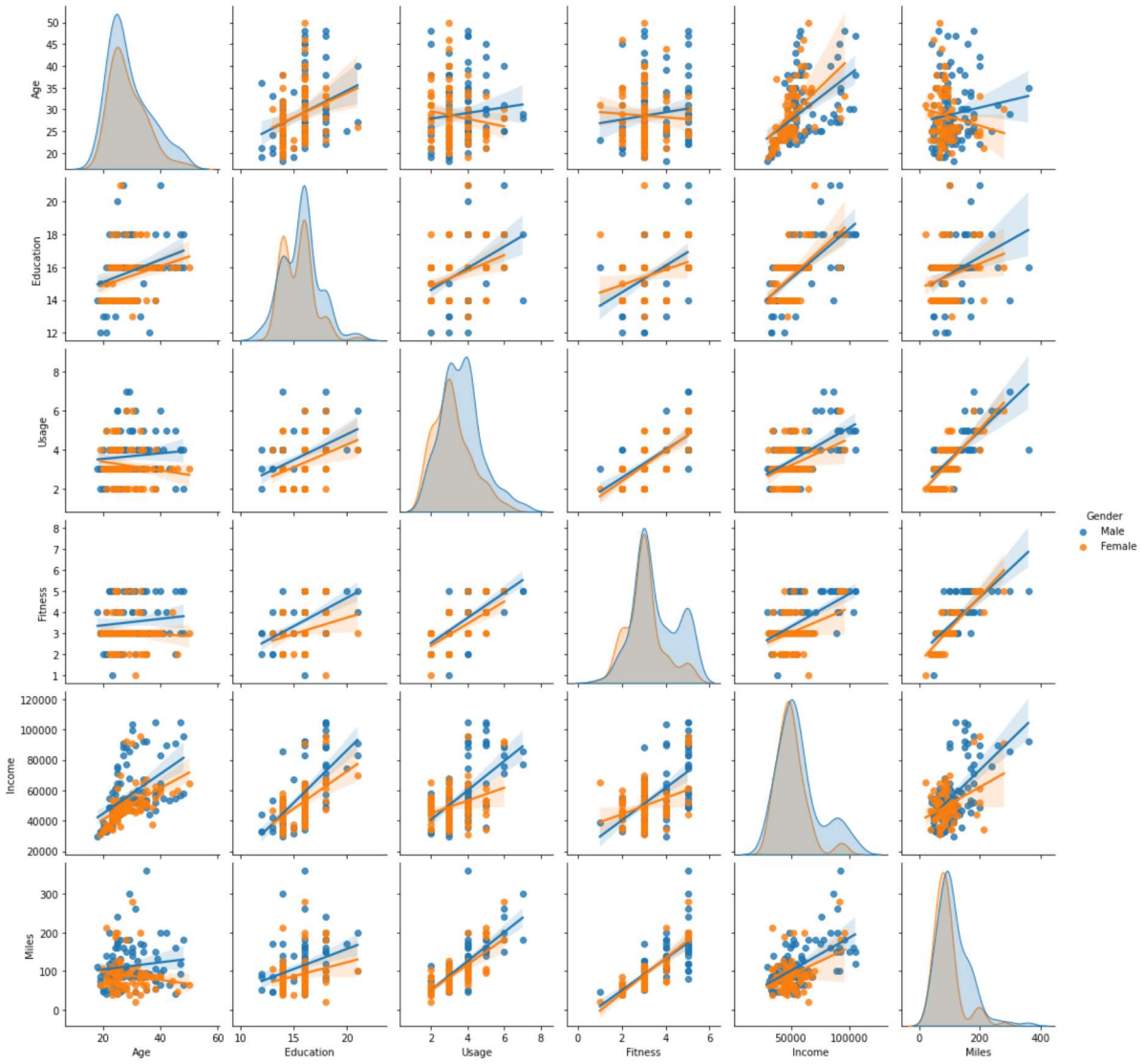
In the above pairplot the correlation with products and different attributes are as similar to previous observation

In [70]:
```
# Marital Status - pair plot
sns.pairplot(df,hue='MaritalStatus',kind='reg')
plt.show()
```



In the above pair plot the correlation with other attributes are pivotted around the marital status of the customer.

In [72]:
```
# Gender Analysis - Pair Plot
sns.pairplot(df,hue='Gender',kind='reg')
plt.show()
```



Here the pair plot's correlation is same as the above mentioned heatmap.

Bivariate Analysis

In [73]:
```
# Average usage of each product type by the customer
df.groupby('Product')['Usage'].mean()
```

Out[73]:
```
Product
KP281    3.087500
KP481    3.066667
KP781    4.775000
Name: Usage, dtype: float64
```

- Mean usage for product KP281 is 3.08
- Mean usage for product KP481 is 3.06
- Mean usage for product KP781 is 4.77

In [74]:
```
# Average Age of customer using each product
df.groupby('Product')['Age'].mean()
```

Out[74]:
```
Product
KP281    28.55
KP481    28.90
KP781    29.10
Name: Age, dtype: float64
```

- Mean Age of the customer who purchased product KP281 is 28.55
- Mean Age of the customer who purchased product KP481 is 28.90
- Mean Age of the customer who purchased product KP781 is 29.10

In [75]:
```
# Average Education of customer using each product
df.groupby('Product')['Education'].mean()
```

Out[75]:
```
Product
KP281    15.037500
KP481    15.116667
KP781    17.325000
Name: Education, dtype: float64
```

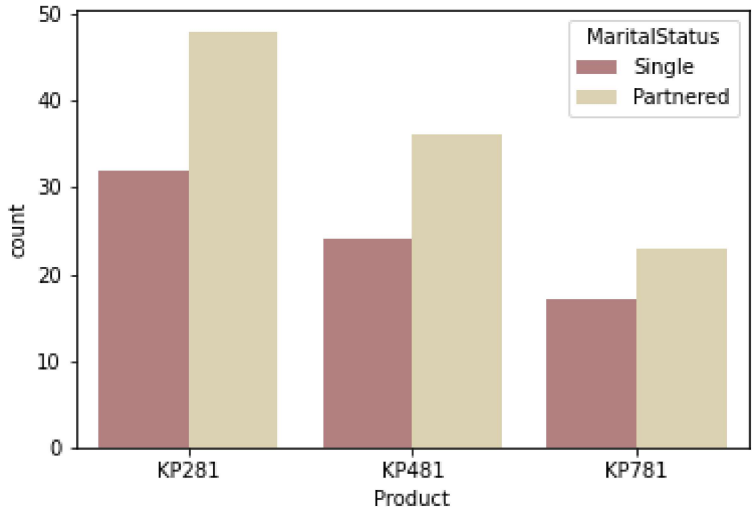
- Mean Education qualification of the customer who purchased product KP281 is 15.03
- Mean Education qualification of the customer who purchased product KP481 is 15.11
- Mean Education qualification of the customer who purchased product KP781 is 17.32

In [76]:
```
# Average customer fitness rating for each product type purchased
df.groupby('Product')['Fitness'].mean()
```

Out[76]:
```
Product
KP281    2.9625
KP481    2.9000
KP781    4.6250
Name: Fitness, dtype: float64
```

- Customer fitness mean for product KP281 is 2.96
- Customer fitness mean for product KP481 is 2.90
- Customer fitness mean for product KP781 is 4.62

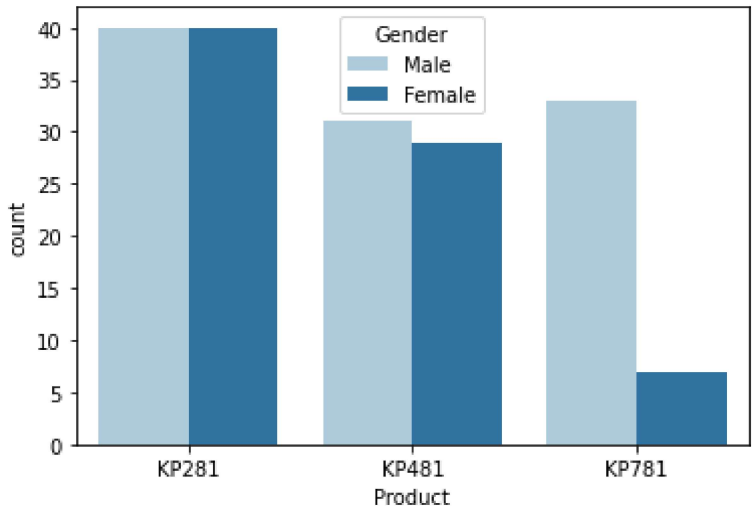
In [93]:
```
# Product purchased among Married/Partnered and Single
sns.countplot(data=df,x='Product',hue='MaritalStatus', palette ='pink')
plt.show()
```



From the above countplot

- KP281 is the most preferred product among customers
- KP481 is the second most preferred product among the customers
- Between Singles and Partnered, Partnered customers are the major product purchasers

In [86]:
```
# Product purchased among Male and Female
sns.countplot(data=df,x='Product',hue='Gender', palette ='Paired')
plt.show()
```

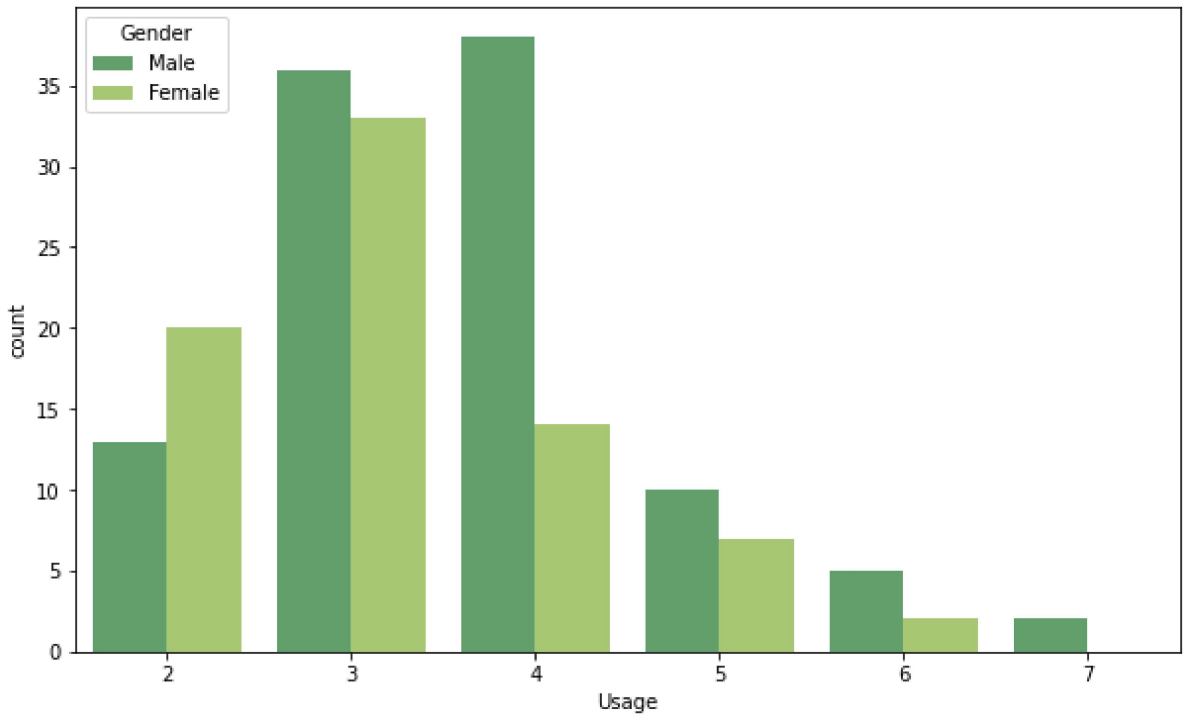


- KP281 Product is the equally preferred by both male and female genders.
- KP781 Product is mostly preferred among the Male customers.
- Overall Male customers are the highest product purchasers.

In [96]:
```
# Count among Gender and their Marital Status
sns.countplot(data=df,x='MaritalStatus',hue='Gender', palette ='Purples')
plt.show()
```

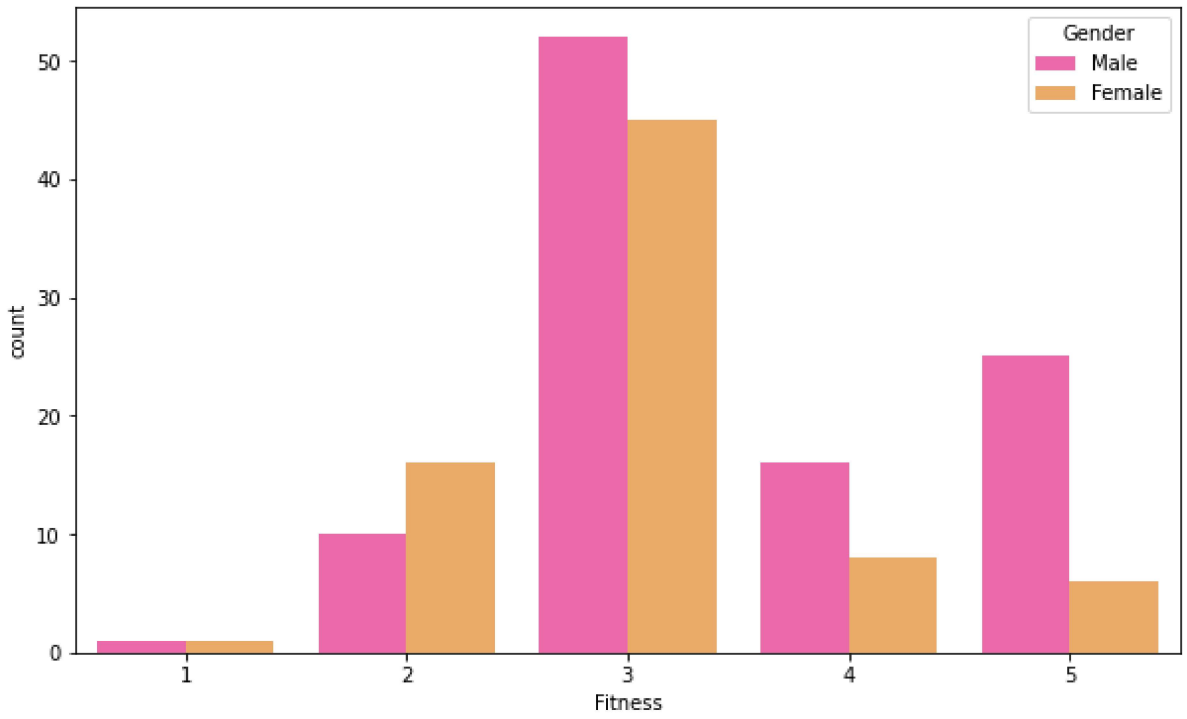
- Partnered customers are the most buyers of aerofit product.
- Out of both Single and Partnered customers, Male customers are significantly high.
- Female customers are considerably low compared to Male customers.

In [98]:
```
# Purchased product usage among Gender
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='Usage',hue='Gender',palette='summer')
plt.show()
```



- Among Male and Female genders, Male's usage is 4 days per week.
- Female customers mostly use 3 days per week.
- Only few Male customers use 7 days per week whereas female customer's maximum usage is only 6 days per week.

In [100…
```
# Fitness rating among the customers categorised by Gender
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='Fitness',hue='Gender',palette='spring')
plt.show()
```



- Among the fitness rating both Male and Female most have rated as average.
- Significant number of Male customers are at Excellent shape compared to Female customers.

Missing Value & Outlier Detection

In [102…
```
df.isna().sum()
```

Out[102]:
```
Product            0
Age                0
Gender             0
Education          0
MaritalStatus      0
Usage              0
Fitness            0
Income             0
Miles              0
Fitness_category   0
dtype: int64
```

No Null values found in any columns.

In [103…
```
df.duplicated().sum()
```

Out[103]:
```
0
```

Outliers

In [104…
```
# Outlier calculation for Miles using Inter Quartile Range

q_75, q_25 = np.percentile(df['Miles'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Miles is", miles_iqr)
```

```
Inter Quartile Range for Miles is 48.75
```

Business Insights based on Non-Graphical and Visual Analysis

In [105…
```
df.Product.value_counts(normalize=True)
```

Out[105]:
```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

- Probability of buying KP281, KP481 & KP781 are 0.44, 0.33 & 0.22 respectively.

In [106…
```
df.Gender.value_counts(normalize=True)
```

Out[106]:
```
Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
```

- Probability of Male customer is 0.57.
- Probability of Female customer is 0.42.

In [107…
```
df.MaritalStatus.value_counts(normalize=True)
```

Out[107]:
```
Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64
```

- Probability of Married/Partnered is 0.59
- Probability of Single is 0.40

Probability for each product for the both genders

In [108…
```
def gender_Probability(gender,df):
    print(f"Prob P(KP781) for {gender}: {round(df['KP781'][gender]/df.loc[gender].s
    print(f"Prob P(KP481) for {gender}: {round(df['KP481'][gender]/df.loc[gender].s
    print(f"Prob P(KP281) for {gender}: {round(df['KP281'][gender]/df.loc[gender].s

df_temp = pd.crosstab(index=df['Gender'],columns=[df['Product']])
print("Prob of Male: ",round(df_temp.loc['Male'].sum()/len(df),3))
print("Prob of Female: ",round(df_temp.loc['Female'].sum()/len(df),3))
```

```
print()
gender_Probability('Male',df_temp)
print()
gender_Probability('Female',df_temp)
```

```
Prob of Male:  0.578
Prob of Female:  0.422

Prob P(KP781) for Male: 0.317
Prob P(KP481) for Male: 0.298
Prob P(KP281) for Male: 0.385

Prob P(KP781) for Female: 0.092
Prob P(KP481) for Female: 0.382
Prob P(KP281) for Female: 0.526
```

Probability of each product for given Marital Status

In [109…

```
def MS_Probability(ms_status,df):
    print(f"Prob P(KP781) for {ms_status}: {round(df['KP781'][ms_status]/df.loc[ms_
    print(f"Prob P(KP481) for {ms_status}: {round(df['KP481'][ms_status]/df.loc[ms_
    print(f"Prob P(KP281) for {ms_status}: {round(df['KP281'][ms_status]/df.loc[ms_

df_temp = pd.crosstab(index=df['MaritalStatus'],columns=[df['Product']])
print("Prob of P(Single): ",round(df_temp.loc['Single'].sum()/len(df),3))
print("Prob of P(Married/Partnered): ",round(df_temp.loc['Partnered'].sum()/len(df)
print()
MS_Probability('Single',df_temp)
print()
MS_Probability('Partnered',df_temp)
```

```
Prob of P(Single):  0.406
Prob of P(Married/Partnered):  0.594

Prob P(KP781) for Single: 0.233
Prob P(KP481) for Single: 0.329
Prob P(KP281) for Single: 0.438

Prob P(KP781) for Partnered: 0.215
Prob P(KP481) for Partnered: 0.336
Prob P(KP281) for Partnered: 0.449
```

Customer Age Group Analysis

In [110…

```
df_cat['age_group'] = df_cat.Age
df_cat.head()
```

Out[110]:

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

In [114…

```
# 0-21 -> Teen
# 22-35 -> Adult
# 36-45 -> Middle Age
# 46-60 -> Elder Age
df_cat.age_group = pd.cut(df.age_group,bins=[0,21,35,45,60],labels=['Teen','Adult',
```

In [116…

```
df_cat.head(10)
```

Out[116]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fitness_catego
0	KP281	18	Male	14	Single	3	4	29562	112	Good Sha
1	KP281	19	Male	15	Single	2	3	31836	75	Average Sha
2	KP281	19	Female	14	Partnered	4	3	30699	66	Average Sha
3	KP281	19	Male	12	Single	3	3	32973	85	Average Sha
4	KP281	20	Male	13	Partnered	4	2	35247	47	Bad Sha
5	KP281	20	Female	14	Partnered	3	3	32973	66	Average Sha
6	KP281	21	Female	14	Partnered	3	3	35247	75	Average Sha
7	KP281	21	Male	13	Single	3	3	32973	85	Average Sha
8	KP281	21	Male	15	Single	5	4	35247	141	Good Sha
9	KP281	21	Female	15	Partnered	2	3	37521	85	Average Sha

In [117…

```
df_cat.age_group.value_counts()
```

Out[117]:

```
Adult         135
Middle Age     22
Teen           17
Elder Age       6
Name: age_group, dtype: int64
```

In [118…

```
df_cat.loc[df_cat.Product=='KP281']["age_group"].value_counts()
```

Out[118]:

```
Adult         56
Middle Age    11
Teen          10
Elder Age      3
Name: age_group, dtype: int64
```

In [119…
```
df_cat.loc[df_cat.Product=='KP481']["age_group"].value_counts()
```

Out[119]:
```
Adult         45
Teen           7
Middle Age     7
Elder Age      1
Name: age_group, dtype: int64
```

In [120…
```
df_cat.loc[df_cat.Product=='KP781']["age_group"].value_counts()
```

Out[120]:
```
Adult         34
Middle Age     4
Elder Age      2
Teen           0
Name: age_group, dtype: int64
```

In [121…
```
pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,margins=True)
```

Out[121]:

age_group	Teen	Adult	Middle Age	Elder Age	All
Product					
KP281	10	56	11	3	80
KP481	7	45	7	1	60
KP781	0	34	4	2	40
All	17	135	22	6	180

In [125…
```
# Conditional and Marginal Probabilities with product type and age group
np.round(pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,normalize='colum
```

Out[125]:

age_group	Teen	Adult	Middle Age	Elder Age	All
Product					
KP281	58.82	41.48	50.00	50.00	44.44
KP481	41.18	33.33	31.82	16.67	33.33
KP781	0.00	25.19	18.18	33.33	22.22

In [126…
```
# Conditional and Marginal Probabilities with product type and age group
np.round(pd.crosstab(index=df_cat.Product,columns=df_cat.age_group,normalize=True,m
```

Out[126]:

age_group	Teen	Adult	Middle Age	Elder Age	All
Product					
KP281	5.56	31.11	6.11	1.67	44.44
KP481	3.89	25.00	3.89	0.56	33.33
KP781	0.00	18.89	2.22	1.11	22.22
All	9.44	75.00	12.22	3.33	100.00

In [127…
```
pd.crosstab(columns=df_cat["Fitness_category"],index=df_cat["Product"])
```

Out[127]:

Product	Average Shape	Bad Shape	Excellent Shape	Good Shape	Poor Shape
KP281	54	14	2	9	1
KP481	39	12	0	8	1
KP781	4	0	29	7	0

In [128…
```
round(pd.crosstab(index=df_cat["Product"],columns=df_cat["Fitness_category"],normal
```

Out[128]:

Product	Average Shape	Bad Shape	Excellent Shape	Good Shape	Poor Shape
KP281	55.67	53.85	6.45	37.50	50.0
KP481	40.21	46.15	0.00	33.33	50.0
KP781	4.12	0.00	93.55	29.17	0.0

In [129…
```
pd.crosstab(index=[df_cat.Product,df_cat.Fitness_category],columns=df_cat.Gender)
```

Out[129]:

Product	Fitness_category	Female	Male
KP281	**Average Shape**	26	28
	Bad Shape	10	4
	Excellent Shape	1	1
	Good Shape	3	6
	Poor Shape	0	1
KP481	**Average Shape**	18	21
	Bad Shape	6	6
	Good Shape	4	4
	Poor Shape	1	0
KP781	**Average Shape**	1	3
	Excellent Shape	5	24
	Good Shape	1	6

In [130…
```
round(pd.crosstab(index=[df_cat.Product,df_cat.Fitness_category],columns=df_cat.Ger
```

Out[130]:

Product	Fitness_category	Gender	Female	Male
KP281	Average Shape		14.44	15.56
	Bad Shape		5.56	2.22
	Excellent Shape		0.56	0.56
	Good Shape		1.67	3.33
	Poor Shape		0.00	0.56
KP481	Average Shape		10.00	11.67
	Bad Shape		3.33	3.33
	Good Shape		2.22	2.22
	Poor Shape		0.56	0.00
KP781	Average Shape		0.56	1.67
	Excellent Shape		2.78	13.33
	Good Shape		0.56	3.33

In [131…
```
round(pd.crosstab(index=[df_cat.Product,df_cat.MaritalStatus],columns=df_cat.Gender
```

Out[131]:

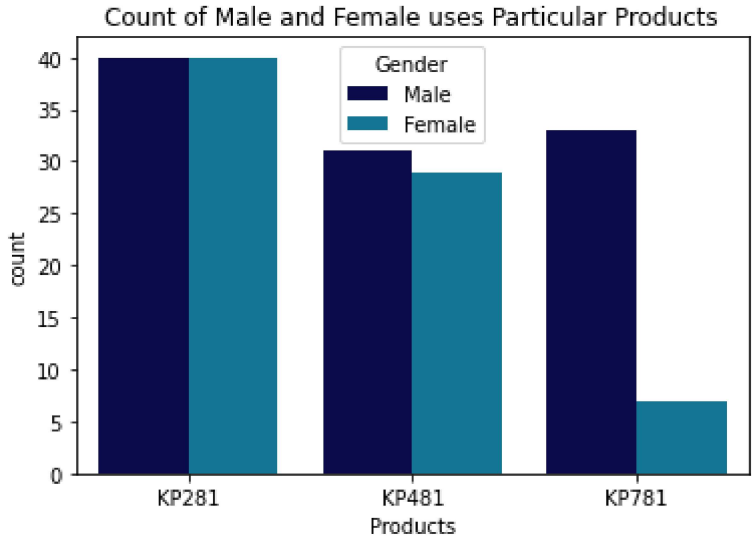
Product	MaritalStatus	Gender	Female	Male
KP281	Partnered		0.15	0.12
	Single		0.07	0.11
KP481	Partnered		0.08	0.12
	Single		0.08	0.06
KP781	Partnered		0.02	0.11
	Single		0.02	0.08

Conditional and Marginal Probabilities

Two-Way Contingency Table

Marginal Probabilities

In [133…
```
sns.countplot(x = "Product", data= df, hue = "Gender", palette = "ocean")
plt.xlabel("Products")
plt.title("Count of Male and Female uses Particular Products")
plt.show()
```



In [134…
```
pd.crosstab([df.Product],df.Gender,margins=True)
```

Out[134]:

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

In [135…
```
np.round(((pd.crosstab(df.Product,df.Gender,margins=True))/180)*100,2)
```

Out[135]:

Gender	Female	Male	All
Product			
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

Marginal Probability

- Probability of Male Customer Purchasing any product is : 57.77 %.
- Probability of Female Customer Purchasing any product is : 42.22 %.

Marginal Probability of any customer buying

- product KP281 is : 44.44 % (cheapest / entry level product)
- product KP481 is : 33.33 % (intermediate user level product)
- product KP781 is : 22.22 % (Advanced product with ease of use that help in covering longer distance)

Conditional Probabilities

In [136…
```
np.round((pd.crosstab([df.Product],df.Gender,margins=True,normalize="columns"))*100
```

Out[136]:

Gender	Female	Male	All
Product			
KP281	52.63	38.46	44.44
KP481	38.16	29.81	33.33
KP781	9.21	31.73	22.22

Probability of Selling Product

KP281 | Female = 52 %

KP481 | Female = 38 %

KP781 | Female = 10 %

KP281 | male = 38 %

KP481 | male = 30 %

KP781 | male = 32 %

Probability of Female customer buying KP281(52.63%) is more than male(38.46%).

KP281 is more recommended for female customers.

Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).

Probability of Female customer buying Product KP481(38.15%) is significantly higher than male (29.80%.)

KP481 product is specifically recommended for Female customers who are intermediate user.

Objective: Customer Profiling for Each Product

Customer profiling based on the 3 product categories provided

KP281

- Easily affordable entry level product, which is also the maximum selling product.
- KP281 is the most popular product among the entry level customers.
- This product is easily afforded by both Male and Female customers.
- Average distance covered in this model is around 70 to 90 miles.
- Product is used 3 to 4 times a week.
- Most of the customer who have purchased the product have rated Average shape as the fitness rating.
- Younger to Elder beginner level customers prefer this product.
- Single female & Partnered male customers bought this product more than single male customers.
- Income range between 39K to 53K have preferred this product.

KP481

- This is an Intermediate level Product.
- KP481 is the second most popular product among the customers.
- Fitness Level of this product users varies from Bad to Average Shape depending on their usage.
- Customers Prefer this product mostly to cover more miles than fitness.
- Average distance covered in this product is from 70 to 130 miles per week.
- More Female customers prefer this product than males.
- Probability of Female customer buying KP481 is significantly higher than male.
- KP481 product is specifically recommended for Female customers who are intermediate user.
- Three different age groups prefer this product - Teen, Adult and middle aged.
- Average Income of the customer who buys KP481 is 49K.

- Average Usage of this product is 3 days per week.
- More Partnered customers prefer this product.
- There are slightly more male buyers of the KP481.
- The distance travelled on the KP481 treadmill is roughly between 75 - 100 Miles. It is also the 2nd most distance travelled model.
- The buyers of KP481 in Single & Partnered, Male & Female are same.
- The age range of KP481 treadmill customers is roughly between 24-34 years.

KP781

- Due to the High Price & being the advanced type, customer prefers less of this product.
- Customers use this product mainly to cover more distance.
- Customers who use this product have rated excelled shape as fitness rating.
- Customer walk/run average 120 to 200 or more miles per week on his product.
- Customers use 4 to 5 times a week at least.
- Female Customers who are running average 180 miles (extensive exercise) , are using product KP781, which is higher than Male average using same product.
- Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).
- Probability of a single person buying KP781 is higher than Married customers. So , KP781 is also recommended for people who are single and exercises more.
- Middle aged to higher age customers tend to use this model to cover more distance.
- Average Income of KP781 buyers are over 75K per annum
- Partnered Female bought KP781 treadmill compared to Partnered Male.
- Customers who have more experience with previous aerofit products tend to buy this product
- This product is preferred by the customer where the correlation between Education and Income is High.

Recommendation

- Female who prefer exercising equipments are very low here. Hence, we should run a marketing campaign on to encourage women to exercise more
- KP281 & KP481 treadmills are preferred by the customers whose annual income lies in the range of 39K - 53K Dollars. These models should promoted as budget treadmills.
- As KP781 provides more features and functionalities, the treadmill should be marketed for professionals and athletes.
- KP781 product should be promotted using influencers and other international atheletes.
- Research required for expanding market beyond 50 years of age considering health pros and cons.
- Provide customer support and recommend users to upgrade from lower versions to next level versions after consistent usages.
- KP781 can be recommended for Female customers who exercises extensively along with easy usage guidance since this type is advanced.
- Target the Age group above 40 years to recommend Product KP781.
