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

Aerofit Case Study

● 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.
● 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 new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics.
● Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
● Construct two-way contingency tables for each AeroFit treadmill product and compute all conditional and marginal probabilities and their insights/impact on the business

In [ ]:
```
data = pd.read_csv('aerofit_treadmill.csv')
data.head()
```

Out[ ]:

	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

Dataset Consists of:
Product: Product Purchased KP281, KP481, or KP781
Age: In years
Gender: Male/Female
Education: in years
MaritalStatus: single or partnered
Usage: average number of times the customer plans to use the treadmill each week
Income: annual income (in $)
Fitness: self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.
Miles: average number of miles the customer expects to walk/run each week

Basic Analysis

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

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

In [ ]:
```
data.dtypes
```

Out[ ]:

	0
Product	object
Age	int64
Gender	object
Education	int64
MaritalStatus	object
Usage	int64
Fitness	int64
Income	int64
Miles	int64

dtype: object

🔍 **Insight:**

- Dataset has 180 rows and 9 columns
- In this dataset, Product, Gender, MaritalStatus are object type and other columns are int type

In [ ]:
```
data.nunique()
```

Out[ ]:

	0
Product	3
Age	32
Gender	2
Education	8
MaritalStatus	2
Usage	6
Fitness	5
Income	62
Miles	37

dtype: int64

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

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

- Aerofit data set has 3 unique product types

In [ ]:
```
data['Age'].unique()
```

Out[ ]:
```
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])
```

- Age of treadmill buyers is ranging from 18 to 42

In [ ]:
```
data['Education'].unique()
```

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

- Customer education ranging from 14 to 21

In [ ]:
```
data['MaritalStatus'].value_counts(normalize=True)*100
```

Out[ ]:

MaritalStatus	proportion
Partnered	59.444444
Single	40.555556

dtype: float64

- Partnered treadmill users percentage is 59.4%
- Single treadmill users percentage is 40.5%

In [ ]:
```
data['Usage'].value_counts(normalize=True)
```

Out[ ]:

Usage	proportion
3	0.383333
4	0.288889
2	0.183333
5	0.094444
6	0.038889
7	0.011111

dtype: float64

- Number of times treadmill usage per week follow patter of 3>4>2>5>6>7

In [ ]:
```
data['Product'].value_counts(normalize=True)*100
```

Out[ ]:

Product	proportion
KP281	44.444444
KP481	33.333333
KP781	22.222222

dtype: float64

- KP281 treadmill users are more compared to other product

In [ ]:
```
data['Gender'].value_counts(normalize=True)*100
```

Out[ ]:

Gender	proportion
Male	57.777778
Female	42.222222

dtype: float64

- Male treadmill users are the majority

In [ ]:
```
data['Education'].value_counts(normalize=True)
```

Out[ ]:

Education	proportion
16	0.472222
14	0.305556
18	0.127778
15	0.027778
13	0.027778
12	0.016667
21	0.016667
20	0.005556

dtype: float64

In [ ]:
```
data['Fitness'].value_counts(normalize=True)
```

Out[ ]:

Fitness	proportion
3	0.538889
5	0.172222
2	0.144444
4	0.133333
1	0.011111

dtype: float64

🔍 **Insight:**

- Product: Data Set has 3 Product KP281, KP481, KP781, where KP281 probabality of selling percentage is more compared to other.
- Gender: Male users are more than the female users(Male=57.7, Female=42.2)
- Eductaion: Customers who has education of 16 are the highest buyers than others
- Fitness: People who rated 3 are the most treadmill users

In [ ]:
```
data.isna().sum()
```

Out[ ]:

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

dtype: int64

* No missing values present in any of the columns

Visual and Non-Visual Analysis and Outliers detection

Univariate Analysis

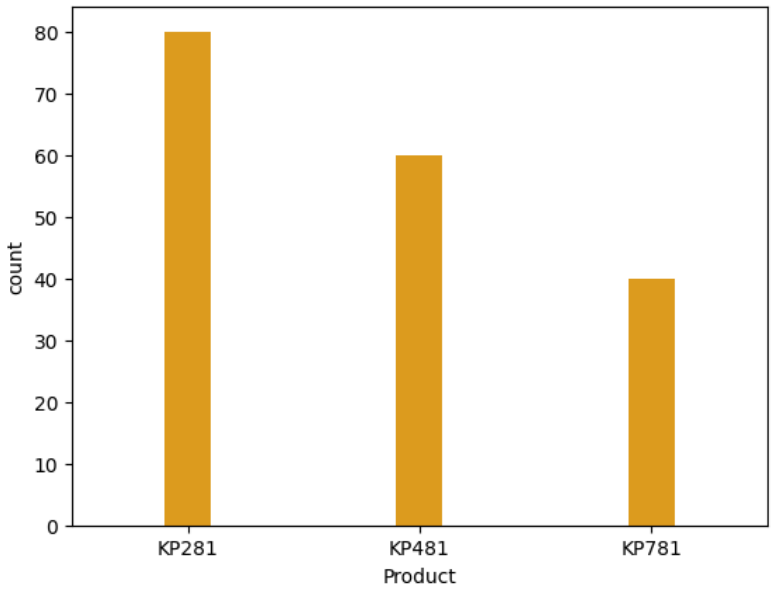
In [ ]:
```
data['Product'].value_counts() #Types of Products in Aerofit
```

Out[ ]:

Product	count
KP281	80
KP481	60
KP781	40

dtype: int64

In [ ]:
```
sns.countplot(data=data, x='Product', color='orange', width=0.2)
plt.show()
```



📊 **Observation:**

- Number of product KP281 sold is 80
- Number of product KP481 sold is 60
- Number of product KP781 sold is 40

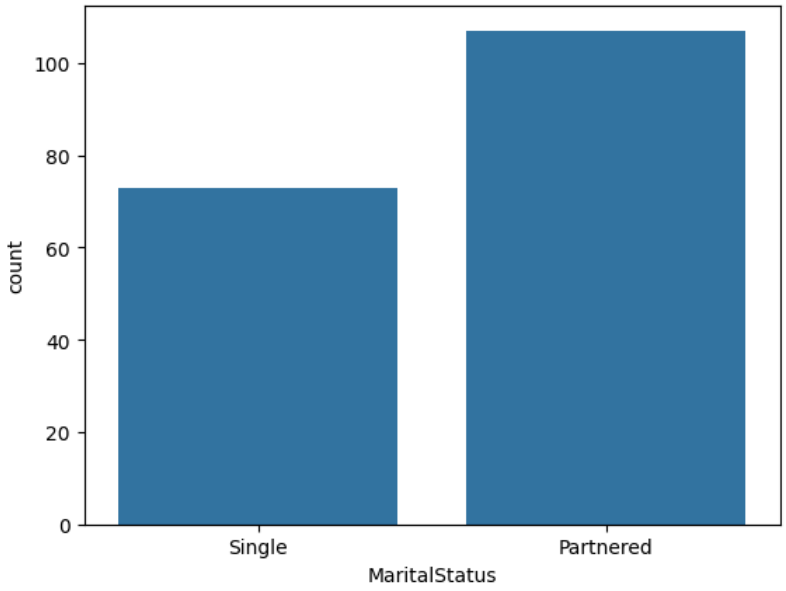
In [ ]:
```
data['MaritalStatus'].value_counts()
```

Out[ ]:

MaritalStatus	count
Partnered	107
Single	73

dtype: int64

In [ ]:
```
sns.countplot(data=data, x='MaritalStatus')
plt.show()
```



📊 **Observation:**

- Number of Partnered customer who purchased are 107
- Number of single customer who purchased are 73

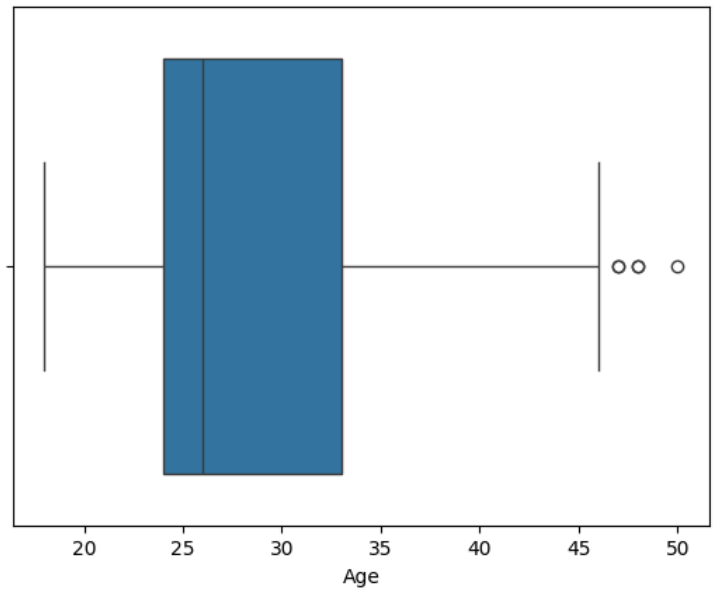
In [ ]:
```
data['Age'].describe()
```

Out[ ]:

	Age
count	180.000000
mean	28.788889
std	6.943498
min	18.000000
25%	24.000000
50%	26.000000
75%	33.000000
max	50.000000

dtype: float64

In [ ]:
```
sns.boxplot(x='Age', data=data)
plt.show()
```



- Median age treadmill users are of the age of 26

In [ ]:
```
# Age column outlier detection

age_25 = np.percentile(data['Age'], 25)
age_75 = np.percentile(data['Age'], 75)
age_iqr = age_75 - age_25
age_upper_limit = age_75 + 1.5*age_iqr
age_outlier = data[data['Age'] > age_upper_limit]
age_outlier
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
78	KP281	47	Male	16	Partnered	4	3	56850	94
79	KP281	50	Female	16	Partnered	3	3	64809	66
139	KP481	48	Male	16	Partnered	2	3	57987	64
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

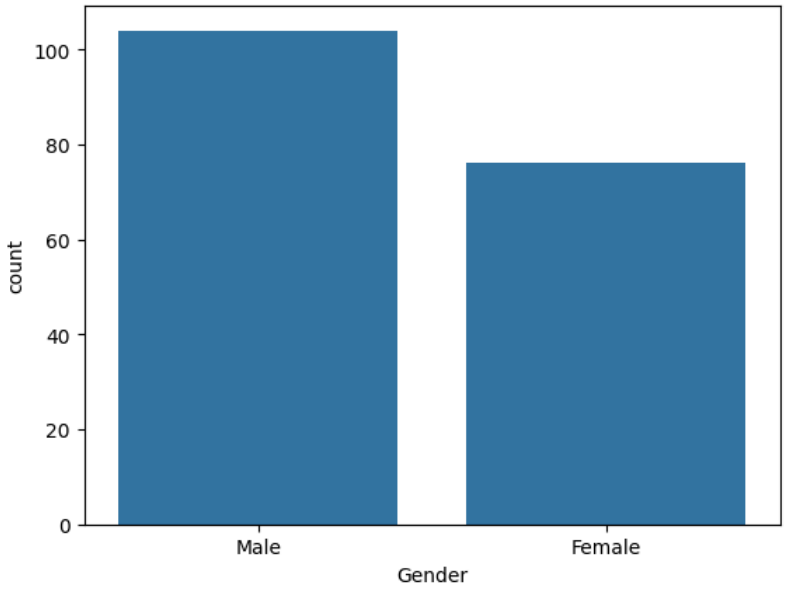
In [ ]:
```
data['Gender'].value_counts()
```

Out[ ]:

Gender	count
Male	104
Female	76

dtype: int64

In [ ]:
```
sns.countplot(data=data, x='Gender')
plt.show()
```



- Majority of the treadmill users are Male

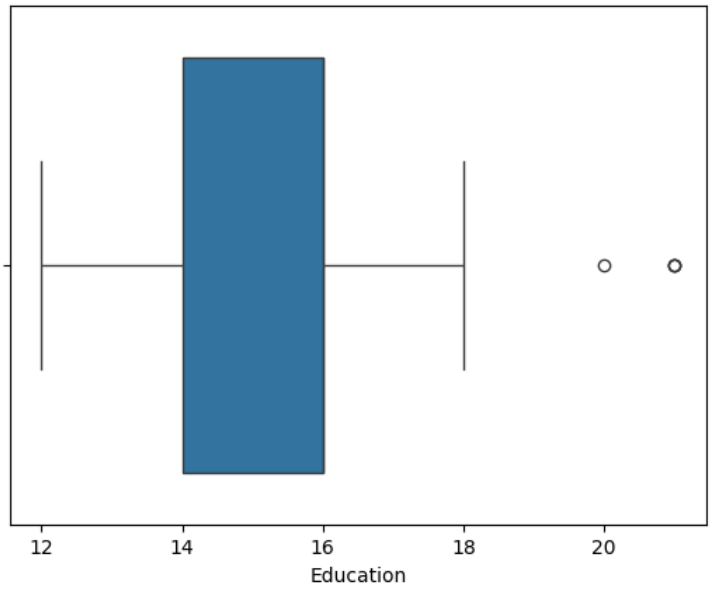
In [ ]:
```
data['Education'].describe()
```

Out[ ]:

	Education
count	180.000000
mean	15.572222
std	1.617055
min	12.000000
25%	14.000000
50%	16.000000
75%	16.000000
max	21.000000

dtype: float64

In [ ]:
```
sns.boxplot(x='Education', data=data)
plt.show()
```



- People with the education in between 14 to 16 are the most of the users

In [ ]:
```
# Education column outlier detection

education_25 = np.percentile(data['Education'], 25)
education_75 = np.percentile(data['Education'], 75)
education_iqr = education_75 - education_25
education_upper_limit = education_75 + 1.5*education_iqr
education_outlier = data[data['Education'] > education_upper_limit]
education_outlier
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
156	KP781	25	Male	20	Partnered	4	5	74701	170
157	KP781	26	Female	21	Single	4	3	69721	100
161	KP781	27	Male	21	Partnered	4	4	90886	100
175	KP781	40	Male	21	Single	6	5	83416	200

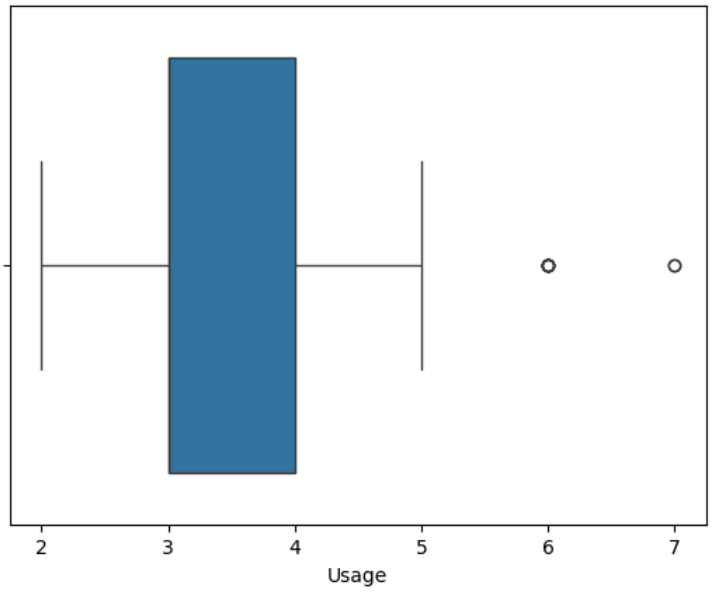
In [ ]:
```
data['Usage'].describe()
```

Out[ ]:

	Usage
count	180.000000
mean	3.455556
std	1.084797
min	2.000000
25%	3.000000
50%	3.000000
75%	4.000000
max	7.000000

dtype: float64

In [ ]:
```
sns.boxplot(x='Usage', data=data)
plt.show()
```



- Customers who are using treadmill 3 to 4 times a week are the most of the users

In [ ]:
```
# Usage column outlier detection

usage_25 = np.percentile(data['Usage'], 25)
usage_75 = np.percentile(data['Usage'], 75)
usage_iqr = usage_75 - usage_25
usage_upper_limit = usage_75 + 1.5*usage_iqr
usage_outlier = data[data['Usage'] > usage_upper_limit]
usage_outlier
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
154	KP781	25	Male	18	Partnered	6	4	70966	180
155	KP781	25	Male	18	Partnered	6	5	75946	240
162	KP781	28	Female	18	Partnered	6	5	92131	180
163	KP781	28	Male	18	Partnered	7	5	77191	180
164	KP781	28	Male	18	Single	6	5	88396	150
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
170	KP781	31	Male	16	Partnered	6	5	89641	260
175	KP781	40	Male	21	Single	6	5	83416	200

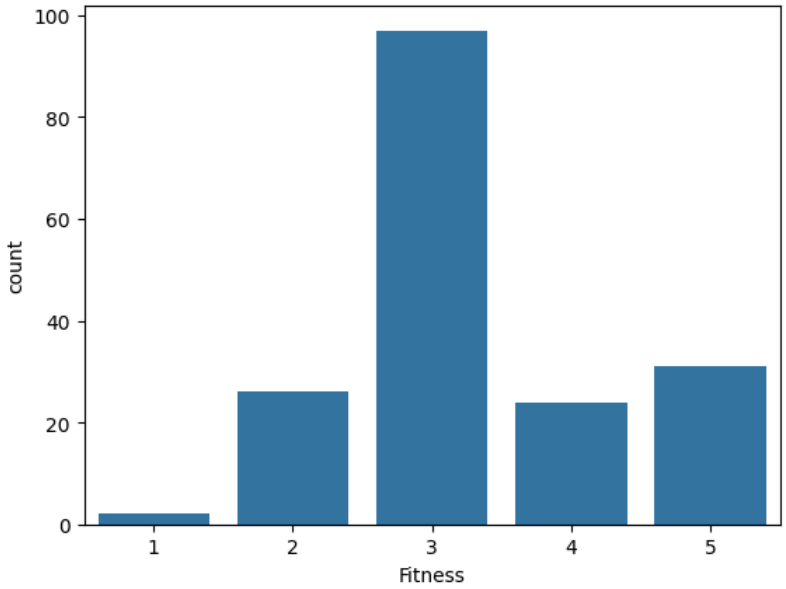
In [ ]:
```
data['Fitness'].value_counts()
```

Out[ ]:

Fitness	count
3	97
5	31
2	26
4	24
1	2

dtype: int64

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



- Customers who rated 3 as a fitness rating are the most of the buyers

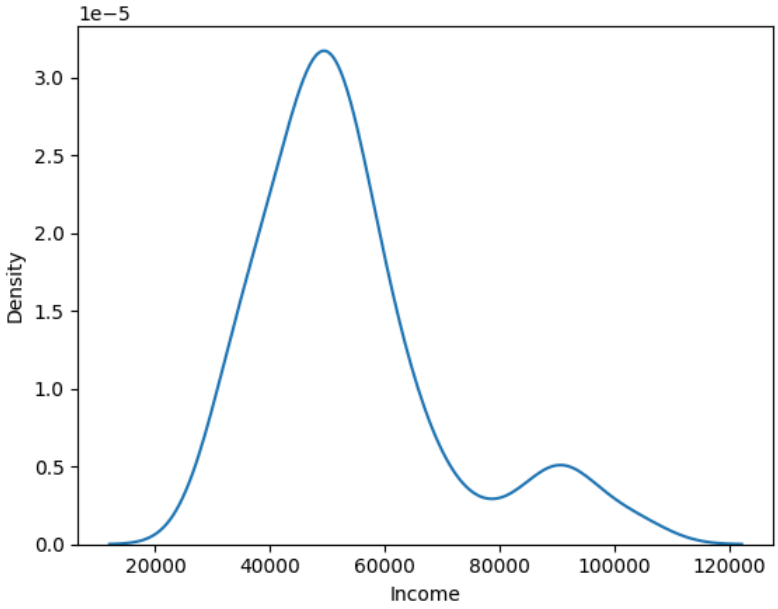
In [ ]:
```
data['Income'].describe()
```

Out[ ]:

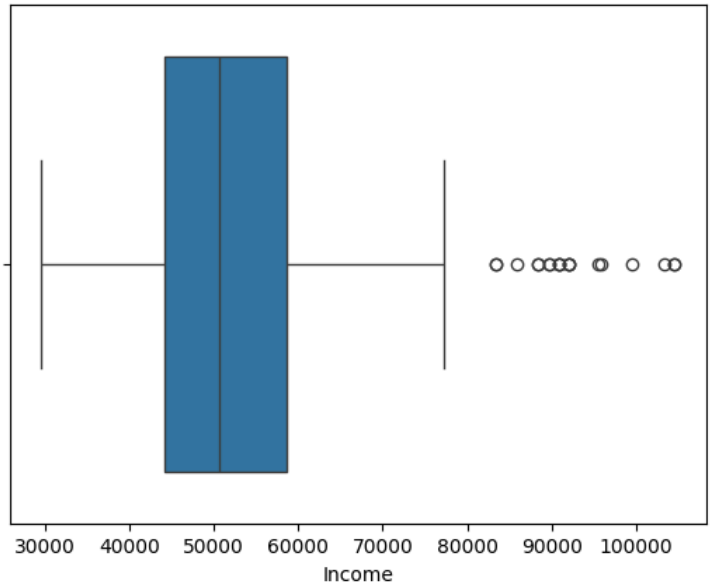
	Income
count	180.000000
mean	53719.577778
std	16506.684226
min	29562.000000
25%	44058.750000
50%	50596.500000
75%	58668.000000
max	104581.000000

dtype: float64

In [ ]:
```
sns.kdeplot(x='Income', data=data)
plt.show()
```



In [ ]:
```
sns.boxplot(x='Income', data=data)
plt.show()
```



- Customers who is having meadian income of 50000 are the most of the buyers

In [ ]:
```
# Income column outlier detection

income_25 = np.percentile(data['Income'], 25)
income_75 = np.percentile(data['Income'], 75)
income_iqr = income_75 - income_25
income_upper_limit = income_75 + 1.5*income_iqr
income_outlier = data[data['Income'] > income_upper_limit]
income_outlier
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
159	KP781	27	Male	16	Partnered	4	5	83416	160
160	KP781	27	Male	18	Single	4	3	88396	100
161	KP781	27	Male	21	Partnered	4	4	90886	100
162	KP781	28	Female	18	Partnered	6	5	92131	180
164	KP781	28	Male	18	Single	6	5	88396	150
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
168	KP781	30	Male	18	Partnered	5	4	103336	160
169	KP781	30	Male	18	Partnered	5	5	99601	150
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
172	KP781	34	Male	16	Single	5	5	92131	150
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

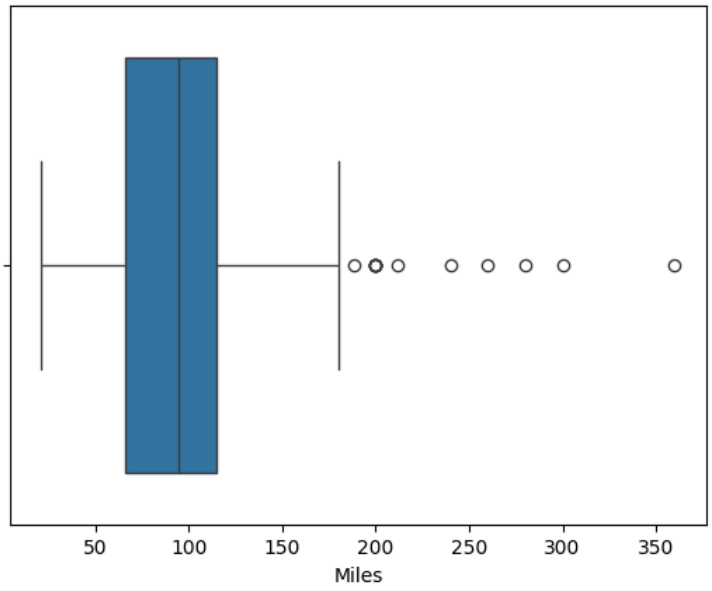
In [ ]:
```
data['Miles'].describe()
```

Out[ ]:

	Miles
count	180.000000
mean	103.194444
std	51.863605
min	21.000000
25%	66.000000
50%	94.000000
75%	114.750000
max	360.000000

dtype: float64

In [ ]:
```
sns.boxplot(x='Miles', data=data)
plt.show()
```



- Customers who is daily walk/run of 66 to 114 miles are the majority of the buyers

In [ ]:
```
# Miles column outlier detection

miles_25 = np.percentile(data['Miles'], 25)
miles_75 = np.percentile(data['Miles'], 75)
miles_iqr = miles_75 - miles_25
miles_upper_limit = miles_75 + 1.5*miles_iqr
miles_outlier = data[data['Miles'] > miles_upper_limit]
miles_outlier
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
23	KP281	24	Female	16	Partnered	5	5	44343	188
84	KP481	21	Female	14	Partnered	5	4	34110	212
142	KP781	22	Male	18	Single	4	5	48556	200
148	KP781	24	Female	16	Single	5	5	52291	200
152	KP781	25	Female	18	Partnered	5	5	61006	200
155	KP781	25	Male	18	Partnered	6	5	75946	240
166	KP781	29	Male	14	Partnered	7	5	85906	300
167	KP781	30	Female	16	Partnered	6	5	90886	280
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
173	KP781	35	Male	16	Partnered	4	5	92131	360
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200

In [ ]:
```
# Cliping below 0.05 and above 0.95 outliers

continuous_cols = ['Age', 'Education', 'Usage', 'Income', 'Fitness', 'Miles']


for i, col in enumerate(continuous_cols):
    lower = data[col].quantile(0.05)
    upper = data[col].quantile(0.95)
    data[col] = np.clip(data[col], lower, upper)
data
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	20.00	Male	14	Single	3.00	4	34053.15	112
1	KP281	20.00	Male	15	Single	2.00	3	34053.15	75
2	KP281	20.00	Female	14	Partnered	4.00	3	34053.15	66
3	KP281	20.00	Male	14	Single	3.00	3	34053.15	85
4	KP281	20.00	Male	14	Partnered	4.00	2	35247.00	47
...	...	...	...	...	...	...	...	...	...
175	KP781	40.00	Male	18	Single	5.05	5	83416.00	200
176	KP781	42.00	Male	18	Single	5.00	4	89641.00	200
177	KP781	43.05	Male	16	Single	5.00	5	90886.00	160
178	KP781	43.05	Male	18	Partnered	4.00	5	90948.25	120
179	KP781	43.05	Male	18	Partnered	4.00	5	90948.25	180

180 rows × 9 columns

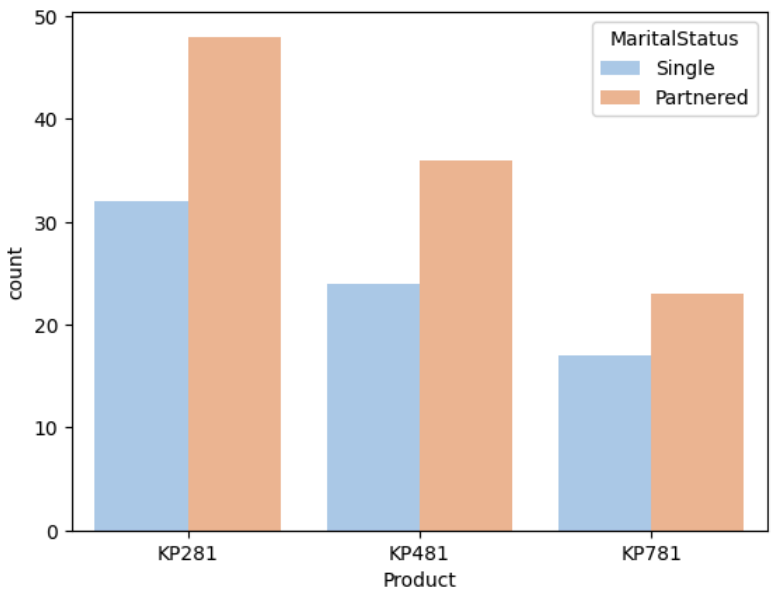
Bi-Varaite Analysis

In [ ]:
```
data.head()
```

Out[ ]:

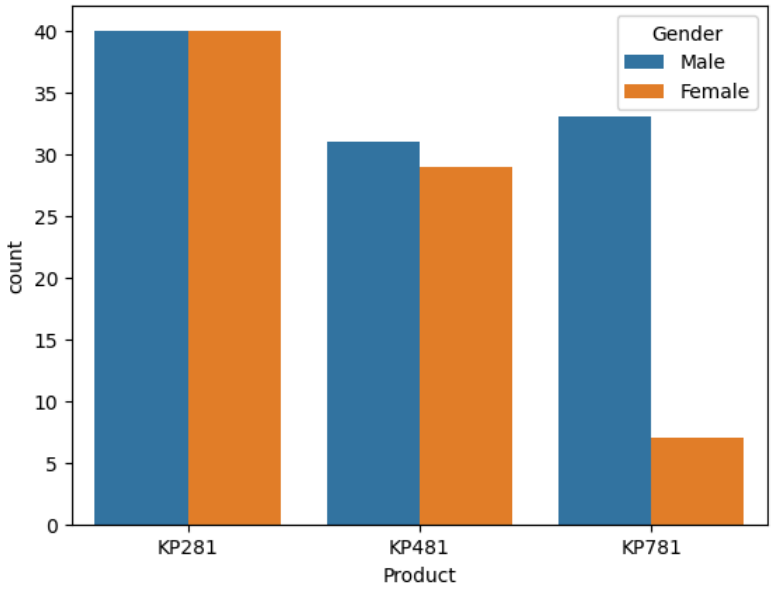
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	20.0	Male	14	Single	3.0	4	34053.15	112
1	KP281	20.0	Male	15	Single	2.0	3	34053.15	75
2	KP281	20.0	Female	14	Partnered	4.0	3	34053.15	66
3	KP281	20.0	Male	14	Single	3.0	3	34053.15	85
4	KP281	20.0	Male	14	Partnered	4.0	2	35247.00	47

In [ ]:
```
sns.countplot(x='Product', hue='MaritalStatus', data=data, palette='pastel')
plt.show()
```



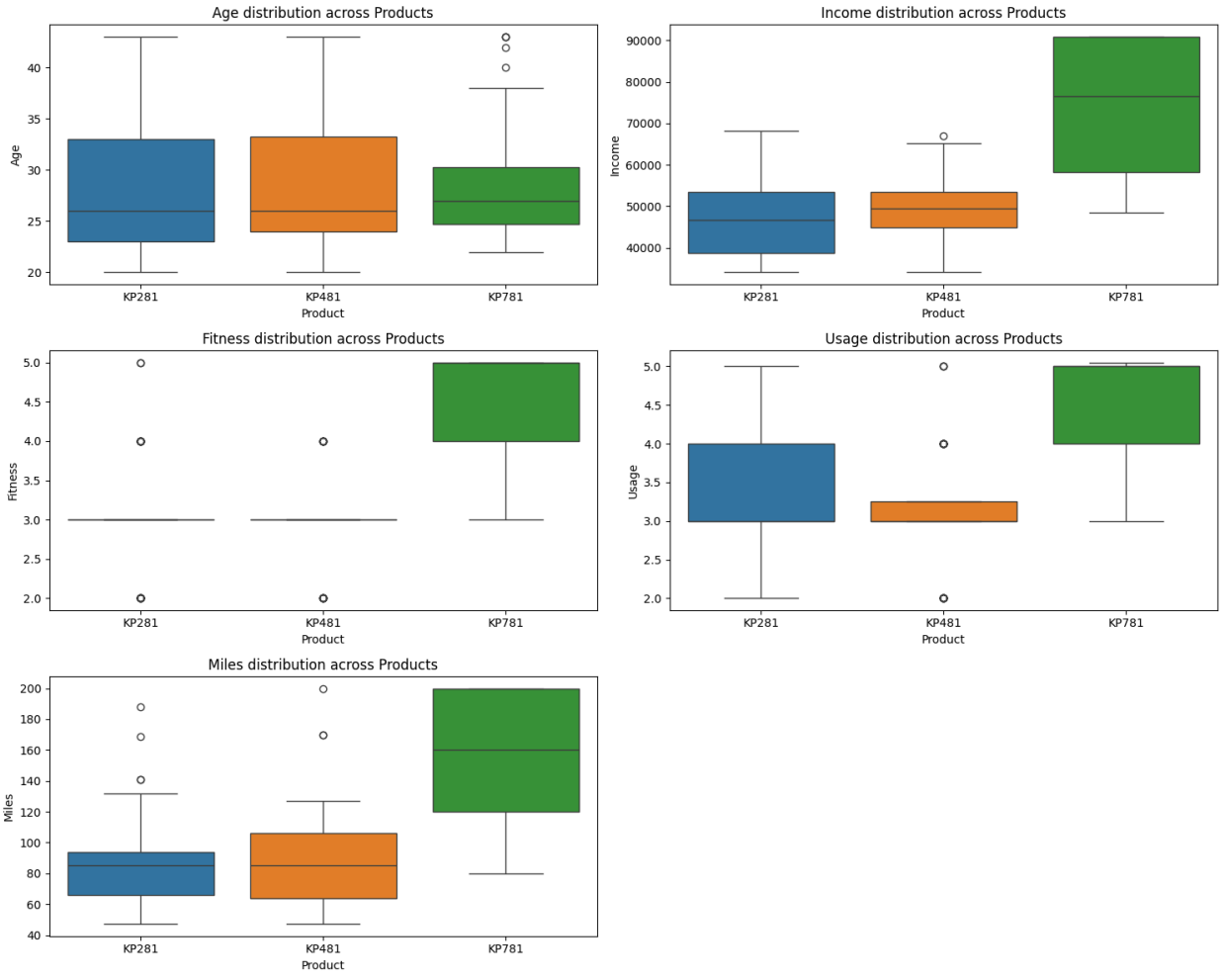
- 📊 Graph shows that Partnered customers have high demand on the treadmill and most likely to buy KP281

In [ ]:
```
sns.countplot(x='Product', hue='Gender', data=data)
plt.show()
```



- 📊 Female customers are least likely to buy KP781 product and it is recommended that they may like KP281 and KP481

In [ ]:
```
continuous_cols = ['Age', 'Income', 'Fitness', 'Usage', 'Miles']

plt.figure(figsize=(15, 12))
for i, col in enumerate(continuous_cols):
    plt.subplot(3, 2, i+1)
    sns.boxplot(data=data, x='Product', y=col, hue='Product')
    plt.title(f'{col} distribution across Products')
plt.tight_layout()
plt.show()
```



🔍 **Insight:**

- Average customer Age of all the 2 products are = 26

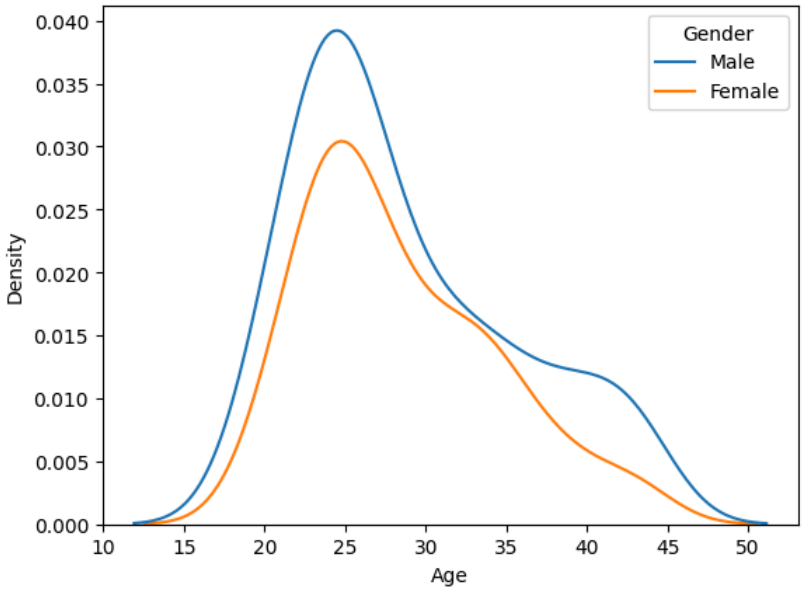
- Customers who is purchase KP781 are the more income buyers
- Average fitness rating of KP281 and KP481 buyers are 3 and KP781 are higher than other two
- Usage per week for KP281 is 3-4, KP481 is 3 and KP781 are 4-5
- Avgerage walk/run Miles/week of KP281 is around 65 to 90, KP481 is around 65 to 110 and KP781 is 120 to 190

In [ ]:
```
data.head()
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	20.0	Male	14	Single	3.0	4	34053.15	112
1	KP281	20.0	Male	15	Single	2.0	3	34053.15	75
2	KP281	20.0	Female	14	Partnered	4.0	3	34053.15	66
3	KP281	20.0	Male	14	Single	3.0	3	34053.15	85
4	KP281	20.0	Male	14	Partnered	4.0	2	35247.00	47

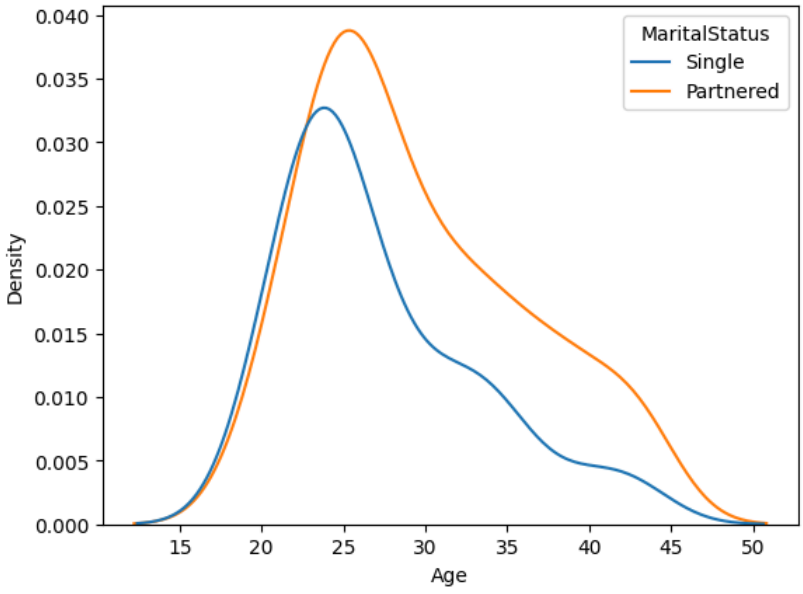
In [ ]:
```
sns.kdeplot(x='Age', hue= 'Gender', data=data)
plt.show()
```



📊 **Observation:**

- Male customers with the age of 20 to 35 years are the most treadmill users

In [ ]:
```
sns.kdeplot(x='Age', hue= 'MaritalStatus', data=data)
plt.show()
```

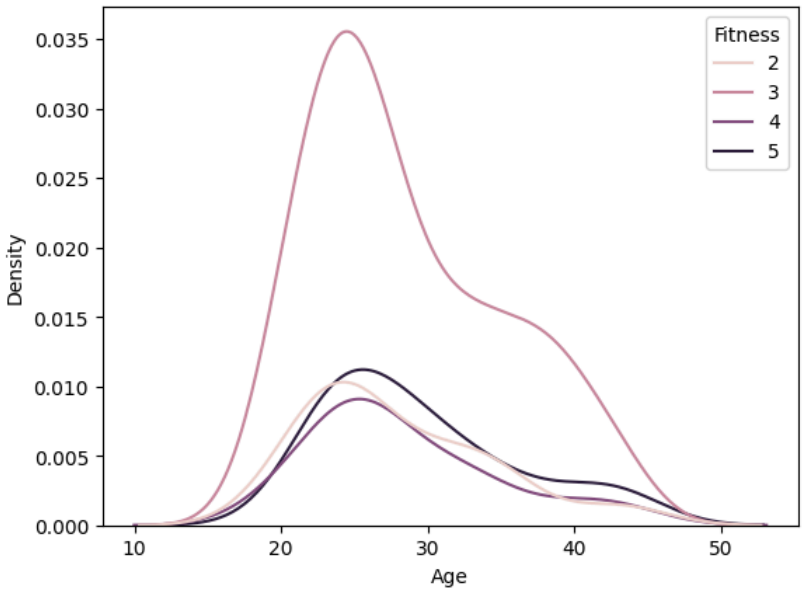


📊 **Observations:-**

- Partnered users with the age of 20 to 30 years are the most users purchased treadmill

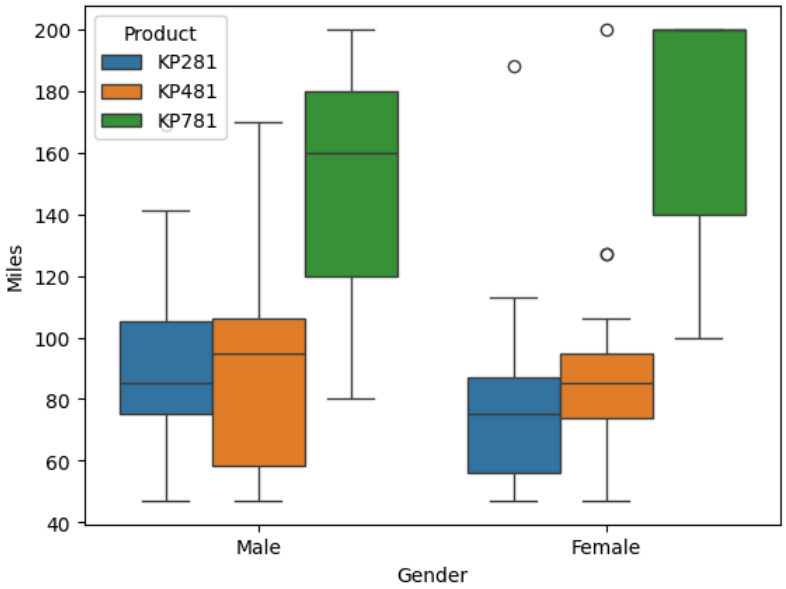
In [ ]:
```
sns.kdeplot(data=data, x='Age',  hue='Fitness')
```

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



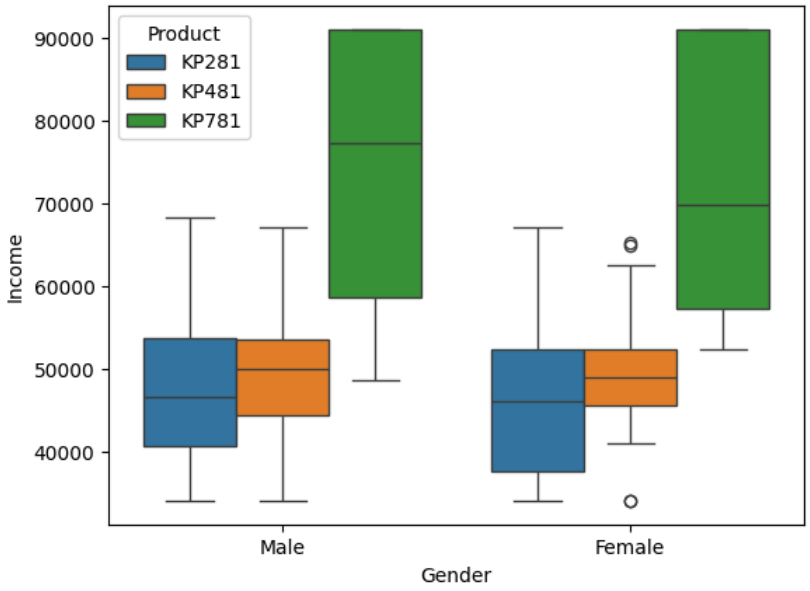
- Most of the users are 3 rated as fitness rating users

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



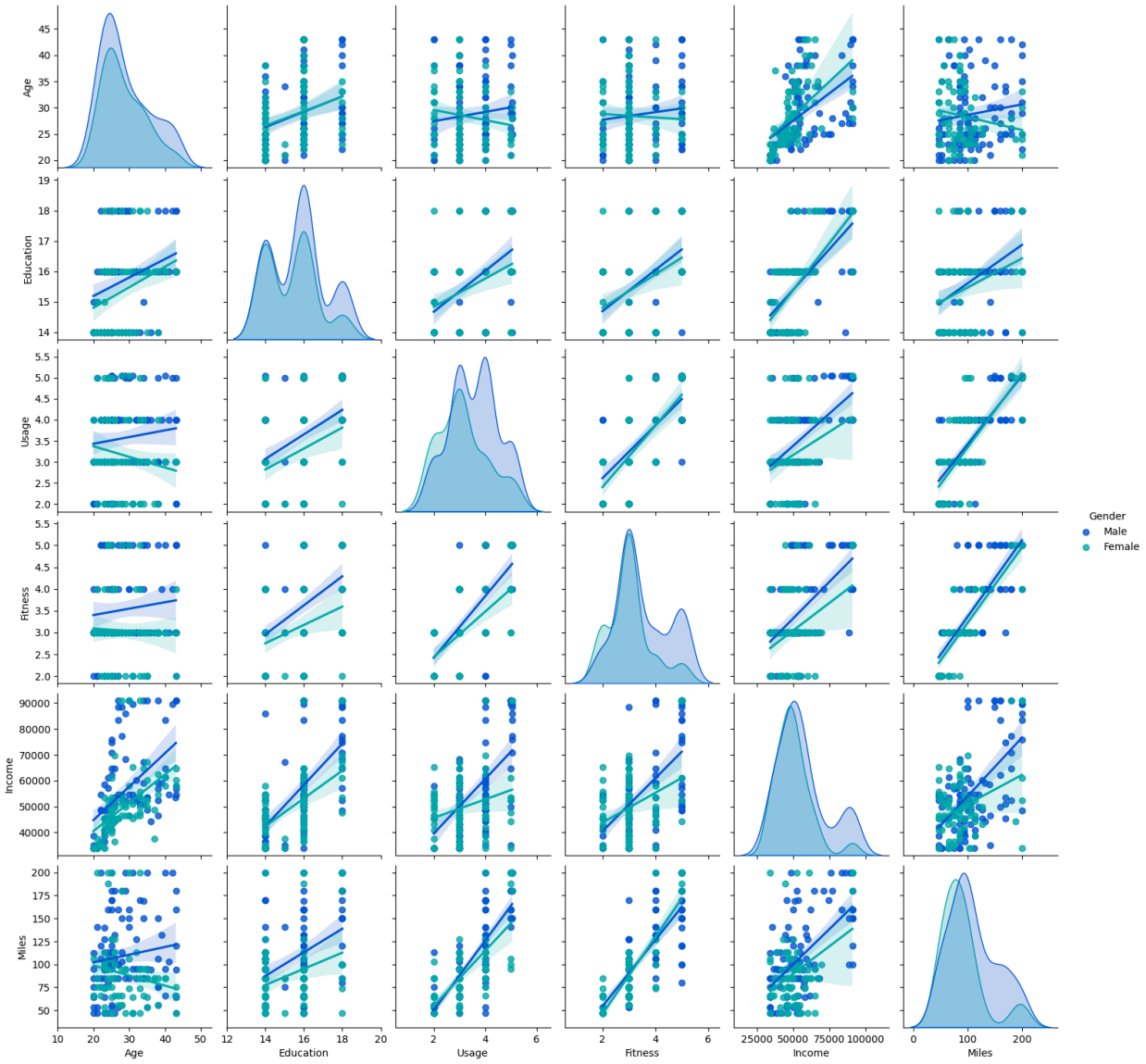
- Miles/Week has impact on product purchase on KP781, would suggest if they walk morethan 120miles/week

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



- Income has positive effect on Product purchase and we can see from the above with greater income customer would like to choose KP781

In [84]:
```
# pairplot

from matplotlib import rcParams
rcParams['figure.figsize'] = 20, 7
sns.pairplot(data, palette='winter', hue='Gender', kind='reg')
plt.show()
```



Probabilistic Insight 🔍:

In [ ]:
```
data.head()
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	20.0	Male	14	Single	3.0	4	34053.15	112
1	KP281	20.0	Male	15	Single	2.0	3	34053.15	75
2	KP281	20.0	Female	14	Partnered	4.0	3	34053.15	66
3	KP281	20.0	Male	14	Single	3.0	3	34053.15	85
4	KP281	20.0	Male	14	Partnered	4.0	2	35247.00	47

In [ ]:
```
pd.crosstab(index=data['Gender'], columns=data['Product'], margins=True, normalize="index") * 100
```

Out[ ]:

Product	KP281	KP481	KP781
Gender			
Female	52.631579	38.157895	9.210526
Male	38.461538	29.807692	31.730769
All	44.444444	33.333333	22.222222

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

Out[ ]:

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

Marginal probabilities

In [ ]:
```
#KP281

(80/180)*100
```

Out[ ]: 44.44444444444444

In [ ]:
```
#KP481

(60/180)*100
```

Out[ ]: 33.33333333333333

In [ ]:
```
#KP781

(40/180)*100
```

Out[ ]: 22.22222222222222

Observations:

- Probability of customer buying KP281 product is 44.4%
- Probability of customer buying KP481 product is 33.3%
- Probability of customer buying KP781 product is 22.2%

In [ ]:
```
data['Product'].value_counts(normalize=True)
```

Out[ ]:

Product	proportion
KP281	0.444444
KP481	0.333333
KP781	0.222222

dtype: float64

In [ ]:
```
data['Gender'].value_counts(normalize=True)
```

Out[ ]:

Gender	proportion
Male	0.577778
Female	0.422222

dtype: float64

In [ ]:
```
data['MaritalStatus'].value_counts(normalize=True)
```

Out[ ]:

MaritalStatus	proportion
Partnered	0.594444
Single	0.405556

dtype: float64

Conditional probabilities

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

Out[ ]:

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

In [ ]:
```
# Probability of purchasing KP281 given that customer is Male (KP281|Male)

(40/104)*100
```

Out[ ]: 38.46153846153847

In [ ]:
```
# Probability of purchasing KP481 given that customer is Male (KP481|Male)

(31/104)*100
```

Out[ ]: 29.807692307692307

In [ ]:
```
# Probability of purchasing KP781 given that customer is Male (KP781|Male)

(33/104)*100
```

Out[ ]: 31.73076923076923

In [ ]:
```
# Probability of purchasing KP281 given that customer is Female (KP281|Female)

(40/76)*100
```

Out[ ]: 52.63157894736842

In [ ]:
```
# Probability of purchasing KP481 given that customer is Female (KP481|Female)

(29/76)*100
```

Out[ ]: 38.15789473684211

In [ ]:
```
# Probability of purchasing KP781 given that customer is Female (KP781|Female)

(7/76)*100
```

Out[ ]: 9.210526315789473

In [ ]:
```
# Probability that Male customer purchases product, give that KP281 shown (Male|KP281)

(40/80)*100
```

Out[ ]: 50.0

In [ ]:
```
# Probability that Male customer purchases product, give that KP481 shown (Male|KP481)

(31/60)*100
```

Out[ ]: 51.66666666666667

In [ ]:
```
# Probability that Male customer purchases product, give that KP781 shown (Male|KP781)

(33/40)*100
```

Out[ ]: 82.5

In [ ]:
```
# Probability that Female customer purchases product, give that KP281 shown (Female|KP281)

(40/80)*100
```

Out[ ]: 50.0

In [ ]:
```
# Probability that Female customer purchases product, give that KP481 shown (Female|KP481)

(29/60)*100
```

Out[ ]: 48.333333333333336

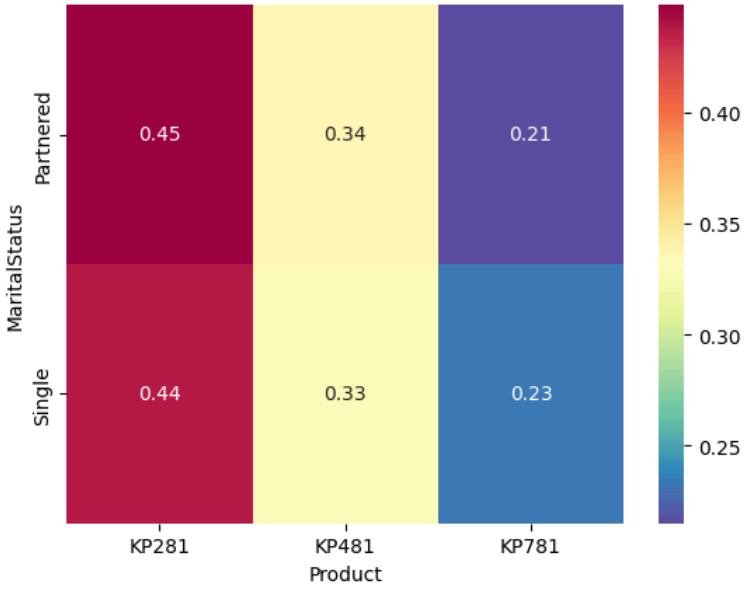
In [ ]:
```
# Probability that Female customer purchases product, give that KP781 shown (Female|KP781)

(7/40)*100
```

Out[ ]: 17.5

🔍 **Insight:**

- Probability of purchasing KP281 given that customer is Male (KP281|Male)=38.46
- Probability of purchasing KP481 given that customer is Male (KP481|Male)=29.80
- Probability of purchasing KP781 given that customer is Male (KP781|Male)=31.73
- Probability of purchasing KP281 given that customer is Female (KP281|Female)=52.63
- Probability of purchasing KP481 given that customer is Female (KP481|Female)=38.15
- Probability of purchasing KP781 given that customer is Female (KP781|Female)=9.21
- Probability that Male customer purchases product, give that KP281 shown (Male|KP281)=50.0
- Probability that Male customer purchases product, give that KP481 shown (Male|KP481)=51.66
- Probability that Male customer purchases product, give that KP781 shown (Male|KP781)=82.50
- Probability that Female customer purchases product, give that KP281 shown (Female|KP281)=50.0
- Probability that Female customer purchases product, give that KP481 shown (Female|KP481)=48.33
- Probability that Female customer purchases product, give that KP781 shown (Female|KP781)=17.5

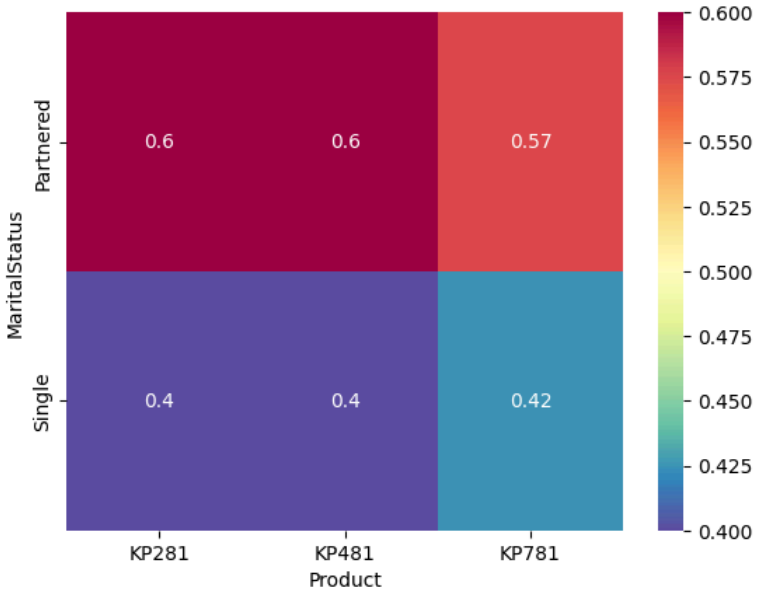
In [ ]:
```
sns.heatmap(pd.crosstab(data['MaritalStatus'], data['Product'], normalize='index'), annot=True, cmap='Spectral_r')
plt.show()
```



Conditional Probability, P(Product | MaritalStatus)

```
1. Probability of buying KP281 given that the marital status is single, P(Product=KP281 |
MaritalStatus=Single) = 0.44.
2. Probability of buying KP481 given that the marital status is single, P(Product=KP481 |
MaritalStatus=Single) = 0.33.
3. Probability of buying KP781 given that the marital status is single, P(Product=781 |
MaritalStatus=Single) = 0.23.
4. Probability of buying KP281 given that the marital status is partnered, P(Product=KP281 |
MaritalStatus=Single) = 0.45.
5. Probability of buying KP481 given that the cmarital status is partnered, P(Product=KP481 |
MaritalStatus=Single) = 0.34.
6. Probability of buying KP781 given that the marital status is partnered, P(Product=KP781 |
MaritalStatus=Single) = 0.21.
```

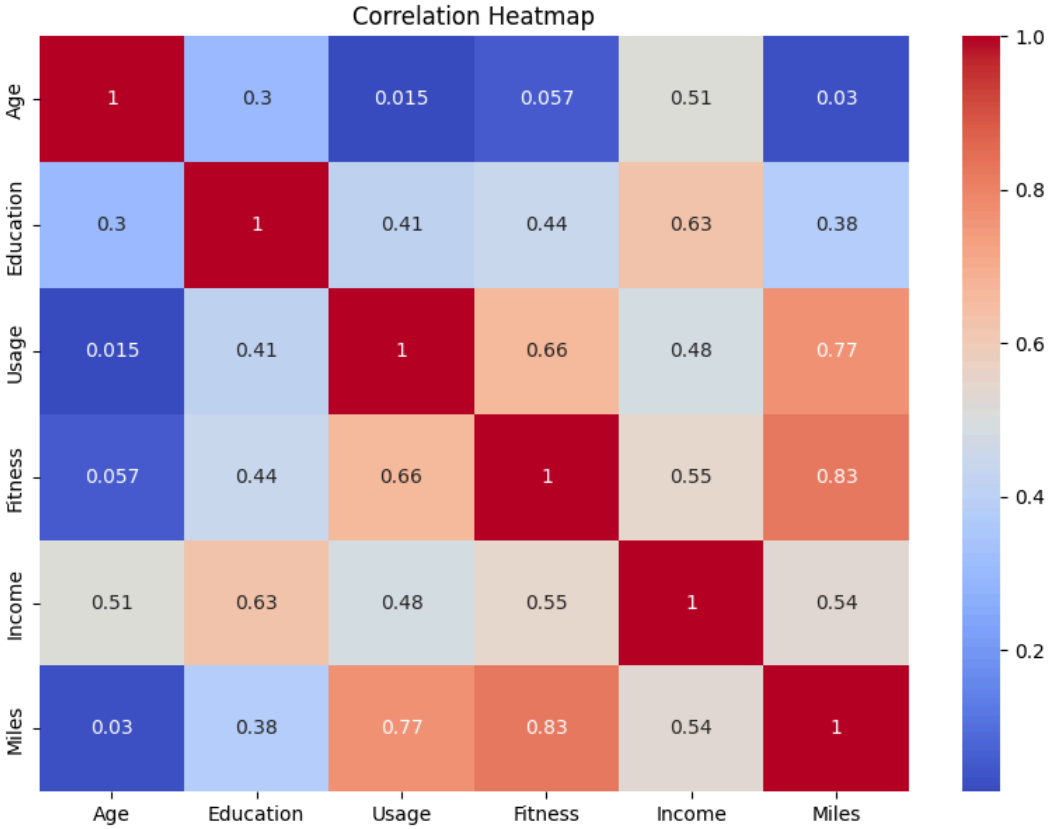
In [ ]:
```
sns.heatmap(pd.crosstab(data['MaritalStatus'], data['Product'], normalize='columns'), annot=True, cmap='Spectral_r')
plt.show()
```



Conditional Probability P(MaritalStatus | Product)

1. Probability of Marital Status being Single given that KP281 is purchased, P(MaritalStatus=Single | Product=KP281) = 0.40.
2. Probability of Marital Status being Parterned given that KP281 is purchased, P(MaritalStatus=Parterned | Product=KP281) = 0.60.
3. Probability of Marital Status being Single given that KP481 is purchased, P(MaritalStatus=Single | Product=KP481) = 0.4.
4. Probability of Marital Status being Partnered given that KP481 is purchased, P(MaritalStatus=Partnered | Product=KP481) = 0.6.
5. Probability of Marital Status being Single given that KP781 is purchased, P(MaritalStatus=Single | Product=KP781) = 0.42.
6. Probability of Marital Status being Partnered given that KP781 is purchased, P(MaritalStatus=Partnered | Product=KP781) = 0.57.

In [ ]:
```
# Correlation Heatmap
numeric_df = data.select_dtypes(include='number')

plt.figure(figsize=(10, 7))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



📊 **Observation:**
Here Pearson co-efficient is used to evalute the correlation between numerical data points. Pearson evalutes the linear relationship between data points.

Noting down the observations which are higher than 0.5.

```
1.Correlation between Age & Income is 0.51
2.Correlation between Education & Income is 0.63.
3.Correlation between Usage & Fitness is 0.67.
4.Correlation between Usage & Income is 0.52.
5.Correlation between Usage & Miles is 0.76.
6.Correlation between Fitness & Income is 0.54.
7.Correlation between Fitness & Miles is 0.79.
8.Correlation between Income & Miles is 0.54.
```

🚹🚺 **Customer Profiling by Product**

🚶 **KP281 – Entry-Level Model**

- Age: Mostly between 22-33 years
- Income: $38,000$–50,000
- Fitness Level: Low (3)
- Usage: 3-4 days/week
- Gender: Gender friendly
- Miles/Week: 70-90
- MaritalStatus: Partnered friendly
- Demographics: Young, single males dominate this segment

Recommendations:

- Position as a starter treadmill for casual users.

🤸 **KP481 – Mid-Tier Model**

- Age: 25–33 years
- Income: $45,000$–55,000
- Fitness Level: Moderate (3–4)
- Usage: 3–4 days/week
- Gender: Higher preference among females
- Miles/Week: 70-100
- Marital Status: Balanced, but slightly more partnered users

Recommendations:

- Position as an all-rounder treadmill for home and shared use.

🏋️ **KP781 – Premium Model**

- Age: 24-30 years
- Income: >$58,000
- Fitness Level: High (4–5)
- Usage: 4–5 days/week
- Gender: Higher preference among males
- Miles/Week: High
- Demographics: Serious fitness users, gym owners, and corporate professionals

Recommendations:

- Market as a high-end, performance-focused treadmill.
- Target corporate wellness buyers, premium fitness clubs, and athletes.
- Highlight smart features, build quality, and long-term value.

Overall Recommendations:

1. Promote KP281 and KP481 treadmills as budget-friendly option, especially targeting customers with annual incomes in the range of 38K - 55K Dollars
2. Market KP781 treadmill as a premium product with advanced features, targeting professionals and athletes.
3. Enhance the marketing strategy for KP781 by associating it with renowned athletes like Neeraj Chopra, Virat Kohili by leveraging their achievements for better outreach.
4. Run special marketing campaigns on Yoga day, Women's Day and Mother's Day to encourage more women to adopt an exercise routine, highlighting the benefits of using our treadmills.
5. Encourage existing customers to upgrade their treadmills to high-end models as their usage increases over time, leading to increased revenue for the business.
6. Ruleout exchange offers for low-end treadmill to buy higher-end treadmill.

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