Problem Statement:

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.

- 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 all packages

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

```
df =pd.read_csv("aerofit_treadmill.csv")
df.head()
```

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

```
df.shape
```

```
(180, 9)
```

```
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
```

```
df.describe()
```

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

```
df.isnull().sum()
```

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

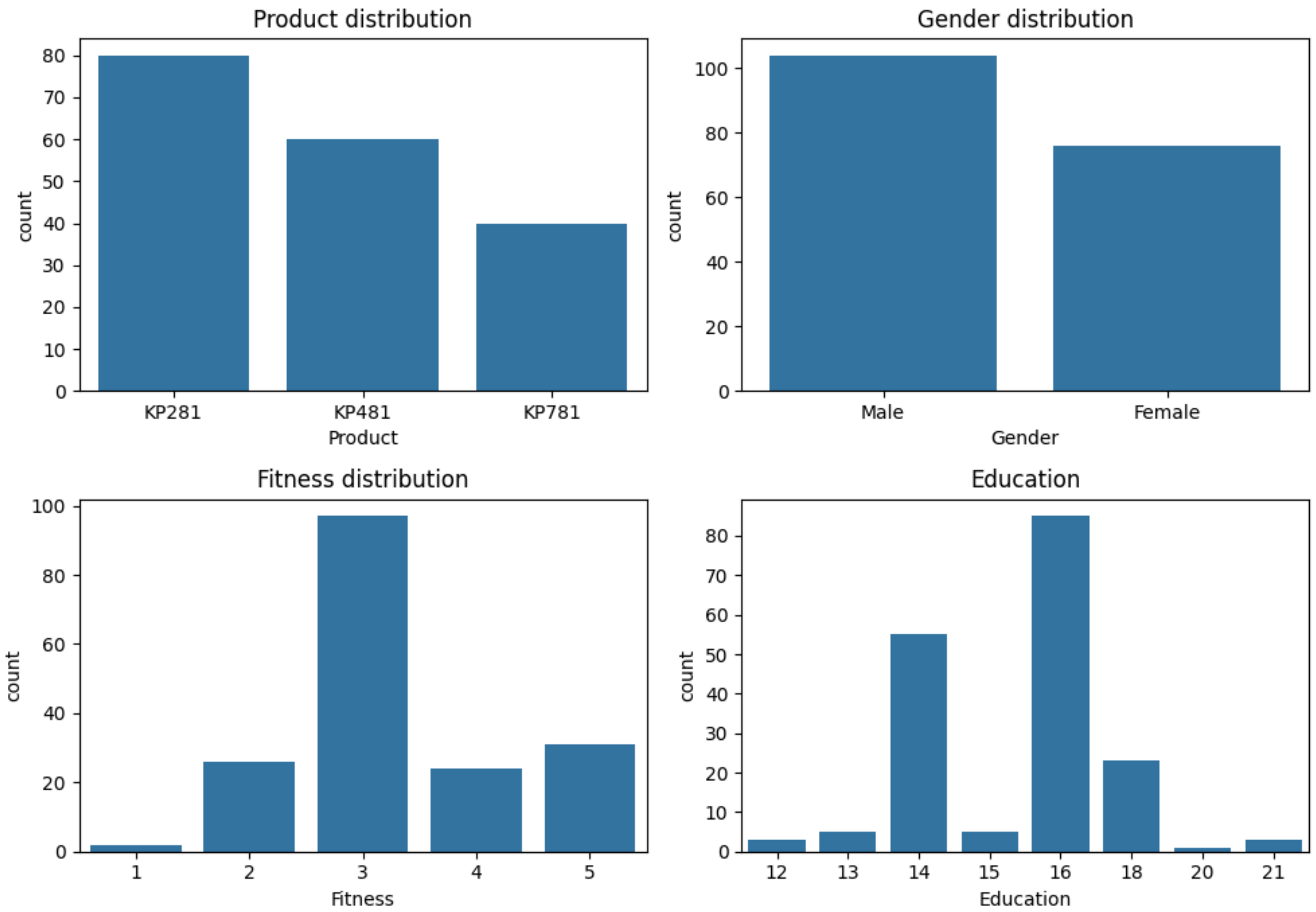
dtype: int64

There are no missing values in these data

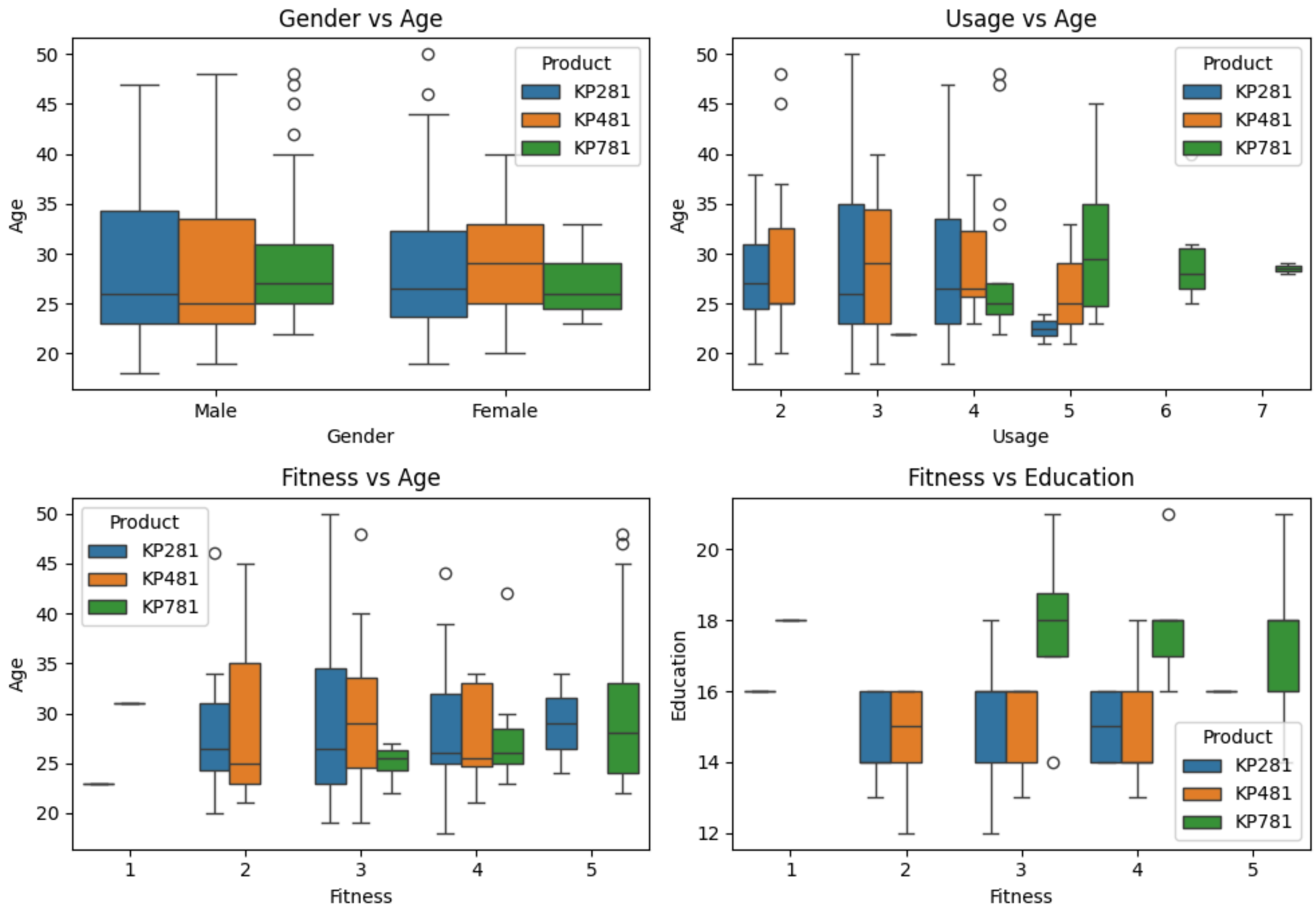
Univariate Analysis

```
plt.subplots(2,2, figsize=(10, 7))
plt.subplot(2,2,1)
plt.title('Product distribution')
sns.countplot(data=df, x='Product')
```

```
plt.subplot(2,2,2)
plt.title('Gender distribution')
sns.countplot(data=df, x='Gender')


plt.subplot(2,2,3)
plt.title('Fitness distribution')
sns.countplot(data=df, x='Fitness')

plt.subplot(2,2,4)
plt.title('Education')
sns.countplot(data=df, x='Education')


plt.tight_layout()
plt.show()
```



```
plt.subplots(2,2, figsize=(10, 7))
plt.subplot(2,2,1)
plt.title('Gender vs Age')
sns.boxplot(data=df, x='Gender', y='Age',hue='Product')

plt.subplot(2,2,2)
plt.title('Usage vs Age')
sns.boxplot(data = df, x='Usage',y='Age' ,hue='Product')


plt.subplot(2,2,3)
plt.title('Fitness vs Age')
sns.boxplot(data = df, x='Fitness',y= 'Age' ,hue='Product')

plt.subplot(2,2,4)
plt.title('Fitness vs Education')
sns.boxplot(data = df, x='Fitness',y='Education' ,hue='Product')


plt.tight_layout()
plt.show()
```




```
probability_of_opting_KP281 = round((df[df['Product'] == 'KP281'].count()['Product']/df['Product'].value_counts().sum()),2)
probability_of_opting_KP481 = round((df[df['Product'] == 'KP481'].count()['Product']/df['Product'].value_counts().sum()),2)
probability_of_opting_KP781 = round((df[df['Product'] == 'KP781'].count()['Product']/df['Product'].value_counts().sum()),2)
probability_of_opting_KP281,probability_of_opting_KP481,probability_of_opting_KP781
```

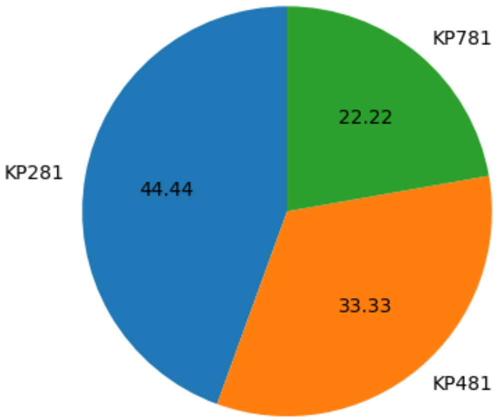
```
(0.44, 0.33, 0.22)
```

probability of opting KP281 is 0.44

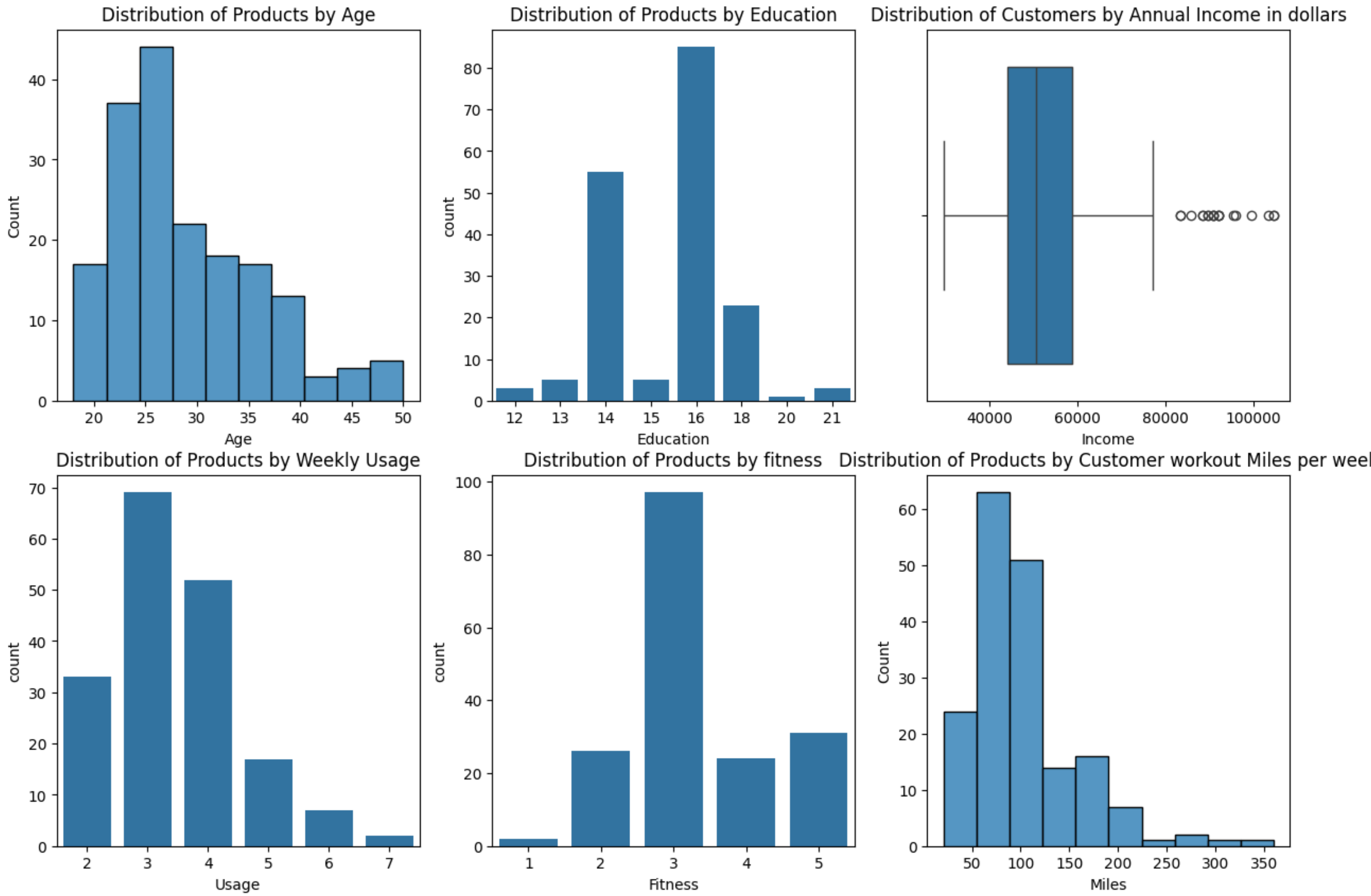
probability of opting KP481 is 0.33

probability of opting KP781 is 0.22

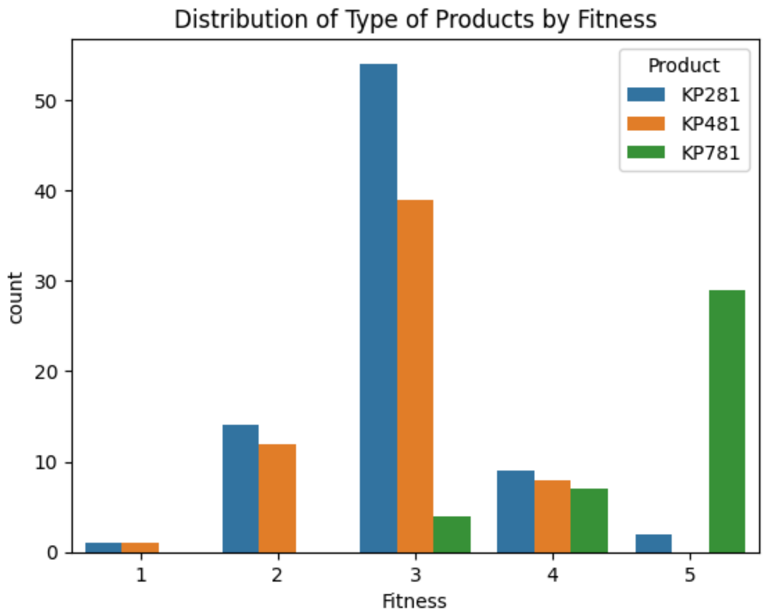
```
product_percent = df['Product'].value_counts().reset_index()
plt.pie(x=product_percent['count'], labels=product_percent['Product'], startangle= 90, autopct='%.2f')
plt.show()
```

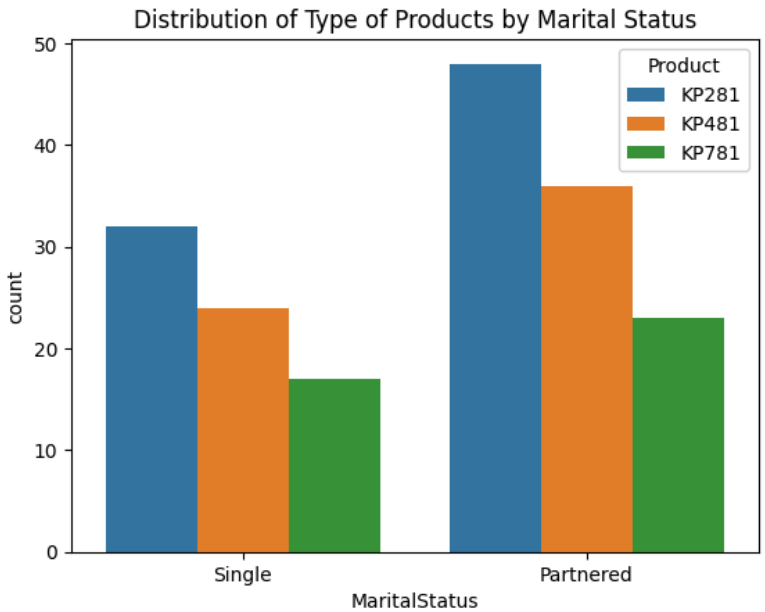



```
fig, ax=plt.subplots(2,3,figsize=(15,10))  #Distribution of products by age
sns.histplot(ax=ax[0,0],data=df['Age'],bins=10)
ax[0,0].set_title('Distribution of Products by Age')
#plt.title('Distribution of Products by Age',ax=ax[0,0])

sns.countplot(ax=ax[0,1],data=df,x=df['Education'])
ax[0,1].set_title('Distribution of Products by Education')


sns.boxplot(ax=ax[0,2],x=df['Income'])
ax[0,2].set_title('Distribution of Customers by Annual Income in dollars')

sns.countplot(ax=ax[1,0],data=df,x=df['Usage'])
ax[1,0].set_title('Distribution of Products by Weekly Usage')

sns.countplot(ax=ax[1,1],data=df,x=df['Fitness'])
ax[1,1].set_title('Distribution of Products by fitness')

sns.histplot(ax=ax[1,2],data=df['Miles'],bins=10)
ax[1,2].set_title('Distribution of Products by Customer workout Miles per week')
plt.show()
```

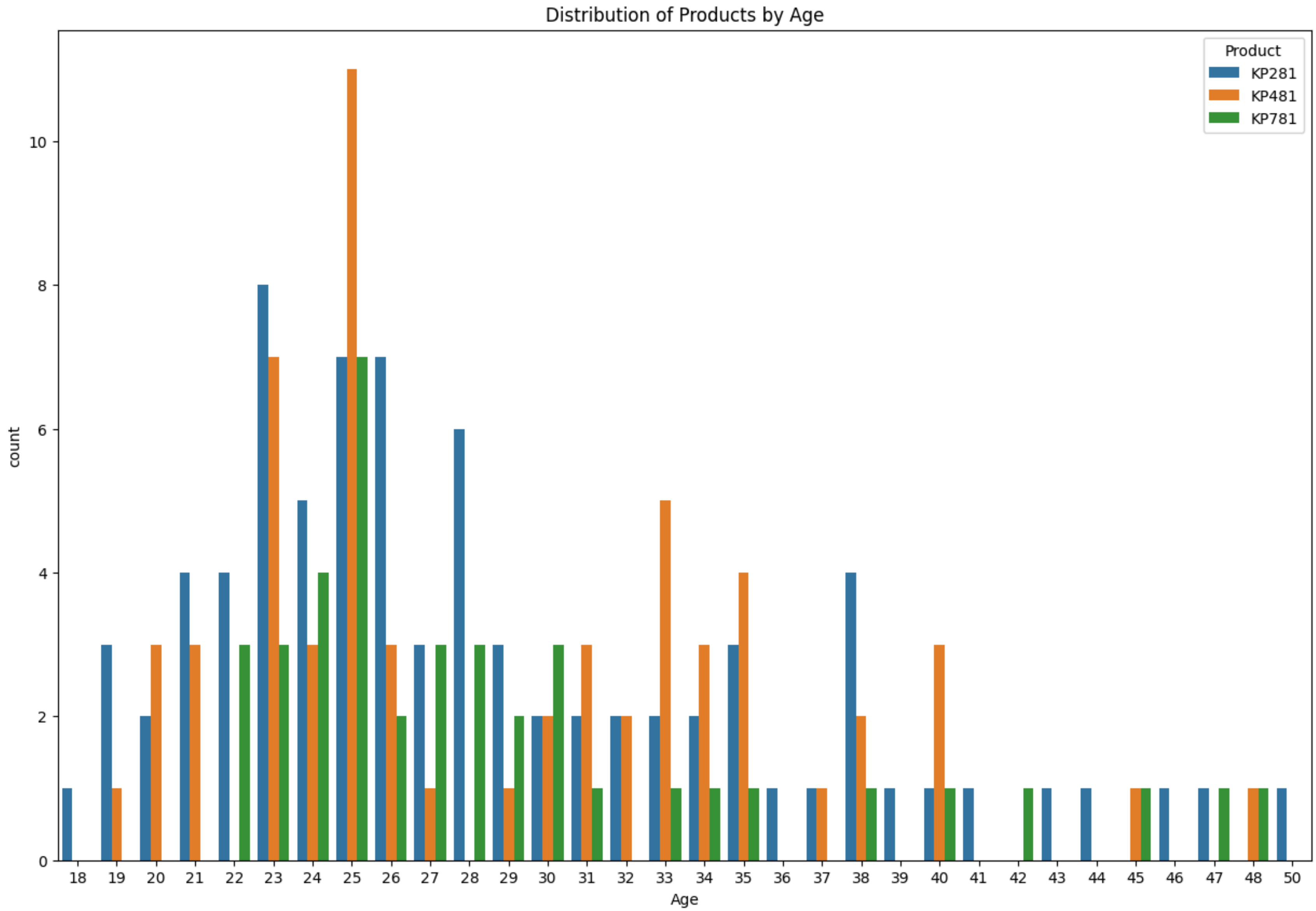



```
sns.countplot(data=df,x='Fitness',hue='Product')
plt.title('Distribution of Type of Products by Fitness')
plt.show()
sns.countplot(data=df,x='MaritalStatus',hue='Product')
plt.title('Distribution of Type of Products by Marital Status')
plt.show()
```



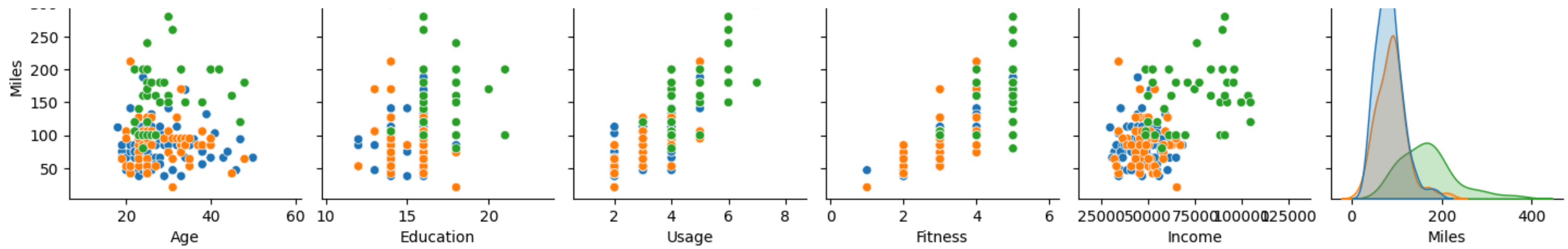



```
plt.figure(figsize=(15,10))
sns.countplot(data=df[['Age','Product']], x=df['Age'],hue='Product')
plt.title('Distribution of Products by Age')
plt.show()
```




```
sns.pairplot(data=df,hue='Product')
plt.show()
```


Age
Education
Usage
Fitness
Income
Product
KP281
KP481
KP781




```
ct1=pd.crosstab(df['Gender'],df['Product'],margins=True,margins_name='Total')
ct1
```

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

```
pd.crosstab(df['Gender'],df['Product'],margins=True,normalize=1)
```

Product Gender	KP281	KP481	KP781	All
Female	0.5	0.483333	0.175	0.422222
Male	0.5	0.516667	0.825	0.577778

```
pd.crosstab(df['Gender'],df['Product'],margins=True,normalize=0)
```

Product Gender	KP281	KP481	KP781
Female	0.526316	0.381579	0.092105
Male	0.384615	0.298077	0.317308
All	0.444444	0.333333	0.222222

Marginal probability of a customer buying KP281,KP481,KP781 are 0.44,0.33,0.22 respectivly

Marginal probability of a male customer buying KP281,KP481,KP781 are 0.38,0.29,0.31 respectivly

Marginal probability of a female customer buying KP281,KP481,KP781 are 0.52,0.38,0.09 respectivly

Here Customers are more willing to buy the base product based on their income,fitness levels i.e KP281 as it has more probability.

Among males and females, males are more interested to buy the higher end treadmill model KP781

Conditional Probabilities of KP281,KP481,KP781 given that customer is female are 0.53,0.38,0.09 and customer is male are 0.28, 0.3, 0.32

Joint probabilty

```
ct1
```

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

```
KP281_and_Female_prob=round(ct1.iloc[0,0]/ct1.Total[2],2)
KP481_and_Female_prob=round(ct1.KP481[0]/ct1.Total[2],2)
KP781_and_Female_prob=round(ct1.KP781[0]/ct1.Total[2],2)

print(f"Joint probabilities of customer being the female wrt the product being KP281,KP481,KP781 are:{KP281_and_Female_prob},{KP481_and_Female_prob},{KP781_and_Female_prob}")
```

```
Joint probabilities of customer being the female wrt the product being KP281,KP481,KP781 are:0.22,0.16,0.04
```

```
KP281_and_male_prob=round(ct1.iloc[0,0]/ct1.Total[2],2)
KP481_and_male_prob=round(ct1.KP481[1]/ct1.Total[2],2)
KP781_and_male_prob=round(ct1.KP781[1]/ct1.Total[2],2)

print(f"Joint probabilities of customer being the male wrt the product being KP281,KP481,KP781 are: {KP281_and_male_prob},{KP481_and_male_prob},{KP781_and_male_prob}")
```

```
Joint probabilities of customer being the male wrt the product being KP281,KP481,KP781 are: 0.22,0.17,0.18
```

Conditional Probabilities

```
prob_KP281_given_Female=round(ct1.iloc[0,0]/ct1.Total[0],2)
prob_KP481_given_Female=round(ct1.KP481[0]/ct1.Total[0],2)
prob_KP781_given_Female=round(ct1.KP781[0]/ct1.Total[0],2)

print(f"Conditional probabilities of customer being the female wrt the product being KP281,KP481,KP781 are:{prob_KP281_given_Female},{prob_KP481_given_Female},{prob_KP781_given_Fe
```

```
Conditional probabilities of customer being the female wrt the product being KP281,KP481,KP781 are:0.53,0.38,0.09
```

```
prob_KP281_given_male=round(ct1.iloc[0,1]/ct1.Total[1],2)
prob_KP481_given_male=round(ct1.KP481[1]/ct1.Total[1],2)
```

```
prob_KP781_given_male=round(ct1.KP781[1]/ct1.Total[1],2)


print(f"Conditional probabilities of customer being the male wrt the product being KP281,KP481,KP781 are:{prob_KP281_given_male},{prob_KP481_given_male},{prob_KP781_given_male}")
```

```
Conditional probabilities of customer being the male wrt the product being KP281,KP481,KP781 are:0.28,0.3,0.32
```