Question : 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.***

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.

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn as sk
```

In [4]:
```
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.c
```

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

Out[5]:

	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

In [6]:
```
df[df['Gender']=='Male'].shape[0]
```

Out[6]:
```
104
```

Aerofit Shape

In [7]:
```
print(f'aerofit has {df.shape[0]} rows  and {df.shape[1]} columns')
```

```
aerofit has 180 rows  and 9 columns
```

In [7]:
```

```

Technical Info of Dataset

In [8]:
```
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 description of dataset

In [9]:
```
df.describe()
```

Out[9]:

	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

Checking missing Value

In [10]:
```
df_missing = df.isnull().sum()
df_missing
```

Out[10]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Unique **Products**

In [11]:
```
no_unique_products = df['Product'].nunique()
print(f"aerofit has {no_unique_products}  of uniques products")
```

```
aerofit has 3  of uniques products
```

In [12]:
```
name_of_unique_products = df['Product'].unique()
print(f"names of unique products are {name_of_unique_products}")
```

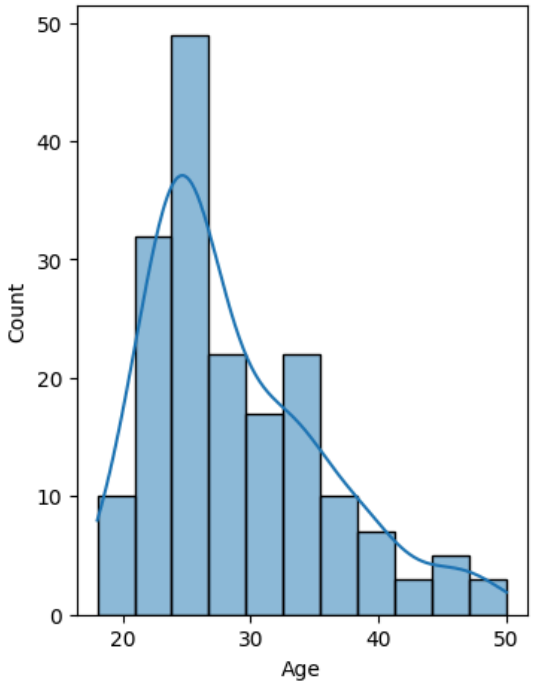
```
names of unique products are ['KP281' 'KP481' 'KP781']
```

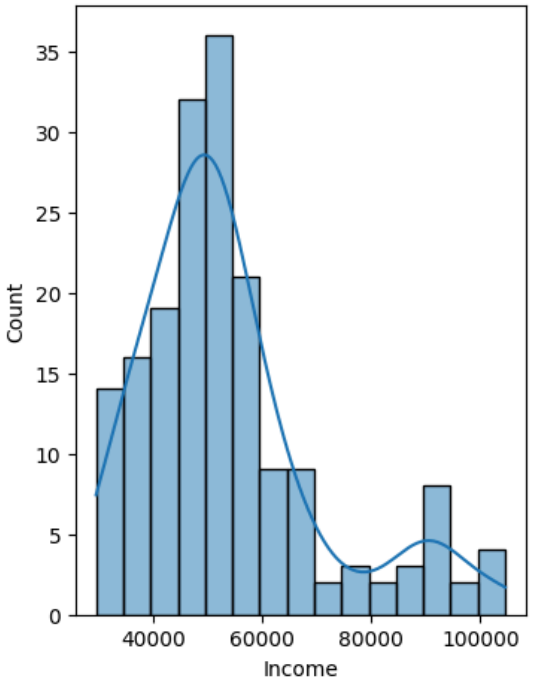
In [13]:
```
number_of_male = df[df['Gender']=='Male'].shape[0]
male_choosing_kP781 = df[(df['Gender']=='Male') & (df['Product']=='KP781')].count()[0]

probability = male_choosing_kP781/number_of_male
print(number_of_male)
print(male_choosing_kP781)
print(f"Probability for male customers going for KP781 is {probability}")
```

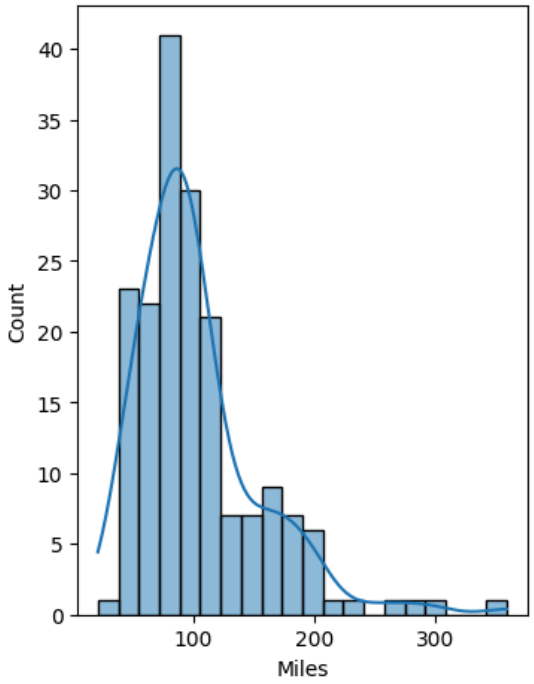
```
104
33
Probability for male customers going for KP781 is 0.3173076923076923
```

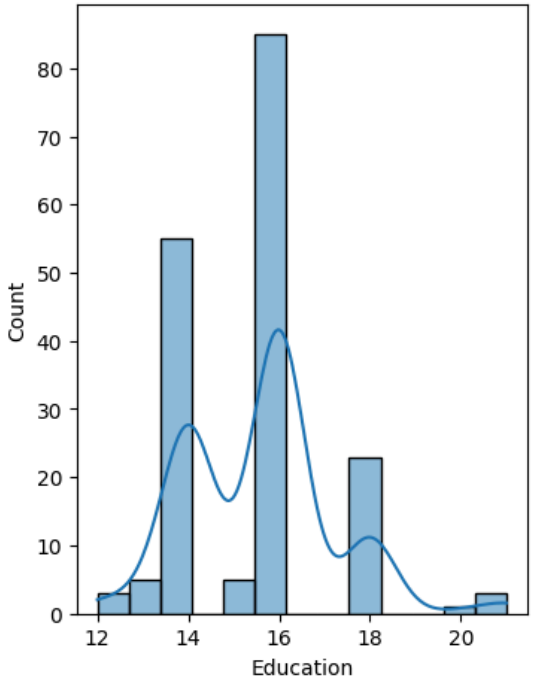
Univariate Analysis

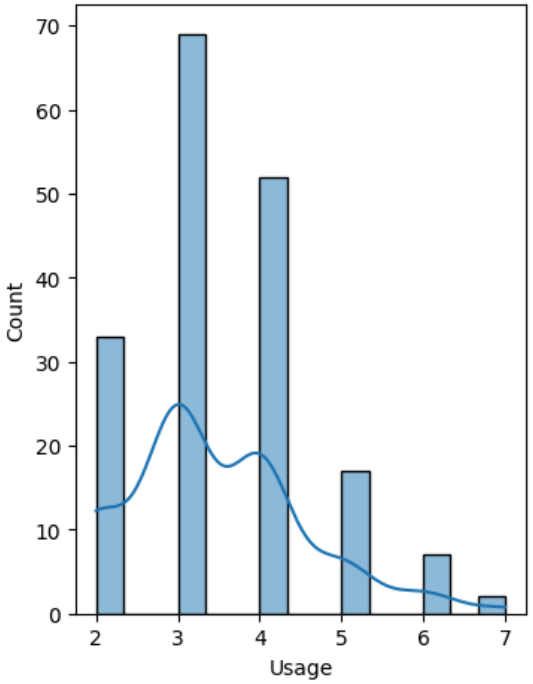
In [14]:
```
fig,axis = plt.subplots(nrows=2,ncols=3,figsize=(12,10))
fig.tight_layout(pad=3)
sns.histplot(data=df,x='Age',ax=axis[0,0],kde=True)
sns.histplot(data=df,x='Income',ax=axis[0,1],kde=True)
sns.histplot(data=df,x='Miles',ax=axis[0,2],kde=True)
sns.histplot(data=df,x='Education',ax=axis[1,0],kde=True)
sns.histplot(data=df,x='Usage',ax=axis[1,1],kde=True)
sns.histplot(data=df,x='Fitness',ax=axis[1,2],kde=True)
plt.show()
```

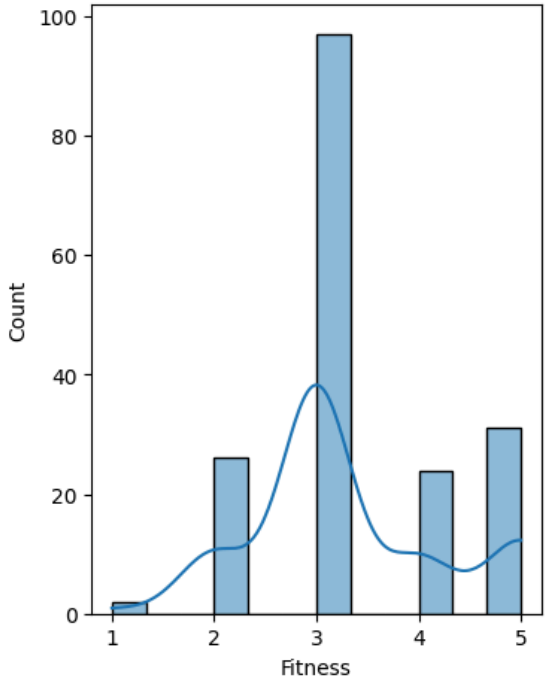

Count
Age
0
10
20
30
40
50
20
30
40
50


Count
Income
0
5
10
15
20
25
30
35
40000
60000
80000
100000


Count
Miles
0
5
10
15
20
25
30
35
40
100
200
300

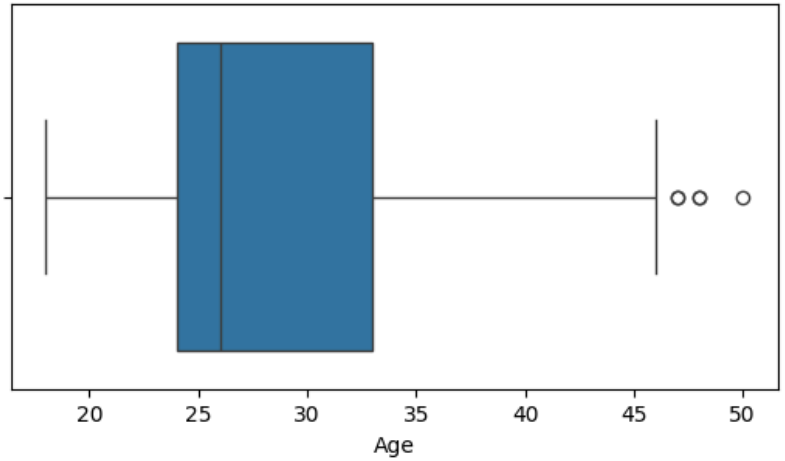

Count
Education
0
10
20
30
40
50
60
70
80
12
14
16
18
20

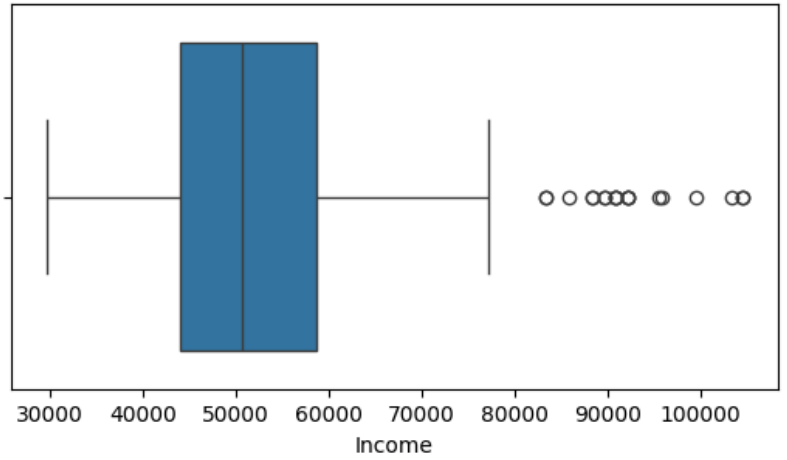

Count
Usage
0
10
20
30
40
50
60
70
2
3
4
5
6
7

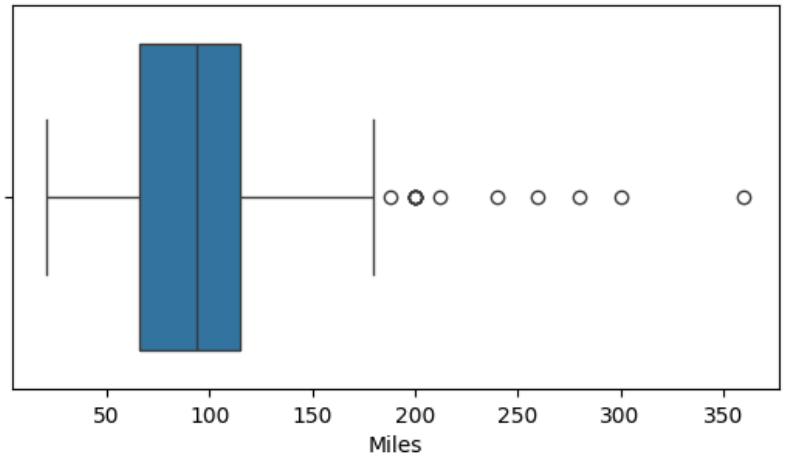

Count
Fitness
0
20
40
60
80
100
1
2
3
4
5

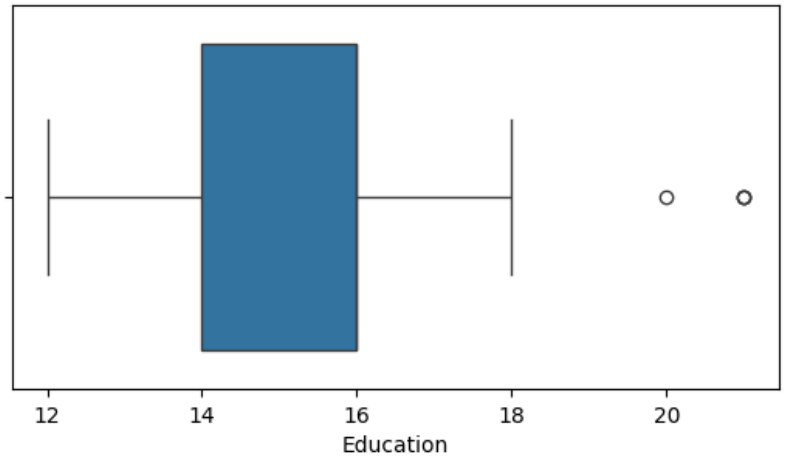
Detect Outliers

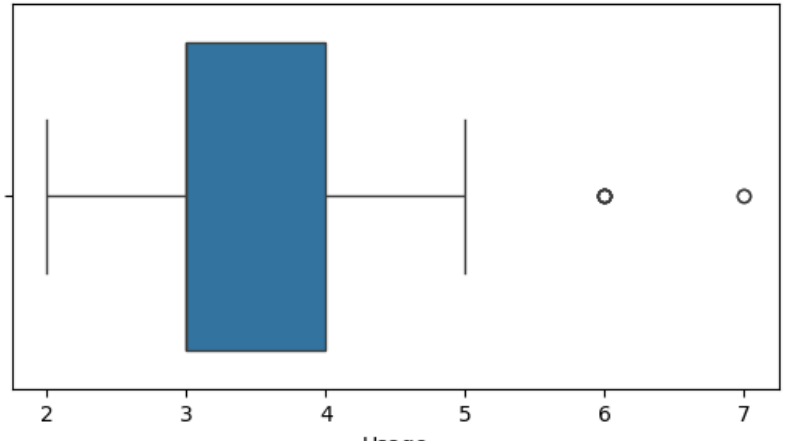
In [15]:
```
fig,axis = plt.subplots(nrows=3,ncols=2,figsize=(12,10))
fig.tight_layout(pad=3)
sns.boxplot(data=df,x='Age',orient='h',ax=axis[0,0])
sns.boxplot(data=df,x='Income',orient='h',ax=axis[0,1])
sns.boxplot(data=df,x='Miles',orient='h',ax=axis[1,0])
sns.boxplot(data=df,x='Education',orient='h',ax=axis[1,1])
sns.boxplot(data=df,x='Usage',orient='h',ax=axis[2,0])
sns.boxplot(data=df,x='Fitness',orient='h',ax=axis[2,1])
plt.show()
```

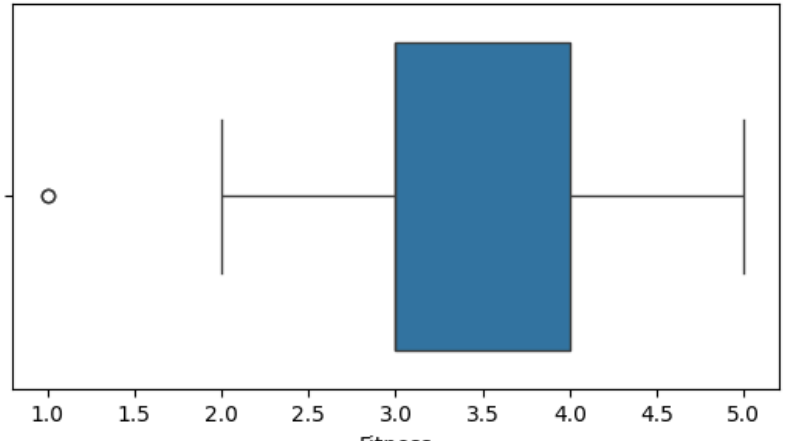

20
25
30
35
40
45
50
Age


30000
40000
50000
60000
70000
80000
90000
100000
Income


50
100
150
200
250
300
350
Miles


12
14
16
18
20
Education


2
3
4
5
6
7


1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

Usage Fitness

In [16]:
```
df['Age'].describe()
```

Out[16]:
```
count    180.000000
mean      28.788889
std        6.943498
min       18.000000
25%       24.000000
50%       26.000000
75%       33.000000
max       50.000000
Name: Age, dtype: float64
```

In [17]:
```
age_25=np.percentile(df['Age'],25)
age_25
```

Out[17]:
```
24.0
```

In [18]:
```
age_50=np.percentile(df['Age'],50)
age_50
```

Out[18]:
```
26.0
```

In [19]:
```
age_75=np.percentile(df['Age'],75)
age_75
```

Out[19]:
```
33.0
```

In [20]:
```
iqr_age=age_75-age_25
iqr_age
```

Out[20]:
```
9.0
```

In [21]:
```
upper_age_limit=age_75+1.5*iqr_age
upper_age_limit
```

Out[21]:
```
46.5
```

In [22]:
```
lower_age_limit= age_25-1.5*iqr_age
lower_age_limit
```

Out[22]:
```
10.5
```

It means that any value above 46.5 will be considered as an outlier in case of age.And Lower age limit is 10.5

In [23]:
```
df['Education'].describe()
```

Out[23]:
```
count    180.000000
mean      15.572222
std        1.617055
min       12.000000
25%       14.000000
50%       16.000000
75%       16.000000
max       21.000000
Name: Education, dtype: float64
```

In [24]:
```
education_25=np.percentile(df['Education'],25)
education_25
```

Out[24]:
```
14.0
```

In [25]:
```
education_50=np.percentile(df['Education'],50)
education_50
```

Out[25]:
```
16.0
```

In [26]:
```
education_75=np.percentile(df['Education'],75)
education_75
```

Out[26]:
```
16.0
```

In [27]:
```
iqr_education=education_75-education_25
iqr_education
```

Out[27]:
```
2.0
```

In [28]:
```
upper_education_limit = education_75+1.5*iqr_education
upper_education_limit
```

Out[28]:
```
19.0
```

In [29]:
```
lower_education_limit = education_25-1.5*iqr_education
lower_education_limit
```

Out[29]:
```
11.0
```

It means any value above 19.0 will be considered as outlier and below 11.0 will also be consider as outlier

In [30]:
```
df['Usage'].describe()
```

Out[30]:
```
count    180.000000
mean       3.455556
std        1.084797
min        2.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        7.000000
Name: Usage, dtype: float64
```

In [31]:
```
treadmill_use_25 = np.percentile(df['Usage'],25)
treadmill_use_25
```

Out[31]:
```
3.0
```

In [32]:
```
treadmill_use_50 = np.percentile(df['Usage'],50)
treadmill_use_50
```

Out[32]:
```
3.0
```

In [33]:
```
treadmill_use_75 = np.percentile(df['Usage'],75)
treadmill_use_75
```

Out[33]:
```
4.0
```

In [34]:
```
treadmill_iqr = treadmill_use_75-treadmill_use_25
treadmill_iqr
```

Out[34]:
```
1.0
```

In [35]:
```
upper_usage_limit = treadmill_use_75 + 1.5*treadmill_iqr
upper_usage_limit
```

Out[35]:
```
5.5
```

In [36]:
```
lower_usage_limit = treadmill_use_25 - 1.5*treadmill_iqr
lower_usage_limit
```

Out[36]:
```
1.5
```

In this case value greater than 5.5 is considered as outliers and lower than 1.5 is also considered as outliers

In [37]:
```
df['Income'].describe()
```

Out[37]:
```
count       180.000000
mean      53719.577778
std       16506.684226
min       29562.000000
25%       44058.750000
50%       50596.500000
75%       58668.000000
max      104581.000000
Name: Income, dtype: float64
```

In [38]:
```
income_25 = np.percentile(df['Income'],25)
income_25
```

Out[38]:
```
44058.75
```

In [39]:
```
income_50 = np.percentile(df['Income'],50)
income_50
```

Out[39]:
```
50596.5
```

In [40]:
```
income_75 = np.percentile(df['Income'],75)
income_75
```

Out[40]:
```
58668.0
```

In [41]:
```
iqr_income = income_75 - income_25
iqr_income
```

Out[41]:
```
14609.25
```

In [42]:
```
upper_limit_income = income_75 + 1.5*iqr_income
upper_limit_income
```

Out[42]:
```
80581.875
```

In [43]:
```
lower_limit_income = income_25 - 1.5*iqr_income
lower_limit_income
```

Out[43]:
```
22144.875
```

In this case the value above 80581 are considered as outliers and value below 22144 is also considered as outliers

In [44]:
```
df['Miles'].describe()
```

Out[44]:
```
count    180.000000
mean     103.194444
std       51.863605
min       21.000000
25%       66.000000
50%       94.000000
75%      114.750000
max      360.000000
Name: Miles, dtype: float64
```

In [45]:
```
mile_25 = np.percentile(df['Miles'],25)
mile_25
```

Out[45]:
```
66.0
```

In [46]:
```
mile_50 = np.percentile(df['Miles'],50)
mile_50
```

Out[46]: 94.0

In [47]:
```
mile_75 = np.percentile(df['Miles'],75)
mile_75
```

Out[47]: 114.75

In [48]:
```
iqr_mile = mile_75 - mile_25
iqr_mile
```

Out[48]: 48.75

In [49]:
```
upper_limit_mile = mile_75 + 1.5*iqr_mile
upper_limit_mile
```

Out[49]: 187.875

In [50]:
```
lower_limit_mile = mile_25 - 1.5*iqr_mile
lower_limit_mile
```

Out[50]: -7.125

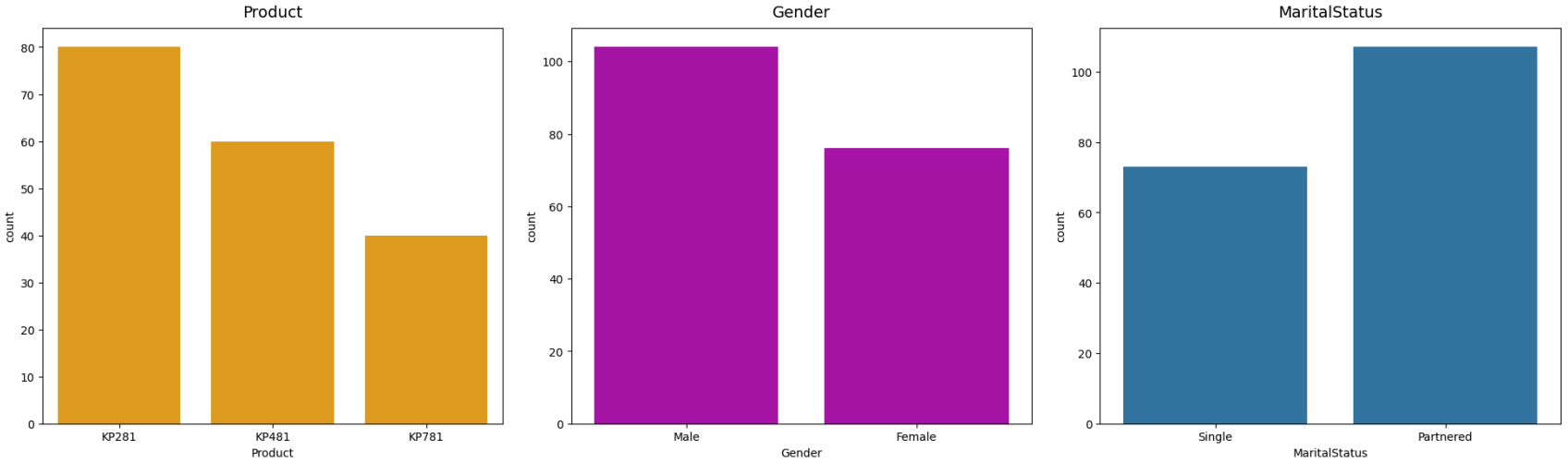
In [50]:
```

```

Outlier :- More number of outliers are seen in miles and Income . While Age,Education and Usuage have comparitively less outlier values

Undertanding the distribution of data for the qualitative attributes

1. Product
2. Gender
3. Marital Status

In [51]:
```
fig,axis = plt.subplots(nrows=1,ncols=3,figsize=(20,6))
fig.tight_layout(pad=3)
sns.countplot(data=df,x='Product',ax=axis[0],color='orange')
sns.countplot(data=df,x='Gender',ax=axis[1],color='m')
sns.countplot(data=df,x='MaritalStatus',ax=axis[2])

axis[0].set_title('Product',fontsize=14,pad=10)
axis[1].set_title('Gender',fontsize=14,pad=10)
axis[2].set_title('MaritalStatus',fontsize=14,pad=10)
plt.show()
```



In [52]:
```
df.head()
```

Out[52]:

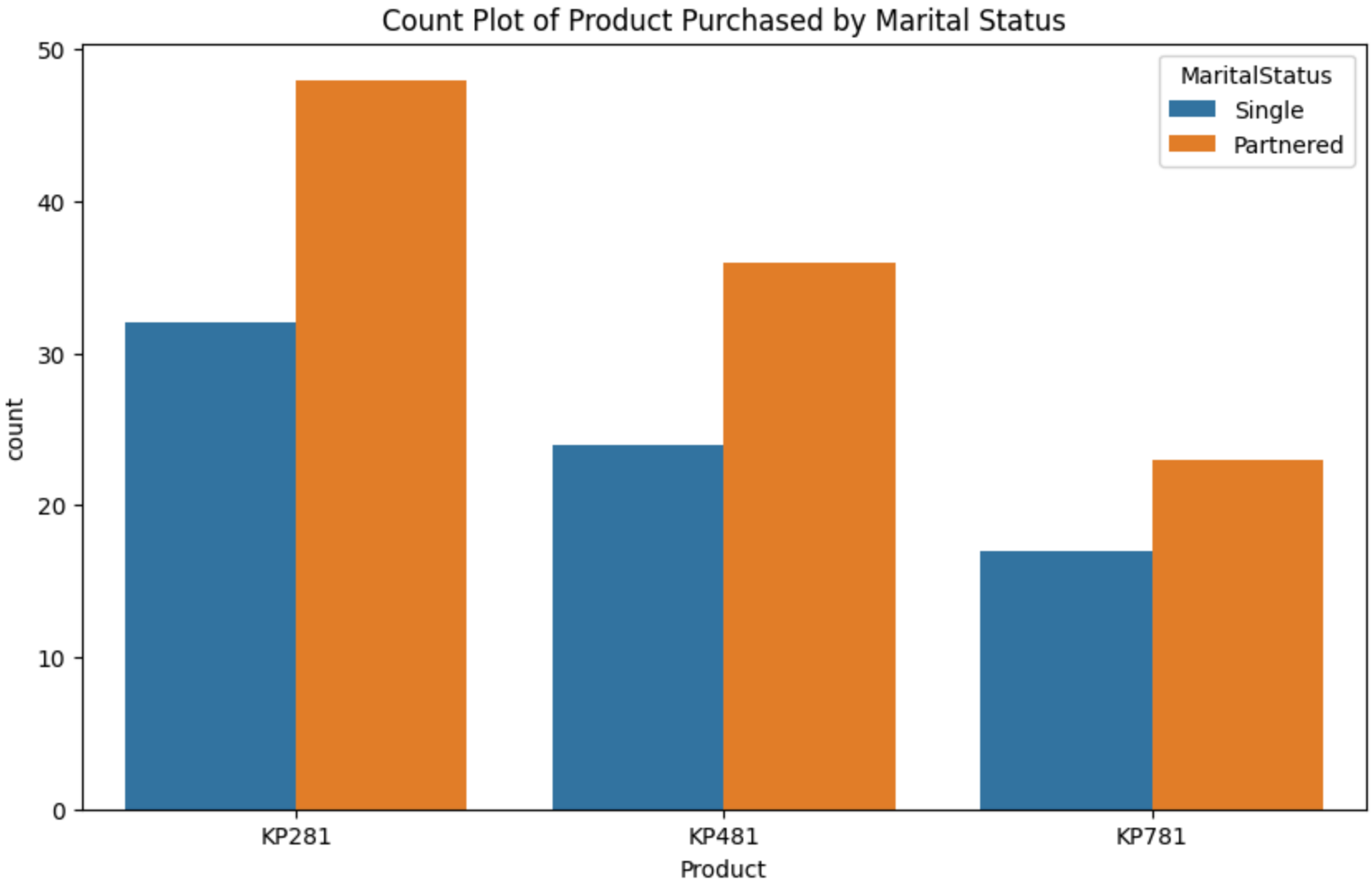
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

In [53]:
```
df1 = df[['Product', 'Gender', 'MaritalStatus']].melt()
normalised_data = df1.groupby(['variable', 'value'])[['value']].count() / len(df)
normalised_data.rename(columns={'value': 'percentage'})
normalised_data
```

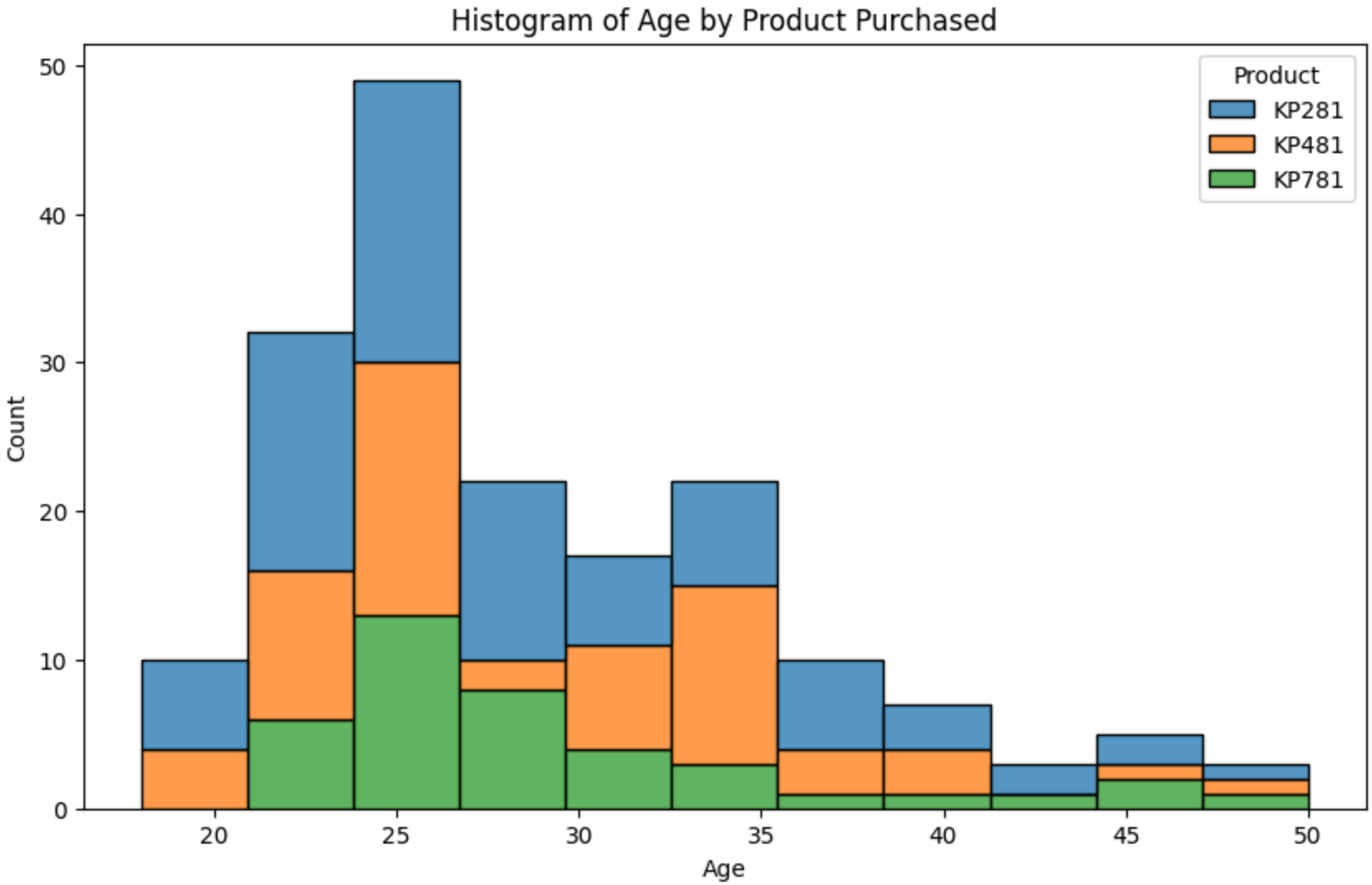
Out[53]:

		value
variable	**value**	
Gender	**Female**	0.422222
	Male	0.577778
MaritalStatus	**Partnered**	0.594444
	Single	0.405556
Product	**KP281**	0.444444
	KP481	0.333333
	KP781	0.222222

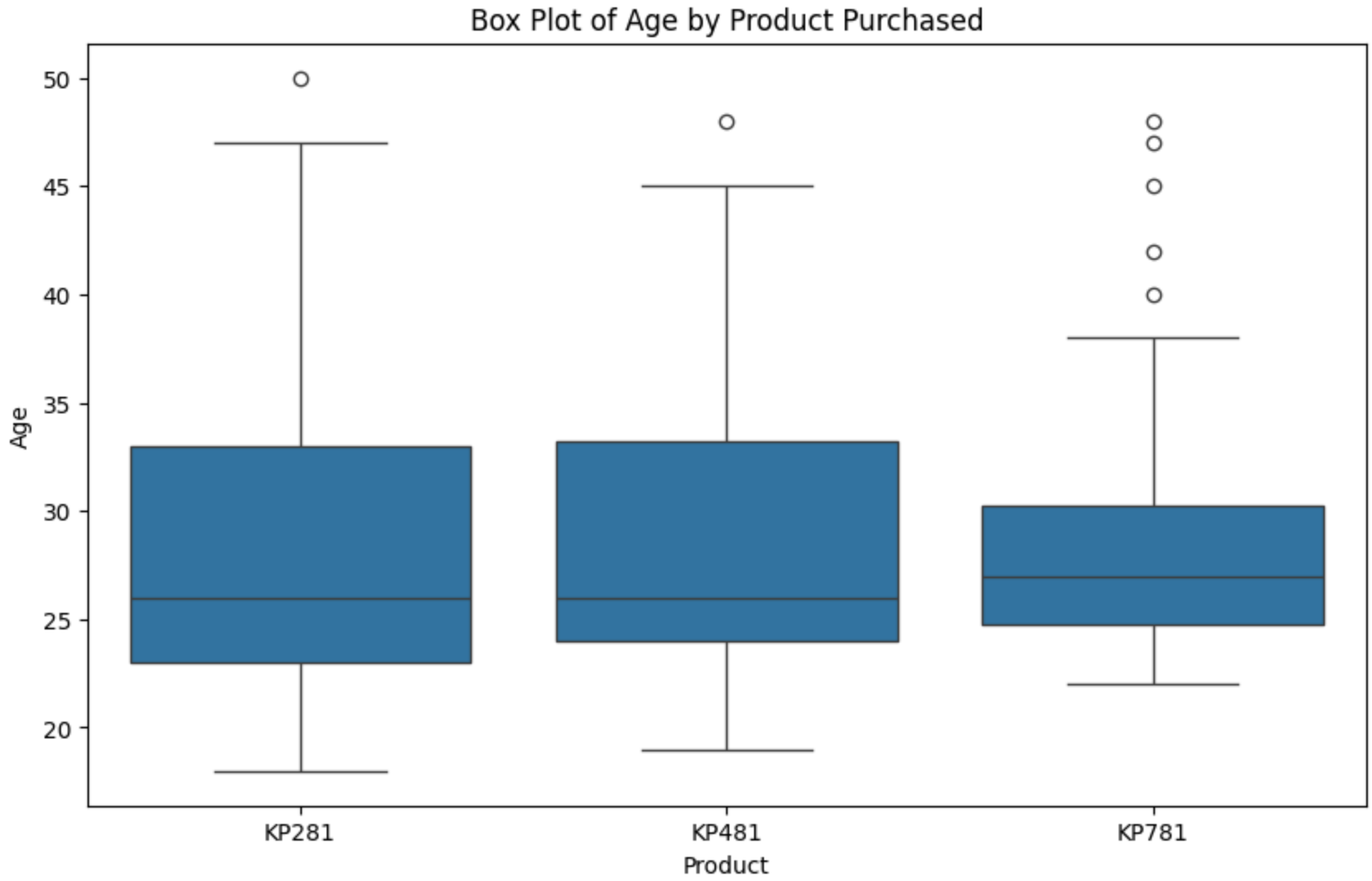
In [54]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='Product', hue='MaritalStatus')
plt.title('Count Plot of Product Purchased by Marital Status')
plt.show()
```



In [55]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='Age', hue='Product', multiple='stack')
plt.title('Histogram of Age by Product Purchased')
plt.show()
```

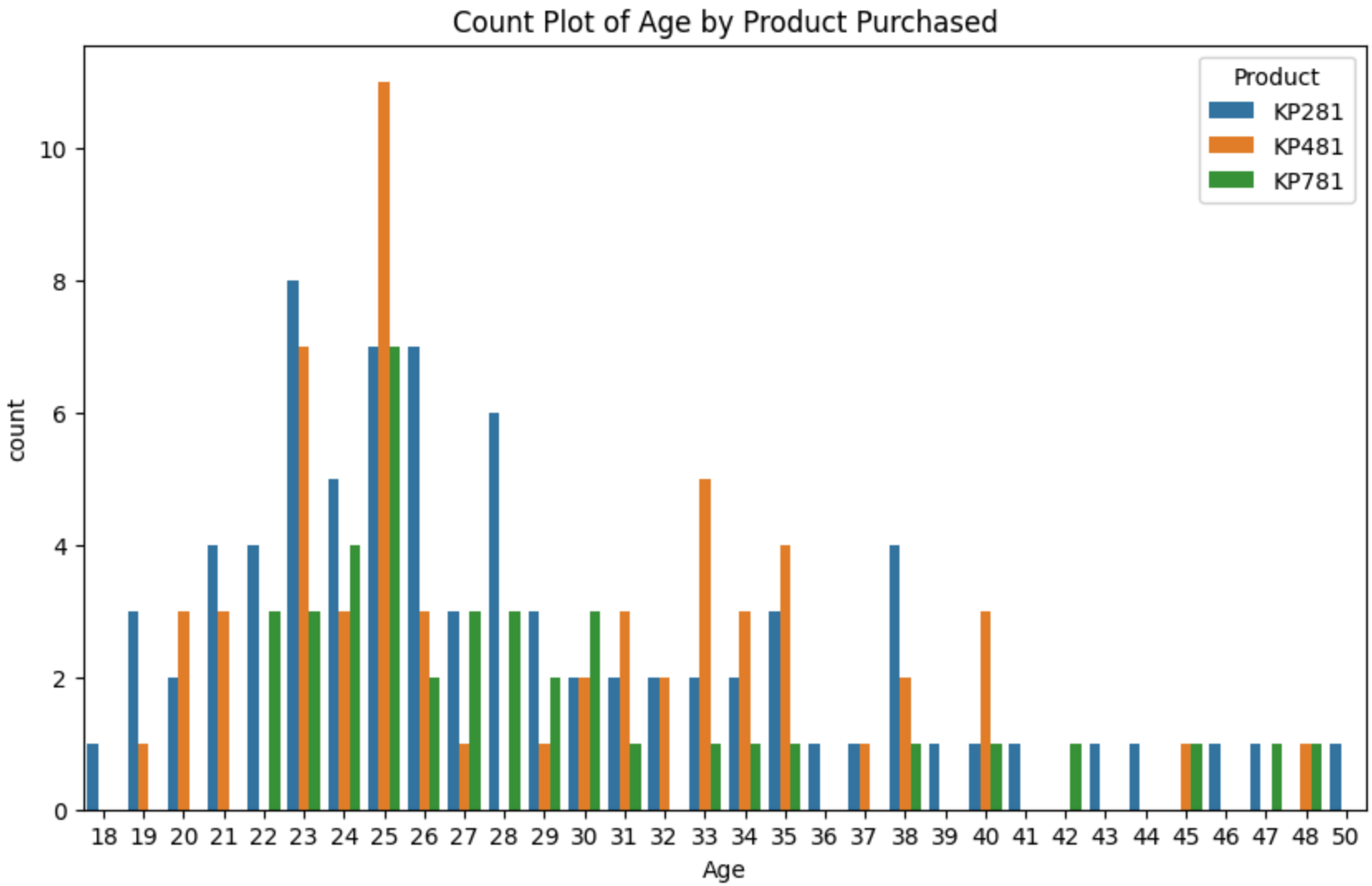


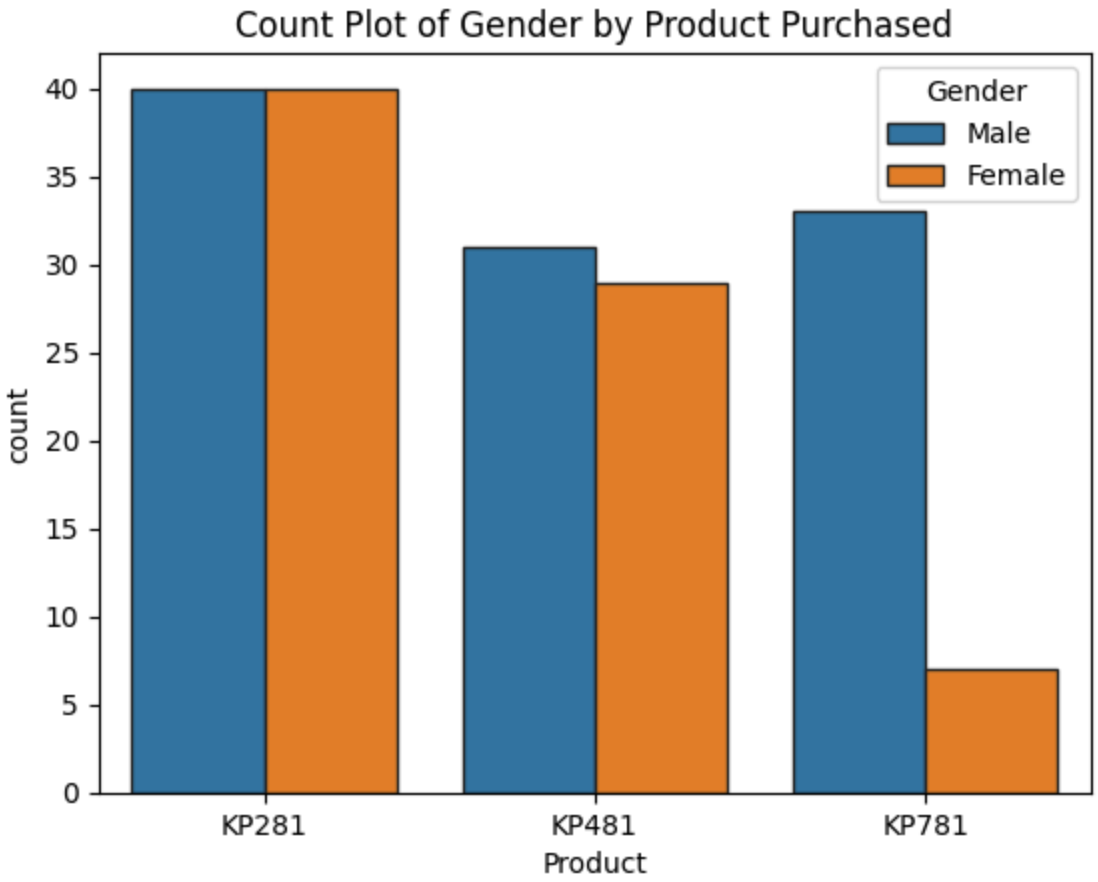
In [56]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='Product', y='Age')
plt.title('Box Plot of Age by Product Purchased')
plt.show()
```



In [57]:
```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='Age',hue='Product')
plt.title('Count Plot of Age by Product Purchased')
plt.show()

sns.countplot(data=df, x='Product', hue='Gender', edgecolor="0.15")
```

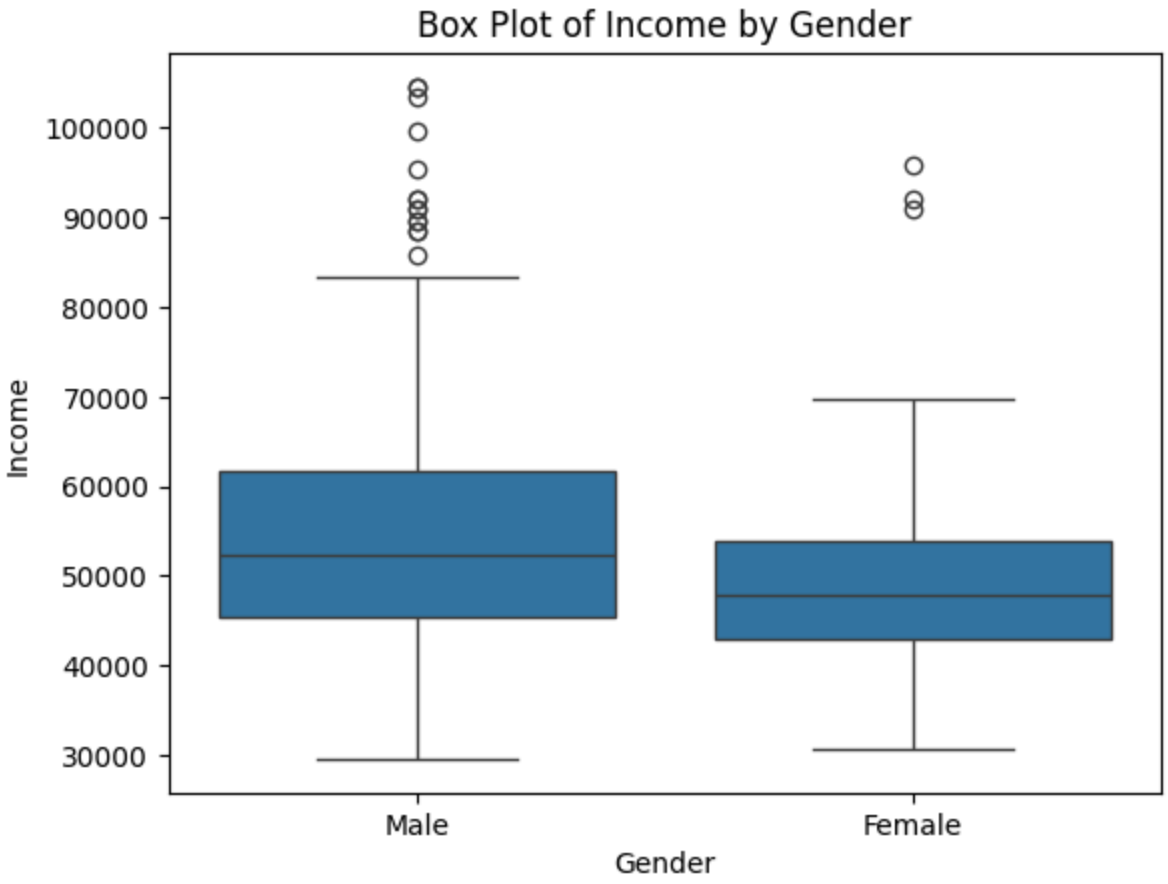
```
plt.title('Count Plot of Gender by Product Purchased')
plt.show()
```





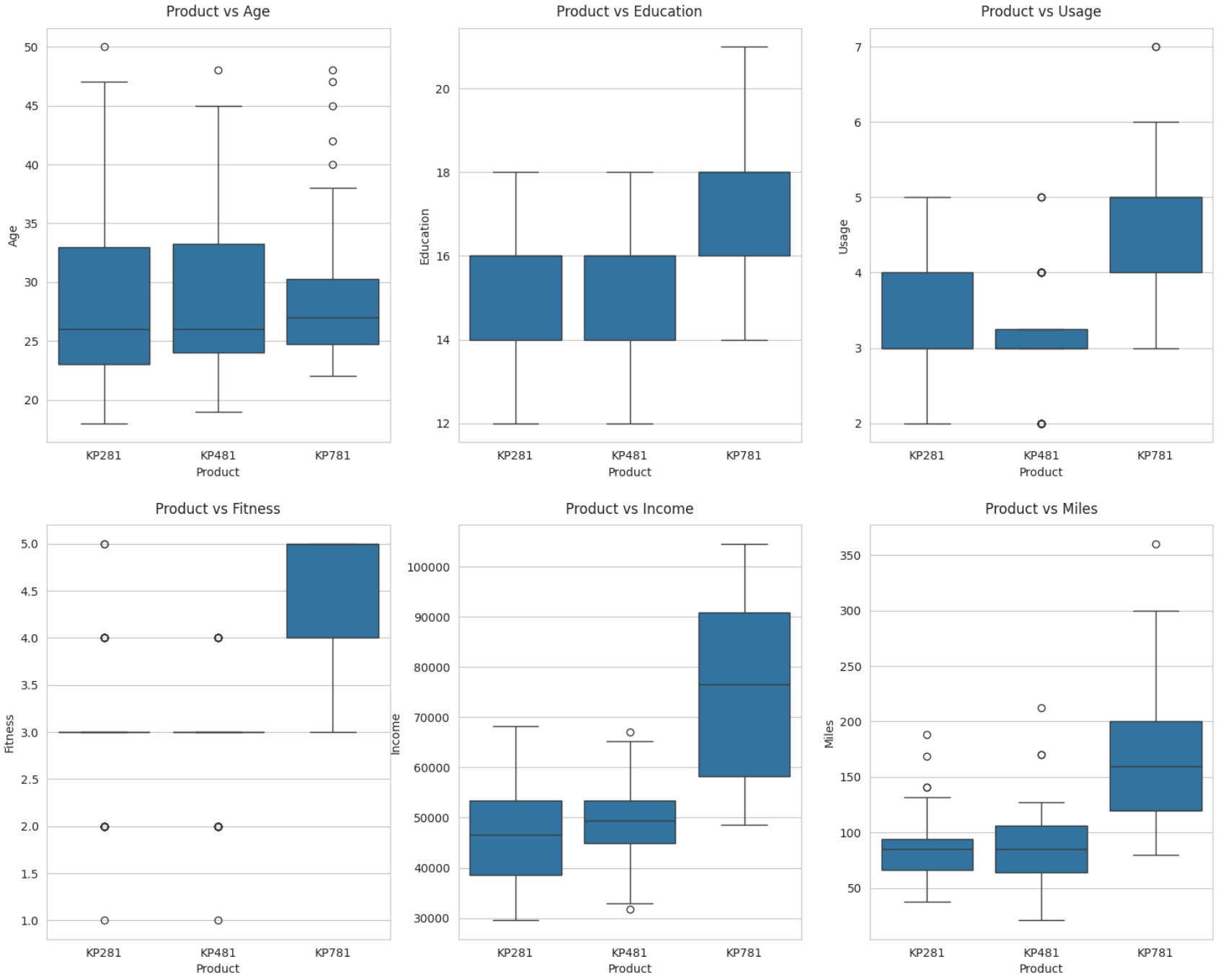
It can be seen that equal number of males and females have bought Kp281 and almost same for product KP481 -But for KP781 most male members have purchased it.

In [58]:
```
sns.boxplot(data=df,x='Gender',y='Income')
plt.title('Box Plot of Income by Gender')
plt.show()
```



Let us check the effect of features on product purchased Features are Age,Education,Usuage,Fitness,Income,Miles

In [59]:
```
attrs = ['Age','Education','Usage','Fitness','Income','Miles']
sns.set_style('whitegrid')
fig,axis = plt.subplots(nrows=2,ncols=3,figsize=(18,10))
fig.subplots_adjust(top=1.2)
count=0
for i in range(2):
  for j in range(3):
    sns.boxplot(data=df,x='Product',y=attrs[count],ax=axis[i,j])
    axis[i,j].set_title(f"Product vs {attrs[count]}", pad = 10,fontsize=12)
    count+=1
plt.show()
```


Product vs Age
Age
Product
KP281
KP481
KP781
Product vs Education
Education
Product vs Usage
Usage
Product vs Fitness
Fitness
Product vs Income
Income
Product vs Miles
Miles

Insights

Product vs Age: -->People of same age group goes for kp281 and kp481 -->where as people going for Kp781 are more between 22 to 38 Product vs Education: -->It can be seen customers who have more than 16yrs of educations tend to go for KP781 more Product vs Usauge:- --->It can be seen that customers who tend to use treadmill greater than 4times a week , are more likely to purchase KP781 product Product vs Fitness -->It can be seen more customer is fit(fitness>3) higher chances of purchasing KP781 Product vs Income --> Higher income of the customer(Income>=6000)higher than chances of customer to purchase the Kp781 product. Product vs Miles --> If the customer wants to walk/run greater than 120 miles per week . It is more likely they will buy Kp781 product

In [60]:
```
df.head()
```

Out[60]:

	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

In [61]:
```
crosstab = pd.crosstab(index=df['Product'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0    count  percentage
Product
KP281       80   44.444444
KP481       60   33.333333
KP781       40   22.222222
```

In [62]:
```
crosstab = pd.crosstab(index=df['Gender'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0   count  percentage
Gender
Female     76   42.222222
Male      104   57.777778
```

In [63]:
```
crosstab = pd.crosstab(index=df['Age'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

col_0	count	percentage
Age		
18	1	0.555556
19	4	2.222222
20	5	2.777778
21	7	3.888889
22	7	3.888889
23	18	10.000000
24	12	6.666667
25	25	13.888889
26	12	6.666667
27	7	3.888889
28	9	5.000000
29	6	3.333333
30	7	3.888889
31	6	3.333333
32	4	2.222222
33	8	4.444444
34	6	3.333333
35	8	4.444444
36	1	0.555556
37	2	1.111111
38	7	3.888889
39	1	0.555556
40	5	2.777778
41	1	0.555556
42	1	0.555556
43	1	0.555556
44	1	0.555556
45	2	1.111111
46	1	0.555556
47	2	1.111111
48	2	1.111111
50	1	0.555556

Checking for correlation between features

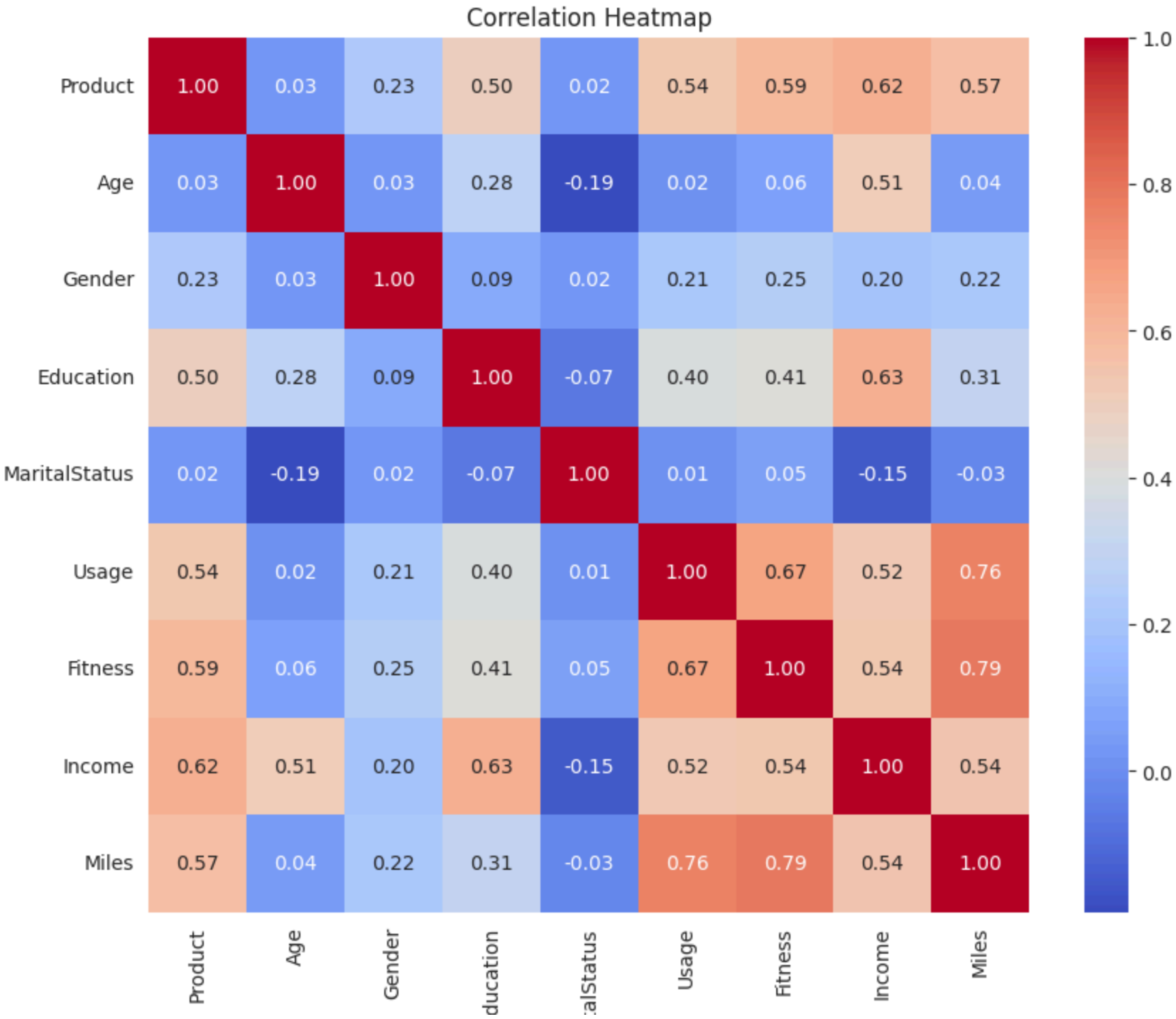
In [64]:
```
df.head()
```

Out[64]:

	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

In [65]:
```
df1 = df.copy()
df1['MaritalStatus'] = df1['MaritalStatus'].astype('category').cat.codes
df1['Gender'] = df1['Gender'].astype('category').cat.codes
df1['Product'] = df1['Product'].astype('category').cat.codes
correlation_matrix = df1.corr()
```

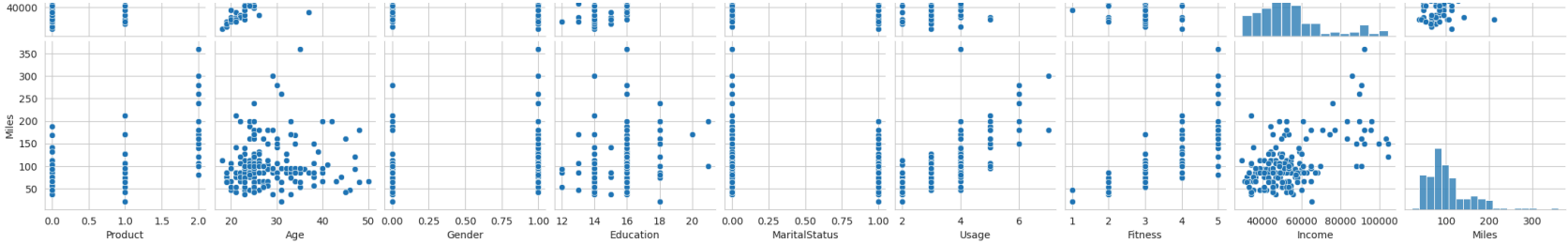
In [66]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```


Correlation Heatmap
Product 1.00 0.03 0.23 0.50 0.02 0.54 0.59 0.62 0.57
Age 0.03 1.00 0.03 0.28 -0.19 0.02 0.06 0.51 0.04
Gender 0.23 0.03 1.00 0.09 0.02 0.21 0.25 0.20 0.22
Education 0.50 0.28 0.09 1.00 -0.07 0.40 0.41 0.63 0.31
MaritalStatus 0.02 -0.19 0.02 -0.07 1.00 0.01 0.05 -0.15 -0.03
Usage 0.54 0.02 0.21 0.40 0.01 1.00 0.67 0.52 0.76
Fitness 0.59 0.06 0.25 0.41 0.05 0.67 1.00 0.54 0.79
Income 0.62 0.51 0.20 0.63 -0.15 0.52 0.54 1.00 0.54
Miles 0.57 0.04 0.22 0.31 -0.03 0.76 0.79 0.54 1.00
Product
Age
Gender
ducation
alStatus
Usage
Fitness
Income
Miles
1.0
0.8
0.6
0.4
0.2
0.0

In [67]:
```
plt.figure(figsize=(10,8))
sns.pairplot(df1)
plt.show()
```

```
<Figure size 1000x800 with 0 Axes>
```


Product
Age
Gender
Education
MaritalStatus
Usage
Fitness
Income



**Customer Profiling **

In [68]:
```
df.head()
```

Out[68]:

	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

In [69]:
```
df_kp1 = df[df['Product']=='KP281']
df_kp2 = df[df['Product']=='KP481']
df_kp3 = df[df['Product']=='KP781']
```

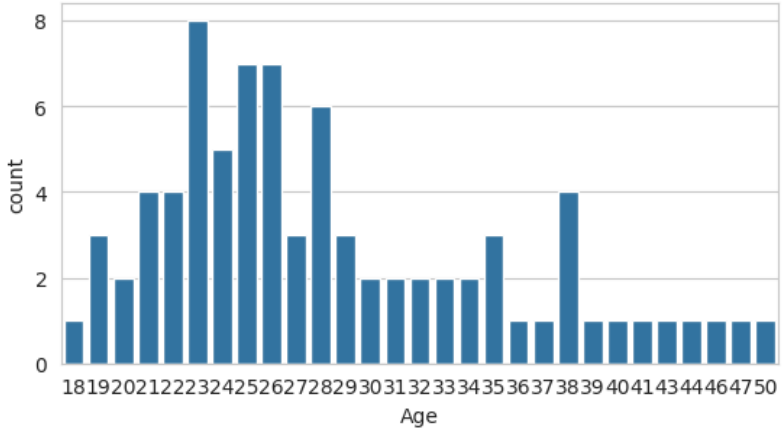
For Product KP1

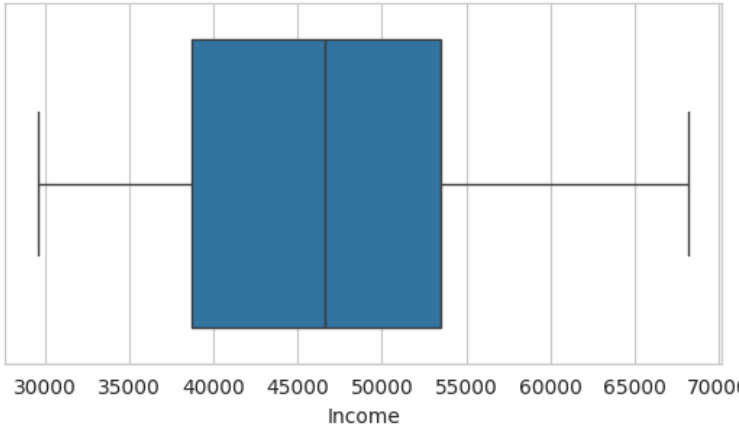
In [70]:
```
df_kp1.head()
```

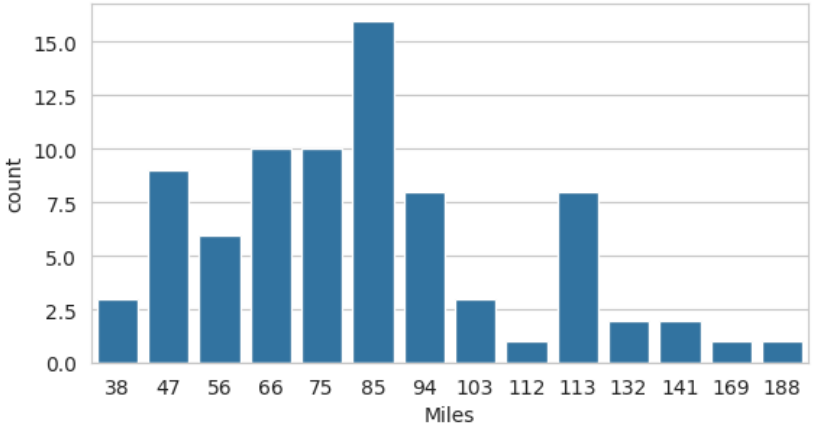
Out[70]:

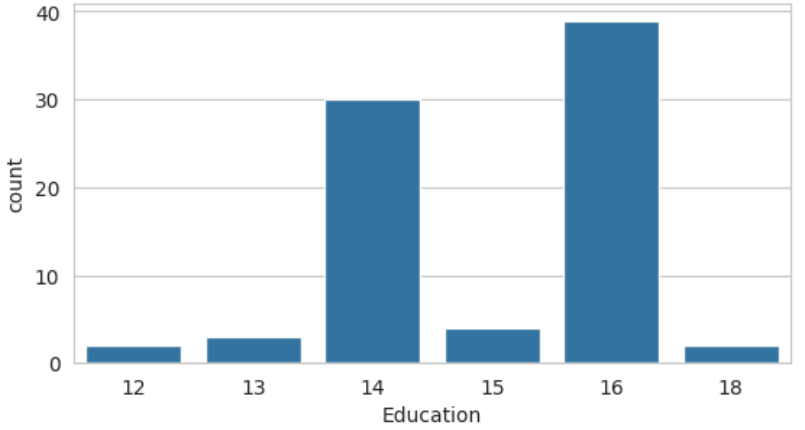
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

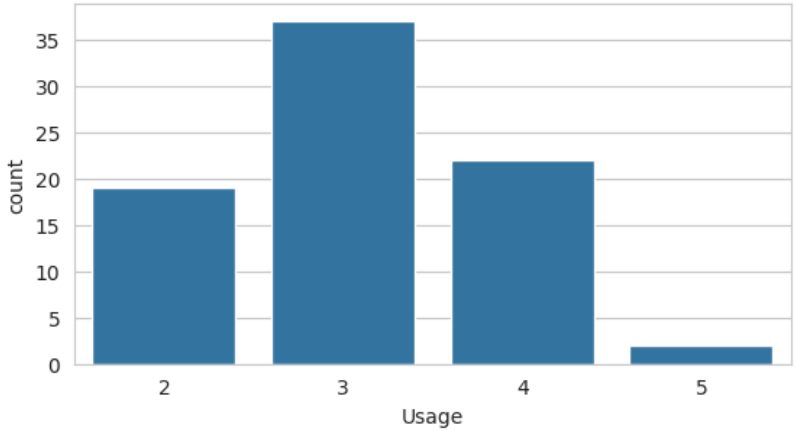
In [71]:
```
fig,axis = plt.subplots(nrows=3,ncols=2,figsize=(12,10))
fig.tight_layout(pad=3)
sns.countplot(data=df_kp1,x='Age',ax=axis[0,0])
sns.boxplot(data=df_kp1,x='Income',ax=axis[0,1])
sns.countplot(data=df_kp1,x='Miles',ax=axis[1,0])
sns.countplot(data=df_kp1,x='Education',ax=axis[1,1])
sns.countplot(data=df_kp1,x='Usage',ax=axis[2,0])
sns.countplot(data=df_kp1,x='Fitness',ax=axis[2,1])
plt.show()
```

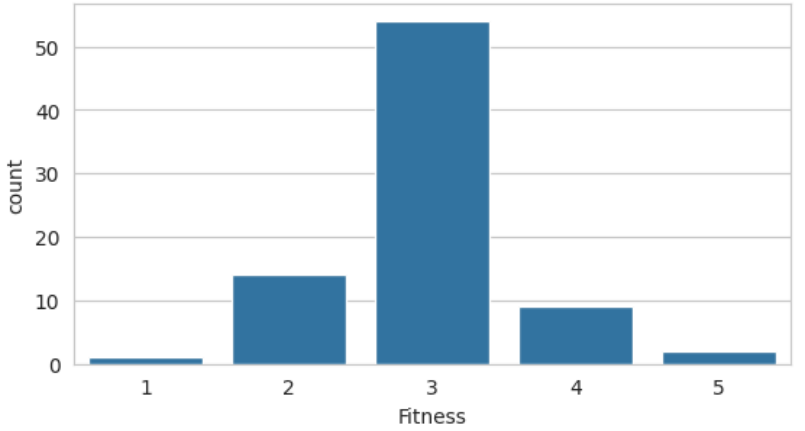

count
Age
18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 43 44 46 47 50


Income
30000 35000 40000 45000 50000 55000 60000 65000 70000


count
Miles
38 47 56 66 75 85 94 103 112 113 132 141 169 188


count
Education
12 13 14 15 16 18


count
Usage
2 3 4 5


count
Fitness
1 2 3 4 5

Insights:- MAximum people using KP281 are of 23,25,26.Hence in 20s .But we can also see the usage is widely spread in all age

In [71]:

In [72]:
```
crosstab = pd.crosstab(index=df_kp1['Gender'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0   count  percentage
Gender
Female     40        50.0
Male       40        50.0
```

In [73]:
```
crosstab = pd.crosstab(index=df_kp1['Usage'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0  count  percentage
Usage
2         19       23.75
3         37       46.25
4         22       27.50
5          2        2.50
```

Insights:- -->Maximum usage of people using KP281 is of 3 times a week. -->Maximum customers using this product has Fitness 3. -->Maximum customers using this product has income range of 40k to 54k -->Maximum customers using this product walks 95 miles. -->Customers buying this has equal ratio 50%. -->Customers buying this are mostly of age 25.

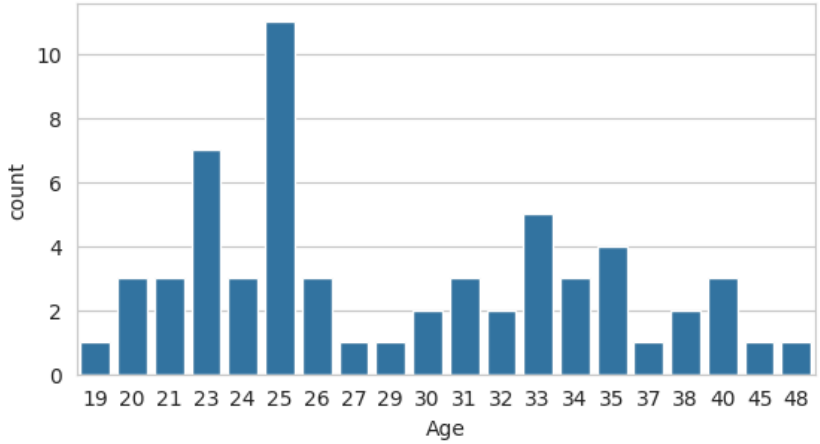
Product KP481

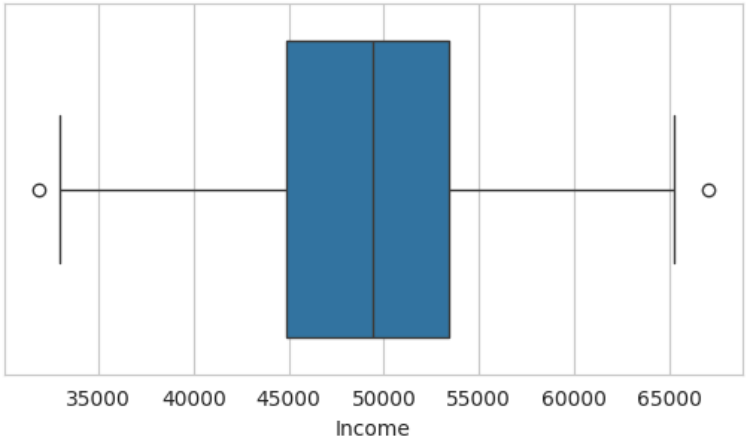
In [74]:
```
df_kp2.head()
```

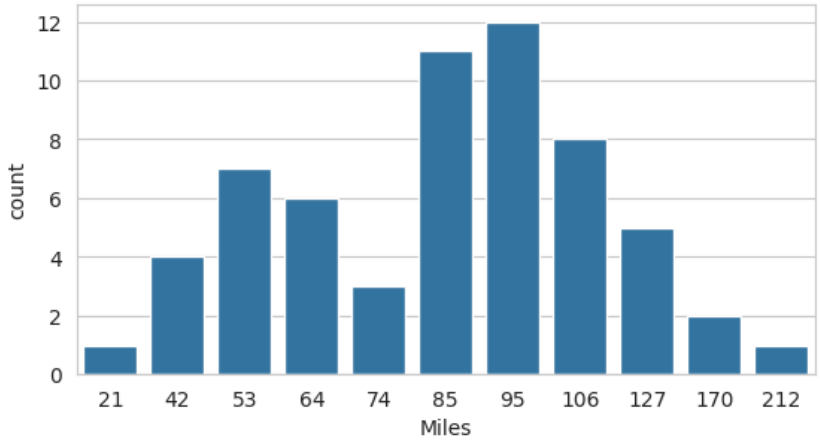
Out[74]:

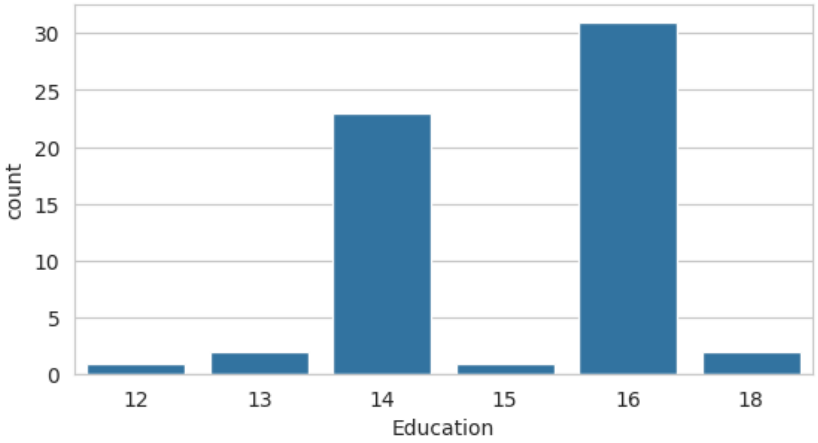
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
80	KP481	19	Male	14	Single	3	3	31836	64
81	KP481	20	Male	14	Single	2	3	32973	53
82	KP481	20	Female	14	Partnered	3	3	34110	106
83	KP481	20	Male	14	Single	3	3	38658	95
84	KP481	21	Female	14	Partnered	5	4	34110	212

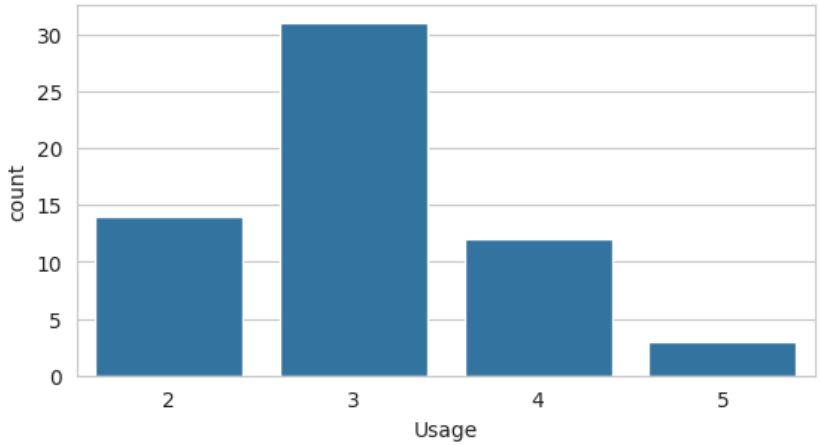
In [75]:
```
fig,axis = plt.subplots(nrows=3,ncols=2,figsize=(12,10))
fig.tight_layout(pad=3)
sns.countplot(data=df_kp2,x='Age',ax=axis[0,0])
sns.boxplot(data=df_kp2,x='Income',ax=axis[0,1])
sns.countplot(data=df_kp2,x='Miles',ax=axis[1,0])
sns.countplot(data=df_kp2,x='Education',ax=axis[1,1])
sns.countplot(data=df_kp2,x='Usage',ax=axis[2,0])
sns.countplot(data=df_kp2,x='Fitness',ax=axis[2,1])
plt.show()
```

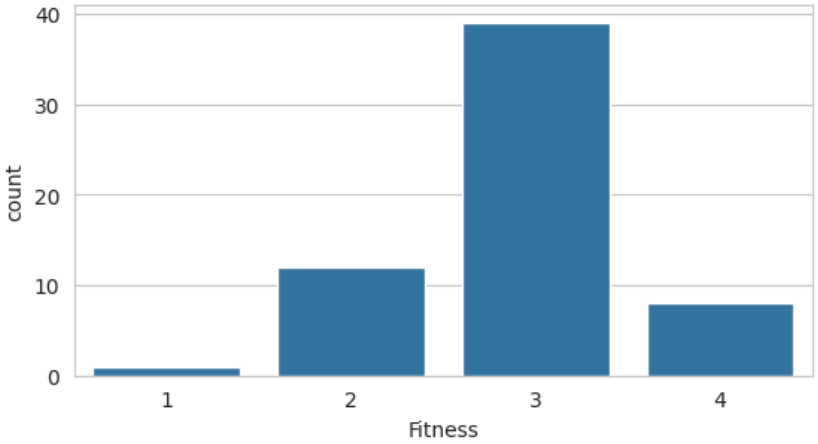

count
Age
19 20 21 23 24 25 26 27 29 30 31 32 33 34 35 37 38 40 45 48


Income
35000 40000 45000 50000 55000 60000 65000


count
Miles
21 42 53 64 74 85 95 106 127 170 212


count
Education
12 13 14 15 16 18


count
Usage
2 3 4 5


count
Fitness
1 2 3 4

In [76]:
```
crosstab = pd.crosstab(index=df_kp2['Gender'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0   count  percentage
Gender
Female     29   48.333333
Male       31   51.666667
```

Insights:-

->Maximum usage is of 3 weeks for this KP481 also. ->Customers prefering this product has fitness levels 3. ->Maximum education is 16 ->Maximum customers buying this product are of age 25 ->Income range of maximum people buying this product is 45000 to 54000 ->Maximum miles walked by customers using this product is 95. -->It can be observed that customers buying this product has 31%male and 29%Female.

PRoduct KP781

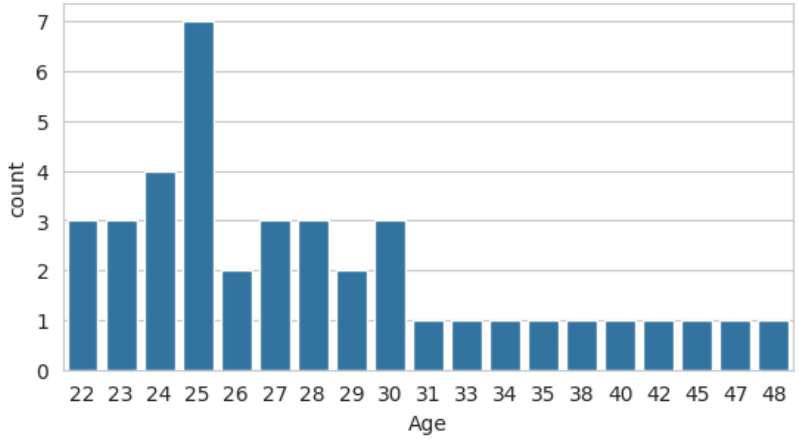
In [77]:
```
df_kp3.head()
```

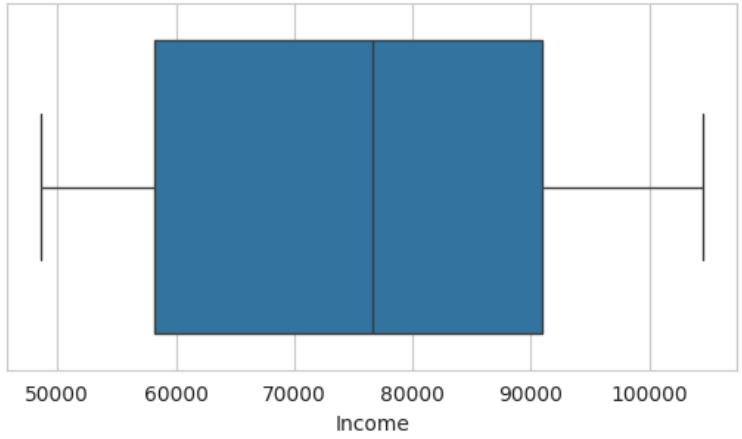
Out[77]:

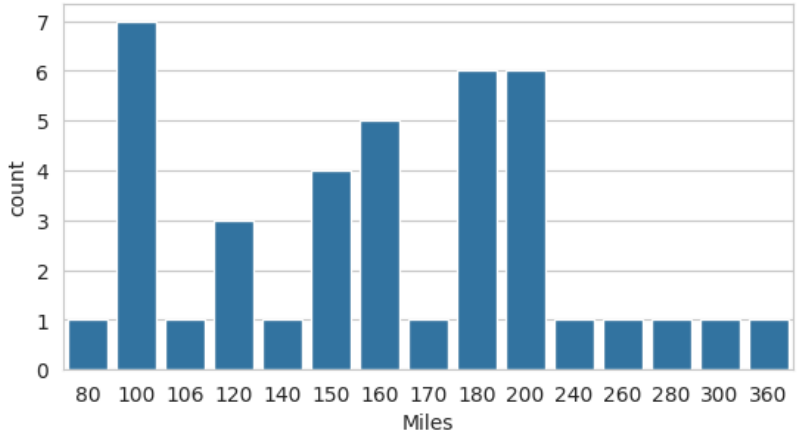
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
140	KP781	22	Male	14	Single	4	3	48658	106
141	KP781	22	Male	16	Single	3	5	54781	120
142	KP781	22	Male	18	Single	4	5	48556	200
143	KP781	23	Male	16	Single	4	5	58516	140
144	KP781	23	Female	18	Single	5	4	53536	100

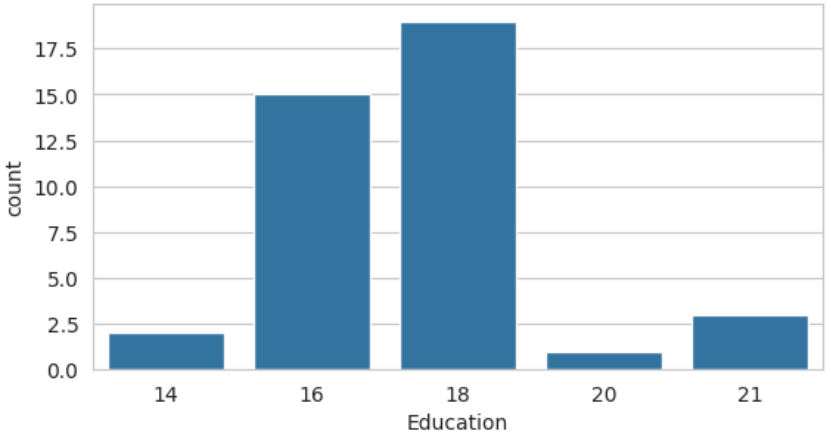
In [78]:
```
fig,axis = plt.subplots(nrows=3,ncols=2,figsize=(12,10))
fig.tight_layout(pad=3)
```

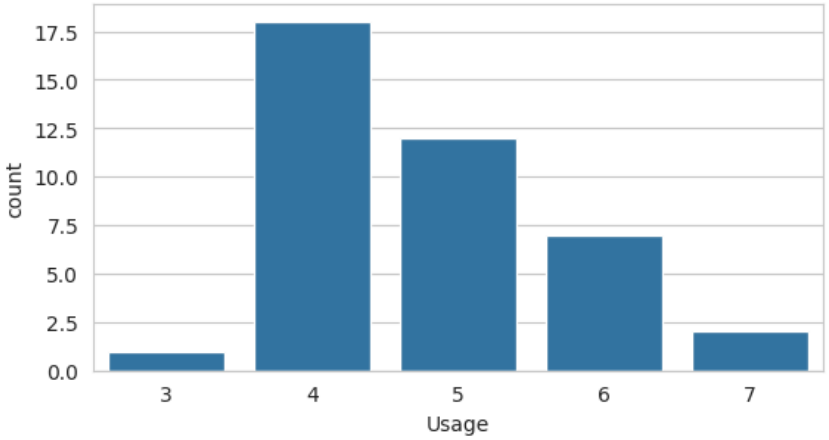
```
sns.countplot(data=df_kp3,x='Age',ax=axis[0,0])
sns.boxplot(data=df_kp3,x='Income',ax=axis[0,1])
sns.countplot(data=df_kp3,x='Miles',ax=axis[1,0])
sns.countplot(data=df_kp3,x='Education',ax=axis[1,1])
sns.countplot(data=df_kp3,x='Usage',ax=axis[2,0])
sns.countplot(data=df_kp3,x='Fitness',ax=axis[2,1])
plt.show()
```

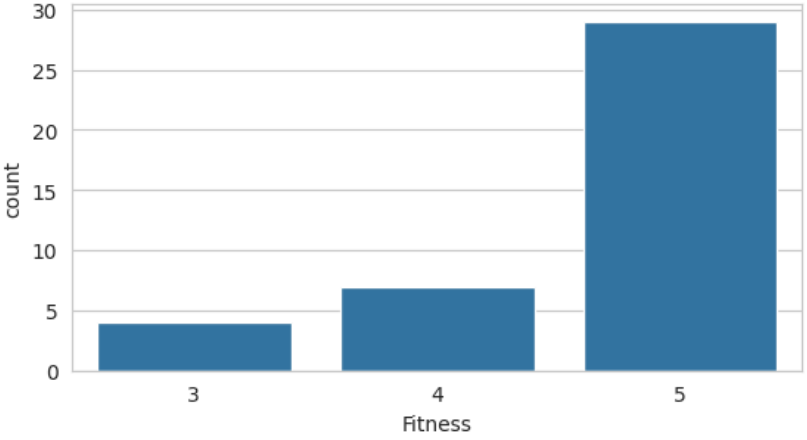

count
Age
22 23 24 25 26 27 28 29 30 31 33 34 35 38 40 42 45 47 48


Income
50000 60000 70000 80000 90000 100000


count
Miles
80 100 106 120 140 150 160 170 180 200 240 260 280 300 360


count
Education
14 16 18 20 21


count
Usage
3 4 5 6 7


count
Fitness
3 4 5

In [79]:
```
crosstab = pd.crosstab(index=df_kp3['Gender'], columns='count')

# Calculating the percentage of each product purchased
crosstab['percentage'] = (crosstab['count'] / crosstab['count'].sum()) * 100

# Display the crosstab with percentages
print(crosstab)
```

```
col_0   count  percentage
Gender
Female      7        17.5
Male       33        82.5
```

Insights:- ->It can be observed that income range of customers here is more of 60000 to 90000 -->It can be observed that maximum usage of the customer using this product is 4 times a week. --->It can be observed that most customers has fitness 5 --->It can be observed that customers using this product walks 100 miles mostly -->It can be observed that customer using this product has education more than 16 --->It can be seen 82.5% males and 17.5%Females purchased it.

Computation and marginal probability

In [80]:
```
df['Product'].value_counts(normalize=True)
```

Out[80]:
```
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: proportion, dtype: float64
```

In [81]:
```
def prob_given_gender(Gender,print_marginal=False):
  if Gender !='Female' and Gender != 'Male':
    raise ValueError("Gender must be 'Female' or 'Male'")
  df_res = pd.crosstab(index=df['Gender'],columns=[df['Product']])
  p_781 = df_res['KP781'][Gender]/df_res.loc[Gender].sum()
  p_481 = df_res['KP481'][Gender]/df_res.loc[Gender].sum()
  p_281 = df_res['KP281'][Gender]/df_res.loc[Gender].sum()

  if print_marginal:
    print(f"p(MALE):{df_res.loc['Male'].sum()/len(df):.2f}")
    print(f"p(FEMALE):{df_res.loc['Female'].sum()/len(df):.2f}")
```

```
  print(f"p(KP781/{Gender}):{p_781:.2f}")
  print(f"p(KP481/{Gender}):{p_481:.2f}")
  print(f"p(KP281/{Gender}):{p_281:.2f}")

prob_given_gender('Male',True)
prob_given_gender("Female")
```

```
p(MALE):0.58
p(FEMALE):0.42
p(KP781/Male):0.32
p(KP481/Male):0.30
p(KP281/Male):0.38
p(KP781/Female):0.09
p(KP481/Female):0.38
p(KP281/Female):0.53
```

**Observations **

1. Dataset has 180rows and 9 columns
2. Dataset has no missing values 3.minimum age of user is 18 and maximum age is 50 4.75% of people have age less than 33 5.minimum number of miles customer expects to walk is 21.000 and maximum is 360.000 6.Number of unique products are 3 and they are 'KP281','Kp481','Kp781' 7.Income and miles have more number of outlier values .Whereas Education,Usuage and fitness have less outlier values. 8.It is seen from observation that product name KP281 is more opted by people.So we can say that there is more demand for entry level trademill 9.We can also observe that Male members occupies higher ratio compared to other group 10.More partnered members are present. 11.In Numerical terms if we say 44.4% people go for KP281,33.3% people go for KP481,22.22% people go for KP781 There are 57% male members and 42.3% are female members out of which out of which 59.44% are partnered and 40.5% are single. 12.It can be seen that equal number of males and females have bought Kp281 and almost same for product KP481 -But for KP781 most male members have purchased it.13.Most partnered members are purchasing products. 13.Probability for male customers going for KP781 is 31.4% 14.There is a positive correlation between age and income.

- There is a negative correlation between age and usage.
- There is a positive correlation between income and miles.
- There is a positive correlation between education and fitness.
- There is a negative correlation between usage and fitness.

Recommendations

- Spread awarness among users about other products and benefits
- Spread Fitness related awarness in females to increase their ratio of contribution in buying. -Give offers on fitness products to attract more users.