Aero Fit Thread Mill Analysis

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.

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.

In [1]:

```
import pandas as pd
import numpy as np
```

In [2]:

```
df = pd.read_csv('aerofit_treadmill.csv')
```

In [3]:

```
df.head(3)
```

Out[3]:

	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

Dataset

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior three months. The dataset has the following features:

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
```

There are no null values in the data , as we can see in above result.

Summary & Descriptions of columns

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

Product Portfolio:

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

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

> The KP781 treadmill is having advanced features that sell for $2,500.

In [5]:

```
# Lets have a look on shape & structure of our data

shp = df.shape

f'Our data contains {shp[0]} records and {shp[1]} columns'
```

Out[5]:

```
'Our data contains 180 records and 9 columns'
```

Descriptive Stats of our Numerical data

In [6]:

```
df.describe(exclude='O')
```

Out[6]:

	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 [7]:

```
df.describe(include='O')
```

Out[7]:

	Product	Gender	MaritalStatus
count	180	180	180
unique	3	2	2
top	KP281	Male	Partnered
freq	80	104	107

In [8]:

```
# Used value-counts method to get unique values & their counts
# i.e. used for categorical variables

def get_proportion(df, col):
    k = df.groupby([col]).size().reset_index().rename({0: 'count'}, axis=1)
    k['proportion'] = round(k['count']/k['count'].sum(), 2)*100
    return k
```

In [9]:

```
get_proportion(df, 'Product')
```

Out[9]:

	Product	count	proportion
0	KP281	80	44.0
1	KP481	60	33.0
2	KP781	40	22.0

In [10]:

```
get_proportion(df, 'Gender')
```

Out[10]:

	Gender	count	proportion
0	Female	76	42.0
1	Male	104	58.0

In [11]:

```
get_proportion(df, 'MaritalStatus')
```

Out[11]:

	MaritalStatus	count	proportion
0	Partnered	107	59.0
1	Single	73	41.0

Insights from Categorical data

Product Column

1. In our data different types of thread mill machines : KP281, KP481, KP781
2. From value counts above we can infer that , KP281 is mostly used with 44% proportion out of total.

Gender

- And we can also see that we have majority of our data is recorded for men (58 %) and 42% of women.

MaritalStatus

- 60 % of data is filled with parterned members & rest 40% of single.

Numerical Column data

Age

1. Minimum age of a person is 18 & maximum is 50.
2. Average age in our recorded data is around 28 with std of 7.

education

- The average education of customers is 15 years, with a range of 12 to 21 years of education.

income

- The average household income of customers is about 53,719USD annually, ranging from as low as 29k to 103k.

fitness

- The average self-rated fitness of customers is 3.3 (on the scale of 1-5), with a range of 1-5.

usage

- On average, customers said they would use the treadmill 3 times a week, with some going as low 2 times weekly to as high as 7 times weekly.

miles

- The average miles expected to be run by the customers weekly is 103 miles, ranging from 23 miles to 360 miles.

In [44]:

```
#overall description of data
k = df[['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
        'Fitness', 'Income', 'Miles']]
pd.pivot_table(k,index=['Product','Gender'],columns=['MaritalStatus'])
```

Out[44]:

		Age		Education		Fitness		Incom
	MaritalStatus	Partnered	Single	Partnered	Single	Partnered	Single	Partne
Product	Gender							
KP281	Female	28.333333	28.692308	14.888889	15.538462	2.851852	2.923077	46153.
	Male	31.380952	25.631579	15.428571	14.473684	2.857143	3.263158	50028.
KP481	Female	30.000000	28.142857	15.200000	15.214286	2.933333	2.785714	49724.
	Male	30.380952	25.200000	15.285714	14.500000	2.904762	3.000000	49378.
KP781	Female	29.000000	24.333333	17.500000	18.333333	5.000000	4.000000	84972.
	Male	30.000000	28.928571	17.421053	16.928571	4.631579	4.642857	81431.

Uni-variate Analysis

In [12]:

```
import matplotlib.pyplot as plt
import seaborn as sns
```

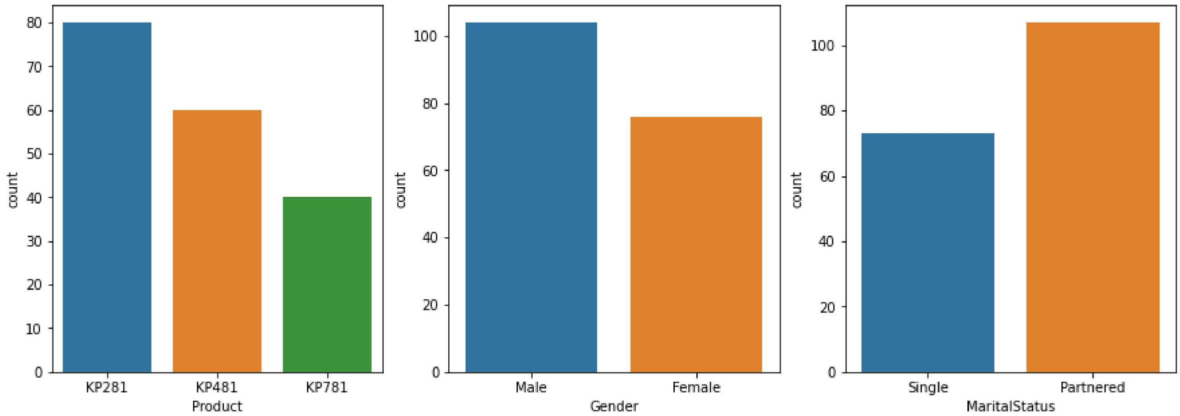
In [13]:

```
fig, axis = plt.subplots(1,3, figsize=(15, 5))

sns.countplot(x='Product', data=df, ax=axis[0])
sns.countplot(x='Gender', data=df, ax=axis[1])
sns.countplot(x='MaritalStatus', data=df, ax=axis[2])
```

Out[13]:

```
<AxesSubplot:xlabel='MaritalStatus', ylabel='count'>
```



Box-plot for Outliers Detection

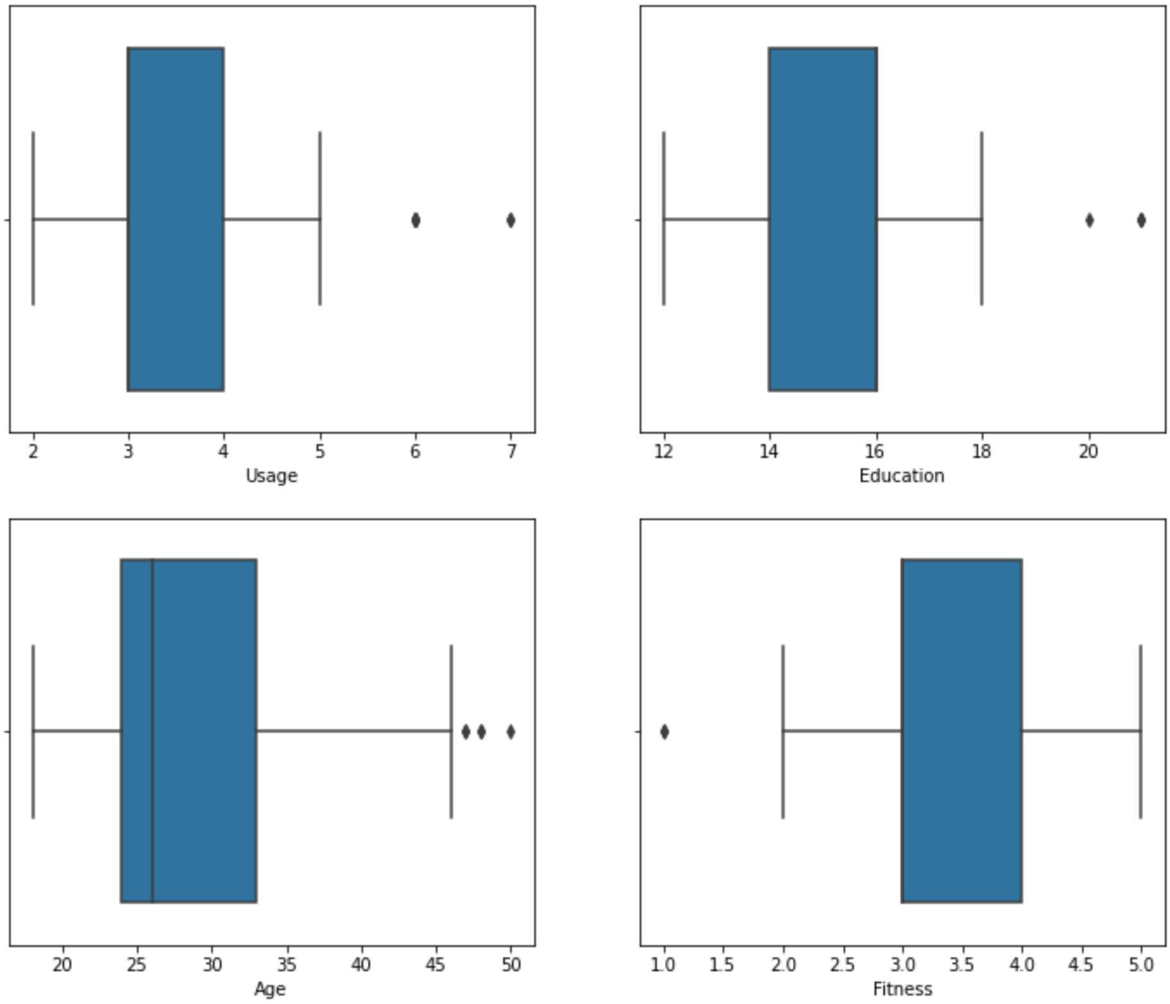
In [14]:

```
fig, axis = plt.subplots(2,2, figsize=(12, 10))

sns.boxplot(data=df, x="Usage", ax=axis[0,0])
sns.boxplot(data=df, x="Education", ax=axis[0,1])
sns.boxplot(data=df, x="Age", orient='h', ax=axis[1,0])
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
```

Out[14]:

```
<AxesSubplot:xlabel='Fitness'>
```



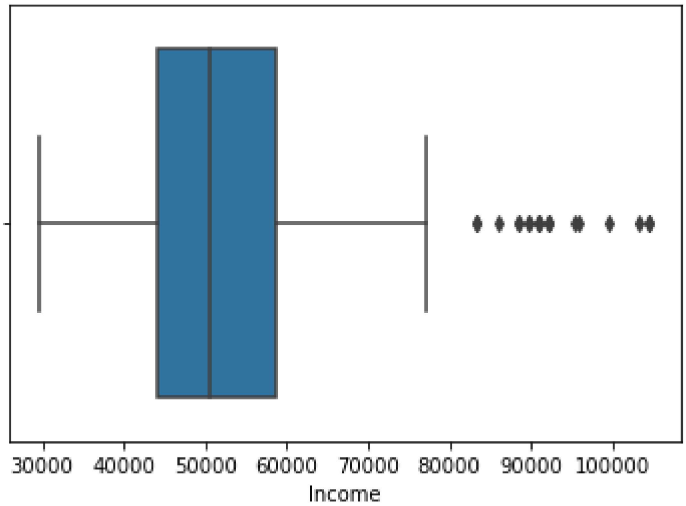
As we can see from above box plots , there are some minor amount of records which can be considered under outliers section.

In [15]:

```
sns.boxplot(data=df, x="Income", orient='h')
```

Out[15]:

```
<AxesSubplot:xlabel='Income'>
```



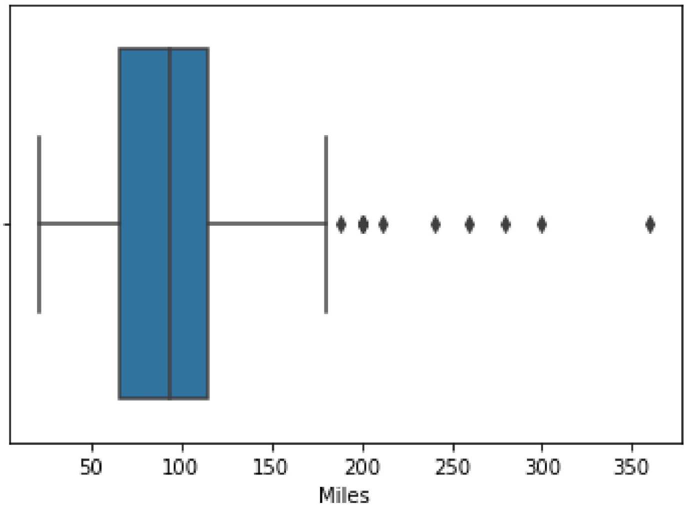
There are customers that earn more than approx. 77K, which are featured outliers. These are likely the customers purchasing the Kp781 model. Most of the customers are in the 40K-50K range with a right-skewed distribution for income.

In [16]:

```
sns.boxplot(data=df, x="Miles", orient='h')
```

Out[16]:

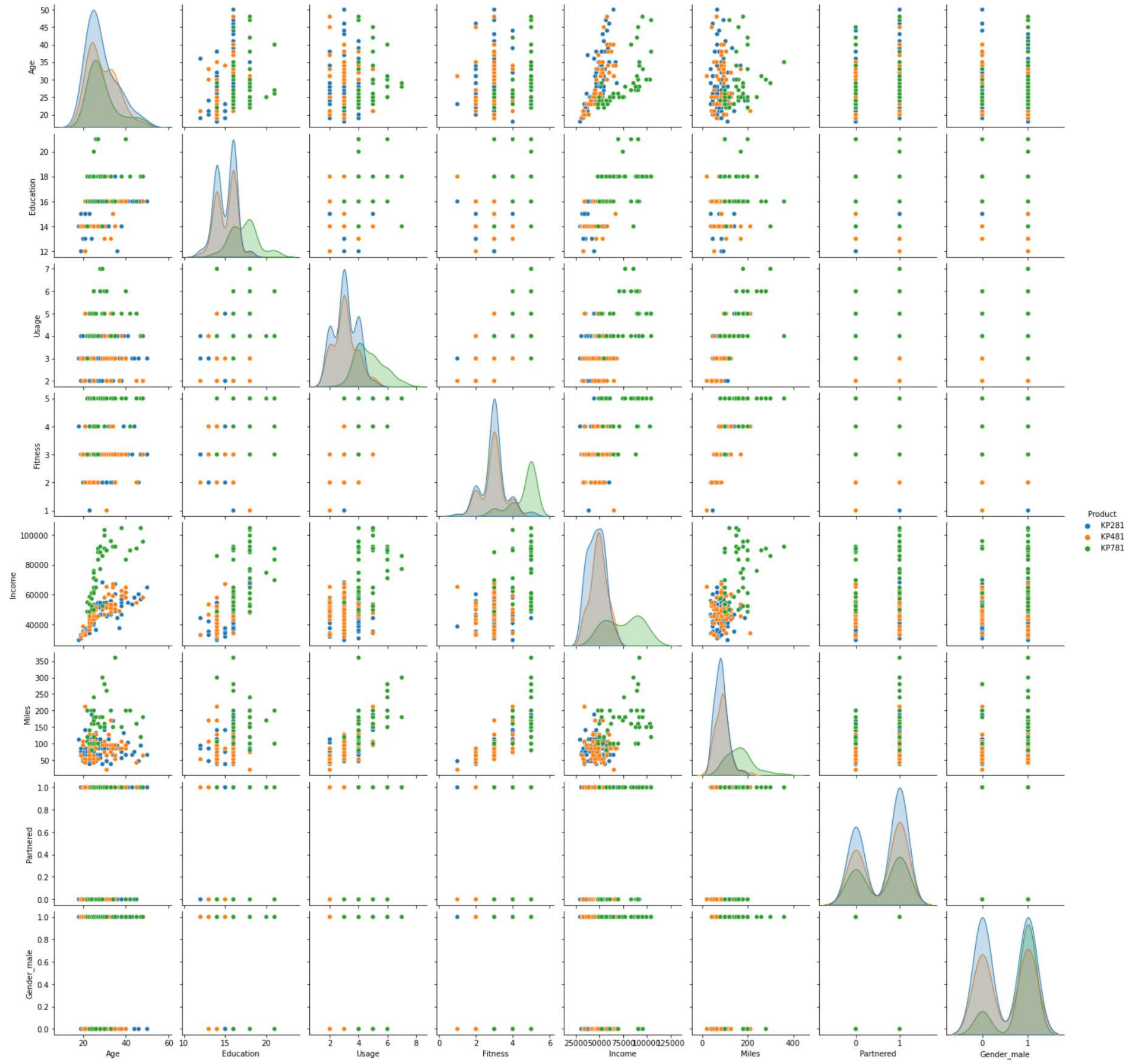
<AxesSubplot:xlabel='Miles'>



Here we can see there are some signoficant amount of outliers and also from describe we have noticed that std is also very high.

In [37]:

```
sns.pairplot(df, hue = 'Product');
```



- Most consumers of any treadmill type fall in the same age ranges.

Histogram Plot

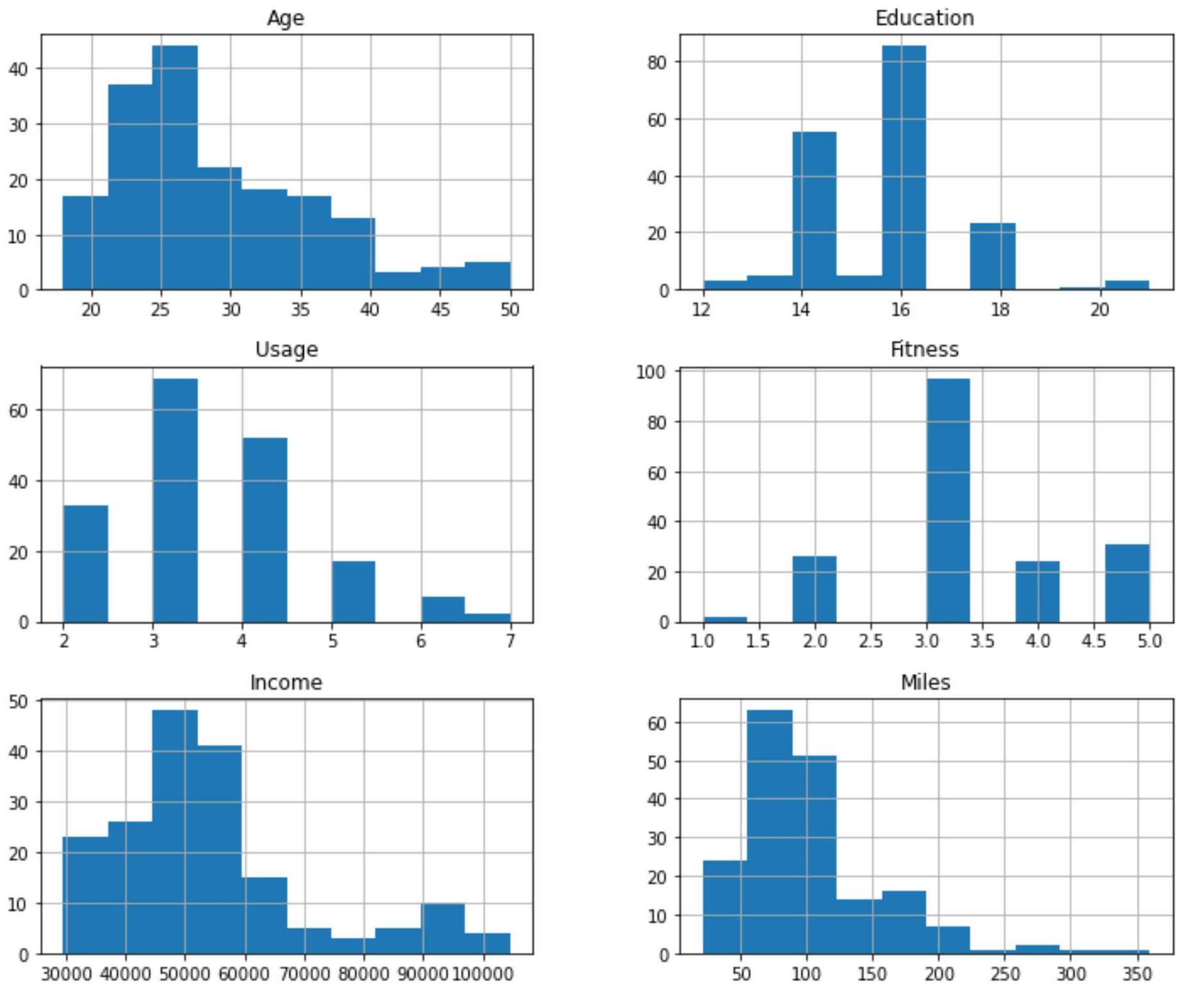
Plotting histogram of all numerical veriables , to get info regarding spread of data

In [17]:

```
df.hist(figsize=(12,10))
```

Out[17]:

```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Education'}>],
       [<AxesSubplot:title={'center':'Usage'}>,
        <AxesSubplot:title={'center':'Fitness'}>],
       [<AxesSubplot:title={'center':'Income'}>,
        <AxesSubplot:title={'center':'Miles'}>]], dtype=object)
```



Age, Usage, Income, and Miles have right-skewed data.

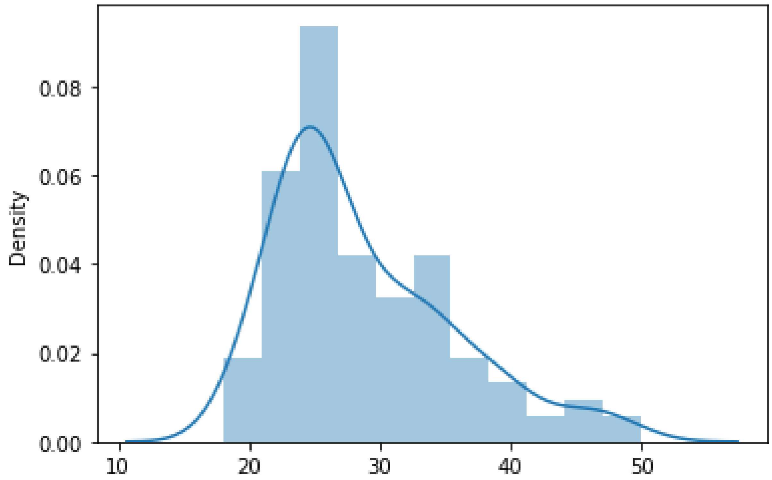
In [18]:

```
sns.distplot(df[['Age']])
```

```
C:\Users\DheerajPranav\anaconda3\lib\site-packages\seaborn\distributions.py:
2619: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a figur
e-level function with similar flexibility) or `histplot` (an axes-level func
tion for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[18]:

```
<AxesSubplot:ylabel='Density'>
```



Bi-Variate Analysis

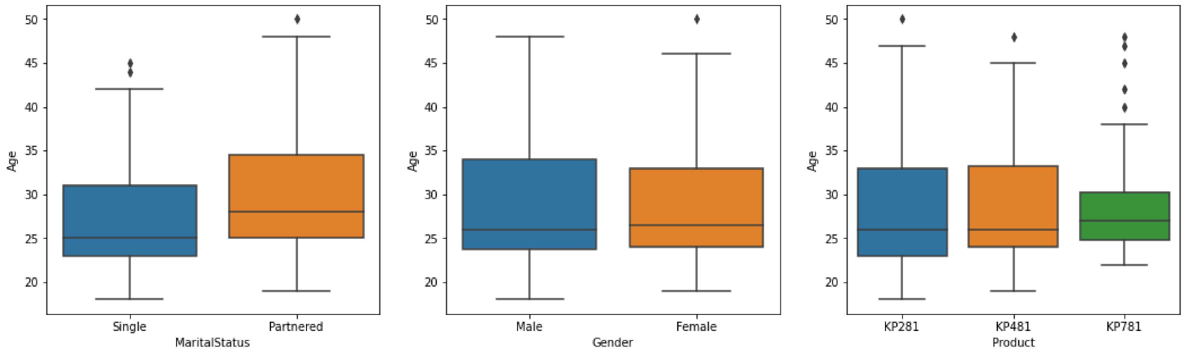
In [19]:

```
fig, axis = plt.subplots(1,3, figsize=(18, 5))

sns.boxplot(data=df, x="MaritalStatus", y="Age", ax=axis[0])
sns.boxplot(data=df, x="Gender", y="Age", ax=axis[1])
sns.boxplot(data=df, x="Product", y="Age", ax=axis[2])
```

Out[19]:

```
<AxesSubplot:xlabel='Product', ylabel='Age'>
```



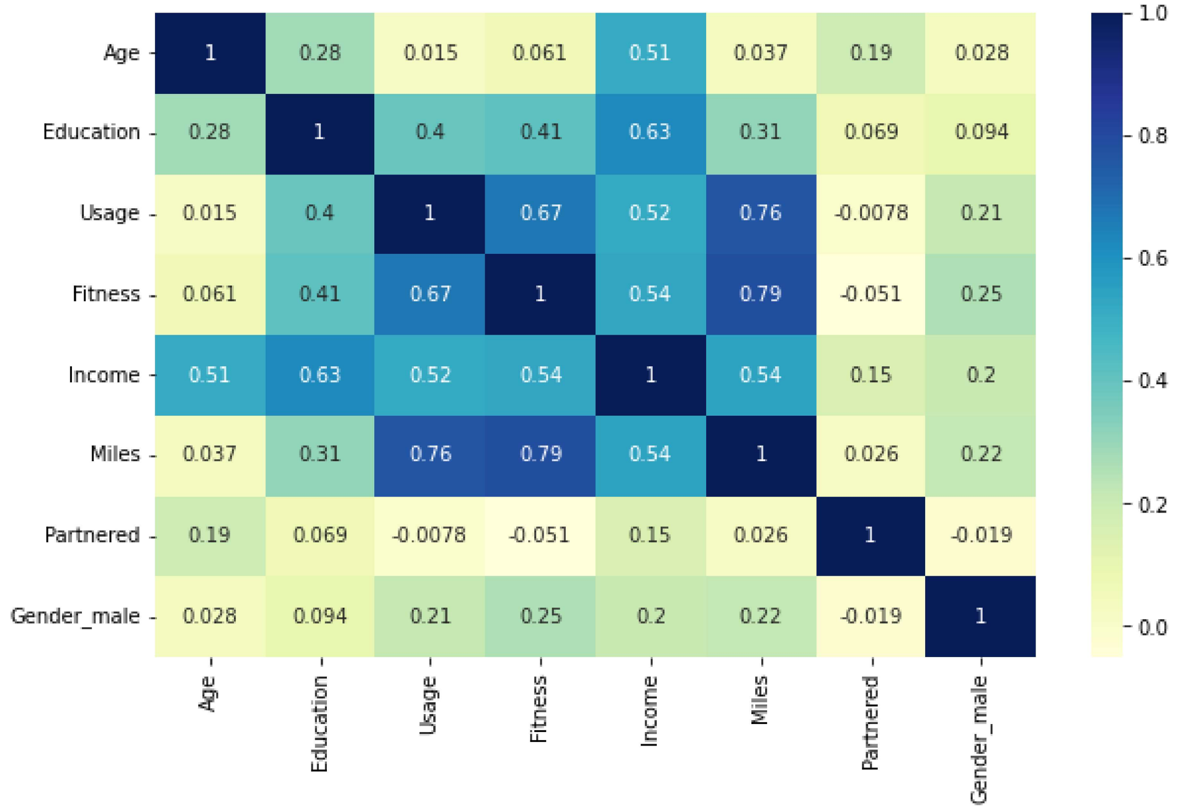
Correlation

In [22]:

```
df['Partnered'] = df[['MaritalStatus']].apply(lambda x: x.map({'Partnered':1,'Single':0}),
df['Gender_male'] = df[['Gender']].apply(lambda x: x.map({'Male':1,'Female':0}), axis=1)
```

In [26]:

```
plt.figure(figsize = (10, 6))
sns.heatmap(df.corr(),  cmap="YlGnBu", annot = True)
plt.show()
```



Correlation Analysis

1. **Age** : This column is correlated with Education (28 %) & Income (51 %)
2. **Education** is highly correlated with income(63 %), as we know those who've studied will get paid higher. xD
3. **Usage** is correlated & making impact on Fitness, Income & miles .
4. **FItness** is strongly correlated with miles

- As we can see for other columns also correlation does exists by darker parts in the plot.

what percent of customers have purchased KP281, KP481, or KP781 in a table

In [32]:

```
k = pd.crosstab(df['Product'],df['Gender'])
k['Female_prop'] = k['Female']/k['Female'].sum()
k['Male_prop'] = k['Male']/k['Male'].sum()
k
```

Out[32]:

Gender Product	Female	Male	Female_prop	Male_prop
KP281	40	40	0.526316	0.384615
KP481	29	31	0.381579	0.298077
KP781	7	33	0.092105	0.317308

We can infer from table as Female proportion were using KP281 the most , & males too

In [45]:

```
df['Product'].value_counts()
```

Out[45]:

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [47]:

```
df[df['Product']=='KP281'].describe(exclude='O')
```

Out[47]:

	Age	Education	Usage	Fitness	Income	Miles	Partnered	Gender_
count	80.000000	80.000000	80.000000	80.00000	80.00000	80.000000	80.000000	80.0(
mean	28.550000	15.037500	3.087500	2.96250	46418.02500	82.787500	0.600000	0.5(
std	7.221452	1.216383	0.782624	0.66454	9075.78319	28.874102	0.492989	0.5(
min	18.000000	12.000000	2.000000	1.00000	29562.00000	38.000000	0.000000	0.0(
25%	23.000000	14.000000	3.000000	3.00000	38658.00000	66.000000	0.000000	0.0(
50%	26.000000	16.000000	3.000000	3.00000	46617.00000	85.000000	1.000000	0.5(
75%	33.000000	16.000000	4.000000	3.00000	53439.00000	94.000000	1.000000	1.0(
max	50.000000	18.000000	5.000000	5.00000	68220.00000	188.000000	1.000000	1.0(

Customer Profiling

KP281

- Most of the customers brought KP281. Making it most popular model.
- Average customer income is 46K

- There is equal distribution for both genders [Male & Female](40 each)
- Average age of customer who purchases KP281 is 28.5, Median is 26.
- Average years of Education of customers is 15, and median is 16.
- They expect to use treadmill 3-4 times a week, their avg rate is around 3.
- Equal amount of males and females bought this model suggesting this model is not gender specfic.
- Majority of the customers who purchased this model are Partnered Females and Single Males compared to Single females and Partnered male. This may be cause of the features this treadmill provides and the cost of treadmill.

Probability Insights

In [34]:

```
def prob(gender, print_marginal=False):

    df1 = pd.crosstab(index=df['Gender'], columns=[df['Product']])
    p_781 = df1['KP781'][gender] / df1.loc[gender].sum()
    p_481 = df1['KP481'][gender] / df1.loc[gender].sum()
    p_281 = df1['KP281'][gender] / df1.loc[gender].sum()

    if print_marginal:
        print(f"P(Male): {df1.loc['Male'].sum()/len(df):.2f}")
        print(f"P(Female): {df1.loc['Female'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{gender}): {p_781:.2f}")
    print(f"P(KP481/{gender}): {p_481:.2f}")
    print(f"P(KP281/{gender}): {p_281:.2f}\n")

p_prod_given_gender('Male', True)
p_prod_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
```

Insights from probability Analysis of Gender & Products:

1. Probability of Males is 58 % & Females is 42.
2. Probability of Kp781 given male is 32 , where as Female is 9
3. Probability of Kp481 given male is 30 , where as Female is 38
4. Probability of Kp281 given male is 38 , where as Female is 53.

In [35]:

```
def prob(status, print_marginal=False):


    df1 = pd.crosstab(index=df['MaritalStatus'], columns=[df['Product']])
    p_781 = df1['KP781'][status] / df1.loc[status].sum()
    p_481 = df1['KP481'][status] / df1.loc[status].sum()
    p_281 = df1['KP281'][status] / df1.loc[status].sum()

    if print_marginal:
        print(f"P(Single): {df1.loc['Single'].sum()/len(df):.2f}")
        print(f"P(Partnered): {df1.loc['Partnered'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{status}): {p_781:.2f}")
    print(f"P(KP481/{status}): {p_481:.2f}")
    print(f"P(KP281/{status}): {p_281:.2f}\n")

p_prod_given_mstatus('Single', True)
p_prod_given_mstatus('Partnered')
```

```
P(Single): 0.41
P(Partnered): 0.59

P(KP781/Single): 0.23
P(KP481/Single): 0.33
P(KP281/Single): 0.44

P(KP781/Partnered): 0.21
P(KP481/Partnered): 0.34
P(KP281/Partnered): 0.45
```

Insights from probability Analysis of Gender & Martial Status:

1. Probability of Single is 41 % & Partnered is 42.
2. Probability of Kp781 given Single is 23 , where as Partnered is 21
3. Probability of Kp481 given Single is 33 , where as Partnered is 34
4. Probability of Kp281 given Single is 44 , where as Partnered is 45.

In [39]:

```
df['Product'].value_counts()
```

Out[39]:

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

Recommendations:

- Recommend the KP281 to users who have high usage rating
- Recommend KP481 to the Single people with usage rating less than 4 to 5
- Recommending the KP781 to the People with higher income as it has more features

- KP281 can be recommended to the females

In [ ]:

```

```