Problem statement

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 the new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics.

Objective of analysis:

- 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.

Column Profiling:

- 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.

Loading dependencies and dataset

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

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [2]:
```
df = pd.read_csv('./data/aerofit_treadmill.txt')
df.head()
```

Out[2]:

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

Basic structure & characteristics of the dataset

Shape of data

In [3]:
```
df.shape
```
Out[3]:
```
(180, 9)
```

Information on dataframe

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
```

Number of null values

In [5]:
```
df.isna().sum()
```
Out[5]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Basic statistics of data

In [6]:
```
df.describe(include='all')
```
Out[6]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

EDA: Basic

Categorical columns

In [7]:
```
df['Product'].value_counts()
```

Out[7]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [8]:
```
df['Gender'].value_counts()
```

Out[8]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [9]:
```
df['MaritalStatus'].value_counts()
```

Out[9]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

Continuous columns

In [10]:
```
df['Age'].nunique()
```

Out[10]:
```
32
```

In [11]:
```
df['Education'].nunique()
```

Out[11]:
```
8
```

In [12]:
```
df['Usage'].nunique()
```

Out[12]:
```
6
```

In [13]:
```
df['Fitness'].nunique()
```

Out[13]:
```
5
```

In [14]:
```
df['Income'].nunique()
```

Out[14]:
```
62
```

In [15]:
```
df['Miles'].nunique()
```

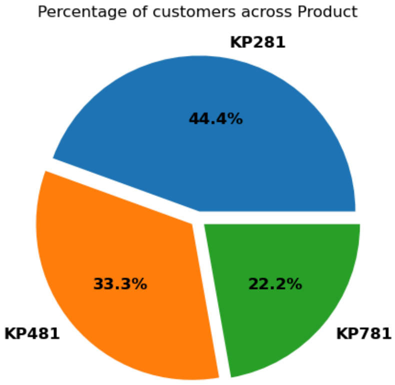
Out[15]:
```
37
```

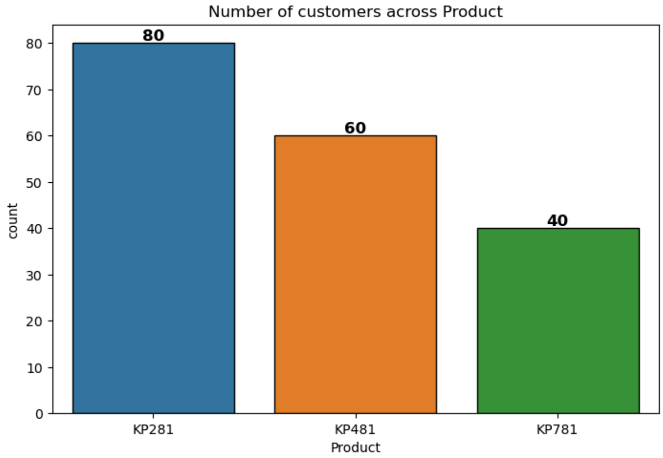
EDA: Detailed

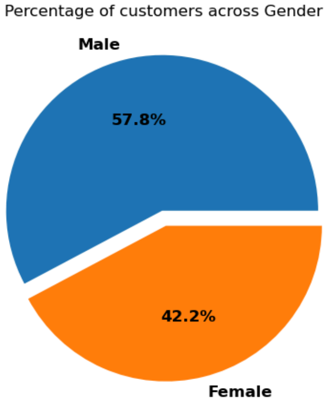
Univariate Analysis

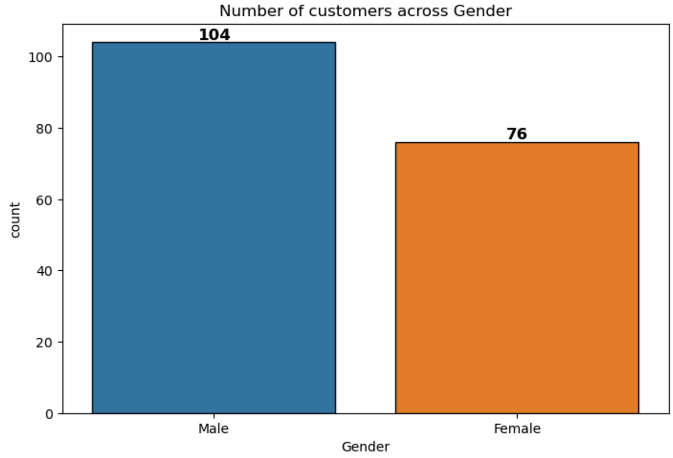
Categorical variables (along with Marginal Probability)

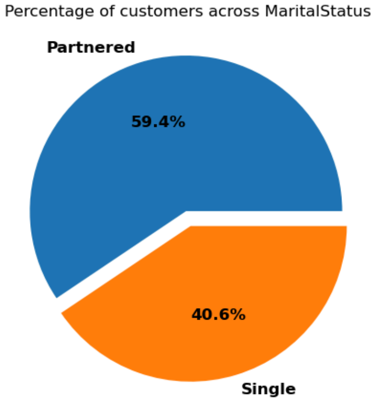
In [16]:
```
cat_features = ['Product', 'Gender', 'MaritalStatus']
fig = plt.figure(figsize=(18, 18))
id = 1
for feature in cat_features:
    plt.subplot(3, 2, id)
    plt.pie(df[feature].value_counts(), labels = df[feature].value_counts().index, explode = (0.05,
        autopct='%.1f%%', textprops = {'fontweight': 'bold', 'fontsize': 12})
    plt.title(f'Percentage of customers across {feature}', fontsize=12)
    plt.subplot(3, 2, id+1)
    f = sns.countplot(data=df, x=feature, edgecolor='black', order=df[feature].value_counts().inde
    for item in f.containers:
        f.bar_label(item, fontsize=12, fontweight='bold')
    plt.title(f'Number of customers across {feature}', fontsize=12)
    id += 2
```

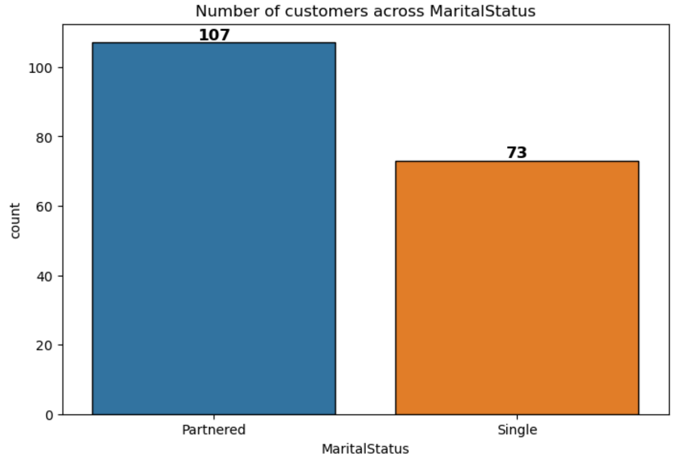












Observations:

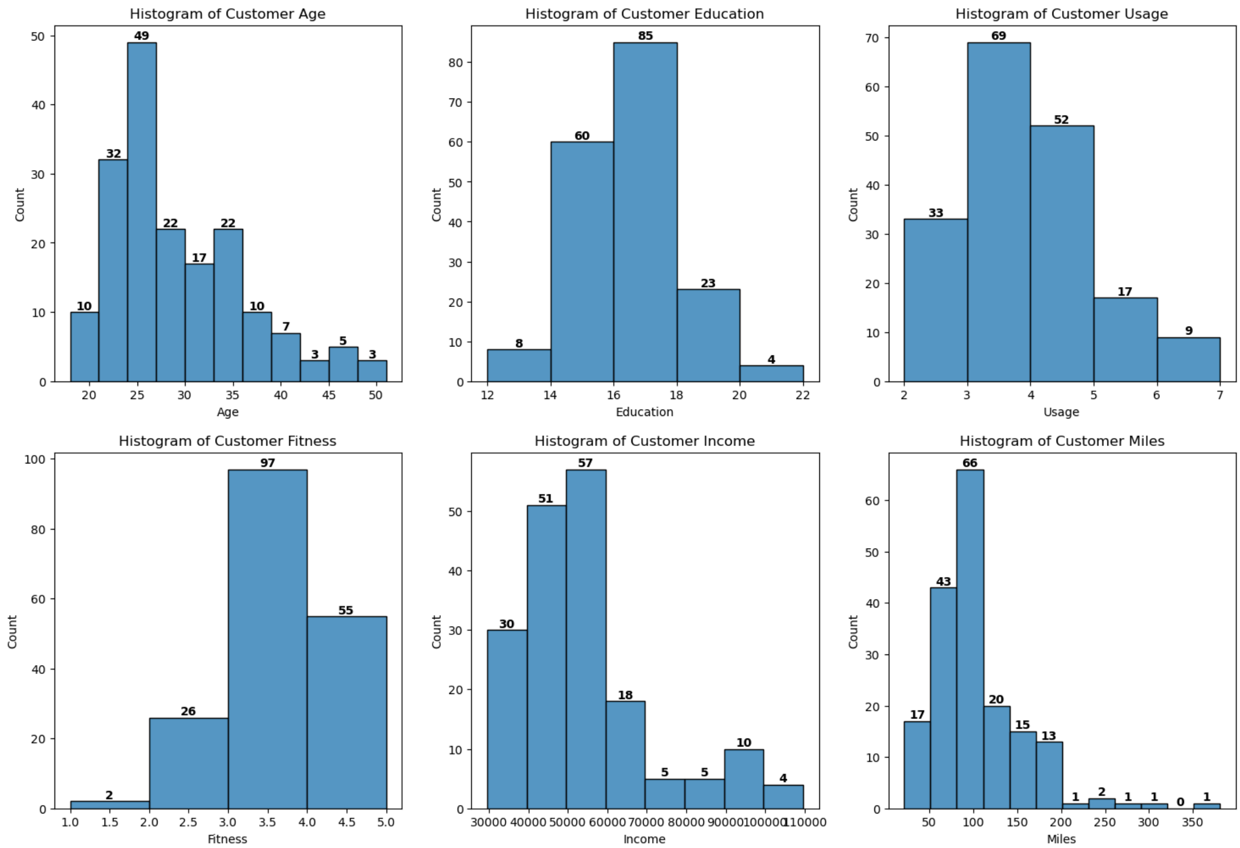
- Treadmills sold by Aerofit: We have a total of 3 treadmills
  - KP281: 44.4%
  - KP481: 33.3%
  - KP781: 22.2%
- Customer Gender
  - Males: 57.8%
  - Females: 42.2%
- Customer Marital Status
  - Partnered customers: 59.4%
  - Single customers: 40.6%

Continuous variables (Histograms & Outlier Treatment)

In [17]:
```
# Continuous features:
cont_features = {'Age':3 , 'Education':2, 'Usage':1, 'Fitness':1, 'Income':10000, 'Miles':30}
```

Histogram

```
In [18]:
fig = plt.figure(figsize=(18, 12))
id = 1
for feature in cont_features:
    plt.subplot(2, 3, id)
    f= sns.histplot(df[feature], binwidth=cont_features[feature])
    for item in f.containers:
        f.bar_label(item, fontsize=10, fontweight='bold')
    plt.title(f'Histogram of Customer {feature}', fontsize=12)
    id += 1
plt.show()
```

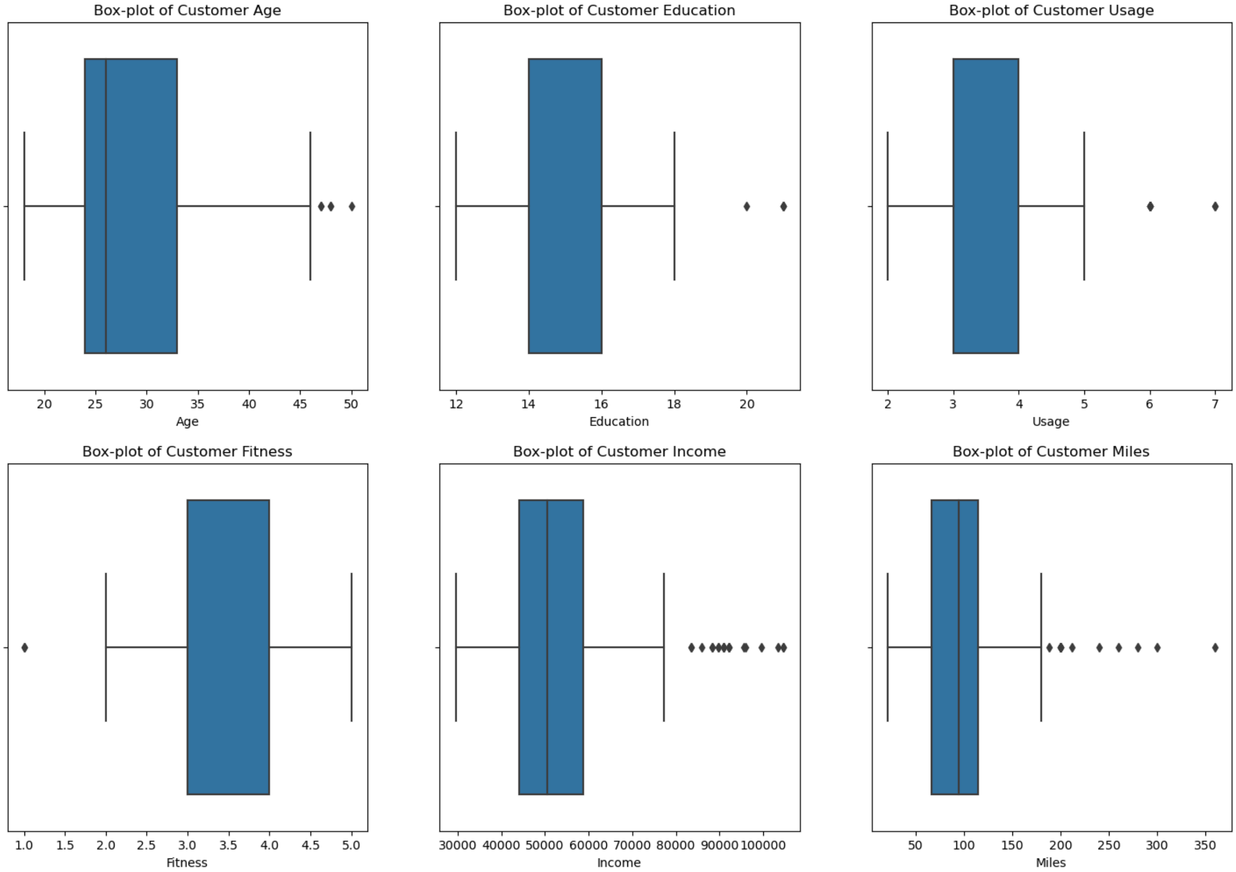


Observations:

- Customer Age
  - Majority of the customers lie between 20-35 in their age
- Customer Education
  - Majority of the customers have 14-17 years in their education
- Customer Usage
  - Majority of the customers thought that they would use the treadmill 3-4 times per week
- Customer Fitness
  - Majority of the customers rated themselves a 3 (Average) in Fitness
- Customer Income
  - Majority of the customers have an annual income in between 30000-70000 USD
- Customer Miles
  - Majority of the customers thought that they would walk/run on the treadmill for 50-110 miles

Box-plots and Outlier Treatment

```
In [19]:
fig = plt.figure(figsize=(18, 12))
id = 1
for feature in cont_features:
    plt.subplot(2, 3, id)
    sns.boxplot(x=df[feature])
    plt.title(f'Box-plot of Customer {feature}', fontsize=12)
    id += 1
plt.show()
```



In [20]:

```
# Detecting outliers:
for feature in cont_features:
    median = np.percentile(df[feature], 50)
    iqr = np.percentile(df[feature], 75) - np.percentile(df[feature], 25)
    lower = np.percentile(df[feature], 25) - 1.5*iqr
    upper = np.percentile(df[feature], 75) + 1.5*iqr
    print(f'{feature}: Median={median}, Lower={lower}, Upper={upper}')
```

```
Age: Median=26.0, Lower=10.5, Upper=46.5
Education: Median=16.0, Lower=11.0, Upper=19.0
Usage: Median=3.0, Lower=1.5, Upper=5.5
Fitness: Median=3.0, Lower=1.5, Upper=5.5
Income: Median=50596.5, Lower=22144.875, Upper=80581.875
Miles: Median=94.0, Lower=-7.125, Upper=187.875
```

Observations:

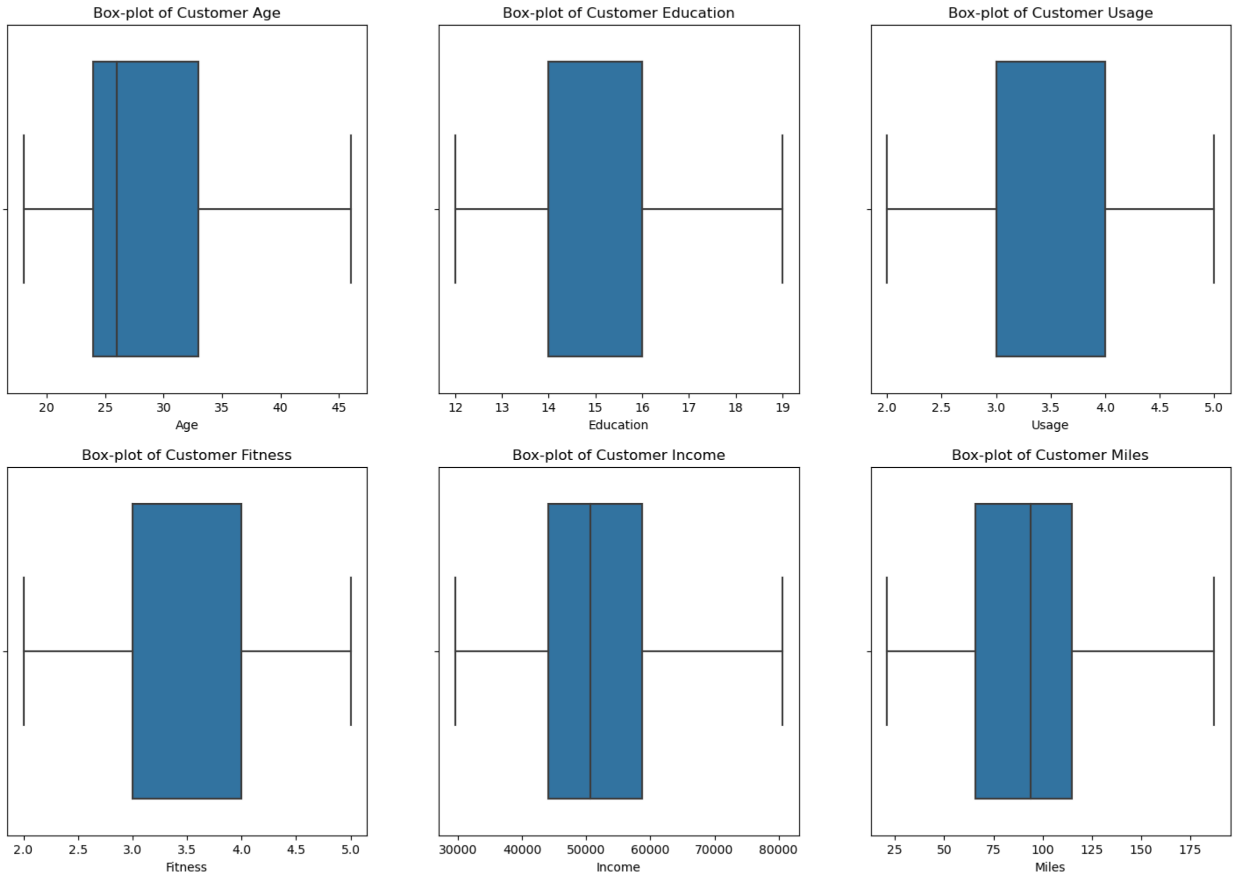
- Customer Age
  - Median: 26 years
  - Outliers above: 46.5 years
- Customer Education
  - Median: 16 years
  - Outliers above: 19 years
- Customer Usage
  - Median: 3 times
  - Outliers above: 5.5 times
- Customer Fitness
  - Median: 3
  - Outliers below: 1.5
- Customer Income
  - Median: 50,596 USD
  - Outliers above: 80,582 USD
- Customer Miles
  - Median: 94 miles
  - Outliers above: 187.8 miles

Outlier Treatment: Setting outliers to the upper/lower whisker

In [21]:
```
df_original = df.copy()
```

In [22]:
```
df.loc[df['Age'] > 46.5, 'Age'] = 46
df.loc[df['Education'] > 19, 'Education'] = 19
df.loc[df['Usage'] > 5.5, 'Usage'] = 5
df.loc[df['Fitness'] < 1.5, 'Fitness'] = 2
df.loc[df['Income'] > 80581, 'Income'] = 80581
df.loc[df['Miles'] > 187, 'Miles'] = 187
```

In [23]:
```
fig = plt.figure(figsize=(18, 12))
id = 1
for feature in cont_features:
    plt.subplot(2, 3, id)
    sns.boxplot(x=df[feature])
    plt.title(f'Box-plot of Customer {feature}', fontsize=12)
    id += 1
plt.show()
```

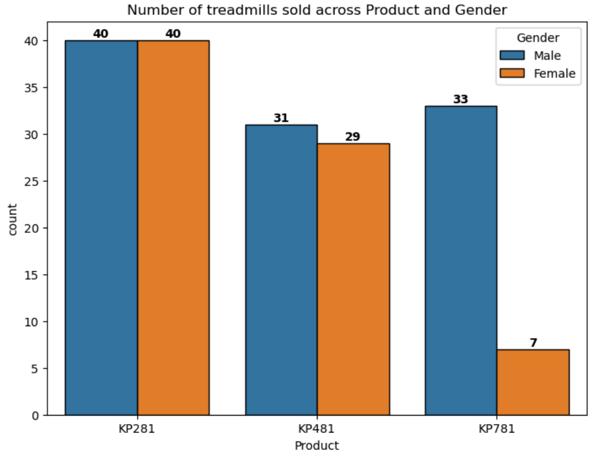


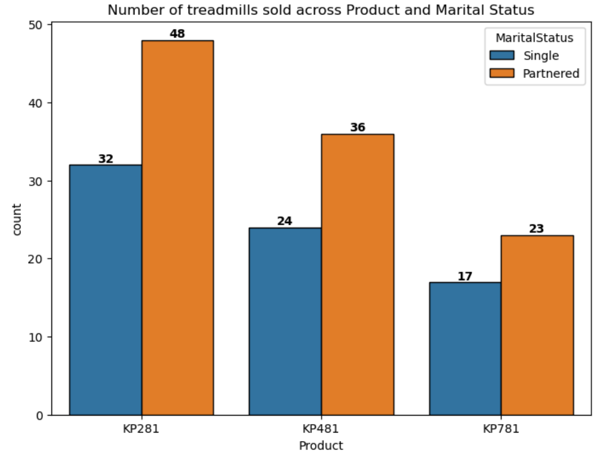
Bivariate Analysis

Number of treadmills sold

- Across Product and Gender
- Across Product and Marital Status

In [24]:
```
fig = plt.figure(figsize=(18, 6))
plt.subplot(1, 2, 1)
f = sns.countplot(data=df, x='Product', hue='Gender', edgecolor='black')
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.title('Number of treadmills sold across Product and Gender')
plt.subplot(1, 2, 2)
f = sns.countplot(data=df, x='Product', hue='MaritalStatus', edgecolor='black')
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.title('Number of treadmills sold across Product and Marital Status')
plt.show()
```





Observations:

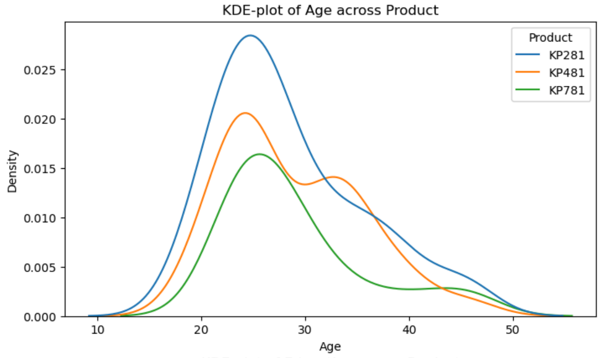
- Across Gender:
  - KP281 and KP481: equally bought b/w males & females
  - KP781: Most customers are male
- Across Marital status:
  - Partnered customers are more than single counterparts for all 3 treadmills

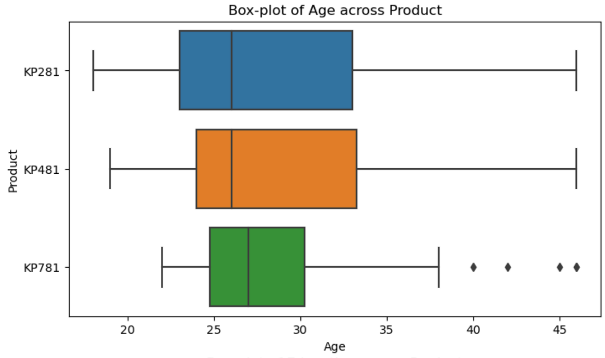
Studying the Continuous Features across Products

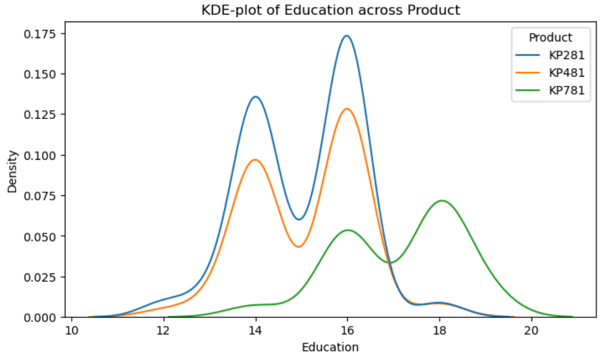
- KDE plots
- Box plots
- Median of continuous features

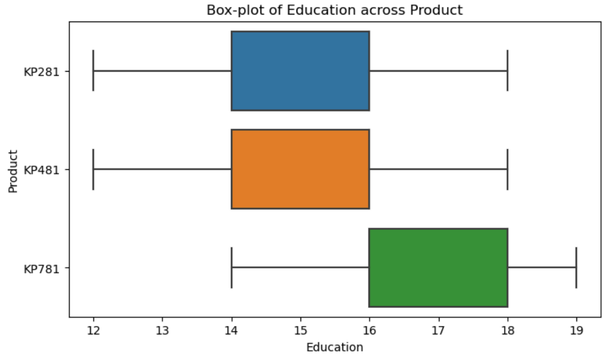
KDE and Box plots

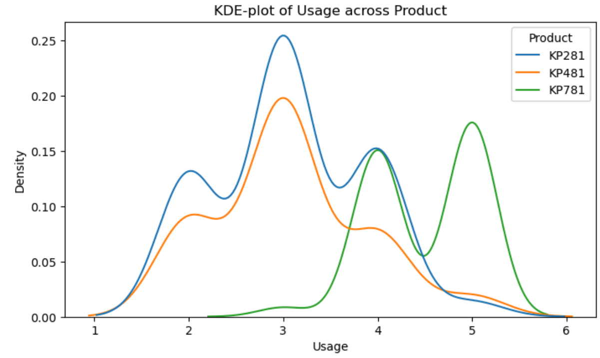
In [25]:
```
fig=plt.figure(figsize=(18, 32))
id = 1
for feature in cont_features:
    plt.subplot(6, 2, id)
    sns.kdeplot(data=df, x=feature, hue='Product')
    plt.title(f'KDE-plot of {feature} across Product')
    plt.subplot(6, 2, id + 1)
    sns.boxplot(data=df, x=feature, y='Product')
    plt.title(f'Box-plot of {feature} across Product')

    id += 2
# fig.suptitle('Continuous features across Product', fontsize=14)
plt.show()
```

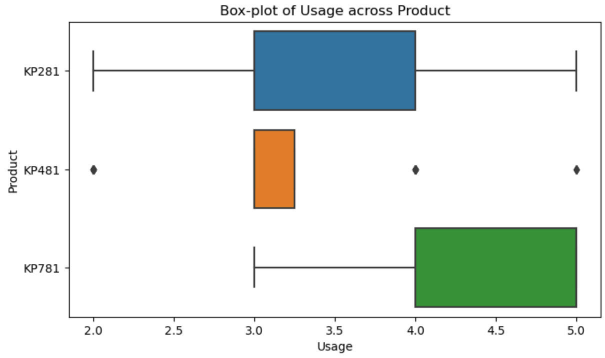

KDE-plot of Age across Product
Product
KP281
KP481
KP781
Density
Age

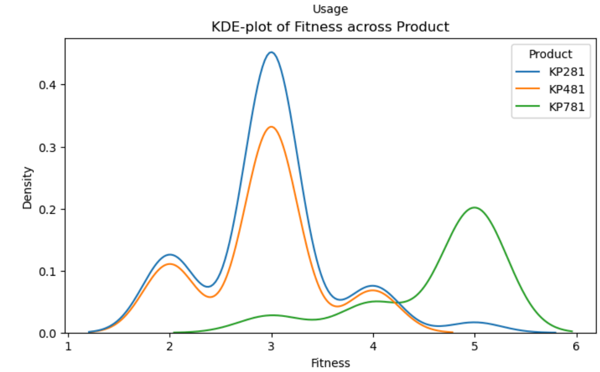

Box-plot of Age across Product
KP281
KP481
KP781
Product
Age

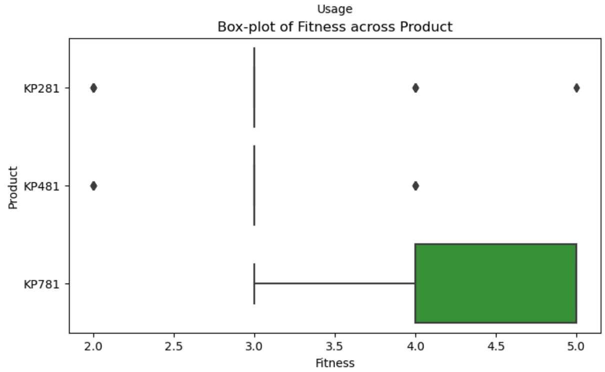

KDE-plot of Education across Product
Product
KP281
KP481
KP781
Density
Education

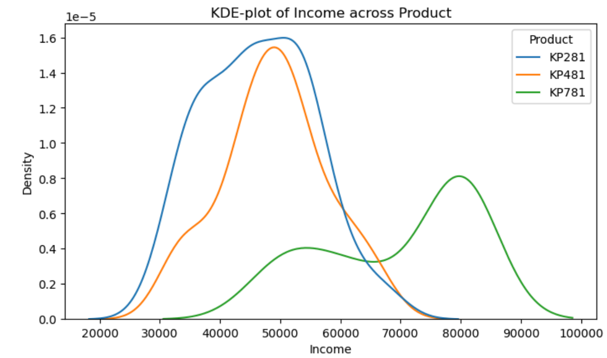

Box-plot of Education across Product
KP281
KP481
KP781
Product
Education

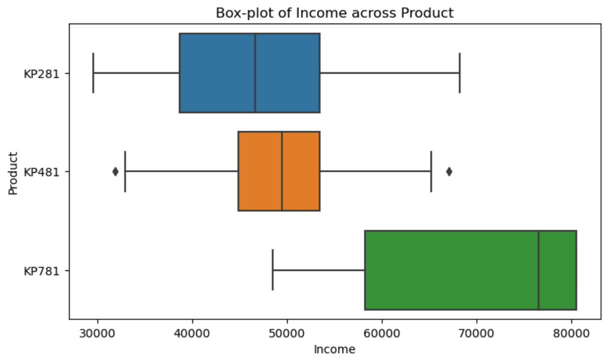

KDE-plot of Usage across Product
Product
KP281
KP481
KP781
Density
Usage

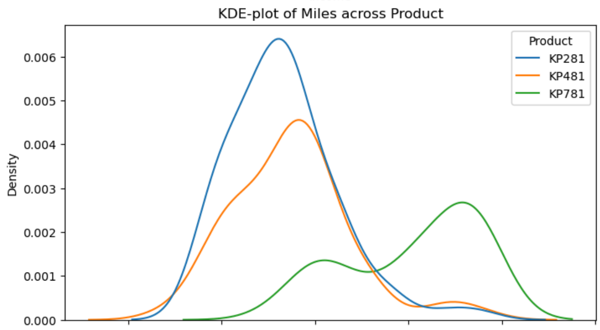

Box-plot of Usage across Product
KP281
KP481
KP781
Product
Usage

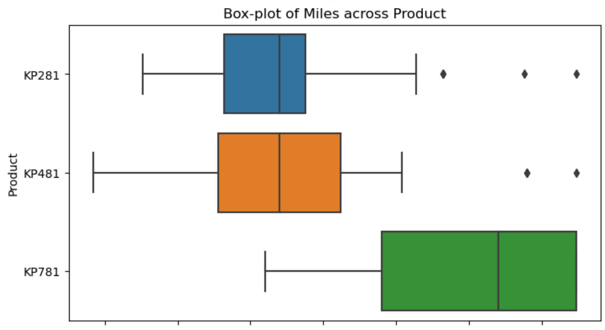

KDE-plot of Fitness across Product
Product
KP281
KP481
KP781
Density
Fitness


Box-plot of Fitness across Product
KP281
KP481
KP781
Product
Fitness


KDE-plot of Income across Product
1e−5
Product
KP281
KP481
KP781
Density
Income


Box-plot of Income across Product
KP281
KP481
KP781
Product
Income


KDE-plot of Miles across Product
Product
KP281
KP481
KP781
Density


Box-plot of Miles across Product
KP281
KP481
KP781
Product

Median of continuous columns

In [26]:
```
cont_features_lst = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
df.groupby('Product')[cont_features_lst].agg('median')
```

Out[26]:

	Age	Education	Usage	Fitness	Income	Miles
Product						
KP281	26.0	16.0	3.0	3.0	46617.0	85.0
KP481	26.0	16.0	3.0	3.0	49459.5	85.0
KP781	27.0	18.0	5.0	5.0	76568.5	160.0

Observations:

1. From KDEplots: The features which impact the choice of buying a specific product are:
   - Education, Usage, Fitness, Income and Miles
2. Given that the products in question are fitness products, the top features which affect the choice of buying would be:
   - Income
   - Fitness
   - Usage
   - Miles
3. We observe that KP281 and KP481 are similar in many ways when it comes to the customer profile (as per the features shown above)
4. KP781 differs from the other 2 products substantially when it comes to the customer Education, Usage, Fitness, Income and Miles

---

- Age:
  - The median age across products is roughly the same
- Education:
  - KP281, KP481: The median number of years in education is 16
  - KP781: The median number of years in education is 18
- Usage:
  - KP281: The median usage is 3 times per week, some customers have reported other usages as well
  - KP481: All the customers reported their expected usage as 3 times a week barring a few
  - KP781: The median usage is 5 times per week
- Fitness:
  - KP281, KP481: The median fitness is 3 times per week, some customers have reported other usages as well
  - KP781: The median fitness is 5 (customers already think they are very fit and hence they probably invested in an expensive product)
- Income:
  - KP281: The median customer income is 46.6K USD
  - KP481: The median customer income is 49.5K USD
  - KP781: The median customer income is 76.6K USD, substantially higher than the other 2 products
- Miles:
  - KP281, KP481: The median miles customer expects to walk/run is 85
  - KP781: The median miles customer expects to walk/run is 160, almost 2X of the other 2

Multivariate Analysis

In [27]:
```
df.corr()
```

Out[27]:

	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.296565	0.015552	0.058312	0.542205	0.024419
Education	0.296565	1.000000	0.391276	0.439050	0.646931	0.362209
Usage	0.015552	0.391276	1.000000	0.660556	0.460975	0.778043
Fitness	0.058312	0.439050	0.660556	1.000000	0.522897	0.832547
Income	0.542205	0.646931	0.460975	0.522897	1.000000	0.506504
Miles	0.024419	0.362209	0.778043	0.832547	0.506504	1.000000

In [28]:
```
plt.figure(figsize=(18, 9))
sns.heatmap(data=df.corr(), cmap='Blues', annot=True)
plt.show()
```

Observations:

The feature combinations which have high correlation are:

- Age, Income
- Education, Income
- Usage, Fitness
- Usage, Miles
- Fitness, Income
- Fitness, Miles
- Income, Miles

We must keep in mind that we are trying to create a customer profile for the different treadmill products. Keeping that objective in mind, we realise that some of the above pairs may not be relevant from the context of business. Thus we do not explore those. However, we will look in depth at the following:

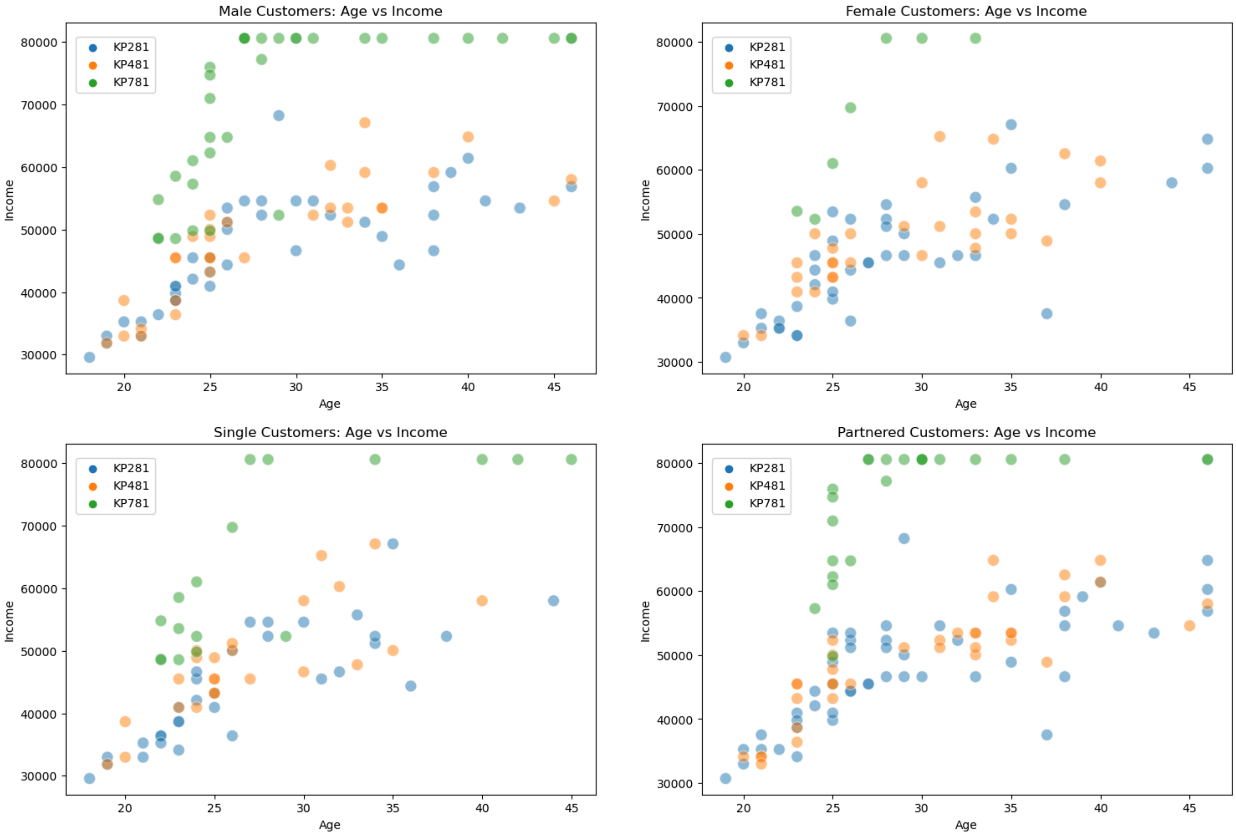
- Age vs Income
- Usage vs Fitness
- Usage vs Miles
- Fitness vs Miles

In [29]:
```
gender_marStat = {'Gender': ['Male', 'Female'], 'MaritalStatus': ['Single', 'Partnered']}
```

Age vs Income

In [30]:
```
fig=plt.figure(figsize=(18, 12))
id = 1
```

```
for feature in gender_marStat:

    df_filter = df.loc[df[feature] == gender_marStat[feature][0]]
    plt.subplot(2, 2, id)
    f = sns.scatterplot(data = df_filter, x = 'Age', y = 'Income', hue='Product', s=100, alpha=0.5
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][0]} Customers: Age vs Income')

    df_filter = df.loc[df[feature] == gender_marStat[feature][1]]
    plt.subplot(2, 2, id+1)
    f = sns.scatterplot(data = df_filter, x = 'Age', y = 'Income', hue='Product', s=100, alpha=0.5
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][1]} Customers: Age vs Income')

    id += 2
```



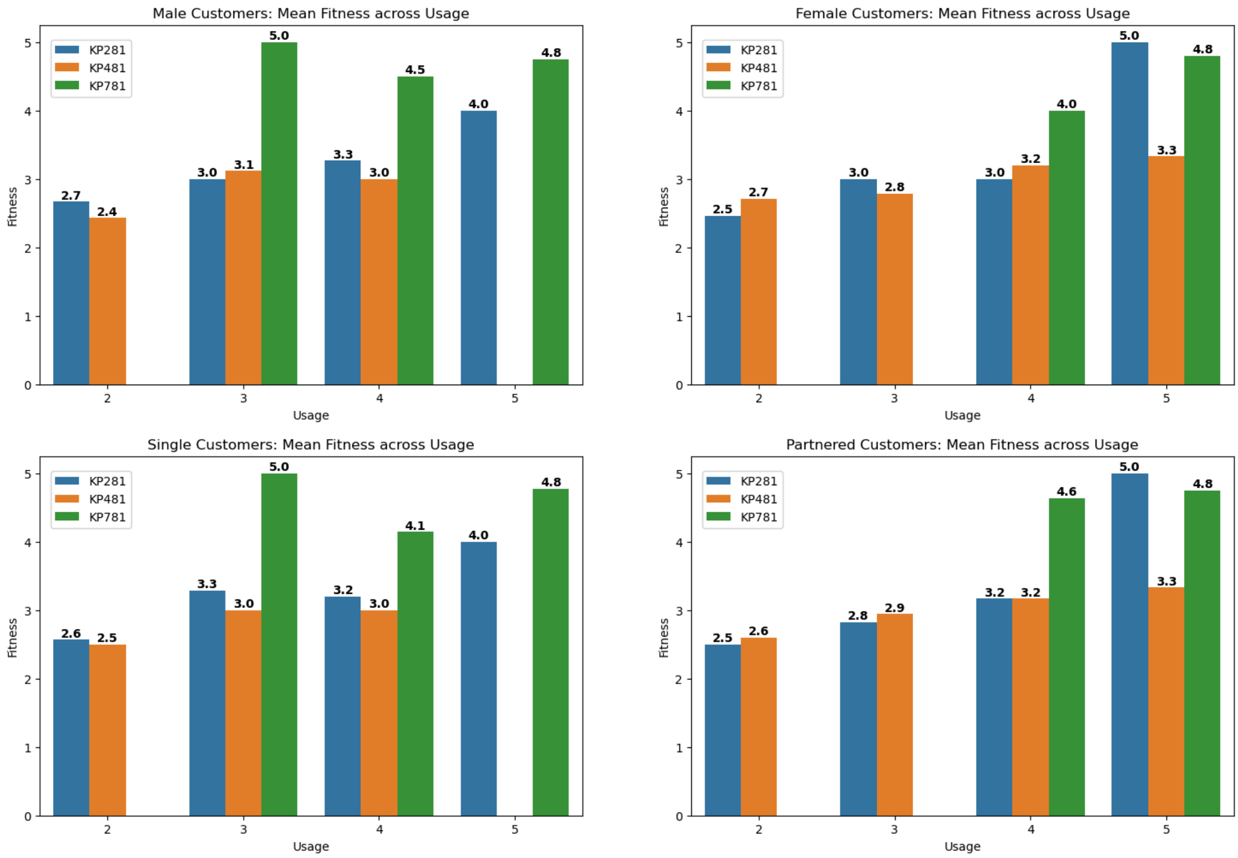
Observations:

- We see a positive correlation b/w Age and Income
- This is to be expected since the income of a person usually increases as he keeps working in his job
- We also see that people whose income > 50,000 USD tend to go for the KP781
- We see a lot of data points where income = 80,000 USD (This is because of the oulier treatment)
    - Number of males who earn >= 80,000 USD is more than that of females

Usage vs Fitness

In [31]:
```
fig=plt.figure(figsize=(18, 12))
id = 1
for feature in gender_marStat:

    df_filter = df.loc[df[feature] == gender_marStat[feature][0]]
    plt.subplot(2, 2, id)
    f = sns.barplot(data = df_filter, x = 'Usage', y = 'Fitness', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][0]} Customers: Mean Fitness across Usage')

    df_filter = df.loc[df[feature] == gender_marStat[feature][1]]
    plt.subplot(2, 2, id+1)
    f = sns.barplot(data = df_filter, x = 'Usage', y = 'Fitness', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
```

```
    plt.title(f'{gender_marStat[feature][1]} Customers: Mean Fitness across Usage')

    id += 2
```

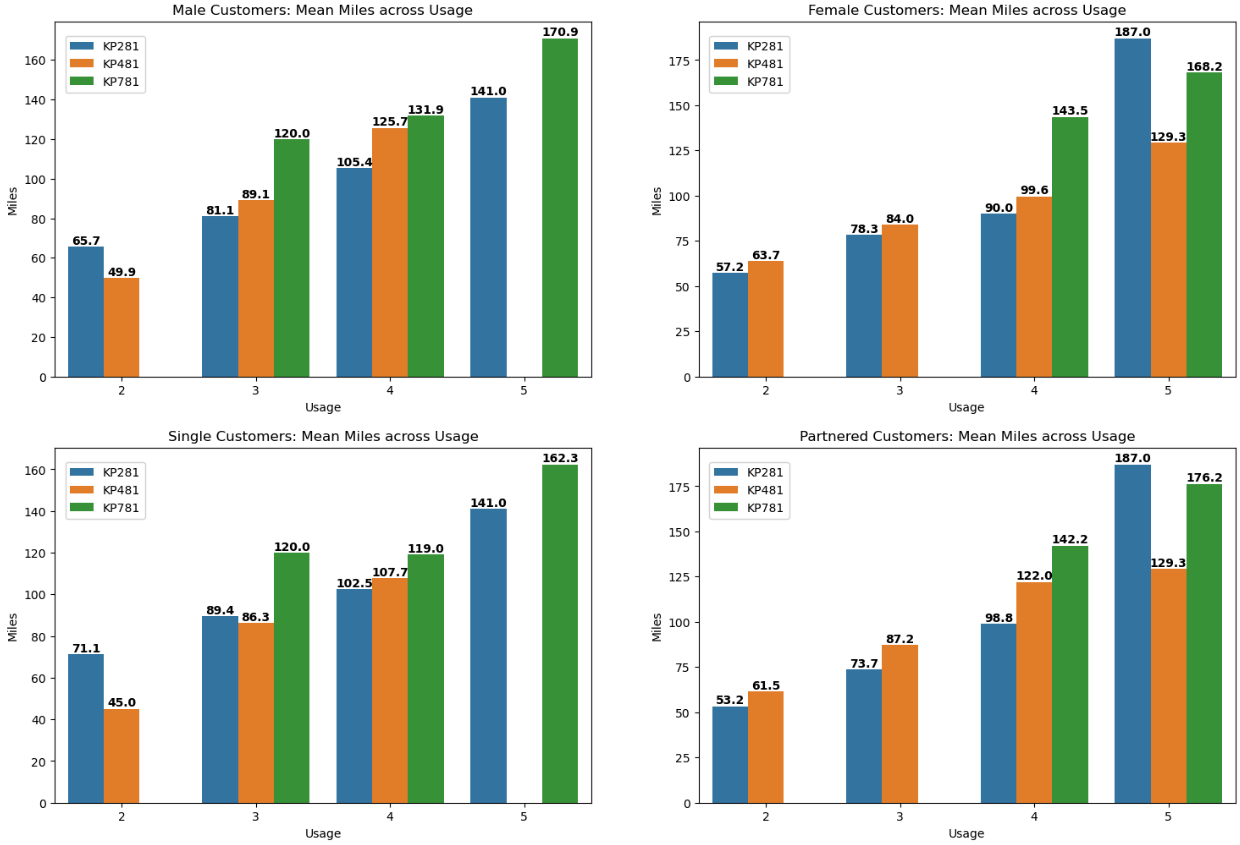


Observations:

- There is a positive correlation b/w usage and fitness
- Usally people with higher usage have a higher mean fitness (again this is not surprising)
- We also observe that people who have opted for the KP781 are more fit

Usage vs Miles

In [32]:
```
fig=plt.figure(figsize=(18, 12))
id = 1
for feature in gender_marStat:

    df_filter = df.loc[df[feature] == gender_marStat[feature][0]]
    plt.subplot(2, 2, id)
    f = sns.barplot(data = df_filter, x = 'Usage', y = 'Miles', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][0]} Customers: Mean Miles across Usage')

    df_filter = df.loc[df[feature] == gender_marStat[feature][1]]
    plt.subplot(2, 2, id+1)
    f = sns.barplot(data = df_filter, x = 'Usage', y = 'Miles', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][1]} Customers: Mean Miles across Usage')

    id += 2
```



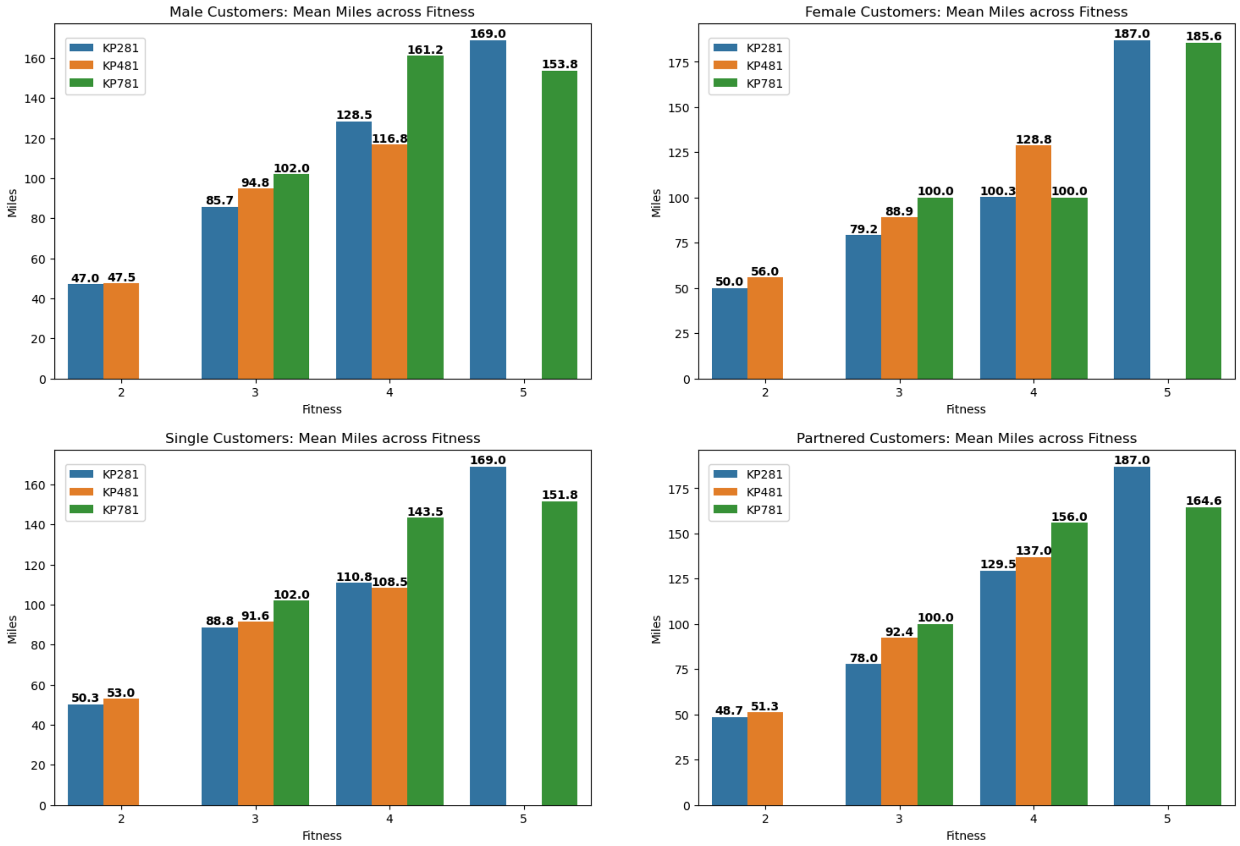
Observations:

- There is a positive correlation b/w usage and miles
- Usally people with higher usage have a higher mean miles (again this is to be expected)
- We also observe that the mean miles of male customers is higher than that of female customers
- Also single customers have higher mean miles than partnered customers

Fitness vs Miles

In [33]:

```
fig=plt.figure(figsize=(18, 12))
id = 1
for feature in gender_marStat:

    df_filter = df.loc[df[feature] == gender_marStat[feature][0]]
    plt.subplot(2, 2, id)
    f = sns.barplot(data = df_filter, x = 'Fitness', y = 'Miles', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][0]} Customers: Mean Miles across Fitness')

    df_filter = df.loc[df[feature] == gender_marStat[feature][1]]
    plt.subplot(2, 2, id+1)
    f = sns.barplot(data = df_filter, x = 'Fitness', y = 'Miles', hue='Product', estimator=np.mean,
    for item in f.containers:
        f.bar_label(item, fmt='%.1f', fontsize=10, fontweight='bold')
    plt.legend(loc=(0.02, 0.8))
    plt.title(f'{gender_marStat[feature][1]} Customers: Mean Miles across Fitness')

    id += 2
```



Observations:

- There is a positive correlation b/w fitness and miles
- Usally people with higher fitness have a higher mean miles (again this is not surprising)

Customer Profiling & Conditional Probabilities

Converting continuous columns into categorical columns

- Age
- Income
- Miles

In [34]:
```
df_profile = df.copy()
```

In [35]:
```
age_33 = np.percentile(df['Age'], 33)
age_67 = np.percentile(df['Age'], 67)
income_33 = np.percentile(df['Income'], 33)
income_67 = np.percentile(df['Income'], 67)
miles_33 = np.percentile(df['Miles'], 33)
miles_67 = np.percentile(df['Miles'], 67)
```

We split the the below columns into the following categories:

- Age:
  - Below 25 years
  - 25-30 years
  - Above 30 years
- Income
  - Low : Below 45480 USD
  - Medium: (45480-54576) USD
  - High: Above 54576 USD
- Miles
  - Low: Below 80 miles
  - Medium: (80-106) miles

- High: Above 106 miles

In [36]:
```
df_profile['Age_Category'] = pd.cut(df['Age'], bins=[df['Age'].min()-5, age_33-1, age_67, df['Age']
df_profile['Income_Category'] = pd.cut(df['Income'], bins=[df['Income'].min()-1000, income_33, inc
df_profile['Mile_Category'] = pd.cut(df['Miles'], bins=[df['Miles'].min()-10, miles_33, miles_67, d
```

In [37]:
```
df_profile['Age_Category'].value_counts(normalize=True)
```

Out[37]:
```
25-30       0.366667
Above_30    0.333333
Below_25    0.300000
Name: Age_Category, dtype: float64
```

In [38]:
```
df_profile['Income_Category'].value_counts(normalize=True)
```

Out[38]:
```
Low       0.350000
Medium    0.344444
High      0.305556
Name: Income_Category, dtype: float64
```

In [39]:
```
df_profile['Mile_Category'].value_counts(normalize=True)
```

Out[39]:
```
Medium    0.366667
Low       0.333333
High      0.300000
Name: Mile_Category, dtype: float64
```

In [40]:
```
df_profile.head()
```

Out[40]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_Category	Income_Category	M
0	KP281	18	Male	14	Single	3	4	29562	112	Below_25	Low	
1	KP281	19	Male	15	Single	2	3	31836	75	Below_25	Low	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Below_25	Low	
3	KP281	19	Male	12	Single	3	3	32973	85	Below_25	Low	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Below_25	Low	

Product Across Customer Gender

In [41]:
```
# Treadmills sold across Product and Gender
pd.crosstab(index=df_profile['Product'], columns=df_profile['Gender'], margins=True)
```

Out[41]:

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

Conditional Probability

In [42]:
```
print('P[Male/KP281]:', 40/80)
print('P[Female/KP281]:', 40/80)
print('-'*50)
print('P[Male/KP481]:', 31/60)
print('P[Female/KP481]:', 29/60)
print('-'*50)
print('P[Male/KP781]:', 33/40)
print('P[Female/KP781]:', 7/40)
print('-'*50)
```

```
P[Male/KP281]: 0.5
P[Female/KP281]: 0.5
--------------------------------------------------
P[Male/KP481]: 0.5166666666666667
P[Female/KP481]: 0.48333333333333334
--------------------------------------------------
P[Male/KP781]: 0.825
P[Female/KP781]: 0.175
--------------------------------------------------
```

Observations:

Across Gender:

- Both men and women are equally likely to buy KP281 and KP481
- Majority of the customer base for KP781 is male

Product Across Customer Marital Status

In [43]:
```
# Treadmills sold across Product and Marital Status
pd.crosstab(index=df_profile['Product'], columns=df_profile['MaritalStatus'], margins=True)
```

Out[43]:

MaritalStatus	Partnered	Single	All
Product			
KP281	48	32	80
KP481	36	24	60
KP781	23	17	40
All	107	73	180

Conditional Probability

In [44]:
```
print('P[Single/KP281]:', 32/80)
print('P[Partnered/KP281]:', 48/80)
print('-'*50)
print('P[Single/KP481]:', 24/60)
print('P[Partnered/KP481]:', 36/60)
print('-'*50)
print('P[Single/KP781]:', 17/40)
print('P[Partnered/KP781]:', 23/40)
print('-'*50)
```

```
P[Single/KP281]: 0.4
P[Partnered/KP281]: 0.6
--------------------------------------------------
P[Single/KP481]: 0.4
P[Partnered/KP481]: 0.6
--------------------------------------------------
P[Single/KP781]: 0.425
P[Partnered/KP781]: 0.575
--------------------------------------------------
```

Observations:

Across Marital Status:

- Partnered customers outnumber single customers for all the products

Product Across both Customer Gender & Customer Marital Status

In [45]:
```
pd.crosstab(index=df['Product'], columns=[df['Gender'], df['MaritalStatus']], margins=True)
```

Out[45]:

Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	27	13	21	19	80
KP481	15	14	21	10	60
KP781	4	3	19	14	40
All	46	30	61	43	180

Conditional Probability

In [46]:

```
print('P[Male & Single/KP281]:', 19/80)
print('P[Male & Partnered/KP281]:', 21/80)
print('P[Female & Single/KP281]:', 13/80)
print('P[Female & Partnered/KP281]:', 27/80)
print('-'*50)
print('P[Male & Single/KP481]:', 10/60)
print('P[Male & Partnered/KP481]:', 21/60)
print('P[Female & Single/KP481]:', 14/60)
print('P[Female & Partnered/KP481]:', 15/60)
print('-'*50)
print('P[Male & Single/KP781]:', 14/40)
print('P[Male & Partnered/KP781]:', 19/40)
print('P[Female & Single/KP781]:', 3/40)
print('P[Female & Partnered/KP781]:', 4/40)
print('-'*50)
```

```
P[Male & Single/KP281]: 0.2375
P[Male & Partnered/KP281]: 0.2625
P[Female & Single/KP281]: 0.1625
P[Female & Partnered/KP281]: 0.3375
--------------------------------------------------
P[Male & Single/KP481]: 0.16666666666666666
P[Male & Partnered/KP481]: 0.35
P[Female & Single/KP481]: 0.23333333333333334
P[Female & Partnered/KP481]: 0.25
--------------------------------------------------
P[Male & Single/KP781]: 0.35
P[Male & Partnered/KP781]: 0.475
P[Female & Single/KP781]: 0.075
P[Female & Partnered/KP781]: 0.1
--------------------------------------------------
```

Observations:

Across Gender & Marital Status:

- For KP281: Partnered Females are most likely to buy
- For KP481: Partnered Males are most likely to buy
- For KP781: Males are most likely to buy, females have very less probability of buying it

Product Across Customer Age Category

In [47]:

```
pd.crosstab(index=df_profile['Product'], columns=df_profile['Age_Category'], margins=True)
```

Out[47]:

Age_Category	Below_25	25-30	Above_30	All
Product				
KP281	27	28	25	80
KP481	17	18	25	60
KP781	10	20	10	40
All	54	66	60	180

In [48]:

```
print('P[Age:Below_25/KP281]:', 27/80)
print('P[Age:25-30/KP281]:', 28/80)
print('P[Age:Above_30/KP281]:', 25/80)
print('-'*50)
print('P[Age:Below_25/KP481]:', 17/60)
print('P[Age:25-30/KP481]:', 18/60)
```

```
print('P[Age:Above_30/KP481]:', 25/60)
print('-'*50)
print('P[Age:Below_25/KP781]:', 10/40)
print('P[Age:25-30/KP781]:', 20/40)
print('P[Age:Above_30/KP781]:', 10/40)
print('-'*50)
```

```
P[Age:Below_25/KP281]: 0.3375
P[Age:25-30/KP281]: 0.35
P[Age:Above_30/KP281]: 0.3125
--------------------------------------------------
P[Age:Below_25/KP481]: 0.2833333333333333
P[Age:25-30/KP481]: 0.3
P[Age:Above_30/KP481]: 0.4166666666666667
--------------------------------------------------
P[Age:Below_25/KP781]: 0.25
P[Age:25-30/KP781]: 0.5
P[Age:Above_30/KP781]: 0.25
--------------------------------------------------
```

Observations:

- For KP281: The probability of customer falling in each age bucket is equally likely
- For KP481: The probability of customer falling in the Above_30 Age ategory is slightly higher than the other 2 categories
- For KP781: Customers falling in the age bracket [25, 30] have the maximum probability of buying it

Product Across Customer Usage

In [49]:
```
pd.crosstab(index=df_profile['Product'], columns=df_profile['Usage'], margins=True)
```

Out[49]:

Usage	2	3	4	5	All
Product					
KP281	19	37	22	2	80
KP481	14	31	12	3	60
KP781	0	1	18	21	40
All	33	69	52	26	180

In [50]:
```
print('P[Usage:2/KP281]:', 19/80)
print('P[Usage:3/KP281]:', 37/80)
print('P[Usage:4/KP281]:', 22/80)
print('P[Usage:5_and_Above/KP281]:', 5/80)
print('-'*50)
print('P[Usage:2/KP481]:', 14/60)
print('P[Usage:3/KP481]:', 31/60)
print('P[Usage:4/KP481]:', 12/60)
print('P[Usage:5_and_Above/KP481]:', 3/60)
print('-'*50)
print('P[Usage:2/KP781]:', 0/40)
print('P[Usage:3/KP781]:', 1/40)
print('P[Usage:4/KP781]:', 18/40)
print('P[Usage:5_and_Above/KP781]:', 21/40)
print('-'*50)
```

```
P[Usage:2/KP281]: 0.2375
P[Usage:3/KP281]: 0.4625
P[Usage:4/KP281]: 0.275
P[Usage:5_and_Above/KP281]: 0.0625
--------------------------------------------------
P[Usage:2/KP481]: 0.23333333333333334
P[Usage:3/KP481]: 0.5166666666666667
P[Usage:4/KP481]: 0.2
P[Usage:5_and_Above/KP481]: 0.05
--------------------------------------------------
P[Usage:2/KP781]: 0.0
P[Usage:3/KP781]: 0.025
P[Usage:4/KP781]: 0.45
P[Usage:5_and_Above/KP781]: 0.525
--------------------------------------------------
```

Observations:

- For KP281, KP481:

- The probability of customer usage being 3 times a week is the highest
- Customer usage being 4 (and above) times a week is really low for these products

- For KP781:
  - Customers whose usage is 4 (and above) times a week form the main customer base
  - Customers with low/average usage (less than 4 times a week) have very less probability of buying this

Product Across Customer Fitness

In [51]:
```python
pd.crosstab(index=df_profile['Product'], columns=df_profile['Fitness'], margins=True)
```

Out[51]:

Fitness / Product	2	3	4	5	All
KP281	15	54	9	2	80
KP481	13	39	8	0	60
KP781	0	4	7	29	40
All	28	97	24	31	180

In [52]:
```python
print('P[Fitness:2_and_Below/KP281]:', 15/80)
print('P[Fitness:3/KP281]:', 54/80)
print('P[Fitness:4/KP281]:', 9/80)
print('P[Fitness:5/KP281]:', 2/80)
print('-'*50)
print('P[Fitness:2_and_Below/KP481]:', 13/60)
print('P[Fitness:3/KP481]:', 39/60)
print('P[Fitness:4/KP481]:', 8/60)
print('P[Fitness:5/KP481]:', 0/60)
print('-'*50)
print('P[Fitness:2_and_Below/KP781]:', 0/40)
print('P[Fitness:3/KP781]:', 4/40)
print('P[Fitness:4/KP781]:', 7/40)
print('P[Fitness:5/KP781]:', 29/40)
print('-'*50)
```

```
P[Fitness:2_and_Below/KP281]: 0.1875
P[Fitness:3/KP281]: 0.675
P[Fitness:4/KP281]: 0.1125
P[Fitness:5/KP281]: 0.025
--------------------------------------------------
P[Fitness:2_and_Below/KP481]: 0.21666666666666667
P[Fitness:3/KP481]: 0.65
P[Fitness:4/KP481]: 0.13333333333333333
P[Fitness:5/KP481]: 0.0
--------------------------------------------------
P[Fitness:2_and_Below/KP781]: 0.0
P[Fitness:3/KP781]: 0.1
P[Fitness:4/KP781]: 0.175
P[Fitness:5/KP781]: 0.725
--------------------------------------------------
```

Observations:

- For KP281, KP481:
  - The probability of customer fitness being 3 is the highest followed by being 2 and below
- For KP781:
  - Customers whose fitness is 5 have the highest probability of buying this product

Product Across Customer Income Category

In [53]:
```python
pd.crosstab(index=df_profile['Product'], columns=df_profile['Income_Category'], margins=True)
```

Out[53]:

Income_Category	Low	Medium	High	All
Product				
KP281	39	30	11	80
KP481	24	24	12	60
KP781	0	8	32	40
All	63	62	55	180

In [54]:

```
print('P[Income:Low/KP281]:', 39/80)
print('P[Income:Medium/KP281]:', 30/80)
print('P[Income:High/KP281]:', 11/80)
print('-'*50)
print('P[Income:Low/KP481]:', 24/60)
print('P[Income:Medium/KP481]:', 24/60)
print('P[Income:High/KP481]:', 12/60)
print('-'*50)
print('P[Income:Low/KP781]:', 0/40)
print('P[Income:Medium/KP781]:', 8/40)
print('P[Income:High/KP781]:', 32/40)
print('-'*50)
```

```
P[Income:Low/KP281]: 0.4875
P[Income:Medium/KP281]: 0.375
P[Income:High/KP281]: 0.1375
--------------------------------------------------
P[Income:Low/KP481]: 0.4
P[Income:Medium/KP481]: 0.4
P[Income:High/KP481]: 0.2
--------------------------------------------------
P[Income:Low/KP781]: 0.0
P[Income:Medium/KP781]: 0.2
P[Income:High/KP781]: 0.8
--------------------------------------------------
```

Observations:

- For KP281, KP481:
    - Customers with Low & Medium incomes form the main customer base
- For KP781:
    - Customers with High income form the main customer base

Product Across Customer Mile Category

In [55]:

```
pd.crosstab(index=df_profile['Product'], columns=df_profile['Mile_Category'], margins=True)
```

Out[55]:

Mile_Category	Low	Medium	High	All
Product				
KP281	38	27	15	80
KP481	21	31	8	60
KP781	1	8	31	40
All	60	66	54	180

In [56]:

```
print('P[Mile:Low/KP281]:', 38/80)
print('P[Mile:Medium/KP281]:', 27/80)
print('P[Mile:High/KP281]:', 15/80)
print('-'*50)
print('P[Mile:Low/KP481]:', 21/60)
print('P[Mile:Medium/KP481]:', 31/60)
print('P[Mile:High/KP481]:', 8/60)
print('-'*50)
print('P[Mile:Low/KP781]:', 1/40)
print('P[Mile:Medium/KP781]:', 8/40)
print('P[Mile:High/KP781]:', 31/40)
print('-'*50)
```

```
P[Mile:Low/KP281]: 0.475
P[Mile:Medium/KP281]: 0.3375
P[Mile:High/KP281]: 0.1875
--------------------------------------------------
P[Mile:Low/KP481]: 0.35
P[Mile:Medium/KP481]: 0.5166666666666667
P[Mile:High/KP481]: 0.13333333333333333
--------------------------------------------------
P[Mile:Low/KP781]: 0.025
P[Mile:Medium/KP781]: 0.2
P[Mile:High/KP781]: 0.775
--------------------------------------------------
```

Observations:

- For KP281:
  - THe probability of Cutomer miles being Low is the highest and being High is the lowest
  - There is a strong declining trend
- For KP481:
  - THe probability of Cutomer miles being Medium is the highest
  - The trend is quite different from what we observe ffor KP281
- For KP781:
  - Customers whose miles are High form the main customer base

Summary of customer profile

For KP281:

- Both men and women are eqaully likely to buy this.
- Partnered customers are more than single customers.
- If we get really specific, partnered females form the largest customer base for this product (almost 34%).
- Customers from all age groups are equally likely to buy this, there is no age bias.
- Customers whose usage is between 2-4 times a week buy this product, very few with usage 5 (and more) times a week prefer this.
- Almost 70% of the customers who bought this product rated themselves a 3 in fitness, very few bought this product whose fitness was 4 and above.
- The majority (87%) of the custmomers fall in the:
  - Low Income bracket (49% below 45480 USD)
  - Medium Income bracket (38% b/w 45480-54576 USD)
- The majority (82%) of the custmomers fall in the:
  - Low Miles bracket (48% below 80 miles)
  - Medium Miles bracket (34% in 80-106 miles)

For KP481:

- Both men and women are eqaully likely to buy this.
- Partnered customers are more than single customers.
- If we get really specific, partnered males form the largest customer base for this product (almost 35%).
- Customers who are above 30 form the largest customer base (almost 42%). The rest 58% is evenly split b/w the other 2 age categories.
- Customers whose usage is between 2-4 times a week buy this product, very few with usage 5 (and more) times a week prefer this.
- 65% of the customers who bought this product rated themselves a 3 in fitness, very few bought this product whose fitness was 4 and above.
- The majority (80%) of the custmomers fall in the:
  - Low Income bracket (40% below 45480 USD)
  - Medium Income bracket (40% b/w 45480-54576 USD)
- The majority (87%) of the custmomers fall in the:
  - Medium Miles bracket (52% in 80-106 miles)
  - Low Miles bracket (35% below 80 miles)

For KP781:

- Mostly men buy this (almost 83%).

- Partnered customers are more than single customers.
- Customers who are b/w 25-30 years form the largest customer base (50%). The rest 50% is evenly split b/w the other 2 age categories.
- Customers whose usage is 4 or more times a week buy this product, very few with usage less than 4 times a week prefer this.
- 73% of the customers who bought this product rated themselves a 5 in fitness, very few bought this product whose fitness was 3 and below.
- The majority (80%) of the custmomers fall in the High Income bracket (above 54576 USD)
  - There are no customers from the Low Income bracket(below 45480 USD)
- The majority (98%) of the custmomers fall in the:
  - High Miles bracket (78% above 106 miles)
  - Medium Miles bracket (20% in 80-106 miles)

Business Insights & Recommendations:

Insights:

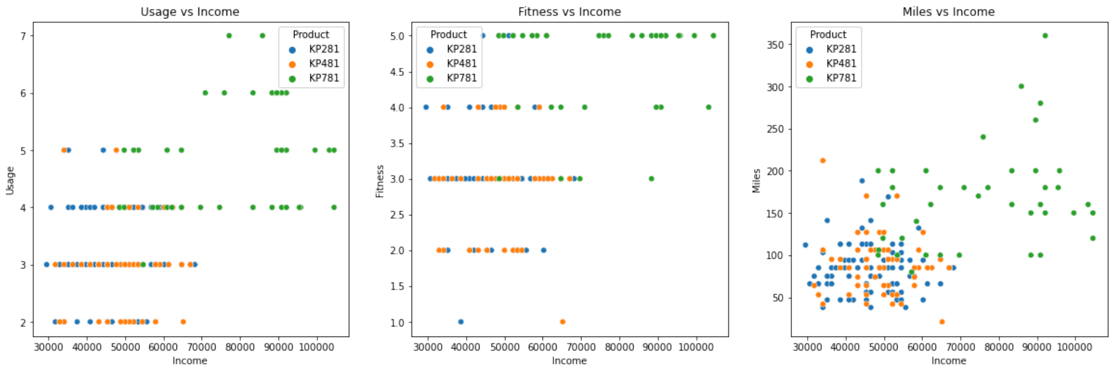
1. Aerofit has 3 treadmills: KP281, KP481 & KP781.
   - KP281 id the most sold product , followed by KP481 in the 2nd place and KP781 in the 3rd place.
2. Expected revenue generated by selling 1 Aerofit treadmill:
   - (KP281_price *P[KP281]) + (KP481_price* P[KP481]) + (KP781_price *P[KP781]) = 1500*|0.444 + 1750*0.333 + 2500*0.222 = 1804 USD
3. Male customers are more than female customers. Also partnered customers are more than single customers.
4. The target customer across the 3 treadmills lies somewhere between 20-35 years in age.
5. Most of the customers' annual income lie in the range 30000-70000 USD.
6. Customer profile for KP281 & KP481 are almost the same.
   - This is to be expected since the price difference b/w the 2 products is very less
   - However some of the key difference b/w the profiles for KP281 and KP481 are:
     - Largest customer base: Partnered females for KP281, partnered males for KP481
     - Age of customers: customers across all age groups buy KP281 while KP481 is more preferred by those who are above 30
     - If we look at the number of customers in the Low Income bracket, we have:
       - 49% of KP281 buyers are in the Low Income bracket
       - 40% of KP481 buyers are in the Low Income bracket
       - Thus KP281 has a larger customer base in the Low Income category than KP481. However this is to be expected since KP281 is the cheapest treadmill.
7. Customer profile for KP781 is quite different from the other 2 treadmills
   - It has been observed tha males dominate the customer base for KP781, females form a mere 13%
   - Customers who buy KP781, with respect to the buyers of KP281 & KP481:
     - are already very fit
     - have a higher weekly usage for the treadmill
     - plan to walk/run a higher number of miles
     - have a higher annual income

Recommendations:

1. Since KP281 is the most popular product, it's manufacturing should get the highest priority
2. Since partnered customers are more than single customers, the treadmills can be sold with some partner incentive
   - For example, upon buying a treadmill, a protein shaker bottle can be given for free with some personalization (like the couple's name can be laminated on the bottle)
3. It is also observed that there is a sharp difference in the median customer income fort KP781 and the other 2 products
   - We can probably look into restructuring the price of the KP781 treadmill.
   - We have found out that people who are fitter, has higher usage and higher miles tend to go for the KP781. However if the price of the treadmill in too high given that their income is low, they will have to settle for the

KP481 or the KP281

- Consider the parameter: Usage
    - From the below figure, we can observe that a lot of customers whose Usage is 4 opted for the KP781.
    - However at the same time there are a lot of customers with Usage=4 who also who bought the KP481 or KP281. But note that these customers have primarily lower annual income.
        - So we can infer that even though their usage was high enough to make them buy KP781, they still bought the lower end treadmills simply because it was unaffordable.
    - If the price of KP781 is reduced, more people may end up buying it. Thus the scale of selling the premium treadmill will increase and that will create a higher profit
- Similar comments can be made about the other parameters: Fitness and Miles



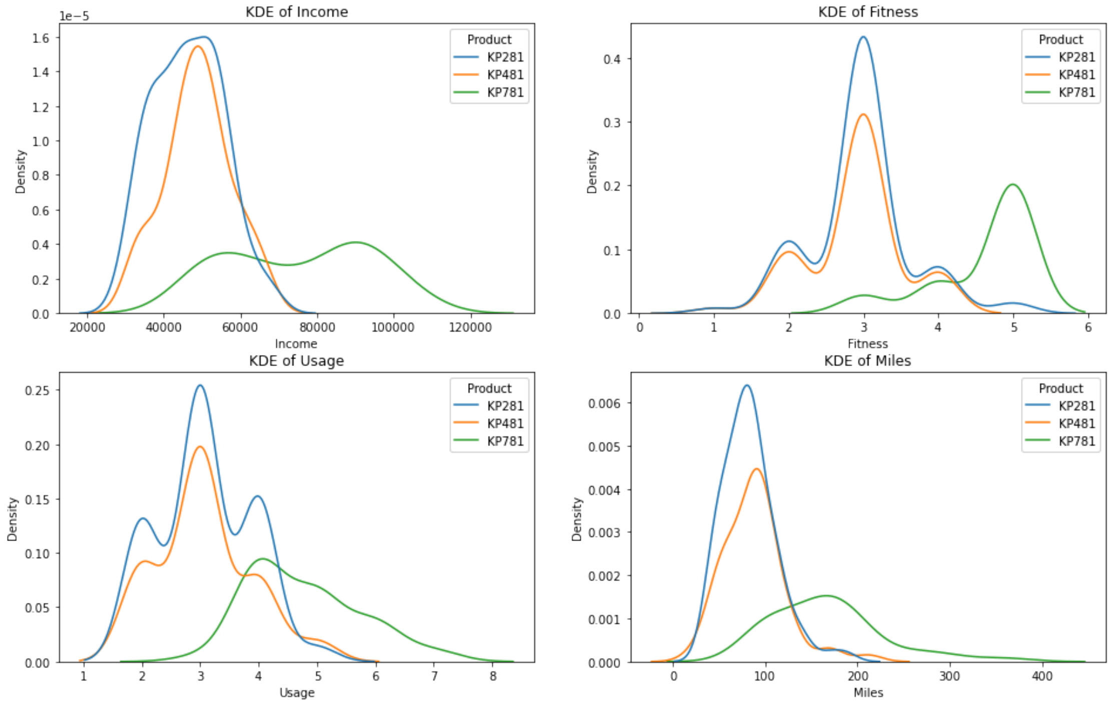
4. Since we have observed that female customers are very few for the KP781, some incentives/discounts may be given to females to create a new demand among them.
5. Aerofit can also try to create a few ad campaigns where there promote the benefits of getting fit and also show some weight loss journeys of their customers using their treadmills.
    - This will help expand into the untapped market of those customers who lack fitness awareness.

Some important observations:

1. Top-3 features that have highest correleation with the Product column? Also provide possible reasons behind those correlations?

- The top-3 features which affect the choice of a product (clearly visible from the KDE plot of these features across Product):
    - Income
    - Fitness
    - Usage/Miles
- ***Why Income?***
    - Income is quite obvious, since any purchase a customer makes is dependent of his/her income
    - For example KP781 is an expensive treadmill and is only bought by those whose annual income is high
- ***Why Fitness?***
    - We must understand that the products in question are fitness products
    - Fitness is a strong factor which determines the choice of products
    - We have observed that those customers who are already very fit bought the premium KP781 treadmill while those with poor or average fitness go for the low-end treadmills
- ***Why usage/miles?***
    - This is also quite straight forward. When a customer has a high or daily usage for a product, he/she usually wants to invest in something that is long lasting, and has as many features as possiblr. If the use case is less, then usually people will not spend a lot on a product.
    - We have also seen that if the expected usage/miles of the customer is high, he/she tends to opt for the KP781 (given that his income allows him to so so)

- For those customers who have bought KP281 and KP481, their overall usage and miles are low



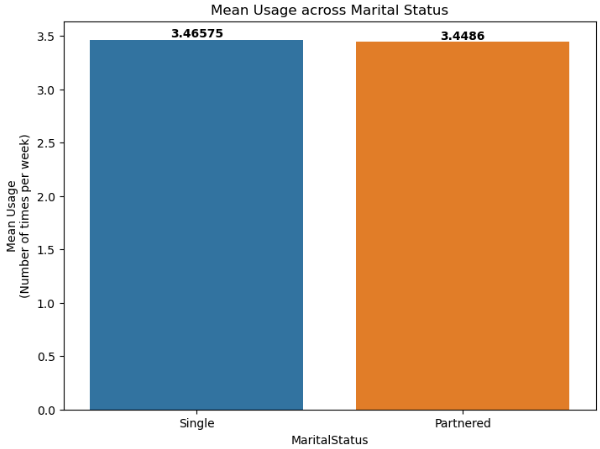
2. How did we identify and treat the outliers in the dataset?

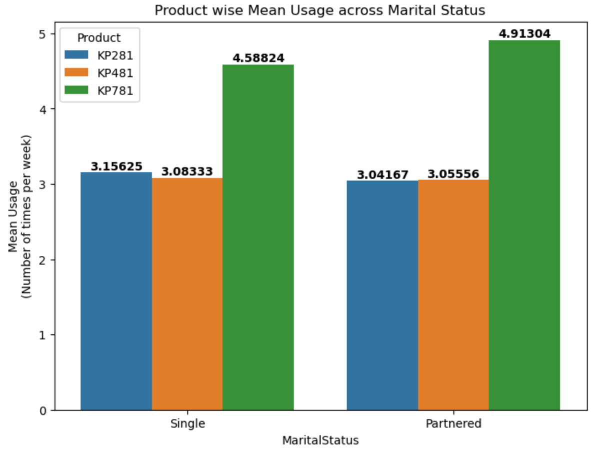
- Outliers were identified(by the 1.5 * IQR rule) and treated
- All the data points which were above/below the upper/lower whisker were assigned the value of the whisker itself

3. Marital Status implies no significant information on the usage of different treadmills. (T/F)

- This statement is True
- AS far as the usage of the treadmills is concerned, Marital Status is not a feature that affects it
- This has been demonstrated in the below figure
- We can observe that the usage pattern for different treadmills roughlt remains the same irrespective of ther Marital Status

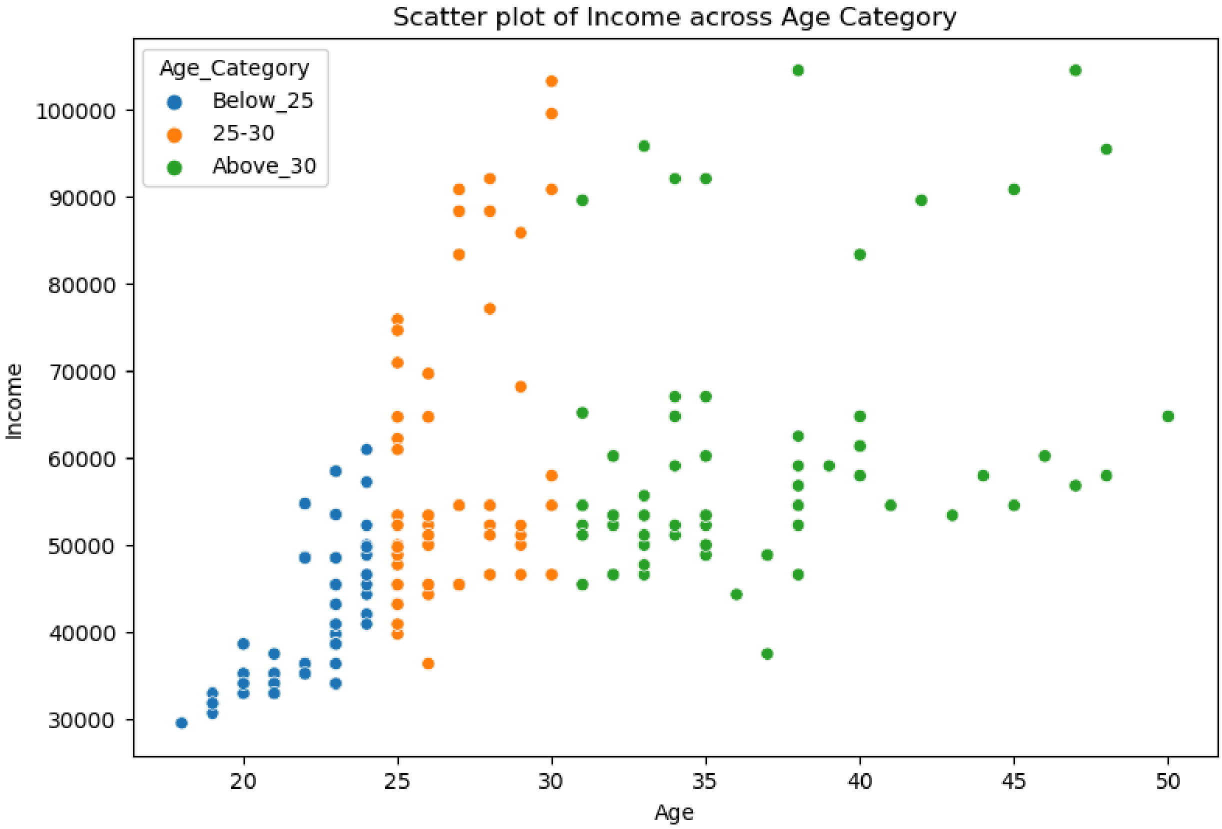
In [57]:
```
fig = plt.figure(figsize=(18, 6))
plt.subplot(1, 2, 1)
f = sns.barplot(x=df_original['MaritalStatus'], y=df_original['Usage'], estimator=np.mean, ci=None
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Mean Usage\n(Number of times per week)')
plt.title('Mean Usage across Marital Status')
plt.subplot(1, 2, 2)
f = sns.barplot(x=df_original['MaritalStatus'], y=df_original['Usage'], hue=df_original['Product'],
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Mean Usage\n(Number of times per week)')
plt.title('Product wise Mean Usage across Marital Status')
plt.show()
```





4. The variance of income in lower ages is smaller as compared to the variance in higher ages

In [58]:
```
plt.figure(figsize=(9, 6))
# sns.kdeplot(x=pd.concat([df_original, df_profile['Age_Category']], axis=1)['Income'], hue=pd.conc
sns.scatterplot(x=pd.concat([df_original, df_profile['Age_Category']], axis=1)['Age'], y=pd.concat
                hue=pd.concat([df_original, df_profile['Age_Category']], axis=1)['Age_Category'])
plt.title('Scatter plot of Income across Age Category')
plt.show()
```



In [59]:
```
pd.pivot(data=pd.concat([df_original, df_profile['Age_Category']], axis=1)[['Age', 'Age_Category']]
```

Out[59]:

Age_Category	Below_25	25-30	Above_30
count	54.000000	66.00000	60.000000
mean	22.166667	26.69697	37.050000
std	1.645463	1.76260	5.097108
min	18.000000	25.00000	31.000000
25%	21.000000	25.00000	33.000000
50%	23.000000	26.00000	35.000000
75%	23.000000	28.00000	40.000000
max	24.000000	30.00000	50.000000

In [60]:
```
# Variance of Income of different age groups:
(pd.pivot(data=pd.concat([df_original, df_profile['Age_Category']], axis=1)[['Age', 'Age_Category']
         columns='Age_Category', values='Age').describe().loc['std'].values)**2
```

Out[60]:
```
array([ 2.70754717,  3.10675991, 25.98050847])
```

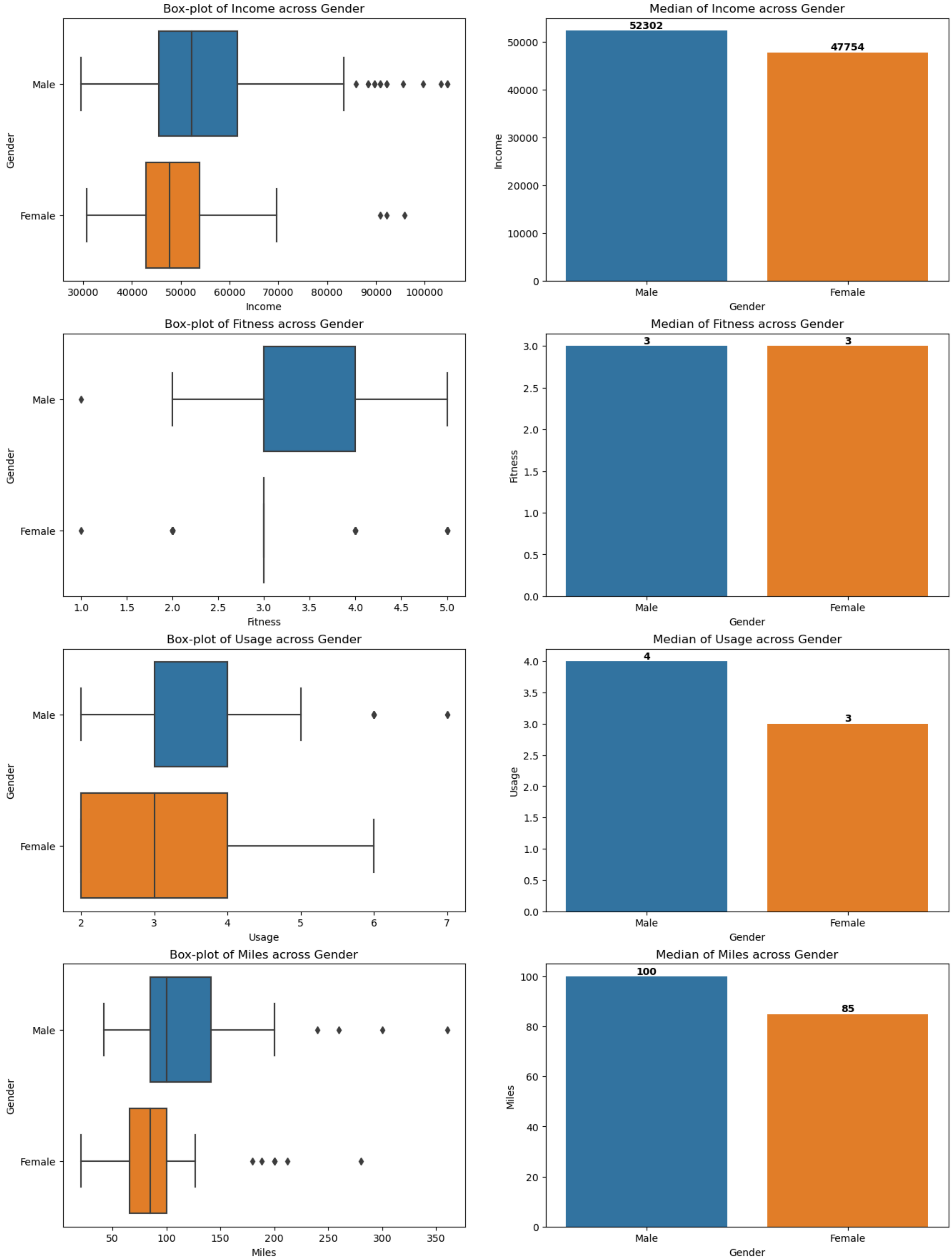
Variance of income for different age groups are as follows:

- Below_25: 2.7
- 25-30: 3.1
- Above 30: 25.98
- In statistics, this is called: 'Heteroscedasticity'

5. What proportion of women have bought the KP781 treadmill? What can be the possible reasons for this?

- KP781 was bought by a total of 40 customers (33 Male and 7 female).
- Thus only 17.5% customers who bought this product were females.
- We know that the customers who have bought KP781 have high:
  - Income
  - Fitness
  - Usage
  - Miles
- Now, we try to see how the above features differ across Gender from the plots below:
  - We can observe that Median value of Income, Usage and Miles are all greater for Males than Females while on fitness, both are the same.
  - Thus this gives us an idea as to why so few women have bought the KP7841 treadmill.

In [61]:
```
kp781_features = ['Income', 'Fitness', 'Usage', 'Miles']
fig = plt.figure(figsize=(16, 22))
id = 1
for feature in kp781_features:
    plt.subplot(4, 2, id)
    sns.boxplot(x=df_original[feature], y=df_original['Gender'])
    plt.title(f'Box-plot of {feature} across Gender')
    plt.subplot(4, 2, id+1)
    f = sns.barplot(data=df_original, x='Gender', y=feature, estimator=np.median, ci=None)
    for item in f.containers:
        f.bar_label(item, fontsize=10, fontweight='bold')
    plt.title(f'Median of {feature} across Gender')
    id += 2
```


Box-plot of Income across Gender
Male
Female
Gender
Income
Median of Income across Gender
52302
47754
Income
Gender
Male
Female
Box-plot of Fitness across Gender
Fitness
Median of Fitness across Gender
3
3
Fitness
Box-plot of Usage across Gender
Usage
Median of Usage across Gender
4
3
Usage
Box-plot of Miles across Gender
Miles
Median of Miles across Gender
100
85
Miles