In [ ]:

```
#Business Problem:
    #1. 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
    #2. Perform descriptive analytics to create a customer profile for each AeroFit treadmill product
       #by developing appropriate tables and charts.
    #3. 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 [526]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.distributions.empirical_distribution import ECDF
from scipy.stats import norm

```

In [527]:

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

Out[527]:

	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
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

In [528]:

```
#describes numerical data and provides a statistical summary
df.describe()
```

Out[528]:

	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 [529]:

```
#describes categorical data
data.describe(include="object").T
```

Out[529]:

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

In [530]:

```
#provides structural summary of a DataFrame
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
```

In [531]:

```
#checks for null values for each column and returns the sum
df.isna().sum()
```

Out[531]:

```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [532]:

```
#Product distribution
df_product = df['Product'].value_counts()
df_product
```

Out[532]:

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

In [91]:

```
#Gender distribution
df_gender = df['Gender'].value_counts()
df_gender
```

Out[91]:

```
Gender
Male      104
Female     76
Name: count, dtype: int64
```

In [41]:

```
#Counts based on marital status
df['MaritalStatus'].value_counts()
```

Out[41]:

```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

In [46]:

```
#Counts based on fitness rating
df['Fitness'].value_counts()
```

Out[46]:

```
Fitness
3    97
5    31
2    26
4    24
1     2
Name: count, dtype: int64
```

In [56]:

```
#Counts based on treadmill used per week
df['Usage'].value_counts()
```

Out[56]:

```
Usage
3    69
4    52
2    33
5    17
6     7
7     2
Name: count, dtype: int64
```

In [533]:

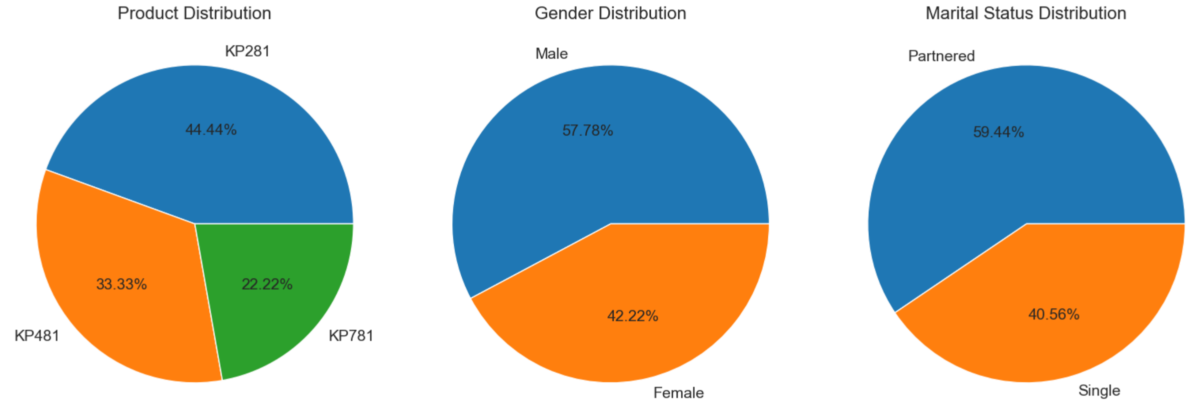
```
#segregated income into different income buckets
df_cp = df
df_cp['Income_levels'] = df_cp['Income']
df_cp["Income_levels"] = pd.cut(df_cp["Income_levels"], bins =[25000,40000,60000,80000,120000], include_lowest=Tru
df_cp["Income_levels"] =df_cp["Income_levels"].astype("object")
df_cp.head()
```

Out[533]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Income_levels
0	KP281	18	Male	14	Single	3	4	29562	112	Low(25k-40k)
1	KP281	19	Male	15	Single	2	3	31836	75	Low(25k-40k)
2	KP281	19	Female	14	Partnered	4	3	30699	66	Low(25k-40k)
3	KP281	19	Male	12	Single	3	3	32973	85	Low(25k-40k)
4	KP281	20	Male	13	Partnered	4	2	35247	47	Low(25k-40k)

In [602]:

```
# Distribution of categorical variables using pie chart

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(16, 10))
axs[0].pie(df['Product'].value_counts(),labels=['KP281','KP481','KP781'] ,autopct='%1.2f%%',textprops={'fontsize':
axs[0].set_title('Product Distribution',fontsize=16)
axs[1].pie(df['Gender'].value_counts(), labels=['Male','Female'] ,autopct='%1.2f%%',textprops={'fontsize': 14})
axs[1].set_title('Gender Distribution',fontsize=16)
axs[2].pie(df['MaritalStatus'].value_counts(), labels=['Partnered','Single'],autopct='%1.2f%%',textprops={'fontsiz
axs[2].set_title('Marital Status Distribution',fontsize=16)
# Adjust spacing between subplots
plt.tight_layout()
plt.show()
```

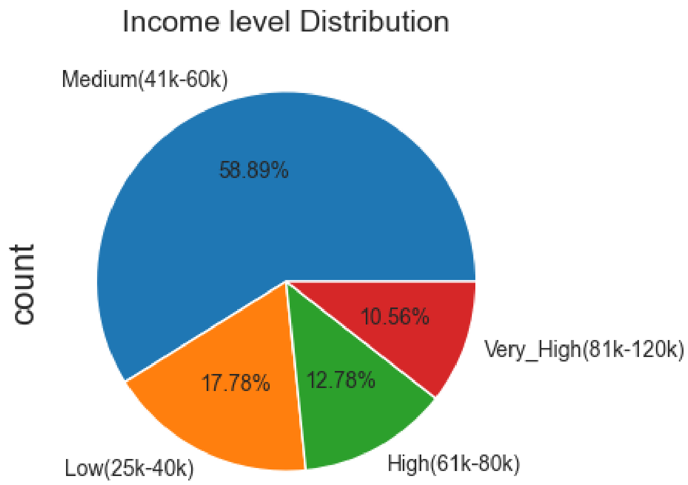


In [620]:

```
plt.figure(figsize=(4,4))
df['Income_levels'].value_counts().plot(kind='pie',autopct='%1.2f%%',textprops={'fontsize': 10})
plt.title('Income level Distribution',fontsize=14)
```

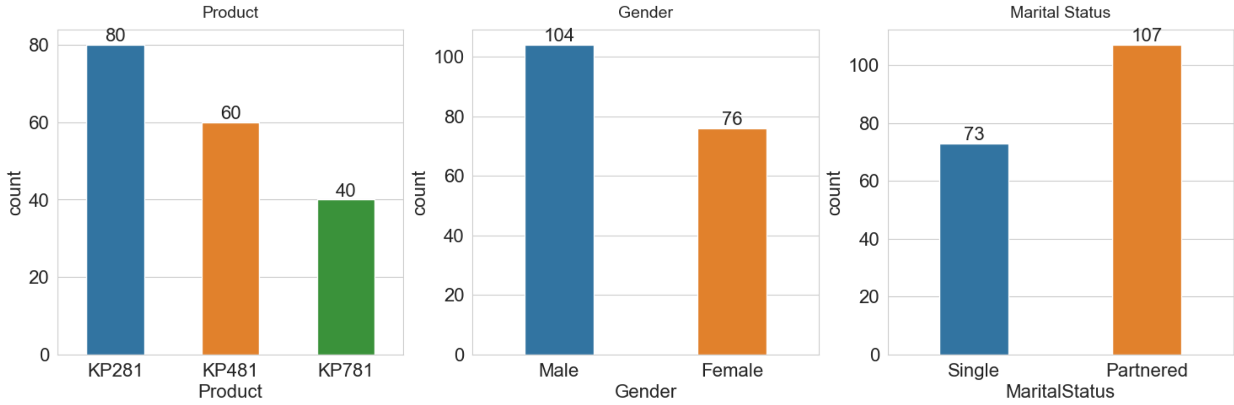
Out[620]:

```
Text(0.5, 1.0, 'Income level Distribution')
```



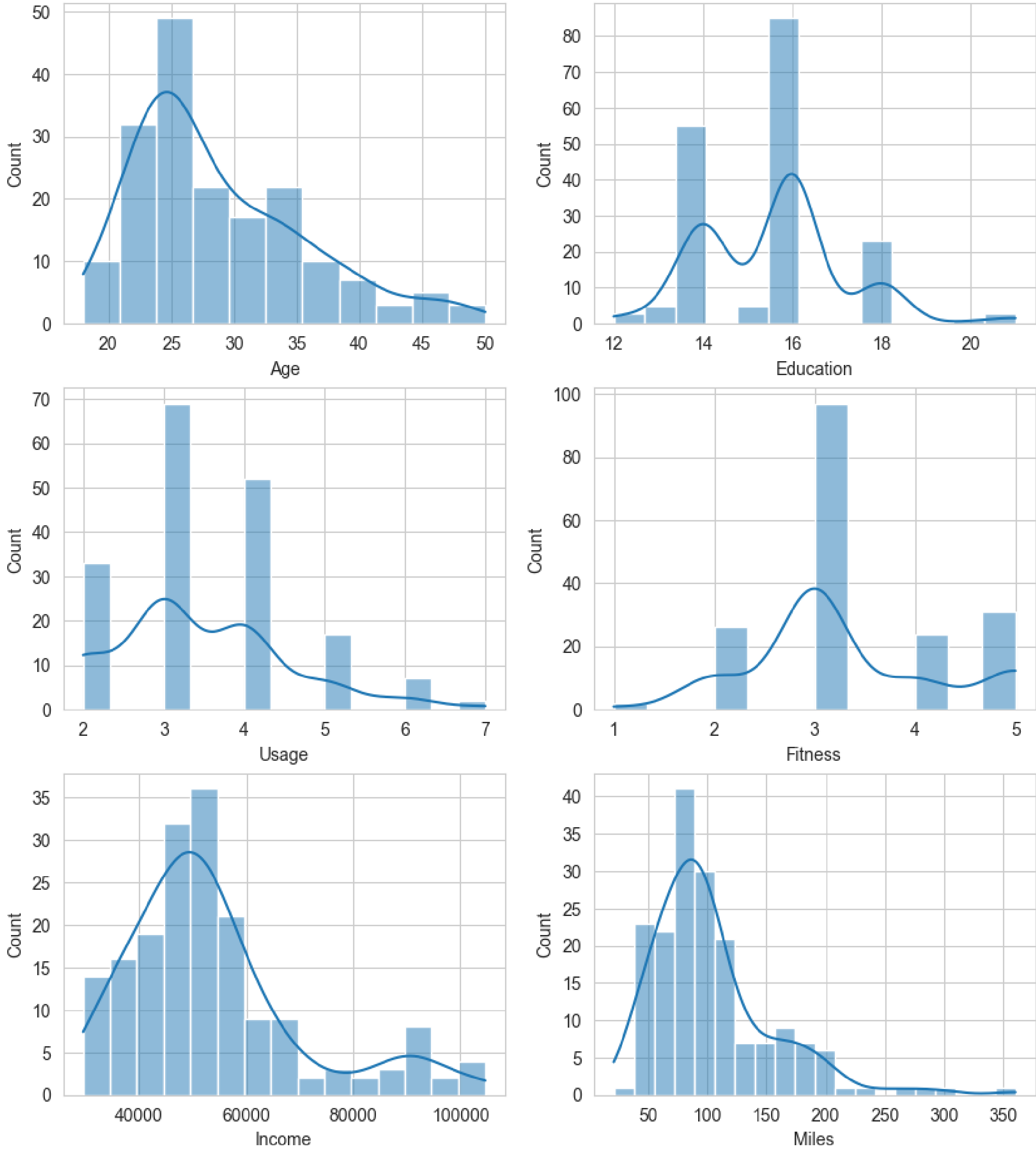
In [601]:

```
#count of products based on the type of threadmill,count of products based on the gender,
#count of products based on their marital status

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(18, 5))
ax1=sns.countplot(data=df, x='Product',width=0.5, ax=axs[0])
ax2=sns.countplot(data=df, x='Gender',width=0.4, ax=axs[1])
ax3=sns.countplot(data=df, x='MaritalStatus',width=0.4, ax=axs[2])
ax1.bar_label(ax1.containers[0])
ax2.bar_label(ax2.containers[0])
ax3.bar_label(ax3.containers[0])
ax1.set_title("Product", pad=10, fontsize=14)
ax2.set_title("Gender", pad=10, fontsize=14)
ax3.set_title("Marital Status", pad=10, fontsize=14)
plt.show()
```



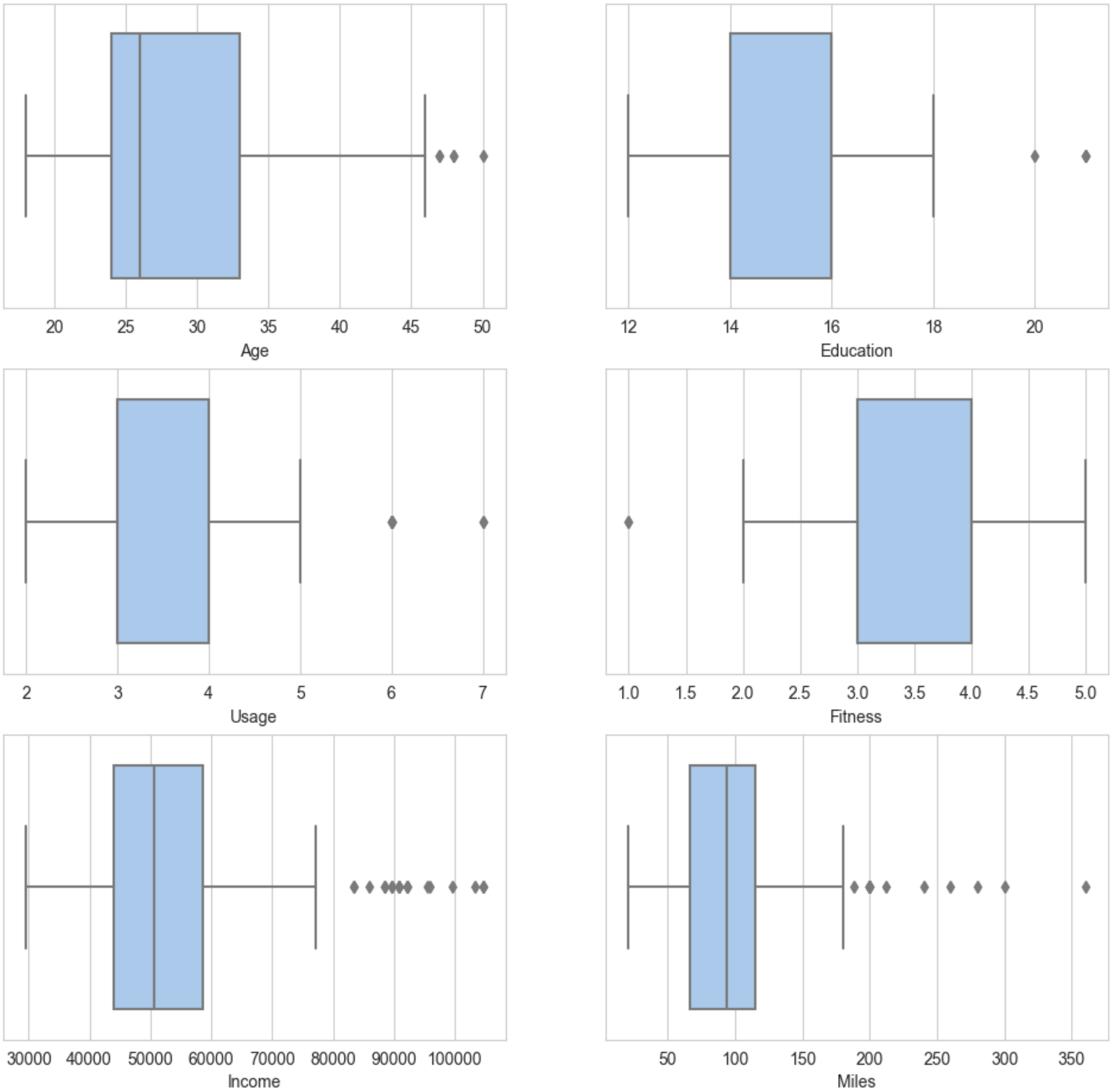
In [376]:

```
#frequency distribution of a continious numerical variables is obtained through histplot
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(10, 8))
fig.subplots_adjust(top=1.2)

sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Education", kde=True, ax=axis[0,1])
sns.histplot(data=df, x="Usage", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Fitness", kde=True, ax=axis[1,1])
sns.histplot(data=df, x="Income", kde=True, ax=axis[2,0])
sns.histplot(data=df, x="Miles", kde=True, ax=axis[2,1])
plt.show()
```



In [372]:

```
# To identify the outliers for each category of the data using boxplot

fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 8))
fig.subplots_adjust(top=1.2)

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



In [307]:

```
#Calculating IQR,25% Quarttile,75% Quartile for Miles category
IQR = np.percentile(df["Miles"],75) - np.percentile(df["Miles"],25)
Q3 = np.percentile(df["Miles"],75)
Q1 = np.percentile(df["Miles"],25)
UpperWhisker_miles = Q3 + (1.5*(IQR))
```

In [603]:

```
IQR,Q3,Q1,UpperWhisker_miles
```

Out[603]:

```
(48.75, 114.75, 66.0, 187.875)
```

In [309]:

```
#To check how many values lie outside the outlier for miles category
outlier_data_miles = data[data["Miles"]>UpperWhisker_miles]
outlier_data_miles.shape[0]
```

Out[309]:

13

In [606]:

```
#Calculating IQR, 25% Quarttile,75% Quartile for Income category
IQR_income = np.percentile(df["Income"],75) - np.percentile(df["Income"],25)
q3 = np.percentile(df["Income"],75)
q1 = np.percentile(df["Income"],25)
UpperWhisker_income = q3 + (1.5*(IQR_income))
```

In [605]:

```
IQR_income,q3,q1,UpperWhisker_income
```

Out[605]:

(14609.25, 58668.0, 44058.75, 80581.875)

In [312]:

```
#To check how many values lie outside the outlier for income category
outlier_data_income = data[data["Income"]>UpperWhisker_income]
outlier_data_income.shape[0]
```

Out[312]:

19

In [509]:

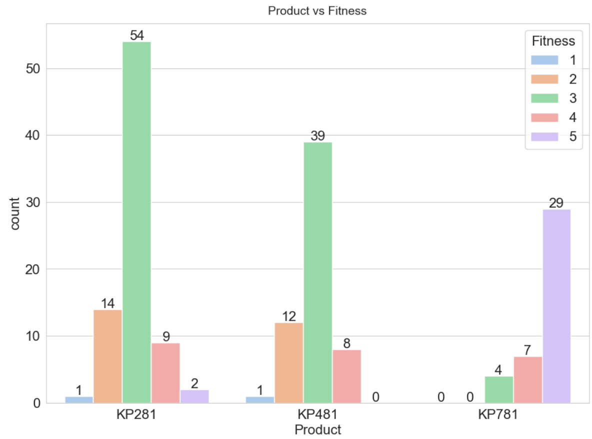
```
df.describe().round(3)
```

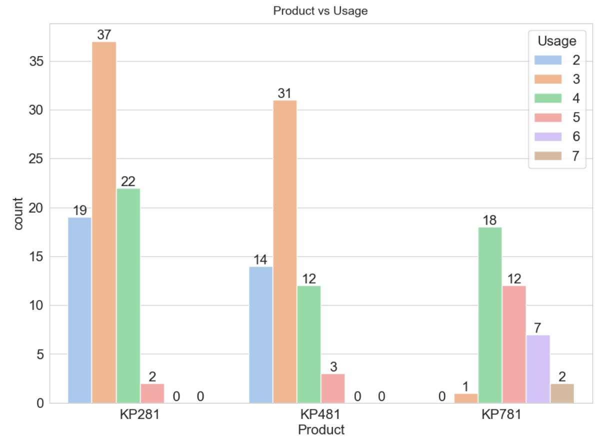
Out[509]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000	180.000	180.000	180.000	180.000	180.000
mean	28.789	15.572	3.456	3.311	53719.578	103.194
std	6.943	1.617	1.085	0.959	16506.684	51.864
min	18.000	12.000	2.000	1.000	29562.000	21.000
25%	24.000	14.000	3.000	3.000	44058.750	66.000
50%	26.000	16.000	3.000	3.000	50596.500	94.000
75%	33.000	16.000	4.000	4.000	58668.000	114.750
max	50.000	21.000	7.000	5.000	104581.000	360.000

In [558]:

```
#Compares count of different product types against diferent types of Gender and Marital status
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(25,8))
axs1 = sns.countplot(data=df, x='Product', hue='Fitness', width=0.8 , palette='pastel', ax=axs[0])
axs2 = sns.countplot(data=df, x='Product', hue='Usage', width=0.8, palette='pastel', ax=axs[1])
axs[0].set_title("Product vs Fitness", pad=10, fontsize=14)
axs[1].set_title("Product vs Usage", pad=10, fontsize=14)

num_bars = len(axs1.patches)
# Add value on top of each bar
for p in axs1.patches:
    height = p.get_height()
    axs1.text(p.get_x() + p.get_width() / 2., height + 0.2, str(round(height)), ha="center")

# Add value on top of each bar
for p in axs2.patches:
    height = p.get_height()
    axs2.text(p.get_x() + p.get_width() / 2., height + 0.2, str(round(height)), ha="center")


plt.show()
```



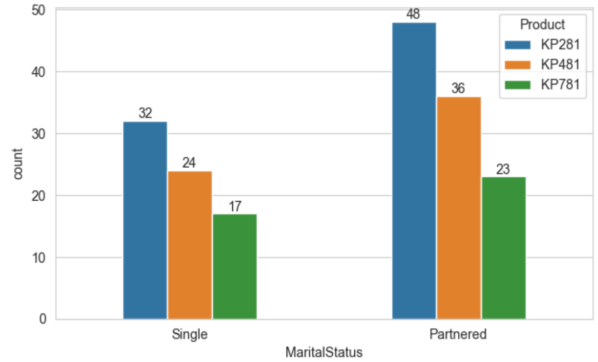


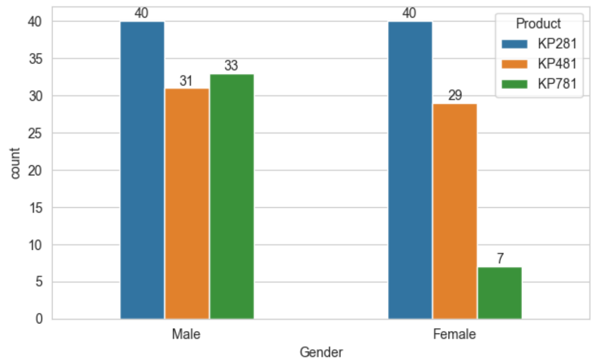
In [463]:

```
#Compares count of different product types against diferent types of Gender and Marital status

fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(16, 3))
fig.subplots_adjust(top=1.2)
ax1=sns.countplot(x='MaritalStatus', hue='Product',width=0.5, data=df,ax=axis[0])
ax2=sns.countplot(x='Gender', hue='Product', width=0.5, data=df,ax=axis[1])
ax1.bar_label(ax1.containers[0])
ax1.bar_label(ax1.containers[1])
ax1.bar_label(ax1.containers[2])
ax2.bar_label(ax2.containers[0])
ax2.bar_label(ax2.containers[1])
ax2.bar_label(ax2.containers[2])
```

Out[463]:

```
[Text(0, 0, '33'), Text(0, 0, '7')]
```



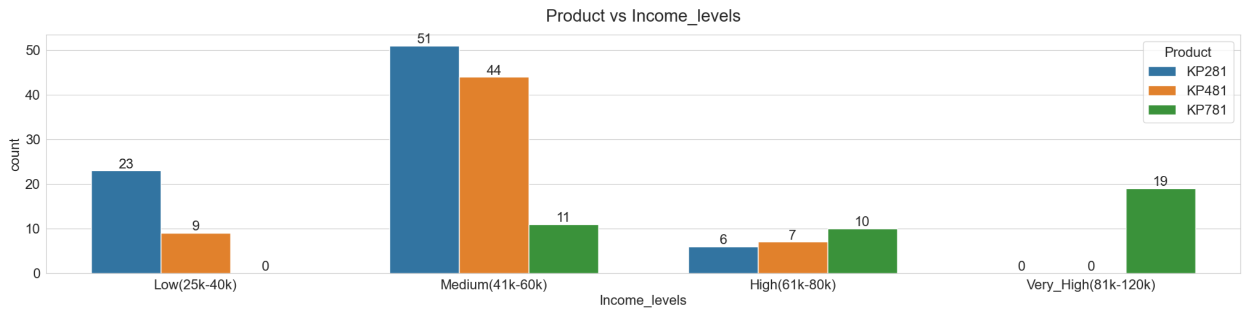


In [612]:

```
#count of product across different income levels
fig, axis = plt.subplots(nrows=1, ncols=1, figsize=(25, 5))
ax = sns.countplot(x='Income_levels', hue='Product', width=0.7, data=df_cp)
ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
ax.bar_label(ax.containers[2])
ax.set_title('Product vs Income_levels',pad =15, fontsize=20)
```

Out[612]:

```
Text(0.5, 1.0, 'Product vs Income_levels')
```

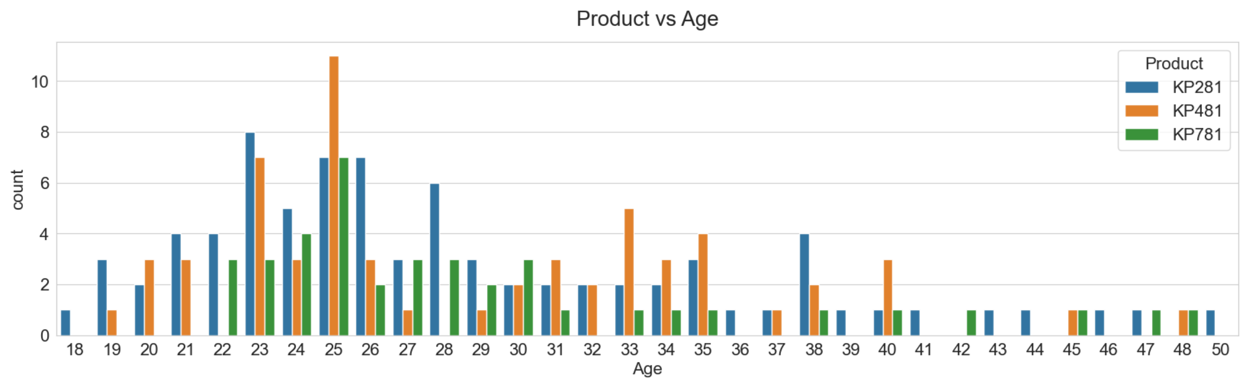


In [615]:

```
#count of product across different age
plt.figure(figsize=(20,5))
ax = sns.countplot(x='Age', hue='Product', data=df)
ax.set_title('Product vs Age',pad =15, fontsize=20)
```

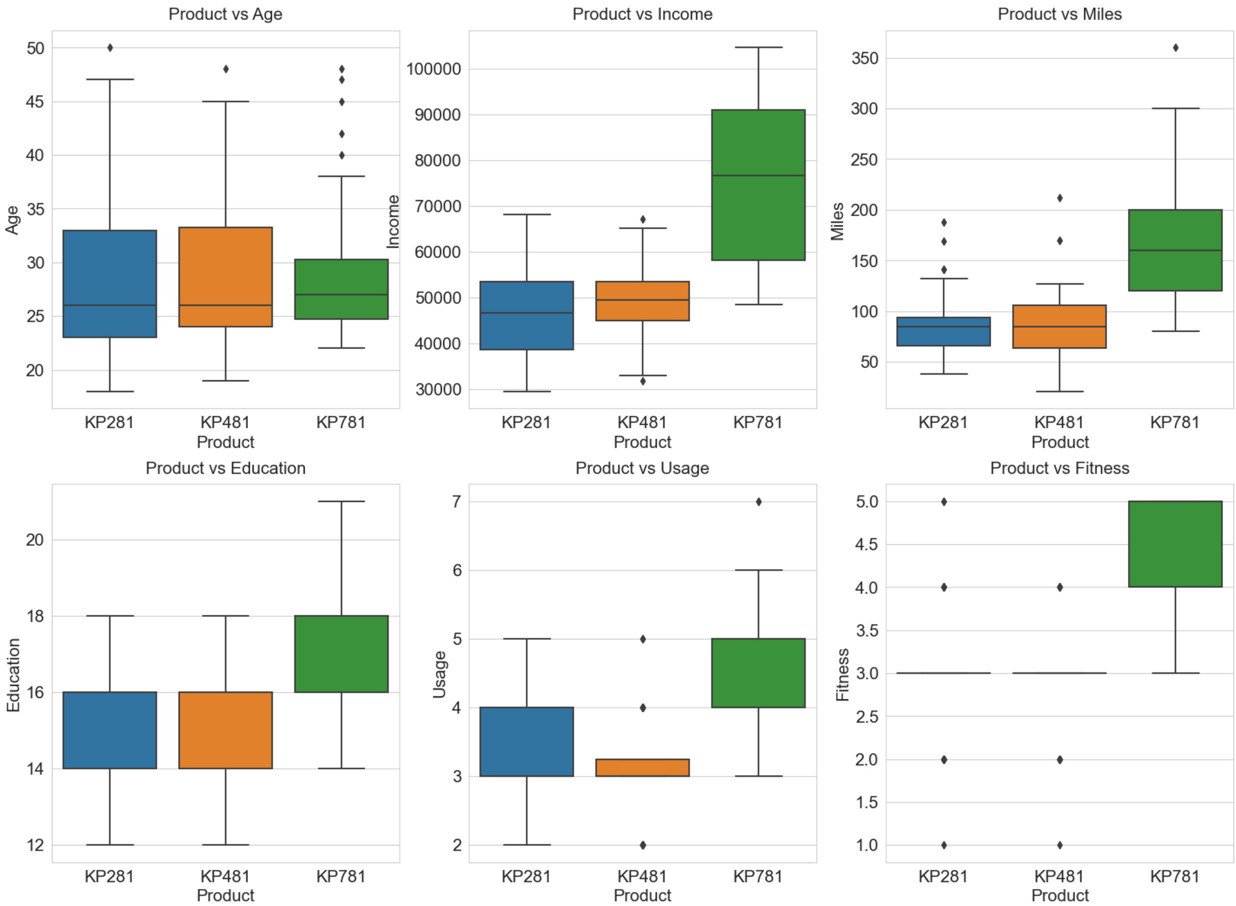
Out[615]:

```
Text(0.5, 1.0, 'Product vs Age')
```



In [573]:

```python
#Check if these data have any correaltion with the product type

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(20, 10))
fig.subplots_adjust(top=1.2)
sns.boxplot(x='Product', y='Age', data=df, ax=axis[0,0])
sns.boxplot(x='Product', y='Income', data=df, ax=axis[0,1])
sns.boxplot(x='Product', y='Miles', data=df, ax=axis[0,2])
sns.boxplot(x='Product', y='Education', data=df, ax=axis[1,0])
sns.boxplot(x='Product', y='Usage', data=df, ax=axis[1,1])
sns.boxplot(x='Product', y='Fitness', data=df, ax=axis[1,2])
axis[0,0].set_title("Product vs Age", pad=10, fontsize=16)
axis[0,1].set_title("Product vs Income", pad=10, fontsize=16)
axis[0,2].set_title("Product vs Miles", pad=10, fontsize=16)
axis[1,0].set_title("Product vs Education", pad=10, fontsize=16)
axis[1,1].set_title("Product vs Usage", pad=10, fontsize=16)
axis[1,2].set_title("Product vs Fitness", pad=10, fontsize=16)
plt.show()
```

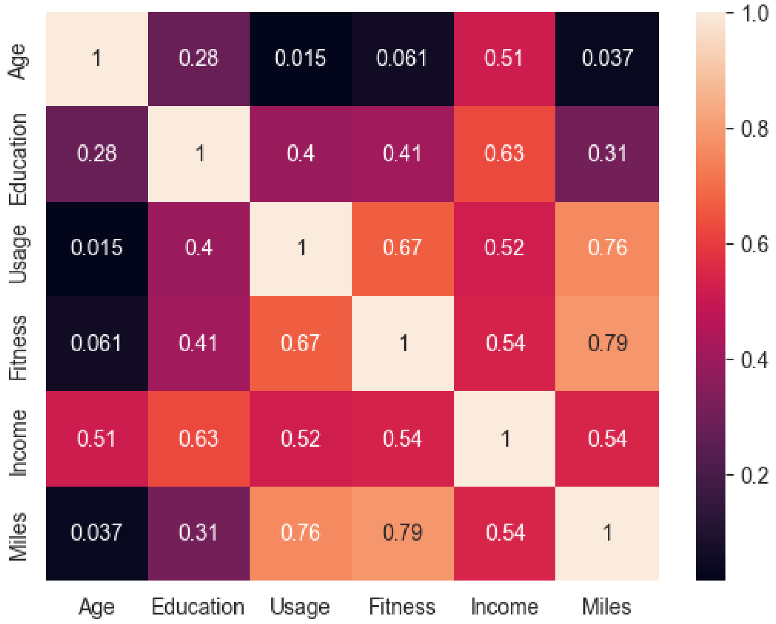


In [388]:

```
#Shows how data values are correlated with every other variable in the table
numeric_data = df.select_dtypes(include='number')
sns.heatmap(numeric_data.corr(),annot=True)
```

Out[388]:

```
<Axes: >
```

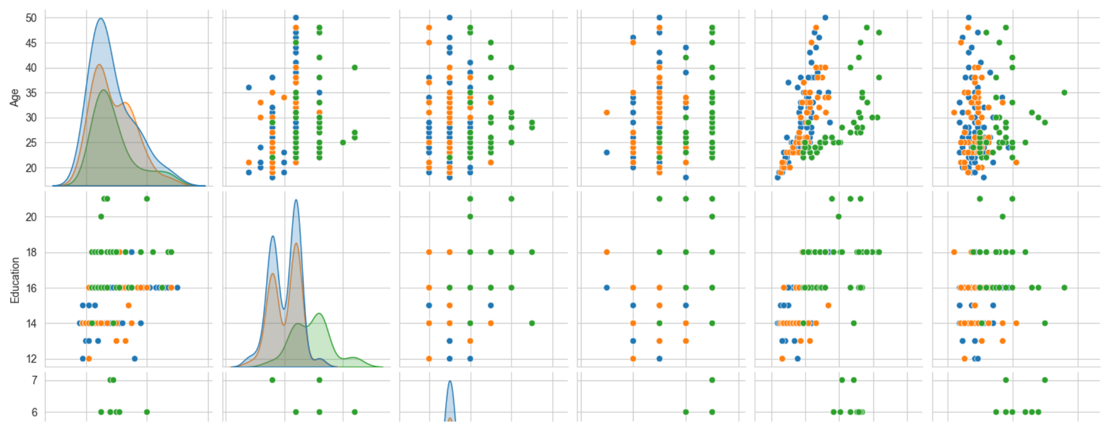


In [198]:

```
#creates number of scatter plots and histograms to visualize the relationships
#between all numerical variables in a dataset
sns.pairplot(df, hue ='Product')
```

Out[198]:

```
<seaborn.axisgrid.PairGrid at 0x162cf76aa50>
```



Marginal and Conditional Probabilities

Gender

In [567]:

```
#Marginal Probability of each product

df_margin =(df['Product'].value_counts()/df.shape[0] *100).round(2)
df_margin
```

Out[567]:

```
Product
KP281    44.44
KP481    33.33
KP781    22.22
Name: count, dtype: float64
```

In [258]:

```
#Conditional Probability of each product given gender which will also normalize margin values

pd.crosstab([df["Product"]],df["Gender"],margins=True)
```

Out[258]:

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

In [259]:

```
#Conditional Probability of each product given gender which normalize over all values

np.round(pd.crosstab(df['Product'],[df['Gender']], normalize=True, margins=True, margins_name='Total')*100,2)
```

Out[259]:

Gender	Female	Male	Total
Product			
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
Total	42.22	57.78	100.00

In [260]:

```
#Conditional Probability of each product given gender which is normalized over each column

np.round(pd.crosstab(df['Product'],[df['Gender']], normalize='columns', margins=True, margins_name='Total')*100,2)
```

Out[260]:

Gender	Female	Male	Total
Product			
KP281	52.63	38.46	44.44
KP481	38.16	29.81	33.33
KP781	9.21	31.73	22.22

Fitness

In [206]:

```
#Conditional Probability of each product given Fitness which also normalize margin values

pd.crosstab([df["Product"]],df["Fitness"],margins=True)
```

Out[206]:

Fitness	1	2	3	4	5	All
Product						
KP281	1	14	54	9	2	80
KP481	1	12	39	8	0	60
KP781	0	0	4	7	29	40
All	2	26	97	24	31	180

In [250]:

```
#Conditional Probability of each product given Fitness which normalize over all values

np.round(pd.crosstab(df['Product'],[df['Fitness']], normalize=True, margins=True, margins_name='Total')*100,2)
```

Out[250]:

Fitness	1	2	3	4	5	Total
Product						
KP281	0.56	7.78	30.00	5.00	1.11	44.44
KP481	0.56	6.67	21.67	4.44	0.00	33.33
KP781	0.00	0.00	2.22	3.89	16.11	22.22
Total	1.11	14.44	53.89	13.33	17.22	100.00

In [266]:

```
#Conditional Probability of each product given Fitness which is normalized over each column

np.round(pd.crosstab(df['Product'],[df['Fitness']], normalize='columns', margins=True, margins_name='Total')*100,2
```

Out[266]:

Fitness	1	2	3	4	5	Total
Product						
KP281	50.0	53.85	55.67	37.50	6.45	44.44
KP481	50.0	46.15	40.21	33.33	0.00	33.33
KP781	0.0	0.00	4.12	29.17	93.55	22.22

MaritalStatus

In [209]:

```
#Conditional Probability of each product given MaritalStatus which will normalize margin values

pd.crosstab([df["Product"]],df["MaritalStatus"],margins=True)
```

Out[209]:

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

In [252]:

```
#Conditional Probability of each product given MaritalStatus which will normalize all values

np.round(pd.crosstab(df['Product'],[df['MaritalStatus']], normalize=True, margins=True, margins_name='Total')*100,
```

Out[252]:

MaritalStatus	Partnered	Single	Total
Product			
KP281	26.67	17.78	44.44
KP481	20.00	13.33	33.33
KP781	12.78	9.44	22.22
Total	59.44	40.56	100.00

In [268]:

```
#Conditional Probability of each product given MaritalStatus which will normalize over each column

np.round(pd.crosstab(df['Product'],[df['MaritalStatus']], normalize='columns', margins=True, margins_name='Total')
```

Out[268]:

MaritalStatus	Partnered	Single	Total
Product			
KP281	44.86	43.84	44.44
KP481	33.64	32.88	33.33
KP781	21.50	23.29	22.22

Usage

In [271]:

```
#Conditional Probability of each product given Usage which will normalize margin values

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

Out[271]:

Usage	2	3	4	5	6	7	Total
Product							
KP281	19	37	22	2	0	0	80
KP481	14	31	12	3	0	0	60
KP781	0	1	18	12	7	2	40
Total	33	69	52	17	7	2	180

In [272]:

```
#Conditional Probability of each product given Usage which will normalize all values

np.round(pd.crosstab(df['Product'],[df['Usage']], normalize=True, margins=True, margins_name='Total')*100,2)
```

Out[272]:

Usage	2	3	4	5	6	7	Total
Product							
KP281	10.56	20.56	12.22	1.11	0.00	0.00	44.44
KP481	7.78	17.22	6.67	1.67	0.00	0.00	33.33
KP781	0.00	0.56	10.00	6.67	3.89	1.11	22.22
Total	18.33	38.33	28.89	9.44	3.89	1.11	100.00

In [273]:

```
#Conditional Probability of each product given Usage which will normalize over each column

np.round(pd.crosstab(df['Product'],[df['Usage']], normalize='columns', margins=True, margins_name='Total')*100,2)
```

Out[273]:

Usage Product	2	3	4	5	6	7	Total
KP281	57.58	53.62	42.31	11.76	0.0	0.0	44.44
KP481	42.42	44.93	23.08	17.65	0.0	0.0	33.33
KP781	0.00	1.45	34.62	70.59	100.0	100.0	22.22

Income_levels

In [539]:

```
#Conditional Probability of each product given Income_levels which will normalize margin values

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

Out[539]:

Income_levels Product	High(61k-80k)	Low(25k-40k)	Medium(41k-60k)	Very_High(81k-120k)	Total
KP281	6	23	51	0	80
KP481	7	9	44	0	60
KP781	10	0	11	19	40
Total	23	32	106	19	180

In [540]:

```
#Conditional Probability of each product given Income_levels which will normalize all values

np.round(pd.crosstab(df['Product'],[df['Income_levels']], normalize=True, margins=True, margins_name='Total')*100,
```

Out[540]:

Income_levels Product	High(61k-80k)	Low(25k-40k)	Medium(41k-60k)	Very_High(81k-120k)	Total
KP281	3.33	12.78	28.33	0.00	44.44
KP481	3.89	5.00	24.44	0.00	33.33
KP781	5.56	0.00	6.11	10.56	22.22
Total	12.78	17.78	58.89	10.56	100.00

In [541]:

```
#Conditional Probability of each product given Income_levels which will normalize over each column

np.round(pd.crosstab(df['Product'],[df['Income_levels']], normalize='columns', margins=True, margins_name='Total')
```

Out[541]:

Income_levels Product	High(61k-80k)	Low(25k-40k)	Medium(41k-60k)	Very_High(81k-120k)	Total
KP281	26.09	71.88	48.11	0.0	44.44
KP481	30.43	28.12	41.51	0.0	33.33
KP781	43.48	0.00	10.38	100.0	22.22