In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_csv('Aerofit.csv')
```

In [3]:
```
df.head()
```

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
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

In [4]:
```
def missingValue(df):
    total_null = df.isnull().sum().sort_values(ascending = False)
    percent = ((df.isnull().sum()/df.isnull().count())*100).sort_values(ascending = False)
    print("Total records = ", df.shape[0])

    md = pd.concat([total_null,percent.round(2)],axis=1,keys=['Total Missing','In Percent'])
    return md
missingValue(df)
```

```
Total records =  180
```

Out[4]:

	Total Missing	In Percent
Product	0	0.0
Age	0	0.0
Gender	0	0.0
Education	0	0.0
MaritalStatus	0	0.0
Usage	0	0.0
Fitness	0	0.0
Income	0	0.0
Miles	0	0.0

no null values

In [5]:
```
df.shape
```

Out[5]: (180, 9)

In [6]:
```
df.describe()
```

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

Checking for data types

In [7]:
```
df.dtypes
```

Out[7]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

Univariate Analysis

In [8]:
```
df.columns
```

Out[8]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

In [9]:
```
df['Product'].unique().tolist()
```

Out[9]:
```
['KP281', 'KP481', 'KP781']
```

There are 3 types of products

In [10]:
```
df.Gender.unique().tolist()
```

Out[10]:
```
['Male', 'Female']
```

In [11]:
```
df.Education.unique().tolist()
print("Education Years ranges from {0} to {1}".format(df['Education'].min(),df['Education'].max())
```

```
Education Years ranges from 12 to 21
```

In [12]:
```
df.MaritalStatus.unique().tolist()
```

Out[12]:
```
['Single', 'Partnered']
```

In [13]:
```
df.Usage.unique().tolist()
print("Number of times the prdocuct is used per week ranges from {0} to {1}".format(df['Usage'].mi
```

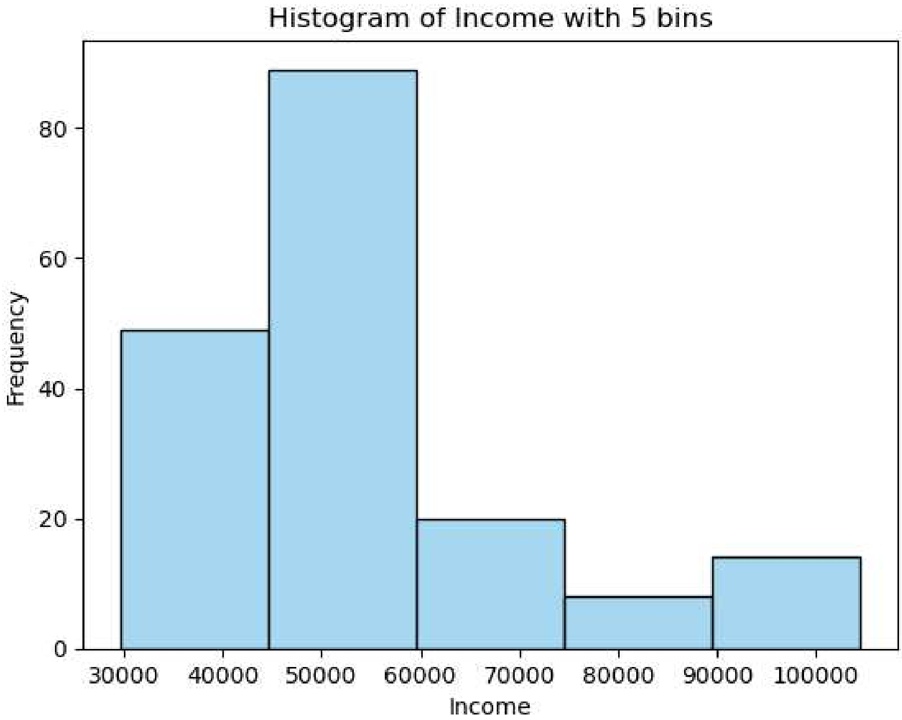
```
Number of times the prdocuct is used per week ranges from 2 to 7
```

In [ ]:

In [14]:
```
sns.histplot(data=df, x='Income', bins=5, color='skyblue', edgecolor='black')

# Adding labels and title
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.title('Histogram of Income with 5 bins')

# Show plot
plt.show()
```



Majority of the users lie in the 45k to 60k income category

In [15]:
```
print("Income in $ ranges from {0} to {1}".format(df['Income'].min(),df['Income'].max()))
```

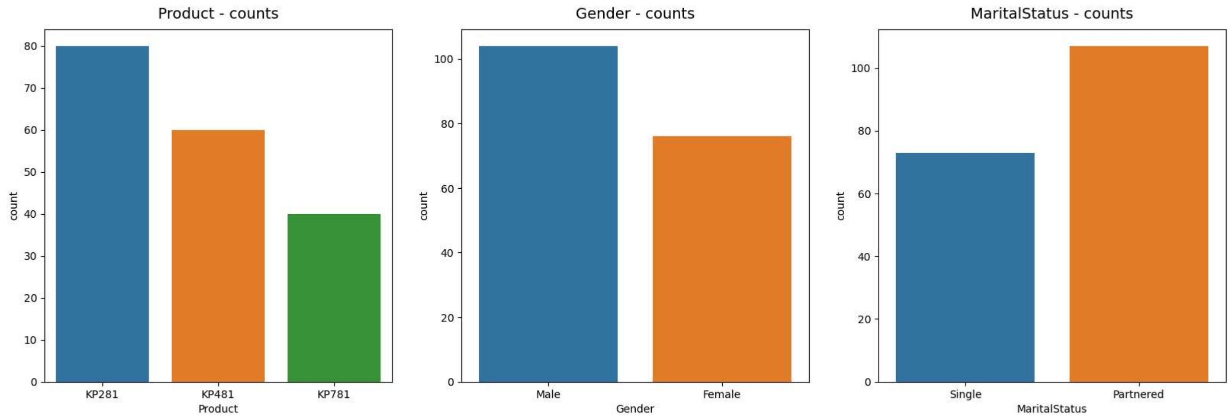
```
Income in $ ranges from 29562 to 104581
```

In [16]:
```
print("Miles run in km ranges from {0} to {1}".format(df['Miles'].min(),df['Miles'].max()))
```

```
Miles run in km ranges from 21 to 360
```

In [17]:
```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 6))
sns.countplot(data=df, x='Product', ax=axs[0])
sns.countplot(data=df, x='Gender', ax=axs[1])
sns.countplot(data=df, x='MaritalStatus', ax=axs[2])

axs[0].set_title("Product - counts", pad=10, fontsize=14)
axs[1].set_title("Gender - counts", pad=10, fontsize=14)
axs[2].set_title("MaritalStatus - counts", pad=10, fontsize=14)
plt.show()
```

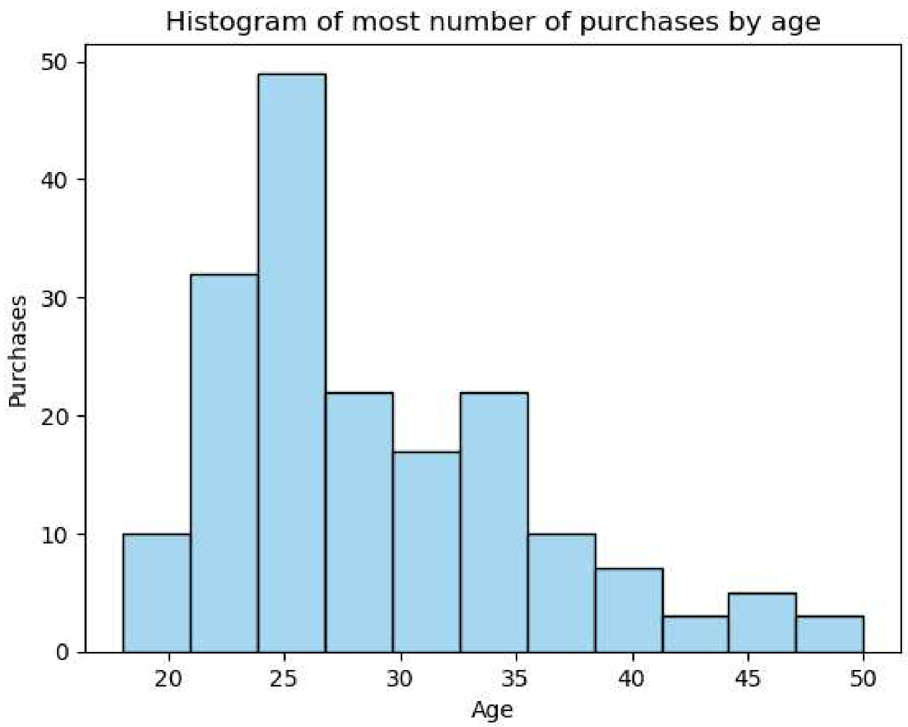


KP281 is the most sold product in the given data

In [18]:
```
sns.histplot(data=df, x='Age', color='skyblue', edgecolor='black')

# Adding labels and title
plt.xlabel('Age')
plt.ylabel('Purchases')
plt.title('Histogram of most number of purchases by age')

# Show plot
plt.show()
```

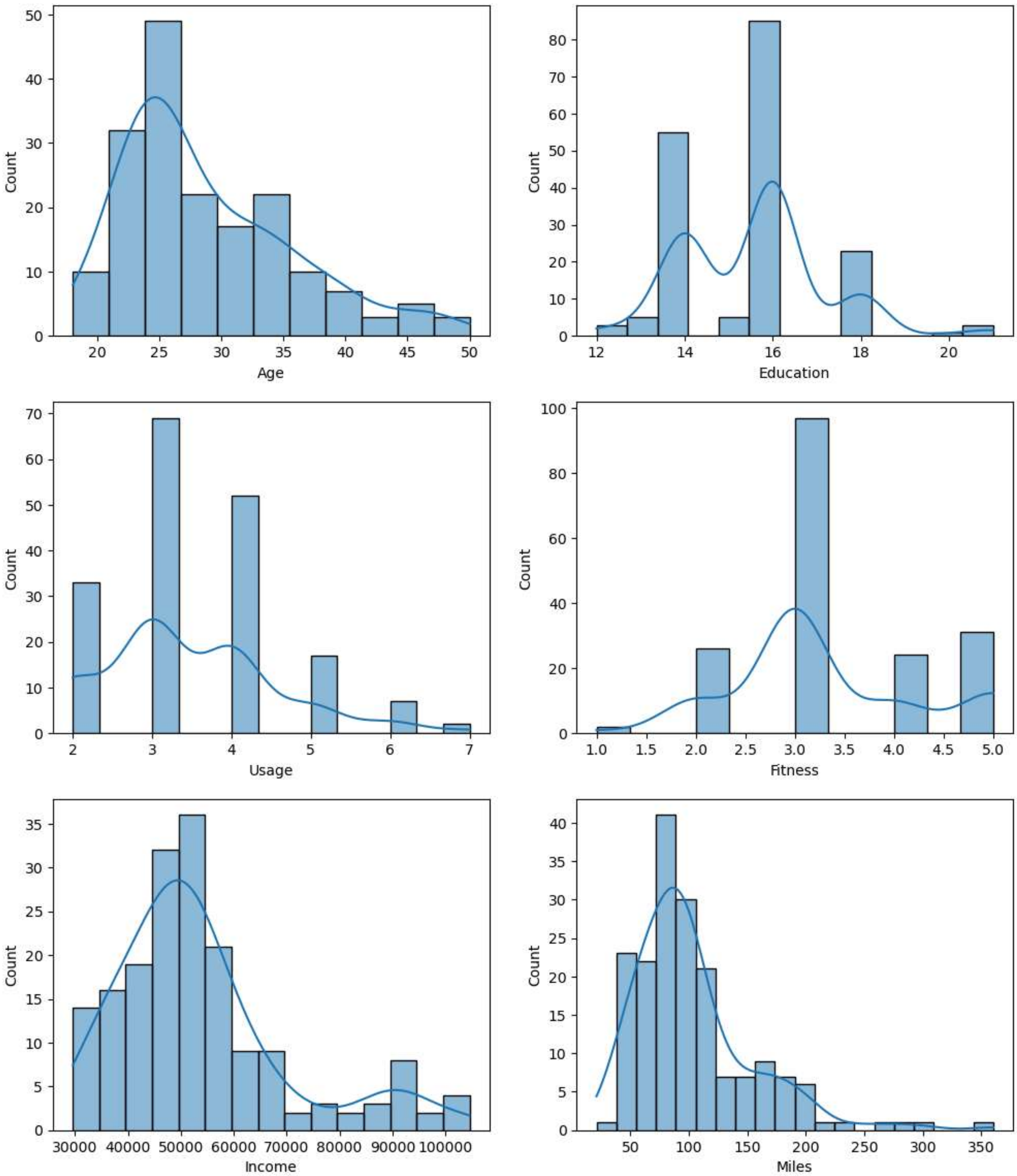


Age 20 to 36 has the most number of purchases

In [19]:
```
percent = df.Gender.value_counts()
plt.figure(figsize=(8,4))
plt.pie(percent.values, labels=percent.index, autopct='%.1f%%', startangle=90, explode=[0.1, 0], t
plt.legend(loc = 'upper right', bbox_to_anchor=(1.2,1))
plt.title('Gender based Purchases', fontsize=16)
plt.show()
```

In [20]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
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()
```

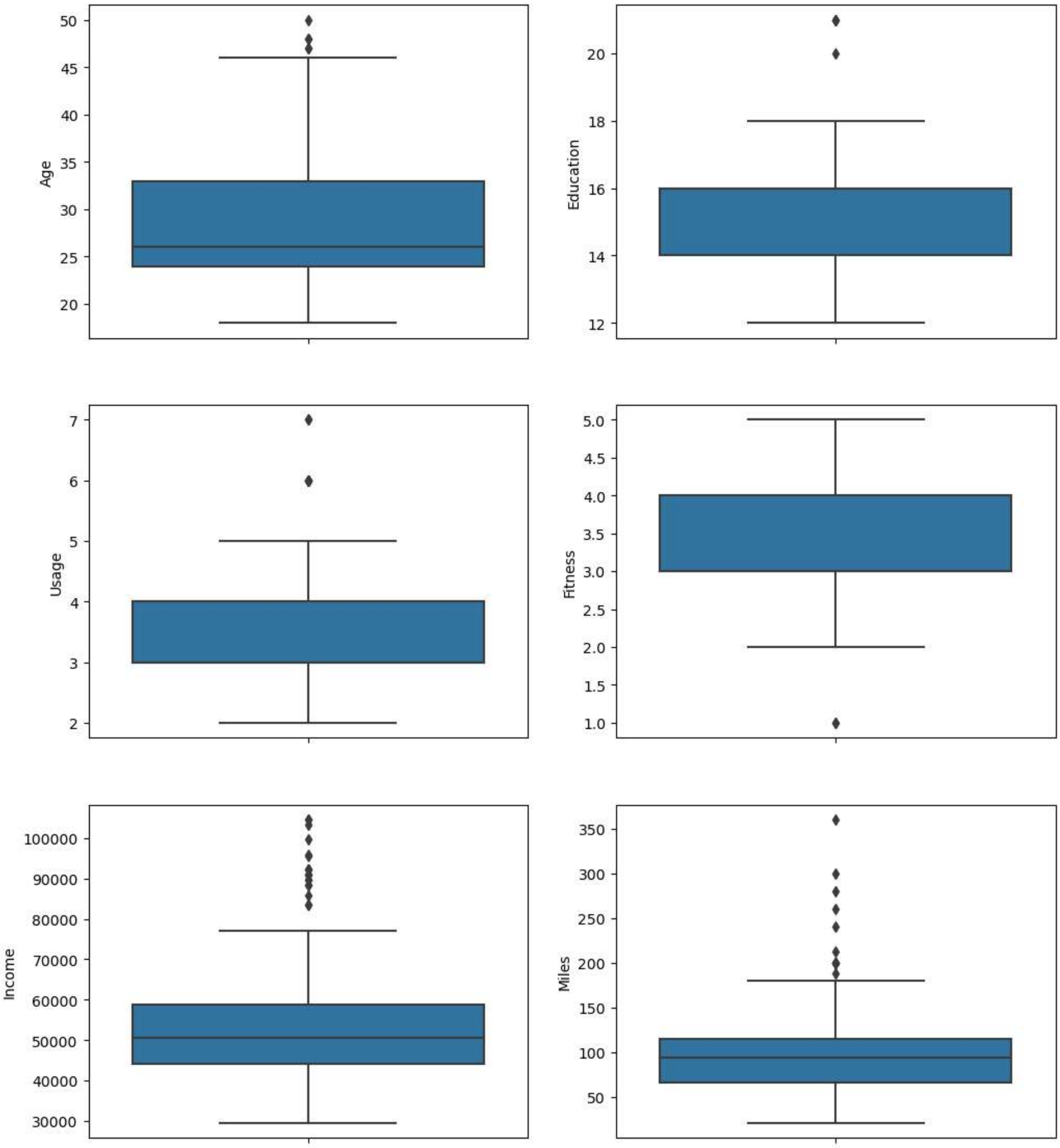


Detecting Outliers

```
In [21]: fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.boxplot(data=df, y="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, y="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, y="Usage", orient='h', ax=axis[1,0])
sns.boxplot(data=df, y="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, y="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, y="Miles", orient='h', ax=axis[2,1])

plt.show()
```



Obervation from the boxplots it is quite clear that:

Age, Education and Usage are having very few outliers. While Income and Miles have more outliers. Majority of Customers fall within the USD 45,000 - USD 60,000 range There are outliers over USD 85,000 Only a few of our customers run more than 180 miles per week|

normalized count for each variable is shown below

In [22]:
```
df1 = df[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count()*100 / len(df)
```

Out[22]:

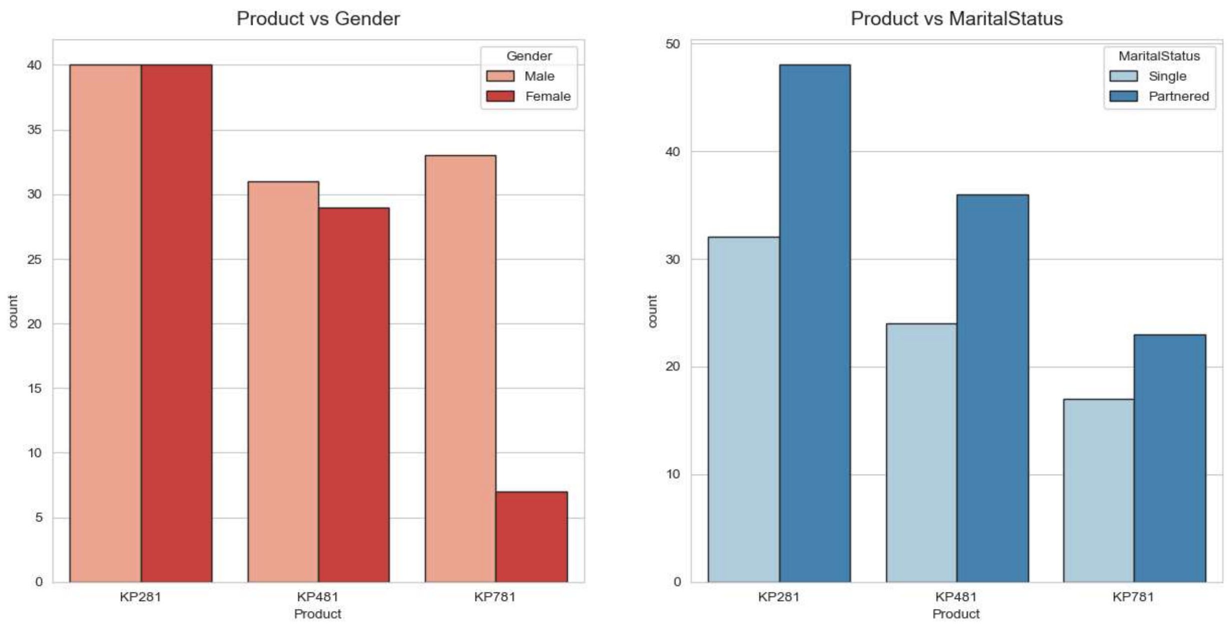
variable	value	value
Gender	Female	42.222222
	Male	57.777778
MaritalStatus	Partnered	59.444444
	Single	40.555556
Product	KP281	44.444444
	KP481	33.333333
	KP781	22.222222

Obervations Product 44.44% of the customers have purchased KP2821 product. 33.33% of the customers have purchased KP481 product. 22.22% of the customers have purchased KP781 product. Gender 57.78% of the customers are Male. MaritalStatus 59.44% of the customers are Partnered.

Bivariate Analysis

Effect of Gender and Marital Status on purchases

In [23]:
```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(15, 7))
sns.countplot(data=df, x='Product', hue='Gender', edgecolor="0.15", palette='Reds', ax=axs[0])
sns.countplot(data=df, x='Product', hue='MaritalStatus', edgecolor="0.15", palette='Blues', ax=axs
axs[0].set_title("Product vs Gender", pad=10, fontsize=14)
axs[1].set_title("Product vs MaritalStatus", pad=10, fontsize=14)
plt.show()
```



Obervations

1. Product vs Gender

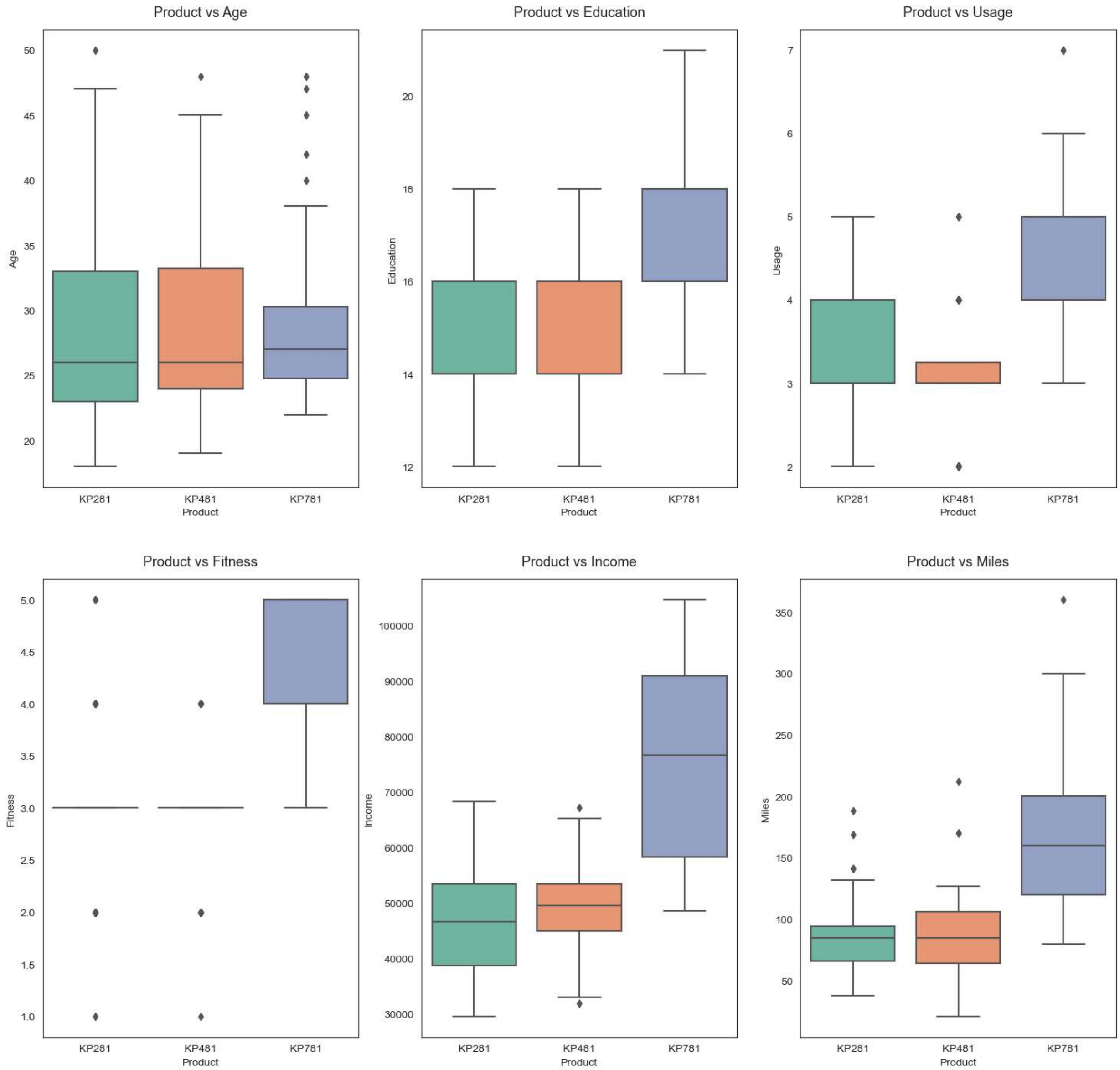
Equal number of males and females have purchased KP281 product and Almost same for the product KP481 However,KP781 most of the customers are males

2. Product vs MaritalStatus

Maried customers are more likely to buy the products

Effect of the following product purchases: Age Education Usage Fitness Income Mile

In [24]:
```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(18, 12))
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=axs[i,j], palette='Set2')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
```



Observations

1. Product vs Age

   Customers purchasing products KP281 & KP481 are having same Age median value. Customers whose age lies between 25-30, are more likely to buy KP781 product.
2. Product vs Education

   Customers whose Education is greater than 16, have more chances to purchase the KP781 product. While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481.
3. Product vs Usage

   Customers who are planning to use the treadmill greater than 4 times a week, are more likely to purchase the KP781 product. While the other customers are likely to purchasing KP281 or KP481.
4. Product vs Fitness

The more the customer is fit (fitness >= 3), higher the chances of the customer to purchase the KP781 product.

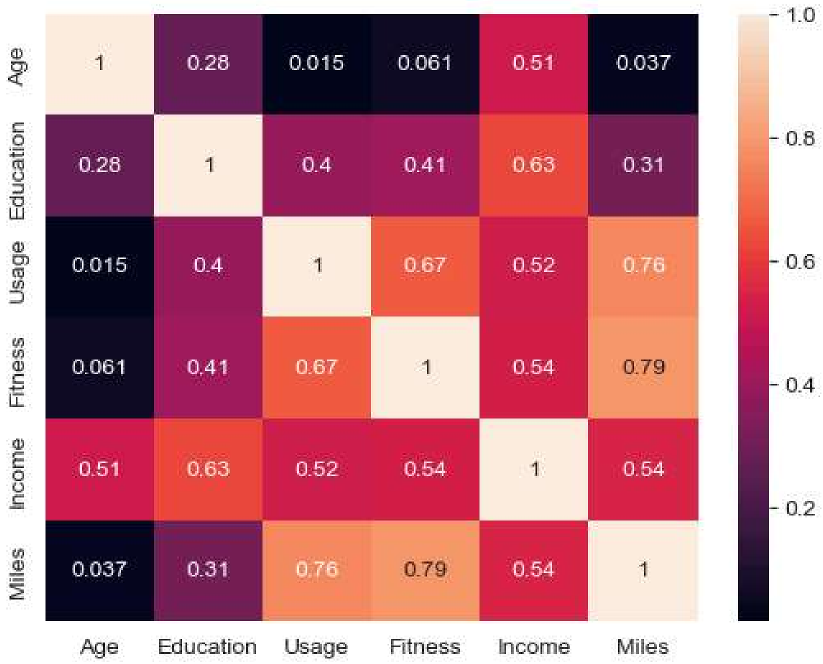
5. Product vs Income

   Higher the Income of the customer (Income >= 60000), higher the chances of the customer to purchase the KP781 product.

6. Product vs Miles

   If the customer expects to walk/run greater than 120 Miles per week, it is more likely that the customer will buy KP781 product.

In [25]:
```
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Conclusion:

1.We have strong relaiton between Fitness and Miles (0.79)

2.We have strong relaiton between Usage and Miles (0.76)

3.We have some relaiton between Fitness and Usage (0.67)

(Marginal Probabilities, Joint Probabilities, Conditional Probabilities)

Product - Gender

Product - Fitness

Product - Age

Product - Marital Status

In [26]:
```
bins_income = [29000, 35000, 60000, 85000,105000]
labels_income = ['Low Income','Lower-middle income','Upper-Middle income', 'High income']
df['IncomeSlab'] = pd.cut(df['Income'],bins_income,labels = labels_income)
df.head()
```

Out[26]:

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

In [27]:
```
pd.crosstab(index=df['Product'], columns=[df['IncomeSlab']],margins=True)
```

Out[27]:

IncomeSlab Product	Low Income	Lower-middle income	Upper-Middle income	High income	All
KP281	8	66	6	0	80
KP481	6	47	7	0	60
KP781	0	11	12	17	40
All	14	124	25	17	180

Percentage of a high-income customer purchasing a treadmill (Marginal Probability)

In [28]:
```
round(17/180,2)
```

Out[28]:
```
0.09
```

Percentage of a high-income customer purchasing a KP781 treadmill (Marginal Probability)

In [29]:
```
round(17/40,2)
```

Out[29]:
```
0.42
```

which is significantly high

In [30]:
```
df['Product'].value_counts(normalize=True)
```

Out[30]:
```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

Probability of each product given gender

In [31]:
```
df1 = pd.crosstab(index=df['Gender'], columns=[df['Product']])
df1
```

Out[31]:

Product Gender	KP281	KP481	KP781
Female	40	29	7
Male	40	31	33

In [32]:
```python
def prob_given_gender(gender, print_marginal=False):
    if gender is not "Female" and gender is not "Male":
        return "Invalid gender value."

    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")

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
```

Probability of each product given MaritalStatus

In [33]:
```python
def prob_given_mstatus(status, print_marginal=False):
    if status is not "Single" and status is not "Partnered":
        return "Invalid marital status value."

    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")

prob_given_mstatus('Single', True)
prob_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
```

Conclusion (Important Observations):

- Model **KP281** is the **best-selling product. 44.0%** of all treadmill **sales go to model KP281.**
- The majority of treadmill customers fall within the **USD 45,000 - USD 80,000** income bracket**. 83%** of treadmills are bought by individuals with incomes between **USD dollor 35000 and 85000.**

- There are only **8%** of customers with **incomes below USD 35000** who buy treadmills.
- **88%** of treadmills are purchased by **customers aged 20 to 40.**
- **Miles and Fitness** & **Miles and Usage** are highly correlated, which means if a customer's fitness level is high they use more treadmills.
- **KP781** is the only model purchased by a customer who has more than **20 years of education and an income of over USD dollor 85,000.**
- With **Fitness level 4 and 5,** the customers tend to use **high-end models** and the **average number of miles is above 150 per week**

Recommendations

- **KP281 & KP481** are popular with customers earning **USD 45,000 and USD 60,000** and can be offered by these companies as **affordable models.**
- **KP781** should be marketed as a **Premium Model** and marketing it to **high income groups and educational over 20 years** market segments could result in more sales.
- Aerofit should conduct **market research** to determine if it can attract customers with **income under USD 35,000 to expand its customer base.**
- The **KP781 is a premium model**, so it is ideally suited for **sporty people** who have a high average weekly mileage.