In [3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm
```

In [5]:
```
Aerofit_data= pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
Aerofit_data
```

Out[5]:

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

Solution 1

In [10]:
```
Aerofit_data.shape
```

Out[10]:
```
(180, 9)
```

In [11]:
```
Aerofit_data.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 [12]:
```
Aerofit_data.describe()
```

Out[12]:

	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 [13]:
```
Aerofit_data.dtypes
```

Out[13]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

In [100…
```
# Identify categorical and numerical columns
categorical_columns = Aerofit_data.select_dtypes(include=['object'])
numerical_columns = Aerofit_data.select_dtypes(include=['int64', 'float64'])

print("Categorical Columns:")
print(categorical_columns)

print("\nNumerical Columns:")
print(numerical_columns)
```

```
Categorical Columns:
    Product  Gender MaritalStatus
0     KP281    Male        Single
1     KP281    Male        Single
2     KP281  Female     Partnered
3     KP281    Male        Single
4     KP281    Male     Partnered
..      ...     ...           ...
175   KP781    Male        Single
176   KP781    Male        Single
177   KP781    Male        Single
178   KP781    Male     Partnered
179   KP781    Male     Partnered

[180 rows x 3 columns]

Numerical Columns:
     Age  Education  Usage  Fitness  Income  Miles
0     18         14      3        4   29562    112
1     19         15      2        3   31836     75
2     19         14      4        3   30699     66
3     19         12      3        3   32973     85
4     20         13      4        2   35247     47
..   ...        ...    ...      ...     ...    ...
175   40         21      6        5   83416    200
176   42         18      5        4   89641    200
177   45         16      5        5   90886    160
178   47         18      4        5  104581    120
179   48         18      4        5   95508    180

[180 rows x 6 columns]
```

Solution 2

In [22]:
```
Aerofit_data.head()
```

Out[22]:

	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 [25]:
```
# Number of unique products
Aerofit_data["Product"].unique()
```

Out[25]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [26]:
```
# Each unique product counts
Aerofit_data["Product"].value_counts()
```

Out[26]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [27]:
```
Aerofit_data["Product"].nunique()
```

Out[27]:
```
3
```

In [31]:
```
len(Aerofit_data["Product"])
```

Out[31]:
```
180
```

In [162…
```
# Each unique Gender counts
Aerofit_data["Gender"].value_counts(dropna=False)
```

Out[162]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [154…
```
# What persentage are male and female are there
Aerofit_data["Gender"].value_counts(normalize=True)*100
```

Out[154]:
```
Male      57.777778
Female    42.222222
Name: Gender, dtype: float64
```

In [33]:
```
Aerofit_data["Age"].nunique()
```

Out[33]:
```
32
```

In [158…
```
# margins= True means to get the total
pd.crosstab(index=Aerofit_data["Gender"], columns=Aerofit_data["Product"], margins=Tru
```

Out[158]:

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

In [159…
```
pd.crosstab(index=Aerofit_data["Gender"], columns=Aerofit_data["Product"], margins=Tru
```

Out[159]:

Product	KP281	KP481	KP781	All
Gender				
Female	22.222222	16.111111	3.888889	42.222222
Male	22.222222	17.222222	18.333333	57.777778
All	44.444444	33.333333	22.222222	100.000000

In [34]:
```
# Both Gender counts
Aerofit_data["Gender"].value_counts()
```

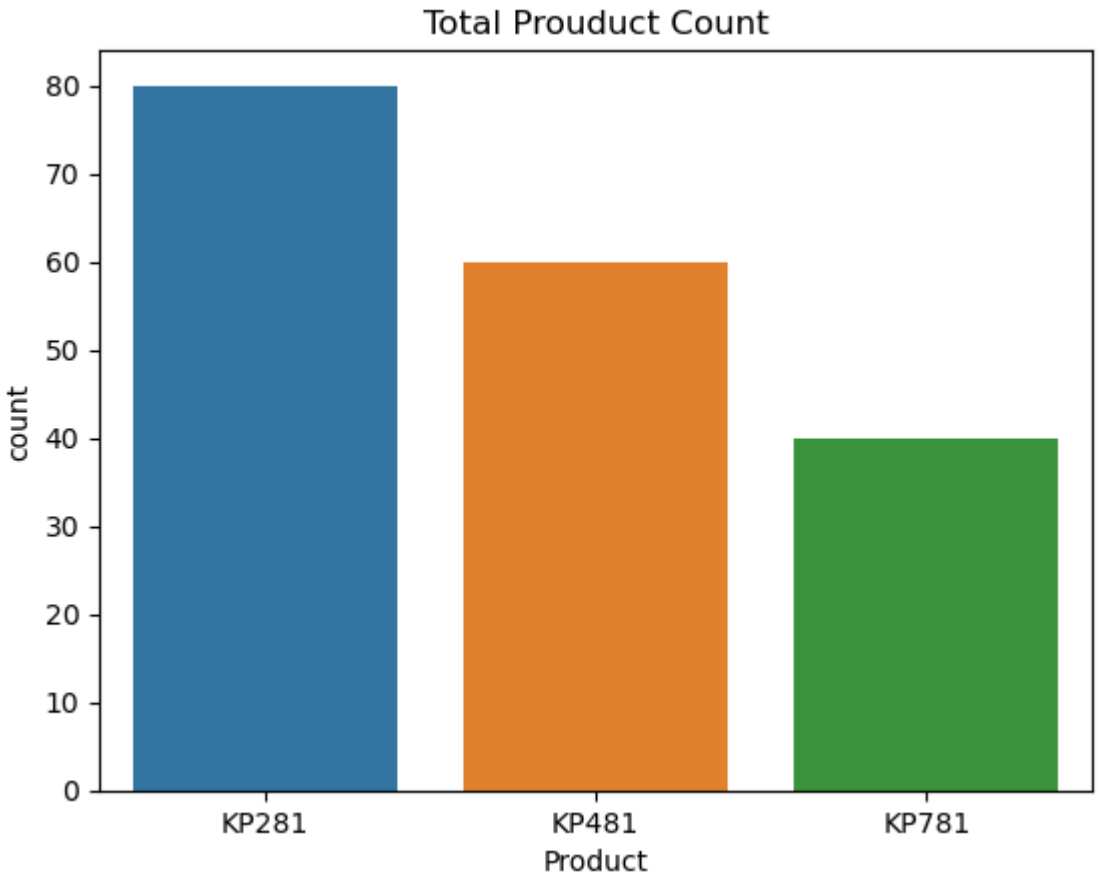
Out[34]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [35]:
```
#Marital status
Aerofit_data["MaritalStatus"].value_counts()
```

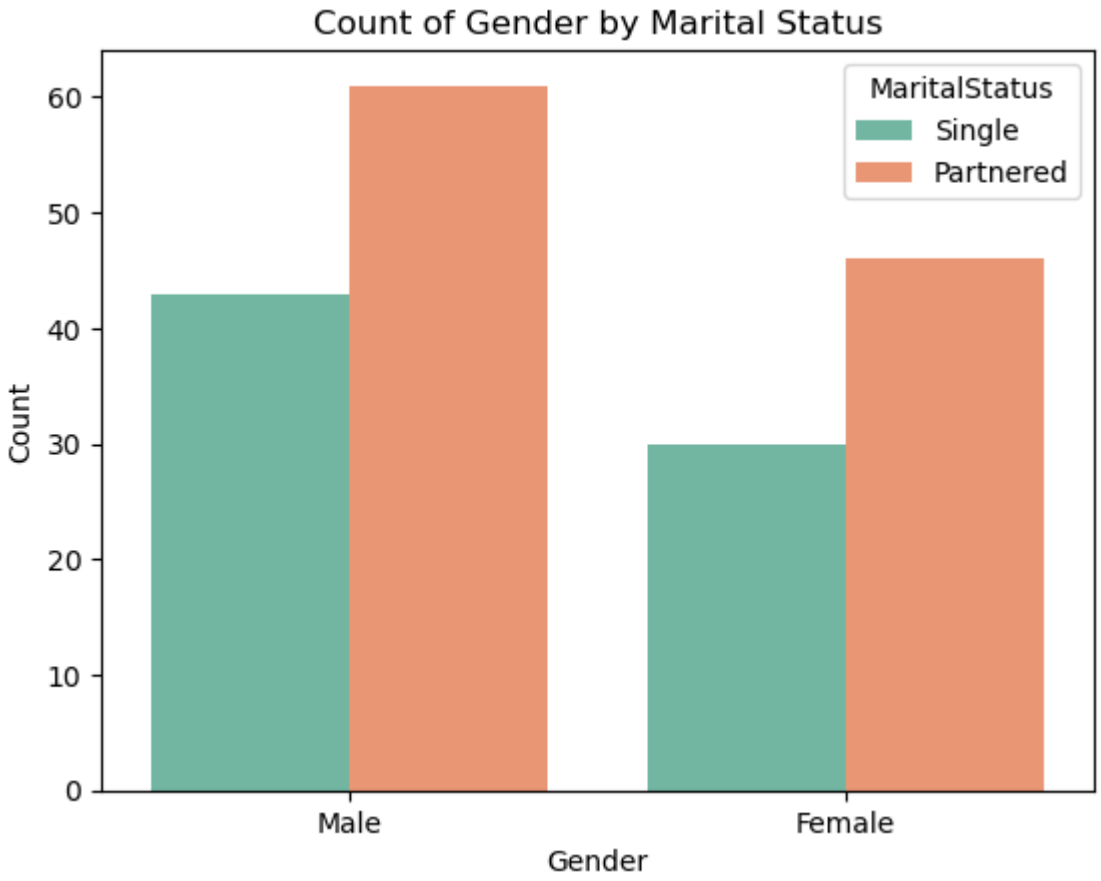
Out[35]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

Soution 3

In [37]:
```
sns.countplot(data=Aerofit_data, x="Product")
plt.title("Total Prouduct Count")
plt.show()
```

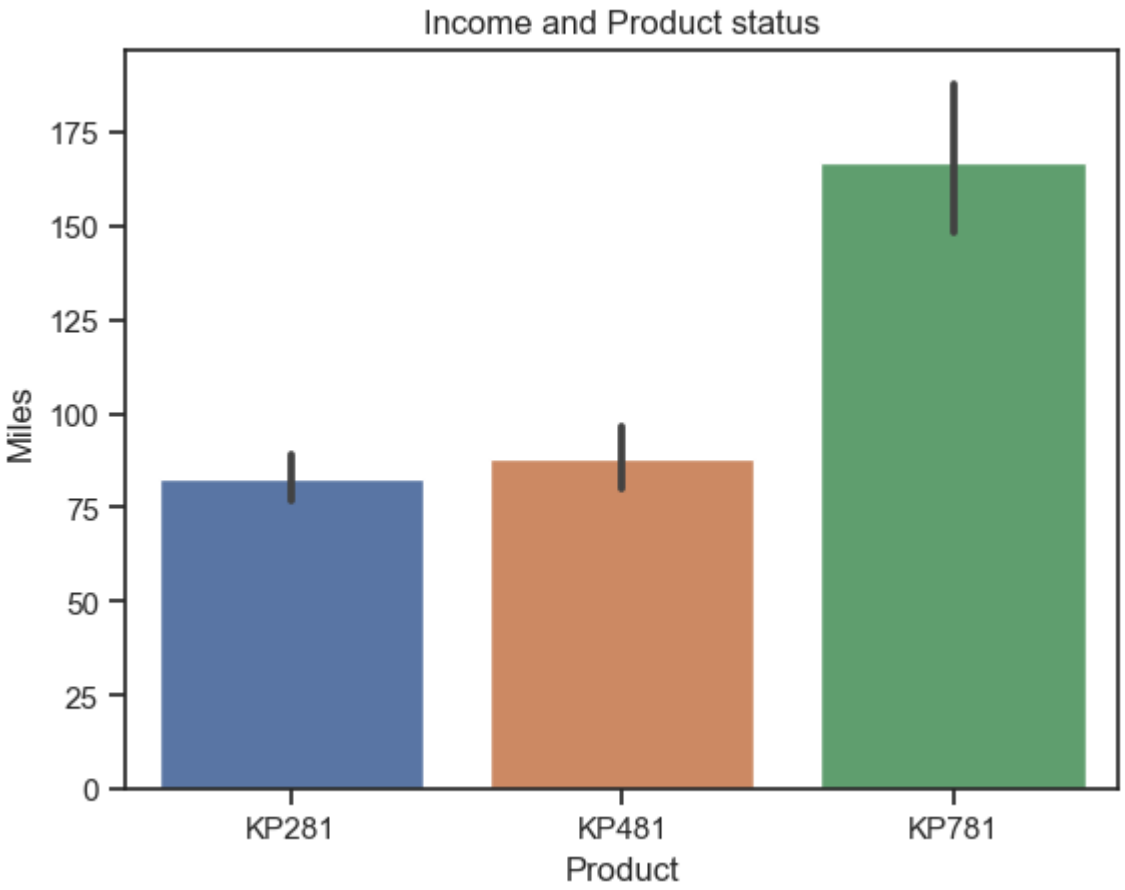


In [60]:
```
sns.countplot(data=Aerofit_data, x="Gender",  hue="MaritalStatus", palette="Set2")
plt.title("Count of Gender by Marital Status")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.show()
```



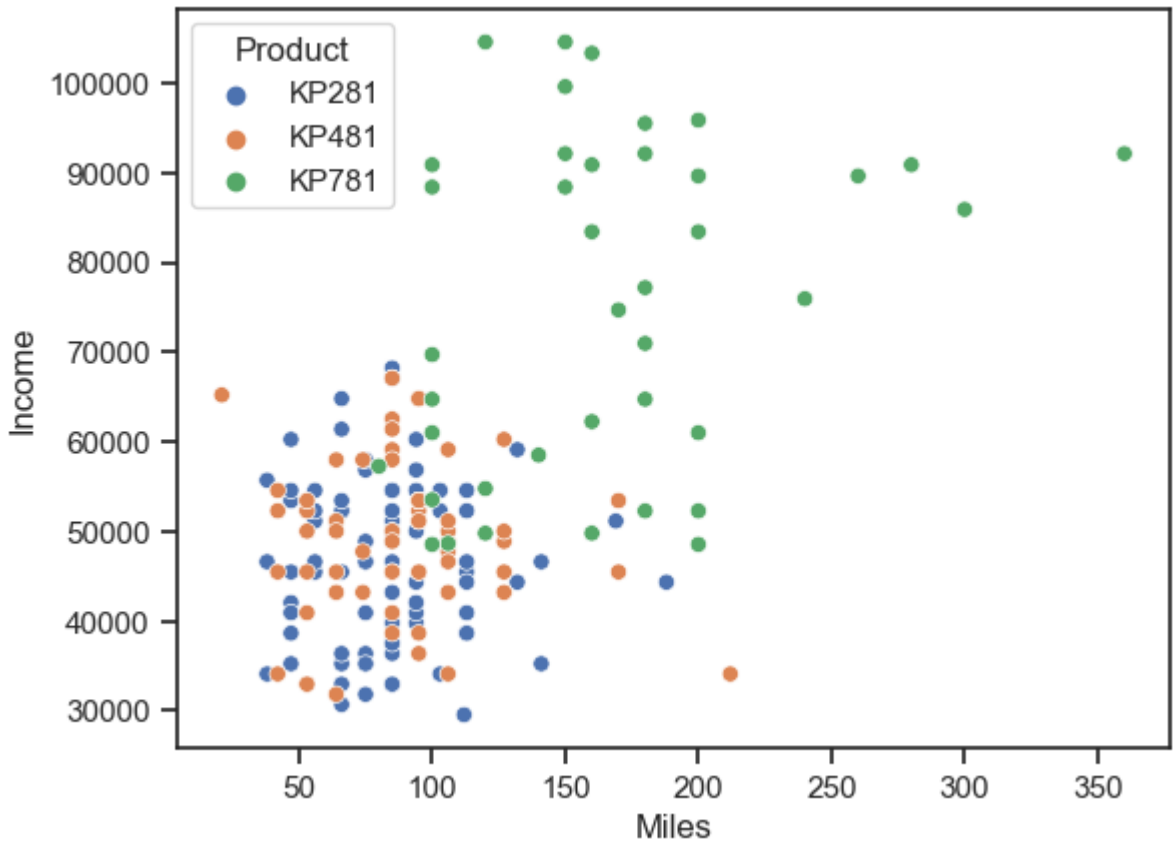
In [142…

```
sns.barplot(data=Aerofit_data, y="Miles", x="Product")
plt.title("Income and Product status")
plt.show()
```



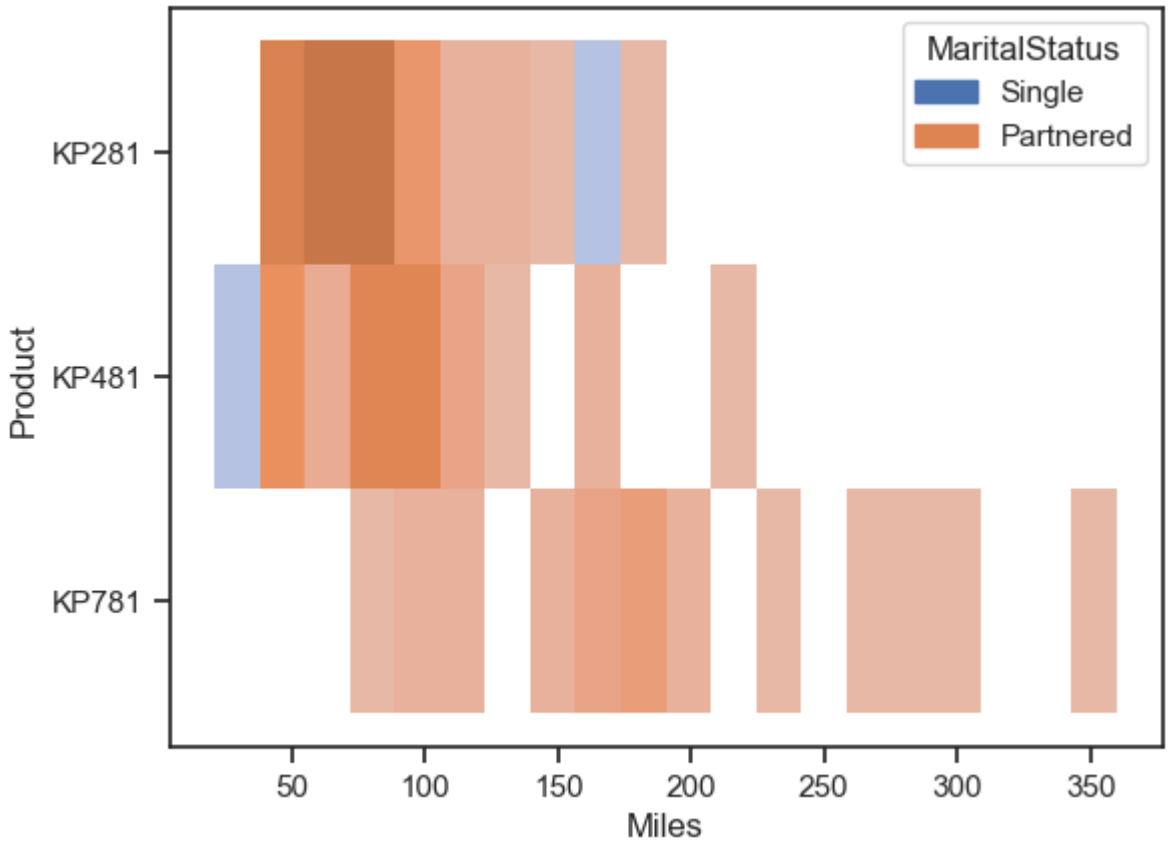
In [148…

```
sns.scatterplot(data=Aerofit_data, x="Miles", y="Income", hue="Product")
plt.show()
```



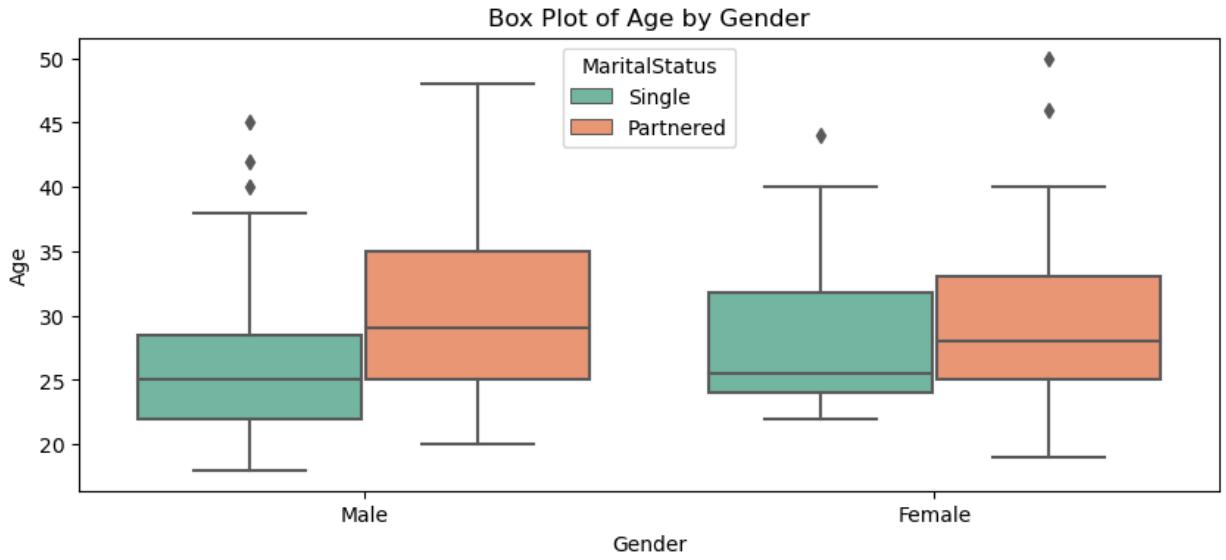
In [139…

```
sns.histplot(data=Aerofit_data, x="Miles", y="Product", hue="MaritalStatus")
plt.show()
```

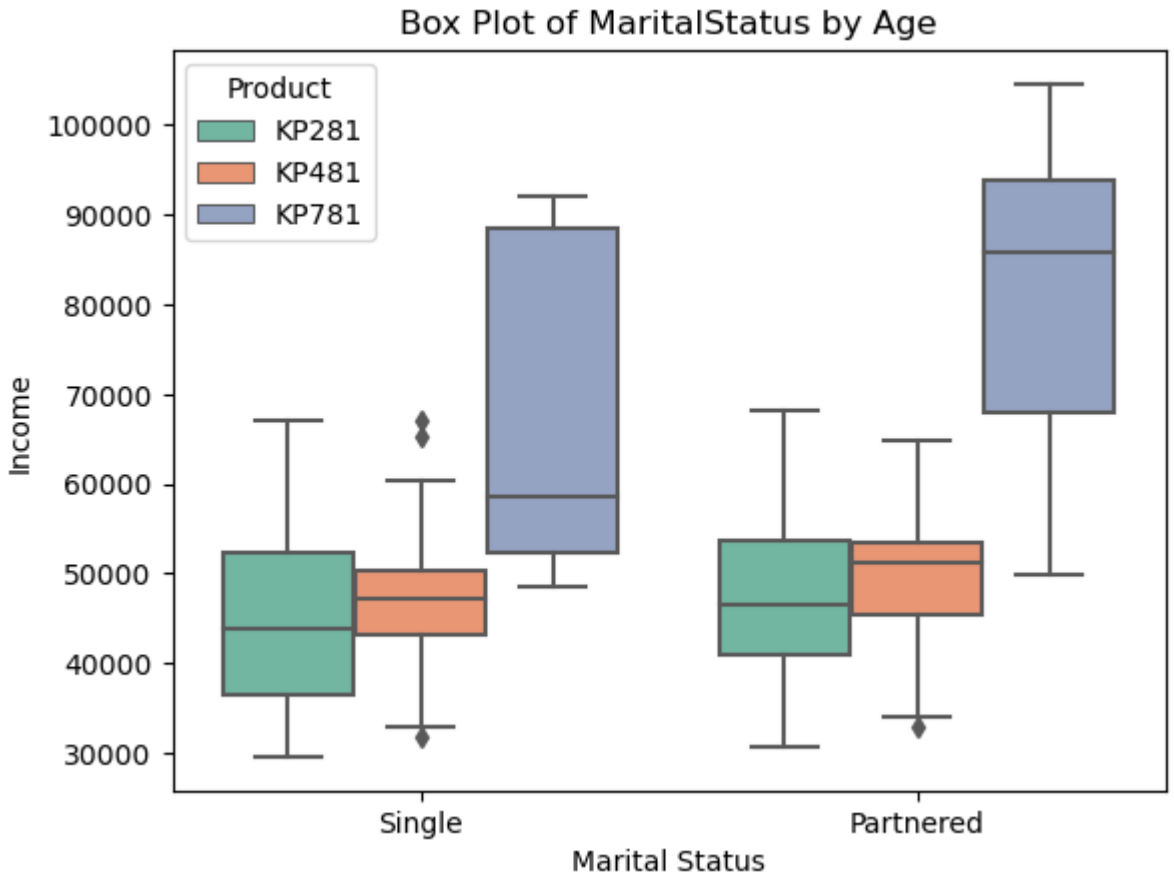


In [84]:

```
# Box plot for numerical variable (Age) by a categorical variable (Gender)
fig, ax = plt.subplots(figsize=(10, 4))
sns.boxplot(data=Aerofit_data, x="Gender", y="Age", hue="MaritalStatus", palette="Set2

# Add labels and title
plt.title("Box Plot of Age by Gender")
plt.xlabel("Gender")
plt.ylabel("Age")

plt.show()
```

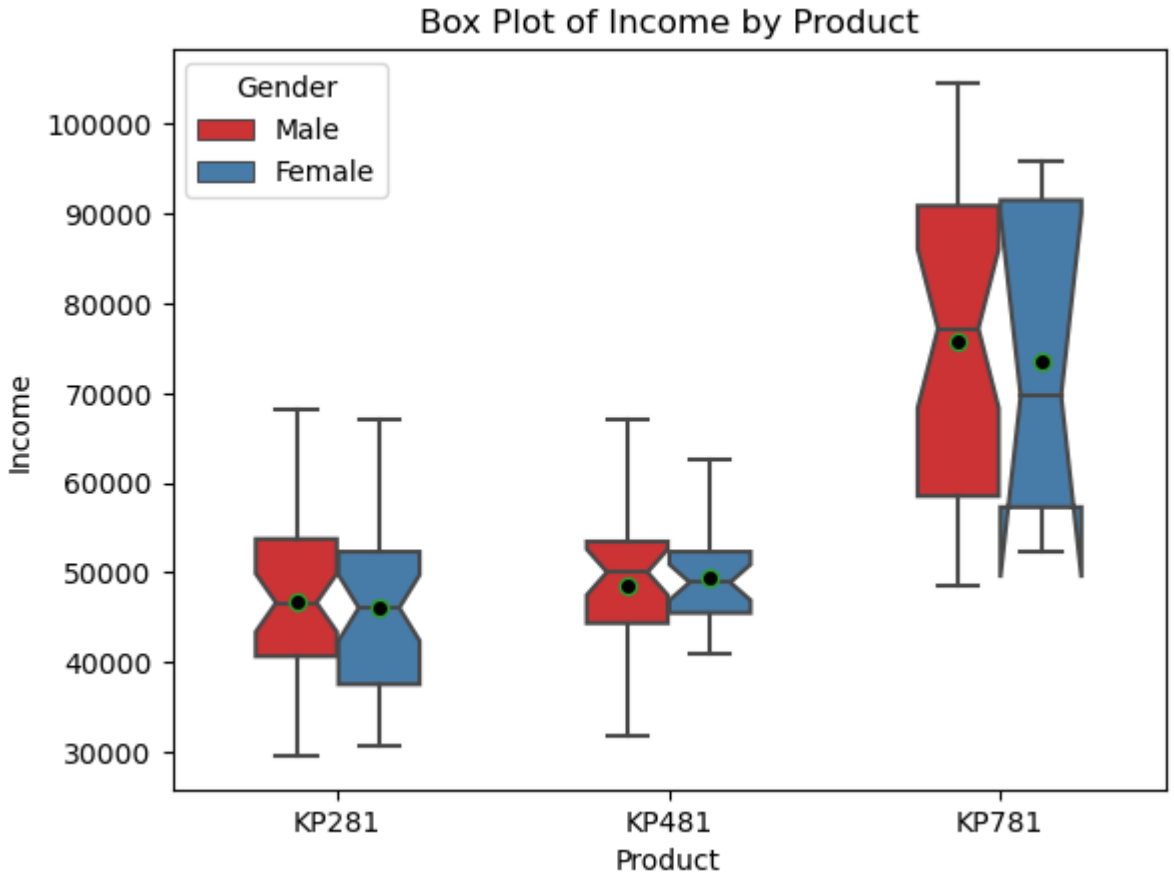


In [87]:
```
sns.boxplot(data=Aerofit_data, x="MaritalStatus", y="Income", hue="Product", palette='

# Add labels and title
plt.title("Box Plot of MaritalStatus by Age")
plt.xlabel("Marital Status")
plt.ylabel("Income")

plt.show()
```

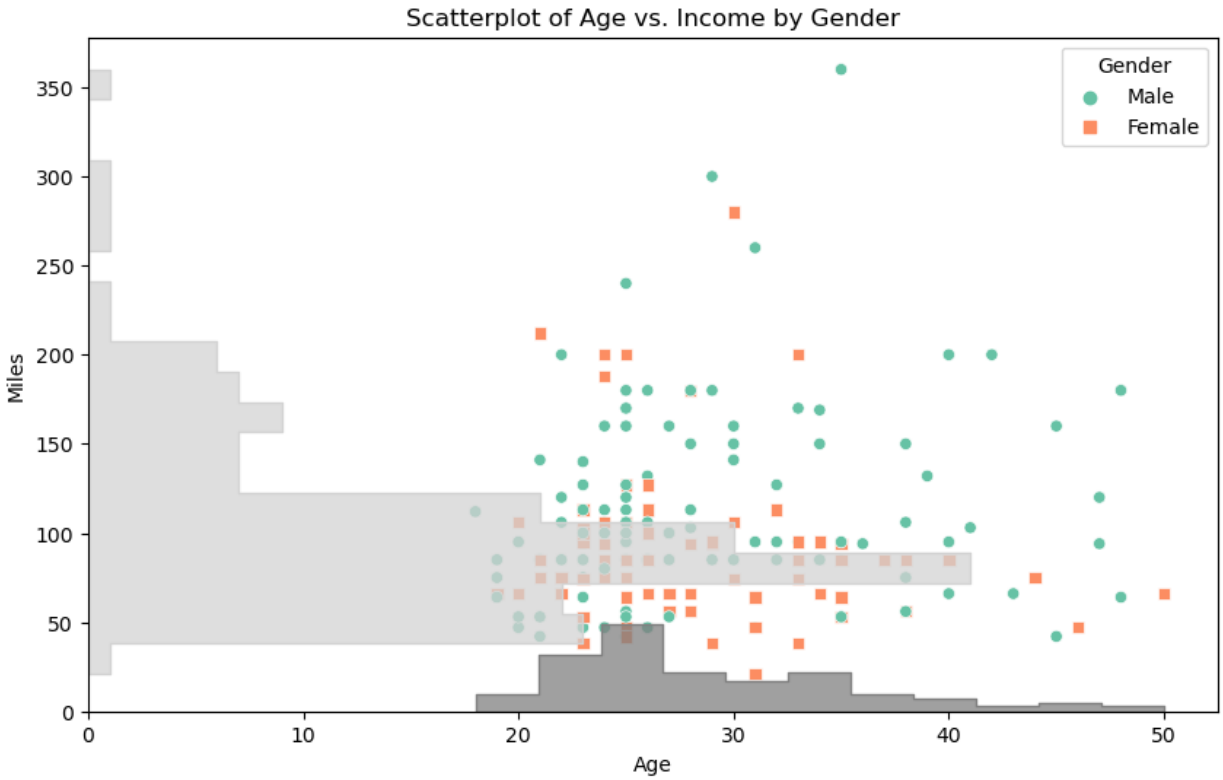


In [80]:
```
sns.boxplot(data=Aerofit_data, x="Product", y="Income", hue="Gender", palette="Set1",
            showfliers=False, notch=True, showcaps=True, showmeans=True, meanprops={'m
            whis=1.5)
```

```
# Add labels and title
plt.title("Box Plot of Income by Product")
plt.xlabel("Product")
plt.ylabel("Income")

plt.show()
```



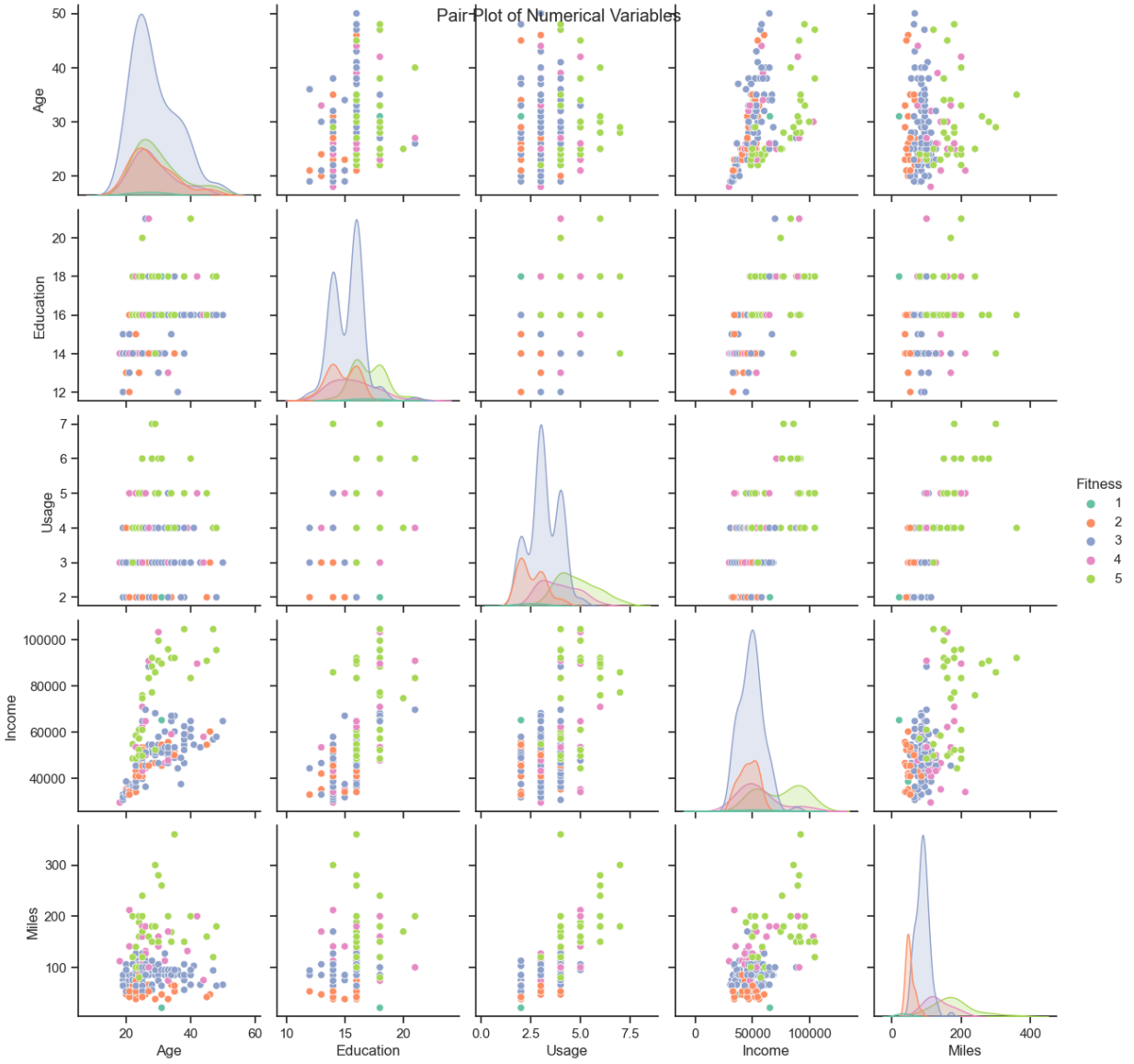
In [92]:
```
# Create a scatterplot with all possible information
plt.figure(figsize=(10, 6))

# Scatter plot
sns.scatterplot(data=Aerofit_data, x="Age", y="Miles", hue="Gender", palette="Set2", s



# Data distribution on the axes
sns.histplot(data=Aerofit_data, x="Age", element="step", common_norm=False, color="gra
sns.histplot(data=Aerofit_data, y="Miles", element="step", common_norm=False, color="l

# Add labels and title
plt.title("Scatterplot of Age vs. Income by Gender")
plt.xlabel("Age")
plt.ylabel("Miles")
plt.show()
```



In [117…

```
# Create a pair plot to visualize relationships between numerical variables
plt.figure(figsize=(12, 6))
sns.set(style="ticks")
sns.pairplot(data= numerical_columns, diag_kind="kde", hue="Fitness", palette="Set2")

plt.suptitle("Pair Plot of Numerical Variables")
plt.show()
```

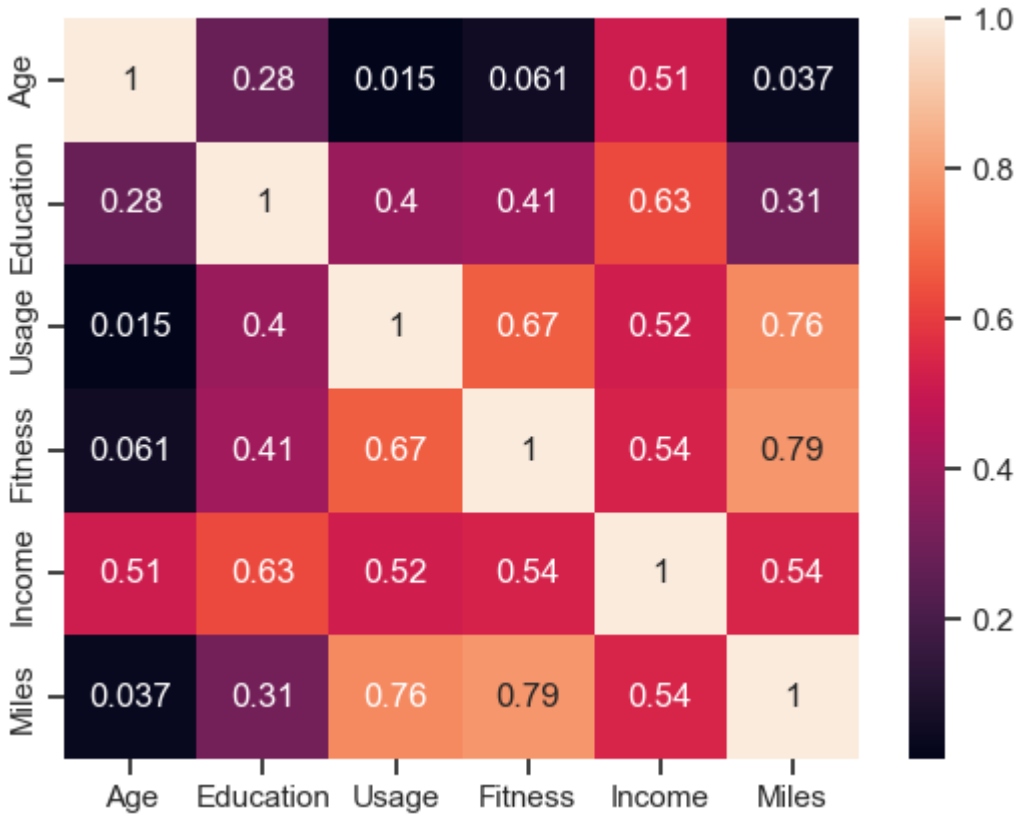
```
<Figure size 1200x600 with 0 Axes>
```



In [151…

```
sns.heatmap(Aerofit_data.corr(),annot=True)
plt.show()
```

```
C:\Users\harsh\AppData\Local\Temp\ipykernel_24172\1691317906.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(Aerofit_data.corr(),annot=True)
```



In [109…
```
#In years
Aerofit_data["Education"].nunique()
```

Out[109]:
```
8
```

In [112…
```
Aerofit_data["Education"].value_counts()
```

Out[112]:
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

In [111…
```
# Usage:The average number of times the customer plans to use the treadmill each week.

Aerofit_data["Usage"].nunique()
```

Out[111]:
```
6
```

In [143…
```
Aerofit_data["Usage"].unique()
```

Out[143]:
```
array([3, 2, 4, 5, 6, 7], dtype=int64)
```

In [113…
```
Aerofit_data["Usage"].value_counts()
```

Out[113]:
```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

In [115…
```
#Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellen
Aerofit_data["Fitness"].value_counts()
```

Out[115]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

Solution 4

In [133…
```
# Column wise null values chceking
Aerofit_data.isnull().sum(axis=0)
```

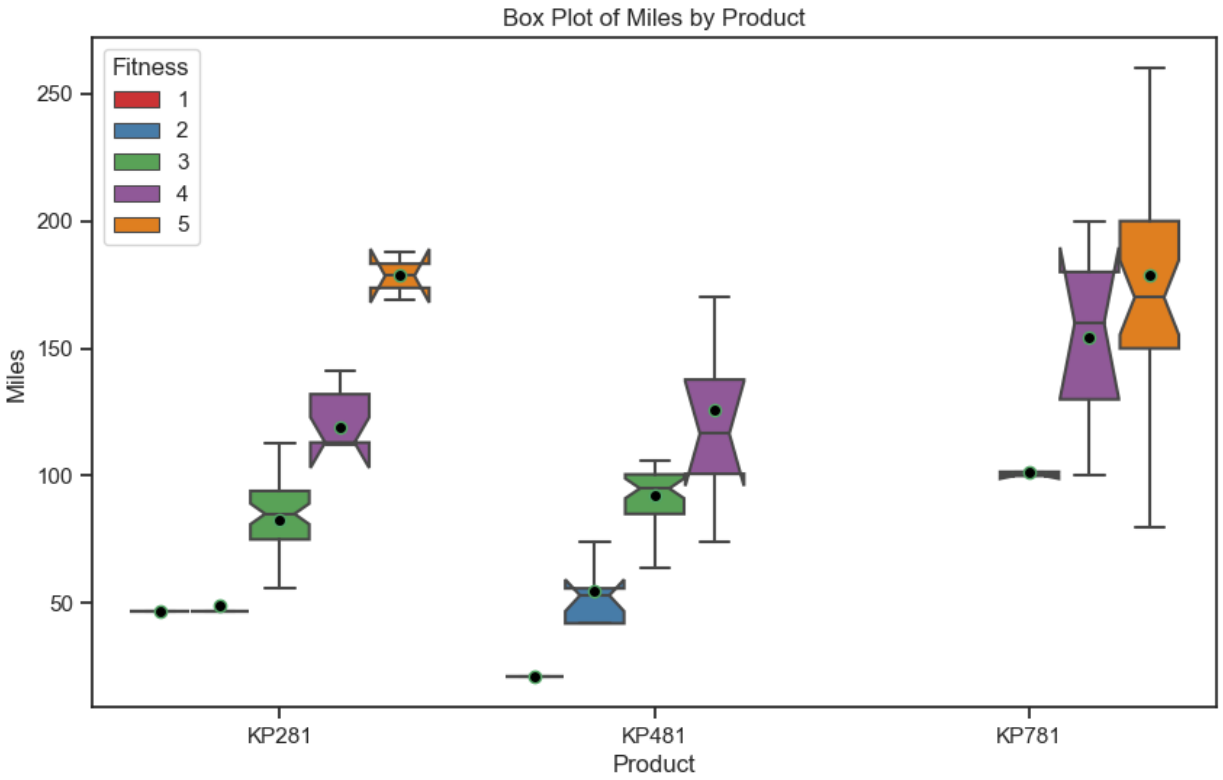
Out[133]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [134…
```
# Row wise null values chceking
Aerofit_data.isnull().sum(axis=1)
```

Out[134]:
```
0      0
1      0
2      0
3      0
4      0
      ..
175    0
176    0
177    0
178    0
179    0
Length: 180, dtype: int64
```

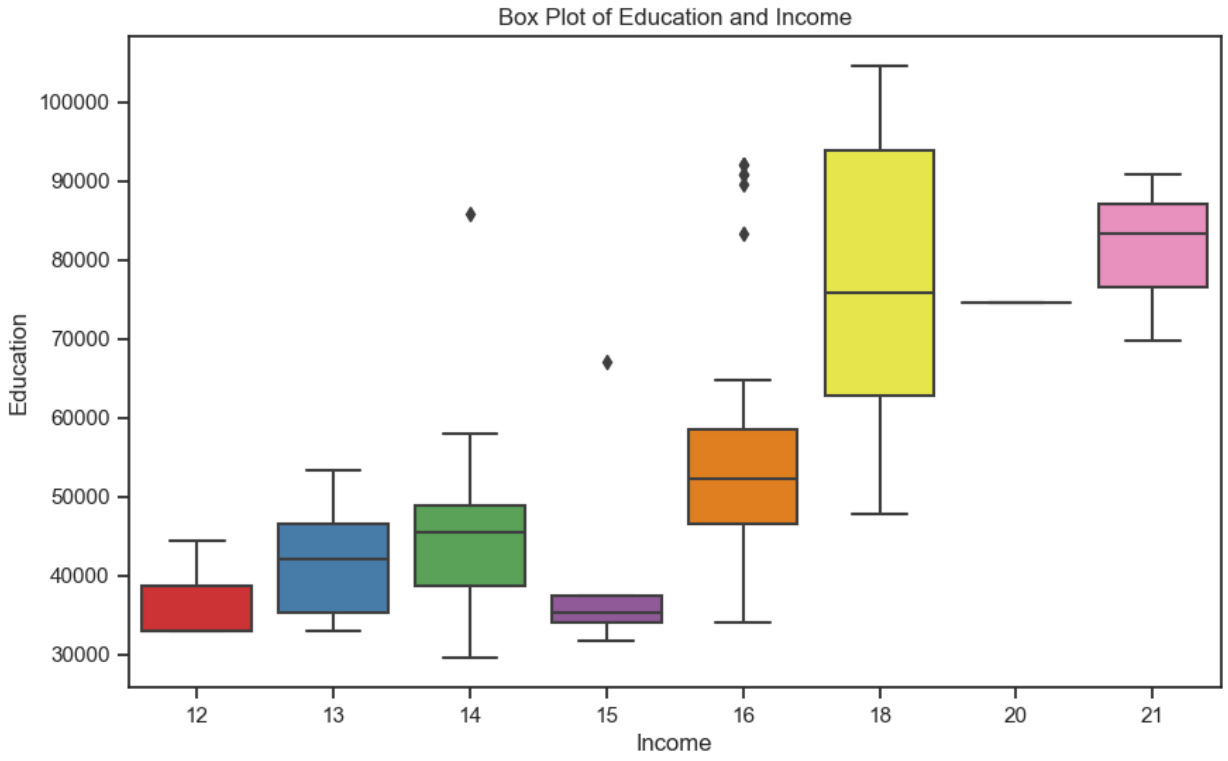
In [123…
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=Aerofit_data, x="Product", y="Miles", hue="Fitness", palette="Set1",
            showfliers=False, notch=True, showcaps=True, showmeans=True, meanprops={'m
            whis=1.5)

# Add labels and title
plt.title("Box Plot of Miles by Product")
plt.xlabel("Product")
plt.ylabel("Miles")
```

```
plt.show()
```



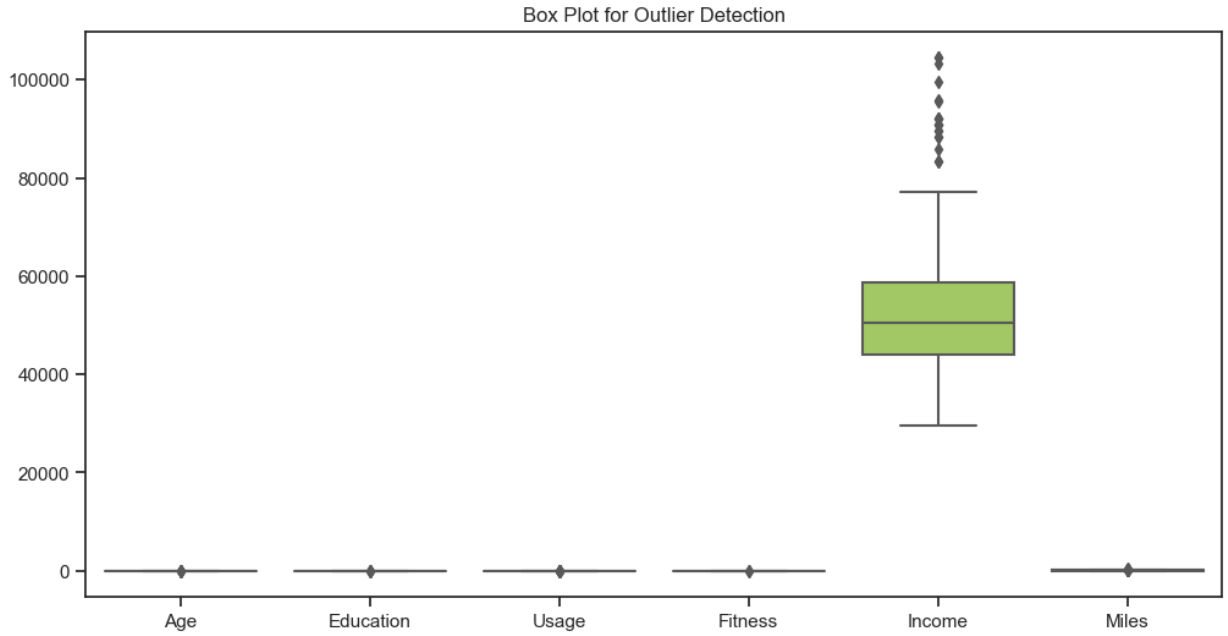
In [146…

```
plt.figure(figsize=(10, 6))
sns.boxplot(data=Aerofit_data, y="Income", x="Education", palette="Set1", meanprops={'
            whis=1.5)

# Add labels and title
plt.title("Box Plot of Education and Income")
plt.xlabel("Income")
plt.ylabel("Education")

plt.show()
```



In [135…

```
# Create box plots to visualize potential outliers
plt.figure(figsize=(12, 6))
sns.boxplot(data=numerical_columns, palette="Set2")
plt.title("Box Plot for Outlier Detection")
plt.show()
```



Solution 5

In [ ]:

```
1. There are 3 categories of products.
   'KP281', 'KP481', and 'KP781' and there running capacity and price increses respect
2. Each product divide on the basis of miles.
3. 'KP781' is costly product through which extra miles (50 to 350 miles) are covered a
```

```
   salary gretaer than 60000 if user is married.
4. As the user education is increasing the income of the user also increaing.
5. 'KP781' is brought by users who want to run more like upto 350 miles.
6. There are 58% male buyer and 42% females.
7. Most Customer are from 22 to 35 Age.
8. For "KP281" male and female buying ratio is 22%.
9. 5 fitness ranking is mostly achived by user of product "KP781"
10. 'KP481' is usually brought buy users having income between 45000 to 55000.
11. For single person median income is 60000 to buy 'KP781' but for marrid it is "9000
12. 'KP281' is most purchased product then "KP481" and "KP781" respectively.
13. Fitness is most corelated with number of miles(Heatmap).
14. 3.89% is probability of female purcahsing "KP781".
15. The probability of male purcahsing "KP781" is 18%.
```

Thankyou

In [ ]:

In [ ]:

In [ ]:

In [ ]: