Business Casestudy Aerofit

Note: I have addressed only questions mentioned in the pdf named Netix Data Exploration Business Case solution Approach

Some plots might not get completely printed on the pdf hence providing google colab link.

https://colab.research.google.com/drive/1-Z_1H79sP0viMM6WGjuY2O7K0jpooIRX?usp=sharing

Business Problem

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. The team has collected the data of 180 customers who have purchased the treadmills from the company.

The data includes the following variables:

1. Product: The type of treadmill purchased
2. Age: The age of customer
3. Gender: The Gender of the customer
4. Education: The education level of the customer(in years)
5. Marital Status: The marital status of the customer
6. Usage: The average number of times the customer uses the treadmill every week
7. Fitness: Self-rated fitness level of the customer, on a scale of 1 to 5
8. Income: The annual income of the customer
9. Miles: The average number of miles the customer expects to walk/run on the treadmill every week

Objectives

1. Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
2. 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.

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.

1.Checking the structure & characteristics of the dataset

```
# Importing necessary libraries

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
```

```
# Loading the aerofit data

!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639992749
```

```
Downloading...
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639992749
To: /content/aerofit_treadmill.csv?1639992749
100% 7.28k/7.28k [00:00<00:00, 22.8MB/s]
```

```
# Assuming 'data' is your DataFrame

data = pd.read_csv("aerofit_treadmill.csv?1639992749")

#Overview of head and tail combined of the netflix dataframe

data
```

	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

Next steps: Generate code with `data` View recommended plots

```
# Get a concise summary of the DataFrame

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
```

Insights

The Aerofit dataset comprises 9 columns, with 3 columns being categorical and 6 columns being numerical. While no columns showing null values.

```
#Check the null values

print('\nColumns with missing value:')
print(data.isnull().any())
```

```
Columns with missing value:
Product          False
Age              False
Gender           False
Education        False
MaritalStatus    False
Usage            False
Fitness          False
Income           False
Miles            False
dtype: bool
```

```
# Display the first few rows of the DataFrame

data.head()
```

	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

Next steps: Generate code with data View recommended plots

```
# Number of columns

data.columns
```

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

```
# Check the shape of the DataFrame

data.shape
```

```
data.shape
```

```
(180, 9)
```

```
#Check the dimensions of the DataFrame

data.ndim
```

```
2
```

**Insights*

The Aerofit dataset is 2 dimensional with 180 enteries and 9 descriptions.

```
# Summary statistics for numerical columns

data.describe(include='all')
```

	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

**Insights*

*No missing values exist in the datase.

*The dataset contains 3 unique products namely-KP281,KP481,KP781.

*KP281 is the most frequently occurring product.

*Age ranges from 18 to 50 years, with a mean of approximately 28.79 years.

*75% of individuals are aged 33 or younger.

*Most individuals have 16 years of education or less; specifically, 75% have attained this level.

*Out of 180 data points, 104 individuals are male, and the remaining are female.

*Both the income and miles variables exhibit high standard deviations, indicating the possible presence of outliers.

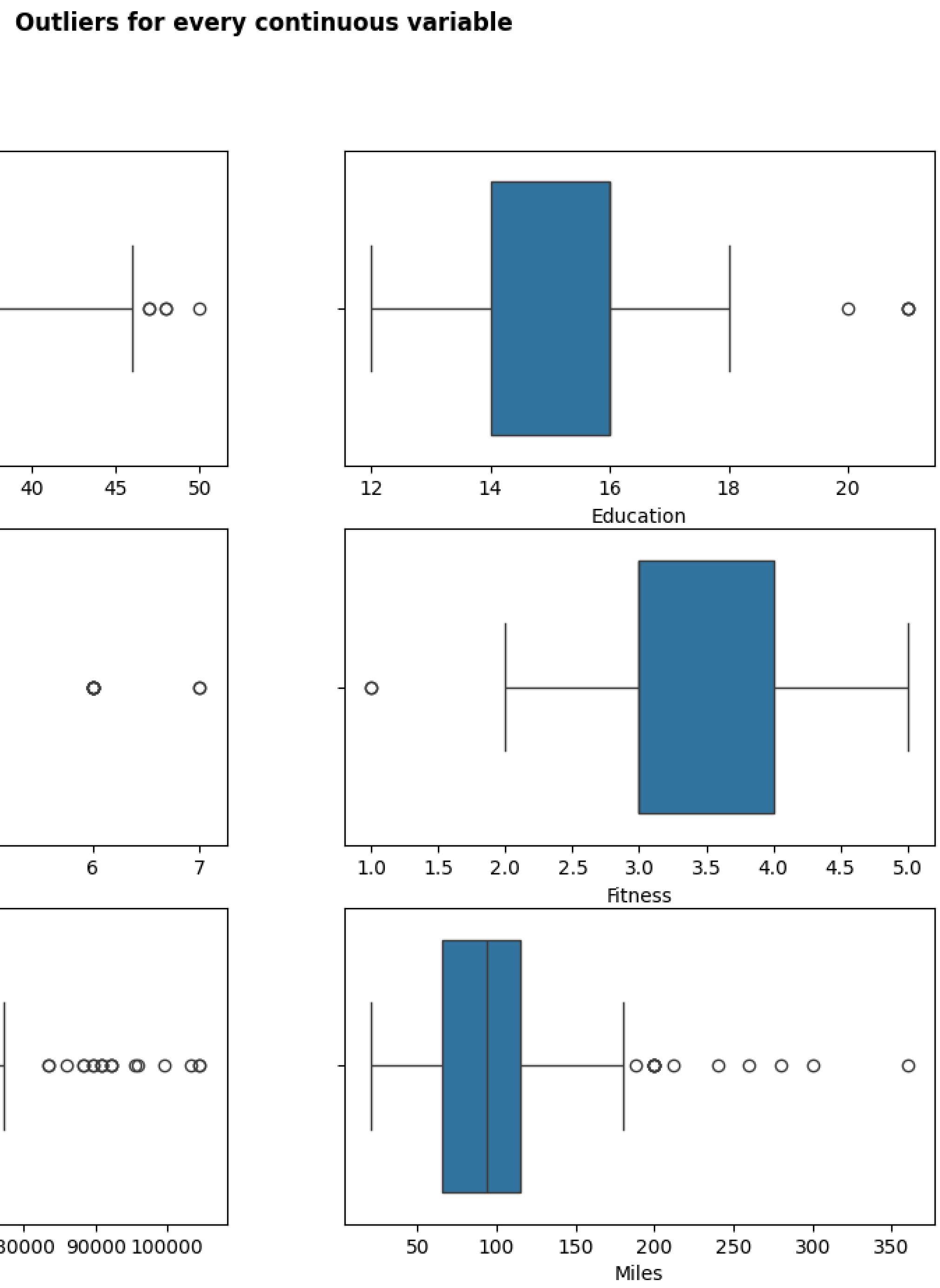
```
# checking the unique values for columns
#overview of values
for i in data.columns:
    print('Unique Values in',i,'column are :-')
    print(data[i].unique())
    print('-'*70)
```

```
Unique Values in Product column are :-
['KP281' 'KP481' 'KP781']
----------------------------------------------------------------------
Unique Values in Age column are :-
[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 43 44 46 47 50 45 48 42]
----------------------------------------------------------------------
Unique Values in Gender column are :-
['Male' 'Female']
----------------------------------------------------------------------
Unique Values in Education column are :-
[14 15 12 13 16 18 20 21]
----------------------------------------------------------------------
Unique Values in MaritalStatus column are :-
['Single' 'Partnered']
----------------------------------------------------------------------
Unique Values in Usage column are :-
[3 2 4 5 6 7]
----------------------------------------------------------------------
Unique Values in Fitness column are :-
[4 3 2 1 5]
----------------------------------------------------------------------
Unique Values in Income column are :-
[ 29562  31836  30699  32973  35247  37521  36384  38658  40932  34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]
----------------------------------------------------------------------
Unique Values in Miles column are :-
[112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]
----------------------------------------------------------------------
```

2.Detect Outliers

a) Find the outliers for every continuous variable in the dataset

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.suptitle("Outliers for every continuous variable", weight='bold')
#fig.subplots_adjust(top=1)

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


Outliers for every continuous variable
20
25
30
35
40
45
50
Age
12
14
16
18
20
Education
2
3
4
5
6
7
Usage
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Fitness
30000
40000
50000
60000
70000
80000
90000
100000
Income
50
100
150
200
250
300
350
Miles

Insights

---

*Age, Education and Usage are having very few outliers

*While Income and Miles are having more outliers.

b) Remove/clip the data between the 5 percentile and 95 percentile

```
# Replace 'continuous_cols' with the names of your continuous variables
continuous_cols = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Step 3: Calculate the 5th and 95th percentiles for each column
percentiles = data[continuous_cols].quantile([0.05, 0.95])

# Step 4: Clip the data to remove outliers
for col in continuous_cols:
    lower_bound = percentiles.loc[0.05, col]
    upper_bound = percentiles.loc[0.95, col]

    # Clip values outside the 5th and 95th percentiles
    data[col] = np.clip(data[col], lower_bound, upper_bound)

# Now data contains the clipped data where outliers are removed
```

```
continuous_cols
percentiles
```

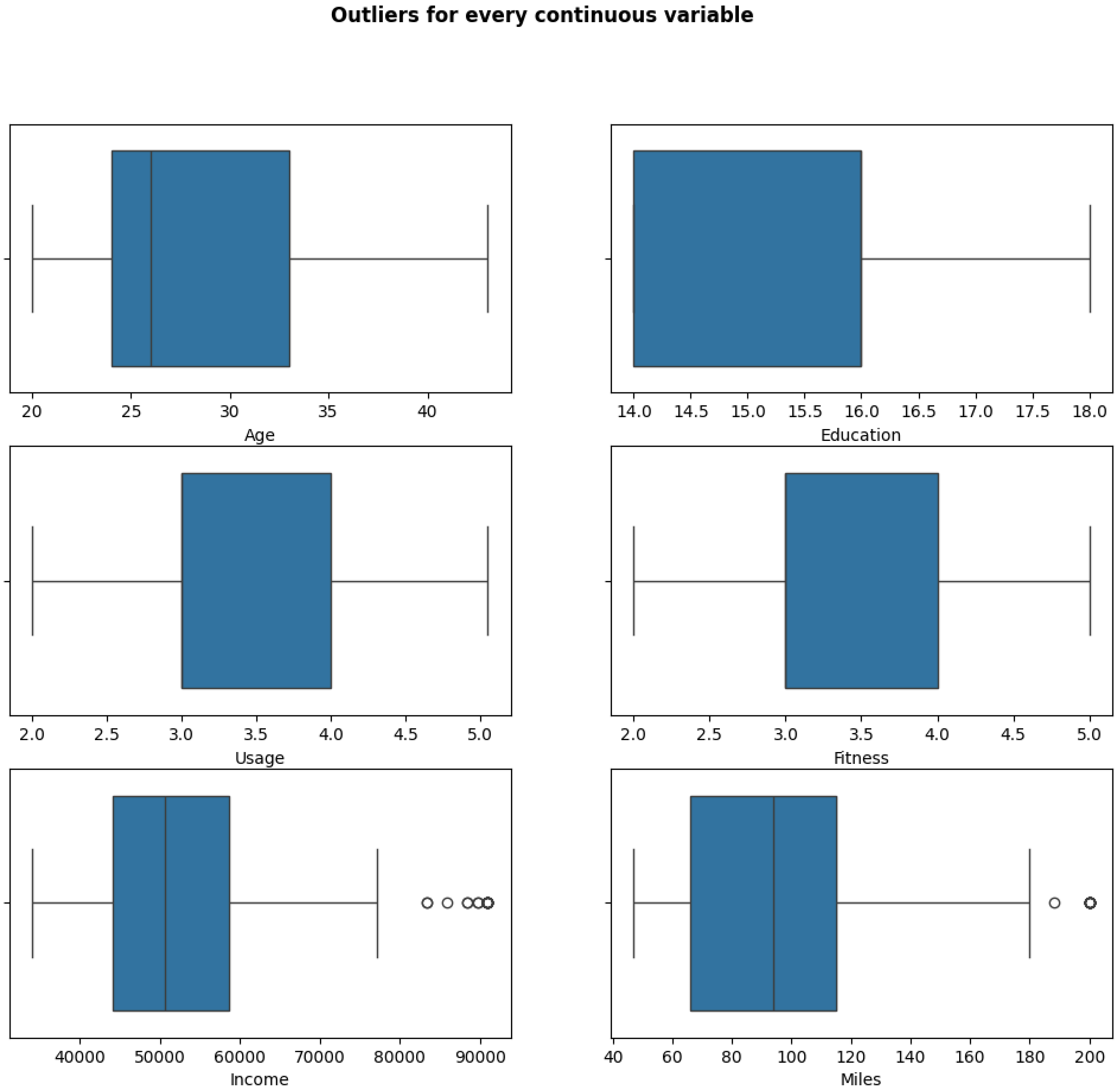
	Age	Education	Usage	Fitness	Income	Miles
0.05	20.00	14.0	2.00	2.0	34053.15	47.0
0.95	43.05	18.0	5.05	5.0	90948.25	200.0

Next steps: Generate code with `percentiles` View recommended plots

c) Observed whether all outliers were clipped

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.suptitle("Outliers for every continuous variable", weight='bold')
#fig.subplots_adjust(top=1)

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

```
sns.boxplot(data=data, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=data, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=data, x="Miles", orient='h', ax=axis[2,1])
plt.show()
```


Outliers for every continuous variable
20
25
30
35
40
Age
14.0
14.5
15.0
15.5
16.0
16.5
17.0
17.5
18.0
Education
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Usage
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Fitness
40000
50000
60000
70000
80000
90000
Income
40
60
80
100
120
140
160
180
200
Miles

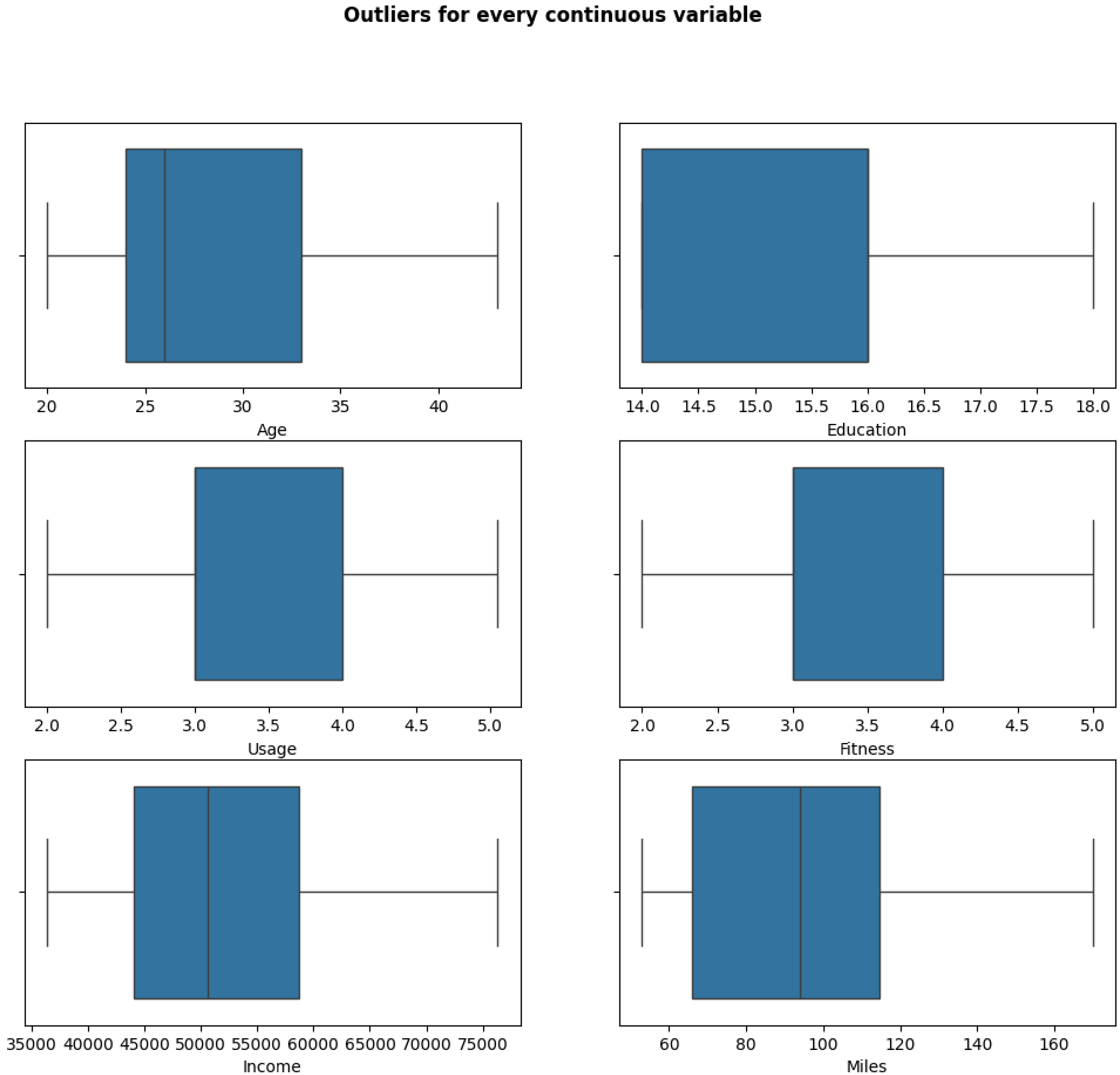
**Insights*

Outliers exceeded 95 and 5 percentile in column Income and Miles

```
#Outlier analysis after readjustments
continuous_cols = ['Income', 'Miles']

# Calculate updated percentiles (e.g., [0.11, 0.89]) for clipping
percentiles = data[continuous_cols].quantile([0.11, 0.89])

# Clip the data to remove outliers using updated percentiles
for col in continuous_cols:
    lower_bound = percentiles.loc[0.11, col]
    upper_bound = percentiles.loc[0.89, col]

    # Clip values outside the 1st and 99th percentiles
    data[col] = np.clip(data[col], lower_bound, upper_bound)

# Now data should contain the clipped data where outliers are removed based on adjusted percentiles
```

d) Outlier analysis after readjustments

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.suptitle("Outliers for every continuous variable", weight='bold')
#fig.subplots_adjust(top=1)

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


Outliers for every continuous variable
20
25
30
35
40
Age
14.0
14.5
15.0
15.5
16.0
16.5
17.0
17.5
18.0
Education
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Usage
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Fitness
35000
40000
45000
50000
55000
60000
65000
70000
75000
Income
60
80
100
120
140
160
Miles

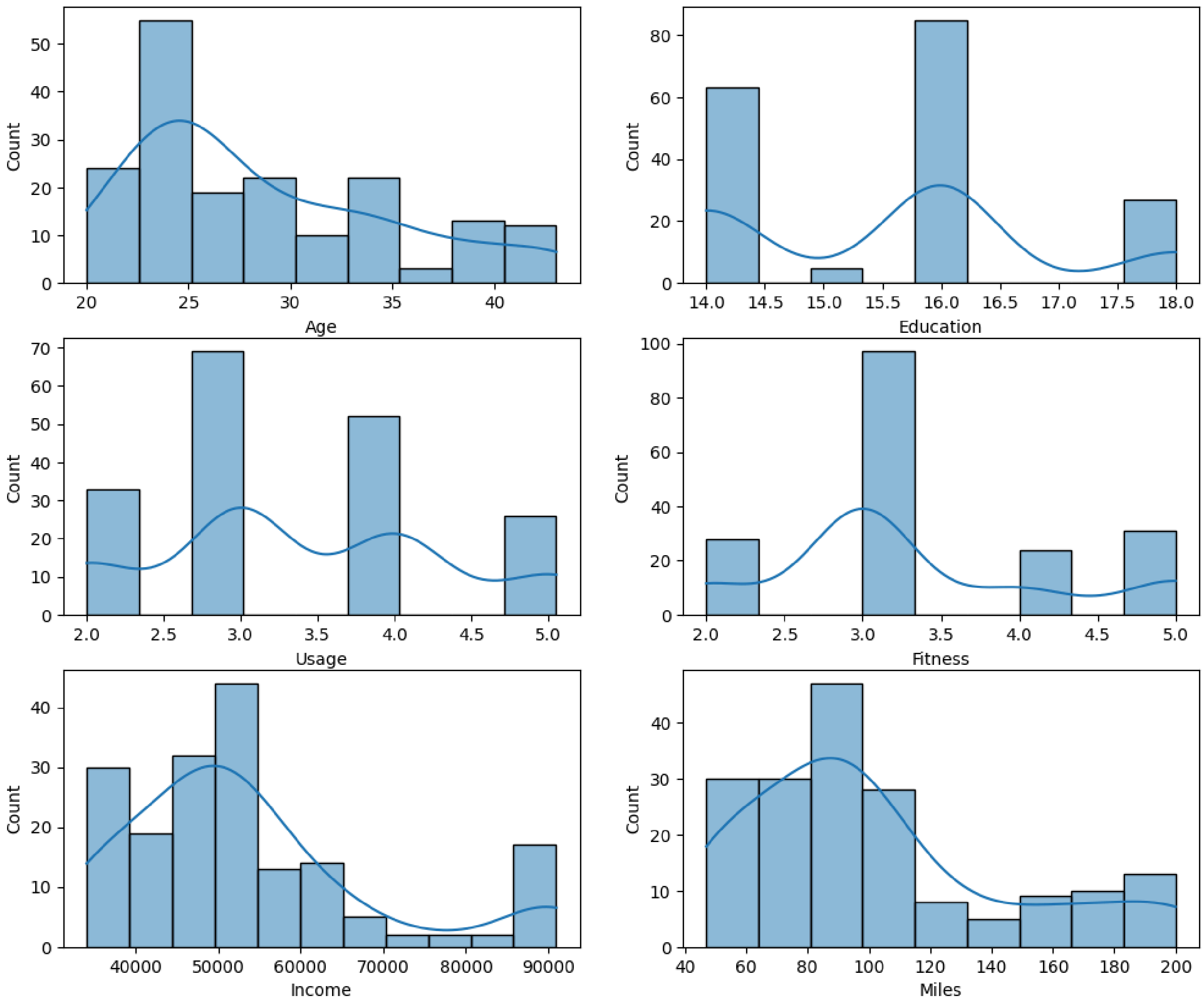
*Insights

All the outliers are removed from every columns.

e) Understanding the distribution of the data for the quantitative atributes:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.suptitle("Distribution of data for continuous variable", weight='bold')
#fig.subplots_adjust(top=0.8)

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

Distribution of data for continuous variable



*Insights

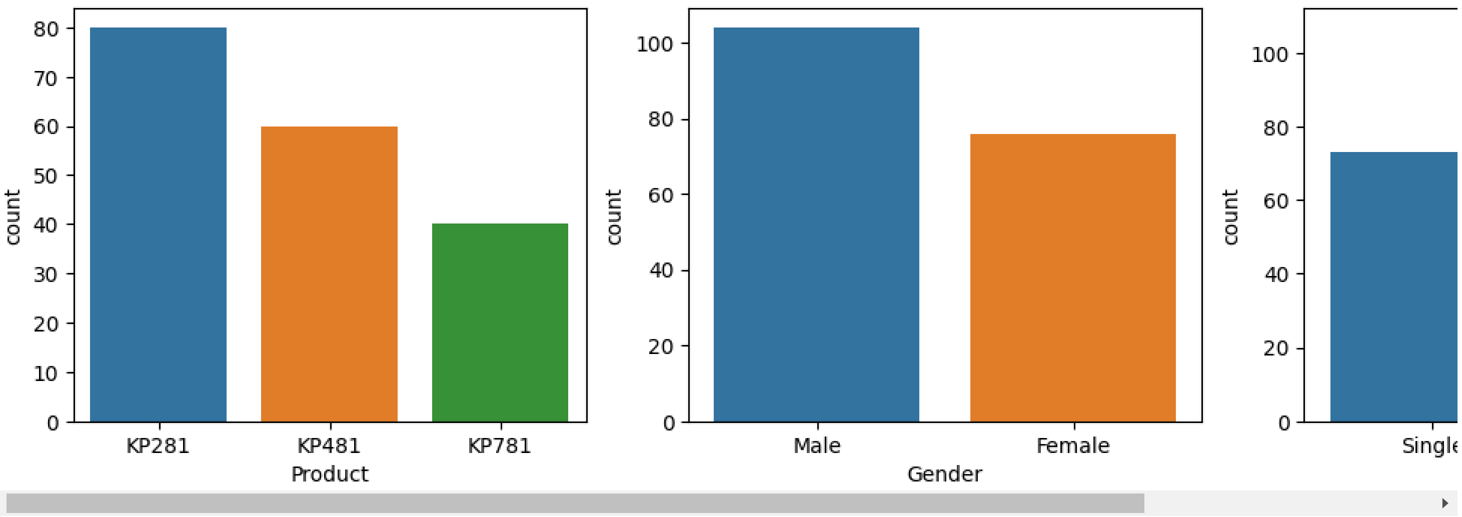
- Most of the customers (more than 80% of the total) are aged between 20 and 30 years.
- Less than 10% customers are aged 40 years and above.
- It can be evidently observed in the above plot that most customers have 16 years of Education, followed by 14 years and 18 years.
- There are about 40% of customers who use treadmills three days a week and about 30% who use them four days a week.
- More than 50% customers rate themselves 3 out of 5 in self rated fitness scale
- Around 30% of the total customers rate themselves 4 or above in the fitness scale.
- Around 70 % of the aerofit customers rate themselves 3 or less than 3 in fitness scale.
- Less than 20 % of aerofit customers have excellent shape.
- Majority of the customers earn in between 35000 and 60000 dollars annually.
- 80 % of the customers annual salary is less than 65000$.
- On the above plot, we can see that most customers expect to walk or run between 40 and 120 miles a week.

3. Check if features like marital status, Gender, and age have any effect on the product purchased.

Find if there is any relationship between the categorical variables and the output variable in the data.

```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(15,4))
fig.suptitle("Countplots for categorical variables", weight='bold')
fig.subplots_adjust(top=0.8)
sns.countplot(data=data, x='Product', ax=axs[0], hue='Product')
sns.countplot(data=data, x='Gender', ax=axs[1], hue='Gender')
sns.countplot(data=data, x='MaritalStatus', ax=axs[2], hue='MaritalStatus')
plt.show()
```

Countplots for categorical variables



**Insights*

- KP281 is the most frequent product.
- Thare are more Males in the data than Females.
- More Partnered persons are there in the data.

```
#normalized count for each variable is shown below
df1 = data[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count() / len(data)
```

variable	value	value
Gender	**Female**	0.422222
	Male	0.577778
MaritalStatus	**Partnered**	0.594444
	Single	0.405556
Product	**KP281**	0.444444
	KP481	0.333333
	KP781	0.222222

Insights

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

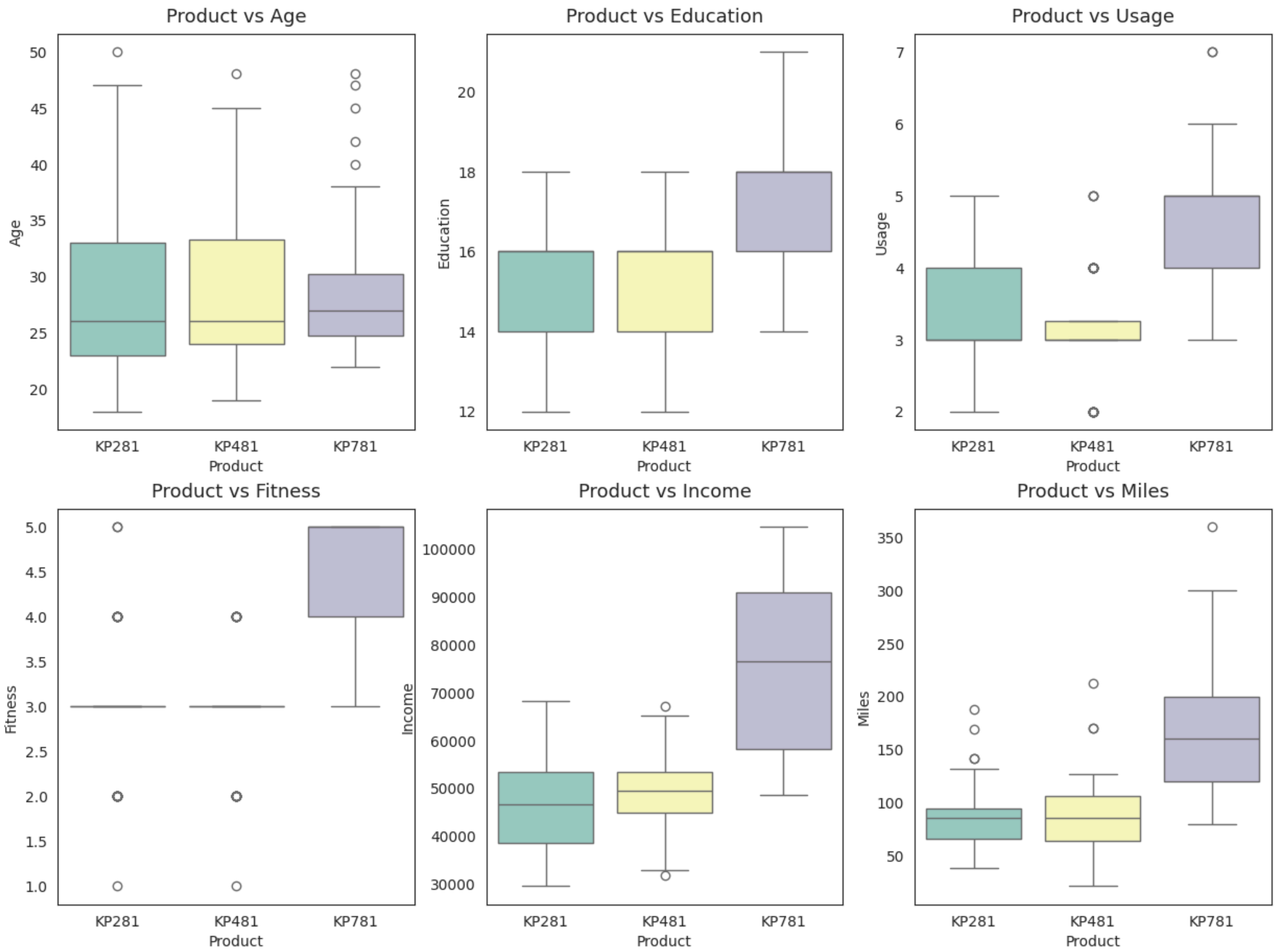
- 57.78% of the customers are Male.
- 42.22% of the customers are Female.

MaritalStatus

- 59.44% of the customers are Partnered.
- 40.56% of the customers are Single.

Find if there is any relationship between the continuous variables and the output variable in the data.

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income','Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(15, 6))
#fig.suptitle("Countplots for categorical variables", weight='bold')
fig.subplots_adjust(top=1.5)
count = 0
for i in range(2):
  for j in range(3):
      sns.boxplot(data=data, x='Product', y=attrs[count], ax=axs[i,j], palette='Set3', hue='Product')
      axs[i,j].set_title(f"Product vs {attrs[count]}", pad=8, fontsize=13)
      count += 1
```


Product vs Age
Age
Product
KP281
KP481
KP781
Product vs Education
Education
Product vs Usage
Usage
Product vs Fitness
Fitness
Product vs Income
Income
Product vs Miles
Miles

**Insights*

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.

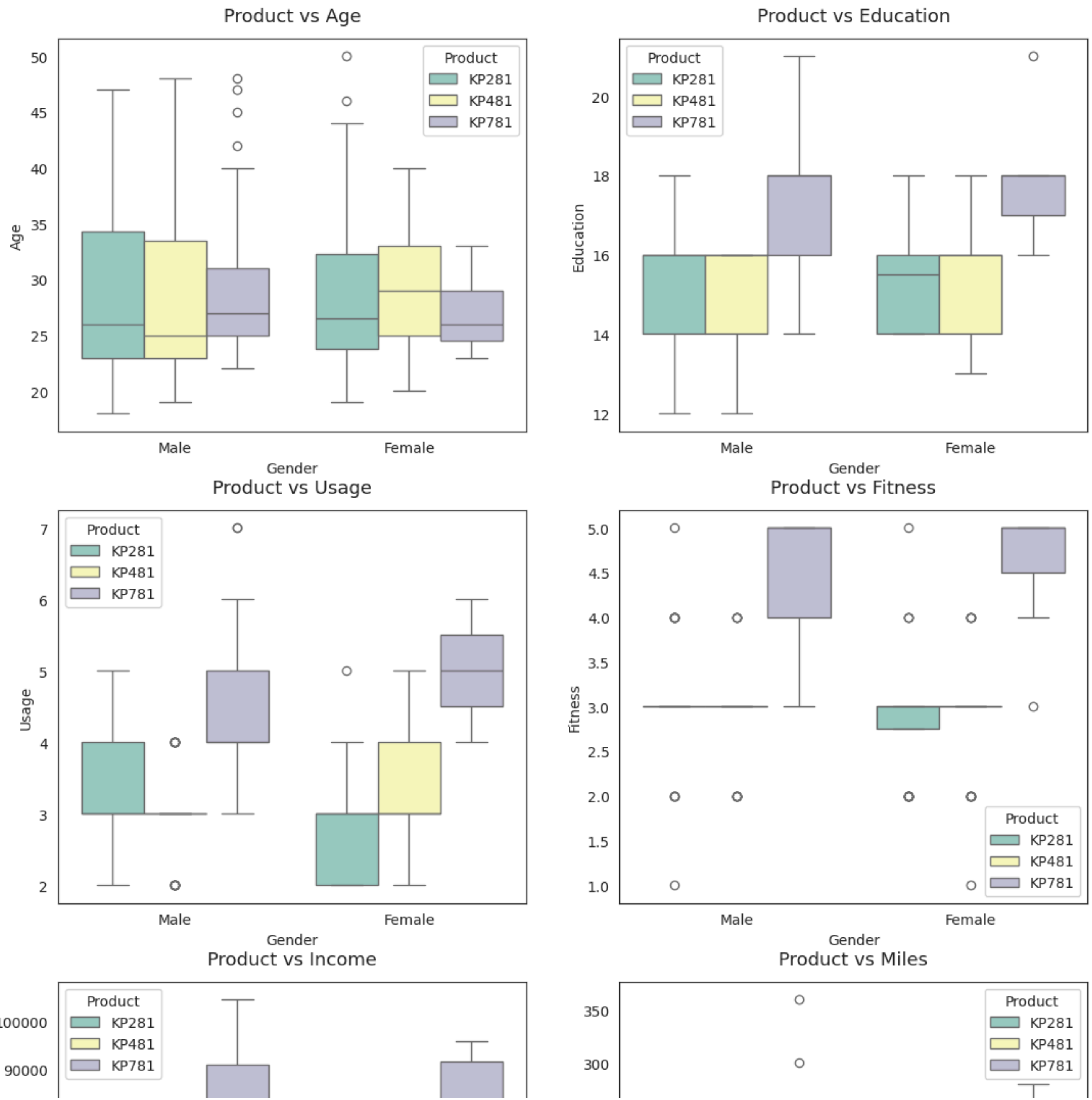
5.Product vs Income:

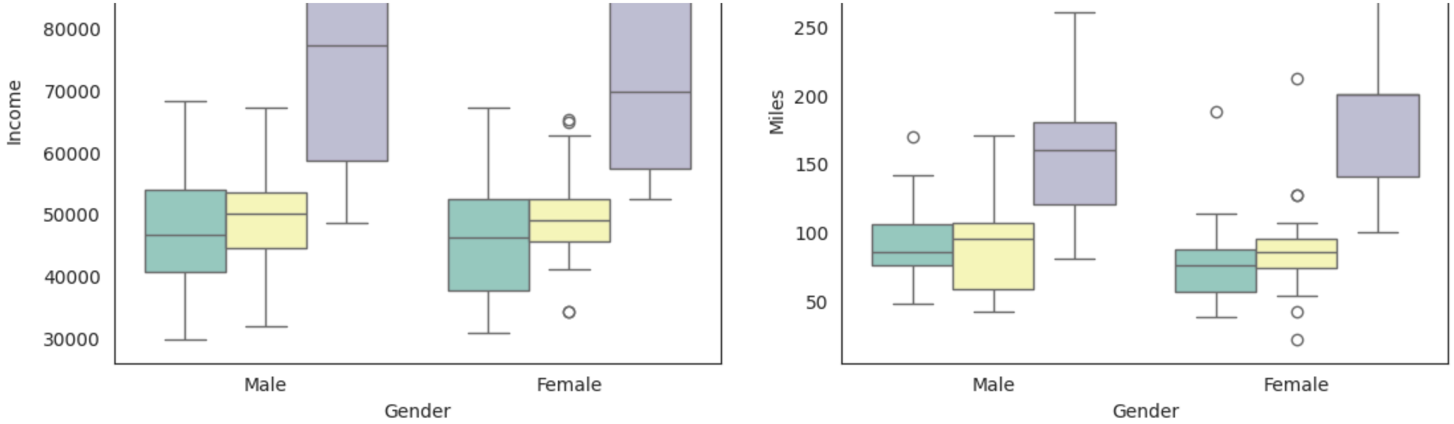
- Higher the Income of the customer (Income >= 60000), higher the chances of the customer to purchase the KP781 product.

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.

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(13, 11))
fig.subplots_adjust(top=1.3)
count = 0
for i in range(3):
    for j in range(2):
        sns.boxplot(data=data, x='Gender', y=attrs[count], hue='Product', ax=axs[i,j], palette='Set3')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
```

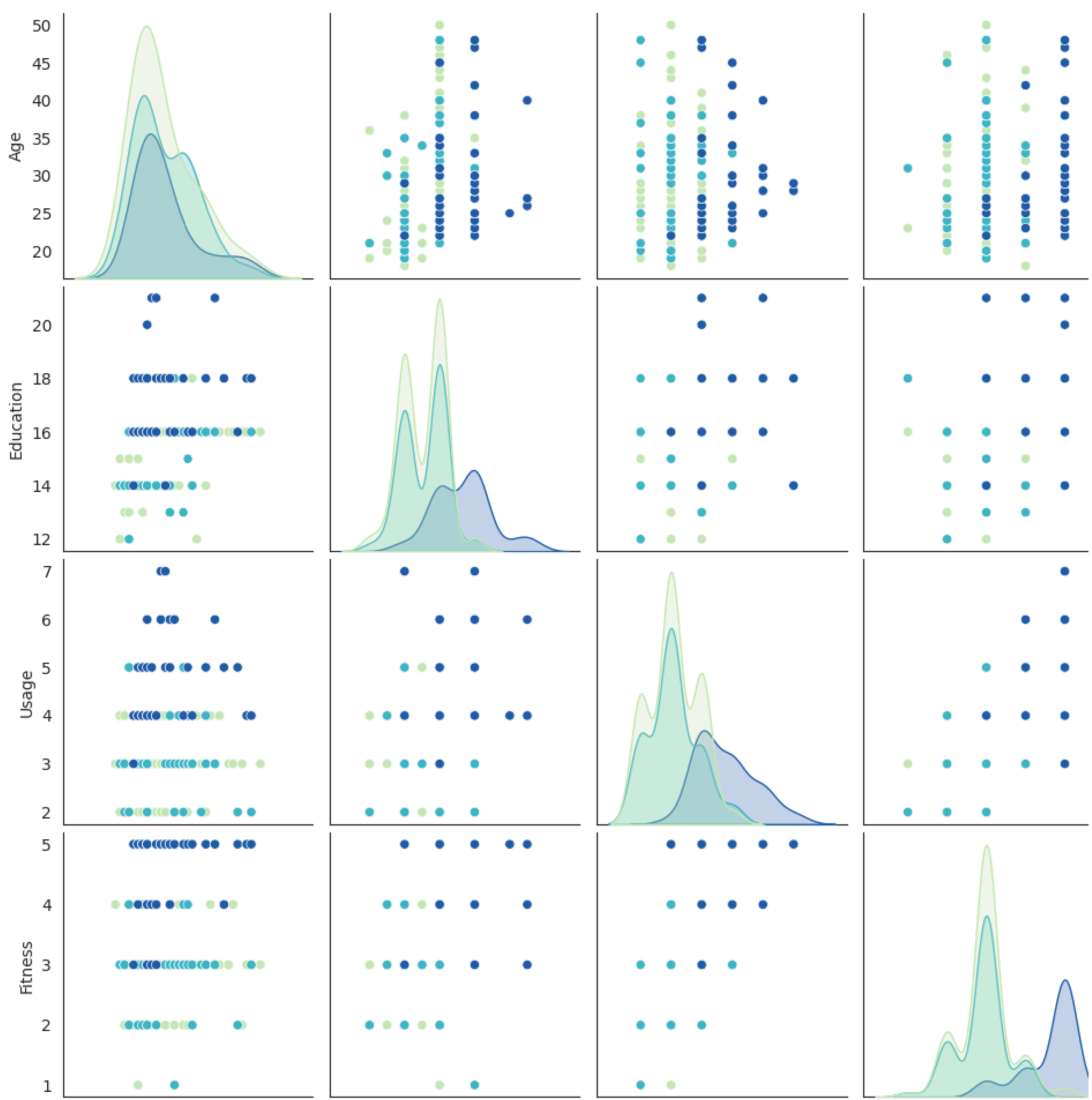

Product vs Age
Age
50
45
40
35
30
25
20
Male
Female
Gender
Product
KP281
KP481
KP781
Product vs Education
Education
20
18
16
14
12
Male
Female
Gender
Product vs Usage
Usage
7
6
5
4
3
2
Male
Female
Gender
Product vs Fitness
Fitness
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Male
Female
Gender
Product vs Income
100000
90000
Product vs Miles
350
300

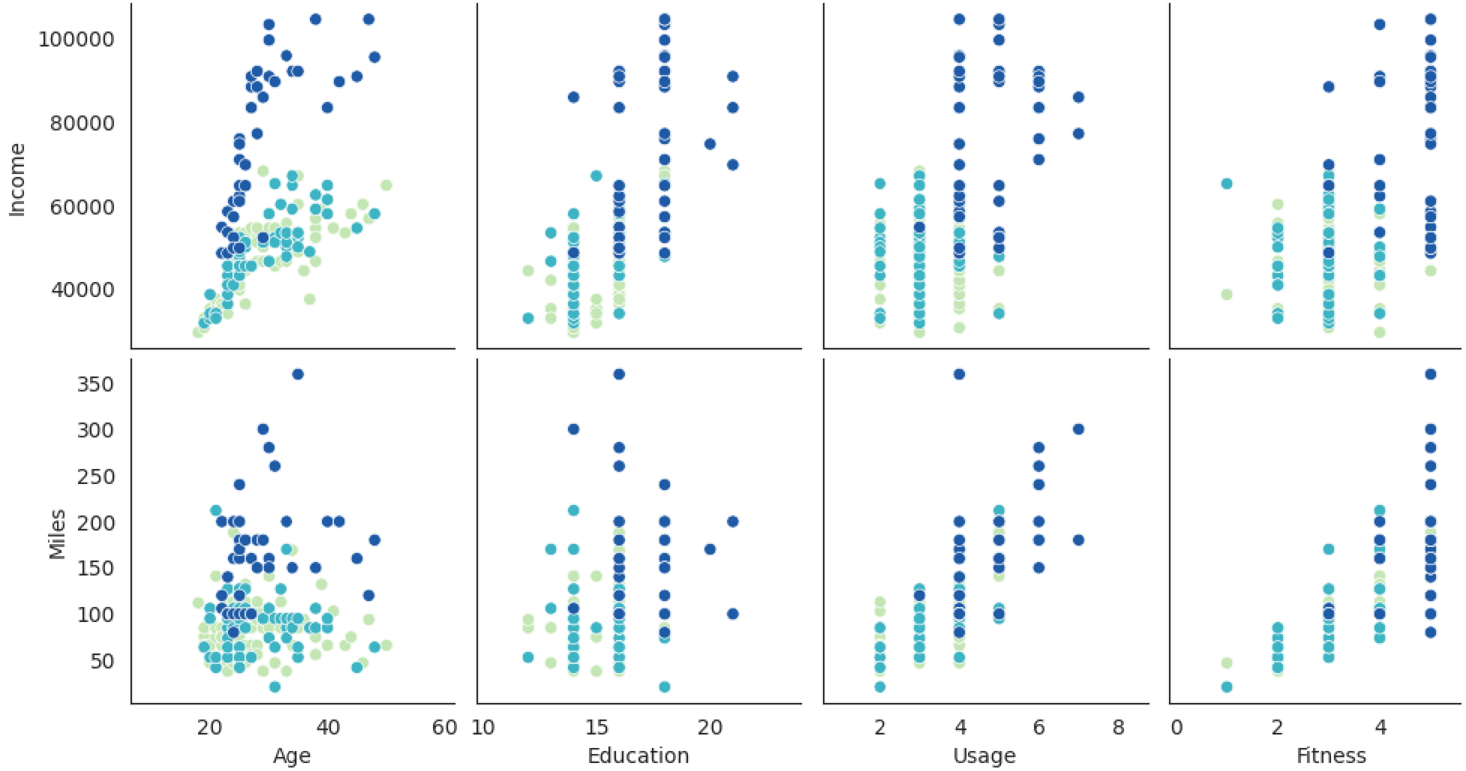


**Insights*

- Very fewer Females prefer KP781.
- KP281 is the most preferred product by both genders, and also both married and single customers, which align with previous observations that it is the most sold product
- Approximately there is a 60-40 split between male and female customers.
- Majority of the customers are married. We can see and assume that Marital Status also has a 60-40 split.
- Females planning to use treadmill 3-4 times a week, are more likely to buy KP481 product

```
import copy
df_copy = copy.deepcopy(data)
sns.pairplot(df_copy, hue ='Product', palette= 'YlGnBu')
plt.show()
```


Age
50
45
40
35
30
25
20
Education
20
18
16
14
12
Usage
7
6
5
4
3
2
Fitness
5
4
3
2
1



4. Representing the Probability

a) Find the marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

```
product_marginal_Probability = data['Product'].value_counts(normalize=True).round(2)
product_marginal_Probability
```

```
Product
KP281    0.44
KP481    0.33
KP781    0.22
Name: proportion, dtype: float64
```

Find the probability that the customer buys a product based on each column.

```
#Marginal Probability of Gender
gender_marginal_Probability = data['Gender'].value_counts(normalize=True).round(2)
gender_marginal_Probability
```

```
Gender
Male      0.58
Female    0.42
Name: proportion, dtype: float64
```

```
#Marginal Probability of Fitness
fitness_marginal_Probability = data['Fitness'].value_counts(normalize=True).round(2)
fitness_marginal_Probability
```

```
Fitness
3    0.54
5    0.17
2    0.16
4    0.13
Name: proportion, dtype: float64
```

```
#Marginal Probability of Marital Status
mStatus_marginal_Probability = data['MaritalStatus'].value_counts(normalize=True).round(2)
mStatus_marginal_Probability
```

```
MaritalStatus
Partnered    0.59
Single       0.41
Name: proportion, dtype: float64
```

b) Find the conditional probability that an event occurs given that another event has occurred.

```
#Probability of the customer's gender, given the product he/she bought a specific Product
(pd.crosstab(data["Gender"],data['Product'])/pd.crosstab(data["Gender"],data['Product']).sum()).round(2)
```

Product Gender	KP281	KP481	KP781
Female	0.5	0.48	0.18
Male	0.5	0.52	0.82

```
#Probability of buying a product, given the Gender of the customer
(pd.crosstab(data["Product"],data['Gender'])/pd.crosstab(data["Product"],data['Gender']).sum()).round(2)
```

Gender	Female	Male
Product		
KP281	0.53	0.38
KP481	0.38	0.30
KP781	0.09	0.32

```
#Probability of buying a product, given the Marital Status of the person
(pd.crosstab(data["Product"],data["MaritalStatus"])/pd.crosstab(data["Product"],data["MaritalStatus"]).sum()).round(2)
```

MaritalStatus	Partnered	Single
Product		
KP281	0.45	0.44
KP481	0.34	0.33
KP781	0.21	0.23

```
#Probability of buying a product, given the Fitness of the person
(pd.crosstab(data["Product"],data["Fitness"])/pd.crosstab(data["Product"],data["Fitness"]).sum()).round(2)
```

Fitness	2	3	4	5
Product				
KP281	0.54	0.56	0.38	0.06
KP481	0.46	0.40	0.33	0.00
KP781	0.00	0.04	0.29	0.94

```
#Probability of buying a product, given the age of a customer
# First we create a Deep-copy to create Bins for different age groups
temp_data = data.copy(deep=True)
bin_labels = ['17-20', '21-25', '26-30', '31-35', '36-40', '41-45', '46-51']
temp_data["Age"] = pd.cut(temp_data['Age'], bins=[17,20,25,30,35,40,45,51], labels= bin_labels)
(pd.crosstab(temp_data['Product'], temp_data["Age"])/pd.crosstab(temp_data['Product'], temp_data["Age"]).sum()).round(2)
```

Age	17-20	21-25	26-30	31-35	36-40	41-45
Product						
KP281	0.6	0.41	0.51	0.34	0.50	0.50
KP481	0.4	0.35	0.17	0.53	0.38	0.17
KP781	0.0	0.25	0.32	0.12	0.12	0.33

```
#Probability of buying a product, given the income of a customer
temp_data = data.copy(deep=True)
bin_labels = ['0k-10k', '10k-20k', '20k-30k', '30k-40k', '40k-50k', '50k-60k', '60k-70k',"70k-80k","80k-90k","90k-100k","100k-110k"]
temp_data["Income"] = pd.cut(temp_data['Income'], bins=[0,10000,20000,30000,40000,50000,60000,70000,80000,90000,100000,110000], labels= bin_labels)
(pd.crosstab(temp_data['Product'], temp_data["Income"])/pd.crosstab(temp_data['Product'], temp_data["Income"]).sum()).round(2)
```

Income	30k-40k	40k-50k	50k-60k	60k-70k	70k-80k
Product					
KP281	0.72	0.49	0.47	0.32	0.0
KP481	0.28	0.41	0.42	0.37	0.0
KP781	0.00	0.10	0.11	0.32	1.0

5. Check the correlation among different factors

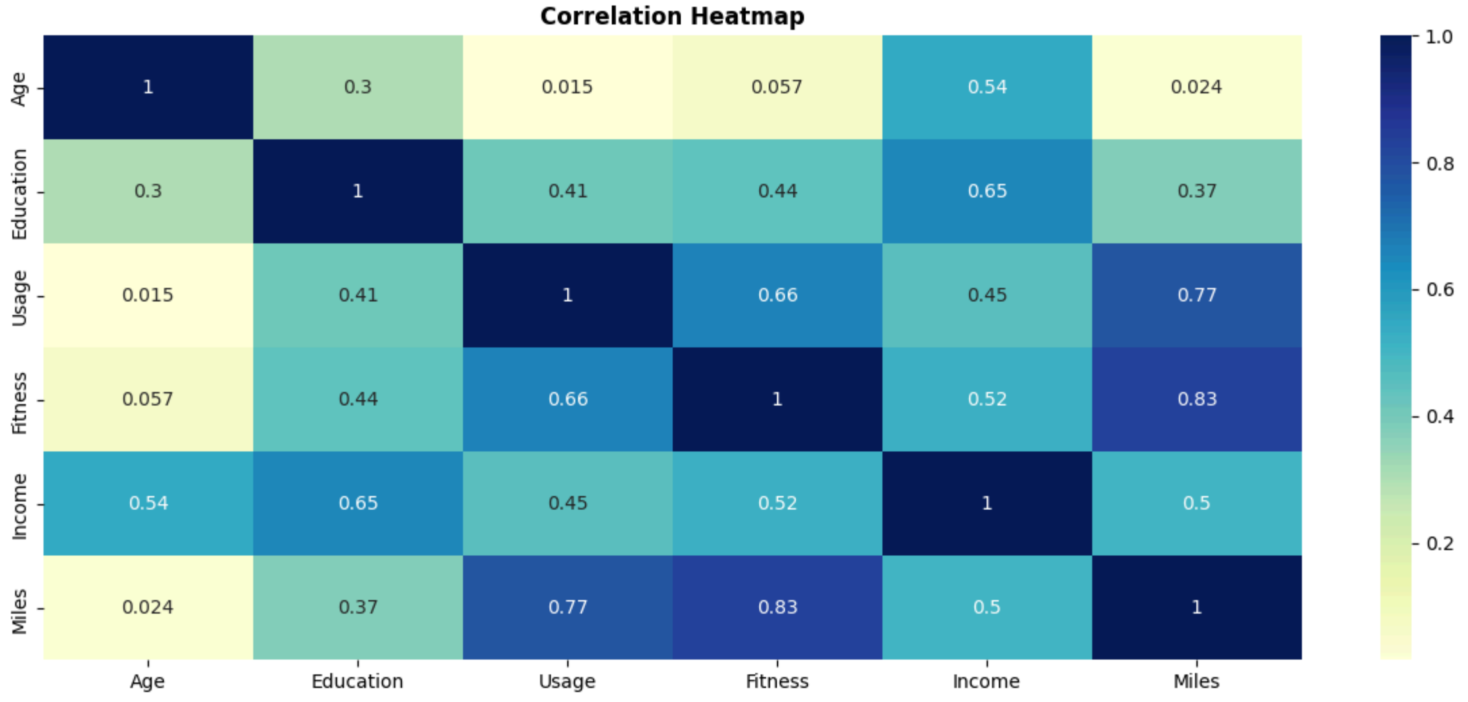
```
#Change datatype to int
data['Usage'] = data['Usage'].astype('int')
data['Fitness'] = data['Fitness'].astype('int')

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    float64
 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    float64
 8   Miles          180 non-null    int64
dtypes: float64(2), int64(4), object(3)
memory usage: 12.8+ KB
```

```
#drop columns with data as object
dat = data.drop(columns=['Product', 'MaritalStatus', 'Gender'])
dat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Age        180 non-null    float64
 1   Education  180 non-null    int64  
 2   Usage      180 non-null    int64  
 3   Fitness    180 non-null    int64  
 4   Income     180 non-null    float64
 5   Miles      180 non-null    int64  
dtypes: float64(2), int64(4)
memory usage: 8.6 KB
```

```
#correlation between the enteries
corr_m = dat.corr()
plt.figure(figsize=(15,6))
fig.subplots_adjust(top=1)
sns.heatmap(corr_m,annot = True, cmap="YlGnBu")
plt.title('Correlation Heatmap', weight='bold')
plt.show()
```



*Insights

- From the pair plot we can see Age and Income are positively correlated and heatmap also suggests a strong correlation between them
- Eductaion and Income are highly correlated as its obvious. Eductation also has significatnt correlation between Fitness rating and Usage of the treadmill.
- Usage is highly correlated with Fitness and Miles as more the usage more the fitness and mileage.

6.Customer profiling and recommendation

Make customer profilings for each and every product.

```
#KP281
data[data['Product'] == 'KP281'].describe().round(2)
```

	Age	Education	Usage	Fitness	Income	Miles
count	80.00	80.00	80.00	80.00	80.00	80.00
mean	28.43	15.12	3.09	2.98	46887.04	83.80
std	6.68	1.07	0.78	0.64	8408.40	26.49
min	20.00	14.00	2.00	2.00	36384.00	53.00
25%	23.00	14.00	3.00	3.00	38658.00	66.00
50%	26.00	16.00	3.00	3.00	46617.00	85.00
75%	33.00	16.00	4.00	3.00	53439.00	94.00
max	43.05	18.00	5.00	5.00	68220.00	170.00

**Insights*

- The mean age of the participants is approximately 28.43 years, with a standard deviation of around 6.68 years.
- On average, participants rated their product usage at around 3.09 on a scale of 1 to 5, with a standard deviation of approximately 0.78
- Similarly, the average fitness level reported is approximately 2.96, with a standard deviation of about 0.66.
- The average income among participants is approximately dollar 46,418 with a minimum of dollar 29,562 and a maximum of $68,220.
- The mean number of miles participants expect to run/walk is approximately 82.79, with astandard deviation of around 28.87

```
#KP781
data[data['Product'] == 'KP781'].describe().round(2)
```

	Age	Education	Usage	Fitness	Income	Miles
count	40.00	40.00	40.00	40.00	40.00	40.00
mean	28.83	17.05	4.50	4.62	67644.38	146.15
std	6.30	1.20	0.55	0.67	10778.11	29.63
min	22.00	14.00	3.00	3.00	48556.00	80.00
25%	24.75	16.00	4.00	4.00	58204.75	120.00
50%	27.00	18.00	5.00	5.00	76138.98	160.00
75%	30.25	18.00	5.00	5.00	76331.95	170.00
max	43.05	18.00	5.00	5.00	76331.95	170.00

**Insights*

- The average age of customers for this specific product is approximately 29.1 years, with aminimum age of 22 years and a maximum age of 48 years.
- On average, customers have an education level of around 17.33 years.
- The average product usage rating is approximately 4.78, with a minimum rating of 3 and a maximum rating of 7.
- The average fitness rating of customers is around 4.63, with a minimum rating of 3 and a maximum rating of 5.
- The majority of customers rated their fitness level as 5, as indicated by the median (50th percentile).
- The average income of customers is approximately $75,441.58.7. Customers, on average, run approximately 166.9 miles

```
#KP481
data[data['Product'] == 'KP481'].describe().round(2)
```

	Age	Education	Usage	Fitness	Income	Miles
count	60.00	60.00	60.00	60.00	60.00	60.00
mean	28.80	15.18	3.07	2.92	49276.85	88.50
std	6.33	1.11	0.80	0.59	8125.66	29.05
min	20.00	14.00	2.00	2.00	36384.00	53.00
25%	24.00	14.00	3.00	3.00	44911.50	64.00
50%	26.00	16.00	3.00	3.00	49459.50	85.00
75%	33.25	16.00	3.25	3.00	53439.00	106.00
max	43.05	18.00	5.00	4.00	67083.00	170.00

*Insights

- The average age of customers for this specific product is approximately 28.9 years, with aminimum age of 19 years and a maximum age of 48 years.
- On average, customers have an education level of around 15.12 years.
- The average product usage rating is approximately 3.07, with a minimum rating of 2 and a maximum rating of 5.
- The average fitness rating of customers is around 2.9, with a minimum rating of 1 and a maximum rating of 4.The majority of customers rated their fitness level as 3, as indicatedby the median (50th percentile).
- The average income of customers is approximately $48,973.65.6. Customers, on average, run approximately 87.93 miles.

Conclusion

- The KP281 is the most sold product with 80 units sold, followed by KP481 with 60 units sold, and KP781 with 40 units sold.

- **Relationship with Age:** No major relationship with Age, but customers purchasing KP781mostly earn more than other people of the same age group.
- **Relationship with Income:–** product KP781 is preferred by high-income earning individuals– since highly-educated customer generally earns more, they prefer product KP781 because they exercise more; their fitness levels are generally on high scale, the number of target miles they set are also higher
- **Relationship with Usage:–** product KP781 is used more compared to others products KP281 and KP481– this product is also preferred by highly-educated customers; this means highly-educated customers tend to exercise more
- **Relationship with Education:** The line-plot shows the gradual increase in fitness levels with the increase in education. Highly educated customers prefer product KP781; they could be more aware of the product's typical features and its usage.
- **Relationship with Fitness:–** product KP781 is preferred by customers with high fitness levels– customers with high fitness levels tend to exercise more and set higher target miles

Recommendations

- The company should focus on marketing KP781 to high-income earning individuals, and highly-educated customers, as they are the major customers for this product.
- The company should also focus on marketing KP781 to customers with high fitness levels, since the product is preferred by customers with high fitness levels.
- A better, high-end, premium product for highly-educated, high income and active customers to increase revenue.
- Since KP281 and KP481 also brings in significant revenue and is preferred by young & learnings individuals, added features and specialized discounts could help boost sales.
- Campaigns to promote KP781 product for females specially.
- Gender Disparity Strategy for KP784: Implement targeted promotions and trials aimed at female customers to boost sales, as only 18% of total sales are currently attributed to them.
- Affordable Pricing and Payment Plans for KP281 and KP481: Offer the KP281 and KP481 Treadmill at competitive prices and provide flexible payment options to cater to customers with diverse budgets.
- User-Friendly App Integration: Develop a treadmill-synced app that tracks users' running mileage, offers real-time feedback, and provides personalized workout recommendations based on their fitness goals, enhancing user engagement and experience.

Overall Insights

- Number of customers who bought products KP281, KP481 and KP781 are in ratio 4 : 3 : 2. That means for every 9 customers, 4 customers bought KP281, 3 bought KP481 and 2 bought KP781.
- There are more male customers than females. Around 60% of the total customers are males.
- There are more customers who are partnered than single. Almost 60% of customers are partnered.
- Age of the customers varies between 18 and 50 years.
- More than 80% of the total customers are aged between 20 and 30 years.
- Annual income of the customers varies in the range of 29562 dollars to 104581 dollars.
- 80 % of the customers annual salary is less than 65000 dollars.
- Expected usage of treadmills lies in the range of 2 to 7 times in a week.
- Expected number of miles that the customer walks or runs vary between 21 miles to 360 miles per week.
- More than 50% customers rate themselves 3 out of 5 in self rated fitness scale
- Around 70 % of the aerofit customers rate themselves 3 or less in fitness scale.

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