Aerofit_Case-Study

March 20, 2024

1 Aerofit Case Study

About Aerofit: 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.

1.1 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.

1.2 Dataset

Dataset that We will be using is here

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior three months. The dataset has the following features:

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

Miles: The average number of miles the customer expects to walk/run each week

1.3 Product Portfolio

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

[2]:
```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
↪original/aerofit_treadmill.csv?1639992749
```

```
--2024-03-20 19:07:31--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/125/original/aerofit_treadmill.csv?1639992749
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
13.249.226.180, 13.249.226.102, 13.249.226.172, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|13.249.226.180|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 7279 (7.1K) [text/plain]
Saving to: 'aerofit_treadmill.csv?1639992749.1'

aerofit_treadmill.c 100%[===================>]   7.11K  --.-KB/s    in 0s

2024-03-20 19:07:31 (144 MB/s) - 'aerofit_treadmill.csv?1639992749.1' saved
[7279/7279]
```

[3]:
```
data = pd.read_csv('aerofit_treadmill.csv?1639992749')
```

1.4 Going Through the Data

[4]:
```
data.head()
```

[4]:

	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

[5]:
```
data.shape
```

[5]: (180, 9)

[6]:
```
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
```

Product, Gender and Marital Status is in string formate and all other are in integer formate

[7]:
```
data.isnull().sum()
```

[7]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

There is No null value in the data set

[8]:
```
data.sort_values(by="Income", ascending=True)
```

[8]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0     KP281   18    Male         14        Single      3        4   29562
2     KP281   19  Female         14     Partnered      4        3   30699
1     KP281   19    Male         15        Single      2        3   31836
80    KP481   19    Male         14        Single      3        3   31836
3     KP281   19    Male         12        Single      3        3   32973
..      …   …      …          …           …      …     …      …
171   KP781   33  Female         18     Partnered      4        5   95866
169   KP781   30    Male         18     Partnered      5        5   99601
168   KP781   30    Male         18     Partnered      5        4  103336
178   KP781   47    Male         18     Partnered      4        5  104581
174   KP781   38    Male         18     Partnered      5        5  104581

     Miles
0      112
2       66
1       75
80      64
3       85
```

```
..      …
171     200
169     150
168     160
178     120
174     150

[180 rows x 9 columns]
```

[9]:
```
data.describe(include='all')
```

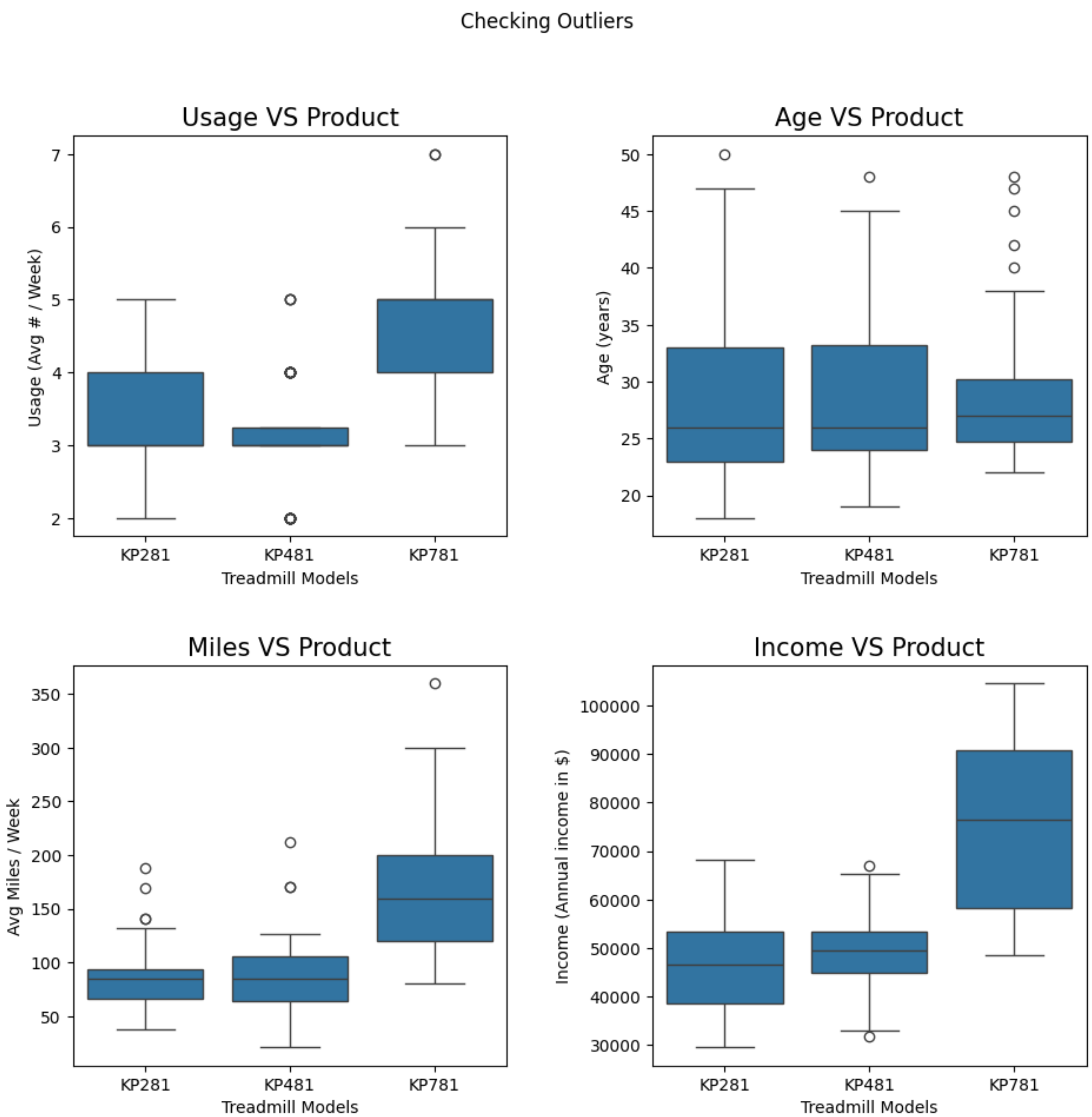
[9]:
```
       Product         Age Gender   Education MaritalStatus       Usage  \
count      180  180.000000    180  180.000000           180  180.000000
unique       3         NaN      2         NaN             2         NaN
top      KP281         NaN   Male         NaN     Partnered         NaN
freq        80         NaN    104         NaN           107         NaN
mean       NaN   28.788889    NaN   15.572222           NaN    3.455556
std        NaN    6.943498    NaN    1.617055           NaN    1.084797
min        NaN   18.000000    NaN   12.000000           NaN    2.000000
25%        NaN   24.000000    NaN   14.000000           NaN    3.000000
50%        NaN   26.000000    NaN   16.000000           NaN    3.000000
75%        NaN   33.000000    NaN   16.000000           NaN    4.000000
max        NaN   50.000000    NaN   21.000000           NaN    7.000000

           Fitness         Income       Miles
count   180.000000     180.000000  180.000000
unique         NaN            NaN         NaN
top            NaN            NaN         NaN
freq           NaN            NaN         NaN
mean      3.311111   53719.577778  103.194444
std       0.958869   16506.684226   51.863605
min       1.000000   29562.000000   21.000000
25%       3.000000   44058.750000   66.000000
50%       3.000000   50596.500000   94.000000
75%       4.000000   58668.000000  114.750000
max       5.000000  104581.000000  360.000000
```

1.5 Observations:

- The average income of customers is $53,719.
- The average distance a user walks on a treadmill is 103 Miles.
- More than 50% of people have a fitness score of 3.
- Average usage of a treadmill by a user is 3.3 times a week.

[10]:
```
plt.figure(figsize=(10,10))
plt.suptitle("Checking Outliers")

plt.subplot(2,2,1)
```

```
sns.boxplot(data, x="Product", y="Usage")
plt.xlabel('Treadmill Models')
plt.ylabel('Usage (Avg # / Week)')
plt.title('Usage VS Product', fontsize = 15)

plt.subplot(2,2,2)
sns.boxplot(data, x="Product", y="Age")
plt.xlabel('Treadmill Models')
plt.ylabel('Age (years)')
plt.title('Age VS Product', fontsize = 15)

plt.subplot(2,2,3)
sns.boxplot(data, x="Product", y="Miles")
plt.xlabel('Treadmill Models')
plt.ylabel('Avg Miles / Week')
plt.title('Miles VS Product', fontsize = 15)

plt.subplot(2,2,4)
sns.boxplot(data, x="Product", y="Income")
plt.xlabel('Treadmill Models')
plt.ylabel('Income (Annual income in $)')
plt.title('Income VS Product', fontsize = 15)



plt.tight_layout(pad=3.0)
plt.show()
```



1.6 Observations:

- Usage per Week:
  - KP781 has the highest median usage per week among the three models.
  - All models have outliers, indicating varying usage patterns among users.
- Age of Users:
  - The median age of users is similar across all three models.
  - The range of ages differs slightly, with KP281 having the widest spread.
- Miles Run:
  - KP781 shows a higher median for miles run compared to the other models.
  - Outliers suggest some users run significantly more miles on this model.
- Income of Users:

  - Users of KP781 have a noticeably higher median income compared to those using KP281 and KX481.
  - Income distribution varies among the models.

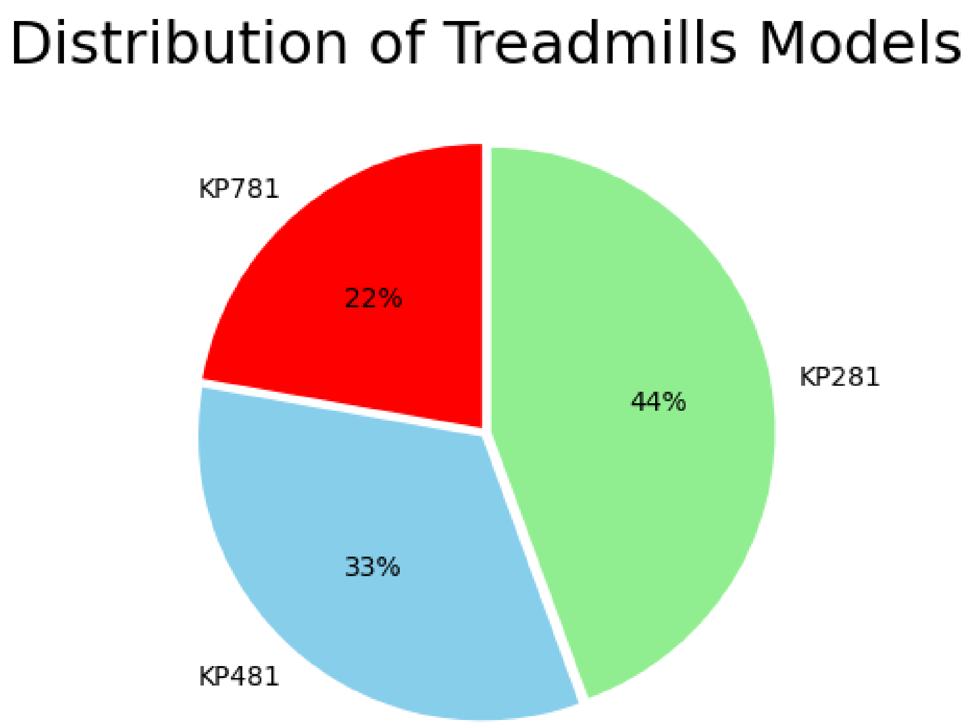
2 Non-Graphical Analysis

[11]:
```
p_count=data['Product'].value_counts()
p_count
```

[11]:
```
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
```

[12]:
```
vals = data['Product'].value_counts()
labels = vals.index
plt.title('Distribution of Treadmills Models', fontsize = 22)
plt.pie(vals, labels=labels, explode = [0.02,0.02,0.02], autopct='%1.0f%%',
        startangle=90, counterclock=False, colors=['lightgreen', 'skyblue',␣
 ↪'red'])
```

[12]:
```
([<matplotlib.patches.Wedge at 0x7f5f718db390>,
  <matplotlib.patches.Wedge at 0x7f5f9c977950>,
  <matplotlib.patches.Wedge at 0x7f5f9c98d210>],
 [Text(1.1029846853969052, 0.1944859475126421, 'KP281'),
  Text(-0.7199221674761052, -0.8579697388466023, 'KP481'),
  Text(-0.7199220469827118, 0.8579698399525605, 'KP781')],
 [Text(0.6105808079875725, 0.10766186380164114, '44%'),
  Text(-0.3985283427099867, -0.47494753400436907, '33%'),
  Text(-0.3985282760082869, 0.4749475899737388, '22%')])
```



2.0.1 Observations:

- KP281 which is a entry level treadmill is purchased the most.
- After KP481 which is mid range treadmill is purchesd most.
- KP781 which is advanced treadmill is purchased least by the custom

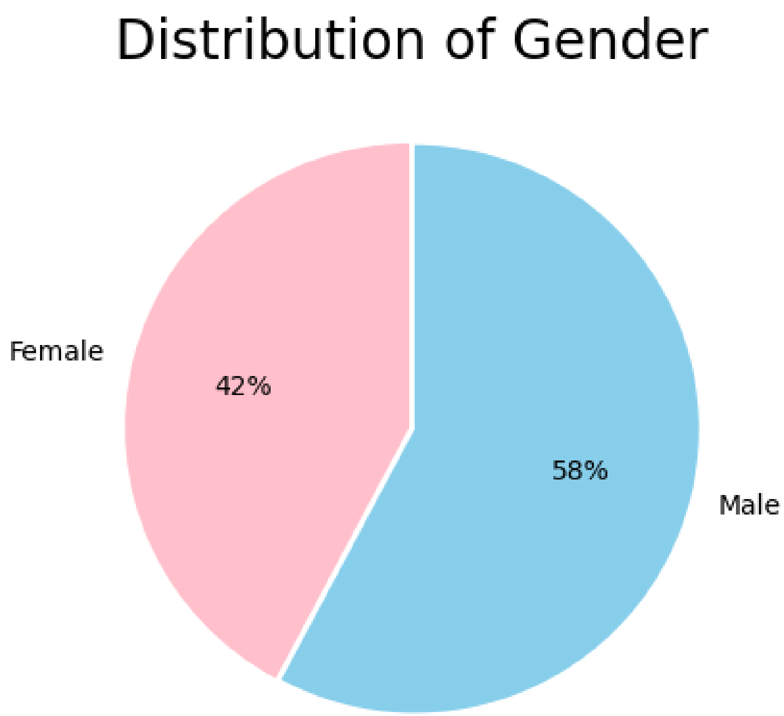
[13]:
```
data['Gender'].value_counts()
```

[13]:
```
Gender
Male      104
Female     76
Name: count, dtype: int64
```

[14]:
```
data_p = data['Gender'].value_counts()
labels = data_p.index
plt.title('Distribution of Gender', fontsize = 20)
plt.pie(data_p, labels=labels, explode = [0.01,0.01], autopct='%1.0f%%',
        startangle=90, counterclock=False, colors=['skyblue', 'pink'])
```

[14]:
```
([<matplotlib.patches.Wedge at 0x7f5f9c998bd0>,
  <matplotlib.patches.Wedge at 0x7f5f9c7ce490>],
 [Text(1.0770282349354128, -0.268533389268279, 'Male'),
```

```
 Text(-1.0770282097934978, 0.2685334901069388, 'Female')],
[Text(0.5918803813609025, -0.14757240311139658, '58%'),
 Text(-0.5918803675441744, 0.1475724585272366, '42%')])
```



2.0.2 Observations:

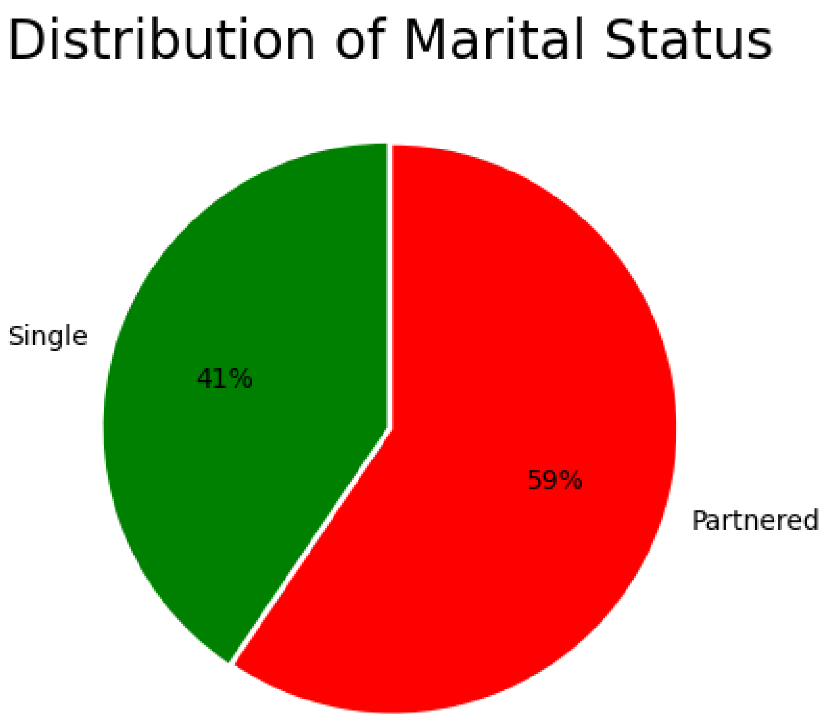
- 58% of the customers are male
- 42% of the customers are female

[15]:
```
data['MaritalStatus'].value_counts()
```

[15]:
```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

[16]:
```
data_p = data['MaritalStatus'].value_counts()
labels = data_p.index
plt.title('Distribution of Marital Status', fontsize = 20)
plt.pie(data_p, labels=labels, explode = [0.01,0.01], autopct='%1.0f%%',
        startangle=90, counterclock=False, colors=['red', 'green'])
```

[16]:
```
([<matplotlib.patches.Wedge at 0x7f5f9c803050>,
  <matplotlib.patches.Wedge at 0x7f5f9c80a450>],
 [Text(1.0614982696658786, -0.3245326231619039, 'Partnered'),
  Text(-1.0614982696658786, 0.32453262316190373, 'Single')],
 [Text(0.5833458959425096, -0.178346756872758, '59%'),
  Text(-0.5833458959425096, 0.1783467568727579, '41%')])
```



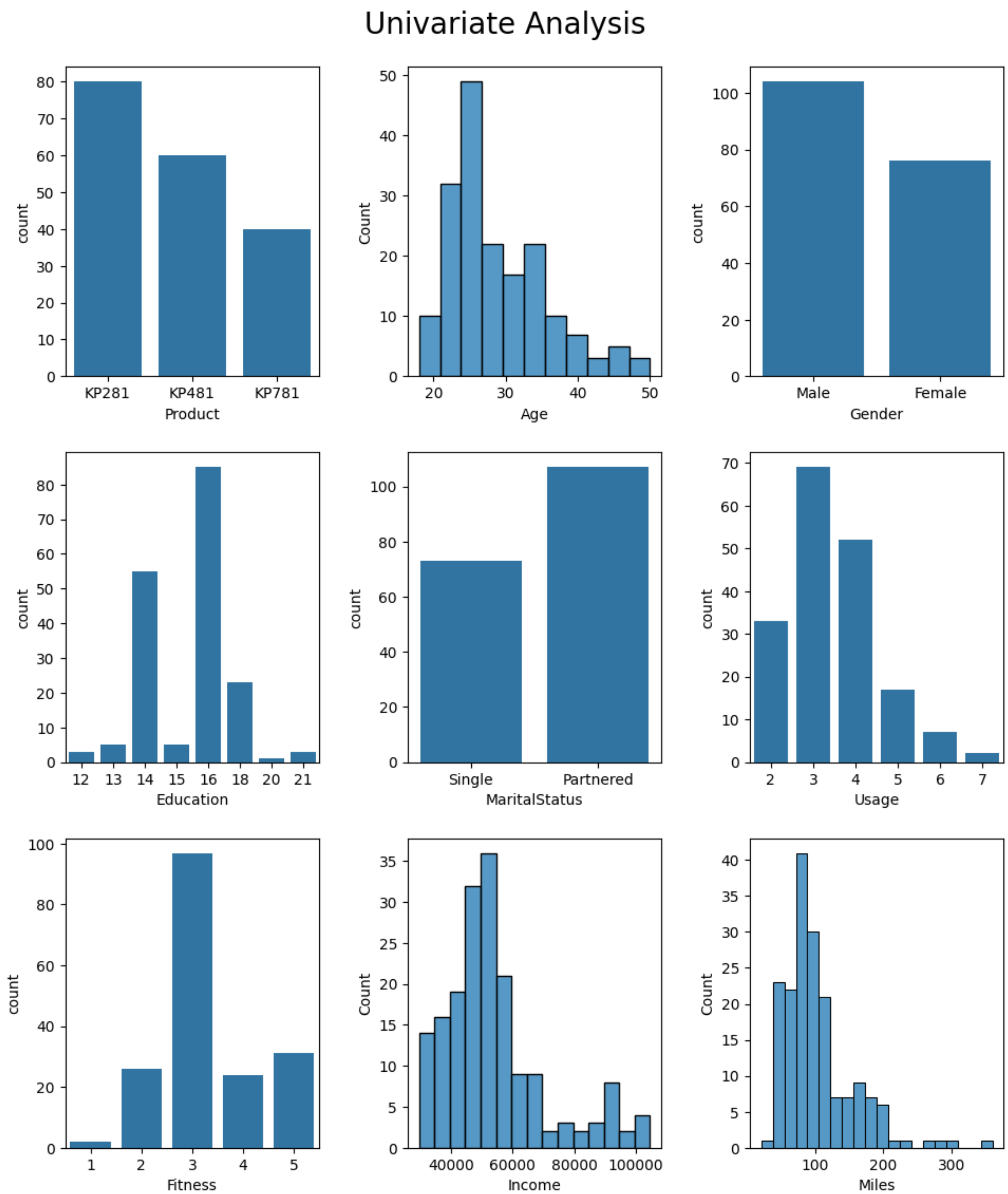
2.0.3 Observations:

- 58% of the customers are married
- 41% of the customers are single

3 Graphical Analysis

[17]:
```
plt.figure(figsize=(10,15))
plt.suptitle('Univariate Analysis', fontsize=20)

# Treadmill Model Counts
plt.subplot(4,3,1)
sns.countplot(data, x= 'Product')
```

```python
# Age Count
plt.subplot(4,3,2)
sns.histplot(data, x= 'Age')

# Gender Count
plt.subplot(4,3,3)
sns.countplot(data, x= 'Gender')

# Education Count
plt.subplot(4,3,4)
sns.countplot(data, x= 'Education')

# Marital Status Count
plt.subplot(4,3,5)
sns.countplot(data, x= 'MaritalStatus')

# Usage Count
plt.subplot(4,3,6)
sns.countplot(data, x= 'Usage')

# Fitness Count
plt.subplot(4,3,7)
sns.countplot(data, x= 'Fitness')

# Income Count
plt.subplot(4,3,8)
sns.histplot(data, x= 'Income')

# Miles Count
plt.subplot(4,3,9)
sns.histplot(data, x= 'Miles')


plt.tight_layout(pad=2.0)
```

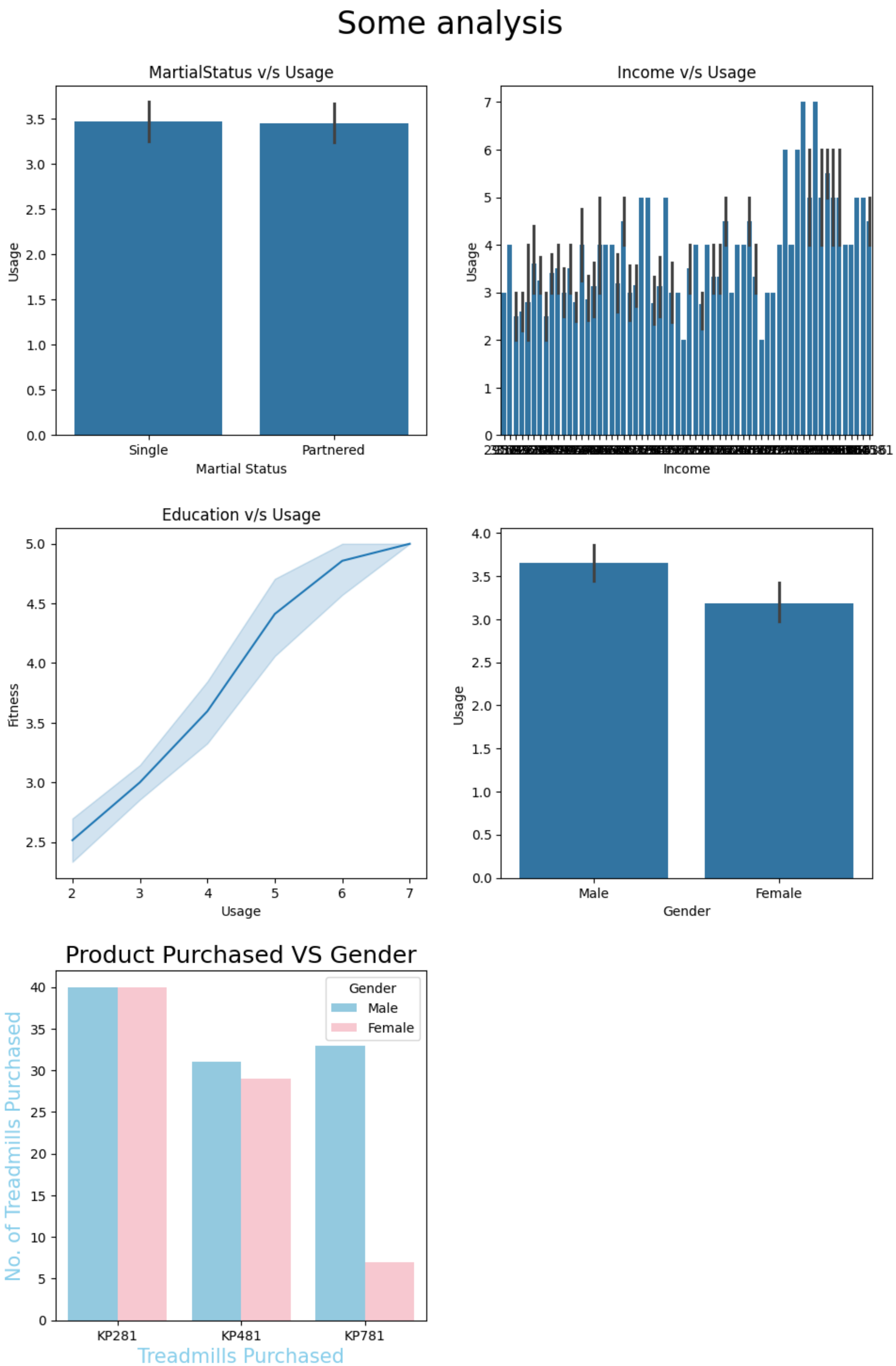


3.0.1 Observations:

- Maximum Number of customers are in Age group of 20 to 30 Years.
- The Company has more number of Male customers than Female customers.
- Maximum Customers have 14-16 Years of Education.
- Maximum Number of customers Lies between 60k Income Group

[18]:

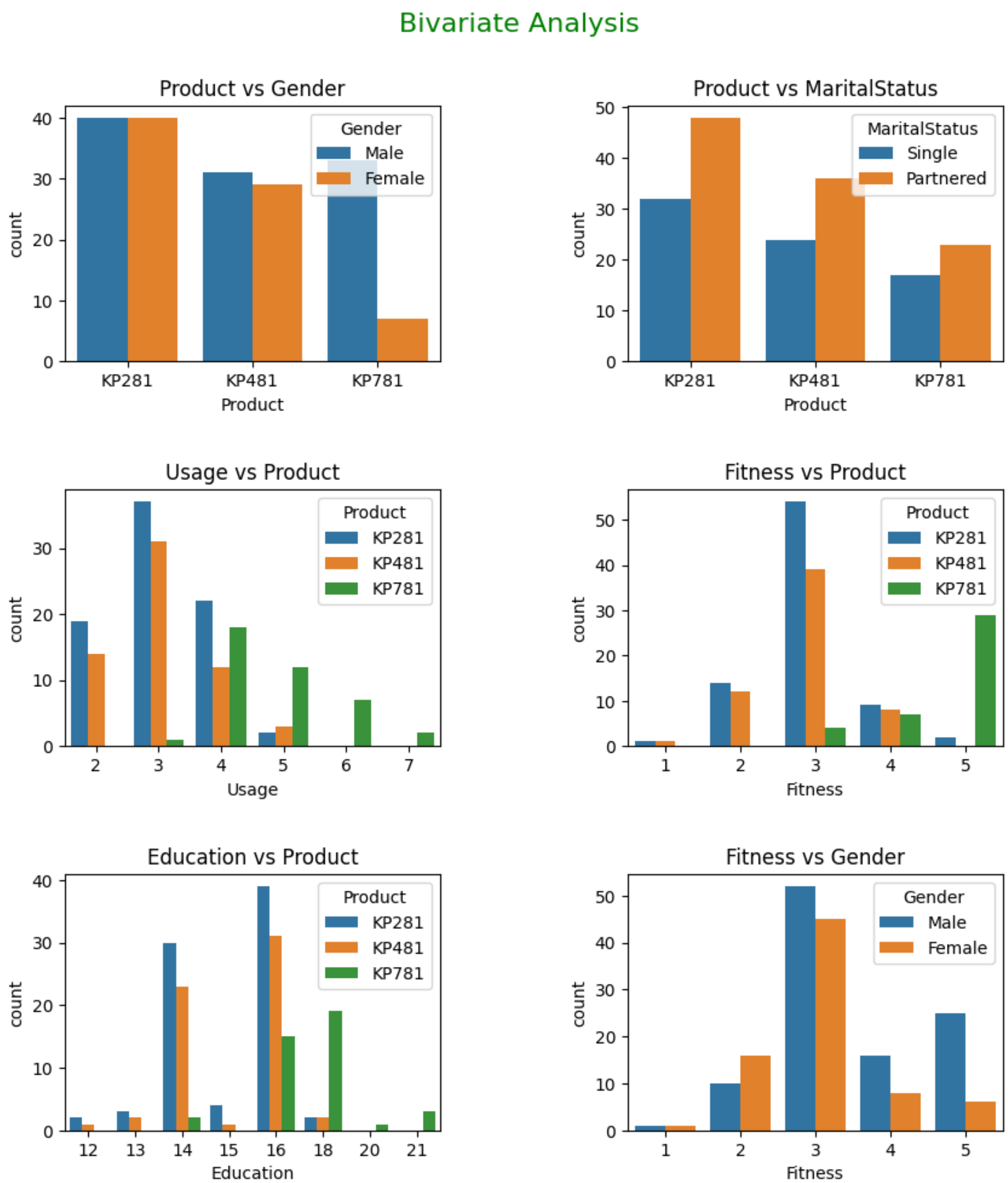
```
plt.figure(figsize=(10,15))
plt.suptitle('Some analysis', fontsize = 24)

plt.subplot(3,2,1)
sns.barplot(data, x='MaritalStatus', y='Usage')
plt.xlabel('Martial Status')
plt.ylabel('Usage')
plt.title('MartialStatus v/s Usage')

plt.subplot(3,2,2)
sns.barplot(data, x='Income', y='Usage')
plt.xlabel('Income')
plt.ylabel('Usage')
plt.title('Income v/s Usage')

plt.subplot(3,2,3)
sns.lineplot(data, x='Usage', y='Fitness')
plt.xlabel('Usage')
plt.ylabel('Fitness')
plt.title('Education v/s Usage')

plt.subplot(3, 2, 4)
sns.barplot(data, x='Gender', y='Usage')
plt.xlabel('Gender')
plt.ylabel('Usage')

custom_palette = ['skyblue', 'pink']

plt.subplot(3, 2, 5)
sns.countplot(data, x='Product', hue='Gender', palette=custom_palette)
plt.title('Product Purchased VS Gender', fontsize= 18, color= 'black')
plt.ylabel('No. of Treadmills Purchased', fontsize= 15, color= 'skyblue')
plt.xlabel('Treadmills Purchased', fontsize= 15, color= 'skyblue')


plt.tight_layout(pad=2.0)
plt.show()
```


Some analysis
MartialStatus v/s Usage
Usage
Single
Partnered
Martial Status
Income v/s Usage
Usage
Income
Education v/s Usage
Fitness
Usage
Usage
Male
Female
Gender
Product Purchased VS Gender
No. of Treadmills Purchased
Gender
Male
Female
KP281
KP481
KP781
Treadmills Purchased

3.0.2 Observations:

- We observe an almost linear relation between education and usage.
- There is almost no relation between martial status and usage

[19]:
```
fig,ax=plt.subplots(3,2,figsize=(10,11))
fig.subplots_adjust(wspace=.5,hspace=.5)
fig.suptitle('Bivariate Analysis',y=.95,fontsize=16,color='green')

sns.countplot(data,x='Product',hue='Gender',ax=ax[0,0])
sns.countplot(data,x='Product',hue='MaritalStatus',ax=ax[0,1])
sns.countplot(data,x='Usage',hue='Product',ax=ax[1,0])
sns.countplot(data,x='Fitness',hue='Product',ax=ax[1,1])
sns.countplot(data,x='Education',hue='Product',ax=ax[2,0])
sns.countplot(data,x='Fitness',hue='Gender',ax=ax[2,1])


ax[0,0].set_title('Product vs Gender')
ax[0,1].set_title('Product vs MaritalStatus')
ax[1,0].set_title('Usage vs Product')
ax[1,1].set_title('Fitness vs Product')
ax[2,0].set_title('Education vs Product')
ax[2,1].set_title('Fitness vs Gender')

plt.show()
```



3.0.3 Observation:

- Customer with 16 years of education prefer to buy KP281
- Customer whose usage is more than 3 days a week prefer machine KP781
- Customer with more than 16 years of education prefer to use KP781

4 Probability

[20]:
```
p_count=data['Product'].value_counts(normalize=True)
p_count
```

[20]:
```
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: proportion, dtype: float64
```

- Probability that people will buy KP281 is 44%
- Probability that people will buy KP481 is 33%
- Probability that people will buy KP781 is 22%

[21]:
```
filtered_data = data[['Product','Gender']]
pd.crosstab(filtered_data['Product'], filtered_data['Gender'], margins=True)
```

[21]:
```
Gender   Female  Male  All
Product
KP281        40    40   80
KP481        29    31   60
KP781         7    33   40
All          76   104  180
```

- the P(Male buying KP781) = 31.7%
- the P(Male buying KP481) = 29.8%
- the P(Male buying KP281) = 38.4%

[22]:
```
print("Probability (Product | Partnered)")
print(data[data["MaritalStatus"] == "Partnered"]["Product"].
 ↪value_counts(normalize=True))

print("\nProbability (Product | Single)")
data[data["MaritalStatus"] == "Single"]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Partnered)
Product
KP281    0.448598
KP481    0.336449
KP781    0.214953
Name: proportion, dtype: float64

Probability (Product | Single)
```

[22]:
```
Product
KP281    0.438356
KP481    0.328767
KP781    0.232877
```

```
Name: proportion, dtype: float64
```

Observation: Single users have higher probability of buying KP781 than Partnered users Partnered users have higher probability of buying KP481.

[23]:
```python
print("Probability (MaritalStatus | KP281)")
print(data[data["Product"] == "KP281"]["MaritalStatus"].
 ↪value_counts(normalize=True))

print("\nProbability (MaritalStatus | KP481)")
print(data[data["Product"] == "KP481"]["MaritalStatus"].
 ↪value_counts(normalize=True))

print("\nProbability (MaritalStatus | KP781)")
print(data[data["Product"] == "KP781"]["MaritalStatus"].
 ↪value_counts(normalize=True))
```

```
Probability (MaritalStatus | KP281)
MaritalStatus
Partnered    0.6
Single       0.4
Name: proportion, dtype: float64

Probability (MaritalStatus | KP481)
MaritalStatus
Partnered    0.6
Single       0.4
Name: proportion, dtype: float64

Probability (MaritalStatus | KP781)
MaritalStatus
Partnered    0.575
Single       0.425
Name: proportion, dtype: float64
```

[24]:
```python
print("\nProbability (Product | Single & Male)")
data[(data["MaritalStatus"] == "Single") & (data["Gender"]=="Male")]["Product"].
 ↪value_counts(normalize=True)
```

```
Probability (Product | Single & Male)
```

[24]:
```
Product
KP281    0.441860
KP781    0.325581
KP481    0.232558
Name: proportion, dtype: float64
```

[25]:
```
print("\nProbability (Product | Partnered & Male)")
data[(data["MaritalStatus"] == "Partnered") &␣
↪(data["Gender"]=="Male")]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Partnered & Male)
```

[25]:
```
Product
KP281    0.344262
KP481    0.344262
KP781    0.311475
Name: proportion, dtype: float64
```

[26]:
```
print(" \nProbability (Product | Single & Female)")
data[(data["MaritalStatus"] == "Single") &␣
↪(data["Gender"]=="Female")]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Single & Female)
```

[26]:
```
Product
KP481    0.466667
KP281    0.433333
KP781    0.100000
Name: proportion, dtype: float64
```

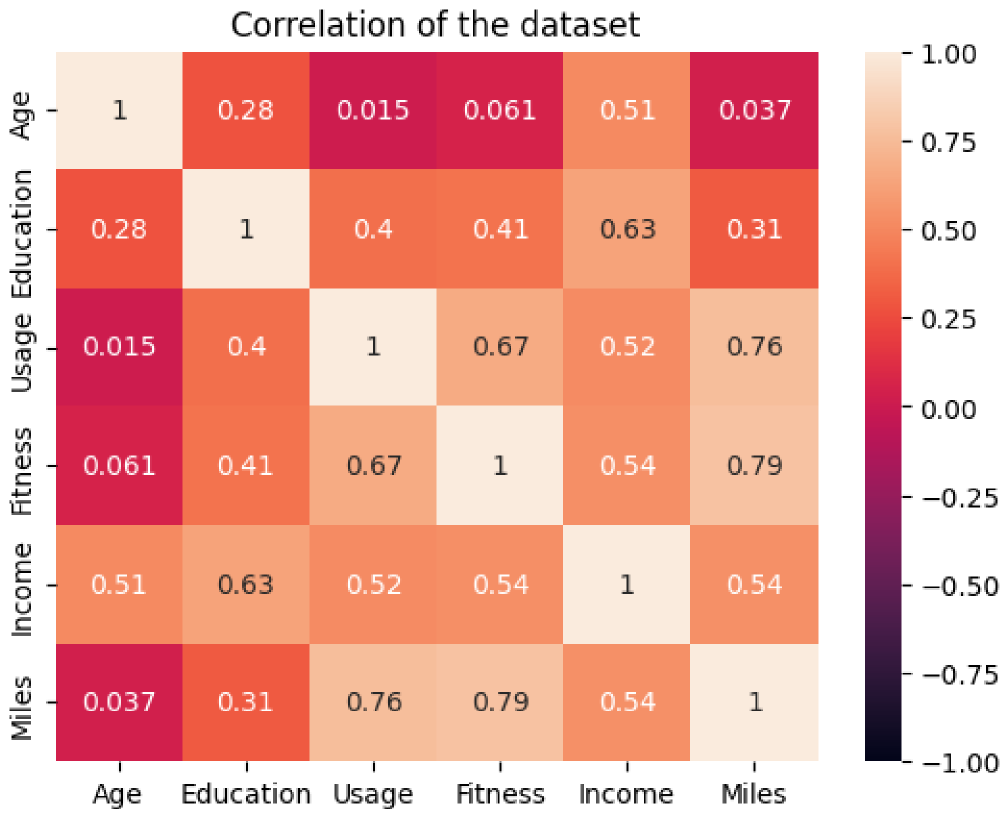
[27]:
```
print("\nProbability (Product | Partnered & Female)")
data[(data["MaritalStatus"] == "Partnered") &␣
↪(data["Gender"]=="Female")]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Partnered & Female)
```

[27]:
```
Product
KP281    0.586957
KP481    0.326087
KP781    0.086957
Name: proportion, dtype: float64
```

5 Correlation among different factors

[28]:
```
continuous_columns = ["Age", "Education", "Usage", "Fitness", "Income", "Miles"]
sns.heatmap(data=data[continuous_columns].corr(), annot=True, vmin=-1, vmax=1)
plt.title("Correlation of the dataset")
plt.show()
```



6 Observations

- Best Selling Treadmill model is 'KP281' while the least sold Treadmill is 'KP781'
- There are more Male customers than Female customers.
- Maximum Number of customers are in Age group of 20 to 30 Years.
- Maximum Customers have 14-16 Years of Education.
- Maximum Number of customers Lies between 60k Income Group
- The company has more number of Married customers than Single Customers.
- Majority of theCustomers use the Treadmill for 3 days a week.
- Most of the customers gave them a self rated Fitness score of 3 while only some customers gave them 1.
- Maximum number of customers runs 94 miles per week on an average on Treadmills.

7 Recomendations

- **KP281:**:
  - Both Male and Female customers are equally likely to buy the model. The company should target more customers with 3 days/week usage for 'KP281'.
  - The company should target more Partnered customers than Single customers for 'KP281'. The company should target more customers with 16 years of education for 'KP281'.

- **KP481:**
  - Male and Female customers are almost equally likely to buy 'KP481'. so, company should target both of them.
  - The company should target more customers with 14-16 years of education for 'KP481'
  - The company should target more Partnered customers than Single customers for 'KP481'.
  - Company should target more customers with 3 days/week usage for 'KP481'.
- **KP781:**
  - Male customers are more likely to buy this product. The company should target more customers with 18 years of education for 'KP781'.
  - Company should target more customers with Usage of 4 days/week for 'KP781'.
  - The company should target more Partnered customers than Single customers for 'KP781'.

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