aerofit-analysis-1

April 19, 2024

1 Problem Statement:

Aerofit seeks to optimize its treadmill product recommendations by identifying unique customer profiles for each variant. Utilizing descriptive analytics and contingency tables, the market research team aims to unveil crucial insights into customer preferences and demographics. The objective is to enable Aerofit to offer personalized recommendations, enhancing customer satisfaction and driving business growth in the competitive fitness equipment market.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import gdown
```

[2]:
```
url = 'https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
  ↪original/aerofit_treadmill.csv?1639992749'
output = 'aerofit.csv'
gdown.download(url, output, quiet=False)
```

```
Downloading…
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/ori
ginal/aerofit_treadmill.csv?1639992749
To: /content/aerofit.csv
100%|      | 7.28k/7.28k [00:00<00:00, 16.1MB/s]
```

[2]:
```
'aerofit.csv'
```

2 1. Load the dataset

[3]:
```
df = pd.read_csv('aerofit.csv')
```

3 2. Understanding the data

[4]:
```
df
```

[4]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0      KP281   18    Male         14        Single      3        4   29562
1      KP281   19    Male         15        Single      2        3   31836
2      KP281   19  Female         14     Partnered      4        3   30699
3      KP281   19    Male         12        Single      3        3   32973
4      KP281   20    Male         13     Partnered      4        2   35247
..       …   …     …          …             …     …      …      …
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641
177    KP781   45    Male         16        Single      5        5   90886
178    KP781   47    Male         18     Partnered      4        5  104581
179    KP781   48    Male         18     Partnered      4        5   95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[5]:
```
df.describe()
```

[5]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
```

```
75%    114.750000
max    360.000000
```

[6]:
```
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
```

[7]:
```
df.shape
```

[7]:
```
(180, 9)
```

[8]:
```
df.isnull().sum()
```

[8]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

[9]:
```
for i in df.columns :
  print(f'{i} => {df[i].
 ↪unique()}\n-------------***************-----------------\n')
```

```
Product => ['KP281' 'KP481' 'KP781']
-------------***************-----------------

Age => [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]
```

```
----------**********----------

Gender => ['Male' 'Female']
----------**********----------

Education => [14 15 12 13 16 18 20 21]
----------**********----------

MaritalStatus => ['Single' 'Partnered']
----------**********----------

Usage => [3 2 4 5 6 7]
----------**********----------

Fitness => [4 3 2 1 5]
----------**********----------

Income => [ 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]
----------**********----------

Miles => [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]
----------**********----------
```

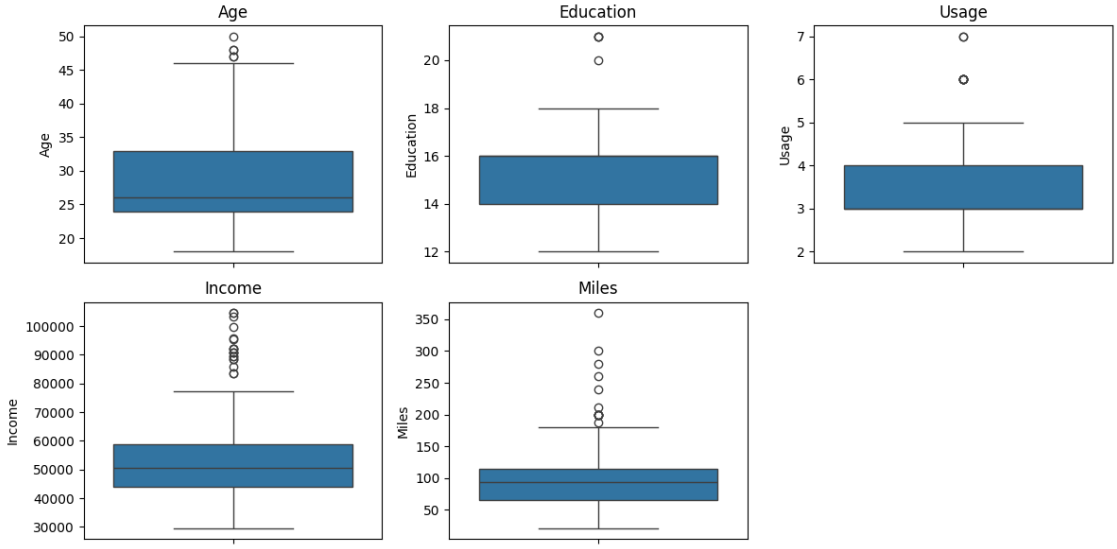
[10]:
```
df.ndim
```

[10]: 2

4 3. Checking for outliers

[11]:
```
# Selecting only continuous variables
continuous_vars = ['Age', 'Education', 'Usage', 'Income', 'Miles']

# Plot boxplots for continuous variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
    plt.subplot(2, 3, i+1)
```

```
    sns.boxplot(data=df[var])
    plt.title(var)
plt.tight_layout()
plt.show()
```

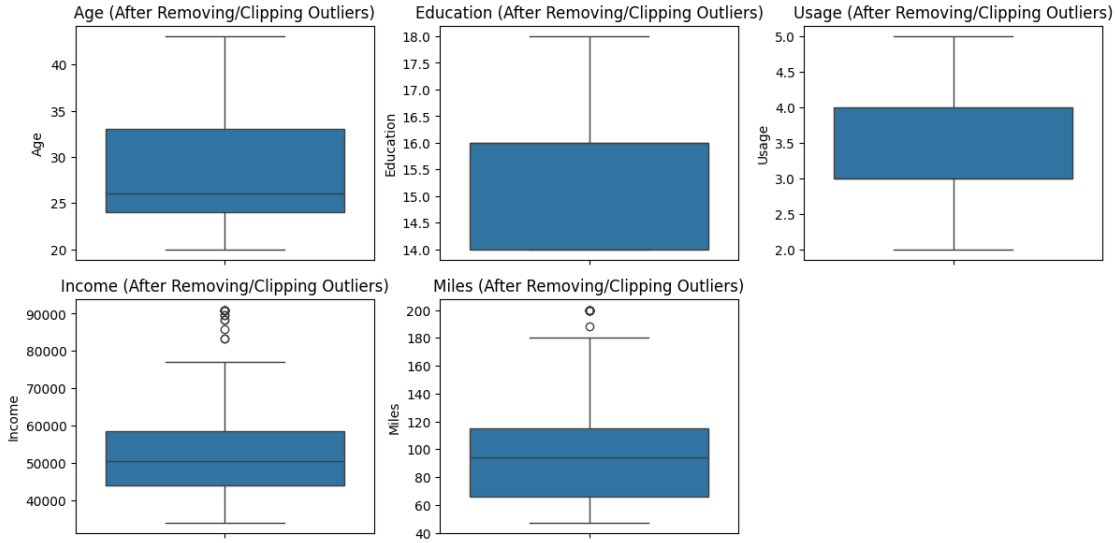


5 4. Treating Outliers

[12]:
```
# Remove or clip outliers between 5th and 95th percentiles
for var in continuous_vars:
    lower_bound = np.percentile(df[var], 5)
    upper_bound = np.percentile(df[var], 95)
    df[var] = np.clip(df[var], lower_bound, upper_bound)
```

[13]:
```
df['Usage'] = df['Usage'].astype(int)
```

[14]:
```
# Verify the removal/clipping of outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
    plt.subplot(2, 3, i+1)
    sns.boxplot(data=df[var])
    plt.title(var + " (After Removing/Clipping Outliers)")
plt.tight_layout()
plt.show()
```



6 5. Analysing the data

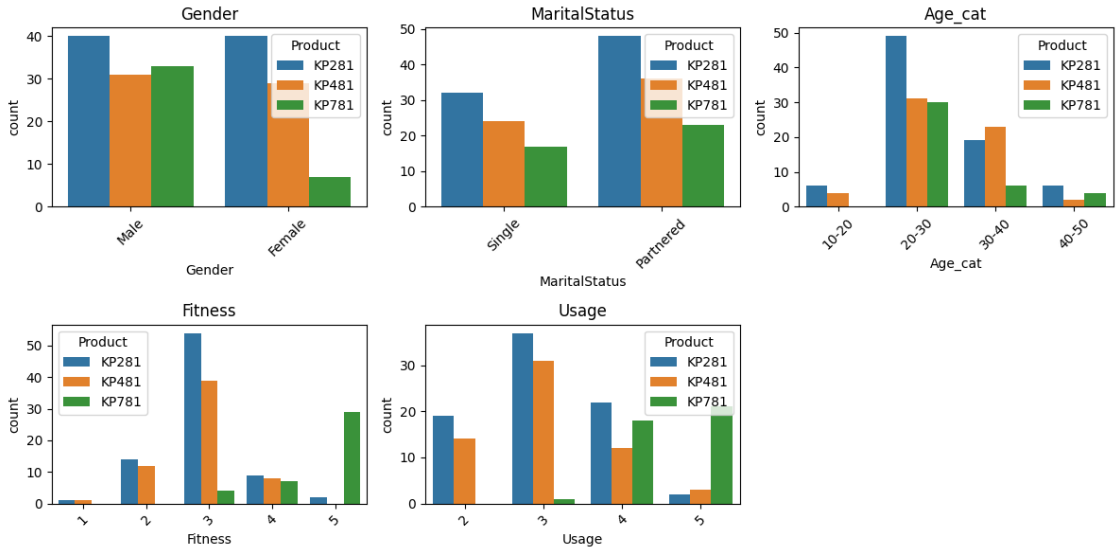
[15]:
```
bins = [10,20,30,40,50]
labels = ['10-20','20-30','30-40','40-50']
df['Age_cat'] = pd.cut(df['Age'],bins = bins,labels = labels)
df['Age_cat']
```

[15]:
```
0      10-20
1      10-20
2      10-20
3      10-20
4      10-20
       ...
175    30-40
176    40-50
177    40-50
178    40-50
179    40-50
Name: Age_cat, Length: 180, dtype: category
Categories (4, object): ['10-20' < '20-30' < '30-40' < '40-50']
```

[16]:
```
# Selecting only categorical variables
categorical_vars = ['Gender','MaritalStatus','Age_cat','Fitness','Usage']
print(df['Usage'].unique())
# Plot countplot for categorical variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(categorical_vars):
    plt.subplot(2, 3, i+1)
```

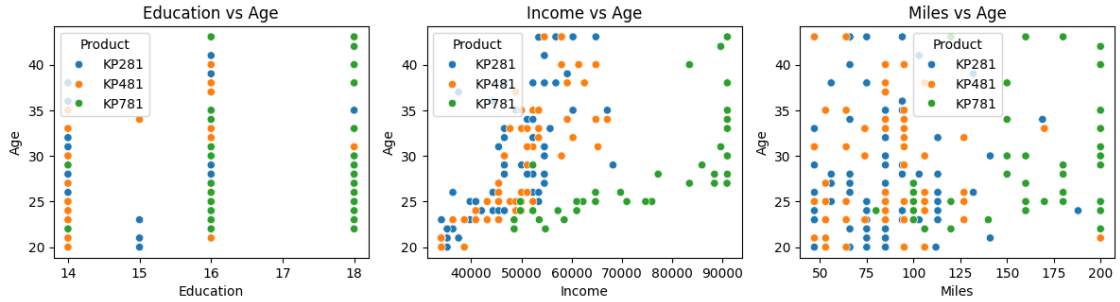
```
    sns.countplot(data=df, x = var, hue = 'Product')
    plt.title(var)
    plt.xticks(rotation=45)
    # if(var == categorical_vars[-1]):
    #   plt.xticks(np.round(np.linspace(min(df[var]), max(df[var]), num=5), 2))
plt.tight_layout()
plt.show()
```

```
[3 2 4 5]
```



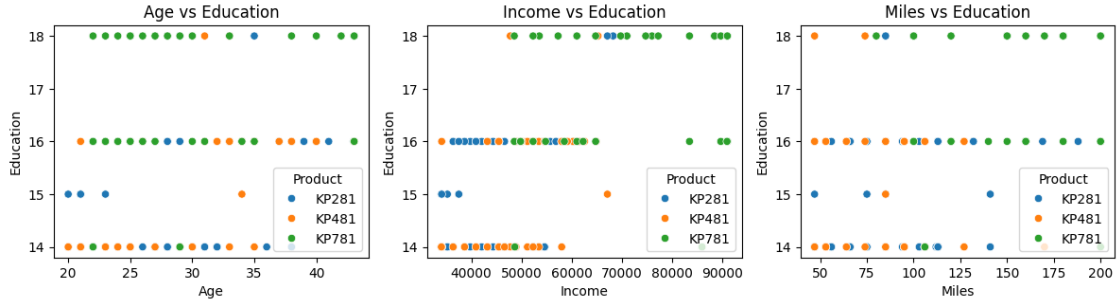
- Very few Females buy **KP781** machine in comparison to males.
- Partnered People prefer more **KP281** and **KP481** than single people.
- Age group between 20-30 buys more KP281.
- People who rate themselves as **3** on scale of **5** in terms of fitness tends to buy **KP281** and **KP481** whereas People who rates them as **5** prefer **KP781**.
- People who buys **KP281** and **KP481** tends to use it **2-4 times** a week.
- People who buys **KP781** tends to use it **4-5 times** a week.

[17]:
```
# Selecting only continuous variables
continuous_vars = ['Education', 'Income', 'Miles']

# Plot boxplots for continuous variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data=df, x = var, y = 'Age', hue = 'Product')
    plt.title(f'{var} vs Age')
plt.tight_layout()
plt.show()
```



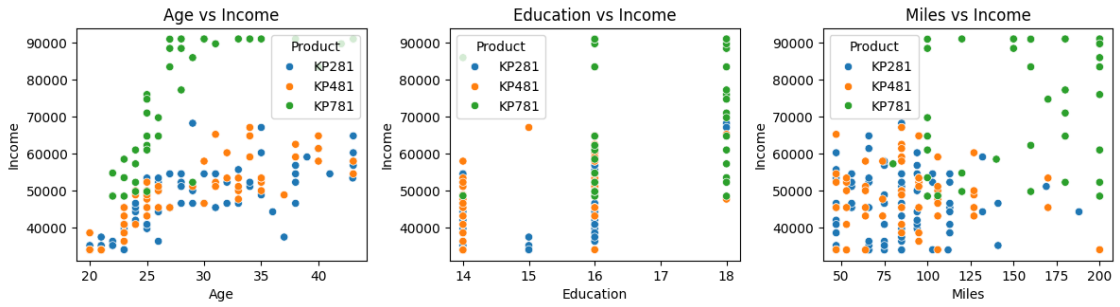
- Highly Educated people prefer **KP781**.
- People between the age 20-30 and Income between 50k-70k prefers to buy KP781 whereas people from all age who have Income greater than 70k buys KP781
- People who runs below 125 miles prefers to buy KP481 and KP281.
- People who runs above 125 miles buys KP781.

[18]:
```
# Selecting only continuous variables
continuous_vars = ['Age', 'Income', 'Miles']

# Plot boxplots for continuous variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data=df, x = var, y = 'Education', hue = 'Product')
    plt.title(f'{var} vs Education')
plt.tight_layout()
plt.show()
```



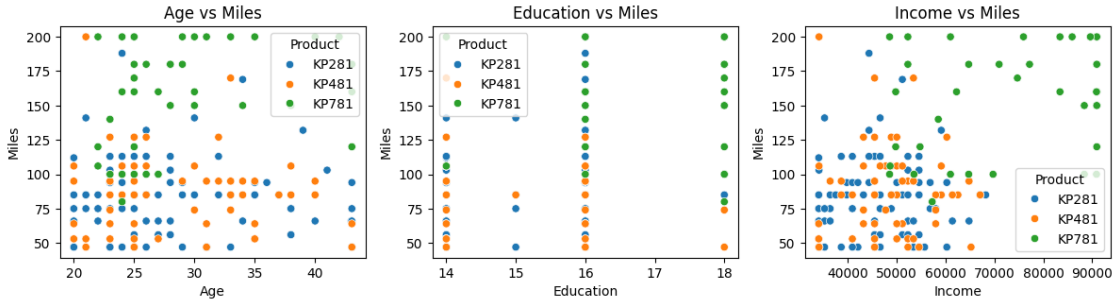
[19]:
```
# Selecting only continuous variables
continuous_vars = ['Age', 'Education', 'Miles']

# Plot boxplots for continuous variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
```

```
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data=df, x = var, y = 'Income', hue = 'Product')
    plt.title(f'{var} vs Income')
plt.tight_layout()
plt.show()
```



- People above income 70k tends to run more than 125 miles therefore prefers KP781.
- People below income 70k tends to run less than 125 miles therefore prefers KP281 and KP481.

[20]:
```
# Selecting only continuous variables
continuous_vars = ['Age', 'Education', 'Income']

# Plot boxplots for continuous variables to detect outliers
plt.figure(figsize=(12, 6))
for i, var in enumerate(continuous_vars):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data=df, x = var, y = 'Miles', hue = 'Product')
    plt.title(f'{var} vs Miles')
plt.tight_layout()
plt.show()
```



[21]:
```
pd.crosstab(index = df['Product'],columns = df['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

Marginal Probability = count of product / Total no. of Product Conditional Probability (A|B)= P(A and B)/P(B)

- **KP281** is bought by **(80/180)*100 = 44.44 %** of people
- **KP481** is bought by **(60/180)*100 = 33.33 %** of people
- **KP481** is bought by **(40/180)*100 = 22.22 %** of people
- Probability of **Female** purchasing a machine is : **76/180 = 0.42**
- Probability of **Male** purchasing a macine is: **104/180 = 0.58**
- Probability of **purchasing KP281 given female** is **P(Purchasing KP281 | Female) = 40/76 = 0.52**
- Probability of **purchasing KP481 given female** is **P(Purchasing KP481 | Female) = 29/76 = 0.38**
- Probability of **purchasing KP781 given female** is **P(Purchasing KP781 | Female) = 7/76 = 0.09**
- Probability of **purchasing KP281 given male** is **P(Purchasing KP281 | Male) = 40/104 = 0.38**
- Probability of **purchasing K481 given male** is **P(Purchasing KP481 | Male) = 31/104 = 0.30**
- Probability of **purchasing KP781 given male** is **P(Purchasing KP781 | Male) = 33/104 = 0.31**

[22]:
```
pd.crosstab(index = df['Product'],columns = df['Education'],margins = True)
```

[22]:
Education	14	15	16	18	All
Product					
KP281	35	4	39	2	80
KP481	26	1	31	2	60
KP781	2	0	15	23	40
All	63	5	85	27	180

- Probability of **14 years** Educated person buying a machine is **63/180 = 0.35**.
- Probability of **15 years** Educated person buying a machine is **5/180 = 0.02**.
- Probability of **16 years** Educated person buying a machine is **85/180 = 0.47**.
- Probability of **18 years** Educated person buying a machine is **27/180 = 0.15**.

- Probability of **purchasing KP281 given education 14 years**: **P(Purchasing KP281 | Education 14) = 35/63 = 0.5556**
- Probability of **purchasing KP481 given education 14 years**: **P(Purchasing KP481 | Education 14) = 26/63 = 0.4127**
- Probability of **purchasing KP781 given education 14 years: P(Purchasing KP781 | Education 14) = 2/63 = 0.0317**
- Probability of **purchasing KP281 given education 15 years: P(Purchasing KP281 | Education 15) = 4/5 = 0.8000**
- Probability of **purchasing KP481 given education 15 years: P(Purchasing KP481 | Education 15) = 1/5 = 0.2000**
- Probability of **purchasing KP781 given education 15 years: P(Purchasing KP781 | Education 15) = 0**
- Probability of **purchasing KP281 given education 16 years: P(Purchasing KP281 | Education 16) = 39/85 = 0.4588**
- Probability of **purchasing KP481 given education 16 years: P(Purchasing KP481 | Education 16) = 31/85 = 0.3647**
- Probability of **purchasing KP781 given education 16 years: P(Purchasing KP781 | Education 16) = 15/85 = 0.1765**
- Probability of purchasing KP281 given education 18 years: P(Purchasing KP281 | Education 18) = 2/27 = 0.0741
- Probability of **purchasing KP481 given education 18 years: P(Purchasing KP481 | Education 18) = 2/27 = 0.0741**
- Probability of **purchasing KP781 given education 18 years: P(Purchasing KP781 | Education 18) = 23/27 = 0.8519**

[23]:
```
pd.crosstab(index = df['Product'],columns = df['Age_cat'],margins = True)
```

[23]:

Age_cat	10-20	20-30	30-40	40-50	All
Product					
KP281	6	49	19	6	80
KP481	4	31	23	2	60
KP781	0	30	6	4	40
All	10	110	48	12	180

- Probability of person from **10-20** Age group buying a machine is **10/180 = 0.05**.
- Probability of person from **20-30** Age group buying a machine is **110/180 = 0.61**.
- Probability of person from **30-40** Age group buying a machine is **48/180 = 0.26**.
- Probability of person from **40-50** Age group buying a machine is **12/180 = 0.06**.
- Probability of **purchasing KP281 given age 10-20: P(Purchasing KP281 | Age 10-20) = 6/10 = 0.6000**
- Probability of **purchasing KP481 given age 10-20: P(Purchasing KP481 | Age 10-20) = 4/10 = 0.4000**

- Probability of **purchasing KP781 given age 10-20: P(Purchasing KP781 | Age 10-20) = 0**
- Probability of **purchasing KP281 given age 20-30: P(Purchasing KP281 | Age 20-30) = 49/110 = 0.4455**
- Probability of **purchasing KP481 given age 20-30: P(Purchasing KP481 | Age 20-30) = 31/110 = 0.2818**
- Probability of **purchasing KP781 given age 20-30: P(Purchasing KP781 | Age 20-30) = 30/110 = 0.2727**
- Probability of **purchasing KP281 given age 30-40: P(Purchasing KP281 | Age 30-40) = 19/48 = 0.3958**
- Probability of **purchasing KP481 given age 30-40: P(Purchasing KP481 | Age 30-40) = 23/48 = 0.4792**
- Probability of **purchasing KP781 given age 30-40: P(Purchasing KP781 | Age 30-40) = 6/48 = 0.1250**
- Probability of **purchasing KP281 given age 40-50: P(Purchasing KP281 | Age 40-50) = 6/12 = 0.5000**
- Probability of **purchasing KP481 given age 40-50: P(Purchasing KP481 | Age 40-50) = 2/12 = 0.1667**
- Probability of **purchasing KP781 given age 40-50: P(Purchasing KP781 | Age 40-50) = 4/12 = 0.3333**

[24]:
```
pd.crosstab(index = df['Product'],columns = df['MaritalStatus'],margins = True)
```

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

- Probability of person buying a machine who has a **partner** is : **107/180 = 0.59**
- Probability of person buying a machine who is **single** is : **73/180 = 0.40** Marital Status:
- Probability of **purchasing KP281 given partnered: P(Purchasing KP281 | Partnered) = 48/107 = 0.4486**
- Probability of **purchasing KP481 given partnered: P(Purchasing KP481 | Partnered) = 36/107 = 0.3364**
- Probability of** purchasing KP781 given partnered: P(Purchasing KP781 | Partnered) = 23/107 = 0.2150**
- Probability of **purchasing KP281 given single: P(Purchasing KP281 | Single) = 32/73 = 0.4384**
- Probability of **purchasing KP481 given single: P(Purchasing KP481 | Single) = 24/73 = 0.3288**
- Probability of **purchasing KP781 given single: P(Purchasing KP781 | Single) = 17/73 = 0.2329**

[25]:
```
pd.crosstab(index = df['Product'],columns = df['Usage'],margins = True)
```

[25]:
Usage	2	3	4	5	All
Product					
KP281	19	37	22	2	80
KP481	14	31	12	3	60
KP781	0	1	18	21	40
All	33	69	52	26	180

- Probability of a person using a machine **2 times** a week is **33/180 = 0.183**
- Probability of a person using a machine **3 times** a week is **69/180 = 0.383**
- Probability of a person using a machine **4 times** a week is **52/180 = 0.289**
- Probability of a person using a machine **5 times** a week is **26/180 = 0.144**

[26]:
```
pd.crosstab(index = df['Product'],columns = df['Fitness'],margins = True)
```

[26]:
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

- Probability of a person buying a machine who rates himself **1 : 2/180 = 0.01**
- Probability of a person buying a machine who rates himself **2 : 26/180 = 0.14**
- Probability of a person buying a machine who rates himself **3 : 97/180 = 0.53**
- Probability of a person buying a machine who rates himself **4 : 24/180 = 0.13**
- Probability of a person buying a machine who rates himself **5 : 31/180 = 0.17**
- Probability of **purchasing KP281 given fitness 1: P(Purchasing KP281 | Fitness 1) = 1/2 = 0.5000**
- Probability of **purchasing KP481 given fitness 1: P(Purchasing KP481 | Fitness 1) = 1/2 = 0.5000**
- Probability of **purchasing KP781 given fitness 1: P(Purchasing KP781 | Fitness 1) = 0**
- Probability of **purchasing KP281 given fitness 2: P(Purchasing KP281 | Fitness 2) = 14/26 = 0.5385**
- Probability of **purchasing KP481 given fitness 2: P(Purchasing KP481 | Fitness 2) = 12/26 = 0.4615**
- Probability of **purchasing KP781 given fitness 2: P(Purchasing KP781 | Fitness 2) = 0**
- Probability of **purchasing KP281 given fitness 3: P(Purchasing KP281 | Fitness 3) = 54/97 = 0.5567**
- Probability of **purchasing KP481 given fitness 3: P(Purchasing KP481 | Fitness 3) = 39/97 = 0.4021**
- Probability of **purchasing KP781 given fitness 3: P(Purchasing KP781 | Fitness 3) = 4/97 = 0.0412**
- Probability of **purchasing KP281 given fitness 4: P(Purchasing KP281 | Fitness 4) = 9/24 = 0.3750**
- Probability of **purchasing KP481 given fitness 4: P(Purchasing KP481 | Fitness 4) = 8/24 = 0.3333**

- Probability of **purchasing KP781 given fitness 4: P(Purchasing KP781 | Fitness 4) = 7/24 = 0.2917**
- Probability of **purchasing KP281 given fitness 5: P(Purchasing KP281 | Fitness 5) = 2/31 = 0.0645**
- Probability of **purchasing KP481 given fitness 5: P(Purchasing KP481 | Fitness 5) = 0**
- Probability of **purchasing KP781 given fitness 5: P(Purchasing KP781 | Fitness 5) = 29/31 = 0.9355**

The df.corr() method computes the correlation between numerical columns only. Since your DataFrame contains categorical variables, we need to convert them into numerical values before computing the correlation matrix. So we are using pd.get_dummies method.

[27]:
```
df_encoded = pd.get_dummies(df)
df_encoded
```

[27]:

	Age	Education	Usage	Fitness	Income	Miles	Product_KP281	\
0	20.00	14	3	4	34053.15	112	True	
1	20.00	15	2	3	34053.15	75	True	
2	20.00	14	4	3	34053.15	66	True	
3	20.00	14	3	3	34053.15	85	True	
4	20.00	14	4	2	35247.00	47	True	
..	…	…	…	…	…	…	…	
175	40.00	18	5	5	83416.00	200	False	
176	42.00	18	5	4	89641.00	200	False	
177	43.05	16	5	5	90886.00	160	False	
178	43.05	18	4	5	90948.25	120	False	
179	43.05	18	4	5	90948.25	180	False	

	Product_KP481	Product_KP781	Gender_Female	Gender_Male	\
0	False	False	False	True	
1	False	False	False	True	
2	False	False	True	False	
3	False	False	False	True	
4	False	False	False	True	
..	…	…	…	…	
175	False	True	False	True	
176	False	True	False	True	
177	False	True	False	True	
178	False	True	False	True	
179	False	True	False	True	

	MaritalStatus_Partnered	MaritalStatus_Single	Age_cat_10-20	\
0	False	True	True	
1	False	True	True	
2	True	False	True	
3	False	True	True	
4	True	False	True	

```
..                        …                    …            …
175                   False                 True          False
176                   False                 True          False
177                   False                 True          False
178                    True                False          False
179                    True                False          False

     Age_cat_20-30  Age_cat_30-40  Age_cat_40-50
0            False          False          False
1            False          False          False
2            False          False          False
3            False          False          False
4            False          False          False
..             …              …              …
175          False           True          False
176          False          False           True
177          False          False           True
178          False          False           True
179          False          False           True

[180 rows x 17 columns]
```

[28]:
```
# Compute correlation matrix
corr_matrix = df_encoded.corr()
corr_matrix
```

[28]:
```
                             Age  Education     Usage   Fitness     Income  \
Age                     1.000000   0.301971  0.015180  0.059047  0.514362
Education               0.301971   1.000000  0.412484  0.419020  0.628597
Usage                   0.015180   0.412484  1.000000  0.656798  0.478615
Fitness                 0.059047   0.419020  0.656798  1.000000  0.535945
Income                  0.514362   0.628597  0.478615  0.535945  1.000000
Miles                   0.029636   0.377294  0.769234  0.822393  0.537297
Product_KP281          -0.029760  -0.294507 -0.290292 -0.326090 -0.399793
Product_KP481           0.017630  -0.202459 -0.245073 -0.304015 -0.203157
Product_KP781           0.015579   0.581570  0.624852  0.734472  0.708203
Gender_Female          -0.027288  -0.128270 -0.213818 -0.254609 -0.203453
Gender_Male             0.027288   0.128270  0.213818  0.254609  0.203453
MaritalStatus_Partnered 0.184322   0.081408 -0.038351 -0.050751  0.139382
MaritalStatus_Single   -0.184322  -0.081408  0.038351  0.050751 -0.139382
Age_cat_10-20          -0.326027  -0.262891 -0.101156 -0.078912 -0.296289
Age_cat_20-30          -0.683491  -0.083438  0.127863  0.068860 -0.184508
Age_cat_30-40           0.590609   0.125177 -0.105385 -0.064816  0.209267
Age_cat_40-50           0.588122   0.182561  0.029830  0.052795  0.261680

                            Miles  Product_KP281  Product_KP481  \
Age                      0.029636      -0.029760       0.017630
```

Education	0.377294	-0.294507	-0.202459
Usage	0.769234	-0.290292	-0.245073
Fitness	0.822393	-0.326090	-0.304015
Income	0.537297	-0.399793	-0.203157
Miles	1.000000	-0.371555	-0.205850
Product_KP281	-0.371555	1.000000	-0.632456
Product_KP481	-0.205850	-0.632456	1.000000
Product_KP781	0.677504	-0.478091	-0.377964
Gender_Female	-0.227791	0.140848	0.087489
Gender_Male	0.227791	-0.140848	-0.087489
MaritalStatus_Partnered	-0.020019	0.010120	0.008001
MaritalStatus_Single	0.020019	-0.010120	-0.008001
Age_cat_10-20	-0.135665	0.075926	0.034300
Age_cat_20-30	0.106789	0.002548	-0.136990
Age_cat_30-40	-0.050046	-0.058992	0.186551
Age_cat_40-50	0.004601	0.029881	-0.094491

	Product_KP781	Gender_Female	Gender_Male	\
Age	0.015579	-0.027288	0.027288	
Education	0.581570	-0.128270	0.128270	
Usage	0.624852	-0.213818	0.213818	
Fitness	0.734472	-0.254609	0.254609	
Income	0.708203	-0.203453	0.203453	
Miles	0.677504	-0.227791	0.227791	
Product_KP281	-0.478091	0.140848	-0.140848	
Product_KP481	-0.377964	0.087489	-0.087489	
Product_KP781	1.000000	-0.267549	0.267549	
Gender_Female	-0.267549	1.000000	-1.000000	
Gender_Male	0.267549	-1.000000	1.000000	
MaritalStatus_Partnered	-0.021168	0.018836	-0.018836	
MaritalStatus_Single	0.021168	-0.018836	0.018836	
Age_cat_10-20	-0.129641	-0.060017	0.060017	
Age_cat_20-30	0.152286	0.035891	-0.035891	
Age_cat_30-40	-0.141019	0.044088	-0.044088	
Age_cat_40-50	0.071429	-0.093191	0.093191	

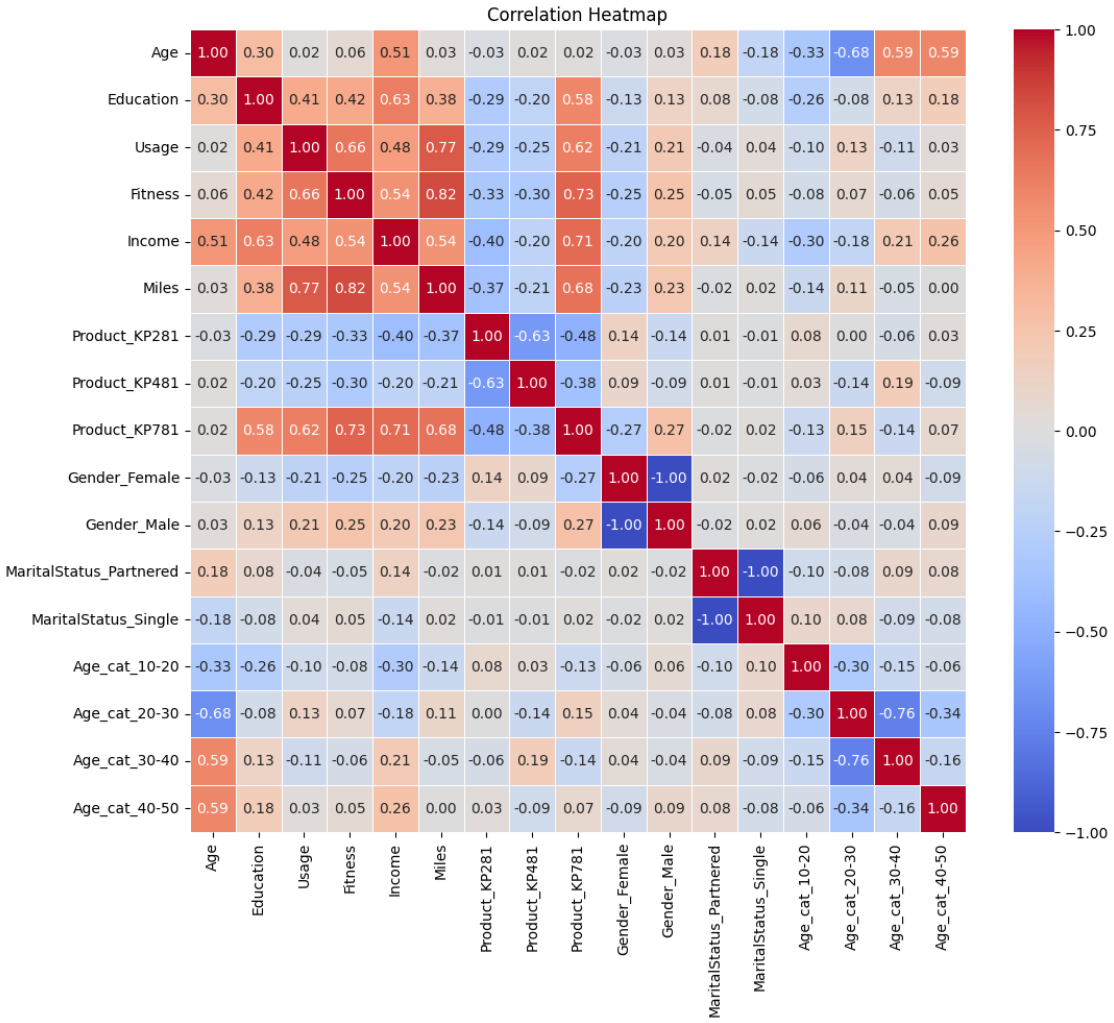
	MaritalStatus_Partnered	MaritalStatus_Single	\
Age	0.184322	-0.184322	
Education	0.081408	-0.081408	
Usage	-0.038351	0.038351	
Fitness	-0.050751	0.050751	
Income	0.139382	-0.139382	
Miles	-0.020019	0.020019	
Product_KP281	0.010120	-0.010120	
Product_KP481	0.008001	-0.008001	
Product_KP781	-0.021168	0.021168	
Gender_Female	0.018836	-0.018836	

Gender_Male	-0.018836	0.018836	
MaritalStatus_Partnered	1.000000	-1.000000	
MaritalStatus_Single	-1.000000	1.000000	
Age_cat_10-20	-0.096048	0.096048	
Age_cat_20-30	-0.078656	0.078656	
Age_cat_30-40	0.088700	-0.088700	
Age_cat_40-50	0.084672	-0.084672	

	Age_cat_10-20	Age_cat_20-30	Age_cat_30-40	\
Age	-0.326027	-0.683491	0.590609	
Education	-0.262891	-0.083438	0.125177	
Usage	-0.101156	0.127863	-0.105385	
Fitness	-0.078912	0.068860	-0.064816	
Income	-0.296289	-0.184508	0.209267	
Miles	-0.135665	0.106789	-0.050046	
Product_KP281	0.075926	0.002548	-0.058992	
Product_KP481	0.034300	-0.136990	0.186551	
Product_KP781	-0.129641	0.152286	-0.141019	
Gender_Female	-0.060017	0.035891	0.044088	
Gender_Male	0.060017	-0.035891	-0.044088	
MaritalStatus_Partnered	-0.096048	-0.078656	0.088700	
MaritalStatus_Single	0.096048	0.078656	-0.088700	
Age_cat_10-20	1.000000	-0.304034	-0.146254	
Age_cat_20-30	-0.304034	1.000000	-0.755929	
Age_cat_30-40	-0.146254	-0.755929	1.000000	
Age_cat_40-50	-0.064820	-0.335030	-0.161165	

	Age_cat_40-50
Age	0.588122
Education	0.182561
Usage	0.029830
Fitness	0.052795
Income	0.261680
Miles	0.004601
Product_KP281	0.029881
Product_KP481	-0.094491
Product_KP781	0.071429
Gender_Female	-0.093191
Gender_Male	0.093191
MaritalStatus_Partnered	0.084672
MaritalStatus_Single	-0.084672
Age_cat_10-20	-0.064820
Age_cat_20-30	-0.335030
Age_cat_30-40	-0.161165
Age_cat_40-50	1.000000

[29]:
```
# Plot heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



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1. **Age and Education:**
   - As people get older, they tend to have higher levels of education. This makes sense because many people pursue more education as they grow older and gain more experience.
2. **Usage and Fitness:**
   - People who use the treadmill more often also tend to rate themselves as being more fit. This suggests that using the treadmill regularly might help people improve their fitness levels.
3. **Income and Education:**

- People with higher levels of education often have higher incomes. This is because education can lead to better job opportunities and higher-paying careers.

4. **Age and Fitness:**
   - Older individuals tend to rate themselves slightly higher in terms of fitness compared to younger individuals. This might be because older people have more experience and confidence in their physical abilities.
5. **Product Preferences:**
   - Certain factors like age, income, and fitness level may influence which treadmill model people prefer. For example, younger people might prefer a simpler, more affordable treadmill (like KP281), while wealthier individuals might opt for a more advanced model (like KP781). Understanding these preferences can help companies tailor their marketing strategies to different customer segments.

6.1 # CONCLUSION

Customer Profiling:

1. **KP281 Treadmill:**
   - **Age Group:** Predominantly purchased by individuals aged between 20 to 30 years old.
   - **Gender:** No significant gender preference observed; purchased by both males and females.
   - **Income Group:** Attracts customers across various income levels, particularly those with lower to moderate incomes.
   - **Fitness Rating:** Preferred by individuals who rate themselves as moderately fit (3 out of 5).
   - **Usage Frequency:** Typically used 2-4 times a week.
   - **Miles Run:** Most commonly purchased by individuals running below 125 miles per week.
2. **KP481 Treadmill:**
   - **Age Group:** No specific age group preference; purchased by individuals across various age ranges.
   - **Gender:** Balanced purchase distribution among both genders.
   - **Income Group:** Attracts customers with moderate incomes.
   - **Fitness Rating:** Preferred by individuals with moderate fitness levels (rated as 3 out of 5).
   - **Usage Frequency:** Typically used 2-4 times a week.
   - **Miles Run:** Commonly purchased by individuals running below 125 miles per week.
3. **KP781 Treadmill:**
   - **Age Group:** Preferred by individuals aged between 20 to 30 years old with higher incomes, as well as by individuals of all ages with incomes above 70k.
   - **Gender:** Slightly favored by males, with fewer female purchases.
   - **Income Group:** Attracts customers with higher incomes, especially those above 70k.
   - **Fitness Rating:** Preferred by individuals who rate themselves as highly fit (5 out of 5).
   - **Usage Frequency:** Typically used 4-5 times a week.
   - **Miles Run:** Primarily purchased by individuals running above 125 miles per week.

Recommendations:

1. **For KP281:**
    - Target marketing efforts towards the 20-30 age group, emphasizing the affordability and basic features of the KP281 treadmill.
    - Create tailored workout programs and incentives to encourage regular usage among customers with moderate fitness levels.
2. **For KP481:**
    - Highlight the versatility and durability of KP481 to appeal to a wide range of age groups and income levels.
    - Offer financing options or promotional discounts to attract customers with moderate incomes who seek a reliable mid-level treadmill option.
3. **For KP781:**
    - Position KP781 as a premium option for serious athletes and fitness enthusiasts, focusing on its advanced features and high-performance capabilities.
    - Provide personalized consultations and demonstrations for potential buyers, showcasing the tailored workout programs and advanced tracking metrics of the KP781 treadmill.

These recommendations align with the observed customer preferences and behaviors, ensuring that each treadmill model is marketed effectively to its target audience.

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