AerofitCS

July 25, 2024

1 1. Introduction

Aerofit, a dynamic player in the fitness industry, traces its origins to M/s. Sachdev Sports Co, established in 1928 by Ram Ratan Sachdev. From its modest beginnings in Hyderabad, India, the company evolved into a leading sports equipment supplier across Andhra Pradesh and Telangana. Recognizing the growing need for fitness solutions, M/s. Sachdev Overseas emerged to import quality fitness equipment under the “Aerofit” brand, ensuring affordability and post-sales excellence.

Driven by a dedication to innovation, Nityasach Fitness Pvt Ltd was founded, spearheaded by director Nityesh Sachdev. With the brand “Aerofit” at its core, the company aimed to bridge the gap between international fitness technology and the Indian market. By importing advanced fitness equipment at accessible price points, Aerofit sought to redefine the industry landscape, prioritizing health and vitality while staying true to its legacy of passion and customer focus.

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.

Objective

Create comprehensive customer profiles for each AeroFit treadmill product through descriptive analytics. Develop two-way contingency tables and analyze conditional and marginal probabilities to discern customer characteristics, facilitating improved product recommendations and informed business decisions.

About Data

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during three months.The data is available in a single csv file

Product Portfolio

The KP281 is an entry-level treadmill that sells for USD 1,500.

The KP481 is for mid-level runners that sell for USD 1,750.

The KP781 treadmill is having advanced features that sell for USD 2,500.

2 2. Exploratory Data Analysis

[2]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import copy
```

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

[3]:

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

[4]:
```
df.tail()
```

[4]:

```
    Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income  \
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
175    200
176    200
177    160
178    120
179    180
```

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

[5]: (180, 9)

[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
```

Insights

- From the above analysis, it is clear that, data has total of 9 features with mixed alpha numeric data. Also we can see that there is no missing data in the columns.
- The data type of all the columns are matching with the data present in them. But we will change the datatype of Usage and Fitness into str(object).

[7]:
```python
#Changing the datatype of Usage and Fitness columns
df['Usage'] = df['Usage'].astype('str')
df['Fitness'] = df['Fitness'].astype('str')

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    object
 6   Fitness        180 non-null    object
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(4), object(5)
memory usage: 12.8+ KB
```

Statistical Summary

[8]:
```python
# statisctical summary of object type columns

df.describe(include = 'object')
```

[8]:

	Product	Gender	MaritalStatus	Usage	Fitness
count	180	180	180	180	180
unique	3	2	2	6	5
top	KP281	Male	Partnered	3	3
freq	80	104	107	69	97

Insights

1. Product - Over the past three months, the KP281 product demonstrated the highest sales performance among the three products, accounting for approximately 44% of total sales.
2. Gender - Based on the data of last 3 months, around 58% of the buyers were Male and 42% were female
3. Marital Status - Based on the data of last 3 months, around 60% of the buyers were Married and 40% were single

[9]:
```
# statisctical summary of numerical data type columns

df.describe()
```

[9]:

	Age	Education	Income	Miles
count	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	53719.577778	103.194444
std	6.943498	1.617055	16506.684226	51.863605
min	18.000000	12.000000	29562.000000	21.000000
25%	24.000000	14.000000	44058.750000	66.000000
50%	26.000000	16.000000	50596.500000	94.000000
75%	33.000000	16.000000	58668.000000	114.750000
max	50.000000	21.000000	104581.000000	360.000000

Insights

1. Age - The age range of customers spans from 18 to 50 year, with an average age of 29 years.
2. Education - Customer education levels vary between 12 and 21 years, with an average education duration of 16 years.
3. Usage - Customers intend to utilize the product anywhere from 2 to 7 times per week, with an average usage frequency of 3 times per week.
4. Fitness - On average, customers have rated their fitness at 3 on a 5-point scale, reflecting a moderate level of fitness.
5. Income - The annual income of customers falls within the range of USD 30,000 to USD 100,000, with an average income of approximately USD 54,000.
6. Miles - Customers' weekly running goals range from 21 to 360 miles, with an average target of 103 miles per week.

Duplicate Detection

[10]:
```
df.duplicated().value_counts()
```

[10]:
```
False    180
Name: count, dtype: int64
```

Insights

There are no duplicate entries in the dataset

Sanity Check for columns

[11]:
```python
# checking the unique values for columns
for i in df.columns:
    print('Unique Values in',i,'column are :-')
    print(df[i].unique())
    print('-'*75)
```

```
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]
---------------------------------------------------------------------------
```

Insights

The dataset does not contain any abnormal values.

Adding new columns for better analysis

- List itemCreating New Column and Categorizing values in Age,Education,Income and Miles to different classes for better visualization

Age Column

- Categorizing the values in age column in 4 different buckets:

1. Young Adult: from 18 - 25
2. Adults: from 26 - 35
3. Middle Aged Adults: 36-45
4. Elder :46 and above

Education Column

- Categorizing the values in education column in 3 different buckets:

1. Primary Education: upto 12
2. Secondary Education: 13 to 15
3. Higher Education: 16 and above

Income Column

- Categorizing the values in Income column in 4 different buckets:

1. Low Income - Upto 40,000
2. Moderate Income - 40,000 to 60,000
3. High Income - 60,000 to 80,000
4. Very High Income - Above 80,000

Miles Column

- Categorizing the values in Miles column in 4 different buckets:

1. Light Activity - Upto 50 miles

2. Moderate Activity - 51 to 100 miles

3. Active Lifestyle - 101 to 200 miles

4. Fitness Enthusiast - Above 200 miles

[12]:
```
#binning the age values into categories
bin_range1 = [17,25,35,45,float('inf')]
bin_labels1 = ['Young Adults', 'Adults', 'Middle Aged Adults', 'Elder']

df['age_group'] = pd.cut(df['Age'],bins = bin_range1,labels = bin_labels1)

#binning the education values into categories
```

```
bin_range2 = [0,12,15,float('inf')]
bin_labels2 = ['Primary Education', 'Secondary Education', 'Higher Education']

df['edu_group'] = pd.cut(df['Education'],bins = bin_range2,labels = bin_labels2)

#binning the income values into categories
bin_range3 = [0,40000,60000,80000,float('inf')]
bin_labels3 = ['Low Income','Moderate Income','High Income','Very High Income']

df['income_group'] = pd.cut(df['Income'],bins = bin_range3,labels = bin_labels3)

#binning the miles values into categories
bin_range4 = [0,50,100,200,float('inf')]
bin_labels4 = ['Light Activity', 'Moderate Activity', 'Active Lifestyle',␣
 ↪'Fitness Enthusiast ']

df['miles_group'] = pd.cut(df['Miles'],bins = bin_range4,labels = bin_labels4)
```

[13]:
```
df.head()
```

[13]:
```
  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

      age_group            edu_group income_group        miles_group
0  Young Adults  Secondary Education   Low Income   Active Lifestyle
1  Young Adults  Secondary Education   Low Income  Moderate Activity
2  Young Adults  Secondary Education   Low Income  Moderate Activity
3  Young Adults    Primary Education   Low Income  Moderate Activity
4  Young Adults  Secondary Education   Low Income     Light Activity
```

3 3.Univariate Analysis

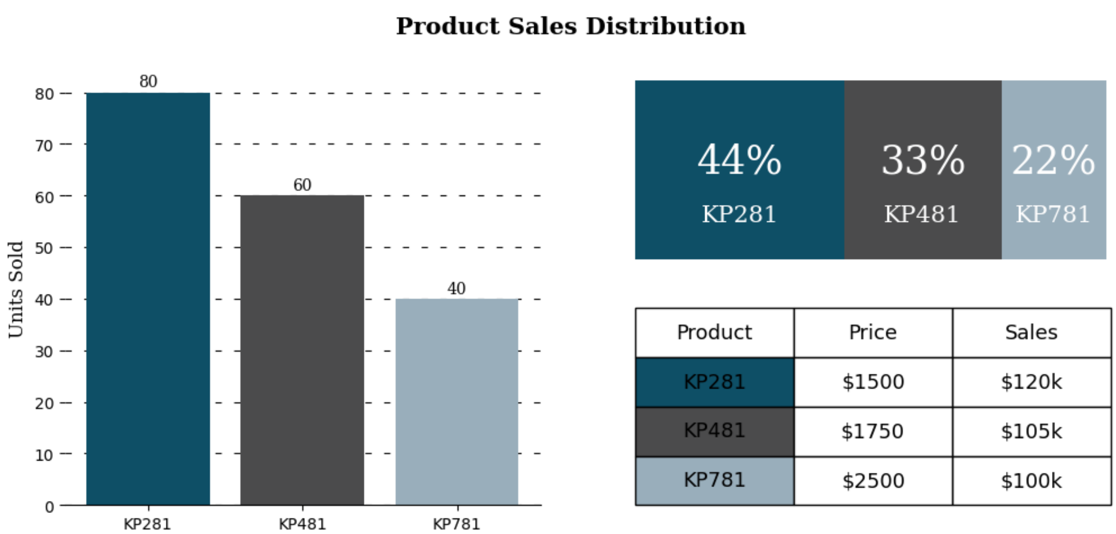
3.1 Categorical Variables

3.1.1 Product Sales Distribution

[14]:
```
#setting the plot style

fig = plt.figure(figsize = (12,5))
gs = fig.add_gridspec(2,2)

                                            #creating plot for product column
```

```
ax0 = fig.add_subplot(gs[:,0])

product_count = df['Product'].value_counts()

color_map = ["#0e4f66", "#4b4b4c",'#99AEBB']

ax0.bar(product_count.index,product_count.values,color = color_map,zorder = 2)

#adding the value_counts
for i in product_count.index:
    ax0.text(i,product_count[i]+2,product_count[i],{'font':'serif','size' :␣
↪10},ha = 'center',va = 'center')

#adding grid lines
ax0.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#adding axis label
ax0.set_ylabel('Units Sold',fontfamily='serif',fontsize = 12)

                                            #creating a plot for product % sale

ax1 = fig.add_subplot(gs[0,1])

product_count['percent'] = ((product_count.values/df.shape[0])* 100).round()

ax1.barh(product_count.index[0],product_count.loc['percent'][0],color =␣
↪"#0e4f66")
ax1.barh(product_count.index[0],product_count.loc['percent'][1],left =␣
↪product_count.loc['percent'][0],color = '#4b4b4c')
ax1.barh(product_count.index[0],product_count.loc['percent'][2],
         left = product_count.loc['percent'][0] + product_count.
↪loc['percent'][1], color = '#99AEBB')
ax1.set(xlim=(0,100))


# adding info to the each bar
product_count['info_percent'] =[product_count['percent'][0]/
↪2,product_count['percent'][0] + product_count['percent'][1]/2,
                                 product_count['percent'][0] +␣
↪product_count['percent'][1] + product_count['percent'][2]/2]
for i in range(3):
```

```python
    ax1.text(product_count['info_percent'][i],0.04,f"{product_count['percent'][i]:.0f}%",
             va = 'center', ha='center',fontsize=25, fontweight='light', fontfamily='serif',color='white')

    ax1.text(product_count['info_percent'][i],-0.2,product_count.index[i],
             va = 'center', ha='center',fontsize=15, fontweight='light', fontfamily='serif',color='white')

#removing the axis lines
ax1.axis('off')

                                        #creating a plot for product portfolio

ax2 = fig.add_subplot(gs[1,1])

product_portfolio = [['KP281','$1500','$120k'],['KP481','$1750','$105k'],['KP781','$2500','$100k']]
color_2d = [['#0e4f66','#FFFFFF','#FFFFFF'],['#4b4b4c','#FFFFFF','#FFFFFF'],['#99AEBB','#FFFFFF','#FFF

table = ax2.table(cellText = product_portfolio, cellColours=color_2d, cellLoc='center',colLabels =['Product','Price','Sales'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax2.axis('off')

#adding title to the visual
fig.suptitle('Product Sales Distribution',fontproperties = {'family':'serif', 'size':15,'weight':'bold'})

plt.show()
```



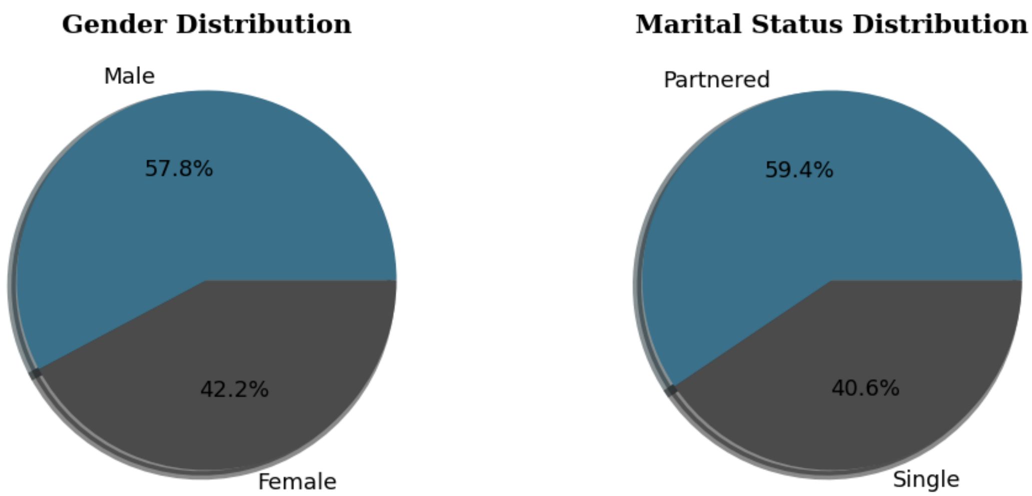
Insights

- The KP281 treadmill model, positioned as an entry-level product, has the highest number of units sold, trailed by the KP481 (mid-level) and KP781 (advanced) models.
- All three models have nearly equal contributions in terms of generating sales revenue.

3.1.2 Gender and Marital Status Disribution

[15]:
```
#setting the plot style
fig = plt.figure(figsize = (12,5))
gs = fig.add_gridspec(1,2)

                                        # creating pie chart for gender disribution
ax0 = fig.add_subplot(gs[0,0])

color_map = ["#3A7089", "#4b4b4c"]
ax0.pie(df['Gender'].value_counts().values,labels = df['Gender'].value_counts().index,autopct = '%.1f%%',
        shadow = True,colors = color_map,wedgeprops = {'linewidth': 5},textprops={'fontsize': 13, 'color': 'black'})

#setting title for visual
ax0.set_title('Gender Distribution',{'font':'serif', 'size':15,'weight':'bold'})

                                        # creating pie chart for marital status
ax1 = fig.add_subplot(gs[0,1])

color_map = ["#3A7089", "#4b4b4c"]
```

```
ax1.pie(df['MaritalStatus'].value_counts().values,labels = df['MaritalStatus'].
↪value_counts().index,autopct = '%.1f%%',
        shadow = True,colors = color_map,wedgeprops = {'linewidth':␣
↪5},textprops={'fontsize': 13, 'color': 'black'})

#setting title for visual
ax1.set_title('Marital Status Distribution',{'font':'serif', 'size':15,'weight':
↪'bold'})

plt.show()
```

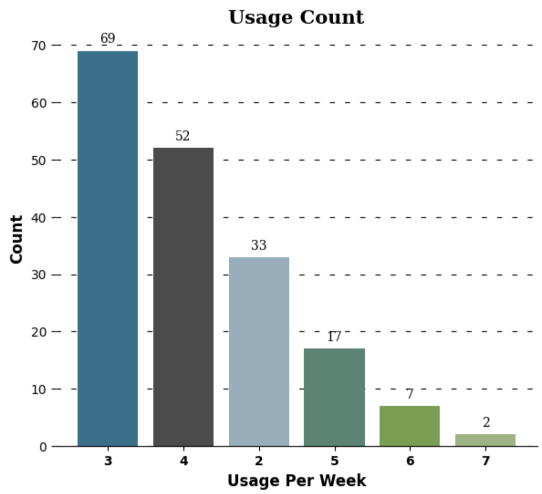


3.1.3 Buyer Fitness and treadmill Usage

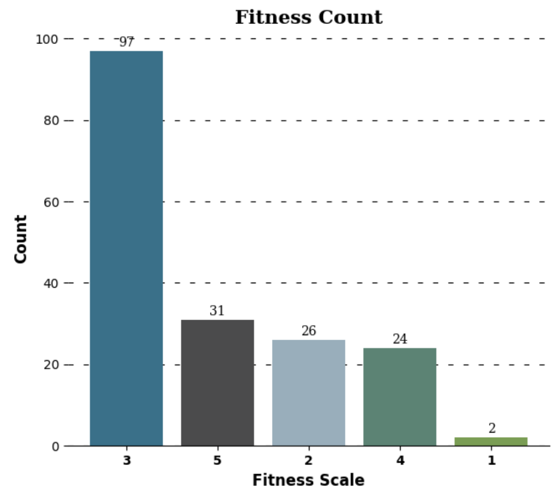
[16]:
```
#setting the plot style
fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,2,height_ratios=[0.65, 0.35])

                                        # creating bar chart for usage␣
↪disribution

ax0 = fig.add_subplot(gs[0,0])
temp = df['Usage'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#7A9D54','#9EB384']
ax0.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)

#adding the value_counts
for i in temp.index:
    ax0.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
↪= 'center')
```

```
#adding grid lines
ax0.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#adding axis label
ax0.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax0.set_xlabel('Usage Per Week',fontweight = 'bold',fontsize = 12)
ax0.set_xticklabels(temp.index,fontweight = 'bold')

#setting title for visual
ax0.set_title('Usage Count',{'font':'serif', 'size':15,'weight':'bold'})

                                        #creating a info table for usage

ax1 = fig.add_subplot(gs[1,0])
usage_info =␣
 ↪[['3','38%'],['4','29%'],['2','19%'],['5','9%'],['6','4%'],['7','1%']]
color_2d =␣
 ↪[["#3A7089",'#FFFFFF'],["#4b4b4c",'#FFFFFF'],['#99AEBB','#FFFFFF'],['#5C8374','#FFFFFF'],['
           ['#9EB384','#FFFFFF']]

table = ax1.table(cellText = usage_info, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Usage Per Week','Percent'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax1.axis('off')

                                        # creating bar chart for fitness scale

ax2 = fig.add_subplot(gs[0,1])
temp = df['Fitness'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#7A9D54','#9EB384']
ax2.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)

#adding the value_counts
for i in temp.index:
    ax2.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
 ↪= 'center')
```

```
#adding grid lines
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#adding axis label
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax2.set_xlabel('Fitness Scale',fontweight = 'bold',fontsize = 12)
ax2.set_xticklabels(temp.index,fontweight = 'bold')

#setting title for visual
ax2.set_title('Fitness Count',{'font':'serif', 'size':15,'weight':'bold'})

                                        #creating a info table for usage

ax1 = fig.add_subplot(gs[1,1])
fitness_info = [['3','54%'],['5','17%'],['2','15%'],['4','13%'],['1','1%']]
color_2d =␣
 ↪[["#3A7089",'#FFFFFF'],["#4b4b4c",'#FFFFFF'],['#99AEBB','#FFFFFF'],['#5C8374','#FFFFFF'],['

table = ax1.table(cellText = fitness_info, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Fitness','Percent'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax1.axis('off')


plt.show()
```



Usage Per Week	Percent
3	38%
4	29%
2	19%
5	9%
6	4%
7	1%



Fitness	Percent
3	54%
5	17%
2	15%
4	13%
1	1%

Insights

- Almost 85% of the customers plan to use the treadmill for 2 to 4 times a week and only 15% using 5 times and above each week
- 54% of the customers have self-evaluated their fitness at a level 3 on a scale of 1 to 5. Furthermore, a substantial 84% of the total customers have rated themselves at 3 or higher, indicating commendable fitness levels.

3.2 Numerical Variables

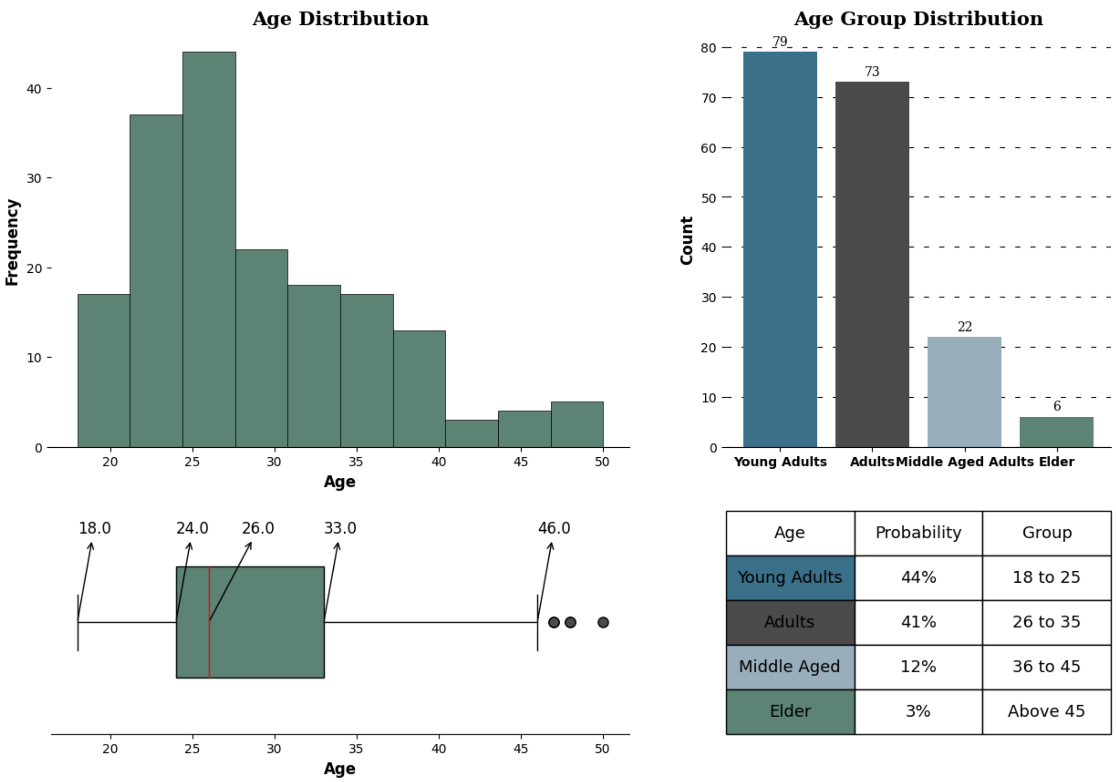
3.2.1 Customer Age Distribution

[17]:
```
#setting the plot style

fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,2,height_ratios=[0.65, 0.35],width_ratios = [0.6,0.4])

                                    #creating age histogram

ax0 = fig.add_subplot(gs[0,0])

ax0.hist(df['Age'],color= '#5C8374',linewidth=0.5,edgecolor='black')
ax0.set_xlabel('Age',fontsize = 12,fontweight = 'bold')
ax0.set_ylabel('Frequency',fontsize = 12,fontweight = 'bold')
```

```
#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#setting title for visual
ax0.set_title('Age Distribution',{'font':'serif', 'size':15,'weight':'bold'})


                                     #creating box plot for age

ax1 = fig.add_subplot(gs[1,0])
boxplot = ax1.boxplot(x = df['Age'],vert = False,patch_artist = True,widths = 0.
 ↪5)

# Customize box and whisker colors
boxplot['boxes'][0].set(facecolor='#5C8374')

# Customize median line
boxplot['medians'][0].set(color='red')

# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor= "#4b4b4c")

#removing the axis lines
for s in ['top','left','right']:
    ax1.spines[s].set_visible(False)

#adding 5 point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']] #getting the␣
 ↪upperlimit,Q1,Q3 and lowerlimit

median = df['Age'].quantile(0.5) #getting Q2

for i,j in info: #using i,j here because of the output type of info list␣
 ↪comprehension

    ax1.annotate(text = f"{i:.1f}", xy = (i,1), xytext = (i,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
 ↪connectionstyle="arc,rad=0"))

    ax1.annotate(text = f"{j:.1f}", xy = (j,1), xytext = (j,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
 ↪connectionstyle="arc,rad=0"))

#adding the median separately because it was included in info list
```

```
ax1.annotate(text = f"{median:.1f}",xy = (median,1),xytext = (median + 2,1.
↪4),fontsize = 12,
            arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

#removing y-axis ticks
ax1.set_yticks([])

#adding axis label
ax1.set_xlabel('Age',fontweight = 'bold',fontsize = 12)

                                    #creating age group bar chart

ax2 = fig.add_subplot(gs[0,1])
temp = df['age_group'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374']
ax2.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)

#adding the value_counts
for i in temp.index:
    ax2.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
↪= 'center')

#adding grid lines
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#adding axis label
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax2.set_xticklabels(temp.index,fontweight = 'bold')

#setting title for visual
ax2.set_title('Age Group Distribution',{'font':'serif', 'size':15,'weight':
↪'bold'})

                                        #creating a table for group info

ax3 = fig.add_subplot(gs[1,1])
age_info = [['Young Adults','44%','18 to 25'],['Adults','41%','26 to␣
↪35'],['Middle Aged','12%','36 to 45'],
            ['Elder','3%','Above 45']]
```

```
color_2d =␣
↪[["#3A7089",'#FFFFFF','#FFFFFF'],["#4b4b4c",'#FFFFFF','#FFFFFF'],['#99AEBB','#FFFFFF','#FFF
            ['#5C8374','#FFFFFF','#FFFFFF']]

table = ax3.table(cellText = age_info, cellColours=color_2d,␣
↪cellLoc='center',colLabels =['Age','Probability','Group'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax3.axis('off')


plt.show()
```



Insights

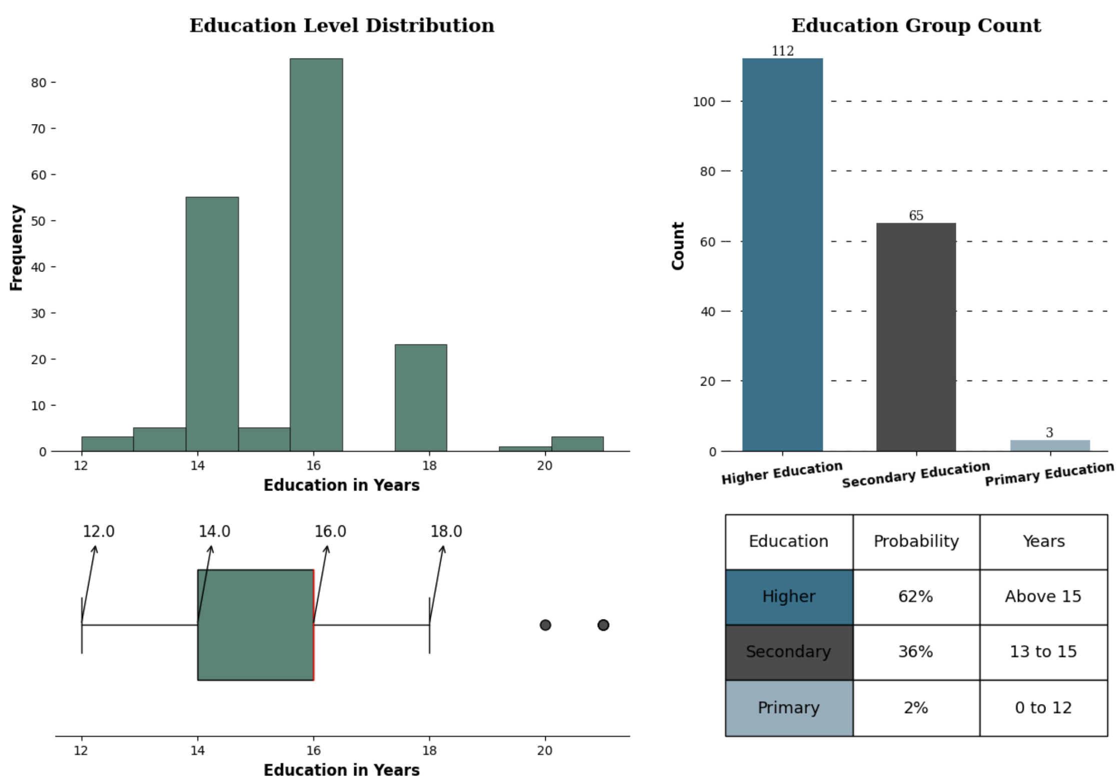
- 85% of the customers fall in the age range of 18 to 35. with a median age of 26, suggesting young people showing more interest in the companies products
- Outliers : As we can see from the box plot, there are `3 outlier's` present in the age data.

3.2.2 Customer Education Distribution

[18]:
```
#setting the plot style

fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,2,height_ratios=[0.65, 0.35],width_ratios = [0.6,0.4])

                                    #creating education histogram

ax0 = fig.add_subplot(gs[0,0])

ax0.hist(df['Education'],color= '#5C8374',linewidth=0.5,edgecolor='black')
ax0.set_xlabel('Education in Years',fontsize = 12,fontweight = 'bold')
ax0.set_ylabel('Frequency',fontsize = 12,fontweight = 'bold')

#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#setting title for visual
ax0.set_title('Education Level Distribution',{'font':'serif', 'size':
 ↪15,'weight':'bold'})


                                     #creating box plot for education

ax1 = fig.add_subplot(gs[1,0])
boxplot = ax1.boxplot(x = df['Education'],vert = False,patch_artist =␣
 ↪True,widths = 0.5)

# Customize box and whisker colors
boxplot['boxes'][0].set(facecolor='#5C8374')

# Customize median line
boxplot['medians'][0].set(color='red')

# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor= "#4b4b4c")

#removing the axis lines
for s in ['top','left','right']:
    ax1.spines[s].set_visible(False)

#adding 5 point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']] #getting the␣
 ↪upperlimit,Q1,Q3 and lowerlimit

median = df['Education'].quantile(0.5) #getting Q2
```

```
for i,j in info: #using i,j here because of the output type of info list␣
↪comprehension

    ax1.annotate(text = f"{i:.1f}", xy = (i,1), xytext = (i,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

    ax1.annotate(text = f"{j:.1f}", xy = (j,1), xytext = (j,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))


#removing y-axis ticks
ax1.set_yticks([])

#adding axis label
ax1.set_xlabel('Education in Years',fontweight = 'bold',fontsize = 12)

                                    #creating education group bar chart

ax2 = fig.add_subplot(gs[0,1])
temp = df['edu_group'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB']
ax2.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2,width =␣
↪0.6)

#adding the value_counts
for i in temp.index:
    ax2.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
↪= 'center')

#adding grid lines
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#adding axis label
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax2.set_xticklabels(temp.index,fontweight = 'bold',rotation = 7)

#setting title for visual
```

```
ax2.set_title('Education Group Count',{'font':'serif', 'size':15,'weight':
 ↪'bold'})


                                        #creating a table for group info

ax3 = fig.add_subplot(gs[1,1])
edu_info = [['Higher','62%','Above 15'],['Secondary','36%','13 to␣
 ↪15'],['Primary','2%','0 to 12']]
color_2d =␣
 ↪[["#3A7089",'#FFFFFF','#FFFFFF'],["#4b4b4c",'#FFFFFF','#FFFFFF'],['#99AEBB','#FFFFFF','#FFF

table = ax3.table(cellText = edu_info, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Education','Probability','Years'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax3.axis('off')


plt.show()
```



Insights

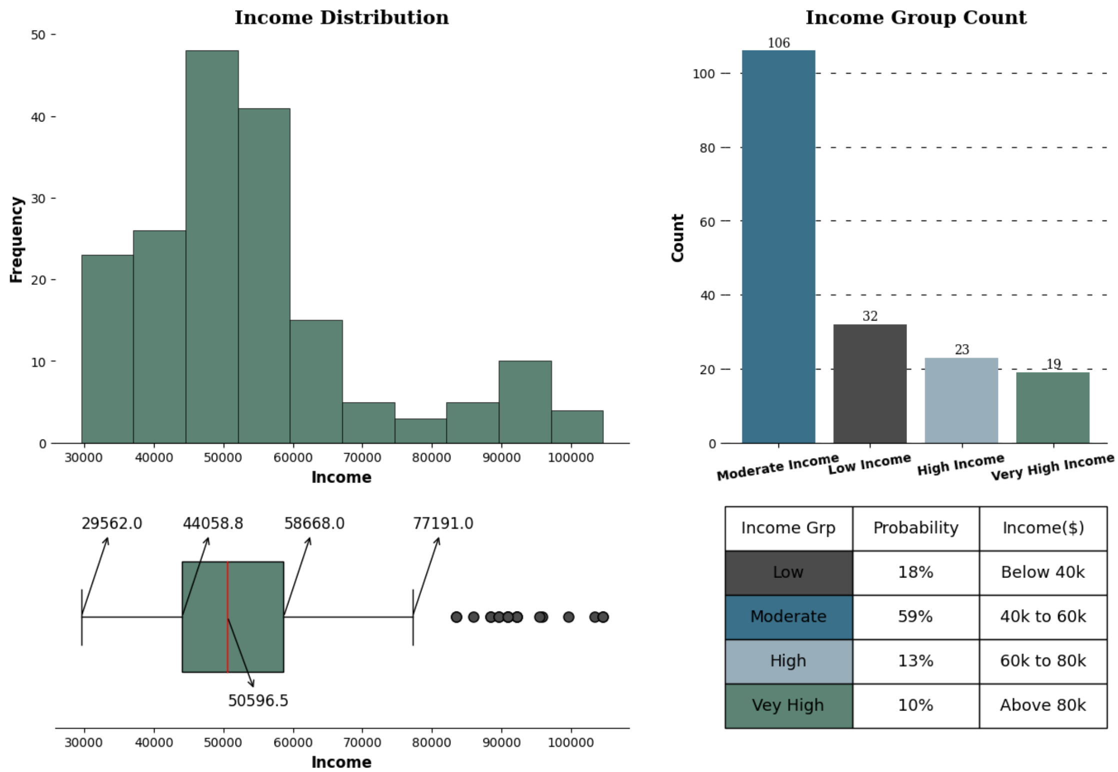
- 98% of the customers have education more than 13 years highlighting a strong inclination among well-educated individuals to purchase the products. It's plausible that health awareness driven by education could play a pivotal role in this trend.
- Outliers : As we can see from the box plot, there are `2 outlier's` present in the education data.

3.2.3 Customer Income Distribution

[19]:
```
#setting the plot style

fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,2,height_ratios=[0.65, 0.35],width_ratios = [0.6,0.4])

                                    #creating Income histogram

ax0 = fig.add_subplot(gs[0,0])

ax0.hist(df['Income'],color= '#5C8374',linewidth=0.5,edgecolor='black')
ax0.set_xlabel('Income',fontsize = 12,fontweight = 'bold')
ax0.set_ylabel('Frequency',fontsize = 12,fontweight = 'bold')

#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#setting title for visual
ax0.set_title('Income Distribution',{'font':'serif', 'size':15,'weight':'bold'})


                                     #creating box plot for Income

ax1 = fig.add_subplot(gs[1,0])
boxplot = ax1.boxplot(x = df['Income'],vert = False,patch_artist = True,widths␣
 ↪= 0.5)

# Customize box and whisker colors
boxplot['boxes'][0].set(facecolor='#5C8374')

# Customize median line
boxplot['medians'][0].set(color='red')

# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor= "#4b4b4c")
```

```
#removing the axis lines
for s in ['top','left','right']:
    ax1.spines[s].set_visible(False)

#adding 5 point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']] #getting the␣
↪upperlimit,Q1,Q3 and lowerlimit

median = df['Income'].quantile(0.5) #getting Q2

for i,j in info: #using i,j here because of the output type of info list␣
↪comprehension

    ax1.annotate(text = f"{i:.1f}", xy = (i,1), xytext = (i,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

    ax1.annotate(text = f"{j:.1f}", xy = (j,1), xytext = (j,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

#adding the median separately because it was included in info list
ax1.annotate(text = f"{median:.1f}",xy = (median,1),xytext = (median,0.
↪6),fontsize = 12,
            arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

#removing y-axis ticks
ax1.set_yticks([])

#adding axis label
ax1.set_xlabel('Income',fontweight = 'bold',fontsize = 12)

                                    #creating Income group bar chart

ax2 = fig.add_subplot(gs[0,1])
temp = df['income_group'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374']
ax2.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)

#adding the value_counts
for i in temp.index:
    ax2.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
↪= 'center')

#adding grid lines
```

```
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#adding axis label
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax2.set_xticklabels(temp.index,fontweight = 'bold',rotation = 9)

#setting title for visual
ax2.set_title('Income Group Count',{'font':'serif', 'size':15,'weight':'bold'})

                                        #creating a table group info

ax3 = fig.add_subplot(gs[1,1])
inc_info = [['Low','18%','Below 40k'],['Moderate','59%','40k to␣
 ↪60k'],['High','13%','60k to 80k'],
            ['Vey High','10%','Above 80k']]
color_2d =␣
 ↪[["#4b4b4c",'#FFFFFF','#FFFFFF'],["#3A7089",'#FFFFFF','#FFFFFF'],['#99AEBB','#FFFFFF','#FFFF
            ['#5C8374','#FFFFFF','#FFFFFF']]

table = ax3.table(cellText = inc_info, cellColours=color_2d, cellLoc='center',
                  colLabels =['Income Grp','Probability','Income($)'],
                  colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(13)

#removing axis
ax3.axis('off')
bin_range3 = [0,40000,60000,80000,float('inf')]
bin_labels3 = ['Low Income','Moderate Income','High Income','Very High Income']

plt.show()
```



Insights

- Almost 60% of the customers fall in the income group of (40k to 60k) dollars suggesting higher inclination of this income group people towards the products.
- Surprisingly 18% of the customers fall in the income group of (<40) suggesting almost 77% of the total customers fall in income group of below 60k and only 23% of them falling in 60k and above income group
- Outliers : As we can see from the box plot, there are `many outlier's` present in the income data.

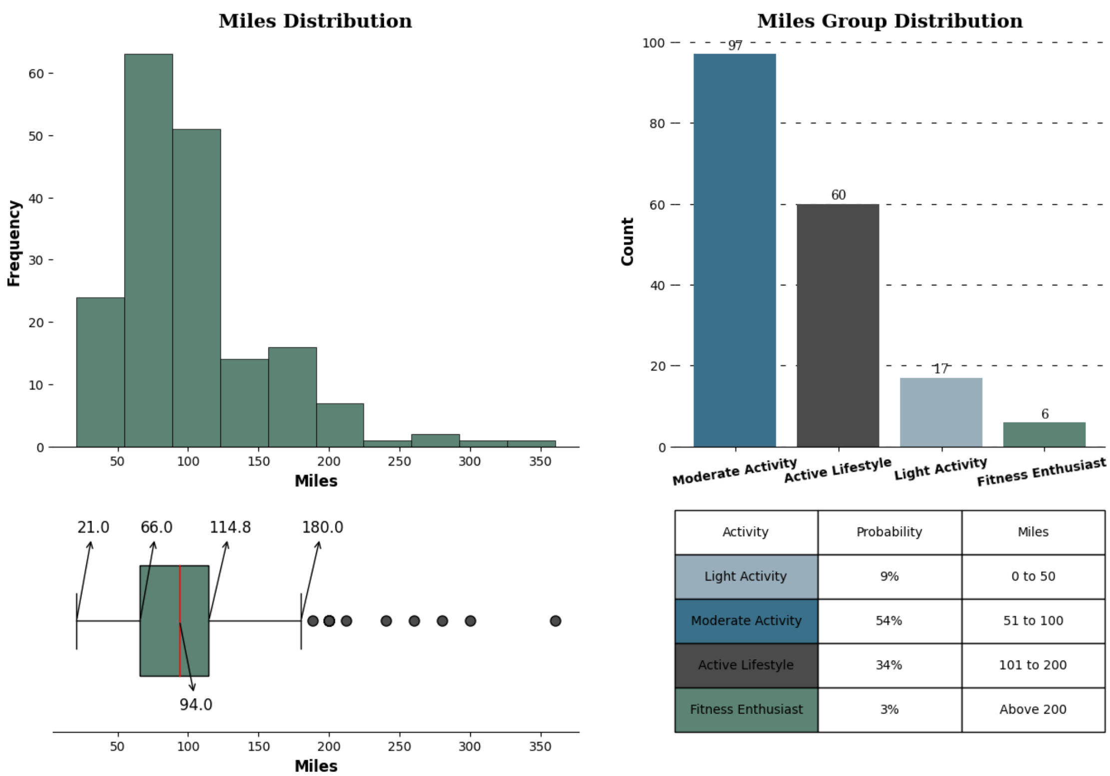
3.2.4 Customers Expected Weekly Mileage

[20]:
```
#setting the plot style

fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,2,height_ratios=[0.65, 0.35],width_ratios = [0.55,0.45])

                                    #creating miles histogram

ax0 = fig.add_subplot(gs[0,0])

ax0.hist(df['Miles'],color= '#5C8374',linewidth=0.5,edgecolor='black')
ax0.set_xlabel('Miles',fontsize = 12,fontweight = 'bold')
```

```
ax0.set_ylabel('Frequency',fontsize = 12,fontweight = 'bold')

#removing the axis lines
for s in ['top','left','right']:
    ax0.spines[s].set_visible(False)

#setting title for visual
ax0.set_title('Miles Distribution',{'font':'serif', 'size':15,'weight':'bold'})


                                     #creating box plot for miles

ax1 = fig.add_subplot(gs[1,0])
boxplot = ax1.boxplot(x = df['Miles'],vert = False,patch_artist = True,widths =␣
 ↪0.5)

# Customize box and whisker colors
boxplot['boxes'][0].set(facecolor='#5C8374')

# Customize median line
boxplot['medians'][0].set(color='red')

# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor= "#4b4b4c")

#removing the axis lines
for s in ['top','left','right']:
    ax1.spines[s].set_visible(False)

#adding 5 point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']] #getting the␣
 ↪upperlimit,Q1,Q3 and lowerlimit

median = df['Miles'].quantile(0.5) #getting Q2

for i,j in info: #using i,j here because of the output type of info list␣
 ↪comprehension

    ax1.annotate(text = f"{i:.1f}", xy = (i,1), xytext = (i,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
 ↪connectionstyle="arc,rad=0"))

    ax1.annotate(text = f"{j:.1f}", xy = (j,1), xytext = (j,1.4),fontsize = 12,
                 arrowprops= dict(arrowstyle="<-", lw=1,␣
 ↪connectionstyle="arc,rad=0"))
```

```
#adding the median separately because it was included in info list
ax1.annotate(text = f"{median:.1f}",xy = (median,1),xytext = (median,0.
↪6),fontsize = 12,
            arrowprops= dict(arrowstyle="<-", lw=1,␣
↪connectionstyle="arc,rad=0"))

#removing y-axis ticks
ax1.set_yticks([])

#adding axis label
ax1.set_xlabel('Miles',fontweight = 'bold',fontsize = 12)


                                    #creating Miles group bar chart

ax2 = fig.add_subplot(gs[0,1])
temp = df['miles_group'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374']
ax2.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)

#adding the value_counts
for i in temp.index:
    ax2.text(i,temp[i]+2,temp[i],{'font':'serif','size' : 10},ha = 'center',va␣
↪= 'center')

#adding grid lines
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#adding axis label
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax2.set_xticklabels(temp.index,fontweight = 'bold',rotation = 9)

#setting title for visual
ax2.set_title('Miles Group Distribution',{'font':'serif', 'size':15,'weight':
↪'bold'})


                                        #creating a table for group info

ax3 = fig.add_subplot(gs[1,1])
miles_info = [['Light Activity','9%','0 to 50'],['Moderate Activity','54%','51␣
↪to 100'],['Active Lifestyle','34%','101 to 200'],
```

```
             ['Fitness Enthusiast','3%','Above 200']]
color_2d =␣
 ↪[['#99AEBB','#FFFFFF','#FFFFFF'],["#3A7089",'#FFFFFF','#FFFFFF'],["#4b4b4c",'#FFFFFF','#FFF
             ['#5C8374','#FFFFFF','#FFFFFF']]

table = ax3.table(cellText = miles_info, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Activity','Probability','Miles'],
                   colLoc = 'center',bbox =[0, 0, 1, 1])

table.set_fontsize(11)

#removing axis
ax3.axis('off')


plt.show()
```



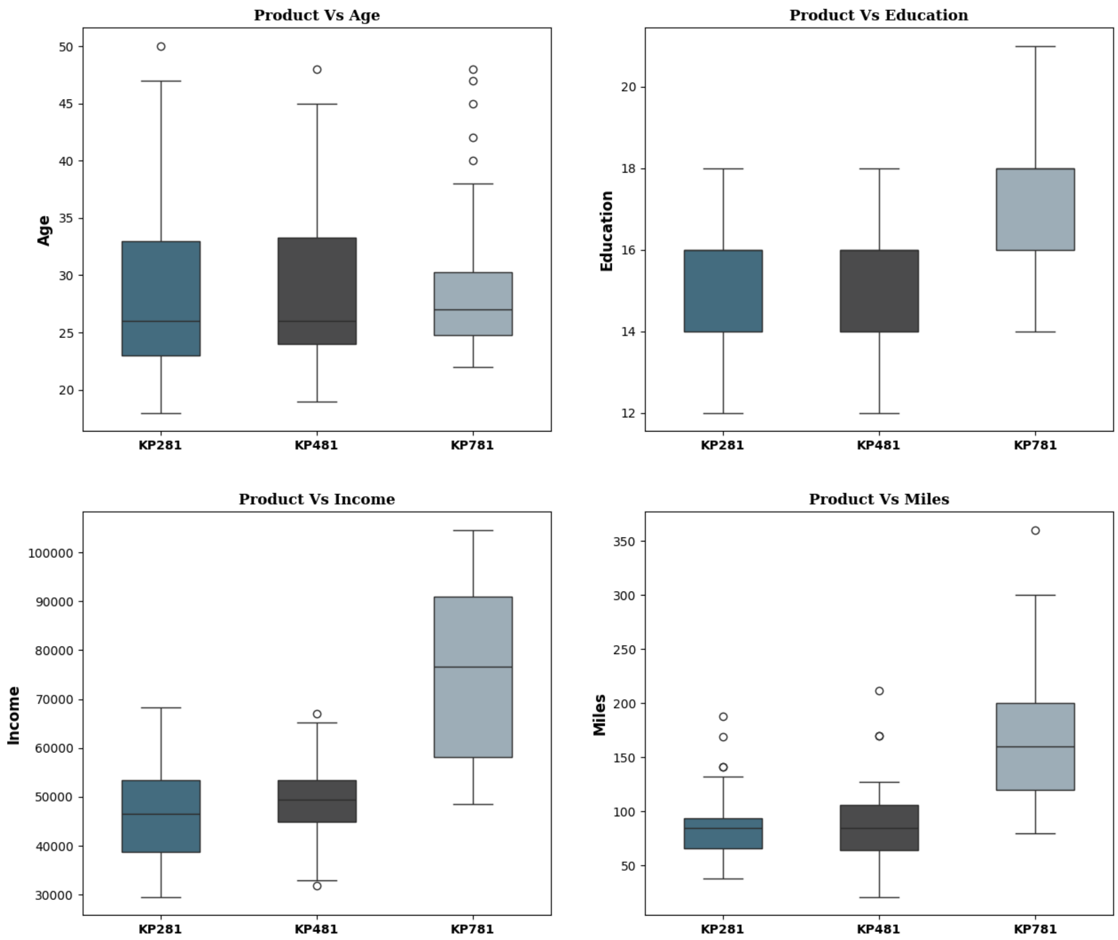
Insights

- Almost 88% of the customers plans to use the treadmill for 50 to 200 miles per week with a median of 94 miles per week.
- Outliers : As we can see from the box plot, there are 8 outlier's present in the miles data.

4 4. Bivariate Analysis

4.1 Analysis of Product Type

[22]:
```
#setting the plot style
fig = plt.figure(figsize = (15,13))
gs = fig.add_gridspec(2,2)

for i,j,k in [(0,0,'Age'),(0,1,'Education'),(1,0,'Income'),(1,1,'Miles')]:

    #plot position
    ax0 = fig.add_subplot(gs[i,j])

    #plot
    sns.boxplot(data = df, x = 'Product', y  = k ,ax = ax0,width = 0.5, palette␣
 ↪=["#3A7089", "#4b4b4c",'#99AEBB'])

    #plot title
    ax0.set_title(f'Product Vs {k}',{'font':'serif', 'size':12,'weight':'bold'})

    #customizing axis
    ax0.set_xticklabels(df['Product'].unique(),fontweight = 'bold')
    ax0.set_ylabel(f'{k}',fontweight = 'bold',fontsize = 12)
    ax0.set_xlabel('')

plt.show()
```



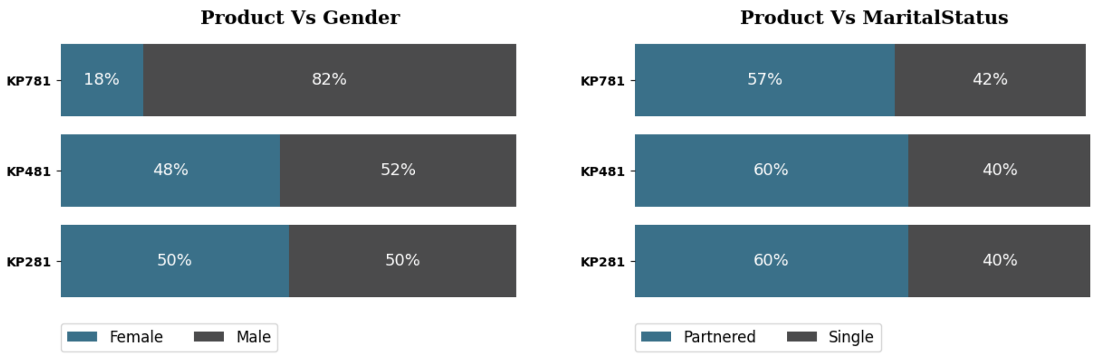
Insights

- The analysis presented above clearly indicates a strong preference for the treadmill model KP781 among customers who possess higher education, higher income levels, and intend to engage in running activities exceeding 150 miles per week.

4.2 Product Preference across Gender and Marital Status

[28]:
```
#setting the plot style
fig = plt.figure(figsize = (15,4))
gs = fig.add_gridspec(1,2)

for r,c,val in [(0,0,'Gender'),(0,1,'MaritalStatus')]:

    ax0 = fig.add_subplot(gs[r,c])

    #creating required df
    df_grp = df.groupby('Product')[val].value_counts(normalize = True).round(2)
    df_grp.name = 'count'
```

```
    df_grp = df_grp.reset_index()
    df_grp = df_grp.pivot(columns = val,index = 'Product',values = 'count')

    #for left parameter in ax.barh
    temp = np.zeros(len(df_grp),dtype = float)
    color_map =  ["#3A7089", "#4b4b4c"]

    #plotting the visual
    for i,j in zip(df_grp.columns,color_map):
        ax0.barh(df_grp.index,width = df_grp[i],left = temp, label = i,color =␣
↪j)
        temp += df_grp[i].values

    #inserting text
    temp = np.zeros(len(df_grp),dtype = float)

    for i in df_grp.columns:
        for j,k in enumerate(df_grp[i]):
            if k < 0.05:
                continue
            ax0.text(k/2 + temp[j],df_grp.index[j],f"{k:.0%}",va = 'center',␣
↪ha='center',fontsize=13, color='white')
        temp += df_grp[i].values

    #removing the axis lines
    for s in ['top','left','right','bottom']:
        ax0.spines[s].set_visible(False)

    #customizing ticks
    ax0.set_xticks([])
    ax0.set_yticklabels(df_grp.index,fontweight = 'bold')

    #plot title
    ax0.set_title(f'Product Vs {val}',{'font':'serif', 'size':15,'weight':
↪'bold'})

    #adding legend
    ax0.legend(loc = (0,-0.15),ncol = 2,fontsize = 12)

plt.show()
```



Insights

1. Gender

- Treadmill model KP781 is preferred more by male customers.
- Both treadmill models, KP481 and KP281, show equal distribution of both the gender

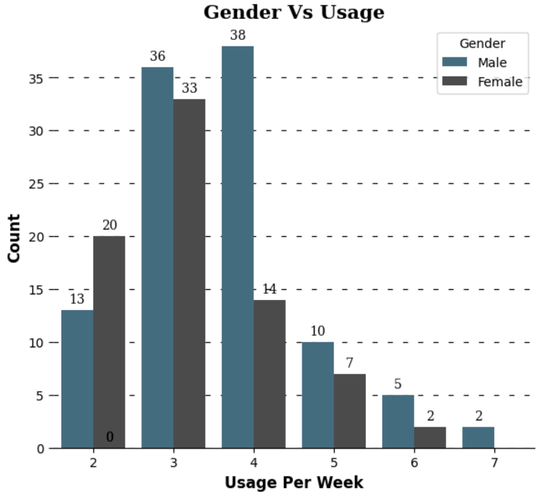
2. Marital Status

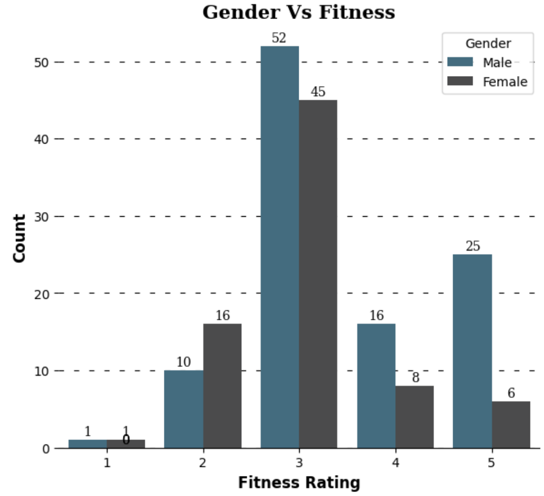
- For all the three treadmill models, there is uniform distribution of Married and Single customers with married customers showing slighly higher preference

4.3 Gender vs Product Usage And Gender Vs Fitness

[29]:
```
#setting the plot style
fig = plt.figure(figsize = (15,6))
gs = fig.add_gridspec(1,2)

                                        # Usage Vs Gender

#creating bar plot
ax1 = fig.add_subplot(gs[0,0])

plot = sns.countplot(data = df, x = 'Usage', hue = 'Gender',order =␣
↪sorted(df['Usage'].unique()),
              ax = ax1,palette = ["#3A7089","#4b4b4c"],zorder = 2)

#adding the value_counts
for i in plot.patches:
    ax1.text(i.get_x()+0.2,i.get_height()+1,f'{i.get_height():.0f}',{'font':
↪'serif','size' : 10},ha = 'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
↪(5,10))

#removing the axis lines
```

```python
for s in ['top','left','right']:
    ax1.spines[s].set_visible(False)

#adding axis label
ax1.set_xlabel('Usage Per Week',fontweight = 'bold',fontsize = 12)
ax1.set_ylabel('Count',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax1.set_title('Gender Vs Usage',{'font':'serif', 'size':15,'weight':'bold'})


                                      # Fitness Vs Gender

#creating bar plot
ax2 = fig.add_subplot(gs[0,1])

plot = sns.countplot(data = df, x = 'Fitness', hue = 'Gender',order =␣
 ↪sorted(df['Fitness'].unique()),
              ax = ax2,palette = ["#3A7089","#4b4b4c"],zorder = 2)

#adding the value_counts
for i in plot.patches:
    ax2.text(i.get_x()+0.2,i.get_height()+1,f'{i.get_height():.0f}',{'font':
 ↪'serif','size' : 10},ha = 'center',va = 'center')

#adding grid lines
ax2.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes =␣
 ↪(5,10))

#removing the axis lines
for s in ['top','left','right']:
    ax2.spines[s].set_visible(False)

#customizing axis labels
ax2.set_xlabel('Fitness Rating',fontweight = 'bold',fontsize = 12)
ax2.set_ylabel('Count',fontweight = 'bold',fontsize = 12)

#setting title for visual
ax2.set_title('Gender Vs Fitness',{'font':'serif', 'size':15,'weight':'bold'})

plt.show()
```





Insights

1. **Gender Vs Usage**

- Almost 70% of Female customers plan to use the treadmill for 2 to 3 times a week whereas almost 70% of Male customer plan to use the treadmill for 3 to 4 times a week

2. **Gender Vs Fitness**

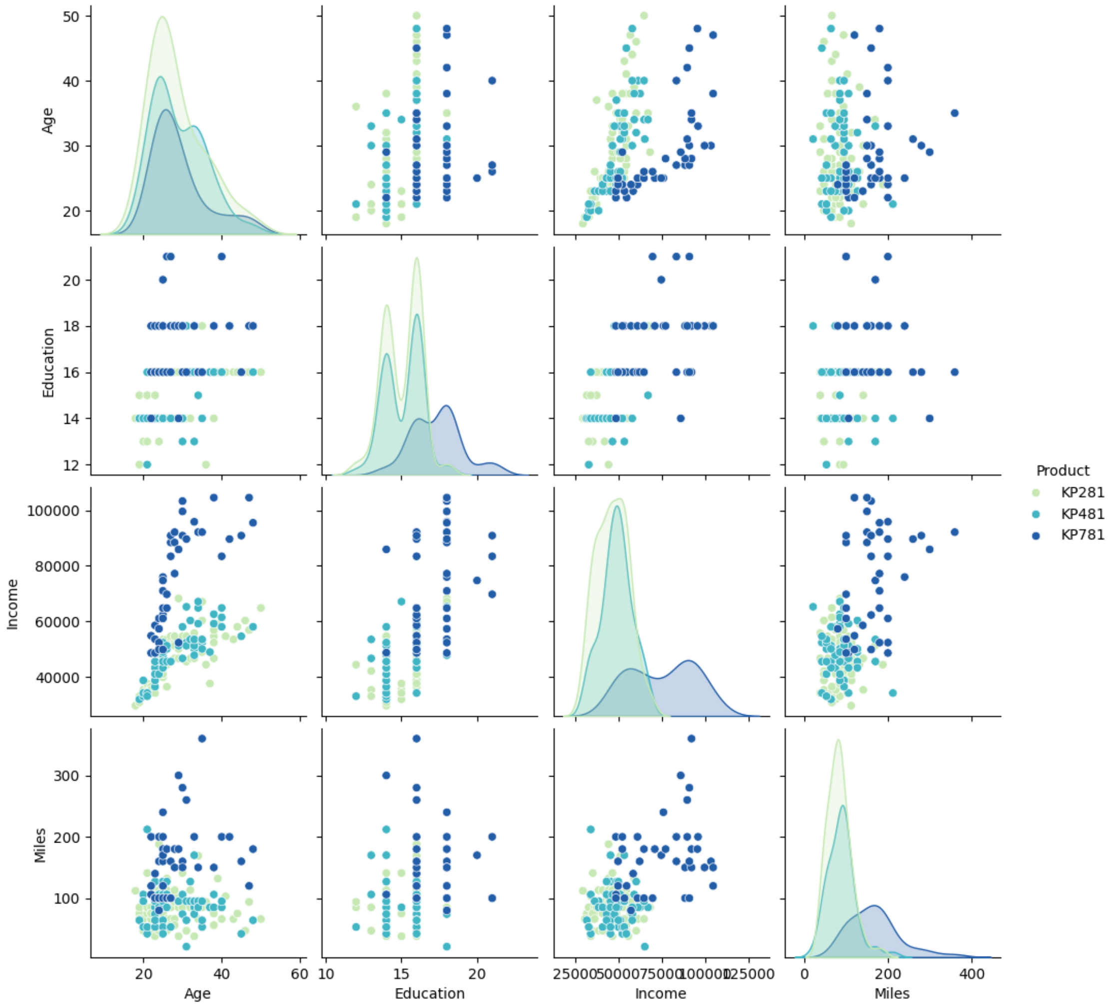
- Almost 80% of Female customers rated themselves between 2 to 3 whereas almost 90% of Male customer rated themselves between 3 to 5 on the fitness scale

5 5. Correlation between Variables

5.1 Pairplot

[30]:
```
df_copy = copy.deepcopy(df)
```

[31]:
```
sns.pairplot(df_copy, hue ='Product', palette= 'YlGnBu')
plt.show()
```



5.2 Heatmap

[32]:
```
# First we need to convert object into int datatype for usage and fitness␣
↪columns

df_copy['Usage'] = df_copy['Usage'].astype('int')
df_copy['Fitness'] = df_copy['Fitness'].astype('int')

df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 13 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
 9   age_group     180 non-null    category
 10  edu_group     180 non-null    category
 11  income_group  180 non-null    category
 12  miles_group   180 non-null    category
dtypes: category(4), int64(6), object(3)
memory usage: 14.2+ KB
```

6 6. Computing Probability - Marginal, Conditional Probability

6.1 Probability of product purchase w.r.t. gender

[34]:
```python
pd.crosstab(index =df['Product'],columns = df['Gender'],margins =
 ↪True,normalize = True ).round(2)
```

[34]:

Gender Product	Female	Male	All
KP281	0.22	0.22	0.44
KP481	0.16	0.17	0.33
KP781	0.04	0.18	0.22
All	0.42	0.58	1.00

Insights

- The Probability of a treadmill being purchased by a female is 42%. The conditional probability of purchasing the treadmill model given that the customer is female is
  1. For Treadmill model KP281 - 22%
  2. For Treadmill model KP281 - 22%
  3. For Treadmill model KP281 - 22%
  4. For Treadmill model KP481 - 16%
  5. For Treadmill model KP781 - 4%
- The Probability of a treadmill being purchased by a male is 58%. The conditional probability of purchasing the treadmill model given that the customer is male is -
  1. For Treadmill model KP281 - 22%
  2. For Treadmill model KP481 - 17%
  3. For Treadmill model KP781 - 18%

6.2 Probability of product purchase w.r.t. Age

[35]:
```
pd.crosstab(index =df['Product'],columns = df['age_group'],margins =␣
↪True,normalize = True ).round(2)
```

[35]:

age_group	Young Adults	Adults	Middle Aged Adults	Elder	All
Product					
KP281	0.19	0.18	0.06	0.02	0.44
KP481	0.16	0.13	0.04	0.01	0.33
KP781	0.09	0.09	0.02	0.01	0.22
All	0.44	0.41	0.12	0.03	1.00

Insights

1.The Probability of a treadmill being purchased by a Young Adult(18-25) is 44%.

The conditional probability of purchasing the treadmill model given that the customer is Young Adult is

- For Treadmill model KP281 - 19%
- For Treadmill model KP481 - 16%
- For Treadmill model KP781 - 9%

2.The Probability of a treadmill being purchased by a Adult(26-35) is 41%.

The conditional probability of purchasing the treadmill model given that the customer is Adult is -

- For Treadmill model KP281 - 18%
- For Treadmill model KP481 - 13%
- For Treadmill model KP781 - 9%

3.The Probability of a treadmill being purchased by a Middle Aged(36-45) is 12%. 4.The Probability of a treadmill being purchased by a Elder(Above 45) is only 3%.

6.3 Probability of product purchase w.r.t. Education level

[36]:
```
pd.crosstab(index =df['Product'],columns = df['edu_group'],margins =␣
↪True,normalize = True ).round(2)
```

[36]:

edu_group	Primary Education	Secondary Education	Higher Education	All
Product				
KP281	0.01	0.21	0.23	0.44
KP481	0.01	0.14	0.18	0.33
KP781	0.00	0.01	0.21	0.22
All	0.02	0.36	0.62	1.00

Insights

1.The Probability of a treadmill being purchased by a customer with Higher Education(Above 15 Years) is 62%.

The conditional probability of purchasing the treadmill model given that the customer has Higher Education is

- For Treadmill model KP281 - 23%

- For Treadmill model KP481 - 18%
- For Treadmill model KP781 - 21%

2.The Probability of a treadmill being purchased by a customer with Secondary Education(13-15 yrs) is 36%.

The conditional probability of purchasing the treadmill model given that the customer has Secondary Education is -

- For Treadmill model KP281 - 21%
- For Treadmill model KP481 - 14%
- For Treadmill model KP781 - 1%

3.The Probability of a treadmill being purchased by a customer with Primary Education(0 to 12 yrs) is only 2%.

6.4 Probability of product purchase w.r.t. Income

[37]:
```
pd.crosstab(index =df['Product'],columns = df['income_group'],margins =␣
↪True,normalize = True ).round(2)
```

[37]:

income_group Product	Low Income	Moderate Income	High Income	Very High Income	All
KP281	0.13	0.28	0.03	0.00	0.44
KP481	0.05	0.24	0.04	0.00	0.33
KP781	0.00	0.06	0.06	0.11	0.22
All	0.18	0.59	0.13	0.11	1.00

Insights

1.The Probability of a treadmill being purchased by a customer with Low Income(<40k) is 18%.

The conditional probability of purchasing the treadmill model given that the customer has Low Income is - * For Treadmill model KP281 - 13%

- For Treadmill model KP481 - 5%
- For Treadmill model KP781 - 0%

2.The Probability of a treadmill being purchased by a customer with Moderate Income(40k - 60k) is 59%.

The conditional probability of purchasing the treadmill model given that the customer has Moderate Income is - * For Treadmill model KP281 - 28%

- For Treadmill model KP481 - 24%
- For Treadmill model KP781 - 6% 3.The Probability of a treadmill being purchased by a customer with High Income(60k - 80k) is 13%

The conditional probability of purchasing the treadmill model given that the customer has High Income is -

- For Treadmill model KP281 - 3%

- For Treadmill model KP481 - 4%
- For Treadmill model KP781 - 6%

4.The Probability of a treadmill being purchased by a customer with Very High Income(>80k) is 11%

The conditional probability of purchasing the treadmill model given that the customer has High Income is -

- For Treadmill model KP281 - 0%
- For Treadmill model KP481 - 0%
- For Treadmill model KP781 - 11%

6.5 Probability of product purchase w.r.t. Marital Status

[38]:
```
pd.crosstab(index =df['Product'],columns = df['MaritalStatus'],margins =␣
↪True,normalize = True ).round(2)
```

[38]:
```
MaritalStatus  Partnered  Single   All
Product
KP281               0.27    0.18  0.44
KP481               0.20    0.13  0.33
KP781               0.13    0.09  0.22
All                 0.59    0.41  1.00
```

Insights

1.The Probability of a treadmill being purchased by a Married Customer is 59%.

The conditional probability of purchasing the treadmill model given that the customer is Married is

- For Treadmill model KP281 - 27%
- For Treadmill model KP481 - 20%
- For Treadmill model KP781 - 13%

2.The Probability of a treadmill being purchased by a Unmarried Customer is 41%.

The conditional probability of purchasing the treadmill model given that the customer is Unmarried is -

- For Treadmill model KP281 - 18%
- For Treadmill model KP481 - 13%
- For Treadmill model KP781 - 9%

6.6 Probability of product purchase w.r.t. Weekly Usage

[39]:
```
pd.crosstab(index =df['Product'],columns = df['Usage'],margins = True,normalize␣
↪= True ).round(2)
```

[39]:

Usage	2	3	4	5	6	7	All
Product							
KP281	0.11	0.21	0.12	0.01	0.00	0.00	0.44
KP481	0.08	0.17	0.07	0.02	0.00	0.00	0.33
KP781	0.00	0.01	0.10	0.07	0.04	0.01	0.22
All	0.18	0.38	0.29	0.09	0.04	0.01	1.00

Insights

1.The Probability of a treadmill being purchased by a customer with Usage 3 per week is 38%.

The conditional probability of purchasing the treadmill model given that the customer has Usage 3 per week is - * For Treadmill model KP281 - 21%

- For Treadmill model KP481 - 17%
- For Treadmill model KP781 - 1%

2.The Probability of a treadmill being purchased by a customer with Usage 4 per week is 29%.

The conditional probability of purchasing the treadmill model given that the customer has Usage 4 per week is - * For Treadmill model KP281 - 12%

- For Treadmill model KP481 - 7%
- For Treadmill model KP781 - 10%

3.The Probability of a treadmill being purchased by a customer with Usage 2 per week is 18%

The conditional probability of purchasing the treadmill model given that the customer has Usage 2 per week is -

- For Treadmill model KP281 - 11%
- For Treadmill model KP481 - 8%
- For Treadmill model KP781 - 0%

6.7 Probability of product purchase w.r.t. Customer Fitness

[40]:
```
pd.crosstab(index =df['Product'],columns = df['Fitness'],margins =␣
↪True,normalize = True ).round(2)
```

[40]:

Fitness	1	2	3	4	5	All
Product						
KP281	0.01	0.08	0.30	0.05	0.01	0.44
KP481	0.01	0.07	0.22	0.04	0.00	0.33
KP781	0.00	0.00	0.02	0.04	0.16	0.22
All	0.01	0.14	0.54	0.13	0.17	1.00

Insights

1.The Probability of a treadmill being purchased by a customer with Average(3) Fitness is 54%.

The conditional probability of purchasing the treadmill model given that the customer has Average Fitness is - * For Treadmill model KP281 - 30%

- For Treadmill model KP481 - 22%
- For Treadmill model KP781 - 2%

2.The Probability of a treadmill being purchased by a customer with Fitness of 2,4,5 is almost 15%.

3.The Probability of a treadmill being purchased by a customer with very low(1) Fitness is only 1%.

6.8 Probability of product purchase w.r.t. weekly mileage

[41]:
```
pd.crosstab(index =df['Product'],columns = df['miles_group'],margins =␣
↪True,normalize = True ).round(2)
```

[41]:
```
miles_group  Light Activity  Moderate Activity  Active Lifestyle  \
Product
KP281                  0.07               0.28              0.10
KP481                  0.03               0.22              0.08
KP781                  0.00               0.04              0.15
All                    0.09               0.54              0.33

miles_group  Fitness Enthusiast   All
Product
KP281                      0.00  0.44
KP481                      0.01  0.33
KP781                      0.03  0.22
All                        0.03  1.00
```

Insights

1.The Probability of a treadmill being purchased by a customer with lifestyle of Light Activity(0 to 50 miles/week) is 9%.

The conditional probability of purchasing the treadmill model given that the customer has Light Activity Lifestyle is -

- For Treadmill model KP281 - 7%
- For Treadmill model KP481 - 3%
- For Treadmill model KP781 - 0%

2.The Probability of a treadmill being purchased by a customer with lifestyle of Moderate Activity(51 to 100 miles/week) is 54%.

The conditional probability of purchasing the treadmill model given that the customer with lifestyle of Moderate Activity is - * For Treadmill model KP281 - 28%

- For Treadmill model KP481 - 22%
- For Treadmill model KP781 - 4%

3.The Probability of a treadmill being purchased by a customer has Active Lifestyle(100 to 200 miles/week) is 33%.

The conditional probability of purchasing the treadmill model given that the customer has Active Lifestyle is - * For Treadmill model KP281 - 10%

- For Treadmill model KP481 - 8%
- For Treadmill model KP781 - 15%

4.The Probability of a treadmill being purchased by a customer who is Fitness Enthusiast(>200 miles/week) is 3% only

7. Customer Profiling

Based on above analysis

1.Probability of purchase of KP281 = 44%

2.Probability of purchase of KP481 = 33%

3.Probability of purchase of KP781 = 22%

4.Customer Profile for KP281 Treadmill:

- Age of customer mainly between 18 to 35 years with few between 35 to 50 years
- Education level of customer 13 years and above
- Annual Income of customer below USD 60,000
- Weekly Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Mileage - 50 to 100 miles 5.Customer Profile for KP481 Treadmill:
- Age of customer mainly between 18 to 35 years with few between 35 to 50 years
- Education level of customer 13 years and above
- Annual Income of customer between USD 40,000 to USD 80,000
- Weekly Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Mileage - 50 to 200 miles

6.Customer Profile for KP781 Treadmill:

- Gender - Male
- Age of customer between 18 to 35 years
- Education level of customer 15 years and above
- Annual Income of customer USD 80,000 and above
- Weekly Usage - 4 to 7 times
- Fitness Scale - 3 to 5
- Weekly Running Mileage - 100 miles and above

8. Recommendations

Marketing Campaigns for KP781

- The KP784 model exhibits a significant sales disparity in terms of gender, with only 18% of total sales attributed to female customers. To enhance this metric, it is recommended to implement targeted strategies such as offering special promotions and trials exclusively designed for the female customers. Affordable Pricing and Payment Plans

- Given the target customer's age, education level, and income, it's important to offer the KP281 and KP481 Treadmill at an affordable price point. Additionally, consider providing flexible payment plans that allow customers to spread the cost over several months. This can make the treadmill more accessible to customers with varying budgets. User-Friendly App Integration

- Create a user-friendly app that syncs with the treadmill. This app could track users' weekly running mileage, provide real-time feedback on their progress, and offer personalized recommendations for workouts based on their fitness scale and goals.This can enhance the overall treadmill experience and keep users engaged.

[ ]:
```

```