Aerofit Case Study done by Akul Vinod

https://colab.research.google.com/drive/1gxExCnwCcUw6fjX_yG0syj72VGIYXmTx#scrollTo=cQpzvnSP0KHf

Question

Raw Problem

Mindset:

Evaluation will be kept lenient, so make sure you attempt this case study. Read the question carefully and try to understand what exactly is being asked. Brainstorm a little. If you're getting an error, remember that Google is your best friend. You can watch the lecture recordings or go through your lecture notes once again if you feel like you're getting confused over some specific topics. Discuss your problems with your peers. Make use of the Slack channel and WhatsApp group. Only if you think that there's a major issue, you can reach out to your Instructor via Slack or Email. There is no right or wrong answer. We have to get used to dealing with uncertainty in business. This is exactly the skill we want to develop.

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.

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.

Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts. For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

Dataset

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:

Dataset link: Aerofit_treadmill.csv

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

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.**

What good looks like?

Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset Detect Outliers (using boxplot, "describe" method by checking the difference between mean and median) Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc) Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or

etc) Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here) Check correlation among different factors using heat maps or pair plots. With all the above steps you can answer questions like: What is the probability of a male customer buying a KP781 treadmill? Customer Profiling - Categorization of users. Probability- marginal, conditional probability. Some recommendations and actionable insights, based on the inferences. Later on, we will see more ways to do "customer segmentation", but this case study in itself is relevant in some real-world scenarios.

Evaluation Criteria

Defining Problem Statement and Analysing basic metrics (10 Points) Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary Non-Graphical Analysis: Value counts and unique attributes (10 Points) Visual Analysis - Univariate & Bivariate (30 Points) For continuous variable(s): Distplot, countplot, histogram for univariate analysis (10 Points) For categorical variable(s): Boxplot (10 Points) For correlation: Heatmaps, Pairplots(10 Points) Missing Value & Outlier Detection (10 Points) Business Insights based on Non-Graphical and Visual Analysis (10 Points) Comments on the range of attributes Comments on the distribution of the variables and relationship between them Comments for each univariate and bivariate plot Recommendations (10 Points) - Actionable items for business. No technical jargon. No complications. Simple action items that everyone can understand

Submission Process:

Type your insights and recommendations in the text editor. Convert your jupyter notebook into PDF (Save as PDF using Chrome browser's Print command), upload it in your Google Drive (set the permission to allow public access), and paste that link in the text editor. Optionally, you may add images/graphs in the text editor by taking screenshots or saving matplotlib graphs using plt.savefig(...). After submitting, you will not be allowed to edit your submission.

Answer

What is Aerofit?

Aerofit is a forward-thinking brand in the fitness industry, rooted in the legacy of M/s. Sachdev Sports Co, a company founded in 1928 by Ram Ratan Sachdev in Hyderabad, India. What began as a regional supplier of sports equipment across Andhra Pradesh and Telangana has grown into a leader in providing cutting-edge fitness solutions.

As the demand for quality fitness equipment increased, M/s. Sachdev Overseas was established to import world-class products under the "Aerofit" brand. The focus remained on offering high-quality, affordable fitness equipment backed by strong post-sales service.

Continuing this legacy of innovation and customer commitment, Nityasach Fitness Pvt Ltd was formed under the leadership of Nityesh Sachdev. With Aerofit at its heart, the company aims to bridge the gap between international fitness technology and the Indian market. By making advanced fitness equipment accessible at competitive prices, Aerofit has reshaped the fitness landscape in India.

Today, Aerofit's diverse product portfolio includes treadmills, exercise bikes, gym equipment, and a wide range of fitness accessories, catering to the needs of fitness enthusiasts across all demographics. With a focus on promoting health, vitality, and customer satisfaction, Aerofit stands as a symbol of quality and innovation in the Indian fitness market.

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

Features of the dataset:

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 shape.

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

Exploratory Data Analysis

In [ ]:

```
#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
```

In [ ]:

```
# loading the dataset
df = pd.read_csv('aerofit.txt')
```

In [ ]:

```
df.head()
```

Out[ ]:

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

In [ ]:

```
df.tail()
```

Out[ ]:

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

In [ ]:

```
df.shape
```

Out[ ]:

```
(180, 9)
```

In [ ]:

```
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

1. **Based on the initial analysis, the dataset consists of 9 features comprising a mix of categorical and numerical data. Additionally, there are no missing values detected across any of the columns.**
2. **The existing data types align appropriately with the values in each column. However, for the purpose of specific analysis or visualization, we will convert the data types of the Usage and Fitness columns to object (string) format.**

Changing the Datatype of Columns

- **Changing the datatype of Usage and Fitness columns**

In [ ]:

```
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
```

In [ ]:

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

Out[ ]:

	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 treadmill emerged as the top-selling model, contributing to roughly 44% of total sales among the three products.**
2. **Gender In the last three months, male customers accounted for approximately 58% of purchases, while female customers made up the remaining 42%.**
3. **Marital Status During the same period, around 60% of the buyers were married, whereas 40% were single.**

In [ ]:

```
df.describe()
```

Out[ ]:

	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**

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**

In [ ]:

```
df.duplicated().value_counts()
```

Out[ ]:

	count
False	180

dtype: int64

Insights

There are no duplicate entries in the dataset

Sanity Check for columns

In [ ]:

```
for i in df.columns:
 print('Unique Values in',i,'column are :-')
 print(df[i].unique())
 print('-'*70)
```

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

Insights

The dataset does not contain any abnormal values

Adding new columns for better analysis

Creating 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:**
5. **Primary Education: upto 12**
6. **Secondary Education: 13 to 15**
7. **Higher Education: 16 and above #Income Column Categorizing the values in Income column in 4 different buckets:**
8. **Low Income - Upto 40,000**
9. **Moderate Income - 40,000 to 60,000**
10. **High Income - 60,000 to 80,000**
11. **Very High Income - Above 80,000 #Miles column Categorizing the values in miles column in 4 different buckets:**
12. **Light Activity - Upto 50 miles**
13. **Moderate Activity - 51 to 100 miles**
14. **Active Lifestyle - 101 to 200 miles**
15. **Fitness Enthusiast - Above 200 miles**

In [ ]:

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

df.head()
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age_group	edu_group	income_group	mi
0	KP281	18	Male	14	Single	3	4	29562	112	Young Adults	Secondary Education	Low Income	
1	KP281	19	Male	15	Single	2	3	31836	75	Young Adults	Secondary Education	Low Income	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Young Adults	Secondary Education	Low Income	

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age_group	edu_group	income_group	mi
3	KP281	19	Male	12	Single	3	3	32973	85	Young Adults	Primary Education	Low Income	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Young Adults	Secondary Education	Low Income	

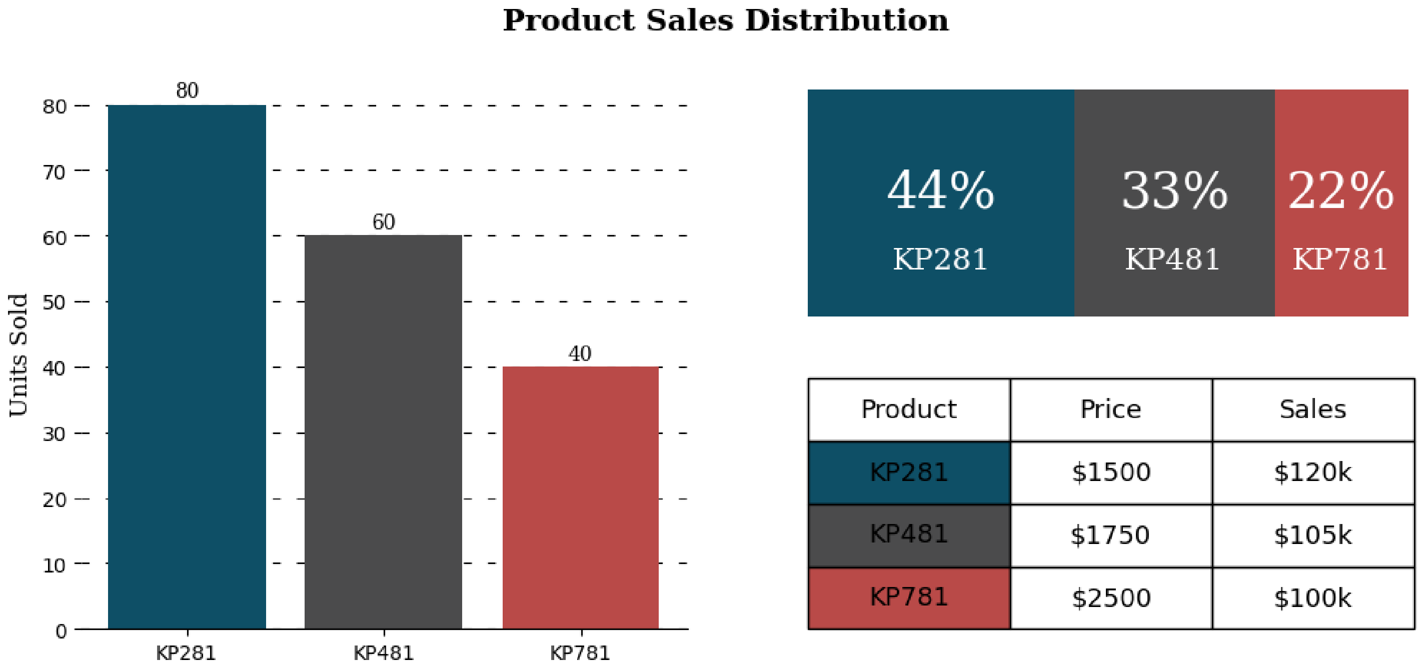
Categorical Variables

1. **Product Sales Distribution**

In [ ]:

```
#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",'#B94A48']
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 = 'cente
r',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 = '#B94
A48')
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):
 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='w
hite')
 ax1.text(product_count['info_percent'][i],-0.2,product_count.index[i],
 va = 'center', ha='center',fontsize=15, fontweight='light', fontfamily='serif',color='w
hite')
#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'],['#B94A48','#
FFFFFF','#FFFFFF']]
table = ax2.table(cellText = product_portfolio, cellColours=color_2d, cellLoc='center',c
```

```
olLabels =['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()
```



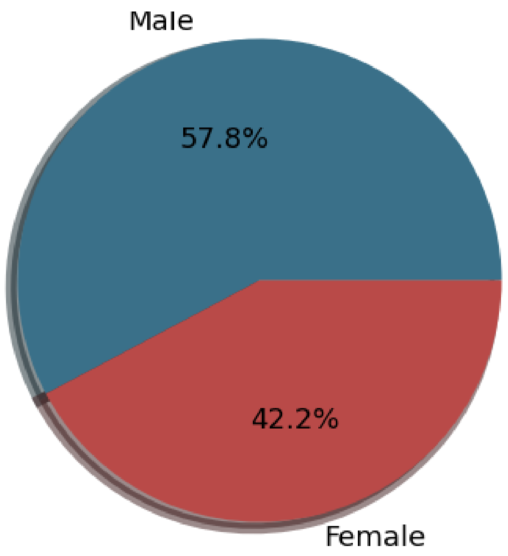
Insights

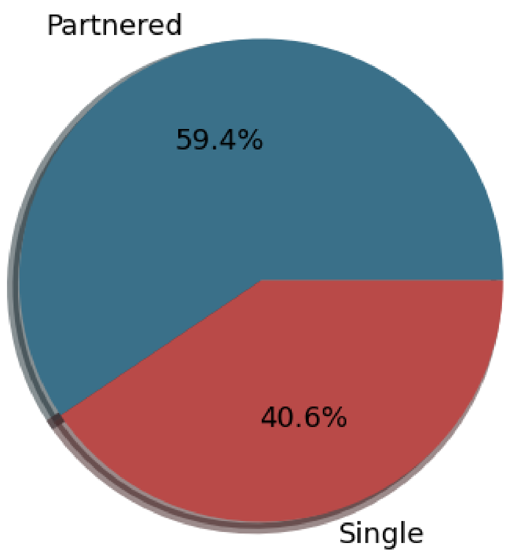
The KP281, designed as an entry-level treadmill, recorded the highest unit sales, followed by the mid-range KP481 and the premium KP781 models. Despite the differences in unit sales, all three models contribute almost equally to the overall sales revenue.

1. **Gender and Marital Status Disribution**

In [ ]:

```
#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", "#b94a48"]
ax0.pie(df['Gender'].value_counts().values,labels = df['Gender'].value_counts().index,au
topct = '%.1f%%',
 shadow = True,colors = color_map,wedgeprops = {'linewidth': 5},textprops={'fontsize': 1
3, '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", "#b94a48"]
ax1.pie(df['MaritalStatus'].value_counts().values,labels = df['MaritalStatus'].value_cou
nts().index,autopct = '%.1f%%',
 shadow = True,colors = color_map,wedgeprops = {'linewidth': 5},textprops={'fontsize': 1
3, 'color': 'black'})
#setting title for visual
ax1.set_title('Marital Status Distribution',{'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



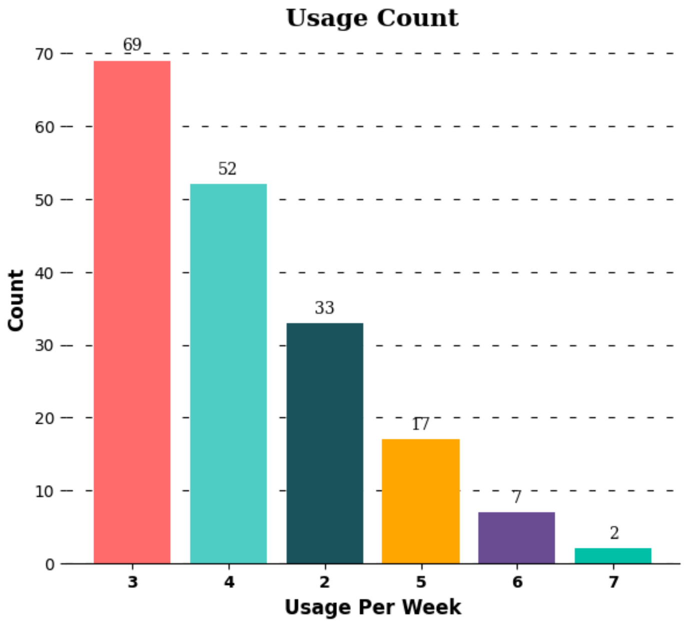


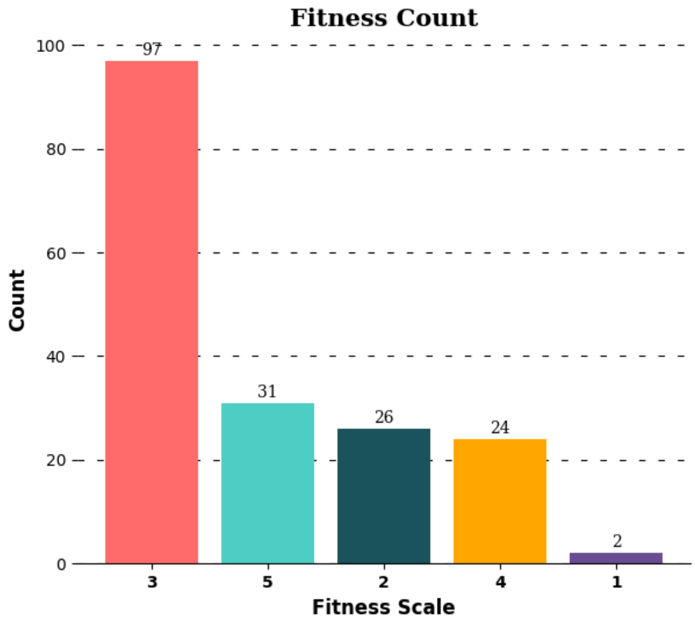
1. **Buyer Fitness and Treadmill Usage**

In [ ]:

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

# updated vibrant color palette
color_map = ["#FF6B6B", "#4ECDC4", "#1A535C", "#FFA600", "#6A4C93", "#00BFA6"]

# creating bar chart for usage distribution
ax0 = fig.add_subplot(gs[0, 0])
temp = df['Usage'].value_counts()
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='cent
er')

# 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)

# axis labels
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')
ax0.set_title('Usage Count', {'font': 'serif', 'size': 15, 'weight': 'bold'})

# 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 = [["#FF6B6B", '#FFFFFF'], ["#4ECDC4", '#FFFFFF'], ["#1A535C", '#FFFFFF'],
            ["#FFA600", '#FFFFFF'], ["#6A4C93", '#FFFFFF'], ["#00BFA6", '#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)
ax1.axis('off')

# creating bar chart for fitness scale
ax2 = fig.add_subplot(gs[0, 1])
temp = df['Fitness'].value_counts()
ax2.bar(x=temp.index, height=temp.values, color=color_map, zorder=2)
```

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

# grid and formatting
ax2.grid(color='black', linestyle='--', axis='y', zorder=0, dashes=(5, 10))
for s in ['top', 'left', 'right']:
    ax2.spines[s].set_visible(False)

ax2.set_ylabel('Count', fontweight='bold', fontsize=12)
ax2.set_xlabel('Fitness Scale', fontweight='bold', fontsize=12)
ax2.set_xticklabels(temp.index, fontweight='bold')
ax2.set_title('Fitness Count', {'font': 'serif', 'size': 15, 'weight': 'bold'})

# info table for fitness
ax1 = fig.add_subplot(gs[1, 1])
fitness_info = [['3', '54%'], ['5', '17%'], ['2', '15%'], ['4', '13%'], ['1', '1%']]
color_2d = [["#FF6B6B", '#FFFFFF'], ["#4ECDC4", '#FFFFFF'], ["#1A535C", '#FFFFFF'],
            ["#FFA600", '#FFFFFF'], ["#6A4C93", '#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)
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

1. **Approximately 85% of customers intend to use the treadmill between 2 to 4 times per week, while only 15% plan to use it 5 times or more weekly.**
2. **A significant 54% of users have rated their fitness level as 3 on a 1–5 scale. Additionally, about 84% have rated themselves 3 or above, reflecting a generally positive self-perception of fitness among customers.**

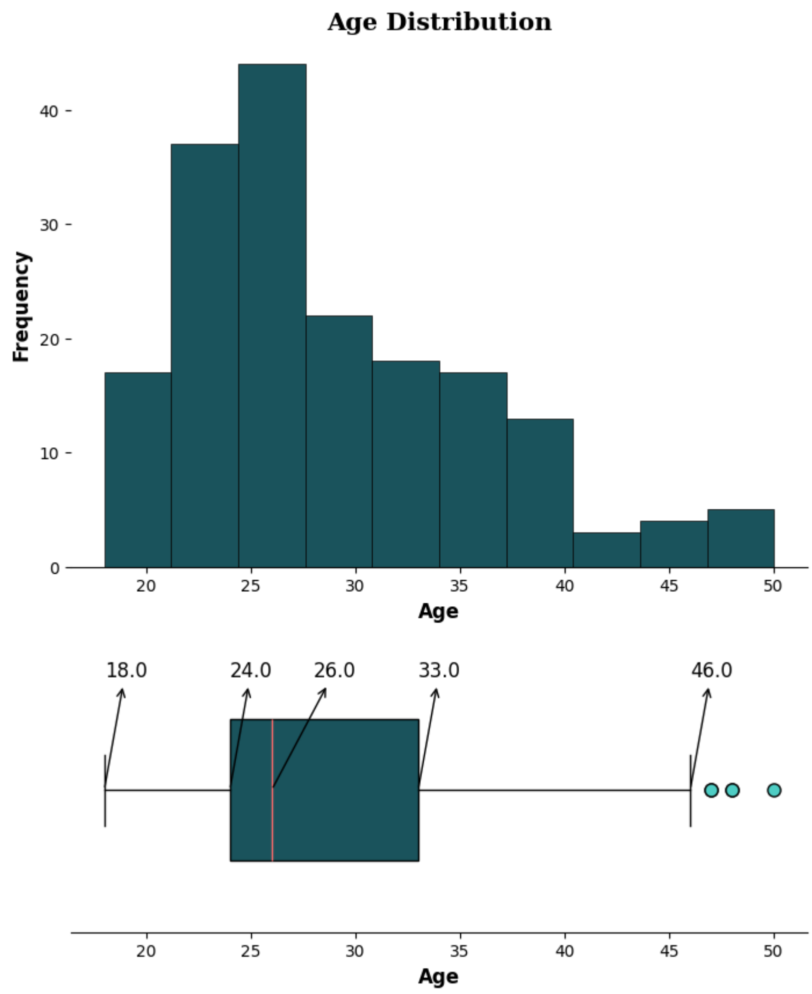
Numerical Variables

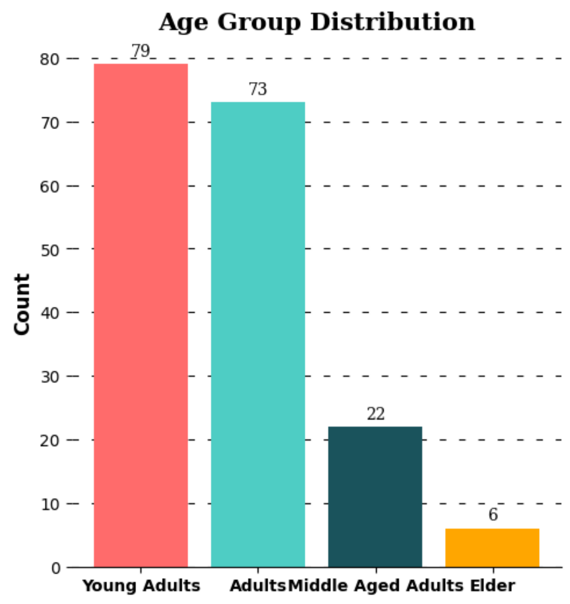
1. **Customer Age Distribution**

In [ ]:

```
# 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='#1A535C', linewidth=0.5, edgecolor='black')  # main histogram
color
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='#1A535C')  # box color
# Customize median line
boxplot['medians'][0].set(color='#FF6B6B')  # median line in bright red
# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor="#4ECDC4")  # teal for outliers

# 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']]  # upper limit, Q1, Q3, lower limit
median = df['Age'].quantile(0.5)  # Q2

for i, j in info:
    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"))

# annotating median separately because it is not 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 palette for bars (4 groups)
color_map = ["#FF6B6B", "#4ECDC4", "#1A535C", "#FFA600"]
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='ce
nter')
```

```
# 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)

# axis labels
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 = [["#FF6B6B", '#FFFFFF', '#FFFFFF'],
            ["#4ECDC4", '#FFFFFF', '#FFFFFF'],
            ["#1A535C", '#FFFFFF', '#FFFFFF'],
            ["#FFA600", '#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()
```





Age	Probability	Group
Young Adults	44%	18 to 25
Adults	41%	26 to 35
Middle Aged	12%	36 to 45
Elder	3%	Above 45

Insights

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

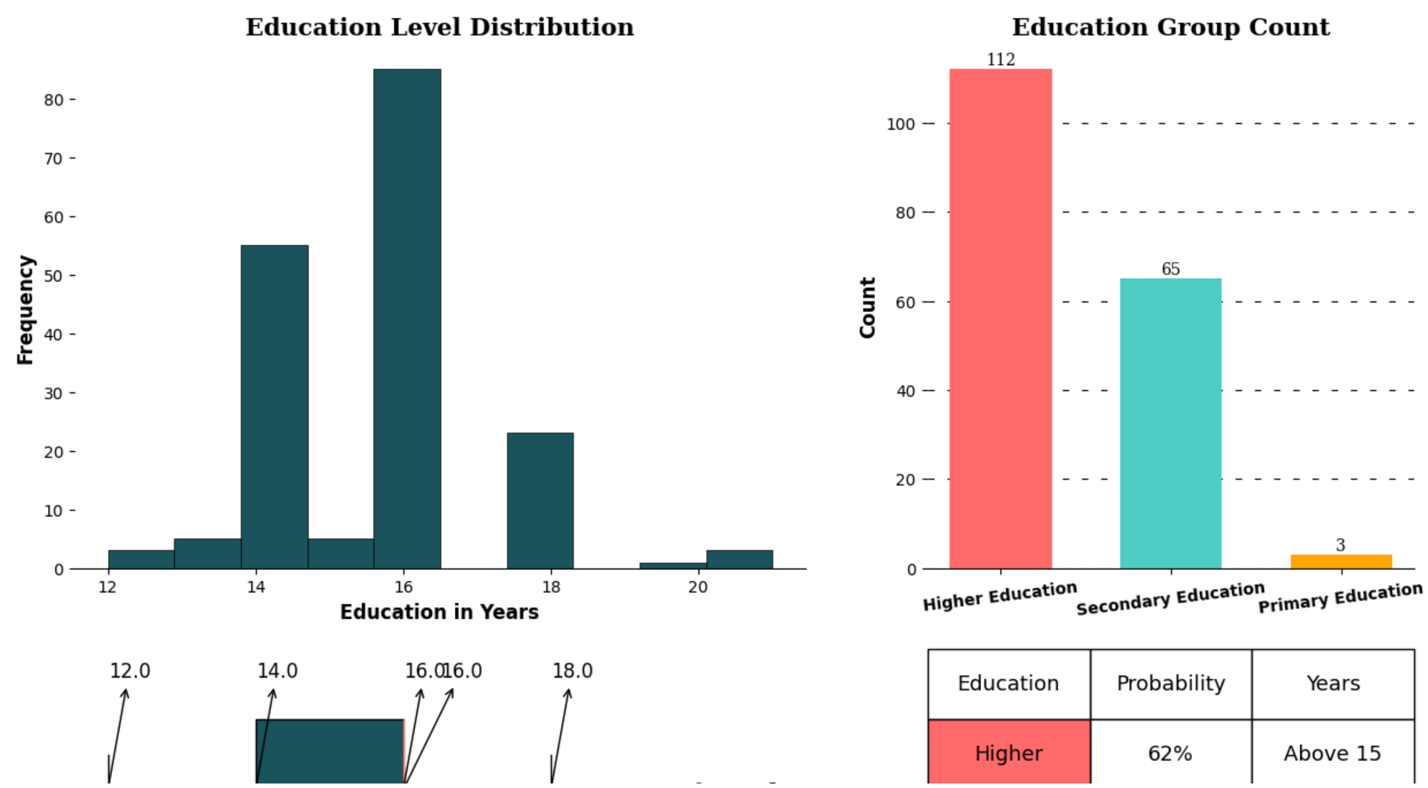
As we can see from the box plot, there are 3 outlier's present in the age data.

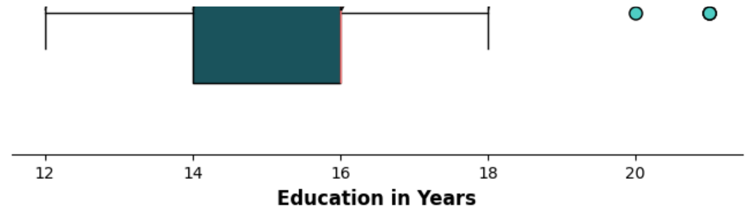
Customer Education Distribution

In [ ]:

```
# 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='#1A535C', linewidth=0.5, edgecolor='black')  # main col
or
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': 'b
old'})

# 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='#1A535C')  # box color
# Customize median line
boxplot['medians'][0].set(color='#FF6B6B')  # median
# Customize outlier markers
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor="#4ECDC4")  # teal outliers

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

for i, j in info:
    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"))

# annotating median separately
ax1.annotate(text=f"{median:.1f}", xy=(median, 1), xytext=(median + 0.5, 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 palette for bars (3 groups)
color_map = ["#FF6B6B", "#4ECDC4", "#FFA600"]
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='ce
nter')

# 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)

# axis labels
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 = [["#FF6B6B", '#FFFFFF', '#FFFFFF'],
            ["#4ECDC4", '#FFFFFF', '#FFFFFF'],
            ["#FFA600", '#FFFFFF', '#FFFFFF']]

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()
```





Secondary	36%	13 to 15
Primary	2%	0 to 12

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

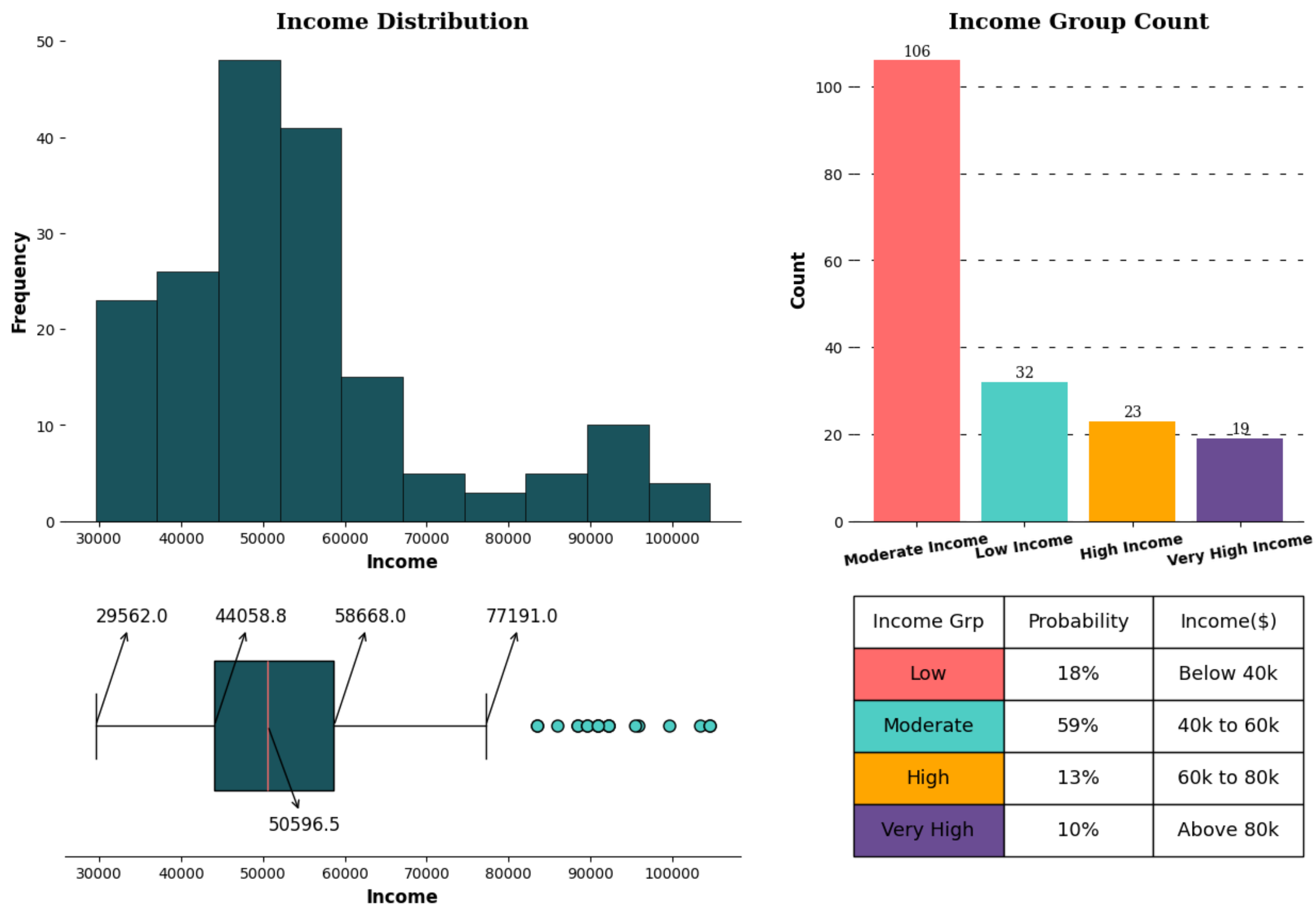
As we can see from the box plot, there are 2 outlier's present in the education data.

Customer Income Distribution

In [ ]:

```
# 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='#1A535C', linewidth=0.5, edgecolor='black')
ax0.set_xlabel('Income', fontsize=12, fontweight='bold')
ax0.set_ylabel('Frequency', fontsize=12, fontweight='bold')
for s in ['top', 'left', 'right']:
    ax0.spines[s].set_visible(False)
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)
boxplot['boxes'][0].set(facecolor='#1A535C')   # main box color
boxplot['medians'][0].set(color='#FF6B6B')      # median line
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor="#4ECDC4")   # outliers

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

# 5-point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']]
median = df['Income'].quantile(0.5)

for i, j in info:
    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"))

ax1.annotate(text=f"{median:.1f}", xy=(median, 1), xytext=(median, 0.6), fontsize=12,
             arrowprops=dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0"))

ax1.set_yticks([])
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 = ["#FF6B6B", "#4ECDC4", "#FFA600", "#6A4C93"]  # 4 groups
```

```
ax2.bar(x=temp.index, height=temp.values, color=color_map, zorder=2)
for i in temp.index:
    ax2.text(i, temp[i] + 2, temp[i], {'font': 'serif', 'size': 10}, ha='center', va='ce
nter')

ax2.grid(color='black', linestyle='--', axis='y', zorder=0, dashes=(5, 10))
for s in ['top', 'left', 'right']:
    ax2.spines[s].set_visible(False)

ax2.set_ylabel('Count', fontweight='bold', fontsize=12)
ax2.set_xticklabels(temp.index, fontweight='bold', rotation=9)
ax2.set_title('Income Group Count', {'font': 'serif', 'size': 15, 'weight': 'bold'})

# creating a table for 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'],
            ['Very High', '10%', 'Above 80k']]

color_2d = [["#FF6B6B", '#FFFFFF', '#FFFFFF'],
            ["#4ECDC4", '#FFFFFF', '#FFFFFF'],
            ["#FFA600", '#FFFFFF', '#FFFFFF'],
            ["#6A4C93", '#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)
ax3.axis('off')

# Bins (unused here, maybe for future binning logic)
bin_range3 = [0, 40000, 60000, 80000, float('inf')]
bin_labels3 = ['Low Income', 'Moderate Income', 'High Income', 'Very High Income']

plt.show()
```



Income Grp	Probability	Income($)
Low	18%	Below 40k
Moderate	59%	40k to 60k
High	13%	60k to 80k
Very High	10%	Above 80k

Insights

1. **A significant 59% of customers belong to the $40k$–60k income group, indicating a strong preference for the products among this segment.**
2. **Interestingly, 18% of customers fall in the below $40kincomegroup, bringingthetotaltoapproximately77$ 60k. In contrast, only 23% of customers have incomes above $60k, highlighting a relatively smaller reach among higher-income segments.**

Outliers

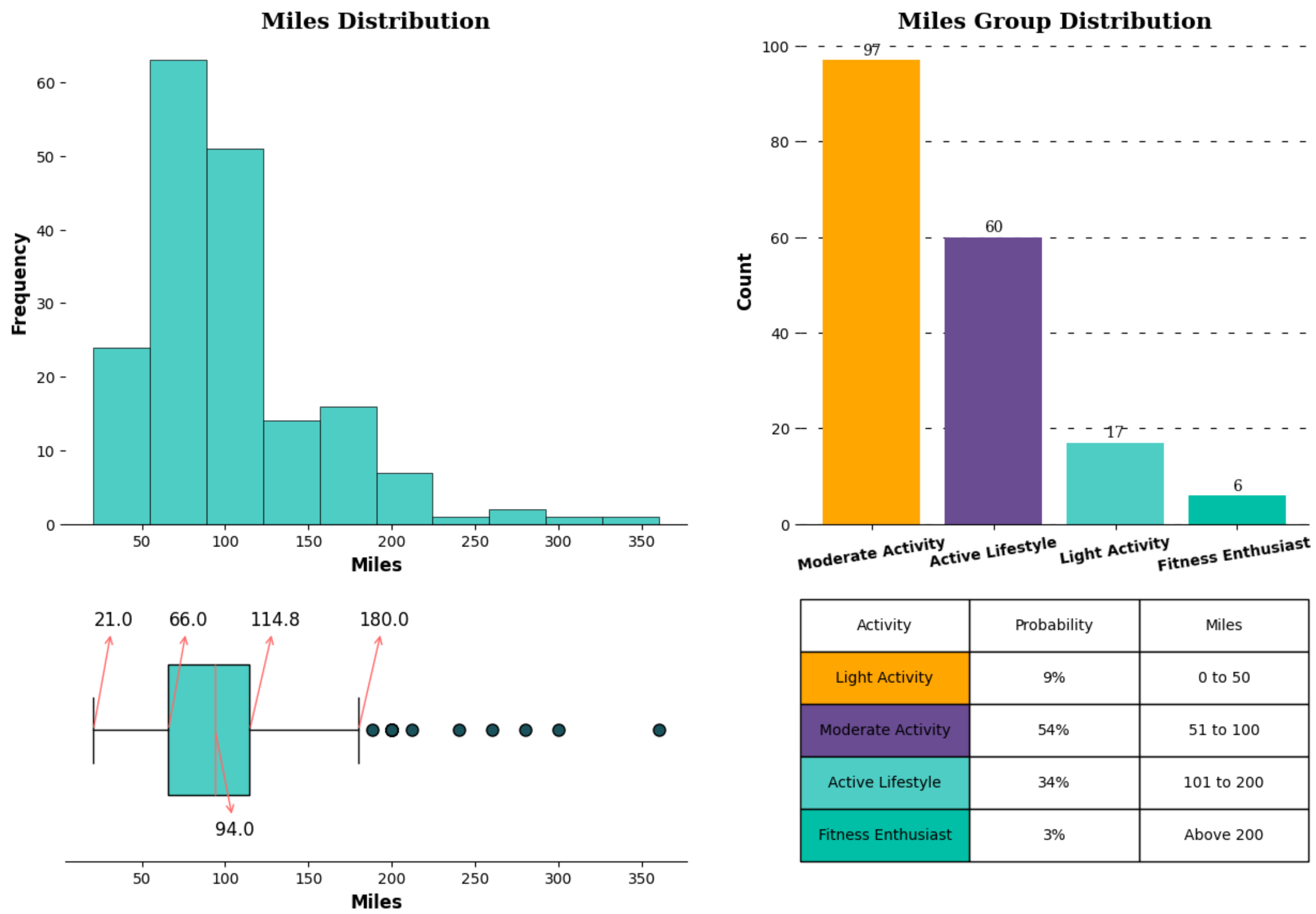
The box plot reveals multiple outliers in the income data, suggesting the presence of unusually high or low income values that deviate significantly from the rest of the distribution.

Customers Expected Weekly Mileage

In [ ]:

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

# Histogram
ax0 = fig.add_subplot(gs[0, 0])
ax0.hist(df['Miles'], color='#4ECDC4', linewidth=0.5, edgecolor='black')
ax0.set_xlabel('Miles', fontsize=12, fontweight='bold')
ax0.set_ylabel('Frequency', fontsize=12, fontweight='bold')
for s in ['top', 'left', 'right']:
    ax0.spines[s].set_visible(False)
ax0.set_title('Miles Distribution', {'font': 'serif', 'size': 15, 'weight': 'bold'})

# Boxplot
ax1 = fig.add_subplot(gs[1, 0])
boxplot = ax1.boxplot(x=df['Miles'], vert=False, patch_artist=True, widths=0.5)
boxplot['boxes'][0].set(facecolor='#4ECDC4')
boxplot['medians'][0].set(color='#FF6B6B')
for flier in boxplot['fliers']:
    flier.set(marker='o', markersize=8, markerfacecolor='#1A535C')
for s in ['top', 'left', 'right']:
    ax1.spines[s].set_visible(False)

info = [i.get_xdata() for i in boxplot['whiskers']]
median = df['Miles'].quantile(0.5)

for i, j in info:
    ax1.annotate(text=f"{i:.1f}", xy=(i, 1), xytext=(i, 1.4), fontsize=12,
                 arrowprops=dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0", col
or='#FF6B6B'))
    ax1.annotate(text=f"{j:.1f}", xy=(j, 1), xytext=(j, 1.4), fontsize=12,
                 arrowprops=dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0", col
or='#FF6B6B'))

ax1.annotate(text=f"{median:.1f}", xy=(median, 1), xytext=(median, 0.6), fontsize=12,
             arrowprops=dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0", color='
#FF6B6B'))
ax1.set_yticks([])
ax1.set_xlabel('Miles', fontweight='bold', fontsize=12)

# Bar Chart
ax2 = fig.add_subplot(gs[0, 1])
temp = df['miles_group'].value_counts()
color_map = ['#FFA600', '#6A4C93', '#4ECDC4', '#00BFA6']  # new custom palette
ax2.bar(x=temp.index, height=temp.values, color=color_map, zorder=2)

for i in temp.index:
    ax2.text(i, temp[i] + 2, temp[i], {'font': 'serif', 'size': 10}, ha='center', va='ce
nter')
```

```
ax2.grid(color='black', linestyle='--', axis='y', zorder=0, dashes=(5, 10))
for s in ['top', 'left', 'right']:
    ax2.spines[s].set_visible(False)

ax2.set_ylabel('Count', fontweight='bold', fontsize=12)
ax2.set_xticklabels(temp.index, fontweight='bold', rotation=9)
ax2.set_title('Miles Group Distribution', {'font': 'serif', 'size': 15, 'weight': 'bold'
})

# Table
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 = [['#FFA600', '#FFFFFF', '#FFFFFF'],
            ['#6A4C93', '#FFFFFF', '#FFFFFF'],
            ['#4ECDC4', '#FFFFFF', '#FFFFFF'],
            ['#00BFA6', '#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)
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 .

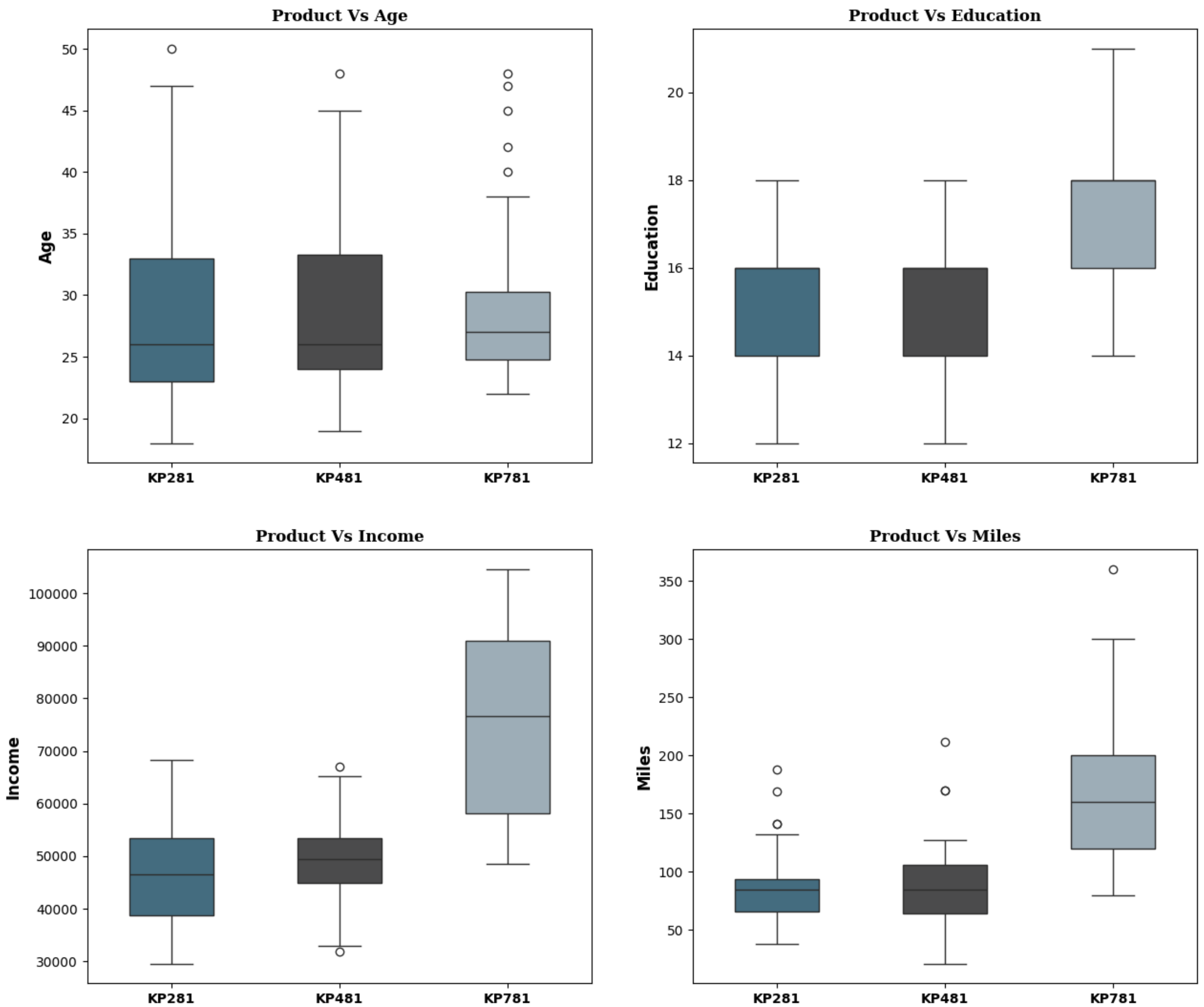
Outliers

As we can see from the box plot, there are 8 outlier's present in the miles data.

Analysis of Product Type

In [ ]:

```
#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

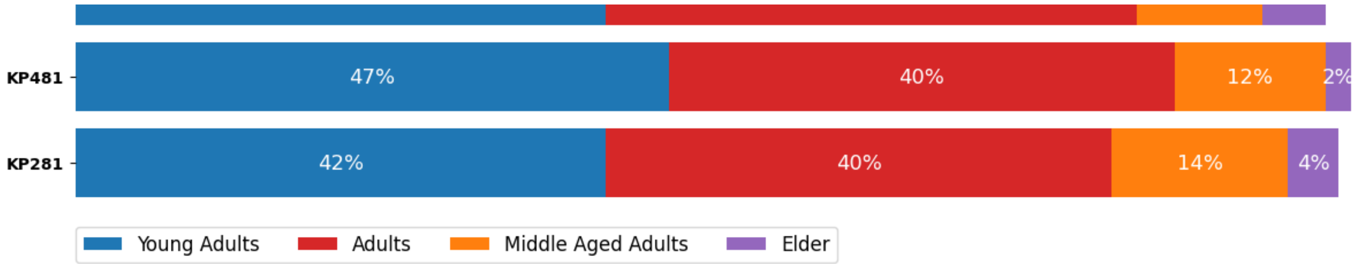
The analysis presented above clearly indicates a strong preference for the treadmill model KP781 among

customers who possess higher education, higher income levels, and intend to engage in running activities exceeding 150 miles per week.

Product Preferences Across Age

In [ ]:

```
# Create figure
fig, ax0 = plt.subplots(figsize=(15, 3))

# Column of interest
val = 'age_group'

# Create required df
df_grp = (
    df.groupby('Product')[val]
    .value_counts(normalize=True)
    .round(2)
    .reset_index(name='proportion')
)

# Pivoting the DataFrame
df_grp = df_grp.pivot(index='Product', columns=val, values='proportion')

# Color map: Blue, Red, Orange, Purple
color_map = ["#1f77b4", "#d62728", "#ff7f0e", "#9467bd"]  # blue, red, orange, purple

# Ensure enough colors for columns
if len(color_map) < len(df_grp.columns):
    raise ValueError("Add more colors to match number of age group categories.")

# Initial offset
temp = np.zeros(len(df_grp), dtype=float)

# Horizontal stacked bars
for i, color in zip(df_grp.columns, color_map):
    ax0.barh(df_grp.index, width=df_grp[i], left=temp, label=i, color=color)
    temp += df_grp[i].fillna(0).values

# Insert text labels
temp = np.zeros(len(df_grp), dtype=float)
for i in df_grp.columns:
    for j, k in enumerate(df_grp[i]):
        if pd.isna(k) or k == 0:
            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].fillna(0).values

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

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

# Title
ax0.set_title('Product Vs Age Group', fontdict={'font': 'serif', 'size': 15, 'weight': 'bold'})

# Legend
ax0.legend(loc=(0, -0.2), ncol=4, fontsize=12)

# Show plot
plt.show()
```



Insights

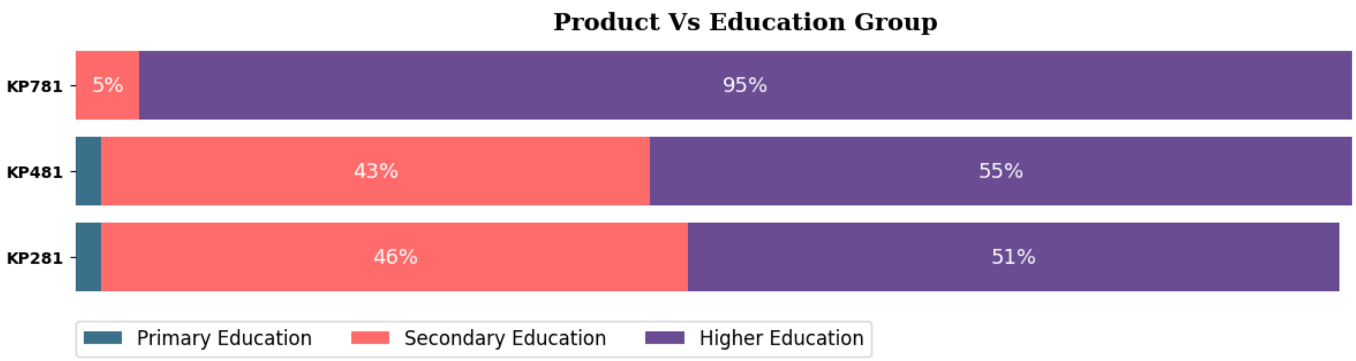
The analysis provided above distinctly demonstrates that there exists no strong correlation between age groups and product preferences. This is evident from the nearly uniform distribution of age groups across all the products.

Product Preferences Across Education Levels

In [ ]:

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

# Plot setup
fig, ax0 = plt.subplots(figsize=(15, 3))

# Value to analyze
val = 'edu_group'

# Create grouped DataFrame
df_grp = (
    df.groupby('Product')[val]
    .value_counts(normalize=True)
    .round(2)
    .reset_index(name='proportion')
)

# Pivoting for visualization
df_grp = df_grp.pivot(index='Product', columns=val, values='proportion')

# Define color map (Blue, Red, Purple)
color_map = ["#3A7089", "#FF6B6B", "#6A4C93"]

# Ensure color list matches column count
if len(color_map) < len(df_grp.columns):
    raise ValueError("Add more colors to match number of education groups.")

# Initial offset
temp = np.zeros(len(df_grp), dtype=float)

# Plot horizontal stacked bars
for i, color in zip(df_grp.columns, color_map):
    ax0.barh(df_grp.index, width=df_grp[i].fillna(0), left=temp, label=i, color=color)
    temp += df_grp[i].fillna(0).values

# Add text labels
temp = np.zeros(len(df_grp), dtype=float)
for i in df_grp.columns:
    for j, k in enumerate(df_grp[i]):
        if pd.isna(k) or 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].fillna(0).values

# Clean up axis lines
for s in ['top', 'left', 'right', 'bottom']:
```

```
    ax0.spines[s].set_visible(False)

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

# Title
ax0.set_title('Product Vs Education Group', fontdict={'font': 'serif', 'size': 15, 'weig
ht': 'bold'})

# Add legend
ax0.legend(loc=(0, -0.2), ncol=3, fontsize=12)

# Show plot
plt.show()
```



Insights

- **The analysis provided above cleary demonstrates the preference of Highly Educated people for treadmill model KP781**
- **For treadmill models KP481 and KP281 , the distribution of customer with Secondary Education and with Higher Education is almost equal**

Gender vs Product Usage And Gender Vs Fitness

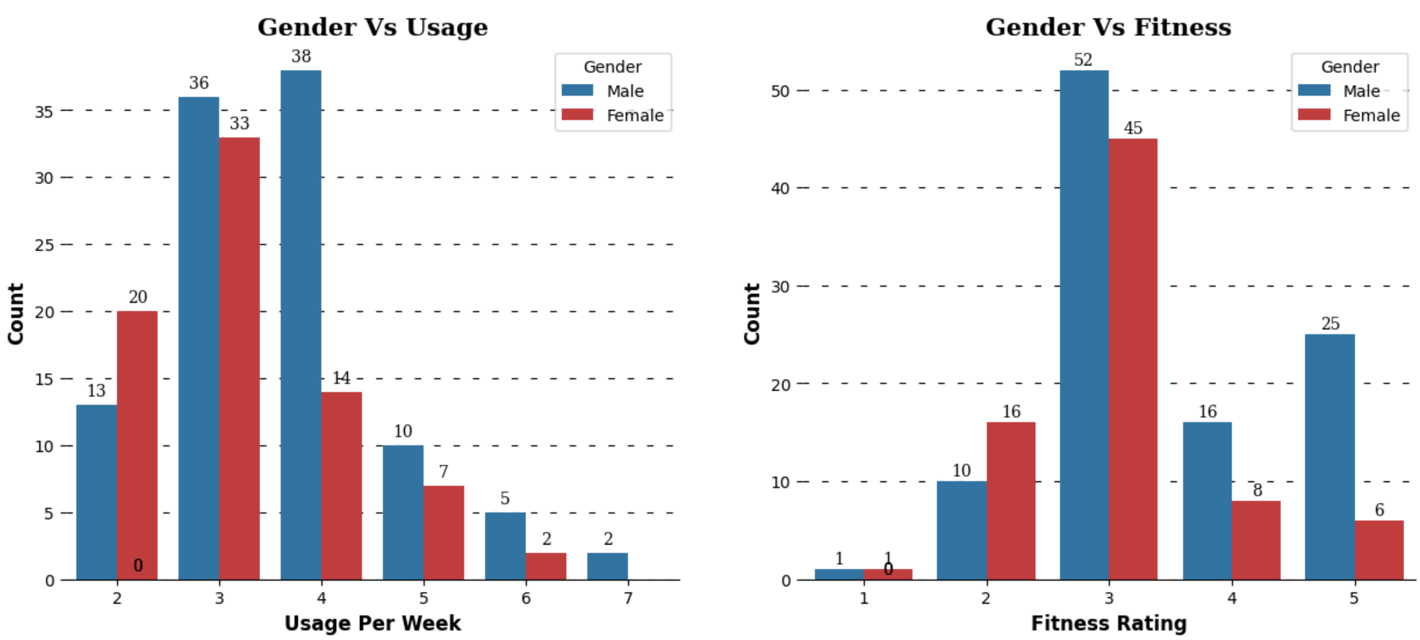
In [ ]:

```
# 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=["#1f77b4", "#d62728"],  # Blue and Red
    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
for s in ['top', 'left', 'right']:
```

```
    ax1.spines[s].set_visible(False)

# adding axis labels
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=["#1f77b4", "#d62728"],  # Blue and Red
    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'})
```

Out[ ]:

```
Text(0.5, 1.0, 'Gender Vs Fitness')
```



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**

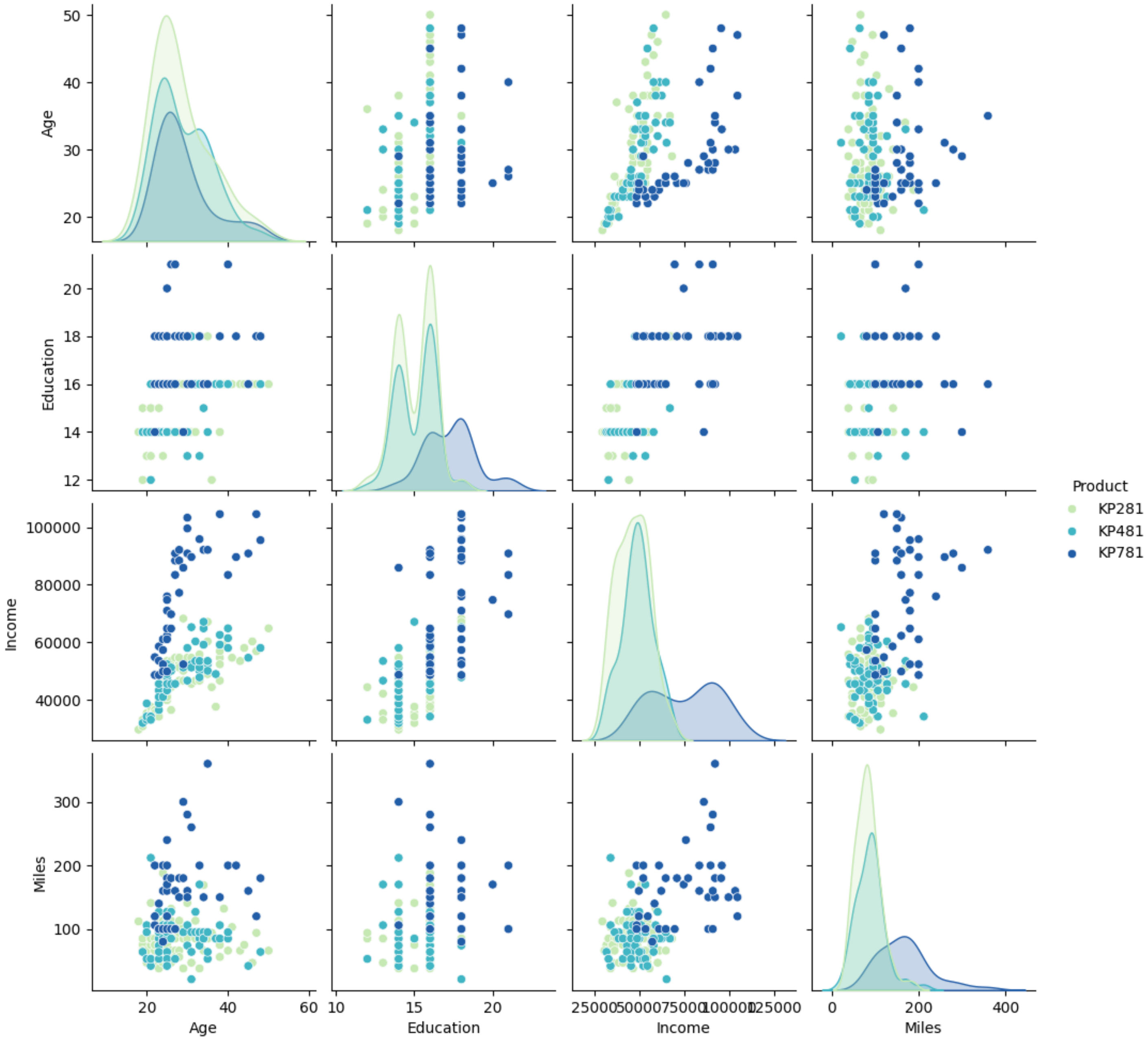
Pairplot

In [ ]:

```
df_copy = copy.deepcopy(df)
```

In [ ]:

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



Heatmap

In [ ]:

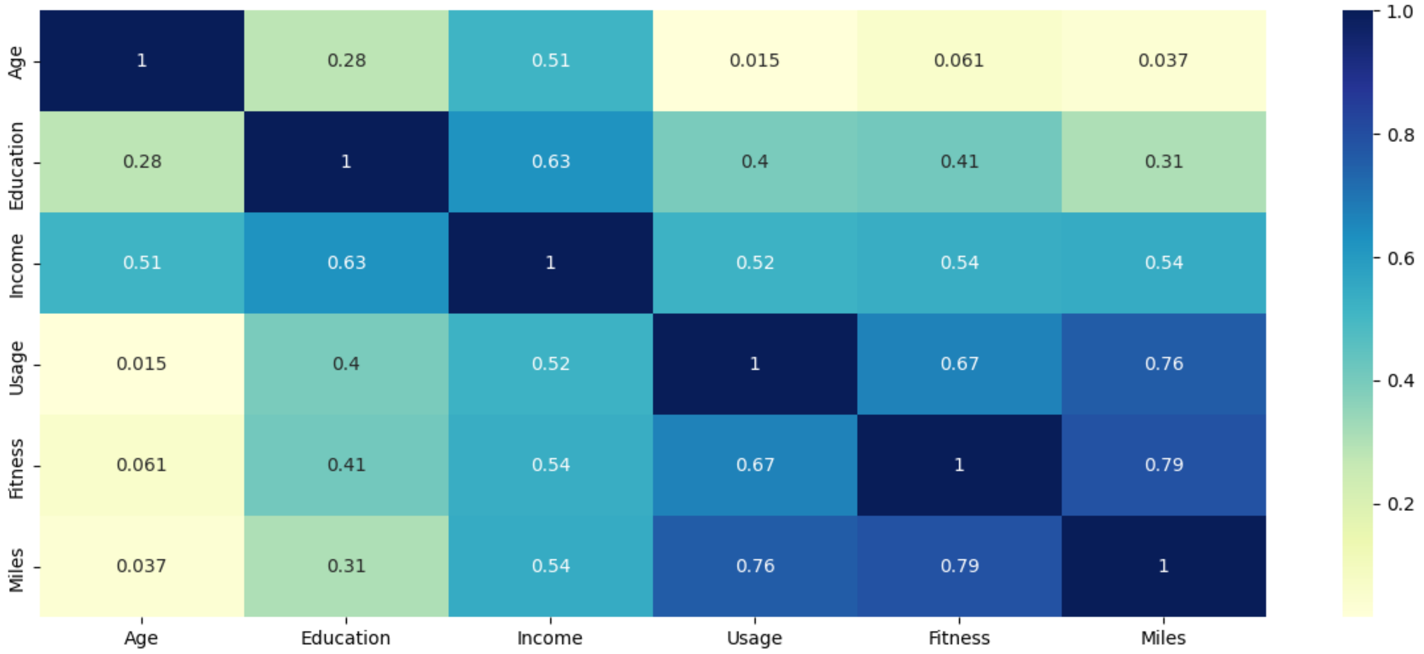
```
df_copy['Usage'] = df_copy['Usage'].astype('int')
df_copy['Fitness'] = df_copy['Fitness'].astype('int')
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 12 columns):
```

```
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
```

In [ ]:

```
numerical_df_copy = df_copy[['Age', 'Education', 'Income', 'Usage', 'Fitness', 'Miles']]

corr_mat = numerical_df_copy.corr()
plt.figure(figsize=(15,6))
sns.heatmap(corr_mat,annot = True, cmap="YlGnBu")
plt.show()
```



Insights

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

Probability of product purchase w.r.t. gender

In [ ]:

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

Out[ ]:

Gender	Female	Male	All
Product			
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

1. **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**
- **For Treadmill model KP281 - 22%**
- **For Treadmill model KP481 - 16%**
- **For Treadmill model KP781 - 4%**

1. **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 -**
- **For Treadmill model KP281 - 22%**
- **For Treadmill model KP481 - 17%**
- **For Treadmill model KP781 - 18%**

Probability of product purchase w.r.t. Age

In [ ]:

```
pd.crosstab(index =df['Product'],columns = df['age_group'],margins = True,normalize = Tr
ue ).round(2)
```

Out[ ]:

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%**

1. **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%**

1. **The Probability of a treadmill being purchased by a Middle Aged(36-45) is 12%**

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

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

In [ ]:

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

Out[ ]:

edu_group Product	Primary Education	Secondary Education	Higher Education	All
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%

1. 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%

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

Probability of product purchase w.r.t. Income

In [ ]:

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

Out[ ]:

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

income_group	Low Income	Moderate Income	High Income	Very High Income	All

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%

1. 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%

1. 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%

1. 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%

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

In [ ]:

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

Out[ ]:

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%

1. 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%

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

In [ ]:

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

Out[ ]:

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%

1. 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%

1. 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%

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

In [ ]:

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

Out[ ]:

Fitness	1	2	3	4	5	All

Fitness Product	1	2	3	4	5	All
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%**

1. **The Probability of a treadmill being purchased by a customer with Fitness of 2,4,5 is almost 15% .**
2. **The Probability of a treadmill being purchased by a customer with very low(1) Fitness is only 1% .**

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

In [ ]:

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

Out[ ]:

miles_group Product	Light Activity	Moderate Activity	Active Lifestyle	Fitness Enthusiast	All
KP281	0.07	0.28	0.10	0.00	0.44
KP481	0.03	0.22	0.08	0.01	0.33
KP781	0.00	0.04	0.15	0.03	0.22
All	0.09	0.54	0.33	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%**

1. **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%**

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

1. 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%

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

Customer Profiling

Based on above analysis

- Probability of purchase of KP281 = 44%
- Probability of purchase of KP481 = 33%
- Probability of purchase of KP781 = 22%

1. 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

1. 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

1. 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

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, 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.