Aerofit Business Case Study - Descriptive Statistics & Probability (Pavithran)

About

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.

In [485…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import math
from scipy.stats import binom
import warnings
warnings.filterwarnings("ignore")
```

In [486…

```
df = pd.read_csv("aerofit_treadmill.csv")
df.head(5)
```

Out[486…

	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

Features of the dataset:

- **Product:** 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.
- **Fitness:** Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.
- **Income:** Annual income (in $)
- **Miles:** The average number of miles the customer expects to walk/run each week

Product Portfolio:

- **KP281:** It is an entry-level treadmill that sells for $1,500.
- **KP481:** This is for mid-level runners that sell for $1,750.
- **KP781:** This treadmill is having advanced features that sell for $2,500.

Finding Shape of the DataFrame

In [487…

```
df.shape
```

Out[487…

```
(180, 9)
```

Using df.shape we come to know the given dataset have 180 rows and 9 columns

In [488…

```
df.ndim
```

Out[488… 2

Using df.ndim we come to know the given dataset is a 2dimnesion

Finding Data Types of each column

In [489…
```
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
```

Using df.info we come to know the data type of each series

Most of the series is in **Integer** datatype and Product, Gender, MaritalStatus are in **Object** datatype format

Finding Null Values in the Dataset

In [490…
```
df.isnull().sum()
```

Out[490…
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Before Exploratry Data Analysis we have to clean the given data set if it contains null values.

We found that there are no null (or) missing values

Unique Attributes & Value_Counts of each Columns

In [491…
```
for i in df.columns:
    print(f"Unique Value of {i}:")
    print(df[i].unique())
    print("-"*50)
    print(f"Total No of {i}: ", df[i].nunique())
    print("-"*50)
    print(f"Value Count of {i}:")
    print(df[i].value_counts().sort_values(ascending= False).head(5))
    print("-"*50)
    print()
```

```
Unique Value of Product:
['KP281' 'KP481' 'KP781']
--------------------------------------------------
Total No of Product:  3
--------------------------------------------------
Value Count of Product:
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Age:
[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 43 44 46 47 50 45 48 42]
--------------------------------------------------
Total No of Age:  32
--------------------------------------------------
Value Count of Age:
Age
25    25
23    18
24    12
26    12
28     9
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Gender:
['Male' 'Female']
--------------------------------------------------
Total No of Gender:  2
--------------------------------------------------
Value Count of Gender:
Gender
Male      104
Female     76
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Education:
[14 15 12 13 16 18 20 21]
--------------------------------------------------
Total No of Education:  8
--------------------------------------------------
Value Count of Education:
Education
16    85
14    55
18    23
15     5
13     5
Name: count, dtype: int64
--------------------------------------------------

Unique Value of MaritalStatus:
['Single' 'Partnered']
--------------------------------------------------
Total No of MaritalStatus:  2
--------------------------------------------------
Value Count of MaritalStatus:
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Usage:
[3 2 4 5 6 7]
--------------------------------------------------
Total No of Usage:  6
--------------------------------------------------
Value Count of Usage:
Usage
3    69
4    52
2    33
5    17
6     7
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Fitness:
[4 3 2 1 5]
--------------------------------------------------
Total No of Fitness:  5
```

```
--------------------------------------------------
Value Count of Fitness:
Fitness
3    97
5    31
2    26
4    24
1     2
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Income:
[ 29562  31836  30699  32973  35247  37521  36384  38658  40932  34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]
--------------------------------------------------
Total No of Income:  62
--------------------------------------------------
Value Count of Income:
Income
45480    14
52302     9
46617     8
54576     8
53439     8
Name: count, dtype: int64
--------------------------------------------------

Unique Value of Miles:
[112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]
--------------------------------------------------
Total No of Miles:  37
--------------------------------------------------
Value Count of Miles:
Miles
85    27
95    12
66    10
75    10
47     9
Name: count, dtype: int64
--------------------------------------------------
```

Insights:

- There are 3 variaties of Treadmill available.
- Most Purchased product is KP281.
- 32 Unique Age groups available.
- 104 Male Customers and 76 Female Customers.
- There are total 8 unique educational levels.
- 107 buyers are married and 73 buyers are single.
- Most customers use the treadmill atleast 3 times per week.
- the highest fitness rating is 3.

Seprating the Products into Seprate dataframes

In [492…

```
# Seperating the products as a new dataframe
df_KP281 = df[df["Product"]== "KP281"]
df_KP281.head(5)
```

Out[492…

	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 [493…

```
# Seperating the products as a new dataframe
df_KP481 = df[df["Product"]== "KP481"]
df_KP481.head(5)
```

Out[493...

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
80	KP481	19	Male	14	Single	3	3	31836	64
81	KP481	20	Male	14	Single	2	3	32973	53
82	KP481	20	Female	14	Partnered	3	3	34110	106
83	KP481	20	Male	14	Single	3	3	38658	95
84	KP481	21	Female	14	Partnered	5	4	34110	212

In [494...

```
# Seperating the products as a new dataframe
df_KP781 = df[df["Product"]== "KP781"]
df_KP781.head(5)
```

Out[494...

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
140	KP781	22	Male	14	Single	4	3	48658	106
141	KP781	22	Male	16	Single	3	5	54781	120
142	KP781	22	Male	18	Single	4	5	48556	200
143	KP781	23	Male	16	Single	4	5	58516	140
144	KP781	23	Female	18	Single	5	4	53536	100

Statistical Summary

Descriptive Analysis:

In [495...

```
print("\nStatistical Summary:")
df.describe()
```

```
Statistical Summary:
```

Out[495...

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

Insights:

- Age: The mean age of customers is 29, median age is 26, Starting age of customers is 18, Maximum age of customers is 50.
- Education: Customers minimum educated years is 12, maximum educated years is 21, mean and median educated years is 16.
- Usage: The Minimum usage is 2 times a week, maximum usage is 7 times a week, mean usage is 3.5 times a week and median usage is 3 times a week.
- Fitness: The mean rating for the fitness is 3.3 and median rating for the fitness is 3.
- Income: The mean income of customers is 53k, minimum income of customers is 29k, maximum income of customers is 104k and median income is 50k.
- Miles: Customers walk/run on average of 103 miles, median of 94 miles, minimum of 21 miles and maximum of 360 miles in a week.

In [496...

```
print("\nStatistical Summary:")
print(df.describe(include = object))
```

```
Statistical Summary:
       Product Gender MaritalStatus
count      180    180           180
unique       3      2             2
top      KP281   Male     Partnered
freq        80    104           107
```

Insights:

- Product: 44% of the sales comes from the product KP281.
- Gender: 58% of the customers is male and 42% is female.
- MaritalStatus: About 60% of the buyers were married and 40% were single.

Statistical Summary Product Wise

In [497…

```
print("\nStatistical Summary for KP281:")
print(df_KP281.describe())
print("*"*75)
print("\nStatistical Summary for KP481:")
print(df_KP481.describe())
print("*"*75)
print("\nStatistical Summary for KP781:")
print(df_KP781.describe())
print("*"*75)
```

```
Statistical Summary for KP281:
             Age  Education      Usage  Fitness        Income       Miles
count  80.000000  80.000000  80.000000  80.00000     80.00000   80.000000
mean   28.550000  15.037500   3.087500   2.96250  46418.02500   82.787500
std     7.221452   1.216383   0.782624   0.66454   9075.78319   28.874102
min    18.000000  12.000000   2.000000   1.00000  29562.00000   38.000000
25%    23.000000  14.000000   3.000000   3.00000  38658.00000   66.000000
50%    26.000000  16.000000   3.000000   3.00000  46617.00000   85.000000
75%    33.000000  16.000000   4.000000   3.00000  53439.00000   94.000000
max    50.000000  18.000000   5.000000   5.00000  68220.00000  188.000000
***************************************************************************

Statistical Summary for KP481:
             Age  Education      Usage  Fitness         Income       Miles
count  60.000000  60.000000  60.000000  60.00000      60.000000   60.000000
mean   28.900000  15.116667   3.066667   2.90000   48973.650000   87.933333
std     6.645248   1.222552   0.799717   0.62977    8653.989388   33.263135
min    19.000000  12.000000   2.000000   1.00000   31836.000000   21.000000
25%    24.000000  14.000000   3.000000   3.00000   44911.500000   64.000000
50%    26.000000  16.000000   3.000000   3.00000   49459.500000   85.000000
75%    33.250000  16.000000   3.250000   3.00000   53439.000000  106.000000
max    48.000000  18.000000   5.000000   4.00000   67083.000000  212.000000
***************************************************************************

Statistical Summary for KP781:
             Age  Education      Usage    Fitness         Income       Miles
count  40.000000  40.000000  40.000000  40.000000       40.00000   40.000000
mean   29.100000  17.325000   4.775000   4.625000    75441.57500  166.900000
std     6.971738   1.639066   0.946993   0.667467    18505.83672   60.066544
min    22.000000  14.000000   3.000000   3.000000    48556.00000   80.000000
25%    24.750000  16.000000   4.000000   4.000000    58204.75000  120.000000
50%    27.000000  18.000000   5.000000   5.000000    76568.50000  160.000000
75%    30.250000  18.000000   5.000000   5.000000    90886.00000  200.000000
max    48.000000  21.000000   7.000000   5.000000   104581.00000  360.000000
***************************************************************************
```

In [498…

```
print("\nStatistical Summary for KP281:")
print(df_KP281.describe(include = object))
print("*"*36)
print("\nStatistical Summary for KP481:")
print(df_KP481.describe(include = object))
print("*"*36)
print("\nStatistical Summary for KP781:")
print(df_KP781.describe(include = object))
print("*"*36)
```

```
Statistical Summary for KP281:
       Product Gender MaritalStatus
count       80     80            80
unique       1      2             2
top      KP281   Male     Partnered
freq        80     40            48
************************************

Statistical Summary for KP481:
       Product Gender MaritalStatus
count       60     60            60
unique       1      2             2
top      KP481   Male     Partnered
freq        60     31            36
************************************

Statistical Summary for KP781:
       Product Gender MaritalStatus
count       40     40            40
unique       1      2             2
top      KP781   Male     Partnered
freq        40     33            23
************************************
```

Feature Engineering/Creating New Columns

Converting Categorical Attributes to Category

New Column for Age Group

In [499…

```
age_bins= [17,29,45,df["Age"].max()]
age_label = ["Adult", "Middle_Aged", "Old"]
df["Age_group"] = pd.cut(df["Age"], bins = age_bins, labels = age_label)
df.head()
```

Out[499…

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

- Categorizing the Age Column into 3 Catagory.
- Adult: 18 - 29.
- Middle_Aged: 30 - 45.
- Old: 46 and Above.

New Column for Usage Group

In [500…

```
usage_bins= [1,3,5,7]
usage_label = ["Low_Usage", "Medium_Usage", "High_Usage"]
df["Usage_group"] = pd.cut(df["Usage"], bins = usage_bins, labels = usage_label)
df.head()
```

Out[500…

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

- Categorizing the Usage Column into 3 Catagory.
- Low_Usage: 2 - 3 Usage Per Week.
- Medium_Usage: 4 - 5 Usage Per Week.
- High_Usage: 6 - 7 Usage Per Week.

New Column for Fitness Group

In [501…

```
fitness_bins= [0,2,3,5]
fitness_label = ["Low_Fitness", "Medium_Fitness", "High_Fitness"]
df["Fitness_group"] = pd.cut(df["Fitness"], bins = fitness_bins, labels = fitness_label)
df.head()
```

Out[501…

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

- Categorizing the Fitness Column into 3 Catagory.
- Low_Fitness: 0 - 2 Ratings.
- Medium_Fitness: 3 Ratings.
- High_Fitness: 4 - 5 Ratings.

New Column for Income Group

In [502…

```
income_bins= [0,40000,70000,df["Income"].max()]
income_label = ["Low_Income", "Medium_Income", "High_Income"]
df["Income_group"] = pd.cut(df["Income"], bins = income_bins, labels = income_label)
df.head()
```

Out[502…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_g
0	KP281	18	Male	14	Single	3	4	29562	112	Adult	Low_Usage	High_Fitness	Low_Inc
1	KP281	19	Male	15	Single	2	3	31836	75	Adult	Low_Usage	Medium_Fitness	Low_Inc
2	KP281	19	Female	14	Partnered	4	3	30699	66	Adult	Medium_Usage	Medium_Fitness	Low_Inc
3	KP281	19	Male	12	Single	3	3	32973	85	Adult	Low_Usage	Medium_Fitness	Low_Inc
4	KP281	20	Male	13	Partnered	4	2	35247	47	Adult	Medium_Usage	Low_Fitness	Low_Inc

- Categorizing the Income Column into 3 Catagory.
- Low_Income: $0-40000$.
- Medium_Income: $40001-70000$.
- High_Income: Above 70000$.

New Column for Miles Group

In [503…

```
miles_bins= [0,50,100,200,df["Miles"].max()]
miles_label = ["Low_Activity", "Medium_Activity", "High_Activity", "VeryHigh_Activity"]
df["Miles_group"] = pd.cut(df["Miles"], bins = miles_bins, labels = miles_label)
df.head()
```

Out[503…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_g
0	KP281	18	Male	14	Single	3	4	29562	112	Adult	Low_Usage	High_Fitness	Low_Inc
1	KP281	19	Male	15	Single	2	3	31836	75	Adult	Low_Usage	Medium_Fitness	Low_Inc
2	KP281	19	Female	14	Partnered	4	3	30699	66	Adult	Medium_Usage	Medium_Fitness	Low_Inc
3	KP281	19	Male	12	Single	3	3	32973	85	Adult	Low_Usage	Medium_Fitness	Low_Inc
4	KP281	20	Male	13	Partnered	4	2	35247	47	Adult	Medium_Usage	Low_Fitness	Low_Inc

- Categorizing the Miles Column into 4 Catagory.
- Low_Activity: 0 - 50 Miles Per Week.
- Medium_Activity: 51 - 100 Miles Per Week.
- High_Activity: 101 - 200 Miles Per Week.
- VeryHigh_Activity: Above 200 Miles Per Week

New Column for Product Price

In [504…
```
# Creating a function to give product price in a new column:
def product_price(x):
    if x == "KP281":
        return 1500
    elif x == "KP481":
        return 1750
    else:
        return 2500
```

In [505…
```
#using apply function we are giving the sales value of each product
df["Product_price"] = df["Product"].apply(lambda x: product_price(x))
df.head()
```

Out[505…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_g
0	KP281	18	Male	14	Single	3	4	29562	112	Adult	Low_Usage	High_Fitness	Low_In
1	KP281	19	Male	15	Single	2	3	31836	75	Adult	Low_Usage	Medium_Fitness	Low_In
2	KP281	19	Female	14	Partnered	4	3	30699	66	Adult	Medium_Usage	Medium_Fitness	Low_In
3	KP281	19	Male	12	Single	3	3	32973	85	Adult	Low_Usage	Medium_Fitness	Low_In
4	KP281	20	Male	13	Partnered	4	2	35247	47	Adult	Medium_Usage	Low_Fitness	Low_In

- The KP281 is an entry-level treadmill that sells for 1500.
- The KP481 is for mid-level runners that sell for 1750.
- The KP781 treadmill is having advanced features that sell for 2500.

In [506…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 15 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  Usage_group    180 non-null    category
 11  Fitness_group  180 non-null    category
 12  Income_group   180 non-null    category
 13  Miles_group    180 non-null    category
 14  Product_price  180 non-null    int64
dtypes: category(5), int64(7), object(3)
memory usage: 15.8+ KB
```

Using df.info we come to know the data type of each series

- Most of the series is in **Integer** datatype and Product, Gender, MaritalStatus are in **Object** datatype format.
- We have converted Catagorical columns to **Catagory** columns so they are now **Catagory** datatypes.

Seprating the Products into Seprate dataframes

In [507…
```
# Seperating the products as a new dataframe
df_KP281 = df[df["Product"]== "KP281"]
df_KP281.head(5)
```

Out[507…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_g
0	KP281	18	Male	14	Single	3	4	29562	112	Adult	Low_Usage	High_Fitness	Low_In
1	KP281	19	Male	15	Single	2	3	31836	75	Adult	Low_Usage	Medium_Fitness	Low_In
2	KP281	19	Female	14	Partnered	4	3	30699	66	Adult	Medium_Usage	Medium_Fitness	Low_In
3	KP281	19	Male	12	Single	3	3	32973	85	Adult	Low_Usage	Medium_Fitness	Low_In
4	KP281	20	Male	13	Partnered	4	2	35247	47	Adult	Medium_Usage	Low_Fitness	Low_In

In [508…
```
# Seperating the products as a new dataframe
df_KP481 = df[df["Product"]== "KP481"]
df_KP481.head(5)
```

Out[508…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_
80	KP481	19	Male	14	Single	3	3	31836	64	Adult	Low_Usage	Medium_Fitness	Low_I
81	KP481	20	Male	14	Single	2	3	32973	53	Adult	Low_Usage	Medium_Fitness	Low_I
82	KP481	20	Female	14	Partnered	3	3	34110	106	Adult	Low_Usage	Medium_Fitness	Low_I
83	KP481	20	Male	14	Single	3	3	38658	95	Adult	Low_Usage	Medium_Fitness	Low_I
84	KP481	21	Female	14	Partnered	5	4	34110	212	Adult	Medium_Usage	High_Fitness	Low_I

In [509…

```python
# Seperating the products as a new dataframe
df_KP781 = df[df["Product"]== "KP781"]
df_KP781.head(5)
```

Out[509…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Incom
140	KP781	22	Male	14	Single	4	3	48658	106	Adult	Medium_Usage	Medium_Fitness	Mediun
141	KP781	22	Male	16	Single	3	5	54781	120	Adult	Low_Usage	High_Fitness	Mediun
142	KP781	22	Male	18	Single	4	5	48556	200	Adult	Medium_Usage	High_Fitness	Mediun
143	KP781	23	Male	16	Single	4	5	58516	140	Adult	Medium_Usage	High_Fitness	Mediun
144	KP781	23	Female	18	Single	5	4	53536	100	Adult	Medium_Usage	High_Fitness	Mediun

Univariate Analysis & Bivariate Analysis:

In [510…

```python
# Creating a function to give values in chart:
def text_format(fig):
    for bar in ax.patches:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, yval, str(yval), ha = "center", va = "bottom")
```

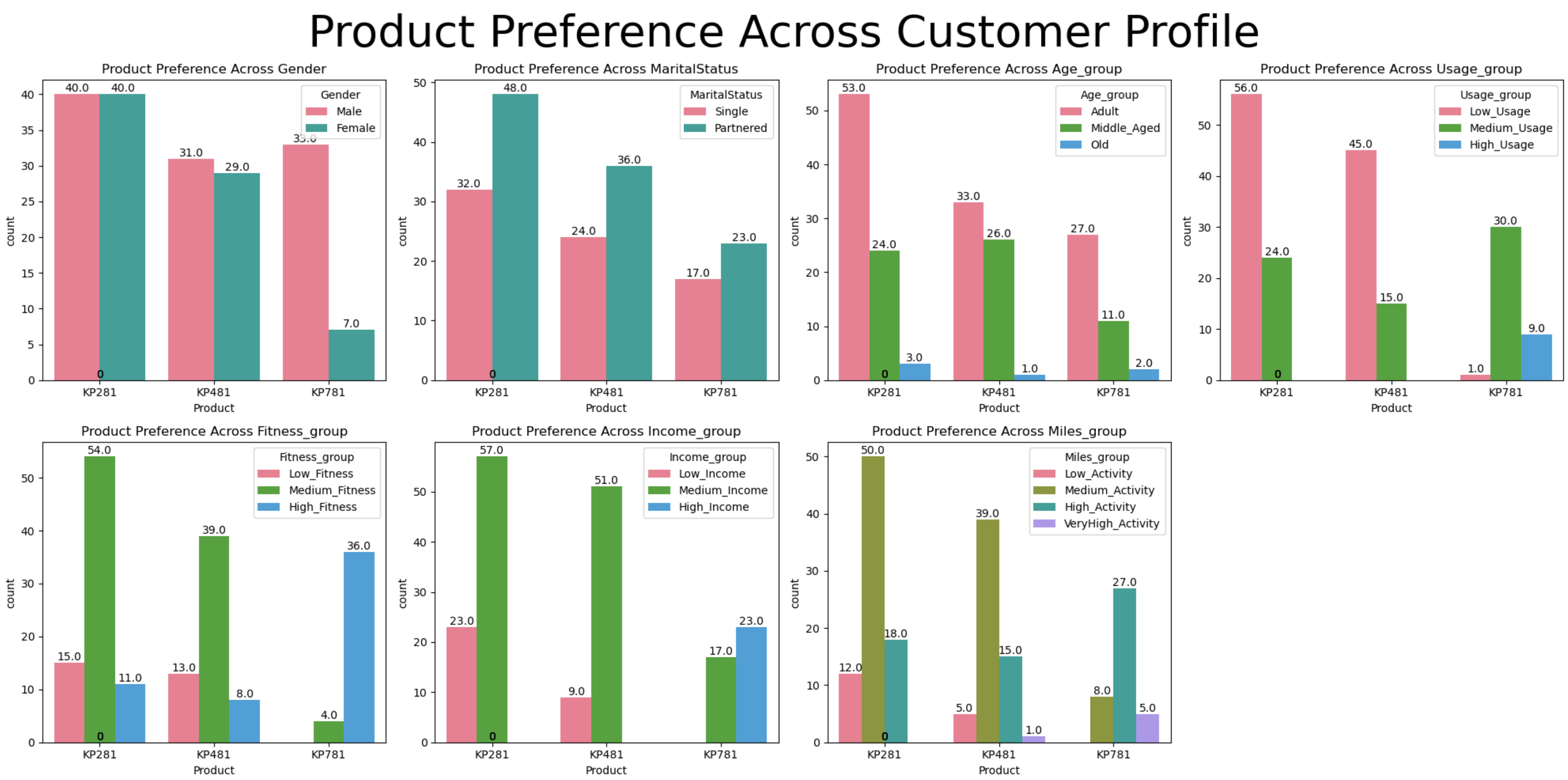
Product Preference Across Customer Profile

In [511…

```python
cat_var = ["Gender", "MaritalStatus", "Age_group", "Usage_group", "Fitness_group","Income_group", "Miles_group"]

plt.figure(figsize=(20,10))

for i,j in enumerate(cat_var):
    plt.subplot(2,4,i+1)
    sns.countplot(x = "Product", hue = j , data = df, palette="husl")
    ax = plt.gca()
    text_format(fig)
    plt.title(f"Product Preference Across {j}")
plt.suptitle("Product Preference Across Customer Profile", fontsize = 40)
plt.tight_layout()
plt.show()
```



Insights:

- Gender: KP781 is more popular with males compared to females.

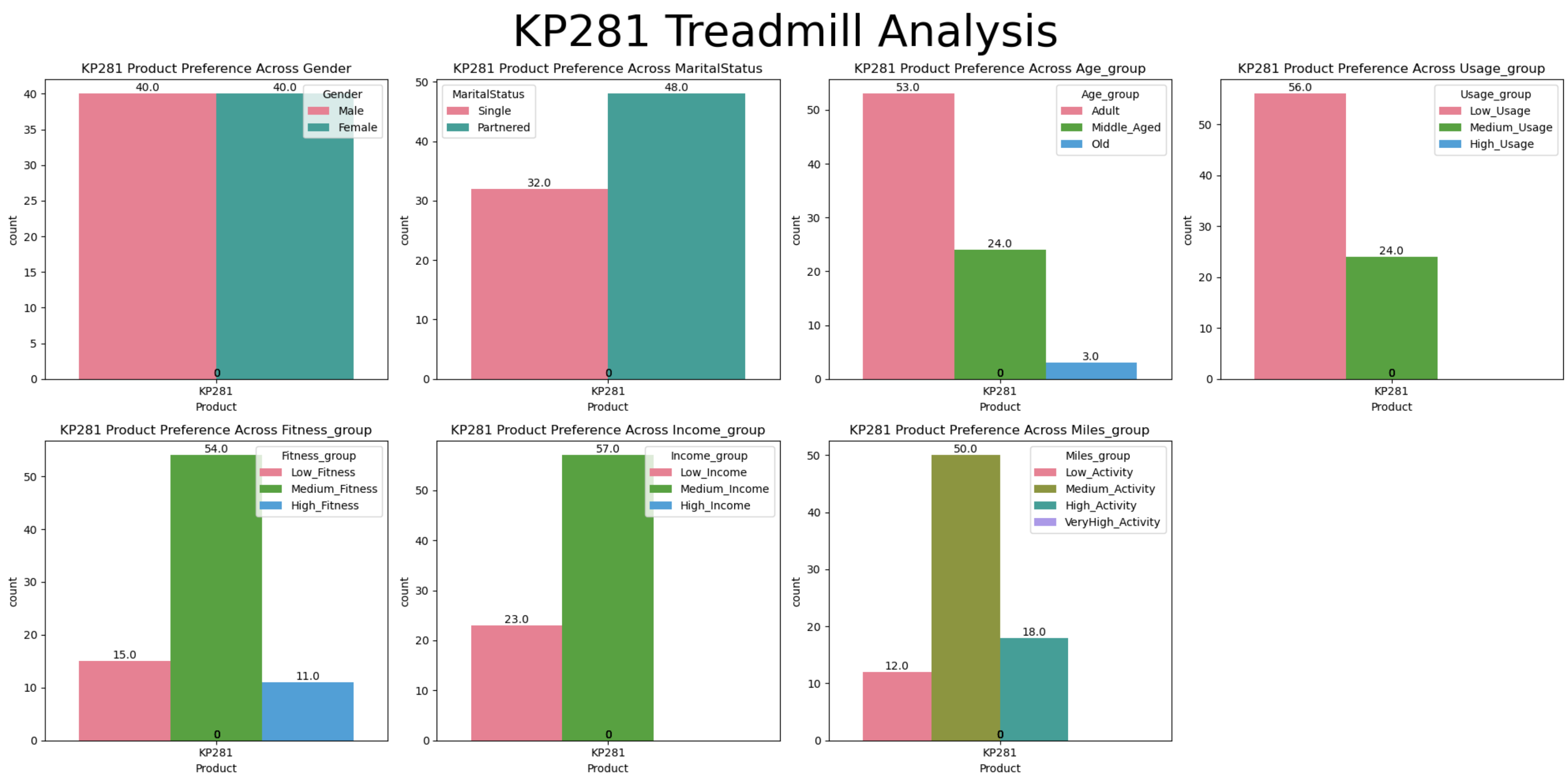
- MaritalStatus: Married people mostly preffer KP281.
- Age Group: Adults mostly prefer KP281 and middle aged people prefer KP481.
- Usage Groups: If the customer is looking for high or medium usage they can go with KP781, for low usage they can go with KP281 or KP481 .
- Fitness Groups: If the customer is high fitness minded we can suggest KP781, for medium fitness minded customer we can suggest KP281 or KP481 .
- Income Groups: Medium income people mostly prefer KP281 then KP481, High income people mostly prefer KP781 and Low income people mostly prefer KP281.
- Miles Groups: if the customer falls under medium miles group they can go with KP281, if Very high activity means go with KP781.
- Sales: 37% sales from KP281, 32.3% sales from KP481 and 30.7% sales from KP781.

Customers Using Treadmill KP281

In [512…

```
cat_var = ["Gender", "MaritalStatus", "Age_group", "Usage_group", "Fitness_group","Income_group", "Miles_group"]

plt.figure(figsize=(20,10))
for i,j in enumerate(cat_var):
    plt.subplot(2,4,i+1)
    sns.countplot(x = "Product", hue = j , data = df_KP281, palette="husl")
    ax = plt.gca()
    text_format(fig)
    plt.title(f"KP281 Product Preference Across {j}")
plt.suptitle("KP281 Treadmill Analysis", fontsize = 40)
plt.tight_layout()
plt.show()
```



Insights:

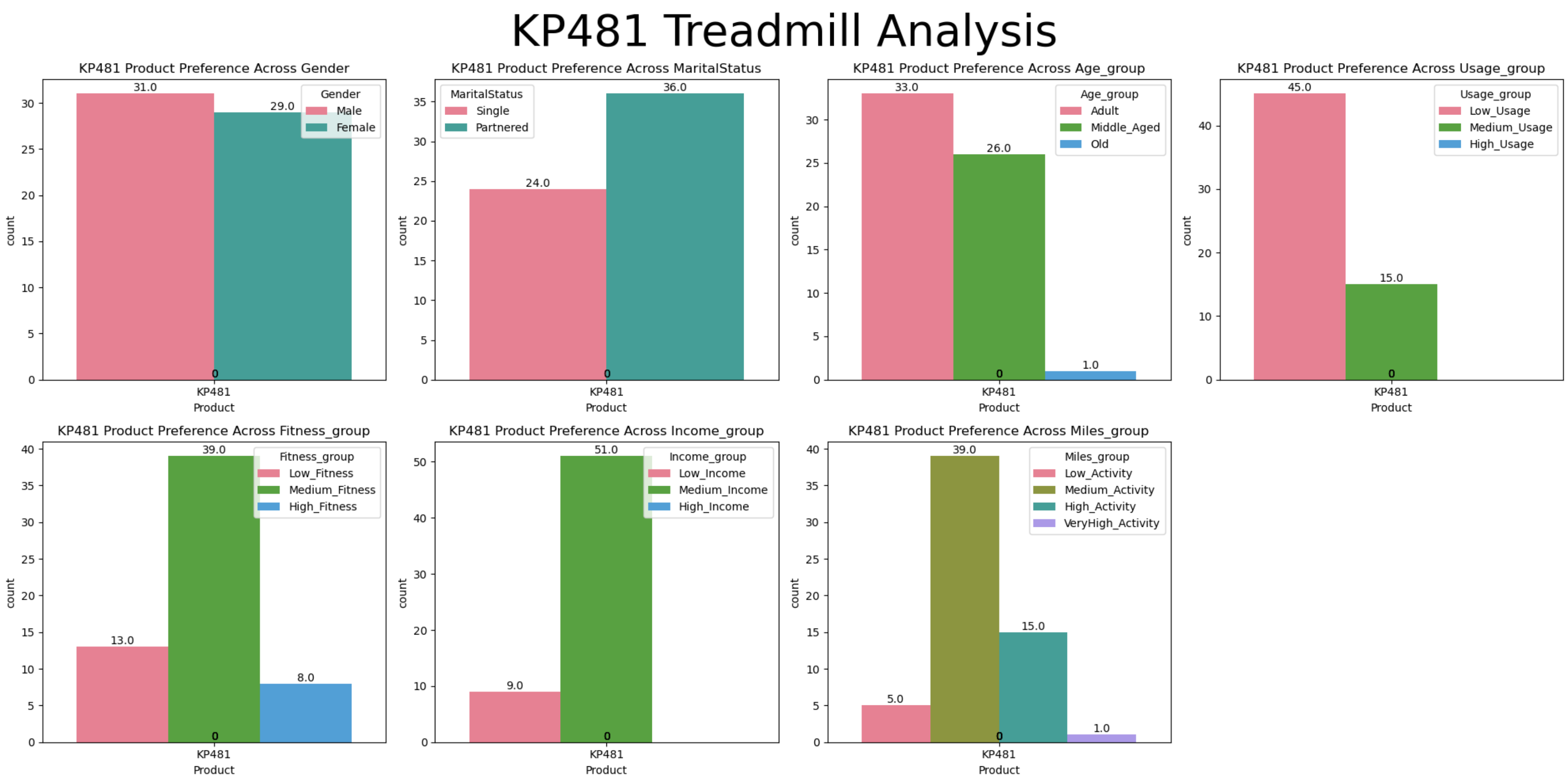
- Gender: the customers using KP281 are 50% male and 50% female .
- Age Group: The customers using KP281 are 66.25% adults, 30% middle aged and 3.75% old people.
- MaritalStatus: The customers using KP281 are 60% married and 40% single.
- Usage Groups: The customers using KP281 are 70% low usage people and 30% medium usage people.
- Fitness Groups: The customers using KP281 are 67.5% medium fitness mind people, 18.75% low fitness minded people and 13.75% high fitness minded people.
- Income Groups: The customers using KP281 are 71.25% medium income people and 28.75% low income people.
- Miles Groups: The customers using KP281 are 62.5% medium activity people, 22.5% high activity people and 15% low activity people.
- Sales: 37% sales from KP281.

Customers Using Treadmill KP481

In [513…

```
cat_var = ["Gender", "MaritalStatus", "Age_group", "Usage_group", "Fitness_group","Income_group", "Miles_group"]
plt.figure(figsize=(20,10))
for i,j in enumerate(cat_var):
    plt.subplot(2,4,i+1)
    sns.countplot(x = "Product", hue = j , data = df_KP481, palette= "husl")
    ax = plt.gca()
    text_format(fig)
    plt.title(f"KP481 Product Preference Across {j}")
```

```
plt.suptitle("KP481 Treadmill Analysis", fontsize = 40)
plt.tight_layout()
plt.show()
```



Insights:

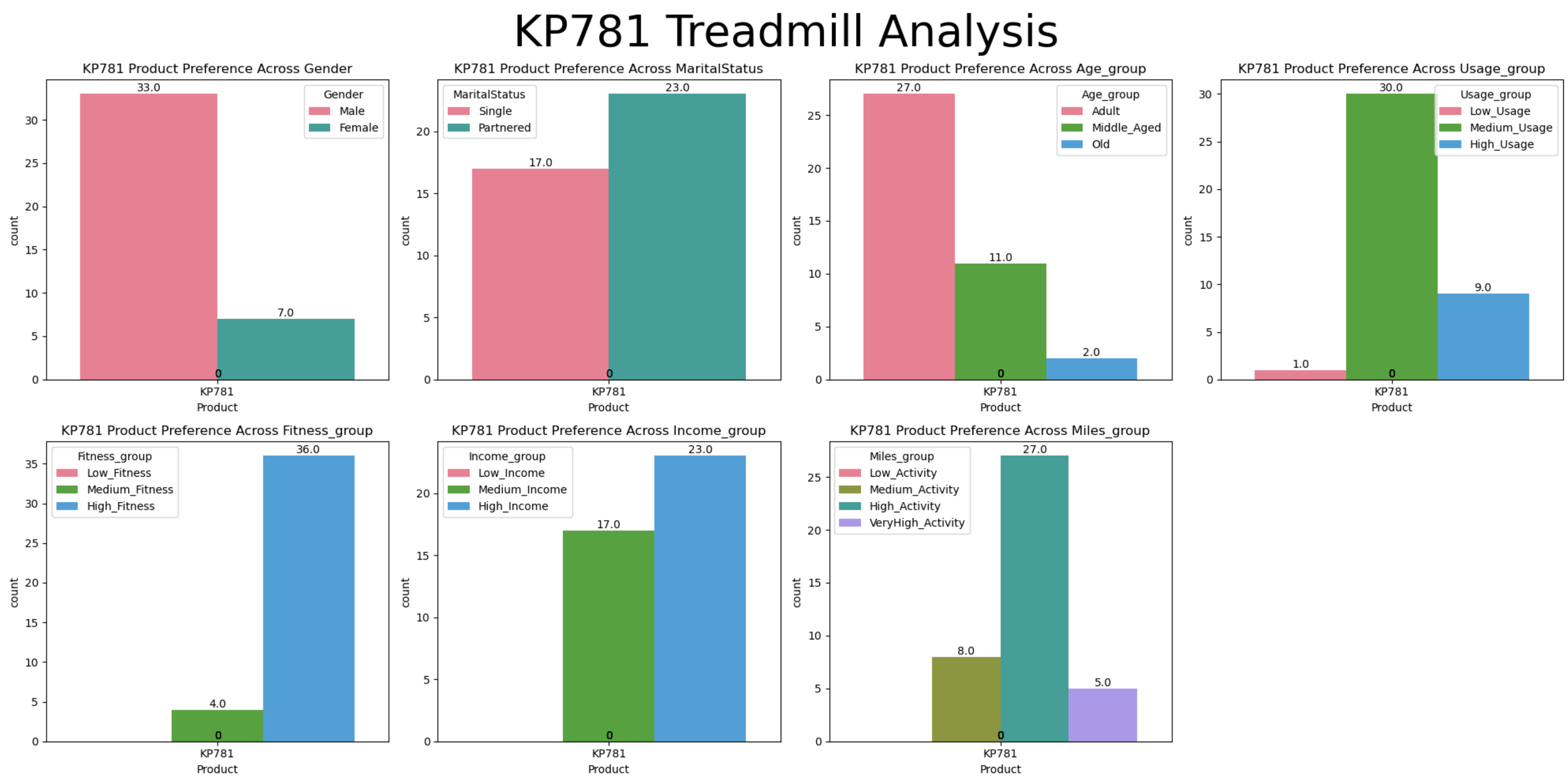
- Gender: the customers using KP481 are 51.7% male and 48.3% female .
- Age Group: The customers using KP481 are 55% adults, 43.3% middle aged and 1.7% old people.
- MaritalStatus: The customers using KP481 are 60% married and 40% single.
- Usage Groups: The customers using KP481 are 75% low usage people, 25% medium usage people.
- Fitness Groups: The customers using KP481 are 65% medium fitness minded people, 21.7% low fitness minded people and 13.3% high fitness minded people.
- Income Groups: The customers using KP481 are 85% medium income people and 15% low income people.
- Miles Groups: The customers using KP481 are 65% medium activity people, 25% high activity people, 8.3% low activity people and 1.7% very high activity people.
- Sales: 32.3% sales from KP481.

Customers Using Treadmill KP781

In [514…

```
cat_var = ["Gender", "MaritalStatus", "Age_group", "Usage_group", "Fitness_group","Income_group", "Miles_group"]

plt.figure(figsize=(20,10))
for i,j in enumerate(cat_var):
    plt.subplot(2,4,i+1)
    sns.countplot(x = "Product", hue = j , data = df_KP781, palette="husl")
    ax = plt.gca()
    text_format(fig)
    plt.title(f"KP781 Product Preference Across {j}")
plt.suptitle("KP781 Treadmill Analysis", fontsize = 40)
plt.tight_layout()
plt.show()
```



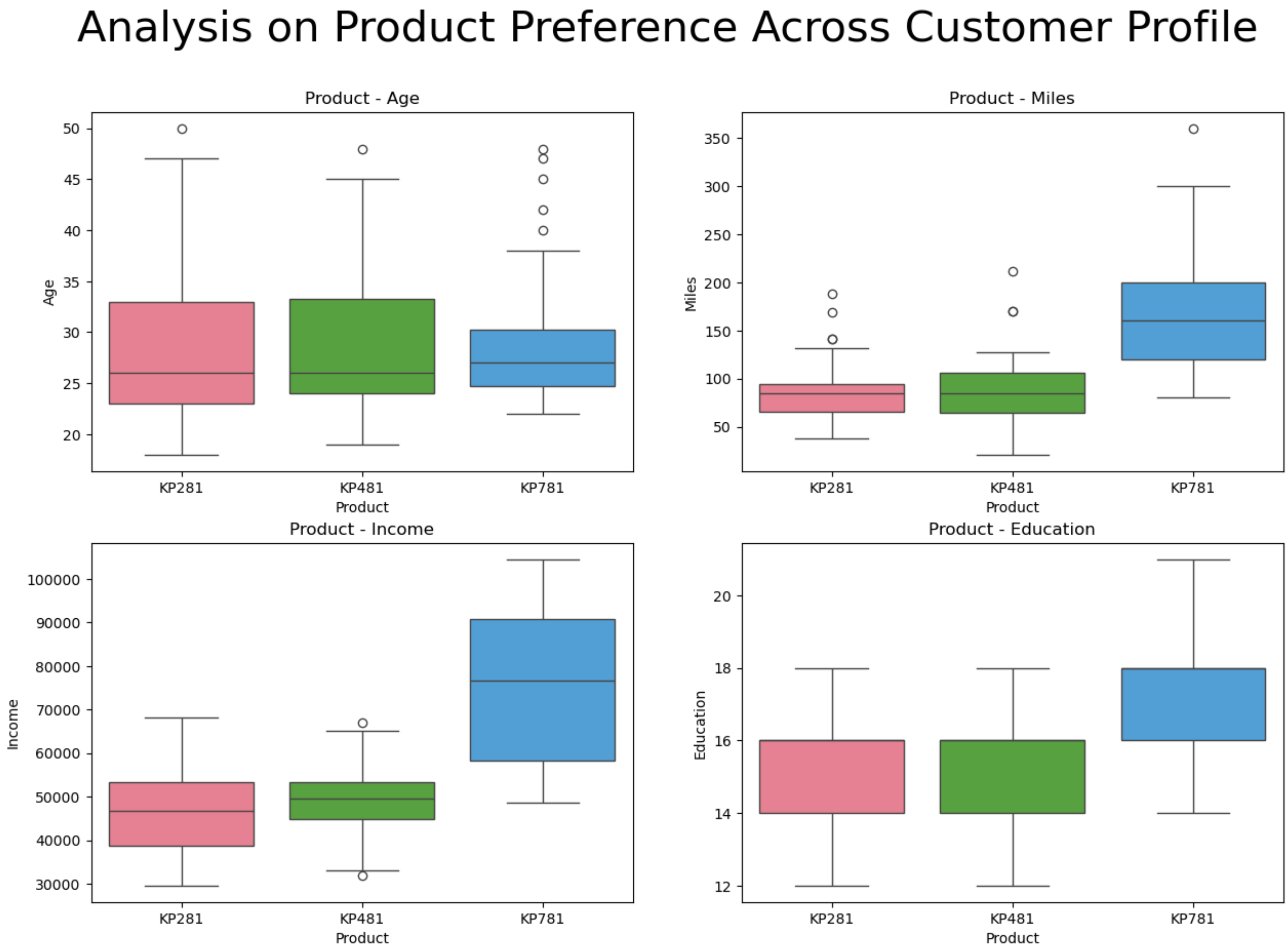
Insights:

- Gender: the customers using KP781 are 82.5% male and 17.5% female .
- Age Group: The customers using KP781 are 67.5% adults, 27.5% middle aged and 5% old people.
- MaritalStatus: The customers using KP781 are 57.5% married and 42.5% single.
- Usage Groups: The customers using KP781 are 75% medium usage people, 22.5% high usage people and 2.5% low usage people.
- Fitness Groups: The customers using KP781 are 90% high fitness minded people and 10% medium fitness minded people.
- Income Groups: The customers using KP781 are 57.5% high income people and 42.5% medium income people.
- Miles Groups: The customers using KP781 are 67.5% high activity people, 20% medium activity people and 12.5% very high activity people.
- Sales: 30.7% sales from KP781.

Analysis on Product Preference Across Customer Profile

In [547…

```
num_var = ["Age","Miles","Income","Education"]
plt.figure(figsize= (15,10))
for i , j in enumerate(num_var):
  plt.subplot(2,2,i+1)
  sns.boxplot(x = "Product", y = j , data = df,palette = "husl")
  plt.title(f"Product - {j}")
plt.suptitle("Analysis on Product Preference Across Customer Profile", fontsize = 30)
plt.show()
```



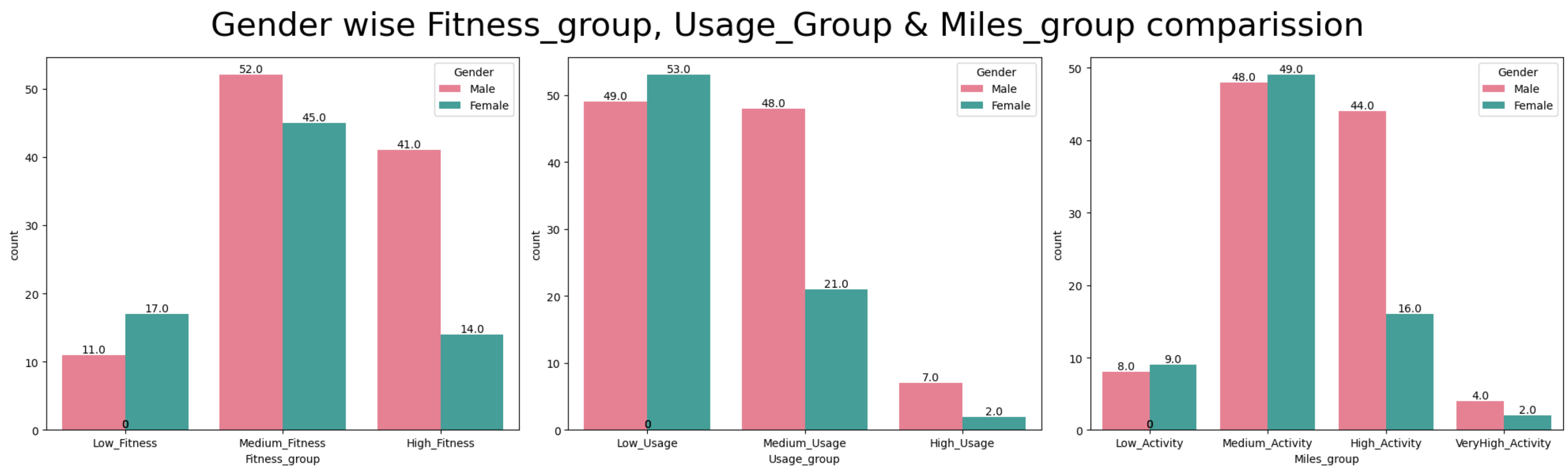
Insights:

- The analysis suggests a clear preference for the KP781 treadmill model among customers with higher education and income levels, who also engage in running activities exceeding 150 miles per week.

Gender wise Fitness_group, Usage_Group & Miles_group comparission

In [516…

```
plt.figure(figsize = (20,6))
plt.subplot(1,3,1)
sns.countplot(x = "Fitness_group",data = df , hue = "Gender", palette = "husl")
ax = plt.gca()
text_format(fig)
plt.subplot(1,3,2)
sns.countplot(x = "Usage_group" , data = df , hue = "Gender" , palette = "husl")
ax = plt.gca()
text_format(fig)
plt.subplot(1,3,3)
sns.countplot(x = "Miles_group" , data = df , hue = "Gender" , palette = "husl")
ax = plt.gca()
text_format(fig)
plt.suptitle("Gender wise Fitness_group, Usage_Group & Miles_group comparission", fontsize = 30)
plt.tight_layout()
plt.show()
```



Insights:

- In Fitness Group:
  - 11 people are male and 17 people are female are comes under Low Fitness Group.
  - 52 people are male and 45 people are female are comes under Medium Fitness Group.
  - 41 people are male and 14 people are female are comes under High Fitness Group.
- In Usage Group:
  - 49 people are male and 53 people are female are comes under Low Usage Group.
  - 48 people are male and 21 people are female are comes under Medium Usage Group.
  - 7 people are male and 2 people are female are comes under High Usage Group.
- In Miles Group:
  - 8 people are male and 9 people are female are comes under Low Activity Group.
  - 48 people are male and 49 people are female are comes under Medium Activity Group.
  - 44 people are male and 16 people are female are comes under High Activity Group.
  - 4 people are male and 2 people are female are comes under Very High Activity Group.

Correlation Among Diffrent Factors

In [517…

```
df_fin = df.copy()
df_fin["Gender"].replace(["Male","Female"],[1,0],inplace = True)
df_fin["MaritalStatus"].replace(["Single","Partnered"],[0,1],inplace = True)
df_fin["Product"].replace(["KP281","KP481","KP781"],[0,1,2], inplace= True)
df_fin.head()
```

Out[517…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	Usage_group	Fitness_group	Income_g
0	0	18	1	14	0	3	4	29562	112	Adult	Low_Usage	High_Fitness	Low_Inc
1	0	19	1	15	0	2	3	31836	75	Adult	Low_Usage	Medium_Fitness	Low_Inc
2	0	19	0	14	1	4	3	30699	66	Adult	Medium_Usage	Medium_Fitness	Low_Inc
3	0	19	1	12	0	3	3	32973	85	Adult	Low_Usage	Medium_Fitness	Low_Inc
4	0	20	1	13	1	4	2	35247	47	Adult	Medium_Usage	Low_Fitness	Low_Inc

In [518…

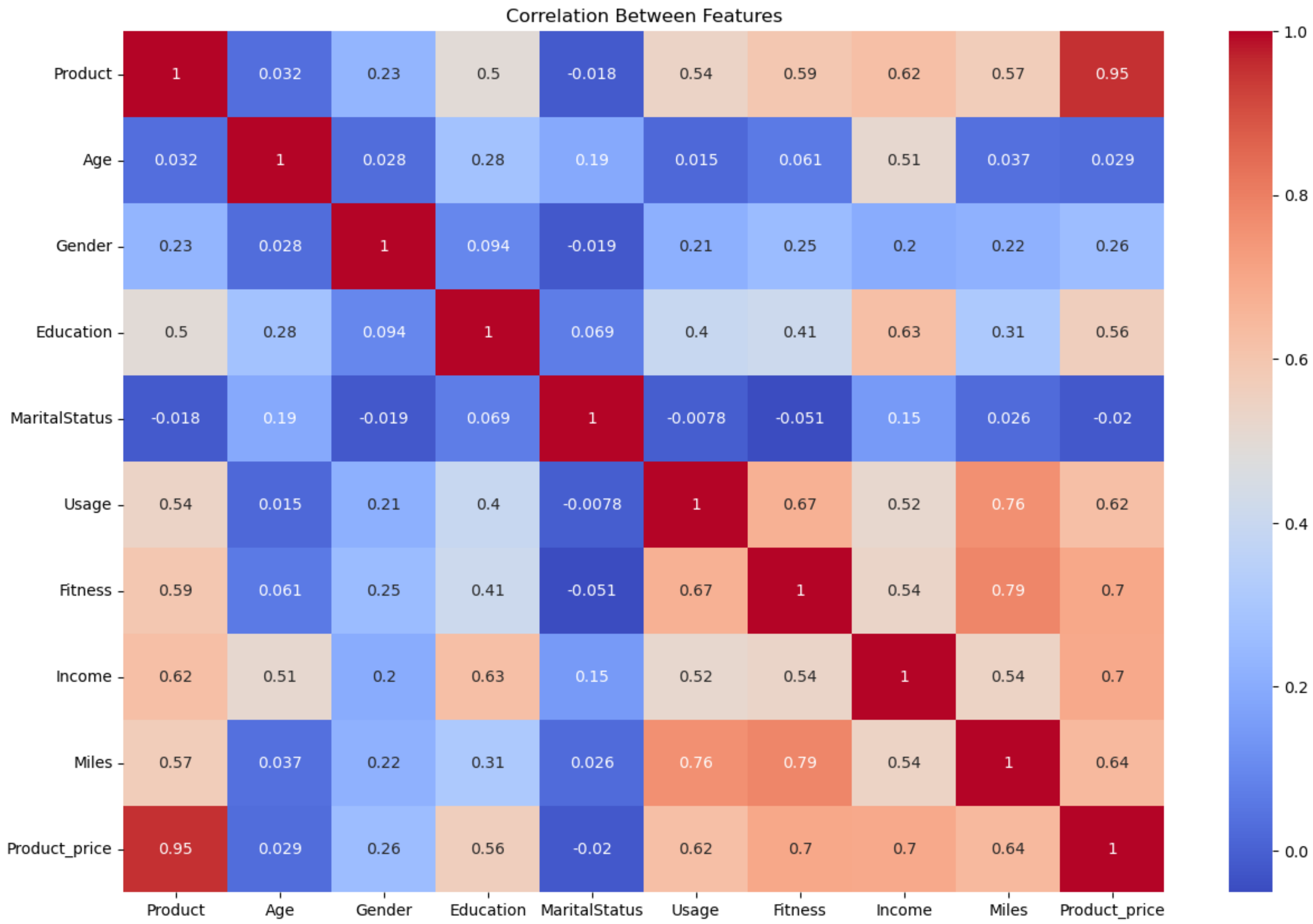
```
df_fin.corr(numeric_only=True)
```

Out[518…

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Product_price
Product	1.000000	0.032225	0.230653	0.495018	-0.017602	0.537447	0.594883	0.624168	0.571596	0.954425
Age	0.032225	1.000000	0.027544	0.280496	0.192152	0.015064	0.061105	0.513414	0.036618	0.029263
Gender	0.230653	0.027544	1.000000	0.094089	-0.018836	0.214424	0.254609	0.202053	0.217869	0.260842
Education	0.495018	0.280496	0.094089	1.000000	0.068569	0.395155	0.410581	0.625827	0.307284	0.563463
MaritalStatus	-0.017602	0.192152	-0.018836	0.068569	1.000000	-0.007786	-0.050751	0.150293	0.025639	-0.020309
Usage	0.537447	0.015064	0.214424	0.395155	-0.007786	1.000000	0.668606	0.519537	0.759130	0.623124
Fitness	0.594883	0.061105	0.254609	0.410581	-0.050751	0.668606	1.000000	0.535005	0.785702	0.696616
Income	0.624168	0.513414	0.202053	0.625827	0.150293	0.519537	0.535005	1.000000	0.543473	0.695847
Miles	0.571596	0.036618	0.217869	0.307284	0.025639	0.759130	0.785702	0.543473	1.000000	0.643923
Product_price	0.954425	0.029263	0.260842	0.563463	-0.020309	0.623124	0.696616	0.695847	0.643923	1.000000

In [519…

```
plt.figure(figsize=(15,10))
sns.heatmap(df_fin.corr(numeric_only=True),annot =True, cmap="coolwarm")
plt.title("Correlation Between Features")
plt.show()
```



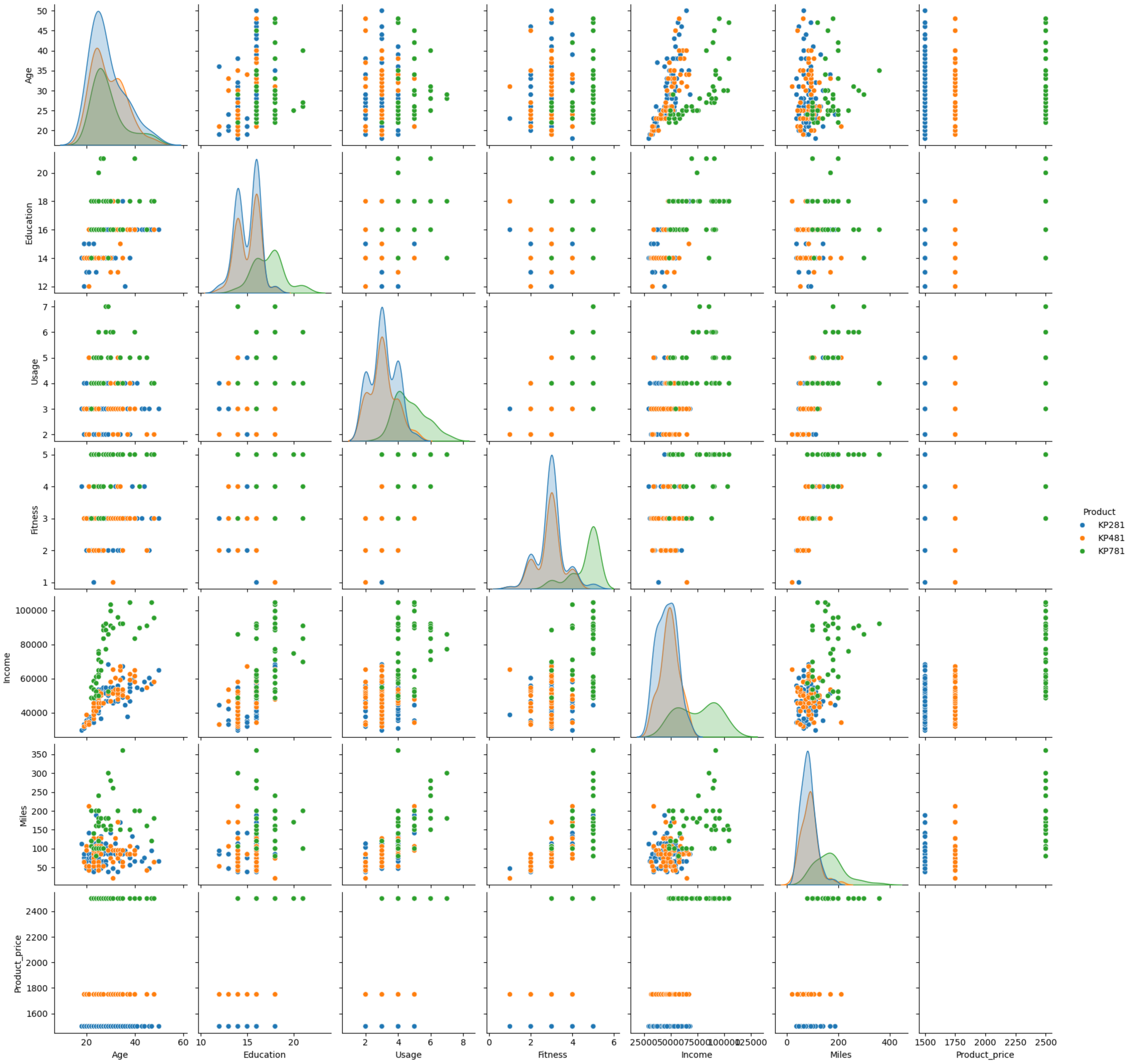
Insights:

- Age & Income: A positive correlation is evident between age and income.
- Education & Income: A positive correlation is evident between Education and income.
- Education & Usage & Fitness: Compared to Income it is havin little bit less positive correlation.
- Usage & Fitness & Miles: A positive correlation is showing between Usage & Fitness & Miles.

Pair Plot Among Diffrent Numerical Values

In [520…

```
sns.pairplot(df, hue="Product")
plt.show()
```



Insights:

- Age & Income: A positive correlation is evident between age and income.
- Education & Income: A positive correlation is evident between Education and income.
- Education & Usage & Fitness: Compared to Income it is havin little bit less positive correlation.
- Usage & Fitness & Miles: A positive correlation is showing between .

Distribution Among Columns

Distribution of Product & Product Sales

In [521…

```
Product_sales = df.groupby("Product")["Product_price"].sum().reset_index()
Product_sales
```

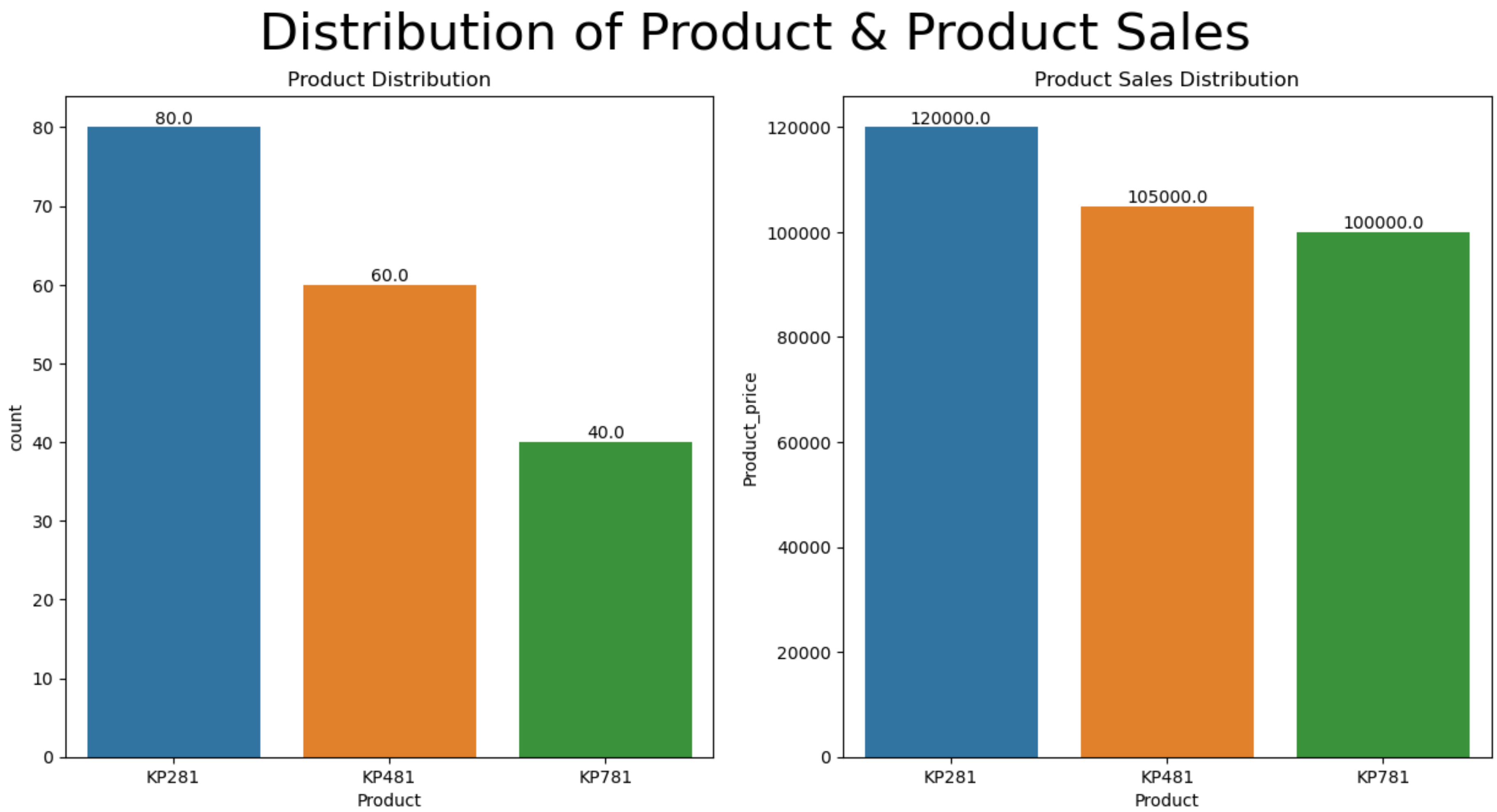
Out[521…

	Product	Product_price
0	KP281	120000
1	KP481	105000
2	KP781	100000

In [522…

```
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
sns.countplot(x= "Product", data = df, hue = "Product")
ax = plt.gca()
text_format(fig)
plt.title("Product Distribution")
plt.subplot(1,2,2)
sns.barplot(x = "Product", y = "Product_price", data = Product_sales, hue = "Product")
```

```
ax = plt.gca()
text_format(fig)
plt.title("Product Sales Distribution")
plt.suptitle("Distribution of Product & Product Sales", fontsize = 30)
plt.show()
```



Insights:

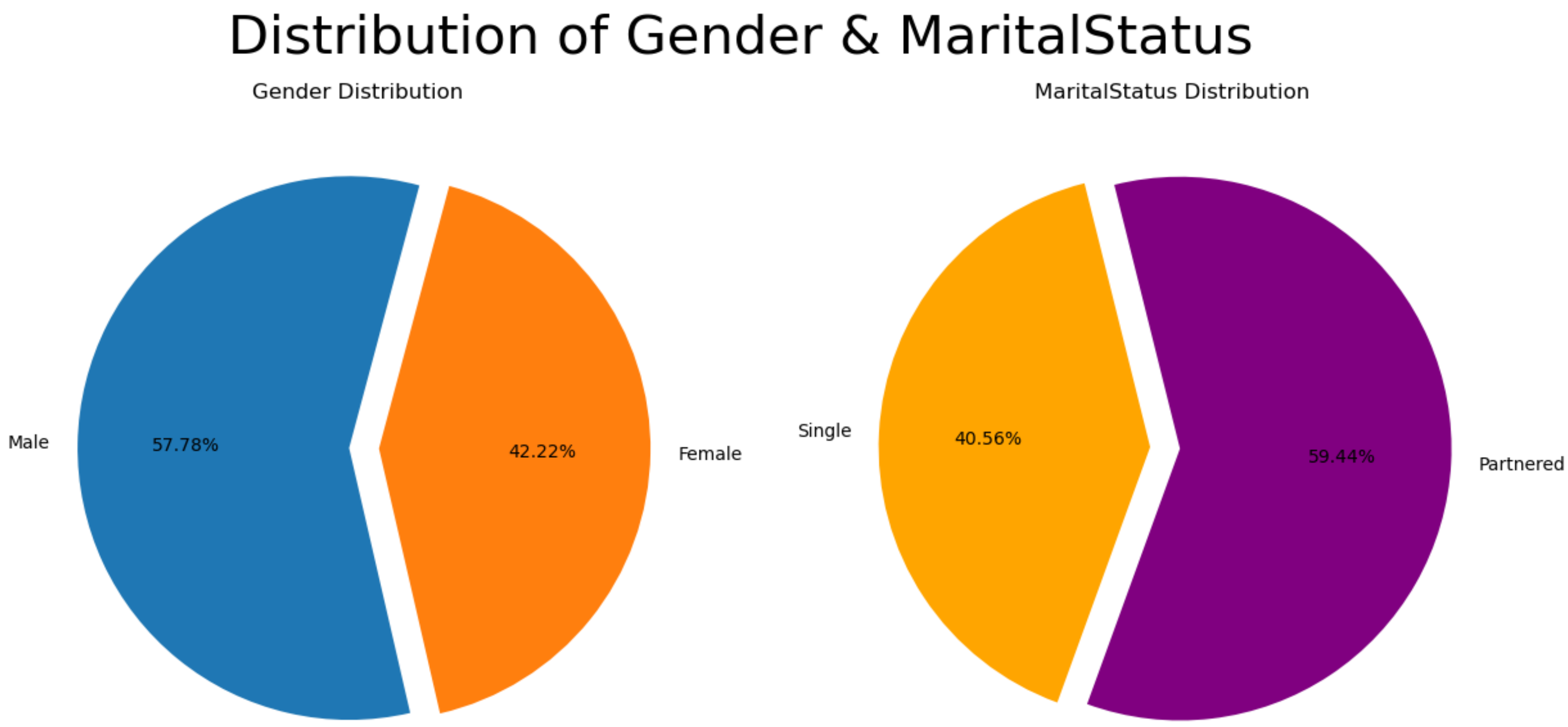
- The KP281 treadmill, positioned as an entry-level model, leads in unit sales, followed by the mid-level KP481 and the advanced KP781 models.
- Despite different target markets, all three treadmill models contribute equally to overall revenue generation, indicating balanced sales performance across product tiers.
- Among the treadmill models, KP281 emerges as the most frequently purchased, while KP481 follows as the second most popular choice, with KP781 being the least preferred option.

Gender & MaritalStatus Distribution

In [549…

```
plt.figure(figsize= (15,7))
plt.subplot(1,2,1)
labels = df["Gender"].value_counts().index
values = df["Gender"].value_counts().values
plt.pie(values, labels= labels, autopct= "%1.2f%%", explode = (0.03, 0.08), startangle=75)
plt.title("Gender Distribution")

plt.subplot(1,2,2)
labels = df["MaritalStatus"].value_counts().index
values = df["MaritalStatus"].value_counts().values
plt.pie(values, labels= labels, autopct= "%1.2f%%",colors= ["purple", "orange"],explode = (0.03, 0.08),startangle=250)
plt.title("MaritalStatus Distribution")
plt.suptitle("Distribution of Gender & MaritalStatus", fontsize = 30)
plt.show()
```



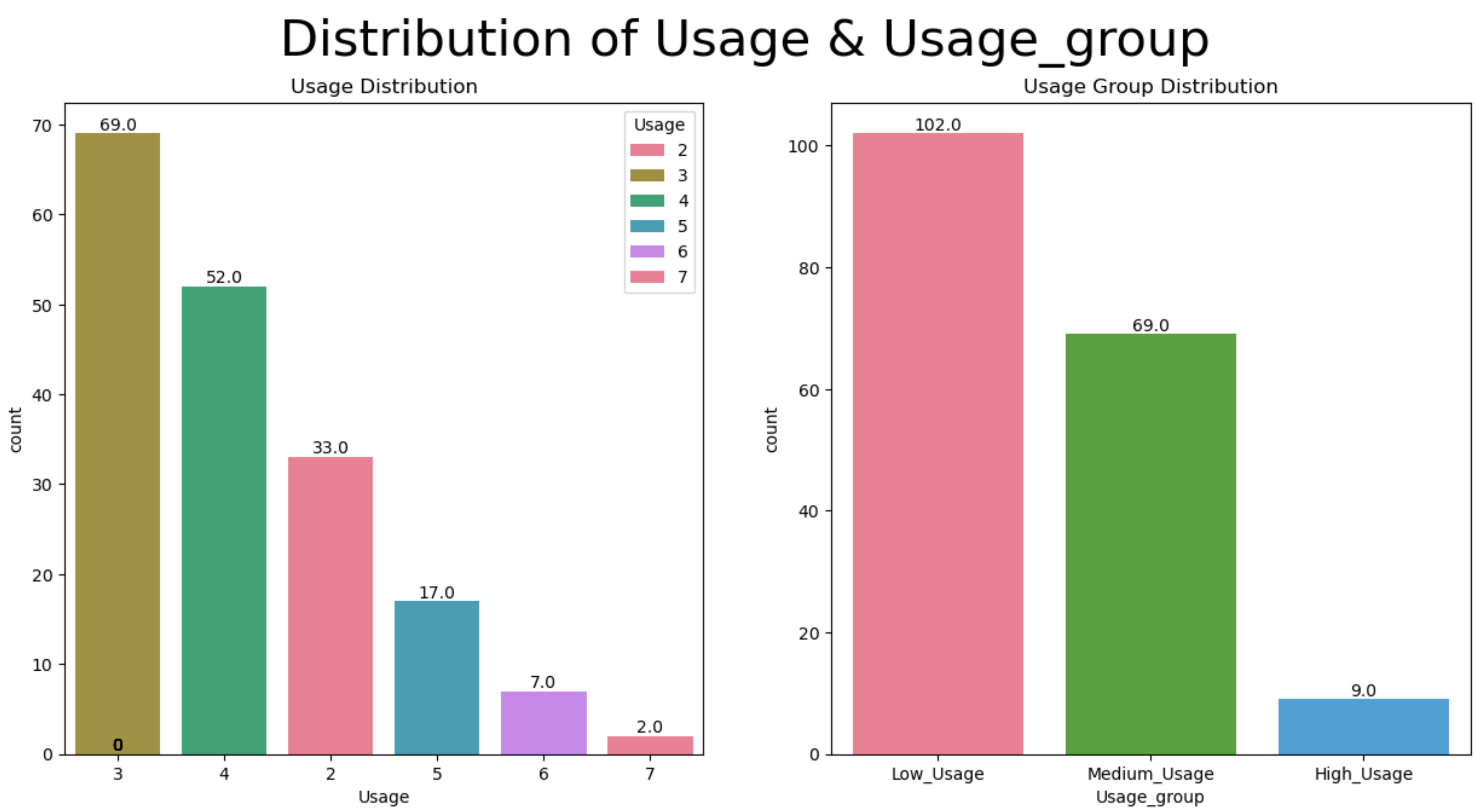
Insights:

- There is a higher preference among males for purchasing the products compared to females.
- There is a higher preference among Married for purchasing the products compared to Singles.

Usage & Usage Group Distribution

In [524…

```
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
sns.countplot(x= "Usage", data = df, hue = "Usage", order = df["Usage"].value_counts().index, palette= "husl")
ax = plt.gca()
text_format(fig)
plt.title("Usage Distribution")
plt.subplot(1,2,2)
sns.countplot(x= "Usage_group", data = df, hue = "Usage_group", order = df["Usage_group"].value_counts().index, palette= "husl
ax = plt.gca()
text_format(fig)
plt.title("Usage Group Distribution")
plt.suptitle("Distribution of Usage & Usage_group", fontsize = 30)
plt.show()
```



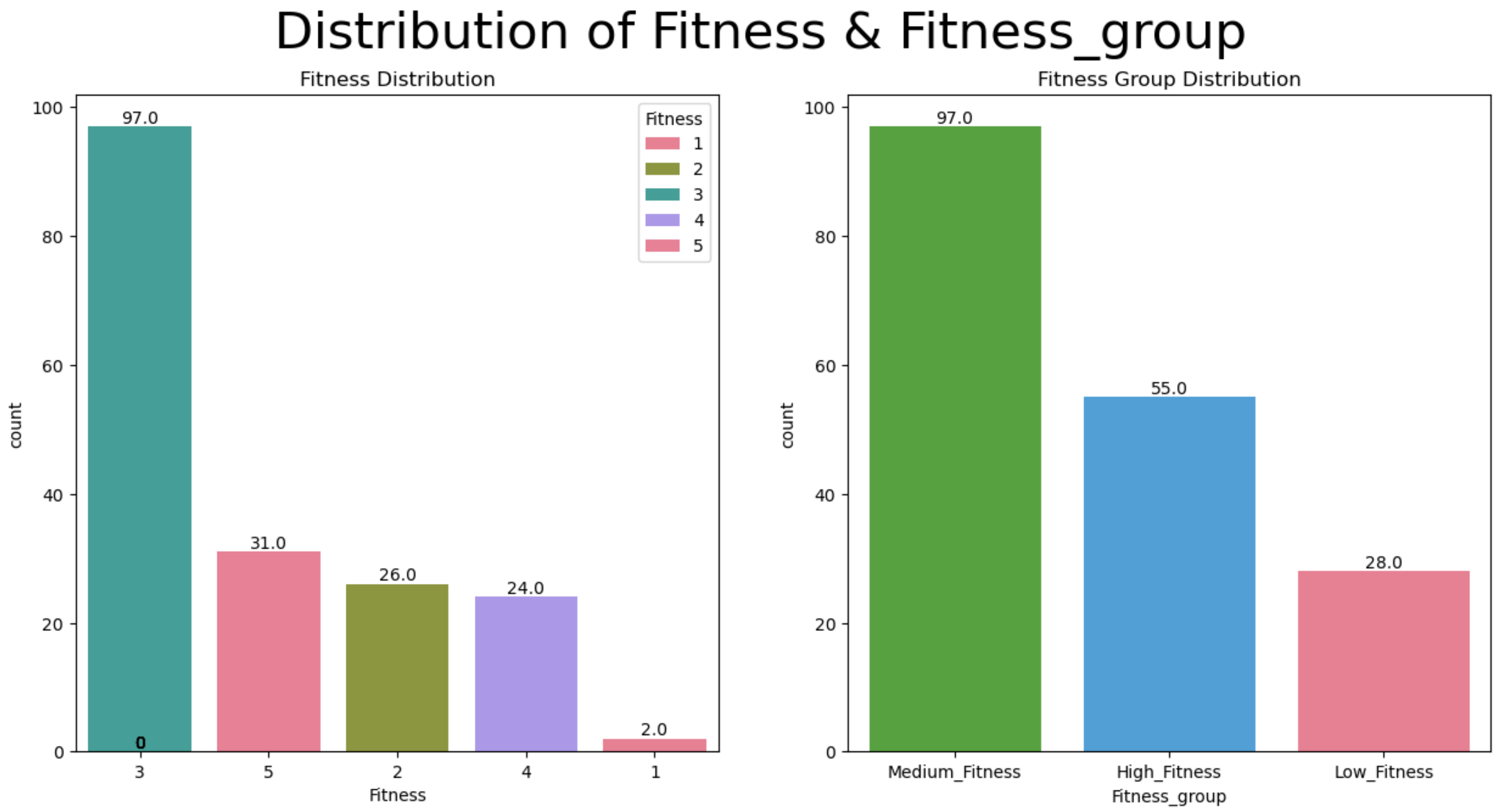
Insights:

- Nearly 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.

Fitness & Fitness Group Distribution

In [525…

```
plt.figure(figsize=(15,7))
plt.subplot(1,2,1)
sns.countplot(x= "Fitness", data = df, hue = "Fitness", order = df["Fitness"].value_counts().index, palette= "husl")
ax = plt.gca()
text_format(fig)
plt.title("Fitness Distribution")
plt.subplot(1,2,2)
sns.countplot(x= "Fitness_group", data = df, hue = "Fitness_group", order = df["Fitness_group"].value_counts().index, palette=
ax = plt.gca()
text_format(fig)
plt.title("Fitness Group Distribution")
plt.suptitle("Distribution of Fitness & Fitness_group", fontsize = 30)
plt.show()
```



Insights:

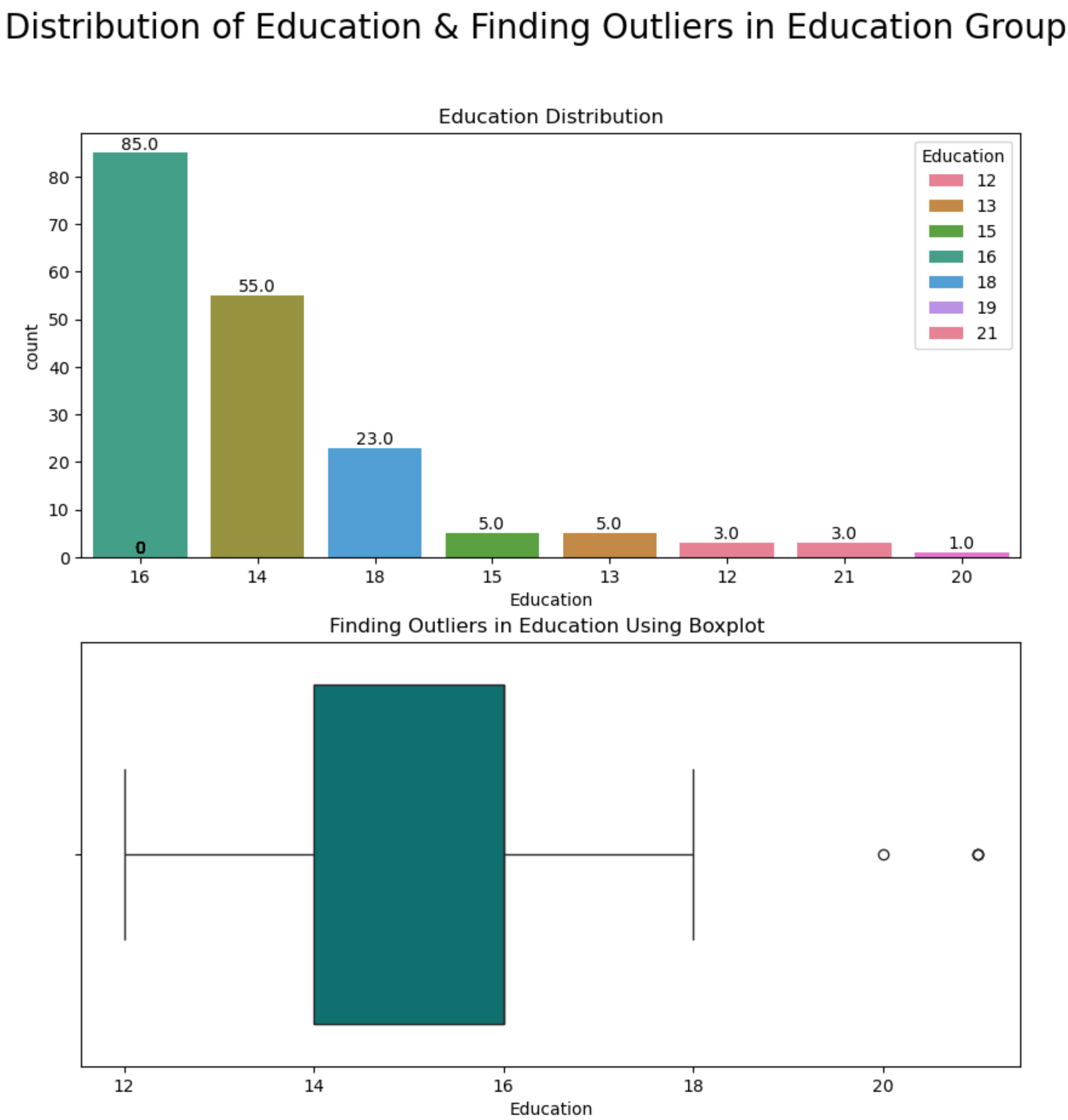
- The majority of participants (68.33%) fall within the "medium_fitness" category (fitness level 3).

Education Distribution & Finding Outliersin Education Group

In [526…

```
plt.figure(figsize=(10,10))
plt.subplot(2,1,1)
sns.countplot(x= "Education", data = df, hue = "Education", order = df["Education"].value_counts().index, palette= "husl")
ax = plt.gca()
text_format(fig)
plt.title("Education Distribution")
plt.subplot(2,1,2)
sns.boxplot(x= "Education", data = df, color= "teal")
plt.title("Finding Outliers in Education Using Boxplot ")

plt.suptitle("Distribution of Education & Finding Outliers in Education Group", fontsize = 20)
plt.show()
```



Insights:

- A significant majority of customers, approximately 91.67%, have education levels of 14 years or higher. This high proportion suggests a strong correlation between higher education and the purchase of aerofit items, possibly driven by increased health awareness and disposable income.

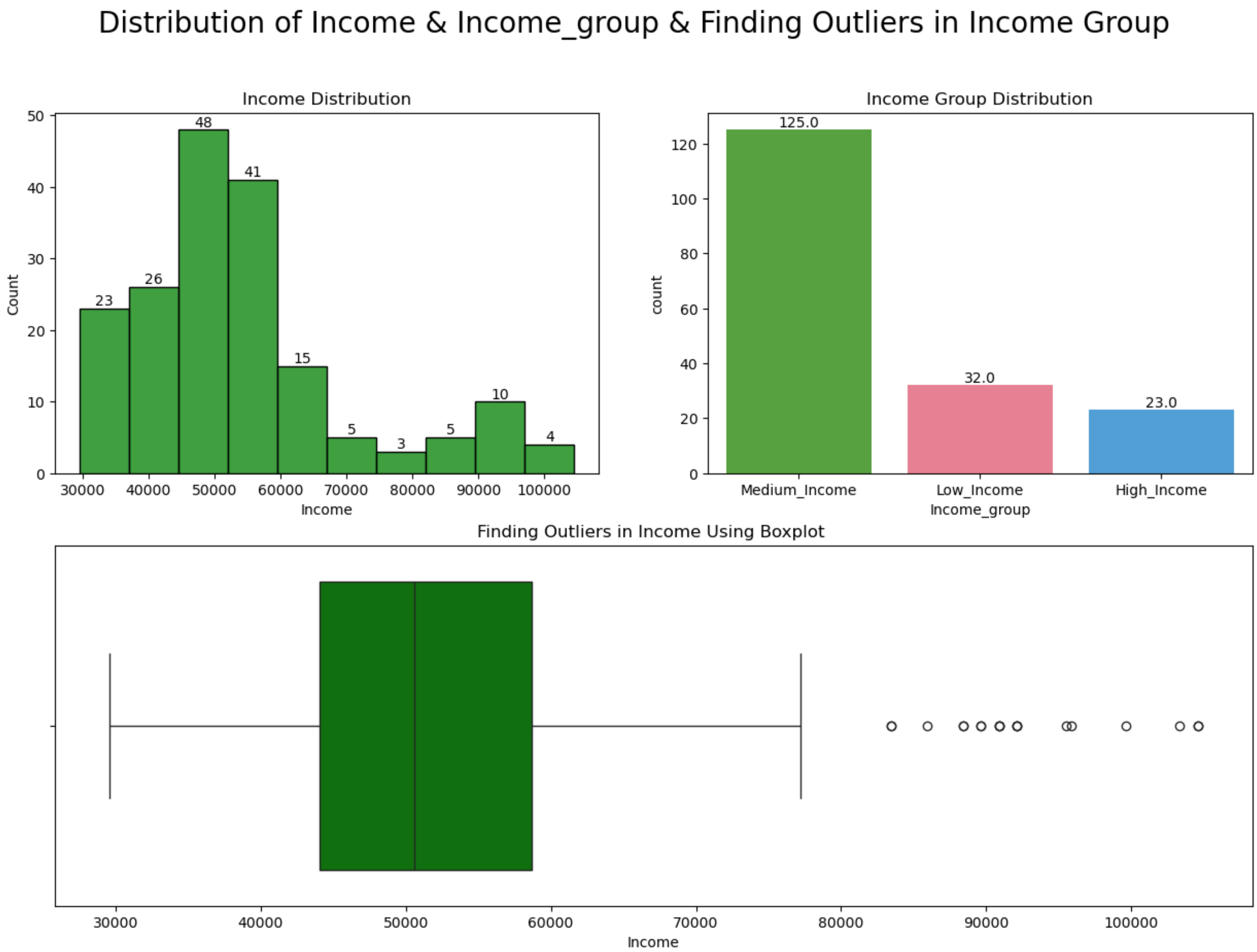
Income & Income Group Distribution

In [527…

```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.histplot(x= "Income",bins = 10,  data = df, kde = False, color= "green")
ax = plt.gca()
text_format(fig)
plt.title("Income Distribution")
plt.subplot(2,2,2)
sns.countplot(x= "Income_group", data = df, hue = "Income_group", order = df["Income_group"].value_counts().index, palette= "h
ax = plt.gca()
text_format(fig)
plt.title("Income Group Distribution")

plt.subplot(2,1,2)
sns.boxplot(x= "Income", data = df, color= "green")
plt.title("Finding Outliers in Income Using Boxplot ")

plt.suptitle("Distribution of Income & Income_group & Finding Outliers in Income Group", fontsize = 20)
plt.show()
```



Insights:

- Medium income people mostly prefer KP281 then KP481, High income people mostly prefer KP781 and Low income people mostly prefer KP281.
- The customers who comes Above 78000$ are outliers

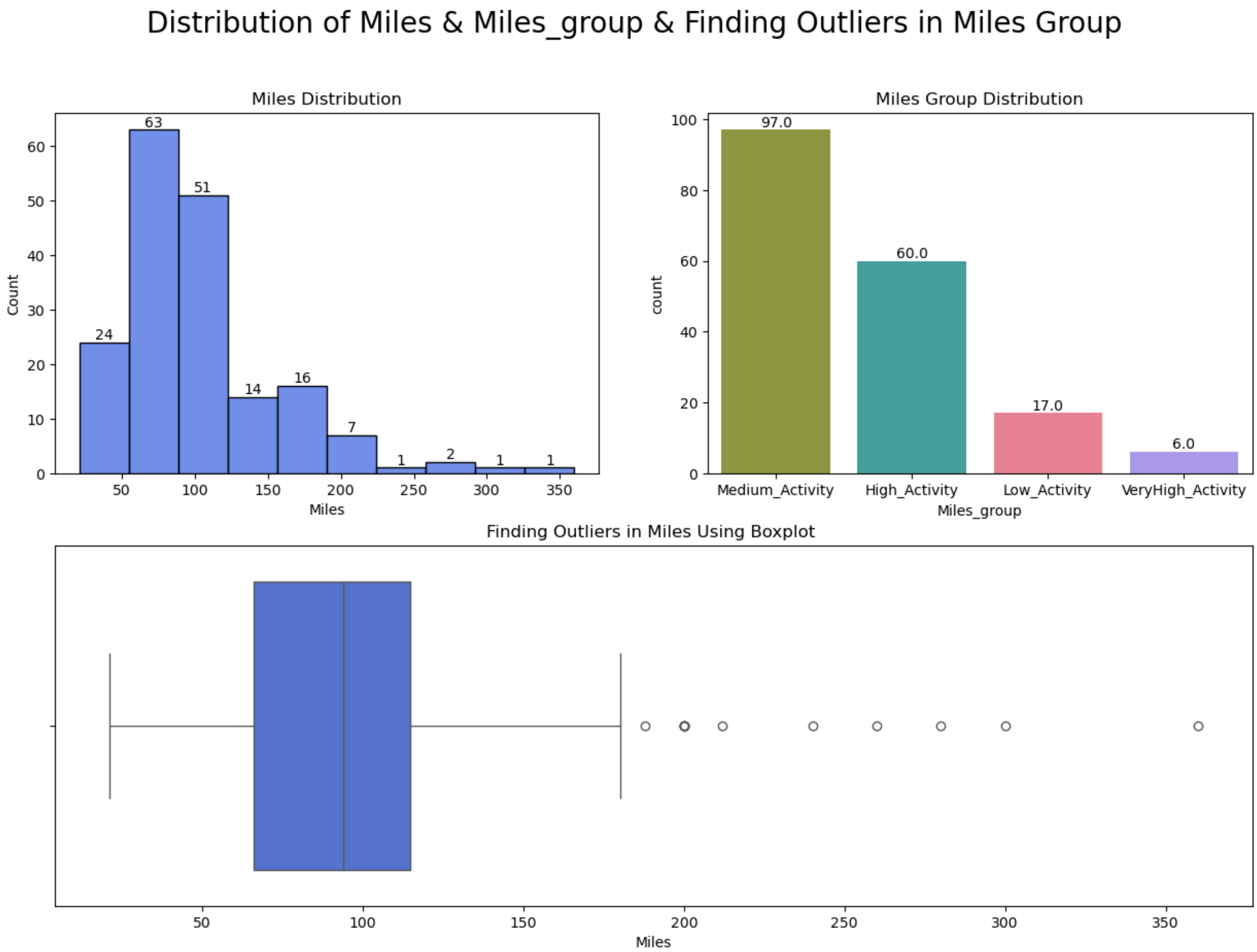
Miles & Miles Group Distribution & Finding Outliers in Miles

In [528…

```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.histplot(x= "Miles",bins = 10,  data = df, kde = False, color= "Royalblue")
ax = plt.gca()
text_format(fig)
plt.title("Miles Distribution")
plt.subplot(2,2,2)
sns.countplot(x= "Miles_group", data = df, hue = "Miles_group", order = df["Miles_group"].value_counts().index, palette= "husl
ax = plt.gca()
text_format(fig)
plt.title("Miles Group Distribution")

plt.subplot(2,1,2)
sns.boxplot(x= "Miles", data = df, color= "RoyalBlue")
plt.title("Finding Outliers in Miles Using Boxplot ")

plt.suptitle("Distribution of Miles & Miles_group & Finding Outliers in Miles Group", fontsize = 20)
plt.show()
```



Insights:

- If the customer falls under medium miles group they can go with KP281, if Very high activity means go with KP781.
- Above 180 miles it is considerd as a Outliers.

Age & Age Group Distribution

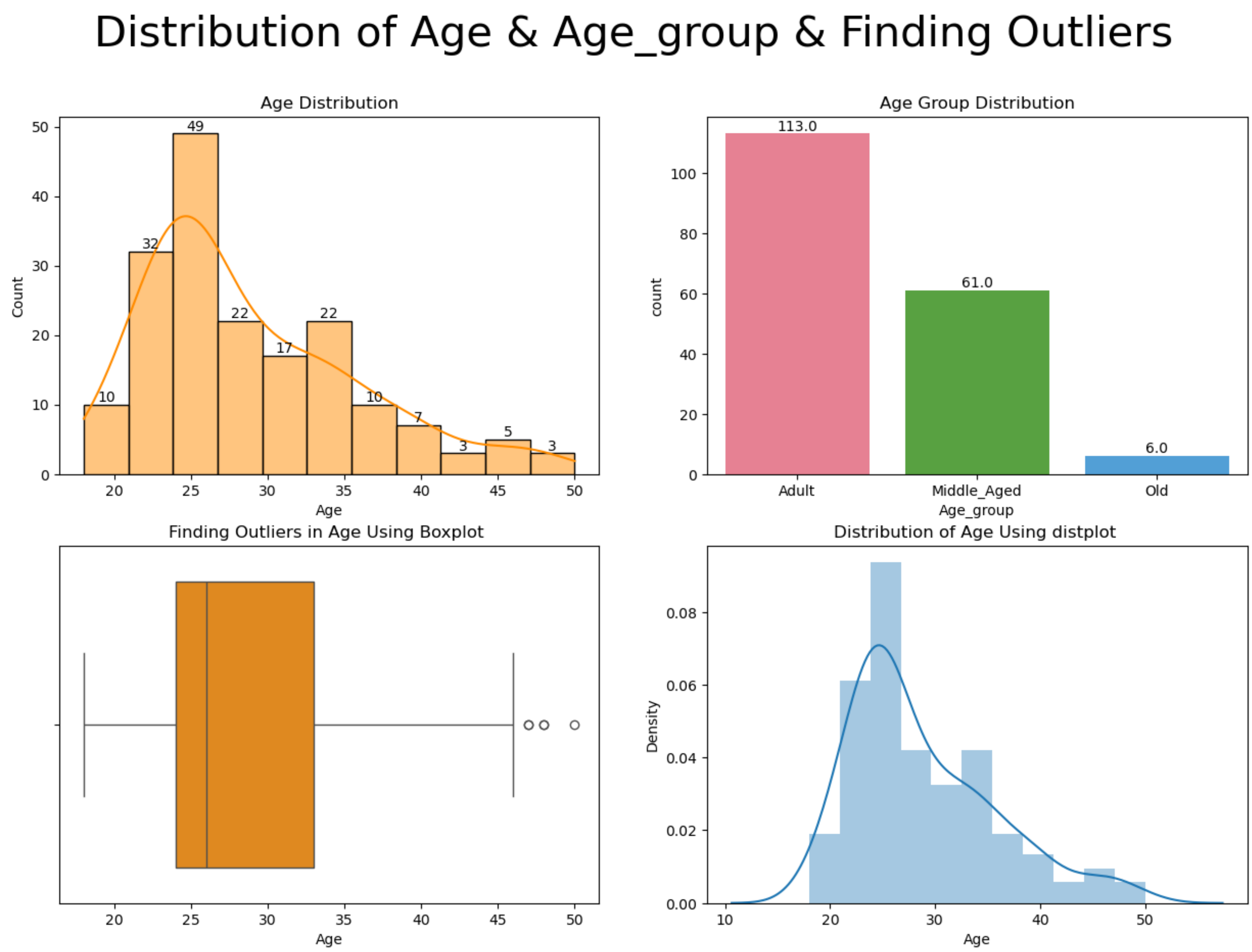
In [529…

```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.histplot(x= "Age",bins = 11,  data = df, kde = True, color= "darkorange")
ax = plt.gca()
text_format(fig)
plt.title("Age Distribution")
plt.subplot(2,2,2)
sns.countplot(x= "Age_group", data = df, hue = "Age_group", order = df["Age_group"].value_counts().index, palette= "husl")
ax = plt.gca()
text_format(fig)
plt.title("Age Group Distribution")

plt.subplot(2,2,3)
sns.boxplot(x= "Age", data = df, color= "darkorange")
plt.title("Finding Outliers in Age Using Boxplot ")

plt.subplot(2,2,4)
sns.distplot(df["Age"], kde= True)
plt.title("Distribution of Age Using distplot ")

plt.suptitle("Distribution of Age & Age_group & Finding Outliers", fontsize = 30)
plt.show()
```



Insights:

- Adults mostly prefer KP281 and middle aged people prefer KP481.
- Above 46 years are considered as Outliers.

Finding Range of each Attributes

In [530…

```
# Get the range of numerical attributes
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
for col in numerical_columns:
    min_val = df[col].min()
    max_val = df[col].max()
    range_val = max_val - min_val
    print(f"Range of {col}: {min_val} to {max_val} (Range: {range_val})")
```

```
Range of Age: 18 to 50 (Range: 32)
Range of Education: 12 to 21 (Range: 9)
Range of Usage: 2 to 7 (Range: 5)
Range of Fitness: 1 to 5 (Range: 4)
Range of Income: 29562 to 104581 (Range: 75019)
Range of Miles: 21 to 360 (Range: 339)
Range of Product_price: 1500 to 2500 (Range: 1000)
```

Contingency Table Creation

In [531…

```
# Contingency table for Product vs Product_price
ct_Product_Product_price = pd.crosstab(df["Product"], df["Product_price"], margins= True, normalize= True)
print("Contingency Table for Product vs Product_price:")
print(ct_Product_Product_price)
print("-"*50)

# Contingency table for Product vs Education
ct_Product_Education = pd.crosstab(df["Education"],df["Product"], margins= True, normalize= True)
print("Contingency Table for Product vs Education:")
print(ct_Product_Education)
print("-"*50)

# Contingency table for Product vs Gender
ct_Product_Gender = pd.crosstab(df["Product"], df["Gender"], margins= True, normalize= True)
print("Contingency Table for Product vs Gender:")
print(ct_Product_Gender)
```

```
print("-"*50)

# Contingency table for Product vs MaritalStatus
ct_Product_MaritalStatus = pd.crosstab(df["Product"], df["MaritalStatus"], margins= True, normalize= True)
print("Contingency Table for Product vs MaritalStatus:")
print(ct_Product_MaritalStatus)
print("-"*50)

# Contingency table for Product vs Usage
ct_Product_Usage = pd.crosstab(df["Product"], df["Usage"], margins= True, normalize= True)
print("Contingency Table for Product vs Usage:")
print(ct_Product_Usage)
print("-"*50)

# Contingency table for Product vs Fitness
ct_Product_Fitness = pd.crosstab(df["Product"], df["Fitness"], margins= True, normalize= True)
print("Contingency Table for Product vs Fitness:")
print(ct_Product_Fitness)
print("-"*50)

# Contingency table for Product vs Age_group
ct_Product_Age_group = pd.crosstab(df["Product"], df["Age_group"], margins= True, normalize= True)
print("Contingency Table for Product vs Age_group:")
print(ct_Product_Age_group)
print("-"*50)

# Contingency table for Product vs Income_group
ct_Product_Income_group = pd.crosstab(df["Product"], df["Income_group"], margins= True, normalize= True)
print("Contingency Table for Product vs Income_group:")
print(ct_Product_Income_group)
print("-"*50)

# Contingency table for Product vs Miles_group
ct_Product_Miles_group = pd.crosstab( df["Miles_group"],df["Product"], margins= True, normalize= True)
print("Contingency Table for Product vs Miles_group:")
print(ct_Product_Miles_group)
print("-"*50)
```

```
Contingency Table for Product vs Product_price:
Product_price      1500      1750      2500       All
Product
KP281          0.444444  0.000000  0.000000  0.444444
KP481          0.000000  0.333333  0.000000  0.333333
KP781          0.000000  0.000000  0.222222  0.222222
All            0.444444  0.333333  0.222222  1.000000
--------------------------------------------------
Contingency Table for Product vs Education:
Product       KP281     KP481     KP781       All
Education
12         0.011111  0.005556  0.000000  0.016667
13         0.016667  0.011111  0.000000  0.027778
14         0.166667  0.127778  0.011111  0.305556
15         0.022222  0.005556  0.000000  0.027778
16         0.216667  0.172222  0.083333  0.472222
18         0.011111  0.011111  0.105556  0.127778
20         0.000000  0.000000  0.005556  0.005556
21         0.000000  0.000000  0.016667  0.016667
All        0.444444  0.333333  0.222222  1.000000
--------------------------------------------------
Contingency Table for Product vs Gender:
Gender     Female      Male       All
Product
KP281    0.222222  0.222222  0.444444
KP481    0.161111  0.172222  0.333333
KP781    0.038889  0.183333  0.222222
All      0.422222  0.577778  1.000000
--------------------------------------------------
Contingency Table for Product vs MaritalStatus:
MaritalStatus  Partnered    Single       All
Product
KP281           0.266667  0.177778  0.444444
KP481           0.200000  0.133333  0.333333
KP781           0.127778  0.094444  0.222222
All             0.594444  0.405556  1.000000
--------------------------------------------------
Contingency Table for Product vs Usage:
Usage           2         3         4         5         6         7       All
Product
KP281    0.105556  0.205556  0.122222  0.011111  0.000000  0.000000  0.444444
KP481    0.077778  0.172222  0.066667  0.016667  0.000000  0.000000  0.333333
KP781    0.000000  0.005556  0.100000  0.066667  0.038889  0.011111  0.222222
All      0.183333  0.383333  0.288889  0.094444  0.038889  0.011111  1.000000
--------------------------------------------------
Contingency Table for Product vs Fitness:
Fitness         1         2         3         4         5       All
Product
KP281    0.005556  0.077778  0.300000  0.050000  0.011111  0.444444
KP481    0.005556  0.066667  0.216667  0.044444  0.000000  0.333333
KP781    0.000000  0.000000  0.022222  0.038889  0.161111  0.222222
All      0.011111  0.144444  0.538889  0.133333  0.172222  1.000000
--------------------------------------------------
Contingency Table for Product vs Age_group:
Age_group     Adult  Middle_Aged       Old       All
Product
KP281      0.294444     0.133333  0.016667  0.444444
KP481      0.183333     0.144444  0.005556  0.333333
KP781      0.150000     0.061111  0.011111  0.222222
All        0.627778     0.338889  0.033333  1.000000
--------------------------------------------------
Contingency Table for Product vs Income_group:
Income_group  Low_Income  Medium_Income  High_Income       All
Product
KP281           0.127778       0.316667     0.000000  0.444444
KP481           0.050000       0.283333     0.000000  0.333333
KP781           0.000000       0.094444     0.127778  0.222222
All             0.177778       0.694444     0.127778  1.000000
--------------------------------------------------
Contingency Table for Product vs Miles_group:
Product               KP281     KP481     KP781       All
Miles_group
Low_Activity       0.066667  0.027778  0.000000  0.094444
Medium_Activity    0.277778  0.216667  0.044444  0.538889
High_Activity      0.100000  0.083333  0.150000  0.333333
VeryHigh_Activity  0.000000  0.005556  0.027778  0.033333
All                0.444444  0.333333  0.222222  1.000000
--------------------------------------------------
```

Insights

- Education
  - Highest Education Level (16 years):
    1. Probability of purchase: 47%.
    2. Preferred models: KP281 (22%), KP481 (17%), KP781 (8%).
  - Moderate Education Level (14 years):

1. Probability of purchase: 31%.
2. Preferred models: KP281 (17%), KP481 (13%), KP781 (1%).

- Gender
  - Females:
    1. Probability of purchase: 42%.
    2. Preferred models: KP281 (22%), KP481 (16%), KP781 (4%).
  - Males:
    1. Probability of purchase: 58%.
    2. Preferred models: KP281 (22%), KP481 (17%), KP781 (18%).
- Marital Status
  - Partnered:
    1. Probability of purchase: 59%.
    2. Preferred models: KP281 (27%), KP481 (20%), KP781 (13%).
  - Single:
    1. Probability of purchase: 41%.
    2. Preferred models: KP281 (18%), KP481 (13%), KP781 (9%).
- Usage
  - High Usage (3 times per week):
    1. Probability of purchase: 38%.
    2. Preferred models: KP281 (21%), KP481 (17%), KP781 (1%).
  - Moderate Usage (4 times per week):
    1. Probability of purchase: 29%.
    2. Preferred models: KP281 (12%), KP481 (7%), KP781 (10%).
- Fitness
  - Moderate Fitness Level (3):
    1. Probability of purchase: 54%.
    2. Preferred models: KP281 (30%), KP481 (22%), KP781 (2%).
  - High Fitness Level (5):
    1. Probability of purchase: 17%.
    2. Preferred models: KP281 (1%), KP481 (0%), KP781 (16%).
- Age Group
  - Adults:
    1. Probability of purchase: 63%
    2. Preferred models: KP281 (29%), KP481 (18%), KP781 (15%).
  - Middle-Aged:
    1. Probability of purchase: 34%.
    2. Preferred models: KP281 (13%), KP481 (14%), KP781 (6%).
- Income Group
  - High Income:
    1. Probability of purchase: 18%.
    2. Preferred models: KP281 (13%), KP481 (5%), KP781 (0%).
  - Moderate Income:
    1. Probability of purchase: 68%.
    2. Preferred models: KP281 (31%), KP481 (28%), KP781 (9%).
  - High Income:
    1. Probability of purchase: 13%.
    2. Preferred models: KP281 (0%), KP481 (0%), KP781 (13%).

Marginal Probability

In [532…

```
#Marginal Probabilities for Product
marginal_Product = ct_Product_Gender.sum(axis=1) / len(df)
print("\nMarginal Probabilities for Product:")
print(marginal_Product)
print("-"*50)

#Marginal Probabilities for Gender
marginal_Gender = ct_Product_Gender.sum(axis=0) / len(df)
print("\nMarginal Probabilities for Gender:")
print(marginal_Gender)
print("-"*50)

#Marginal Probabilities for Age_group
marginal_Age_group = ct_Product_Age_group.sum(axis=0) / len(df)
print("\nMarginal Probabilities for Age_group:")
print(marginal_Age_group)
print("-"*50)

#Marginal Probabilities for Income_group
```

```
marginal_Income_group = ct_Product_Income_group.sum(axis=0) / len(df)
print("\nMarginal Probabilities for Income_group:")
print(marginal_Income_group)
print("-"*50)
```

```
Marginal Probabilities for Product:
Product
KP281    0.004938
KP481    0.003704
KP781    0.002469
All      0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Gender:
Gender
Female    0.004691
Male      0.006420
All       0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Age_group:
Age_group
Adult          0.006975
Middle_Aged    0.003765
Old            0.000370
All            0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Income_group:
Income_group
Low_Income       0.001975
Medium_Income    0.007716
High_Income      0.001420
All              0.011111
dtype: float64
--------------------------------------------------

Product
KP281    0.004938
KP481    0.003704
KP781    0.002469
All      0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Gender:
Gender
Female    0.004691
Male      0.006420
All       0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Age_group:
Age_group
Adult          0.006975
Middle_Aged    0.003765
Old            0.000370
All            0.011111
dtype: float64
--------------------------------------------------

Marginal Probabilities for Income_group:
Income_group
Low_Income       0.001975
Medium_Income    0.007716
High_Income      0.001420
All              0.011111
dtype: float64
--------------------------------------------------
```

Conditional Probability

In [533…

```
# Conditional probability of Gender given Product (P(Gender|Product))
conditional_Gender_given_Product = ct_Product_Gender.div(ct_Product_Gender.sum(axis=1), axis=0)
print("\nConditional Probability of Gender given Product:")
print(conditional_Gender_given_Product)
print("-"*50)

# Conditional probability of Product given Gender (P(Product|Gender))
conditional_Product_given_Gender = ct_Product_Gender.div(ct_Product_Gender.sum(axis=0), axis=1)
print("\nConditional Probability of Product given Gender:")
print(conditional_Product_given_Gender)
```

```
print("-"*50)

# Conditional probability of Product given Age_group (P(Product|Age_group))
conditional_Product_given_Age_group = ct_Product_Age_group.div(ct_Product_Age_group.sum(axis=0), axis=1)
print("\nConditional Probability of Product given Age_group:")
print(conditional_Product_given_Age_group)
print("-"*50)

# Conditional probability of Product given Income_group (P(Product|Income_group))
conditional_Product_given_Income_group = ct_Product_Income_group.div(ct_Product_Income_group.sum(axis=0), axis=1)
print("\nConditional Probability of Product given Income_group:")
print(conditional_Product_given_Income_group)
print("-"*50)
```

```
Conditional Probability of Gender given Product:
Gender      Female      Male  All
Product
KP281     0.250000  0.250000  0.5
KP481     0.241667  0.258333  0.5
KP781     0.087500  0.412500  0.5
All       0.211111  0.288889  0.5
--------------------------------------------------

Conditional Probability of Product given Gender:
Gender      Female      Male       All
Product
KP281     0.263158  0.192308  0.222222
KP481     0.190789  0.149038  0.166667
KP781     0.046053  0.158654  0.111111
All       0.500000  0.500000  0.500000
--------------------------------------------------

Conditional Probability of Product given Age_group:
Age_group     Adult  Middle_Aged       Old       All
Product
KP281      0.234513     0.196721  0.250000  0.222222
KP481      0.146018     0.213115  0.083333  0.166667
KP781      0.119469     0.090164  0.166667  0.111111
All        0.500000     0.500000  0.500000  0.500000
--------------------------------------------------

Conditional Probability of Product given Income_group:
Income_group  Low_Income  Medium_Income  High_Income       All
Product
KP281           0.359375          0.228          0.0  0.222222
KP481           0.140625          0.204          0.0  0.166667
KP781           0.000000          0.068          0.5  0.111111
All             0.500000          0.500          0.5  0.500000
--------------------------------------------------
```

Customer Profiling of Each Product:

Customer Profile for KP281 Treadmill:

- Gender: the customers using KP281 are 50% male and 50% female .
- Age Group: The customers using KP281 are 66.25% adults, 30% middle aged and 3.75% old people.
- MaritalStatus: The customers using KP281 are 60% married and 40% single.
- Usage Groups: The customers using KP281 are 70% low usage people and 30% medium usage people.
- Fitness Groups: The customers using KP281 are 67.5% medium fitness mind people, 18.75% low fitness minded people and 13.75% high fitness minded people.
- Income Groups: The customers using KP281 are 71.25% medium income people and 28.75% low income people.
- Miles Groups: The customers using KP281 are 62.5% medium activity people, 22.5% high activity people and 15% low activity people.
- Sales: 37% sales from KP281.

Customer Profile for KP481 Treadmill:

- Gender: the customers using KP481 are 51.7% male and 48.3% female .
- Age Group: The customers using KP481 are 55% adults, 43.3% middle aged and 1.7% old people.
- MaritalStatus: The customers using KP481 are 60% married and 40% single.
- Usage Groups: The customers using KP481 are 75% low usage people, 25% medium usage people.
- Fitness Groups: The customers using KP481 are 65% medium fitness minded people, 21.7% low fitness minded people and 13.3% high fitness minded people.
- Income Groups: The customers using KP481 are 85% medium income people and 15% low income people.
- Miles Groups: The customers using KP481 are 65% medium activity people, 25% high activity people, 8.3% low activity people and 1.7% very high activity people.
- Sales: 32.3% sales from KP481.

Customer Profile for KP781 Treadmill:

- Gender: the customers using KP781 are 82.5% male and 17.5% female .
- Age Group: The customers using KP781 are 67.5% adults, 27.5% middle aged and 5% old people.
- MaritalStatus: The customers using KP781 are 57.5% married and 42.5% single.
- Usage Groups: The customers using KP781 are 75% medium usage people, 22.5% high usage people and 2.5% low usage people.
- Fitness Groups: The customers using KP781 are 90% high fitness minded people and 10% medium fitness minded people.
- Income Groups: The customers using KP781 are 57.5% high income people and 42.5% medium income people.
- Miles Groups: The customers using KP781 are 67.5% high activity people, 20% medium activity people and 12.5% very high activity people.
- Sales: 30.7% sales from KP781.

Business Insights

- **Comments on Relationship Between Variables**
  - **Age vs Income:** There is a positive correlation between age and income, suggesting that older customers tend to have higher incomes and may be more likely to purchase premium products like KP283.
  - **Gender vs Product Preference:** Female customers show a stronger preference for KP281, while male customers are more evenly distributed across all products.
  - **Usage Group vs Fitness Group:** There is no strong relationship between usage group and fitness group, suggesting that these factors do not significantly influence product preference.

- **Comments on the Distribution of Variables**
  - **Gender Distribution:** The distribution shows a slight imbalance with more male customers than female customers. However, female customers have a higher preference for KP281.
  - **Age Group Distribution:** The distribution is skewed towards younger age groups, indicating that AeroFit's marketing efforts should focus on this demographic.
  - **Income Group Distribution:** The distribution indicates that customers with higher incomes are more likely to purchase AeroFit products.

- **Comments on the Range of Attributes**
  - **Age Group:** The age range of customers is between 20 and 60 years, with a majority in the younger age groups. This suggests that AeroFit's products are more appealing to younger demographics.
  - **Income Group:** The income range varies widely, but there is a higher concentration of customers in the middle to high-income brackets. This indicates that AeroFit's products are priced attractively for this segment.
  - **Product Preference:** The range of product preferences shows that KP281 is the most popular product, followed by KP282 and then KP283.

Recommendations

Here are actionable recommendations for the AeroFit business:

- **Gender-Specific Campaigns:** Design specific marketing campaigns targeting female customers to increase sales of KP281.

- **Target Younger Demographics:** Focus marketing efforts on younger age groups (20-40 years) as they show higher preference for AeroFit products.

- **Income-Based Segmentation:** Segment your customer base by income and tailor your marketing strategies accordingly to maximize sales.

- **Broaden Market to Include Older Age Groups:**
  - **Action:** Study and create plans to sell treadmills to people over 50.
  - **Details:** Evaluate the health advantages and possible risks of treadmill use for seniors.
- **Position KP281 as a Female-Friendly Product:** Emphasize features that appeal to female customers when promoting KP281.