Aerofit - Descriptive Statistics & Probability

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

1. Problem Statement and Analysing basic metrics

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.

About Data

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

Product Purchased:KP281, KP481, or KP781

Age: In years

Gender: Male/Female

Education: In years

MaritalStatus: Single or partnered

Usage: The average number of times the customer plans to use the treadmill each week.

Income: Annual income (in $)

Fitness: Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.

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

Product Portfolio:

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

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

3. The KP781 treadmill is having advanced features that sell $ 2,500

Exploratory Data Analysis

In [2]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

```python
warnings.filterwarnings('ignore')
import copy
```

In [3]:
```python
# Loading the dataset
df = pd.read_csv('aerofit_treadmill.csv')
```

In [4]:
```python
df.head()
```

Out[4]:

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

In [5]:
```python
df.tail()
```

Out[5]:

	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 [6]:
```python
df.shape
```

Out[6]:
```
(180, 9)
```

In [7]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Product        180 non-null    object
 1   Age            180 non-null    int64 
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64 
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64 
 6   Fitness        180 non-null    int64 
 7   Income         180 non-null    int64 
 8   Miles          180 non-null    int64 
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

Insights

From the above analysis, it is clear that, data has total of 9 features with mixed alpha numeric data. Also we can see that there is no missing data in the columns.

conversion of categorical attributes to 'category'

In [8]:
```
df["Gender"]=df["Gender"].astype("category")
df["MaritalStatus"]=df["MaritalStatus"].astype("category")
df["Product"]=df["Product"].astype("category")
```

statistical summary

In [9]:
```
 #statisctical summary of categorical  type columns
df.describe(include = 'category')
```

Out[9]:

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

Insights

Based on the "freq" value (frequency), KP281 seems to be the best-selling product (80).

Sales appear to be skewed towards males, with a higher frequency for males across all products

Individuals with "Partnered" marital status seem to be the most frequent buyers overall (107).

In [10]:
```
#statisctical summary of numerical type columns
df.describe()
```

Out[10]:

	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 age demographic of customers ranges from 18 to 50 years, with a mean age of 29 years.

Education: Customers' educational attainment spans from 12 to 21 years, with an average duration of schooling of 16 years.

Usage: Customers plan to use the product between 2 and 7 times per week, with an average frequency of 3 times per week.

Fitness: On average, customers rate their fitness level at 3 out of 5, indicating a moderate level of fitness.

Income: Customers' annual incomes fall within the range of USD 30,000 to USD 100,000, with an average income of approximately USD 54,000.

Miles: Customers' weekly running targets vary from 21 to 360 miles, with an average goal of 103 miles per week.

2. Non-Graphical Analysis

In [11]:
```
df.duplicated().value_counts()
```

Out[11]:
```
False    180
Name: count, dtype: int64
```

Insights

There are no duplicate entries in the dataset

In [12]:
```
#number of unique values in our data
for i in df.columns:
  print(i,':',df[i].nunique())
```

```
Product : 3
Age : 32
Gender : 2
Education : 8
MaritalStatus : 2
Usage : 6
Fitness : 5
Income : 62
Miles : 37
```

In [14]:
```
# checking the unique values for columns
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']
Categories (3, object): ['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']
Categories (2, object): ['Female', 'Male']
----------------------------------------------------------------------
Unique Values in Education column are :-
[14 15 12 13 16 18 20 21]
----------------------------------------------------------------------
Unique Values in MaritalStatus column are :-
['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
----------------------------------------------------------------------
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 is quite good and it does not contain any abnormal values.

In [13]:
```
#checking null values in every column of our data
df.isnull().sum()
```

Out[13]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

Insights

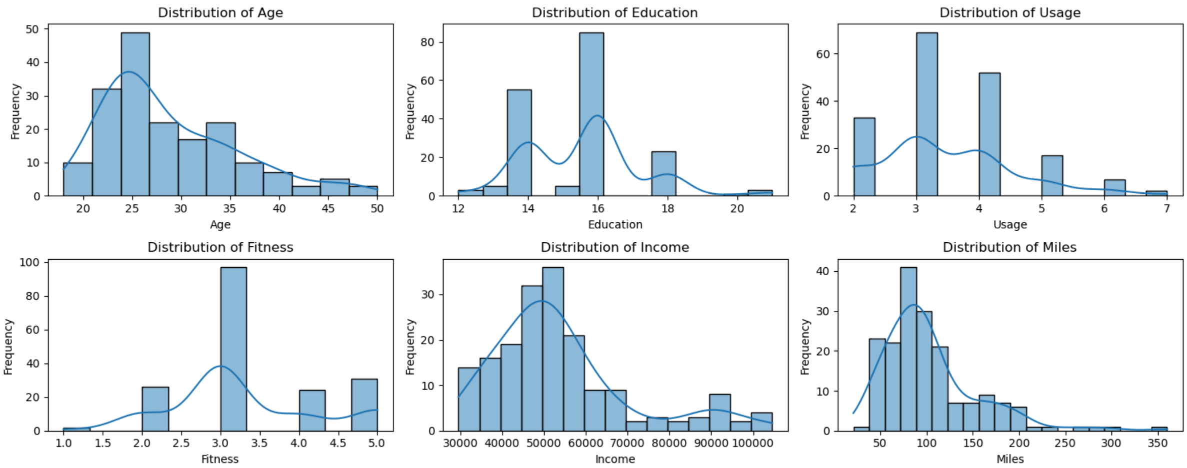
There are no null values in the given dataset

3 .Visual Analysis - Univariate & Bivariate

3.1 Univariate analysis: It examines a single variable at a time to understand its distribution, central tendency, and variability.

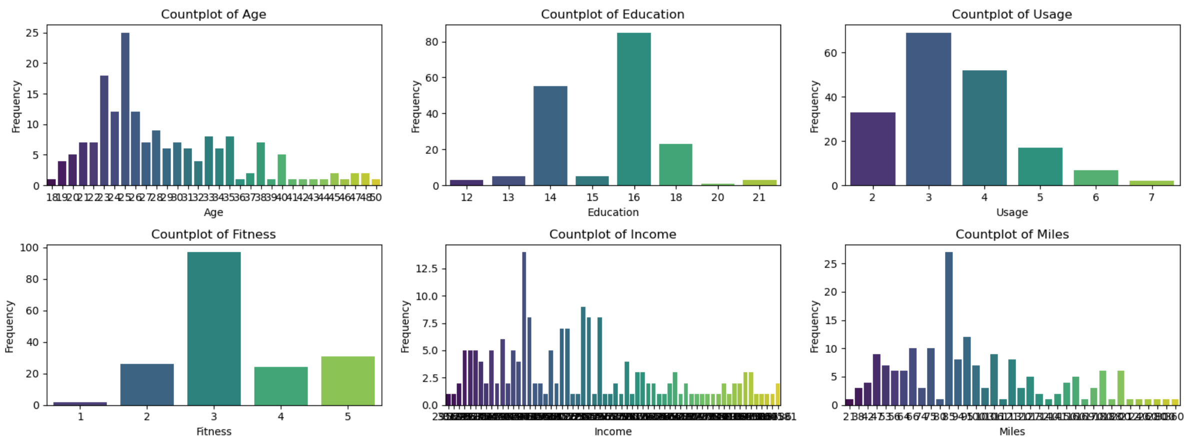
continuous variables

In [59]:
```
# Assuming 'continuous_vars' is a list containing names of continuous variables
continuous_vars = ['Age', 'Education','Usage','Fitness','Income', 'Miles']

# Calculate the number of rows needed based on the length of continuous_vars
num_rows = len(continuous_vars) // 3  # Integer division to get whole number of row
if len(continuous_vars) % 3 != 0:
    num_rows += 1  # Add 1 if there are remaining variables

# Create subplots with three columns for each row
fig, axes = plt.subplots(num_rows, 3, figsize=(15, num_rows*3))

# Flatten axes array to simplify iteration
axes = axes.flatten()

# Iterate over each continuous variable and corresponding subplot
for i, col in enumerate(continuous_vars):
    sns.histplot(df[col], ax=axes[i], kde=True)  # Create distplot on each subplot
    axes[i].set_title(f"Distribution of {col}")  # Set title for each subplot
    axes[i].set_xlabel(col)  # Add x-axis label
    axes[i].set_ylabel("Frequency")  # Add y-axis label

# Hide empty subplots if the number of variables is not divisible by 3
for j in range(len(continuous_vars), len(axes)):
    axes[j].axis('off')

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```

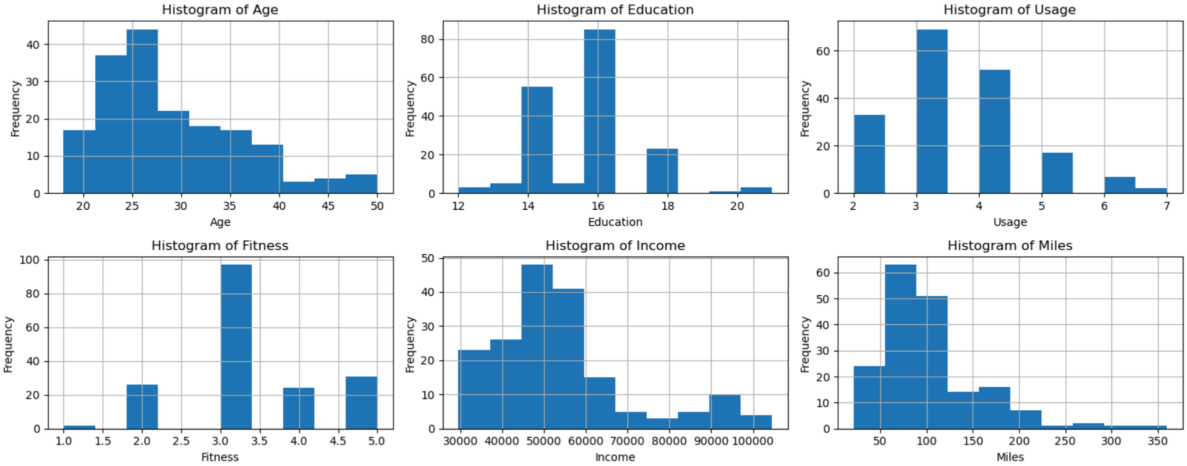


In [61]:
```
# Calculate the number of rows needed based on the length of continuous_vars
num_rows = len(continuous_vars) // 3  # Integer division to get whole number of row
if len(continuous_vars) % 3 != 0:
    num_rows += 1  # Add 1 if there are remaining variables

# Create subplots with three columns for each row
fig, axes = plt.subplots(num_rows, 3, figsize=(16, num_rows*3))

# Flatten axes array to simplify iteration
axes = axes.flatten()
```

```
# Iterate over each continuous variable and corresponding subplot
for i, col in enumerate(continuous_vars):
    sns.countplot(data=df, x=col, ax=axes[i], palette='viridis')
    axes[i].set_title(f"Countplot of {col}")  # Set title for each subplot
    axes[i].set_xlabel(col)  # Add x-axis label
    axes[i].set_ylabel("Frequency")  # Add y-axis label

# Hide empty subplots if the number of variables is not divisible by 3
for j in range(len(continuous_vars), len(axes)):
    axes[j].axis('off')

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



In [62]:
```
# Calculate the number of rows needed based on the length of continuous_vars
num_rows = len(continuous_vars) // 3  # Integer division to get whole number of row
if len(continuous_vars) % 3 != 0:
    num_rows += 1  # Add 1 if there are remaining variables

# Create subplots with three columns for each row
fig, axes = plt.subplots(num_rows, 3, figsize=(15, num_rows*3))

# Flatten axes array to simplify iteration
axes = axes.flatten()

# Iterate over each continuous variable and corresponding subplot
for i, col in enumerate(continuous_vars):
    df[col].hist(ax=axes[i])  # Create histogram on each subplot
    axes[i].set_title(f"Histogram of {col}")  # Set title for each subplot
    axes[i].set_xlabel(col)  # Add x-axis label
    axes[i].set_ylabel("Frequency")  # Add y-axis label

# Hide empty subplots if the number of variables is not divisible by 3
for j in range(len(continuous_vars), len(axes)):
    axes[j].axis('off')

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



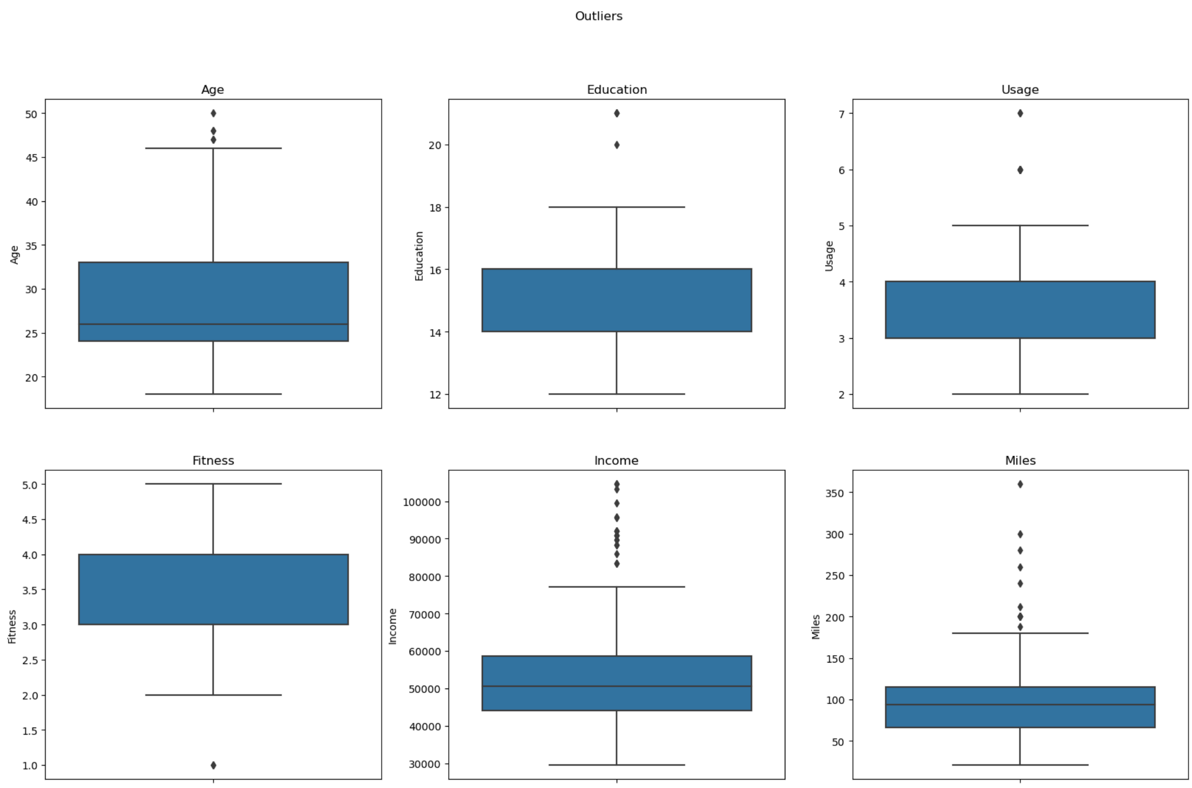
Insights

Most of the users are around 25 years of age, having 16 years of education with around $50000 of annual income.

Majority of the users have fitness of level 3, use the treadmill 3 times a week and walk/run around 90 miles each week

In [68]:

```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))
for i in range(2):
    for j in range(3):
        variable = continuous_vars[i * 3 + j]
        sns.boxplot(ax=axes[i, j], data=df, y=variable)
        axes[i, j].set_title(variable)

plt.suptitle("Outliers")
plt.show();
```



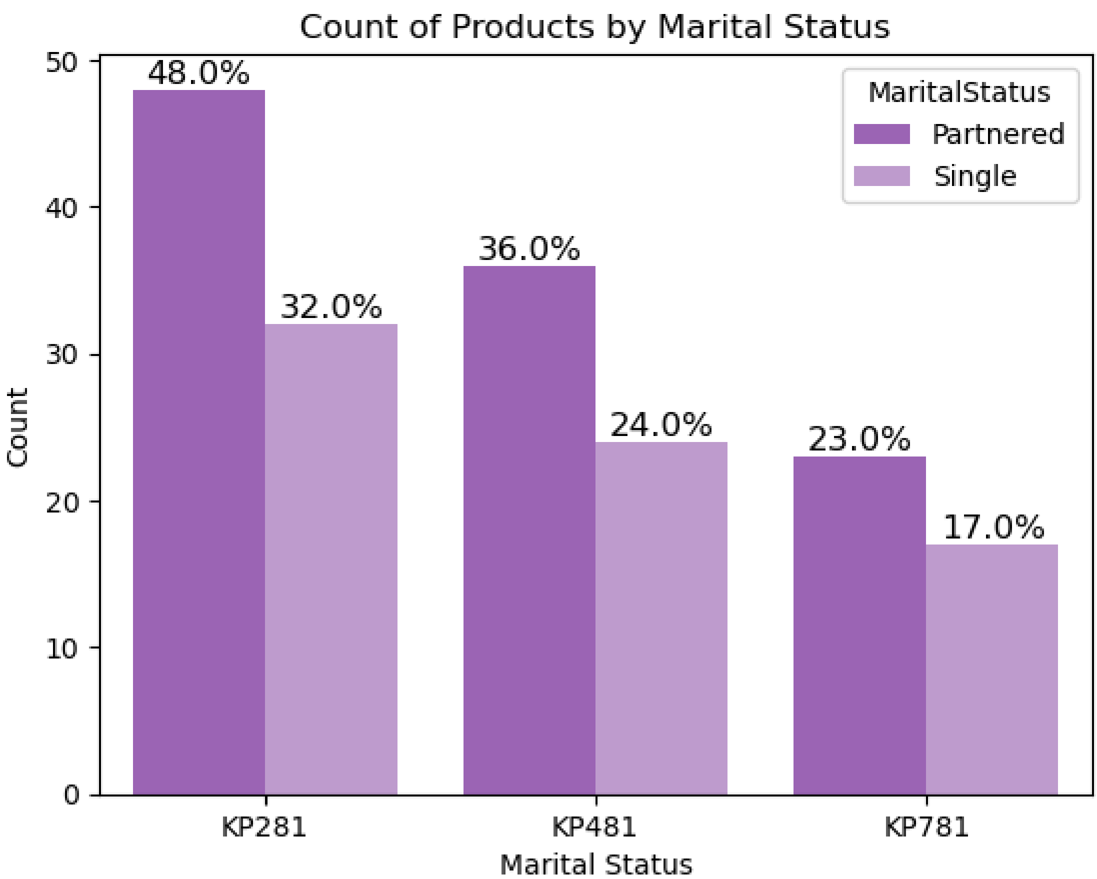
Insights

There appear to be numerous outliers in the Income and Miles columns.

3.2 Bivariate analysis refers to a statistical method used to examine the relationship between two variables. It's a fundamental technique for exploring how changes in one variable might be associated with changes in another.

Products Vs Marital Status

In [ ]:
```
custom_palette =sns.diverging_palette(290, 300, s=60)
marital_status_counts = df['MaritalStatus'].value_counts()
sns.countplot(x="Product", hue="MaritalStatus", data=df, palette=custom_palette)
plt.xlabel("Marital Status")
plt.ylabel("Count")
plt.title("Count of Products by Marital Status")
def format_percentages(x):
    return f"{x:.1f}%"  # Customize format string (e.g., "{x:.2f}%" for two decimal

# Add percentages to countplot bars
for container in plt.gca().containers:  # Get container objects for bars
    rects = container.get_children()  # Get individual bar rectangles
    for rect in rects:
        height = rect.get_height()  # Get bar height
        plt.text(rect.get_x() + rect.get_width() / 2, height + 0.05, format_percent

plt.show()
```



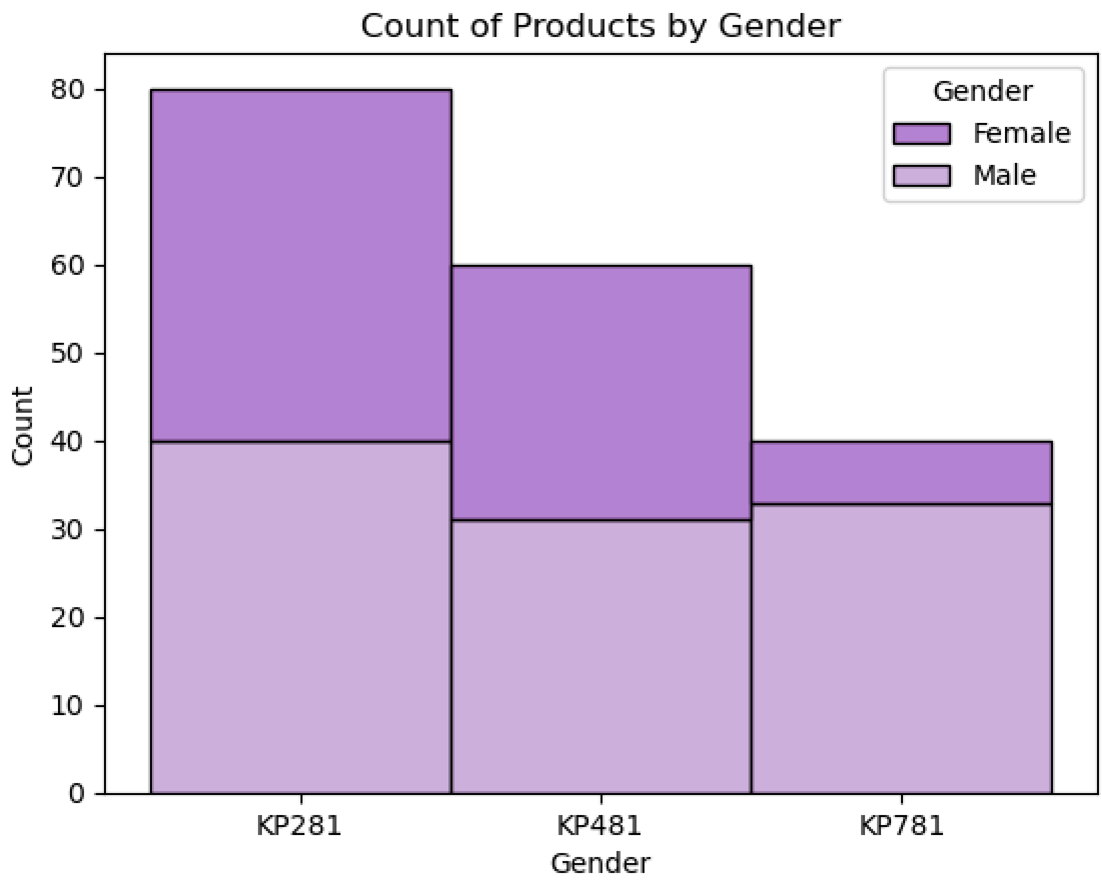
Insights

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

Products Vs Gender

In [184…

```
# Histogram for Gender and product purchased
sns.histplot(df, x='Product', hue='Gender', multiple="stack",palette=custom_palette
plt.xlabel("Gender")
plt.ylabel("Count")
plt.title("Count of Products by Gender")
plt.show()
```



Products Vs Age

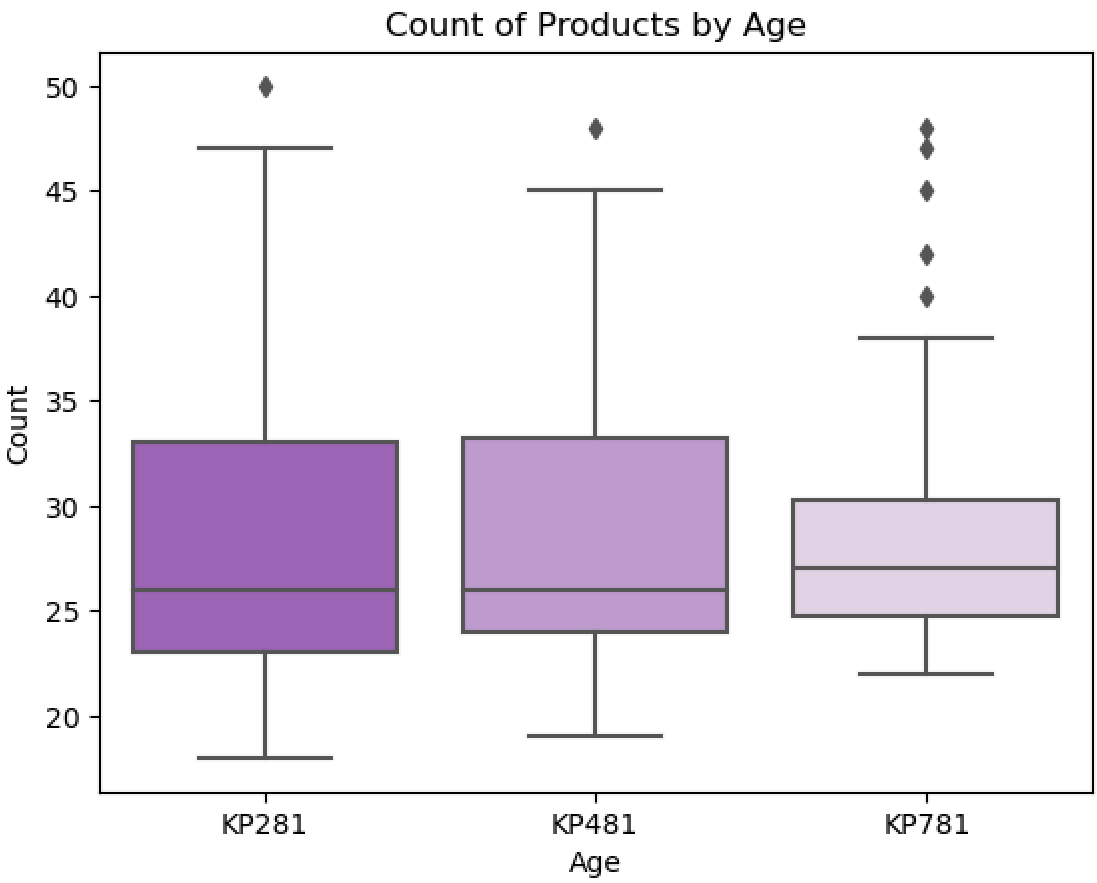
Insights

Treadmill model KP781 is preferred more by male customers .

Both treadmill models, KP481 and KP281 , show equal distribution of both the gender

In [185…

```
# Boxplot for age and product purchased
sns.boxplot(x='Product', y='Age', data=df,palette=custom_palette)
plt.xlabel("Age")
plt.ylabel("Count")
plt.title("Count of Products by Age")
plt.show()
```



Insights

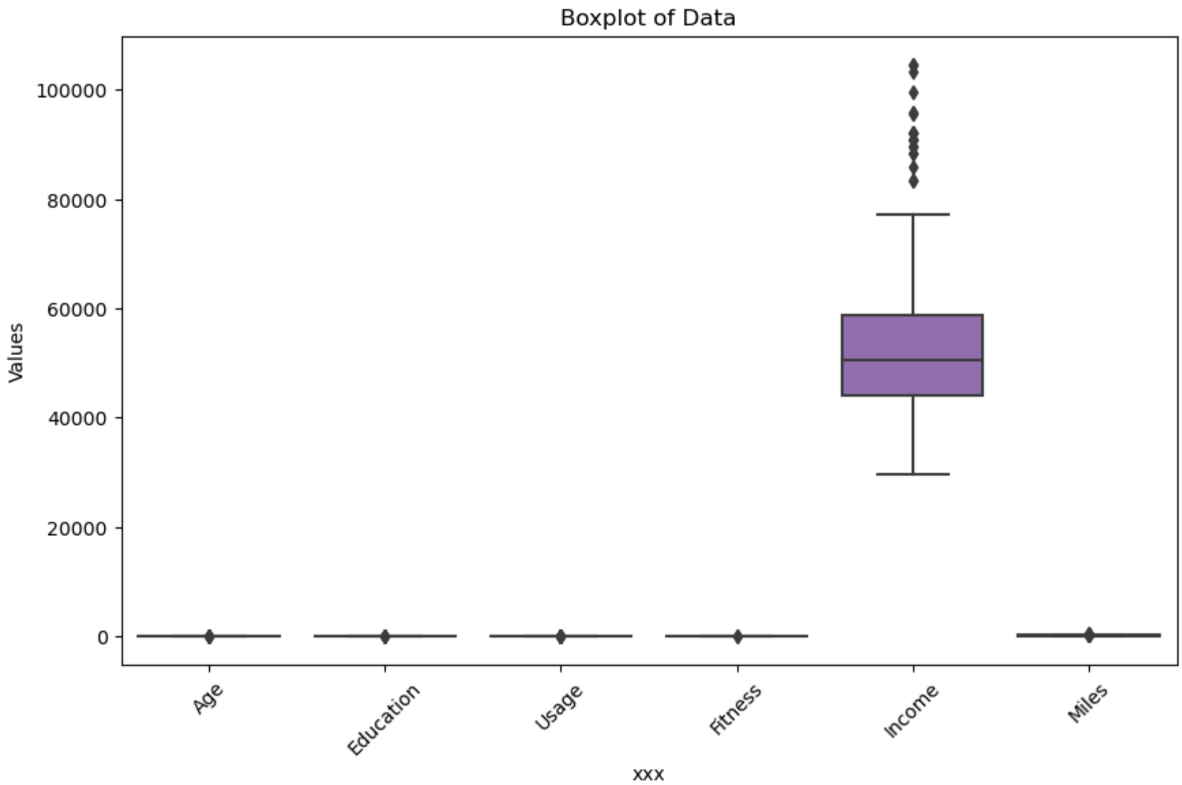
Customers between the ages of 23 and 32 tend to purchase the Treadmills KP281 and KP481, whereas KP781 seems to be less popular among this age group.

4. Detecting Outliers using describe method

In [111…

```
# Function to detect outliers
def detect_outliers(df):
    outliers_detected = {}  # Dictionary to store outlier detection results

    # Step 1: Visualize potential outliers using boxplots
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=df)
    plt.title("Boxplot of Data")
    plt.xlabel("Variables")
    plt.ylabel("Values")
    plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
    plt.show()

    # Step 2: Calculate summary statistics using the "describe" method
    summary_stats = df.describe()

    for column in df.select_dtypes(include='number').columns:
        # Calculate IQR
        q1 = summary_stats.loc['25%', column]
        q3 = summary_stats.loc['75%', column]
        iqr = q3 - q1

        # Calculate Z-scores
        z_scores = (df[column] - df[column].mean()) / df[column].std()

        # Identify outliers using Z-scores and IQR
```

```
        outliers = df[(abs(z_scores) > 3) | (df[column] < q1 - 1.5 * iqr) | (df[co]

        # Add outliers information to dictionary
        if not outliers.empty:
            outliers_detected[column] = {
                "outlier_values": outliers.index.tolist(),
                "z_scores": z_scores[outliers.index].tolist(),
            }

    return outliers_detected

# Example usage
outliers = detect_outliers(df.copy())  # Avoid modifying the original DataFrame

if outliers:
    print("Outliers detected:")
    for variable, info in outliers.items():
            print(f"Variable: {variable}")
            print(f"  - Outlier indices: {info['outlier_values']}")
            print(f"  - Z-scores: {info['z_scores']}")
else:
      print("No outliers detected.")
```



```
Outliers detected:
Variable: Age
  - Outlier indices: [78, 79, 139, 178, 179]
  - Z-scores: [2.622757399223028, 3.054816275239024, 2.7667770245616934, 2.6227573
99223028, 2.7667770245616934]
Variable: Education
  - Outlier indices: [156, 157, 161, 175]
  - Z-scores: [2.73817406186012, 3.356582256508579, 3.356582256508579, 3.356582256
508579]
Variable: Usage
  - Outlier indices: [154, 155, 162, 163, 164, 166, 167, 170, 175]
  - Z-scores: [2.345548857312817, 2.345548857312817, 2.345548857312817, 3.26738028
59510426, 2.345548857312817, 3.2673802859510426, 2.345548857312817, 2.345548857312
817, 2.345548857312817]
Variable: Fitness
  - Outlier indices: [14, 117]
  - Z-scores: [-2.4102480715054155, -2.4102480715054155]
Variable: Income
  - Outlier indices: [159, 160, 161, 162, 164, 166, 167, 168, 169, 170, 171, 172,
173, 174, 175, 176, 177, 178, 179]
  - Z-scores: [1.7990543597494595, 2.1007503231388793, 2.2515983048335895, 2.32702
2295680944, 2.1007503231388793, 1.9499023414441694, 2.2515983048335895, 3.00583821
3307139, 2.779566240765074, 2.1761743139862344, 2.553294268223009, 2.3270222956809
44, 2.327022295680944, 3.081262204154494, 1.7990543597494595, 2.1761743139862344,
2.2515983048335895, 3.081262204154494, 2.5316060845094723]
Variable: Miles
  - Outlier indices: [23, 84, 142, 148, 152, 155, 166, 167, 170, 171, 173, 175, 17
6]
  - Z-scores: [1.635165085584643, 2.0979173403979843, 1.8665412129913137, 1.866541
2129913137, 1.8665412129913137, 2.637794971013549, 3.794675608046903, 3.4090487290
35785, 3.023421850024667, 1.8665412129913137, 4.951556245080257, 1.866541212991313
7, 1.8665412129913137]
```

Insights

There appear to be numerous outliers in the Income and Miles columns.

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 [188…

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

In [189…

```
df.head()
```

Out[189]:

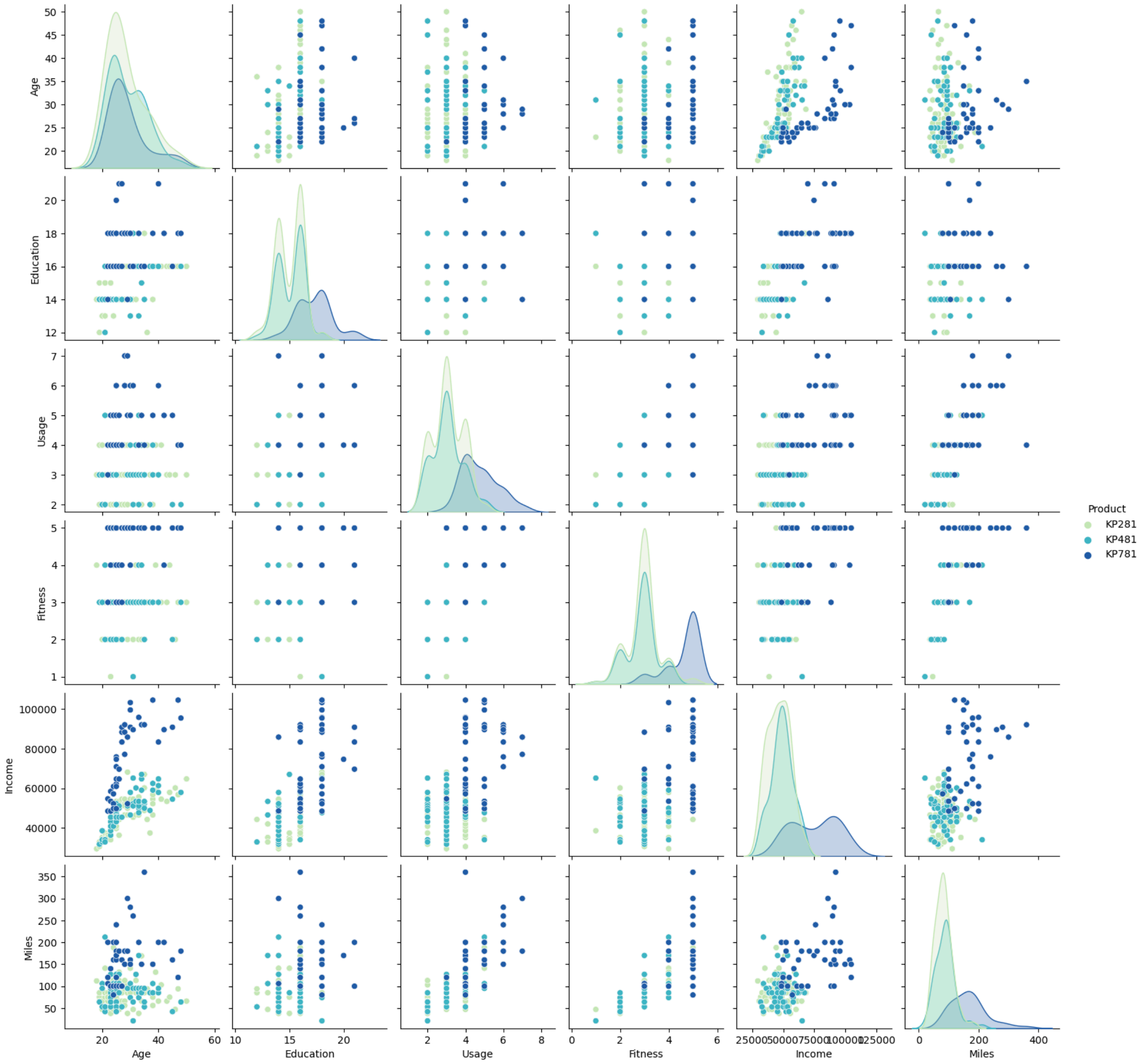
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age_group	e
0	KP281	18	Male	14	Single	3	4	29562	112	Young Adults	S
1	KP281	19	Male	15	Single	2	3	31836	75	Young Adults	S
2	KP281	19	Female	14	Partnered	4	3	30699	66	Young Adults	S
3	KP281	19	Male	12	Single	3	3	32973	85	Young Adults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

5. Correlation between Variables

Pairplot

In [199…

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



Insights

From above plots we can clearly distinguish the user of KP781 based on Fitness, Miles, Income and Usage

The users of KP281 and KP481 are similar in pattern. This will require a deeper analysis to differentiate between the two.

Heatmap

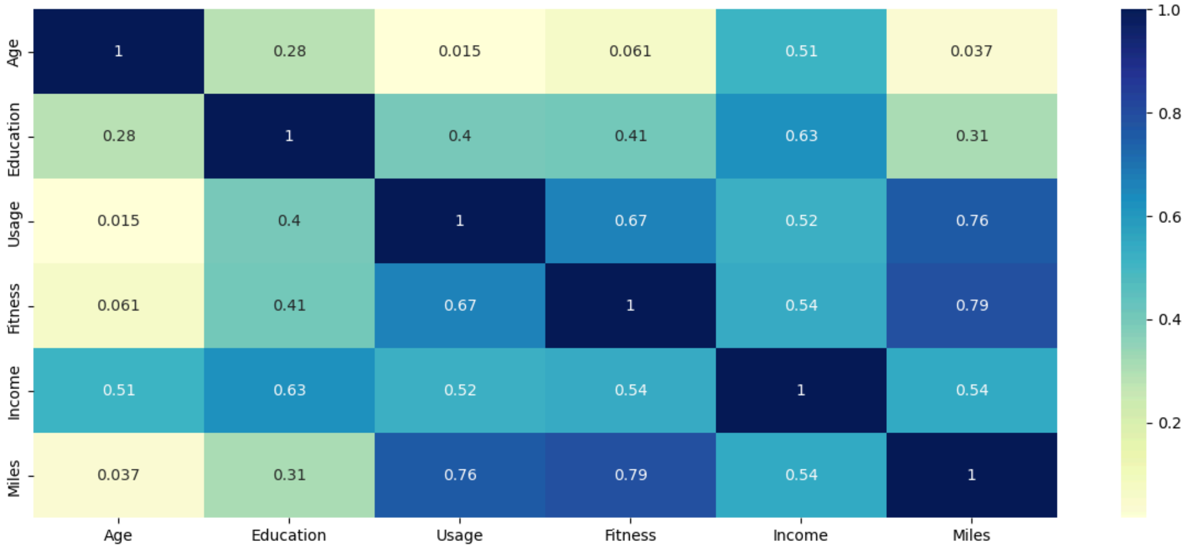
In [205…

```
# First we need to convert object into int datatype for usage and fitness columns
df_copy['Usage'] = df_copy['Usage'].astype('int64')
df_copy['Fitness'] = df_copy['Fitness'].astype('int64')
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype   
---  ------         --------------  -----   
 0   Product        180 non-null    category
 1   Age            180 non-null    int64   
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64   
 4   MaritalStatus  180 non-null    category
 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(7), int64(6)
memory usage: 10.9 KB
```

In [206…

```
numeric_df = df_copy.select_dtypes(include=['float64', 'int64'])
corr_mat = numeric_df.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.

6. Probability

In [196…

```
cross_tab = pd.crosstab(index=df['Product'], columns='count')

# Calculate the marginal probability by dividing each frequency by the total number
marginal_prob = cross_tab / cross_tab.sum()
```

```
# Print the marginal probability table
print("Marginal Probability of Treadmill Models:")
print(marginal_prob)
```

```
Marginal Probability of Treadmill Models:
col_0       count
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
```

Insights

Probability that a user will buy KP281 is 44%

Probability that a user will buy KP481 is 44%

Probability that a user will buy KP781 is 22%

KP281 is the most popular product

6.1 Probability of a male customer buying a KP781 treadmill

In [207…

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

Out[207]:

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

Insights

1.Probability of 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%

2. 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%

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

In [208…
```
pd.crosstab(index =df['Product'],columns = df['age_group'],margins = True,normalize
```
Out[208]:

age_group / Product	Young Adults	Adults	Middle Aged Adults	Elder	All
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 Elder(Above 45) is only 3%

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

In [210…
```
pd.crosstab(index =df['Product'],columns = df['edu_group'],margins = True,normaliz
```
Out[210]:

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% .

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

In [ ]:
```
pd.crosstab(index =df['Product'],columns = df['income_group'],margins = True,norma
```

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%

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

In [212…

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

Out[212]:

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%

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

In [213…

```
pd.crosstab(index =df['Product'],columns = df['Usage'],margins = True,normalize = T
```

Out[213]:

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%

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

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

For Treadmill model KP281 - 11%

For Treadmill model KP481 - 8%

For Treadmill model KP781 - 0%

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

In [215…

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

Out[215]:

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% .

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

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

In [217…

```
pd.crosstab(index =df['Product'],columns = df['miles_group'],margins = True,normali
```

Out[217]:

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 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

7. Customer Profiling

Based on above analysis

1. Probability of purchase of KP281 = 44%

2. Probability of purchase of KP481 = 33%

3. Probability of purchase of KP781 = 22%

Customer Profile for KP281 Treadmill:

1. Age of customer mainly between 18 to 35 years with few between 35 to 50 years

2. Education level of customer 13 years and above

3. Annual Income of customer below USD 60,000 Weekly Usage - 2 to 4 times

4. Fitness Scale - 2 to 4 Weekly Running Mileage - 50 to 100 miles

Customer Profile for KP481 Treadmill:

1. Age of customer mainly between 18 to 35 years with few between 35 to 50 years

2. Education level of customer 13 years and above

3. Annual Income of customer between USD 40,000 to USD 80,000 Weekly Usage - 2 to 4 times

4. Fitness Scale - 2 to 4 Weekly Running Mileage - 50 to 200 miles

Customer Profile for KP781 Treadmill:

1. Gender - Male

2. Age of customer between 18 to 35 years

3. Education level of customer 15 years and above

4.Annual Income of customer USD 80,000 and above Weekly Usage - 4 to 7 times

5.Fitness Scale - 3 to 5 Weekly Running Mileage - 100 miles and above

8. Recommendations

Marketing Campaigns for KP781

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

Affordable Pricing and Payment Plans

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

User-Friendly App Integration

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

In [ ]:

```

```