aerofit-case-study-mohana-final

October 29, 2023

##Import Libraries and load data

[144]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm

from google.colab import drive
drive.mount('/content/drive')

data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/aerofit_treadmill.
 ↪csv')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

##1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset

[145]:
```
data
```

[145]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0     KP281   18    Male         14        Single      3        4   29562
1     KP281   19    Male         15        Single      2        3   31836
2     KP281   19  Female         14     Partnered      4        3   30699
3     KP281   19    Male         12        Single      3        3   32973
4     KP281   20    Male         13     Partnered      4        2   35247
..      …   …     …         …           …    …      …      …
175   KP781   40    Male         21        Single      6        5   83416
176   KP781   42    Male         18        Single      5        4   89641
177   KP781   45    Male         16        Single      5        5   90886
178   KP781   47    Male         18     Partnered      4        5  104581
179   KP781   48    Male         18     Partnered      4        5   95508

     Miles
0      112
1       75
2       66
```

```
3       85
4       47
..      …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[146]:
```
data.shape
```

[146]:
```
(180, 9)
```

[147]:
```
data.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
```

[148]:
```
data.describe()
```

[148]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
```

```
count    180.000000
mean     103.194444
std       51.863605
min       21.000000
25%       66.000000
50%       94.000000
75%      114.750000
max      360.000000
```

[149]:
```
data.isnull().sum()
```

[149]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

[150]:
```
data['Product'].value_counts()
```

[150]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

[151]:
```
data['Age'].value_counts()
```

[151]:
```
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
38     7
21     7
22     7
27     7
31     6
34     6
29     6
20     5
```

```
40     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
43     1
41     1
39     1
36     1
42     1
Name: Age, dtype: int64
```

[152]:
```
data['Gender'].value_counts()
```

[152]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

[153]:
```
data['MaritalStatus'].value_counts()
```

[153]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

[154]:
```
data['Usage'].value_counts()
```

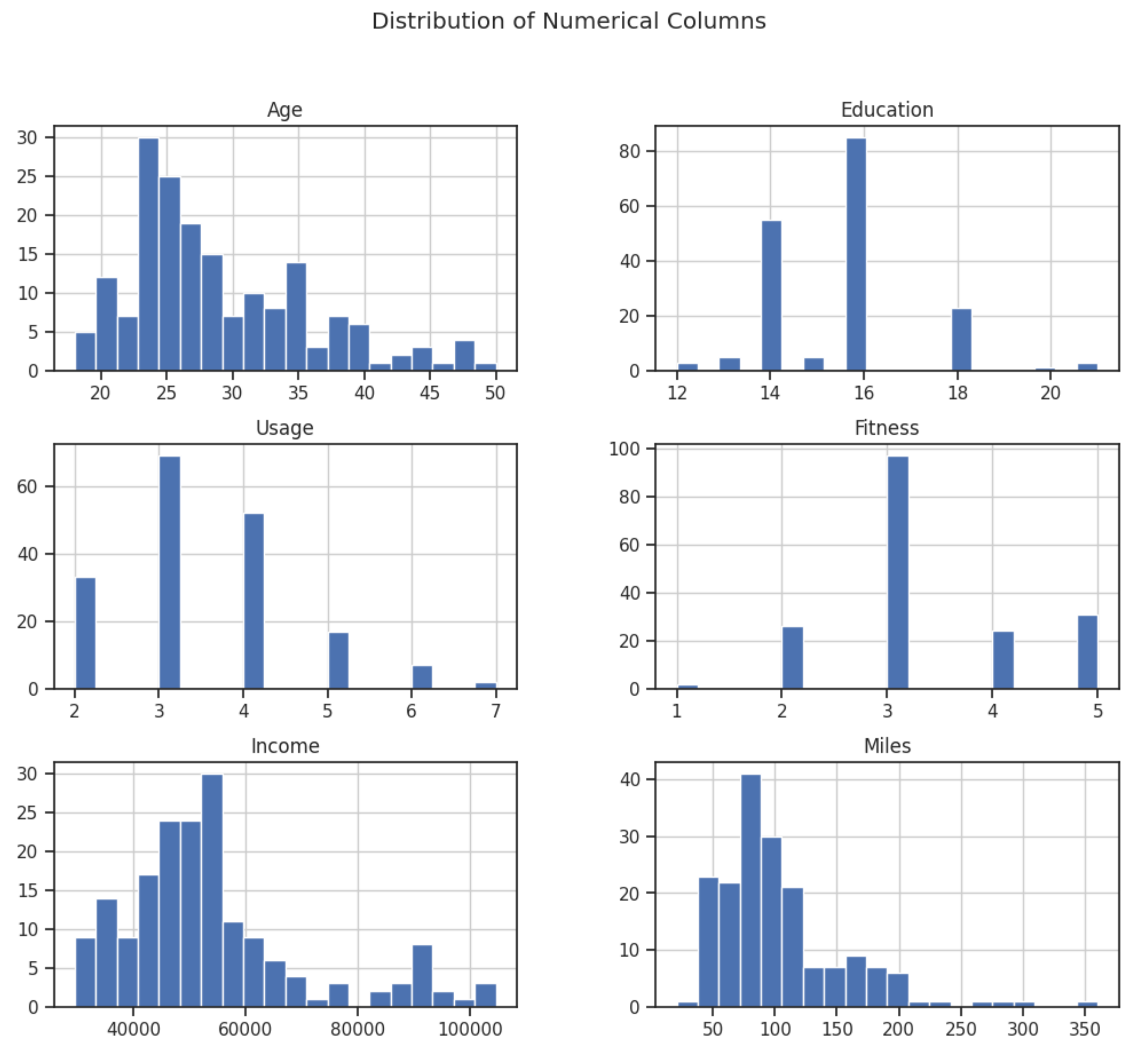
[154]:
```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

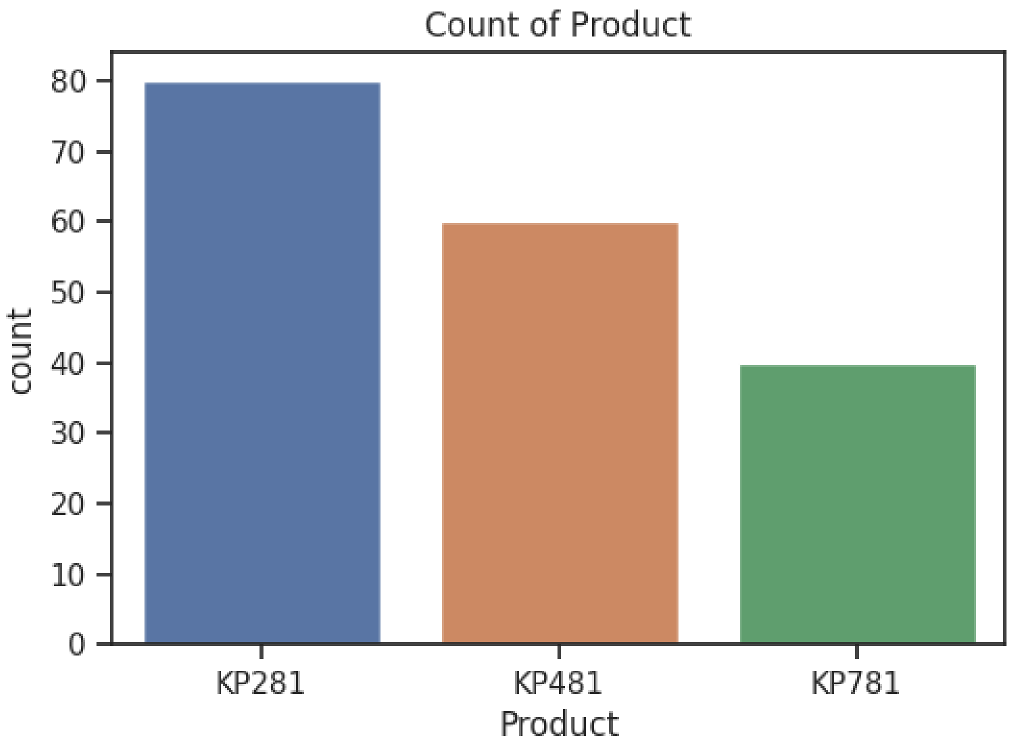
[155]:
```
data.nunique()
```

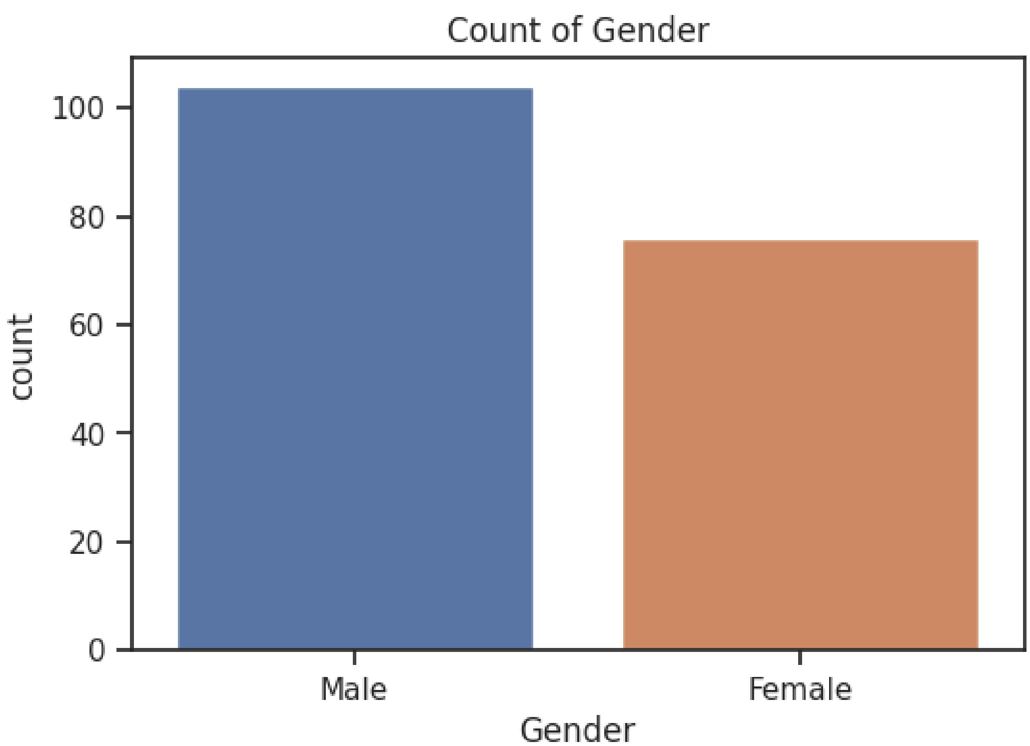
[155]:
```
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
```

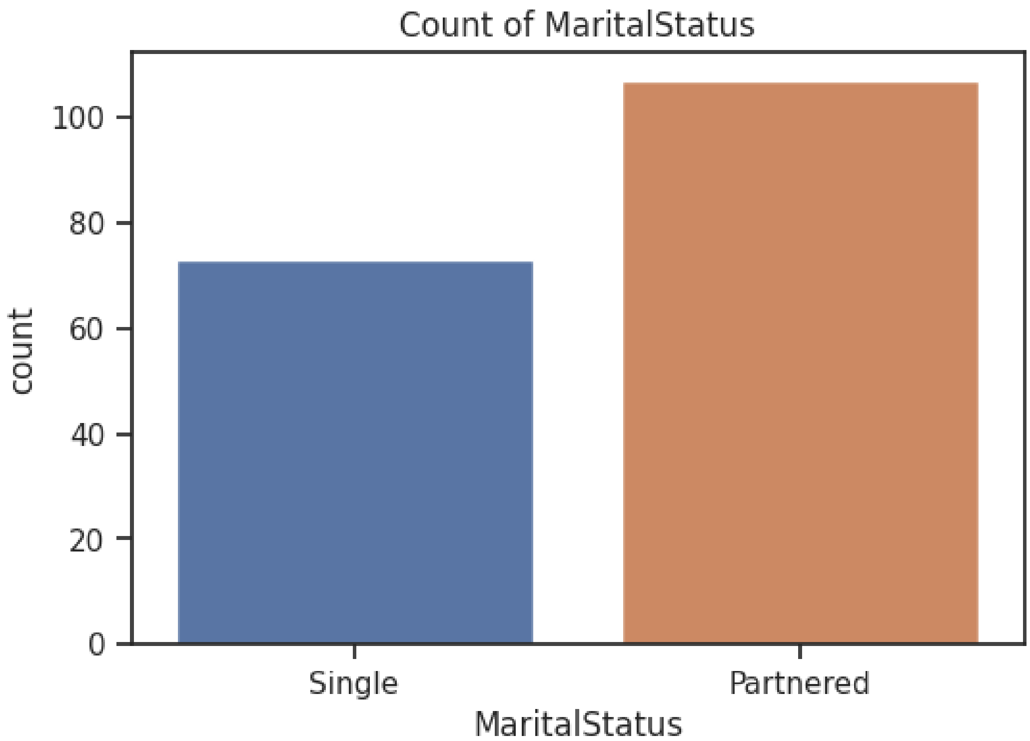
```
Usage              6
Fitness            5
Income            62
Miles             37
dtype: int64
```

[156]:
```python
# Visualize the distribution of numerical columns using histograms
data.hist(bins=20, figsize=(12, 10))
plt.suptitle('Distribution of Numerical Columns')
plt.show()

# Visualize the count of categorical columns using bar plots

plt.figure(figsize=(6, 4))
sns.countplot(x='Product', data=data)
plt.title('Count of Product')

plt.figure(figsize=(6, 4))
sns.countplot(x='Gender', data=data)
plt.title('Count of Gender')

plt.figure(figsize=(6, 4))
sns.countplot(x='MaritalStatus', data=data)
plt.title('Count of MaritalStatus')
plt.show()
```


Distribution of Numerical Columns
Age
Education
Usage
Fitness
Income
Miles


Count of Product
80
70
60
50
40
30
20
10
0
count
KP281
KP481
KP781
Product


Count of Gender
100
80
60
40
20
0
count
Male
Female
Gender



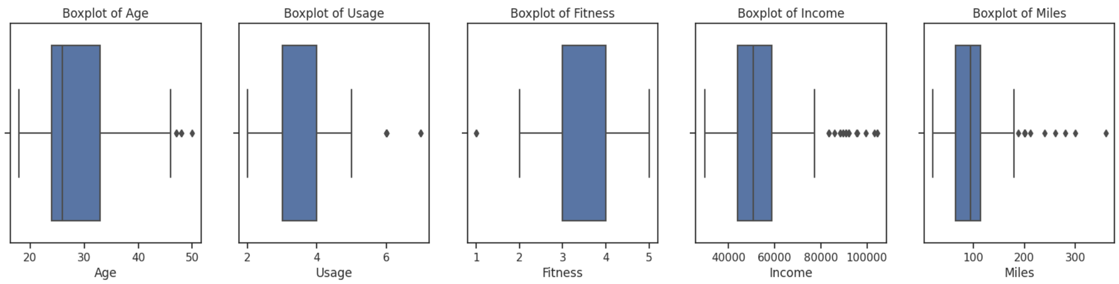
0.0.1 Insights :-

- There are complete 180 rows of data in 9 columns
- There are no NA/Null values and so Data Cleanup is not required
- All the columns are in proper data format (Integers as int, Strings as object) and so no requirement of data conversions/type casting
- KP281 is the most used product by customers compared to other products.
- We can see more male customers compared to female customers.
- Marital status impacts product purchases, as we can see more couples are buying compared to singles
- Most of the customers have an income of less than 60k.
- Most of the customers have a fitness level of 3.0
- People within the age group of 23 to 35 are more in number.

##2. Detect Outliers (using boxplot, "describe" method by checking the difference between mean and median)

[157]:
```
plt.figure(figsize=(20, 4))

plt.subplot(1, 5, 1)
sns.boxplot(x=data['Age'])
plt.title('Boxplot of Age')
```

```
plt.subplot(1, 5, 2)
sns.boxplot(x=data['Usage'])
plt.title('Boxplot of Usage')

plt.subplot(1, 5, 3)
sns.boxplot(x=data['Fitness'])
plt.title('Boxplot of Fitness')

plt.subplot(1, 5, 4)
sns.boxplot(x=data['Income'])
plt.title('Boxplot of Income')

plt.subplot(1, 5, 5)
sns.boxplot(x=data['Miles'])
plt.title('Boxplot of Miles')

plt.show()


# Get summary statistics using the describe method
describe_stats = data.describe()

# Calculate the difference between mean and median for each numerical column
difference_info = []
for column in describe_stats.columns:
    mean_value = describe_stats.loc['mean', column]
    median_value = describe_stats.loc['50%', column]  # 50% corresponds to the␣
↪median in the describe method output
    difference = mean_value - median_value
    difference_info.append({'Column': column, 'Mean': mean_value, 'Median':␣
↪median_value, 'Difference': difference})

# Create a DataFrame from the list of dictionaries
df = pd.DataFrame(difference_info)

print("\n\nDifference between Mean and Median for Numerical Columns (from␣
↪describe method):\n")
print(df)
```




```
Difference between Mean and Median for Numerical Columns (from describe method):

      Column          Mean   Median   Difference
0        Age     28.788889     26.0     2.788889
1  Education     15.572222     16.0    -0.427778
2      Usage      3.455556      3.0     0.455556
3    Fitness      3.311111      3.0     0.311111
4     Income  53719.577778  50596.5  3123.077778
5      Miles    103.194444     94.0     9.194444
```

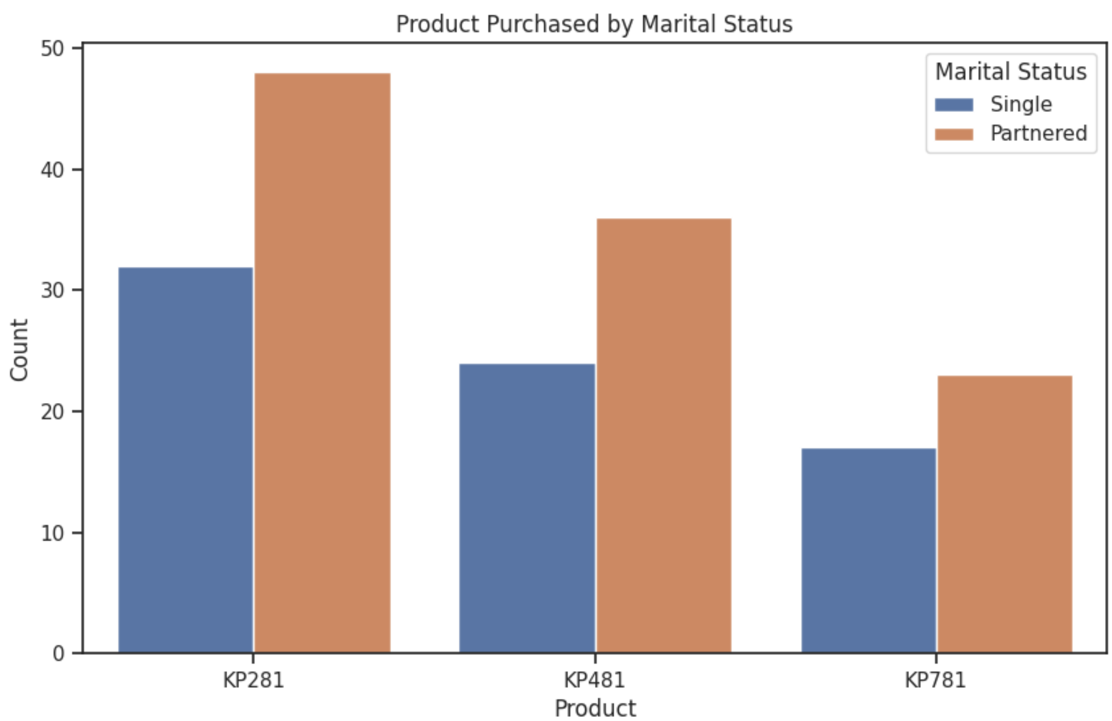
0.0.2 Insights :-

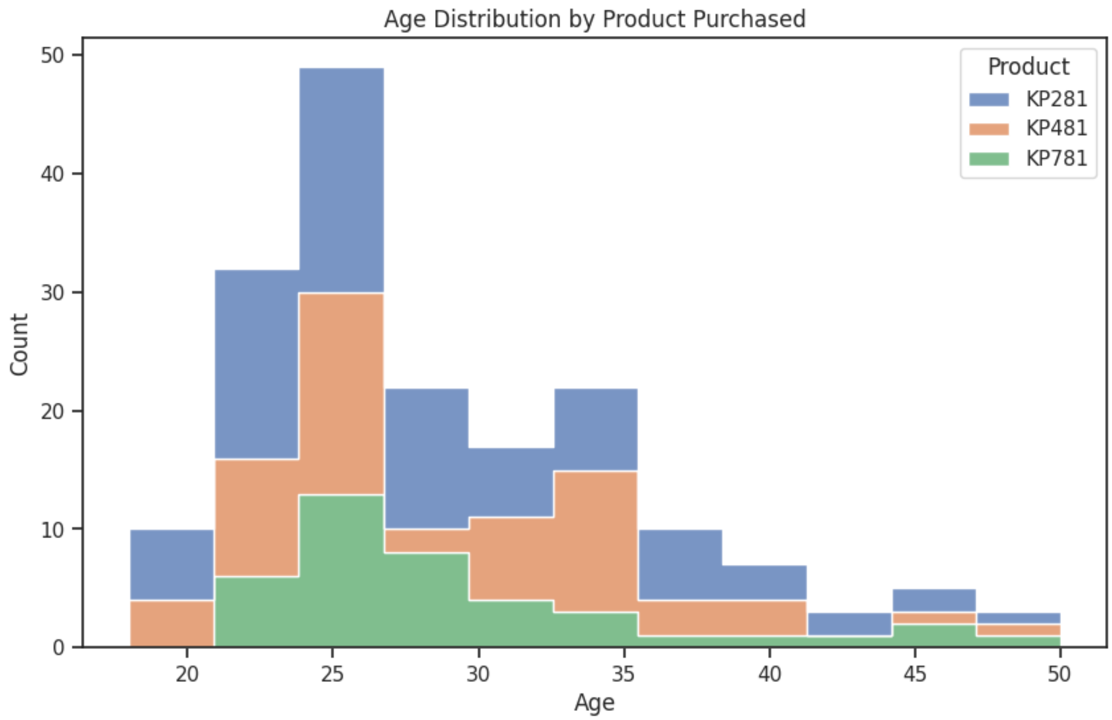
- Most of the people are within the age group of 23 to 35 and we can observe there were few outliers within 45 to 50.
- Most people are using the treadmill 3 to 4 times a week. There were few outlier customers using 6 to 7 times a week.
- Most people have a fitness level between 3 to 4 and there were few outlier customers with fitness level 1.
- Most people have an income between 40-60k. However there are few outlier customers having an income of more than 80k.
- Mean and median have slight differences in all the columns except for Income.

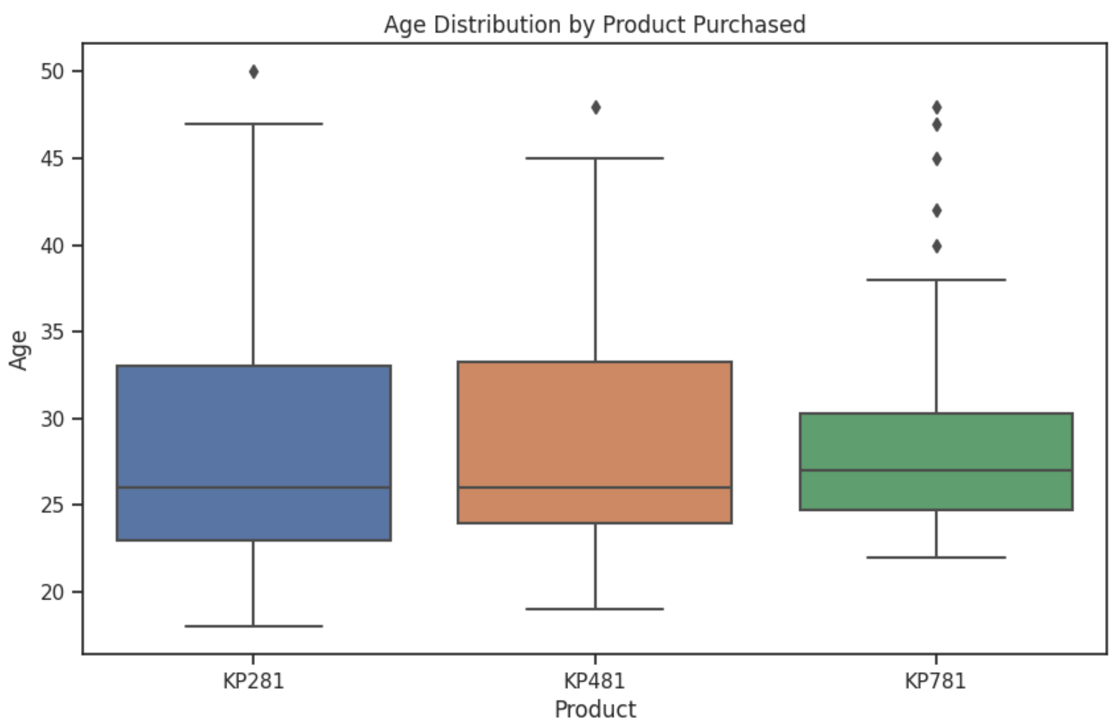
##3. **Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc)**

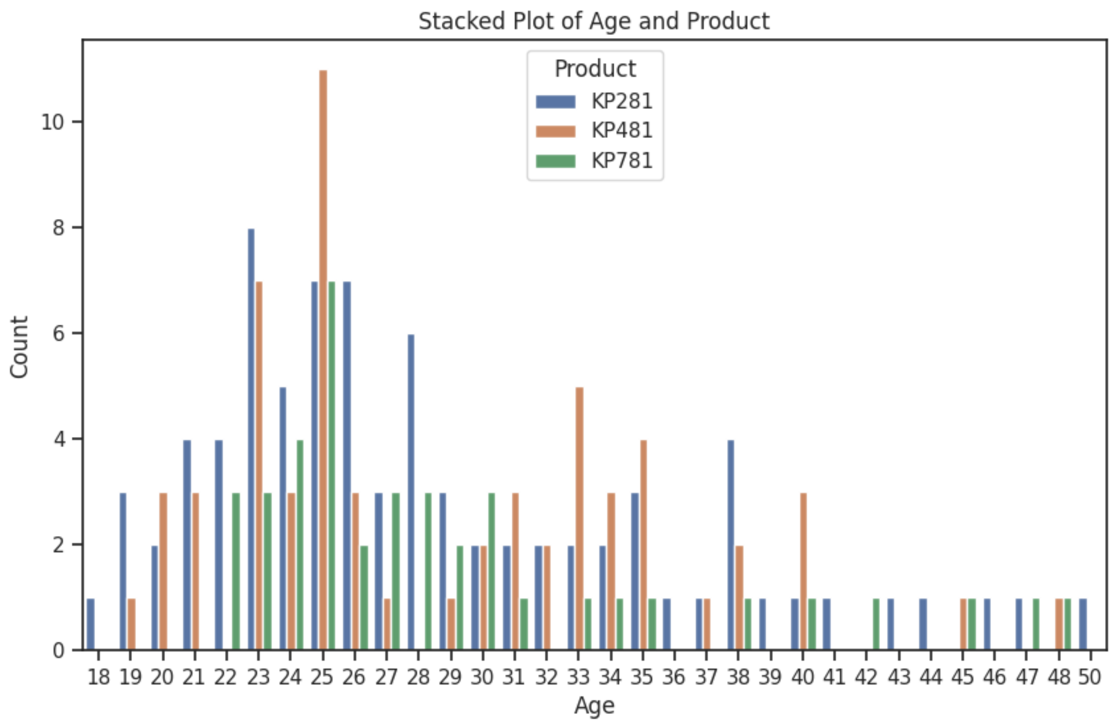
[158]:
```
# Countplot for Product and MaritalStatus
plt.figure(figsize=(10, 6))
sns.countplot(x='Product', hue='MaritalStatus', data=data)
plt.title('Product Purchased by Marital Status')
plt.xlabel('Product')
plt.ylabel('Count')
plt.legend(title='Marital Status')
plt.show()

# Histogram for Age by Product
```

```python
plt.figure(figsize=(10, 6))
sns.histplot(data=data, x='Age', hue='Product', multiple='stack',␣
↪element='step', common_norm=False)
plt.title('Age Distribution by Product Purchased')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()

# Boxplot for Age by Product
plt.figure(figsize=(10, 6))
sns.boxplot(x='Product', y='Age', data=data)
plt.title('Age Distribution by Product Purchased')
plt.xlabel('Product')
plt.ylabel('Age')
plt.show()

grouped_data = data.groupby(['Age', 'Product']).size().reset_index(name='Count')
# Stack plot for Age and Product with Product as hue
plt.figure(figsize=(10, 6))
sns.barplot(data=grouped_data, x='Age', y='Count', hue='Product', dodge=True)
plt.title('Stacked Plot of Age and Product')
plt.xlabel('Age')
plt.ylabel('Count')
plt.legend(title='Product')
plt.show()
```




Age Distribution by Product Purchased
Product
KP281
KP481
KP781
Count
Age
0
10
20
30
40
50
20
25
30
35
40
45
50


Age Distribution by Product Purchased
Age
Product
KP281
KP481
KP781
20
25
30
35
40
45
50



0.0.3 Insights :-

- Marital status impacts product purchases, as we can see more couples are buying compared to singles
- Age also impacts product purchases, as we can see people in their 20s to 30s are more ready to buy compared with people in their 50s or more.
- KP281 and KP481 have similar purchase rates and have a wide range of customers compared with KP781.

##4. Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)

[159]:
```
# Calculate marginal probabilities using pandas.crosstab
marginal_probabilities = pd.crosstab(index=data['Product'],
 ↪columns='Percentage', normalize=True) * 100

# Display the table with marginal probabilities
print("Marginal Probability Table (in percentage):\n")
print(marginal_probabilities)
```

```
Marginal Probability Table (in percentage):

col_0    Percentage
```

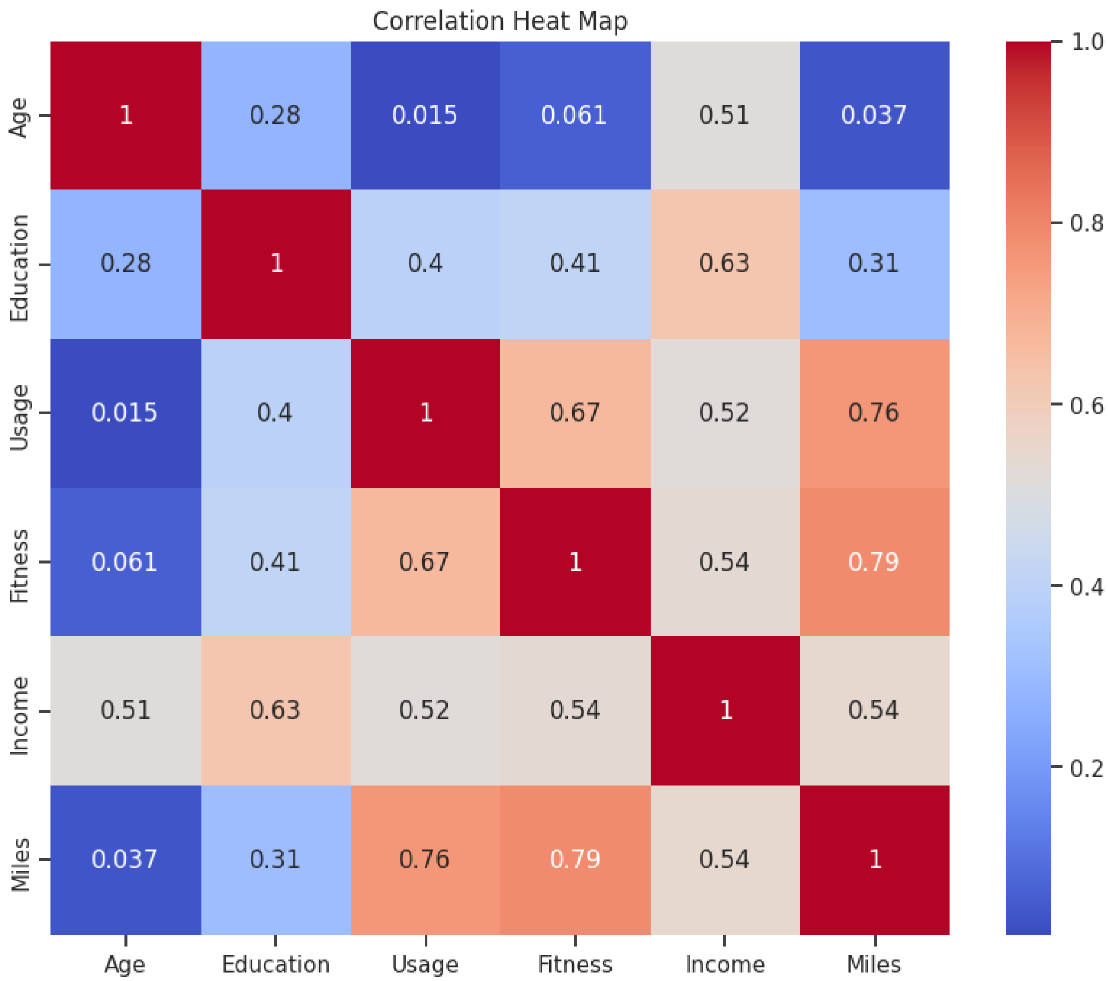
```
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

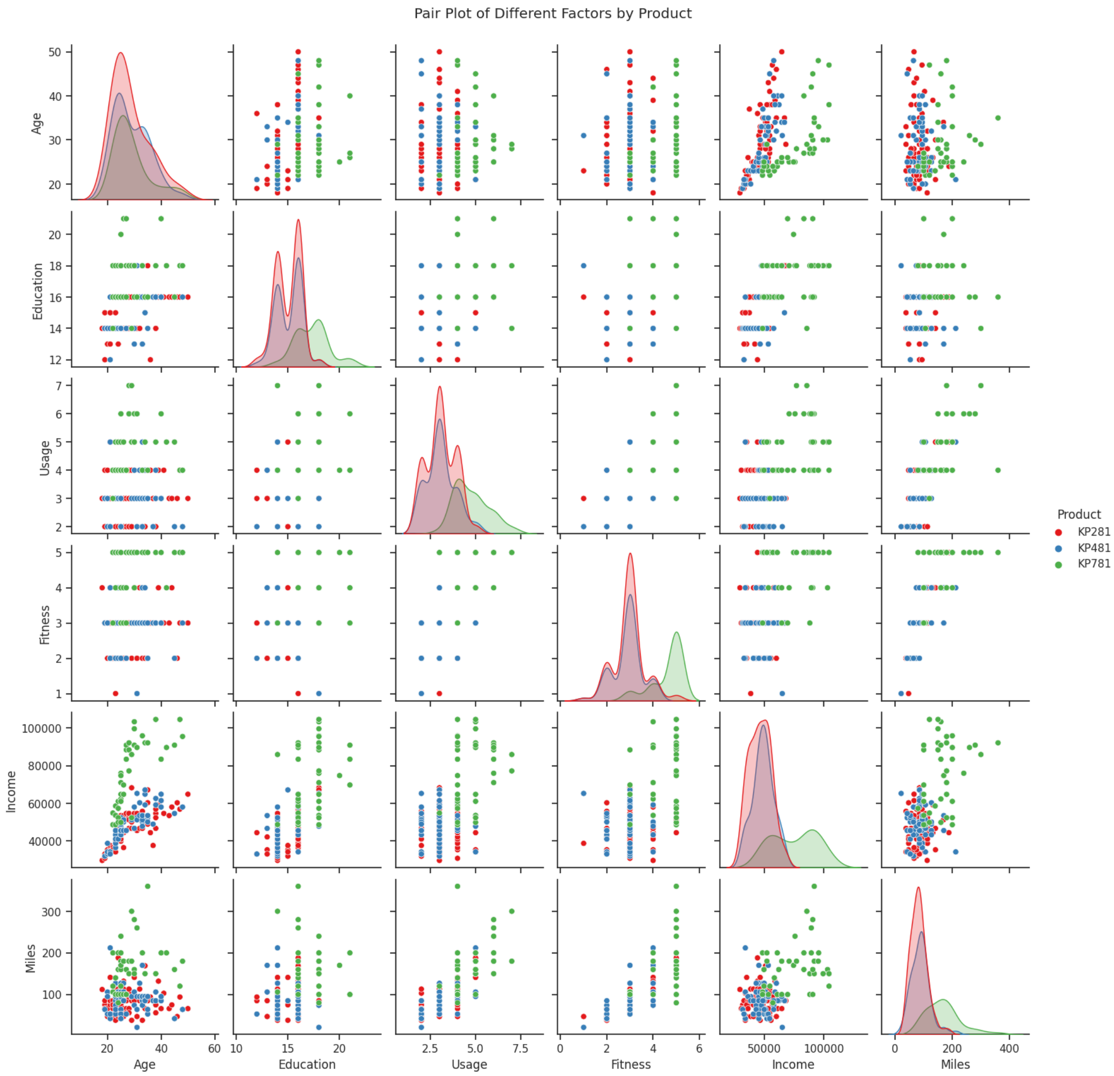
0.0.4 Insights :-

- The marginal probability of purchasing KP281,KP481 and KP781 treadmills are 44.4%, 33.3% and 22.2% respectively.

##5. **Check correlation among different factors using heat maps or pair plots.**

[160]:
```
plt.figure(figsize=(10, 8))

# Create a heatmap for the correlation matrix
sns.heatmap(data=data.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Heat Map')
plt.show()

# Set up the pair plot
sns.set(style="ticks")
sns.pairplot(data, hue="Product", palette="Set1")
plt.suptitle("Pair Plot of Different Factors by Product", y=1.02)
plt.show()
```


Correlation Heat Map
Age
Education
Usage
Fitness
Income
Miles
1
0.28
0.015
0.061
0.51
0.037
0.4
0.41
0.63
0.31
0.67
0.52
0.76
0.54
0.79
1.0
0.8
0.6
0.4
0.2

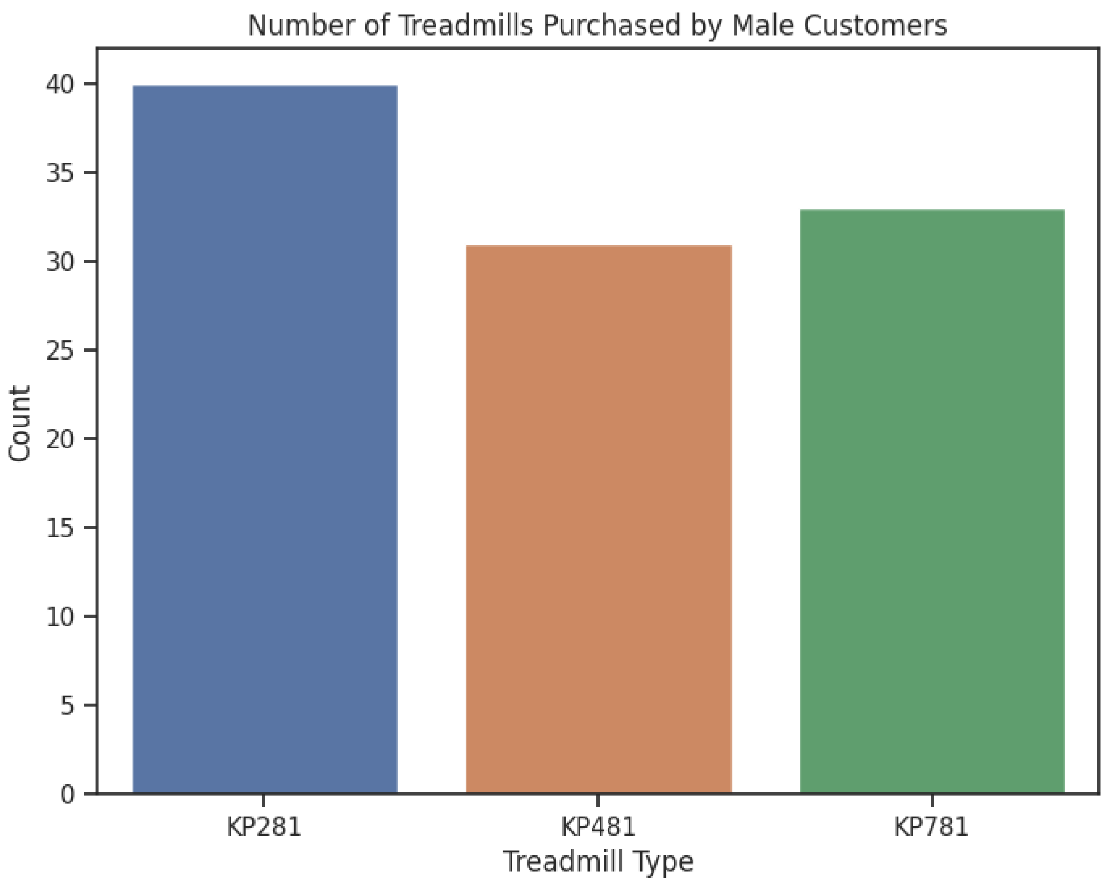


##6. What is the probability of a male customer buying a KP781 treadmill?

[161]:
```
# Create a bar plot for different treadmill types purchased by male customers
plt.figure(figsize=(8, 6))
sns.countplot(x='Product', data=data.loc[data['Gender'] == 'Male'])
plt.title('Number of Treadmills Purchased by Male Customers')
plt.xlabel('Treadmill Type')
plt.ylabel('Count')

# Calculate the total number of male customers
male_customers = len(data.loc[data['Gender'] == 'Male'])

# Calculate the number of male customers who bought KP781 treadmill
```

```python
male_customers_KP781 = len(data.loc[(data['Gender'] == 'Male') &␣
↪(data['Product'] == 'KP781')])

# Calculate the probability of a male customer buying a KP781 treadmill
probability_male_KP781 = male_customers_KP781 / male_customers

print("Probability of a male customer buying a KP781 treadmill:",␣
↪probability_male_KP781,"\n\n")

plt.show()
```

```
Probability of a male customer buying a KP781 treadmill: 0.3173076923076923
```



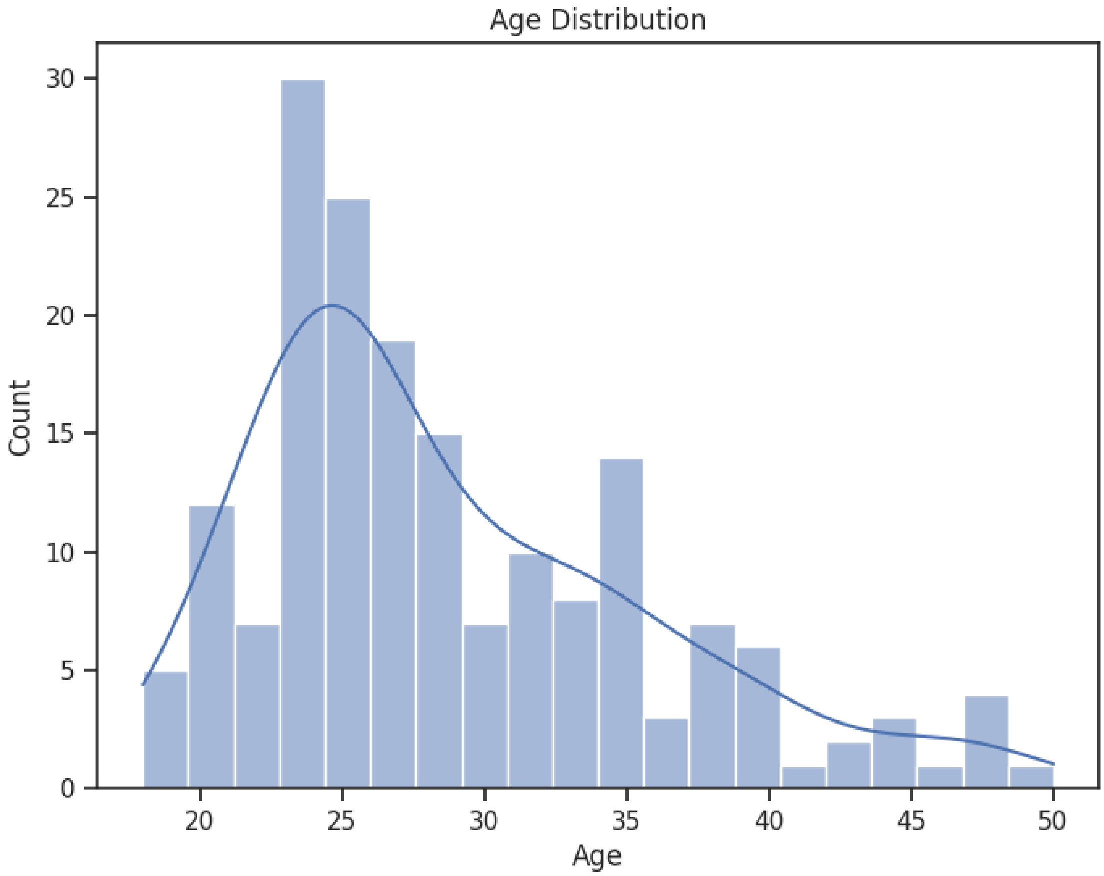
0.0.5 Insights :-

- Probability of a male customer buying a KP781 treadmill: 0.31

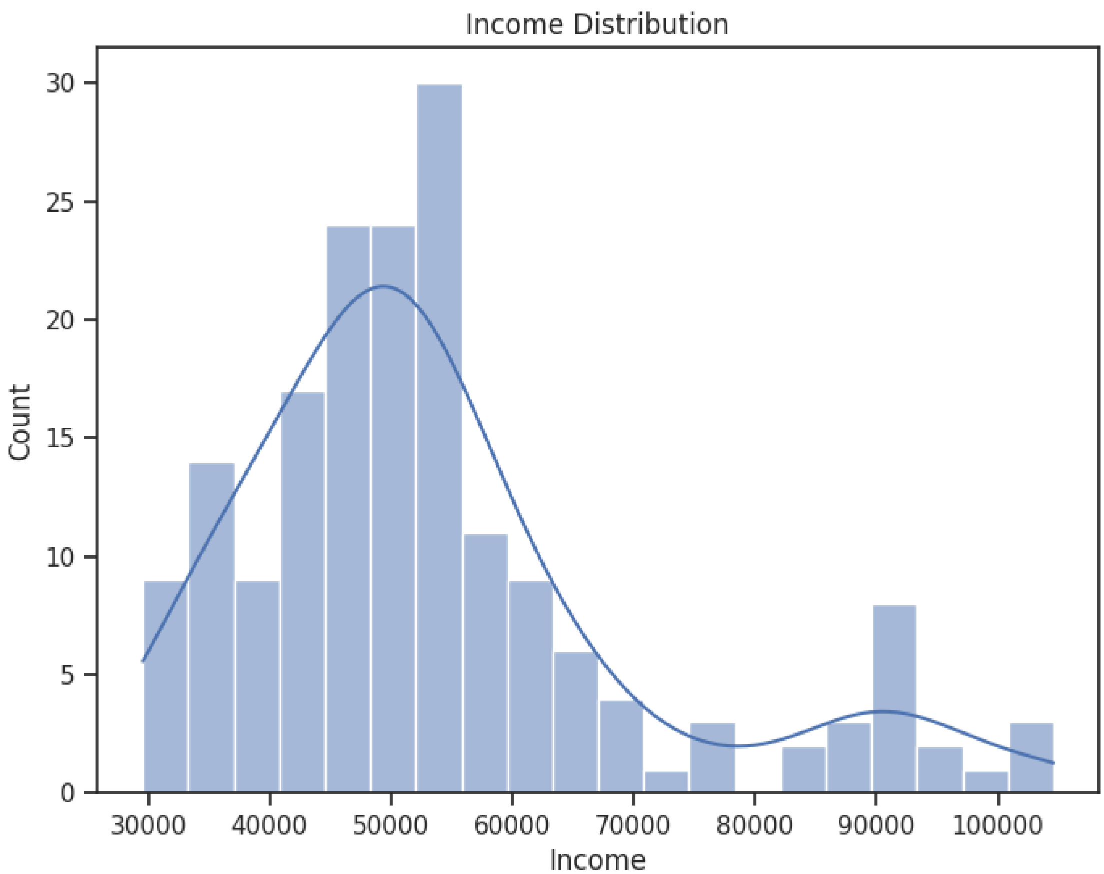
##7. **Customer Profiling - Categorization of users.**

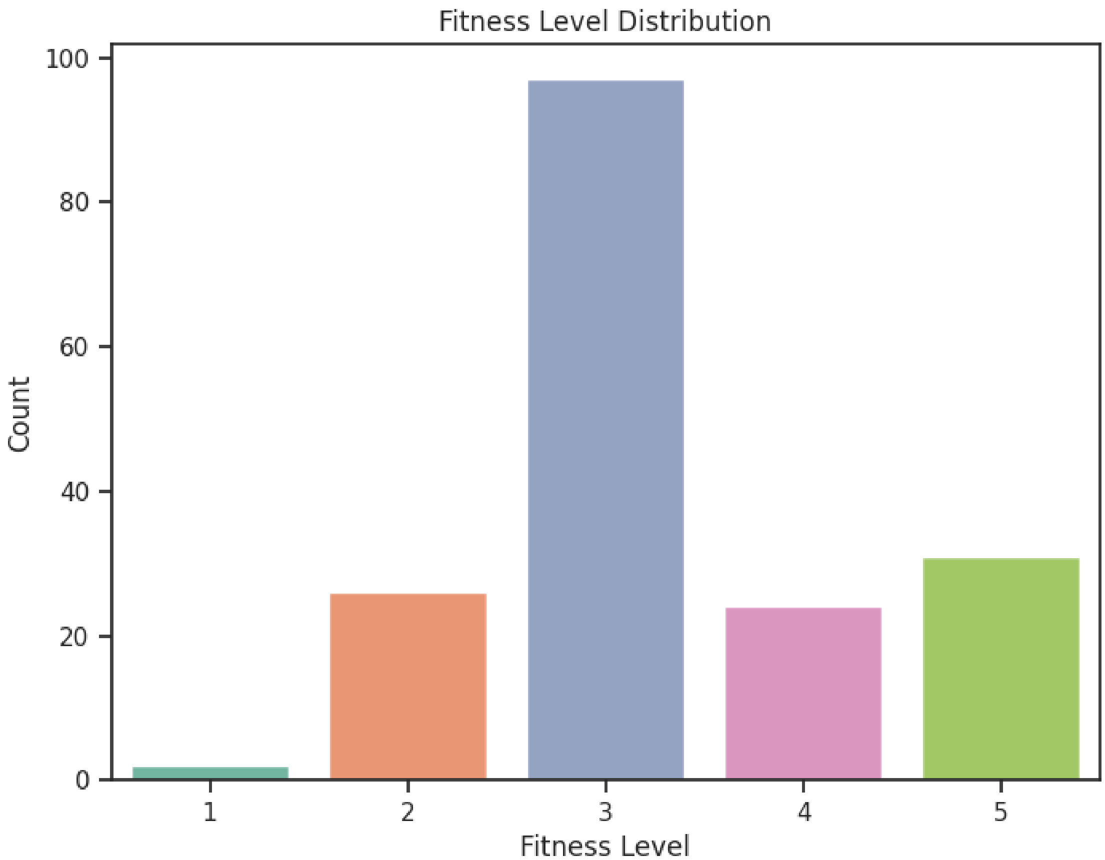
[162]:

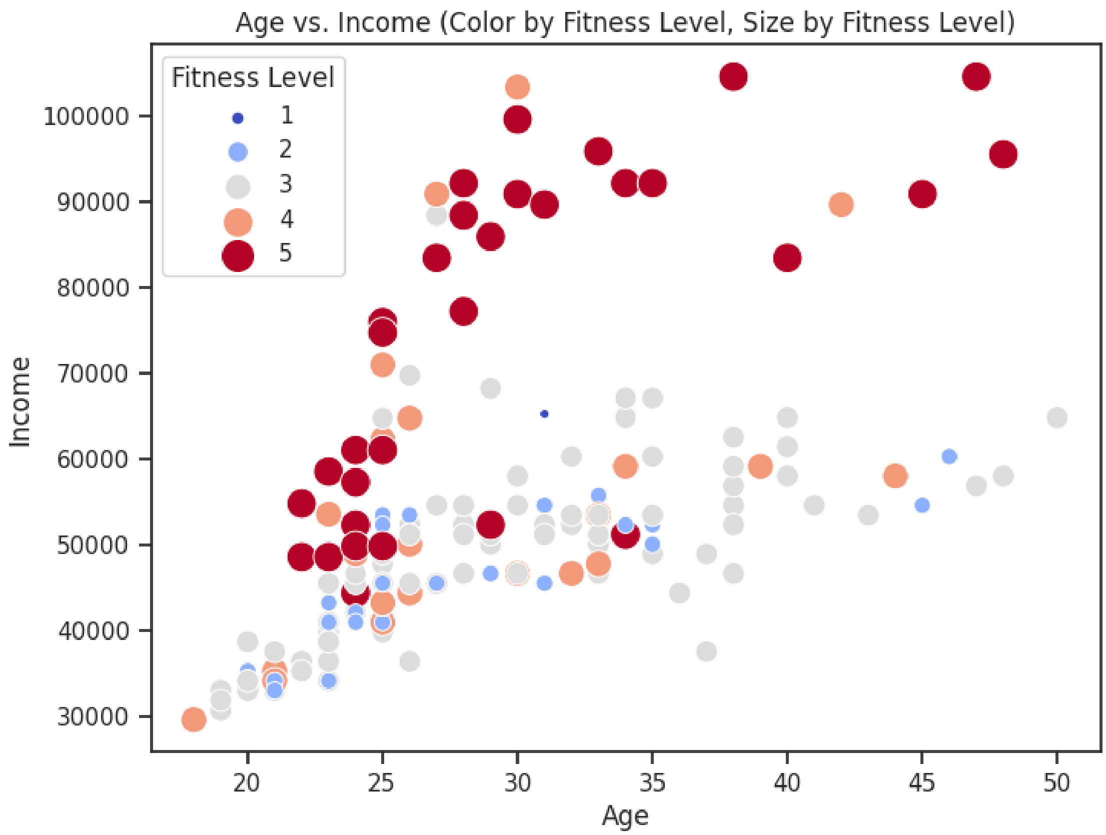
```
# Plot the age distribution
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Age', bins=20, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()

# Plot the income distribution
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Income', bins=20, kde=True)
plt.title('Income Distribution')
plt.xlabel('Income')
plt.ylabel('Count')
plt.show()

# Plot the fitness level distribution
plt.figure(figsize=(8, 6))
sns.countplot(data=data, x='Fitness', palette='Set2')
plt.title('Fitness Level Distribution')
plt.xlabel('Fitness Level')
plt.ylabel('Count')
plt.show()

# Scatter plot for Age vs. Income
plt.figure(figsize=(8, 6))
sns.scatterplot(data=data, x='Age', y='Income', hue='Fitness',␣
↪palette='coolwarm', size='Fitness', sizes=(20, 200))
plt.title('Age vs. Income (Color by Fitness Level, Size by Fitness Level)')
plt.xlabel('Age')
plt.ylabel('Income')
plt.legend(title='Fitness Level')
plt.show()

# Box plot for Age vs. Fitness Level
plt.figure(figsize=(8, 6))
sns.boxplot(data=data, x='Fitness', y='Age', palette='Set2')
plt.title('Age vs. Fitness Level')
plt.xlabel('Fitness Level')
plt.ylabel('Age')
plt.show()
```



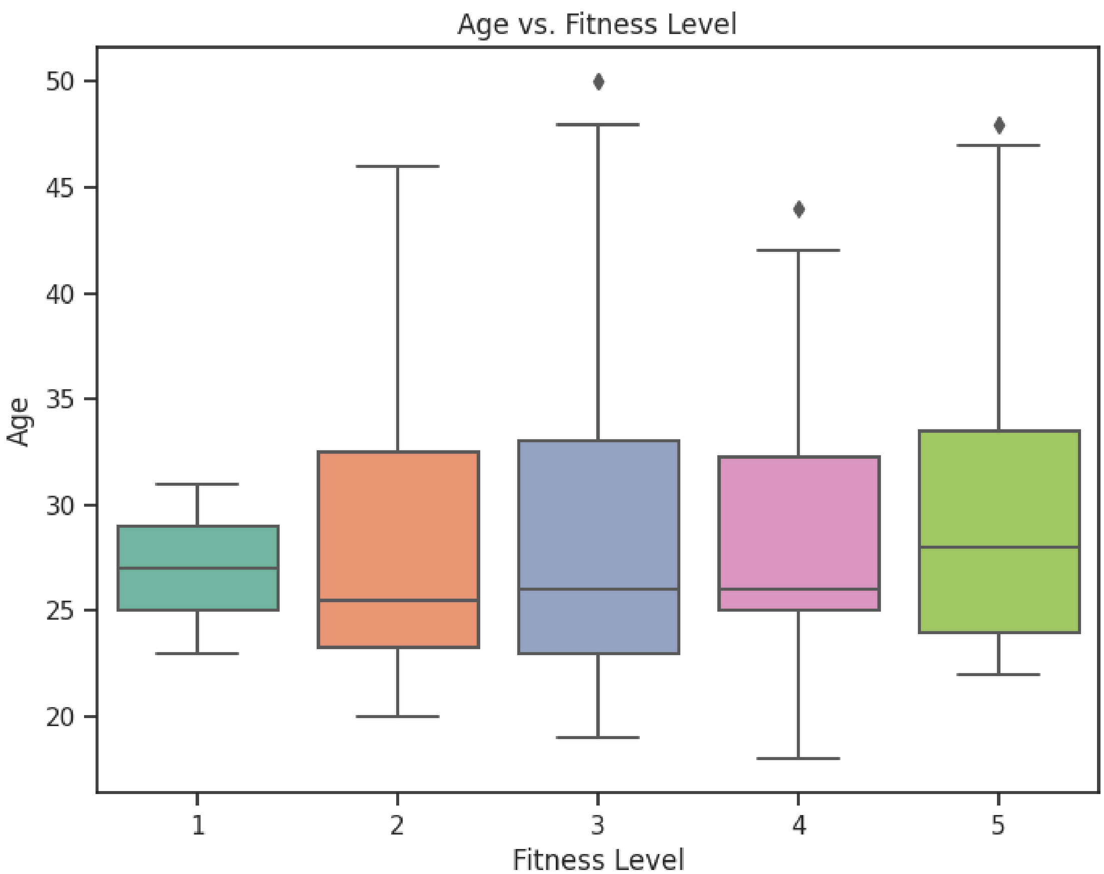
Age Distribution
Count
Age
0
5
10
15
20
25
30
20
25
30
35
40
45
50


Income Distribution
Count
0
5
10
15
20
25
30
30000
40000
50000
60000
70000
80000
90000
100000
Income


Fitness Level Distribution
Count
Fitness Level
0
20
40
60
80
100
1
2
3
4
5



Age vs. Income (Color by Fitness Level, Size by Fitness Level)
Fitness Level
1
2
3
4
5
100000
90000
80000
70000
60000
50000
40000
30000
Income
20
25
30
35
40
45
50
Age



0.0.6 Insights :-

- Most of the people are within the age group of 23 to 35.
- Most people are having an income between 30k to 70k.
- Most people have a fitness level 3 irrespective of their age

##8. **Probability - marginal, conditional probability.**

[163]:
```
# Total number of customers
total_customers = len(data)

# Unique product types
unique_products = data['Product'].unique()

# Calculate and print marginal and conditional probabilities for each product
for product in unique_products:
    # Marginal Probability of buying the current product
    marginal_probability_product = np.round(len(data[data['Product'] ==␣
 ↪product]) / total_customers,2)
```

```
    # Conditional Probability of buying the current product given that the␣
↪customer is male
    male_customers = len(data[data['Gender'] == 'Male'])
    male_customers_buying_product = len(data[(data['Gender'] == 'Male') &␣
↪(data['Product'] == product)])
    conditional_probability_product_given_male = np.
↪round(male_customers_buying_product / male_customers,2)

    # Conditional Probability of buying the current product given that the␣
↪customer is female
    female_customers = len(data[data['Gender'] == 'Female'])
    female_customers_buying_product = len(data[(data['Gender'] == 'Female') &␣
↪(data['Product'] == product)])
    conditional_probability_product_given_female = np.
↪round(female_customers_buying_product / female_customers,2)

    print(f"Product: {product}")
    print(f"Marginal Probability of buying {product}:␣
↪{marginal_probability_product}")
    print(f"Conditional Probability of buying {product} given that the customer␣
↪is male: {conditional_probability_product_given_male}")
    print(f"Conditional Probability of buying {product} given that the customer␣
↪is female: {conditional_probability_product_given_female}")
    print("----")
```

```
Product: KP281
Marginal Probability of buying KP281: 0.44
Conditional Probability of buying KP281 given that the customer is male: 0.38
Conditional Probability of buying KP281 given that the customer is female: 0.53
----
Product: KP481
Marginal Probability of buying KP481: 0.33
Conditional Probability of buying KP481 given that the customer is male: 0.3
Conditional Probability of buying KP481 given that the customer is female: 0.38
----
Product: KP781
Marginal Probability of buying KP781: 0.22
Conditional Probability of buying KP781 given that the customer is male: 0.32
Conditional Probability of buying KP781 given that the customer is female: 0.09
----
```

0.0.7 Insights :-

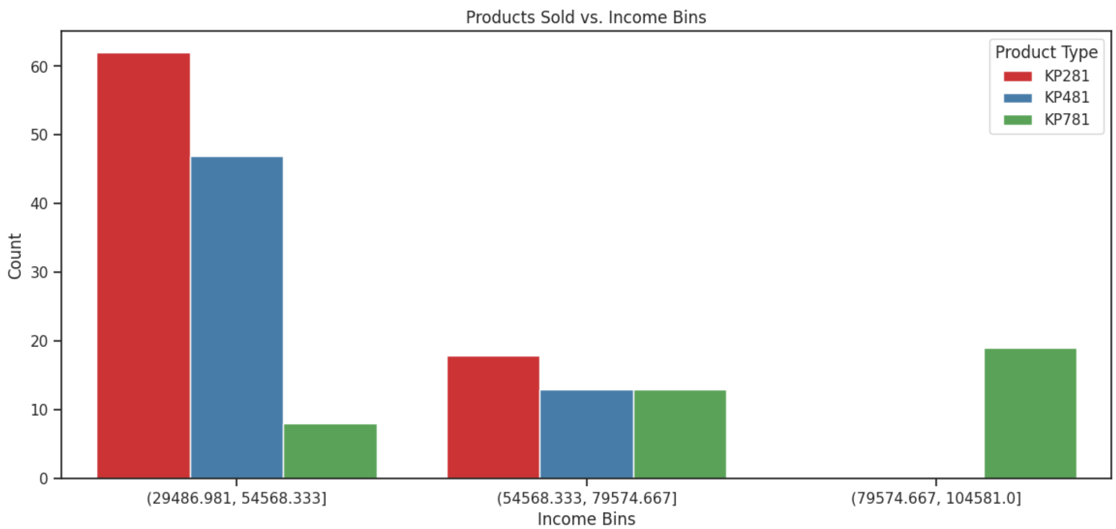
- Marginal Probability of buying KP281: 0.44
- Conditional Probability of buying KP281 given that the customer is male: 0.38
- Conditional Probability of buying KP281 given that the customer is female: 0.53
- Marginal Probability of buying KP481: 0.33

- Conditional Probability of buying KP481 given that the customer is male: 0.3
- Conditional Probability of buying KP481 given that the customer is female: 0.38
- Marginal Probability of buying KP781: 0.22
- Conditional Probability of buying KP781 given that the customer is male: 0.32
- Conditional Probability of buying KP781 given that the customer is female: 0.09

##**More Analysis**

###**Income vs Product**

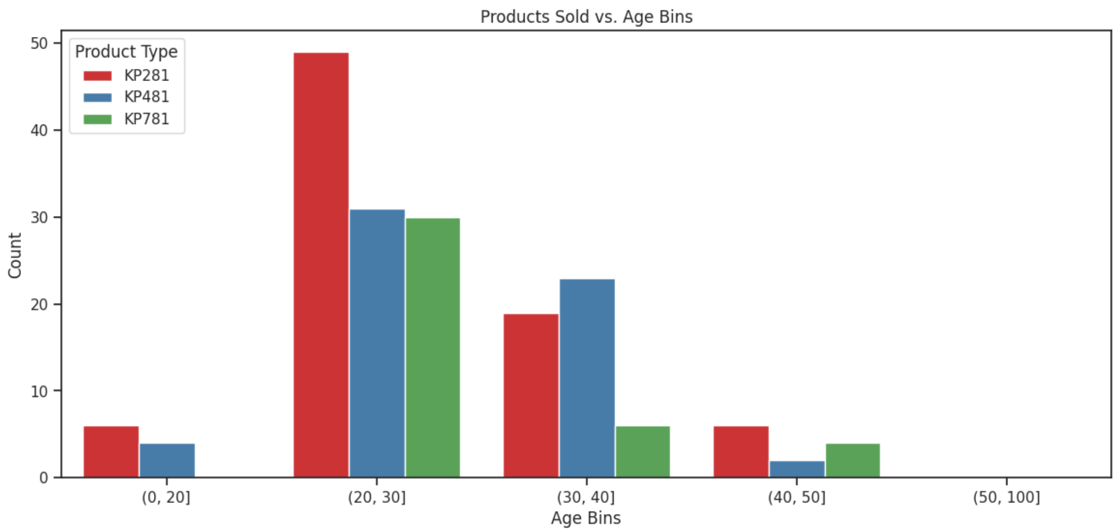
[164]:
```
# Create 3 equal bins for income
data['Income Bins'] = pd.cut(data['Income'], bins=3)

# Set up the countplot
plt.figure(figsize=(14, 6))
sns.countplot(x='Income Bins', data=data, hue='Product', palette='Set1')
plt.title('Products Sold vs. Income Bins')
plt.xlabel('Income Bins')
plt.ylabel('Count')
plt.legend(title='Product Type')
plt.show()
```



###**Age vs Product**

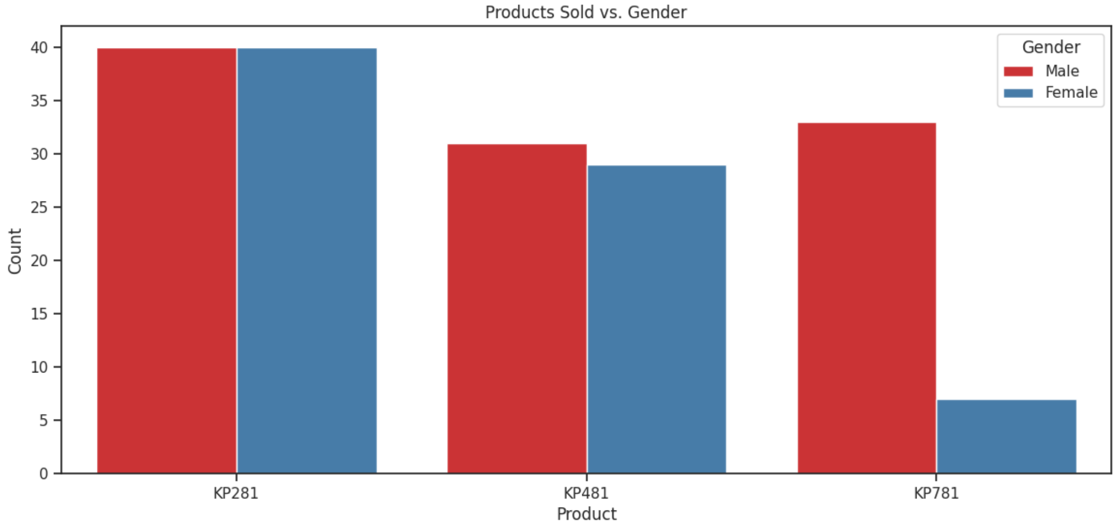
[165]:
```
age_bins = [0, 20, 30, 40, 50, 100]

data['Age Bins'] = pd.cut(data['Age'], bins=age_bins)

# Set up the countplot
plt.figure(figsize=(14, 6))
sns.countplot(x='Age Bins', data=data, hue='Product', palette='Set1')
```

```
plt.title('Products Sold vs. Age Bins')
plt.xlabel('Age Bins')
plt.ylabel('Count')
plt.legend(title='Product Type')
plt.show()
```



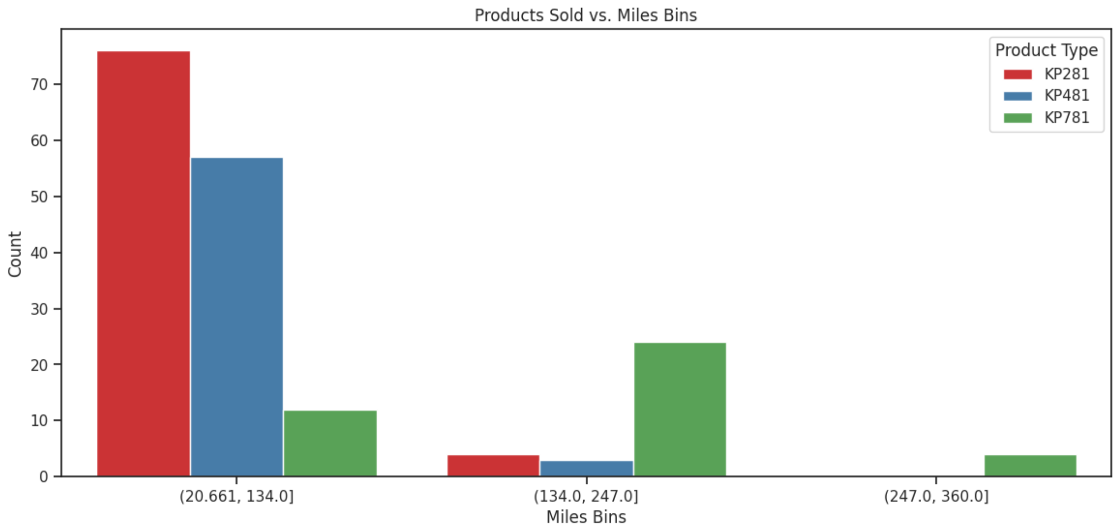
###Gender vs Product

[166]:
```
plt.figure(figsize=(14, 6))
sns.countplot(x='Product', data=data, hue='Gender', palette='Set1')
plt.title('Products Sold vs. Gender')
plt.xlabel('Product')
plt.ylabel('Count')
plt.legend(title='Gender')
plt.show()
```



###Miles vs Product

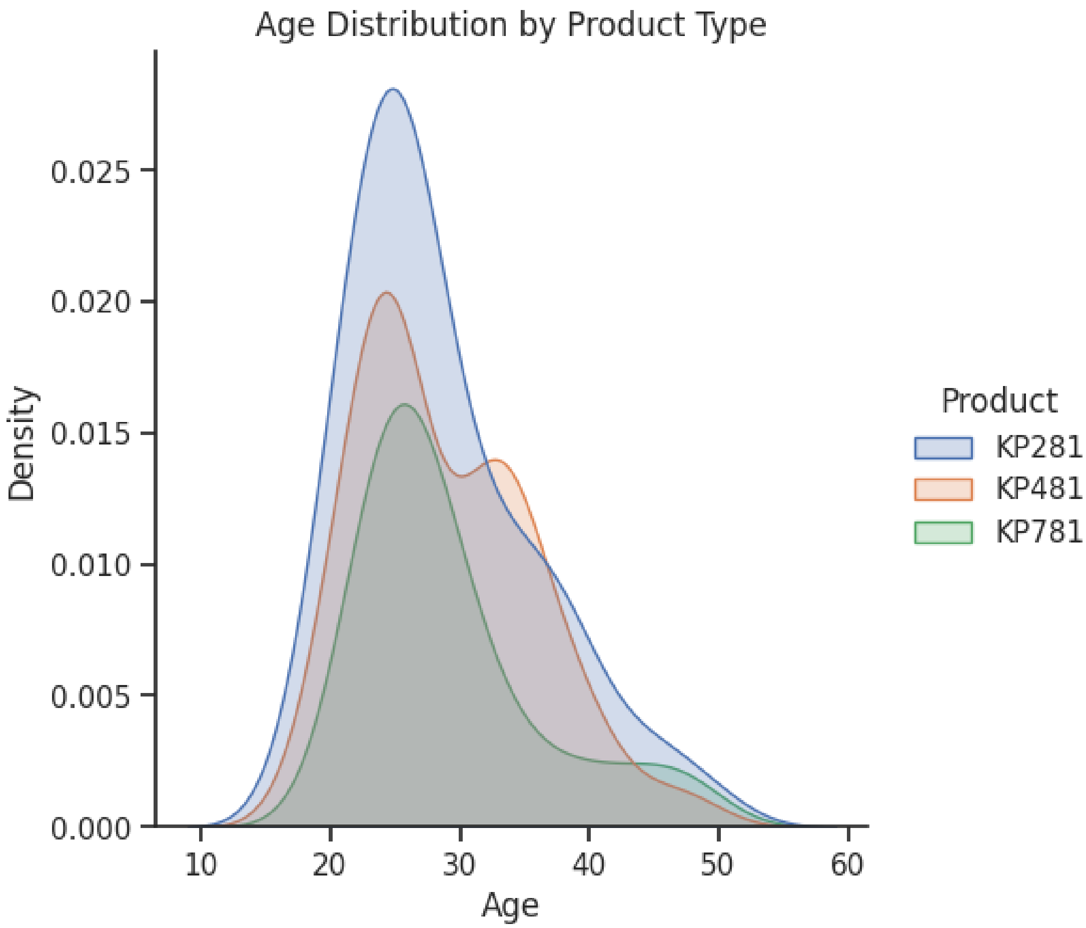
[167]:
```python
# Create 3 equal bins for Miles
data['Miles Bins'] = pd.cut(data['Miles'], bins=3)

# Set up the countplot
plt.figure(figsize=(14, 6))
sns.countplot(x='Miles Bins', data=data, hue='Product', palette='Set1')
plt.title('Products Sold vs. Miles Bins')
plt.xlabel('Miles Bins')
plt.ylabel('Count')
plt.legend(title='Product Type')
plt.show()
```

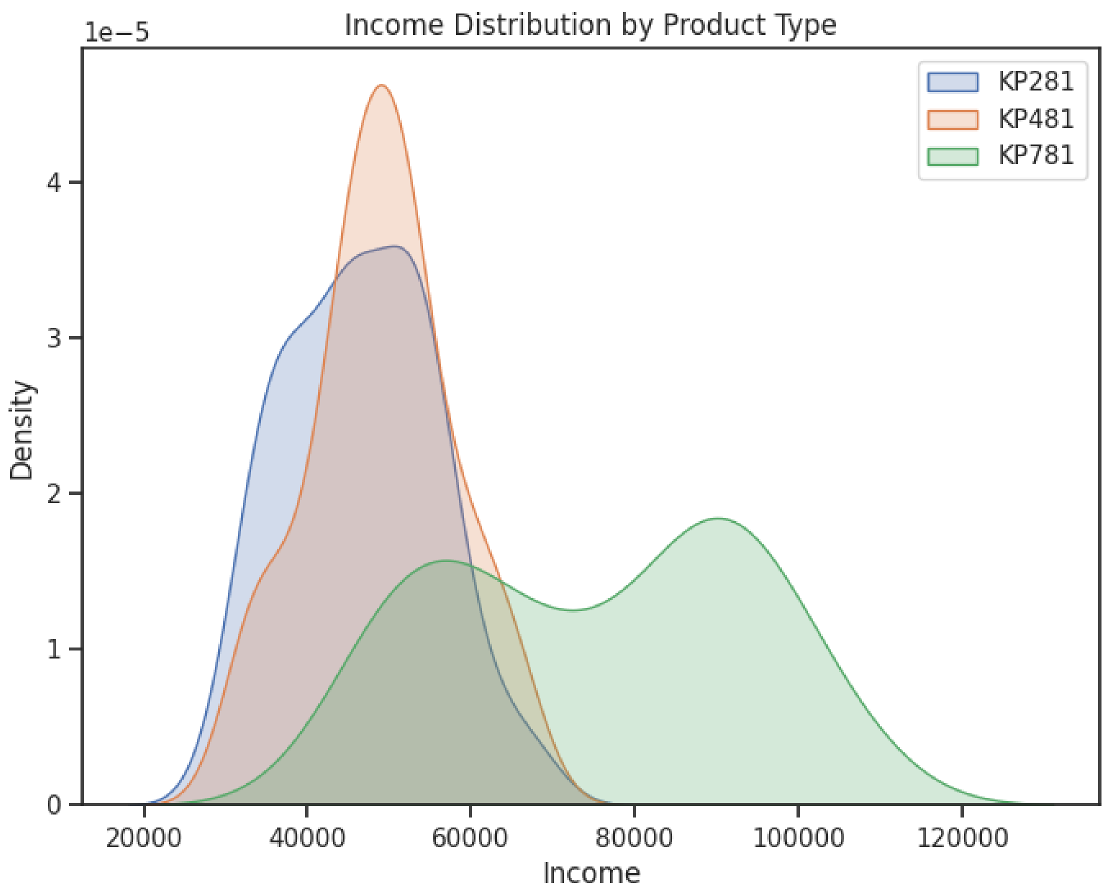


###Distplot and Kdeplot of product against Age, Income

[168]:
```
# Plot Distplot for 'Age' based on different 'Product' types using displot
plt.figure(figsize=(8, 6))
sns.displot(data=data, x='Age', hue='Product', kind='kde', fill=True)
plt.title('Age Distribution by Product Type')
plt.xlabel('Age')
plt.ylabel('Density')
plt.show()

# Plot Distplot for 'Income' based on different 'Product' types using kdeplot
plt.figure(figsize=(8, 6))
sns.kdeplot(data[data['Product'] == 'KP281']['Income'], fill=True,␣
 ↪label='KP281')
sns.kdeplot(data[data['Product'] == 'KP481']['Income'], fill=True,␣
 ↪label='KP481')
sns.kdeplot(data[data['Product'] == 'KP781']['Income'], fill=True,␣
 ↪label='KP781')
plt.title('Income Distribution by Product Type')
plt.xlabel('Income')
plt.ylabel('Density')
plt.legend()
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```


Age Distribution by Product Type
Density
0.025
0.020
0.015
0.010
0.005
0.000
10
20
30
40
50
60
Age
Product
KP281
KP481
KP781



##9. **Some recommendations and actionable insights, based on the inferences.**

0.0.8 Insights & Recommendations:-

- KP281 treadmill is the most popular product, purchased by 80 customers.
- KP481 and KP781 treadmills are also favoured, with 60 and 40 customers respectively.
- We can see more male customers compared to female customers.
- Marital status impacts product purchases, as we can see more couples are buying compared to singles
- Most of the customers have an income of less than 60k.
- Most of the customers have a fitness level of 3.0
- People within the age group of 23 to 35 are more in number.
- People with higher income(greater than 75k) are only purchasing advanced treadmill(KP781).
- Entry-level treadmill(KP281) is being used by both males and females equally whereas advanced treadmill(KP781) is mostly used by males only.
- Average usage sessions per week range from 2 to 7, with a mean of 3.5 sessions.
- By providing student discounts we can get more customers for entry-level treadmill.
- From the given data it seems that high-income customers are only opting for advanced-level treadmills, so the company can also think of providing seasonal discounts to attract mid-level income customers.

- Providing personalized workout plans and nutrition guidance can get more customers.
- Since the majority of customers (107 out of 180) are partnered, suggesting potential family-oriented marketing strategies.