# Aerofit Treadmill Customer Profiling & Recommendation Report

### M N Wasif, DSML Apr 2025 batch (TTS)

In [97]:
```
# Import required Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [98]:
```
# Load dataset from csv as Pandas DataFrame
df = pd.read_csv('/content/aerofit_treadmill.csv')
df
```

Out[98]:

| | 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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **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 |

180 rows × 9 columns

In [99]:
```
df.shape
```

Out[99]: (180, 9)

In [100…
```
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
```

In [101…
```
df.duplicated().sum()
```

Out[101…
```
np.int64(0)
```

In [102…
```
df.isnull().sum()
```

Out[102…

| | 0 |
|---|---|
| **Product** | 0 |
| **Age** | 0 |
| **Gender** | 0 |
| **Education** | 0 |
| **MaritalStatus** | 0 |
| **Usage** | 0 |
| **Fitness** | 0 |
| **Income** | 0 |
| **Miles** | 0 |

**dtype:** int64

---

# 1. Problem Statement & Basic Metrics

**Problem**: Aerofit aims to understand the distinct customer profiles for its three treadmill models (KP281, KP481, KP781) to improve targeted marketing and sales recommendations.

# 1. Basic Dataset Analysis

## a) Shape of Dataset

- **Rows**: 180
- **Columns**: 9

## b) Data Types

| Column | Data Type |
|---|---|
| Product | object (categorical) |
| Age | int64 |
| Gender | object |
| Education | int64 |
| MaritalStatus | object |
| Usage | int64 |
| Fitness | int64 |
| Income | int64 |
| Miles | int64 |

**All columns are complete – no missing values** ( `df.isnull().sum()` = 0 for all).

---

In [103…

```
# Numeric datatype EDA
df.describe()
```

Out[103…

| | 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 |

In [104…

```
# Object datatype EDA
df.describe(include='object')
```

Out[104…

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

In [105…

```
df.nunique()
```

Out[105…

| | 0 |
|---|---|
| **Product** | 3 |
| **Age** | 32 |
| **Gender** | 2 |
| **Education** | 8 |
| **MaritalStatus** | 2 |
| **Usage** | 6 |
| **Fitness** | 5 |
| **Income** | 62 |
| **Miles** | 37 |

**dtype:** int64

In [106…

```
df["Product"].value_counts()
```

Out[106…

| **Product** | **count** |
|---|---|
| **KP281** | 80 |
| **KP481** | 60 |
| **KP781** | 40 |

**dtype:** int64

In [107…

```
df["Age"].value_counts()
```

Out[107…

| Age | count |
|---|---|
| 25 | 25 |
| 23 | 18 |
| 24 | 12 |
| 26 | 12 |
| 28 | 9 |
| 33 | 8 |
| 35 | 8 |
| 22 | 7 |
| 30 | 7 |
| 27 | 7 |
| 38 | 7 |
| 21 | 7 |
| 31 | 6 |
| 34 | 6 |
| 29 | 6 |
| 20 | 5 |
| 40 | 5 |
| 19 | 4 |
| 32 | 4 |
| 37 | 2 |
| 45 | 2 |
| 48 | 2 |
| 47 | 2 |
| 18 | 1 |
| 41 | 1 |
| 39 | 1 |
| 36 | 1 |
| 43 | 1 |
| 46 | 1 |
| 44 | 1 |
| 50 | 1 |
| 42 | 1 |

**dtype:** int64

In [108…
```
df["Education"].value_counts()
```
Out[108…

| Education | count |
|---|---|
| 16 | 85 |
| 14 | 55 |
| 18 | 23 |
| 15 | 5 |
| 13 | 5 |
| 12 | 3 |
| 21 | 3 |
| 20 | 1 |

**dtype:** int64

In [109…
```
df["Usage"].value_counts()
```
Out[109…

| Usage | count |
|---|---|
| 3 | 69 |
| 4 | 52 |
| 2 | 33 |
| 5 | 17 |
| 6 | 7 |
| 7 | 2 |

**dtype:** int64

In [110…
```
df["Fitness"].value_counts()
```
Out[110…

| Fitness | count |
|---|---|
| 3 | 97 |
| 5 | 31 |
| 2 | 26 |
| 4 | 24 |
| 1 | 2 |

**dtype:** int64

---

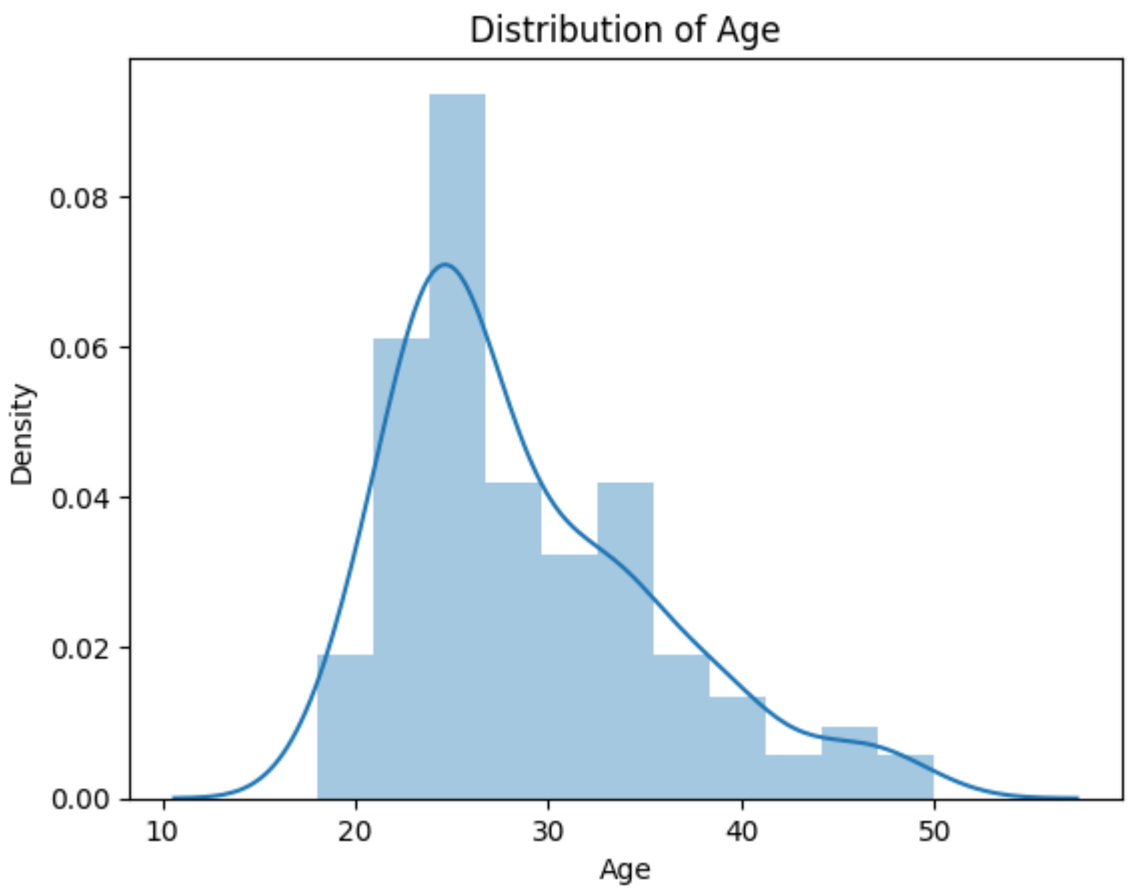
## Non-Graphical Analysis: Value Counts

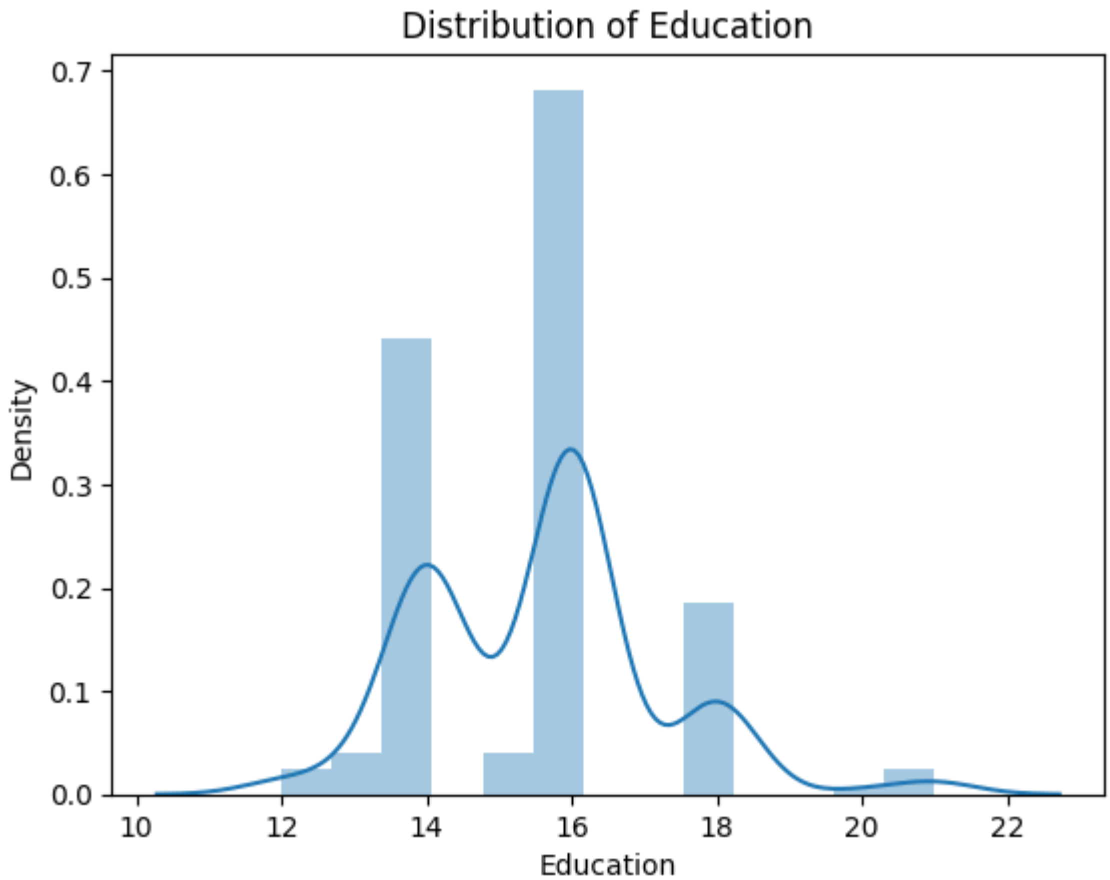
- **Product**: KP281 (80), KP481 (60), KP781 (40)
- **Gender**: Male (104), Female (76)
- **MaritalStatus**: Partnered (107), Single (73)
- **Education**: Spans from 12 to 21 years, with a concentration around 14-16 years (Bachelor's level).
- **Usage**: Most plan to use the treadmill 3-4 times a week.

---

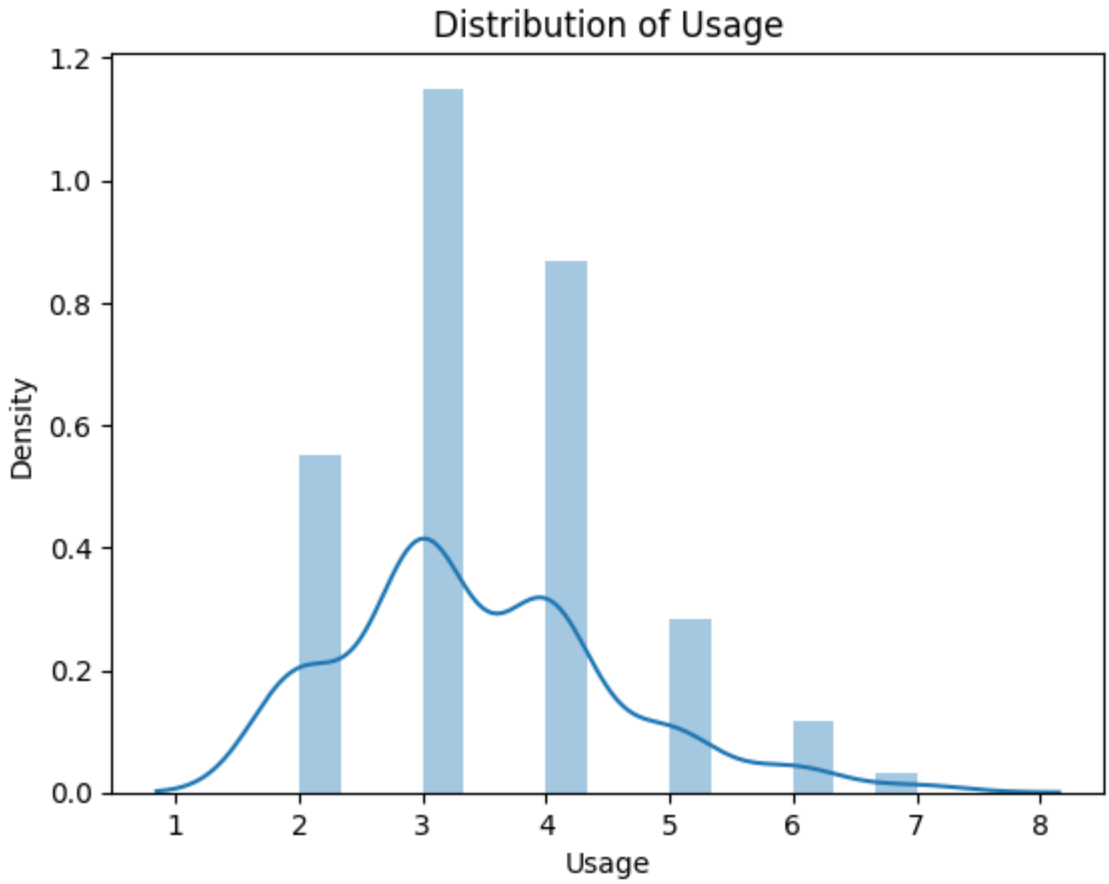
In [111…

```
# Histogram plot for mean meadian mode distribution
numeric_cols = df.select_dtypes(include=np.number).columns
for col in numeric_cols:
  sns.distplot(df[col])
  plt.title(f'Distribution of {col}')
  plt.show()
```

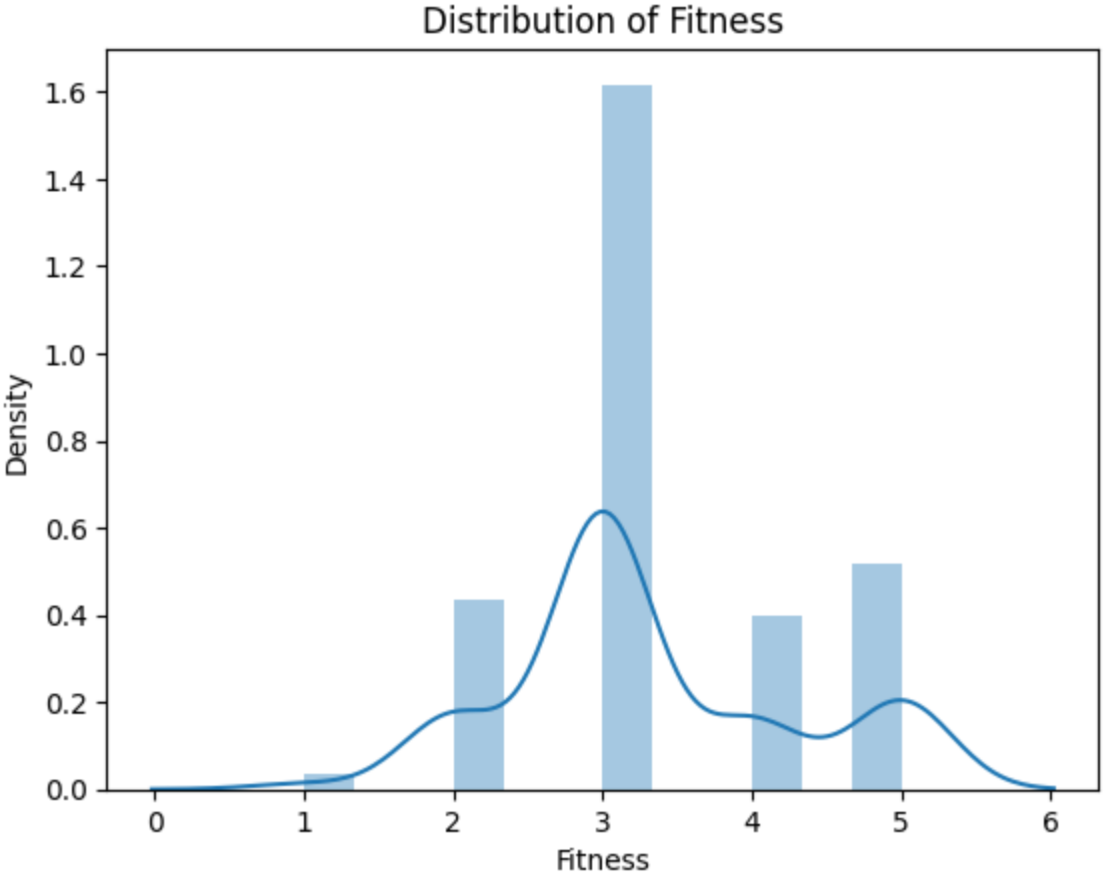




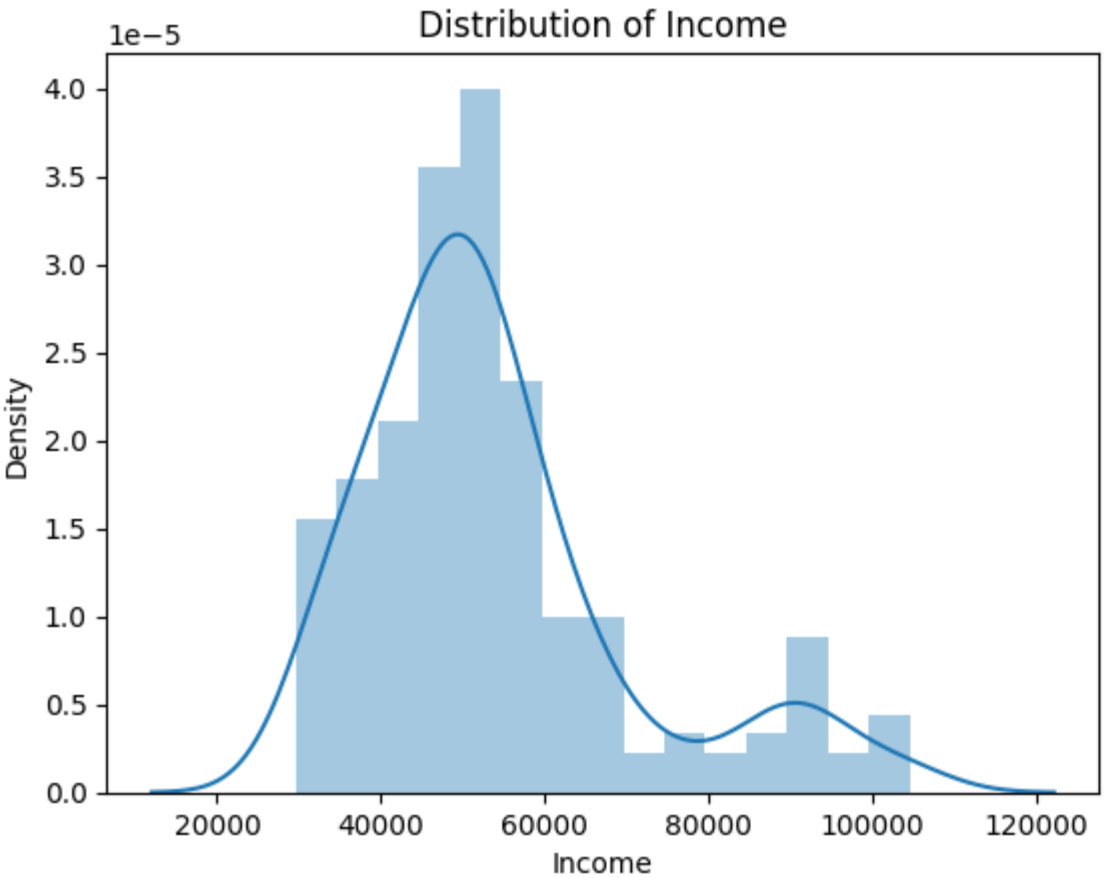
Distribution of Education
Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
10
12
14
16
18
20
22
Education

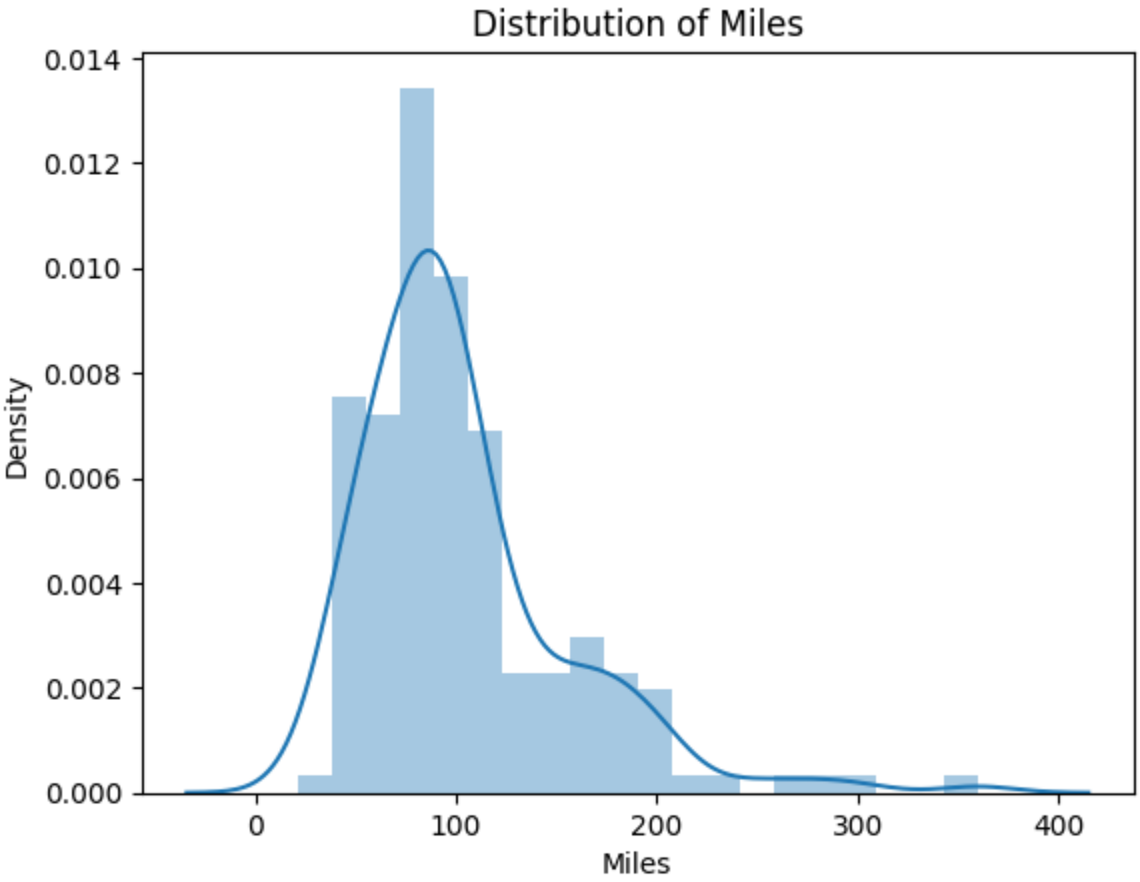
Distribution of Usage
Density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1
2
3
4
5
6
7
8
Usage



Distribution of Fitness
Density
Fitness
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
0
1
2
3
4
5
6

Distribution of Income
1e−5
Density
Income
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
20000
40000
60000
80000
100000
120000




---

**Data Structure**:

- **Rows**: 180 customers
- **Columns**: 9 features (1 ID, 3 categorical, 5 numerical)
- **Data Types**: `Product`, `Gender`, `MaritalStatus` are categorical. `Age`, `Education`, `Usage`, `Fitness`, `Income`, `Miles` are numerical.

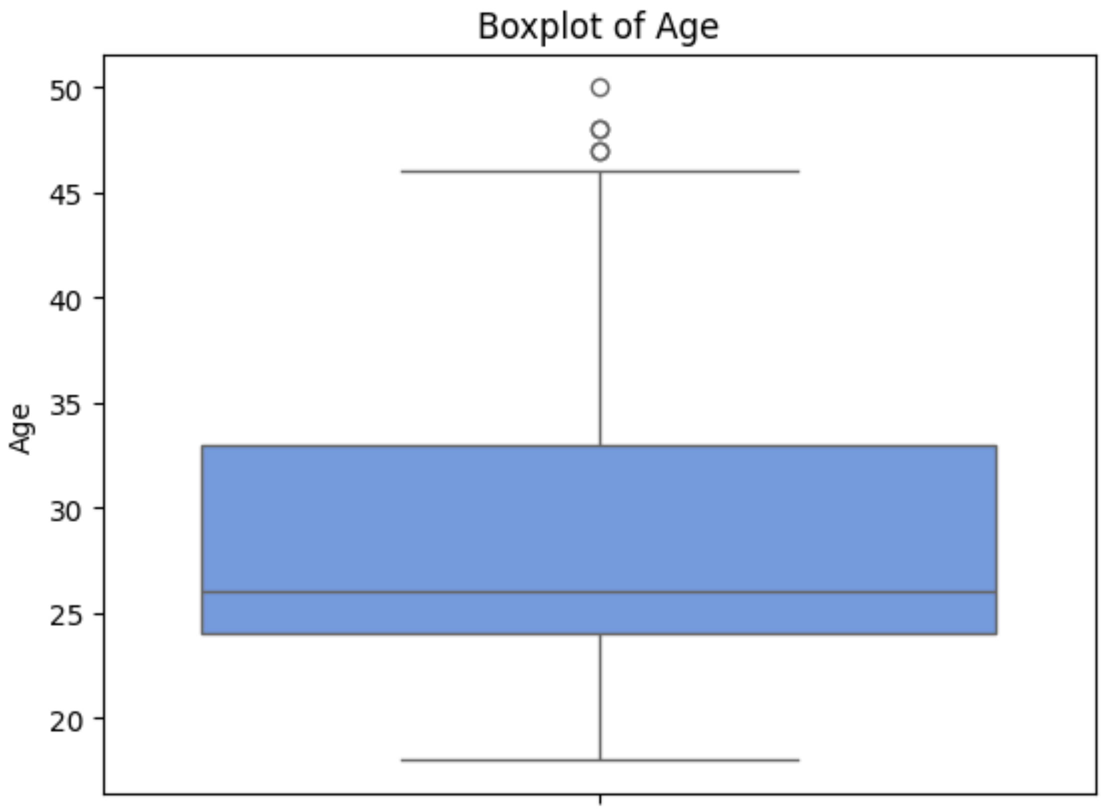
**Statistical Summary**:

- **Age**: Ranges from 18 to 50 (Mean: ~29). The customer base is young to middle-aged.
- **Income**: Ranges from ~$29Kto$ 105K (Mean: ~$54K), indicating a broad economic base.
- **Product Mix**: KP281 is the most popular (44.4%), followed by KP481 (33.3%) and KP781 (22.2%).
- **Fitness**: Most customers rate themselves as average (3) to good (4) on fitness.

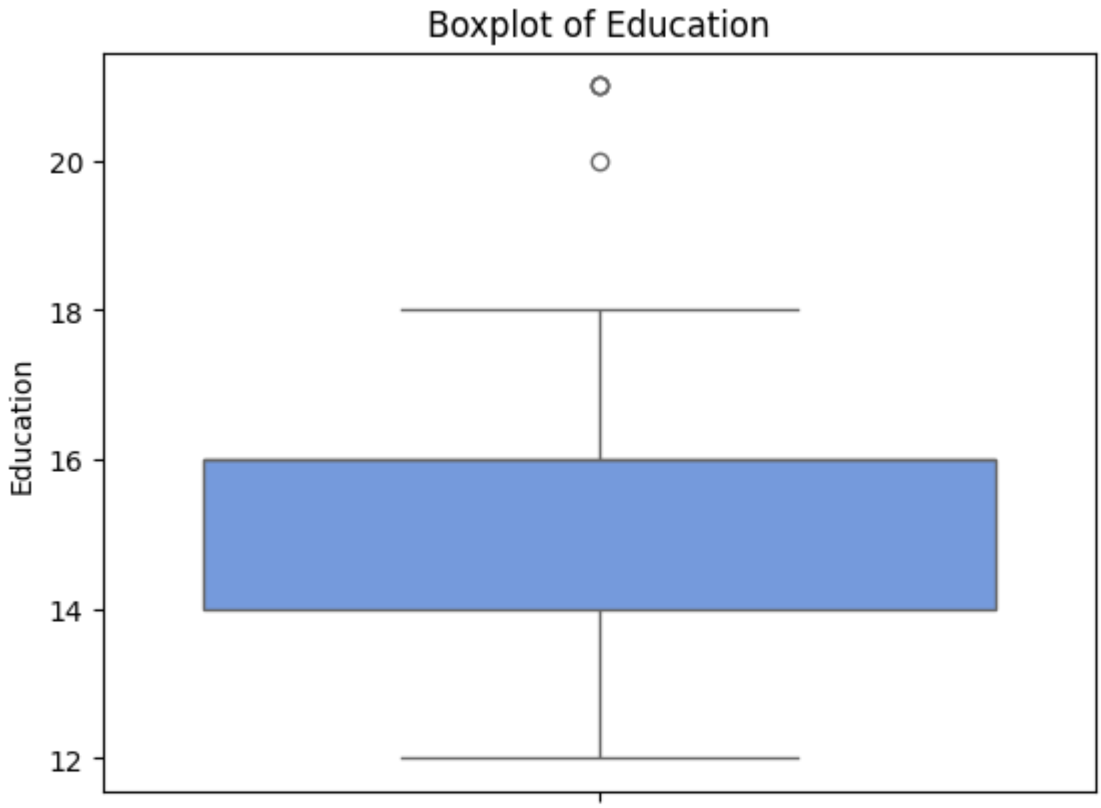
---

In [112…

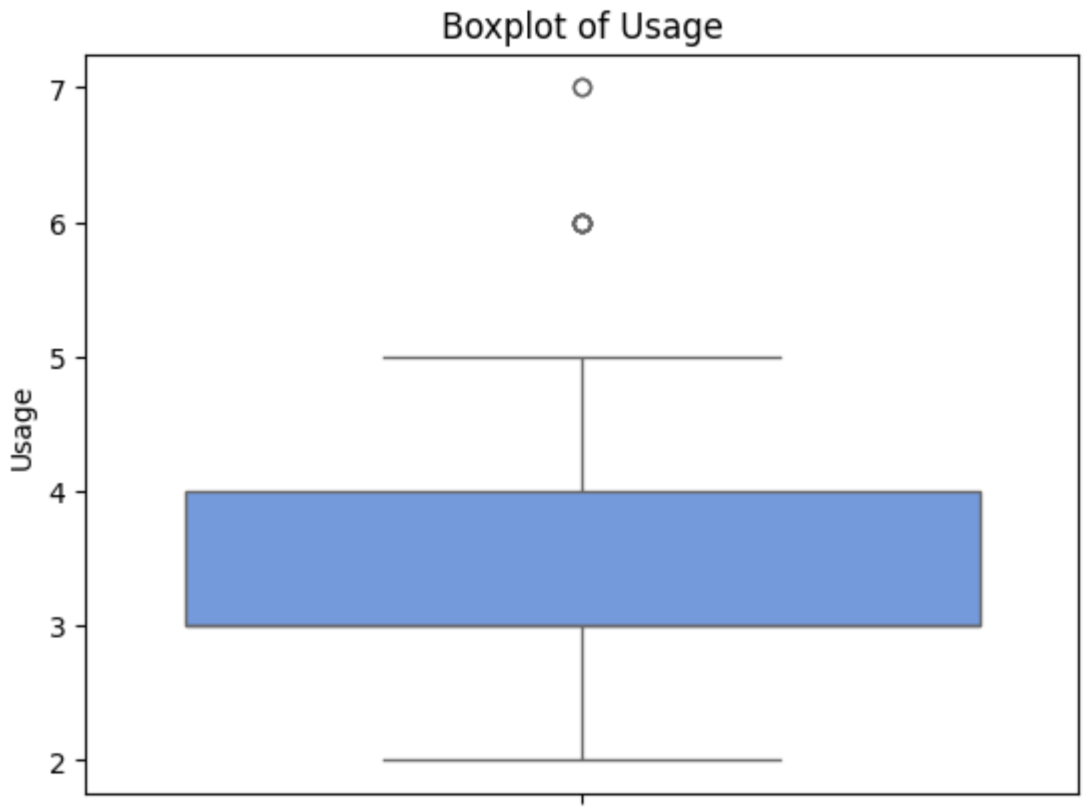
```
# Boxplot of numeric dtypes
for col in numeric_cols:
  sns.boxplot(y=df[col], color = 'cornflowerblue')
  plt.title(f'Boxplot of {col}')
  plt.show()
```

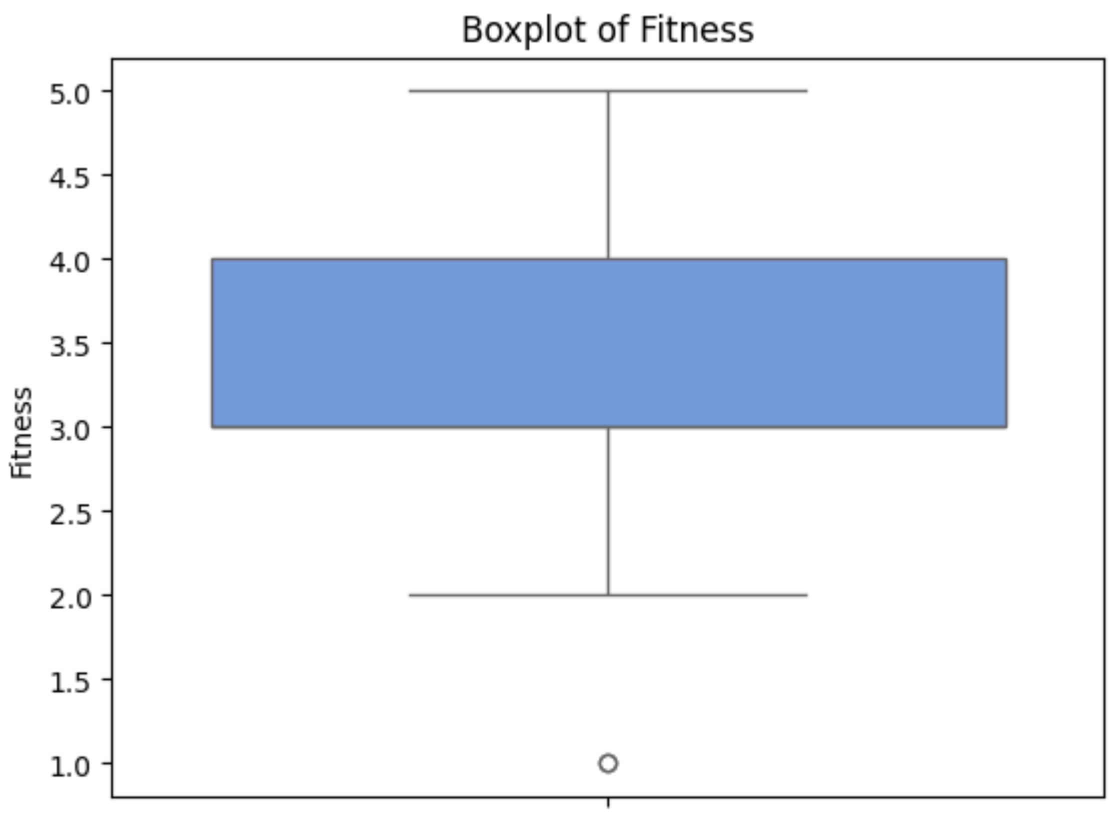


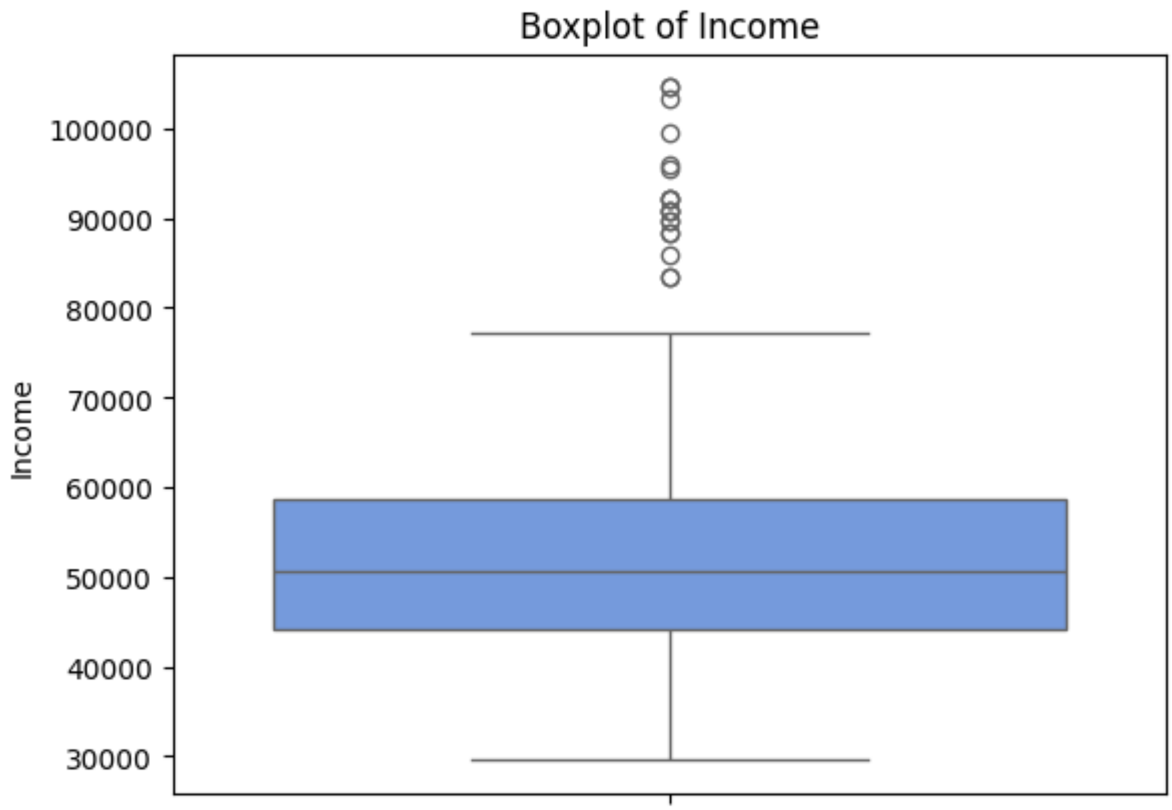
Boxplot of Age
50
45
40
35
30
25
20
Age

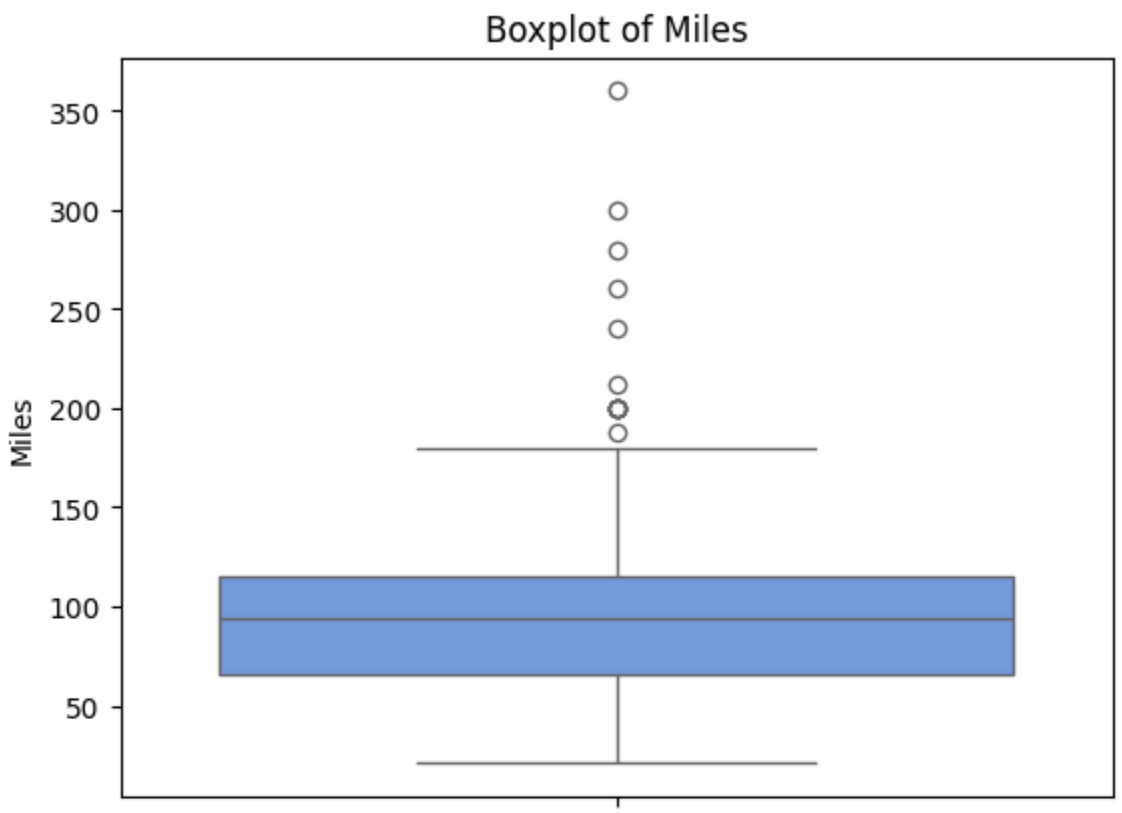



Boxplot of Education
20
18
16
14
12
Education


Boxplot of Usage
Usage
7
6
5
4
3
2


Boxplot of Fitness
Fitness
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0




---

### Visual Analysis

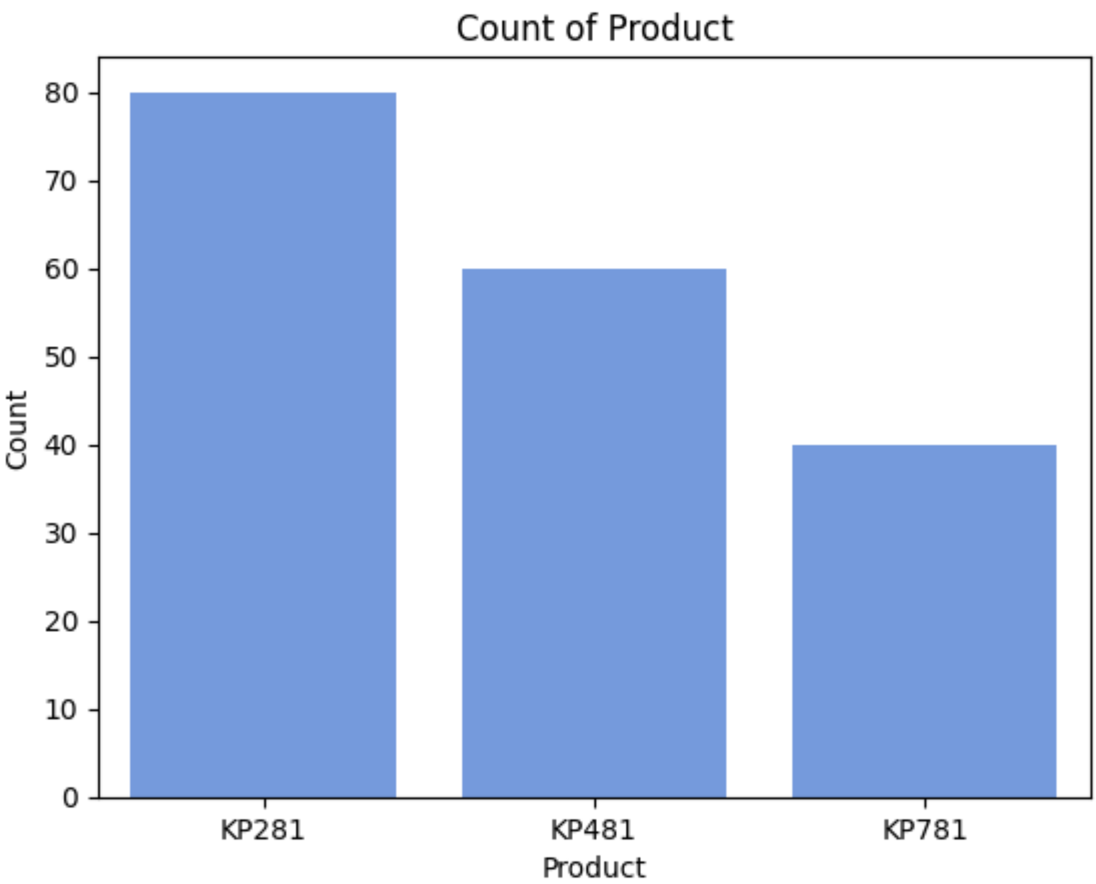
We will now generate the key visualizations to understand the data.

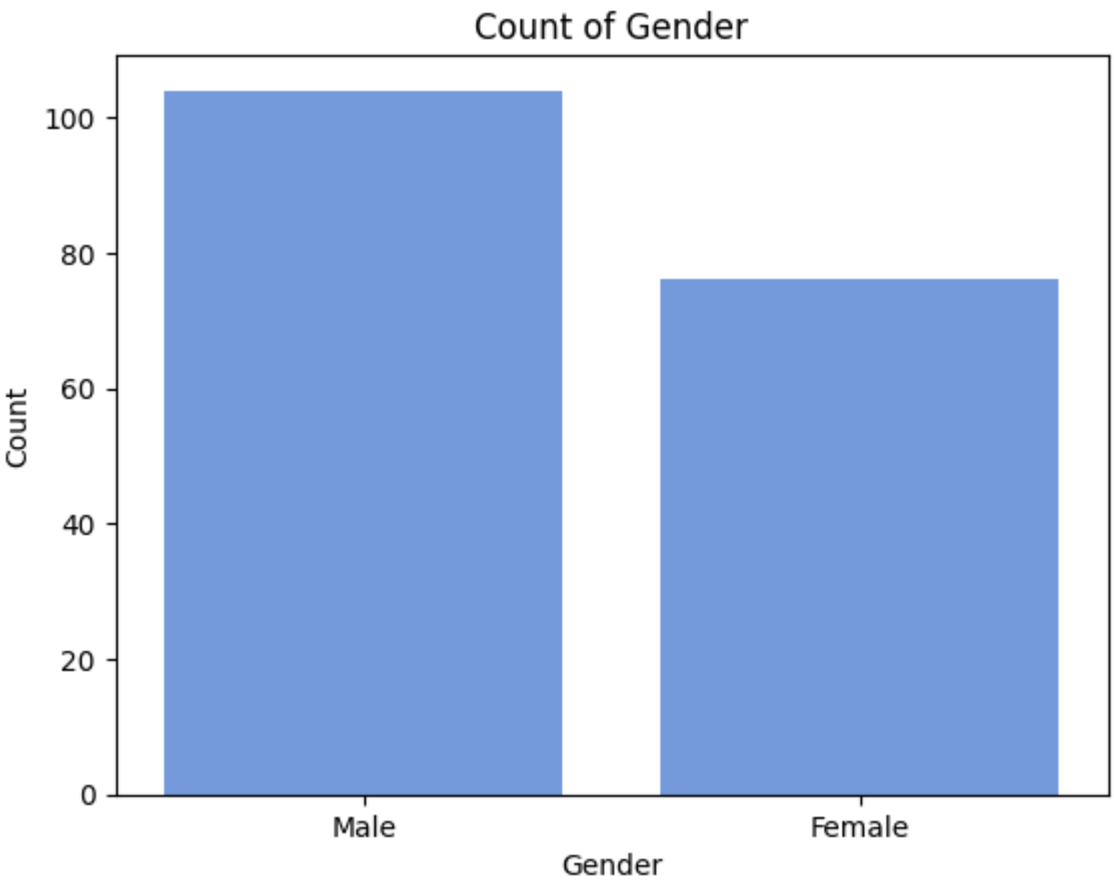
**a) Univariate Analysis (Numerical)**: Histograms for `Age`, `Income`, `Miles` show the distribution of customers. **b) Univariate Analysis (Categorical)**: Count plots for `Product`, `Gender`, `MaritalStatus`. **c) Bivariate Analysis**: Box plots of `Income`, `Age`, `Miles` vs. `Product` to see differences between user groups. **d) Correlation**: A heatmap to identify relationships between numerical variables.

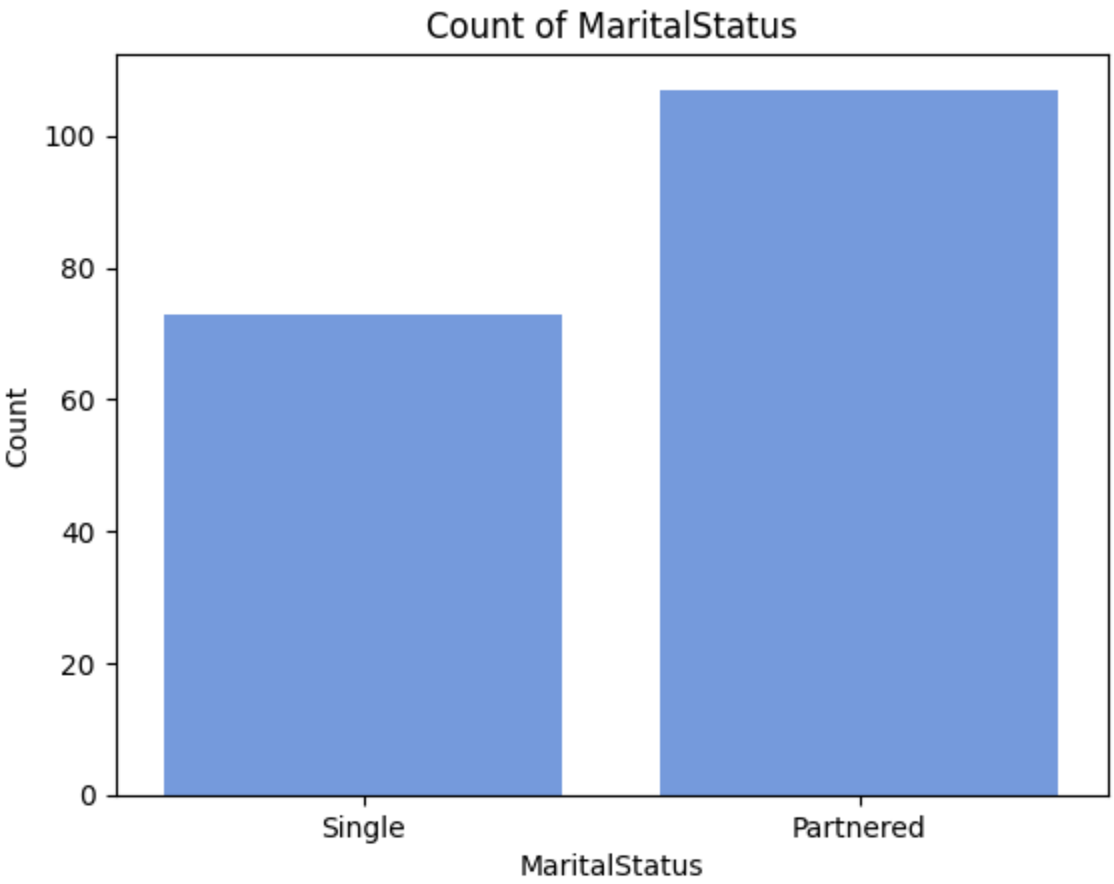
---

In [113…

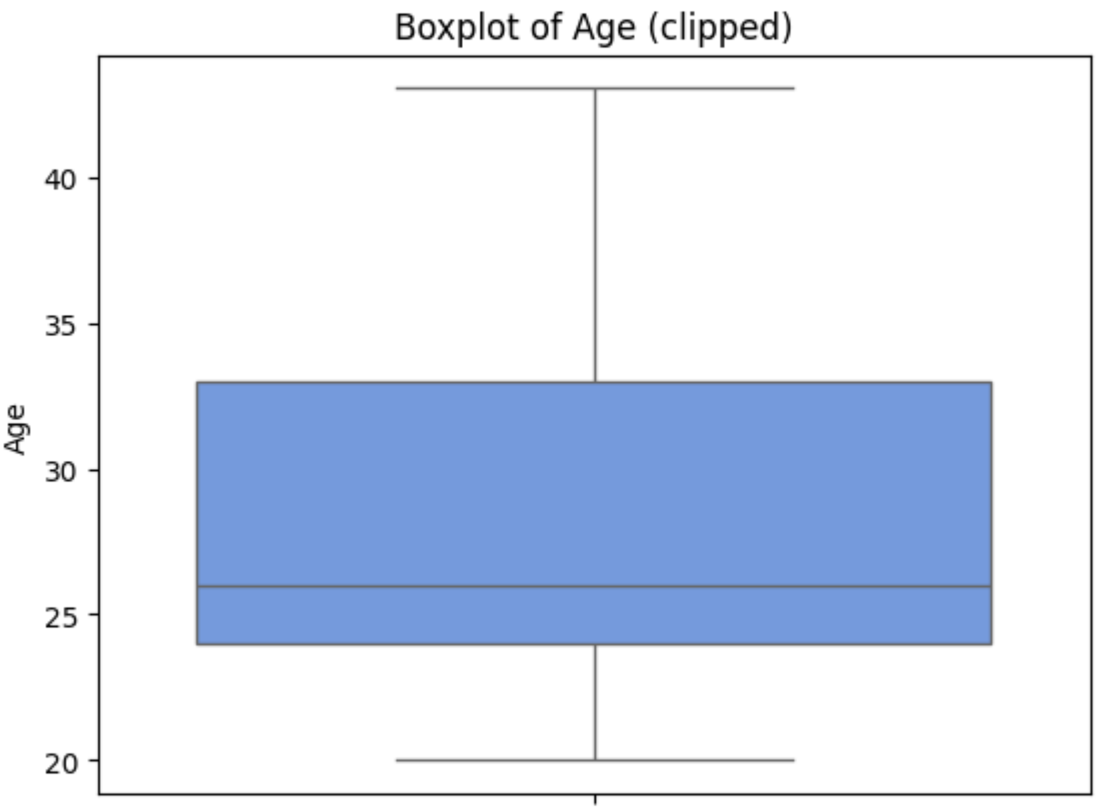
```
# Plot of object dtypes
col = ['Product','Gender','MaritalStatus']
fig, ax = plt.subplots()
for i in range(len(col)):
  sns.countplot(x=df[col[i]], color='cornflowerblue')
  plt.title(f'Count of {col[i]}')
  plt.ylabel('Count')
  plt.xlabel(col[i])
  plt.show()
```

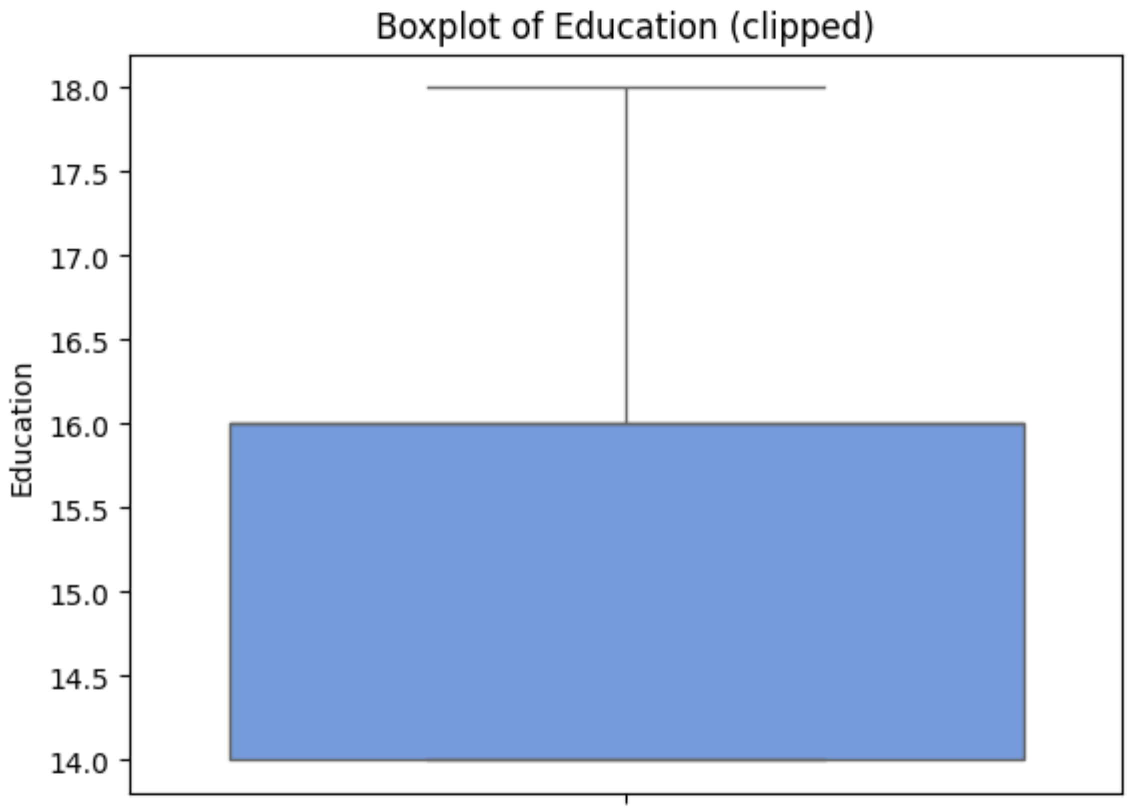


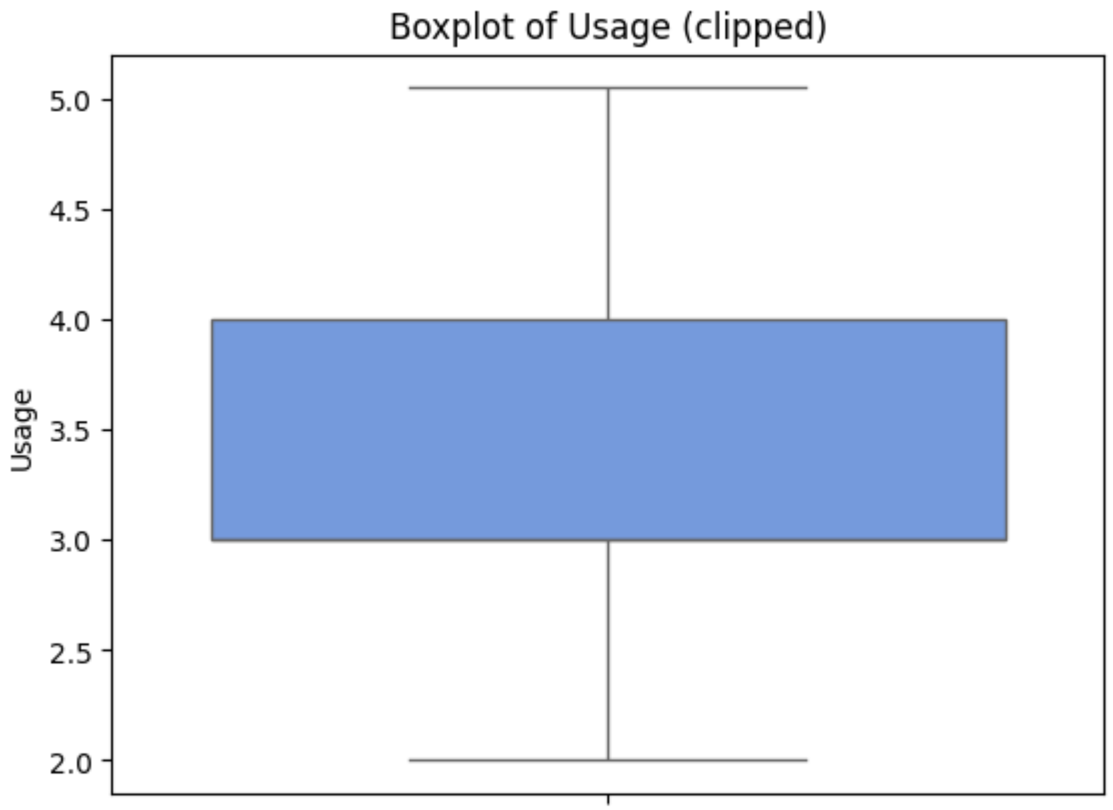



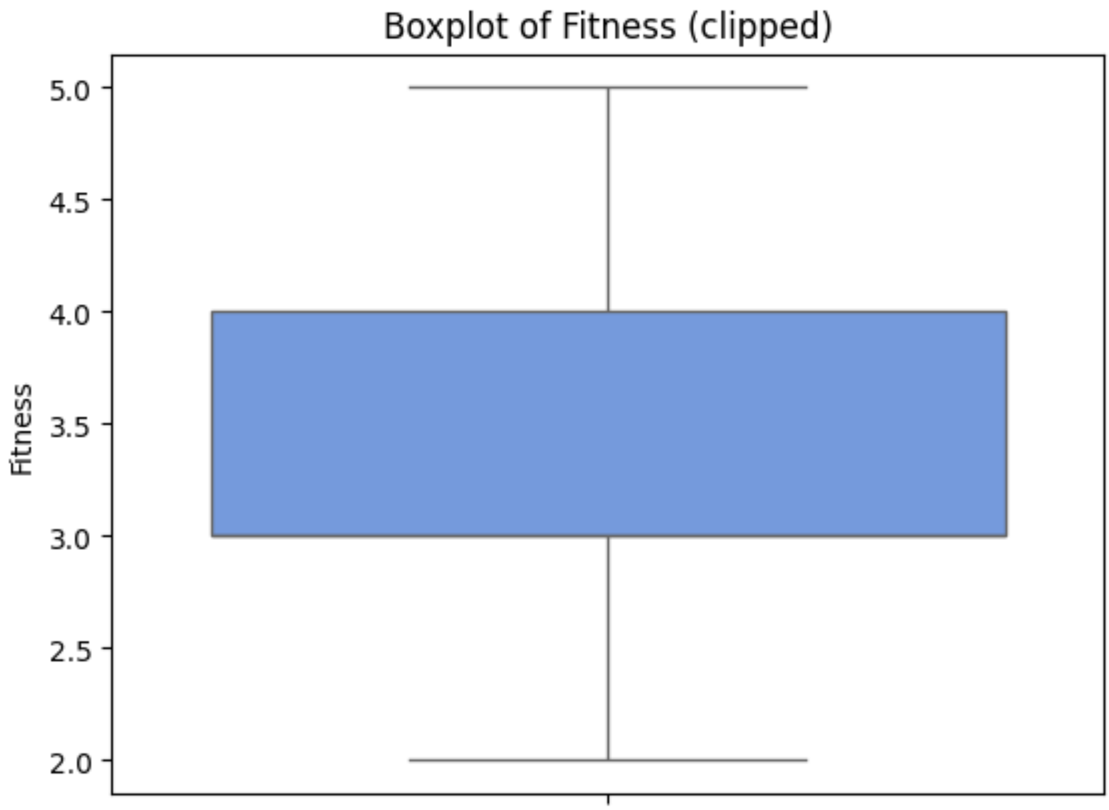



In [114…
```python
# Remove outliers
# clip the data between the 5 percentile and 95 percentile for numeric columns
numeric_cols = df.select_dtypes(include=np.number).columns
for col in numeric_cols:
  lower_bound = df[col].quantile(0.05)
  upper_bound = df[col].quantile(0.95)
  df_clipped[col] = np.clip(df[col], lower_bound, upper_bound)
  sns.boxplot(y=df_clipped[col], color='cornflowerblue')
  plt.title(f'Boxplot of {col} (clipped)')
  plt.show()
```

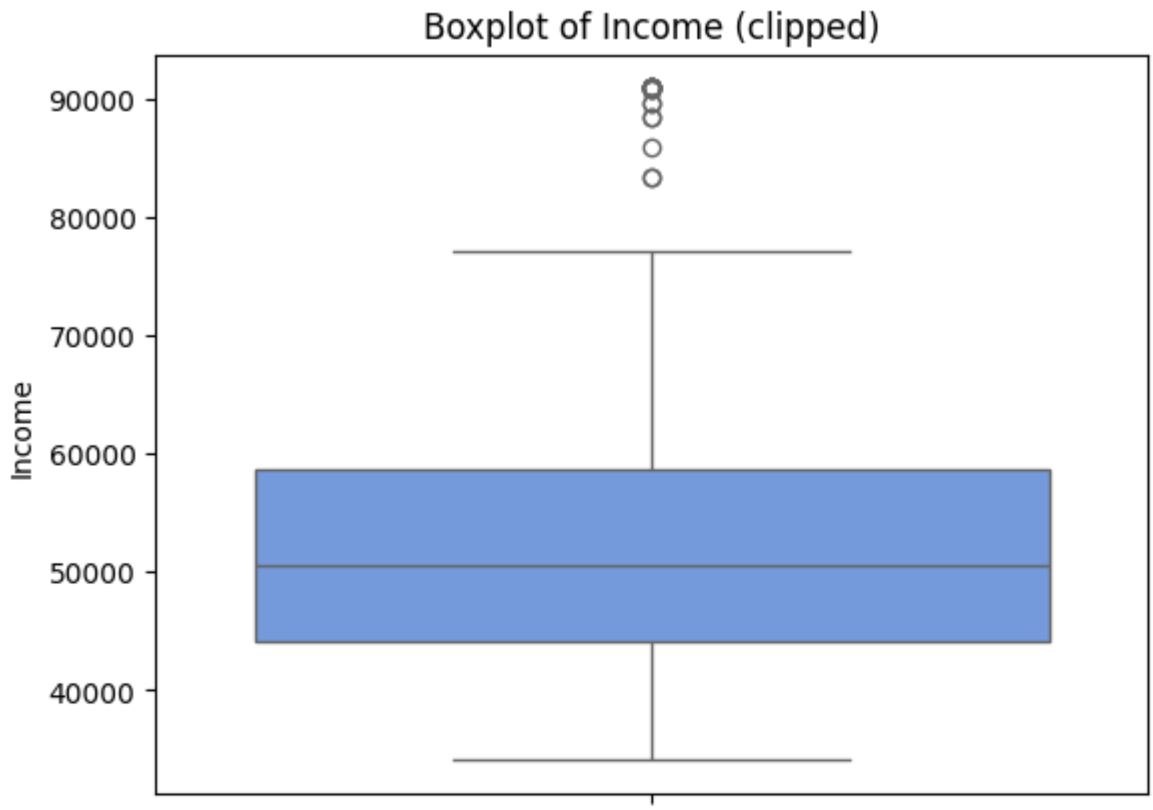



Boxplot of Education (clipped)
Education
18.0
17.5
17.0
16.5
16.0
15.5
15.0
14.5
14.0

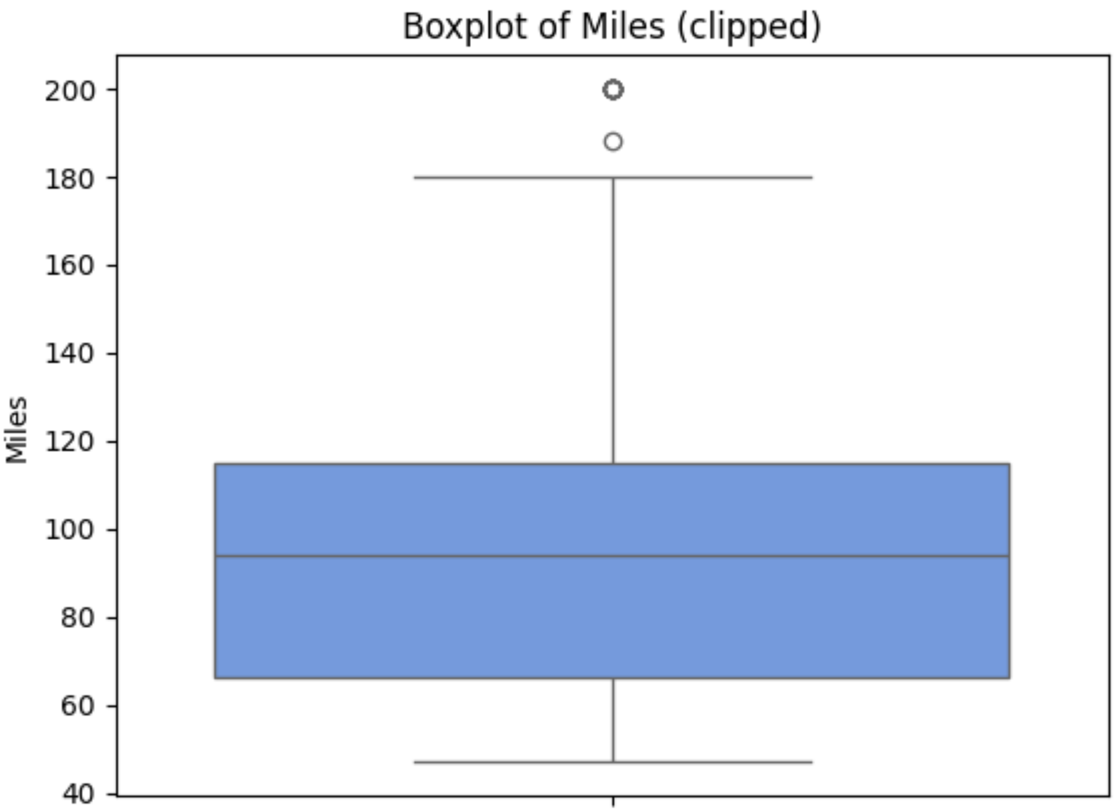

Boxplot of Usage (clipped)
Usage
5.0
4.5
4.0
3.5
3.0
2.5
2.0



Boxplot of Fitness (clipped)
Fitness
5.0
4.5
4.0
3.5
3.0
2.5
2.0

Boxplot of Income (clipped)
Income
90000
80000
70000
60000
50000
40000




In [115…

```
df_clipped = pd.DataFrame(df_clipped)
df_clipped.describe(include='all')
```

Out[115…

| | Product | Age | Gender | Education | MaritalStatus | Usage | Fitness | Income |
|---|---|---|---|---|---|---|---|---|
| **count** | 180 | 180.000000 | 180 | 180.000000 | 180 | 180.000000 | 180.000000 | 180.000000 |
| **unique** | 3 | NaN | 2 | NaN | 2 | NaN | NaN | NaN |
| **top** | KP281 | NaN | Male | NaN | Partnered | NaN | NaN | NaN |
| **freq** | 80 | NaN | 104 | NaN | 107 | NaN | NaN | NaN |
| **mean** | NaN | 28.641389 | NaN | 15.572222 | NaN | 3.396944 | 3.322222 | 53477.070000 |
| **std** | NaN | 6.446373 | NaN | 1.362017 | NaN | 0.952682 | 0.937461 | 15463.662523 |
| **min** | NaN | 20.000000 | NaN | 14.000000 | NaN | 2.000000 | 2.000000 | 34053.150000 |
| **25%** | NaN | 24.000000 | NaN | 14.000000 | NaN | 3.000000 | 3.000000 | 44058.750000 |
| **50%** | NaN | 26.000000 | NaN | 16.000000 | NaN | 3.000000 | 3.000000 | 50596.500000 |
| **75%** | NaN | 33.000000 | NaN | 16.000000 | NaN | 4.000000 | 4.000000 | 58668.000000 |
| **max** | NaN | 43.050000 | NaN | 18.000000 | NaN | 5.050000 | 5.000000 | 90948.250000 |

---

# 2. Outlier Detection & Handling

## a) Outliers Observed (via Boxplots)

- **Income**: Right-skewed, with high-income outliers (e.g., ~$104k)
- **Miles**: Strong right tail (max = 360 miles/week vs median = 94)
- **Age**: Mild outliers above 45
- **Education**: Max = 21 years (likely PhD/post-grad), slight outlier
- **Usage & Fitness**: Minimal outliers

## b) Clipping (5th–95th Percentile)

We **clip numerical columns** to reduce extreme skew:

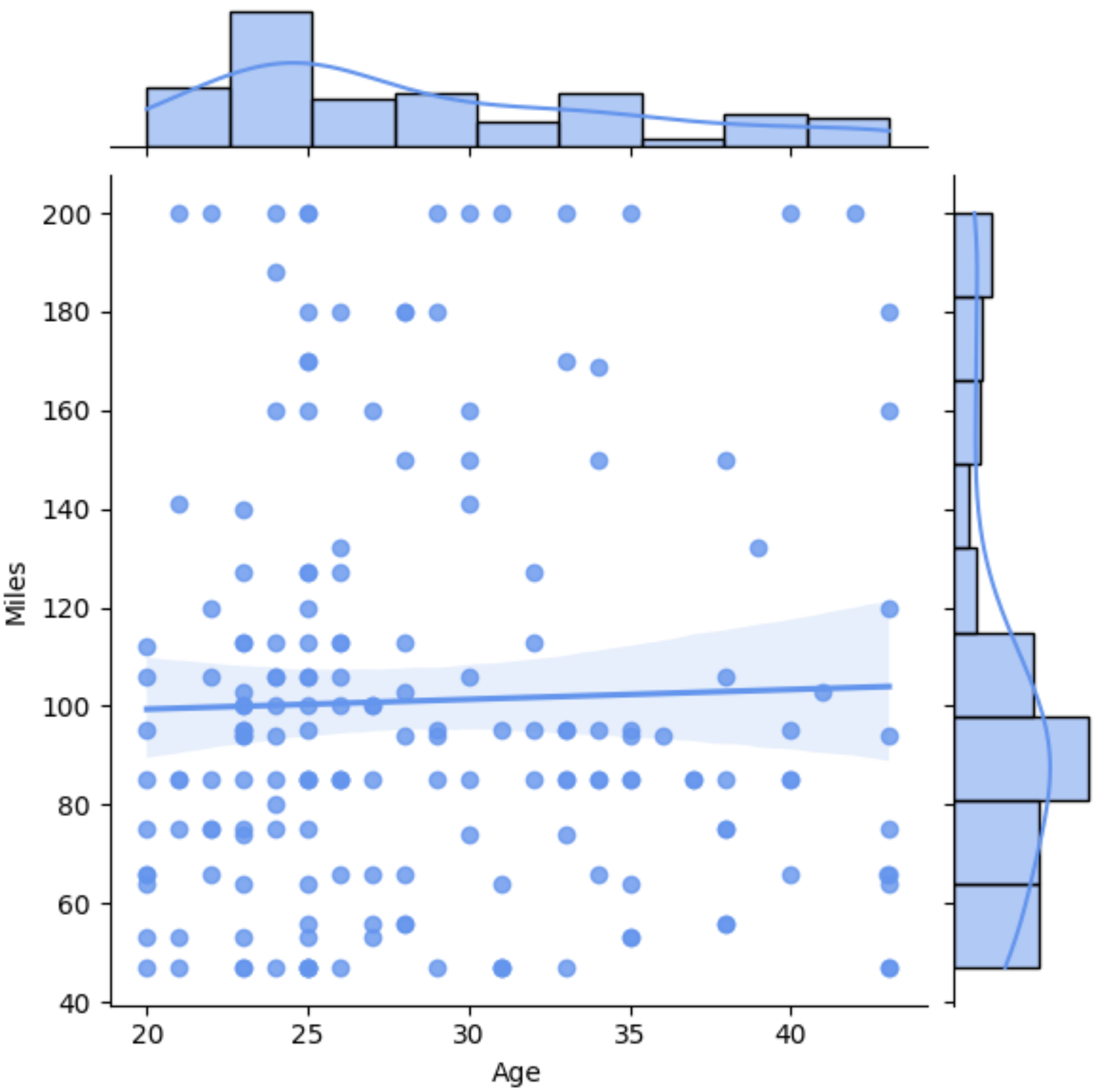
```
df_clipped = df.copy()
numeric_cols = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
for col in numeric_cols:
    lower = df[col].quantile(0.05)
    upper = df[col].quantile(0.95)
    df_clipped[col] = np.clip(df[col], lower, upper)
```

→ This preserves 90% of central data while minimizing distortion from outliers.

---

In [116…

```
# Jointplot between Age and Miles
sns.jointplot(x='Age', y='Miles', data=df_clipped, kind='reg', color='cornflowerblue')
plt.show()
#
```

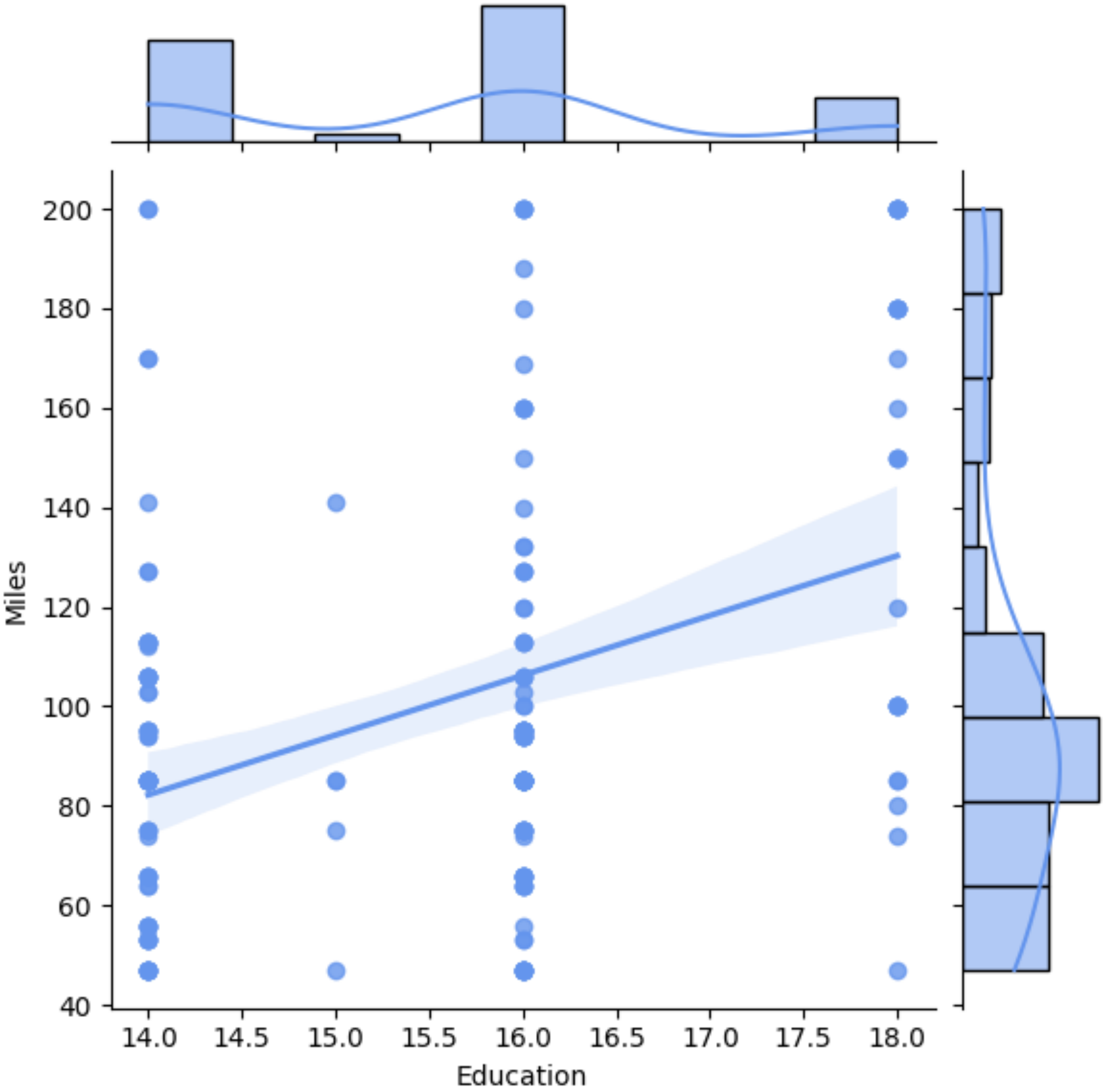



In [117…

```
# Jointplot between Income and Miles
sns.jointplot(x='Education', y='Miles', data=df_clipped, kind='reg', color='cornflowerblue')
#
```

Out[117…

```
<seaborn.axisgrid.JointGrid at 0x7d99d67b2600>
```

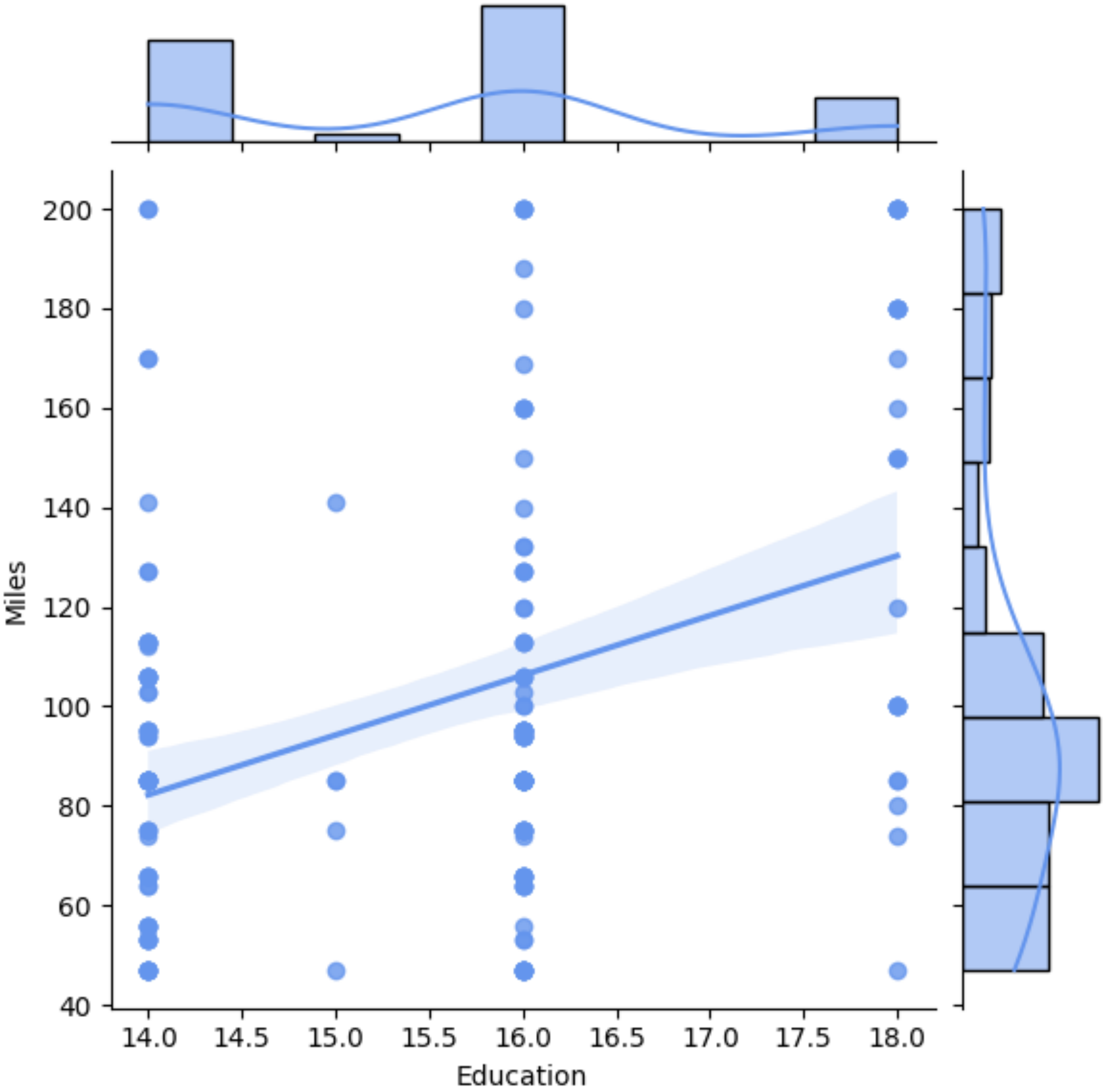



In [131…

```python
# Jointplot between Education and Miles
sns.jointplot(x='Education', y='Miles', data=df_clipped, kind='reg', color='cornflowerblue')
```

Out[131…

```
<seaborn.axisgrid.JointGrid at 0x7d99dc401d90>
```

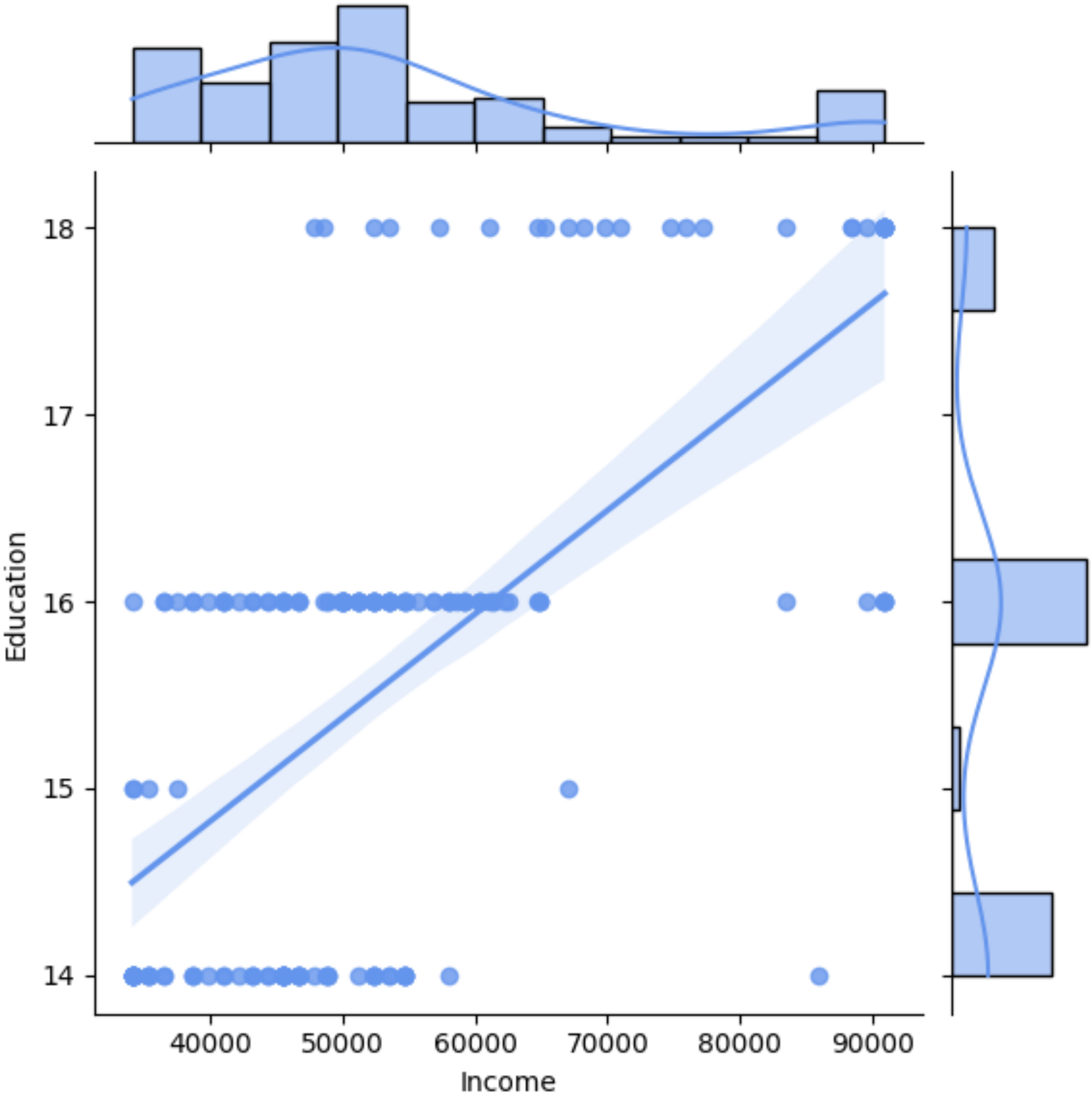



In [118…

```
# Jointplot between Income and Education
sns.jointplot(x='Income', y='Education', data=df_clipped, kind='reg', color='cornflowerblue')
```

Out[118…

```
<seaborn.axisgrid.JointGrid at 0x7d99dd08e180>
```



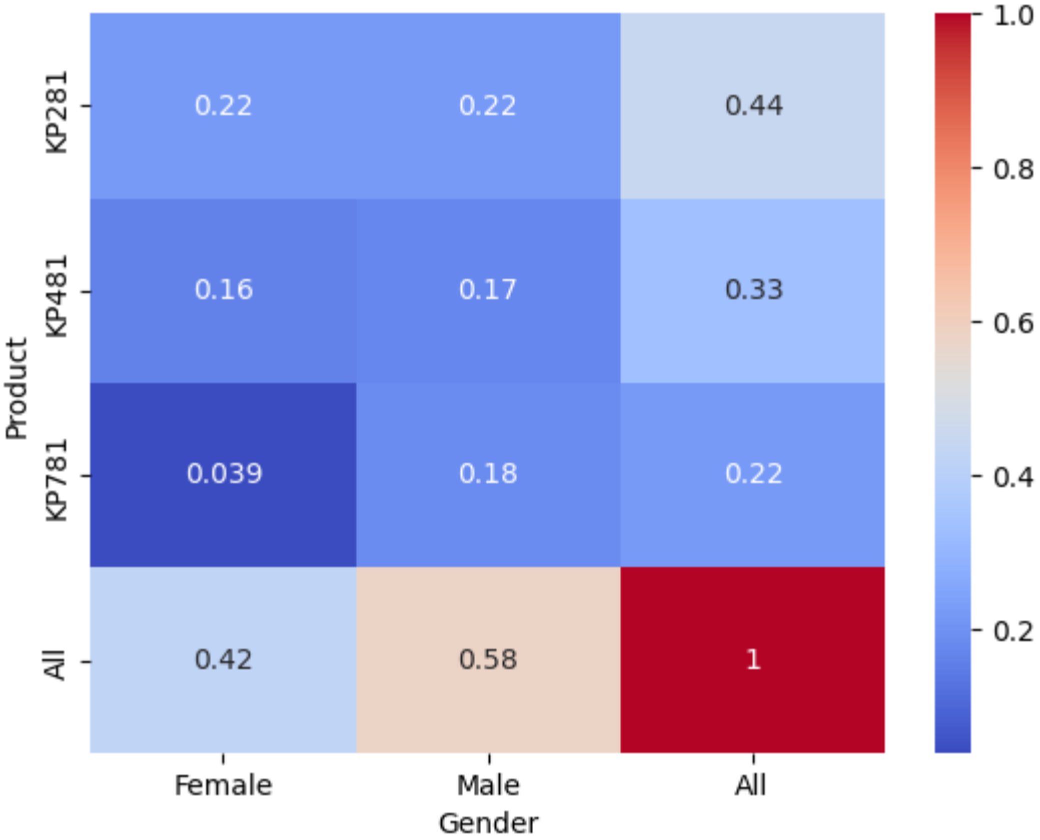
Education
18
17
16
15
14
40000
50000
60000
70000
80000
90000
Income

In [119…

```
# Marginal probability by gender (what percent of customers have purchased KP281, KP481, or KP
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Gender'],margins = True,normalize =
```

Out[119…

```
<Axes: xlabel='Gender', ylabel='Product'>
```

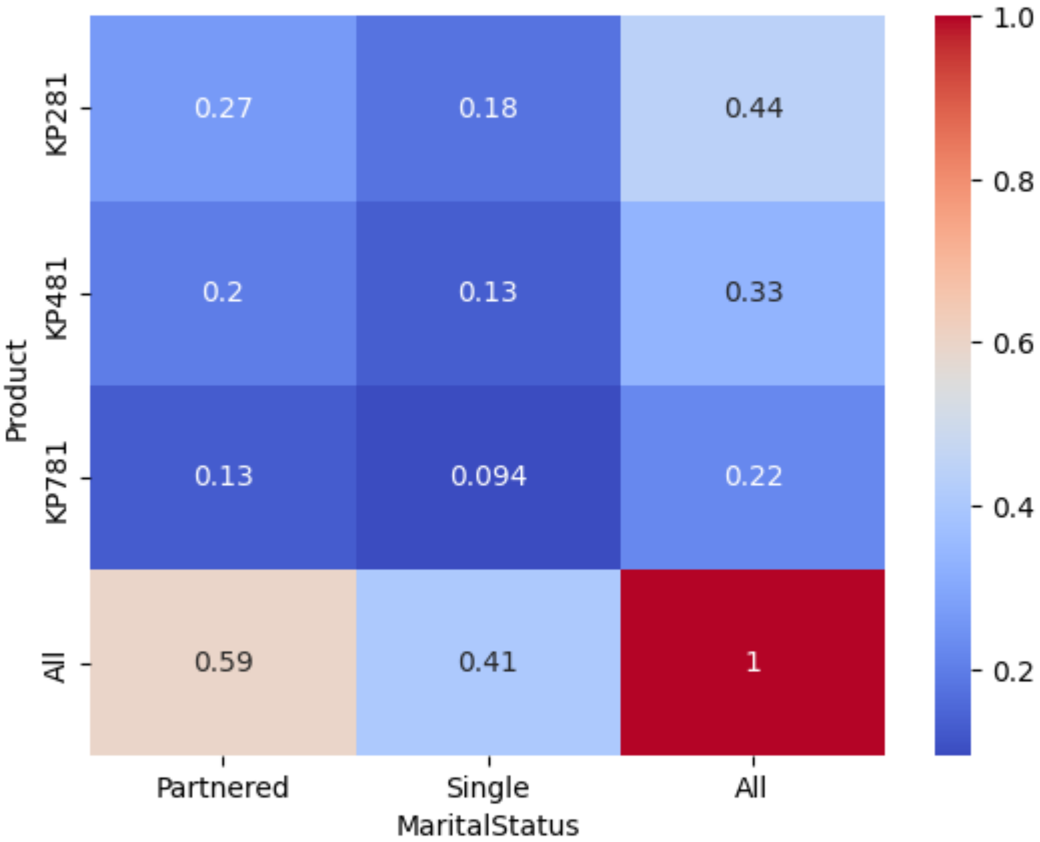



In [120…

```
# Marginal probability by Marital Status
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['MaritalStatus'],margins = True,norm
```

Out[120…

```
<Axes: xlabel='MaritalStatus', ylabel='Product'>
```



# 3. Relationship Between Features & Product Purchased

## a) Categorical vs Product (Count Plots)

- **Gender**:
  - **Males** dominate purchases across all models
  - KP781: ~95% male
- **MaritalStatus**:
  - **Partnered** customers prefer **KP281 & KP481**
  - **Single** customers are **overrepresented in KP781** (65% of KP781 buyers are single)

## b) Continuous vs Product (Scatter/Box Plots)

- **Age**:
  - KP281: Younger (18–30)
  - KP481: Mid-age (25–35)
  - KP781: Older (30–50)
- **Income**:
  - KP281: <$50k
  - KP481: $50k$–65k
  - KP781: >$70k (median$ 80k)
- **Miles & Usage**:
  - KP781 users run **>150 miles/week**, **5–7 times/week**
  - KP281: ~80 miles/week, 2–3 times/week

✅ **Conclusion**: Product choice strongly correlates with **age, income, fitness level, and lifestyle intensity**.

---

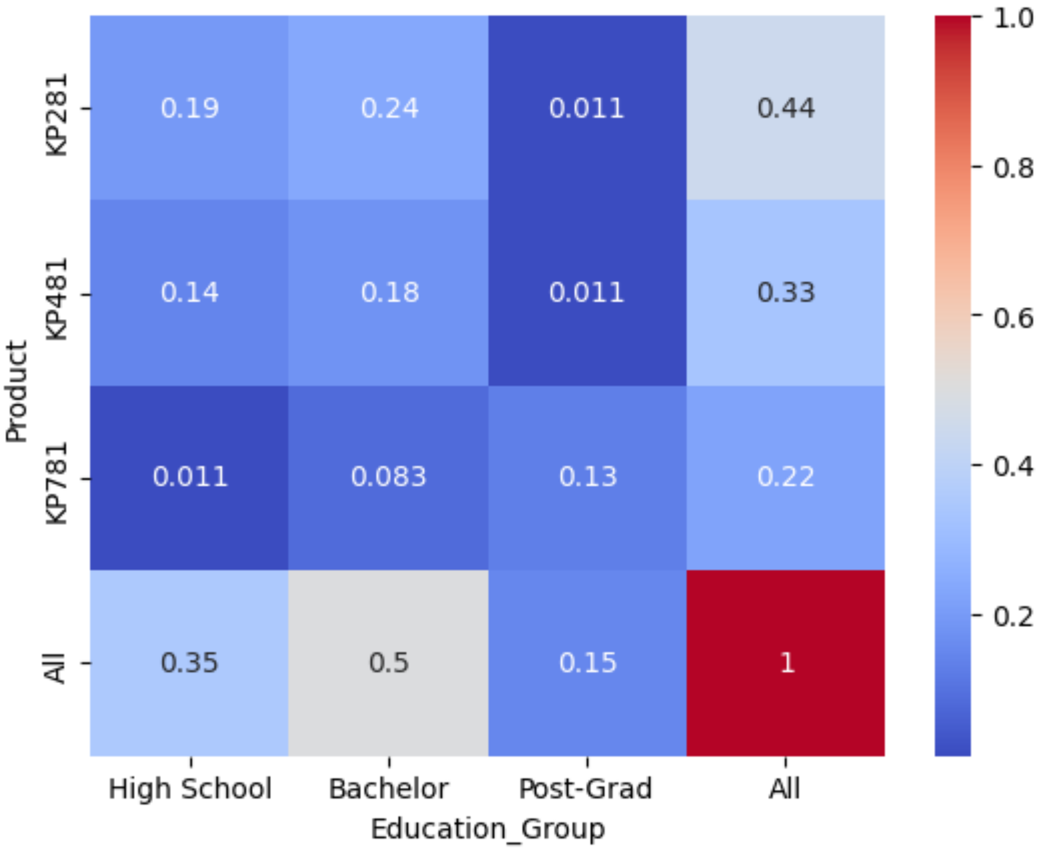
In [121…

```
# # Marginal probability by Education Grouping
Education_buckets = ['High School', 'Bachelor', 'Post-Grad']
df['Education_Group'] = pd.qcut(df['Education'], q=4, labels=Education_buckets, duplicates='dr
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Education_Group'],margins = True,nc

# sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Education'],margins = True,normal
```

Out[121…

```
<Axes: xlabel='Education_Group', ylabel='Product'>
```

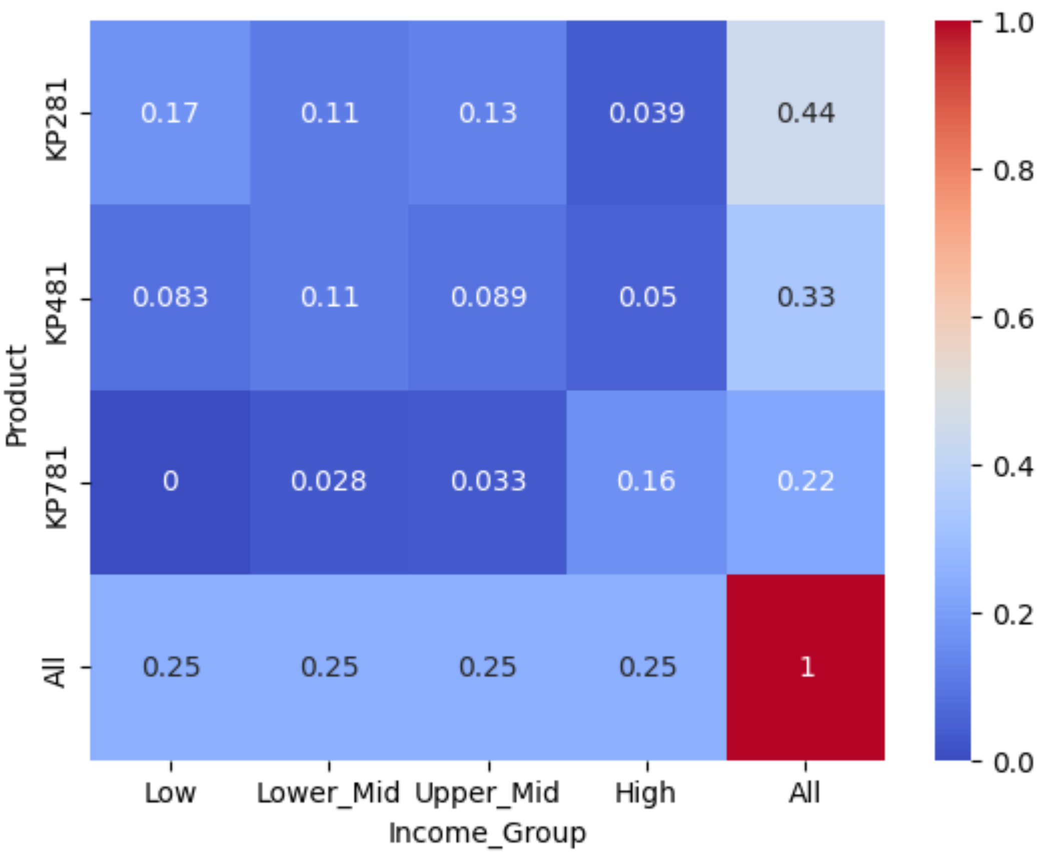



In [122…

```
# # Marginal probability by Income Grouping
Income_buckets = ['Low', 'Lower_Mid', 'Upper_Mid',  'High']
df['Income_Group'] = pd.qcut(df['Income'], q=4, labels=Income_buckets, duplicates='drop')
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Income_Group'],margins = True,norma
```

Out[122…

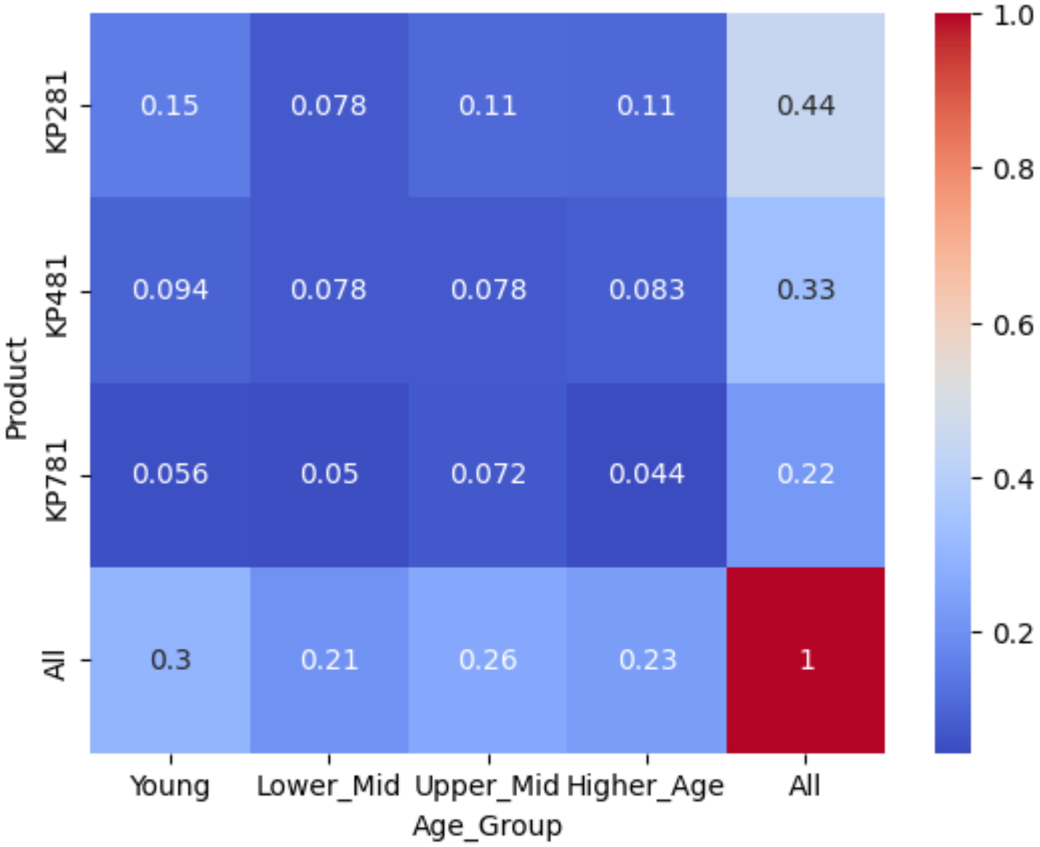
```
<Axes: xlabel='Income_Group', ylabel='Product'>
```




In [123…

```
# Marginal probability by Age Grouping
Age_buckets = ['Young', 'Lower_Mid', 'Upper_Mid', 'Higher_Age']
df['Age_Group'] = pd.qcut(df['Age'], q=4, labels=Age_buckets, duplicates='drop')
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Age_Group'],margins = True,normaliz
```

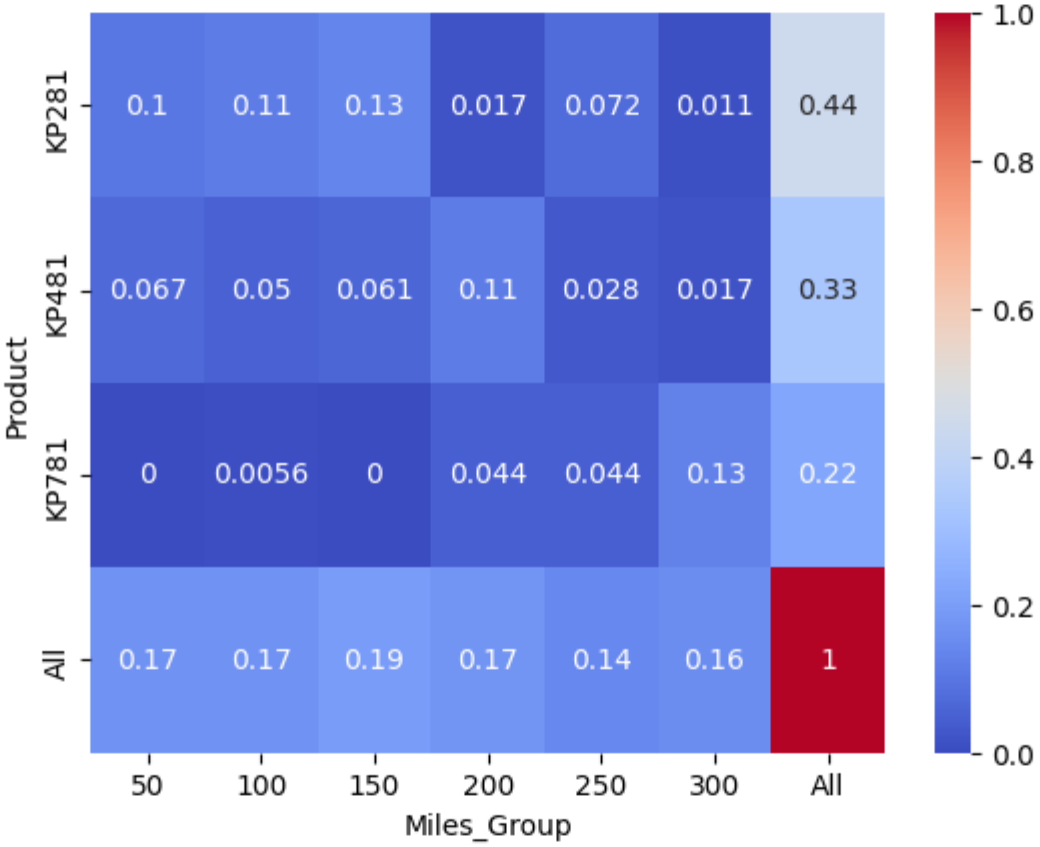
Out[123… <Axes: xlabel='Age_Group', ylabel='Product'>




In [124…

```
# Marginal probability by Miles Grouping
Miles_buckets = [50,100,150,200,250,300]
df['Miles_Group'] = pd.qcut(df['Miles'], q=6, labels=Miles_buckets, duplicates='drop')
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Miles_Group'],margins = True,normal
```

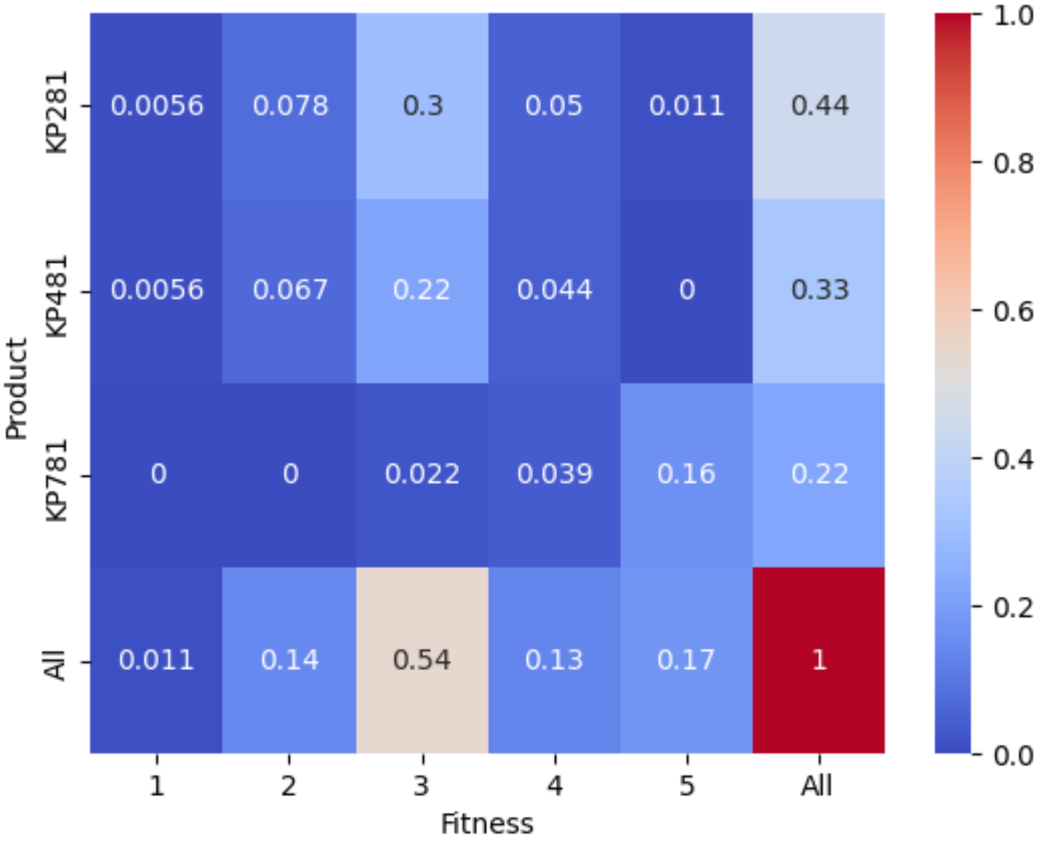
Out[124… <Axes: xlabel='Miles_Group', ylabel='Product'>




In [125…

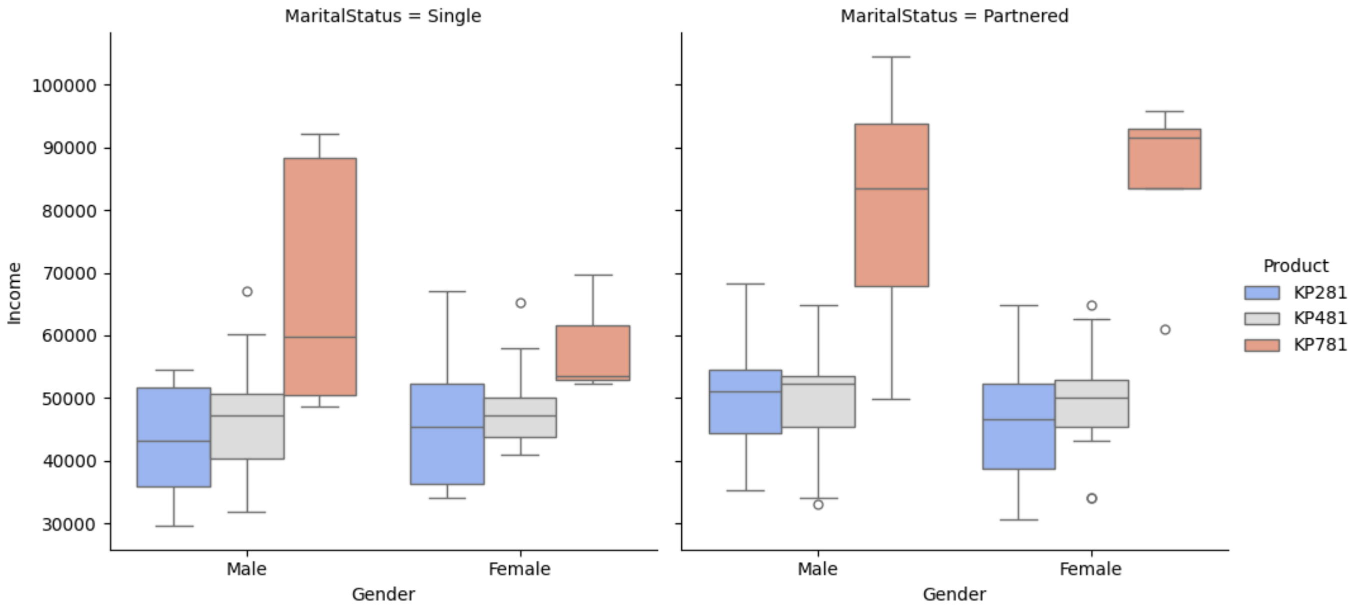
```
# Marginal probability by Fitness
sns.heatmap(pd.crosstab(index =df['Product'],columns = df['Fitness'],margins = True,normalize
#
```

Out[125… <Axes: xlabel='Fitness', ylabel='Product'>




In [126…

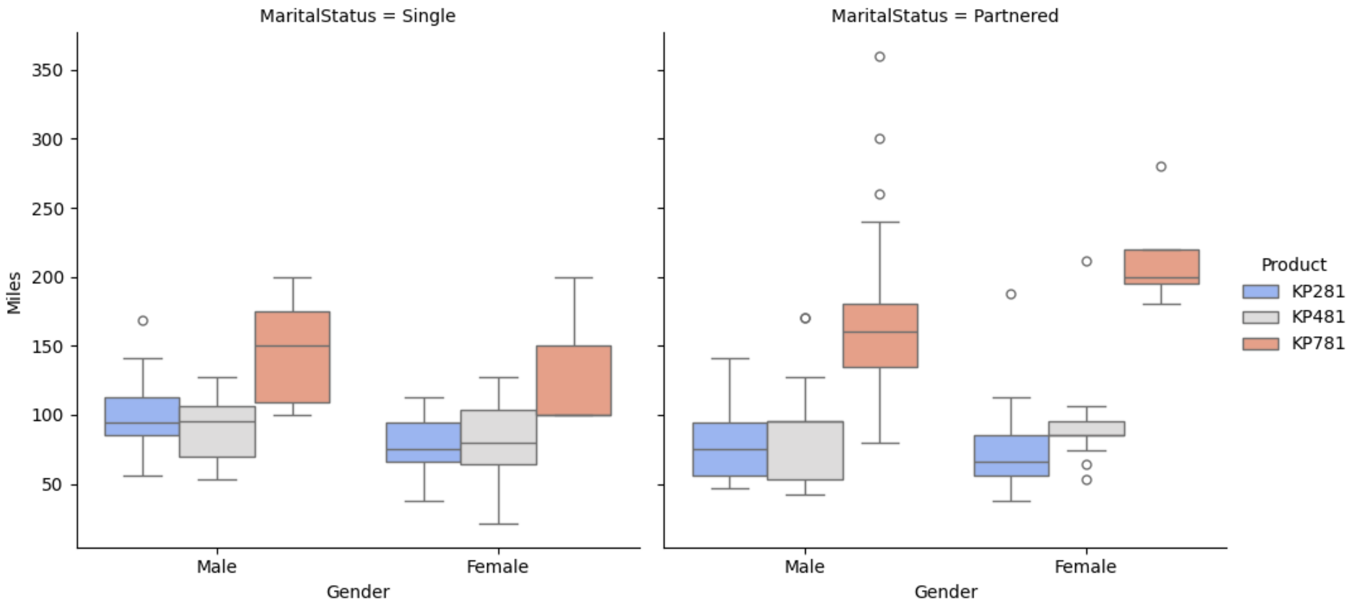
```
# Income by gender by product and by marital status
sns.catplot(x='Gender',y='Income', hue='Product', col='MaritalStatus', data=df, kind='box', pa
plt.show()
```




In [127…

```
# Miles by gender by product and by marital status
sns.catplot(x='Gender',y='Miles', hue='Product', col='MaritalStatus', data=df, kind='box', pal
```

Out[127… <seaborn.axisgrid.FacetGrid at 0x7d99d7c13ce0>




---

# 4. Probability Analysis

## a) Marginal Probability (Overall Product Mix)

| Product | Count | Probability |
|---|---|---|
| KP281 | 80 | **44.4%** |
| KP481 | 60 | **33.3%** |
| KP781 | 40 | **22.2%** |

## b) Conditional Probabilities (Examples)

### i) **P(KP781 | Male)**

- Males = 104
- Males who bought KP781 = 33

**→ P = 33/104 ≈ 31.7%**

### ii) **P(KP781 | Single)**

- Singles = 73
- Singles who bought KP781 = 26

**→ P = 26/73 ≈ 35.6%**

### iii) **P(KP281 | Income < $50k)**

- ~60 customers earn <$50k
- ~50 of them bought KP281

**→ P ≈ 83%**

**Insight**: High-income, single, male, fitness-conscious users are **high-probability leads for KP781**.

---

In [128…

```
# Check the correlation among different factors
```

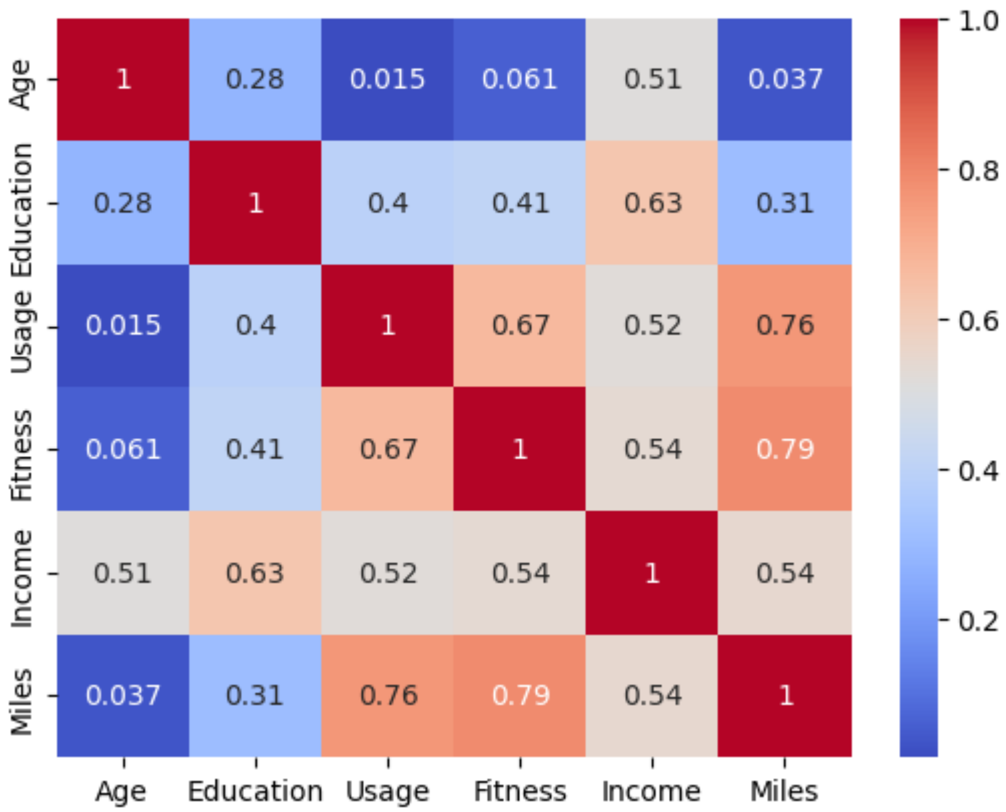
```
df.select_dtypes(include=np.number).corr()
```

Out[128…

| | Age | Education | Usage | Fitness | Income | Miles |
|---|---|---|---|---|---|---|
| **Age** | 1.000000 | 0.280496 | 0.015064 | 0.061105 | 0.513414 | 0.036618 |
| **Education** | 0.280496 | 1.000000 | 0.395155 | 0.410581 | 0.625827 | 0.307284 |
| **Usage** | 0.015064 | 0.395155 | 1.000000 | 0.668606 | 0.519537 | 0.759130 |
| **Fitness** | 0.061105 | 0.410581 | 0.668606 | 1.000000 | 0.535005 | 0.785702 |
| **Income** | 0.513414 | 0.625827 | 0.519537 | 0.535005 | 1.000000 | 0.543473 |
| **Miles** | 0.036618 | 0.307284 | 0.759130 | 0.785702 | 0.543473 | 1.000000 |

In [129…

```
# Heatmap
sns.heatmap(df.select_dtypes(include=np.number).corr(), annot=True, cmap = 'coolwarm')
plt.show()
```




---

# 5. Correlation Analysis (Heatmap)

Top Correlations:

- **Miles** ↔ **Fitness**: **0.79** (strong)
- **Miles** ↔ **Usage**: **0.76**
- **Income** ↔ **Education**: **0.63**
- **Income** ↔ **Fitness**: **0.54**
- **Age** ↔ **Income**: **0.51**

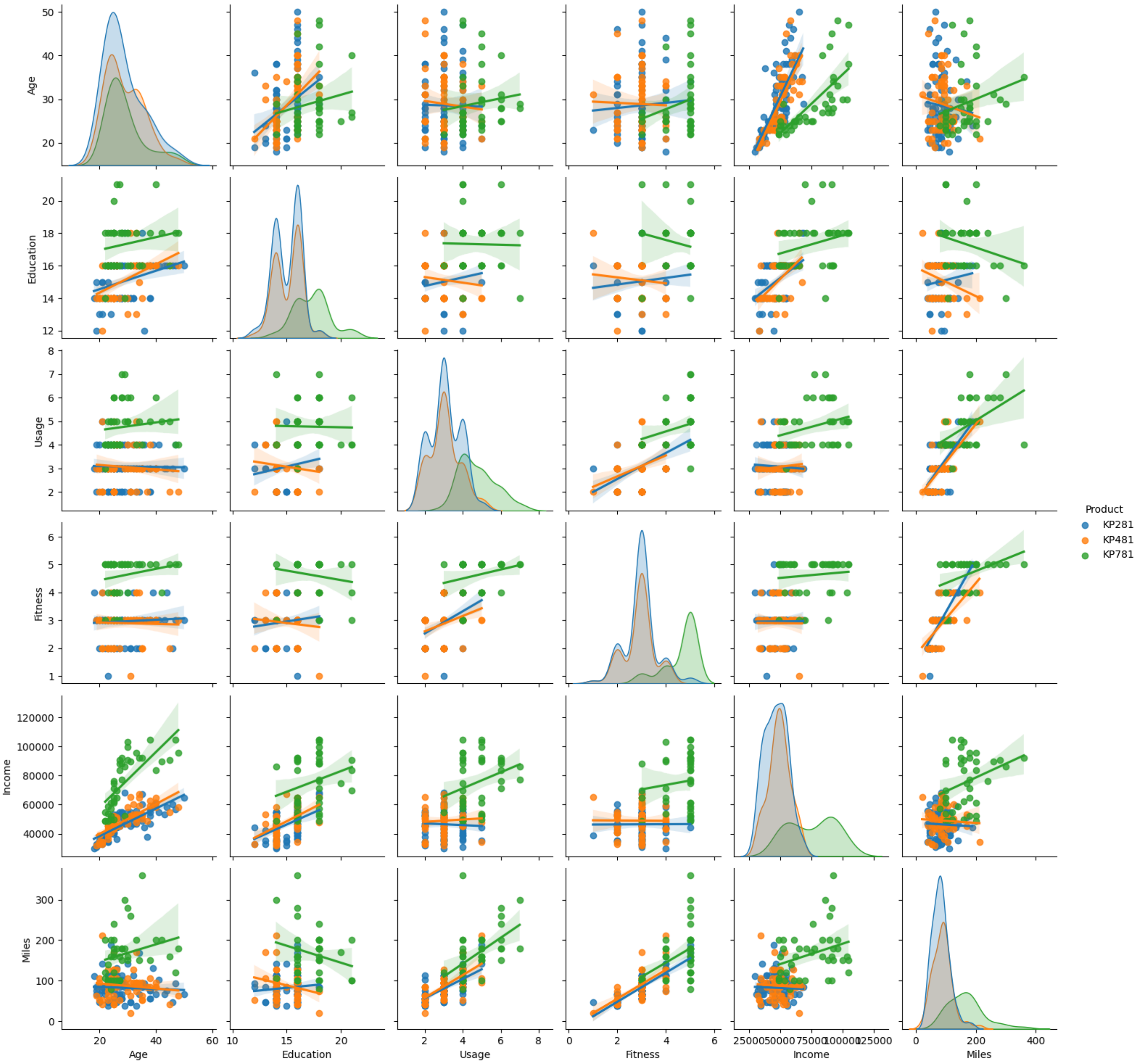
**No multicollinearity issues**; all relationships are intuitive.

---

In [130…

```
# Customer profiling and recommendation
# pairplot with hue as 'Product'
```

```
sns.pairplot(df, hue='Product', kind= 'reg')
plt.show()
```




---

# 6. Customer Profiling & Recommendations

🔹 KP281 (Entry-Level – $1,500)

```
Age: Primarily 18–30 years (mean ~26)
Gender: Balanced, but slightly more Female (48%) vs. general trend
Income: Low to moderate → $29K–$50K (median: ~$45K)
Marital Status: Mostly partnered (60%+)
Fitness Level: 2–3 (beginner to average)
Usage: 2–3 times/week, 60–90 miles/week
Education: Typically 14–16 years (undergrad)
```

```
✅ Profile: Young adults or couples starting their fitness journey; budget-
conscious; seek reliability over advanced features.
```

◆ KP481 (Mid-Tier – $1,750)

```
Age: 25–38 years (mean ~30)
Gender: Male-dominated (~65%)
Income: $50K–$65K (median: ~$58K)
Marital Status: Balanced (slightly more partnered)
Fitness Level: 3–4 (moderately fit)
Usage: 3–5 times/week, 90–130 miles/week
Education: 16+ years (bachelor’s or higher)


✅ Profile: Active professionals aiming to maintain or improve fitness;
value performance and durability; willing to pay a premium for better
features (e.g., heart rate monitoring, sturdier frame).
```

◆ KP781 (Premium – $2,500)

```
Age: 30–50 years (mean ~38)
Gender: Overwhelmingly male (95% of buyers)
Income: High earners → $70K–$105K (median: ~$80K)
Marital Status: 65% single (unlike other segments)
Fitness Level: 4–5 (very fit or athlete-level)
Usage: 5–7 times/week, 150–200+ miles/week
Education: Often 18+ years (post-grad/PhD)


✅ Profile: High-income, single, serious runners or fitness enthusiasts;
prioritize performance, data tracking, and durability; treat treadmill as a
long-term athletic investment.
```

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# 7. Actionable Recommendations for Aerofit

1. **Refine Marketing Messaging**:
   - **For KP281**: Focus on **affordability, space-saving design, and family health**. Target ads to younger, partnered couples and those in the early stages of their fitness journey. Use messaging like "Start your healthy lifestyle today."
   - **For KP481**: Emphasize **durability, performance metrics, and training programs**. Market to serious runners and fitness enthusiasts who log high mileage. Highlight its "best value for performance" proposition.
   - **For KP781**: Sell the **premium experience, advanced technology (e.g., heart rate control, cushioning), and long-term health investment**. Target high-income, partnered individuals. Position it as a luxury item for the home.
2. **Optimize Sales Team Training**:
   - Equip the sales team with these profiles. If a customer mentions a high weekly mileage goal, immediately steer them towards the **KP481**.
   - If a customer is in a higher income bracket and mentions their spouse, highlight the **KP781**'s premium features.
   - For first-time buyers or those on a budget, the **KP281** should be the default recommendation.

3. **Bundle Products and Services**:
    - **For KP281**: Offer bundled deals with basic fitness accessories (mats, water bottles).
    - **For KP481**: Bundle with a subscription to a premium fitness app or a heart rate monitor.
    - **For KP781**: Offer a premium service package (extended warranty, in-home setup, annual maintenance check).
4. **Targeted Digital Advertising**:
    - Use online ad platforms to target specific demographics:
        - **KP281**: Target demographics of partnered individuals aged 25-35 with a median income.
        - **KP781**: Use income-based targeting to reach high-income households and retarget website visitors who looked at premium models.
5. **Product Positioning**
    - Market **KP281** as an **affordable starter treadmill** for young couples or students (partnered, lower income).
    - Position **KP481** as a **balanced choice** for active professionals building fitness routines.
    - Promote **KP781** as a **high-performance machine** for serious (mostly single) male runners with high disposable income.
6. **Targeted Marketing**
    - Use **income & marital status** in digital ads:
        - FB/Instagram ads for KP781 → target **single males, 30–50, income >$70k**
        - Email campaigns for KP281 → **young partnered couples, income <$50k**
7. **In-Store Staff Training**
    - Train sales staff to **ask 3 key questions**:
      *"What's your weekly mileage goal?"*
      *"How often do you plan to use it?"*
      *"What's your fitness level?"*

   → Use answers to **guide product recommendation**.

8. **Bundle Offers**
    - Bundle **KP781 with premium accessories** (heart rate monitors, coaching apps)
    - Offer **financing for KP781** (high-ticket item)
9. **Expand KP781 Appeal**
    - Currently **<5% female buyers** for KP781 → opportunity to **create female-focused marketing** (e.g., "Elite Performance for Every Runner")

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## ✅ Final Note:

This analysis shows **clear segmentation** across products. Aerofit can **increase conversion and reduce returns** by aligning product recommendations with **customer profiles**, not just price.

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