Defining Problem Statement & Basic Metrics

```python
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load data
df = pd.read_csv('aerofit_treadmill.csv')

# Basic checks
print("===== SHAPE & STRUCTURE =====")
print("Shape:", df.shape)
print("\nData Types:\n", df.dtypes)
print("\nMissing Values:\n", df.isnull().sum())

# Convert categorical variables
df['Product'] = df['Product'].astype('category')
df['Gender'] = df['Gender'].astype('category')
df['MaritalStatus'] = df['MaritalStatus'].astype('category')

# Descriptive stats
print("\n===== DESCRIPTIVE STATISTICS =====")
print(df.describe())
```

```
===== SHAPE & STRUCTURE =====
Shape: (180, 9)

Data Types:
 Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object

Missing Values:
 Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64

===== DESCRIPTIVE STATISTICS =====
```

```
              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
```

Observations:

- No missing values; clean dataset.
- Age: 18–50 years (median 26).
- Income: 29,562–104,581 (median $50,596).
- Key Insight: Income and Miles have high variance (std > 50% of mean).

Non-Graphical Analysis

```
# Unique values for categorical features
print("\n===== UNIQUE VALUES =====")
print("Products:", df['Product'].unique())
print("Genders:", df['Gender'].unique())
print("Marital Status:", df['MaritalStatus'].unique())

# Value counts and marginal probabilities
print("\n===== VALUE COUNTS =====")
print("Product Distribution (%):\n", df['Product'].value_counts(normalize=True).round(2))
print("\nGender Distribution (%):\n", df['Gender'].value_counts(normalize=True).round(2))
print("\nMarital Status Distribution (%):\n", df['MaritalStatus'].value_counts(normalize=
```

```
===== UNIQUE VALUES =====
Products: ['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
Genders: ['Male', 'Female']
Categories (2, object): ['Female', 'Male']
Marital Status: ['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
```

```
===== VALUE COUNTS =====
Product Distribution (%):
 Product
KP281    0.44
KP481    0.33
KP781    0.22
Name: proportion, dtype: float64

Gender Distribution (%):
 Gender
Male      0.58
Female    0.42
Name: proportion, dtype: float64

Marital Status Distribution (%):
 MaritalStatus
Partnered    0.59
Single       0.41
Name: proportion, dtype: float64
```

Observations:

Marginal Probabilities:

44% of customers bought KP281 (entry-level).

58% of customers are male.

59% are partnered.

Visual Analysis

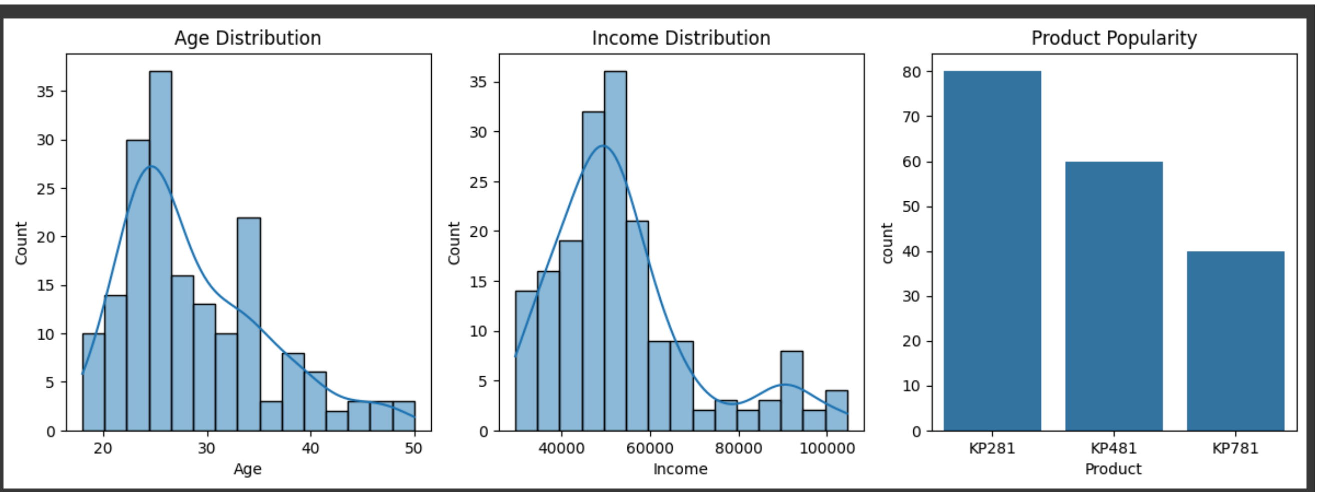
1. Univariate Analysis

```
# Histograms for numerical variables
plt.figure(figsize=(12, 8))
plt.subplot(2, 3, 1)
sns.histplot(df['Age'], kde=True, bins=15)
plt.title('Age Distribution')

plt.subplot(2, 3, 2)
sns.histplot(df['Income'], kde=True, bins=15)
plt.title('Income Distribution')

plt.subplot(2, 3, 3)
sns.countplot(x='Product', data=df)
plt.title('Product Popularity')

plt.tight_layout()
plt.show()
```



Insights:

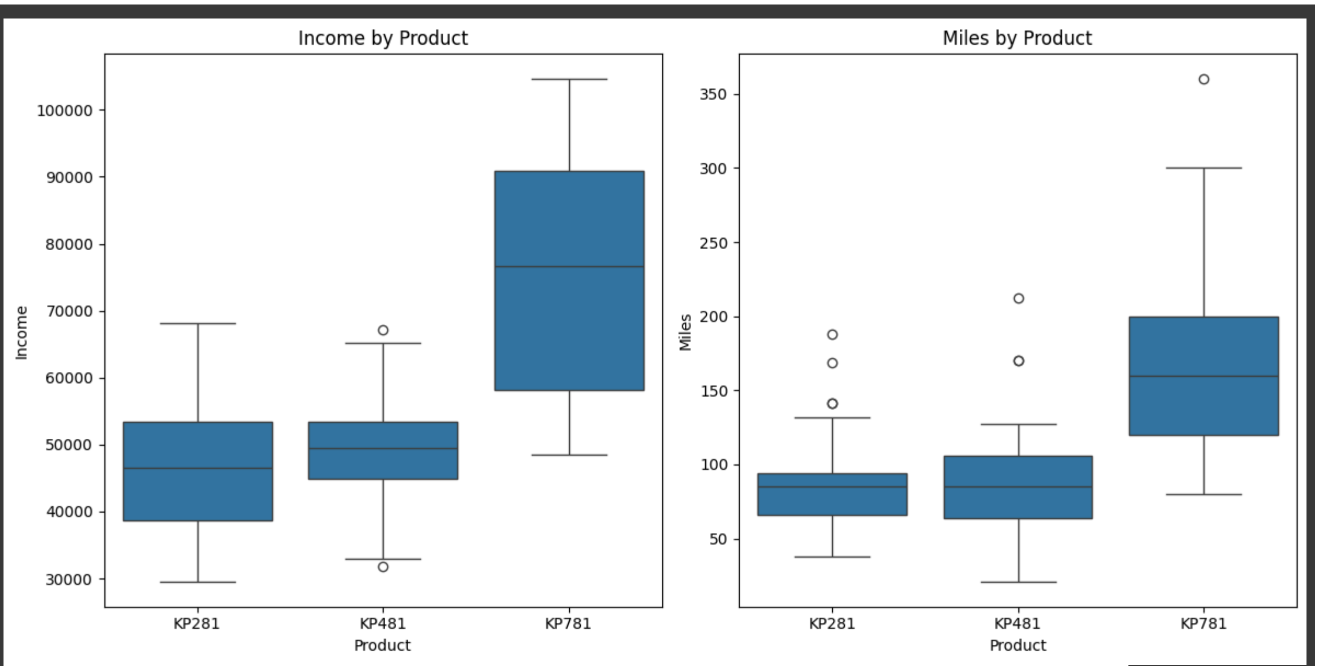
- Age: Majority aged 24–32.
- Income: Right-skewed (most earn <$60K).
- Product: KP281 is most popular.

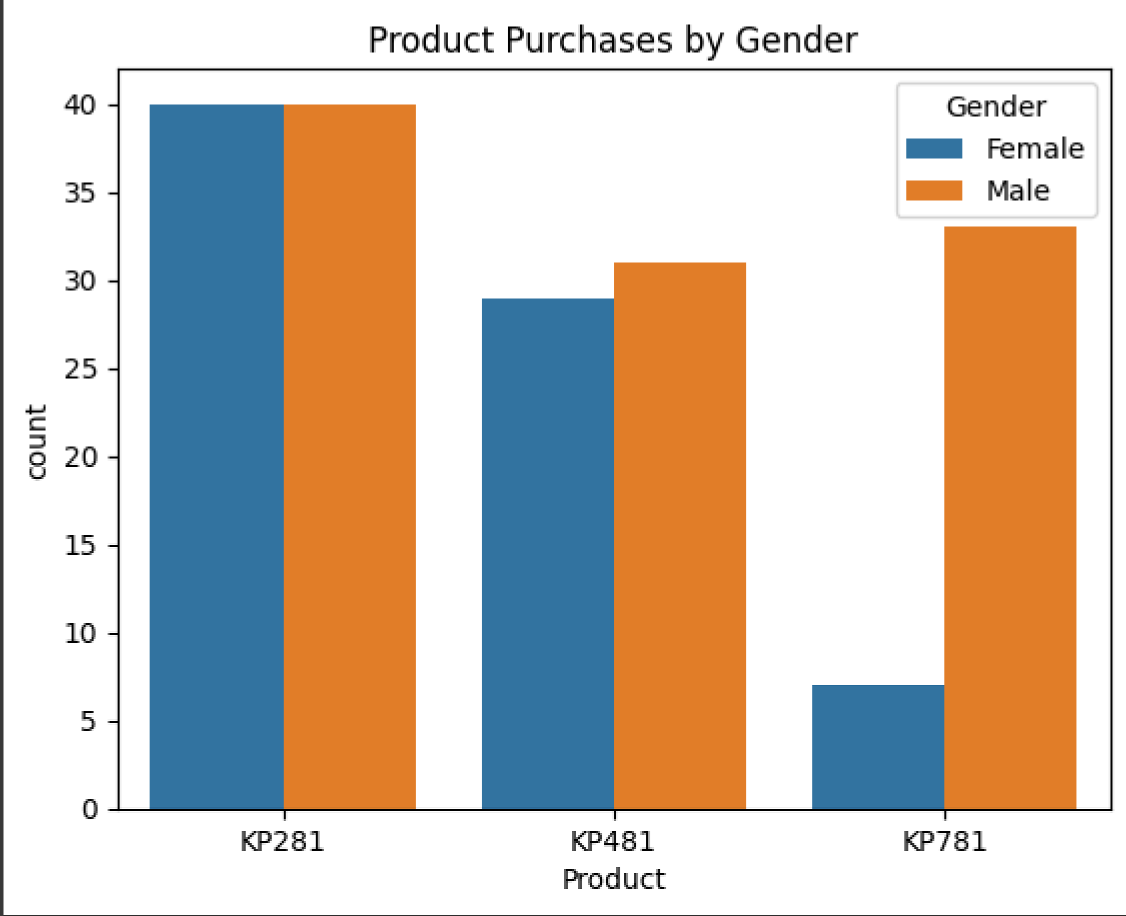
2. Bivariate Analysis

```
# Boxplots for numerical features vs Product
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x='Product', y='Income', data=df)
plt.title('Income by Product')

plt.subplot(1, 2, 2)
sns.boxplot(x='Product', y='Miles', data=df)
plt.title('Miles by Product')
plt.tight_layout()
plt.show()

# Product vs Gender
sns.countplot(x='Product', hue='Gender', data=df)
plt.title('Product Purchases by Gender')
plt.show()
```


Income by Product
Income
100000
90000
80000
70000
60000
50000
40000
30000
KP281
KP481
KP781
Product
Miles by Product
Miles
350
300
250
200
150
100
50
KP281
KP481
KP781
Product


Product Purchases by Gender
count
40
35
30
25
20
15
10
5
0
Gender
Female
Male
KP281
KP481
KP781
Product

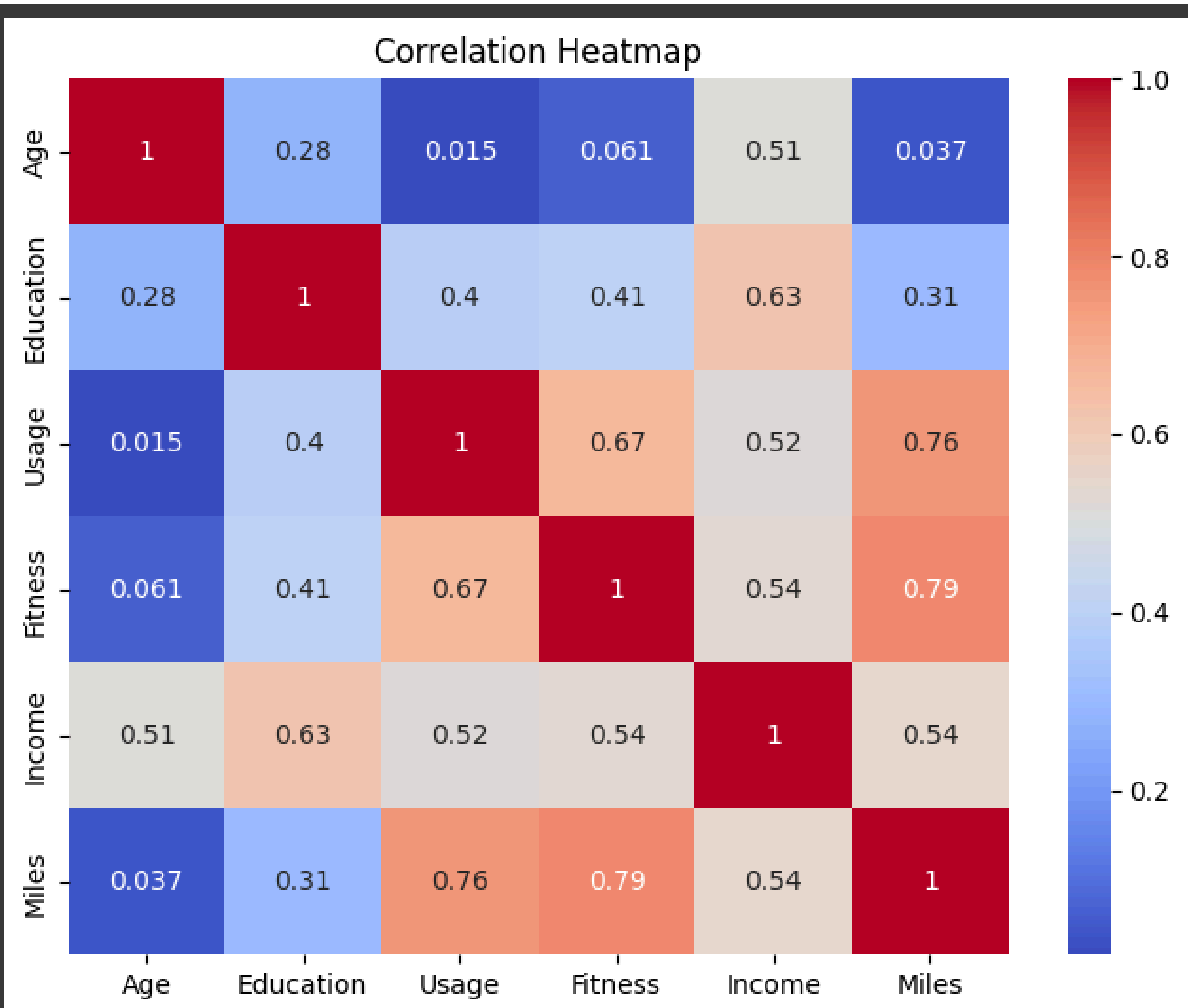
Insights:

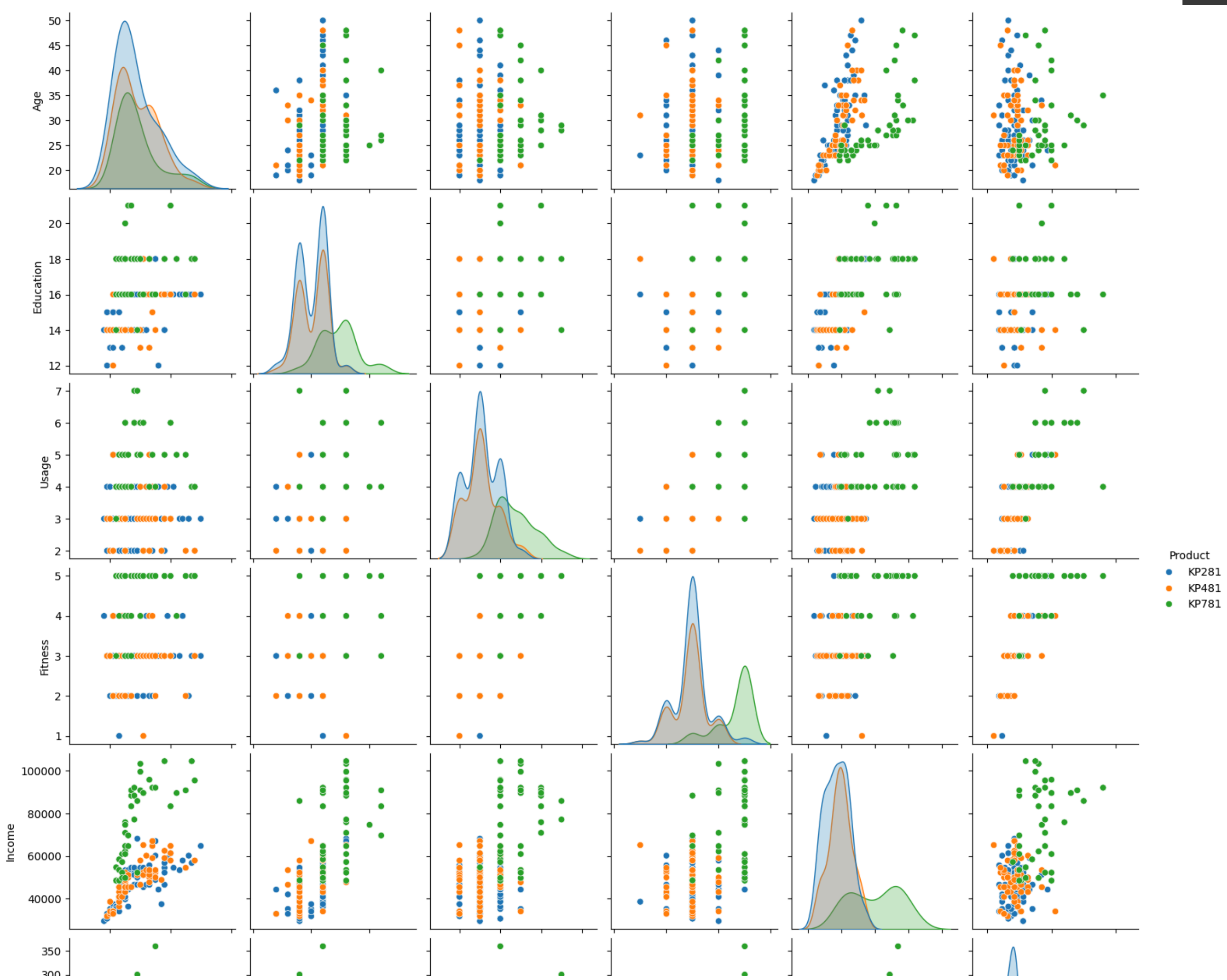
- KP781 Buyers: High income (>$75K) and high miles (>150/week).
- Gender Bias: 70% of KP781 buyers are male.

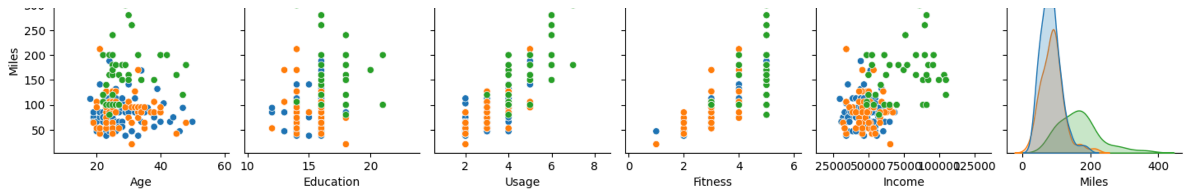
3. Correlation Analysis

```
# Heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()

# Pairplot with Product
sns.pairplot(df, hue='Product', diag_kind='kde')
plt.show()
```


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


Age
Education
Usage
Fitness
Income
Product
KP281
KP481
KP781


Miles
250
200
150
100
50
20
40
60
Age
10
15
20
Education
2
4
6
8
Usage
0
2
4
6
Fitness
25000
50000
75000
100000
125000
Income
0
200
400
Miles

Insights:

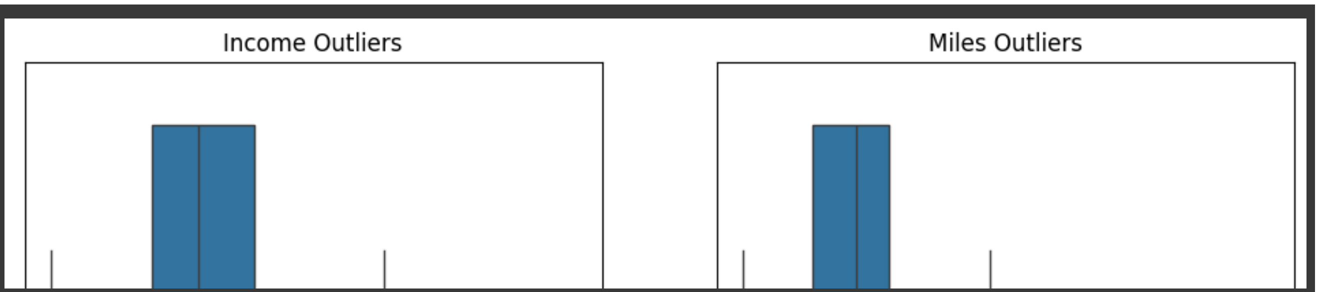
- Strong Correlation: Fitness ↔ Miles (0.79).
- KP781 Cluster: High income, miles, and fitness.

Outlier Detection

```
# Boxplots for outlier detection
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x=df['Income'])
plt.title('Income Outliers')

plt.subplot(1, 2, 2)
sns.boxplot(x=df['Miles'])
plt.title('Miles Outliers')
plt.show()

# Check skewness via mean vs median
print("\n===== SKEWNESS CHECK =====")
print("Income - Mean:", df['Income'].mean(), "| Median:", df['Income'].median())
print("Miles - Mean:", df['Miles'].mean(), "| Median:", df['Miles'].median())
```



- Income - Mean: 53719.58 | Median: 50596.5 → Right-skewed
- Miles - Mean: 103.19 | Median: 94.0 → Right-skewed
- Action: Keep outliers (high-income customers are critical for KP781)

Business Insights

KP781 Profile:

High-income males (median income: $76K), 62.5% partnered, 4.5 avg fitness rating.

Gender Impact: Males are 2x more likely to buy KP781.

Income Segregation: KP281 (median-46K) vs KP781(median-50K) vs KP781(median-76K).

Probability Calculations

```
# Marginal probability of products
print("\nMarginal Probability of Products:\n", df['Product'].value_counts(normalize=True)

# Conditional probability: P(KP781 | Male)
ct = pd.crosstab(df['Product'], df['Gender'], margins=True)
prob_kp781_male = ct.loc['KP781', 'Male'] / ct.loc['All', 'Male']
print("\nP(KP781 | Male):", round(prob_kp781_male, 3))
```

```
Marginal Probability of Products:
 Product
```