AeroFit Case Study Solution(google collab link)

Problem Statement

AeroFit is a company that sells fitness equipment, especially treadmills. The company has three models of treadmills:

- **KP281:** Entry-level ($1500)
- **KP481:** Mid-level ($1750)
- **KP781:** Advanced ($2500)

The business team wants to understand:

- Who are the customers buying each treadmill?
- What customer characteristics (age, gender, marital status, fitness level, income, usage, etc.) affect treadmill choice?
- Can we create customer profiles for each treadmill model?

Goal of This Case Study

This analysis of the dataset of customers who purchased treadmills in the last 3 months aims to:

- Describe the customers using tables, graphs, and statistics.
- Check probabilities – for example, what percentage of customers buy the KP281, or what is the probability that a male customer buys the KP781.
- Find patterns in data (like the effect of age, income, fitness, marital status, etc. on the product purchased).
- Give business recommendations in simple terms so AeroFit can suggest the right treadmill to new customers.

Analysis Steps

1. Import dataset and explore its structure.
2. Check for missing values & outliers.
3. Perform univariate analysis (each column separately).
4. Conduct bivariate analysis (relationship between product purchased and other features).
5. Calculate marginal and conditional probabilities.
6. Build customer profiles for each treadmill type.
7. Provide final recommendations.

Step 1: Importing dataset and checking structure:

```python
# Step 1: Import libraries and dataset
import pandas as pd

# Load the dataset
df = pd.read_csv("/content/aerofit_treadmill (3).csv")

# Check first 5 rows
print("Preview of dataset:")
print(df.head())

# Shape of dataset
print("\nShape of dataset (rows, columns):", df.shape)

# Info about datatypes
print("\nDataset Info:")
print(df.info())

# Summary statistics
print("\nStatistical Summary:")
print(df.describe(include='all'))
```

```
Preview of dataset:
  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

Shape of dataset (rows, columns): (180, 9)

Dataset 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
None

Statistical Summary:
       Product         Age Gender   Education MaritalStatus       Usage  \
count      180  180.000000    180  180.000000           180  180.000000
unique       3         NaN      2         NaN             2         NaN
top      KP281         NaN   Male         NaN     Partnered         NaN
freq        80         NaN    104         NaN           107         NaN
mean       NaN   28.788889    NaN   15.572222           NaN    3.455556
std        NaN    6.943498    NaN    1.617055           NaN    1.084797
min        NaN   18.000000    NaN   12.000000           NaN    2.000000
25%        NaN   24.000000    NaN   14.000000           NaN    3.000000
50%        NaN   26.000000    NaN   16.000000           NaN    3.000000
75%        NaN   33.000000    NaN   16.000000           NaN    4.000000
max        NaN   50.000000    NaN   21.000000           NaN    7.000000

           Fitness         Income       Miles
count   180.000000     180.000000  180.000000
unique         NaN            NaN         NaN
top            NaN            NaN         NaN
freq           NaN            NaN         NaN
mean      3.311111   53719.577778  103.194444
std       0.958869   16506.684226   51.863605
min       1.000000   29562.000000   21.000000
25%       3.000000   44058.750000   66.000000
50%       3.000000   50596.500000   94.000000
75%       4.000000   58668.000000  114.750000
max       5.000000  104581.000000  360.000000
```

The dataset has 180 customers and 9 features (like age, gender, income, fitness, treadmill purchased). There are no missing values, and the average customer is 29 years old with ~$53K income and uses the treadmill about 3–4 times per week.

Step 2: Outlier detection (using boxplots & describe method)

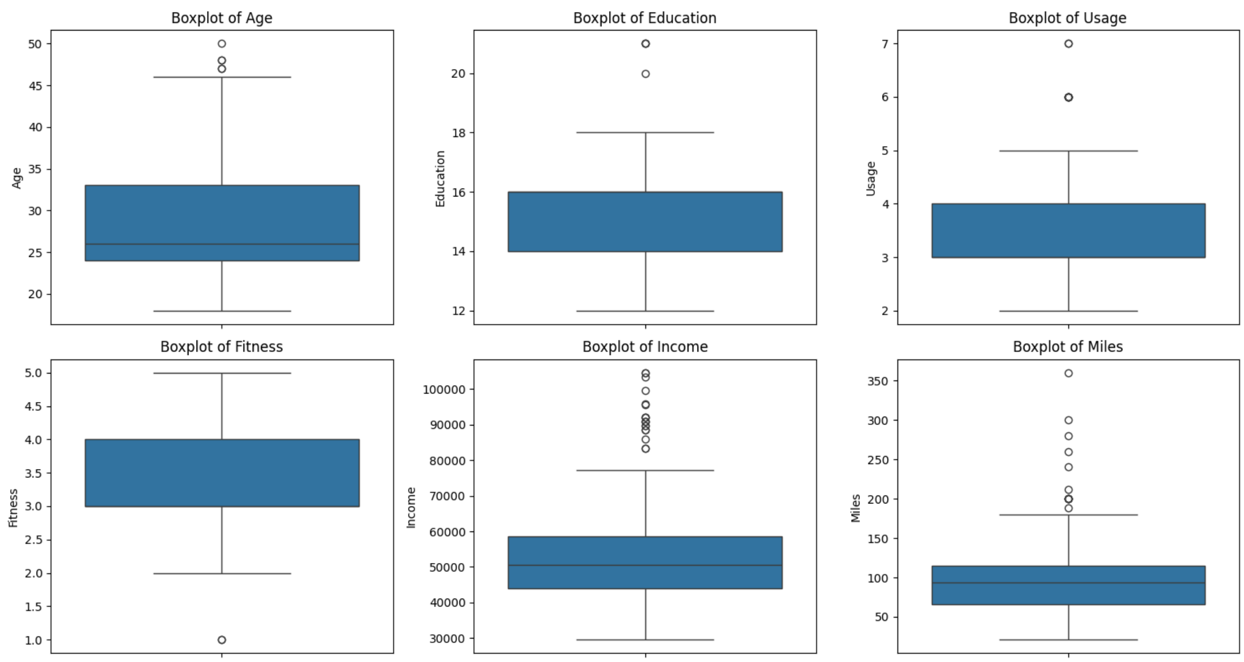
```
import matplotlib.pyplot as plt
import seaborn as sns

# Step 2: Outlier Detection

# 1. Check statistical summary
print("Summary statistics:")
print(df.describe())

# 2. Boxplots for numeric columns
num_cols = ["Age", "Education", "Usage", "Fitness", "Income", "Miles"]

plt.figure(figsize=(15,8))
for i, col in enumerate(num_cols, 1):
   plt.subplot(2, 3, i)
   sns.boxplot(y=df[col])
   plt.title(f"Boxplot of {col}")
plt.tight_layout()
plt.show()
```

Summary 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



Most features are within normal range, but Income and Miles show many outliers (some very high earners and heavy users). A few outliers are also seen in Age, Education, and Usage, but they look reasonable and not data errors. These outliers likely represent real extreme customers (e.g., athletes or wealthy buyers), so we will keep them.

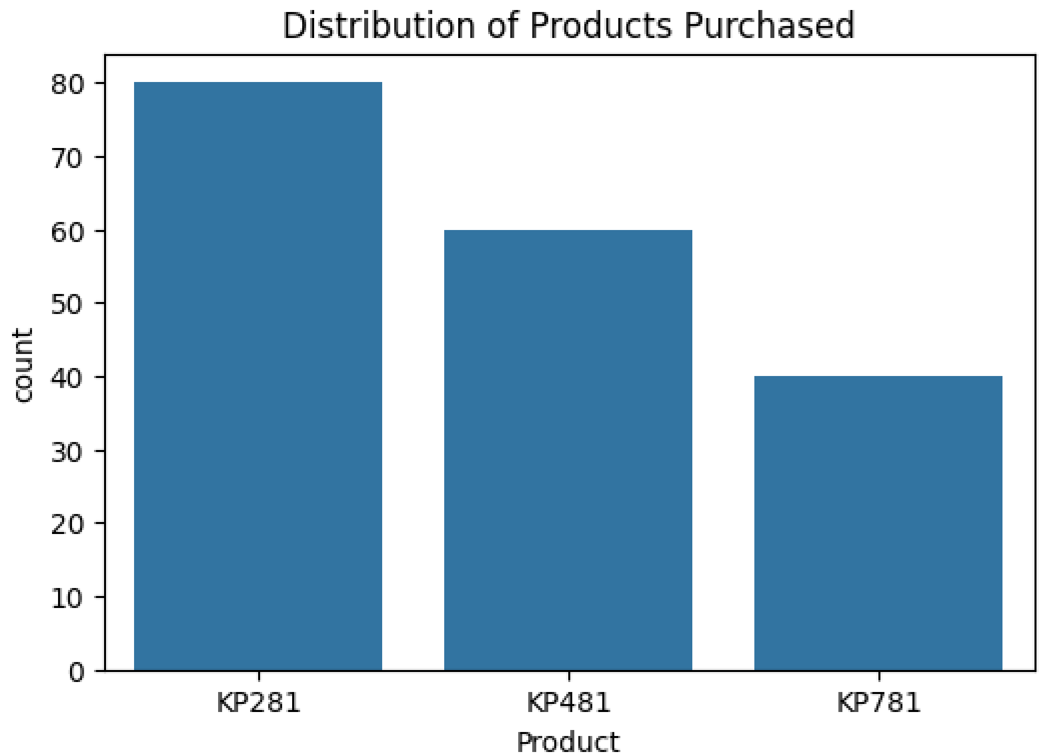
Step 3: Univariate Analysis (distribution of each variable)

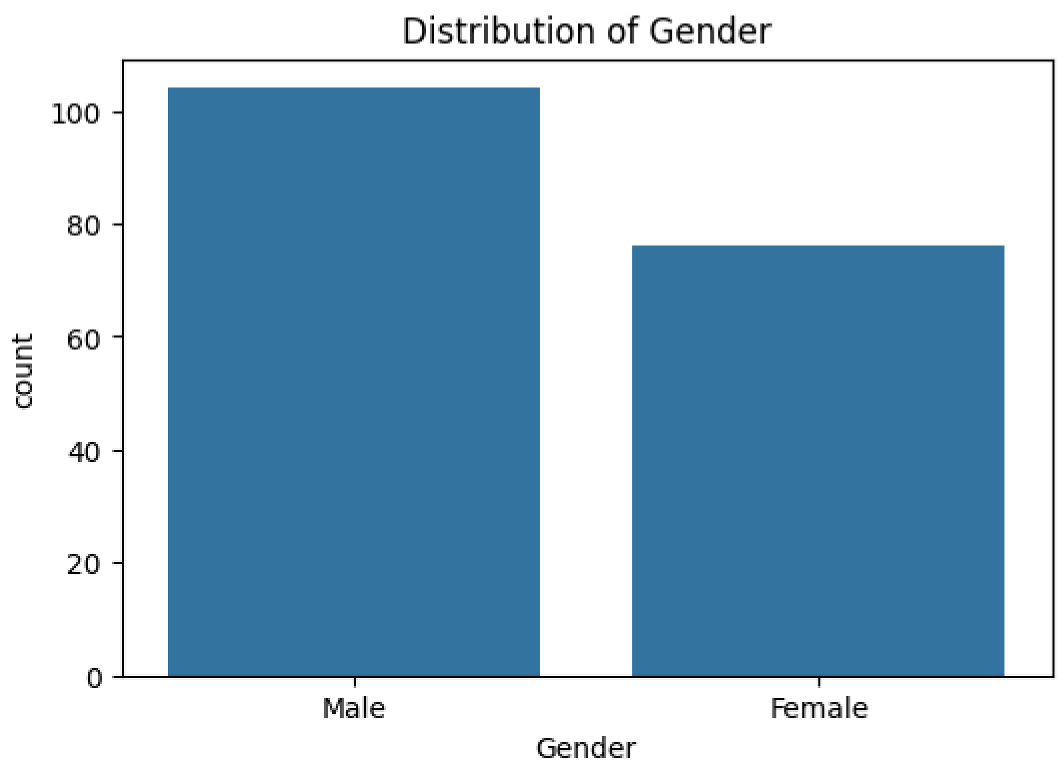
We i use:

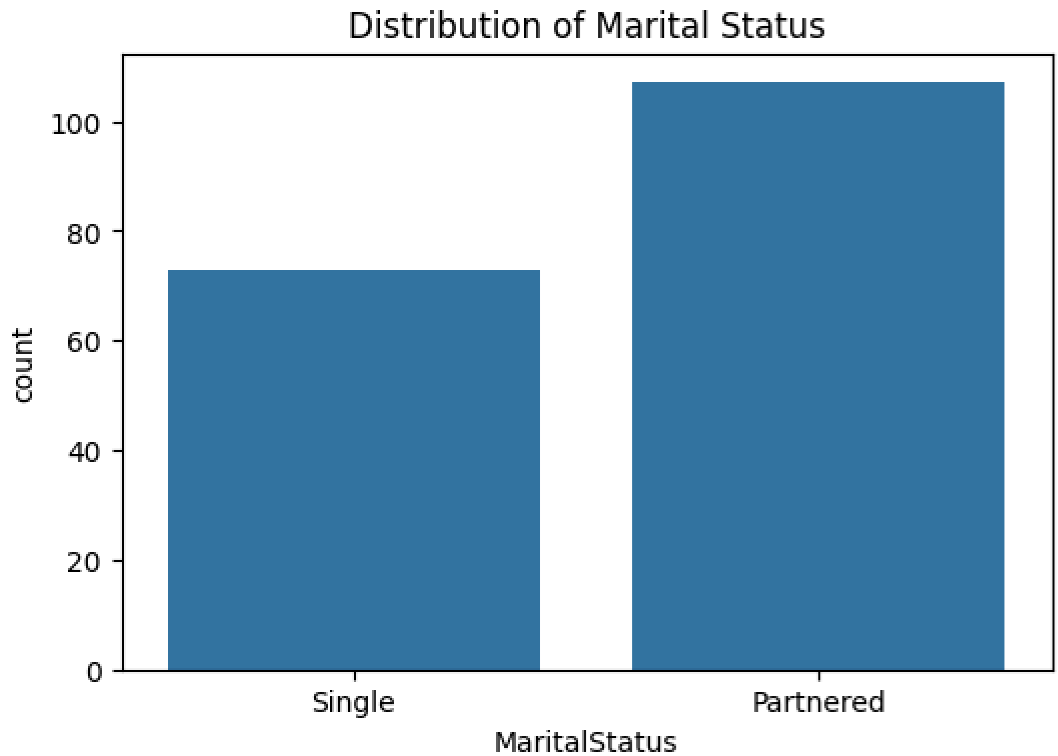
Countplot / Pie chart → for categorical (Product, Gender, MaritalStatus).

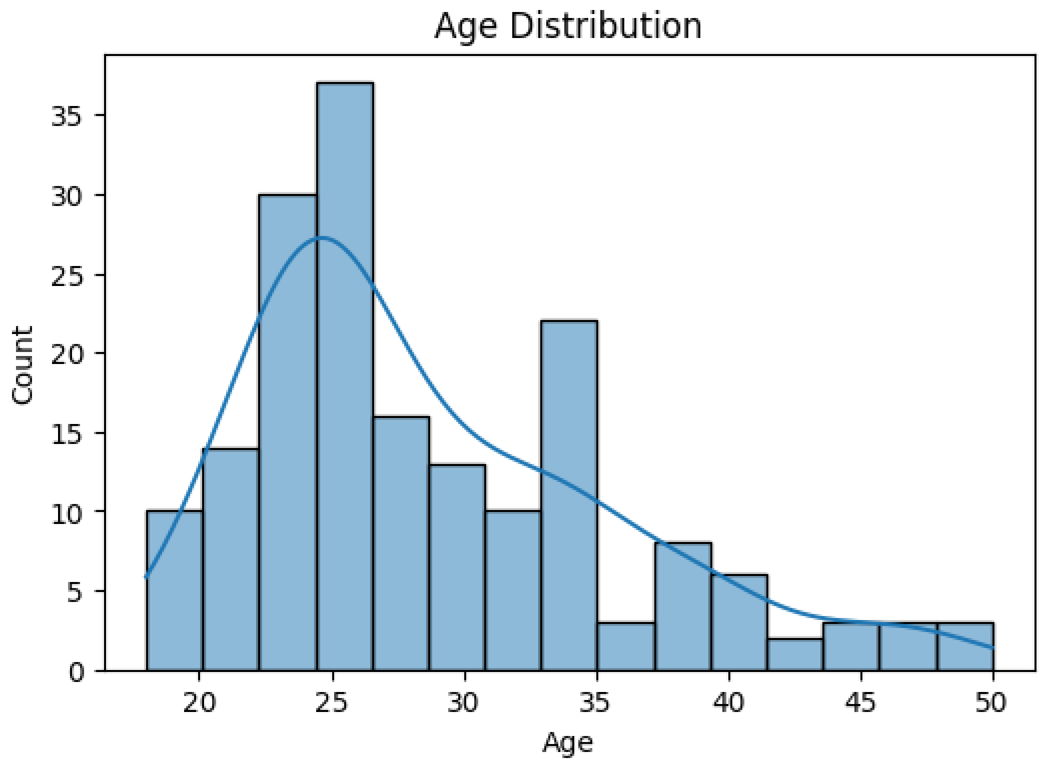
Histplot / Distplot → for numeric (Age, Education, Usage, Fitness, Income, Miles).

```python
# Step 3: Univariate Analysis
import matplotlib.pyplot as plt
import seaborn as sns

# 1. Product Purchased
plt.figure(figsize=(6,4))
sns.countplot(x='Product', data=df)
plt.title("Distribution of Products Purchased")
plt.show()

# 2. Gender
plt.figure(figsize=(6,4))
sns.countplot(x='Gender', data=df)
plt.title("Distribution of Gender")
plt.show()

# 3. Marital Status
plt.figure(figsize=(6,4))
sns.countplot(x='MaritalStatus', data=df)
plt.title("Distribution of Marital Status")
plt.show()

# 4. Age Distribution
plt.figure(figsize=(6,4))
sns.histplot(df['Age'], bins=15, kde=True)
plt.title("Age Distribution")
plt.show()

# 5. Income Distribution
plt.figure(figsize=(6,4))
sns.histplot(df['Income'], bins=20, kde=True)
plt.title("Income Distribution")
plt.show()

# 6. Miles Distribution
plt.figure(figsize=(6,4))
sns.histplot(df['Miles'], bins=20, kde=True)
plt.title("Miles Distribution")
plt.show()
```

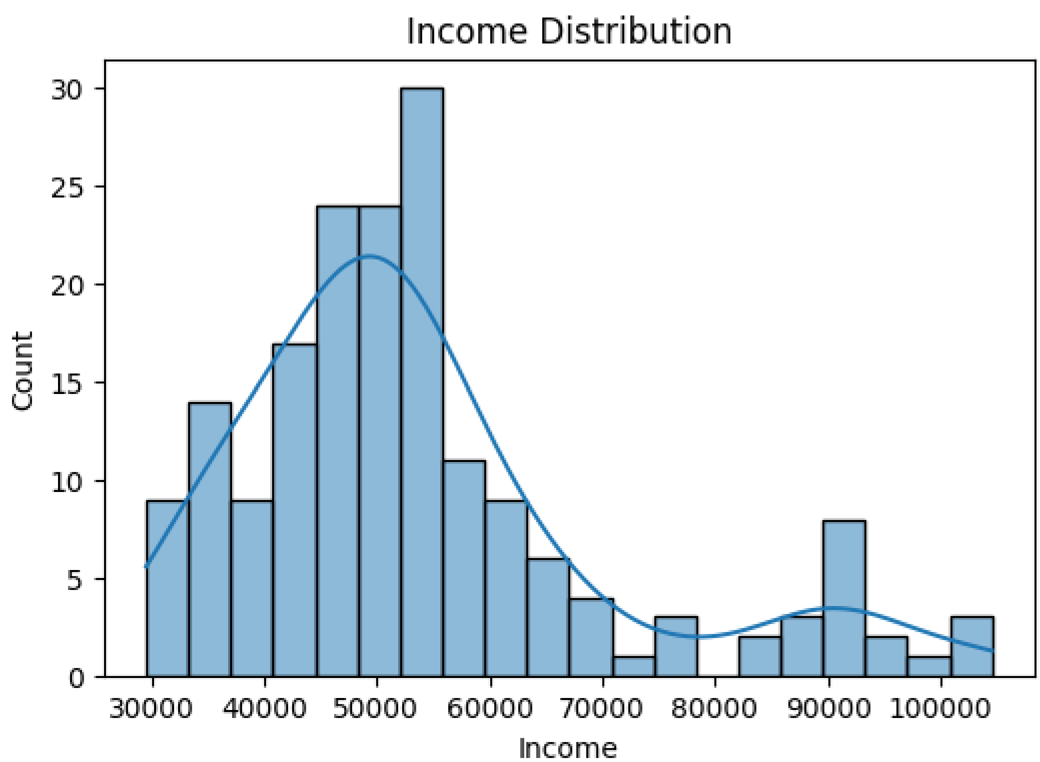

Distribution of Products Purchased
count
80
70
60
50
40
30
20
10
0
KP281
KP481
KP781
Product


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

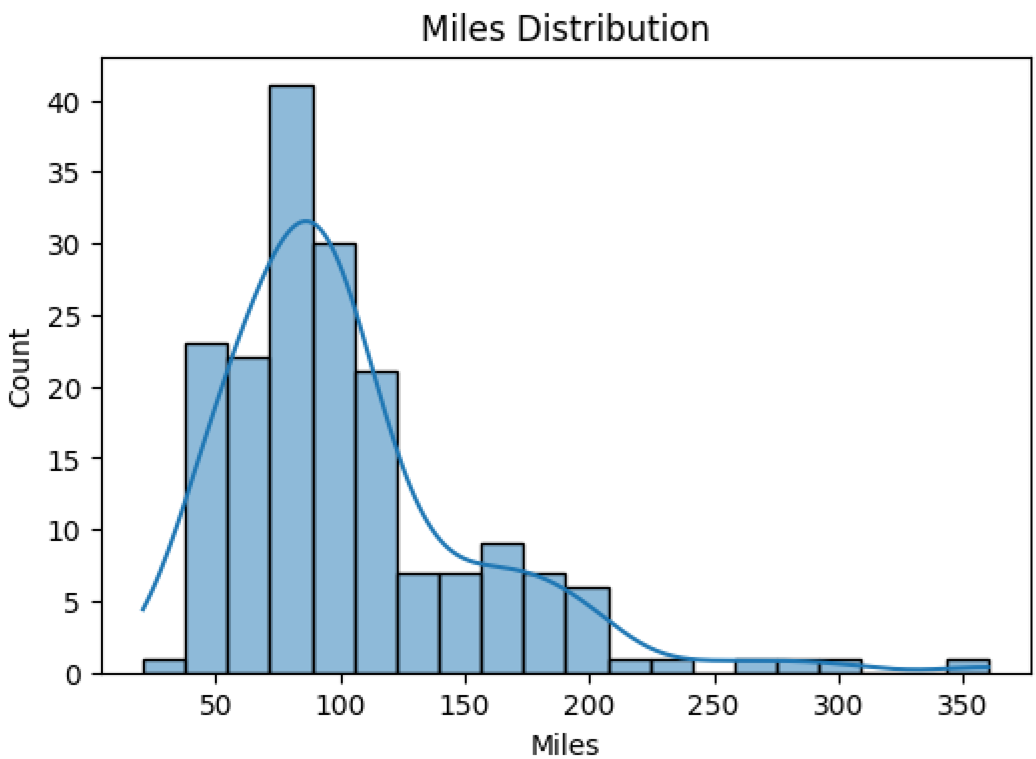

Distribution of Marital Status
count
100
80
60
40
20
0
Single
Partnered
MaritalStatus



Age Distribution
Count
Age



Income Distribution
Count
Income



Product Purchased → Most customers purchased KP281 (entry-level), followed by KP481 and KP781.

Gender → Majority are Male customers, though females also form a good share.

Marital Status → More customers are Partnered than Single.

Age → Customers are mostly 20–35 years old, with a peak around mid-20s.

Income → Income is mostly between

$40K-$

60K, but a few high-income customers exist.

Miles → Most customers expect to run 50–120 miles per week, though some extreme fitness users go much higher.

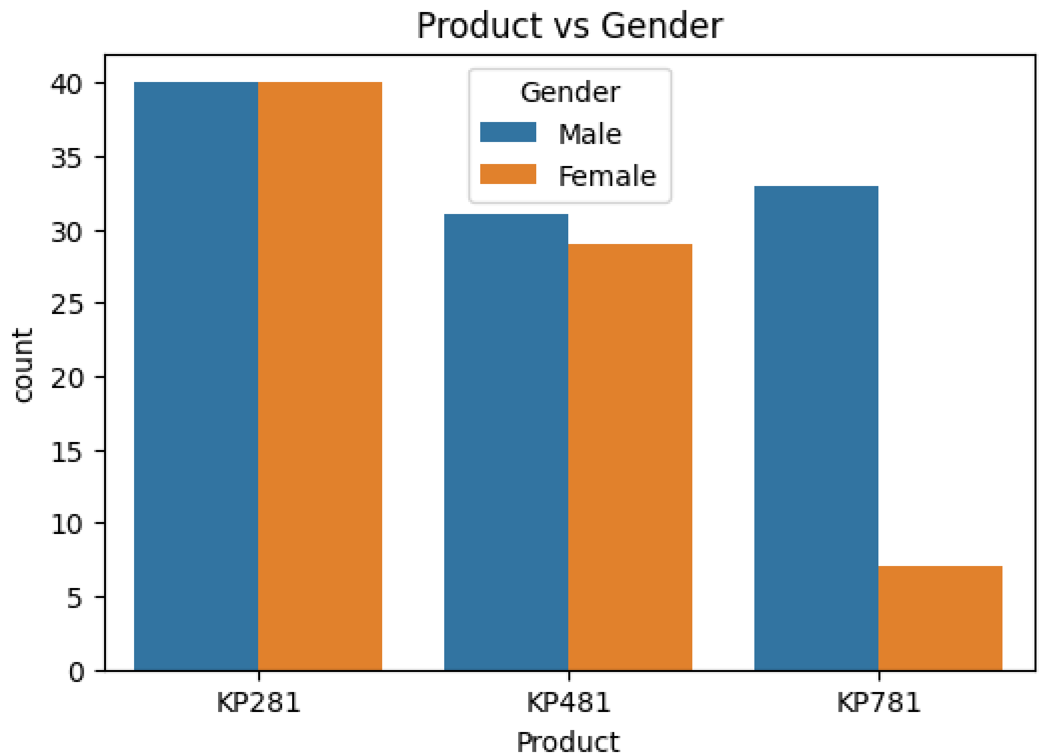
Step 3b: Bivariate Analysis (Product vs other features)

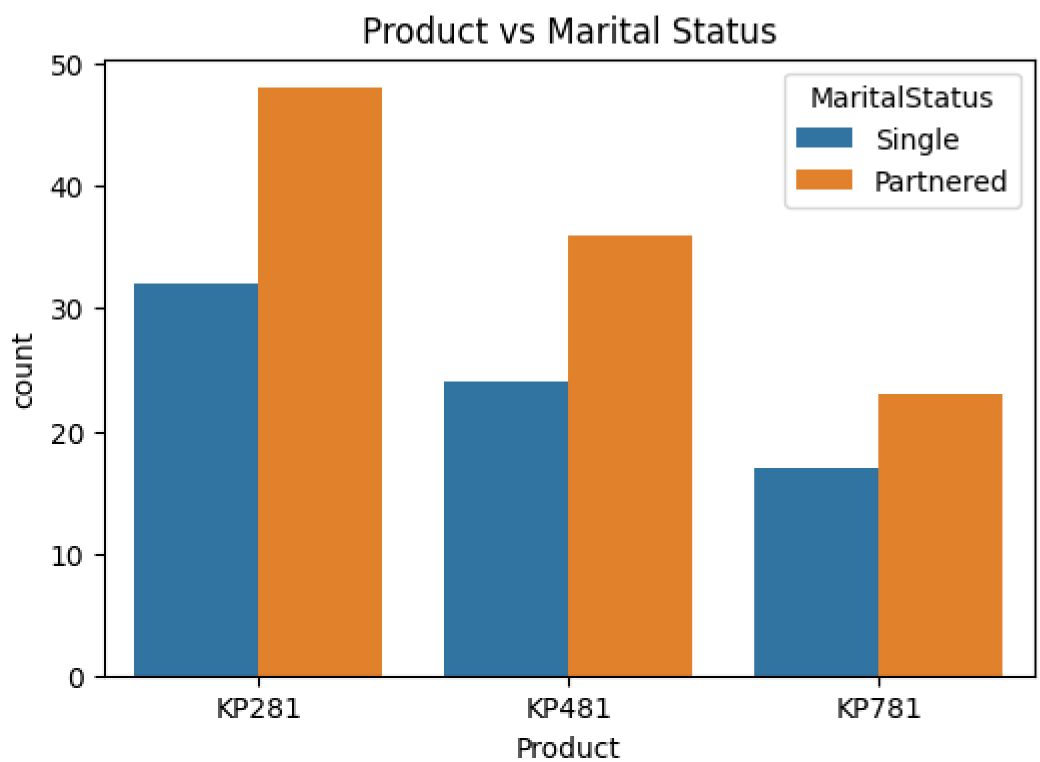
i will use Countplots for categorical features (Product vs Gender, Marital Status).

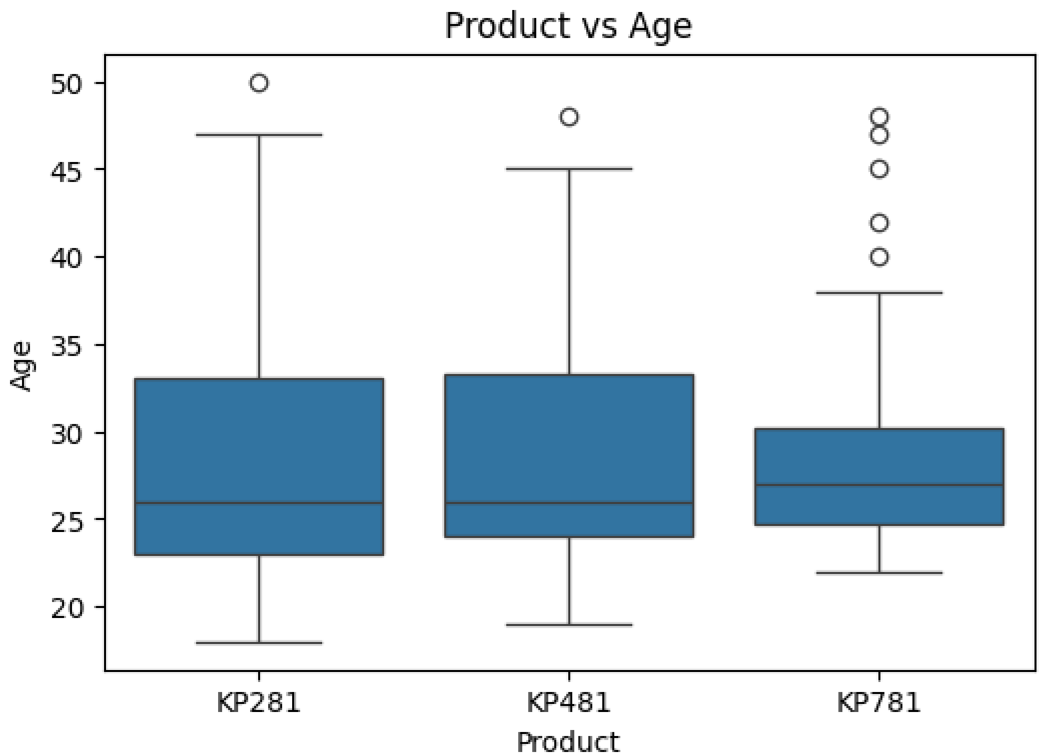
Boxplots/Violin plots for numeric features (Product vs Age, Income, Usage, Fitness, Miles).

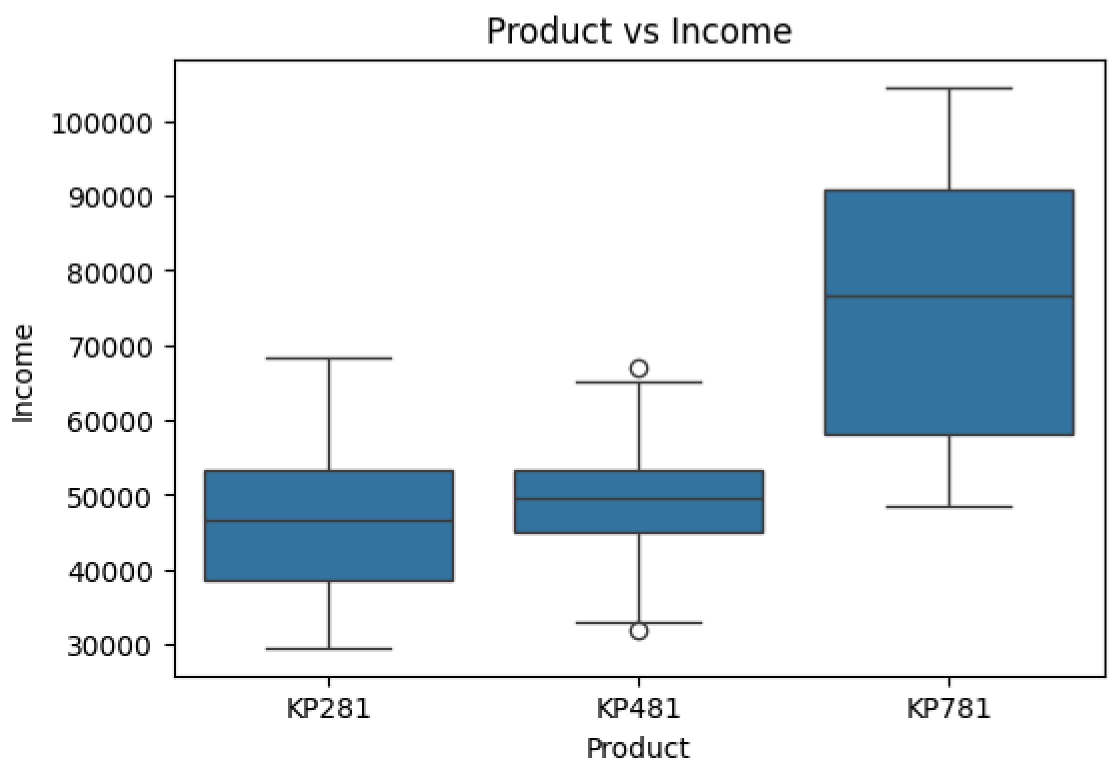
```
# Step 4: Bivariate Analysis

# 1. Product vs Gender
plt.figure(figsize=(6,4))
sns.countplot(x="Product", hue="Gender", data=df)
plt.title("Product vs Gender")
plt.show()

# 2. Product vs Marital Status
plt.figure(figsize=(6,4))
sns.countplot(x="Product", hue="MaritalStatus", data=df)
plt.title("Product vs Marital Status")
plt.show()

# 3. Product vs Age
plt.figure(figsize=(6,4))
sns.boxplot(x="Product", y="Age", data=df)
plt.title("Product vs Age")
plt.show()

# 4. Product vs Income
plt.figure(figsize=(6,4))
sns.boxplot(x="Product", y="Income", data=df)
plt.title("Product vs Income")
plt.show()

# 5. Product vs Fitness
plt.figure(figsize=(6,4))
sns.boxplot(x="Product", y="Fitness", data=df)
```

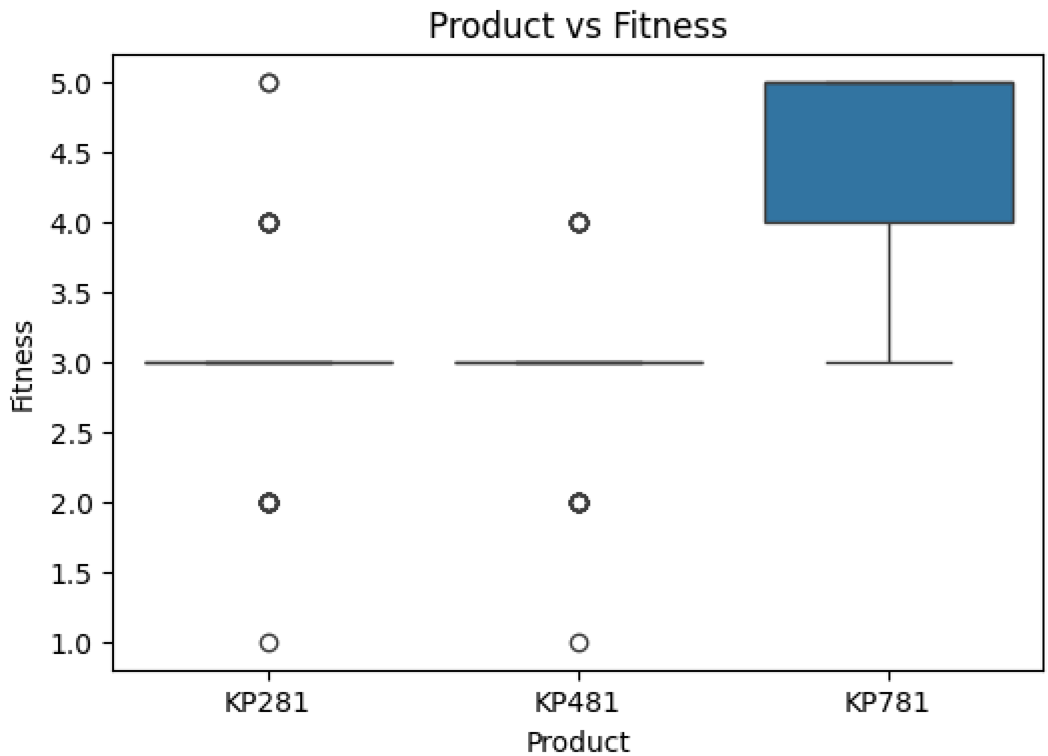
```
plt.title("Product vs Fitness")
plt.show()

# 6. Product vs Miles
plt.figure(figsize=(6,4))
sns.boxplot(x="Product", y="Miles", data=df)
plt.title("Product vs Miles")
plt.show()
```

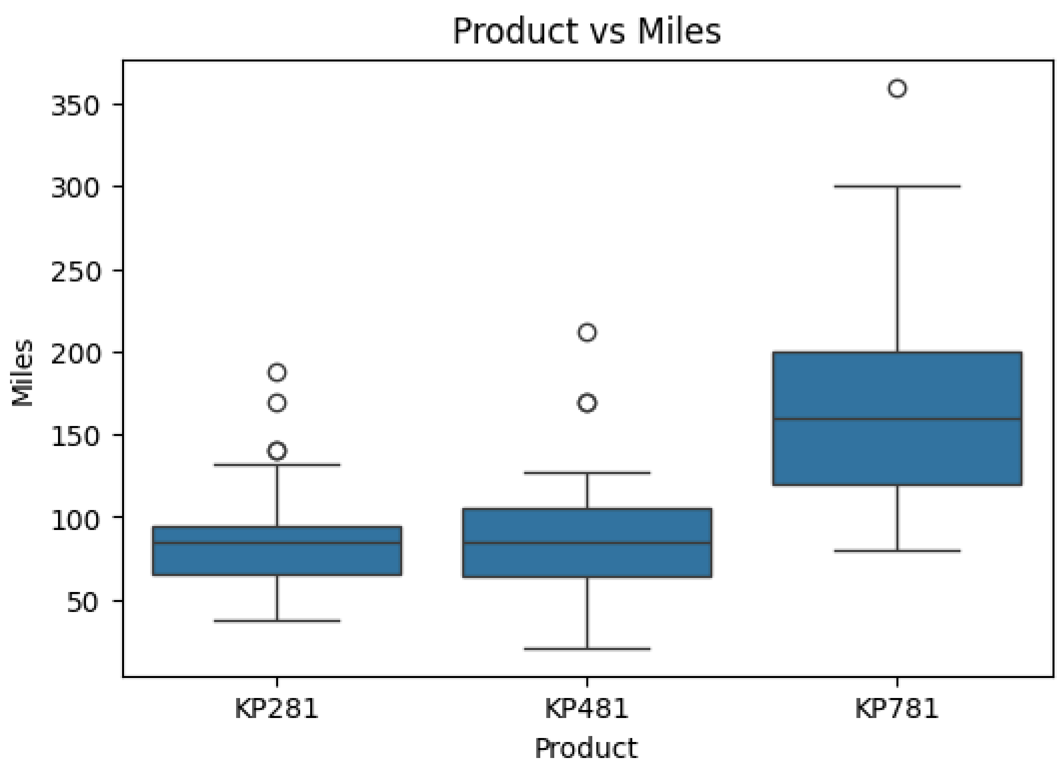

Product vs Gender
Gender
Male
Female
count
0
5
10
15
20
25
30
35
40
KP281
KP481
KP781
Product


Product vs Marital Status
MaritalStatus
Single
Partnered
count
0
10
20
30
40
50
KP281
KP481
KP781
Product


Product vs Age
Age
50
45
40
35
30
25
20
KP281
KP481
KP781
Product


Product vs Income
Income
100000
90000
80000
70000
60000
50000
40000
30000
KP281
KP481
KP781
Product





Product vs Gender → Both males and females buy all products, but entry-level KP281 is more common among males.

Product vs Marital Status → Partnered people tend to buy mid and high-end models more compared to singles.

Product vs Age → Younger customers (20–30 yrs) mostly buy KP281, while older customers (30–40 yrs) go for KP781.

Product vs Income → Higher income customers prefer KP781, while lower income customers buy KP281.

Product vs Fitness → KP781 buyers have higher fitness ratings (4–5), while KP281/KP481 buyers usually rate 2–3.

Product vs Miles → KP781 buyers plan to run more miles per week, showing they are serious runners, while KP281 buyers expect fewer miles.

Step 4: Marginal & Conditional Probability (using crosstab + probability calculations)

What % of customers purchased KP281, KP481, or KP781? (marginal probability)

What is the probability that a male customer buys KP781? (conditional probability)

```
# Step 5: Marginal & Conditional Probabilities

import pandas as pd

# Marginal Probability - product distribution
product_counts = df['Product'].value_counts(normalize=True) * 100
print("Marginal Probability (Product Distribution %):")
print(product_counts)

# Two-way contingency table: Product vs Gender
gender_table = pd.crosstab(df['Gender'], df['Product'], margins=True)
print("\nContingency Table: Product vs Gender")
print(gender_table)

# Conditional probability: P(Product | Gender)
```

```python
cond_prob_gender = pd.crosstab(df['Gender'], df['Product'],
normalize='index') * 100
print("\nConditional Probability of Product given Gender:")
print(cond_prob_gender)

# Two-way contingency table: Product vs Marital Status
marital_table = pd.crosstab(df['MaritalStatus'], df['Product'],
margins=True)
print("\nContingency Table: Product vs Marital Status")
print(marital_table)

# Conditional probability: P(Product | Marital Status)
cond_prob_marital = pd.crosstab(df['MaritalStatus'], df['Product'],
normalize='index') * 100
print("\nConditional Probability of Product given Marital Status:")
print(cond_prob_marital)
```

```
Marginal Probability (Product Distribution %):
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: proportion, dtype: float64

Contingency Table: Product vs Gender
Product  KP281  KP481  KP781  All
Gender
Female      40     29      7   76
Male        40     31     33  104
All         80     60     40  180

Conditional Probability of Product given Gender:
Product      KP281      KP481      KP781
Gender
Female   52.631579  38.157895   9.210526
Male     38.461538  29.807692  31.730769

Contingency Table: Product vs Marital Status
Product        KP281  KP481  KP781  All
MaritalStatus
Partnered         48     36     23  107
Single            32     24     17   73
All               80     60     40  180
```

```
Conditional Probability of Product given Marital Status:
Product              KP281      KP481      KP781
MaritalStatus
Partnered        44.859813  33.644860  21.495327
Single           43.835616  32.876712  23.287671
```

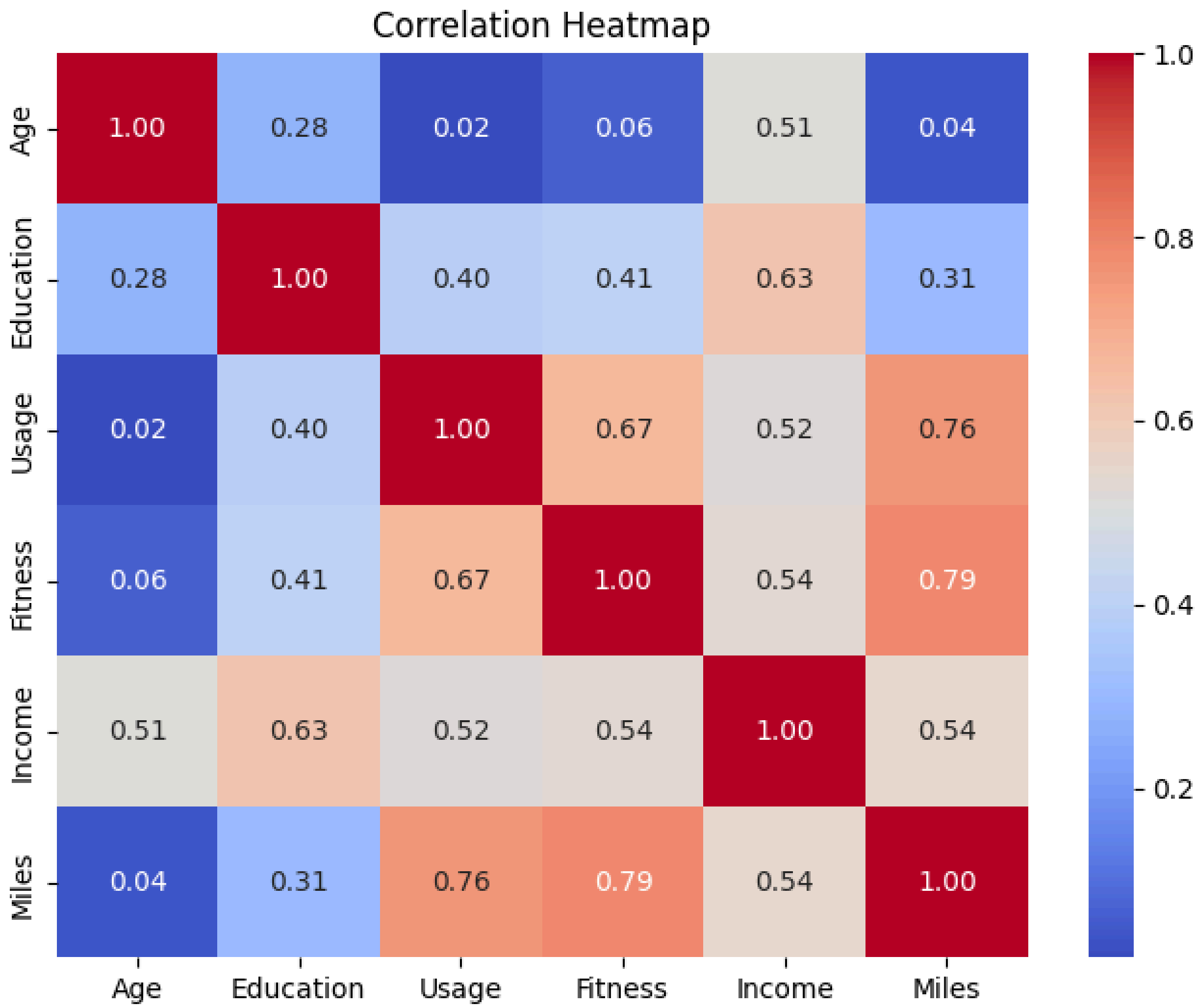
Marginal Probability → Around 44% customers bought KP281, 33% bought KP481, and 22% bought KP781.

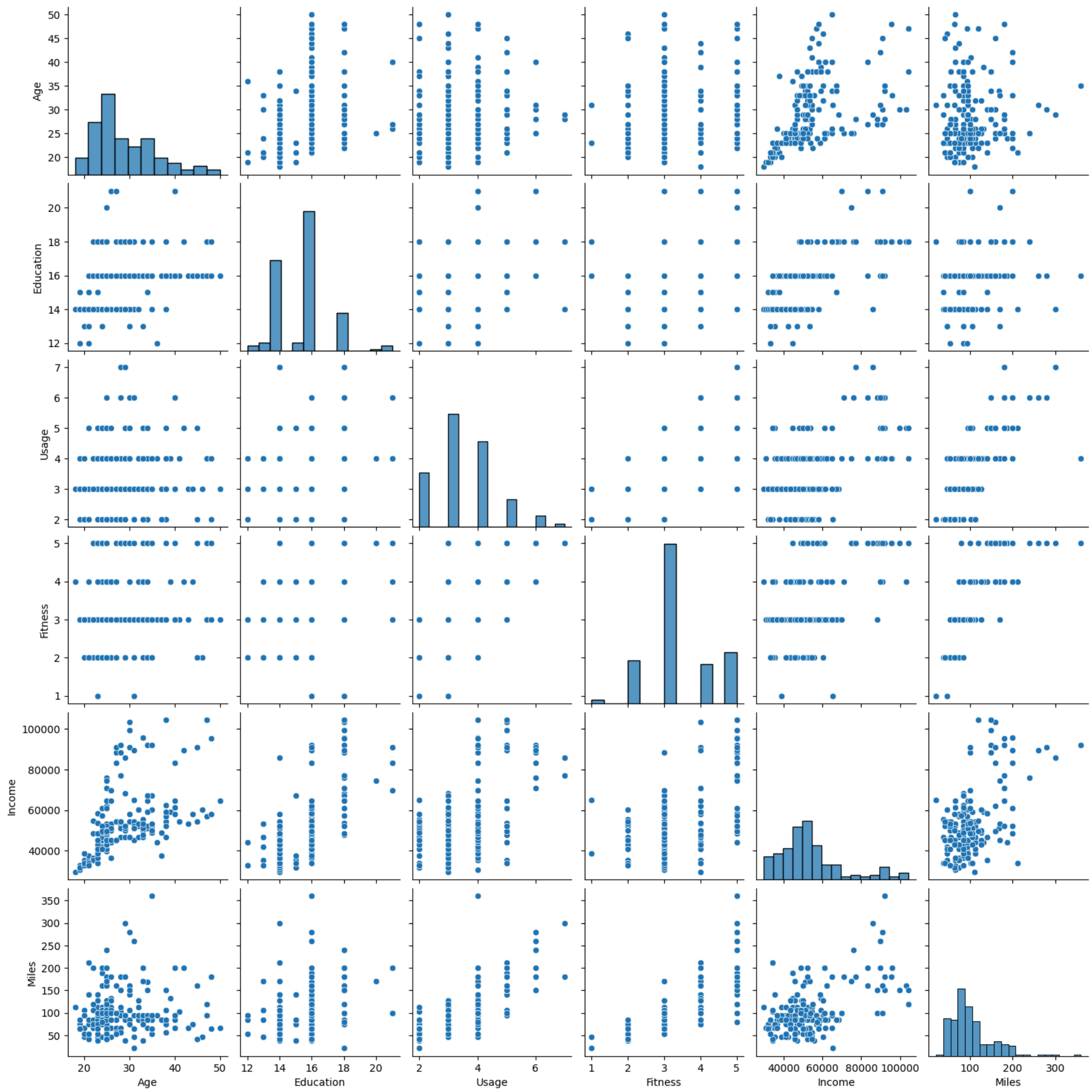
By Gender → Females mostly buy KP281 (53%), while males are more balanced, with 32% of them choosing the advanced KP781.

By Marital Status → Partnered and single customers show similar patterns, but singles have a slightly higher preference for KP781.

Step 5: Correlation Analysis (Heatmap & Pairplot)

```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only numeric columns
num_df = df.select_dtypes(include=['int64', 'float64'])

# Correlation matrix
corr_matrix = num_df.corr()

# Heatmap
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()

# Pairplot (optional detailed view)
sns.pairplot(num_df)
plt.show()
```


Correlation Heatmap
Age
Education
Usage
Fitness
Income
Miles
1.00 0.28 0.02 0.06 0.51 0.04
0.28 1.00 0.40 0.41 0.63 0.31
0.02 0.40 1.00 0.67 0.52 0.76
0.06 0.41 0.67 1.00 0.54 0.79
0.51 0.63 0.52 0.54 1.00 0.54
0.04 0.31 0.76 0.79 0.54 1.00
1.0
0.8
0.6
0.4
0.2



Age and Income are positively related → older customers tend to earn more.

Fitness, Usage, and Miles are strongly connected → fit customers run more miles and use treadmills more often.

Education shows little to no correlation with other features.

Step 6: Customer Profiles + Business Insights (who buys which treadmill)

```
# Conditional probability: P(Product | Gender)
cond_prob_gender = pd.crosstab(df['Gender'], df['Product'],
normalize='index') * 100
print(cond_prob_gender)
```

```
Product       KP281      KP481      KP781
Gender
Female    52.631579  38.157895   9.210526
Male      38.461538  29.807692  31.730769
```

Males are 3x more likely than females to buy the high-end KP781.

Females mostly prefer the entry-level KP281.

Step 7: Customer Profiling (Categorization of Users)

KP281 (Entry-level, $1500)

Age: Mostly 18–28 years

Income: Lower (~

30K–

45K)

Fitness: 2–3 (average fitness)

Usage: 2–3 times per week, fewer miles

Demographics: More males and singles Profile: Young beginners, casual users, budget-conscious buyers.

KP481 (Mid-level, $1750)

Age: 25–35 years

Income: Medium (~

45K–

60K)

Fitness: 3–4 (regular exercisers)

Usage: 3–4 times per week, moderate miles

Demographics: Balanced mix of males & females, many partnered Profile: Regular fitness users who want balance of features & price.

KP781 (Advanced, $2500)

Age: 30–40 years

Income: High (~$60K+)

Fitness: 4–5 (fit/athletic customers)

Usage: 5–7 times per week, high miles

Demographics: Mostly males, more partnered Profile: Serious fitness enthusiasts, athletes, or high-income professionals.

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step 8: Probability — Marginal & Conditional Summary

```
# Marginal probability (product %)
product_dist = df['Product'].value_counts(normalize=True) * 100
print(product_dist)

# Conditional by Gender
cond_by_gender = pd.crosstab(df['Gender'], df['Product'],
normalize='index') * 100
print(cond_by_gender.round(2))

# Conditional by Marital Status
cond_by_marital = pd.crosstab(df['MaritalStatus'], df['Product'],
normalize='index') * 100
```

```
print(cond_by_marital.round(2))
```

```
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: proportion, dtype: float64
Product  KP281  KP481  KP781
Gender
Female   52.63  38.16   9.21
Male     38.46  29.81  31.73
Product        KP281  KP481  KP781
MaritalStatus
Partnered      44.86  33.64  21.50
Single         43.84  32.88  23.29
```

Most customers buy entry-level KP281 (44%), while KP781 is the least common (22%).

Males are much more likely to choose KP781 (32%), while females mostly prefer KP281 (53%).

Marital status has little effect — partnered and single customers show almost the same product mix.

Step 9: Final Recommendations & Actionable Insights

KP281 (Entry-level, $1500)

Target: Young customers (18–28), lower income, beginners.

Action: Promote through student discounts, online ads, and budget-friendly bundles.

Upgrade Path: Offer trade-in or loyalty schemes to move them later to KP481/KP781.

2. KP481 (Mid-level, $1750)

Target: Working adults (25–35), medium income, fitness-conscious.

Action: Position as the best value option in ads; highlight durability and family usage.

Promotion: Bundle with fitness accessories (mats, dumbbells) to increase appeal.

3. KP781 (Advanced, $2500)

Target: High-income (>$60K), older (30–40), serious fitness users (Fitness 4–5).

Action: Market in premium gyms, health clubs, corporate wellness programs.

Branding: Highlight advanced features, long durability, and performance.

4. Gender-based strategy

Males are 3x more likely to buy KP781 → target premium treadmill ads to men.

Females prefer KP281 → offer affordable starter packages and fitness apps bundled with KP281.

5. General actions

Use personalized recommendations (based on age, income, and fitness score).

Run email campaigns suggesting the "best treadmill" for new customers after survey inputs.

Cross-sell accessories (shoes, mats, wearables) to enhance customer lifetime value.

With this, you've completed all 9 questions:

Dataset Overview

Outlier Detection

Effect of Features

Marginal Probability

Correlation

Conditional Probability

Customer Profiling

Probabilities Summary

Recommendations

** AeroFit Treadmill Case Study SUMMARY**

AeroFit sells three treadmills:

KP281 (Entry model, $1500)

KP481 (Mid model, $1750)

KP781 (Advanced model, $2500)

The company wanted to know: What kind of people buy each treadmill?

🔍 What We Found

General Info

Data had 180 customers.

No missing values.

Average age was 29 years.

Average income was $53K per year.

People planned to run about 100 miles per week.

Product Choice

44% bought KP281 (entry level).

33% bought KP481 (mid).

22% bought KP781 (advanced).

Who Buys What

KP281 → Young (18–28), lower income, fitness beginners, more males, casual users.

KP481 → Adults (25–35), medium income, regular fitness users, balanced males & females.

KP781 → Older (30–40), higher income, high fitness, heavy treadmill users, mostly males.

Gender Effect

Females: 53% buy KP281, only 9% buy KP781.

Males: 32% buy KP781, so they are more likely to choose the advanced model.

Other Factors

Age & Income go together → older people earn more.

Fitness, Usage, and Miles go together → fit people run more and use treadmill more often.

Business Recommendations

KP281 → Market to young, budget customers (students, new professionals). Show it as a good starting treadmill.

KP481 → Promote as “best value” to working adults and families. Add bundle offers (mats, dumbbells).

KP781 → Target high-income, serious fitness users. Advertise in premium gyms, wellness clubs, and to executives.

Gender Strategy → Promote KP781 more towards men, KP281 starter packs more towards women.

Upgrade Path → Give trade-in or loyalty discounts to move customers from KP281 → KP481 → KP781 over time.

In short:

Most customers buy the entry model (KP281).

Men are more likely to buy the premium KP781.

Income, age, and fitness level strongly affect which treadmill people buy.

AeroFit can grow sales by targeting the right product to the right group and offering upgrade plans.