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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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

```
from google.colab import files
```

```
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving aerofit_treadmill.csv to aerofit_treadmill (3).csv
```

```
df=pd.read_csv('aerofit_treadmill.csv')
```

```
df.head()
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	20.0	Male	14	Single	3.0	4	34053.15	112
1	KP281	20.0	Male	15	Single	2.0	3	34053.15	75
2	KP281	20.0	Female	14	Partnered	4.0	3	34053.15	66
3	KP281	20.0	Male	14	Single	3.0	3	34053.15	85
4	KP281	20.0	Male	14	Partnered	4.0	2	35247.00	47

```
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
```

```
print(f"Number of rows: {df.shape[0]}")
print(f"Number of columns: {df.shape[1]}")
```

```
Number of rows: 180
Number of columns: 9
```

```
df.isna().any()
```

	0
Product	False
Age	False
Gender	False
Education	False
MaritalStatus	False
Usage	False
Fitness	False
Income	False
Miles	False

dtype: bool

```
df.describe(include="all")
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

Key Observations:

1. The dataset has no missing values.
2. There are three treadmill models(KP281, KP481, KP781).
3. KP281 is the most popular model, purchased by 80 customers.
4. Males (104) form the majority of buyers (57.8%).
5. The average customer age is 28.8 years, with most between 24-33 years old.
6. 107 customers are partnered, indicating a higher purchase tendency among them.
7. Customers plan to use their treadmills 3.46 times per week on average.
8. The average annual income is $53,719, with a wide range from$29,562 to $104,581.
9. Customers expect to walk or run around 103 miles per week on average.
10. Higher-income individuals and frequent users are potential targets for premium models like KP781.

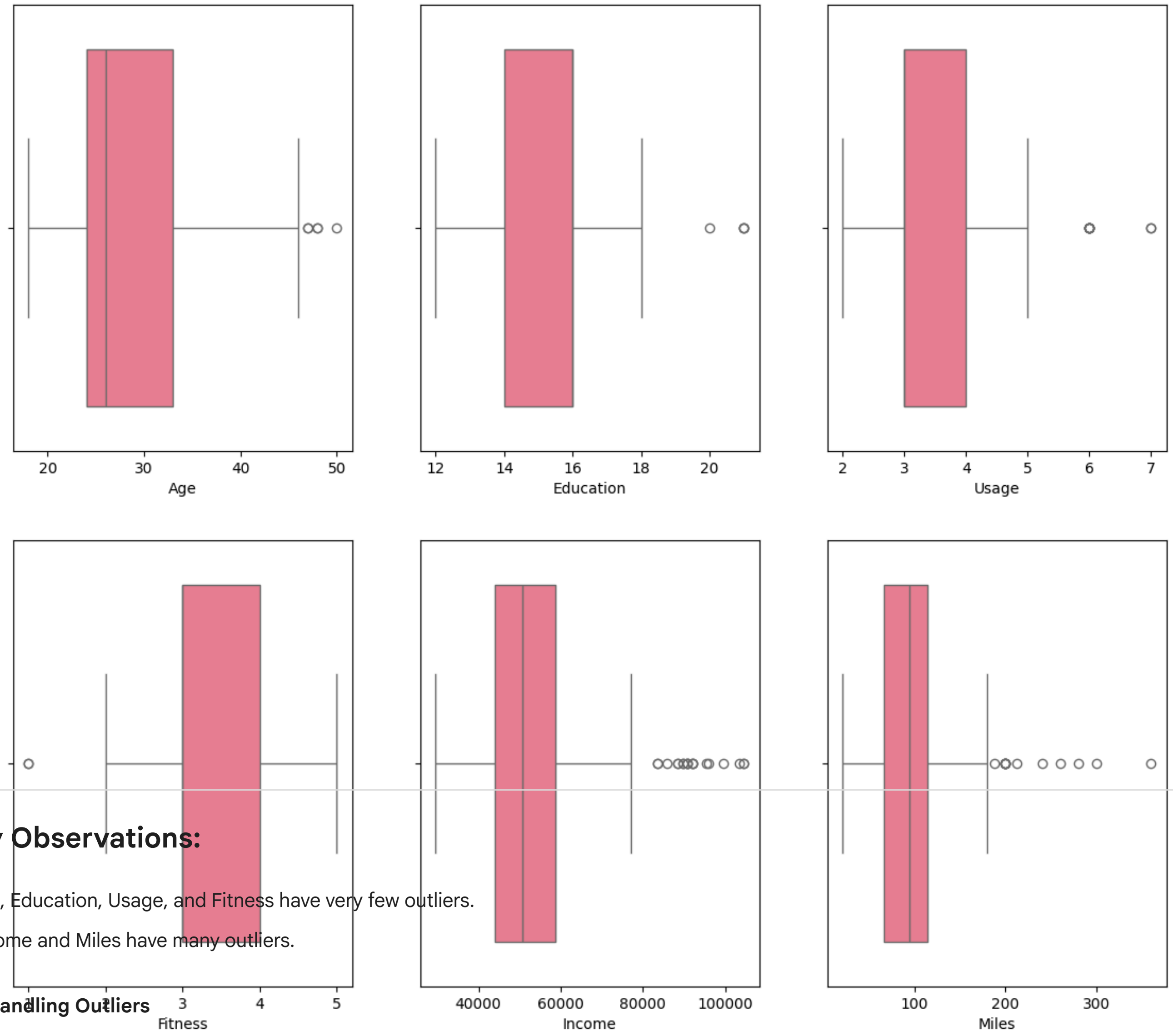
2. Detect Outliers

```
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
```

```
plt.figure(figsize=(14,12))

plt.subplot(2,3,1)
sns.boxplot(data=df,x='Age')
plt.subplot(2,3,2)
sns.boxplot(data=df,x='Education')
plt.subplot(2,3,3)
sns.boxplot(data=df,x='Usage')
plt.subplot(2,3,4)
sns.boxplot(data=df,x='Fitness')
plt.subplot(2,3,5)
sns.boxplot(data=df,x='Income')
plt.subplot(2,3,6)
sns.boxplot(data=df,x='Miles')
plt.show()
```



Key Observations:

1.Age, Education, Usage, and Fitness have very few outliers.

2.Income and Miles have many outliers.

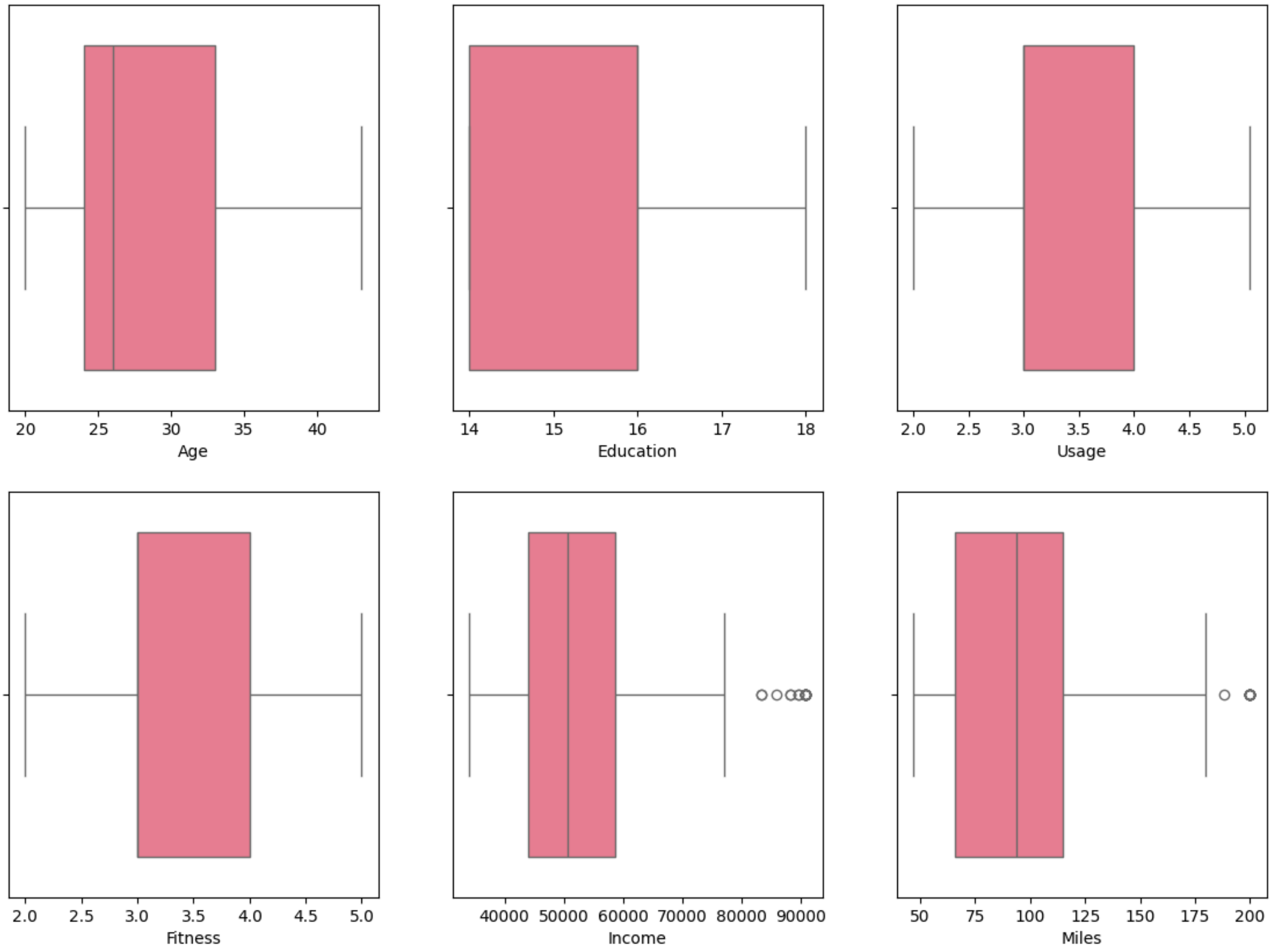
--> **Handling Outliers**

```
cols= ["Age", "Education", "Usage", "Fitness", "Income", "Miles"]
for col in cols:
  lower_bound=np.percentile(df[col],5)
  upper_bound=np.percentile(df[col],95)
  df[col]=np.clip(df[col],lower_bound,upper_bound)
```

```
plt.figure(figsize=(14,10))

plt.subplot(2,3,1)
sns.boxplot(data=df,x='Age')
plt.subplot(2,3,2)
```

```
sns.boxplot(data=df,x='Education')
plt.subplot(2,3,3)
sns.boxplot(data=df,x='Usage')
plt.subplot(2,3,4)
sns.boxplot(data=df,x='Fitness')
plt.subplot(2,3,5)
sns.boxplot(data=df,x='Income')
plt.subplot(2,3,6)
sns.boxplot(data=df,x='Miles')
plt.show()
```



Observations After Clipping:

1.Clipping helped in reducing extreme values in most numerical columns.

2.Some outliers are still present in Income and Miles.

3.The data distribution is now more stable and less skewed.

4.No data points were removed, only adjusted within a defined range.

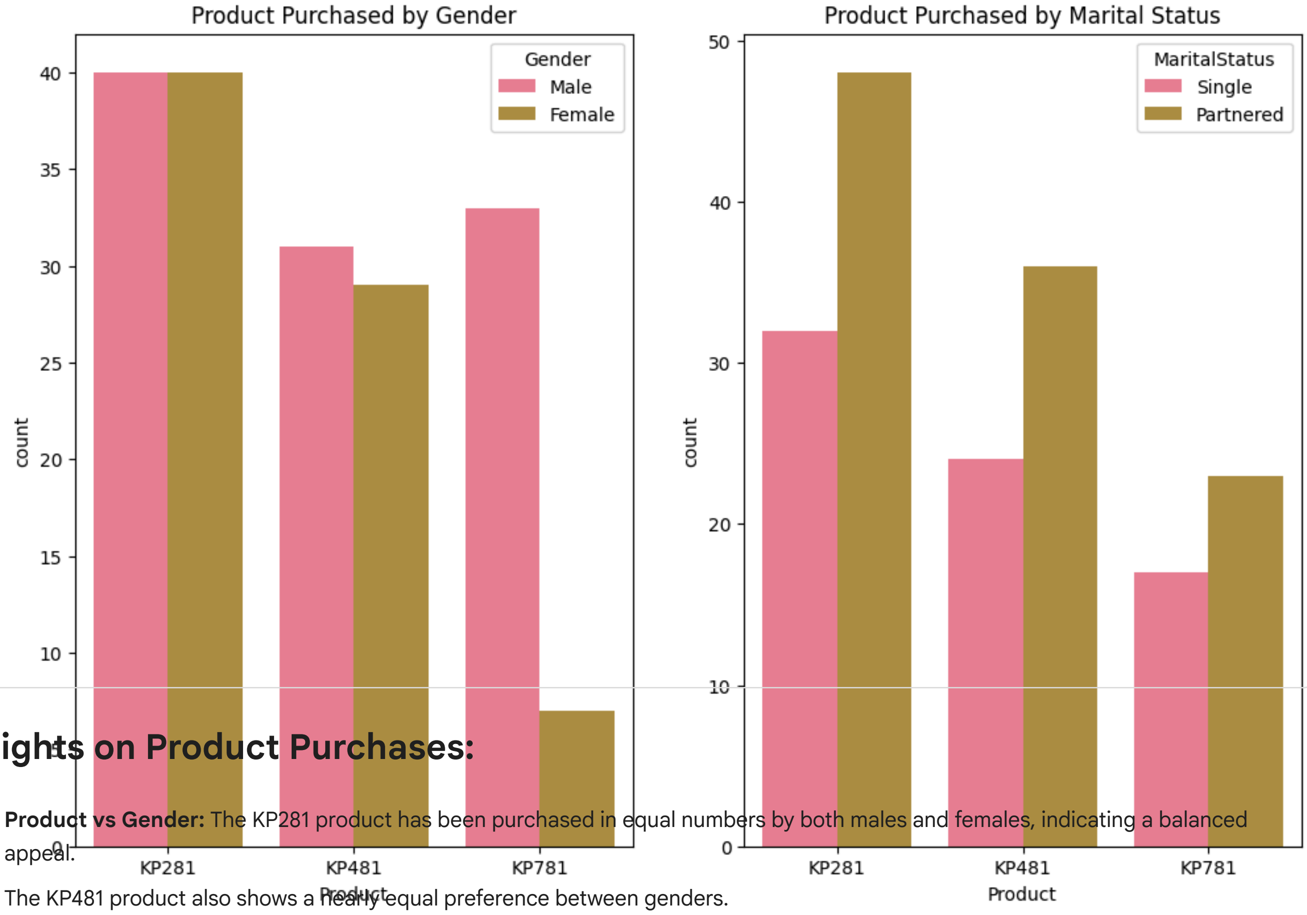
5.Features like Age and Fitness now show a more controlled spread.

3. Check if features like marital status, Gender, and age have any effect on the product purchased

Relationship between the categorical variables and the output variable in the data

```
plt.figure(figsize=(12, 8))
plt.subplot(1,2,1)
sns.countplot(x='Product', hue='Gender', data=df)
```

```
plt.title("Product Purchased by Gender")
plt.subplot(1,2,2)
sns.countplot(x='Product', hue='MaritalStatus', data=df)
plt.title("Product Purchased by Marital Status")
plt.show()
```



Insights on Product Purchases:

1. **Product vs Gender:** The KP281 product has been purchased in equal numbers by both males and females, indicating a balanced appeal.

   The KP481 product also shows a nearly equal preference between genders.

   The KP781 product is highly favored by male customers, suggesting it might cater more to their fitness needs or preferences.

2. **Product vs Marital Status:** Partnered customers are significantly more likely to purchase gym equipment, suggesting that fitness might be a shared lifestyle choice among couples.

   This could indicate a trend where partnered individuals invest more in home workouts or shared fitness goals.

Relationship between the continuous variables and the output variable in the data.

```
num_cols = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
```

```
plt.figure(figsize=(14, 12))
for i, col in enumerate(num_cols, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(x='Product', y=col, data=df, palette='viridis')
    plt.title(f'{col} vs Product Purchased')
plt.show()
```

```
<ipython-input-163-61bb2feb3739>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se

  sns.boxplot(x='Product', y=col, data=df, palette='viridis')
<ipython-input-163-61bb2feb3739>:4: FutureWarning:

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  sns.boxplot(x='Product', y=col, data=df, palette='viridis')
```
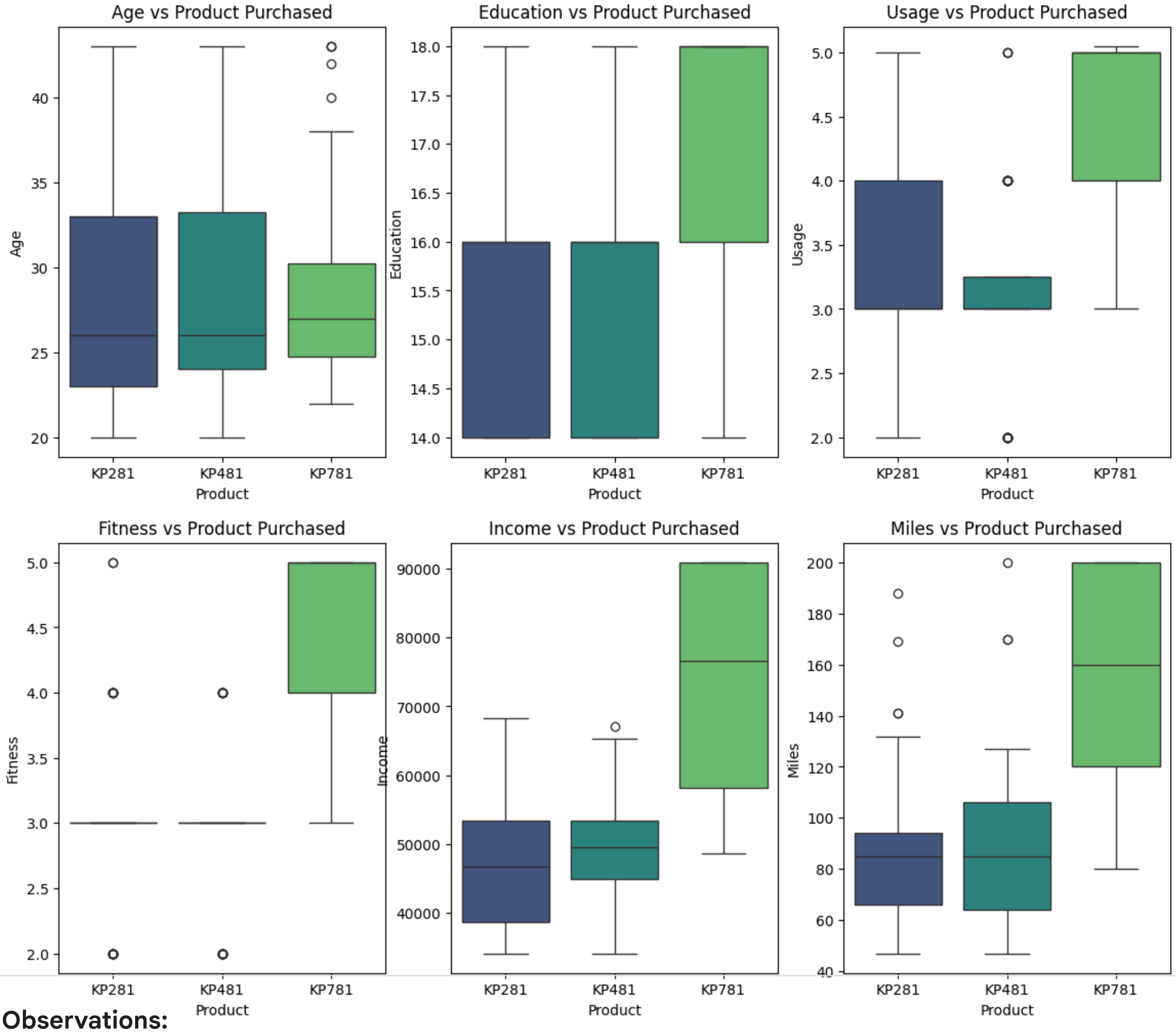



Key Observations:

1. Age vs Product Preference:

Customers purchasing KP281 and KP481 have a similar age distribution. The KP781 model is preferred by customers aged 25–30. 2. ### Education vs Product Preference: Customers with higher education (above 16 years) ter of education show an equal preference for KP281 and KP481. 3. ### Usage Frequency treadmill more than 4 times per week prefer KP781. Less frequent users tend to buy KP28

Preference: A fitness level of 3 or higher increases the likelihood of purchasing KP781. 5. ### Income vs Product Preference: Customers with an income of ₹60,000 or more are more likely to opt for KP781. 6. ### Distance Covered vs Product Preference: Customers expecting to walk/run over 120 miles per week are more inclined to purchase KP781.

4.Representing the Probability

Marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

```
marginal_prob = pd.crosstab(index=df['Product'], columns='count', normalize=True) * 100
```

```
print(marginal_prob)
```

```
col_0        count
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

The probability that the customer buys a product based on each column.

--> Probability By Gender

```
prob_by_gender = pd.crosstab(df['Gender'], df['Product'], normalize='columns')
print(prob_by_gender)
```

```
Product  KP281     KP481  KP781
Gender
Female     0.5  0.483333  0.175
Male       0.5  0.516667  0.825
```

--> Probability By Marital Status

```
prob_by_marital_status = pd.crosstab(df['MaritalStatus'], df['Product'], normalize='columns')
print(prob_by_marital_status)
```

```
Product        KP281  KP481  KP781
MaritalStatus
Partnered        0.6    0.6  0.575
Single           0.4    0.4  0.425
```

The conditional probability that an event occurs given that another event has occurred.

```
conditional_prob = pd.crosstab(df['Gender'], df['Product'], normalize=0)  # Normalize row-wise
print(conditional_prob)
```

```
Product     KP281     KP481     KP781
Gender
Female   0.526316  0.381579  0.092105
Male     0.384615  0.298077  0.317308
```

Observations:

1.Product Popularity:

KP281 is the most purchased product (44.44%).

KP481 follows with (33.33%) of purchases.

KP781 has the least buyers (22.22%).

2.Gender-Based Purchase Trends:

Men prefer KP781 (82.5%), indicating a preference for advanced treadmills.

Women purchase KP481 more (48.3%), showing a balanced preference. KP281 is equally popular among both genders.

3.Marital Status Influence:

Married customers are more likely to buy any product, especially KP281 and KP781.

Single customers have a lower tendency to buy KP781.

4.Conditional Probability Insights:

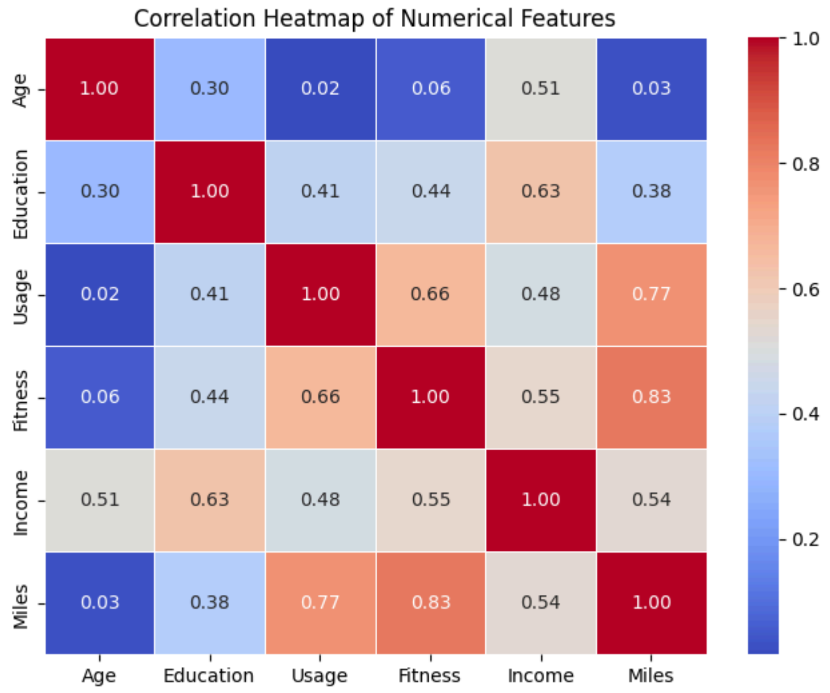
A female customer has a higher chance of purchasing KP281 (52.6%).

A male customer is more likely to buy KP781 (31.7%).

5. Check the correlation among different factors

```
num_df = df.select_dtypes(include=['number'])
corr_matrix = num_df.corr()
```

```
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```



Observations from the Correlation Heatmap:

1.Income & Age: Older customers tend to have higher incomes.

2.Usage & Age: Younger customers use the treadmill more often.

3.Fitness & Usage: Fitter people use the treadmill more frequently.

4.Product & Income: High-income customers prefer premium products (KP781).

5.Product & Miles: Customers who plan to run more miles per week choose high-end models.

6.Education & Income: Higher education levels are linked to higher income.

7.Age & Product Choice: Younger customers may prefer KP781 over KP281.

6.Customer Profiling and Recommendations

Customer Profiling for Each Product

1. KP281 Buyers:

Age Group: Mostly purchased by 18-25 years old.

Gender: Equally preferred by both males and females.

Income Level: Lower to moderate income (below $40,000).

Usage: 2-4 times per week.

Fitness Level: Moderate (2-3 fitness score).

Miles Covered: Less than 100 miles per week.

2. KP481 Buyers:

Age Group: Mostly 25-35 years old.

Gender: Slightly more preferred by males.

Income Level: Middle-income $(40, 000-$60,000).

Usage: 3-5 times per week.

Fitness Level: Fitness score of 3-4.

Miles Covered: 100-120 miles per week.

3. KP781 Buyers:

Age Group: Mostly 25-30 years old.

Gender: Mostly purchased by males.

Income Level: Higher-income (above $60,000).

Usage: More than 4 times per week.

Fitness Level: High (4+ fitness score).

Miles Covered: More than 120 miles per week.

Recommendations Based on Analysis:

KP281 (Budget-Friendly Option):

1.Best for beginners and casual users.

2.Should be marketed as an affordable, easy-to-use treadmill.

3.Target students, young professionals, and home users.

KP481 (Balanced Choice):

1.Appeals to regular users who want a mix of quality and affordability.

2.Can be promoted as a reliable, long-term fitness investment.

3.Ideal for working professionals and fitness-conscious buyers.

KP781 (Premium Model):

1.Designed for serious fitness enthusiasts.

2.Should highlight advanced features, durability, and high performance.

3.Market to high-income individuals, athletes, and gym owners.

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