In [ ]:
```
from logging import warning
import numpy as np

import pandas as pd

import datetime

import matplotlib.pyplot as plt

import seaborn as sns

import copy

import warnings
warnings.filterwarnings('ignore')
```

Problem Statement

Aerofit wants to identify the characteristics of customers purchasing each treadmill (KP281, KP481, KP781). The goal is to create customer profiles, detect outliers, and analyze probabilities (marginal, conditional, joint) to provide business insights for targeted marketing and product recommendations.

1. Analysis of basic metrics

In [ ]:
```
df = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets
df
```

Out[ ]:

	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

180 rows × 9 columns

Shape of data

In [ ]:

```
df.shape
```

Out[ ]:

```
(180, 9)
```

Data types of the provided attributes

In [ ]:

```
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
```

Conversion of categorical attributes to 'category'

In [ ]:

```
df["Product"] = df["Product"].astype("category")
df["Gender"] = df["Gender"].astype("category")
df["MaritalStatus"] = df["MaritalStatus"].astype("category")
```

Product → categorical (KP281, KP481, KP781).

Age → numeric.

Gender → categorical.

Education → numeric (years).

MaritalStatus → categorical (Single, Partnered).

Usage → numeric (weekly usage).

Fitness → numeric (self-rating).

Income → numeric (annual income).

Miles → numeric (expected miles of treadmill usage).

In [ ]:

```
df.head()
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	I
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	

Missing values per column

In [92]:

```
missing_value_column_list = df.isnull().any().to_frame()
missing_value_column_list
missing_value_columns = missing_value_column_list[missing_value_column_list[
missing_value_columns
```

Out[92]:

	0

- There are no missing values in any of the columns of the given dataset.

Statistical summary

Numeric attributes

In [ ]:
```
df.describe()
```

Out[ ]:

	Age	Education	Usage	Fitness	Income	Mi
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000

Comments on Range of Attributes

1. **Age** - Customers are mainly young adults, with a few older buyers. Aerofit's treadmills appeal primarily to younger demographic groups.
2. **Education** - Customers generally have 15–17 years of education (college level). Education does not vary much across customers.
3. **Usage (days/week)** - Majority of customers are moderate users, but there is a subgroup that uses treadmills much more frequently.
4. **Fitness (self-rating)** - Customers generally rate themselves as moderately fit; fitness scores are clustered, not much variation.
5. **Income** - Customers come from diverse income groups, from mid-income to high-income professionals. Income is a key differentiator between product types.
6. **Miles (monthly distance)** - Customers range from casual walkers (~20–40 miles/month) to heavy runners (200+ miles/month). Product choice is strongly linked with mileage.

Categorical attributes

In [ ]:
```
df.describe(include="category")
```

Out[ ]:

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

2. Non-Graphical Analysis: Value counts and unique attributes

In [ ]:
```
df.nunique()
```

Out[ ]:

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

dtype: int64

In [ ]:
```
df["MaritalStatus"].unique()
```

Out[ ]:
```
['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
```

In [ ]:
```
df["Gender"].unique()
```

Out[ ]:
```
['Male', 'Female']
Categories (2, object): ['Female', 'Male']
```

In [ ]:
```
df["Product"].unique()
```

Out[ ]:
```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

Unique attributes in categorical columns:

- Product: 3 (KP281, KP481, KP781)
- Gender: 2 (Male, Female)
- MaritalStatus: 2 (Single, Partnered)

Value counts for categorical variables

In [ ]:
```
df["Product"].value_counts(normalize=True) * 100
```

Out[ ]:

	proportion
Product	
KP281	44.444444
KP481	33.333333
KP781	22.222222

dtype: float64

In [ ]:
```
df["Gender"].value_counts(normalize=True) * 100
```

Out[ ]:

	proportion
Gender	
Male	57.777778
Female	42.222222

dtype: float64

In [ ]:
```
df["MaritalStatus"].value_counts(normalize=True) * 100
```

Out[ ]:

	proportion
MaritalStatus	
Partnered	59.444444
Single	40.555556

dtype: float64

Comments on Categorical Attributes

1. KP281, which is the entry-level threadmill sells more than other two categories and we can also notice that quantity sold decreases when price increases.KP281 (~ 44%) is most purchased, followed by KP481 (~ 33%) and KP781 (~ 22%). → KP281 is the mass-market treadmill, KP781 is a niche premium product.

2. Males are utilising threadmill significantly higher than Females.

3. Married people are utilising threadmill significantly higher than singles.

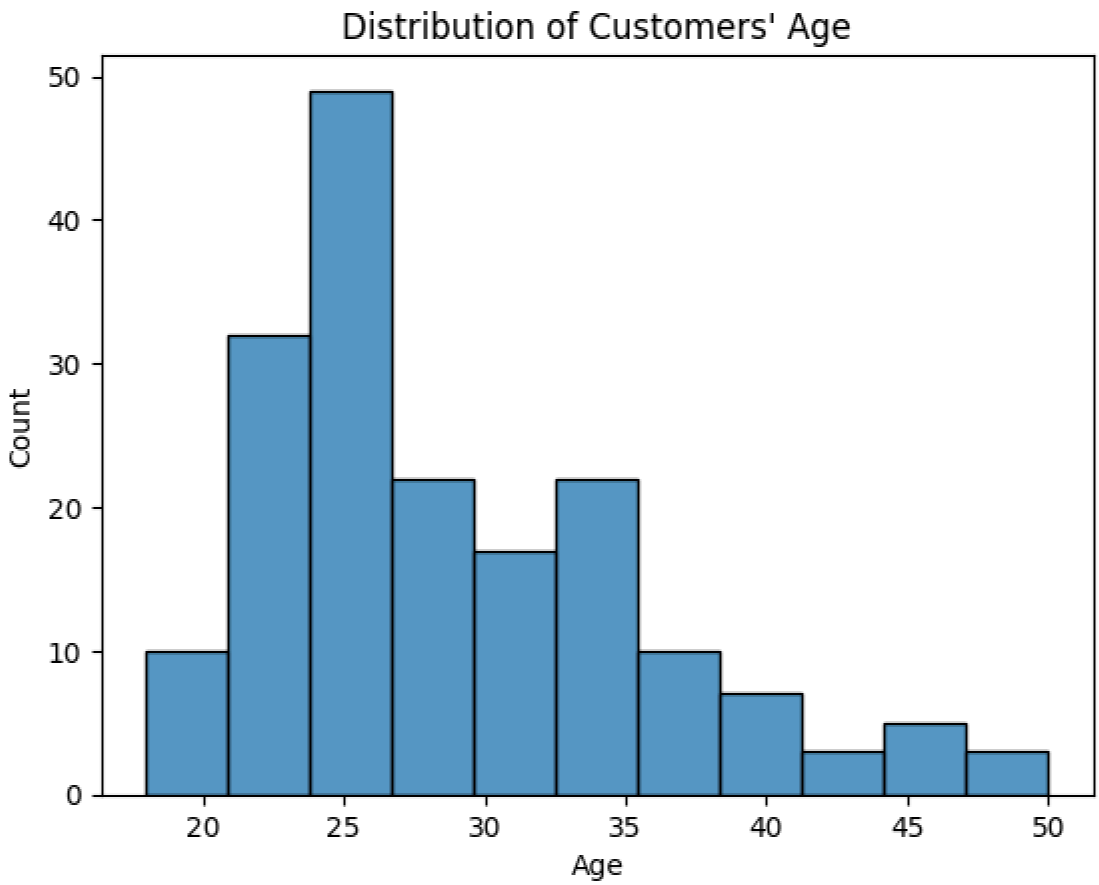
3. Visual Analysis - Univariate & Bivariate

For Continuous variables(Univariate):

In [ ]:
```
Age = df['Age']
Education = df['Education']
Income = df['Income']
Usage = df["Usage"]
Fitness = df["Fitness"]
Miles = df["Miles"]
```

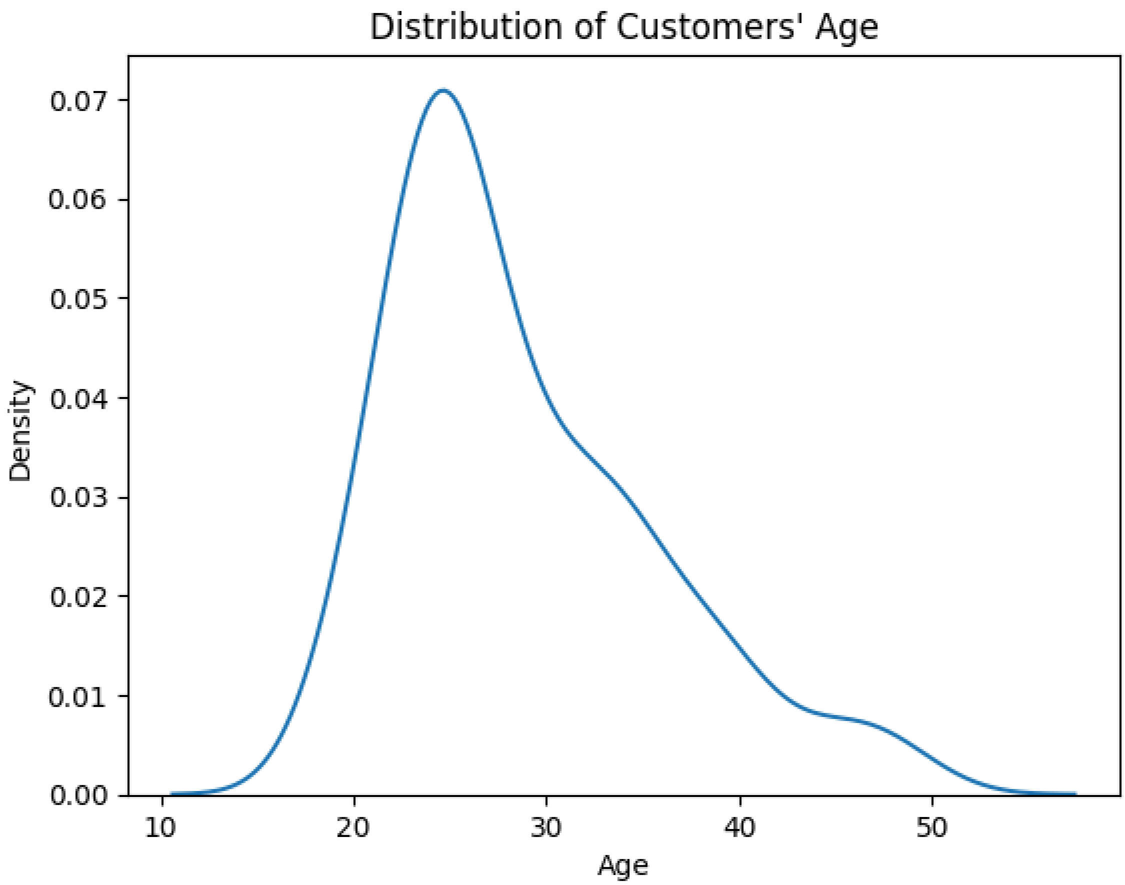
Age

In [ ]:
```
sns.histplot(data=df,x="Age")
plt.title("Distribution of Customers' Age")
plt.show()
```



In [ ]:

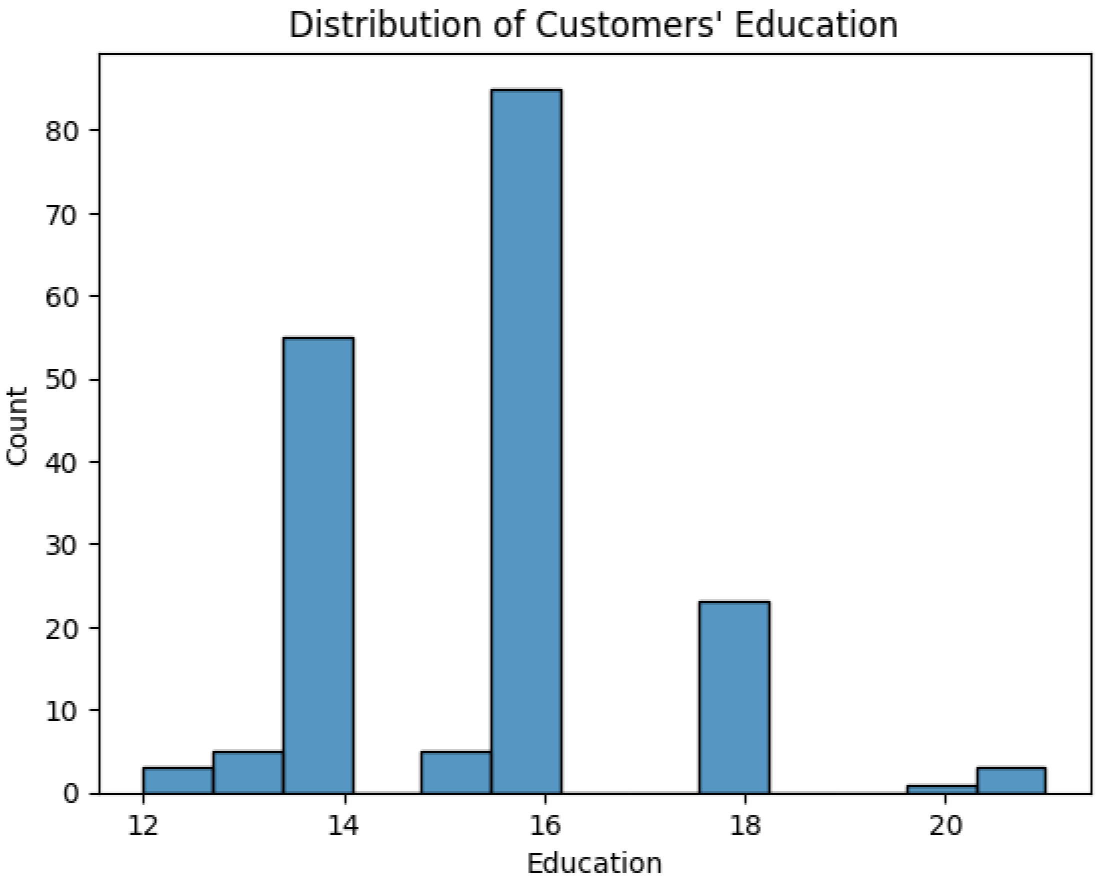
```
sns.kdeplot(data=df,x="Age")
plt.title("Distribution of Customers' Age")
plt.show()
```



The age distribution is slightly right-skewed, with most customers between 20–35 years. Very few older customers pull the mean upward. Aerofit treadmills are primarily used by young adults.

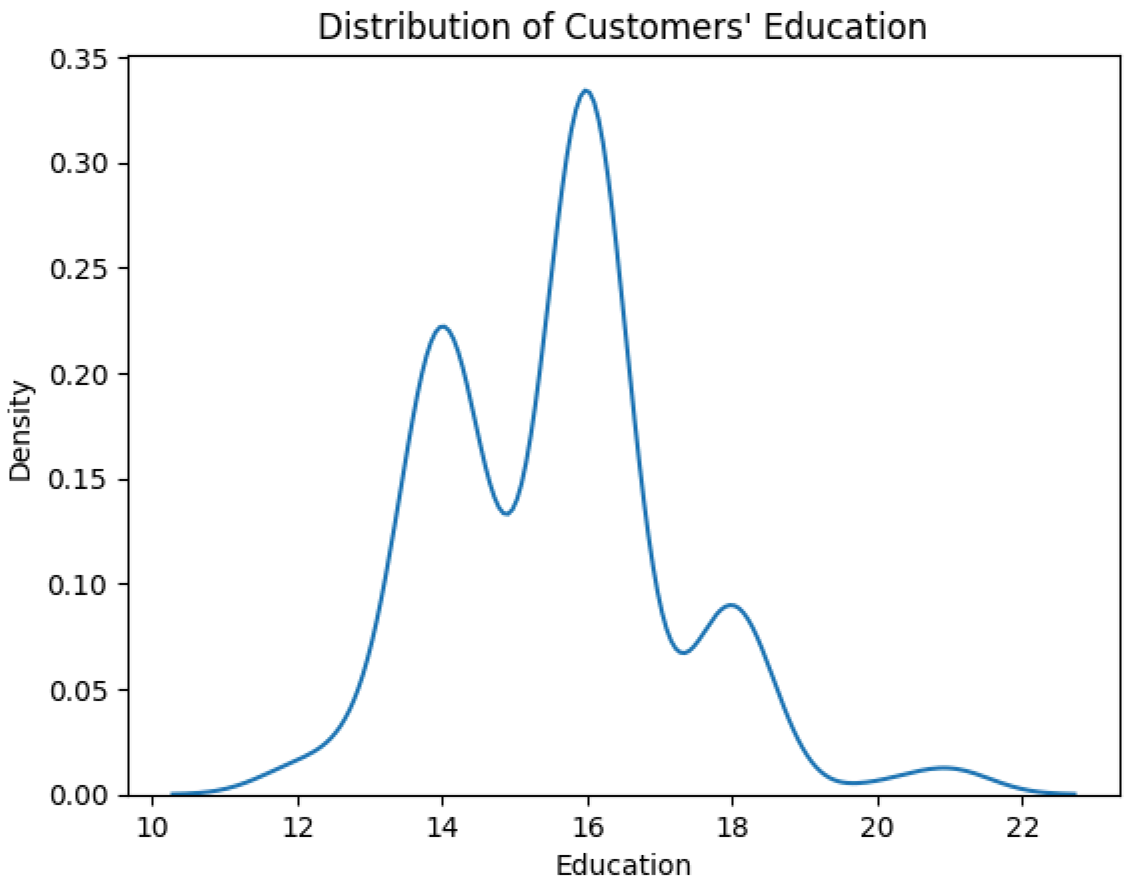
Education

In [ ]:
```
sns.histplot(data=df,x="Education")
# sns.histplot(data=df,x="Education")
plt.title("Distribution of Customers' Education")
plt.show()
```



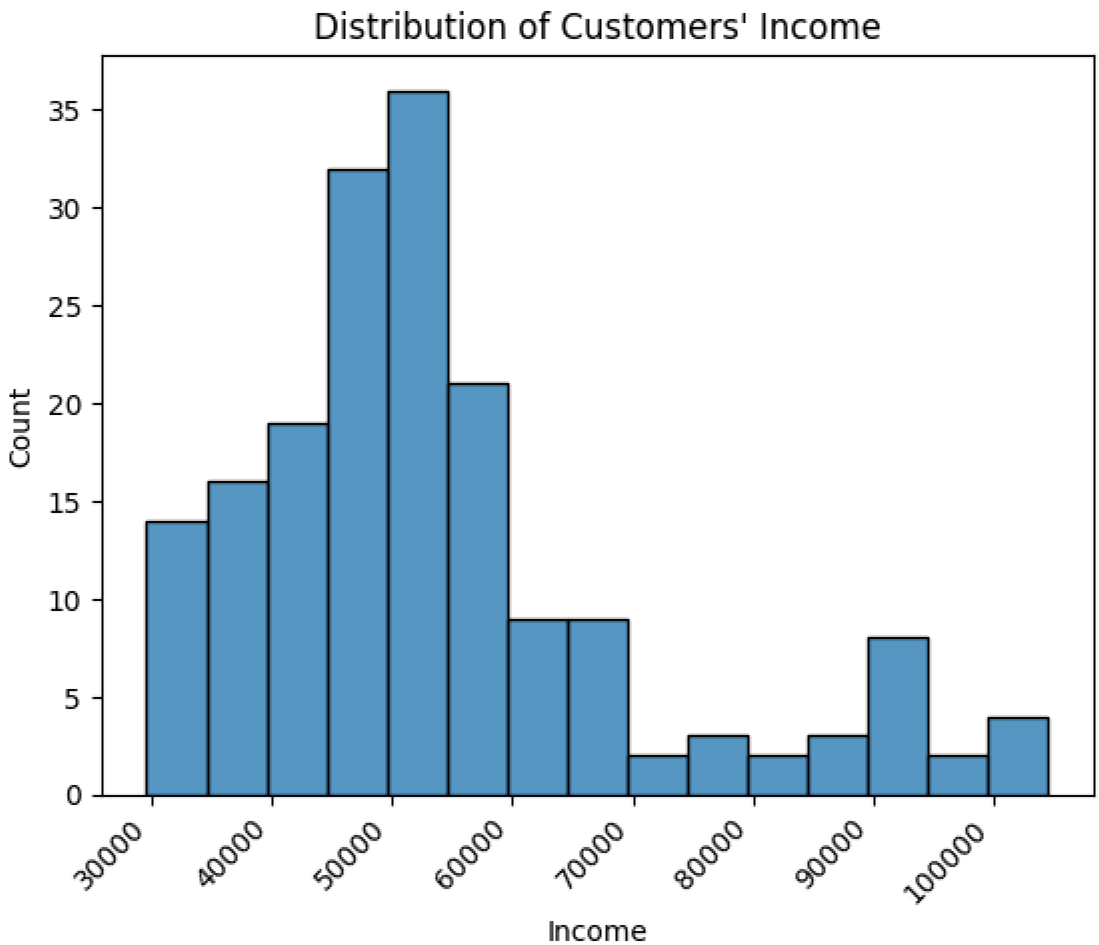
Education levels are tightly clustered between 15–17 years, showing most customers are college-educated. This attribute does not vary much across products.

In [ ]:
```
sns.kdeplot(data=df,x="Education")
plt.title("Distribution of Customers' Education")
plt.show()
```



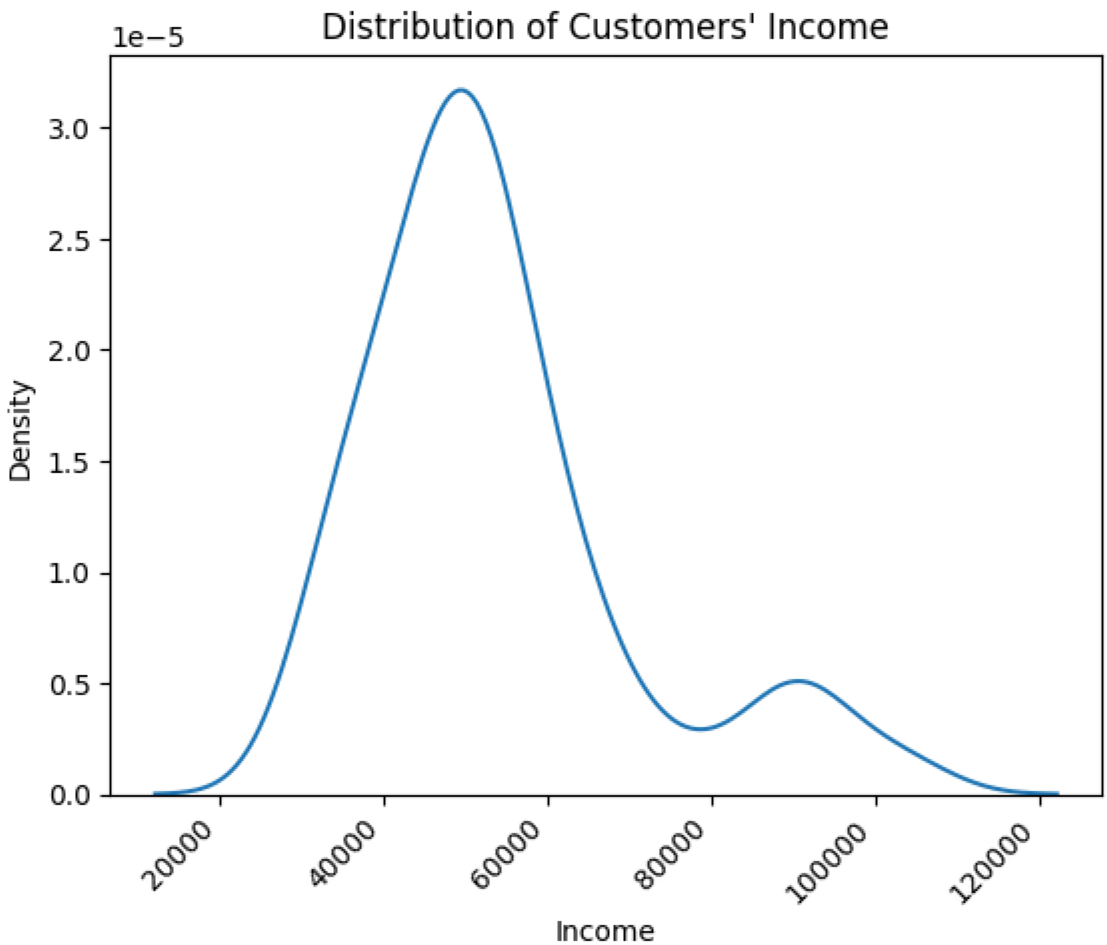
Income

In [ ]:
```
sns.histplot(data=df,x="Income")
plt.title("Distribution of Customers' Income")
plt.xticks(rotation = 45,ha="right")
plt.show()
```



Income distribution is wide, ranging from ₹29k to ₹104k, with most customers earning ₹40k–₹60k. This confirms Aerofit’s customer base spans from mid-income to high-income professionals.

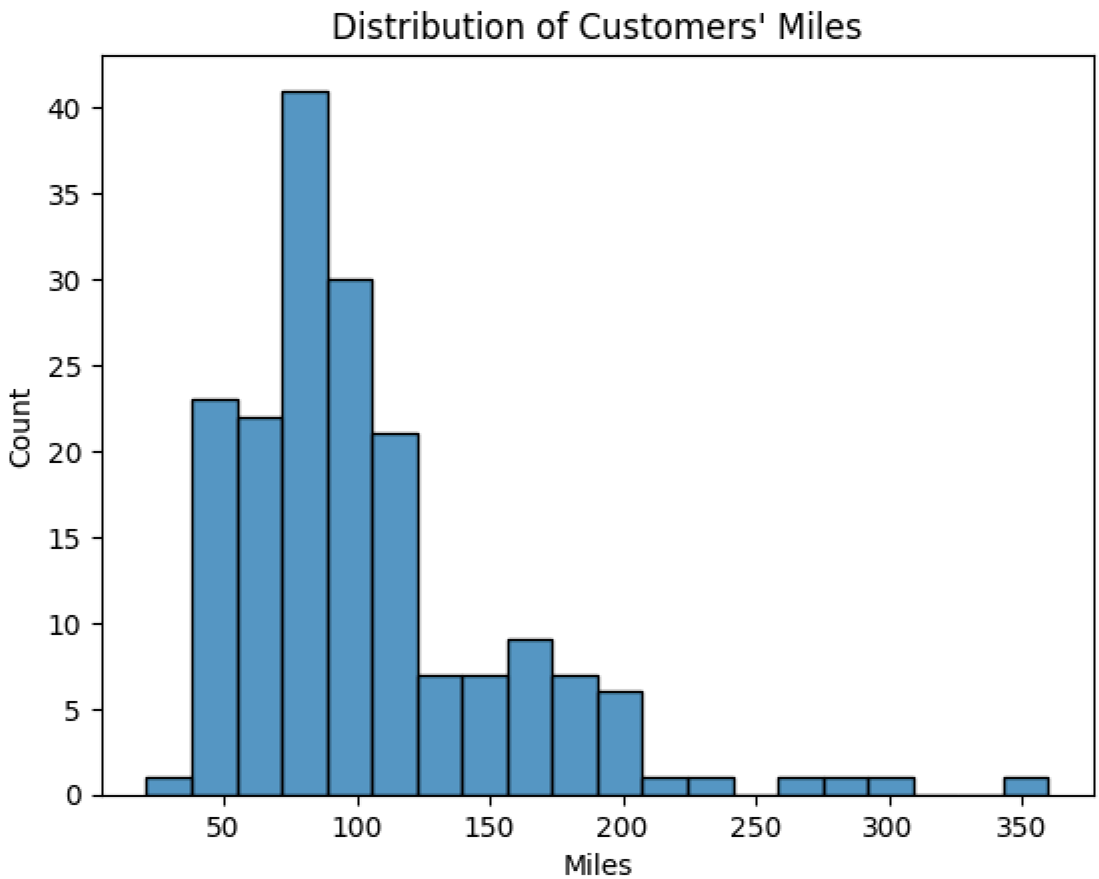
In [ ]:
```
sns.kdeplot(data=df,x="Income")
plt.title("Distribution of Customers' Income")
plt.xticks(rotation = 45,ha="right")
plt.show()
```



Miles

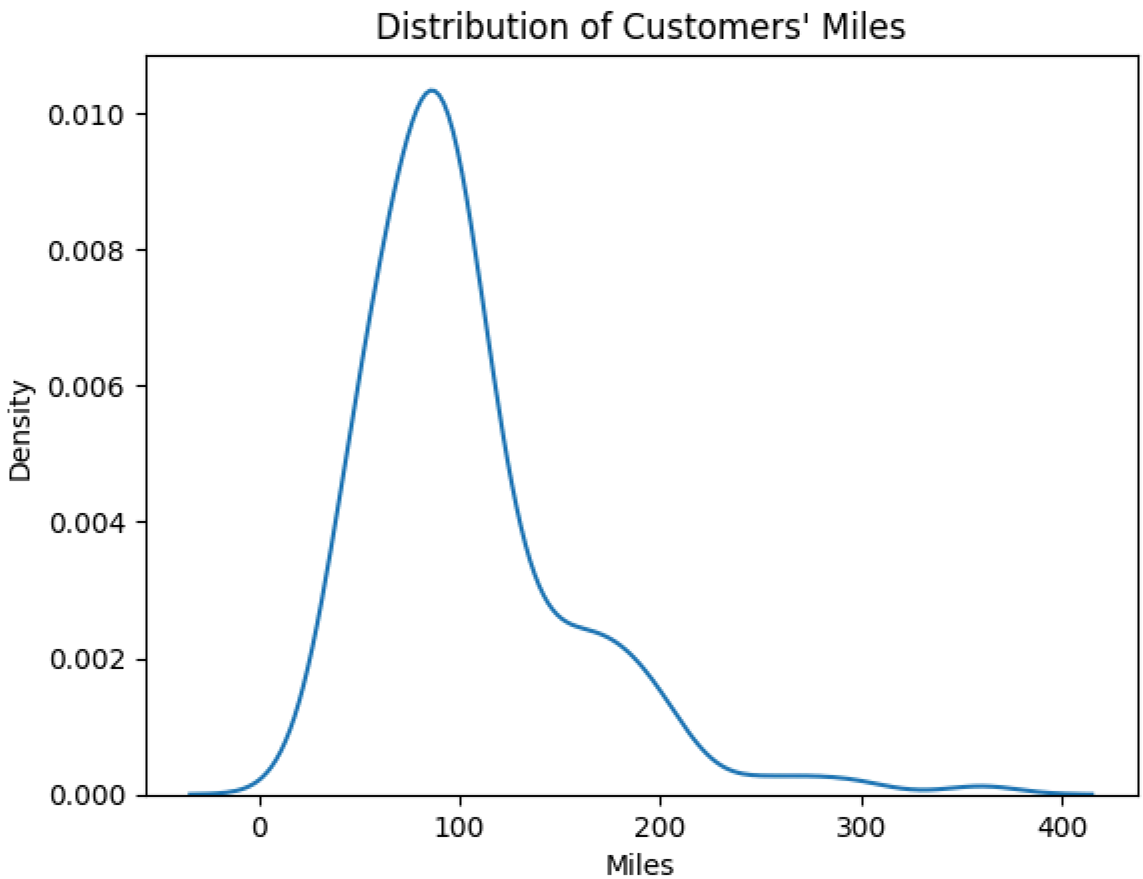
In [ ]:

```
sns.histplot(data=df,x="Miles")
plt.title("Distribution of Customers' Miles")
plt.show()
```



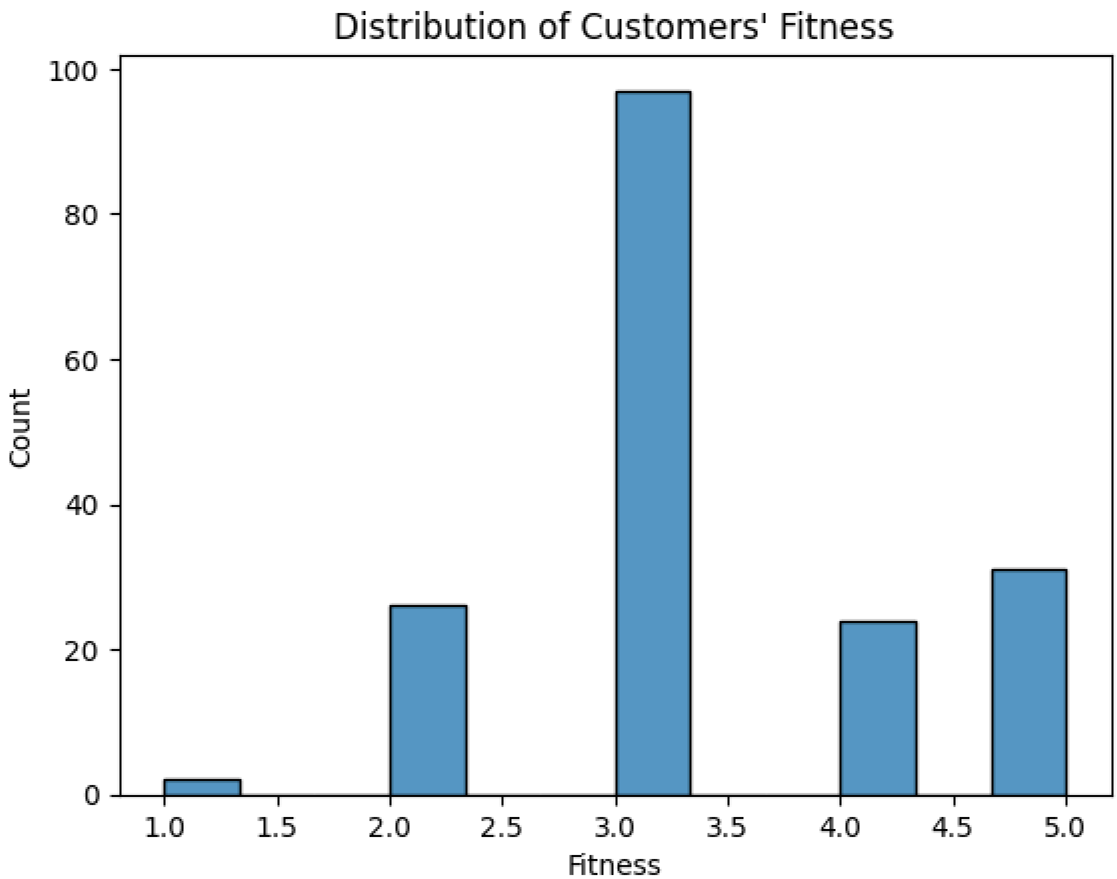
The mileage distribution is right-skewed, with most customers running 80–120 miles per month. A small segment exceeds 200 miles, representing serious athletes.

In [ ]:
```
sns.kdeplot(data=df,x="Miles")
plt.title("Distribution of Customers' Miles")
plt.show()
```

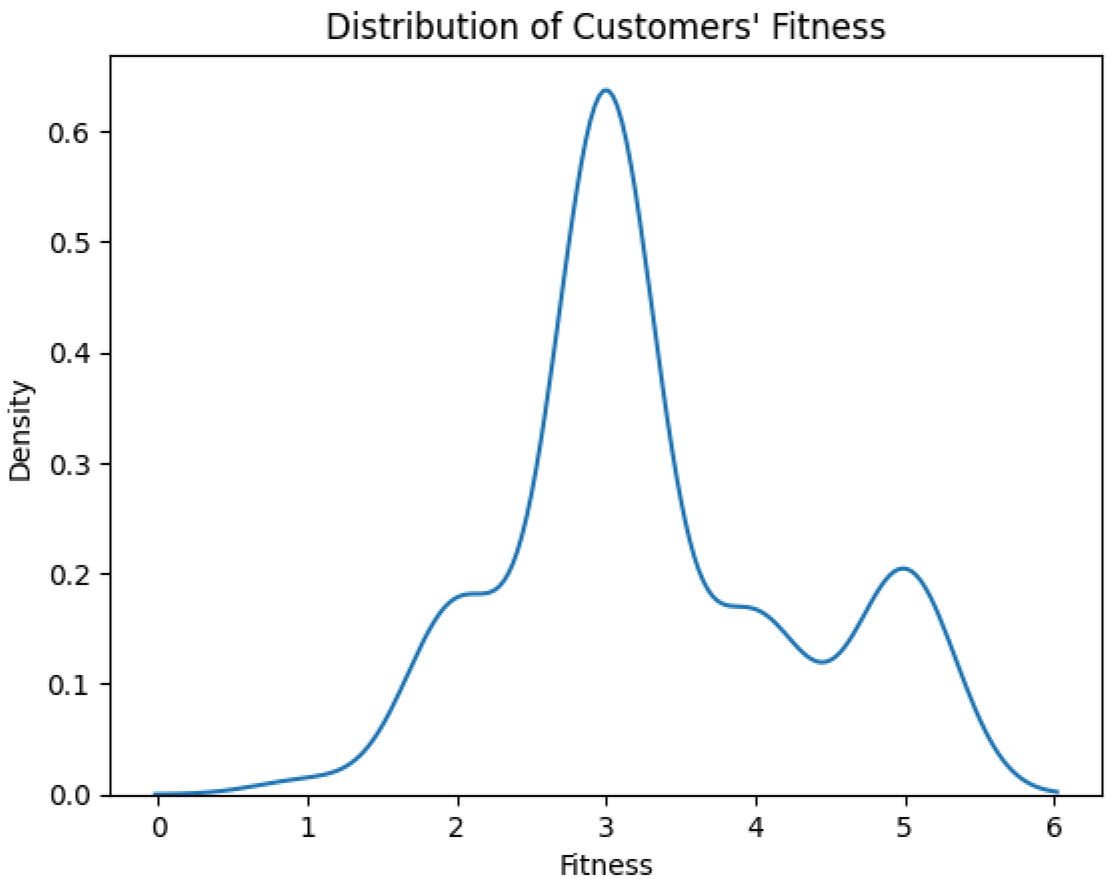


Fitness

In [ ]:
```
sns.histplot(data=df,x="Fitness")
plt.title("Distribution of Customers' Fitness")
plt.show()
```



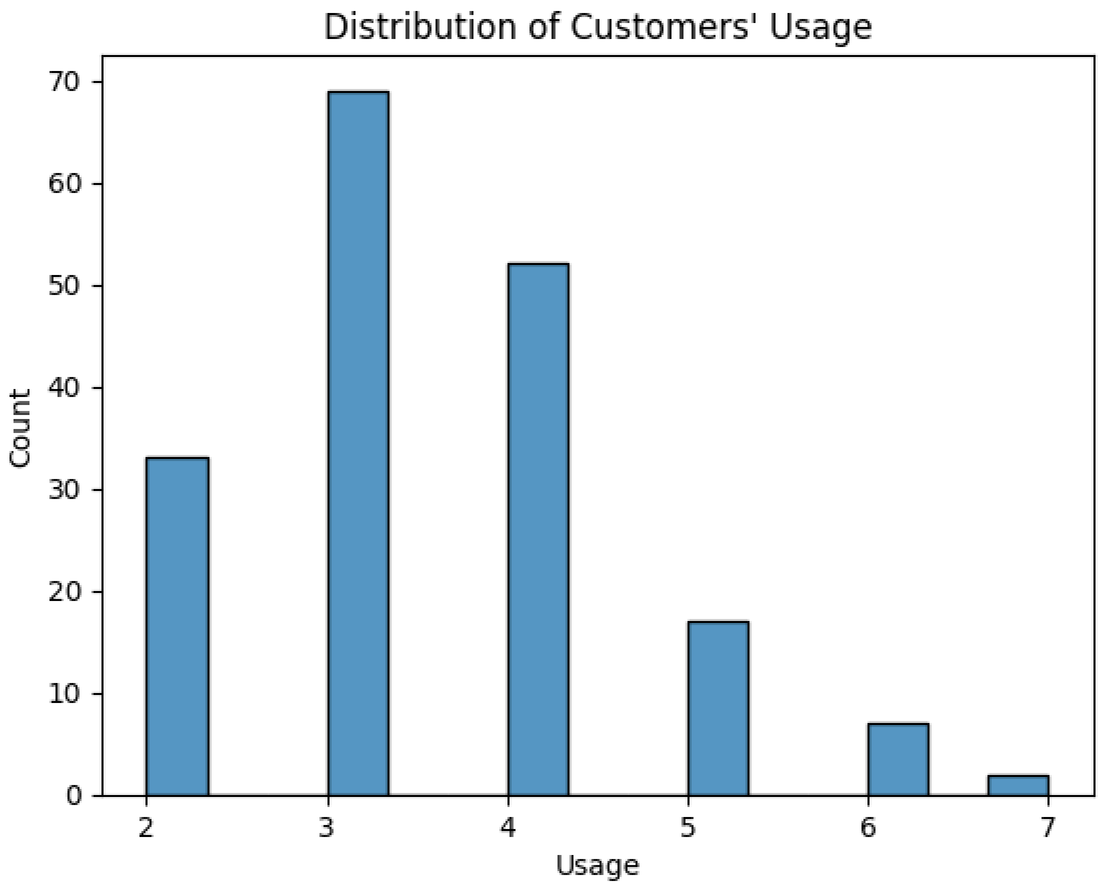
In [ ]:
```
sns.kdeplot(data=df,x="Fitness")
plt.title("Distribution of Customers' Fitness")
plt.show()
```



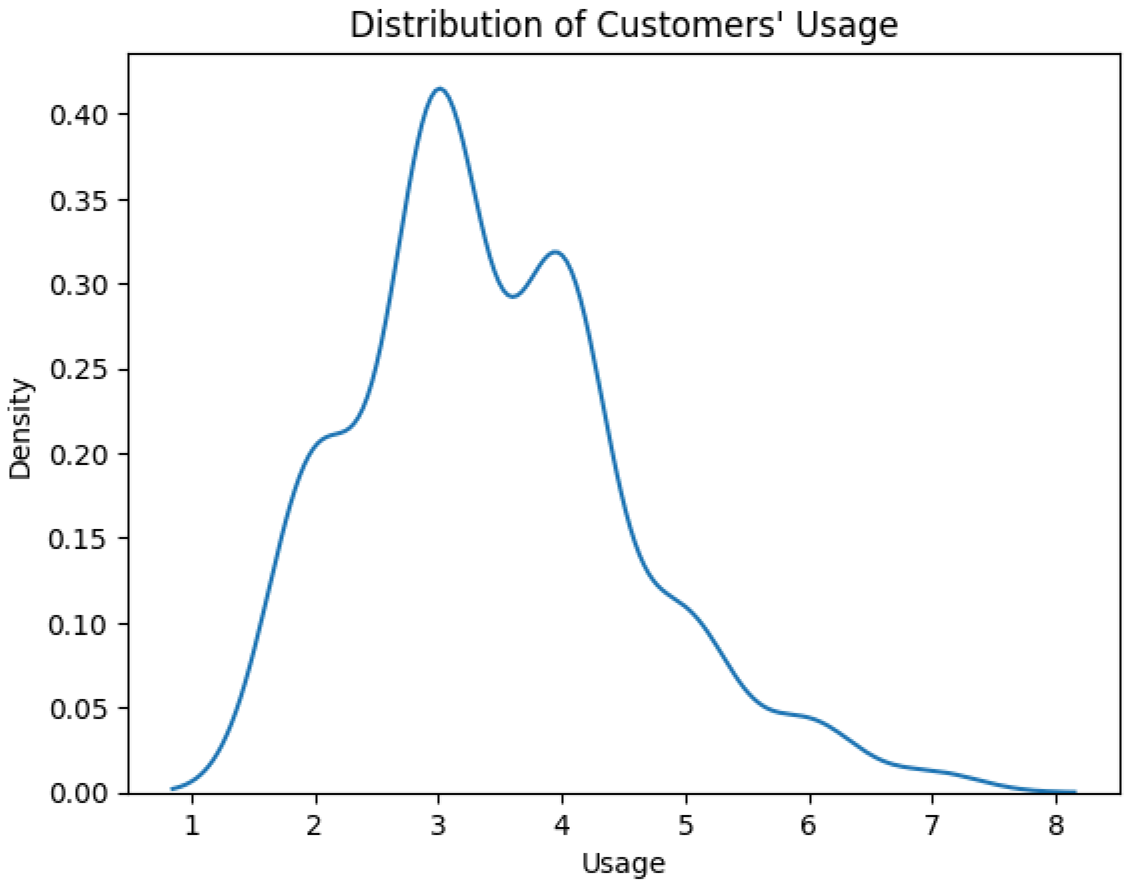
Fitness self-ratings are clustered around 3–4 (on a 1–5 scale). Few customers rate themselves very low or very high. Customers generally perceive themselves as moderately fit.

Usage

In [ ]:
```
sns.histplot(data=df,x="Usage")
plt.title("Distribution of Customers' Usage")
plt.show()
```



In [ ]:
```
sns.kdeplot(data=df,x="Usage")
plt.title("Distribution of Customers' Usage")
plt.show()
```

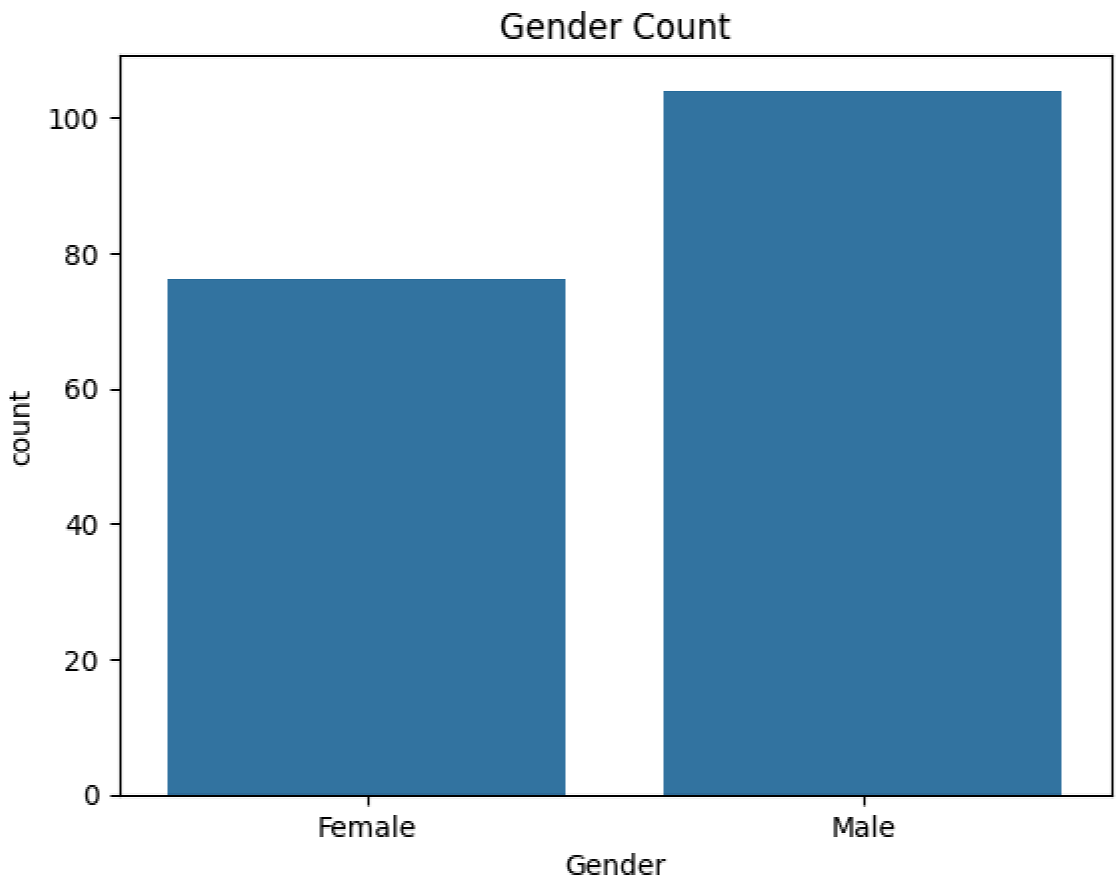


Most customers use treadmills 2–4 times per week. A smaller segment uses it very frequently (5–7 times), showing the mix of casual and dedicated users.

For Categorical Variables (Univariate and Bivariate)

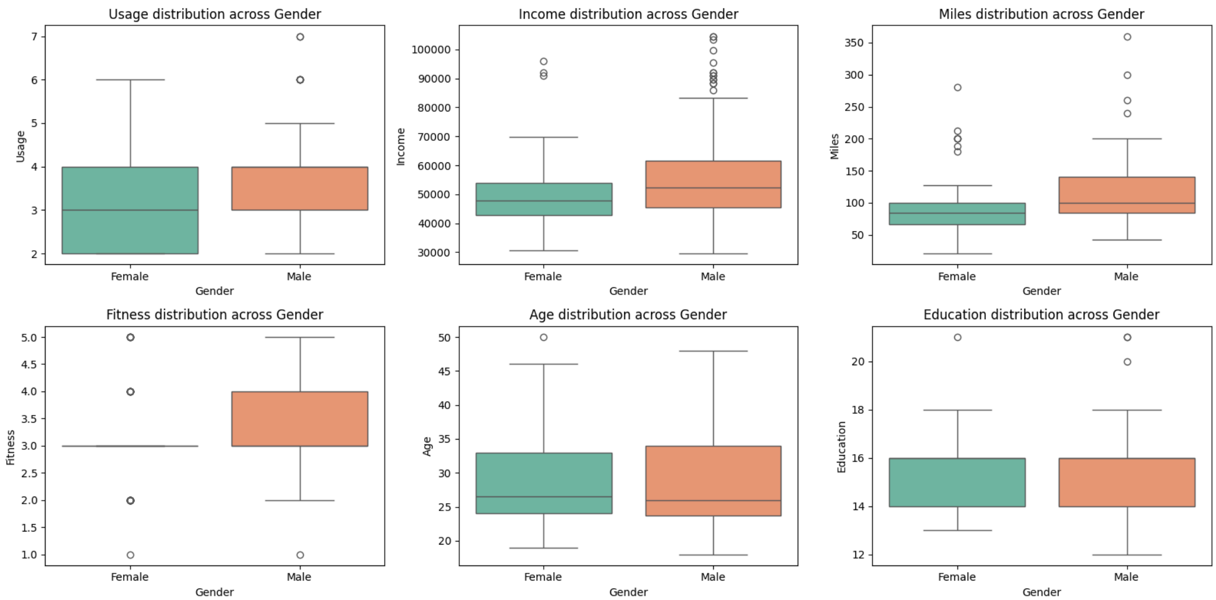
Gender

In [ ]:
```
sns.countplot(data=df, x="Gender")
plt.title("Gender Count")
plt.show()
```



Male usage is bit higher than the Female usage.

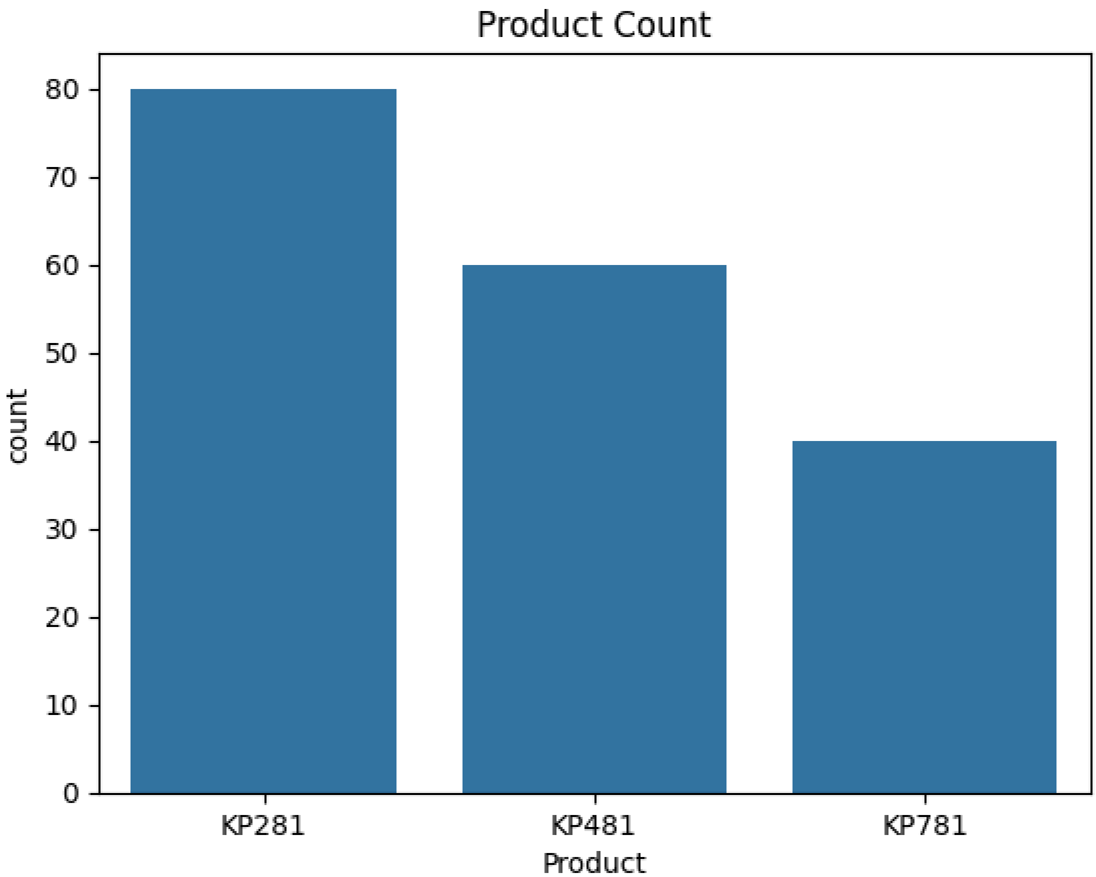
In [ ]:
```
fig,axes = plt.subplots(2,3,figsize=(16,8))

sns.boxplot(data=df, x="Gender",y="Usage",hue="Gender",palette="Set2",ax = a
axes[0,0].set_title("Usage distribution across Gender")


sns.boxplot(data=df, x="Gender",y="Income",hue="Gender",palette="Set2",ax =
axes[0,1].set_title("Income distribution across Gender")

sns.boxplot(data=df, x="Gender",y="Miles",hue="Gender",palette="Set2",ax = a
axes[0,2].set_title("Miles distribution across Gender")

sns.boxplot(data=df, x="Gender",y="Fitness",hue="Gender",palette="Set2",ax =
axes[1,0].set_title("Fitness distribution across Gender")

sns.boxplot(data=df, x="Gender",y="Age",hue="Gender",palette="Set2",ax = axe
axes[1,1].set_title("Age distribution across Gender")

sns.boxplot(data=df, x="Gender",y="Education",hue="Gender",palette="Set2",ax
axes[1,2].set_title("Education distribution across Gender")


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



- Males have slightly higher median income (~₹52k vs ₹47k) and much greater spread (more outliers), indicating wider affordability. Females are more clustered in income levels.
- Males show greater variability in mileage, including very high-mileage outliers. Females are more consistent but still include a niche group of extreme runners.
- Females show a wider range of treadmill usage, while males are more consistent around 3–4 days/week.
- KP281 and KP481 have balanced gender distribution, while KP781 is strongly male-dominated (82.5% male buyers).

Product

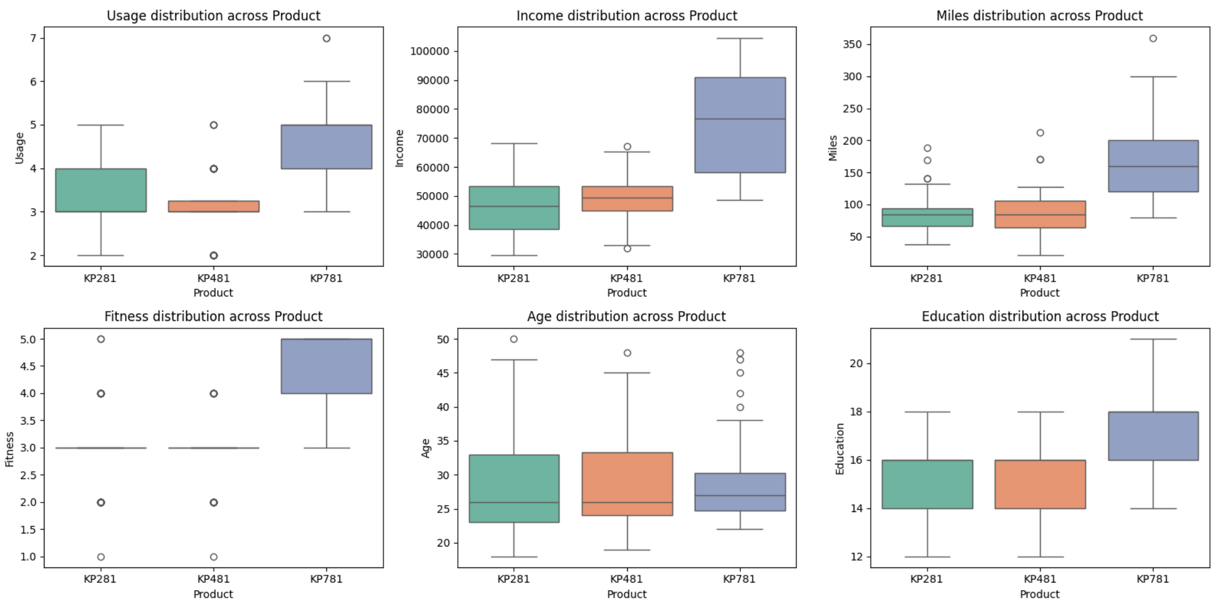
In [ ]:
```
sns.countplot(data=df, x="Product")
plt.title("Product Count")
plt.show()
```



KP281, which is the entry-level threadmill sells more than other two categories and we can also notice that quantity sold decreases when price increases.

In [ ]:
```
plt.figure(figsize=(16,8))

plt.subplot(2,3,1)
sns.boxplot(data=df, x="Product",y="Usage",hue="Product",palette="Set2")
plt.title("Usage distribution across Product")

plt.subplot(2,3,2)
sns.boxplot(data=df, x="Product",y="Income",hue="Product",palette="Set2")
plt.title("Income distribution across Product")


plt.subplot(2,3,3)
sns.boxplot(data=df, x="Product",y="Miles",hue="Product",palette="Set2")
plt.title("Miles distribution across Product")


plt.subplot(2,3,4)
sns.boxplot(data=df, x="Product",y="Fitness",hue="Product",palette="Set2")
plt.title("Fitness distribution across Product")


plt.subplot(2,3,5)
sns.boxplot(data=df, x="Product",y="Age",hue="Product",palette="Set2")
plt.title("Age distribution across Product")
```

```python
plt.subplot(2,3,6)
sns.boxplot(data=df, x="Product",y="Education",hue="Product",palette="Set2")
plt.title("Education distribution across Product")

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

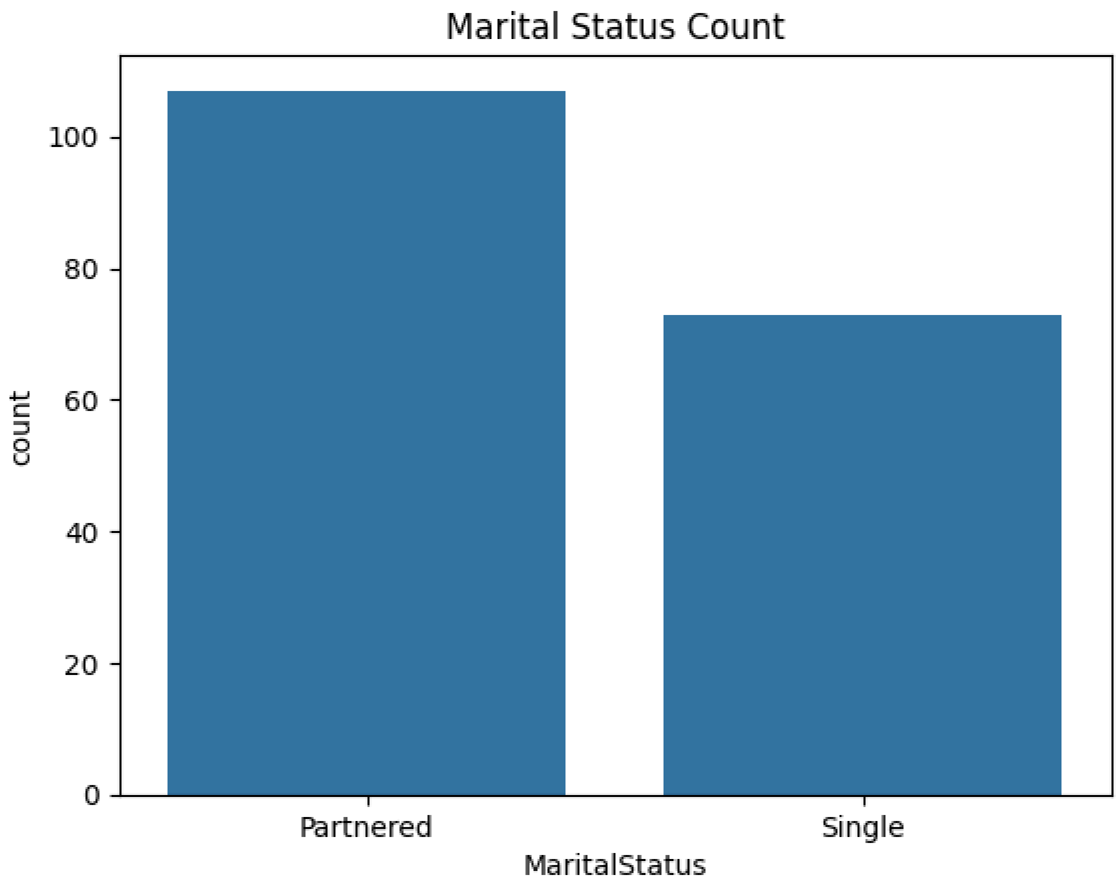


- KP781 customers have significantly higher median income (₹46k) and KP481 (~ ₹49k). This confirms Income as the key differentiator between product tiers.
- KP781 customers run far more miles (median ~ 160) compared to KP281/481 (~ 85 miles). Product choice clearly aligns with treadmill usage intensity.
- KP781 customers use treadmills ~ 5 days/week, while KP281/481 users average ~ 3 days/week. KP481 shows unusually tight clustering (very consistent usage).
- KP781 customers rate fitness higher (~ 4.6/5) than KP281/481 (~ 3/5), showing premium buyers are more fitness-conscious.

Marital Status

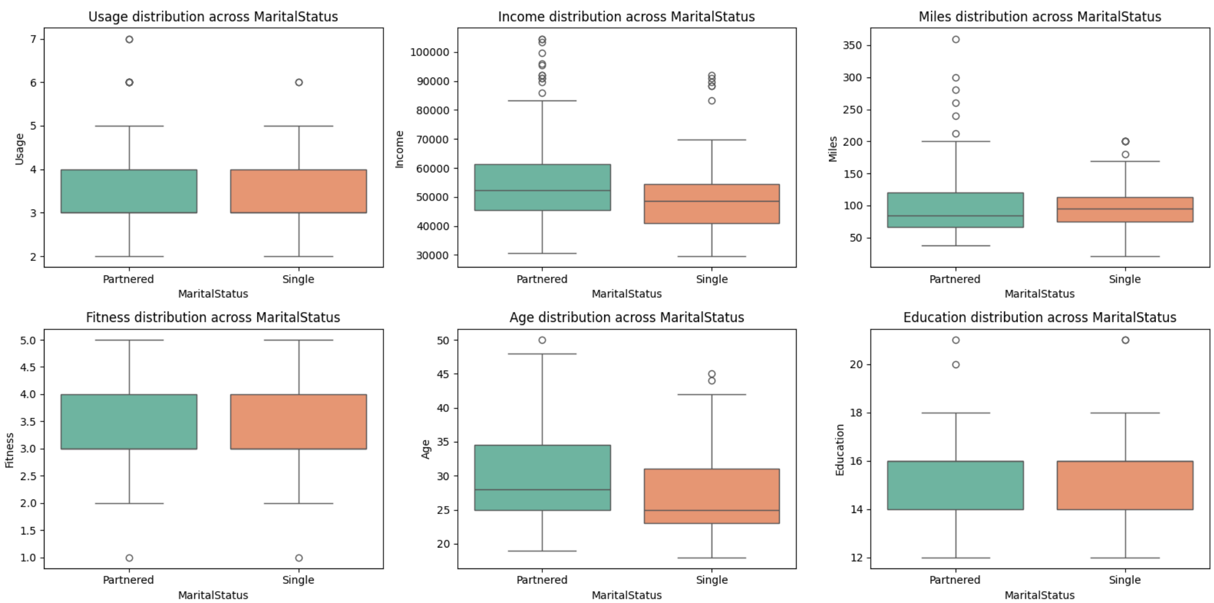
In [ ]:

```python
sns.countplot(data=df, x="MaritalStatus")
plt.title("Marital Status Count")
plt.show()
```




```
In [ ]: plt.figure(figsize=(16,8))

plt.subplot(2,3,1)
sns.boxplot(data=df, x="MaritalStatus",y="Usage",hue="MaritalStatus",palette
plt.title("Usage distribution across MaritalStatus")

plt.subplot(2,3,2)
sns.boxplot(data=df, x="MaritalStatus",y="Income",hue="MaritalStatus",palett
plt.title("Income distribution across MaritalStatus")


plt.subplot(2,3,3)
sns.boxplot(data=df, x="MaritalStatus",y="Miles",hue="MaritalStatus",palette
plt.title("Miles distribution across MaritalStatus")


plt.subplot(2,3,4)
sns.boxplot(data=df, x="MaritalStatus",y="Fitness",hue="MaritalStatus",palet
plt.title("Fitness distribution across MaritalStatus")


plt.subplot(2,3,5)
sns.boxplot(data=df, x="MaritalStatus",y="Age",hue="MaritalStatus",palette="
plt.title("Age distribution across MaritalStatus")


plt.subplot(2,3,6)
sns.boxplot(data=df, x="MaritalStatus",y="Education",hue="MaritalStatus",pal
```

```python
plt.title("Education distribution across MaritalStatus")

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



- All products show ~60% Partnered, ~40% Single. Marital status does not strongly influence treadmill choice.

Comments on Distributions and Relationship between the Variables

- Distributions show that most Aerofit customers are young adults with moderate fitness levels, treadmill usage (~ 3 days/week), and mileage (~ 80–120 miles/month). Income and Miles have wide ranges, revealing both budget and premium buyers, as well as casual and serious users.

- Relationship analysis highlights that treadmill Usage and Miles are strongly correlated, confirming logical consistency. Fitness ratings also positively relate to usage behavior. Income, while not strongly related to treadmill usage, is the key factor differentiating product choice, especially for KP781 buyers. Age and Education show little variation across products, suggesting limited influence on customer segmentation.

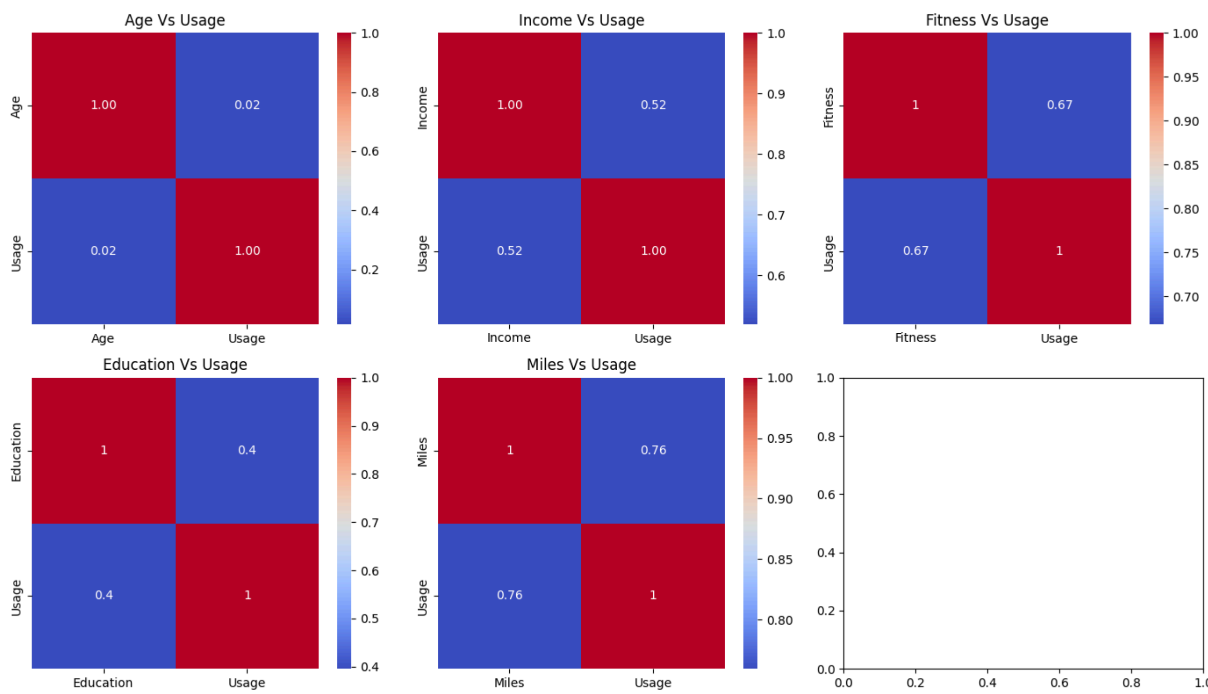
For Correlation (between continuous variables)

Age,Income,Fitness and Education Vs Usage Correlation

In [ ]:
```python
Age_usage = df[['Age','Usage']].corr()
Income_Usage = df[['Income','Usage']].corr()
```

```
Fitness_Usage = df[["Fitness",'Usage']].corr()
Education_Usage = df[["Education",'Usage']].corr()
Miles_Usage = df[["Miles",'Usage']].corr()
```

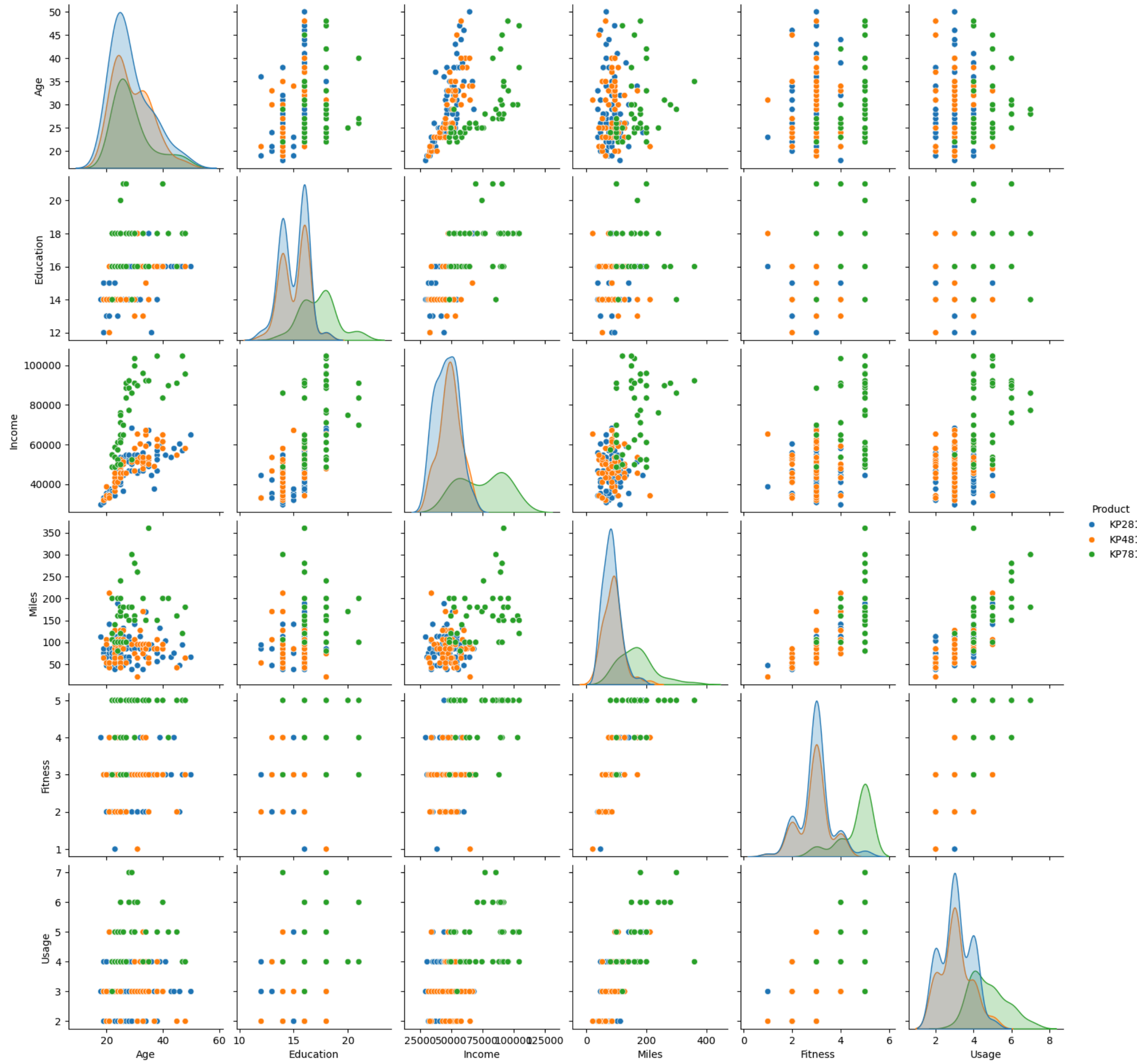
In [ ]:
```
fig,axes = plt.subplots(2,3,figsize=(14,8))

sns.heatmap(Age_usage,cmap='coolwarm',annot=True,fmt=".2f",ax= axes[0,0])
axes[0,0].set_title("Age Vs Usage")


sns.heatmap(Income_Usage,cmap='coolwarm',annot=True,fmt=".2f",ax= axes[0,1])
axes[0,1].set_title("Income Vs Usage")


sns.heatmap(Fitness_Usage,cmap='coolwarm',annot=True,ax= axes[0,2])
axes[0,2].set_title("Fitness Vs Usage")

sns.heatmap(Education_Usage,cmap='coolwarm',annot=True,ax= axes[1,0])
axes[1,0].set_title("Education Vs Usage")

sns.heatmap(Miles_Usage,cmap='coolwarm',annot=True,ax= axes[1,1])
axes[1,1].set_title("Miles Vs Usage")

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



Strong positive correlation between Usage and Miles (~0.7). Income is weakly correlated with Usage and Miles, confirming that higher income does not necessarily mean more treadmill use. Fitness moderately correlates with Usage.

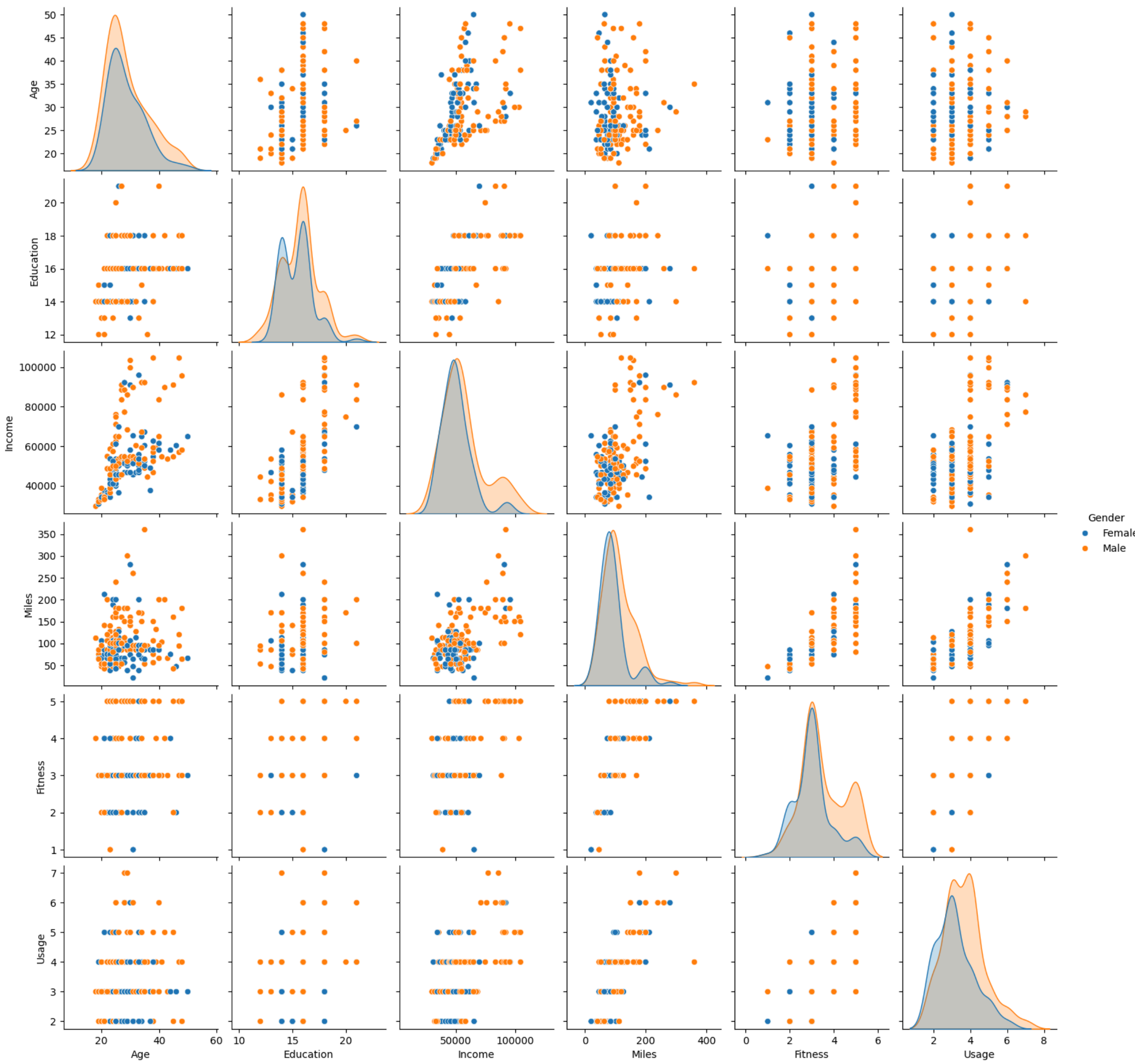
Corelation between variables across product category

In [91]:
```
sns.pairplot(data= df,vars= ['Age','Education','Income','Miles','Fitness','U
plt.show()
```



- By observing Diagonal density plots,we can see that Product differentiation is strongest by Income, Miles, Usage, Fitness, not by Age or Education.
- By observing Scatter Plots KP781 buyers are distinct: high income, high usage, high mileage, high fitness. KP281/481 overlap, targeting average customers.

In [ ]:
```
sns.pairplot(data= df,vars= ['Age','Education','Income','Miles','Fitness','U
plt.show()
```



- By observing Diagonal Density plots,we can notice that Gender differences appear mainly in Income and Miles. Other variables (Age, Education, Fitness, Usage) are balanced.
- By observing Scatter plots,we can see that Male customers dominate the extreme segments (very high income, very high mileage), while female customers are more consistent

4. Outliers detection

Outlier Check - Numeric columns

In [ ]:

```
def mean_median_outlier_check(df, cols=None, threshold_mild=0.3, threshold_s

    if cols is None:
```

```python
        cols = df.select_dtypes(include=[np.number]).columns.tolist()

    records = []
    for col in cols:
        desc = df[col].describe()
        mean_val = desc["mean"]
        median_val = desc["50%"]
        std_val = desc["std"]
        q1 = desc["25%"]
        q3 = desc["75%"]
        iqr = q3 - q1
        diff = abs(mean_val - median_val)

        ratio_std = diff / std_val if std_val > 0 else np.nan
        ratio_iqr = diff / iqr if iqr > 0 else np.nan

        # Flag based on std (primary)
        if ratio_std >= threshold_strong:
            flag = "Strong skew/outliers"
        elif ratio_std >= threshold_mild:
            flag = "Mild skew/outliers"
        else:
            flag = "Symmetric"

        records.append({
            "col": col,
            "mean": mean_val,
            "median": median_val,
            "std": std_val,
            "IQR": iqr,
            "mean-median": diff,
            "diff/std": ratio_std,
            "diff/IQR": ratio_iqr,
            "flag": flag
        })

    return pd.DataFrame(records)
```

In [ ]:

```python
numeric_cols = ["Age","Education","Usage","Fitness","Income","Miles"]

outlier_check = mean_median_outlier_check(df, cols=numeric_cols)
print(outlier_check)
```

```
         col          mean   median           std       IQR  mean-median  \
0        Age     28.788889     26.0      6.943498      9.00     2.788889   
1  Education     15.572222     16.0      1.617055      2.00     0.427778   
2      Usage      3.455556      3.0      1.084797      1.00     0.455556   
3    Fitness      3.311111      3.0      0.958869      1.00     0.311111   
4     Income  53719.577778  50596.5  16506.684226  14609.25  3123.077778   
5      Miles    103.194444     94.0     51.863605     48.75     9.194444   

   diff/std  diff/IQR                flag  
0  0.401655  0.309877  Mild skew/outliers  
1  0.264541  0.213889           Symmetric  
2  0.419945  0.455556  Mild skew/outliers  
3  0.324456  0.311111  Mild skew/outliers  
4  0.189201  0.213774           Symmetric  
5  0.177281  0.188604           Symmetric  
```

- Outlier detection using the mean–median method revealed mild skew in Age, **Usage, and Fitness**, suggesting the presence of customers who are significantly older, use the treadmill much more frequently, or report unusually high fitness levels compared to the majority.
- **Income, Education, and Miles** appeared symmetric overall, but Income and Miles showed group-level outliers when analyzed by Product and Gender, indicating that subgroup analysis provides more actionable insights than overall summary statistics.
- This analysis is done at dataset-level. Next we'll proceed with group-level because both perspectives matter.

Outlier Check - Group level

In [ ]:
```
df.groupby("Gender",observed=False).size()
```

Out[ ]:

	0
Gender	
Female	76
Male	104

dtype: int64

Since,our dataset has no missing values, df.groupby("Gender").size() is enough.

In [ ]:
```
df.groupby("Product",observed=False).size()
```

Out[ ]:

Product	0
KP281	80
KP481	60
KP781	40

dtype: int64

In [ ]:

```
df.groupby("MaritalStatus",observed=False).size()
```

Out[ ]:

MaritalStatus	0
Partnered	107
Single	73

dtype: int64

Very small groups (say < 20–30 rows) often don't give stable patterns in boxplots or summaries.But,None of the groups are too small. The smallest group is KP781 with 40 rows, which is still okay for analysis. That means all 3 categorical variables (Gender, Product, MaritalStatus) can be included for boxplots and bivariate analysis.

In [ ]:

```
cols = ["Age","Education","Usage","Fitness","Income","Miles"]
group_gender = "Gender"
Q1 = df.groupby(group_gender)[cols].quantile(0.25)
Q3 = df.groupby(group_gender)[cols].quantile(0.75)
IQR = Q3 - Q1
IQR
```

Out[ ]:

Gender	Age	Education	Usage	Fitness	Income	Miles
Female	9.00	2.0	2.0	0.0	10874.25	34.0
Male	10.25	2.0	1.0	1.0	16131.25	56.0

In [ ]:

```
cols = ["Age","Education","Usage","Fitness","Income","Miles"]
group_product = "Product"
Q1 = df.groupby(group_product)[cols].quantile(0.25)
Q3 = df.groupby(group_product)[cols].quantile(0.75)
IQR = Q3 - Q1
IQR
```

Out[ ]:

Product	Age	Education	Usage	Fitness	Income	Miles
KP281	10.00	2.0	1.00	0.0	14781.00	28.0
KP481	9.25	2.0	0.25	0.0	8527.50	42.0
KP781	5.50	2.0	1.00	1.0	32681.25	80.0

In [ ]:

```
cols = ["Age","Education","Usage","Fitness","Income","Miles"]
group_MaritalStatus = "MaritalStatus"
Q1 = df.groupby(group_MaritalStatus)[cols].quantile(0.25)
Q3 = df.groupby(group_MaritalStatus)[cols].quantile(0.75)
IQR = Q3 - Q1
IQR
```

Out[ ]:

MaritalStatus	Age	Education	Usage	Fitness	Income	Miles
Partnered	9.5	2.0	1.0	1.0	15722.0	54.0
Single	8.0	2.0	1.0	1.0	13644.0	38.0

In [ ]:

```
df.groupby("Gender")["Income"].median()
```

Out[ ]:

Gender	Income
Female	47754.0
Male	52302.0

dtype: float64

In [ ]:

```
df.groupby("Product")["Income"].median()
```

Out[ ]:

Product	Income
KP281	46617.0
KP481	49459.5
KP781	76568.5

dtype: float64

Gender

Usage & Miles show clear differences:

- Female customers show more variation in treadmill usage (IQR = 2) compared to males (IQR = 1).
- Male customers show wider spread in miles run (IQR = 56) compared to females (IQR = 34).
- Income has slightly higher variability among males (IQR = 16,131 vs 10,874), suggesting further segmentation by income might be useful for male customers.
- Age, Education, and Fitness did not show meaningful separation between genders and were excluded from further analysis.

Product

Strong differences observed across products:

- Income: Customers of KP781 have significantly higher median income (₹76k) compared to KP281 (₹46k) and KP481 (₹49k).
- Miles: KP781 customers run substantially more miles (IQR = 80) compared to KP281 (IQR = 28) and KP481 (IQR = 42).
- Usage: KP481 customers show very consistent treadmill usage (IQR = 0.25), indicating a specific user pattern.
- Age: KP781 customers have a narrower age range (IQR = 5.5) than other models, suggesting a more concentrated age group.

These insights highlight Income, Miles, Usage, and Age as key differentiators across products.

Marital Status

Income and Miles show slight differences:

- Partnered customers have marginally higher income (₹15.7k vs ₹13.6k) and run more miles (IQR = 54 vs 38).
- However, the overall differences between Partnered and Single customers are not strong enough to drive major business recommendations.
- Other variables (Age, Education, Fitness, Usage) did not show significant distinctions and were excluded.

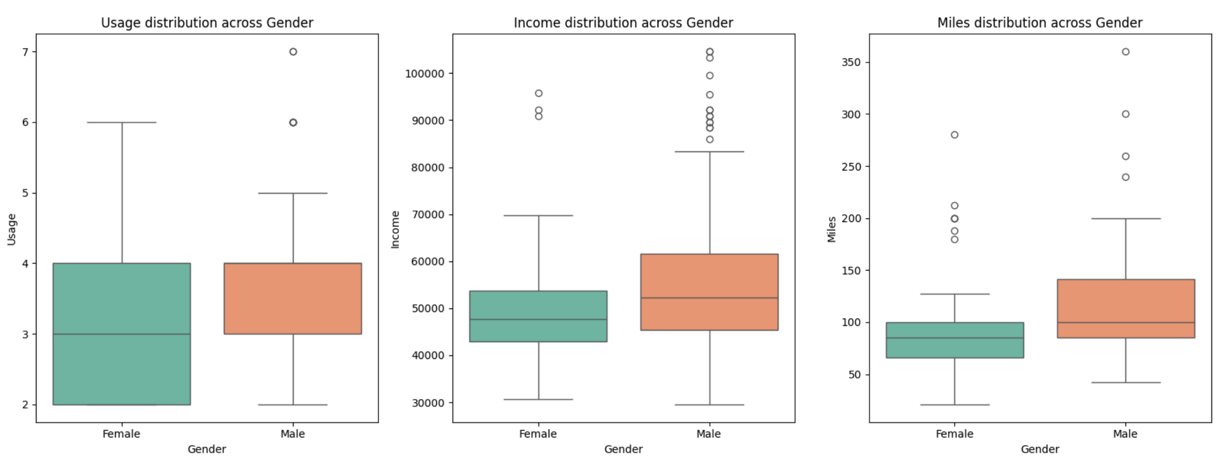
Hence from above analysis, we finalized boxplots where variability really matters.

1. **Gender** → Usage, Miles, (optionally Income).
2. **Product** → Income, Miles, Usage, Age.
3. **Marital Status** → Income, Miles (since only mild insights there).

Outlier detection was performed only on variables where group differences were meaningful (as identified in the boxplot analysis). This included Usage and Miles across Gender, and Income, Miles, Usage, and Age across Product. Other variables (such as Education or Fitness) were excluded, as they showed no significant group-level separation.

Gender - considered outliers

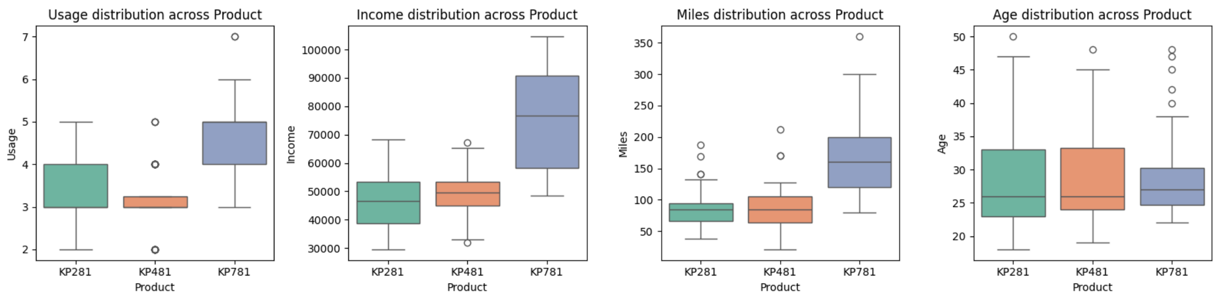
In [ ]:
```
fig,axes = plt.subplots(1,3,figsize=(16,6))

sns.boxplot(data=df, x="Gender",y="Usage",hue="Gender",palette="Set2",ax = a
axes[0].set_title("Usage distribution across Gender")


sns.boxplot(data=df, x="Gender",y="Income",hue="Gender",palette="Set2",ax = 
axes[1].set_title("Income distribution across Gender")

sns.boxplot(data=df, x="Gender",y="Miles",hue="Gender",palette="Set2",ax = a
axes[2].set_title("Miles distribution across Gender")

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



Product - considered outliers

In [ ]:

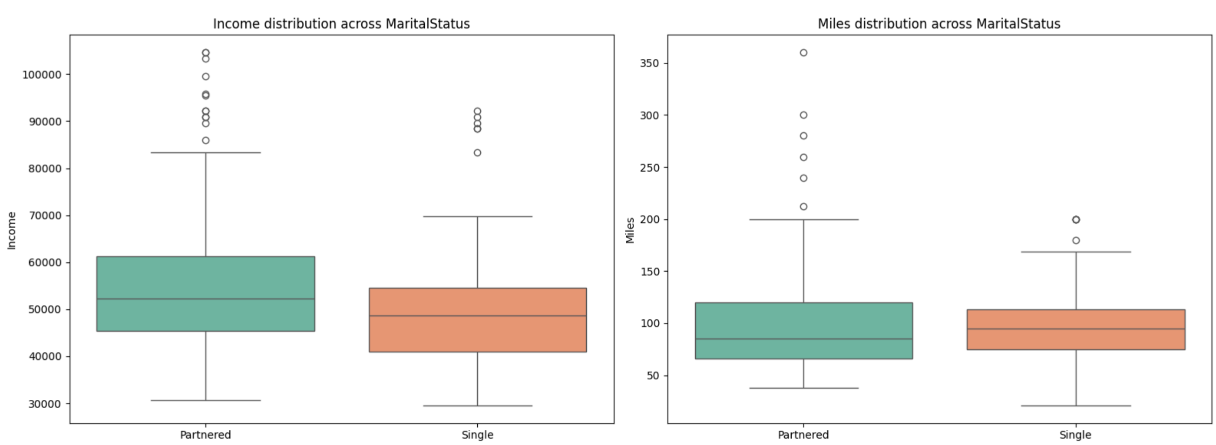
```
fig,axes = plt.subplots(1,4,figsize=(16,4))

sns.boxplot(data=df, x="Product",y="Usage",hue="Product",palette="Set2",ax =
axes[0].set_title("Usage distribution across Product")


sns.boxplot(data=df, x="Product",y="Income",hue="Product",palette="Set2",ax
axes[1].set_title("Income distribution across Product")

sns.boxplot(data=df, x="Product",y="Miles",hue="Product",palette="Set2",ax =
axes[2].set_title("Miles distribution across Product")

sns.boxplot(data=df, x="Product",y="Age",hue="Product",palette="Set2",ax = a
axes[3].set_title("Age distribution across Product")

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



Marital Status - considered outliers

In [ ]:

```
fig,axes = plt.subplots(1,2,figsize=(16,6))

sns.boxplot(data=df, x="MaritalStatus",y="Income",hue="MaritalStatus",palett
axes[0].set_title("Income distribution across MaritalStatus")

sns.boxplot(data=df, x="MaritalStatus",y="Miles",hue="MaritalStatus",palette
axes[1].set_title("Miles distribution across MaritalStatus")

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



Outliers Analysis

In [ ]:

```
def outlier_summary(df, group_col, value_cols, return_outlier_rows=False):

    records = []
    outliers_dict = {}

    grouped = df.groupby(group_col, observed=False)

    for gval, sub in grouped:
        n = len(sub)
        if n == 0:
            continue
        for col in value_cols:
            # skip if column not numeric
            if col not in sub.columns:
                raise KeyError(f"{col} not in dataframe")
            ser = sub[col].dropna()
            if ser.empty:
                q1 = q3 = iqr = lower = upper = np.nan
                out_cnt = 0
                out_rows = sub.iloc[0:0]  # empty
            else:
                q1 = ser.quantile(0.25)
                q3 = ser.quantile(0.75)
                iqr = q3 - q1
                lower = q1 - 1.5 * iqr
                upper = q3 + 1.5 * iqr
                is_out = (ser < lower) | (ser > upper)
                out_cnt = int(is_out.sum())
                out_rows = sub.loc[is_out.index[is_out].tolist()] if out_cnt

            out_pct = (out_cnt / n) * 100 if n > 0 else 0.0

            records.append({
                "group_col": group_col,
                "group_value": gval,
                "col": col,
                "n": n,
                "q1": q1,
                "q3": q3,
                "iqr": iqr,
                "lower": lower,
                "upper": upper,
                "outlier_count": out_cnt,
                "outlier_pct": out_pct
            })

            if return_outlier_rows:
                outliers_dict[(gval, col)] = sub.loc[is_out.index[is_out].to

    summary_df = pd.DataFrame.from_records(records,
                                           columns=["group_col","group_value"
    # optional sort
```

```
    summary_df = summary_df.sort_values(["col","group_value"]).reset_index(c

    if return_outlier_rows:
        return summary_df, outliers_dict
    return summary_df
```

Product level

In [ ]:
```
# Product
summary_product = outlier_summary(df, group_col="Product", value_cols=["Inco
display(summary_product)
```

	group_col	group_value	col	n	q1	q3	iqr	lower
0	Product	KP281	Age	80	23.00	33.00	10.00	8.000
1	Product	KP481	Age	60	24.00	33.25	9.25	10.125
2	Product	KP781	Age	40	24.75	30.25	5.50	16.500
3	Product	KP281	Income	80	38658.00	53439.00	14781.00	16486.500
4	Product	KP481	Income	60	44911.50	53439.00	8527.50	32120.250
5	Product	KP781	Income	40	58204.75	90886.00	32681.25	9182.875
6	Product	KP281	Miles	80	66.00	94.00	28.00	24.000
7	Product	KP481	Miles	60	64.00	106.00	42.00	1.000
8	Product	KP781	Miles	40	120.00	200.00	80.00	0.000
9	Product	KP281	Usage	80	3.00	4.00	1.00	1.500
10	Product	KP481	Usage	60	3.00	3.25	0.25	2.625
11	Product	KP781	Usage	40	4.00	5.00	1.00	2.500

- For **Age**, most groups were consistent, but KP781 had ~12.5% customers outside the typical age band, indicating a small minority segment of atypical age buyers.
- For **Income**, only KP481 showed a small fraction of outliers (~3%), suggesting a few customers purchase outside the core income group.
- For **Miles**, KP281 and KP481 each had ~5% of customers with unusually high/low mileage expectations, indicating a niche segment of heavy or light treadmill users.
- For **Usage**, KP481 showed ~48% flagged as outliers, but this is due to extremely narrow variability (IQR = 0.25). This suggests remarkably consistent treadmill usage among KP481 customers rather than true anomalies.

Gender level

In [ ]:
```
# Gender
summary_gender = outlier_summary(df, group_col="Gender", value_cols= ["Usage
display(summary_gender)
```

	group_col	group_value	col	n	q1	q3	iqr	lower
0	Gender	Female	Income	76	42921.75	53796.00	10874.25	26610.375
1	Gender	Male	Income	104	45480.00	61611.25	16131.25	21283.125
2	Gender	Female	Miles	76	66.00	100.00	34.00	15.000
3	Gender	Male	Miles	104	85.00	141.00	56.00	1.000
4	Gender	Female	Usage	76	2.00	4.00	2.00	-1.000
5	Gender	Male	Usage	104	3.00	4.00	1.00	1.500

- **Male**: 13.5% outliers → fairly large.A significant minority of males fall outside the main income range. This reinforces our earlier insight that male incomes are more variable, so segmentation (entry-level vs premium treadmills) makes sense.
- **Female**: 9.2% outliers → quite high. Some females run either unusually high or low mileage compared to the majority. This may point to a niche subgroup (e.g., serious female runners).
- **Usage**: Usage is mostly consistent, with only small deviations for Male which we can ignore.

Marital Status

In [ ]:
```
summary_marital = outlier_summary(df, group_col="MaritalStatus", value_cols=
display(summary_marital)
```

	group_col	group_value	col	n	q1	q3	iqr	lower	u
0	MaritalStatus	Partnered	Income	107	45480.0	61202.0	15722.0	21897.0	84
1	MaritalStatus	Single	Income	73	40932.0	54576.0	13644.0	20466.0	75
2	MaritalStatus	Partnered	Miles	107	66.0	120.0	54.0	-15.0	
3	MaritalStatus	Single	Miles	73	75.0	113.0	38.0	18.0	

- For **Income**, both Partnered (11.2%) and Single (8.2%) groups showed notable outliers, suggesting the presence of high-income individuals across both groups.

- For **Miles**, ~5–7% of customers in both groups had unusual mileage expectations. Since this pattern is balanced, it provides limited additional insight so it can be ignored.

5. Customer Profiling

Numeric variables

In [ ]:
```
df.groupby("Product")[["Age","Income","Miles","Usage","Fitness","Education"]
```

Out[ ]:

	Age			Income			
	mean	median	std	mean	median	std	mea
Product							
KP281	28.55	26.0	7.221452	46418.025	46617.0	9075.783190	82.78750
KP481	28.90	26.0	6.645248	48973.650	49459.5	8653.989388	87.93333
KP781	29.10	27.0	6.971738	75441.575	76568.5	18505.836720	166.90000

1. **Income:** KP781: ~75k (much higher, std 18k → wide spread), KP281/KP481: ~46–49k (lower, narrower spread). Clear signal: KP781 = premium, higher-income buyers.

2. **Miles:** KP781: 167 mean miles , ~2x KP 281/481 (83-88). KP781 users run way more → serious runners.

3. **Usage:** KP781: ~4.8 days/week vs ~3 days for KP281/481. KP781 = frequent users.

4. **Fitness:** KP781: ~4.6 vs ~3 for others. More fitness-conscious, likely advanced.

5. **Education:** KP781: ~17.3 years vs ~15 for others.More educated → higher-income link.

6. **Age:** All ~28–29 → not a big differentiator.

Categorical variables

In [ ]:
```
pd.crosstab(df["Product"], df["Gender"], normalize="index") * 100
```

Out[ ]:

Gender	Female	Male
Product		
KP281	50.000000	50.000000
KP481	48.333333	51.666667
KP781	17.500000	82.500000

In [ ]:
```
pd.crosstab(df["Product"], df["MaritalStatus"], normalize="index") * 100
```

Out[ ]:

MaritalStatus	Partnered	Single
Product		
KP281	60.0	40.0
KP481	60.0	40.0
KP781	57.5	42.5

1. **Gender:** KP781: 82.5% Male → heavily male-dominated.

   KP281 & KP481: ~50-50 split. Male customers drive premium product sales.

2. **Marital Status:** All ~60% Partnered, 40% Single → no strong difference.

Based on the above calculated descriptive analytics, Aerofit’s treadmills attract distinct customer segments:

1. **KP281**: Balanced gender distribution, moderate income (~₹46k), casual users with ~3 days/week usage. Best suited for general customers.

2. **KP481**: Similar to KP281 in age and income, but with more consistent usage patterns. Represents mid-tier buyers.

3. **KP781**: Premium segment — higher income (~ ₹75k), frequent users (~5 days/week, 167 miles/month), more educated, and predominantly male (82.5%). This product is strongly positioned for serious runners and high-income professionals.

6. Probability Analysis (Marginal & Conditional)

Marginal Probability

Here, we're going to consider probability of each product being purchased ignoring everything else.

In [ ]:
```
df["Product"].value_counts(normalize=True)*100
```

Out[ ]:

Product	proportion
KP281	44.444444
KP481	33.333333
KP781	22.222222

dtype: float64

KP281 is the most popular treadmill (~ 44%), while KP781 is niche (~ 22%), but higher-end.

Joint Probability

Product and Gender

In [ ]:
```
pd.crosstab(df["Product"],df["Gender"],normalize='all')*100
```

Out[ ]:

Gender Product	Female	Male
KP281	22.222222	22.222222
KP481	16.111111	17.222222
KP781	3.888889	18.333333

Conditional Probability

Gender given Product

In [ ]:
```
pd.crosstab(df['Product'],df['Gender'],normalize='index')* 100
```

Out[ ]:

Gender	Female	Male
Product		
KP281	50.000000	50.000000
KP481	48.333333	51.666667
KP781	17.500000	82.500000

Marital Status given Product

In [ ]:
```
pd.crosstab(df["Product"], df["MaritalStatus"], normalize="index") * 100
```

Out[ ]:

MaritalStatus	Partnered	Single
Product		
KP281	60.0	40.0
KP481	60.0	40.0
KP781	57.5	42.5

- Marginal: ~22% of customers buy KP781.
- Conditional: Among KP781 buyers, 82.5% are Male → clear male skew and married people tend to buy more than single in all the three product categories.

- **Marginal Probability** : KP281 is purchased by ~44% of customers, KP481 by ~33%, and KP781 by ~22%.
- **Conditional Probability (Gender):** Among KP781 buyers, ~82.5% are male, showing strong male dominance in premium product purchases. By contrast, KP281 and KP481 buyers are evenly split between genders.
- **Conditional Probability (Marital Status)**: For all products, ~60% of buyers are Partnered and ~40% Single, showing no strong difference.
- **Joint Probability**: Only ~4% of all customers are Female KP781 buyers, suggesting an opportunity to target premium female customers.

7. Insights and Recommendations for Aerofit

1. **KP281 (Entry-Level Product)**

- Profile: Attracts balanced gender split, moderate-income customers (~ ₹46k), with casual treadmill usage (~ 3 times/week).
- Probability: 44% marginal probability → most popular product.
- Action: Market KP281 as the default treadmill for average customers. Campaigns should highlight affordability and general fitness benefits.

2. **KP481 (Mid-Tier Product)**

- Profile: Similar age and income as KP281, but users show highly consistent usage behavior.
- Probability: 33% marginal probability → second most popular product.
- Action: Position KP481 as a reliable, steady-use treadmill for disciplined users. Emphasize durability and stability in marketing.

3. **KP781 (Premium Product)**

- Profile: Higher-income (~ ₹75k), highly educated (~ 17 yrs), heavy users (~ 5 days/week, ~ 167 miles/month), fitness-conscious (~ 4.6/5). Predominantly male (82.5%).
- Probability: Only 22% marginal probability → niche but valuable.
- Action:
  - Target Segment: Focus sales on high-income male customers who are serious runners.
  - Growth Opportunity: Very few female customers buy KP781 (~4% of all customers). Aerofit can develop female-focused campaigns (e.g., “premium fitness for women athletes”) to grow this untapped segment.

4. **Marital Status**

- Analysis shows little difference across products (~60% Partnered vs ~40% Single for all treadmills).
- Action: Marital status should not be used as a key segmentation factor in marketing strategies.