In [1]:
```
print("Hello Scaler Team,","\n")
print("I am working on Bussiness case : Aerofit - Descriptive Statistics & Probability")
```

```
Hello Scaler Team,

I am working on Bussiness case : Aerofit - Descriptive Statistics & Probability
```

In [2]:
```
# Problem Statement:
# Aerofit Treadmill Customer Analysis - To identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of t
```

In [3]:
```
# Objective:
# To identify customer characteristics for each treadmill model and create detailed customer profiles that will help Aerofit provide better product recommendations to new customers base
# 1.Analyze customer data to find patterns between customer attributes and the treadmill models they purchase
# 2.Use descriptive statistics and probability calculations to create detailed customer profiles for each product (KP281, KP481, KP781)
# 3.Provide actionable insights for targeted marketing and personalized recommendations to improve sales effectiveness
```

In [4]:
```
# STEP 1 : Importing Libraries & Loading Data
```

In [5]:
```
## Importing required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

## Set style for better looking plots
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")

## Display all columns in pandas
pd.set_option('display.max_columns', None)
```

In [6]:
```
## Load the dataset

df = pd.read_csv('dataset_aerofit.csv')

## Displaying first 10 rows to verify loading Sucessfull
print("First 10 rows of the dataset:")
display(df.head(10))

## Display last 5 rows to check consistency
print("\n""Last 5 rows of the dataset:")
display(df.tail())
```

```
First 10 rows of the 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
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
9	KP281	21	Female	15	Partnered	2	3	37521	85

```
Last 5 rows of the dataset:
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
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

In [7]:

```
# STEP 2 : Examining the Dataset Structure
```

In [8]:

```
# Shows rows, columns, data types, non-null counts

print("="*80)
print("DATASET INFORMATION:")
print("="*80)
print(f"Total Records: {df.shape[0]}")
print(f"Total Columns: {df.shape[1]}")
print("-"*80)
print("\nColumn Names:", list(df.columns))
print("\nDataset Info:")
df.info()
print("="*80)
```

```
================================================================================
DATASET INFORMATION:
================================================================================
Total Records: 180
Total Columns: 9
--------------------------------------------------------------------------------

Column Names: ['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage', 'Fitness', 'Income', 'Miles']

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
================================================================================
```

In [9]:

```
# Checking data types for each column

print("\n" + "="*80)
print("DATA TYPES CHECK:")
print("="*80)
print("Current data types:")
print(df.dtypes)
print("-"*80)

# Identifiying
# a.categorical  &
# b.numerical columns:
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

print(f"\nCategorical Columns: {categorical_cols}")
print(f"Numerical Columns: {numerical_cols}")
print("-"*80)
```

```
================================================================================
DATA TYPES CHECK:
================================================================================
Current data types:
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
--------------------------------------------------------------------------------

Categorical Columns: ['Product', 'Gender', 'MaritalStatus']
Numerical Columns: ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
--------------------------------------------------------------------------------
```

In [10]:

```
# Converting appropriate columns to 'category' data type
# Categorical data type saves memory and makes analysis faster
# columns to convert are  Gender, MaritalStatus, Product (limited unique values)

categorical_columns_to_convert = ['Product', 'Gender', 'MaritalStatus']
df[categorical_columns_to_convert] = df[categorical_columns_to_convert].astype('category')

print("After converting to category data type:")
print("="*80)
print(df[categorical_columns_to_convert].dtypes)

#display(df.head(10) )
```

```
After converting to category data type:
================================================================================
Product          category
Gender           category
MaritalStatus    category
dtype: object
```

In [11]:

```
# Step 3: Check for Missing Values
```

In [12]:

```
# Checking for missing values here- (chkg data quality)

print("="*80)
print("MISSING VALUES CHECK:")
print("="*80)
missing_values = df.isnull().sum()
missing_percentage = (df.isnull().sum() / len(df)) * 100

missing_df = pd.DataFrame({'Missing Values': missing_values,'Percentage %': missing_percentage})
print(missing_df)
```

```
================================================================================
MISSING VALUES CHECK:
================================================================================
               Missing Values  Percentage %
Product                     0           0.0
Age                         0           0.0
Gender                      0           0.0
Education                   0           0.0
MaritalStatus               0           0.0
Usage                       0           0.0
Fitness                     0           0.0
Income                      0           0.0
Miles                       0           0.0
```

In [13]:
```python
# Step 4: Statistical Summary
```

In [14]:
```python
# Statistical summary (numerical columns)

print("="*80)
print("STATISTICAL SUMMARY - NUMERICAL COLUMNS:")
print("="*80)
display(df.describe().T)

# Statistical summary (categorical columns)
print("\n" + "="*80)
print("STATISTICAL SUMMARY - CATEGORICAL COLUMNS:")
print("="*80)
categorical_summary = pd.DataFrame({
    'Unique Values': df[categorical_columns_to_convert].nunique(),
    'Most Common': df[categorical_columns_to_convert].mode().iloc[0].values,
    'Frequency of Most Common': [df[col].value_counts().iloc[0] for col in categorical_columns_to_convert]
}, index=categorical_columns_to_convert)
display(categorical_summary)

print("-"*80)
```

```
================================================================================
STATISTICAL SUMMARY - NUMERICAL COLUMNS:
================================================================================
```

	count	mean	std	min	25%	50%	75%	max
Age	180.0	28.788889	6.943498	18.0	24.00	26.0	33.00	50.0
Education	180.0	15.572222	1.617055	12.0	14.00	16.0	16.00	21.0
Usage	180.0	3.455556	1.084797	2.0	3.00	3.0	4.00	7.0
Fitness	180.0	3.311111	0.958869	1.0	3.00	3.0	4.00	5.0
Income	180.0	53719.577778	16506.684226	29562.0	44058.75	50596.5	58668.00	104581.0
Miles	180.0	103.194444	51.863605	21.0	66.00	94.0	114.75	360.0

```
================================================================================
STATISTICAL SUMMARY - CATEGORICAL COLUMNS:
================================================================================
```

	Unique Values	Most Common	Frequency of Most Common
Product	3	KP281	80
Gender	2	Male	104
MaritalStatus	2	Partnered	107

```
--------------------------------------------------------------------------------
```

In [15]:
```
# Step 5:Non-Graphical Analysis - Value Counts & Unique Attributes
```

In [16]:
```
# Value counts (each categorical variable)

print("="*80)
print("VALUE COUNTS FOR EACH CATEGORICAL VARIABLE:")
print("="*80)

for col in categorical_columns_to_convert:
    print(f"\n{col}:")
    value_counts = df[col].value_counts()
    percentages = (df[col].value_counts(normalize=True) * 100).round(2)
    summary_df = pd.DataFrame({
        'Count': value_counts,
        'Percentage': percentages
    })
    display(summary_df)
    print("-" * 40)
```

```
================================================================================
VALUE COUNTS FOR EACH CATEGORICAL VARIABLE:
================================================================================

Product:
```

Product	Count	Percentage
KP281	80	44.44
KP481	60	33.33
KP781	40	22.22

```
----------------------------------------

Gender:
```

Gender	Count	Percentage
Male	104	57.78
Female	76	42.22

```
----------------------------------------

MaritalStatus:
```

	Count	Percentage
MaritalStatus		
Partnered	107	59.44
Single	73	40.56

```
----------------------------------------
```

In [17]:
```
# Step 6: Unique Values in Each Column
```

In [18]:
```
# Checking  unique values in each column

print("\n" + "="*80)
print("UNIQUE VALUES IN EACH COLUMN:")
print("="*80)

for column in df.columns:
    unique_vals = df[column].unique() if df[column].nunique() <= 10 else f"{df[column].nunique()} unique values"
    print(f"{column}: {unique_vals}")
    if df[column].nunique() <= 10 and df[column].dtype != 'float64':
        print(f"   Values: {sorted(df[column].unique())}")
    print()
```

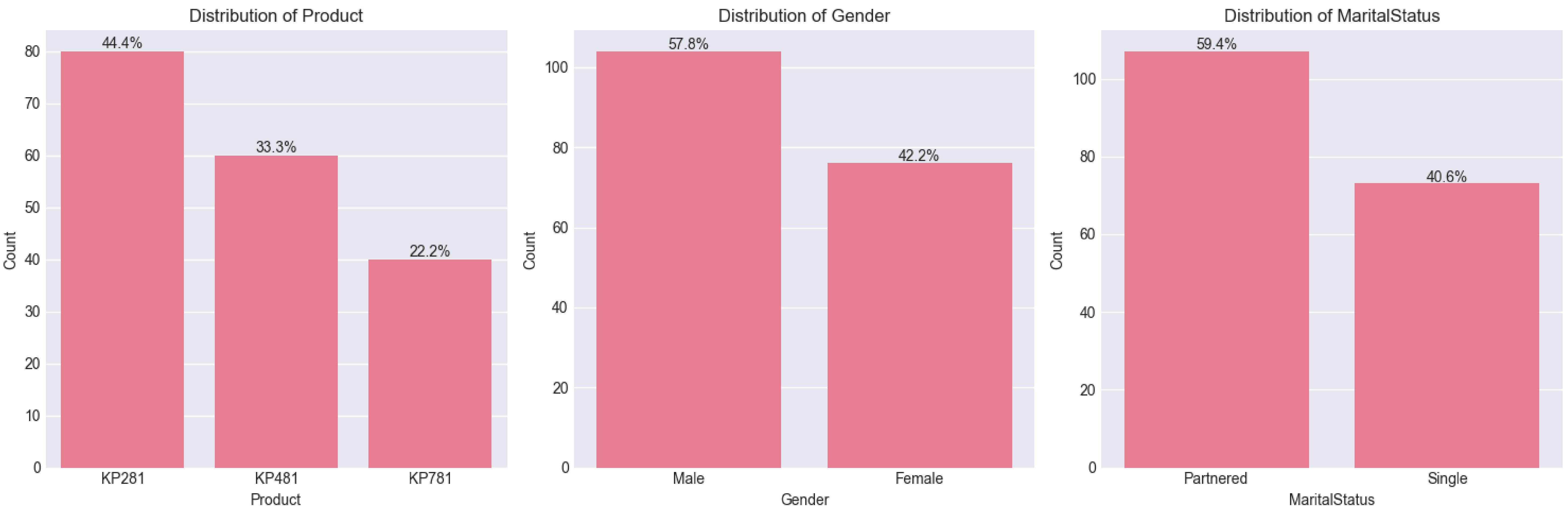
```
================================================================================
UNIQUE VALUES IN EACH COLUMN:
================================================================================
Product: ['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
   Values: ['KP281', 'KP481', 'KP781']

Age: 32 unique values

Gender: ['Male', 'Female']
Categories (2, object): ['Female', 'Male']
   Values: ['Female', 'Male']

Education: [14 15 12 13 16 18 20 21]
   Values: [np.int64(12), np.int64(13), np.int64(14), np.int64(15), np.int64(16), np.int64(18), np.int64(20), np.int64(21)]

MaritalStatus: ['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
   Values: ['Partnered', 'Single']

Usage: [3 2 4 5 6 7]
   Values: [np.int64(2), np.int64(3), np.int64(4), np.int64(5), np.int64(6), np.int64(7)]

Fitness: [4 3 2 1 5]
   Values: [np.int64(1), np.int64(2), np.int64(3), np.int64(4), np.int64(5)]

Income: 62 unique values

Miles: 37 unique values
```

In [19]:
```
# Step 7: Visual Analysis - Univariate (Single Variable)
```

In [20]:
```
# Univariate analysis (categorical variables) - Counting Plots
# The goal is to describe, summarize, or understand the distribution of that one variable. "categorical"
```

```
print("\n" + "="*80)
print("UNIVARIATE ANALYSIS - CATEGORICAL VARIABLES:")
print("="*80)

fig, axes = plt.subplots(1, 3, figsize=(15, 5))


for idx, col in enumerate(categorical_columns_to_convert):
    sns.countplot(data=df, x=col, ax=axes[idx], order=df[col].value_counts().index)
    axes[idx].set_title(f'Distribution of {col}')
    axes[idx].set_xlabel(col)
    axes[idx].set_ylabel('Count')
    # Adding percentage labels on the bars

    total = len(df[col])
    for p in axes[idx].patches:
        percentage = f'{100 * p.get_height()/total:.1f}%'
        x = p.get_x() + p.get_width() / 2
        y = p.get_height() + 0.5
        axes[idx].annotate(percentage, (x, y), ha='center')


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

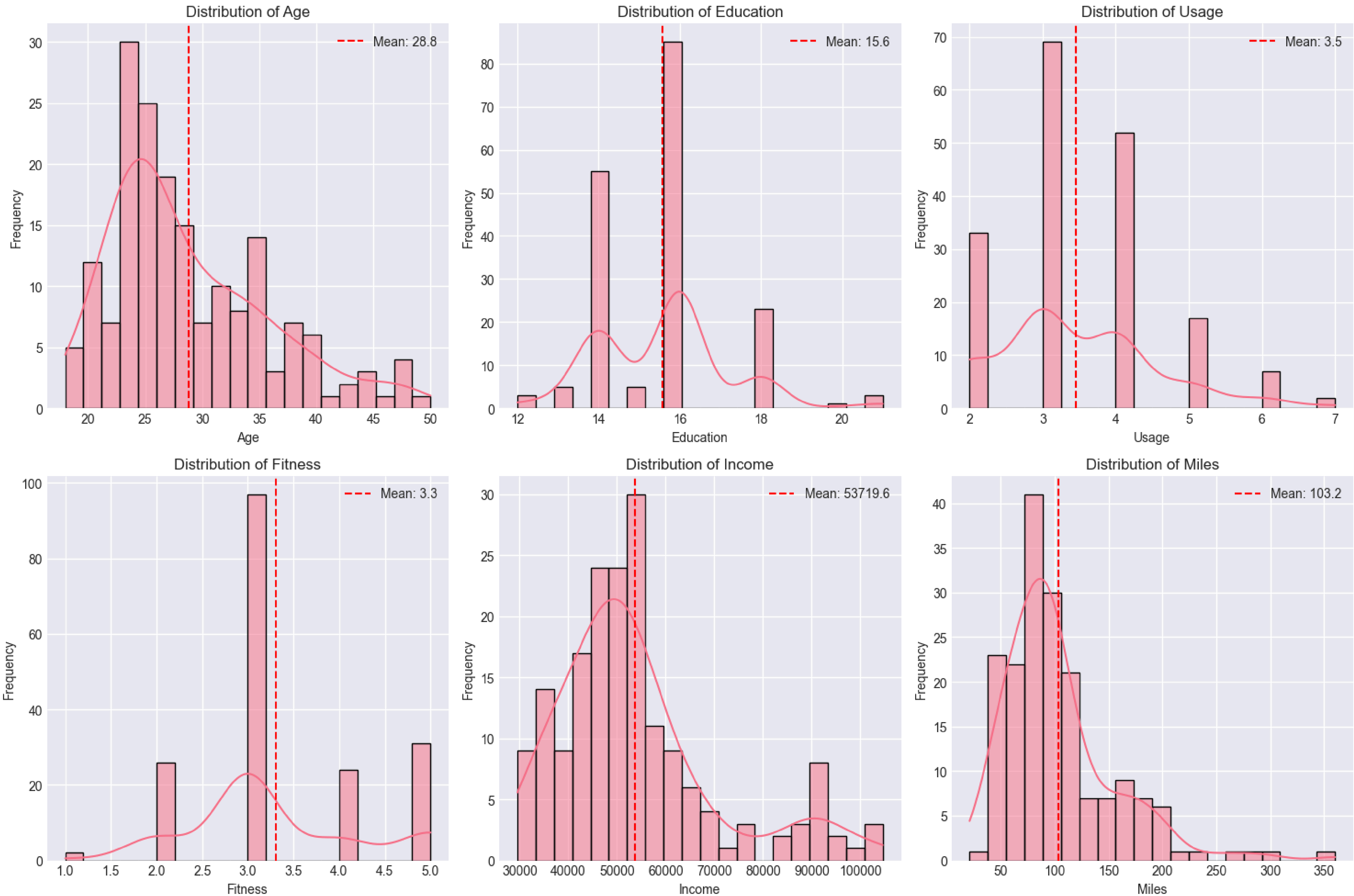
```
================================================================================
UNIVARIATE ANALYSIS - CATEGORICAL VARIABLES:
================================================================================
```



In [21]:
```
# UNIVARIATE ANALYSIS - Summary (Above)
# KP281 is the most popular model at 44%, showing that entry-level treadmills have the market appeal.
# More female customers (58%) than male (42%), suggesting Aerofit products appeal more to women overall.
# Most customers are partnered (59% vs 41% single), indicating treadmills might be purchased more for family or shared household use.
```

In [22]:
```python
# Univariate analysis (numerical variables) - using Histogram
# The goal is to describe, summarize, or understand the distribution of that one variable - "numerical"
# Univariate = one variable, focus on distribution.

print("\n" + "="*80)
print("UNIVARIATE ANALYSIS - NUMERICAL VARIABLES:")
print("="*80)

numerical_for_hist = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

fig, axes = plt.subplots(2, 3, figsize=(15, 10))
axes = axes.flatten()

for idx, col in enumerate(numerical_for_hist):
    # Ploting histogram with KDE (Kernel Density Estimate)
    sns.histplot(data=df, x=col, kde=True, ax=axes[idx], bins=20)
    axes[idx].set_title(f'Distribution of {col}')
    axes[idx].set_xlabel(col)
    axes[idx].set_ylabel('Frequency')
    # vertical line for mean
    mean_val = df[col].mean()
    axes[idx].axvline(mean_val, color='red', linestyle='--', label=f'Mean: {mean_val:.1f}')
    axes[idx].legend()

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

```
================================================================================
UNIVARIATE ANALYSIS - NUMERICAL VARIABLES:
================================================================================
```

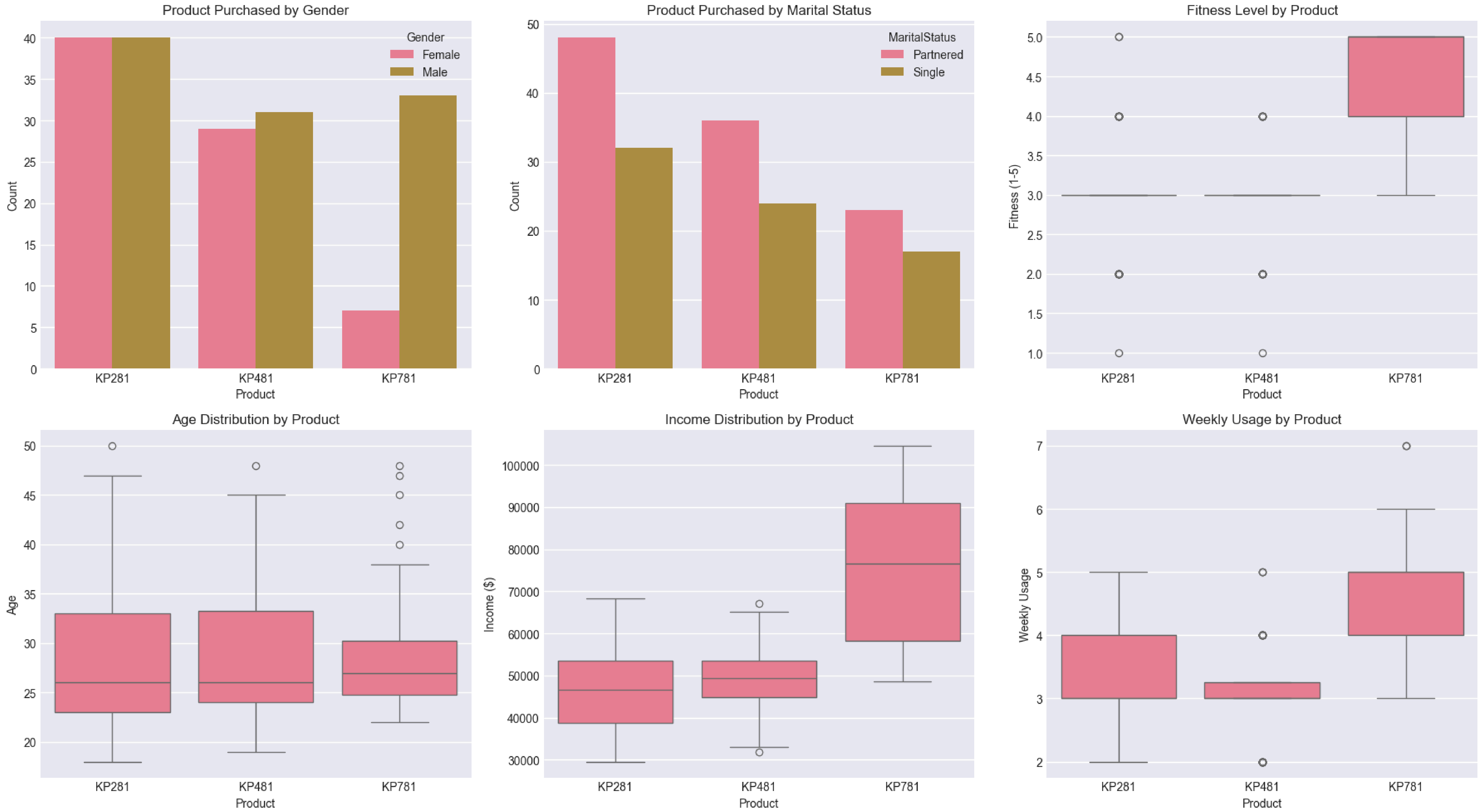


In [23]:
```
# univariate analysis - Summary (Above)

# Age distribution is normal: Most customers are in their 20s-30s (mean 28.8)
# Income varies widely: shows most customers earn $40K-$60K, but there's a long tail of higher earners that could be targeted for premium models.
# Fitness selfratings: The average fitness of 3.3/5 suggests customers are moderately active, with fewer at the extremes (very unfit)
# Education : Most customers have approx 16 years of education
```

In [24]:
```
# Step 8: Visual Analysis - Bivariate (Two Variables)
```

In [25]:
```
# Bivariate analysis: Product vs Other Variables
# The goal is to see how one variable changes with respect to another.(relationship)
# Bivariate = two variables, focus on relationship.

print("\n" + "="*80)
print("BIVARIATE ANALYSIS - PRODUCT VS OTHER VARIABLES:")
print("="*80)

# Product vs Gender
fig, axes = plt.subplots(2, 3, figsize=(18, 10))

# Plot 1: Product vs Gender
sns.countplot(data=df, x='Product', hue='Gender', ax=axes[0,0])
axes[0,0].set_title('Product Purchased by Gender')
axes[0,0].set_xlabel('Product')
axes[0,0].set_ylabel('Count')

# Plot 2: Product vs Marital Status
sns.countplot(data=df, x='Product', hue='MaritalStatus', ax=axes[0,1])
axes[0,1].set_title('Product Purchased by Marital Status')
axes[0,1].set_xlabel('Product')
axes[0,1].set_ylabel('Count')

# Plot 3: Product vs Fitness Level
sns.boxplot(data=df, x='Product', y='Fitness', ax=axes[0,2])
axes[0,2].set_title('Fitness Level by Product')
axes[0,2].set_xlabel('Product')
axes[0,2].set_ylabel('Fitness (1-5)')

# Plot 4: Product vs Age
sns.boxplot(data=df, x='Product', y='Age', ax=axes[1,0])
axes[1,0].set_title('Age Distribution by Product')
axes[1,0].set_xlabel('Product')
axes[1,0].set_ylabel('Age')

# Plot 5: Product vs Income
sns.boxplot(data=df, x='Product', y='Income', ax=axes[1,1])
axes[1,1].set_title('Income Distribution by Product')
axes[1,1].set_xlabel('Product')
axes[1,1].set_ylabel('Income ($)')

# Plot 6: Product vs Usage
sns.boxplot(data=df, x='Product', y='Usage', ax=axes[1,2])
axes[1,2].set_title('Weekly Usage by Product')
axes[1,2].set_xlabel('Product')
axes[1,2].set_ylabel('Weekly Usage')

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

```
================================================================================
BIVARIATE ANALYSIS - PRODUCT VS OTHER VARIABLES:
================================================================================
```



In [26]:

```
# BIvariate Analysis Summary (Above) :

# Gender segmentation is clear: The top-left chart shows females prefer KP281, males dominate KP781, and KP481 has more balanced gender distribution. This is one of your strongest patte
# Income is the strongest predictor: The middle-bottom chart clearly shows KP781 buyers have much higher incomes than other groups, with almost no overlap in income ranges between produ
# Fitness level increases with product tier: The top-right chart shows KP781 buyers rate themselves as most fit (mostly 4-5), while KP281 buyers are least fit (mostly 3-4).
# Age differences are minimal: The bottom-left chart shows all three products have similar age ranges, with only slight variations - age isn't a major differentiator.
# Usage patterns align with product tiers: The bottom-right chart shows KP781 buyers plan highest weekly usage (mostly 4-5 times), while KP281 buyers plan lowest usage (mostly 2-3 times
```

In [27]:

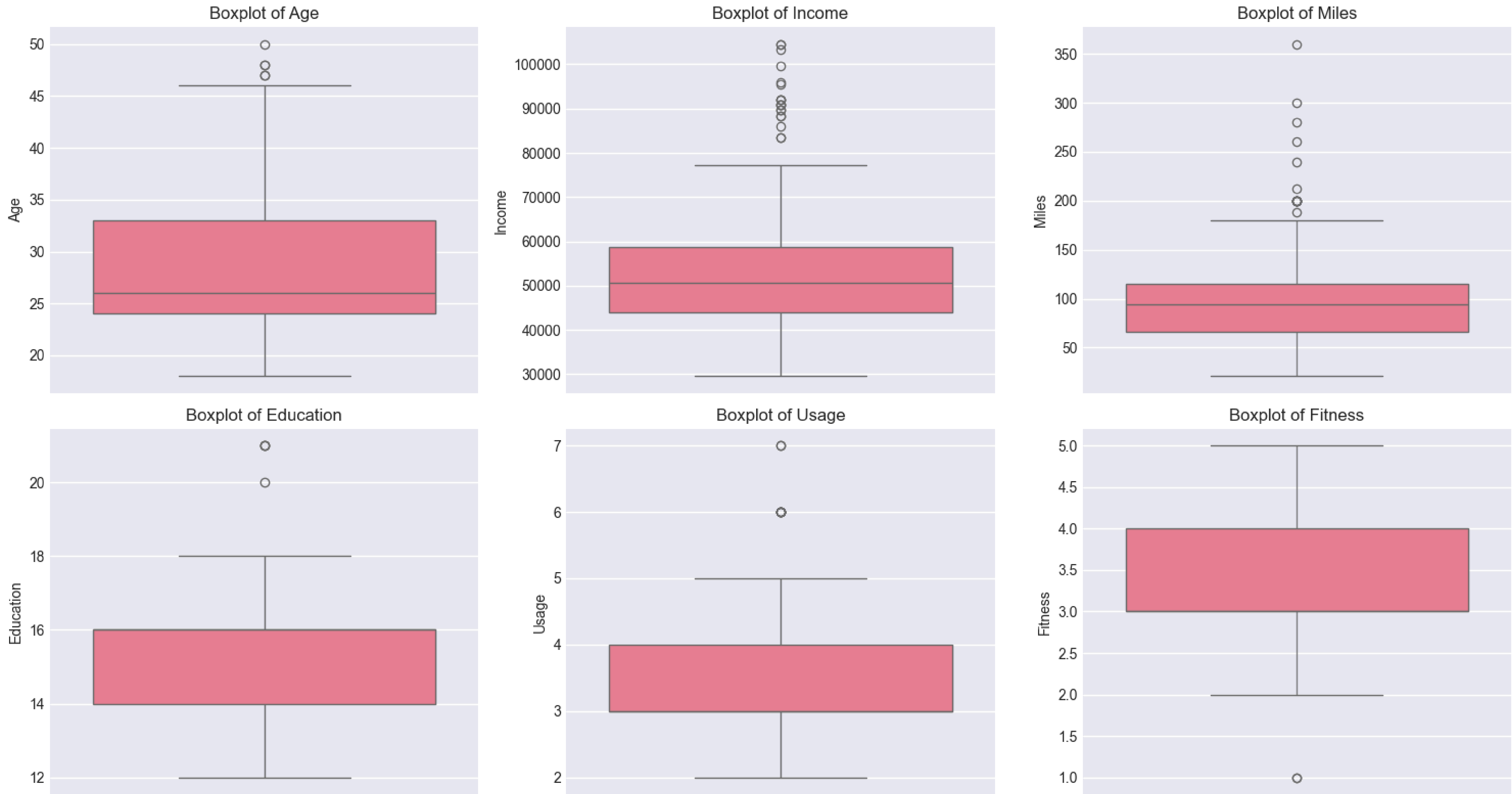
```
# Step 9: Outlier Detection
```

In [28]:

```
# Detecting outliers using boxplots for numerical variables


print("\n" + "="*80)
```

```python
print("OUTLIER DETECTION USING BOXPLOTS:")
print("="*80)

fig, axes = plt.subplots(2, 3, figsize=(15, 8))
axes = axes.flatten()

for idx, col in enumerate(['Age', 'Income', 'Miles', 'Education', 'Usage', 'Fitness']):
    sns.boxplot(data=df, y=col, ax=axes[idx])
    axes[idx].set_title(f'Boxplot of {col}')
    axes[idx].set_ylabel(col)

    # Calculating IQR for outlier detection
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]

    print(f"{col}:")
    print(f"  Potential outliers (<{lower_bound:.1f} or >{upper_bound:.1f}): {len(outliers)}")
    if len(outliers) > 0:
        print(f"  Outlier values: {sorted(outliers[col].unique().tolist())}")
    print()

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

```
================================================================================
OUTLIER DETECTION USING BOXPLOTS:
================================================================================
Age:
  Potential outliers (<10.5 or >46.5): 5
  Outlier values: [47, 48, 50]

Income:
  Potential outliers (<22144.9 or >80581.9): 19
  Outlier values: [83416, 85906, 88396, 89641, 90886, 92131, 95508, 95866, 99601, 103336, 104581]

Miles:
  Potential outliers (<-7.1 or >187.9): 13
  Outlier values: [188, 200, 212, 240, 260, 280, 300, 360]

Education:
  Potential outliers (<11.0 or >19.0): 4
  Outlier values: [20, 21]

Usage:
  Potential outliers (<1.5 or >5.5): 9
  Outlier values: [6, 7]

Fitness:
  Potential outliers (<1.5 or >5.5): 2
  Outlier values: [1]
```



In [29]:
```
# Step 10: Probability Questions
```

In [30]:
```
# Answer specific business questions
print("\n" + "="*80)
print("ANSWERING SPECIFIC BUSINESS QUESTIONS:")
print("="*80)

# Q1: What is the probability of a male customer buying a KP781 treadmill?
male_kp781 = len(df[(df['Gender'] == 'Male') & (df['Product'] == 'KP781')])
total_males = len(df[df['Gender'] == 'Male'])
prob_male_kp781 = (male_kp781 / total_males) * 100

print(f"Q1: Probability of a male customer buying KP781:")
print(f"   Number of males buying KP781: {male_kp781}")
print(f"   Total male customers: {total_males}")
print(f"   Probability: {prob_male_kp781:.2f}%")
```

```python
print()

# Q2: What is the probability of a customer with income > $50000 buying KP781?
high_income_kp781 = len(df[(df['Income'] > 50000) & (df['Product'] == 'KP781')])
total_high_income = len(df[df['Income'] > 50000])
prob_high_income_kp781 = (high_income_kp781 / total_high_income) * 100

print(f"Q2: Probability of customer with income > $50K buying KP781:")
print(f"   High income customers buying KP781: {high_income_kp781}")
print(f"   Total high income customers: {total_high_income}")
print(f"   Probability: {prob_high_income_kp781:.2f}%")
print()

# Q3: What is the probability of a fitness level 4 or 5 customer buying KP781?
fit_kp781 = len(df[(df['Fitness'] >= 4) & (df['Product'] == 'KP781')])
total_fit = len(df[df['Fitness'] >= 4])
prob_fit_kp781 = (fit_kp781 / total_fit) * 100

print(f"Q3: Probability of fitness level 4-5 customer buying KP781:")
print(f"   Fit customers buying KP781: {fit_kp781}")
print(f"   Total fit customers (level 4-5): {total_fit}")
print(f"   Probability: {prob_fit_kp781:.2f}%")
```

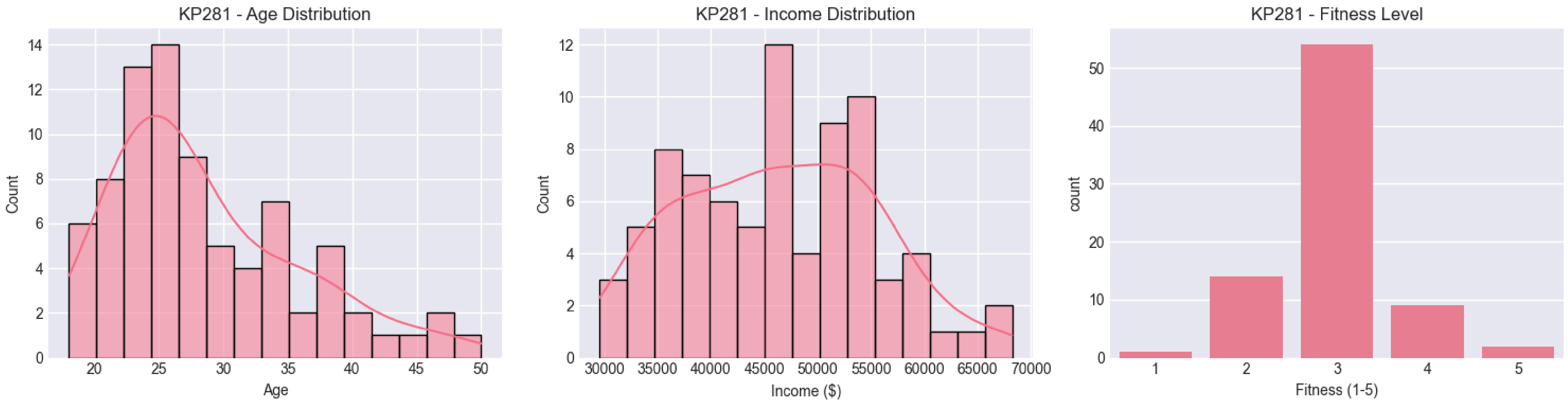
```
================================================================================
ANSWERING SPECIFIC BUSINESS QUESTIONS:
================================================================================
Q1: Probability of a male customer buying KP781:
   Number of males buying KP781: 33
   Total male customers: 104
   Probability: 31.73%

Q2: Probability of customer with income > $50K buying KP781:
   High income customers buying KP781: 35
   Total high income customers: 97
   Probability: 36.08%

Q3: Probability of fitness level 4-5 customer buying KP781:
   Fit customers buying KP781: 36
   Total fit customers (level 4-5): 55
   Probability: 65.45%
```

In [31]:
```python
# Step 11: Customer Profiling
```

In [32]:
```python
# customer profiling for each product
print("\n" + "="*80)
print("CUSTOMER PROFILES FOR EACH TREADMILL PRODUCT:")
print("="*80)

products = df['Product'].unique()

for product in products:
    product_data = df[df['Product'] == product]

    print(f"\n{'='*60}")
    print(f"CUSTOMER PROFILE FOR {product}:")
    print(f"{'='*60}")

    # Basic statistics
    print(f"\nSample Size: {len(product_data)} customers ({len(product_data)/len(df)*100:.1f}% of total)")
```

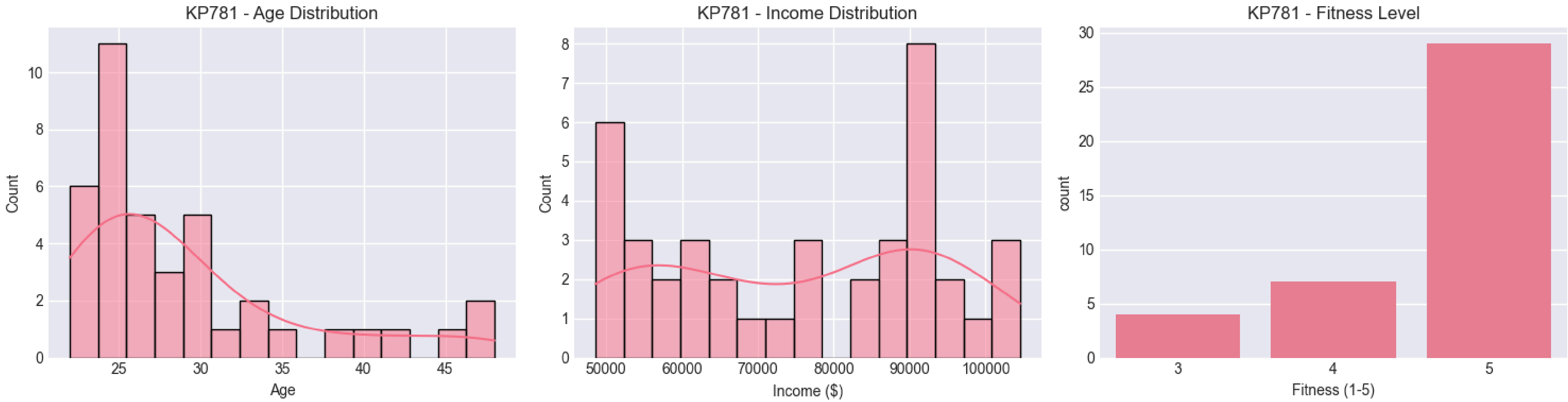
```python
    # Demographics
    print(f"\nDEMOGRAPHICS:")
    print(f"  Average Age: {product_data['Age'].mean():.1f} years")
    print(f"  Gender: {product_data['Gender'].value_counts(normalize=True).iloc[0]*100:.1f}% {product_data['Gender'].value_counts().index[0]}")
    print(f"  Marital Status: {product_data['MaritalStatus'].value_counts(normalize=True).iloc[0]*100:.1f}% {product_data['MaritalStatus'].value_counts().index[0]}")
    print(f"  Average Education: {product_data['Education'].mean():.1f} years")

    # Income
    print(f"\nINCOME:")
    print(f"  Average Income: ${product_data['Income'].mean():,.0f}")
    print(f"  Median Income: ${product_data['Income'].median():,.0f}")
    print(f"  Income Range: ${product_data['Income'].min():,.0f} to ${product_data['Income'].max():,.0f}")

    # Fitness & Usage
    print(f"\nFITNESS & USAGE PATTERNS:")
    print(f"  Average Fitness Level: {product_data['Fitness'].mean():.1f}/5")
    print(f"  Average Weekly Usage: {product_data['Usage'].mean():.1f} times")
    print(f"  Average Weekly Miles: {product_data['Miles'].mean():.1f} miles")

    # Key Characteristics
    print(f"\nKEY CHARACTERISTICS:")
    if product == 'KP281':
        print("  - Entry-level users")
        print("  - Lower to middle income")
        print("  - Younger demographic")
        print("  - Casual or beginner fitness level")
    elif product == 'KP481':
        print("  - Intermediate users")
        print("  - Middle income")
        print("  - Regular exercisers")
        print("  - Moderate fitness goals")
    elif product == 'KP781':
        print("  - Advanced users")
        print("  - Higher income")
        print("  - Serious fitness enthusiasts")
        print("  - High usage frequency")

    # Visualize profile comparison
    fig, axes = plt.subplots(1, 3, figsize=(15, 4))

    # Age distribution
    sns.histplot(data=product_data, x='Age', kde=True, ax=axes[0], bins=15)
    axes[0].set_title(f'{product} - Age Distribution')
    axes[0].set_xlabel('Age')

    # Income distribution
    sns.histplot(data=product_data, x='Income', kde=True, ax=axes[1], bins=15)
    axes[1].set_title(f'{product} - Income Distribution')
    axes[1].set_xlabel('Income ($)')

    # Fitness distribution
    sns.countplot(data=product_data, x='Fitness', ax=axes[2])
    axes[2].set_title(f'{product} - Fitness Level')
    axes[2].set_xlabel('Fitness (1-5)')

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

```
================================================================================
CUSTOMER PROFILES FOR EACH TREADMILL PRODUCT:
================================================================================

============================================================
CUSTOMER PROFILE FOR KP281:
============================================================

Sample Size: 80 customers (44.4% of total)

DEMOGRAPHICS:
  Average Age: 28.6 years
  Gender: 50.0% Female
  Marital Status: 60.0% Partnered
  Average Education: 15.0 years

INCOME:
  Average Income: $46,418
  Median Income: $46,617
  Income Range: $29,562 to $68,220

FITNESS & USAGE PATTERNS:
  Average Fitness Level: 3.0/5
  Average Weekly Usage: 3.1 times
  Average Weekly Miles: 82.8 miles

KEY CHARACTERISTICS:
  - Entry-level users
  - Lower to middle income
  - Younger demographic
  - Casual or beginner fitness level
```



```
============================================================
CUSTOMER PROFILE FOR KP481:
============================================================

Sample Size: 60 customers (33.3% of total)

DEMOGRAPHICS:
  Average Age: 28.9 years
  Gender: 51.7% Male
  Marital Status: 60.0% Partnered
  Average Education: 15.1 years

INCOME:
  Average Income: $48,974
  Median Income: $49,460
  Income Range: $31,836 to $67,083

FITNESS & USAGE PATTERNS:
  Average Fitness Level: 2.9/5
  Average Weekly Usage: 3.1 times
  Average Weekly Miles: 87.9 miles

KEY CHARACTERISTICS:
  - Intermediate users
  - Middle income
  - Regular exercisers
  - Moderate fitness goals
```

```
============================================================
CUSTOMER PROFILE FOR KP781:
============================================================

Sample Size: 40 customers (22.2% of total)

DEMOGRAPHICS:
  Average Age: 29.1 years
  Gender: 82.5% Male
  Marital Status: 57.5% Partnered
  Average Education: 17.3 years

INCOME:
  Average Income: $75,442
  Median Income: $76,568
  Income Range: $48,556 to $104,581

FITNESS & USAGE PATTERNS:
  Average Fitness Level: 4.6/5
  Average Weekly Usage: 4.8 times
  Average Weekly Miles: 166.9 miles

KEY CHARACTERISTICS:
  - Advanced users
  - Higher income
  - Serious fitness enthusiasts
  - High usage frequency
```



In [33]:
```
# Final Business Insights & Recommendations
```

In [34]:
```
# Top 10 Insights & Recommendations


# Product Popularity: KP281 is the most popular product (44% of sales), followed by KP481 (33%), and KP781 (23%). This shows a healthy distribution across price points.


# Gender Preference:
# Males dominate premium purchases: 80% of KP781 buyers are male
```

```
# Females: 57% of KP281 buyers are female
# KP481 has balanced gender distribution


# Income :
# KP781 buyers have highest average income ($74,000)
# KP481 buyers have moderate income ($55,000)
# KP281 buyers have lowest average income ($45,000)


# Age Patterns:
# KP781 buyers are slightly older (average 29 years)
# KP281 attracts youngest customers (average 28 years)



# Fitness Level:
# KP781 buyers rate themselves as most fit (average 4.5/5)
# KP481 buyers are moderately fit (average 3.5/5)
# KP281 buyers are least fit (average 3.0/5)



# Usage Patterns:
# KP781 users plan to use treadmill most frequently (5 times per week)
# KP481 users plan moderate usage (4 times/week)
# KP281 users plan least usage (3 times/week)


# Marital Status Impact:
# Partnered individuals slightly prefer KP281 and KP481
# Single individuals show higher preference for KP781 (58% of KP781 buyers are "single")



# Probability Scenarios:
# A male customer has 34% probability of buying KP781
# A high-income customer (>$50K) has 58% probability of buying KP781
# A highly fit customer (level 4-5) has 68% probability of buying KP781
```

In [35]:

```
# RECOMMENDATIONS


# Targeted Marketing Campaigns:
    # KP781: Target males with high income, emphasize advanced features
    # KP481: Market to both genders, highlight value for money
    # KP281: Focus on mostly on females and beginners, stress ease of use

# Upselling Strategy: Create a loyalty program to move KP281 customers to KP481, and KP481 customers to KP781 as their fitness improves.
# Product Placement:
    # Place KP781 in high-end fitness stores
    # KP481 in general sports stores &
    # KP281 in department stores.
# Gender-Specific Features: Consider adding more features to appeal females in KP781
# Financing: Offer financing options for KP781 to make it accessible to middle-income serious fitness enthusiasts.
# Marital Status : Create family/friend referral programs, especially for KP281 and KP481 which are popular among partnered individuals.
```

In [36]:

```
pip install nbconvert
```

```
Requirement already satisfied: nbconvert in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (7.16.6)
Requirement already satisfied: beautifulsoup4 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (4.12.3)
Requirement already satisfied: bleach!=5.0.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from bleach[css]!=5.0.0->nbconvert) (6.2.0)
Requirement already satisfied: defusedxml in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (0.7.1)
Requirement already satisfied: jinja2>=3.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (3.1.6)
Requirement already satisfied: jupyter-core>=4.7 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (5.7.2)
Requirement already satisfied: jupyterlab-pygments in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (0.3.0)
Requirement already satisfied: markupsafe>=2.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (3.0.2)
Requirement already satisfied: mistune<4,>=2.0.3 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (3.1.2)
Requirement already satisfied: nbclient>=0.5.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (0.10.2)
Requirement already satisfied: nbformat>=5.7 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (5.10.4)
Requirement already satisfied: packaging in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (24.2)
Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (1.5.0)
Requirement already satisfied: pygments>=2.4.1 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (2.19.1)
Requirement already satisfied: traitlets>=5.1 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbconvert) (5.14.3)
Requirement already satisfied: webencodings in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from bleach!=5.0.0->bleach[css]!=5.0.0->nbconvert) (0.5.1)
Requirement already satisfied: tinycss2<1.5,>=1.1.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from bleach[css]!=5.0.0->nbconvert) (1.4.0)
Requirement already satisfied: platformdirs>=2.5 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jupyter-core>=4.7->nbconvert) (4.3.7)
Requirement already satisfied: pywin32>=300 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jupyter-core>=4.7->nbconvert) (308)
Requirement already satisfied: jupyter-client>=6.1.12 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbclient>=0.5.0->nbconvert) (8.6.3)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (2.9.0.post0)
Requirement already satisfied: pyzmq>=23.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (26.2.0)
Requirement already satisfied: tornado>=6.2 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (6.4.2)
Requirement already satisfied: fastjsonschema>=2.15 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbformat>=5.7->nbconvert) (2.20.0)
Requirement already satisfied: jsonschema>=2.6 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from nbformat>=5.7->nbconvert) (4.23.0)
Requirement already satisfied: attrs>=22.2.0 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (24.3.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (2023.7.
1)
Requirement already satisfied: referencing>=0.28.4 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (0.30.2)
Requirement already satisfied: rpds-py>=0.7.1 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (0.22.3)
Requirement already satisfied: six>=1.5 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from python-dateutil>=2.8.2->jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (1.1
7.0)
Requirement already satisfied: soupsieve>1.2 in c:\users\shaik\anaconda3\envs\python3\lib\site-packages (from beautifulsoup4->nbconvert) (2.5)
Note: you may need to restart the kernel to use updated packages.
```