AEROFIT 🏋 - DESCRIPTIVE STATISTICS & PROBABILITY 💹

About Aerofit 💪

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

Business Problem 👀

The market research team at AeroFit wants to

- Identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers.
- The team decides to investigate whether there are differences across the product with respect to customer characteristics

Objective 🎯

Perform descriptive analytics to create a customer profile for each

- AeroFit treadmill product by developing appropriate tables and charts.
- For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

About Dataset 🧻

The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior **three months**. The dataset has the following features:

Product Portfolio:

- The **KP281** is an entry-level treadmill that sells for **$1,500**.
- The **KP481** is for mid-level runners that sell for **$1,750**.
- The **KP781** treadmill is having advanced features that sell for **$2,500**.

Getting help from Libraries 📚

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading the data.... ⏯

In [2]:
```
df = pd.read_csv('aerofit_treadmill.csv')
```

Exploring the data... 🔎

In [3]:
```
df.head()
```

Out[3]:

	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

In [4]:
```
df.shape
```

Out[4]:
```
(180, 9)
```

🔍 OBSERVATION 🔎

The Dataset has 180 rows and 9 columns.

- **Product Purchased:** KP281, KP481, or KP781
- **Age:** In years
- **Gender:** Male/Female
- **Education:** In years
- **MaritalStatus:** Single or partnered
- **Usage**: The average number of times the customer plans to use the treadmill each week.
- **Income:** Annual income (in $)
- **Fitness:** Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.
- **Miles:** The average number of miles the customer expects to walk/run each week

In [5]:
```
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
```

🔍 OBSERVATION 🔎

- The columns **Product**, **Gender** and **MaritalStatus** are **object** datatype.
- The columns **Age**, **Education**, **Usage**, **Fitness**, **Income** and **Miles** are **int64** datatype

Descriptive statistics 📄

In [6]:
```
df.describe().T
```

Out[6]:

	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

🔍 OBSERVATION 🔎

- **Age:** The range is between **18 years to 50 years** and the average age is **29 years**.
- **Education:** The range is between **12 years to 21 years** and the average education is **16 years**.
- **Usage:** The customer use the treadmill from **2 to 7 times** a week with the average usage of **3 times** per week.
- **Fitness:** In the Self-rated fitness on a **1-to-5 scale**, where **1 is the poor shape** and **5 is the excellent shape**, the average fitness is **3**.
- **Income:** The range of anual income is between **30,000 USD TO 105,000 USD** and the average income is **54,000 USD**.
- **Miles:** The customer expects to walk/run each week in the range between **21 miles to 360 miles** with average of **103 miles**.

In [7]:
```
df.describe(include = "object").T
```

Out[7]:

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

🔍 OBSERVATION 🔎

For the past three months, the **highest sales** 💰 contribution were from

- The **KP281** is an entry-level treadmill.
- The **Male buyers** ♂ were more than the female buyers.
- The **Married buyers** 💍 were more than the single.

Checking the missing values and Nulls 🔎

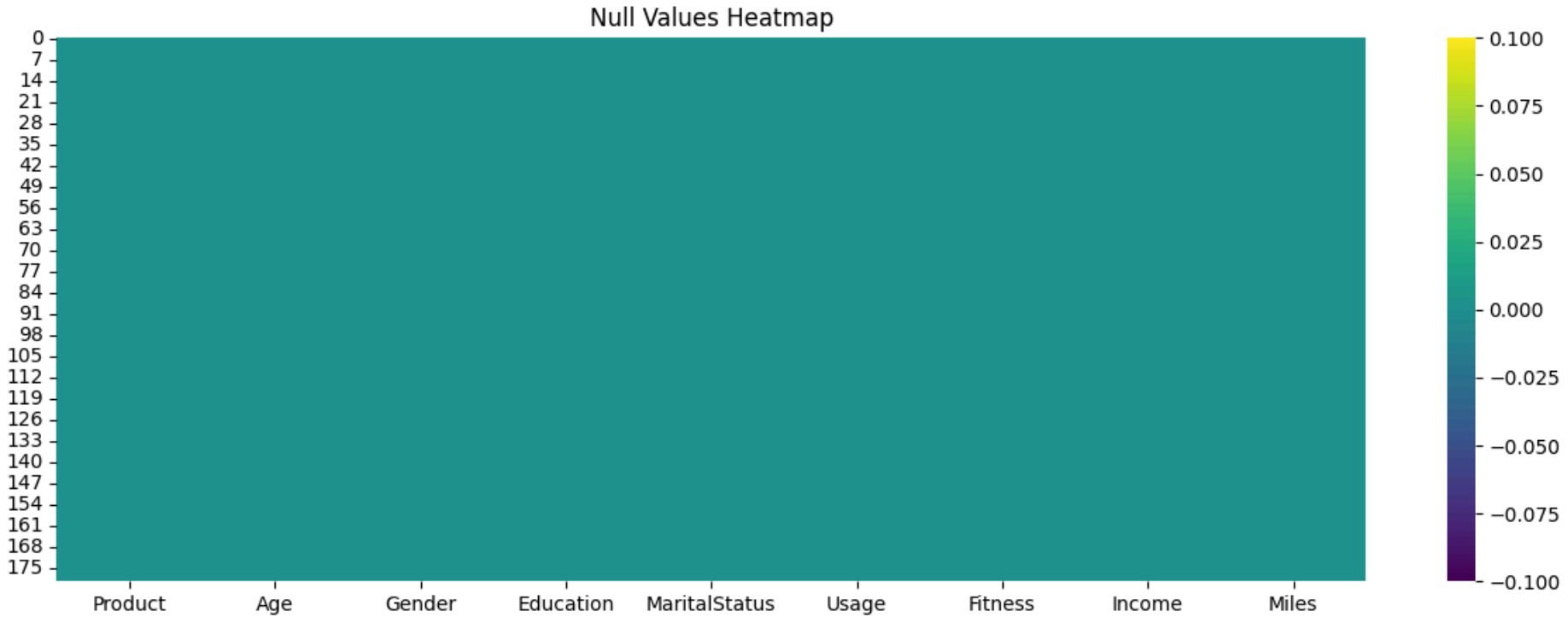
In [8]:
```
#Checking for duplicates:
df.duplicated().sum()
```

Out[8]:
```
0
```

In [9]:
```
#Checking for nulls:
df.isna().sum()
```

Out[9]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [10]:
```
#Null value heatmap:
plt.figure(figsize = (15,5))
sns.heatmap(df.isnull(), cmap='viridis')
plt.title('Null Values Heatmap')
plt.show()
```

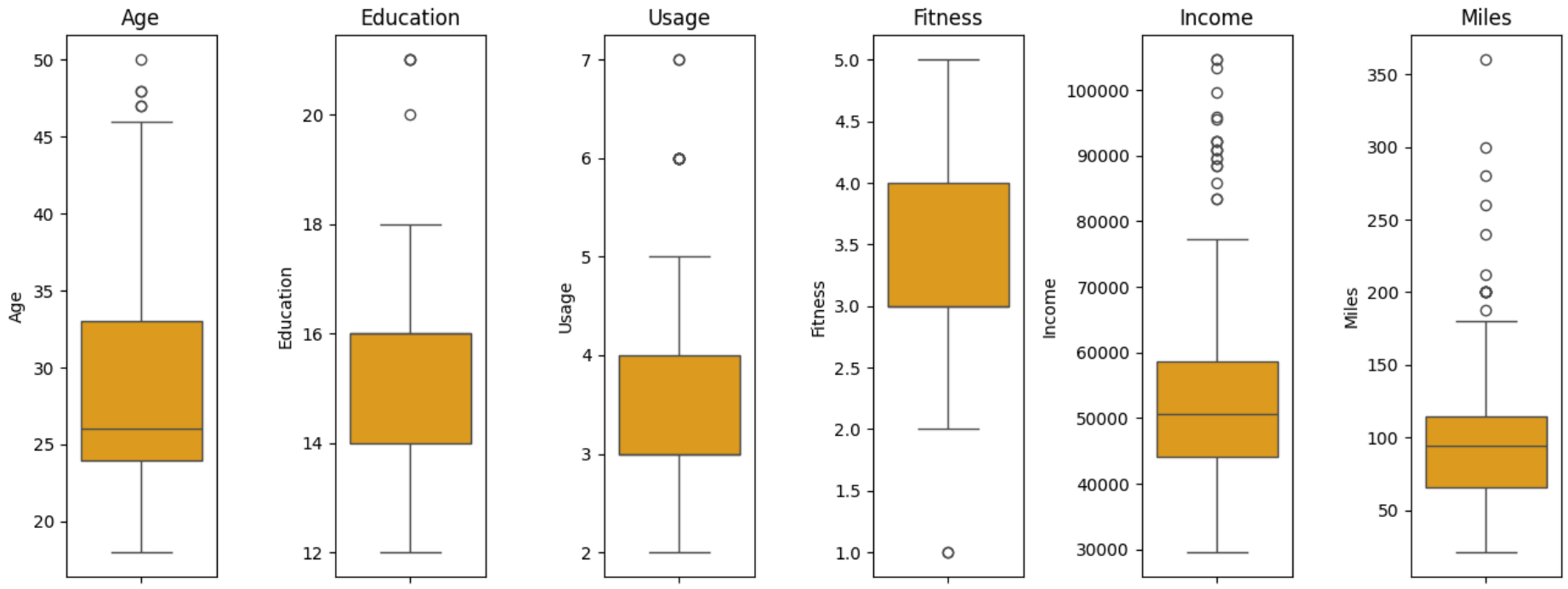


🔎 OBSERVATION 🔎

There are no duplicates and null values in the dataset.

Detect Outliers 🦹

In [11]:
```
# Create box plots for each continuous variable

continuous_vars = df.select_dtypes(include=['int64'])
plt.figure(figsize=(13, 5))
for i, col in enumerate(continuous_vars.columns):
    plt.subplot(1, len(continuous_vars.columns), i+1)
    sns.boxplot(df[col], color='orange')
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [12]:
```
columns_to_check = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

#Function to calculate percentage of outliers
def detect_outliers_and_percentage(column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    percentage_outliers = (len(outliers) / len(df)) * 100
    return percentage_outliers

# calculate percentage of outliers
for col in columns_to_check:
    percentage = detect_outliers_and_percentage(col)
    print(f"Percentage of outliers in column '{col}': {percentage:.2f}%")
    print()
```

```
Percentage of outliers in column 'Age': 2.78%

Percentage of outliers in column 'Education': 2.22%

Percentage of outliers in column 'Usage': 5.00%

Percentage of outliers in column 'Fitness': 1.11%

Percentage of outliers in column 'Income': 10.56%

Percentage of outliers in column 'Miles': 7.22%
```

Univariate Analysis 📊

In [4]:
```
#Creating Fitness_Shape column:
def cat(x):
  if x == 1:
    return "Poor"
  if x == 2:
    return "Bad"
  if x == 3:
    return "Average"
  if x == 4:
    return "Good"
  else:
    return "Excellent"

df["Fitness_Shape"] = df["Fitness"].apply(cat)
```

In [5]:
```
df.head()
```

Out[5]:

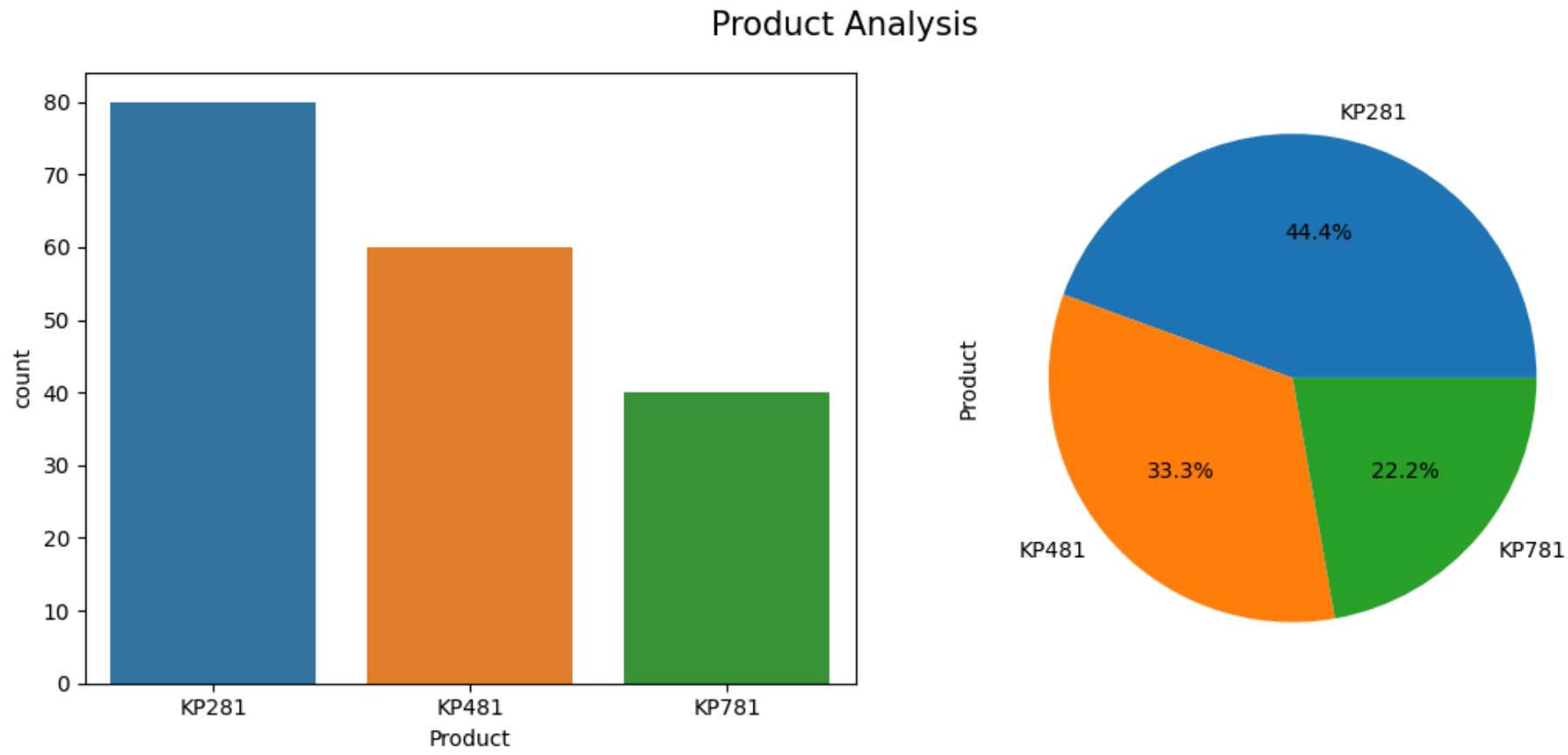
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fitness_Shape
0	KP281	18	Male	14	Single	3	4	29562	112	Good
1	KP281	19	Male	15	Single	2	3	31836	75	Average
2	KP281	19	Female	14	Partnered	4	3	30699	66	Average
3	KP281	19	Male	12	Single	3	3	32973	85	Average
4	KP281	20	Male	13	Partnered	4	2	35247	47	Bad

Note 📓

Fitness_Shape column is newly created based on the Fitness column.

- 5 - Excellent
- 4 - Good
- 3 - Average
- 2 - Bad
- 1 - Poor

In [15]:
```
#Product Analysis:
plt.figure(figsize=(11, 5))

plt.subplot(1, 2, 1)
sns.countplot(x = "Product", data = df, hue="Product")

plt.subplot(1, 2, 2)
df["Product"].value_counts(normalize=True).plot(kind = "pie", autopct = "%1.1f%%")

plt.suptitle("Product Analysis", fontsize = 15)
plt.tight_layout()
plt.show()
```

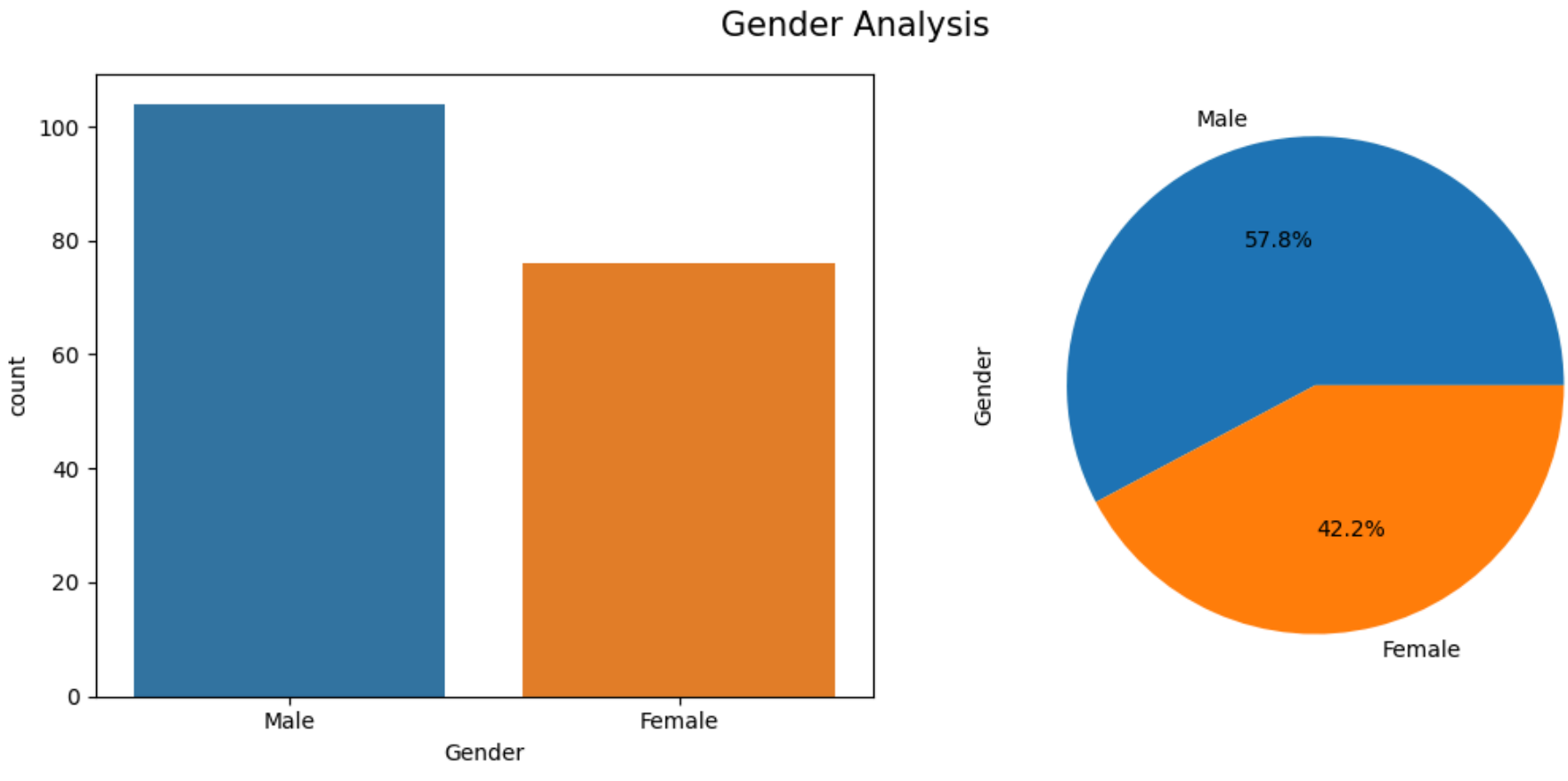


🔍 OBSERVATION 🔎

From the above analysis we can conclude that,

- 🥇 The **KP281** is an entry-level treadmill that sells for **$1,500** has contributed about **44%** of the overall sales 🤑
- 🥈 The **KP481** is for mid-level runners that sell for **$1,750** has contributed about **33%** of the overall sales 💰
- 🥉 The **KP781** treadmill is having advanced features that sell for **$2,500** has contributed about **22%** of the overall sales 💰

In [16]:
```
#Gender Analysis:
plt.figure(figsize=(11, 5))

plt.subplot(1, 2, 1)
sns.countplot(x = "Gender", data = df, hue="Gender")

plt.subplot(1, 2, 2)
df["Gender"].value_counts(normalize=True).plot(kind = "pie", autopct = "%1.1f%%")

plt.suptitle("Gender Analysis", fontsize = 15)
plt.tight_layout()
plt.show()
```

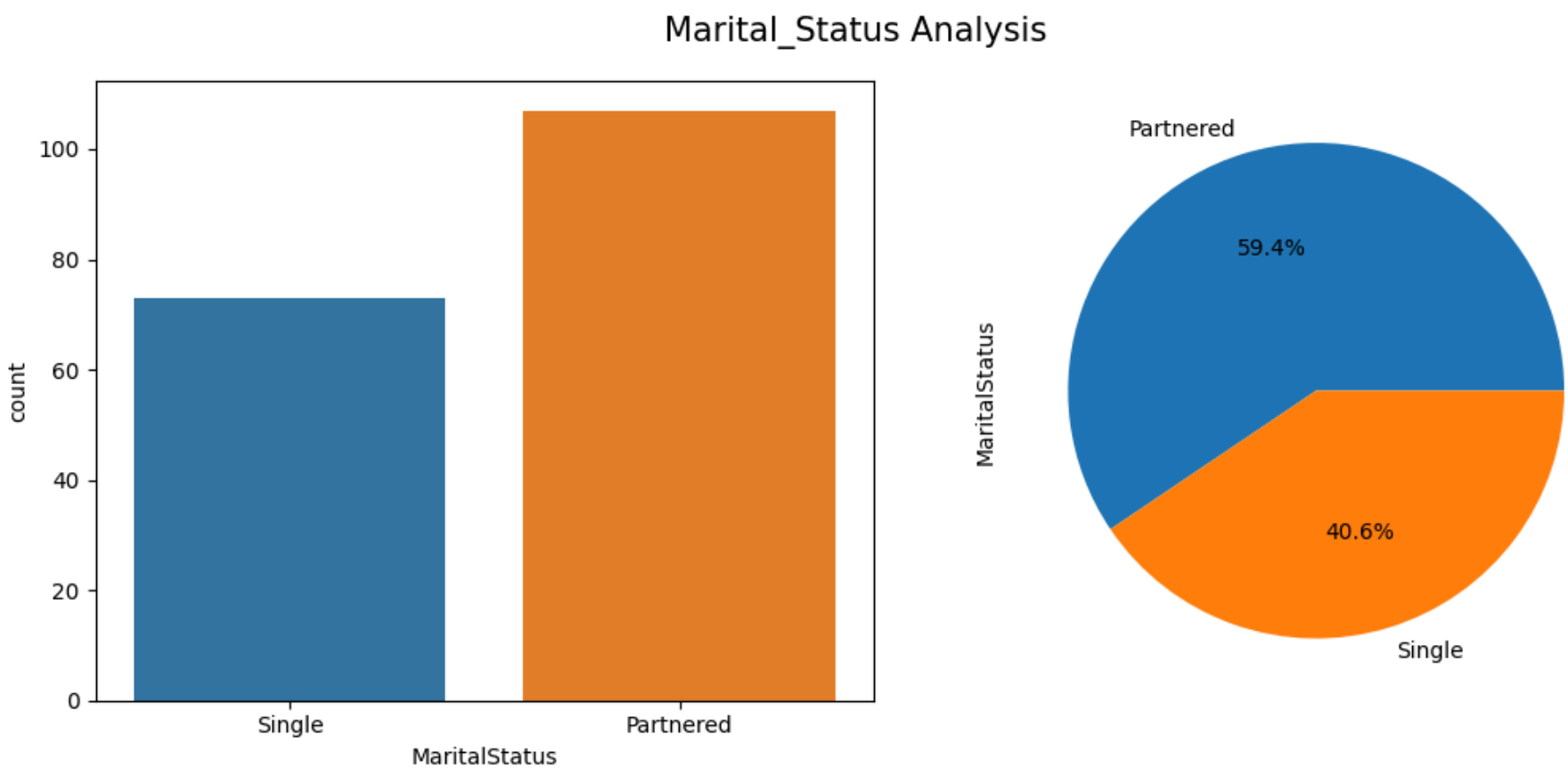


🔍 OBSERVATION 🔎

From the above analysis we can conclude that,

- 🥇 **Male** ♂ has contributed about **58%** of the overall sales 🤑
- 🥈 **Female** ♀ has contributed about **42%** of the overall sales 💰

In [17]:
```
#Marital_Status Analysis:
plt.figure(figsize=(11, 5))

plt.subplot(1, 2, 1)
sns.countplot(x = "MaritalStatus", data = df, hue="MaritalStatus")

plt.subplot(1, 2, 2)
df["MaritalStatus"].value_counts(normalize=True).plot(kind = "pie", autopct = "%1.1f%%")

plt.suptitle("Marital_Status Analysis", fontsize = 15)
plt.tight_layout()
plt.show()
```



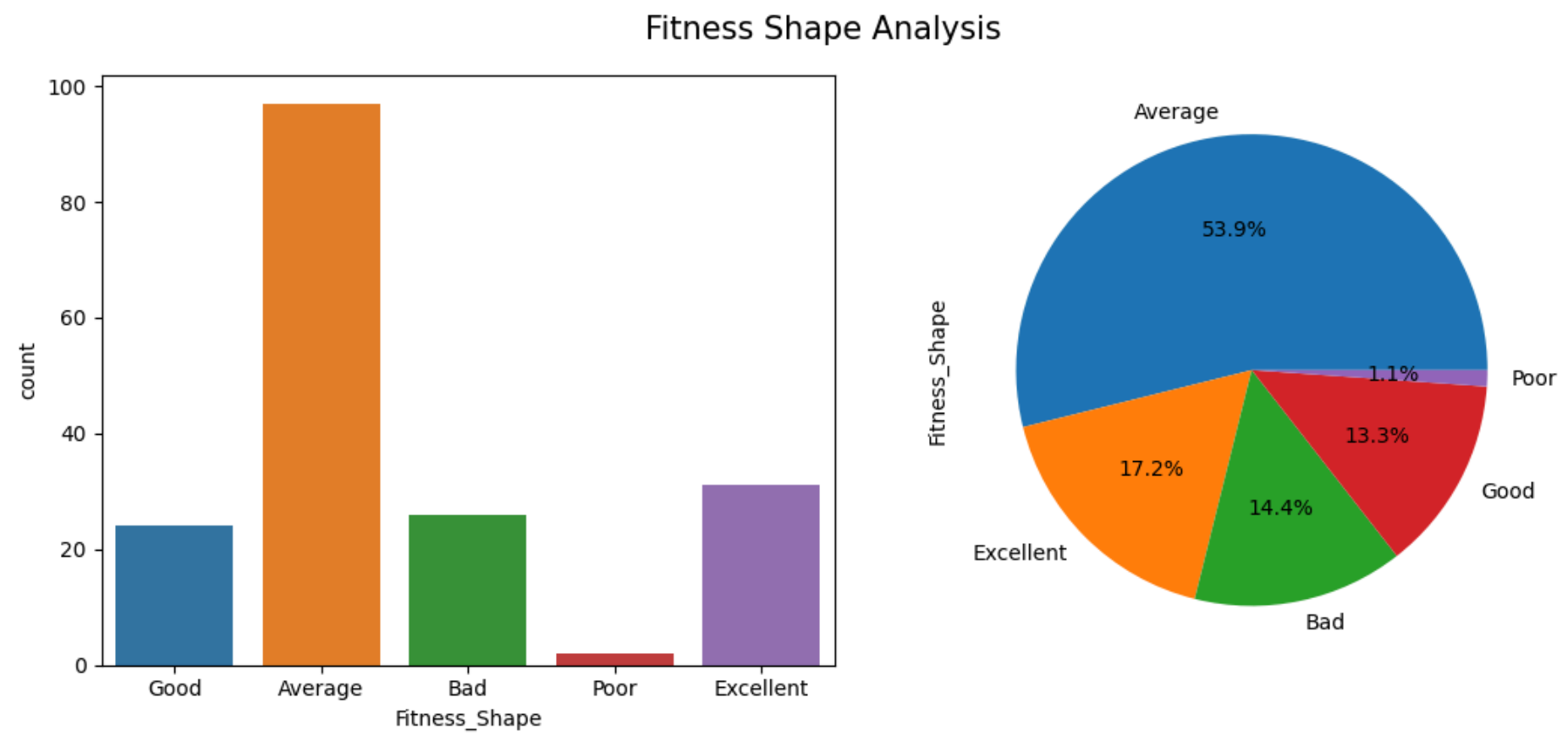
🔍 OBSERVATION 🔎

From the above analysis we can conclude that,

- 🥇 **Partnered** has contributed about **59%** of the overall sales 🤑. This is may be to maintain a **healthy relationship** 💪 😀
- 🥈 **Single** has contributed about **41%** of the overall sales 💰

In [18]:
```
#Fitness Shape Analysis:
plt.figure(figsize=(11, 5))

plt.subplot(1, 2, 1)
```

```
sns.countplot(x = "Fitness_Shape", data = df, hue="Fitness_Shape")

plt.subplot(1, 2, 2)
df["Fitness_Shape"].value_counts(normalize=True).plot(kind = "pie", autopct = "%1.1f%%")

plt.suptitle("Fitness Shape Analysis", fontsize = 15)
plt.tight_layout()
plt.show()
```

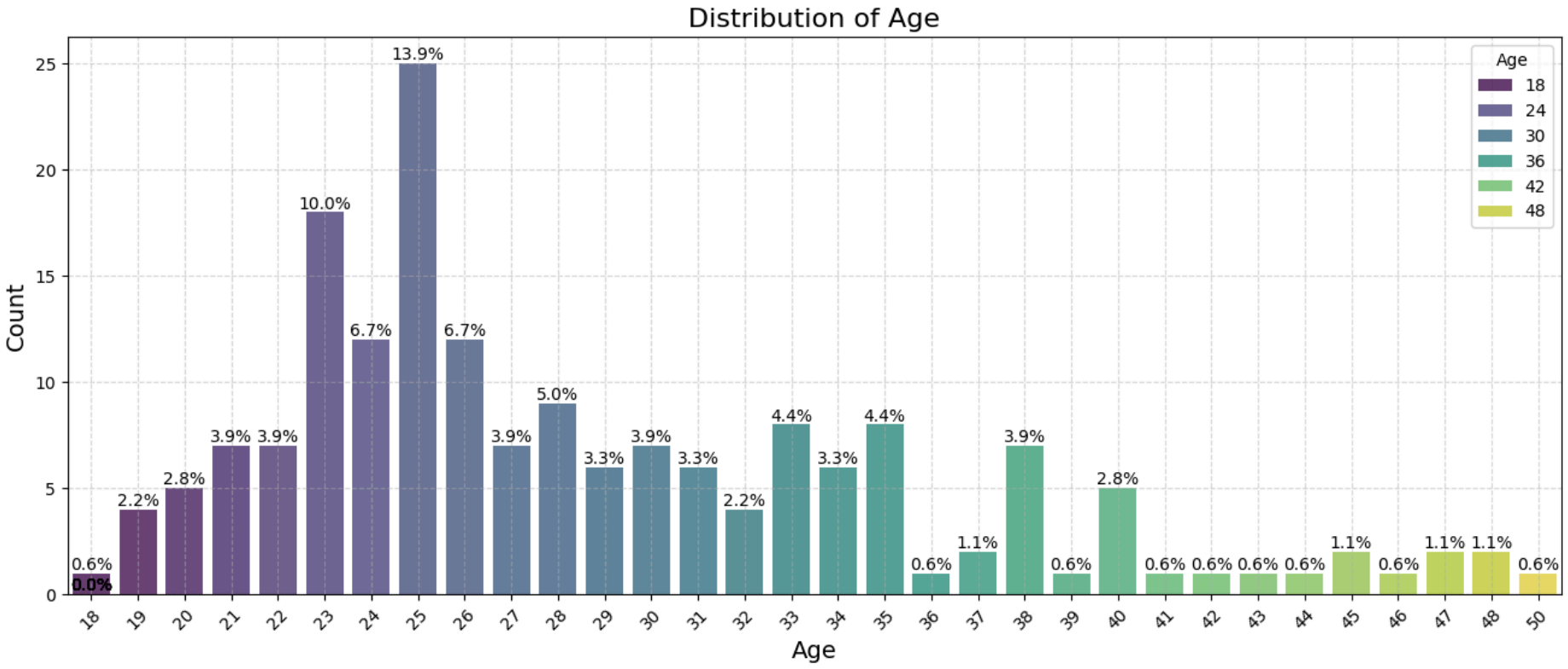


🔍 OBSERVATION 🔎

From the above analysis we can conclude that in the Self-rated fitness on a 1-to-5 scale, the person with

- 🥇 The **Avarage shape(3)** has contributed around **54%** of the overall sales 🤑
- 🥈 The **Excellent shape(5)** has contributed around **17%** of the overall sales 💰
- 🥉 The **Bad shape(2)** has contributed around **14%** of the overall sales 💰
- The **God shape(4)** has contributed around **13%** of the overall sales 💰
- The **Poor shape(1)** has contributed around **1%** of the overall sales 💰

In [19]:
```
#Distribution of Age

# Create the count plot
plt.figure(figsize=(16, 6))
ax = sns.countplot(x = "Age", data = df, palette="viridis", hue = "Age", alpha=0.8)

# Set plot title and axis labels
plt.title("Distribution of Age", fontsize=16)

# Adjust tick labels
plt.xticks(rotation=45, fontsize=10)

# Add grid lines
plt.grid(True, linestyle='--', alpha=0.5)

# Calculate the percentage contribution of each age category
total_count = len(df)
for patch in ax.patches:
    height = patch.get_height()
    pct = (height / total_count) * 100
    ax.annotate(f'{pct:.1f}%', (patch.get_x() + patch.get_width() / 2., height),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

# Set the title and axis labels of the plot
plt.title("Distribution of Age", fontsize=16)
plt.xlabel("Age", fontsize=14)
plt.ylabel("Count", fontsize=14)
plt.show()
```

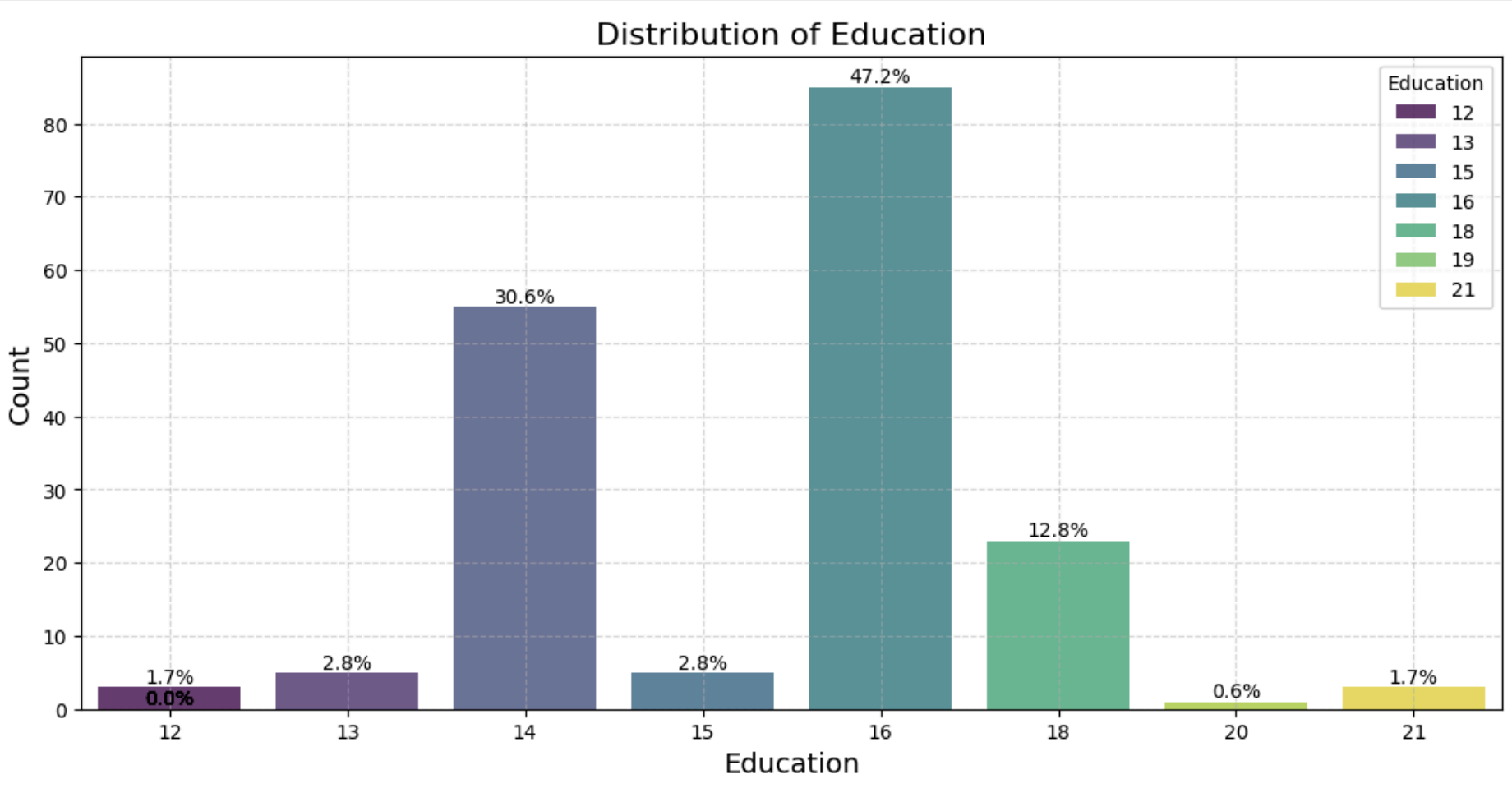


🔍 OBSERVATION 🔎

From the above analysis we can conclude that,

- 🥇 The person with the age of **25 years** has contributed around **14%** of the overall sales 🤑
- 🥈 The person with the age of **23 years** has contributed around **10%** of the overall sales 💰
- 🥉 The person with the age of **24 years** and **26 years** has contributed around **7%** of the overall sales 💰

In [20]:
```
#Distribution of Education

# Create the count plot
plt.figure(figsize=(13, 6))
ax = sns.countplot(x = "Education", data = df, palette="viridis", hue = "Education", alpha=0.8)

# Set plot title and axis labels
plt.title("Distribution of Education", fontsize=16)

# Add grid lines
plt.grid(True, linestyle='--', alpha=0.5)

# Calculate the percentage contribution of each age category
total_count = len(df)
for patch in ax.patches:
    height = patch.get_height()
    pct = (height / total_count) * 100
    ax.annotate(f'{pct:.1f}%', (patch.get_x() + patch.get_width() / 2., height),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

# Set the title and axis labels of the plot
plt.title("Distribution of Education", fontsize=16)
plt.xlabel("Education", fontsize=14)
plt.ylabel("Count", fontsize=14)
plt.show()
```

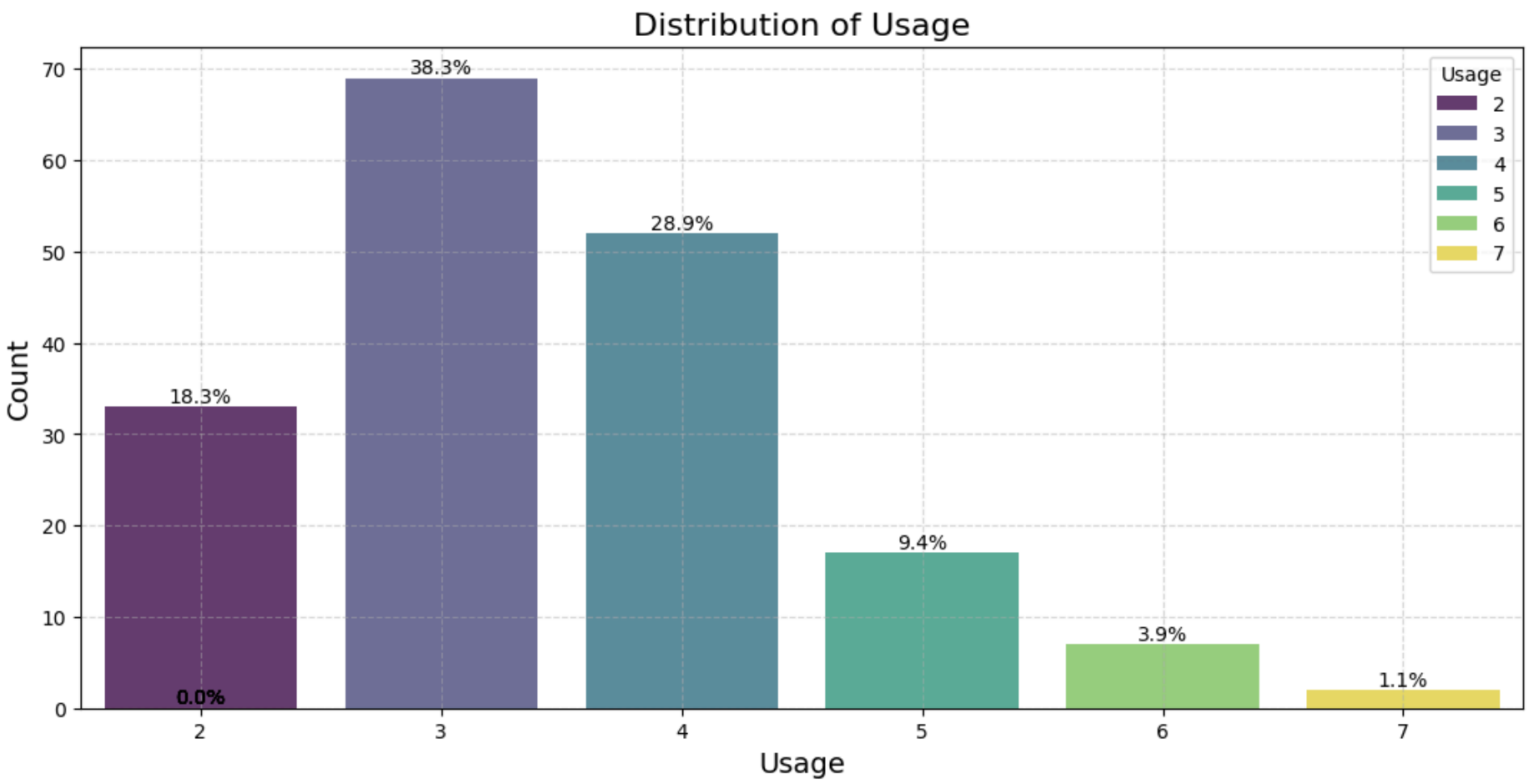


🔍 OBSERVATION 🔎

From the above analysis we can conclude that,

- 🥇 The Education of **16 years** has contributed around **47%** of the overall sales 🤑
- 🥈 The Education of **14 years** has contributed around **31%** of the overall sales 💰
- 🥉 The Education of **18 years** has contributed around **13%** of the overall sales 💰

In [21]:
```
#Distribution of Usage

# Create the count plot
plt.figure(figsize=(13, 6))
ax = sns.countplot(x = "Usage", data = df, palette="viridis", hue = "Usage", alpha=0.8)

# Set plot title and axis labels
plt.title("Distribution of Usage", fontsize=16)

# Add grid lines
plt.grid(True, linestyle='--', alpha=0.5)

# Calculate the percentage contribution of each age category
total_count = len(df)
for patch in ax.patches:
    height = patch.get_height()
    pct = (height / total_count) * 100
    ax.annotate(f'{pct:.1f}%', (patch.get_x() + patch.get_width() / 2., height),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

# Set the title and axis labels of the plot
plt.title("Distribution of Usage", fontsize=16)
plt.xlabel("Usage", fontsize=14)
plt.ylabel("Count", fontsize=14)
plt.show()
```



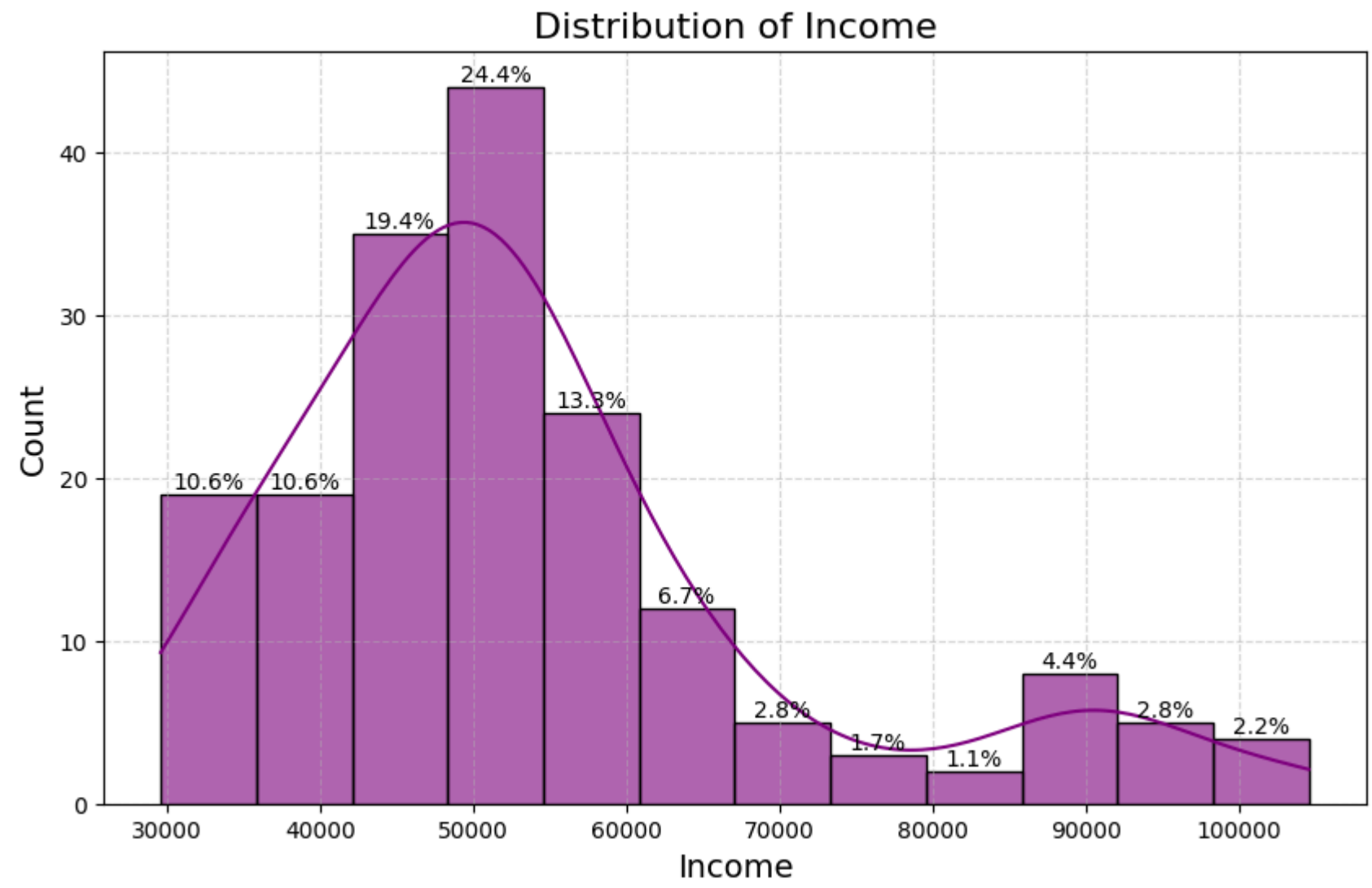
🔍 OBSERVATION 🔎

From the above analysis we can conclude that the person who uses the treadmill,

- 🥇 **3 times** each week has contributed around **38%** of the overall sales 🤑
- 🥈 **4 times** each week has contributed around **29%** of the overall sales 💰
- 🥉 **2 times** each week has contributed around **18%** of the overall sales 💰

In [22]:
```
#Distribution of Income

plt.figure(figsize=(10, 6))
ax = sns.histplot(x="Income", bins=12, data=df, kde=True, color="purple", alpha=0.6)

# Calculate the percentage contribution of each income category
total_count = len(df)
for patch in ax.patches:
    height = patch.get_height()
    pct = (height / total_count) * 100
    plt.text(patch.get_x() + patch.get_width() / 2., height, f'{pct:.1f}%', ha='center', va='bottom')
```

```
# Set plot title and axis labels
plt.title("Distribution of Income", fontsize=16)
plt.xlabel("Income", fontsize=14)
plt.ylabel("Count", fontsize=14)

# Add grid lines
plt.grid(True, linestyle='--', alpha=0.5)

# Show plot
plt.show()
```

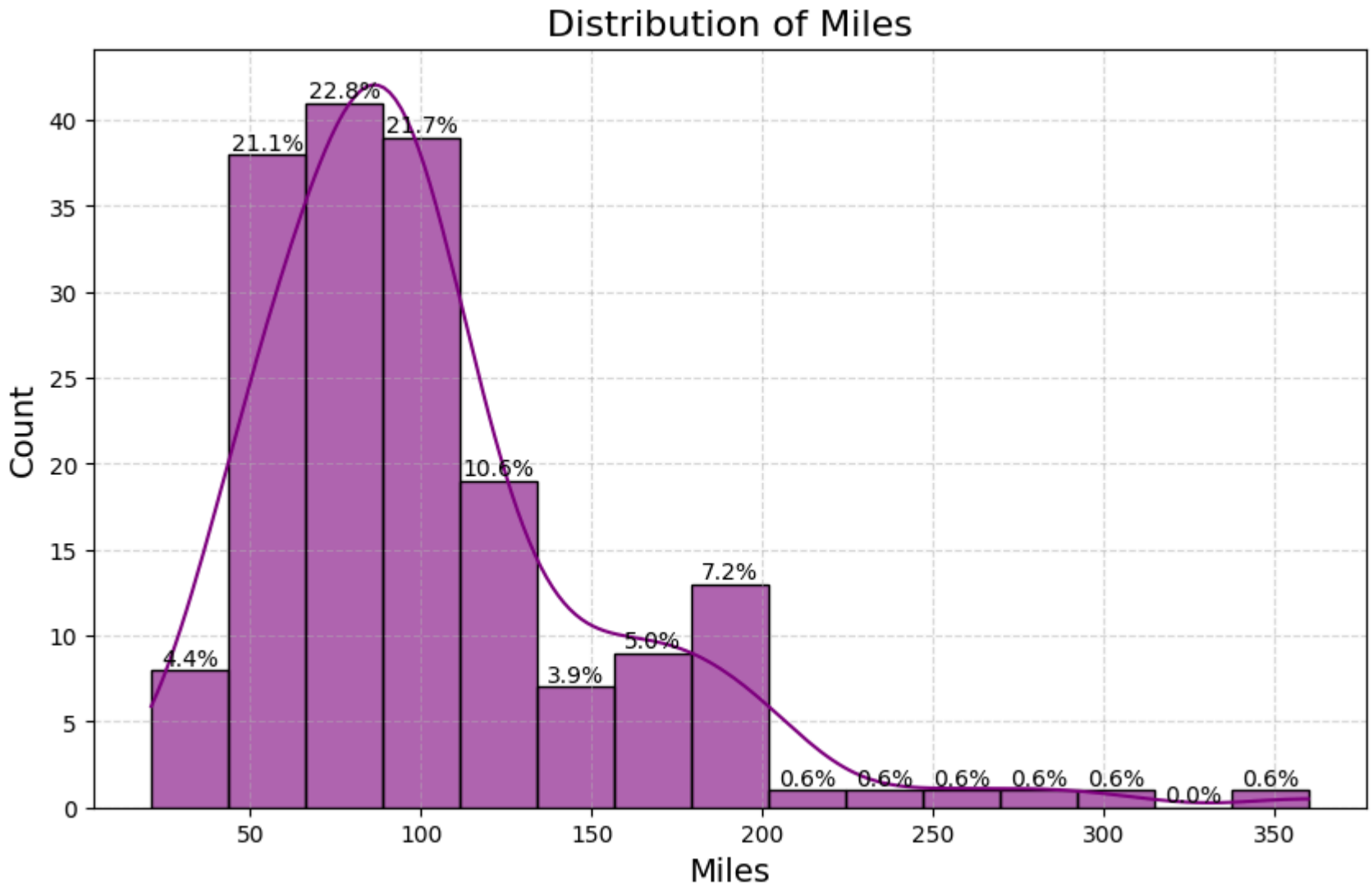


🔍 OBSERVATION 🔎

From the above analysis we can conclude that the person who uses the treadmill,

- The people between the income group 💸 of around **45K USD and 55K USD** has contrubuted around **57%** of the overall sales 💰

In [23]:
```
#Distribution of Miles

plt.figure(figsize=(10, 6))
ax = sns.histplot(x="Miles", bins=15, data=df, kde=True, color="purple", alpha=0.6)

# Calculate the percentage contribution of each income category
total_count = len(df)
for patch in ax.patches:
    height = patch.get_height()
    pct = (height / total_count) * 100
    plt.text(patch.get_x() + patch.get_width() / 2., height, f'{pct:.1f}%', ha='center', va='bottom')

# Set plot title and axis labels
plt.title("Distribution of Miles", fontsize=16)
plt.xlabel("Miles", fontsize=14)
plt.ylabel("Count", fontsize=14)

# Add grid lines
plt.grid(True, linestyle='--', alpha=0.5)

# Show plot
plt.show()
```



🔍 OBSERVATION 🔎

- From the above analysis we can conclude that the customers who **walk 🚶 /run 🏃 50 to 100 miles**| each week has contributed around **66%** of the overall sales 💰

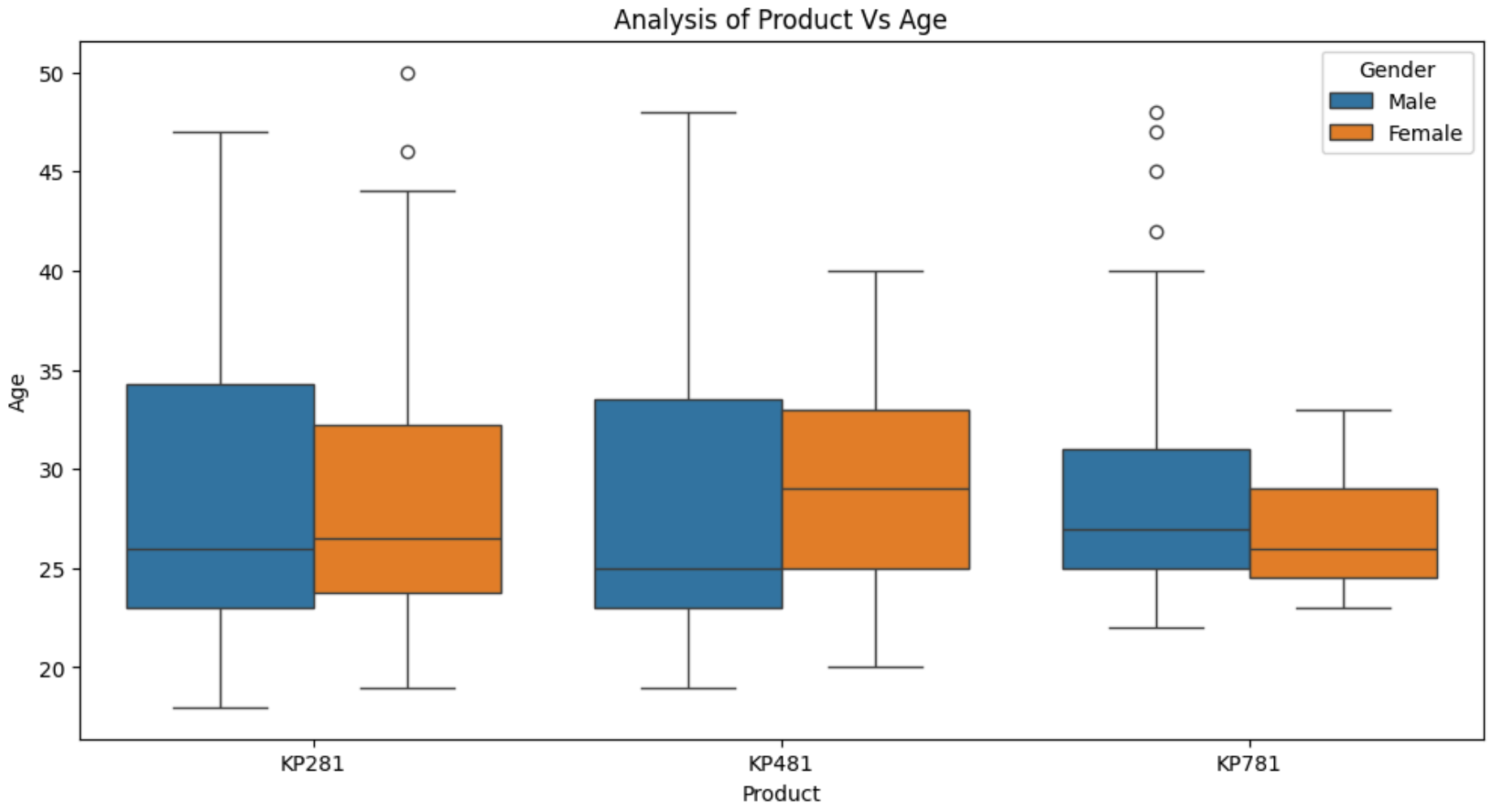
Bivariate Analysis 📊

In [24]:
```
medians = df.groupby(['Product', 'Gender'])['Age'].median().reset_index()
medians
```

Out[24]:

	Product	Gender	Age
0	KP281	Female	26.5
1	KP281	Male	26.0
2	KP481	Female	29.0
3	KP481	Male	25.0
4	KP781	Female	26.0
5	KP781	Male	27.0

In [25]:
```
# Analysis of Product Vs Age:

plt.figure(figsize=(12, 6))
sns.boxplot(x='Product', y='Age',hue = "Gender", data=df)
plt.title('Analysis of Product Vs Age')
plt.xlabel('Product')
plt.ylabel('Age')
plt.show()
```



🔍 OBSERVATION for KP281 treadmill 🔎

- Median age for **male** is **26 years**
- Median age for **female** is **26 years**

Both male and female are of with same age group prefer **KP281 treadmill**

🔍 OBSERVATION for KP481 treadmill 🔎

- Median age for **male** is **25 years**
- Median age for **female** is **29 years**

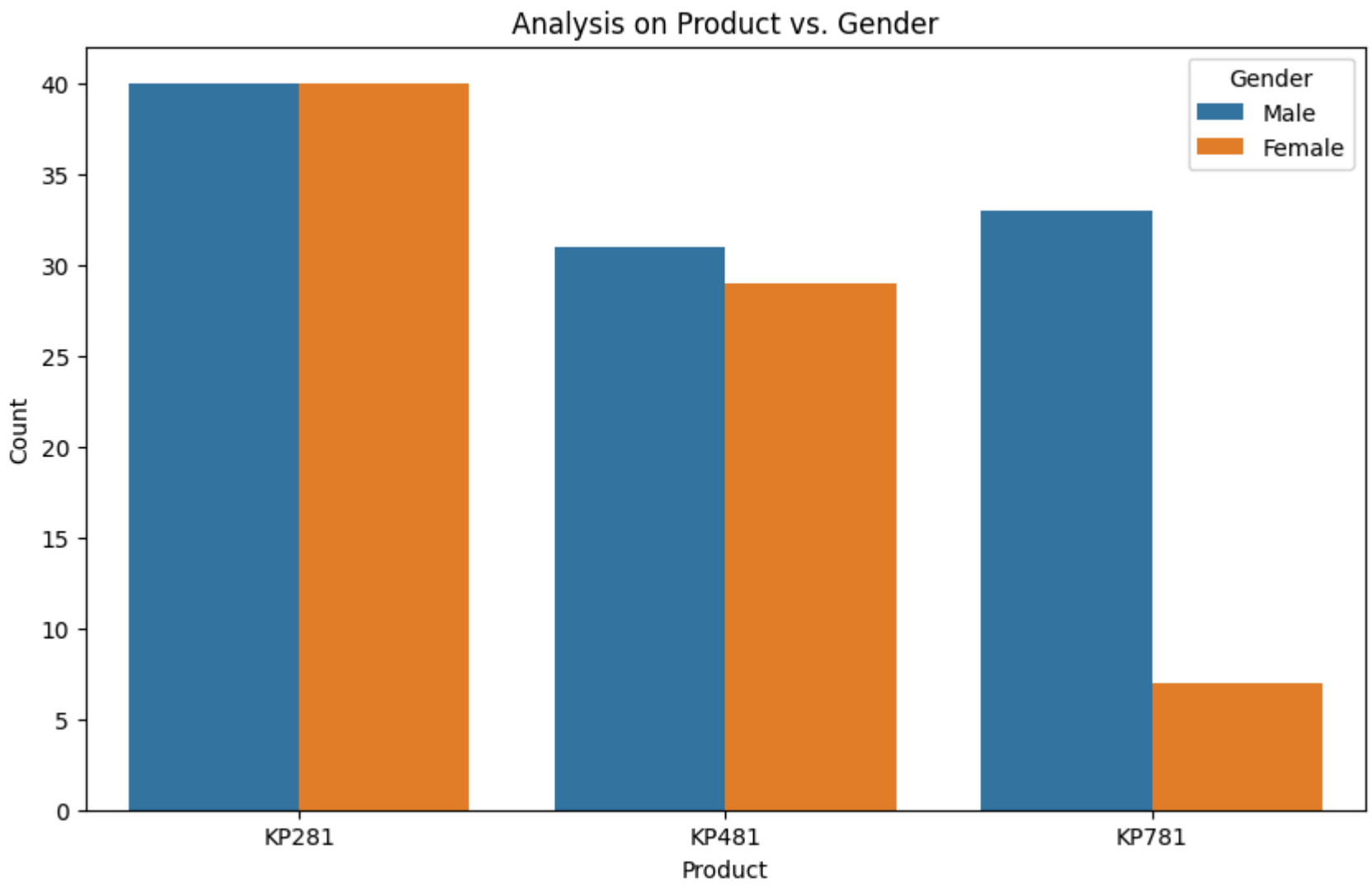
When compared to male little elder female are prefering **KP481 treadmill**

🔍 OBSERVATION for KP781 treadmill 🔎

- Median age for **male** is **27 years**
- Median age for **female** is **26 years**

When compared to female little elder male are prefering **KP781 treadmill**

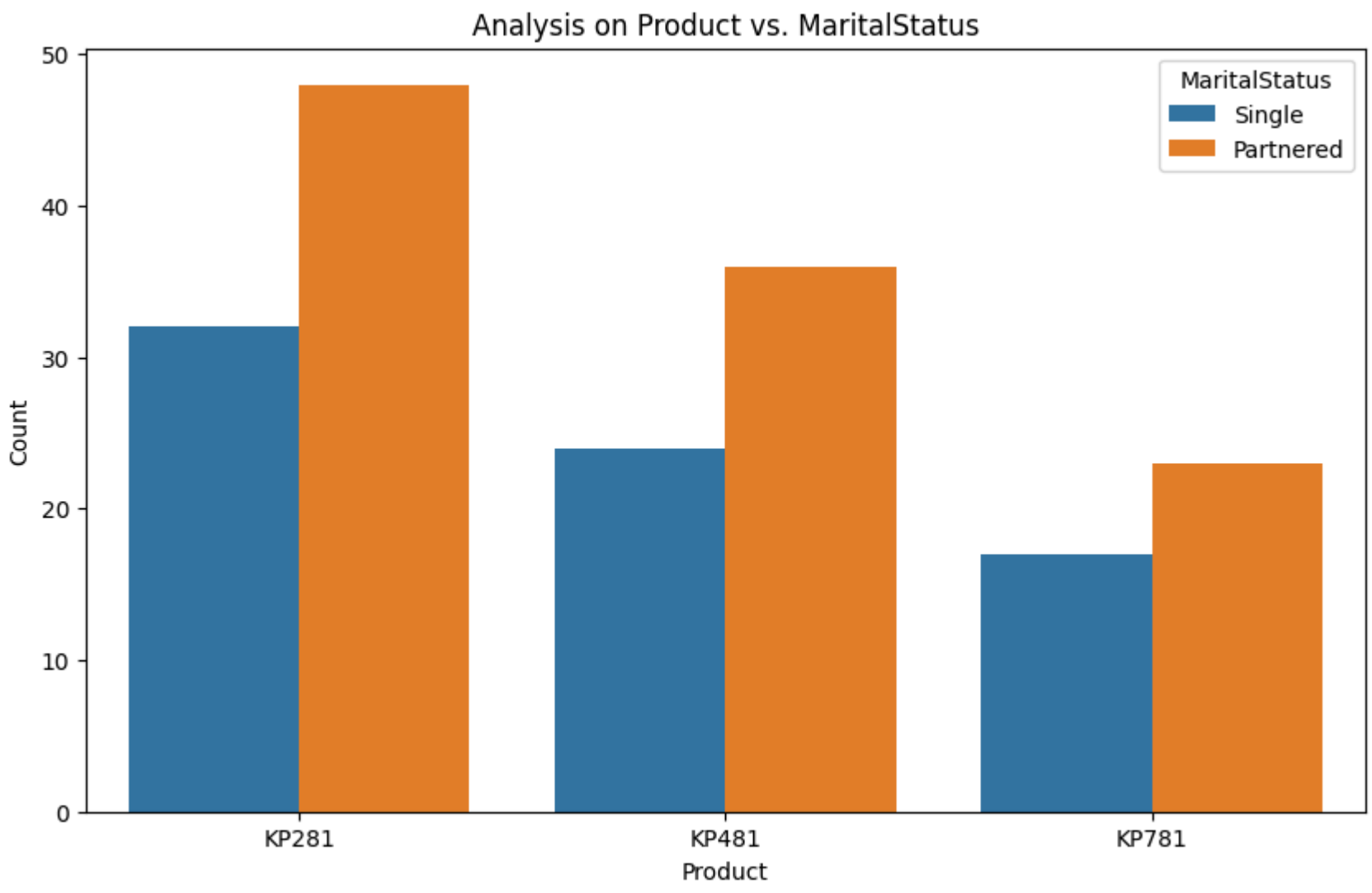
In [26]:
```
# Analysis of Product Vs Gender:

plt.figure(figsize=(10, 6))
sns.countplot(x='Product', hue='Gender', data=df)

plt.title('Analysis on Product vs. Gender')
plt.xlabel('Product')
plt.ylabel('Count')

plt.legend(title='Gender')
plt.show()
```



🔍 OBSERVATION 🔎

- Both Male and Female are **equally** preferring **KP281 treadmill**.
- When compared to Female, **more Male are preferring KP481 treadmill**.
- When compared to Female, **more Male are preferring KP781 treadmill**.

In [27]:
```
# Analysis of Product Vs MaritalStatus:

plt.figure(figsize=(10, 6))
sns.countplot(x = "Product", data = df, hue = "MaritalStatus")

plt.title('Analysis on Product vs. MaritalStatus')
plt.xlabel('Product')
plt.ylabel('Count')

plt.legend(title='MaritalStatus')
plt.show()
```

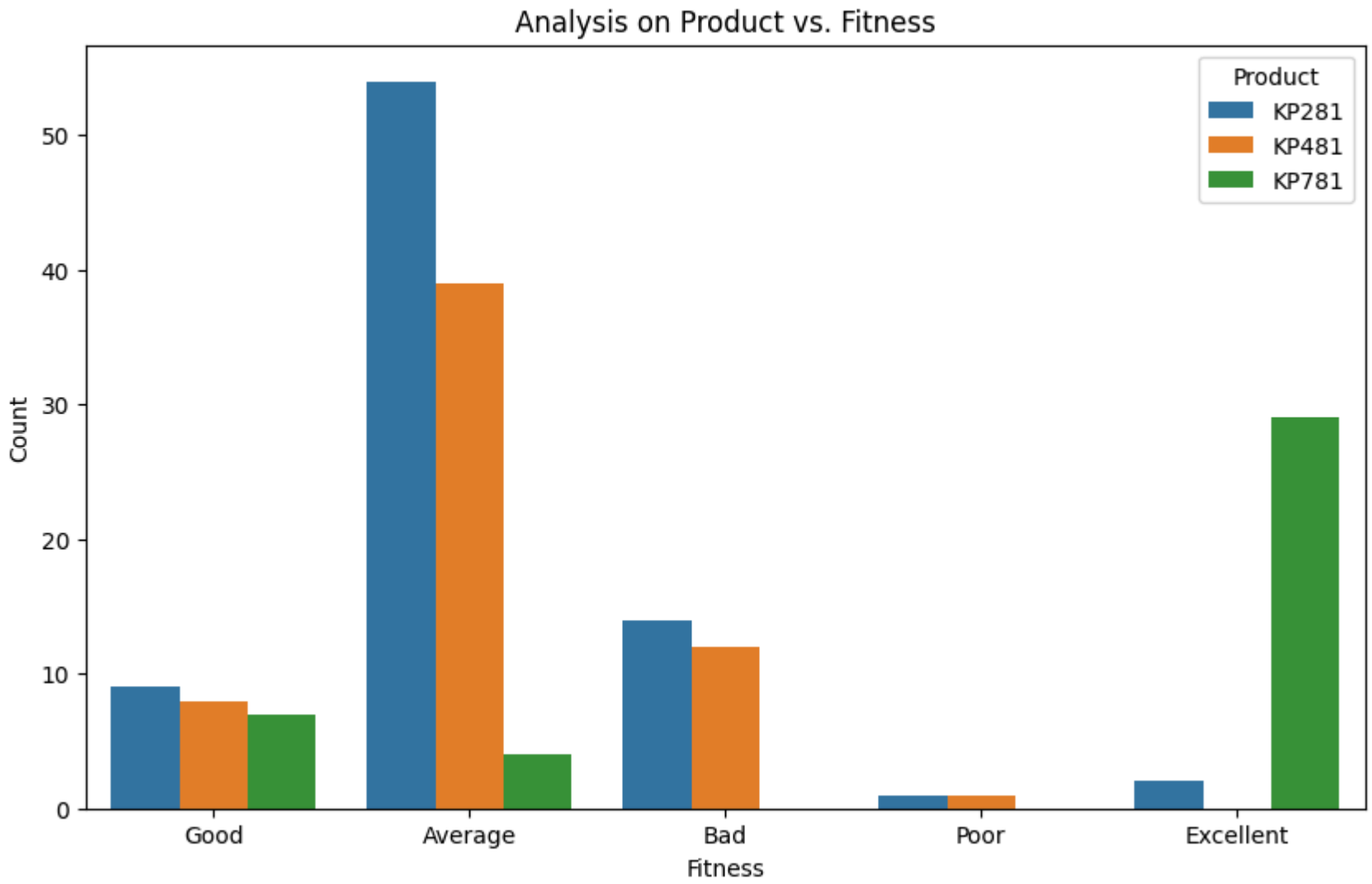


🔍 OBSERVATION 🔎

- When compared to Single, **Partnered** people are preferring **KP281 treadmill**

- When compared to Single, **Partnered** people are preferring **KP481 treadmill** *When compared to Single, **Partnered** people are preferring **KP781 treadmill**

In [28]:
```
# Analysis of Product Vs Fitness:

plt.figure(figsize=(10, 6))
sns.countplot(x = "Fitness_Shape", data = df, hue="Product")

plt.title('Analysis on Product vs. Fitness')
plt.xlabel('Fitness')
plt.ylabel('Count')

plt.legend(title='Product')
plt.show()
```



🔍 OBSERVATION 🔎

From the above analysis we can conclude that in the Self-rated fitness on a 1-to-5 scale, the person

The Good shape:

- First preference is **KP281 treadmill**
- Second Preference is **KP481 treadmill**
- Third preference is **KP781 treadmill**

The Average shape:

- First preference is **KP281 treadmill**
- Second Preference is **KP481 treadmill**
- Third preference is **KP781 treadmill**

The people having Average shape **mostly prefer KP281 and KP481 treadmill** when compared to KP781 treadmill.

The Bad shape:

- First preference is **KP281 treadmill**
- Second Preference is **KP481 treadmill**

The people with Bad shape don't prefer KP781 treadmill.

The Poor shape:

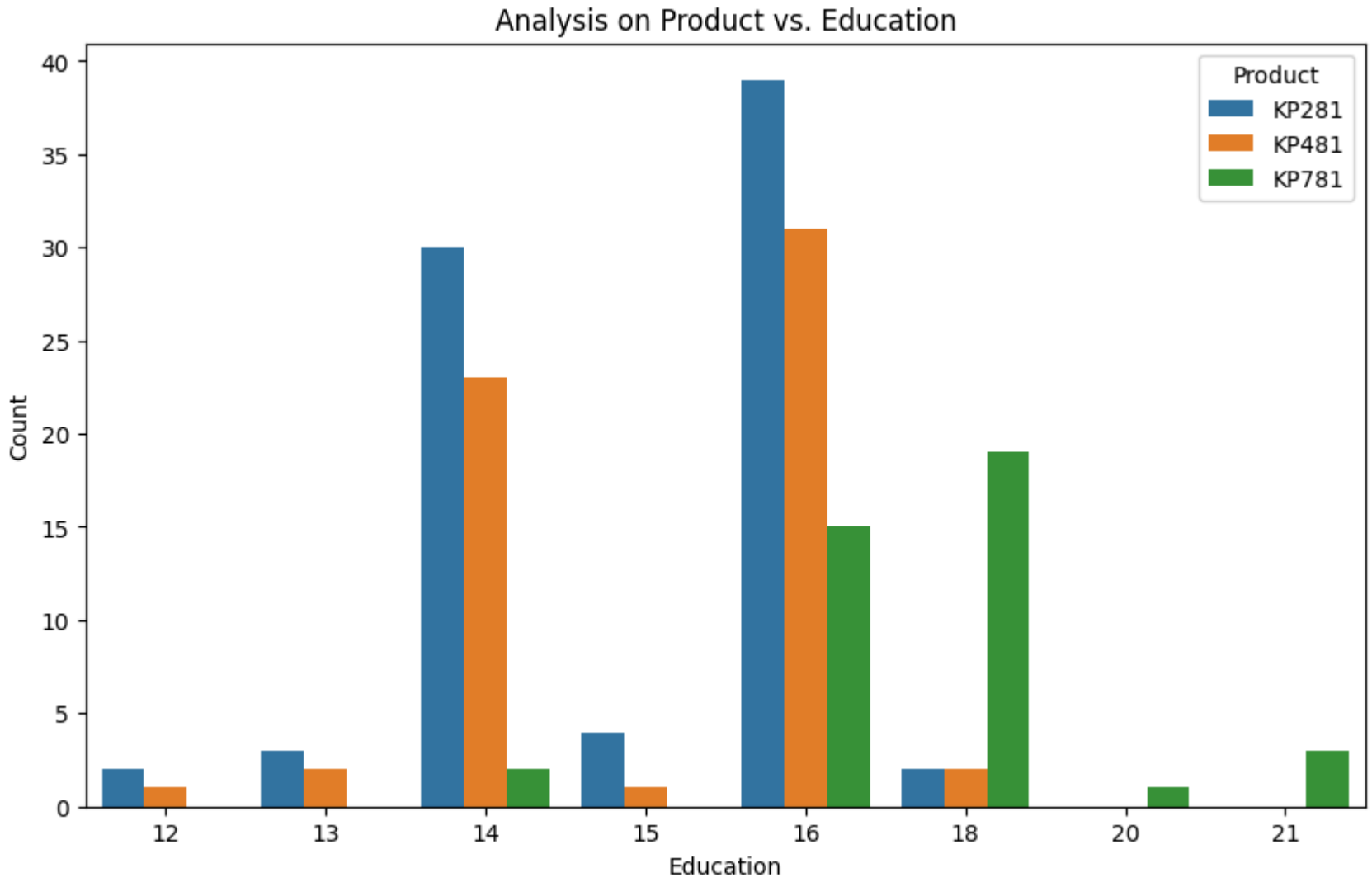
The people with poor shape **equally prefer KP281 and KP481 treadmill**.

The Bad shape:

- First preference is **KP781 treadmill**
- Second Preference is **KP281 treadmill**

The people with Bad shape don't prefer KP481 treadmill.

In [29]:
```
# Analysis of Product Vs Education:

plt.figure(figsize=(10, 6))
sns.countplot(x = "Education", data = df, hue="Product")

plt.title('Analysis on Product vs. Education')
plt.xlabel('Education')
plt.ylabel('Count')

plt.legend(title='Product')
plt.show()
```



🔍OBSERVATION for KP281 treadmill🔎

As per the above analysis,

- The First preference is **16 years**.
- Second Preference is **14 years**.
- Third preference is **15 years**.

🔍OBSERVATION for KP481 treadmill🔎

As per the above analysis,

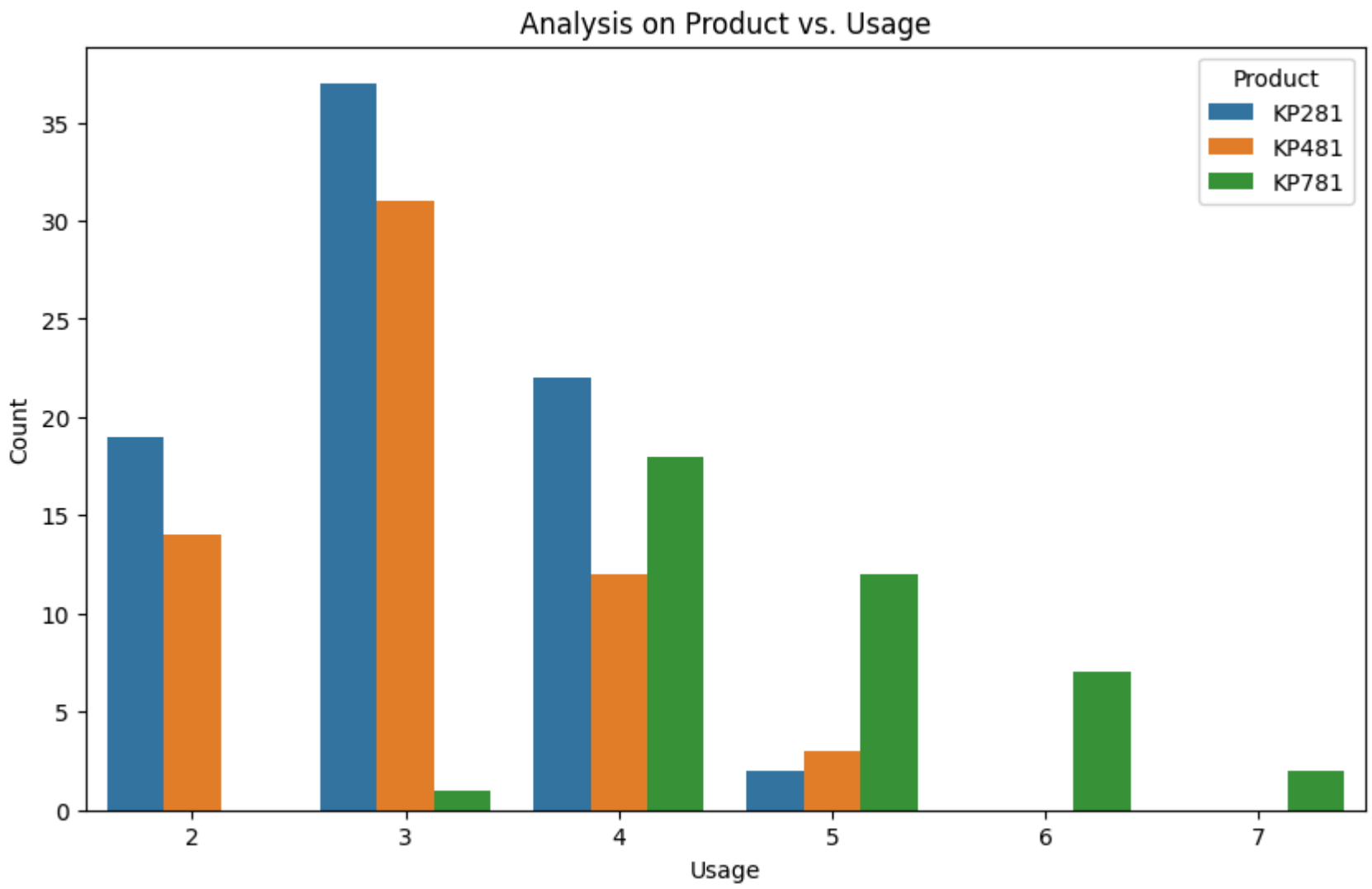
- The First preference is **16 years**.
- Second Preference is **14 years**.
- Third preference is **13 years**.

🔍OBSERVATION for KP781 treadmill🔎

As per the above analysis,

- The First preference is **18 years**.
- Second Preference is **16 years**.
- Third preference is **21 years**.

In [30]:
```
# Analysis of Product Vs Usage:

plt.figure(figsize=(10, 6))
sns.countplot(x = "Usage", data = df, hue="Product")

plt.title('Analysis on Product vs. Usage')
plt.xlabel('Usage')
plt.ylabel('Count')

plt.legend(title='Product')
plt.show()
```



🔍OBSERVATION for KP281 treadmill🔎

- **First prefernce** is for the customers who use the treadmill for an average of **3 times a week**.
- **Second prefernce** is for the customers who use the treadmill for an average of **4 times a week**.
- **Third prefernce** is for the customers who use the treadmill for an average of **2 times a week**.

🔍OBSERVATION for KP481 treadmill🔎

- **First prefernce** is for the customers who use the treadmill for an average of **3 times a week**.
- **Second prefernce** is for the customers who use the treadmill for an average of **2 times a week**.
- **Third prefernce** is for the customers who use the treadmill for an average of **4 times a week**.

🔍OBSERVATION for KP781 treadmill🔎

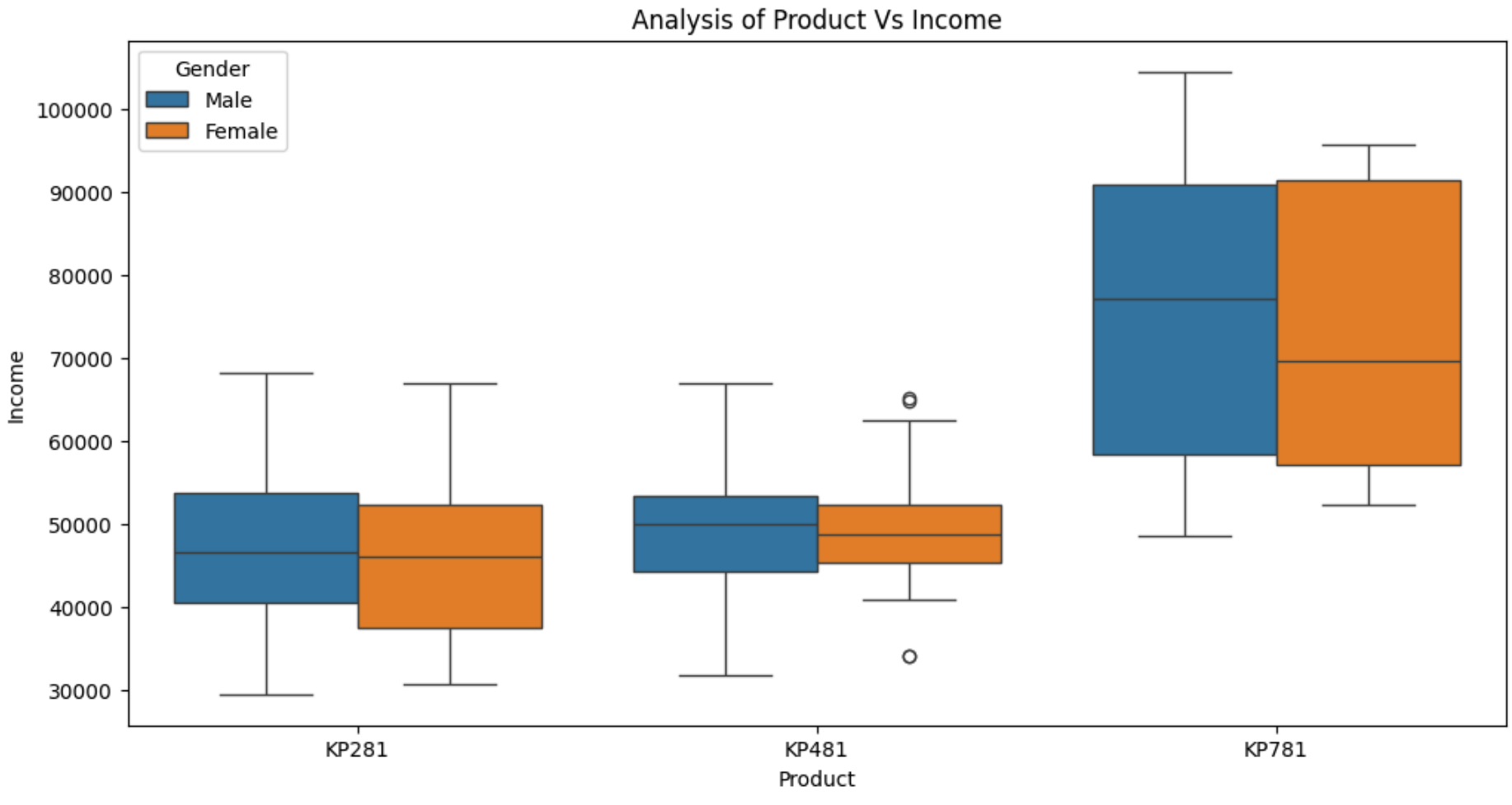
- **First prefernce** is for the customers who use the treadmill for an average of **4 times a week**.
- **Second prefernce** is for the customers who use the treadmill for an average of **5 times a week**.
- **Third prefernce** is for the customers who use the treadmill for an average of **6 times a week**.

In [31]:
```
# Analysis of Income Vs Gender:

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

Out[31]:

	Product	Gender	Income
0	KP281	Female	46048.5
1	KP281	Male	46617.0
2	KP481	Female	48891.0
3	KP481	Male	50028.0
4	KP781	Female	69721.0
5	KP781	Male	77191.0

In [32]:
```
# Analysis of Income Vs Gender:

plt.figure(figsize=(12, 6))
sns.boxplot(x='Product', y='Income',hue = "Gender", data=df)
plt.title('Analysis of Product Vs Income')
plt.xlabel('Product')
plt.ylabel('Income')
plt.show()
```



🔍OBSERVATION for KP281 treadmill🔎

The **median income** of male and female having **46000 USD** prefer **KP281 treadmill** and the male income is little bit high than female.

🔍OBSERVATION for KP481 treadmill🔎

The **median income** of **male** having **50000 USD** and **female** having **49000 USD** prefer **KP481 treadmill** and the male income is little bit high than female.

🔍OBSERVATION for KP781 treadmill🔎

The **median income** of **male** having **77000 USD** and **female** having **70000 USD** prefer **KP781 treadmill** and the male income is high than female.

CONCLUSION😀

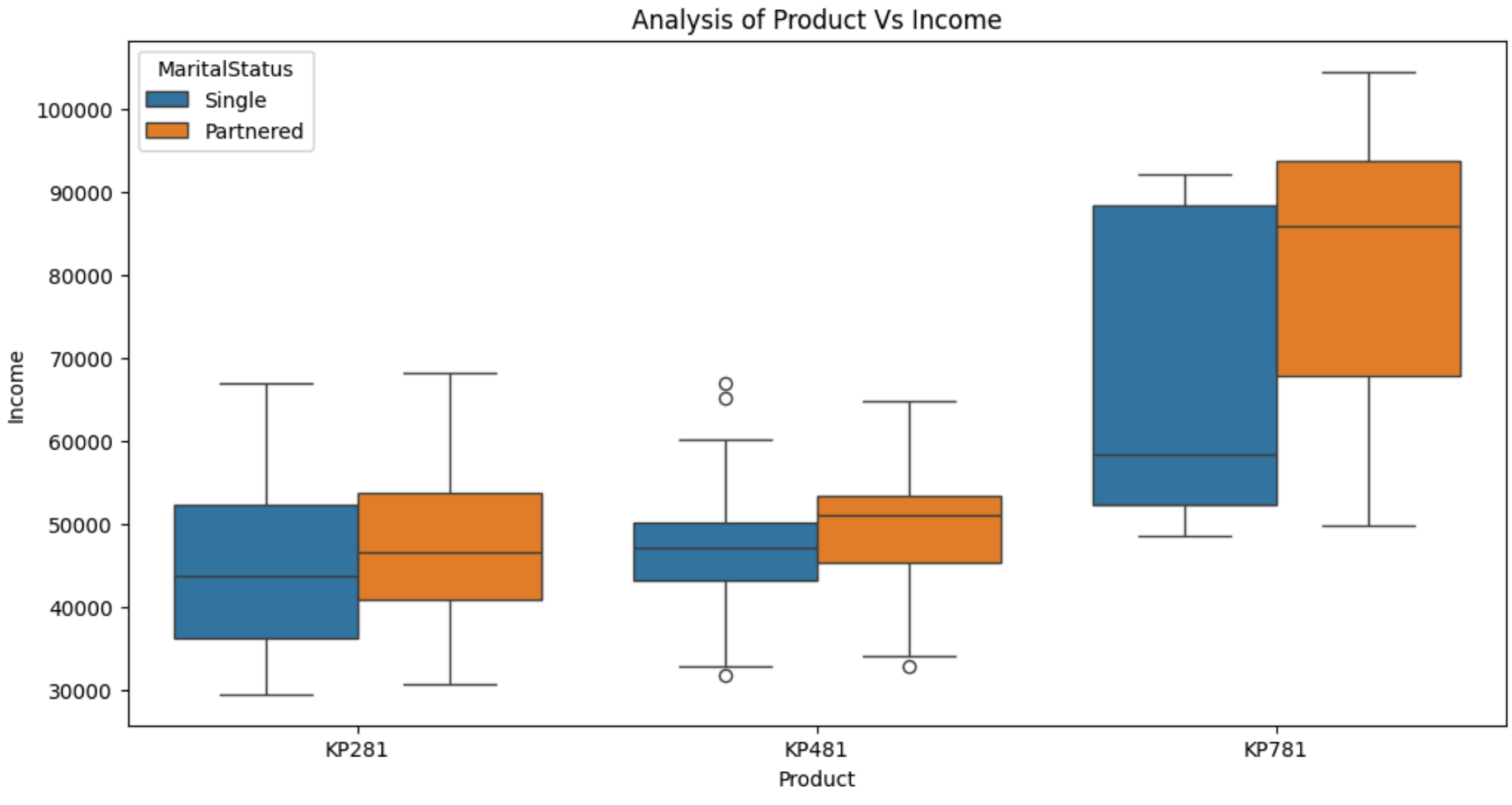
- The people with the income between **45000 to 50000 USD** 💸 prefer both **KP281 and KP481 treadmill**.
- The people with the high income **above 70000 USD** 💰 prefer both **KP781 treadmill**.

In [33]:
```
df.groupby(["Product", "MaritalStatus"])["Income"].median().reset_index()
```

Out[33]:

	Product	MaritalStatus	Income
0	KP281	Partnered	46617.0
1	KP281	Single	43774.5
2	KP481	Partnered	51165.0
3	KP481	Single	47185.5
4	KP781	Partnered	85906.0
5	KP781	Single	58516.0

In [34]:
```
# Analysis of Income Vs MaritalStatus:

plt.figure(figsize=(12, 6))
sns.boxplot(x='Product', y='Income',hue = "MaritalStatus", data=df)
plt.title('Analysis of Product Vs Income')
plt.xlabel('Product')
plt.ylabel('Income')
plt.show()
```



🔍OBSERVATION for KP281 treadmill🔎

The **median income** of **single** having **44000 USD** and **partnered** having **47000 USD** prefer **KP281 treadmill** and the partnered having more income higher than single prefer KP281.

🔍OBSERVATION for KP481 treadmill🔎

The **median income** of **single** having **47000 USD** and **partnered** having **51000 USD** prefer **KP481 treadmill** and the partnered having more income higher than single prefer KP481.

🔍OBSERVATION for KP781 treadmill🔎

The **median income** of **single** having **59000 USD** and **partnered** having **86000 USD** prefer **KP781 treadmill** and the partnered having more income higher than single prefer KP781.

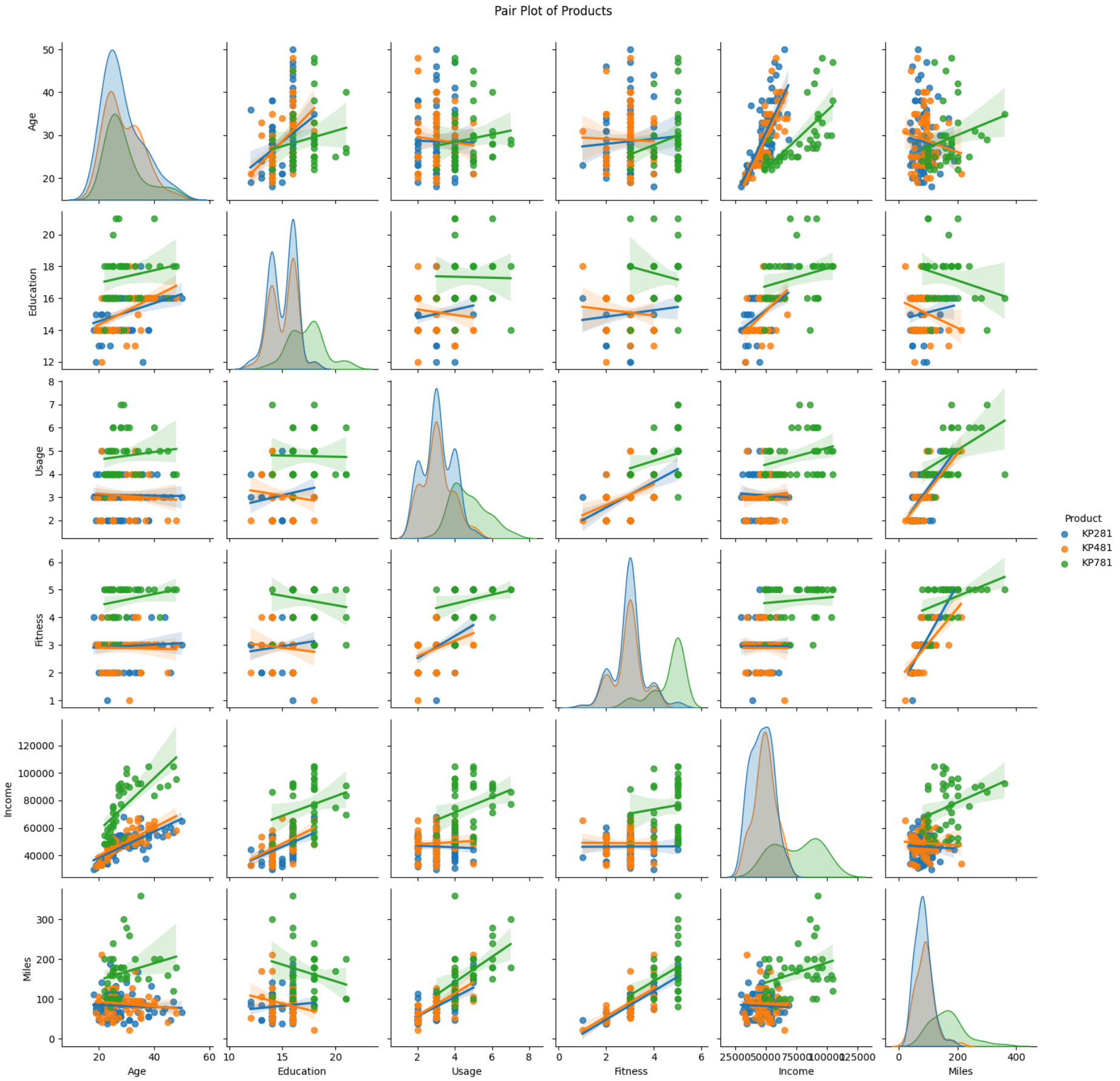
CONCLUSION😀

- The **single and partnered** having median income income in between **44000 and 51000 USD** 💸 prefer both **KP281 and KP481 treadmill**.
- The **single and partnered** having high median income income in between **60000 and 86000 USD** 💰 prefer both **KP781 treadmill**.

Correlation Analysis 🤝

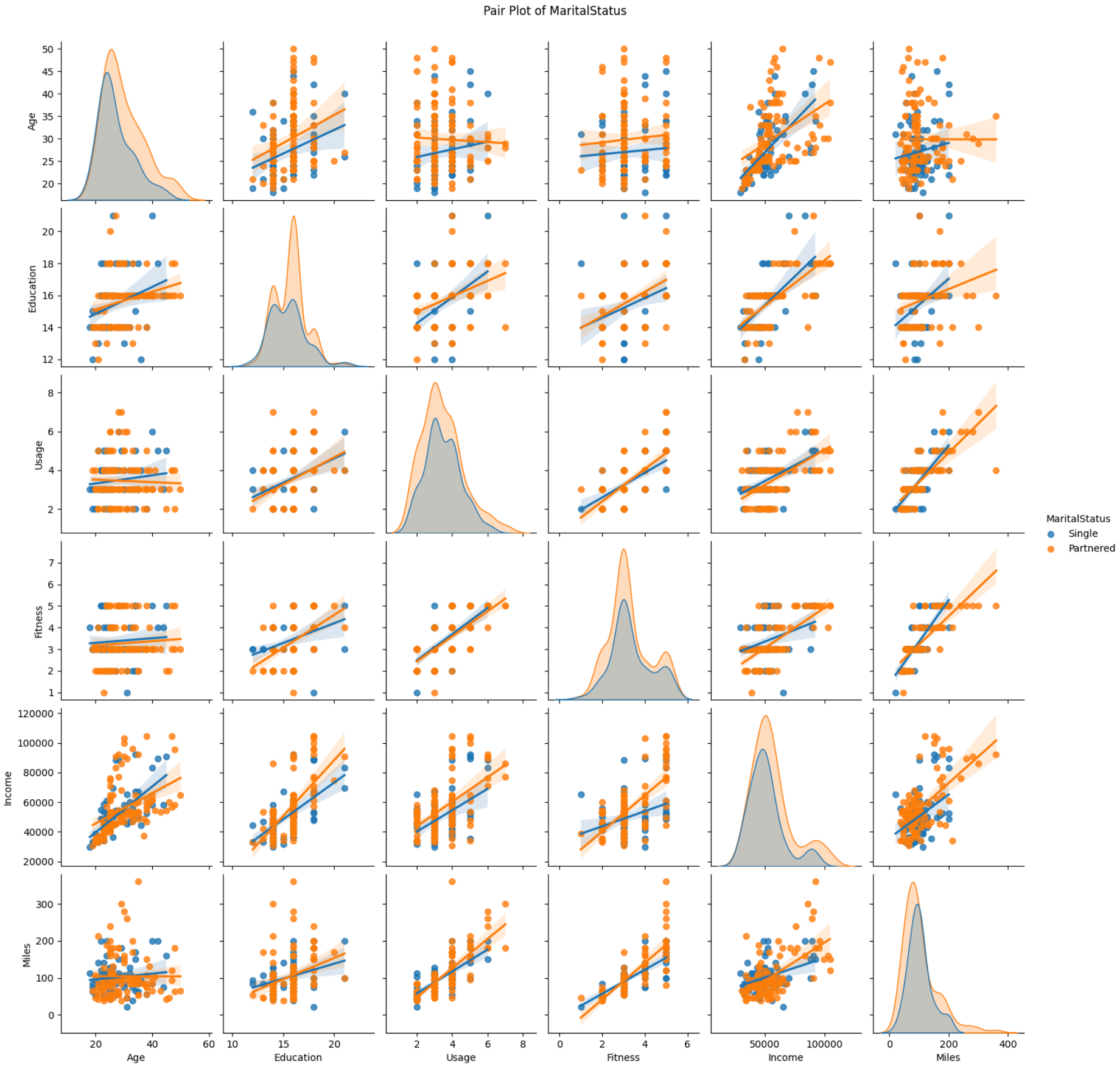
In [ ]:
```
#Pair Plot of Products

plt.figure(figsize=(10, 5))
sns.pairplot(data=df, hue="Product", kind='reg')

plt.suptitle("Pair Plot of Products", y=1.02)

plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



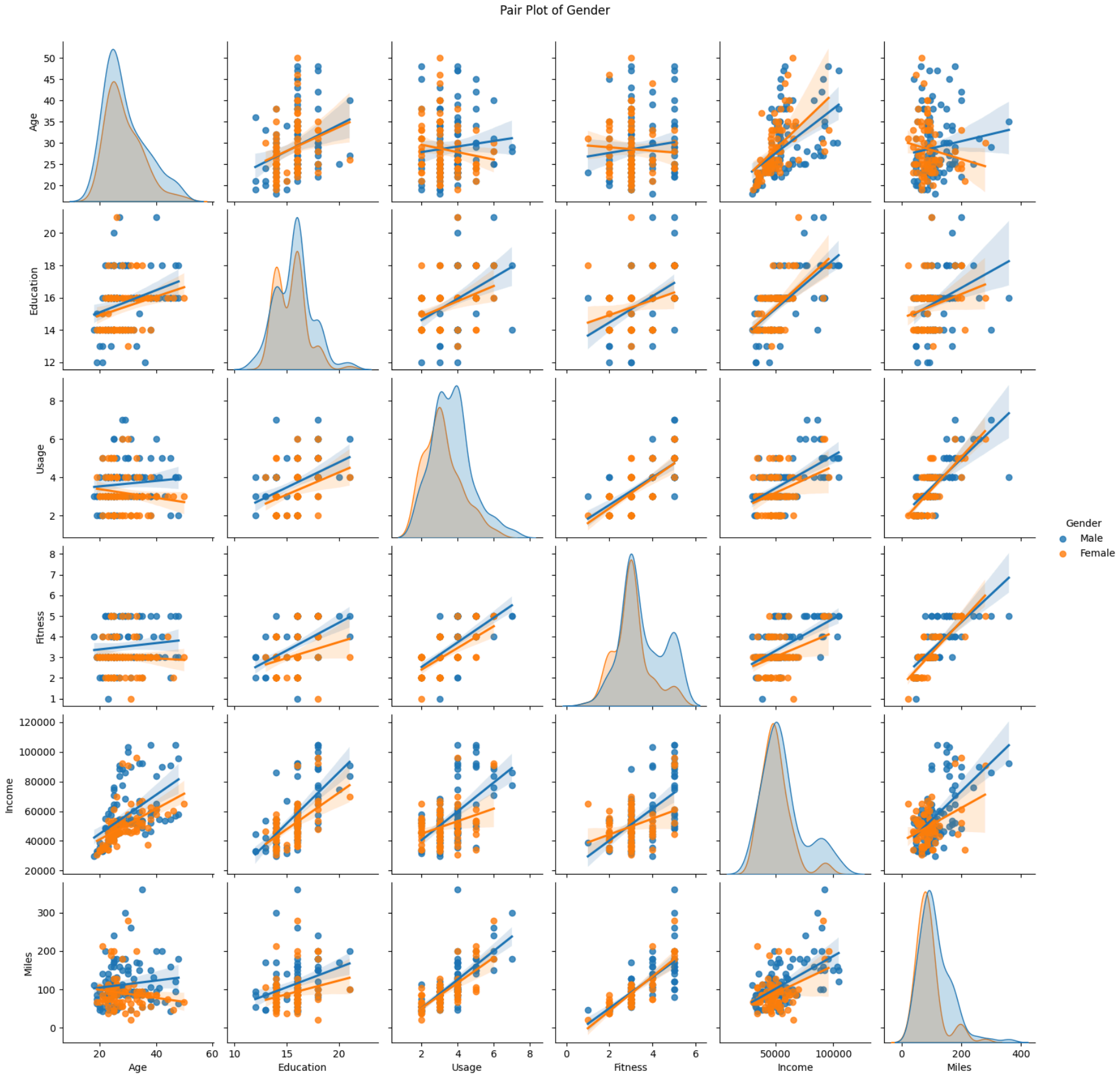
In [49]:
```
#Pair Plot of MaritalStatus

plt.figure(figsize=(10, 5))
sns.pairplot(data=df, hue="MaritalStatus", kind='reg')

plt.suptitle("Pair Plot of MaritalStatus", y=1.02)
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```

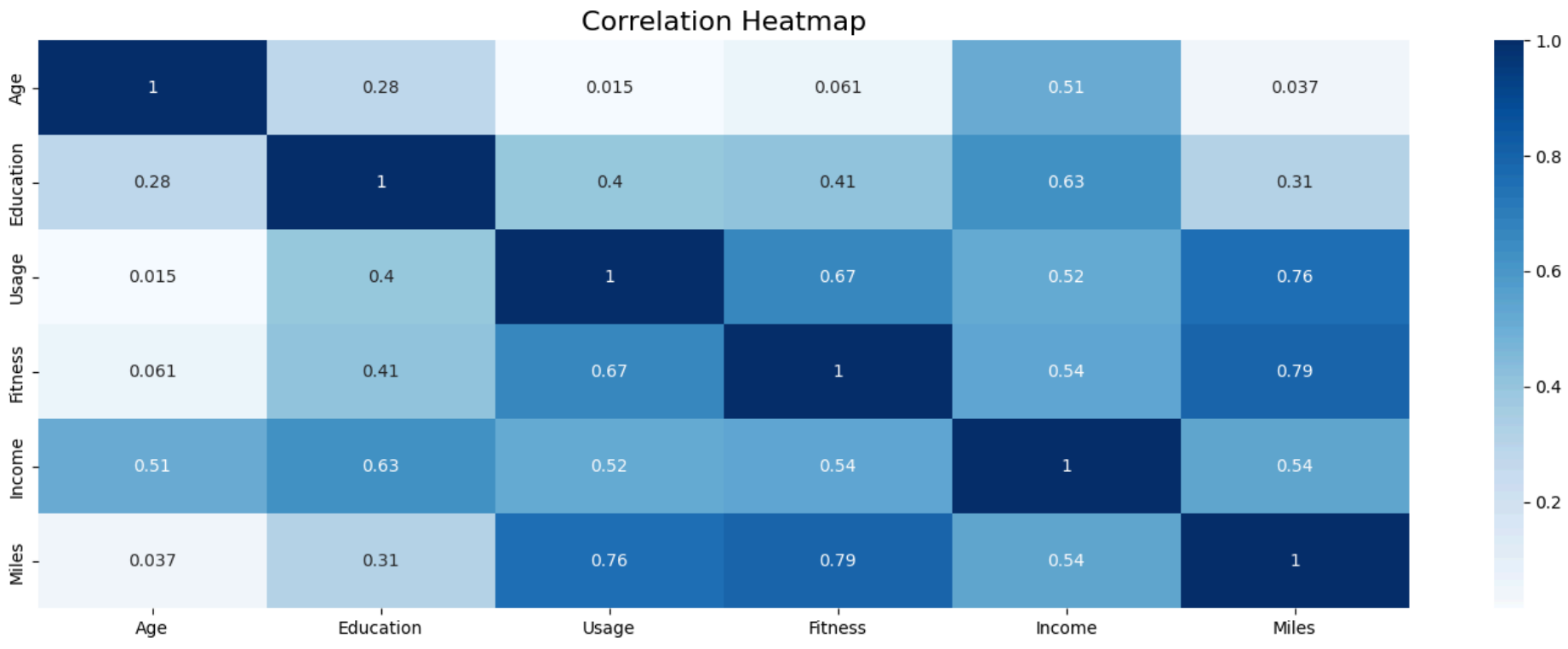


In [50]:
```
#Pair Plot of Gender

plt.figure(figsize=(10, 5))
sns.pairplot(data=df, hue="Gender", kind='reg')

plt.suptitle("Pair Plot of Gender", y=1.02)

plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



In [35]:
```
#Correlation Heatmap:

df_numeric = df.select_dtypes(include=['int64'])
plt.figure(figsize=(18, 6))
sns.heatmap(df_numeric.corr(), annot=True, cmap="Blues")

# Set title for the heatmap
plt.title("Correlation Heatmap", fontsize=16)


# Show the plot
plt.show()
```



Probablity ❓ / 💯

Marginal probability 👉

In [6]:
```
#Marginal probability of Products:

product_value_counts = ((df["Product"].value_counts(normalize=True)) * 100).round(2)
product_value_counts_df = pd.DataFrame(product_value_counts)
product_value_counts_df.columns = ['Percentage']
styled_table = product_value_counts_df.style.background_gradient(cmap='Blues').format("{:.2f}")
styled_table
```

Out[6]:

	Percentage
KP281	44.44
KP481	33.33
KP781	22.22

In [7]:
```
#Marginal probability of Gender:

Gender_value_counts = ((df["Gender"].value_counts(normalize = True)) *100).round(2)
Gender_value_counts_df = pd.DataFrame(Gender_value_counts)
Gender_value_counts_df.columns = ['Percentage']
styled_table = Gender_value_counts_df.style.background_gradient(cmap='Blues').format("{:.2f}")
styled_table
```

Out[7]:

	Percentage
Male	57.78
Female	42.22

In [8]:
```
#Marginal probability of MaritalStatus:

MaritalStatus_value_counts = ((df["MaritalStatus"].value_counts(normalize = True)) *100).round(2)
MaritalStatus_value_counts_df = pd.DataFrame(MaritalStatus_value_counts)
MaritalStatus_value_counts_df.columns = ['Percentage']
styled_table = MaritalStatus_value_counts_df.style.background_gradient(cmap='Blues').format("{:.2f}")
styled_table
```

Out[8]:

	Percentage
Partnered	59.44
Single	40.56

In [9]:
```
#Marginal probability of Fitness_Shape:

Fitness_Shape_value_counts = ((df["Fitness_Shape"].value_counts(normalize = True)) *100).round(2)
Fitness_Shape_value_counts_df = pd.DataFrame(Fitness_Shape_value_counts)
Fitness_Shape_value_counts_df.columns = ['Percentage']
styled_table = Fitness_Shape_value_counts_df.style.background_gradient(cmap='Blues').format("{:.2f}")
styled_table
```

Out[9]:

	Percentage
Average	53.89
Excellent	17.22
Bad	14.44
Good	13.33
Poor	1.11

Conditional probability 👉

Product with gender ♂/♀

In [40]:
```
#Cross tab on Product and Gender:

Pob_P_G1 = round(pd.crosstab(index=df["Product"], columns=df["Gender"], margins = True, normalize=True)*100,2)
Pob_P_G1
```

Out[40]:

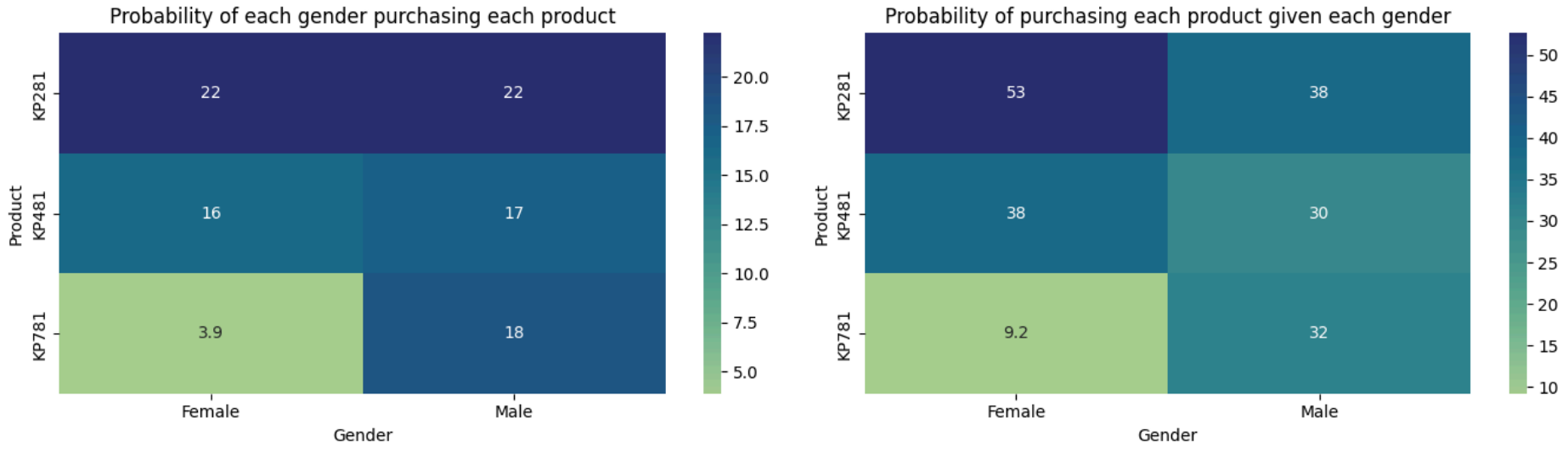
Gender	Female	Male	All
Product			
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

In [41]:
```
#Cross tab on Product and Gender:

Pob_P_G2 = round(pd.crosstab(index=df["Product"], columns=df["Gender"], normalize="columns") * 100, 2)
Pob_P_G2
```

Out[41]:

Gender	Female	Male
Product		
KP281	52.63	38.46
KP481	38.16	29.81
KP781	9.21	31.73

In [42]:
```
#Representation of the above table in the form of heatmap:

plt.figure(figsize=(14,4))

plt.subplot(1,2,1)
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["Gender"],normalize=True)*100,2), annot=True, cmap="crest")
plt.title("Probability of each gender purchasing each product")

plt.subplot(1,2,2)
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["Gender"],normalize="columns")*100,2), annot=True, cmap="crest")
plt.title("Probability of purchasing each product given each gender")

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



🔍 OBSERVATION for KP281 treadmill 🔎

1). The overall Probabilities of purchase of KP281 is an entry-level treadmill is **44%**

- The probablity of **Male** is **22%**
- The probablity of **Female** is **22%**

Therefore we can conclude that both men and women are **equally preferring KP281** at overall level.

2). The overall Probabilitiy of Male for all treadmill is 58%

- Among all Male the probability of preferring KP281 ie) **P(KP281|Male) is 38%**

3). The overall Probabilitiy of Female for all treadmill is 42%

- Among all Female the probability of preferring KP281 ie) **P(KP281|Female) is 53%**

From point 2 and 3 we can conclude that most of the **Female purchasing KP281 is more than Male**.

CONCLUSION 😀

- 🥇 The **first target** 🎯 should for **KP281** treadmill should be **Female** ♀
- 🥈 The **Second target** 🎯 should for **KP281** treadmill should be **Male** ♂

🔍 OBSERVATION for KP481 treadmill 🔎

1). The overall Probabilities of purchase of KP481 is an entry-level treadmill is **33%**

- The probablity of **Male** is **17%**
- The probablity of **Female** is **16%**

Therefore we can conclude that both men and women are **almost equally preferring KP481** at overall level.

2). The overall Probabilitiy of Male for all treadmill is 58%

- Among all Male the probability of preferring KP481 ie) **P(KP481|Male) is 30%**

3). The overall Probabilitiy of Female for all treadmill is 42%

- Among all Female the probability of preferring KP481 ie) **P(KP481|Female) is 38%**

From point 2 and 3 we can conclude that most of the **Female purchasing KP481 is more than Male**.

CONCLUSION 😀

- 🥇 The **first target** 🎯 should for **KP481** treadmill should be **Female** ♀
- 🥈 The **Second target** 🎯 should for **KP481** treadmill should be **Male** ♂

🔍 OBSERVATION for KP781 treadmill 🔎

1). The overall Probabilities of purchase of KP781 is an entry-level treadmill is **22%**

- The probablity of **Male** is **18%**
- The probablity of **Female** is **4%**

Therefore we can conclude that **men are preferring KP781** more than female at overall level.

2). The overall Probabilitiy of Male for all treadmill is 58%

- Among all Male the probability of preferring KP781 ie) **P(KP781|Male) is 32%**

3). The overall Probabilitiy of Female for all treadmill is 42%

- Among all Female the probability of preferring KP781 ie) **P(KP781|Female) is 9%**

From point 2 and 3 we can conclude that most of the **Male purchasing KP781 is more than Female**.

CONCLUSION 😀

- 🥇 The **first target** 🎯 should for **KP781** treadmill should be **Male** ♂
- 🥈 The **Second target** 🎯 should for **KP781** treadmill should be **Female** ♀

Product with Marital Status 👫

In [43]:
```
#Cross tab on Product and MaritalStatus:

Pob_P_M1 = round(pd.crosstab(index=df["Product"], columns=df["MaritalStatus"], margins = True, normalize=True)*100,2)
Pob_P_M1
```

Out[43]:

MaritalStatus	Partnered	Single	All
Product			
KP281	26.67	17.78	44.44
KP481	20.00	13.33	33.33
KP781	12.78	9.44	22.22
All	59.44	40.56	100.00

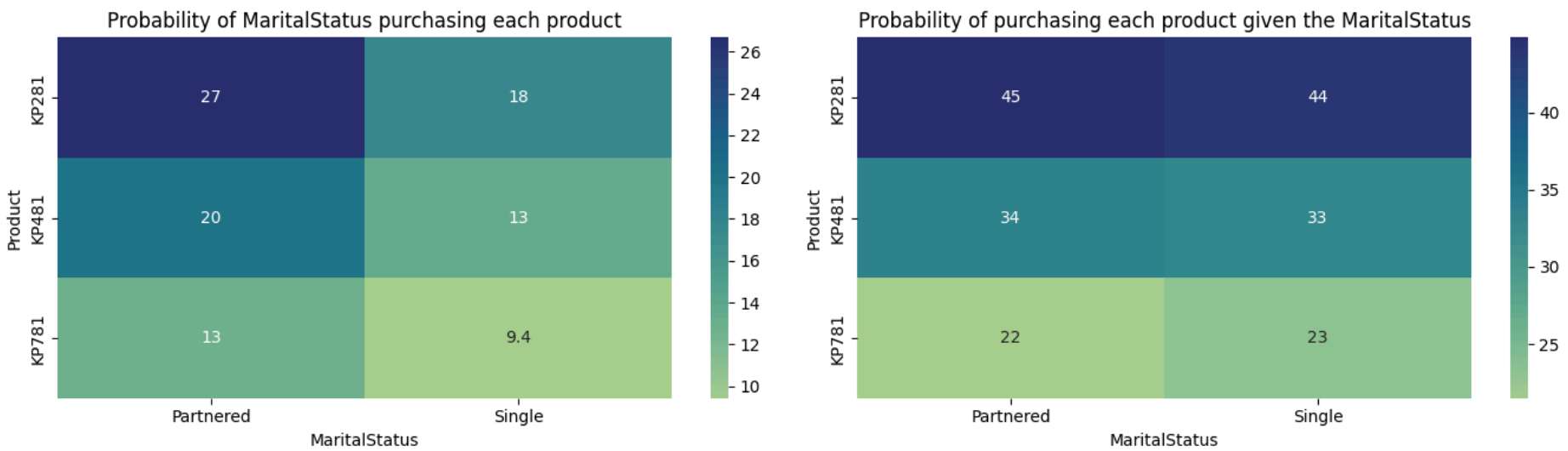
In [44]:
```
#Cross tab on Product and MaritalStatus:

Pob_P_M2 = round(pd.crosstab(index=df["Product"], columns=df["MaritalStatus"], normalize="columns") * 100, 2)
Pob_P_M2
```

Out[44]:

MaritalStatus	Partnered	Single
Product		
KP281	44.86	43.84
KP481	33.64	32.88
KP781	21.50	23.29

In [45]:
```
#Representation of the above table in the form of heatmap:

plt.figure(figsize=(14,4))

plt.subplot(1,2,1)
```

```
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["MaritalStatus"],normalize=True)*100,2), annot=True, cmap="crest")
plt.title("Probability of MaritalStatus purchasing each product")

plt.subplot(1,2,2)
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["MaritalStatus"],normalize="columns")*100,2), annot=True, cmap="cre
plt.title("Probability of purchasing each product given the MaritalStatus")

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



🔍 OBSERVATION for KP281 treadmill 🔎

1). The overall Probabilities of purchase of KP281 is an entry-level treadmill is **44%**

- The probablity of **Partnered** is **27%**
- The probablity of **Single** is **18%**

Therefore we can conclude that **Partnered people are preferring KP281** more than Single at overall level.

2). The overall Probabilitiy of Partnered for all treadmill is 59%

- Among all Partnered the probability of preferring KP281 ie) **P(KP281|Partnered) is 45%**

3). The overall Probabilitiy of Single for all treadmill is 41%

- Among all Single the probability of preferring KP281 ie) **P(KP281|Single) is 44%**

From point 2 and 3 we can conclude that **both Partnered and Single prefer KP281 treadmill equally but Partnered is little bit high**

CONCLUSION 😀

- **Both Partnered and Single** are the targets 🎯 for **KP281 treadmill**.

🔍 OBSERVATION for KP481 treadmill 🔎

1). The overall Probabilities of purchase of KP481 treadmill is **33%**

- The probablity of **Partnered** is **20%**
- The probablity of **Single** is **13%**

Therefore we can conclude that **Partnered people are preferring KP481** more than Single at overall level.

2). The overall Probabilitiy of Partnered for all treadmill is 59%

- Among all Partnered the probability of preferring KP481 ie) **P(KP481|Partnered) is 34%**

3). The overall Probabilitiy of Single for all treadmill is 41%

- Among all Single the probability of preferring KP481 ie) **P(KP481|Single) is 33%**

From point 2 and 3 we can conclude that **both Partnered and Single prefer KP481 treadmill equally but Partnered is little bit high**

CONCLUSION 😀

- **Both Partnered and Single** are the targets 🎯 for **KP481 treadmill**.

🔍 OBSERVATION for KP781 treadmill 🔎

1). The overall Probabilities of purchase of KP781 treadmill is **22%**

- The probablity of **Partnered** is **13%**
- The probablity of **Single** is **9%**

Therefore we can conclude that **Partnered people are preferring KP781** more than Single at overall level.

2). The overall Probabilitiy of Partnered for all treadmill is 59%

- Among all Partnered the probability of preferring KP781 ie) **P(KP781|Partnered) is 22%**

3). The overall Probabilitiy of Single for all treadmill is 41%

- Among all Single the probability of preferring KP781 ie) **P(KP781|Single) is 23%**

From point 2 and 3 we can conclude that **both Partnered and Single prefer KP781 treadmill equally but Single is little bit high**

CONCLUSION 😀

- **Both Partnered and Single** are the targets 🎯 for **KP781 treadmill**.

Product with Fitness Shape 💪

In [46]:
```
#Cross tab on Product and Fitness_Shape:

Pob_P_F1 = round(pd.crosstab(index=df["Product"], columns=df["Fitness_Shape"], margins = True, normalize=True)*100,2)
Pob_P_F1
```

Out[46]:

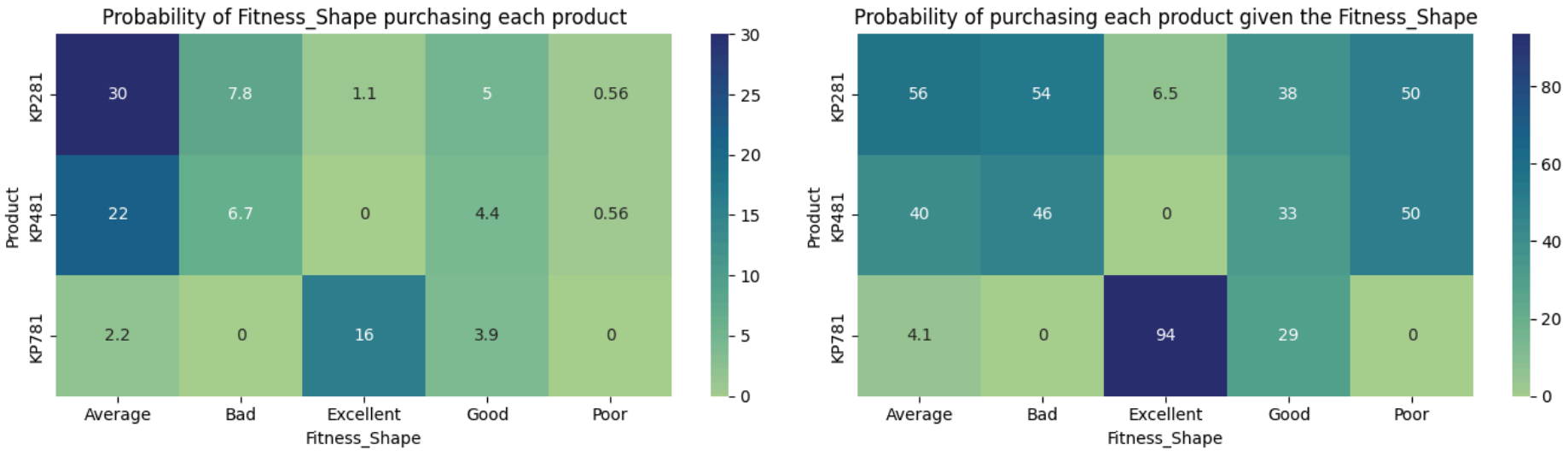
Fitness_Shape	Average	Bad	Excellent	Good	Poor	All
Product						
KP281	30.00	7.78	1.11	5.00	0.56	44.44
KP481	21.67	6.67	0.00	4.44	0.56	33.33
KP781	2.22	0.00	16.11	3.89	0.00	22.22
All	53.89	14.44	17.22	13.33	1.11	100.00

In [47]:
```
#Cross tab on Product and Fitness_Shape:

Pob_P_F2 = round(pd.crosstab(index=df["Product"], columns=df["Fitness_Shape"], normalize="columns") * 100, 2)
Pob_P_F2
```

Out[47]:

Fitness_Shape	Average	Bad	Excellent	Good	Poor
Product					
KP281	55.67	53.85	6.45	37.50	50.0
KP481	40.21	46.15	0.00	33.33	50.0
KP781	4.12	0.00	93.55	29.17	0.0

In [48]:
```
#Representation of the above table in the form of heatmap:

plt.figure(figsize=(14,4))

plt.subplot(1,2,1)
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["Fitness_Shape"],normalize=True)*100,2), annot=True, cmap="crest")
plt.title("Probability of Fitness_Shape purchasing each product")

plt.subplot(1,2,2)
sns.heatmap(round(pd.crosstab(index=df["Product"], columns=df["Fitness_Shape"],normalize="columns")*100,2), annot=True, cmap="cre
plt.title("Probability of purchasing each product given the Fitness_Shape")

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



🔍 OBSERVATION for KP281 treadmill 🔎

1) The overall probability of purchase of KP281 is **44%**

- The probability of **Average shape** 🎯 people purchasing it is **30%**
- The probability of **Bad shape** people purchasing it is **8%**

- The probability of **Excellent Shape** people purchasing it is **1%**
- The probability of **Good Shape** people purchasing it is **5%**
- The probability of **Poor Shape** people purchasing it is **0.5%**

Therefore we can conclude that the people with the **Average shape people are preferring KP281 more**

2) The overall Probablity of Average shape people purchasing all treadmill is 54%

- Among all Average shape people the probablity of KP281 ie) **P(KP281|Average shape)🎯 is 56%**

3) The overall Probablity of Bad shape people purchasing all treadmill 14%

- Among all Bad shape people the probablity of KP281 ie) **P(KP281|Bad shape)🎯 is 54%**

4) The overall Probablity of Excellent shape people purchasing all treadmill 17%

- Among all Excellent shape people the probablity of KP281 ie) **P(KP281|Excellent shape) is 6.5%**

5) The overall Probablity of Good shape people purchasing all treadmill 13%

- Among all Good shape people the probablity of KP281 ie) **P(KP281|Good shape)🎯 is 38%**

6) The overall Probablity of Poor shape people purchasing all treadmill 1%

- Among all Poor shape people the probablity of KP281 ie) **P(KP281|Poor shape)🎯 is 50%**

CONCLUSION😀

Average, Bad, Good and Poor Shape people are the targets for **KP281 treadmill** and among those the **first target is Average Shape people 🎯**

🔍OBSERVATION for KP481 treadmill🔎

1) The overall probability of purchase of KP481 is **33%**

- The probability of **Average shape🎯** people purchasing it is **22%**
- The probability of **Bad shape** people purchasing it is **7%**
- The probability of **Excellent Shape** people purchasing it is **0%**
- The probability of **Good Shape** people purchasing it is **4%**
- The probability of **Poor Shape** people purchasing it is **0.5%**

Therefore we can conclude that the **Average shape people are preferring KP481 more**

2) The overall Probablity of Average shape people purchasing all treadmill is 54%

- Among all Average shape people the probablity of KP481 ie) **P(KP481|Average shape)🎯 is 40%**

3) The overall Probablity of Bad shape people purchasing all treadmill 14%

- Among all Bad shape people the probablity of KP481 ie) **P(KP481|Bad shape)🎯 is 46%**

4) The overall Probablity of Excellent shape people purchasing all treadmill 17%

- Among all Excellent shape people the probablity of KP481 ie) **P(KP481|Excellent shape) is 0%**

5) The overall Probablity of Good shape people purchasing all treadmill 13%

- Among all Good shape people the probablity of KP481 ie) **P(KP481|Good shape)🎯 is 33%**

6) The overall Probablity of Poor shape people purchasing all treadmill 1%

- Among all Poor shape people the probablity of KP481 ie) **P(KP481|Poor shape)🎯 is 50%**

CONCLUSION😀

Average, Bad, Good and Poor Shape people are the targets for **KP481 treadmill** and among those the **first target is Bad Shape people🎯**

🔍OBSERVATION for KP781 treadmill🔎

1) The overall probability of purchase of KP781 is **22%**

- The probability of **Average shape** people purchasing it is **2%**
- The probability of **Bad shape** people purchasing it is **0%**
- The probability of **Excellent Shape🎯** people purchasing it is **16%**

- The probability of **Good Shape** people purchasing it is **4%**
- The probability of **Poor Shape** people purchasing it is **0%**

Therefore we can conclude that the **Excellent shape people are preferring KP781 more**

2) The overall Probablity of Average shape people purchasing all treadmill is 54%

- Among all Average shape people the probablity of KP781 ie) **P(KP781|Average shape) is 4%**

3) The overall Probablity of Bad shape people purchasing all treadmill 14%

- Among all Bad shape people the probablity of KP781 ie) **P(KP781|Bad shape) is 0%**

4) The overall Probablity of Excellent shape people purchasing all treadmill 17%

- Among all Excellent shape people the probablity of KP781 ie) **P(KP781|Excellent shape)🎯 is 93%**

5) The overall Probablity of Good shape people purchasing all treadmill 13%

- Among all Good shape people the probablity of KP781 ie) **P(KP781|Good shape)🎯 is 29%**

6) The overall Probablity of Poor shape people purchasing all treadmill 1%

- Among all Poor shape people the probablity of KP781 ie) **P(KP781|Poor shape) is 0%**

CONCLUSION 😀

Excellent and Good Shape people are the targets for **KP781 treadmill** and among those the **first target is Excellent Shape people🎯**

Customer Profile👉

🥇 For KP281 Treadmill 🏃

- It is an entry-level treadmill that sells for **$1,500**.
- It has contributed about **44%** of the overall sales.
- **Both Male and Female** with age of **26 years** are equally preferring KP281 Treadmill.
- Regarding Fitness preference,
  - First - **Average shape (3)** people.
  - Second - **Bad shape (2)** people.
  - Third - **good shape (4)** people.
- Regarding Education preference,
  - First - **16 years**.
  - Second - **14 years**.
  - Third - **15 years**.
- Regarding Usage preference,
  - First - **3 times a week**.
  - Second - **4 times a week**.
  - Third - **2 times a week**.
- The median income of **male and female having 46000 USD** prefer KP281 treadmill and the **male income is little bit high than female**.
- The median income of **single having 44000 USD and partnered having 47000 USD** prefer KP281 treadmill and the **partnered having more income higher than single** prefer KP281.
- Regarding gender preference,
  - First - **Female**
  - Second - **Male**
- Regarding Marital Status preference, **Both Partnered and Single** are the targets for KP281 treadmill.

🥈 For KP481 Treadmill 🏃

- It is a mid-level treadmill that sell for **$1,750**.
- It has contributed about **33%** of the overall sales.
- The median age of **Male having 25 years** and **Female having 29 years** are preferring KP481 Treadmill.
- Regarding Fitness preference,
  - First - **Bad shape (2)** people.
  - Second - **Average shape (3)** people.
  - Third - **good shape (4)** people.
- Regarding Education preference,
  - First - **16 years**.

    - Second - **14 years**.
    - Third - **13 years**.
- Regarding Usage preference,
    - First - **3 times a week**.
    - Second - **2 times a week**.
    - Third - **4 times a week**.
- The median income of **male having 50000 USD and female having 49000 USD** prefer KP481 treadmill and the male income is little bit high than female.
- The median income of **single having 47000 USD and partnered having 51000 USD** prefer KP481 treadmill and the **partnered having more income higher than single** prefer KP481.
- Regarding gender preference,
    - First - **Female**
    - Second - **Male**
- Regarding Marital Status preference, **Both Partnered and Single** are the targets for KP481 treadmill.

🥉 For KP781 Treadmill 🏃

- It is the treadmill is having advanced features that sell for **$2,500**.
- It has contributed about **22%** of the overall sales.
- The median age of **Male having 27 years and Female having 26 years** are preferring KP781 Treadmill.
- Regarding Fitness preference,
    - First - **Excellent shape (5)** people.
    - Second - **good shape (4)** people.
    - Third - **Average shape (3)** people
- Regarding Education preference,
    - First - **18 years**.
    - Second - **16 years**.
    - Third - **21 years**.
- Regarding Usage preference,
    - First - **4 times a week**.
    - Second - **5 times a week**. *Third - **6 times a week**.
- The median income of **male having 77000 USD and female having 70000 USD** prefer KP781 treadmill and the **male income is high than female**.
- The median income of **single having 59000 USD and partnered having 86000 USD** prefer KP781 treadmill and the partnered having more income higher than single prefer KP781.
- Regarding gender preference,
    - First - **Male**.
    - Second - **Female**.
- Regarding Marital Status preference, **Both Partnered and Single** are the targets for KP281 treadmill.

Recommendations 🤝

For KP281 and KP481 treadmill 💡

- Since the **price is so attrective** it has good customer base.
- Since it has good number of customers, **continuously innovate, and upgrade** the product to stay ahead of competitors and can get enough feedback to improve further.
- Expand the product line by introducing **variations or complementary products** that appeal to existing customers or attract new ones. This could include offering different sizes, Flavors, colours, or features to cater to diverse preferences.
- Since KP281 and KP481 are more popular product among the average shape customers, create **specialized versions of KP281 and KP481 designed specifically for individuals with average body shapes**. This could include features such as adjustable sizing, ergonomic designs, or customized fit options to enhance comfort and satisfaction.
- **Develop marketing campaigns that promote body positivity**, highlighting how the KP281 and KP481 are suitable for individuals of all body shapes and sizes. Emphasize the benefits of the product in **enhancing confidence, comfort, and self-esteem for those with average body shapes**.
- Since KP281 and KP481 are more popular among female, **develop targeted marketing campaigns that specifically appeal to female consumers**. Utilize channels and messaging that resonate with female interests, preferences, and values to effectively reach and engage this demographic.
- **Collaborate with influencers, or bloggers especially female** who represent average body shapes. Partnering with individuals who promote body positivity and diversity can help amplify the message and reach a wider audience of potential customers.
- **Keep a close eye on competitor activities and market trends within the female consumer segment**. Stay informed about emerging products, innovations, and marketing strategies targeting women and adapt strategies accordingly to maintain a competitive edge.
- Since KP281 and KP481 are **more popular among Partnered than single**, develop marketing content and messaging that emphasizes the benefits of KP281 and KP481 for **strengthening relationships and fostering connection between partners**. Highlight how using the

product together can create shared memories and deepen emotional bonds.

For KP781 treadmill 💡

- It has some advanced features and is suitable for the customers having more **passion about their fitness**.
- Since KP781 is more popular product among the excellent shape customers, **create specialized versions of KP781 designed specifically for individuals with a excellent body shapes**. This could include features such as adjustable sizing, ergonomic designs, or customized fit options to enhance comfort and satisfaction.
- **Emphasize the fitness and performance benefits** of KP781 for individuals with excellent body shapes. Position the product as a tool for **enhancing athletic performance, improving strength, and achieving peak physical condition**.
- Since KP781 is more popular among male, **develop targeted marketing campaigns that specifically appeal to male consumers**. Utilize channels and messaging that resonate with male interests, preferences, and values to effectively reach and engage this demographic.
- **Collaborate with influencers, or bloggers especially male who represent excellent body shapes**. Partnering with individuals who promote body positivity and diversity can help amplify the message and reach a wider audience of potential customers.
- **Keep a close eye on competitor activities and market trends within the male consumer segment**. Stay informed about emerging products, innovations, and marketing strategies targeting men and adapt strategies accordingly to maintain a competitive edge.
- Since KP781 is more popular among Partnered than single, develop marketing content and messaging that emphasizes the benefits of KP781 for **strengthening relationships and fostering connection between partners**. Highlight how using the product together can create shared memories and deepen emotional bonds.
- Since KP781 is more popular among high income people, **offer exclusive access or benefits to high-income consumers** as part of a loyalty program or membership scheme. This could include early access to new product releases, VIP events, personalized services, or concierge support tailored to their needs.