AEROFIT BUSINESS CASE

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.-

PROBLEM STATEMENT AND ANALYSING BASIC METRICS -

PROBLEM STATEMENT

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.

1)Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.

2)For each AeroFit treadmill product, construct 2 - way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business

Import Libraries

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Loading Dataset

In [4]:
```
df = pd.read_csv("aerofit_treadmill.txt")
```

In [4]:
```
df.head(10)
```

Out[4]:

	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

In [5]:
```python
df.shape # shape of data
```

Out[5]:
```
(180, 9)
```

In [6]:
```python
df.info() # information about the data
```

```
<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 [7]:
```python
df.dtypes # data types of all the attributes
```

Out[7]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

In [8]:
```python
df.describe() # statistical summary
```

Out[8]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

In [9]:
```python
df.describe(include = object) # Description of data type-> object  columns
```

Out[9]:

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

In [10]:

```
df.columns
```

Out[10]:

```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

In [6]:

```
# Converting Int data type of fitness rating to object data type
df_cat = df
df_cat["Fitness_category"] = df.Fitness
df_cat.head()
```

Out[6]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fit
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 [7]:

```
df_cat["Fitness_category"].replace(
    {1:'Poor  Shape',
     2:'Bad Shape',
     3:'Average  Shape',
     4:'Good Shape',
     5:'Excellent Shape'},inplace = True)
```

In [8]:

```
df_cat["MaritalStatus"].replace({'Partnered':'Married'},inplace  =  True)
```

In [9]:

```
df_cat.head()
```

Out[9]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fit
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	Married	4	3	30699	66	
3	KP281	19	Male	12	Single	3	3	32973	85	
4	KP281	20	Male	13	Married	4	2	35247	47	

MISSING VALUE DETECTION/NULL VALUE DETECTION

In [7]:
```
df_cat.isna().sum()
```

Out[7]:
```
Product             0
Age                 0
Gender              0
Education           0
MaritalStatus       0
Usage               0
Fitness             0
Income              0
Miles               0
Fitness_category    0
dtype: int64
```

Insight - In the aerofit dataset no null/missing values were detected.

NON-GRAPHICAL ANALYSIS

In [15]:
```
df_cat.nunique() # unique values of all the attributes
```

Out[15]:
```
Product              3
Age                 32
Gender               2
Education            8
MaritalStatus        2
Usage                6
Fitness              5
Income              62
Miles               37
Fitness_category     5
dtype: int64
```

Value counts of each attribute

In [16]:
```
df_cat["Product"].value_counts()
```

Out[16]:
```
Product
KP281    80
KP481    60
KP781    40
Name: count, dtype: int64
```

In [120…
```
df_cat["Age"].value_counts().head()
```

Out[120…
```
Age
25    25
23    18
24    12
26    12
28     9
Name: count, dtype: int64
```

In [121…
```
df_cat["Gender"].value_counts()
```

Out[121…
```
Gender
Male      104
Female     76
Name: count, dtype: int64
```

In [122…
```
df_cat["Education"].value_counts()
```

Out[122…
```
Education
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: count, dtype: int64
```

In [123…
```
df_cat["MaritalStatus"].value_counts()
```

Out[123…
```
MaritalStatus
Married    107
Single      73
Name: count, dtype: int64
```

In [124…
```
df_cat["Usage"].value_counts()
```

Out[124…
```
Usage
3    69
4    52
2    33
5    17
6     7
7     2
Name: count, dtype: int64
```

In [56]:
```
df_cat["Fitness"].value_counts().sort_index()
```

Out[56]:
```
Fitness
1     2
2    26
3    97
4    24
5    31
Name: count, dtype: int64
```

In [126…
```
df_cat['Income'].nunique()
```

Out[126…
```
62
```

In [127…
```
df_cat["Income"].value_counts().head()
```

Out[127…
```
Income
45480    14
52302     9
46617     8
54576     8
53439     8
Name: count, dtype: int64
```

In [128…
```
df_cat["Miles"].value_counts().head()
```

Out[128…
```
Miles
85    27
95    12
66    10
75    10
47     9
Name: count, dtype: int64
```

In [7]:
```
df_cat
```

Out[7]:

	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	Married	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Married	4	2	35247	47
...	...	...	...	...	...	...	...	...	...
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	Married	4	5	104581	120
179	KP781	48	Male	18	Married	4	5	95508	180

180 rows × 10 columns

In [132…
```
# for unique list of products, listed in percentage


a = df_cat["Product"].value_counts(normalize = True) * 100
product = np.round(a,2)
product
```

Out[132…
```
Product
KP281    44.44
KP481    33.33
KP781    22.22
Name: proportion, dtype: float64
```

In [133…
```
b = df_cat["MaritalStatus"].value_counts(normalize = True) * 100
MaritalStatus = np.round(b,2)
MaritalStatus
```

Out[133…
```
MaritalStatus
Married    59.44
Single     40.56
Name: proportion, dtype: float64
```

In [134…
```
c = df_cat["Gender"].value_counts(normalize = True) * 100
Gender = np.round(c,2)
Gender
```

Out[134…
```
Gender
Male      57.78
Female    42.22
Name: proportion, dtype: float64
```

In [55]:
```
d = df_cat['Fitness_category'].value_counts(normalize = True) * 100
Fitness_category = np.round(d,2)
Fitness_category
```

Out[55]:
```
Fitness_category
Average Shape      53.89
Excellent Shape    17.22
Bad Shape          14.44
Good Shape         13.33
Poor Shape          1.11
Name: proportion, dtype: float64
```

In [11]:
```
usage  =  df_cat['Usage'].value_counts(normalize=True).map(lambda  calc:round(100*c
usage
```

Out[11]:

	Usage	proportion
0	3	38.33
1	4	28.89
2	2	18.33
3	5	9.44
4	6	3.89
5	7	1.11

In [60]:
```
f = df_cat['Miles'].value_counts(normalize = True) * 100
Miles = np.round(f,2)
Miles.head()
```

Out[60]:
```
Miles
85    15.00
95     6.67
66     5.56
75     5.56
47     5.00
Name: proportion, dtype: float64
```

In [62]:
```
g = df_cat['Age'].value_counts(normalize = True) * 100
Age = np.round(g,2)
Age.head()
```

Out[62]:
```
Age
25    13.89
23    10.00
24     6.67
26     6.67
28     5.00
Name: proportion, dtype: float64
```

In [64]:
```
h = df_cat['Education'].value_counts(normalize = True) * 100
Education = np.round(h,2)
Education.head()
```

Out[64]:
```
Education
16    47.22
14    30.56
18    12.78
15     2.78
13     2.78
Name: proportion, dtype: float64
```

In [66]:
```
i = df_cat['Income'].value_counts(normalize = True) * 100
Income = np.round(h,2)
Income.head()
```

Out[66]:
```
Education
16    47.22
14    30.56
18    12.78
15     2.78
13     2.78
Name: proportion, dtype: float64
```

In [12]:
```
df_cat.groupby("Age")["Product"].count().head()
```

Out[12]:
```
Age
18    1
19    4
20    5
21    7
22    7
Name: Product, dtype: int64
```

Converting columns - Age, Miles, Income, Education into groups

In [13]:
```
# Define age bins and labels
bins = [0, 18, 30, 40, 60, 100]  # Customize these bins according to your age gr
```

```python
labels = ['0-18', '19-30', '31-40', '41-60', '61+']

# Create a new column 'AgeGroup' using cut
df_cat['AgeGroup'] = pd.cut(df_cat['Age'], bins=bins, labels=labels, right=False
```

In [14]:

```python
miles_bins = [0, 50, 100, 150, 200, 250, 300, 350, 400]
miles_labels = ['0-50', '51-100', '101-150', '151-200', '201-250','251-300', '30
df_cat['MilesGroup'] = pd.cut(df_cat['Miles'], bins=miles_bins, labels=miles_lab
```

In [15]:

```python
income_bins = [0, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000, 90000,
income_labels = ['0-10000', '10001-20000', '20001-30000', '30001-40000', '40001-
df_cat['IncomeGroup'] = pd.cut(df_cat['Income'], bins=income_bins, labels=income
```

In [16]:

```python
edu_years_bins = [0, 12, 16, 18, 20, 25]
edu_years_labels = ['0-12', '13-16', '17-18', '19-20', '21+']
df_cat['EducationYearsGroup'] = pd.cut(df_cat['Education'], bins=edu_years_bins,
df_cat.head()
```

Out[16]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fit
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	Married	4	3	30699	66	
3	KP281	19	Male	12	Single	3	3	32973	85	
4	KP281	20	Male	13	Married	4	2	35247	47	

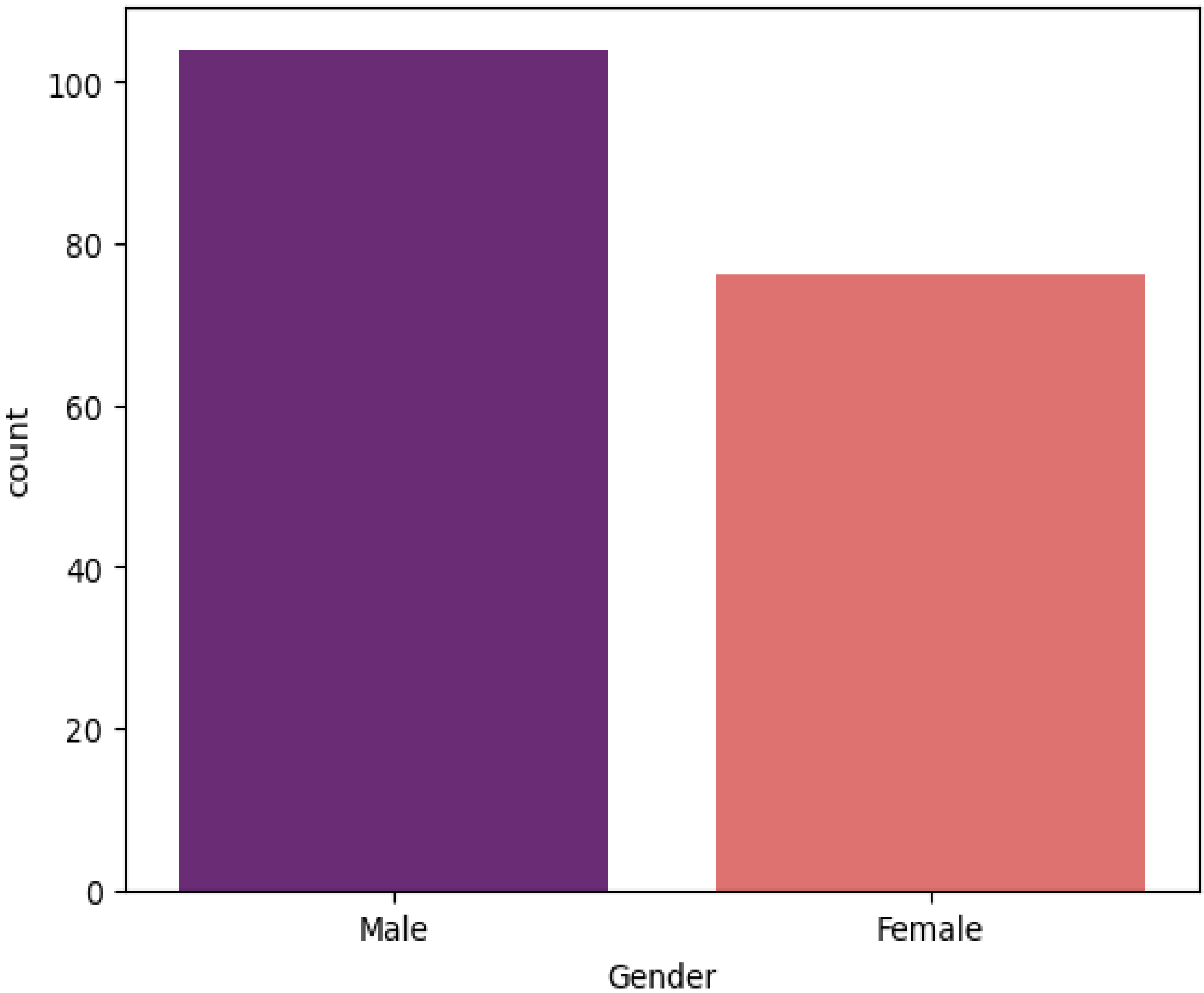
VISUAL ANALYSIS

Univariate

Countplot

In [136…

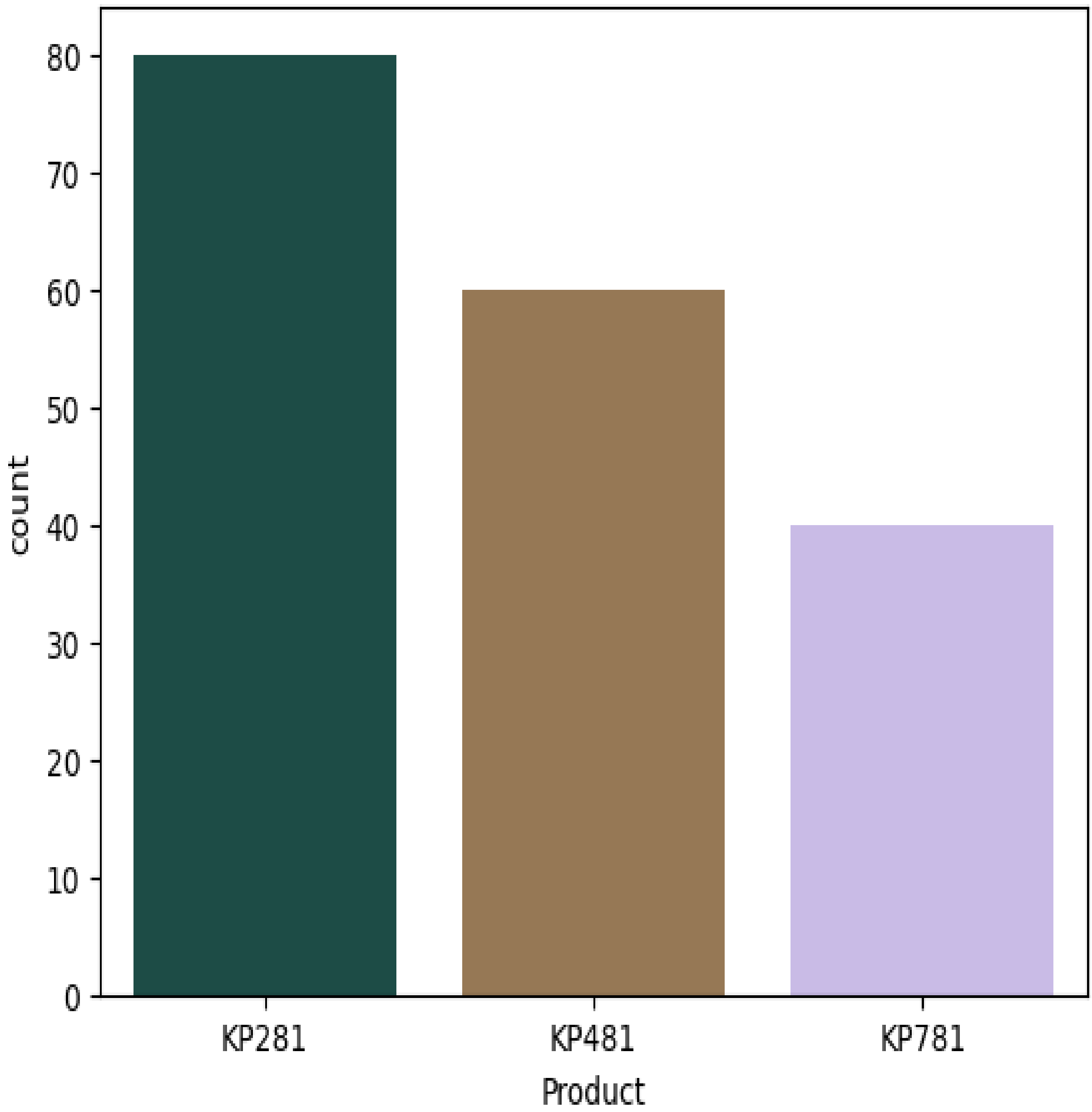
```
sns.countplot(df_cat,x = "Gender",palette = "magma")
plt.show()
```



Insight - In our dataset, there is a higher proportion of males than females.

In [138…

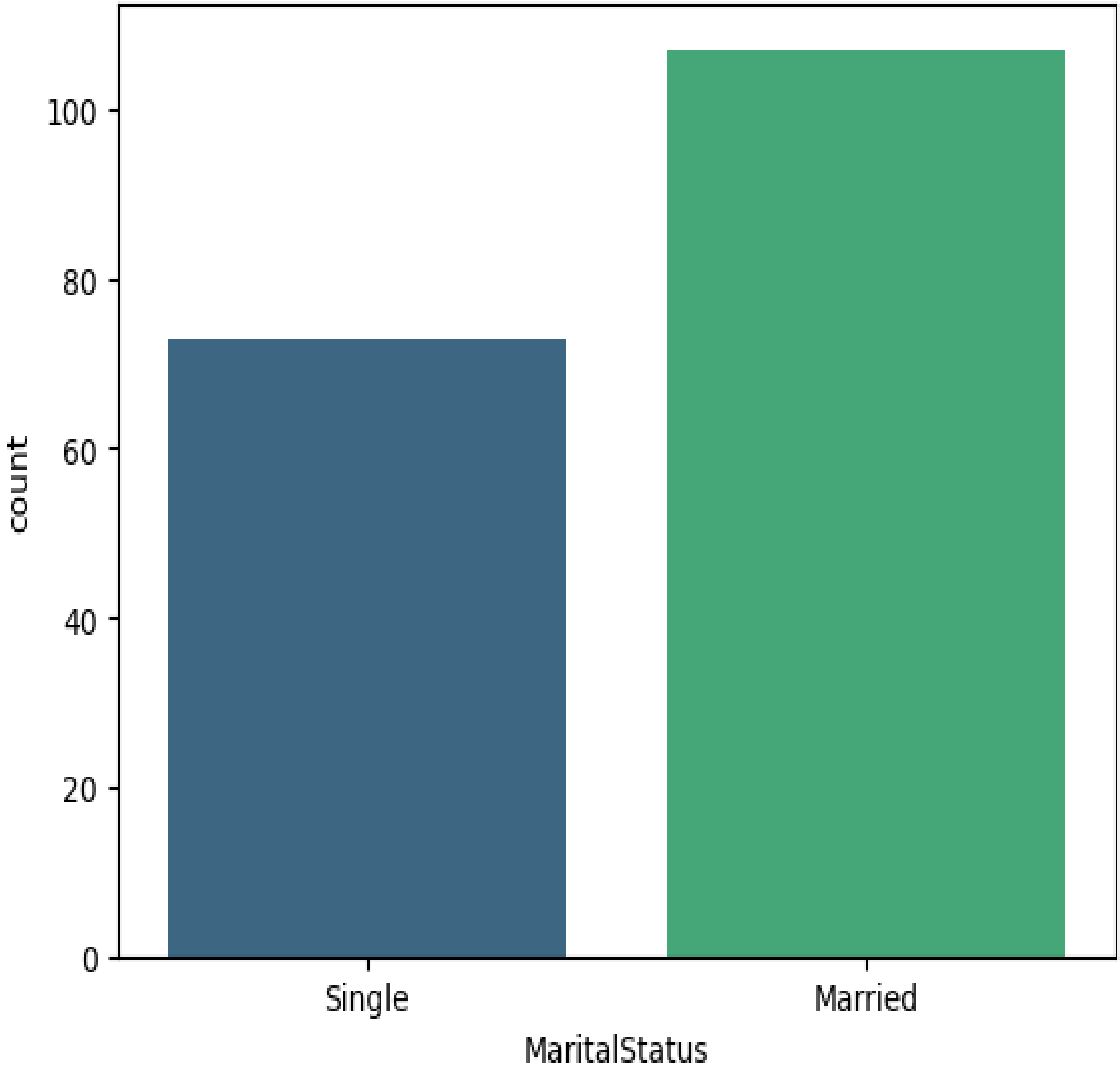
```
sns.countplot(df_cat,x = "Product",palette = "cubehelix")
plt.show()
```



Insight - Based on the preceding observation, it is evident that product KP281 has recorded the highest sales.

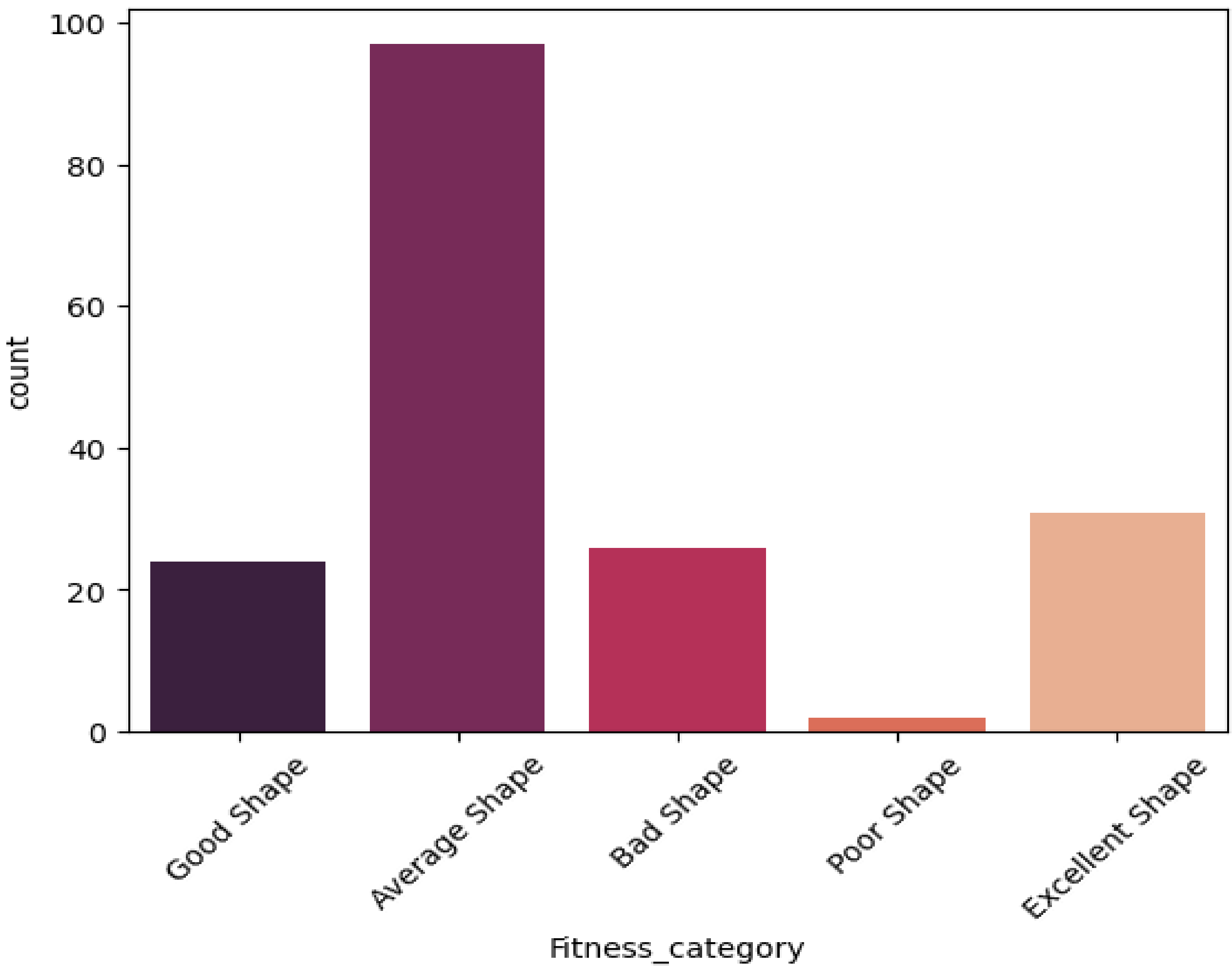
In [139…

```python
sns.countplot(df_cat,x = "MaritalStatus",palette = "viridis")
plt.show()
```



Insight - In our dataset, the count of married individualsexceeds that of unmarried or single individuals.

```
In [140…  sns.countplot(df_cat,x = 'Fitness_category',palette = "rocket")
          plt.xticks(rotation = 45)
          plt.show()
```

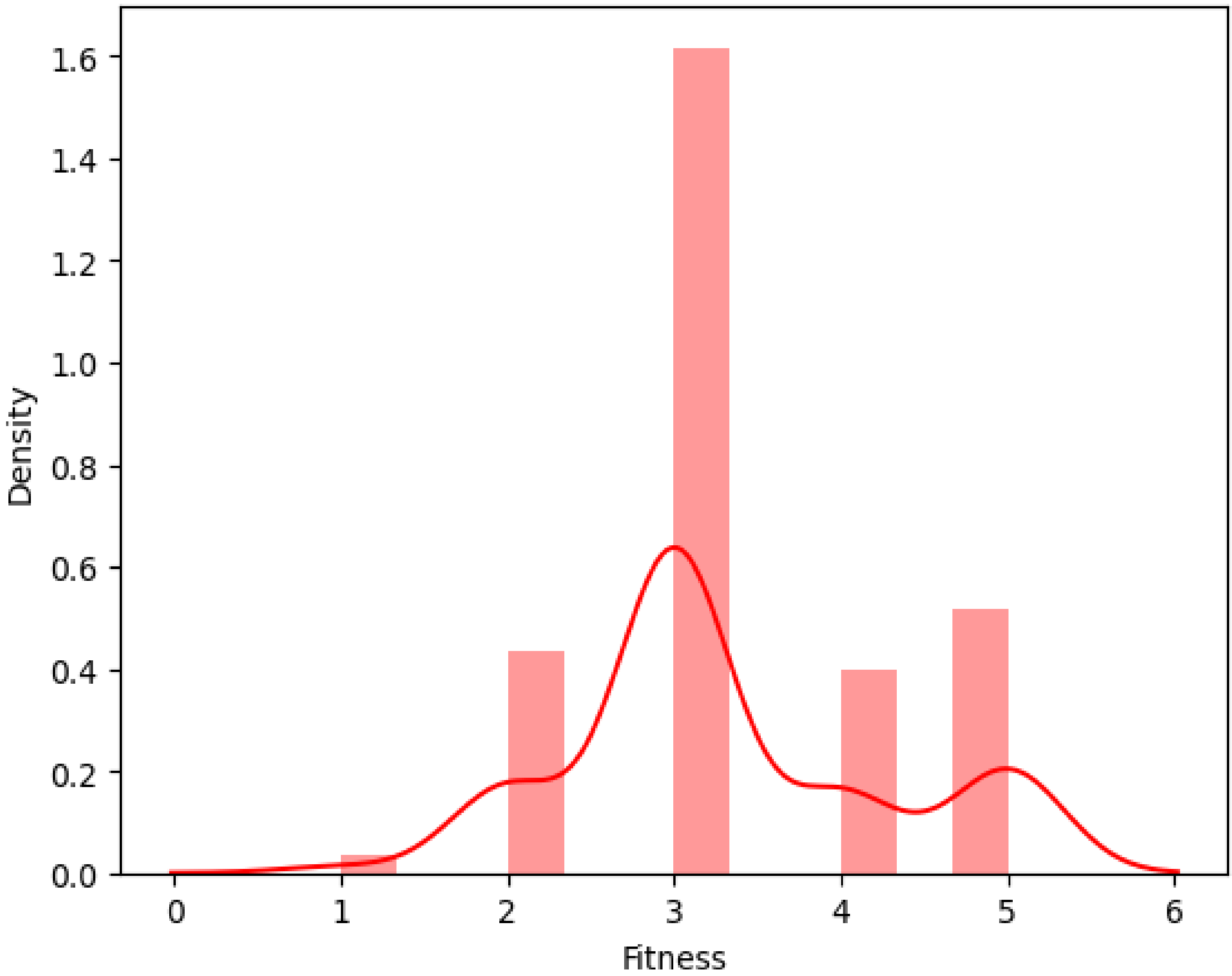


Insight - The majority of individuals in our dataset exhibit an average body shape.

Distplot

In [141…

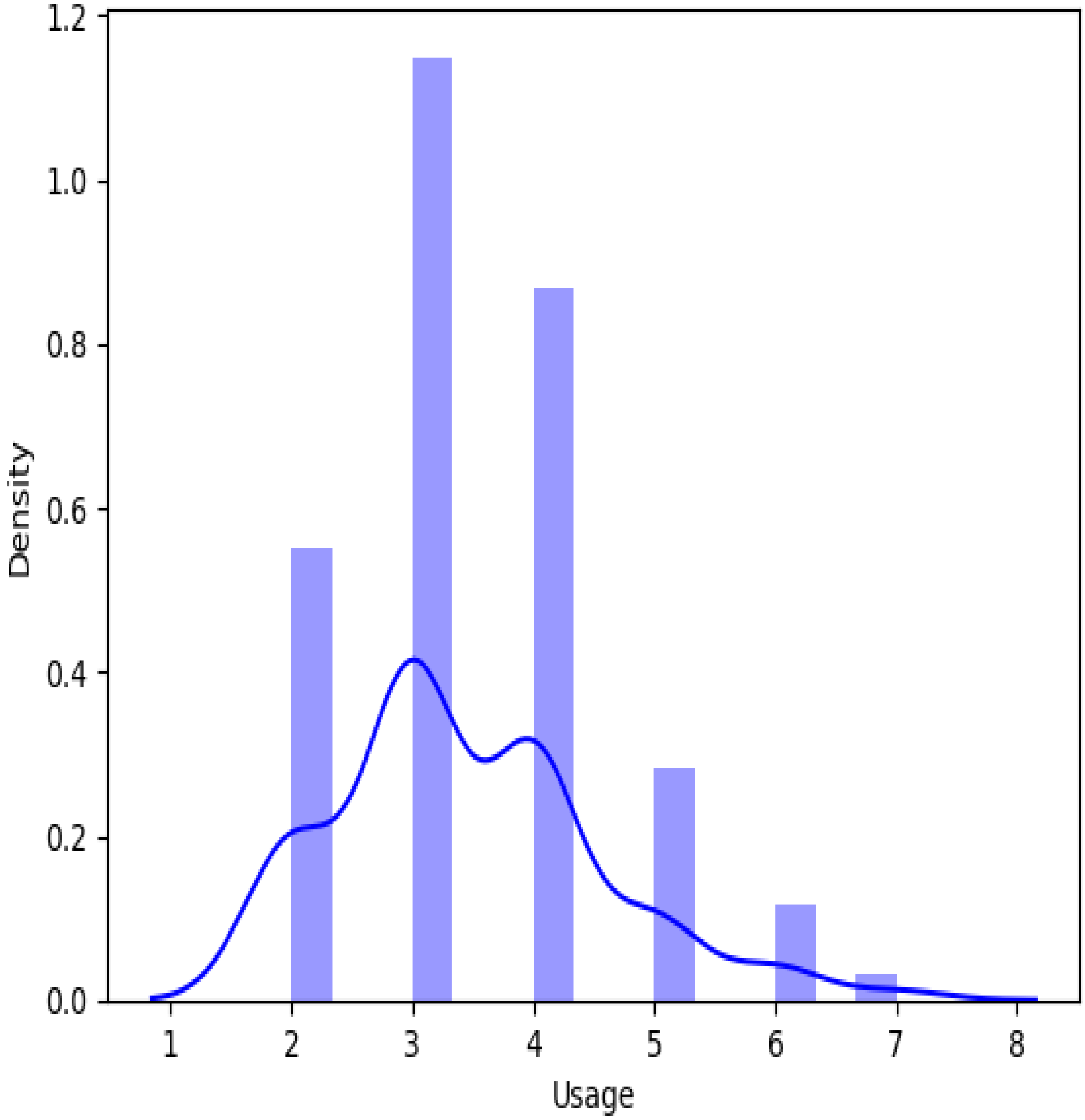
```
sns.distplot(df_cat.Fitness,color = "red")
plt.show()
```



Insight - Fitness level 3 is the predominant category among individuals in our dataset.

In [142…

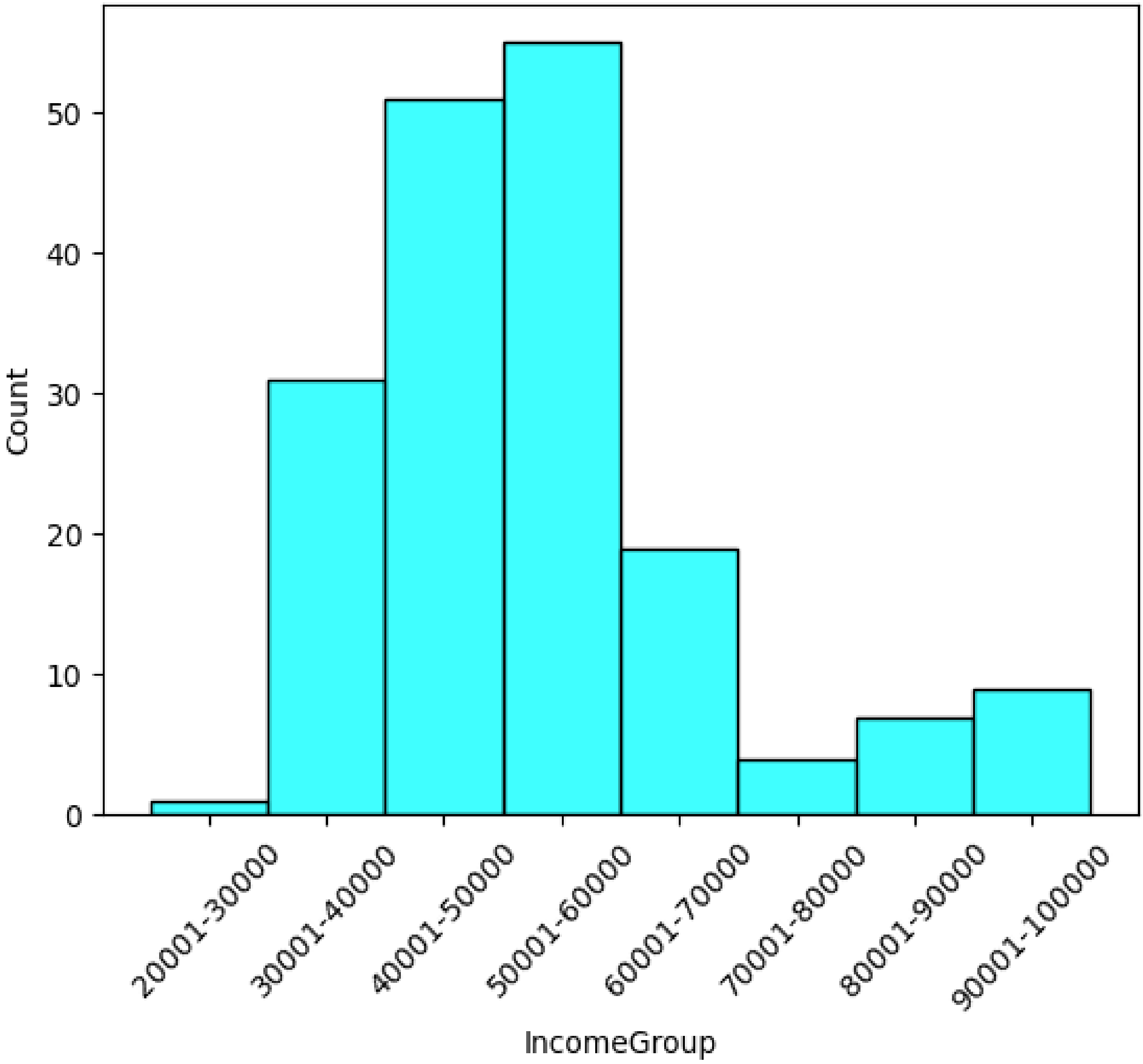
```
sns.distplot(df_cat["Usage"],color = "blue")
plt.show()
```



Insight - Based on the distplot above, it can be inferred that a significant portion of individuals prefer to use the treadmill three times per week.

Histplot

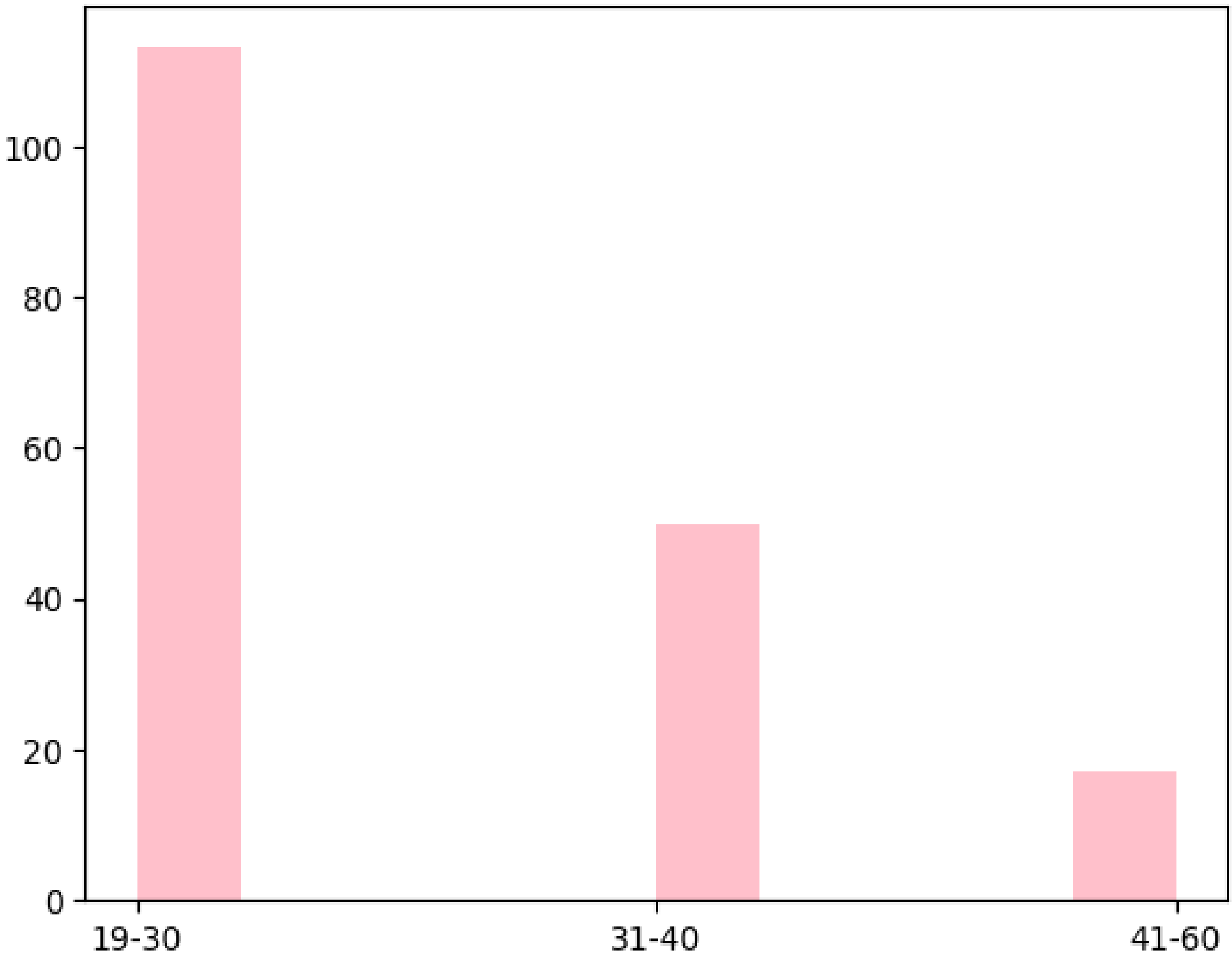
In [37]:
```
sns.histplot(df_cat,x = "IncomeGroup",color = "cyan")
plt.xticks(rotation = 45)
plt.show()
```



Insight - In the Aerofit dataset, the majority of individuals fall within the income range of 50001-60000 dollars.

In [86]:

```
plt.hist(df_cat["AgeGroup"],bins = 10,color = "pink")
plt.show()
```

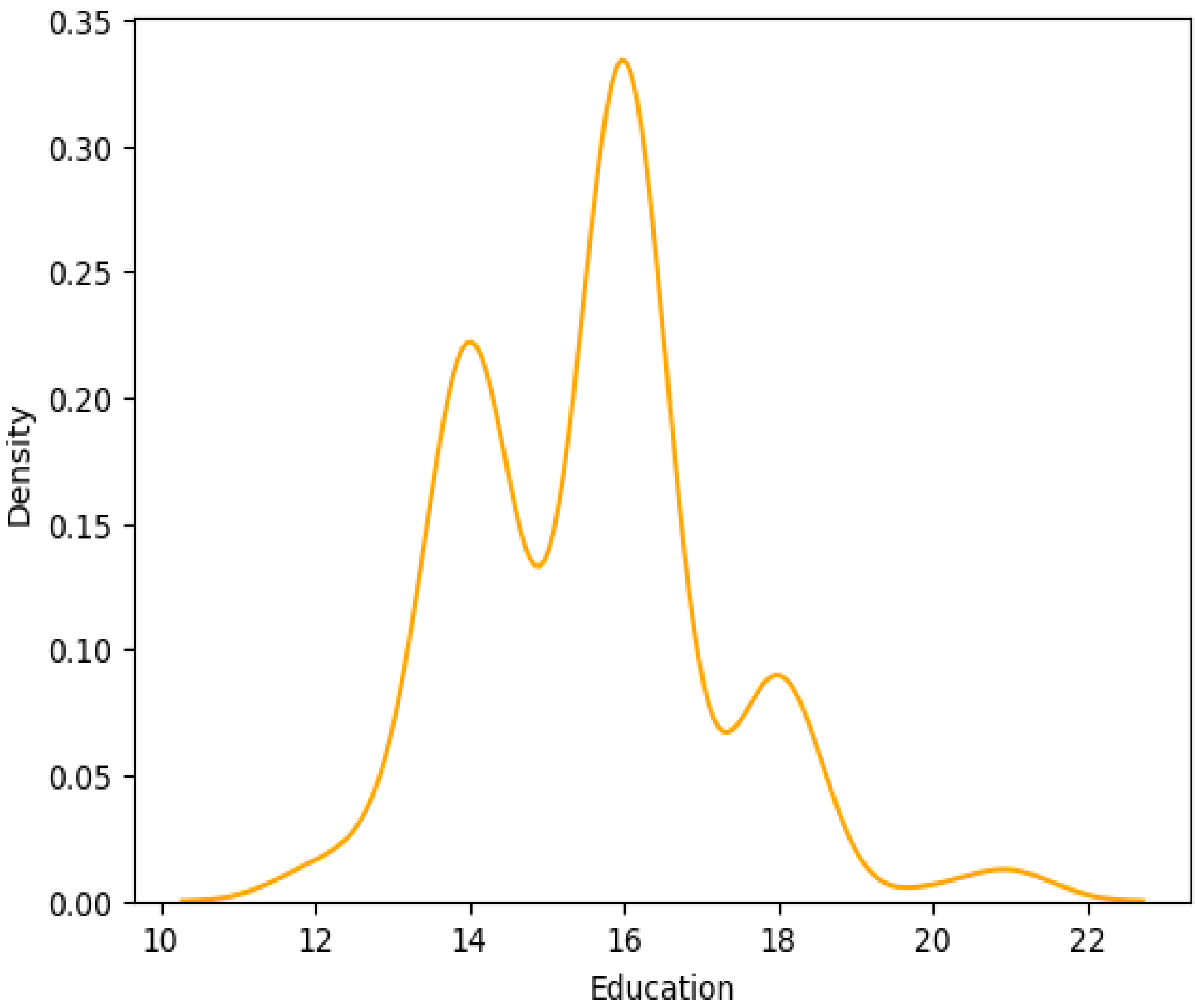


Insight - The age group 19-30 dominates the users of thetreadmill in our dataset, indicating a preference for treadmill usage among young individuals.

Kdeplot

In [145…

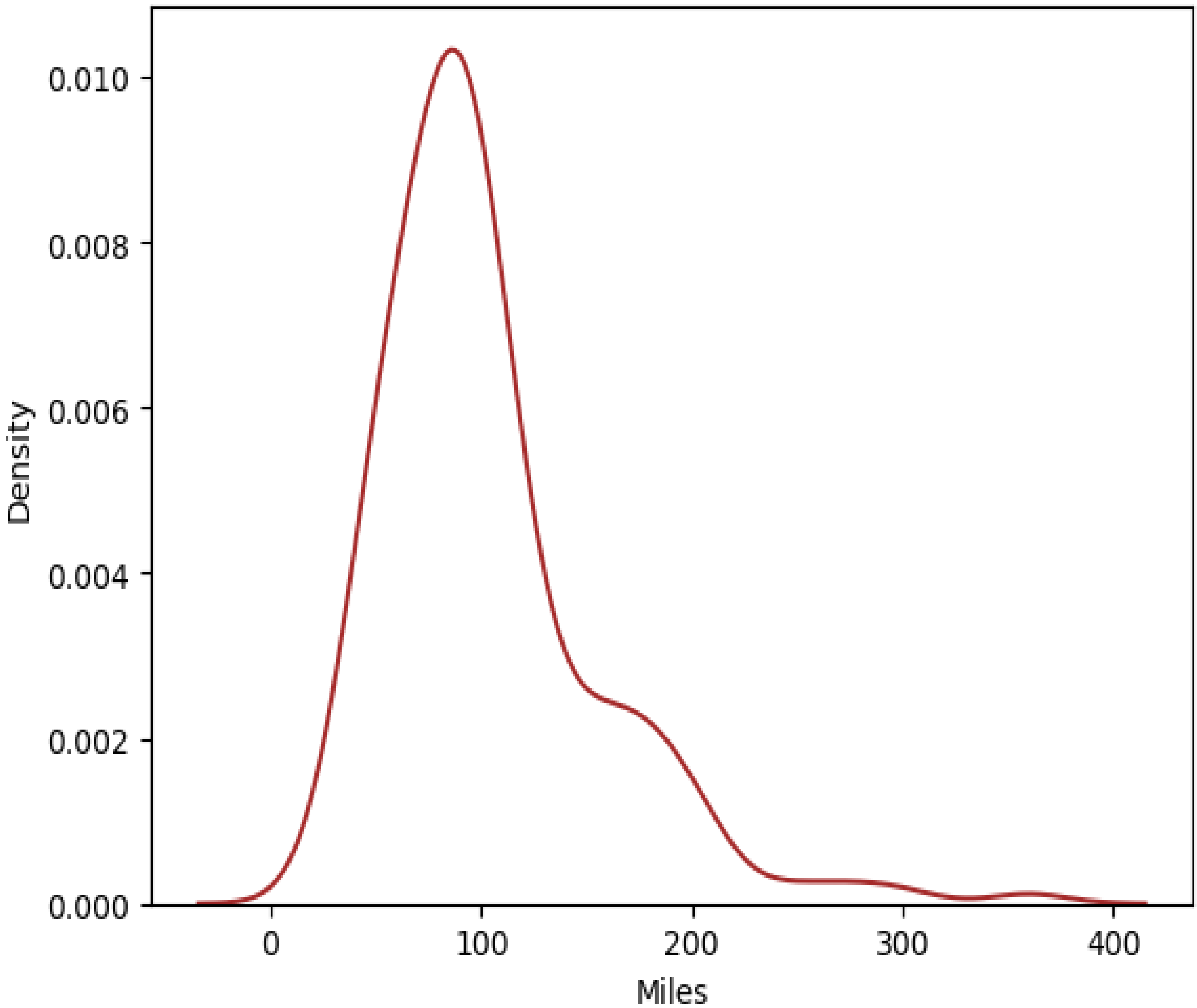
```
sns.kdeplot(df_cat["Education"],color = "orange")
plt.show()
```



Insight - The majority of treadmill buyers in our dataset have completed 16 years of education.

In [146…

```
sns.kdeplot(df_cat['Miles'],color = "brown")
plt.show()
```



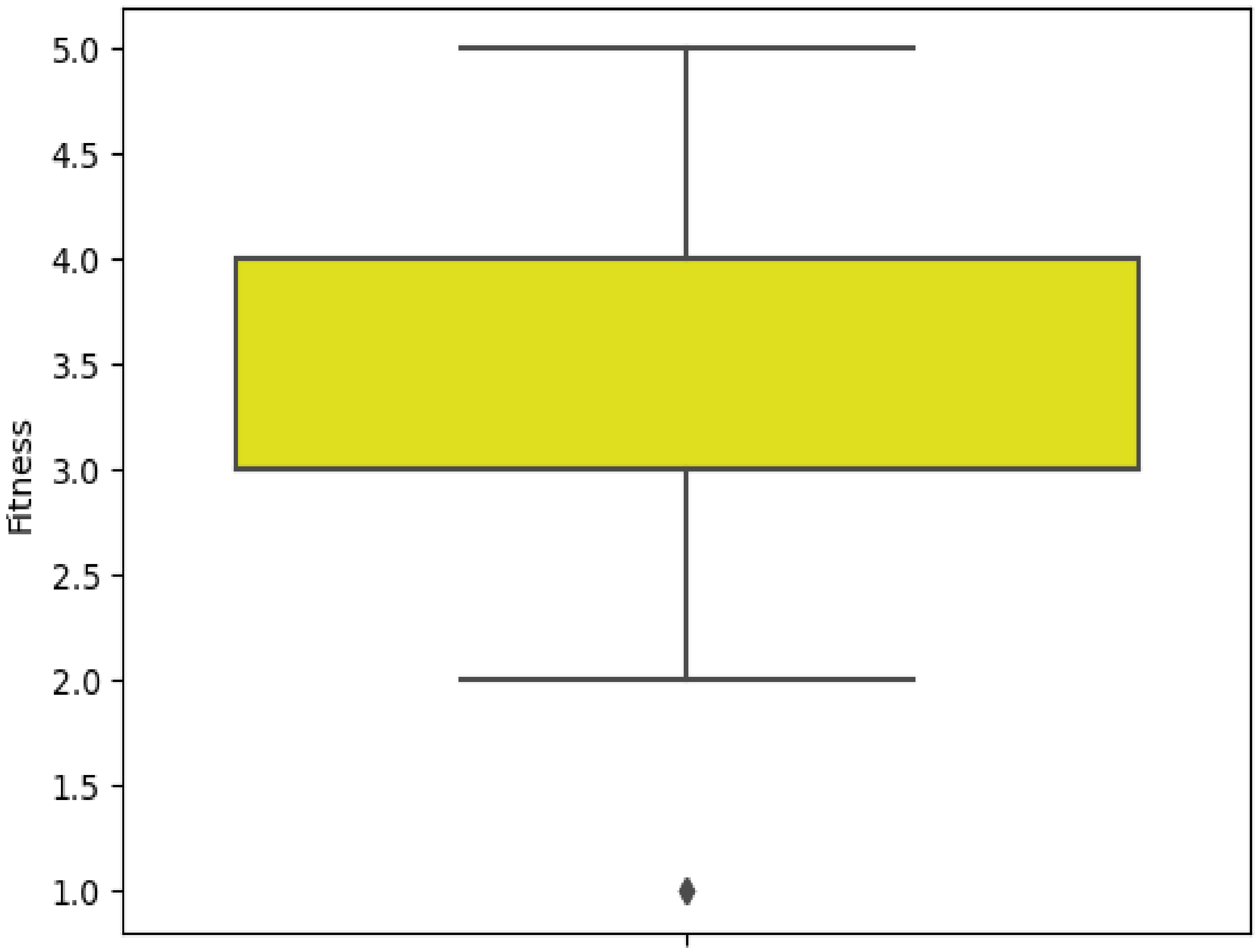
Insight - A significant number of individuals express a preference for walking approximately 85 miles.

categorical variables

Boxplot

In [147…

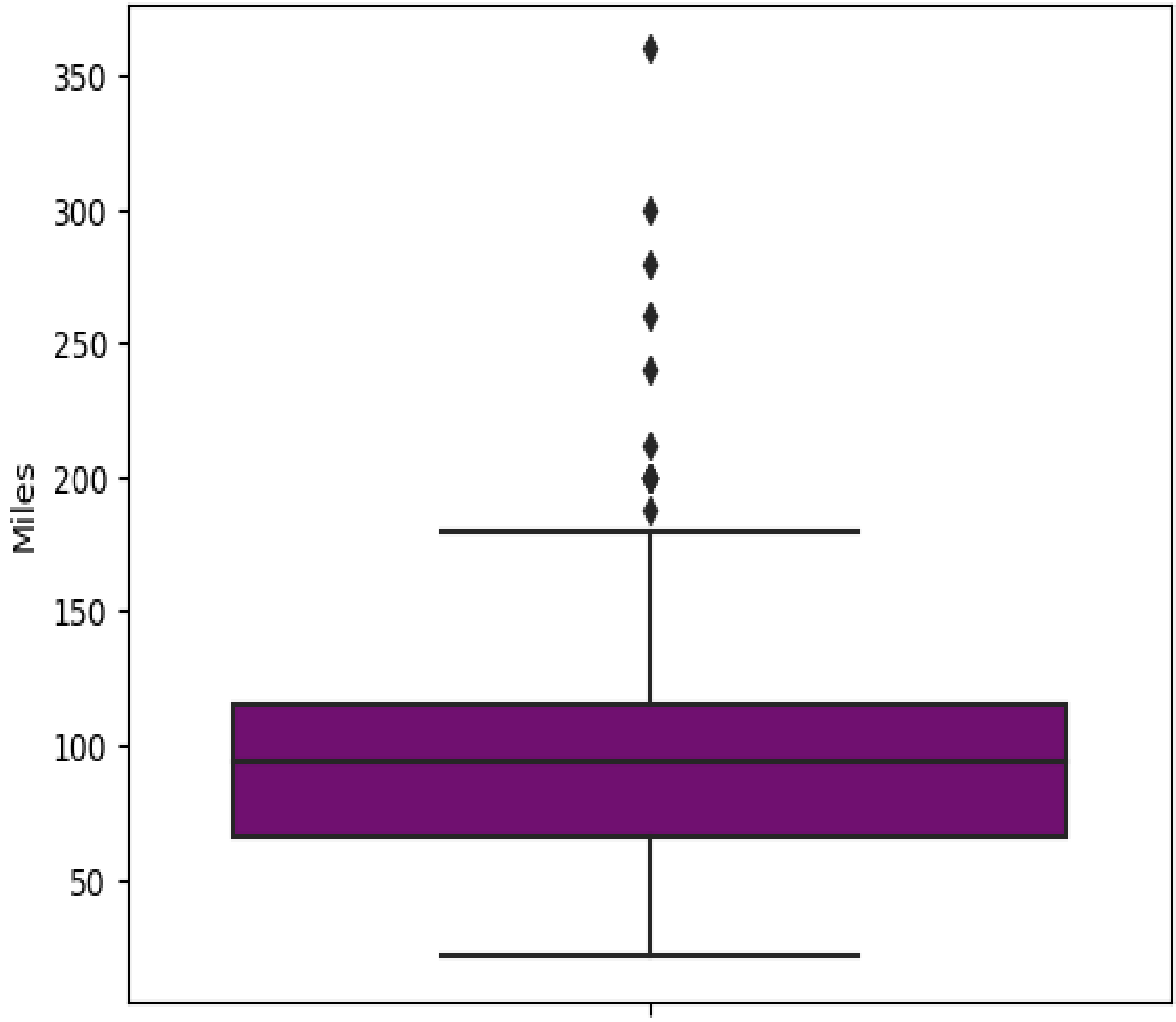
```
sns.boxplot(y = df_cat['Fitness'],color = "yellow")
plt.show()
```



Insight - The boxplot analysis reveals that there are very few customers with a fitness level around 1.0, indicating that these instances are outliers in the dataset.

In [148…

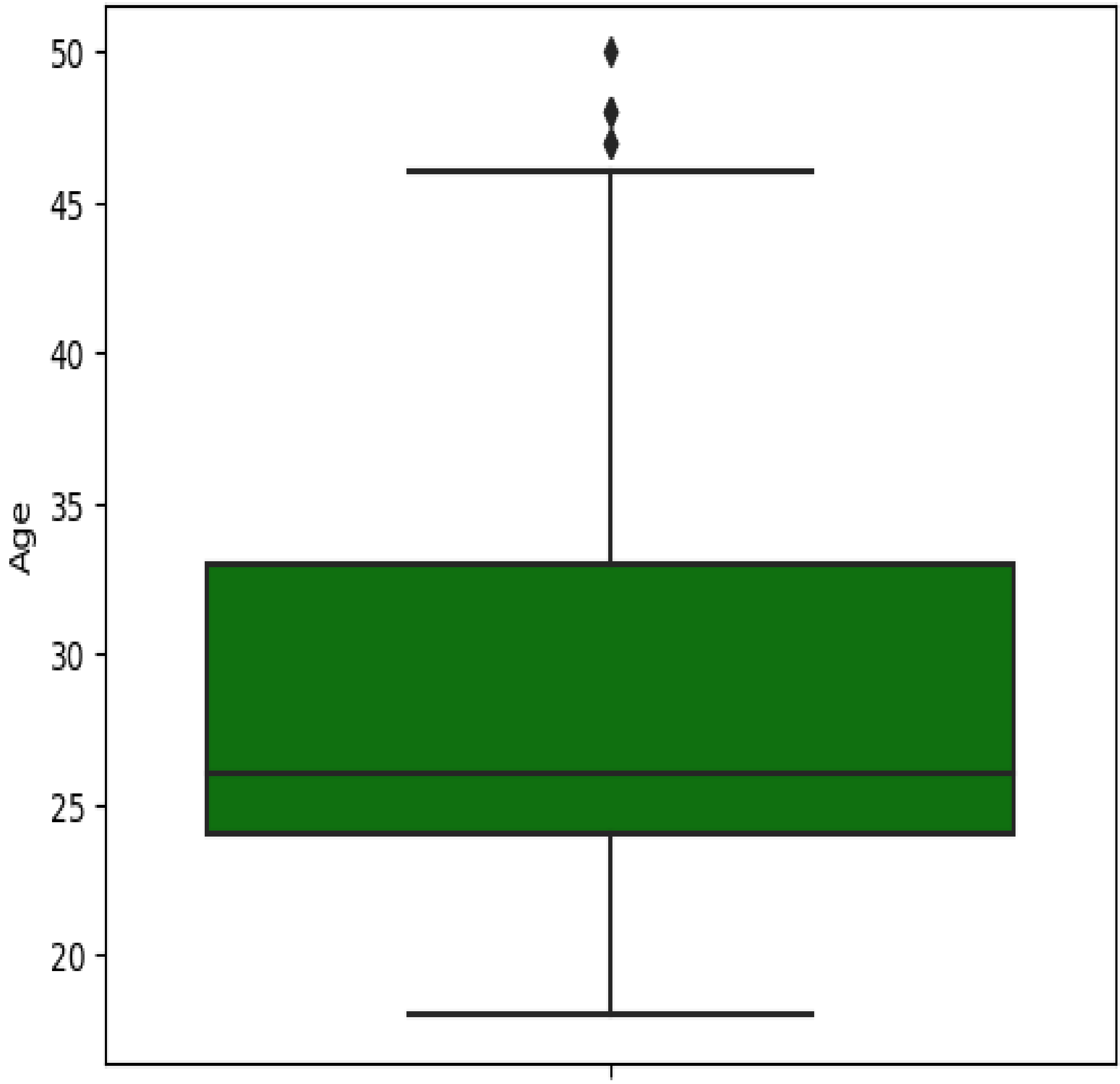
```
sns.boxplot(y = df_cat['Miles'],color = 'purple')
plt.show()
```



Insight - There is a minimal number of customers in our dataset who indicate a preference for walking distances above 200 miles, as suggested by the upper whisker in the data distribution.

In [149…

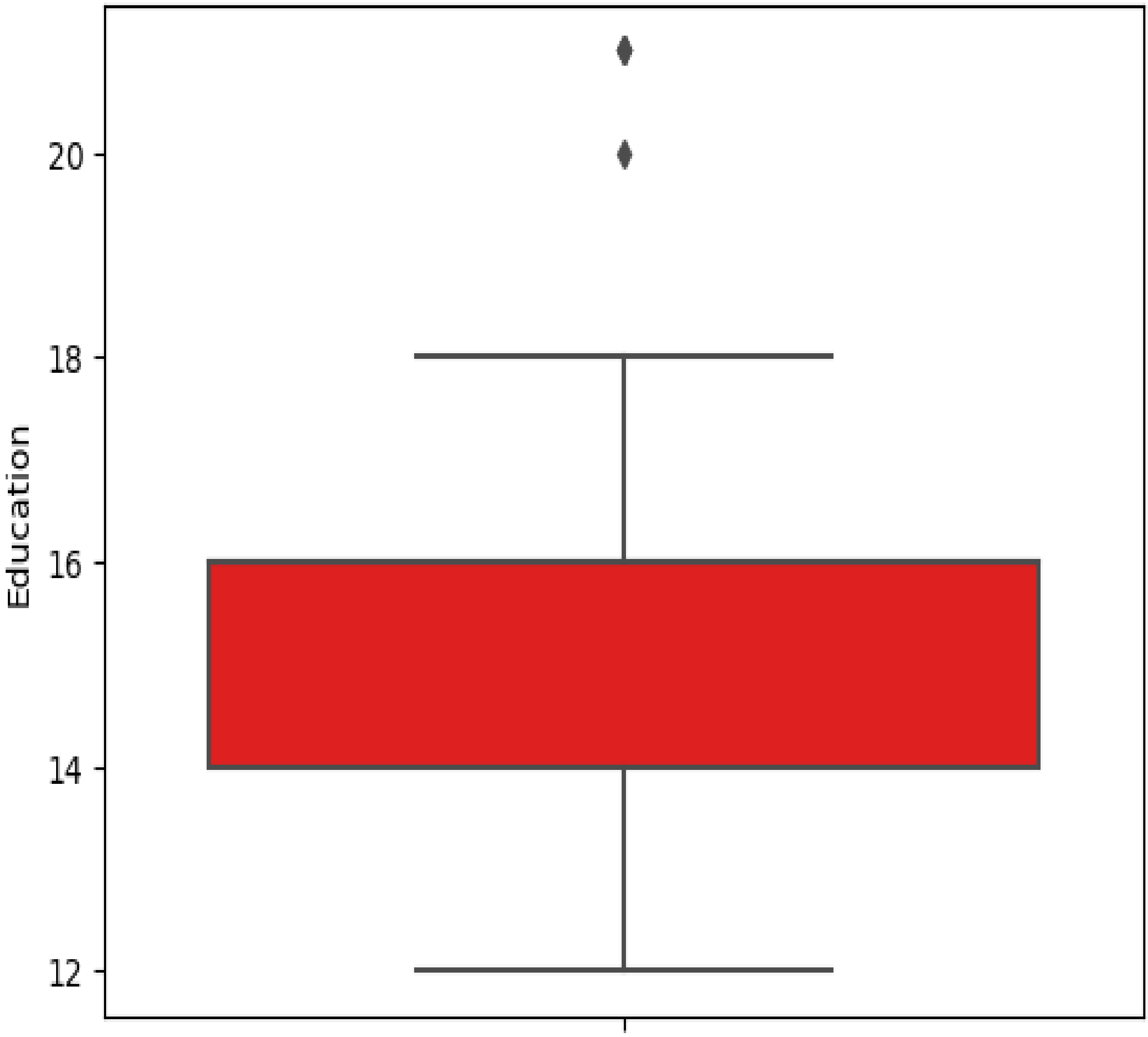
```
sns.boxplot(y = df_cat["Age"],color = "Green")
plt.show()
```



Insight - Outliers are observed in the dataset for individuals above 45 years of age.

In [150…

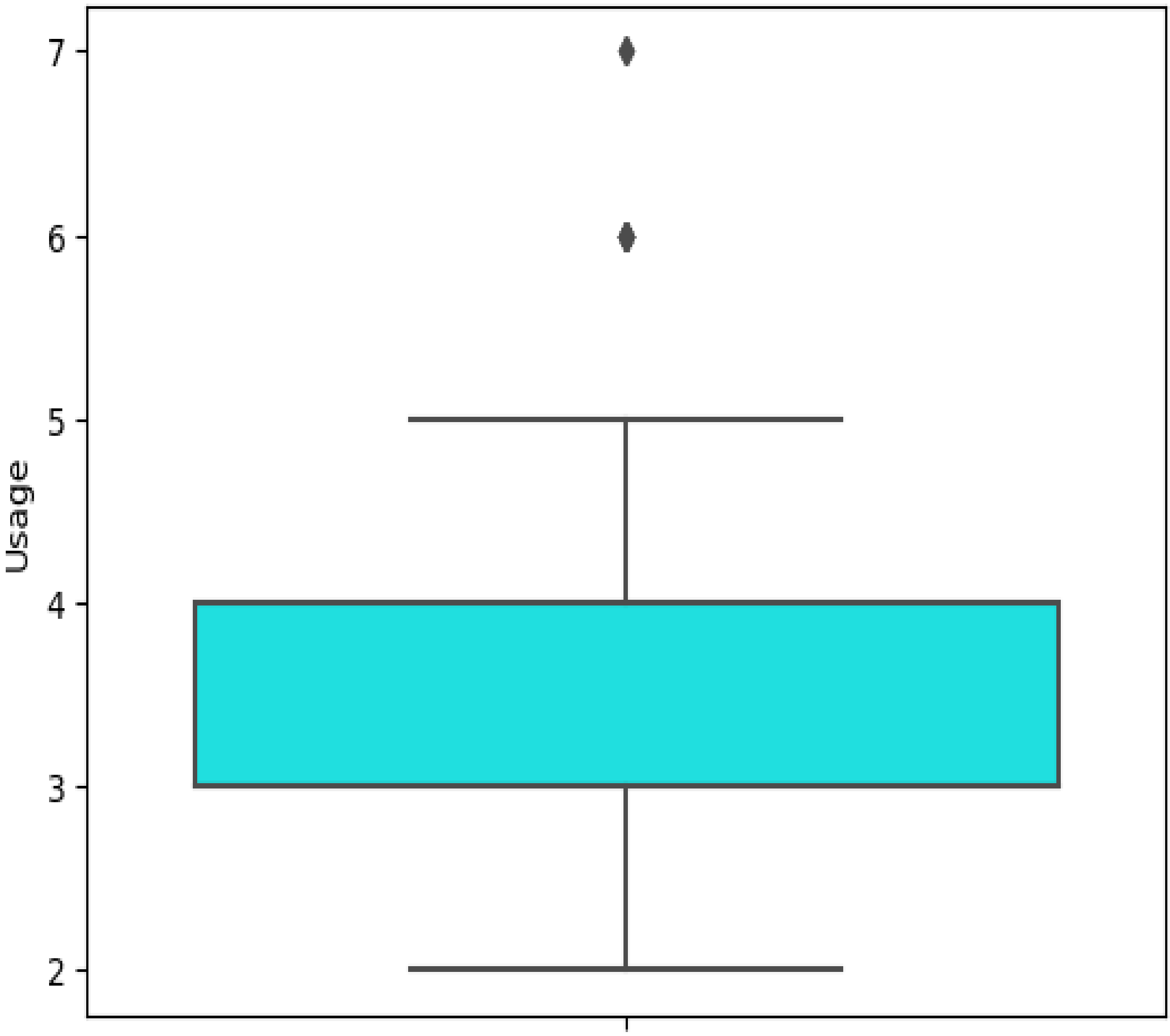
```
sns.boxplot(y = df_cat['Education'],color = "Red")
plt.show()
```



Insight - A small number of individuals in the dataset have an education level exceeding 18 years.

In [151…

```
sns.boxplot(y = df_cat["Usage"],color = "cyan")
plt.show()
```

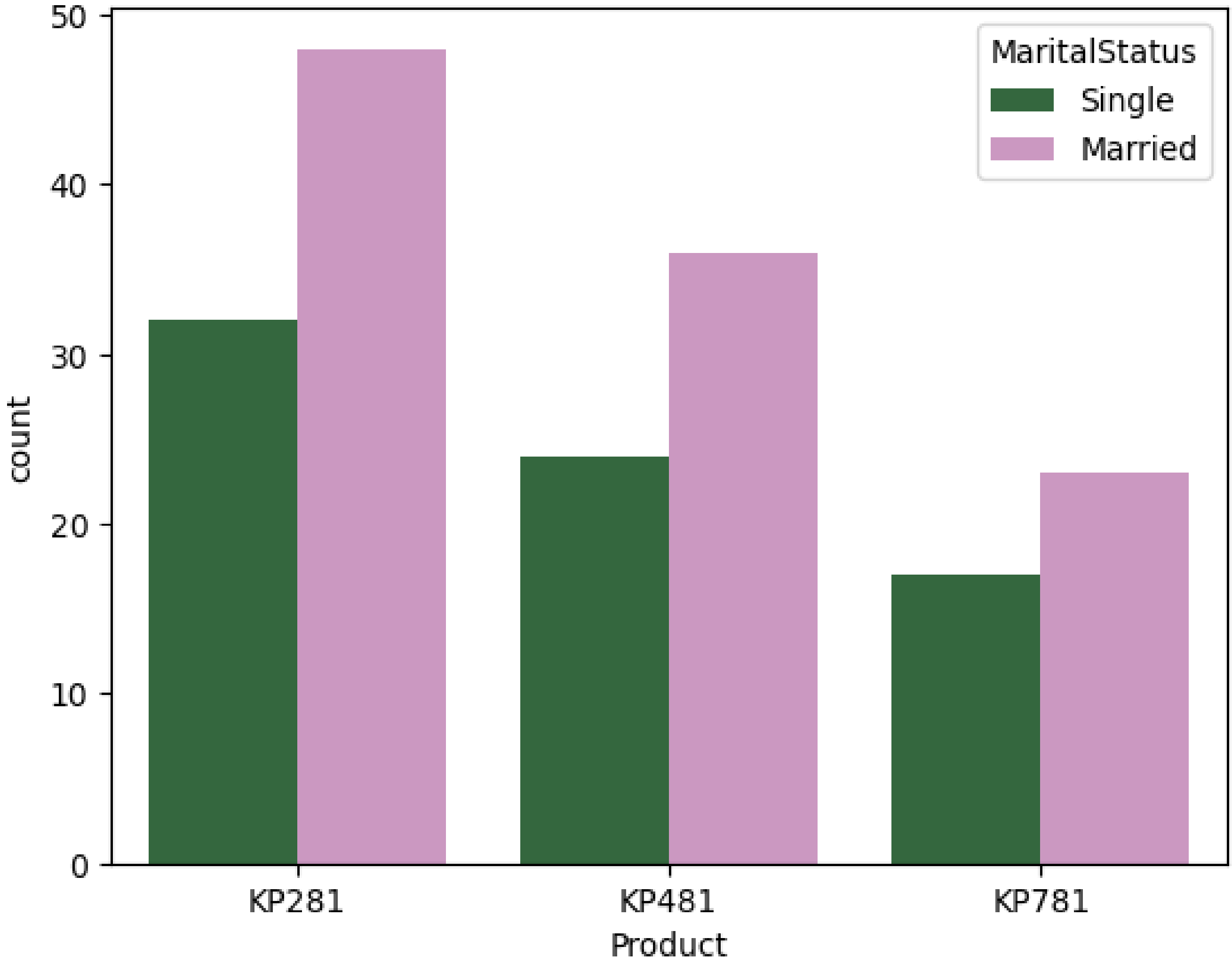


Insight - The boxplot analysis indicates outliers in the range of 6-7 days per week, suggesting that very few individuals use the treadmill at this frequency.

Bivariate Analysis

In [104…

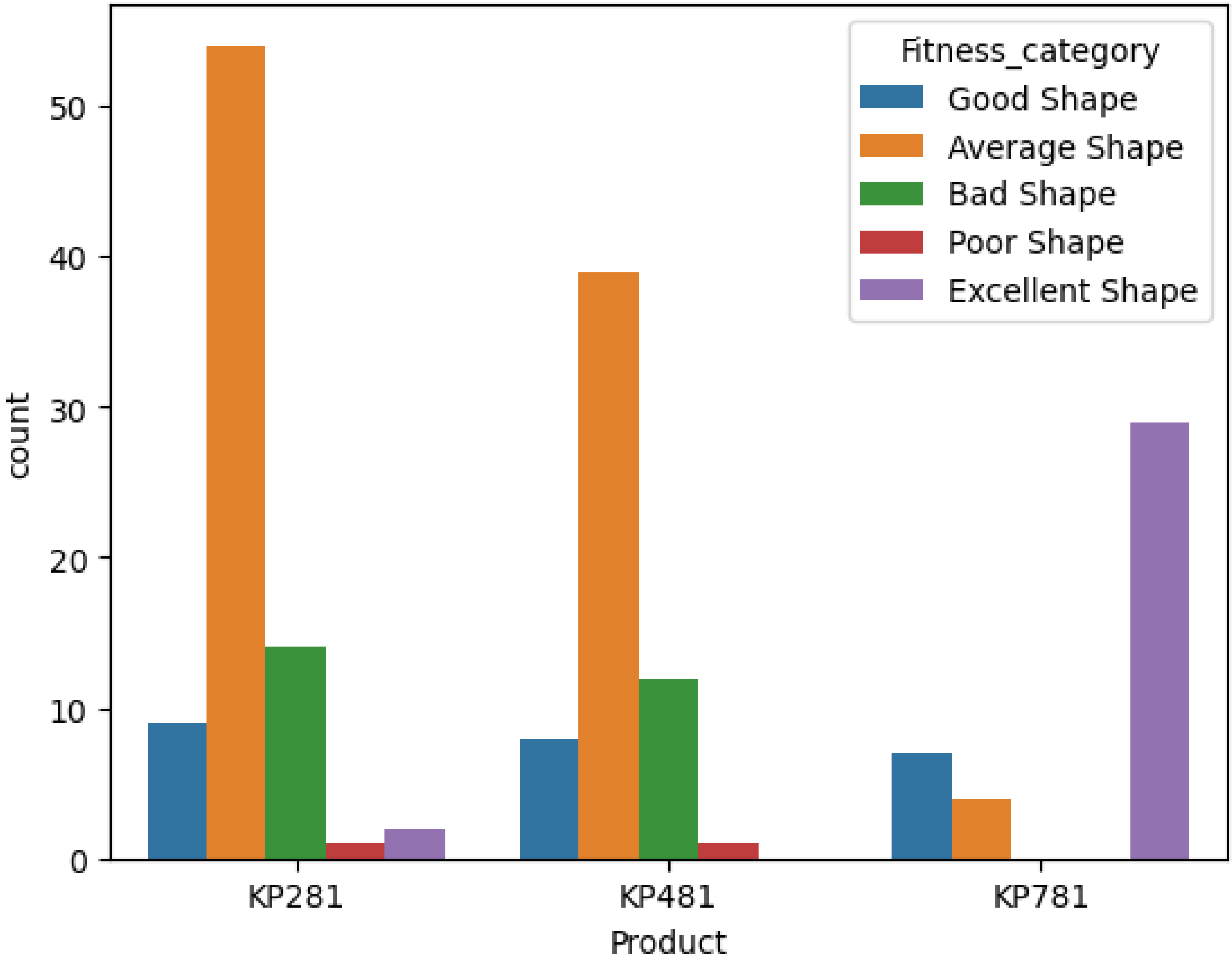
```
sns.countplot(df_cat,x = 'Product',hue = 'MaritalStatus',palette = "cubehelix")
plt.show()
```



Insight - In the Aerofit dataset, a predominant trend is observed where a significant number of individuals are married, and the product KP281 emerges as their preferredchoice.

In [103…

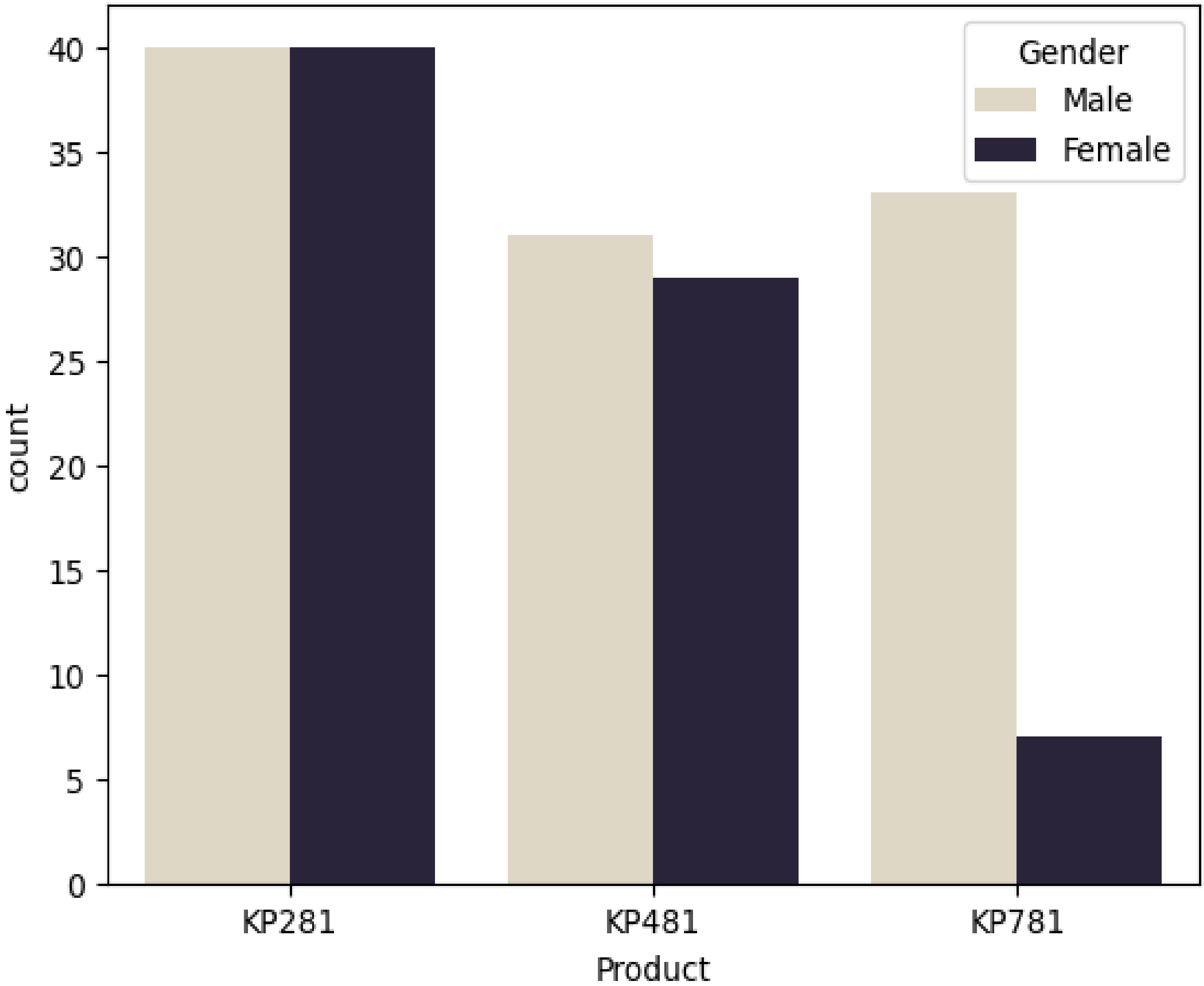
```
sns.countplot(df_cat,x = 'Product',hue = 'Fitness_category')
plt.show()
```



Insight - The analysis reveals that individuals who purchase either KP281 or KP481 predominantly have an average body shape. In contrast, a substantial proportion of those buying KP781 exhibit an excellent body shape.

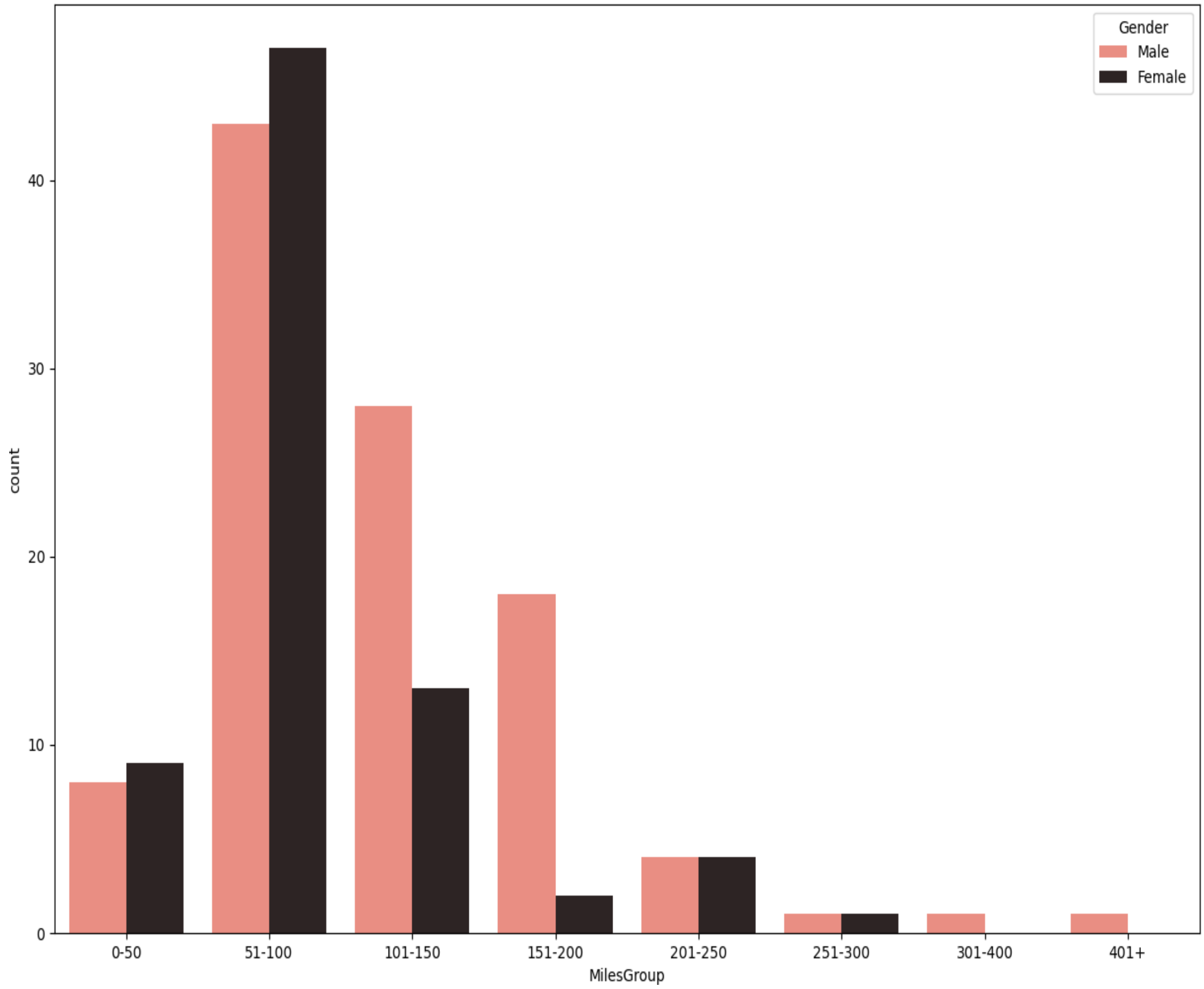
In [102…

```python
sns.countplot(df_cat,x = 'Product',hue = 'Gender',palette = "ch:s=-.2,r=.6")
plt.show()
```



Insight - The majority of treadmill buyers of all three products are males.

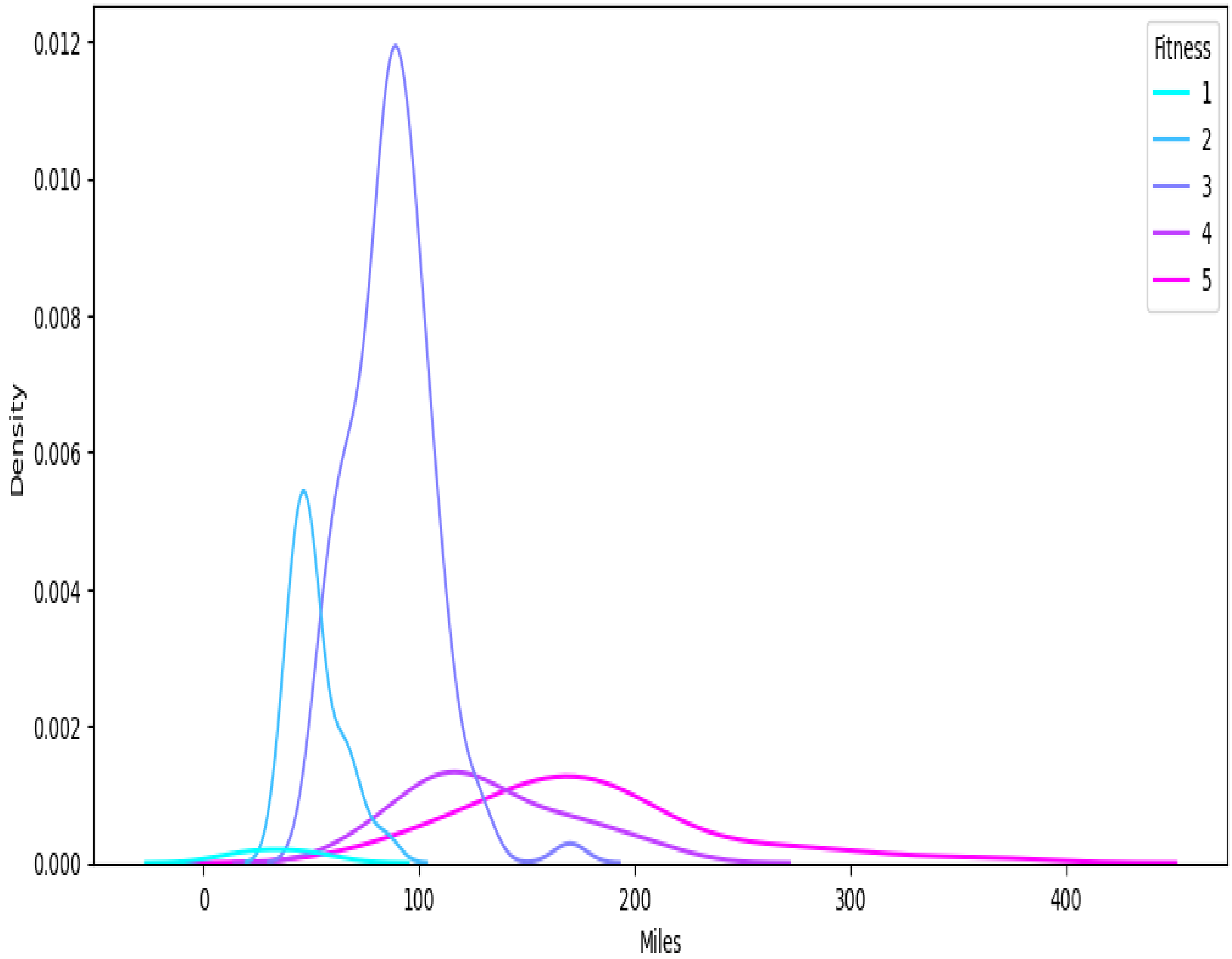
In [40]:
```
plt.figure(figsize = (15,10))
sns.countplot(df_cat,x = 'MilesGroup',hue = 'Gender',palette = "dark:salmon_r")
plt.show()
```



Insight - Based on the preceding observation, it can be concluded that a significant number of individuals prefer towalk distances ranging from 51 to 100 miles.

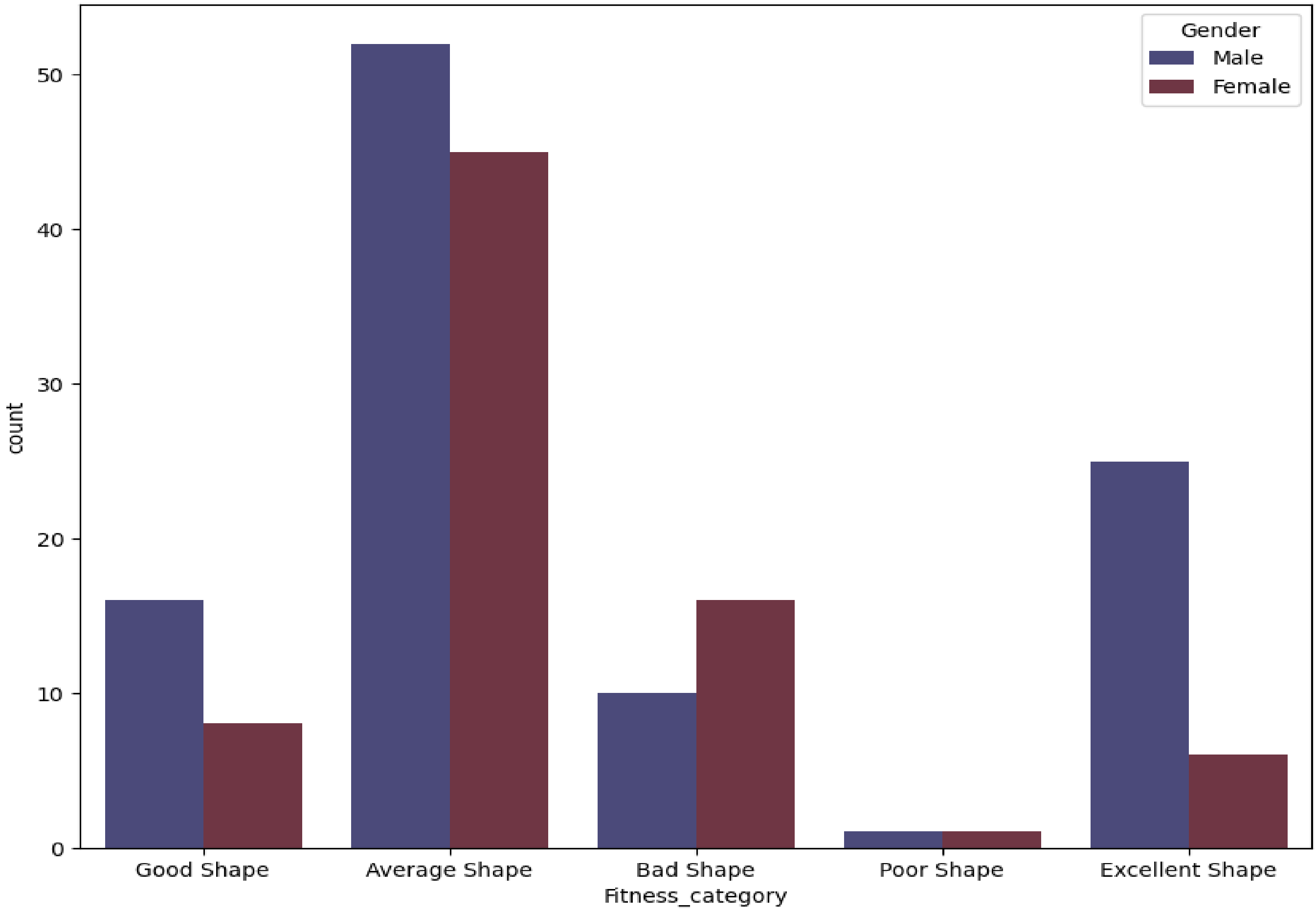
In [42]:

```
plt.figure(figsize=(12,5))
sns.kdeplot(data=df_cat,x='Miles',hue='Fitness',palette  =  "cool")
plt.show()
```



Insight - The KDE plot indicates a direct relationship between miles walked and fitness level in the dataset, suggesting that as the distance covered increases, thefitness level tends to rise.

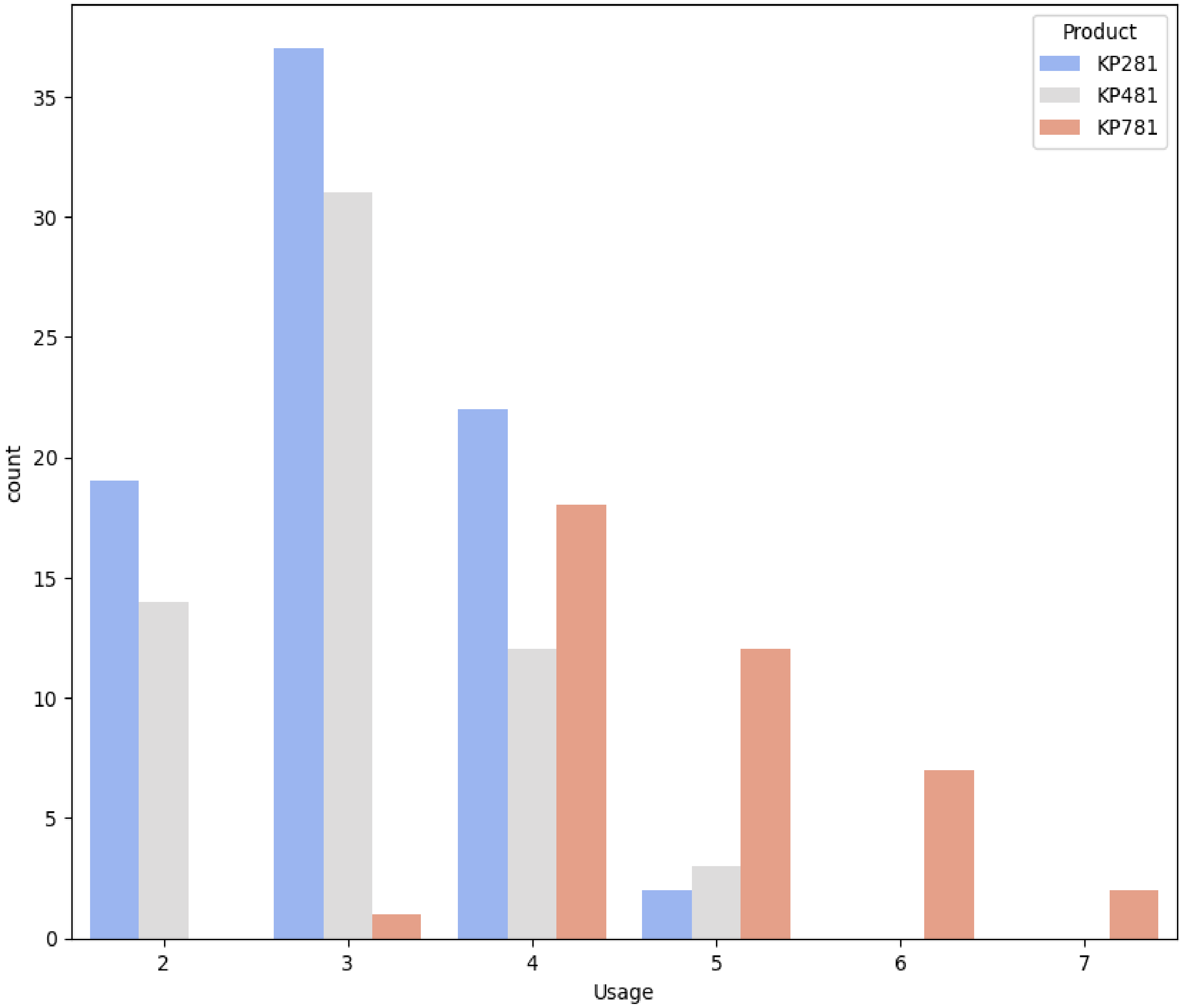
In [97]:
```
plt.figure(figsize = (10,8))
sns.countplot(df_cat,x = 'Fitness_category',hue = 'Gender',palette = "icefire")
plt.show()
```



Insight - The majority of individuals in the dataset exhibit an average body shape. Poor shape is the least common and is observed equally in both genders, while excellent shape is more prevalent among males.

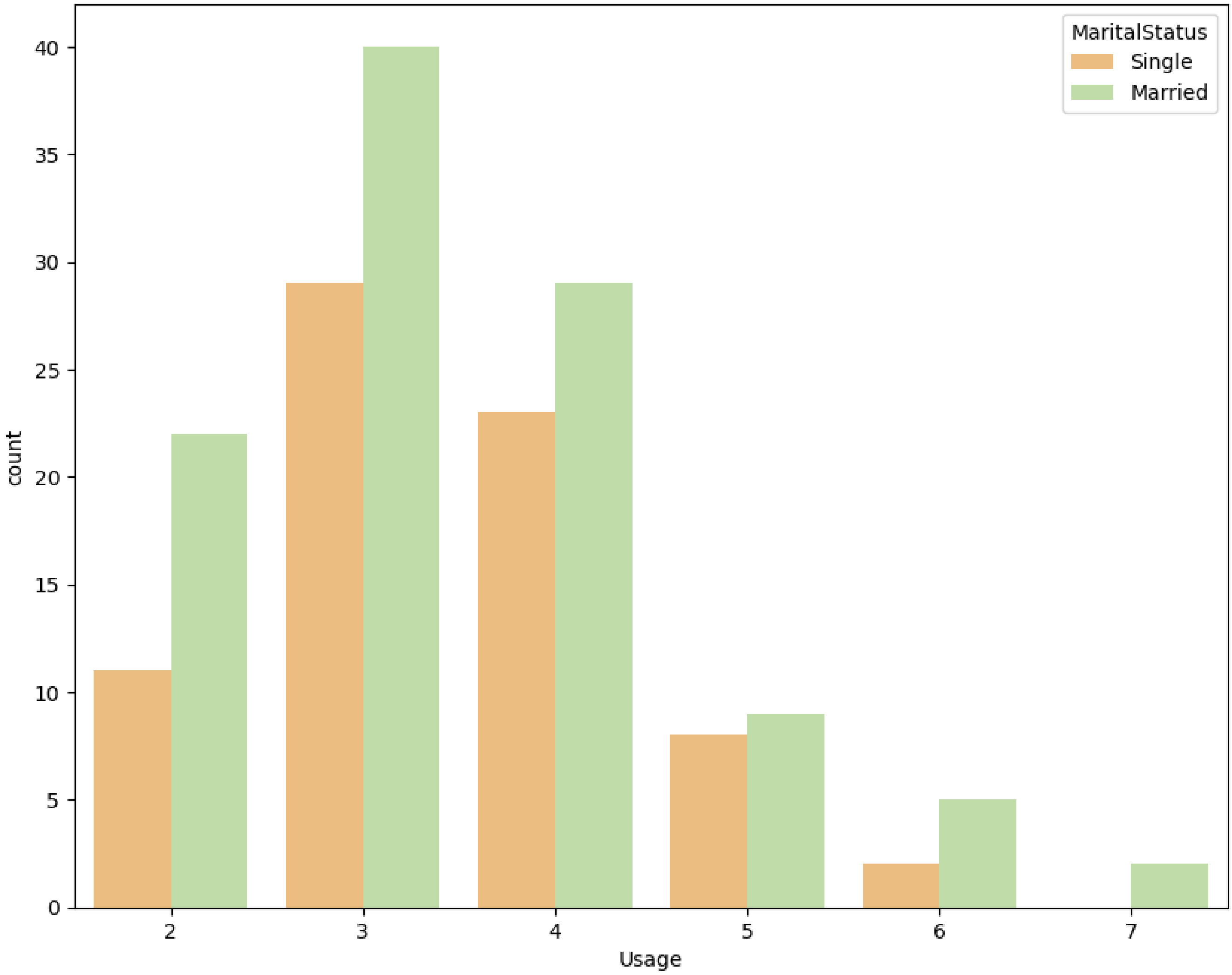
In [96]:

```
plt.figure(figsize = (10,8))
sns.countplot(df_cat,x = 'Usage',hue = 'Product',palette = "coolwarm")
plt.show()
```



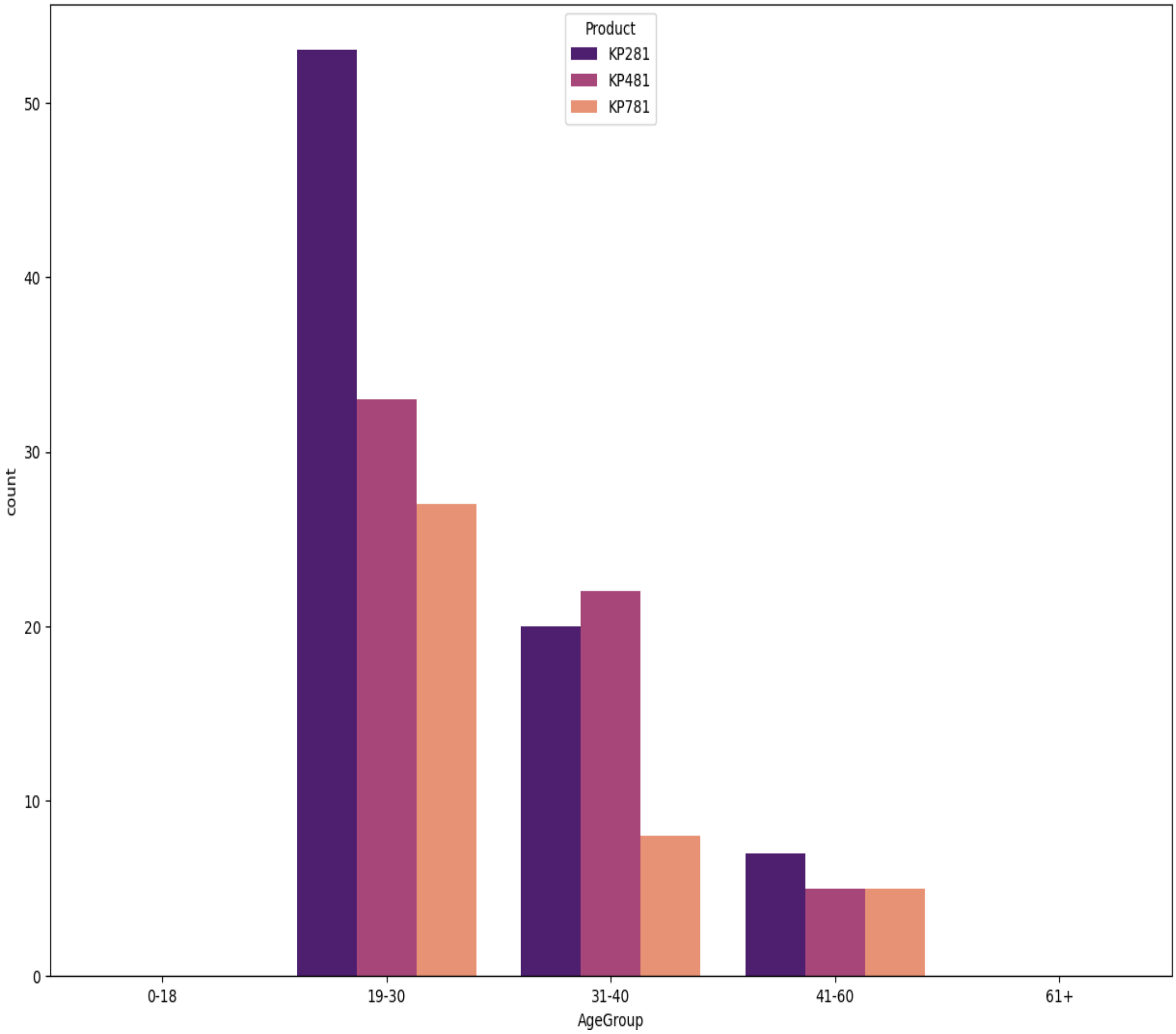
Insight - The usage pattern indicates that individuals primarily use products KP281 and KP481 three days per week, while product KP781 is most frequently used four times per week.

```
In [95]: plt.figure(figsize = (10,8))
sns.countplot(df_cat,x = 'Usage',hue = 'MaritalStatus',palette = "Spectral")
plt.show()
```



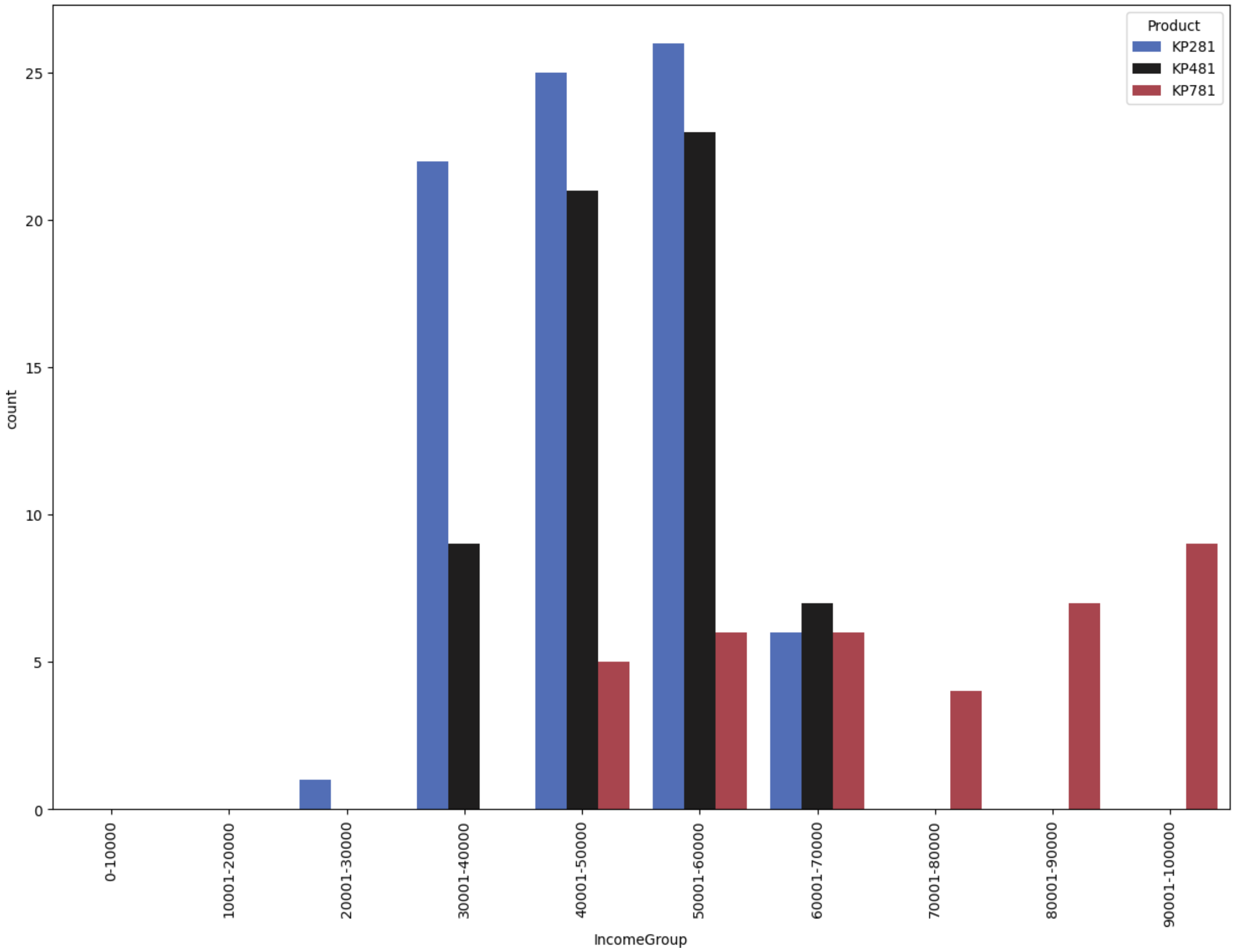
Insight - Both single and married individuals exhibit a common trend of using the treadmill predominantly three times a week.

In [43]:
```
plt.figure(figsize = (15,10))
sns.countplot(df_cat,x = 'AgeGroup',hue = 'Product',palette = "magma")
plt.show()
```



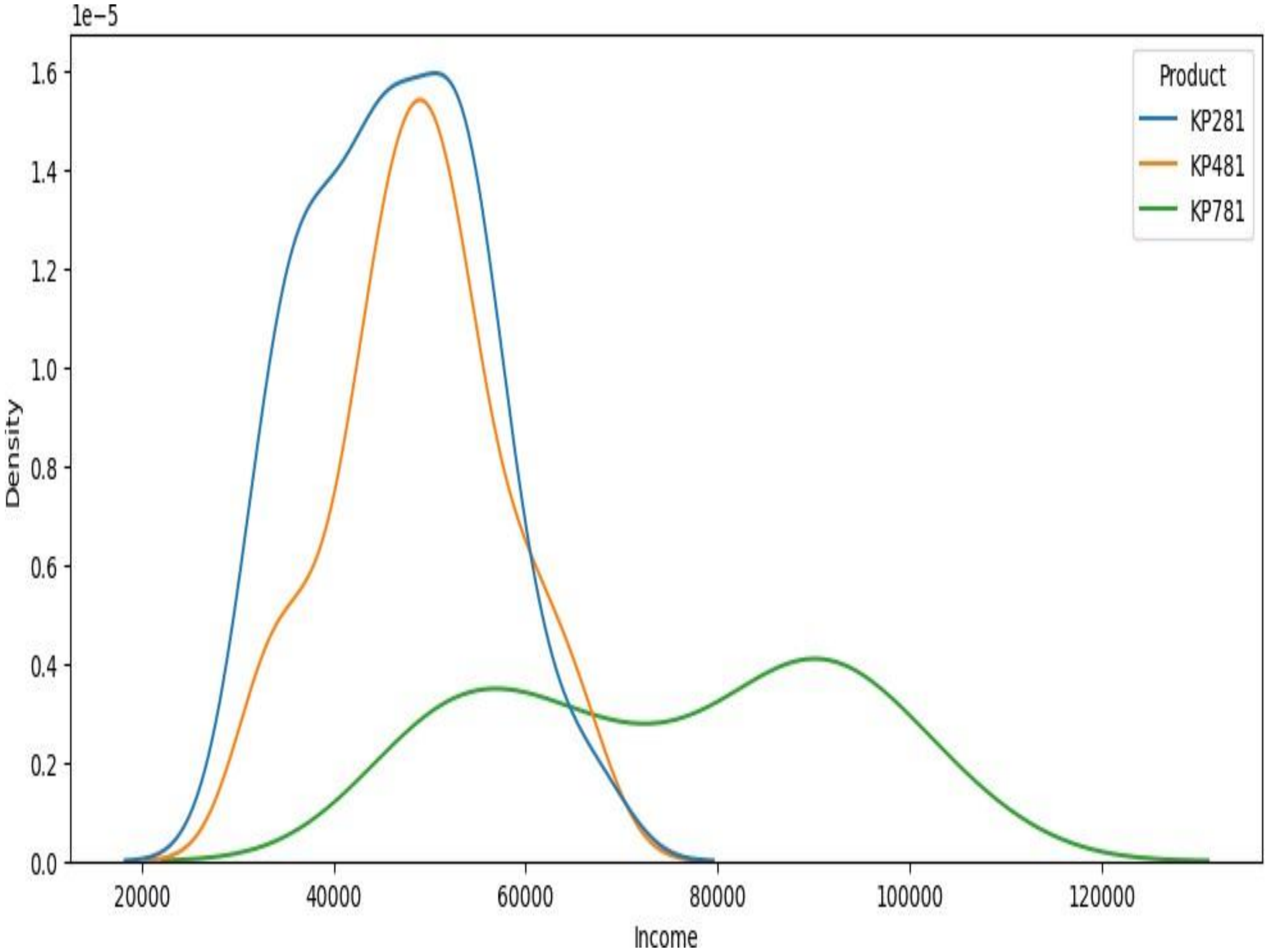
Insight - The age group 19-30 shows the highest usage across all three products in our dataset.

In [44]:
```
plt.figure(figsize = (15,10))
sns.countplot(df_cat,x = 'IncomeGroup',hue = 'Product',palette = "icefire")
plt.xticks(rotation = 90)
plt.show()
```



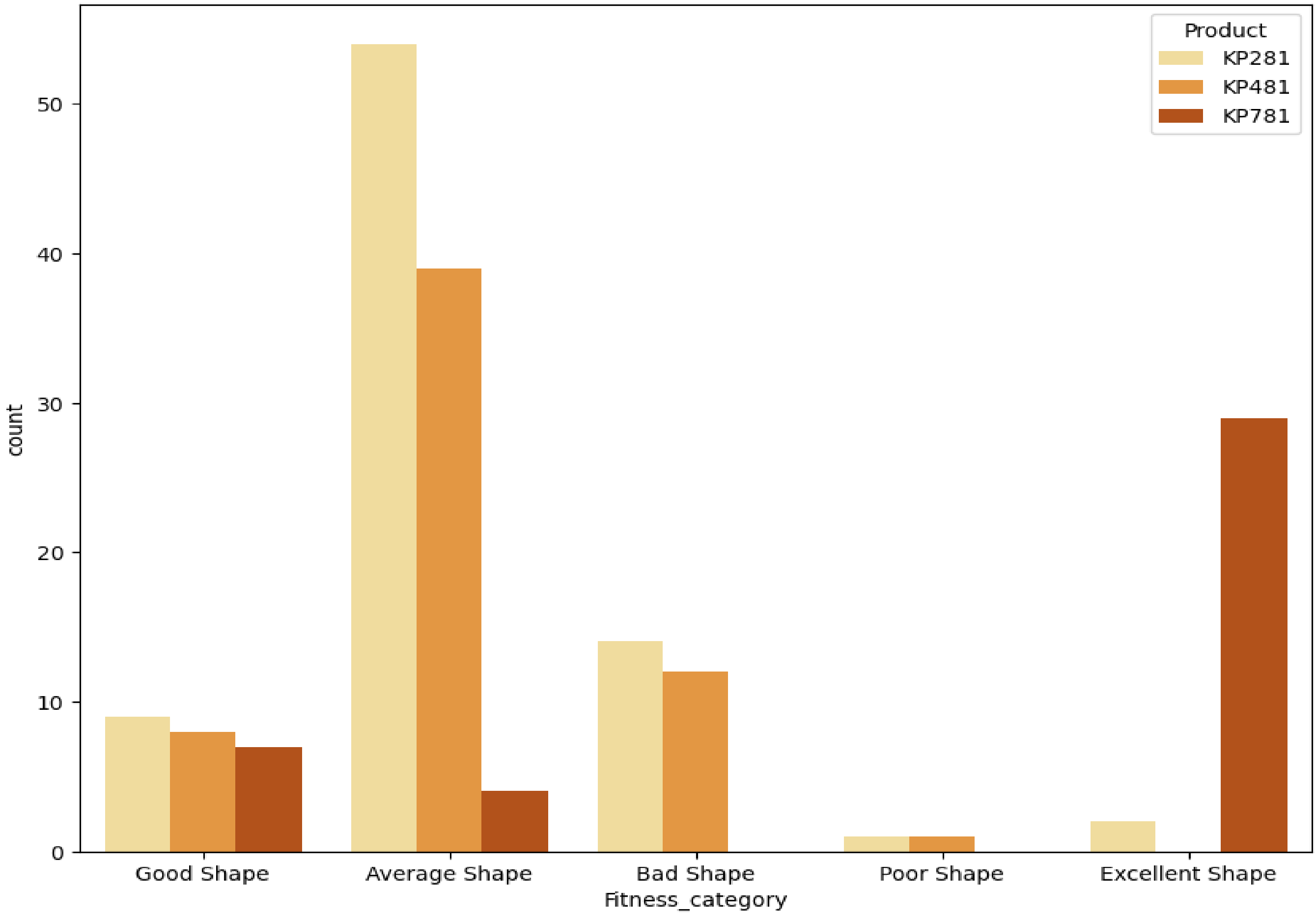
Insight - The analysis indicates that individuals with an income between 50001-60000 dollars tend to purchase KP281 and KP481 in higher quantities. On the other hand, KP781 is more commonly bought by individuals with an income exceeding 100,000 dollars.

In [94]:
```
plt.figure(figsize=(12,5))
sns.kdeplot(data=df_cat,x='Income',hue='Product')
plt.show()
```



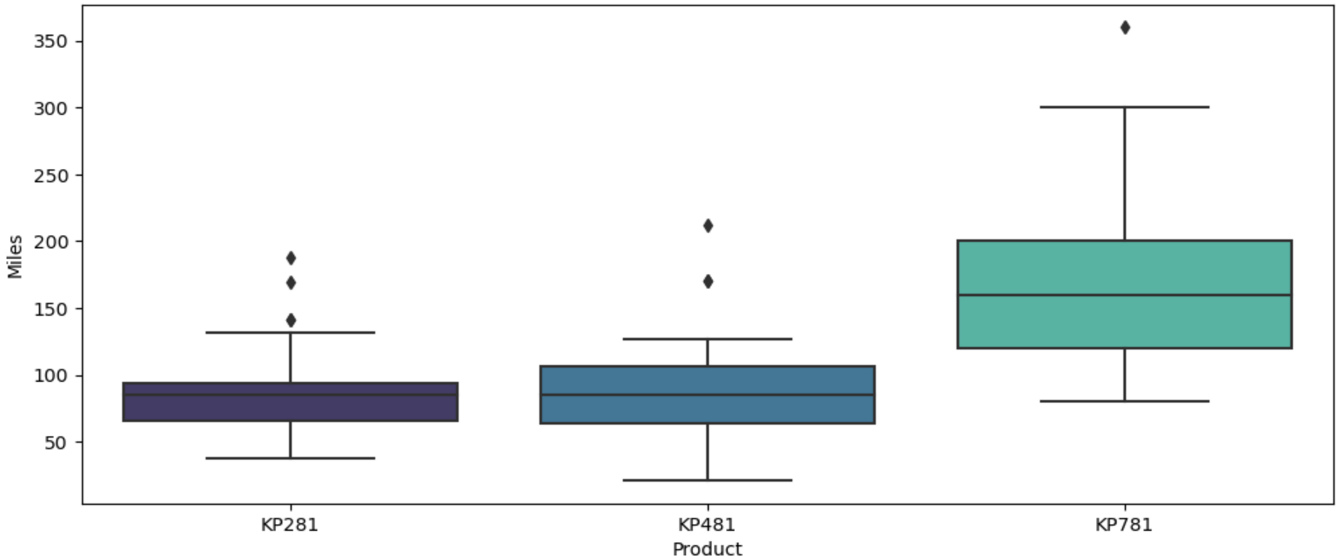
Insight - Individuals with higher income levels tend to opt for the KP781 product, which is priced at the maximum of $2,500. Meanwhile, those in the middle-income range are more inclined to purchase entry-level and mid-level treadmills.

In [92]:
```
plt.figure(figsize = (10,8))
sns.countplot(df_cat,x = 'Fitness_category',hue = 'Product',palette = "YlOrBr")
plt.show()
```



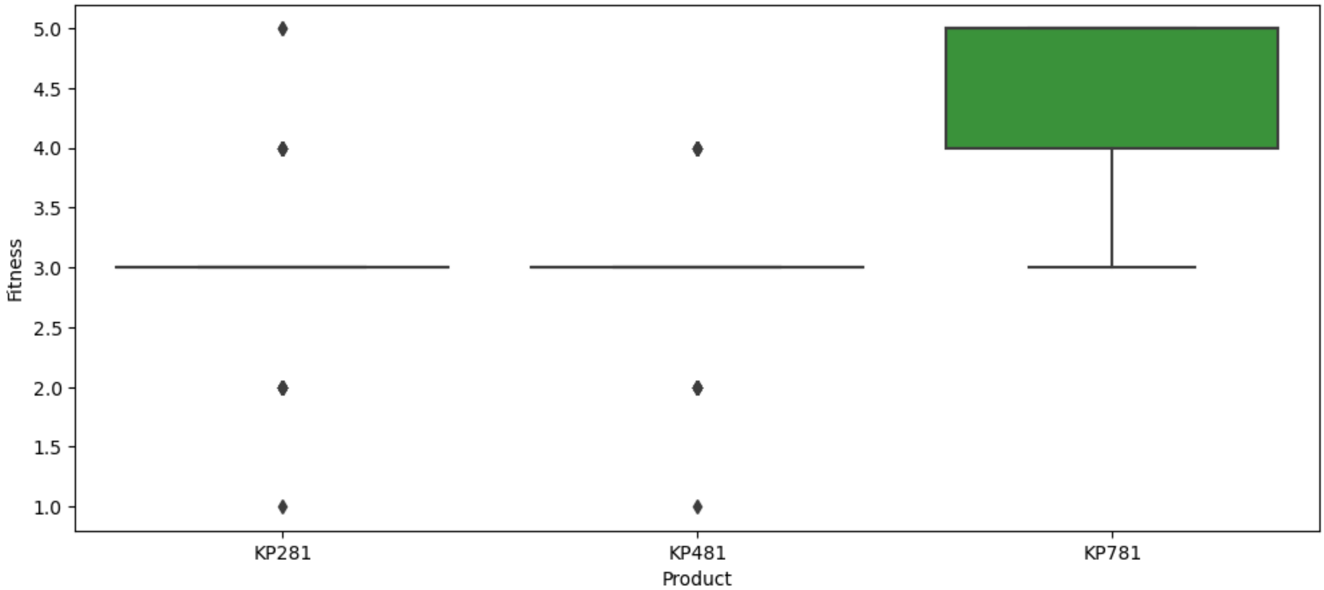
Insight - Users of the advanced-level treadmill, KP781, predominantly exhibit an excellent body shape, whereas individuals using the other two treadmills tend to have an average body-shape.

In [82]:
```
plt.figure(figsize=(12,5))
sns.boxplot(y='Miles',x='Product',data=df_cat,palette  =  "mako")
plt.show()
```



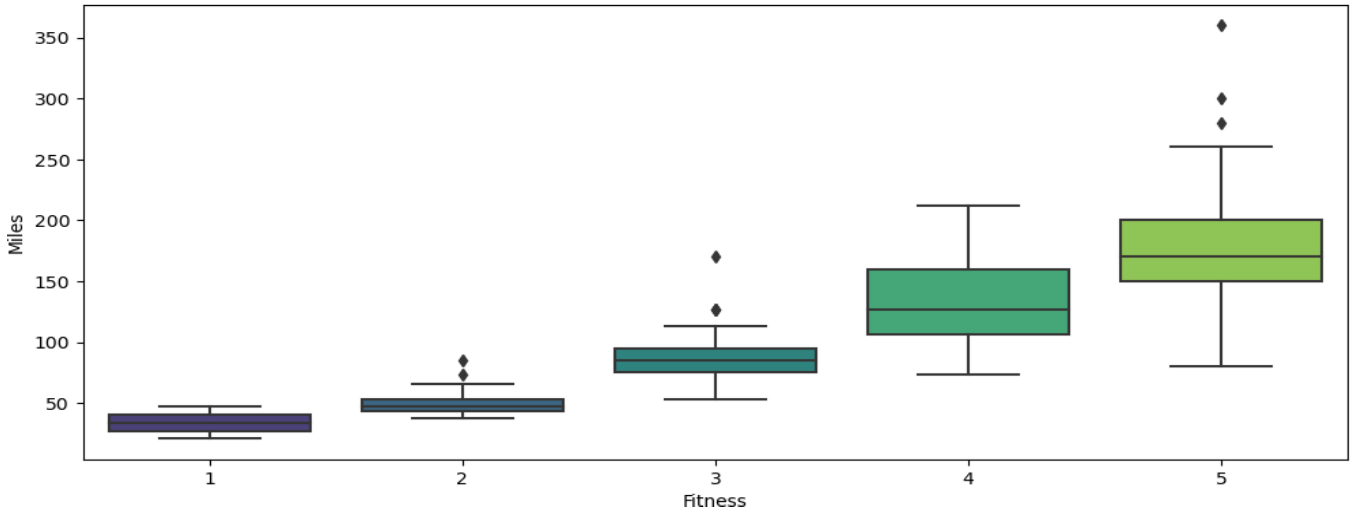
Insight - In the case of products KP281 and KP481, outliers were observed above 150 miles, whereas for KP781, outliers were identified around 350 miles.

In [83]:
```
plt.figure(figsize=(12,5))
sns.boxplot(x='Product',y='Fitness',data=df)
plt.show()
```



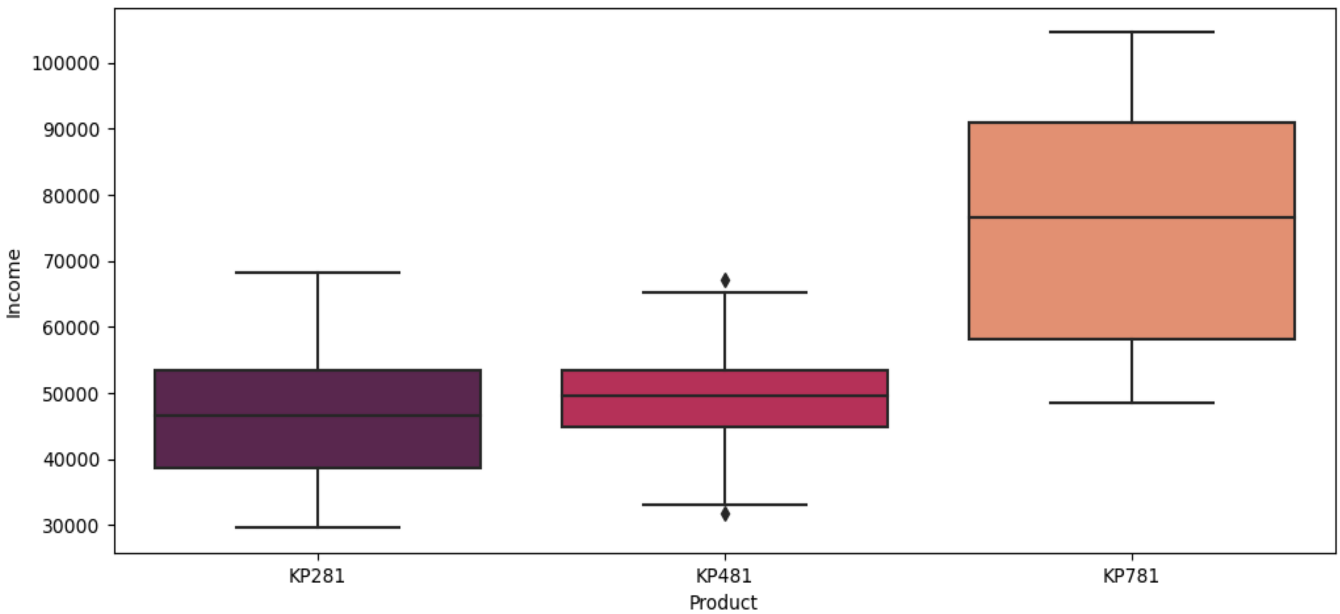
Insight - Outliers were identified both above and below fitness level 3 for both KP281 and KP481. However, no outliers were detected for KP781 in relation to fitness levels.

```
In [46]: plt.figure(figsize=(12,5))
         sns.boxplot(x='Fitness',y='Miles',data=df_cat,palette  =  "viridis")
         plt.show()
```



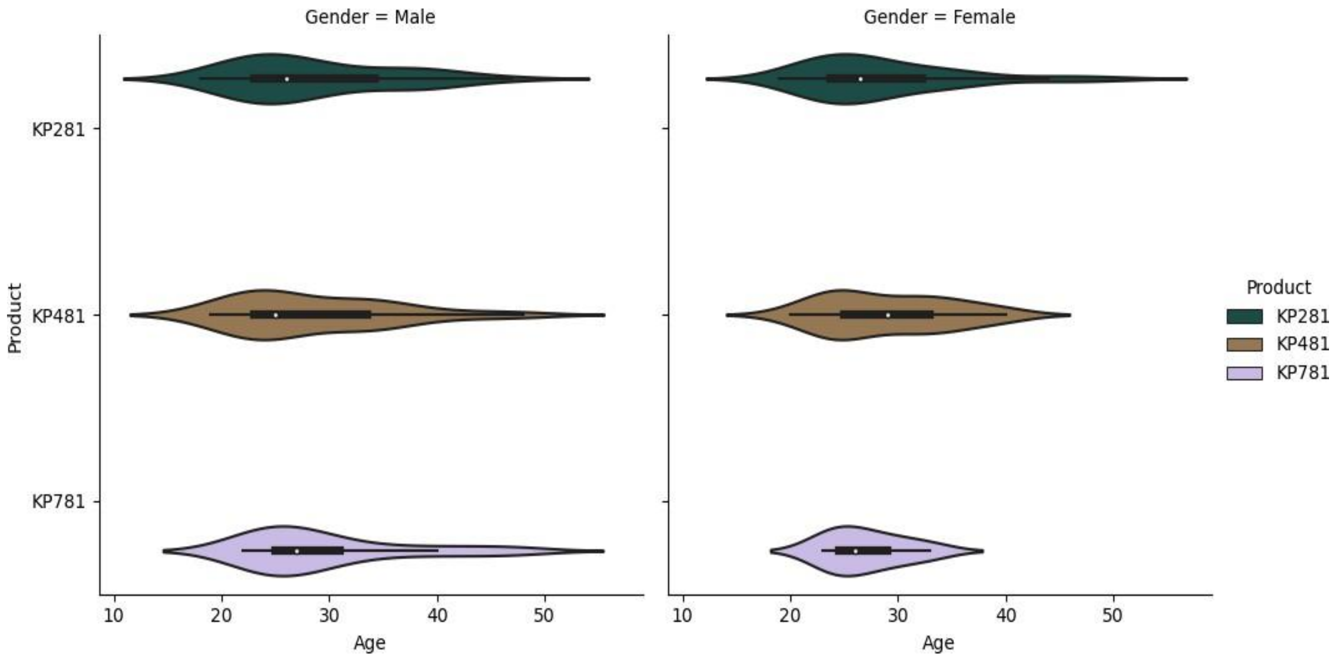
Insight - In the boxplot depicting fitness versus miles, outliers were observed for fitness levels 2, 3, and 5.Conversely, no outliers were identified for fitness levels 1and 4.

```
In [79]: plt.figure(figsize = (12,5))
         sns.boxplot(x = 'Product',y= 'Income',data = df_cat,palette = 'rocket')
         plt.show()
```



Insight - Outliers were observed around $70,000 for the product KP481, whereas no outliers were found for KP281and KP781.

In [86]:
```
sns.catplot(x='Age',y='Product',hue='Product',col='Gender',data=df_cat,kind='vio
plt.show()
```



Insights -

- In the catplot analysis, it appears that male customers are evenly distributed among the three product types.
- Female customers show a preference for using products KP281 and KP481 more than the advanced KP781 product.
- Additionally, it seems that female customers tend to favor less complicated products compared to their male counterparts.

Correlation

Heatmap

In [35]:
```
df1  =  df_cat[['Age','Income','Education','Usage','Fitness','Miles']]
```

In [36]:
```
df1.head()
```

Out[36]:

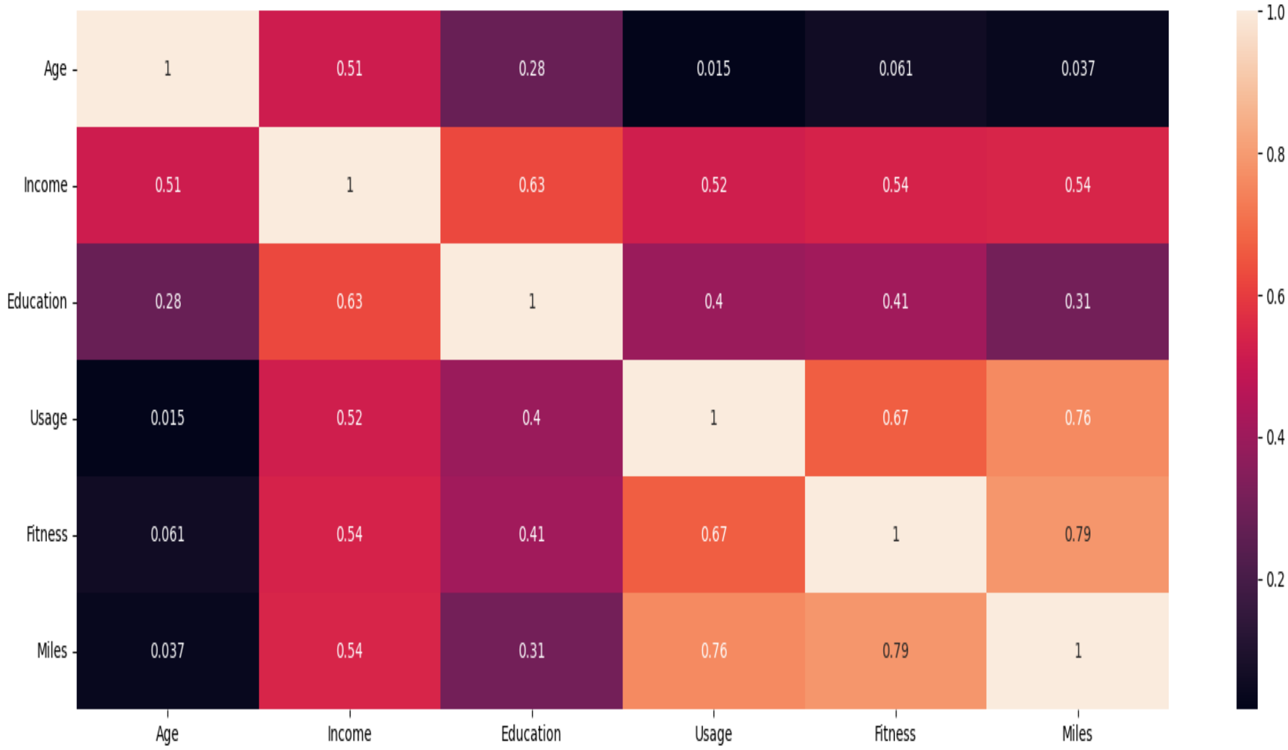
	Age	Income	Education	Usage	Fitness	Miles
0	18	29562	14	3	4	112
1	19	31836	15	2	3	75
2	19	30699	14	4	3	66
3	19	32973	12	3	3	85
4	20	35247	13	4	2	47

In [37]:
```python
df1.corr()
```

Out[37]:

	Age	Income	Education	Usage	Fitness	Miles
Age	1.000000	0.513414	0.280496	0.015064	0.061105	0.036618
Income	0.513414	1.000000	0.625827	0.519537	0.535005	0.543473
Education	0.280496	0.625827	1.000000	0.395155	0.410581	0.307284
Usage	0.015064	0.519537	0.395155	1.000000	0.668606	0.759130
Fitness	0.061105	0.535005	0.410581	0.668606	1.000000	0.785702
Miles	0.036618	0.543473	0.307284	0.759130	0.785702	1.000000

In [38]:
```python
plt.figure(figsize=(20,6))
ax  =  sns.heatmap(df1.corr(),annot=True,cmap='rocket')
plt.yticks(rotation=0)
plt.show()
```

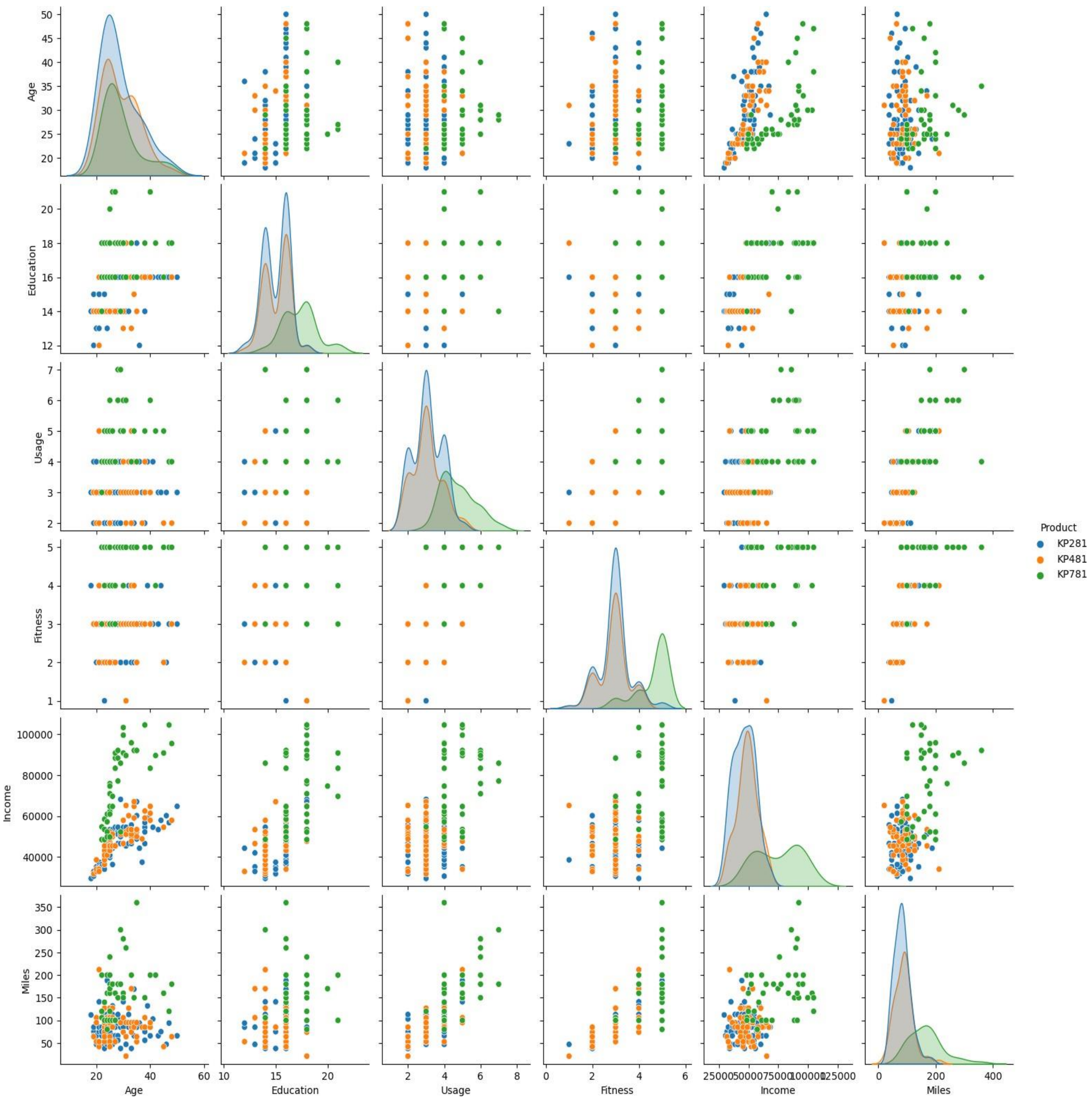


Insights

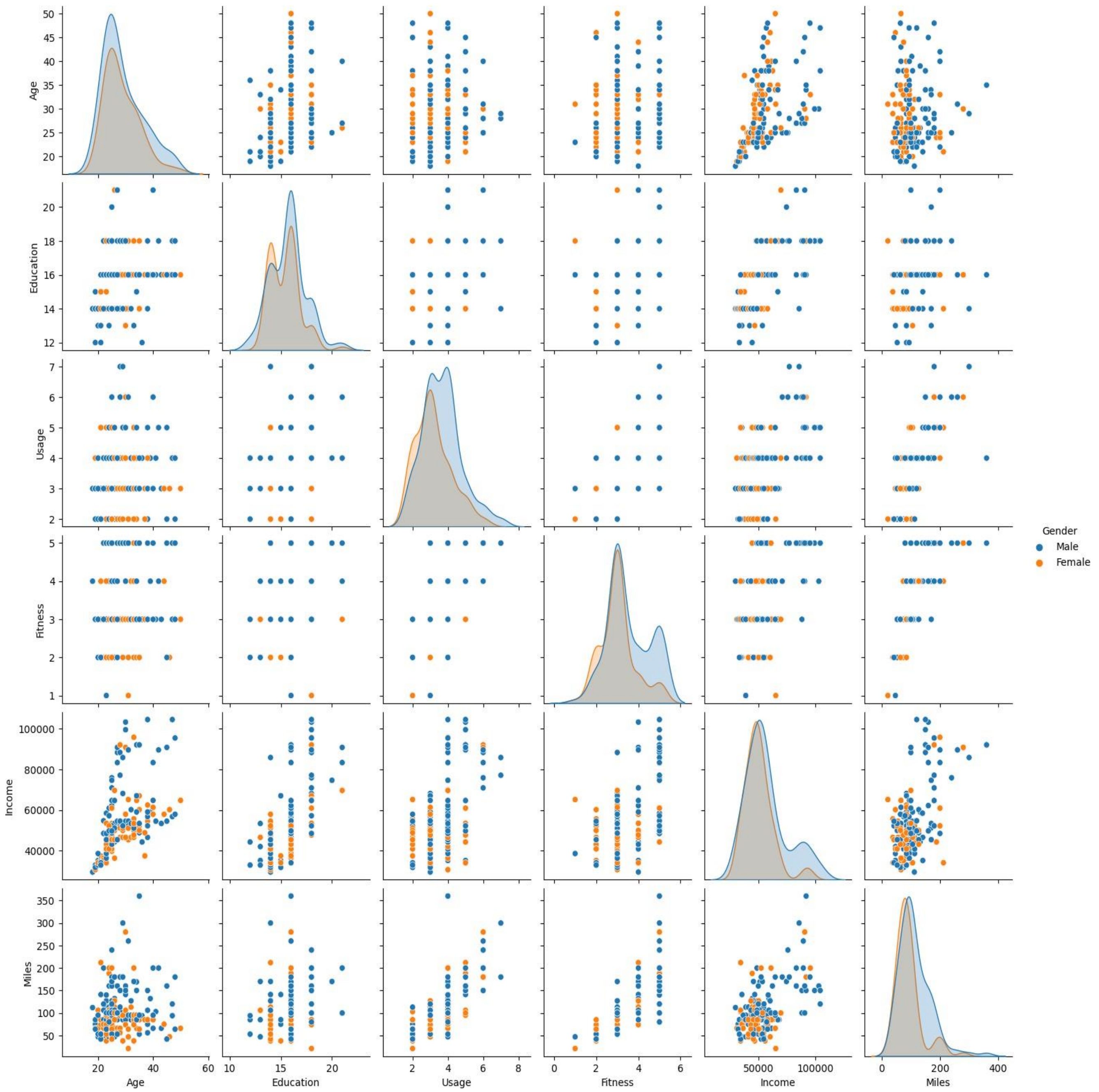
- Correlation between Age and Miles is 0.03
- Correlation between Education and Income is 0.62
- Correlation between Usage and Fitness is 0.66
- Correlation between Fitness and Age is 0.06
- Correlation between Income and Usage is 0.52
- Correlation between Miles and Age is 0.03

Pairplot

In [90]:
```
sns.pairplot(df_cat,hue = "Product")
plt.show()
```



In [39]:
```
sns.pairplot(df_cat,hue = 'Gender')
plt.show()
```



OUTLIER DETECTION

Outlier calculation for various parameters using Inter Quartile Range

In [12]:
```
q_75, q_25 = np.percentile(df['Miles'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Miles is", miles_iqr)
```

```
Inter Quartile Range for Miles is 48.75
```

In [23]:
```
q_75, q_25 = np.percentile(df_cat['Age'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Age is", miles_iqr)
```

```
Inter Quartile Range for Age is 9.0
```

In [24]:
```
q_75, q_25 = np.percentile(df_cat['Income'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Income is", miles_iqr)
```

```
Inter Quartile Range for Income is 14609.25
```

In [25]:
```
q_75, q_25 = np.percentile(df_cat['Usage'], [75 ,25])
miles_iqr = q_75 - q_25
```

```
print("Inter Quartile Range for Usage is", miles_iqr)
```

```
Inter Quartile Range for Usage is 1.0
```

In [26]:
```
q_75, q_25 = np.percentile(df_cat['Fitness'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Fitness is", miles_iqr)
```

```
Inter Quartile Range for Fitness is 1.0
```

In [27]:
```
q_75,  q_25  = np.percentile(df_cat['Education'],  [75  ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Education is", miles_iqr)
```

```
Inter Quartile Range for Education is 2.0
```

PROBABILITY

Two-way contingency tables and probabilities(conditional and marginal)

In [51]:
```
df_cat.Product.value_counts(normalize = True)
```

Out[51]:
```
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: proportion, dtype: float64
```

Insight - The probability of buying KP281, KP481 & KP781 was 0.44, 0.33 & 0.22 respectively.

In [52]:
```
df_cat.Gender.value_counts(normalize = True)
```

Out[52]:
```
Gender
Male      0.577778
Female    0.422222
Name: proportion, dtype: float64
```

Insight - The probability of male customers was found to be 0.57 while that of female customers it was 0.42.

In [53]:
```
df_cat.MaritalStatus.value_counts(normalize = True)
```

Out[53]:
```
MaritalStatus
Married    0.594444
Single     0.405556
Name: proportion, dtype: float64
```

Insight - The probability of married customers was 0.59 while that of single customers it was 0.40.

In [54]:
```
df_cat.AgeGroup.value_counts(normalize = True)
```

Out[54]:
```
AgeGroup
19-30    0.627778
31-40    0.277778
41-60    0.094444
0-18     0.000000
61+      0.000000
Name: proportion, dtype: float64
```

Insight - If the probability of the age group 19-30 is 0.62, it suggests that there is a relatively high likelihood of individuals falling within this age range in the dataset.

In [55]:
```
df_cat.Fitness_category.value_counts(normalize = True)
```

Out[55]:
```
Fitness_category
Average Shape      0.538889
Excellent Shape    0.172222
Bad Shape          0.144444
Good Shape         0.133333
Poor Shape         0.011111
Name: proportion, dtype: float64
```

Insight - If the probability of having an average shape among customers is 0.53, it indicates that there is a relatively high likelihood of individuals in the dataset having an average body shape.

In [22]:
```
df_cat.loc[df_cat.Product=='KP281']["Gender"].value_counts(normalize  =  True)
```

Out[22]:
```
Gender
Male      0.5
Female    0.5
Name: proportion, dtype: float64
```

Insight - The probability of both the genders buying the product KP281 was found to be 0.5.

In [23]:
```
df_cat.loc[df_cat.Product=='KP481']["Gender"].value_counts(normalize  =  True)
```

Out[23]:
```
Gender
Male      0.516667
Female    0.483333
Name: proportion, dtype: float64
```

Insight - The probability of male customers buying the product KP481 was 0.51 while that of female customers it was 0.48.

In [26]:
```
df_cat.loc[df_cat.Product=='KP781']["Gender"].value_counts(normalize  =  True)
```

Out[26]:
```
Gender
Male      0.825
Female    0.175
Name: proportion, dtype: float64
```

Insight - The probability of male customers buying the product KP781 was 0.82, on the otherhand for female customers it was found to be 0.17.

In [27]:
```
df_cat.loc[df_cat.Product=='KP281']["MaritalStatus"].value_counts(normalize  =  Tr
```

Out[27]:
```
MaritalStatus
Married    0.6
Single     0.4
Name: proportion, dtype: float64
```

Insight - The probability of married customers buying the product KP281 was 0.6 & that of single customers it was 0.4.

In [30]:
```
df_cat.loc[df_cat.Product=='KP481']["MaritalStatus"].value_counts(normalize  =  Tr
```

Out[30]:
```
MaritalStatus
Married    0.6
Single     0.4
Name: proportion, dtype: float64
```

Insight - If the probability of married customers buying the product KP481 is 0.6 and the probability for single customers is 0.4, it implies that there is a higher likelihood of married customers purchasing KP481 compared to single customers.

In [31]:
```
df_cat.loc[df_cat.Product=='KP781']["MaritalStatus"].value_counts(normalize  =  Tr
```

Out[31]:
```
MaritalStatus
Married    0.575
Single     0.425
Name: proportion, dtype: float64
```

Insight - If the probability of married customers buying the product KP781 is 0.57 and the probability for single customers is 0.42, it suggests that there is a higher likelihood of married customers purchasing KP781 compared to single customers.

In [19]:
```
pd.crosstab(df_cat.Gender,  df_cat.Product)
```

Out[19]:

Product	KP281	KP481	KP781
Gender			
Female	40	29	7
Male	40	31	33

In [73]:
```
round(pd.crosstab(index  =  [df_cat.Product],  columns  =  df_cat.Gender,normalize  =
```

Out[73]:

Gender	Female	Male
Product		
KP281	0.22	0.22
KP481	0.16	0.17
KP781	0.04	0.18

In [22]:
```
pd.crosstab(df_cat.MaritalStatus,df_cat.Product)
```

Out[22]:

Product	KP281	KP481	KP781
MaritalStatus			
Married	48	36	23
Single	32	24	17

In [72]:
```
round(pd.crosstab(index=[df_cat.Product,df_cat.MaritalStatus],columns=df_cat.Gen
```

Out[72]:

	Gender	Female	Male
Product	**MaritalStatus**		
KP281	**Married**	0.15	0.12
	Single	0.07	0.11
KP481	**Married**	0.08	0.12
	Single	0.08	0.06
KP781	**Married**	0.02	0.11
	Single	0.02	0.08

In [71]:
```
pd.crosstab(df_cat.Usage,df_cat.Product)
```

Out[71]:

Product	KP281	KP481	KP781
Usage			
2	19	14	0
3	37	31	1
4	22	12	18
5	2	3	12
6	0	0	7
7	0	0	2

In [74]:
```
round(pd.crosstab(index=[df_cat.Product],columns=df_cat.Usage,normalize=True),2)
```

Out[74]:

Usage	2	3	4	5	6	7
Product						
KP281	0.11	0.21	0.12	0.01	0.00	0.00
KP481	0.08	0.17	0.07	0.02	0.00	0.00
KP781	0.00	0.01	0.10	0.07	0.04	0.01

In [27]:

```
pd.crosstab(df_cat.Fitness,df_cat.Product)
```

Out[27]:

Product	KP281	KP481	KP781
Fitness			
1	1	1	0
2	14	12	0
3	54	39	4
4	9	8	7
5	2	0	29

In [75]:

```
round(pd.crosstab(index=[df_cat.Product],columns=df_cat.Fitness,normalize=True),
```

Out[75]:

Fitness	1	2	3	4	5
Product					
KP281	0.01	0.08	0.30	0.05	0.01
KP481	0.01	0.07	0.22	0.04	0.00
KP781	0.00	0.00	0.02	0.04	0.16

In [28]:

```
pd.crosstab(df_cat.Fitness_category,df_cat.Product)
```

Out[28]:

Product	KP281	KP481	KP781
Fitness_category			
Average Shape	54	39	4
Bad Shape	14	12	0
Excellent Shape	2	0	29
Good Shape	9	8	7
Poor Shape	1	1	0

In [13]:

```
round(pd.crosstab(index=[df_cat.Product,df_cat.Fitness_category],columns=df_cat.
```

Out[13]:

Product	Fitness_category	Female	Male
KP281	Average Shape	14.44	15.56
	Bad Shape	5.56	2.22
	Excellent Shape	0.56	0.56
	Good Shape	1.67	3.33
	Poor Shape	0.00	0.56
KP481	Average Shape	10.00	11.67
	Bad Shape	3.33	3.33
	Good Shape	2.22	2.22
	Poor Shape	0.56	0.00
KP781	Average Shape	0.56	1.67
	Excellent Shape	2.78	13.33
	Good Shape	0.56	3.33

In [14]:

```
pd.crosstab(df_cat.AgeGroup,df_cat.Product)
```

Out[14]:

AgeGroup	KP281	KP481	KP781
19-30	53	33	27
31-40	20	22	8
41-60	7	5	5

In [68]:

```
np.round(pd.crosstab(index=df_cat.Product,columns=df_cat.AgeGroup,normalize='col
```

Out[68]:

Product	19-30	31-40	41-60	All
KP281	46.90	40.0	41.18	44.44
KP481	29.20	44.0	29.41	33.33
KP781	23.89	16.0	29.41	22.22

In [47]:

```
pd.crosstab(df_cat.EducationYearsGroup,df_cat.Product)
```

Out[47]:

Product	KP281	KP481	KP781
EducationYearsGroup			
13-16	39	27	2
17-18	39	31	15
19-20	2	2	19
21+	0	0	4

In [77]:

```
round(pd.crosstab(index=[df_cat.Product],columns=df_cat.EducationYearsGroup,norm
```

Out[77]:

EducationYearsGroup	13-16	17-18	19-20	21+
Product				
KP281	0.22	0.22	0.01	0.00
KP481	0.15	0.17	0.01	0.00
KP781	0.01	0.08	0.11	0.02

In [48]:

```
pd.crosstab(df_cat.MilesGroup,df_cat.Product)
```

Out[48]:

Product	KP281	KP481	KP781
MilesGroup			
0-50	12	5	0
51-100	50	39	1
101-150	16	13	12
151-200	2	2	16
201-250	0	1	7
251-300	0	0	2
301-400	0	0	1
401+	0	0	1

In [78]:

```
round(pd.crosstab(index=[df_cat.Product],columns=df_cat.MilesGroup,normalize=Tru
```

Out[78]:

MilesGroup	0-50	51-100	101-150	151-200	201-250	251-300	301-400	401+
Product								
KP281	0.07	0.28	0.09	0.01	0.00	0.00	0.00	0.00
KP481	0.03	0.22	0.07	0.01	0.01	0.00	0.00	0.00
KP781	0.00	0.01	0.07	0.09	0.04	0.01	0.01	0.01

In [49]:

```
pd.crosstab(df_cat.IncomeGroup,df_cat.Product)
```

Out[49]:

Product	KP281	KP481	KP781
IncomeGroup			
20001-30000	1	0	0
30001-40000	22	9	0
40001-50000	25	21	5
50001-60000	26	23	6
60001-70000	6	7	6
70001-80000	0	0	4
80001-90000	0	0	7
90001-100000	0	0	9

In [79]:
```
round(pd.crosstab(index=[df_cat.Product],columns=df_cat.IncomeGroup,normalize=Tr
```

Out[79]:

IncomeGroup	20001-30000	30001-40000	40001-50000	50001-60000	60001-70000	70001-80000	80001-90000	90001-100000
Product								
KP281	0.01	0.12	0.14	0.15	0.03	0.00	0.00	0.00
KP481	0.00	0.05	0.12	0.13	0.04	0.00	0.00	0.00
KP781	0.00	0.00	0.03	0.03	0.03	0.02	0.04	0.05

In [14]:
```
round(pd.crosstab(index=[df_cat.Product,df_cat.MaritalStatus],columns=df_cat.Gen
```

Out[14]:

	Gender	Female	Male
Product	**MaritalStatus**		
KP281	**Married**	0.15	0.12
	Single	0.07	0.11
KP481	**Married**	0.08	0.12
	Single	0.08	0.06
KP781	**Married**	0.02	0.11
	Single	0.02	0.08

In [34]:
```
def  p_prod_given_gender(gender,  print_marginal=False):
    if gender is not "Female" and gender is not "Male":
        return "Invalid gender value."

    df1  =  pd.crosstab(index=df['Gender'],  columns=[df['Product']])
    p_781 = df1['KP781'][gender] / df1.loc[gender].sum()
    p_481  =  df1['KP481'][gender]  /  df1.loc[gender].sum()
    p_281  =  df1['KP281'][gender]  /  df1.loc[gender].sum()

    if  print_marginal:
```

```python
        print(f"P(Male):  {df1.loc['Male'].sum()/len(df):.2f}")
        print(f"P(Female):  {df1.loc['Female'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{gender}):  {p_781:.2f}")
    print(f"P(KP481/{gender}):  {p_481:.2f}")
    print(f"P(KP281/{gender}): {p_281:.2f}\n")
p_prod_given_gender('Male', True)
p_prod_given_gender('Female')
```

```
P(Male): 0.58
P(Female): 0.42

P(KP781/Male):  0.32
P(KP481/Male):  0.30
P(KP281/Male):  0.38

P(KP781/Female):  0.09
P(KP481/Female):  0.38
P(KP281/Female):  0.53
```

In [36]:

```python
def  p_prod_given_mstatus(status,  print_marginal=False):
    if status is not "Single" and status is not "Married":
        return "Invalid marital status value."

    df1  =  pd.crosstab(index=df['MaritalStatus'],  columns=[df['Product']])
    p_781 = df1['KP781'][status] / df1.loc[status].sum()
    p_481  = df1['KP481'][status]  /  df1.loc[status].sum()
    p_281  =  df1['KP281'][status]  /  df1.loc[status].sum()

    if  print_marginal:
        print(f"P(Single):  {df1.loc['Single'].sum()/len(df):.2f}")
        print(f"P(Partnered):  {df1.loc['Married'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{status}):  {p_781:.2f}")
    print(f"P(KP481/{status}):  {p_481:.2f}")
    print(f"P(KP281/{status}):  {p_281:.2f}\n")

p_prod_given_mstatus('Single',  True)
p_prod_given_mstatus('Married')
```

```
P(Single): 0.41
P(Partnered):  0.59

P(KP781/Single):  0.23
P(KP481/Single):  0.33
P(KP281/Single):  0.44

P(KP781/Married):  0.21
P(KP481/Married):  0.34
P(KP281/Married):  0.45
```

CUSTOMER PROFILING

KP281

- The KP281 is an entry-level product with a price tag of 1,500 dollars, making it the most preferred choice among customers.

- Married individuals show a higher preference for KP281 compared to single customers.
- The majority of individuals using KP281 have an average body shape.
- The probability of both genders using KP281 is equal, standing at 0.22.
- The maximum usage frequency for KP281 is observed at 3 days per week.
- The age group 19-30 demonstrates a higher usage of this product.
- Customers with an income range between 50,001 and 60,000 dollars are the predominant buyers of KP281.
- Most customers of KP281 engage in walking distances between 50-100 miles.
- Fitness level 3 is the most common among users of KP281.
- Income range between 30K to 50K have preferred this product.

KP481

- This intermediate-level product, priced at 1750 dollars has a higher prevalence among male customers.
- On average, users engage with this product three days per week.
- Notably, outliers were identified in the income range of 60,000 dollars to 70,000 dollars for the KP481, indicating that individuals earning less than 70,000 dollars also purchased this product.
- This treadmill is particularly popular among teenagers and middle-aged individuals.
- A significant portion of married customers also shows a preference for this product.
- Fitness level 3 is more common among people using this product.
- The fitness levels associated with this product span from bad shape to average shape, with no instances of customers in excellent shape using it.
- Users of this product typically walk distances ranging from 50 to 100 miles per week.

KP781

- KP781 stands out as a top-tier product with advanced features, making it the most exoensive among the three treadmills.
- Owing to its high price and advanced nature, there is a lower customer preference for this product.
- Its popularity is notably higher among married males.
- The probability of male customers buying the product KP781 is 33%, on the otherhand for female customers it is 7%.
- Similar to the other two products, it is commonly favored by young individals.
- Users typically engage with the KP781 4-5 times per week.
- Those who incorporate this treadmill into their routine tend to maintain excellent physical fitness.
- Users of this advanced treadmill often cover distances ranging from 100-200 miles per week, with some enthusiasts surpassing the 350 mile mark.
- Individuals using KP781 generally exhibit fitness levels in the range of 4-5.

BUSINESS INSIGHTS BASED ON NON-GRAPHICAL AND VISUAL ANALYSIS

1. Among the three treadmills in the Aerofit dataset, KP281 emerged as the preferred choice for users.
2. Treadmill usage is more prevalent among males, suggesting a greater fitness concern among males compared to females.
3. Married individuals were observed to use the treadmill more frequently than their single counterparts.
4. Users of either KP281 or KP481 tended to have a body shape ranging from bad to average, whereas those using KP781 exhibited an excellent body shape.
5. Excellent body shape was more commonly observed in males than in females.
6. The treadmill is most favored by young people (teen to young adult age group).

7. The average usage frequency for KP281 and KP481 was found to be three times per week, while for KP781, it was four days per week.

8. Individuals with 17-18 years of education were observed to prefer KP281 or KP481, while those with 19-20 years of education opted for KP781, the more advanced featured product.

9. People with higher income levels showed a greater preference for purchasing the KP781 product.

10. Users of KP281 and KP48 typically walks 500-100 miles per week, whereas those on KP781 tend to cover 100-200 miles per week, with some individuals wailking up to350 miles.

RECOMMENDATIONS

- Given that KP281 emerged as the preferred choice among the three treadmills, it might be beneficial to highlight its features and benefits in marketing and sales efforts.
- Focus marketing efforts toward males, as treadmill usage is more prevalent among them. Consider tailoring promotions or features that specifically appeal to male fitness concerns.
- Since married individuals were observed to use the treadmill more frequently, consider marketing strategies that appeal to couples or highlight the benefits of shared fitness activities for married individuals.
- Highlight the association between excellent body shape and the use of KP781. This could be a key selling point for individuals seeking specific fitness outcomes.
- Target marketing efforts towards young people (teen to young adult age group) who favor treadmill usage the most. This could involve creating engaging and youth-oriented promotional content.
- Emphasize the convenience and effectiveness of KP781 by promoting its four-day per week usage frequency, potentially appealing to users looking for a more intensive workout routine.
- Tailor marketing messages to individuals with 17-18 years of education for KP281 or KP481, highlighting features that align with their preferences. For those with 19-20 years of education, focus on promoting the advanced features of KP781.
- Given that people with higher income levels prefer KP781, target advertising to higher-income brackets. Emphasize the premium features and benefits associated with KP781 to justify the higher price point.