About Company

"**Company X** is a leading brand in the fitness equipment industry. It offers a wide product range including machines like treadmills, exercise bikes, gym equipment, and fitness accessories, catering to a diverse range of customers across various demographics."

Scenario:

The market research team at Company X wants to identify the characteristics of the target audience for each type of treadmill offered by the company. The goal is to provide more personalized recommendations for new customers. To achieve this, the team aims to investigate whether there are differences across the products concerning customer characteristics.

Objective:

Conduct descriptive analytics to create a detailed customer profile for each treadmill product sold by Company X. This will involve developing appropriate tables and charts that display key customer characteristics.

Method:

For each treadmill product, the following will be performed:

```
Construct two-way contingency tables to analyze relationships between
customer characteristics and treadmill types.
Compute all conditional and marginal probabilities.
Derive business insights from the results and assess their potential
impact on decision-making for marketing and customer recommendations.
```

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:

- 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

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.
```

What we will try to do:

- Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset
- Detect Outliers (using boxplot, “describe” method by checking the difference between mean and median)
- Check if features like marital status, age have any effect on the product purchased (using countplot, histplots, boxplots etc)
- Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)
- Check correlation among different factors using heat maps or pair plots.
- With all the above steps you can answer questions like: What is the probability of a male customer buying a KP781 treadmill?
- Customer Profiling - Categorization of users.
- Probability- marginal, conditional probability.
- Some recommendations and actionable insights, based on the inferences.

In [56]:
```
# Importing dependencies

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

In [57]:
```
df = pd.read_csv('aerofit_treadmill.txt')
```

There are 3 products treadmills mentioned which is of models:

KP281(entry-level) --> $1,500

KP481 (mid-level) --> $1,750

KP781 (adv features) --> $2,500

In [58]:
```
df.head()
```

Out[58]:

	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 [59]:
```python
df.tail()
```

Out[59]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

In [60]:
```python
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
```

In [61]:
```python
df.shape
```

Out[61]:
```
(180, 9)
```

In [62]:
```python
'''
Product
Age
Gender
Education
MaritalStatus
Usage
Fitness
Income
Miles

'''
```

Out[62]:
```
'\nProduct\nAge\nGender\nEducation\nMaritalStatus\nUsage\nFitness\nIncome\nMiles\n\n'
```

In [63]:
```python
df.describe()
```

Out[63]:

	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 [64]:
```
df.describe(include= 'all')
```

Out[64]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.00
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.19
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.86
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.00
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.00
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.00
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.75
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.00

Observations:

- We can observe frome the above table that are as below:
- df has no missing values in data- the df is consist of 3 unique product and kP281 is the most frequently occuring product
- Total 180 data points, 104 are male, and the rest are female.
- The age ranges from 18 to 50 years, with an avg age of 28.79 years.
- Most individuals have 16 years of education, with 75% having 16 years or less.
- The standard deviation for both income and miles is very high, indicating the presence of potential outliers.

In [65]:
```
# Available unique products:

df['Product'].unique()
```

Out[65]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

```
# As data seems to majorly clean, and sanitised we can directly jump to
statistical analysis
# If we see few columns like usage and fitness are like the numerical
data types which basically should be of string to treat them
accordingly.
```

In [66]:
```
df['Usage'] = df['Usage'].astype('str')
df['Fitness'] = df['Fitness'].astype('str')
```

In [67]:
```
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    object
 6   Fitness        180 non-null    object
 7   Income         180 non-null    int64 
 8   Miles          180 non-null    int64 
dtypes: int64(4), object(5)
memory usage: 12.8+ KB
```

In [68]:

```
# Check for the duplicates:
df.duplicated().value_counts()

# Results are pointing that there are no rows which are duplicate in the data
```

Out[68]:

```
False    180
Name: count, dtype: int64
```

In [69]:

```
# We can sagregate the data types wise the summary using describe: Object types and Inte
```

In [70]:

```
# Object type
df.describe(include= 'object')
```

Out[70]:

	Product	Gender	MaritalStatus	Usage	Fitness
count	180	180	180	180	180
unique	3	2	2	6	5
top	KP281	Male	Partnered	3	3
freq	80	104	107	69	97

Observation:

- Highest sales reported in KP281 with 80 sold in the reported data, majority of buyers reported to be male i.e., around 104 out of 180 and if we have to consider the marital status then 107 were married who purchased our product.
- Most of the buyers who purchased or products are belonged to the Usage and fitness category of 3 i.e., those who are planning to use the maching 3 times a week and are of average shape as 3 being average and 5 being excellent shape.

In [71]:

```
# Non- Object type of analysis
df.describe()
```

Out[71]:

	Age	Education	Income	Miles
count	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	53719.577778	103.194444
std	6.943498	1.617055	16506.684226	51.863605
min	18.000000	12.000000	29562.000000	21.000000
25%	24.000000	14.000000	44058.750000	66.000000
50%	26.000000	16.000000	50596.500000	94.000000

75%	33.000000	16.000000	58668.000000	114.750000
max	50.000000	21.000000	104581.000000	360.000000

Observations:

- Age - Min 18 to max 50 with avg of 28.79 years, with std of 6.9, having >75% of customers less than or equal to 33
- Education - Min 12 to max 21 with avg of 15.57 years, with std of 1.61 (No outlier exp), having >75% of customers less than or equal to 16.
- Income - if we see the std and 75% of total samples are below or equal to 50668 while max is 104581, which is indicating outliers to be present.
- Miles - if we see the std as 51 and 75% of total samples are below or equal to 114 while max is 360, which is indicating outliers to be present.

In [72]:
```
# We can check the list of unique values in the columns using teh loop:

for i in df.columns:
    print(i)
    print(df[i].unique())
```

```
Product
['KP281' 'KP481' 'KP781']
Age
[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 43 44 46 47 50 45 48 42]
Gender
['Male' 'Female']
Education
[14 15 12 13 16 18 20 21]
MaritalStatus
['Single' 'Partnered']
Usage
['3' '2' '4' '5' '6' '7']
Fitness
['4' '3' '2' '1' '5']
Income
[ 29562  31836  30699  32973  35247  37521  36384  38658  40932  34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]
Miles
[112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]
```

> As few columns are having contineous data like Age, Education, Income and Miles which we can better analyse if we convert that to the bins

In [73]:
```
# Age: As in above snip we can see the age is in the range of 18 to 42 then we can have

#binning the age values into categories
bin_age = [17,25,35,45, 55]
bin_agecat = ['Young', 'Adults', 'Adults+', 'Elder']
```

```
df['age Category'] = pd.cut(df['Age'],bins = bin_age,labels = bin_agecat)
```

In [74]:
```
# Education also needs kind of binning

bin_ed = [0,12,15,25]
bin_edcat = ['Primary', 'Secondary', 'Higher']

df['edu_class'] = pd.cut(df['Education'],bins = bin_ed,labels = bin_edcat)
```

In [75]:
```
# Incom binning

bin_inc =[0, 40000, 60000, 80000, 110000 ]
bin_incat = ['small', 'medium', 'high', 'very high']

df['inc_class'] = pd.cut(df['Income'], bins = bin_inc, labels=bin_incat)
```

In [76]:
```
# miles binning

bin_mils = [0, 50, 100, 200, 400]
bin_milscat = ['low', 'mod', 'high', 'very high']
df['miles_class'] = pd.cut(df['Miles'], bins = bin_mils, labels= bin_milscat)
```

In [77]:
```
# After binning the data below will be the structure for the dataframe
df.head()
```

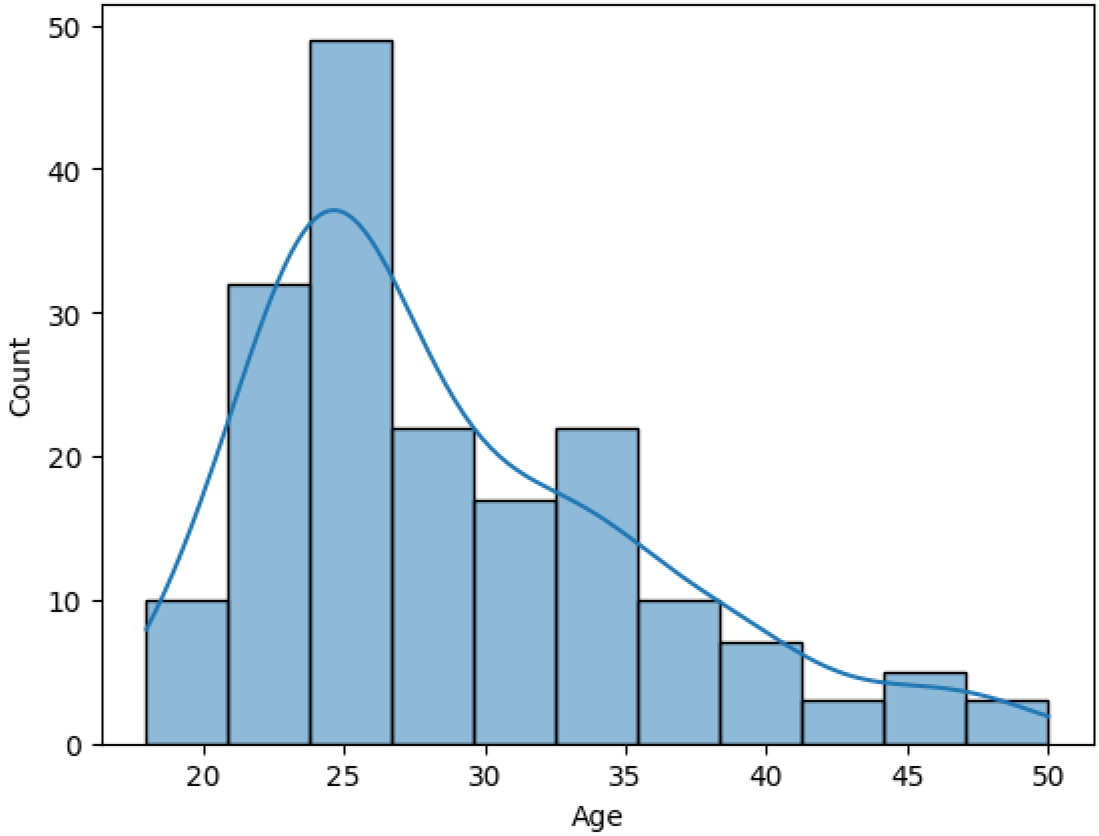
Out[77]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age Category	edu_class	inc_
0	KP281	18	Male	14	Single	3	4	29562	112	Young	Secondary	
1	KP281	19	Male	15	Single	2	3	31836	75	Young	Secondary	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Young	Secondary	
3	KP281	19	Male	12	Single	3	3	32973	85	Young	Primary	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Young	Secondary	

Univariate Analysis

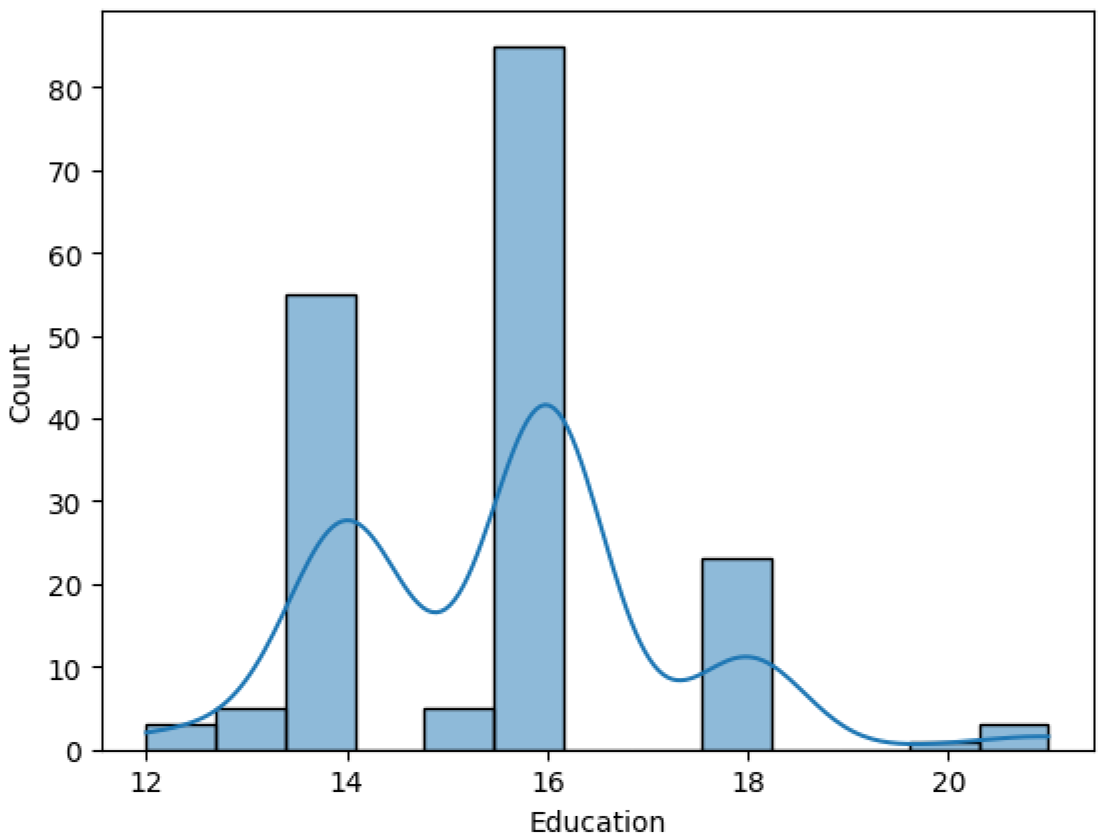
In [78]:
```
sns.histplot(data=df, x="Age", kde=True)

# Majority of the points are lying between 22.5 to 27.5
```

Out[78]: <Axes: xlabel='Age', ylabel='Count'>



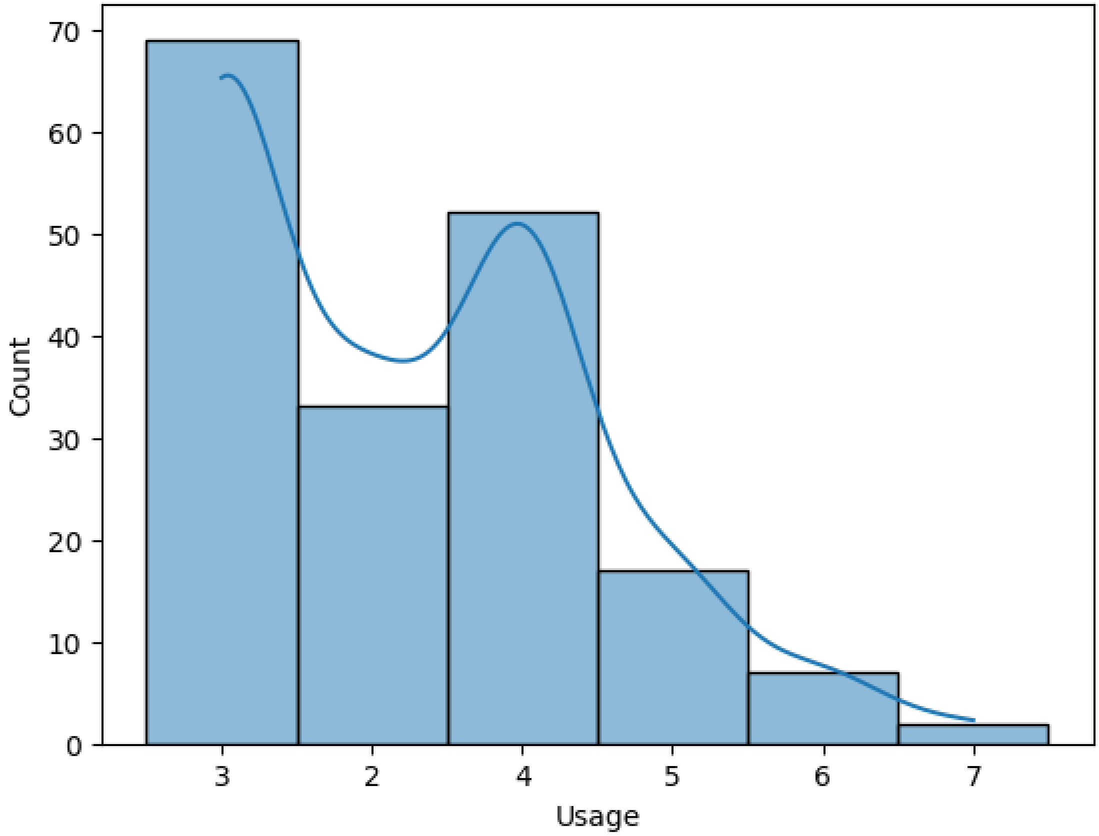
In [79]:
```
sns.histplot(data=df, x="Education", kde=True)
```

Out[79]: <Axes: xlabel='Education', ylabel='Count'>



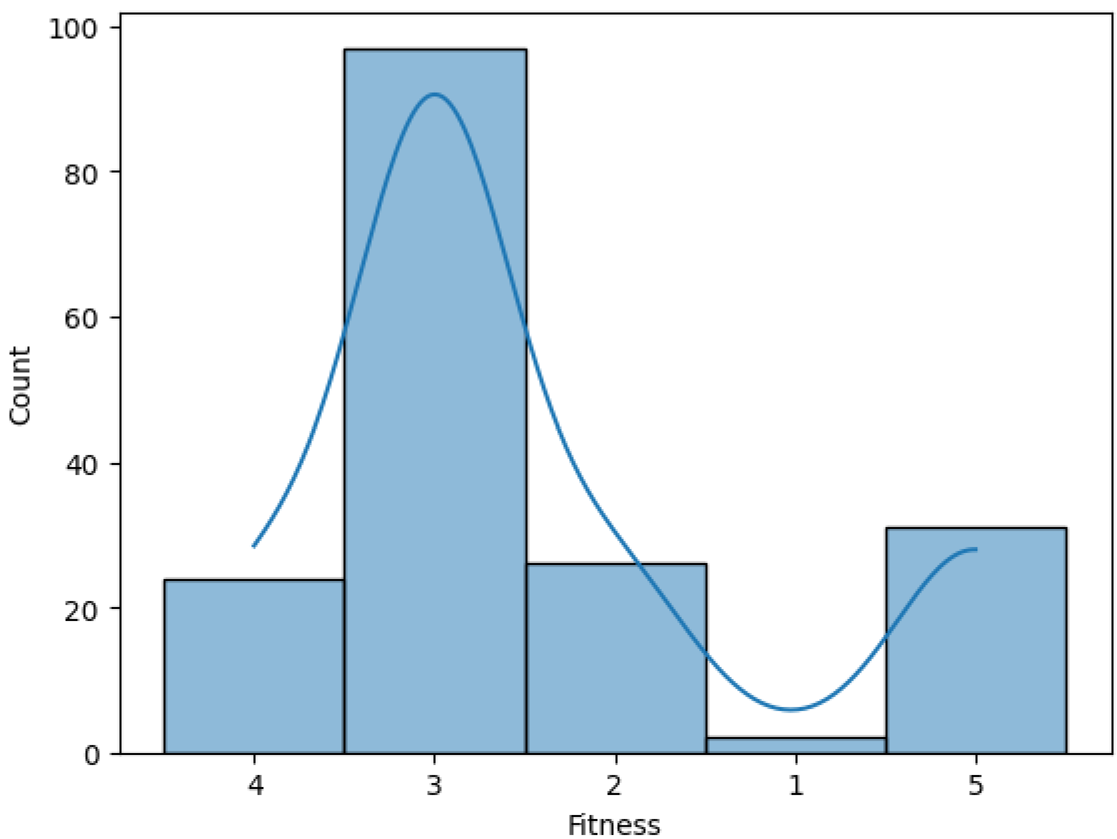
In [80]:
```
sns.histplot(data=df, x="Usage", kde=True)
```

Out[80]: <Axes: xlabel='Usage', ylabel='Count'>



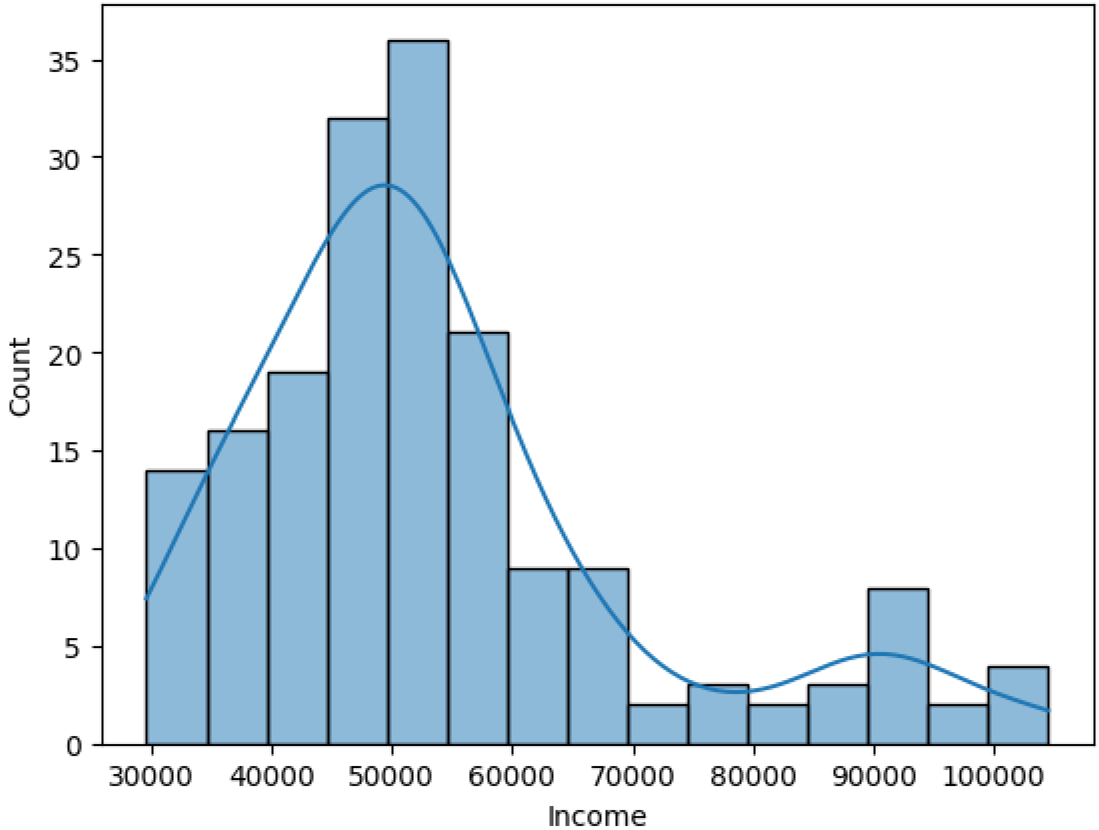
In [81]:
```
sns.histplot(data=df, x="Fitness", kde=True)
```

Out[81]: <Axes: xlabel='Fitness', ylabel='Count'>



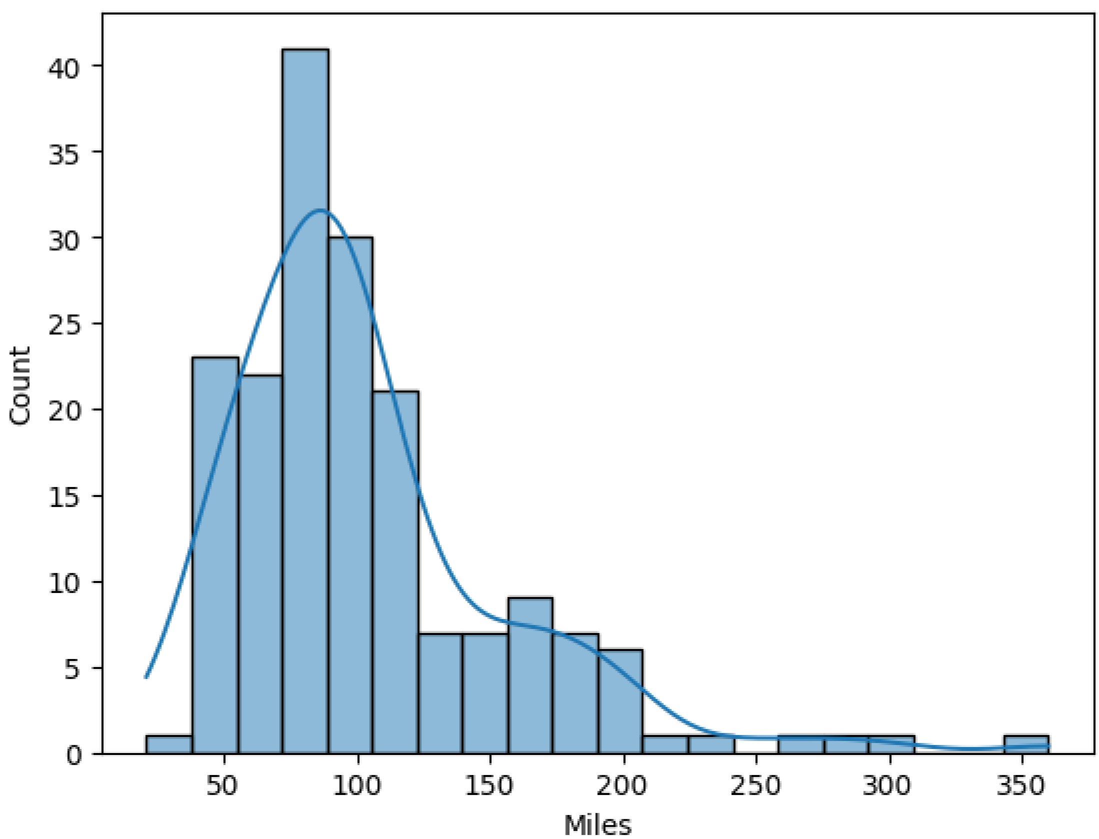
In [82]:
```
sns.histplot(data=df, x="Income", kde=True)
# Majorly the population belongs to the 45K to 55K
```

Out[82]: <Axes: xlabel='Income', ylabel='Count'>




```
In [83]: sns.histplot(data=df, x="Miles", kde=True)
```

```
Out[83]: <Axes: xlabel='Miles', ylabel='Count'>
```



Observation :

Age data is rightly skewed whcich will be pointing otliers possible on the higher side of the age range with major people belongs to 22.5 to 25 years

Frequent users are from the category 3 and 4 which we need to more focus on

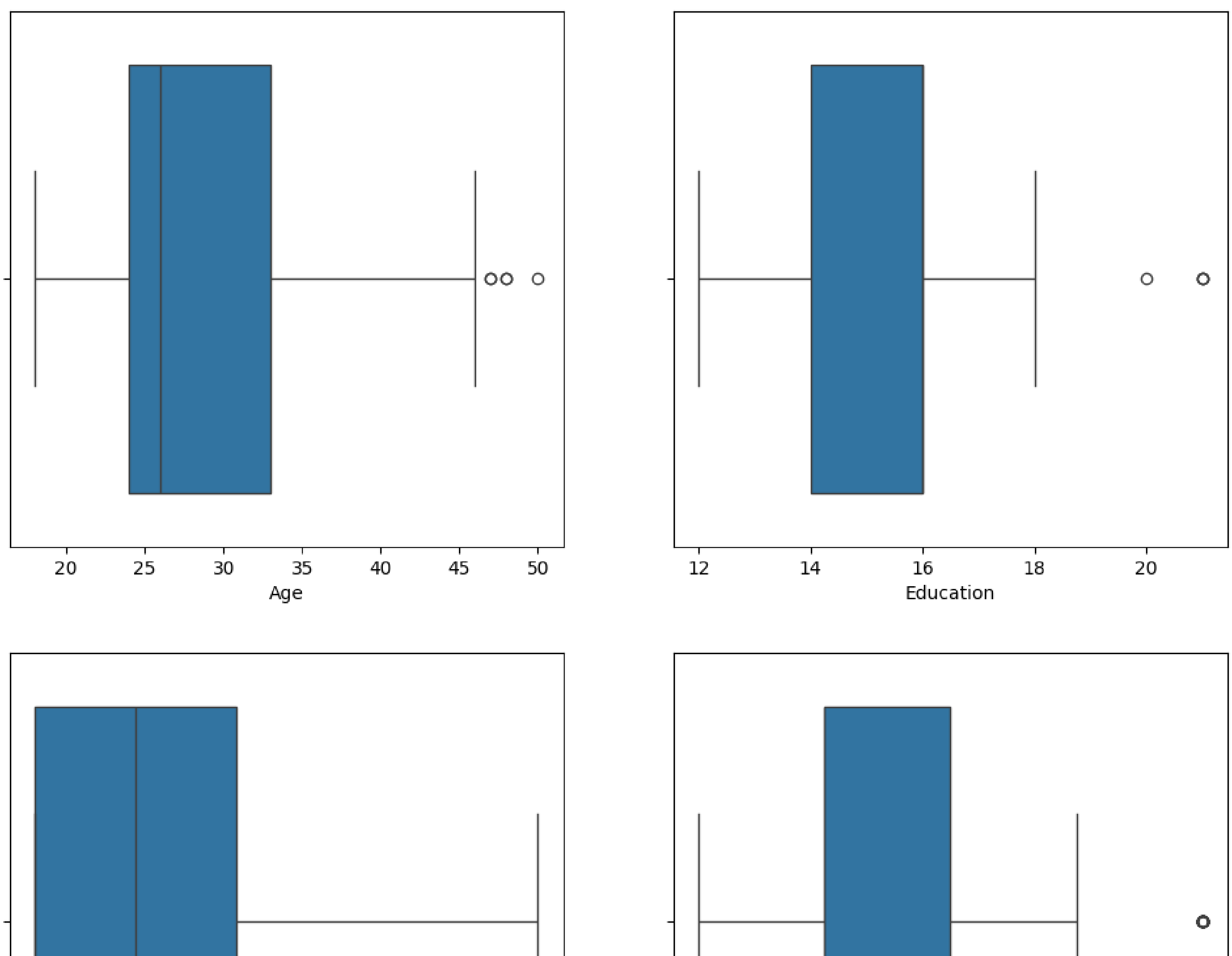
Fitness wise the people mostly belongs to category 3

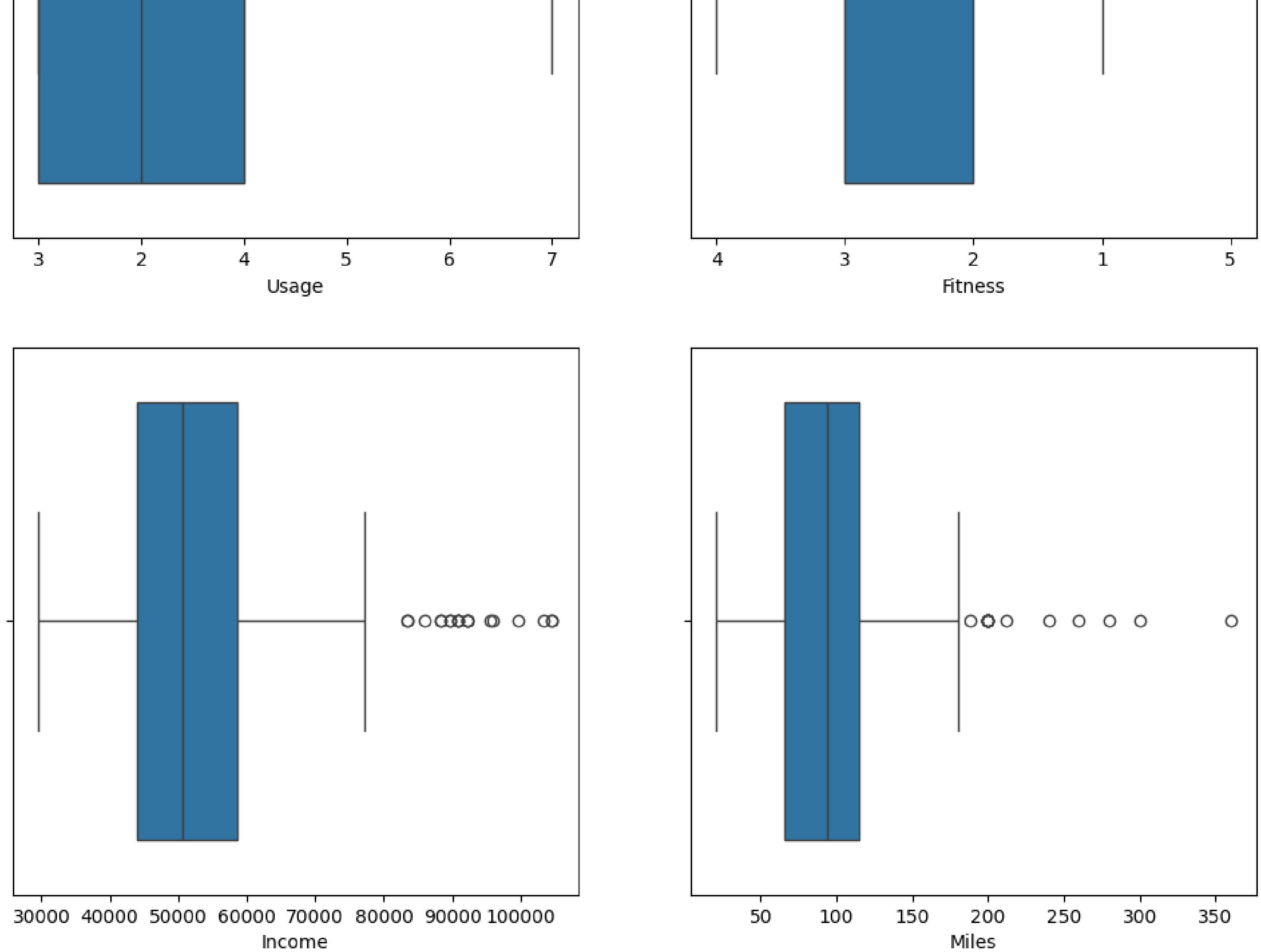
Income wise majority of our samples are in the range of 45K to 55K with the right skewed data

Miles that they will run are 50 to 120 per week

Outliers detection : Box-Plot

In [84]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.5)

sns.boxplot(data=df, x="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, x="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, x="Usage", orient='h', ax=axis[1,0])
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, x="Miles", orient='h', ax=axis[2,1])
plt.show()

# In below tables we can see that there are outliers present in few columns that are Age
```





Observation:

> Visually w can observe that there are few outliers present in Fitness, Age and Eucation and more outliers present in Income and Miles while no outliers seen in usage

In [85]:

```
# Product wise share in total collected records

df.head()
```

Out[85]:

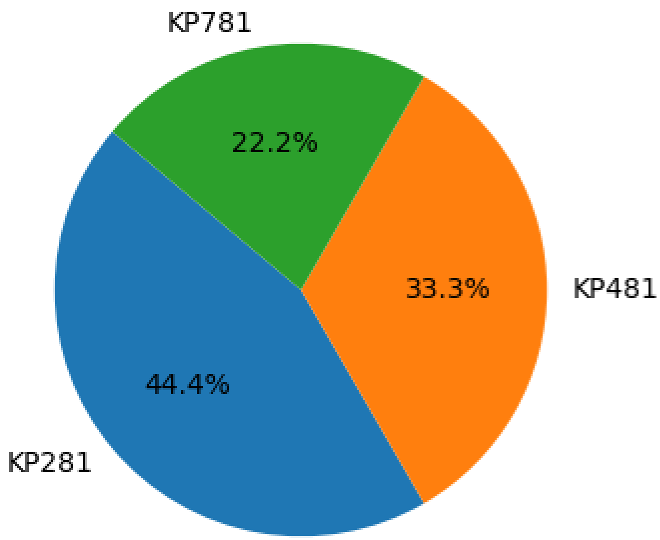
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age Category	edu_class	inc_
0	KP281	18	Male	14	Single	3	4	29562	112	Young	Secondary	
1	KP281	19	Male	15	Single	2	3	31836	75	Young	Secondary	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Young	Secondary	
3	KP281	19	Male	12	Single	3	3	32973	85	Young	Primary	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Young	Secondary	

In [86]:

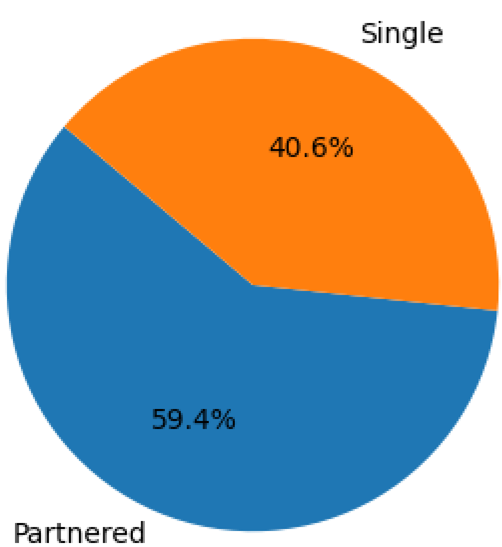
```
# Discreate variables

# Best way to show the spread among the various products is pie chart

product_count1 = df['Product'].value_counts()
product_count = df['Product'].value_counts(normalize= True)*100
print(product_count)
```

```
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: proportion, dtype: float64
```

In [87]:
```
plt.figure(figsize=(4, 4))
plt.pie(product_count1, labels=product_count1.index, autopct='%1.1f%%', startangle=140)
plt.show()
```

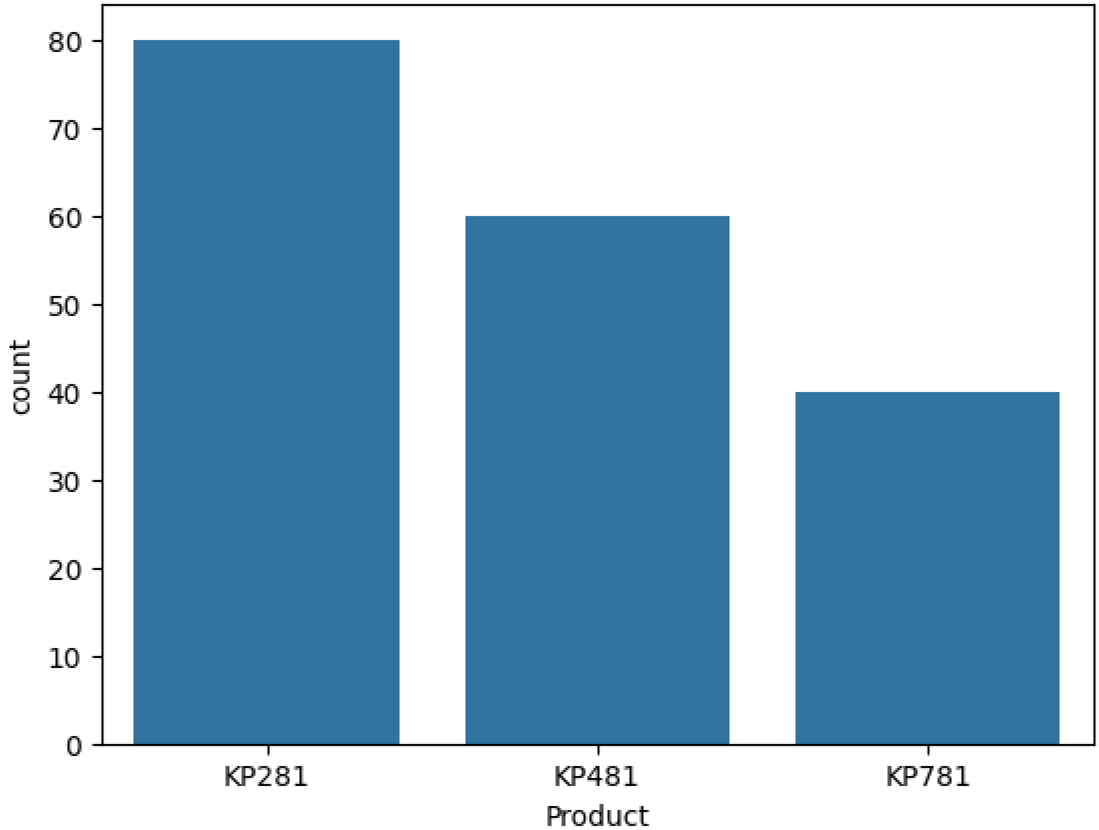


In [88]:
```
#  Similarly we can also showcase the spread of samples collected by the gender

Marital_count1 = df['MaritalStatus'].value_counts()

plt.figure(figsize=(4, 4))
plt.pie(Marital_count1, labels=Marital_count1.index, autopct='%1.1f%%', startangle=140)
plt.show()
```

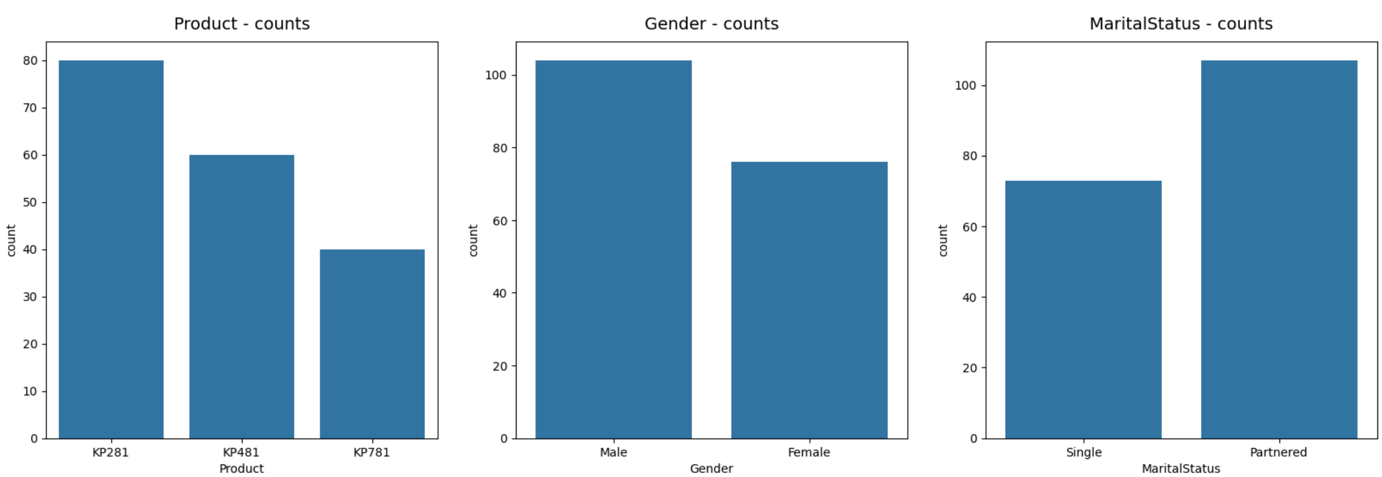


In [89]:
```
sns.barplot(product_count1)
```

Out[89]:
```
<Axes: xlabel='Product', ylabel='count'>
```



In [90]:
```python
# Countplots to see the counts of different values in each discreate variables

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 6))
sns.countplot(data=df, x='Product', ax=axs[0])
sns.countplot(data=df, x='Gender', ax=axs[1])
sns.countplot(data=df, x='MaritalStatus', ax=axs[2])

axs[0].set_title("Product - counts", pad=10, fontsize=14)
axs[1].set_title("Gender - counts", pad=10, fontsize=14)
axs[2].set_title("MaritalStatus - counts", pad=10, fontsize=14)
plt.show()
```



In [91]:
```python
df_melted = df[['Product', 'Gender', 'MaritalStatus', 'Fitness', 'Usage']].melt()
df_2 = df_melted.groupby(['variable', 'value'])[['value']].count() / len(df)*100
df_2
```

Out[91]:

variable	value	value
Fitness	**1**	1.111111
	2	14.444444

	3	53.888889
	4	13.333333
	5	17.222222
Gender	**Female**	42.222222
	Male	57.777778
MaritalStatus	**Partnered**	59.444444
	Single	40.555556
Product	**KP281**	44.444444
	KP481	33.333333
	KP781	22.222222
Usage	**2**	18.333333
	3	38.333333
	4	28.888889
	5	9.444444
	6	3.888889
	7	1.111111

Observation:

> We can observe from the above table that almost 54% people who are purchasing are falls under fiteness category 3 which means niether too poor or too excelent in terms of shape.
>
> 58% of total who are purchasing are males and 60% are married people.
>
> Product model no KP281 is most polular product among all three products which is reporting almost 44% of total sales share.
>
> And if we compare the customers according t their intentional usage, they mostly fall under the 3 times per week which is almost 38 folloed by 4 times/week.

In [92]:

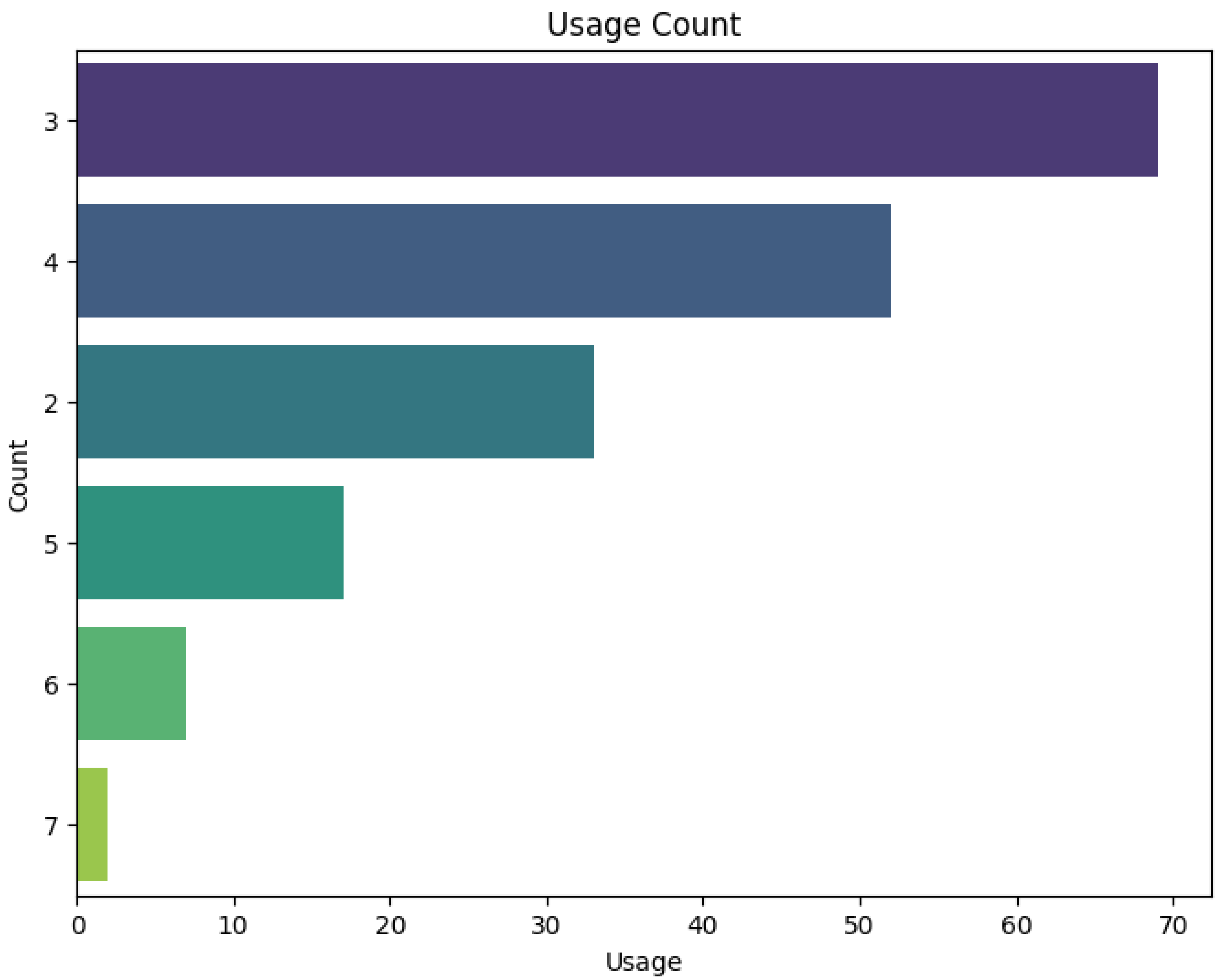
```
usage_count = df['Usage'].value_counts().sort_values(ascending= False)
Fitness_count = df['Fitness'].value_counts().sort_values(ascending= False)

usage_count, Fitness_count
```

Out[92]:

```
(Usage
 3    69
 4    52
 2    33
 5    17
 6     7
 7     2
 Name: count, dtype: int64,
 Fitness
 3    97
 5    31
 2    26
 4    24
 1     2
 Name: count, dtype: int64)
```

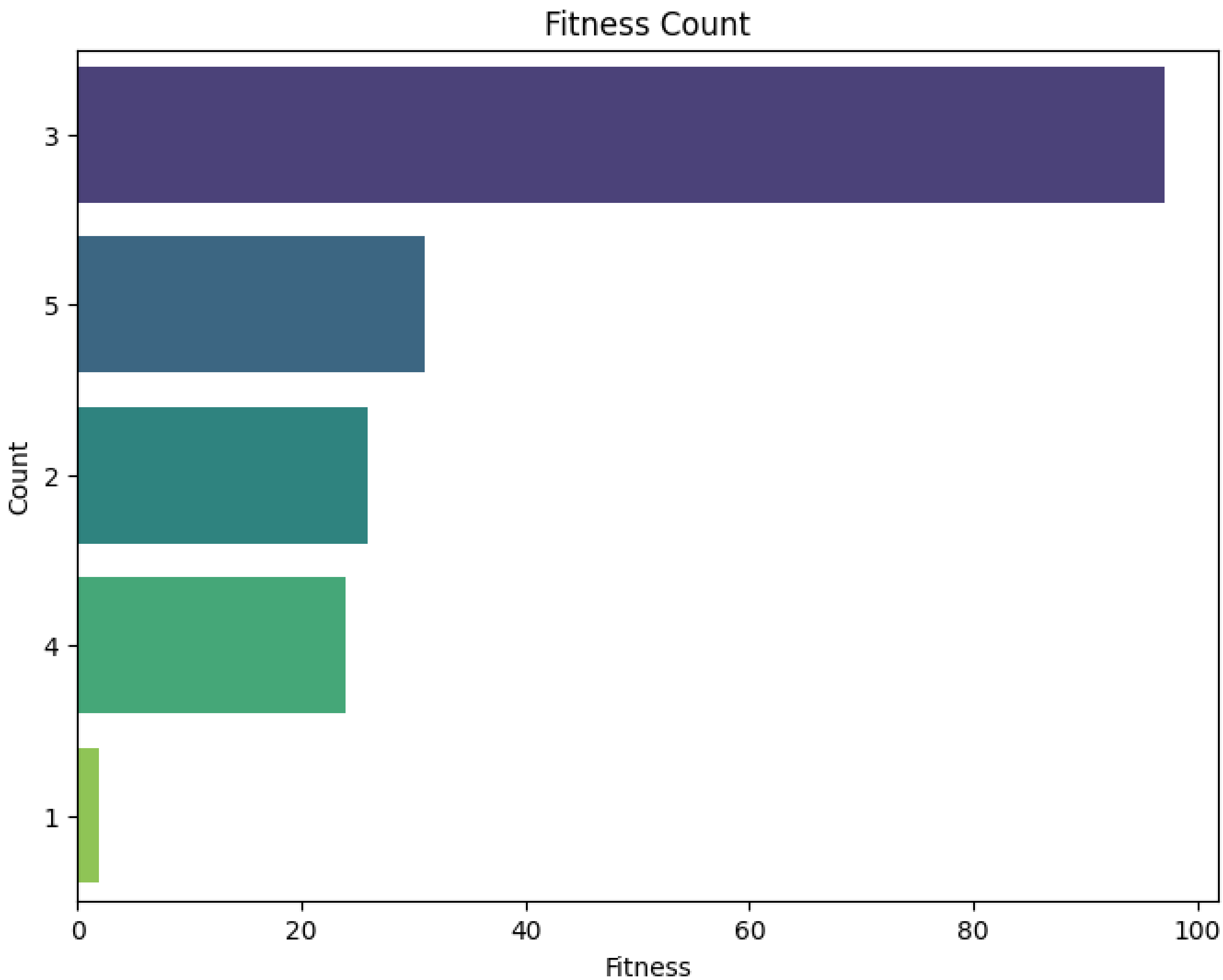
In [93]:
```
# Create a count plot
plt.figure(figsize=(8, 6))
sns.barplot(x=usage_count.values, y=usage_count.index, palette='viridis')
plt.title('Usage Count')
plt.xlabel('Usage')
plt.ylabel('Count')
plt.show()
```

```
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\63306537.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=usage_count.values, y=usage_count.index, palette='viridis')
```



In [94]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x=Fitness_count.values, y=Fitness_count.index, palette='viridis')
plt.title('Fitness Count')
plt.xlabel('Fitness')
plt.ylabel('Count')
plt.show()
```

```
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\3367085388.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=Fitness_count.values, y=Fitness_count.index, palette='viridis')
```



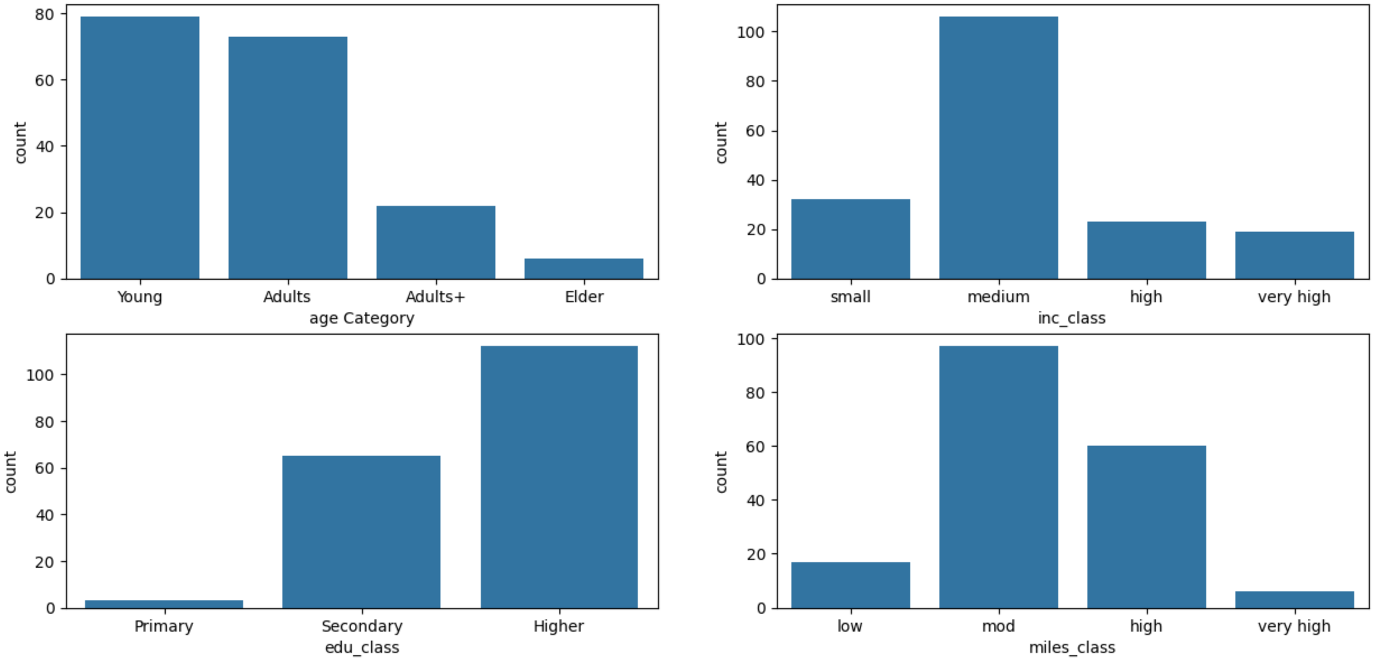
In [95]:
```
df.head()
```

Out[95]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age Category	edu_class	inc_
0	KP281	18	Male	14	Single	3	4	29562	112	Young	Secondary	
1	KP281	19	Male	15	Single	2	3	31836	75	Young	Secondary	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Young	Secondary	
3	KP281	19	Male	12	Single	3	3	32973	85	Young	Primary	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Young	Secondary	

In [96]:
```
fig = plt.figure(figsize = (15,7))
gs = fig.add_gridspec(2,2)
ax1 = fig.add_subplot(gs[0,0])
sns.countplot(data= df, x = 'age Category')
ax2 = fig.add_subplot(gs[1,0])
sns.countplot(data= df, x = 'edu_class')
ax2 = fig.add_subplot(gs[0,1])
sns.countplot(data= df, x = 'inc_class')
ax2 = fig.add_subplot(gs[1,1])
sns.countplot(data= df, x = 'miles_class')
```

Out[96]:
```
<Axes: xlabel='miles_class', ylabel='count'>
```



⍰ Insights

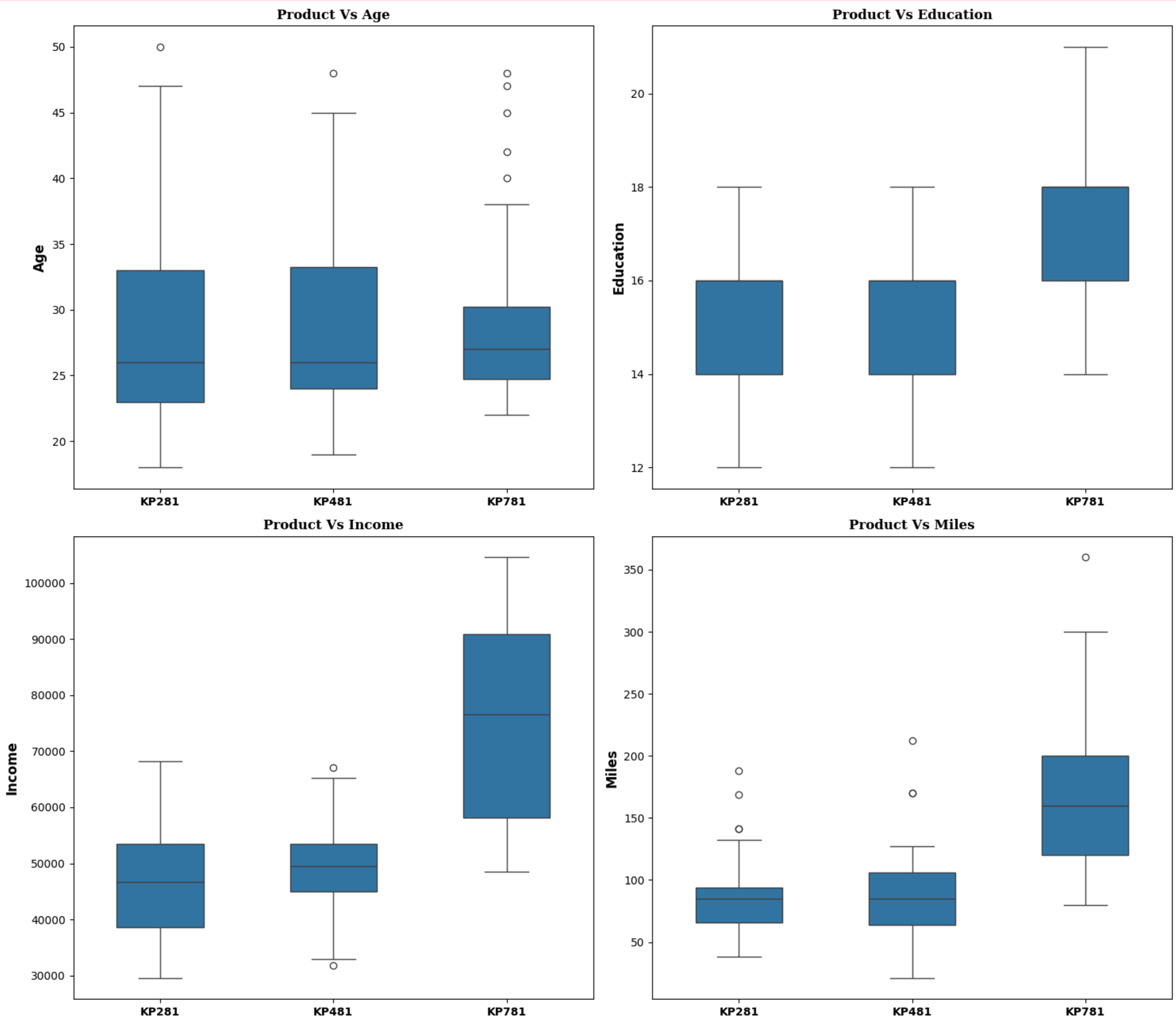
- Young adults category of the customers both are equally interested in purcahsing the equipments.
- Majority of purchasers belongs to the income groups of medium size ranging from 40 to 60K followed by small i.e <40K.
- Education with the Secondary and Higher clases are more interested purchasing the equipments.
- Also the people who are purchasing are of miles class mod and high.

In [97]:

```
# Define the order of plots and corresponding titles
plot_order = [(0, 0, 'Age', 'Age'), (0, 1, 'Education', 'Education'),
              (1, 0, 'Income', 'Income'), (1, 1, 'Miles', 'Miles')]

# Create the figure and grid layout
fig = plt.figure(figsize=(15, 13))
gs = fig.add_gridspec(2, 2)
for i, j, k, title in plot_order:
    # Plot position
    ax = fig.add_subplot(gs[i, j])
    # Plot using Seaborn's boxplot
    sns.boxplot(data=df, x='Product', y=k, ax=ax, width=0.5)
    # Set plot title
    ax.set_title(f'Product Vs {title}', {'font': 'serif', 'size': 12, 'weight': 'bold'})
     # Customize axes
    ax.set_xticklabels(df['Product'].unique(), fontweight='bold')
    ax.set_ylabel(f'{title}', fontweight='bold', fontsize=12)
    ax.set_xlabel('')

# Adjust layout
fig.tight_layout()

# Show plot
plt.show()
```

```
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\3191481928.py:16: UserWarning: set_ti
cklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or u
sing a FixedLocator.
  ax.set_xticklabels(df['Product'].unique(), fontweight='bold')
```

```
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\3191481928.py:16: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(df['Product'].unique(), fontweight='bold')
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\3191481928.py:16: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(df['Product'].unique(), fontweight='bold')
C:\Users\chavad\AppData\Local\Temp\ipykernel_20056\3191481928.py:16: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(df['Product'].unique(), fontweight='bold')
```



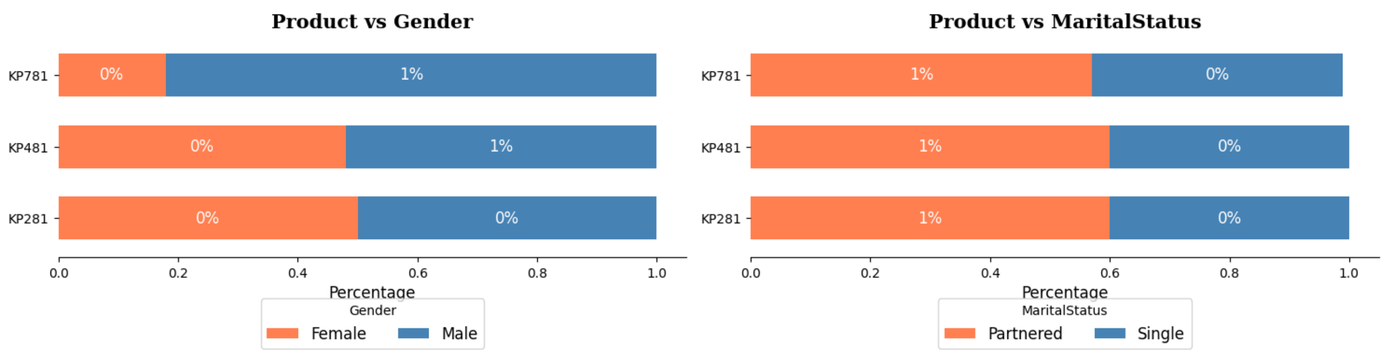
Observation

- We can clearly see that with higher education, Income and Miles the prefference for the KP781 is higher while that is also preffred by the young people that is people in the range of 22.5 to 37.5

In [116…

```
# Set up the figure and subplots
fig, axs = plt.subplots(1, 2, figsize=(15, 4))

color_palette = ["#FF7F50", "#4682B4"]

columns = ['Gender', 'MaritalStatus']
```

```
for ax, col in zip(axs, columns):

    df_grp = df.groupby('Product')[col].value_counts(normalize=True).round(2).unstack().

    df_grp.plot(kind='barh', stacked=True, ax=ax, color=color_palette, width=0.6, edgeco

    for i in ax.containers:
        ax.bar_label(i, label_type='center', fmt='%.0f%%', fontsize=12, color='white')

    ax.set_title(f'Product vs {col}', fontsize=15, fontweight='bold', fontfamily='serif'
    ax.set_xlabel('Percentage', fontsize=12)
    ax.set_ylabel('')  # Hide the default y-axis label
    ax.spines[['top', 'right', 'left']].set_visible(False)  # Remove spines for a cleane
    ax.legend(title=col, loc='upper center', ncol=2, fontsize=12, bbox_to_anchor=(0.5, -

plt.tight_layout()

plt.show()
```

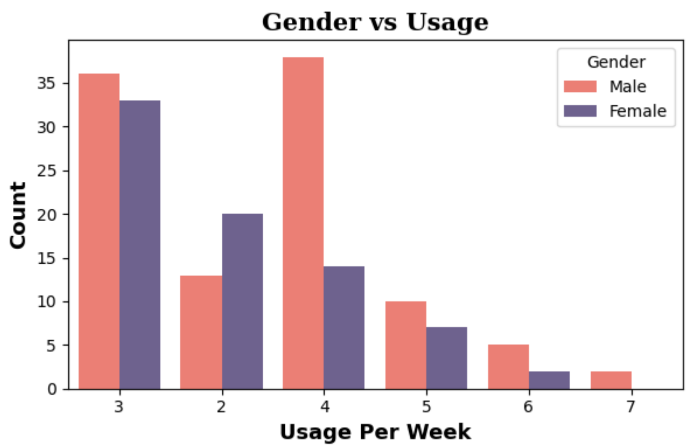


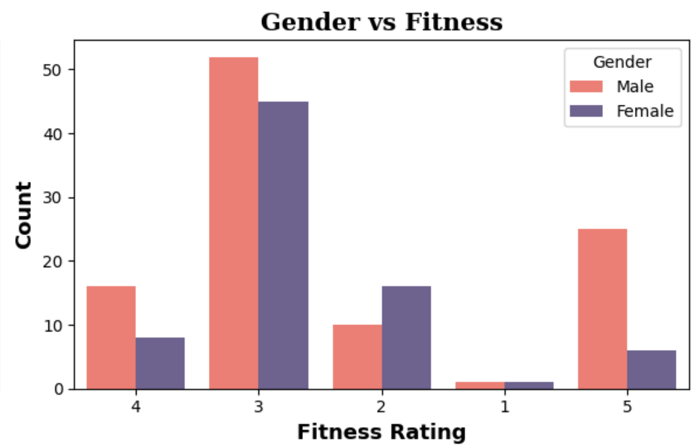
Observation:

- Males are main contributor for 781 purchase while in rest all models the contribution is more or less same
- on an average married people have equal prefferences in all 3 categories for product type.

In [117…

```
# Plotting Gender vs Usage and Fitness
fig, axs = plt.subplots(1, 2, figsize=(12, 4))

# Gender vs Usage
sns.countplot(data=df, x='Usage', hue='Gender', palette=["#FF6F61", "#6B5B95"], ax=axs[0
axs[0].set_title('Gender vs Usage', fontsize=15, fontweight='bold', fontfamily='serif')
axs[0].set_xlabel('Usage Per Week', fontsize=13, fontweight='bold')
axs[0].set_ylabel('Count', fontsize=13, fontweight='bold')
axs[0].legend(title='Gender', loc='upper right')

# Gender vs Fitness
sns.countplot(data=df, x='Fitness', hue='Gender', palette=["#FF6F61", "#6B5B95"], ax=axs
axs[1].set_title('Gender vs Fitness', fontsize=15, fontweight='bold', fontfamily='serif'
axs[1].set_xlabel('Fitness Rating', fontsize=13, fontweight='bold')
axs[1].set_ylabel('Count', fontsize=13, fontweight='bold')
axs[1].legend(title='Gender', loc='upper right')

fig.tight_layout()

plt.show()
```





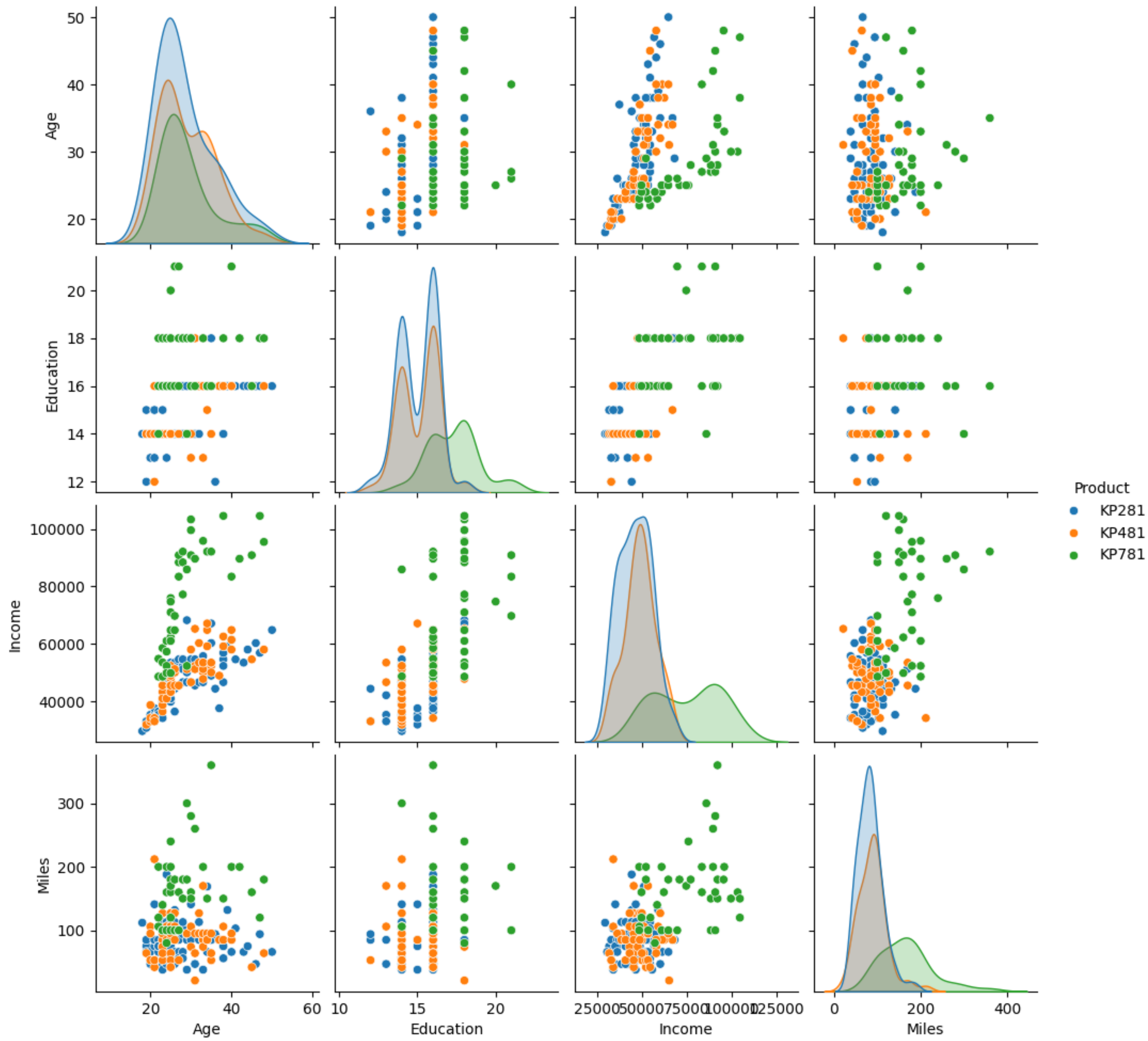
Observation

- Only category whcih has female dominance is the user group which want to use twice a week, in rest all user groups males are dominant
- 3 times a week has closer diff between male and feemale in terms of user shares
- 4 time a week has bigger difference between the no of males and females, in terms of purchase and use
- If we consider the type of physique, out of total people who are purchasing belongs to the average/ middle kind of physique.

Pairplot for Corelation Checks

In [118…

```
sns.pairplot(df, hue ='Product')
plt.show()
```



Observation

> If u see the income vs age scatter plot that will show slight +ve correlation which we can furthre cross check by values using Heatmap

Heatmap

- First we need to convert the object data type for usage and fitness columns which we have changed as the 'Str' type

In [101…

```
df_copy = copy.deepcopy(df[['Age','Education','Usage','Fitness','Income','Miles']])
df_copy['Usage'] = df_copy['Usage'].astype('int')
df_copy['Fitness'] = df_copy['Fitness'].astype('int')

df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 6 columns):
```

```
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Age        180 non-null    int64
 1   Education  180 non-null    int64
 2   Usage      180 non-null    int32
 3   Fitness    180 non-null    int32
 4   Income     180 non-null    int64
 5   Miles      180 non-null    int64
dtypes: int32(2), int64(4)
memory usage: 7.2 KB
```

In [102…

```
corr_mat = df_copy.corr()

plt.figure(figsize=(15,6))

sns.heatmap(corr_mat,annot = True, cmap='viridis')

plt.show()
```

Observation for Heatmap and Pairplot shows:

- The pair plot shows a positive correlation between Age vs Income, which has been reconfirmed with the heatmap
- Usage is highly correlated with Fitness and Miles, as increased usage leads to higher fitness levels and greater mileage.
- Education vs Income has high correlation and its understood too
- Education has a significant correlation with both Fitness and Usage.

Statistical Analysis regarding the probability

In [103…

```
# Products vs Gender Probability
pd.crosstab(index =df['Product'],columns = df['Gender'],margins = True,normalize = True
```

Out[103]:

Gender	Female	Male	All
Product			

KP281	0.22	0.22	0.44
KP481	0.16	0.17	0.33
KP781	0.04	0.18	0.22
All	0.42	0.58	1.00

Observation

- Above table shows the probability of varius incidences like probability of purchasing the KP281 given that th customer is femal will be 22%
- Similarly we can read others too

In [104…

```
# Products vs Education class probability
pd.crosstab(index =df['Product'],columns = df['edu_class'],margins = True,normalize = Tr
```

Out[104]:

edu_class	Primary	Secondary	Higher	All
Product				
KP281	0.01	0.21	0.23	0.44
KP481	0.01	0.14	0.18	0.33
KP781	0.00	0.01	0.21	0.22
All	0.02	0.36	0.62	1.00

- Probability being the purchaser choosing the KP481 given tht the purchaser is having secondary education will be 14%

In [105…

```
# Products vs Age category probability
pd.crosstab(index =df['Product'],columns = df['age Category'],margins = True,normalize =
```

Out[105]:

age Category	Young	Adults	Adults+	Elder	All
Product					
KP281	0.19	0.18	0.06	0.02	0.44
KP481	0.16	0.13	0.04	0.01	0.33
KP781	0.09	0.09	0.02	0.01	0.22
All	0.44	0.41	0.12	0.03	1.00

In [106…

```
# Products vs Marital status probability
pd.crosstab(index =df['Product'],columns = df['MaritalStatus'],margins = True,normalize
```

Out[106]:

MaritalStatus	Partnered	Single	All
Product			
KP281	0.27	0.18	0.44
KP481	0.20	0.13	0.33
KP781	0.13	0.09	0.22
All	0.59	0.41	1.00

In [107…

```
# Products vs Income class probability
```

```
pd.crosstab(index =df['Product'],columns = df['inc_class'],margins = True,normalize = Tr
```

Out[107]:

inc_class / Product	small	medium	high	very high	All
KP281	0.13	0.28	0.03	0.00	0.44
KP481	0.05	0.24	0.04	0.00	0.33
KP781	0.00	0.06	0.06	0.11	0.22
All	0.18	0.59	0.13	0.11	1.00

In [108…

```
# Products vs Usage probability
pd.crosstab(index =df['Product'],columns = df['Usage'],margins = True,normalize = True )
```

Out[108]:

Usage / Product	2	3	4	5	6	7	All
KP281	0.11	0.21	0.12	0.01	0.00	0.00	0.44
KP481	0.08	0.17	0.07	0.02	0.00	0.00	0.33
KP781	0.00	0.01	0.10	0.07	0.04	0.01	0.22
All	0.18	0.38	0.29	0.09	0.04	0.01	1.00

In [109…

```
# Products vs Fitness probability
pd.crosstab(index =df['Product'],columns = df['Fitness'],margins = True,normalize = True
```

Out[109]:

Fitness / Product	1	2	3	4	5	All
KP281	0.01	0.08	0.30	0.05	0.01	0.44
KP481	0.01	0.07	0.22	0.04	0.00	0.33
KP781	0.00	0.00	0.02	0.04	0.16	0.22
All	0.01	0.14	0.54	0.13	0.17	1.00

In [110…

```
# Products vs Miles class probability
pd.crosstab(index =df['Product'],columns = df['miles_class'],margins = True,normalize =
```

Out[110]:

miles_class / Product	low	mod	high	very high	All
KP281	0.07	0.28	0.10	0.00	0.44
KP481	0.03	0.22	0.08	0.01	0.33
KP781	0.00	0.04	0.15	0.03	0.22
All	0.09	0.54	0.33	0.03	1.00

Recomendations and Suggestions

- The likelihood of purchase is 44% for KP281, 33% for KP481, and 22% for KP781.
- Customers are predominantly aged between the range of 18 - 35 years and runs 50 to 100 miles per week.

- Customers have at least 13 years of education and have an annual income of less than USD 60,000.
- Customers use the treadmill 2 to 3 times per week while major people who are purchasing the equipments belongs to Fitness category of '3'

Suggestion

- Majorly if we see the data lower income groups and lower eductaion level are contributing lesser share for which we can target those customers
  - We can provide them with the better monetory plan to invest in halth and less educated needs to eductaed using campaign
  - Also major share of KP281 indicates that is price driven as mostly middle income bracket is investing, whome we can push to buy better machine with some better installments plan
  - Also if we see that KP781 is popular in males its having majro disaparity wrt females, it seems its unpopular and we can probe further into this why?and is there other reason than price?
  - KP781 if we see is popular in the people with the higher eductaion, higher income and higher miles capacity. while 281 is popular across the broader range of age groups.