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.

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.
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 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
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 good looks like?

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.
Later on, we will see more ways to do “customer segmentation”, but this case study in itself is relevant in some real-world scenarios.

Topics Covered:

Defining Problem Statement and Analysing basic metrics
Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary
Non-Graphical Analysis: Value counts and unique attributes
Visual Analysis - Univariate & Bivariate
For continuous variable(s): Distplot, countplot, histogram for univariate analysis
For categorical variable(s): Boxplot

```
For correlation: Heatmaps, Pairplots
Missing Value & Outlier Detection
Business Insights based on Non-Graphical and Visual Analysis
Comments on the range of attributes
Comments on the distribution of the variables and relationship between them
Comments for each univariate and bivariate plot
Recommendations - Actionable items for business. No technical jargon. No complications.
Simple action items that everyone can understand
```

Our goal is to indentify type of people who choose which product

In [1]:

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

In [2]:

```
os.chdir('C:\\Users\Ashok kumar\Desktop\chanu\DSML_Course\DataSet')
```

In [3]:

```
df= pd.read_csv('aerofit_treadmill.csv')
```

In [4]:

```
df.head()
```

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

In [5]:

```
df.describe()
```

Out[5]:

	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 [6]:

```
df.shape
```

Out[6]:

```
(180, 9)
```

In [7]:

```
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
```

we can say that there are no null values in the dataset and it looks good

In [8]:

```
df.Product.unique()
```

Out[8]:

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

There are only 3 types of products available in the dataset, we can change them into cateogorical data type

In [9]:

```
dummy_product=pd.get_dummies(df.Product)
```

In [10]:

```
dummy_product.shape
```

Out[10]:

```
(180, 3)
```

In [11]:

```
df=pd.concat([dummy_product.iloc[:,1:],df],axis=1)
```

In [12]:

```
df.head()
```

Out[12]:

	KP481	KP781	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	M
0	0	0	KP281	18	Male	14	Single	3	4	29562	
1	0	0	KP281	19	Male	15	Single	2	3	31836	
2	0	0	KP281	19	Female	14	Partnered	4	3	30699	
3	0	0	KP281	19	Male	12	Single	3	3	32973	
4	0	0	KP281	20	Male	13	Partnered	4	2	35247	

We can identify the type of product using the two columns KP481 and KP781

The main goal of this project is to identify the kind of product the customer purchases according to their characteristics

In [13]:

```
df.nunique()
```

Out[13]:

```
KP481             2
KP781             2
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

There are many values in Income and Age we can seperate them into buckets

In [14]:

```
df['Age_cut'] = pd.cut(df['Age'],bins= [17,22,27,32,37,42,47,51],labels=['18-22','22-27','2
```

In [15]:

```
df['Income_cut'] = pd.cut(df['Income'],bins=[29561,35000,40000,45000,50000,55000,60000,6500
                          labels=['35000','40000','45000','50000','55000','60000','65000','
```

In [16]:

```
df.Gender.value_counts()
```

Out[16]:

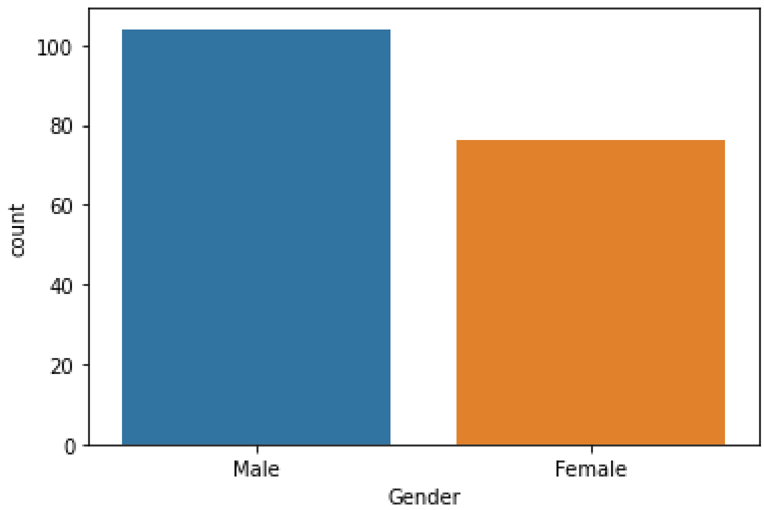
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [17]:

```
sns.countplot(x=df.Gender)
```

Out[17]:

```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



More male people are present compared to female

In [18]:

```
df.MaritalStatus.value_counts()
```

Out[18]:

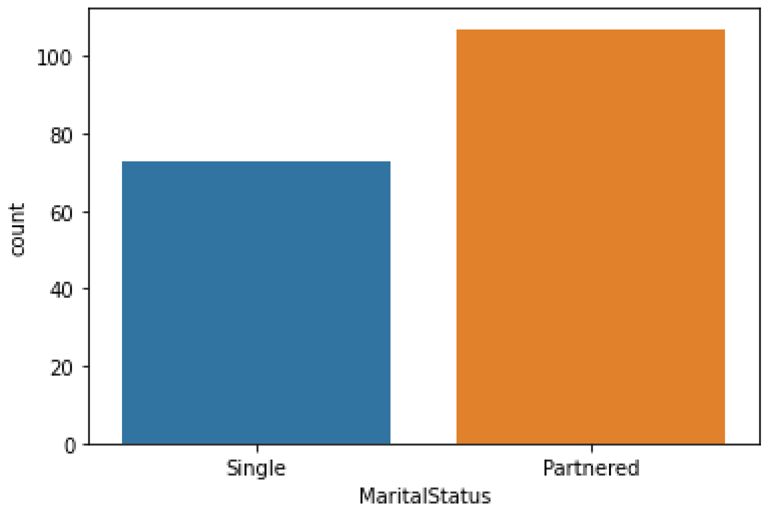
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

In [19]:

```
sns.countplot(x=df.MaritalStatus)
```

Out[19]:

```
<AxesSubplot:xlabel='MaritalStatus', ylabel='count'>
```



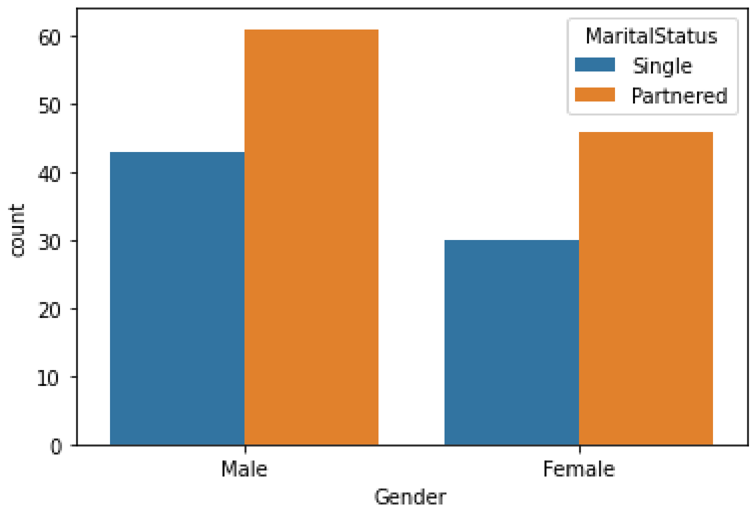
There are more Partnered people compared to single people

In [20]:

```
sns.countplot(x=df.Gender,hue=df.MaritalStatus)
```

Out[20]:

```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



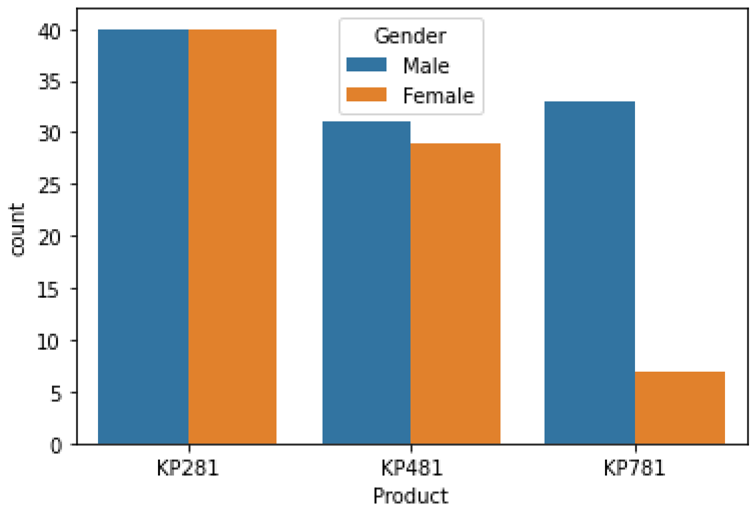
There are more Partnered people compared to single people in both male and female

In [21]:

```
sns.countplot(x=df.Product,hue=df.Gender)
```

Out[21]:

```
<AxesSubplot:xlabel='Product', ylabel='count'>
```



People who use KP781 are more Males compared to female

In [22]:

```
gender_marital_df=pd.crosstab(index=df.Product,columns = [df.Gender,df.MaritalStatus],margi
gender_marital_df
```

Out[22]:

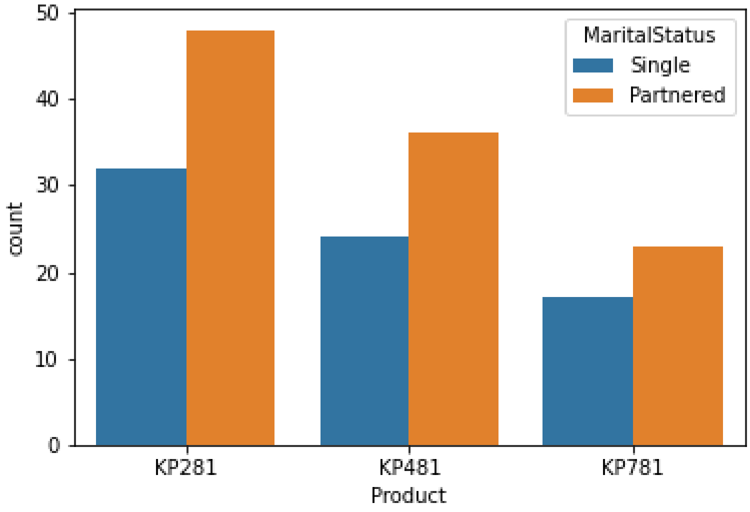
Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	27	13	21	19	80
KP481	15	14	21	10	60
KP781	4	3	19	14	40
All	46	30	61	43	180

In [23]:

```
sns.countplot(x=df.Product,hue=df.MaritalStatus)
```

Out[23]:

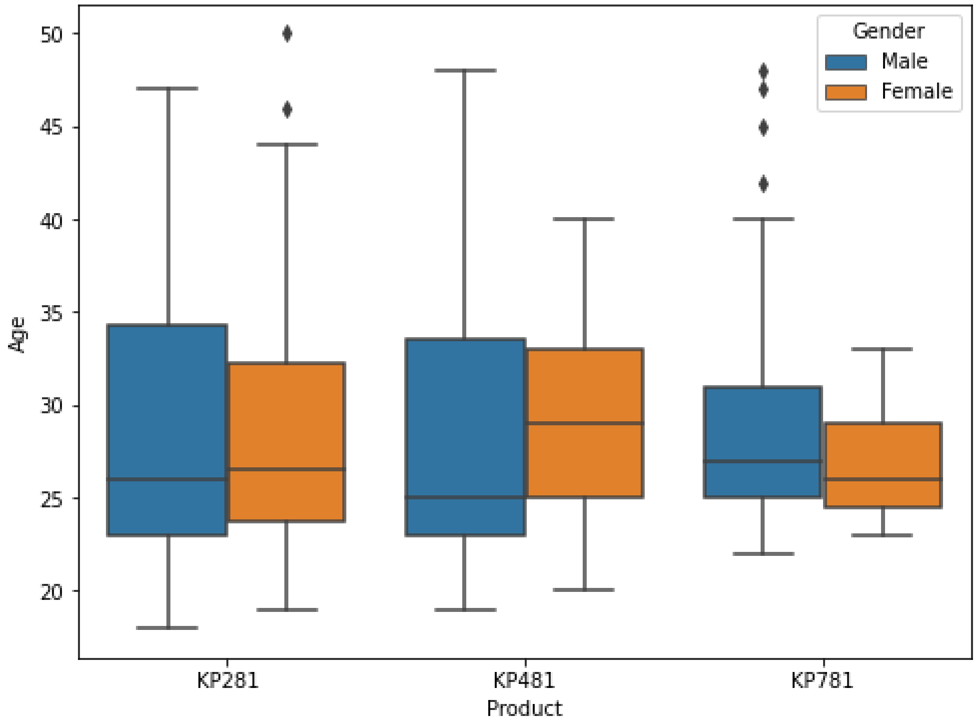
```
<AxesSubplot:xlabel='Product', ylabel='count'>
```



More partnered people use the Products compared to Single people

In [24]:

```
plt.figure(figsize=(8,6))
sns.boxplot(y=df.Age,x=df.Product,hue=df.Gender)
plt.show()
```



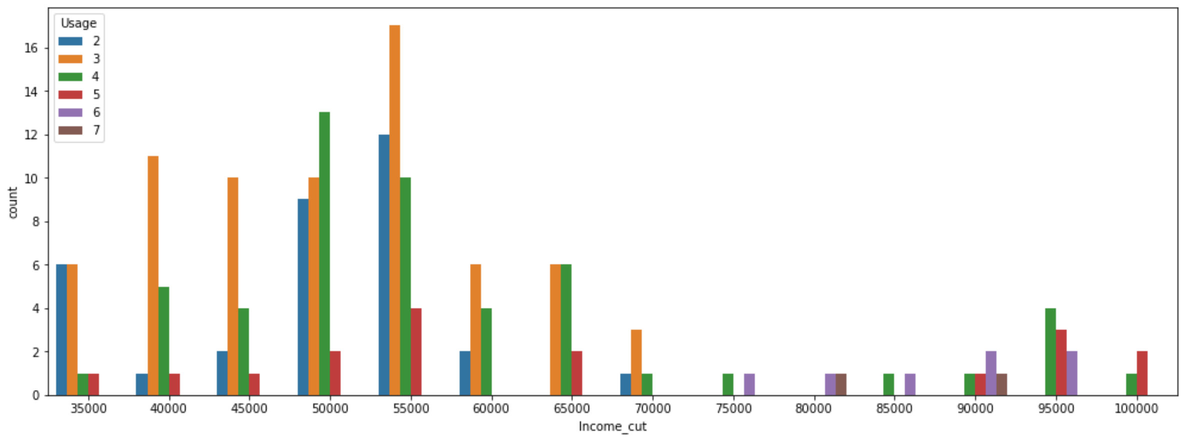
There are more outliers in KP281 Female users and KP781 Male users

In [25]:

```
plt.figure(figsize=(17,6))
sns.countplot(x=df.Income_cut,hue=df.Usage)
```

Out[25]:

```
<AxesSubplot:xlabel='Income_cut', ylabel='count'>
```



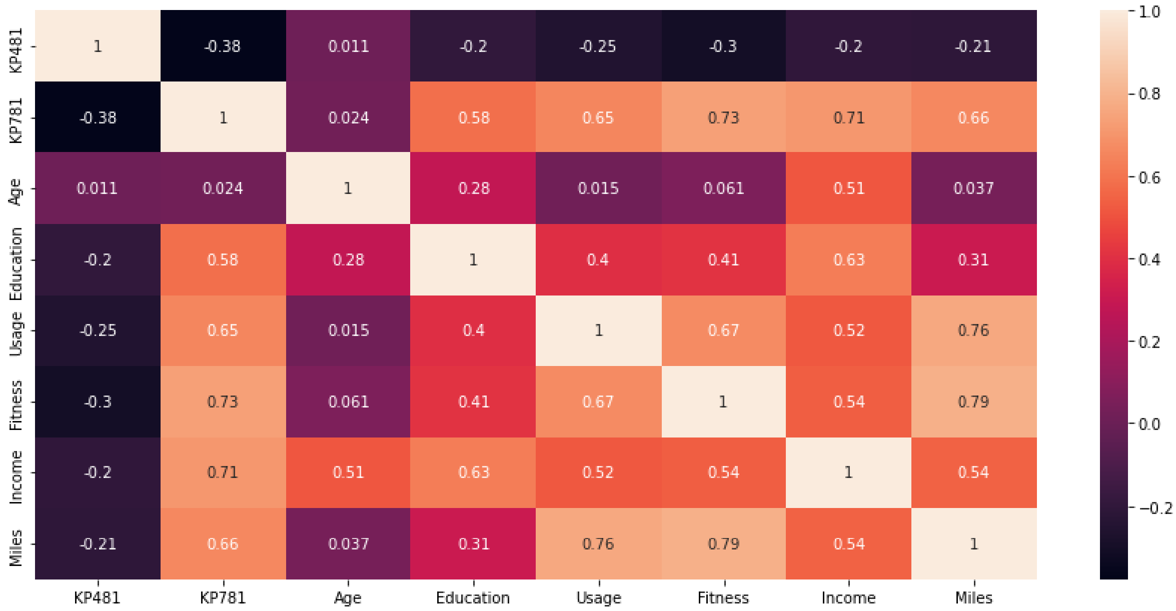
As the income increases Usage of products is more

In [26]:

```
plt.figure(figsize=(15,7))
sns.heatmap(df.corr(),annot=True)
```

Out[26]:

<AxesSubplot:>



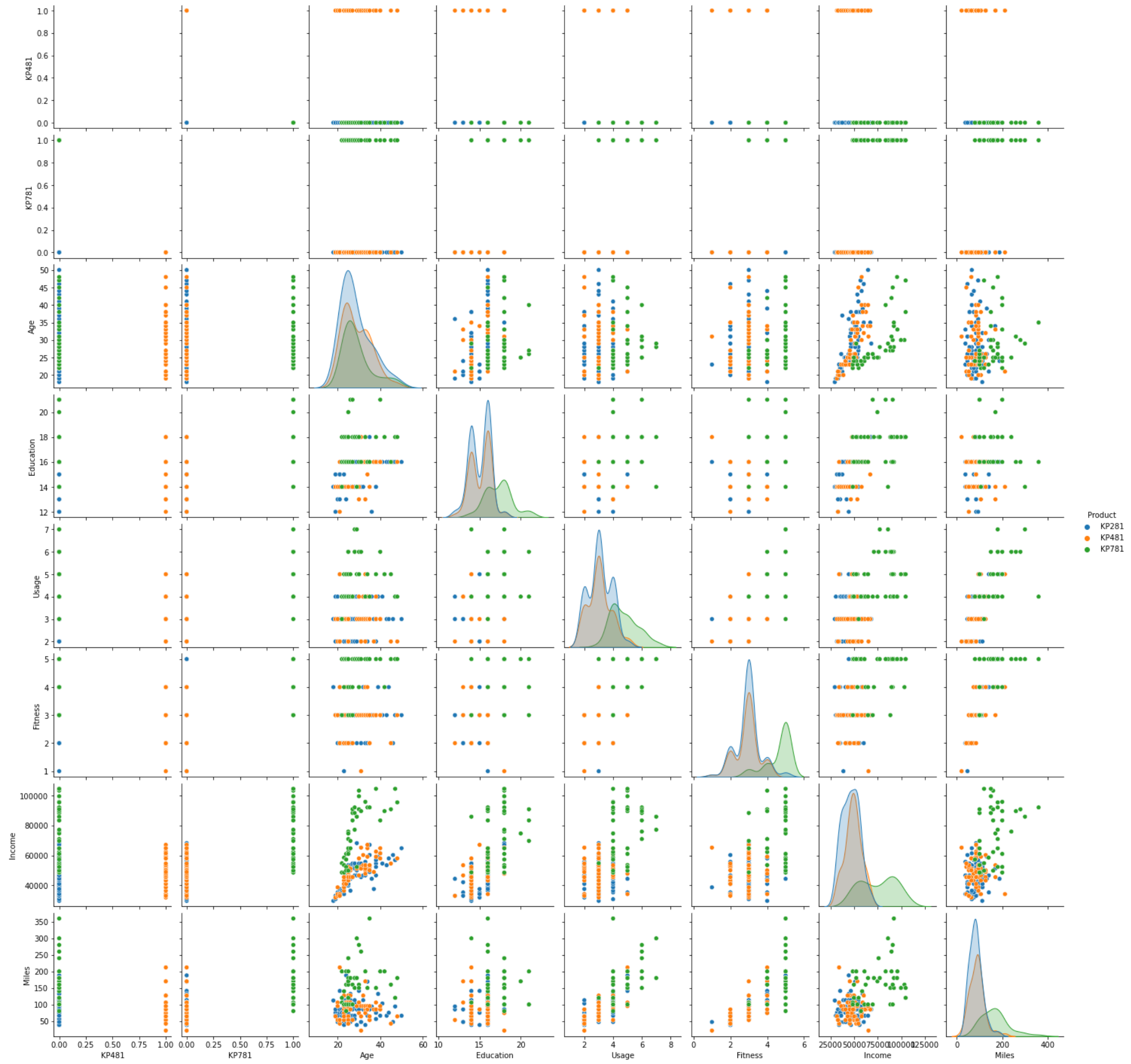

```
From above plot we can get some meaningful insights.
1) People with high usage runs for more miles
2) Plople with more education have more income thus they are likely to use KP781 Product
3) People who use KP781 are fit
4) As Age increases Income also Increases
5) People who runs more miles are fit
```

In [27]:

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

Out[27]:

<seaborn.axisgrid.PairGrid at 0x25dc9cf91c0>



In [28]:

```
df.loc[(df.Product == 'KP781') & (df.Age > 18) & (df.Age <= 33) ]['Usage'].value_counts()
```

Out[28]:

```
4    15
5     8
6     6
7     2
3     1
Name: Usage, dtype: int64
```

In [29]:

```
df.loc[(df.Product == 'KP781') & (df.Age > 18) & (df.Age <= 33) ]['Income_cut'].value_count
```

Out[29]:

```
50000     5
65000     5
95000     5
55000     4
90000     4
60000     2
75000     2
80000     2
70000     1
85000     1
100000    1
35000     0
40000     0
45000     0
Name: Income_cut, dtype: int64
```

In [30]:

```
kp781_df=df[df.Product == 'KP781']
```

In [31]:

```
kp781_df.head()
```

Out[31]:

	KP481	KP781	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income
140	0	1	KP781	22	Male	14	Single	4	3	48658
141	0	1	KP781	22	Male	16	Single	3	5	54781
142	0	1	KP781	22	Male	18	Single	4	5	48556
143	0	1	KP781	23	Male	16	Single	4	5	58516
144	0	1	KP781	23	Female	18	Single	5	4	53536

In [32]:

```
pd.crosstab(index=kp781_df.Income_cut,columns=[kp781_df.Age_cut,kp781_df.Usage],normalize=T
```

Out[32]:

Age_cut	18-22		22-27			27-32			32-37		37-42		
Usage	3	4	4	5	6	5	6	7	4	5	5	6	
Income_cut													
50000	0.000	0.05	0.050	0.025	0.000	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.0
55000	0.025	0.00	0.000	0.050	0.000	0.025	0.00	0.000	0.00	0.000	0.000	0.000	0.0
60000	0.000	0.00	0.050	0.000	0.000	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.0
65000	0.000	0.00	0.075	0.050	0.000	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.0
70000	0.000	0.00	0.025	0.000	0.000	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.0
75000	0.000	0.00	0.025	0.000	0.025	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.0
80000	0.000	0.00	0.000	0.000	0.025	0.000	0.00	0.025	0.00	0.000	0.000	0.000	0.0
85000	0.000	0.00	0.025	0.000	0.000	0.000	0.00	0.000	0.00	0.000	0.000	0.025	0.0
90000	0.000	0.00	0.025	0.000	0.000	0.000	0.05	0.025	0.00	0.000	0.025	0.000	0.0
95000	0.000	0.00	0.025	0.000	0.000	0.025	0.05	0.000	0.05	0.025	0.000	0.000	0.0
100000	0.000	0.00	0.000	0.000	0.000	0.025	0.00	0.000	0.00	0.000	0.025	0.000	0.0
All	0.025	0.05	0.300	0.125	0.050	0.075	0.10	0.050	0.05	0.025	0.050	0.025	0.0

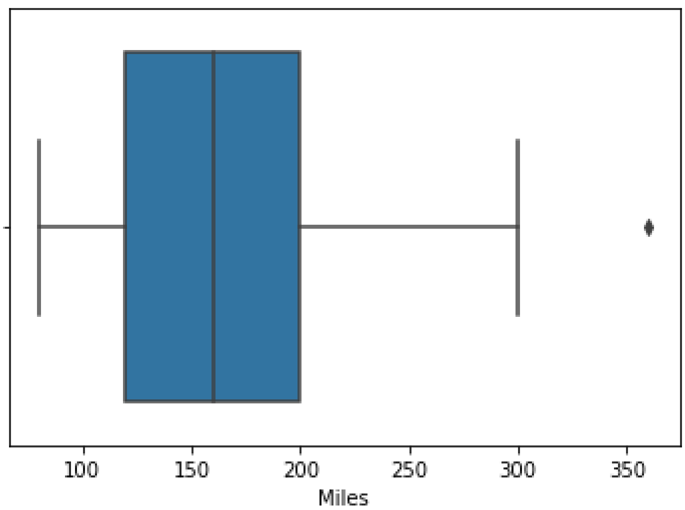
From above we can say that people whose age is in between 18 and 33 and their usage is greater than 4 usually and income greater than 50K and people with more age and higher income go for KP781

In [33]:

```
sns.boxplot(x=kp781_df.Miles)
```

Out[33]:

```
<AxesSubplot:xlabel='Miles'>
```



People who runs more miles uses KP781 Product

In [34]:

```
df.loc[(df.Product == 'KP481') ]['Fitness'].value_counts()
```

Out[34]:

```
3    39
2    12
4     8
1     1
Name: Fitness, dtype: int64
```

In [35]:

```
df.loc[(df.Product == 'KP481') ]['Usage'].value_counts()
```

Out[35]:

```
3    31
2    14
4    12
5     3
Name: Usage, dtype: int64
```

In [36]:

```
df.loc[(df.Product == 'KP481')]['Income_cut'].value_counts()
```

Out[36]:

```
55000     18
50000     15
35000      6
45000      6
60000      5
65000      5
40000      3
70000      2
75000      0
80000      0
85000      0
90000      0
95000      0
100000     0
Name: Income_cut, dtype: int64
```

In [37]:

```
kp481_df=df[df.Product == 'KP481']
```

In [38]:

```
kp481_df.head()
```

Out[38]:

	KP481	KP781	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income
80	1	0	KP481	19	Male	14	Single	3	3	31836
81	1	0	KP481	20	Male	14	Single	2	3	32973
82	1	0	KP481	20	Female	14	Partnered	3	3	34110
83	1	0	KP481	20	Male	14	Single	3	3	38658
84	1	0	KP481	21	Female	14	Partnered	5	4	34110

In [39]:

```
pd.crosstab(index=kp481_df.Usage,columns=[kp481_df.Fitness,kp481_df.Income_cut],normalize=T
```

Out[39]:

Fitness	**1**	**2**							
Income_cut	**70000**	**35000**	**45000**	**50000**	**55000**	**35000**	**40000**	**45000**	**5000**
Usage									
2	0.016667	0.033333	0.00	0.016667	0.033333	0.016667	0.00	0.016667	0.03333
3	0.000000	0.000000	0.05	0.000000	0.050000	0.033333	0.05	0.000000	0.0500C
4	0.000000	0.000000	0.00	0.016667	0.000000	0.000000	0.00	0.000000	0.08333
5	0.000000	0.000000	0.00	0.000000	0.000000	0.000000	0.00	0.000000	0.01666
All	0.016667	0.033333	0.05	0.033333	0.083333	0.050000	0.05	0.016667	0.18333

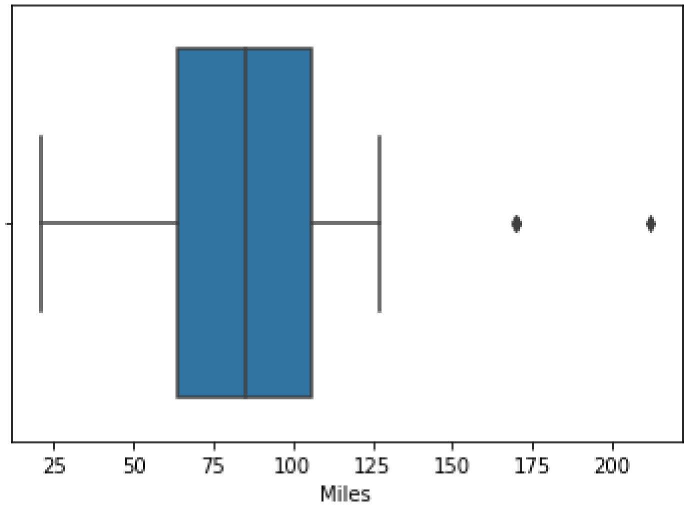
From above we can say that people with people with weekly usage of 3 days and income between 35K to 50K prefer KP481

In [40]:

```
sns.boxplot(x=kp481_df.Miles)
```

Out[40]:

```
<AxesSubplot:xlabel='Miles'>
```



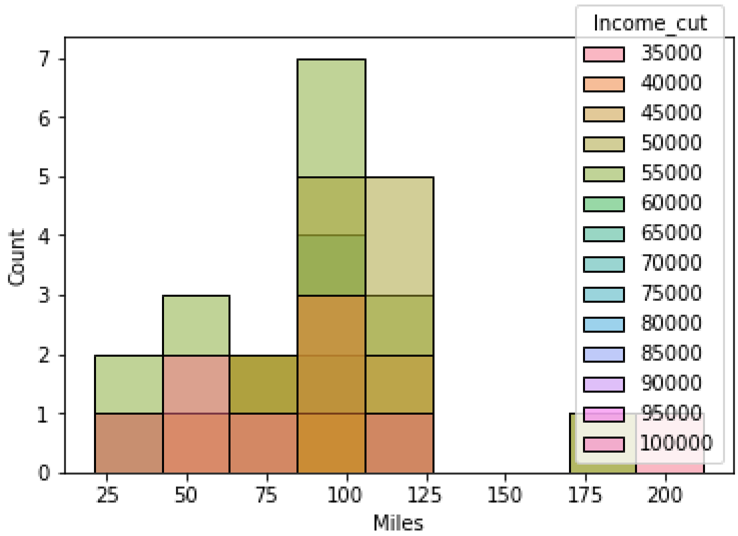
Miles for the users who use KP281 and KP481 almost identical, lets compare with Income of the users

In [41]:

```
sns.histplot(x=kp481_df.Miles,hue=kp481_df.Income_cut)
```

Out[41]:

```
<AxesSubplot:xlabel='Miles', ylabel='Count'>
```



People who use KP481 have more income than users who use KP281

In [42]:

```
kp281_df=df[df.Product == 'KP281']
```

In [43]:

```
kp281_df.head()
```

Out[43]:

	KP481	KP781	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	M
0	0	0	KP281	18	Male	14	Single	3	4	29562	
1	0	0	KP281	19	Male	15	Single	2	3	31836	
2	0	0	KP281	19	Female	14	Partnered	4	3	30699	
3	0	0	KP281	19	Male	12	Single	3	3	32973	
4	0	0	KP281	20	Male	13	Partnered	4	2	35247	

In [44]:

```
pd.crosstab(index=kp281_df.Age_cut,columns=[kp281_df.Income_cut,kp281_df.Usage],normalize=T
```

Out[44]:

Income_cut	35000			40000				45000			...	5(
Usage	2	3	4	2	3	4	5	2	3	4	...	
Age_cut												
18-22	0.0125	0.05	0.0125	0.0125	0.0500	0.0250	0.0125	0.0000	0.0000	0.0000	...	0.(
22-27	0.0250	0.00	0.0000	0.0000	0.0375	0.0375	0.0000	0.0125	0.0625	0.0375	...	0.(
27-32	0.0000	0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.(
32-37	0.0000	0.00	0.0000	0.0000	0.0125	0.0000	0.0000	0.0000	0.0000	0.0125	...	0.(
37-42	0.0000	0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.(
42-47	0.0000	0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.(
47-50	0.0000	0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.(
All	0.0375	0.05	0.0125	0.0125	0.1000	0.0625	0.0125	0.0125	0.0625	0.0500	...	0.(

8 rows × 23 columns

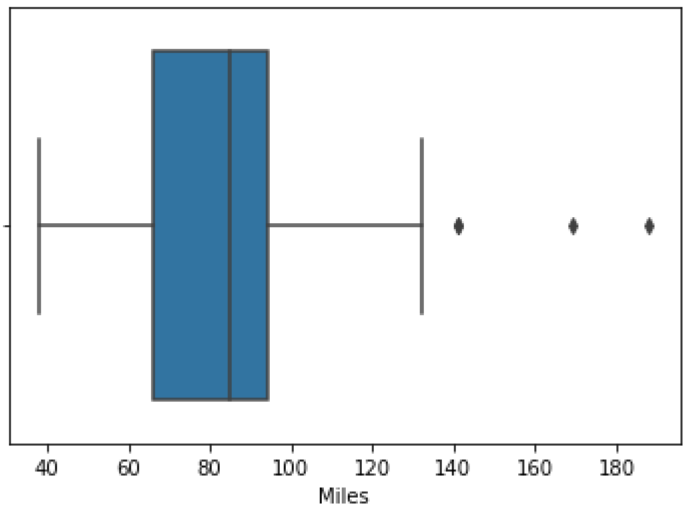
People with less income and with less usage and people with more income and less usage usually go for KP281 Product

In [45]:

```
sns.boxplot(x=kp281_df.Miles)
```

Out[45]:

```
<AxesSubplot:xlabel='Miles'>
```



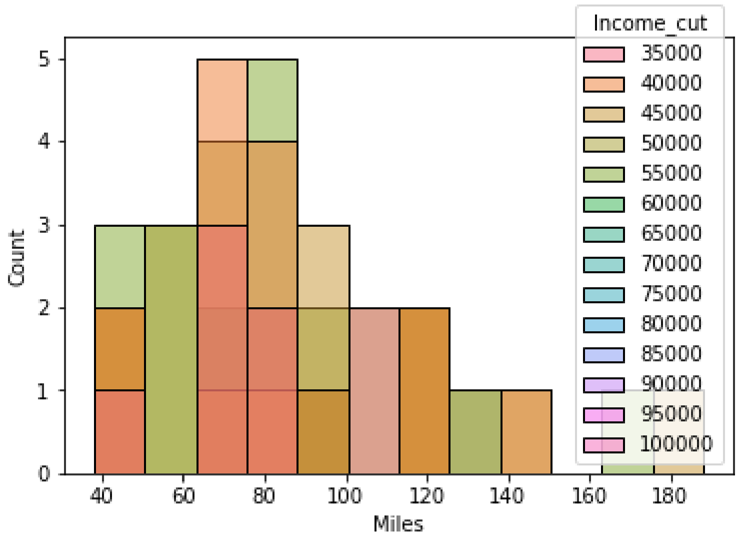
People who use KP281 runs less than 130 miles

In [46]:

```
sns.histplot(x=kp281_df.Miles,hue=kp281_df.Income_cut)
```

Out[46]:

```
<AxesSubplot:xlabel='Miles', ylabel='Count'>
```



People who use KP281 have less income compared to people who use KP481 Product

```
INSIGHTS:
People whose age is in between 18 and 33 and their usage is greater than 4 or more and
income greater than 50K and people with more age and usually higher income people go for
KP781.

People with weekly usage of 3 days and income between 35K to 50K prefer KP481.

People with less income and with less usage and people with more income and less usage
usually go for KP281 Product.
People who use KP281 have less income compared to people who use KP481 Product remaining
features are almost same for KP281 and KP281 Users
```

In [ ]: