Business Case Study: Aerofit

Loading data and required modules for analysis

web-link

In [ ]:
```
FILENAME = 'Aerofit_treadmill.csv'
AEROFIT_WEBLINK = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.csv?1639992749"
```

Load required Libraries

In [ ]:
```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme()
```

Load data file

In [ ]:
```
df = pd.read_csv(AEROFIT_WEBLINK)
```

Problem Statement and basic metrics

In [ ]:
```
1. For each product, create customer profile
    a. Highlight: Differences across products with respective to customer characteristics
2. For each product, Two-way contingency tables, compute all marginal probabilities and insights on business
    a. contingency tables
    b. All conditional and marginal probabilities
    c. comments
```

Basic Metrics

Shape of data

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

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

In [ ]:
```
# observation:
we have 180 records of data and 9 columns (features)
```

data types

In [ ]:
```
# data types of each of 9 columns
df.dtypes
```

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

In [ ]:
```
# store columns of different dtypes seperates for later use

numerical_variables             = ['Age', 'Education', 'Usage', 'Income', 'Miles']
categorical_variables           = ['Product', 'Gender', 'MaritalStatus', 'Fitness']

discrete_numerical_variables    = ['Education', 'Usage']
continuous_numerical_variables  = ['Age', 'Income', 'Miles']
```

Statistical summary

Numerical data

In [ ]:
```
# other analysis:
#
pd.DataFrame.from_dict(
    {
        'mean'  : df[numerical_variables].agg('mean'),
```

```
        'median': df[numerical_variables].agg('median'),
        'mode'  : df[numerical_variables].agg('mode').loc[0]
    },
    orient='index'
)
```

Out[ ]:

	Age	Education	Usage	Income	Miles
mean	28.788889	15.572222	3.455556	53719.577778	103.194444
median	26.000000	16.000000	3.000000	50596.500000	94.000000
mode	25.000000	16.000000	3.000000	45480.000000	85.000000

In [ ]:

```
# measure: mean, std dev, skewness, median
df[numerical_variables].describe()
```

Out[ ]:

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

In [ ]:

```
Key Points:
1.  Range for "Age" column is [18 yrs, 50 yrs] with average age as 29.8 years
2.  Range for "Education" is [12 yrs, 21 yrs] with average Education of 15.6 yrs
3.  Range for "Usage" column is [2, 7] (per week) with average usage as 3.4 yrs
5.  Range for "Income" column is [$29562, $104581] with average income as $53719.6
6.  Range for expected walking "Miles" column is [21, 360] miles with average 103 miles
```

Categorical data:

In [ ]:

```
# categories in each of categorical attributes:

data = {
    'categorical_variables': categorical_variables,
    'categories (comma seperated)':[', '.join(df[col].unique().astype('str')) for col in categorical_variables]
}
pd.DataFrame.from_dict(data).set_index('categorical_variables')
```

Out[ ]:

categorical_variables	categories (comma seperated)
Product	KP281, KP481, KP781
Gender	Male, Female
MaritalStatus	Single, Partnered
Fitness	4, 3, 2, 1, 5

Observation

In [ ]:

```
we have 180 records of data and 9 columns (features)
Understanding of features:

Product
        Type:  String, Ordinal Categorical
        Explanation:  As it contains 3 categories (KP281, KP481, or KP781) which can be ordered by price or features

Age
        Type:  integer, Discrete Numerical
        Explanation:  As it contains numbers but are not continous.
        (There aren't infinite 'age' values possible between say 24 and 25)

Gender
        Type:  String, Nominal Categorical
        Explanation:  As it contains 2 categories: Male, Female and cannot be ordered

Education
        Type:  integer, Discrete Numerical
        Explanation:  As it contains numbers (years) and not continous.

MaritalStatus
        Type:  String, Nominal Categorical
        Explanation:  As it contains 2 categories: Single,Partnered and cannot be ordered
```

```
Usage
        Type:  integer, Discrete Numerical
        Explanation:  As it contains discrete integers between 1 and 7

Fitness
        Type:  integer, Ordinal Categorical
        Explanation:  As it contains 1,2,3,4,5 as categories, and can be ordered.

Income
        Type:  integer, Continous Numerical
        Explanation:  As many numerical values are possible

Miles
        Type:  integer, Continous Numerical
        Explanation:  As many numerical values are possible
```

Value counts and unique attributes

In [ ]:
```
df['Product'].value_counts()
```

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

In [ ]:
```
df['Gender'].value_counts()
```

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

In [ ]:
```
df['MaritalStatus'].value_counts()
```

Out[ ]:
```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

In [ ]:
```
df['Fitness'].value_counts()
```

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

In [ ]:
```
# unique entries (number of categories) in each categorical attrib
df[categorical_variables].nunique()
```

Out[ ]:
```
Product          3
Gender           2
MaritalStatus    2
Fitness          5
dtype: int64
```

Observations

In [ ]:
```
1. For "Product"
    Most frequent value is "KP281", which implies this is the most bought threadmill product
    Followed by "KP481" and "KP781" respectively
2. There are more male(104) customer than female(73)
3. There are more partnered customers (107)
4. For "Fitness", "3" is the most observed category
5. There are 3 products in the data, 5 Fitness levels as expected
```

Missing Values and Outlier detection

In [ ]:
```
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
```

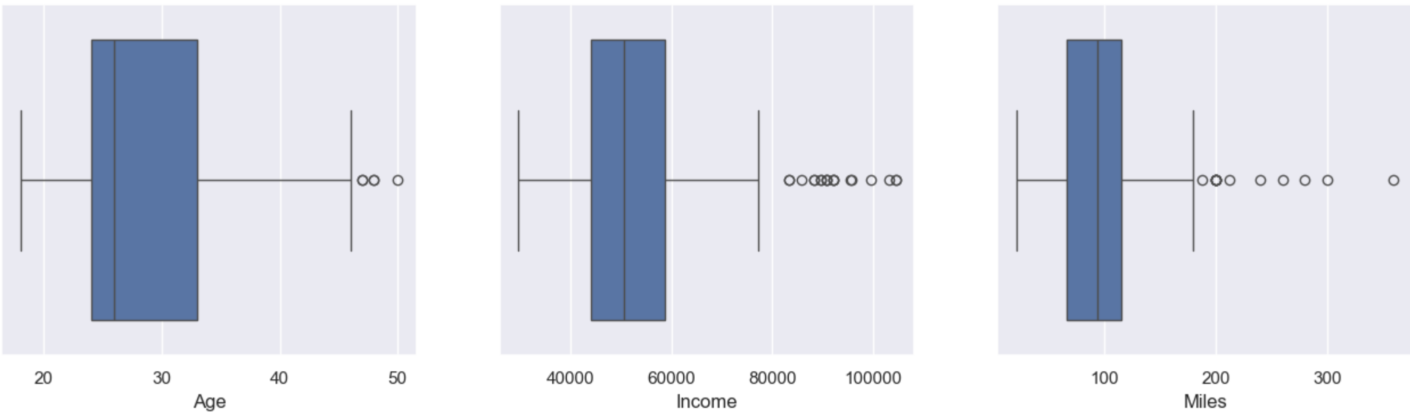
In [ ]:

```
Observation: There are no null values in all columns
```

In [ ]:

```
fig, axes = plt.subplots(1, len(continuous_numerical_variables), figsize=(16,4))

i = 0
for col in continuous_numerical_variables:
    sns.boxplot(data=df, x=col, ax=axes[i])
    i += 1
```



In [ ]:

```
df_out = df[continuous_numerical_variables].quantile([0.25, 0.75])         # get 25th and 75th quantile
df_out.loc['IQR'] = df_out.loc[0.75] - df_out.loc[0.25]                    # calculate inter quartile range

# minimum threshold for outliers: Q[25] - 1.5*IQR
df_out.loc['OUT_MIN'] = df_out.loc[0.25] - 1.5*df_out.loc['IQR']

# max threshold for outliers: Q[25] - 1.5*IQR
df_out.loc['OUT_MAX'] = df_out.loc[0.75] + 1.5*df_out.loc['IQR']

# count of outliers less than OUT_MIN
df_out.loc['count(values < OUT_MIN)'] = [(df[c] < df_out.loc['OUT_MIN', c]).sum() for c in df_out.columns]

# count of outliers greater than OUT_MIX
df_out.loc['count(values > OUT_MAX)'] = [(df[c] > df_out.loc['OUT_MAX', c]).sum() for c in df_out.columns]

# total number of vaues
df_out.loc['Total # of records'] = len(df)

# total count outliers
df_out.loc['Total # of outliers'] = df_out.loc['count(values < OUT_MIN)'] + df_out.loc['count(values > OUT_MAX)']

df_out.loc["% of outliers count"] = 100*df_out.loc['Total # of outliers']/len(df)

df_out
```

Out[ ]:

	Age	Income	Miles
0.25	24.000000	44058.750000	66.000000
0.75	33.000000	58668.000000	114.750000
IQR	9.000000	14609.250000	48.750000
OUT_MIN	10.500000	22144.875000	-7.125000
OUT_MAX	46.500000	80581.875000	187.875000
count(values < OUT_MIN)	0.000000	0.000000	0.000000
count(values > OUT_MAX)	5.000000	19.000000	13.000000
Total # of records	180.000000	180.000000	180.000000
Total # of outliers	5.000000	19.000000	13.000000
% of outliers count	2.777778	10.555556	7.222222

Observations

In [ ]:
```
1. For all attributes, there are no missing values
2. For Age, there are very less outliers (2.78%),
   For Income, Miles there are more outliers (10.55% and 7.22% respectively)
   NOTE: Please refer table in last cell > row "Total # of outliers" to know number of outliers
```

Visual Analysis

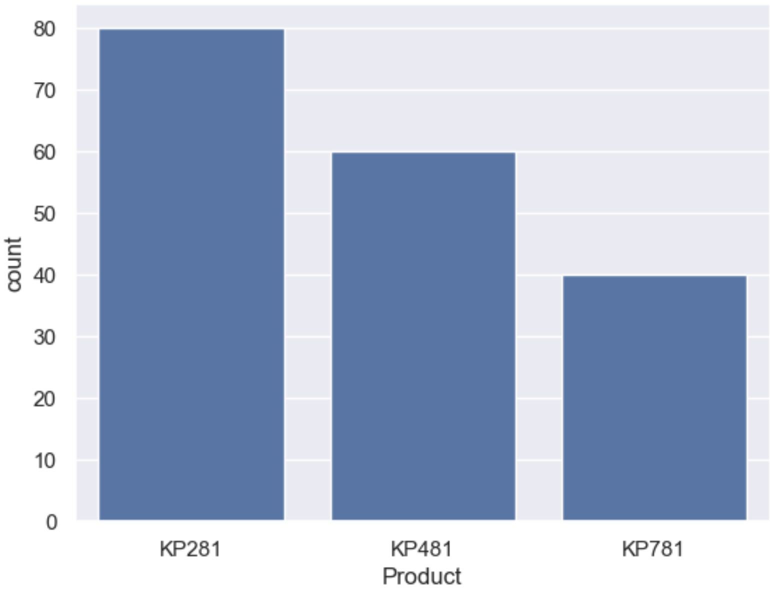
Univariate Analysis

Countplots

Product type

In [ ]:
```
sns.countplot(data=df, x='Product')
```

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



In [ ]:
```
df_product_count = df.groupby('Product')[['Product']].count()
df_product_count.index.name = 'Product Type'
df_product_count.rename({'Product': 'Count'}, axis=1, inplace=True)
df_product_count['Price'] = [1500, 1750, 2500]
df_product_count['% of total units sold'] = df_product_count['Count']*100/180
df_product_count['Sales($)'] = df_product_count['Count']*df_product_count['Price']

df_product_count
```

Out[ ]:

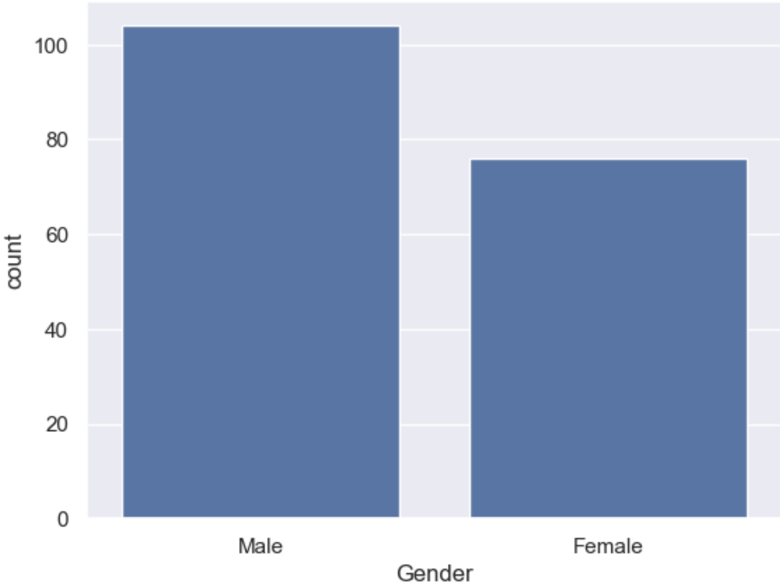
Product Type	Count	Price	% of total units sold	Sales($)
KP281	80	1500	44.444444	120000
KP481	60	1750	33.333333	105000
KP781	40	2500	22.222222	100000

In [ ]:
```
Comments:
1. KP281 is the most selling product (44.4% of total units sold)
2. Sales from all units almost same
```

Gender

In [ ]:
```
sns.countplot(data=df, x='Gender')
```

Out[ ]: <Axes: xlabel='Gender', ylabel='count'>



In [ ]:
```
df_gender_count = df.groupby('Gender')[['Gender']].count()
df_gender_count.index.name = 'gender'
df_gender_count.rename({'Gender': 'Count'}, inplace=True, axis=1)
df_gender_count['%'] = df_gender_count['Count']*100/180

df_gender_count
```

Out[ ]:

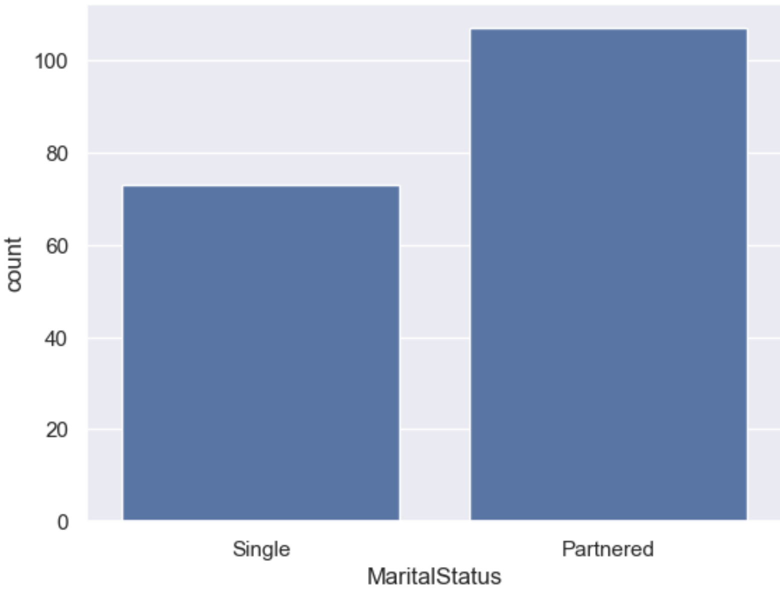
	Count	%
gender		
Female	76	42.222222
Male	104	57.777778

In [ ]:
```
Comments:
1. There are slightly more male customers (57.8%) compared to female customers (42.2%)
```

Marital Status

In [ ]:
```
sns.countplot(data=df, x='MaritalStatus')
```

Out[ ]: <Axes: xlabel='MaritalStatus', ylabel='count'>



In [ ]:
```
df_ms_count = df.groupby('MaritalStatus')[['MaritalStatus']].count()
df_ms_count.index.name = 'MaritalStatus '
df_ms_count.rename({'MaritalStatus': 'Count'}, inplace=True, axis=1)
df_ms_count['%'] = df_ms_count['Count']*100/180

df_ms_count
```

Out[ ]:

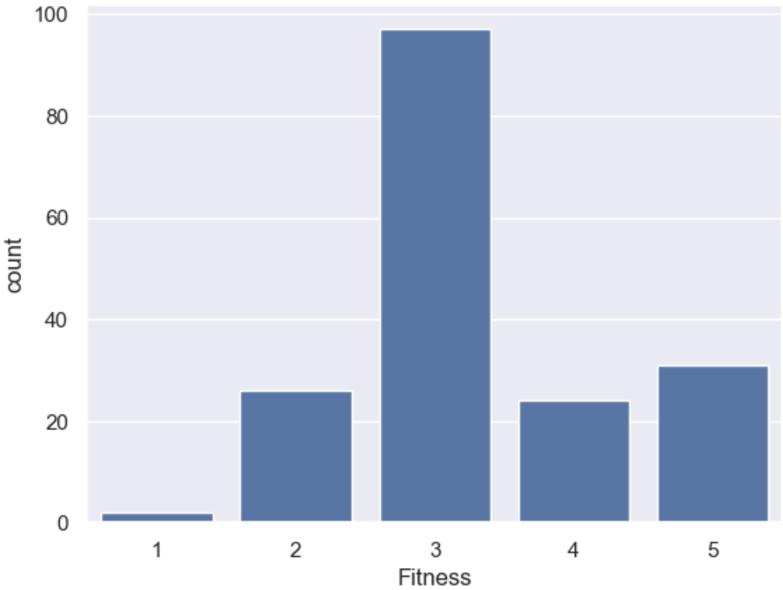
MaritalStatus	Count	%
Partnered	107	59.444444
Single	73	40.555556

In [ ]:
```
Comment:
Among the customers, more of them are partnered(~60%), about (~40%) of them are single.
```

Fitness Rating

In [ ]:
```
sns.countplot(data=df, x='Fitness')
```

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



In [ ]:
```
df_f_count = df.groupby('Fitness')[['Fitness']].count()
df_f_count.index.name = 'Fitness '
df_f_count.rename({'Fitness': 'Count'}, inplace=True, axis=1)
df_f_count['%'] = df_f_count['Count']*100/180

df_f_count
```

Out[ ]:

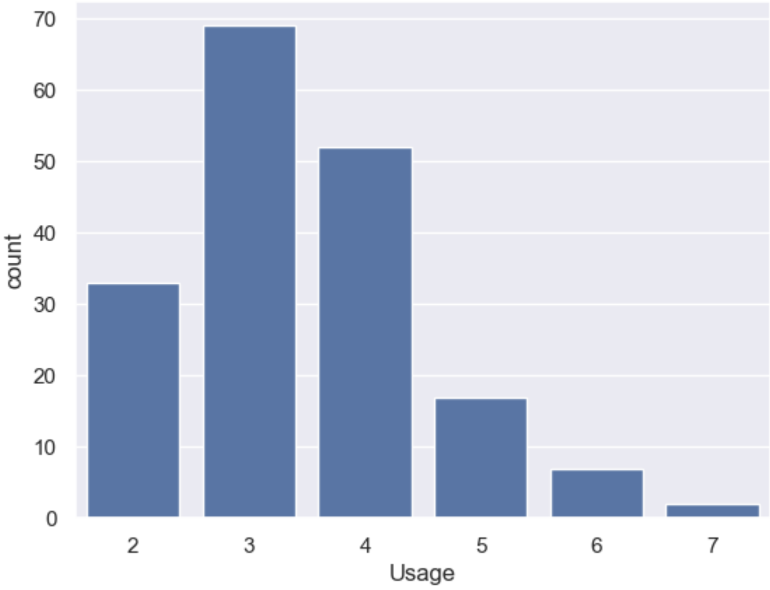
Fitness	Count	%
1	2	1.111111
2	26	14.444444
3	97	53.888889
4	24	13.333333
5	31	17.222222

In [ ]:
```
Comments:
Most the customers (~ 54%) rate themselves in as 3 in terms of fitness.
```

Usage

In [ ]:
```
sns.countplot(data=df, x='Usage')
```

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



In [ ]:
```
df_u_count = df.groupby('Usage')[['Usage']].count()
df_u_count.index.name = 'Usage '
df_u_count.rename({'Usage': 'Count'}, inplace=True, axis=1)
df_u_count['%'] = df_u_count['Count']*100/180

df_u_count
```

Out[ ]:

Usage	Count	%
2	33	18.333333
3	69	38.333333
4	52	28.888889
5	17	9.444444
6	7	3.888889
7	2	1.111111

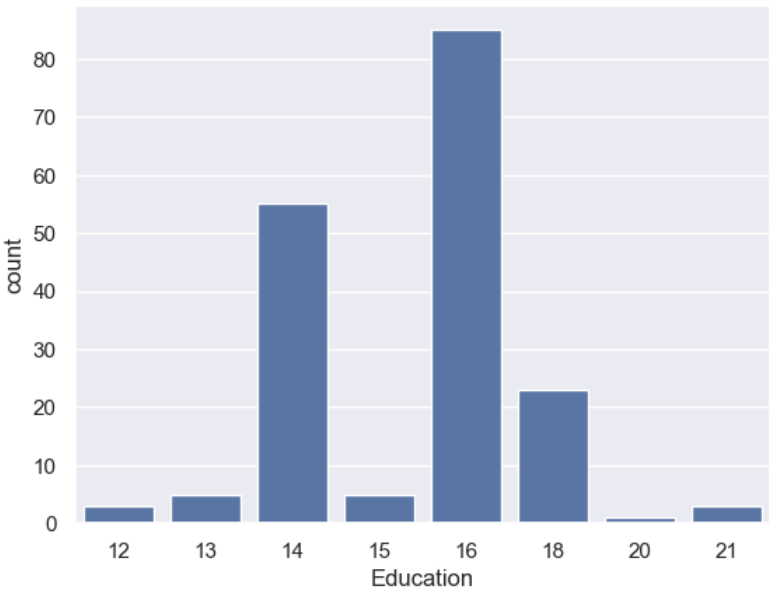
In [ ]:
```
Comments:
1. Around 67% of customers plan to use threadmill 3-4 times a week.
    Where as
        only 18% customers plan to use threadmill less than 3 times a week and
        only 14% customers plan to use threadmill more than 4 times a week.
```

Histograms

Education

In [ ]:
```
sns.countplot(data=df, x='Education')
```

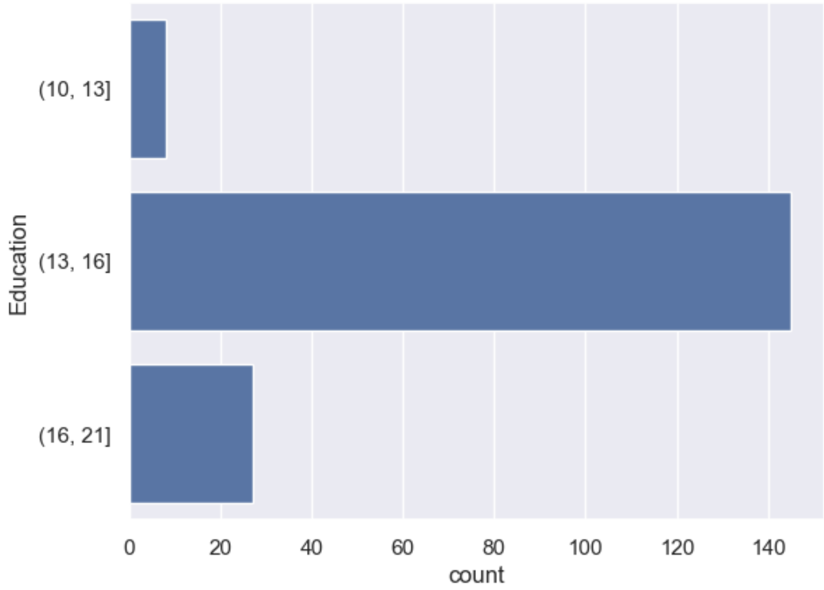
Out[ ]: <Axes: xlabel='Education', ylabel='count'>



In [ ]:
```python
# binning helps us with some inights:

sns.countplot(pd.cut(df['Education'], [10, 13, 16, 21]))
```

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



In [ ]:
```python
def bins_agg(col, lims):
    buckets = pd.cut(df[col], lims)
    df1 = pd.DataFrame({col: buckets, 'count': df[col]})
    df1 = df1.groupby(col)[['count']].count()
    df1['%'] = df1['count']*100/180
    return df1

bins_agg('Education', [10, 13, 16, 21])
```

```
C:\Users\Ravikumar.Gorre\AppData\Local\Temp\ipykernel_16188\1948980971.py:4: FutureWarning: The default of observed=False is deprecated and wi
ll be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future defau
lt and silence this warning.
  df1 = df1.groupby(col)[['count']].count()
```

Out[ ]:

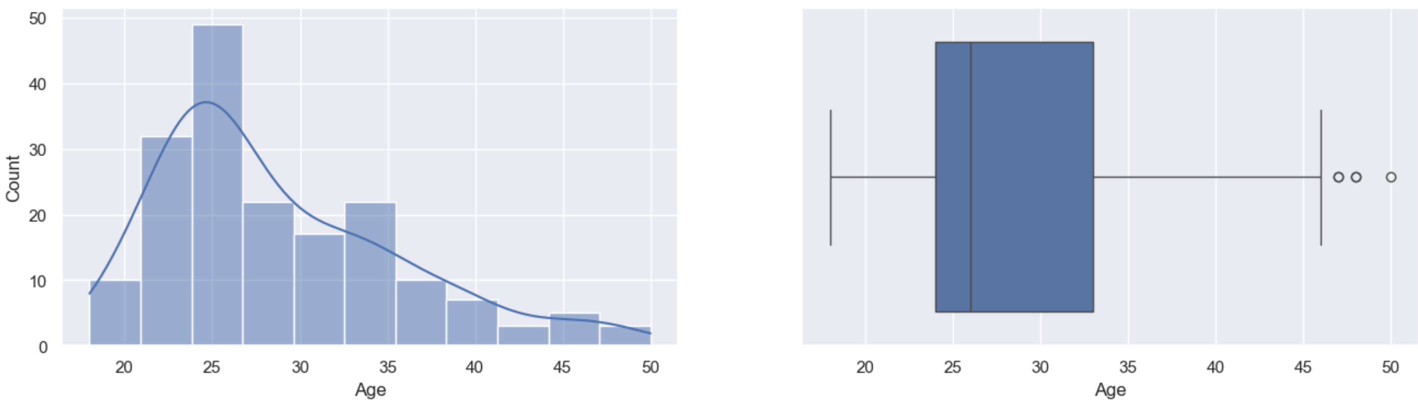
	count	%
Education		
(10, 13]	8	4.444444
(13, 16]	145	80.555556
(16, 21]	27	15.000000

In [ ]:
```
1. Most the customers have 14-to-16 years of education (80.5%)
```

Distplots

Age

In [ ]:
```python
def distnbox(col):
    fig, axes = plt.subplots(1, 2, figsize=(16,4))
    sns.histplot(data=df, x=col, ax=axes[0], kde=True)
    sns.boxplot(data=df, x=col, ax=axes[1])
distnbox('Age')
```



In [ ]:
```python
bins_agg('Age', [10, 20, 30, 40, 50])
```

```
C:\Users\Ravikumar.Gorre\AppData\Local\Temp\ipykernel_16188\1948980971.py:4: FutureWarning: The default of observed=False is deprecated and wi
ll be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future defau
lt and silence this warning.
  df1 = df1.groupby(col)[['count']].count()
```

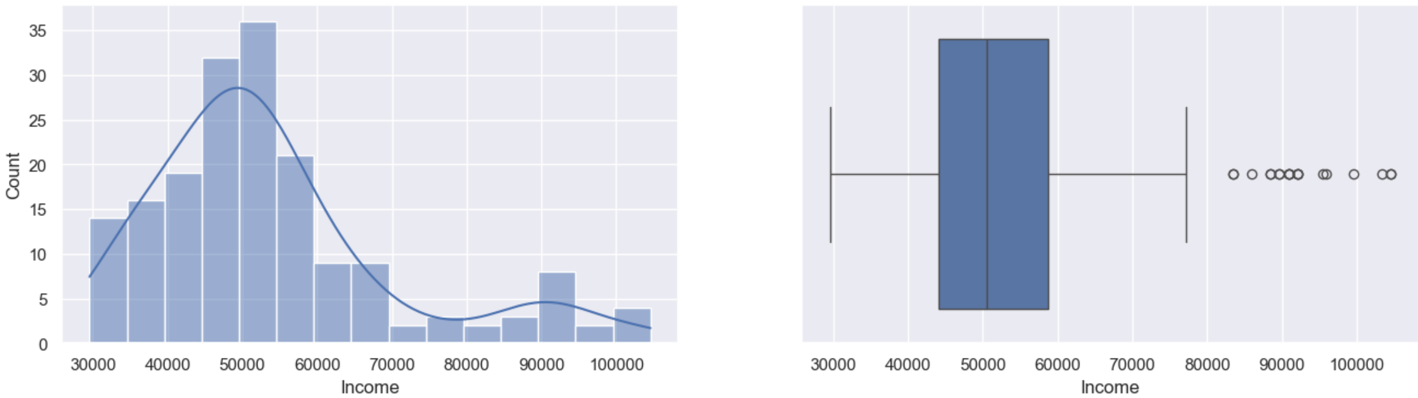
Out[ ]:

Age	count	%
(10, 20]	10	5.555556
(20, 30]	110	61.111111
(30, 40]	48	26.666667
(40, 50]	12	6.666667

In [ ]:
```
Comments:
1. Over 60% of custoemr fall in the age range 21-30 yrs
amd 27% fall in age range 30-40 yrs
```

Income

In [ ]:
```
distnbox('Income')
```



In [ ]:
```
bins_agg('Income', [df['Income'].min(), 40000, 60000, df['Income'].max()])
```

```
C:\Users\Ravikumar.Gorre\AppData\Local\Temp\ipykernel_16188\1948980971.py:4: FutureWarning: The default of observed=False is deprecated and wi
ll be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future defau
lt and silence this warning.
  df1 = df1.groupby(col)[['count']].count()
```

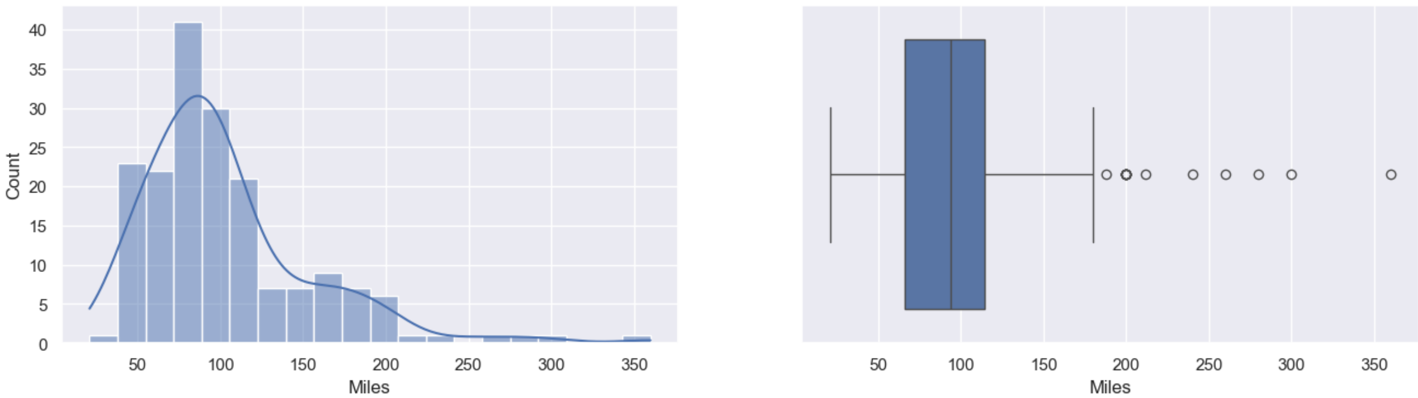
Out[ ]:

Income	count	%
(29562, 40000]	31	17.222222
(40000, 60000]	106	58.888889
(60000, 104581]	42	23.333333

In [ ]:
```
Comments:
1. 58% of of customers have income around $40000 to $60000
Only 17% are below this range and 23% are above $60000
```

Miles

In [ ]:
```
distnbox('Miles')
```



In [ ]:
```
bins_agg('Miles', [df['Miles'].min(), 100, 200, 300, df['Miles'].max()])
```

```
C:\Users\Ravikumar.Gorre\AppData\Local\Temp\ipykernel_16188\1948980971.py:4: FutureWarning: The default of observed=False is deprecated and wi
ll be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future defau
lt and silence this warning.
  df1 = df1.groupby(col)[['count']].count()
```

Out[ ]:

Miles	count	%
(21, 100]	113	62.777778
(100, 200]	60	33.333333
(200, 300]	5	2.777778
(300, 360]	1	0.555556

In [ ]:

```
Comments:
1. Around 96$ customers plan to walk/run less than 200 miles
2. Around 63% customers plan to walk/run less than 100 miles
3. Vert less customers (~4%) plan to walk/run more than 200 miles (High activity)
```

Correlation plots

In [ ]:

```
sns.heatmap(df[numerical_variables].corr())
```

Out[ ]: <Axes: >

In [ ]:

```
u = df['Gender'].unique().tolist()
```

In [ ]:

```
df_num = df.copy()
for c in categorical_variables:
    u = df[c].unique().tolist()
    df_num[c] = df[c].apply(lambda x:u.index(x))
df_num.head()
```

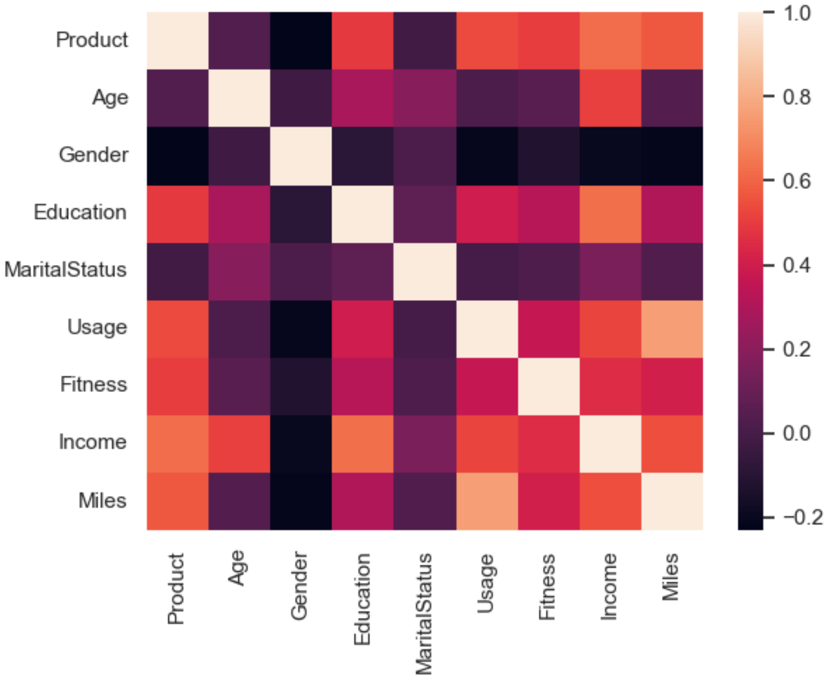
Out[ ]:

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

In [ ]:

```
sns.heatmap(df_num.corr())
```

Out[ ]: <Axes: >

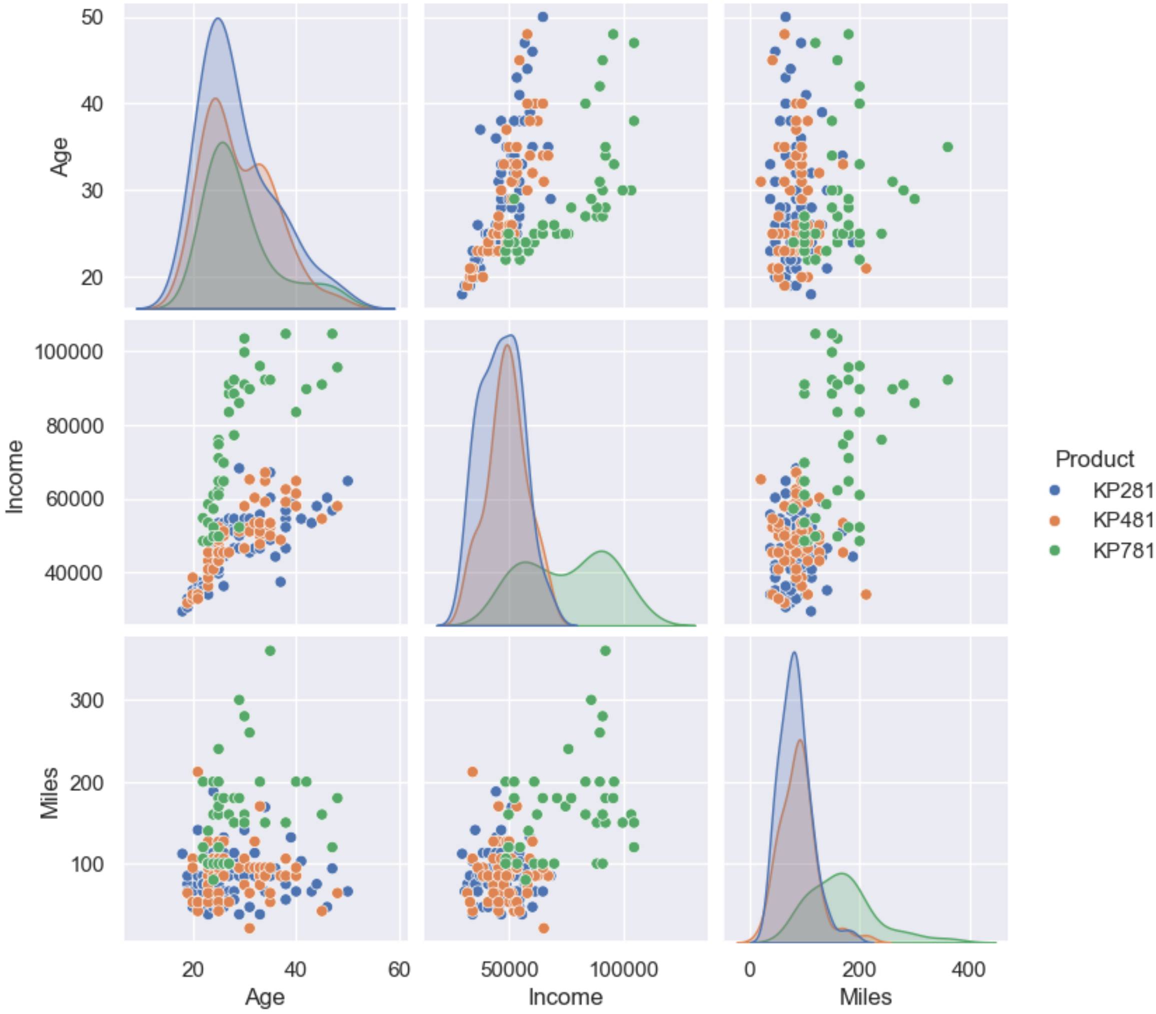


In [ ]:
```
# pair plot for continous numerical variables
sns.pairplot(df, hue='Product')
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x2290df2dc10>

In [ ]:
```python
# pair plot for continous numerical variables
sns.pairplot(df[continuous_numerical_variables+['Product']], hue='Product')
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x2291267e030>



In [ ]:
```python
df.columns
```

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

Summary/Obeservations

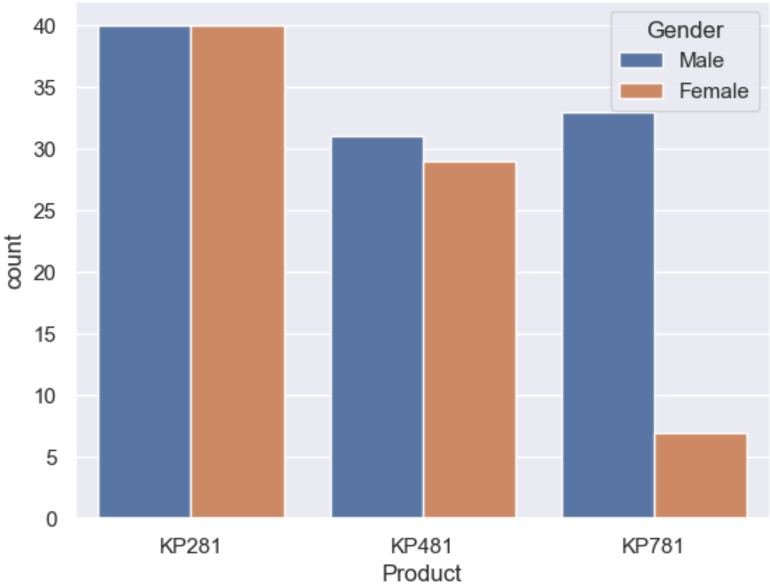
In [ ]:
```
1. Income has correlation with Age and Miles, weak correlation with education
2. Usage has correlation with miles
```

Bivariate Analysis

Product vs Gender

In [ ]:
```python
sns.countplot(df, hue='Gender', x='Product')
```

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

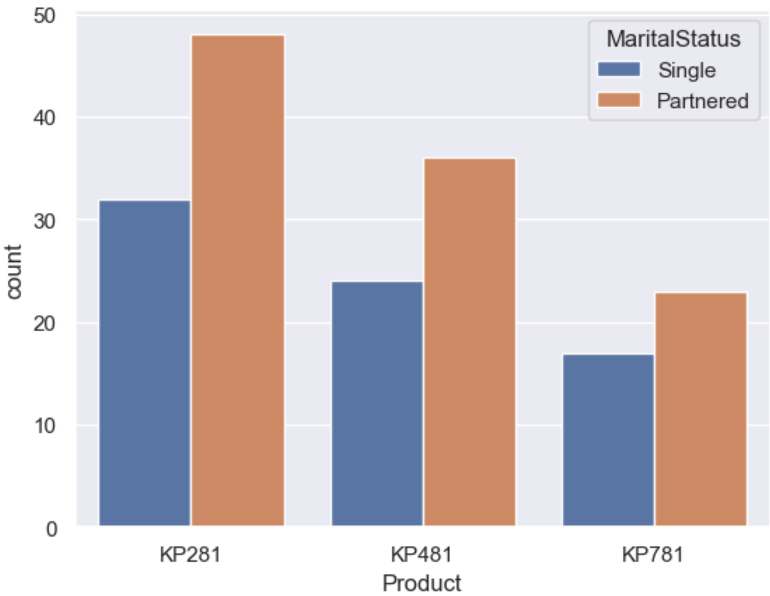


In [ ]:
```
Product "KP781" is bought by Male customers more than Female customers
Product "KP481" and "KP281" is bought by both Male and Female customers
```

Product vs Marital Status

In [ ]:
```
# checking effect of variables on Product purchased:
sns.countplot(df, x='Product', hue='MaritalStatus')
```

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

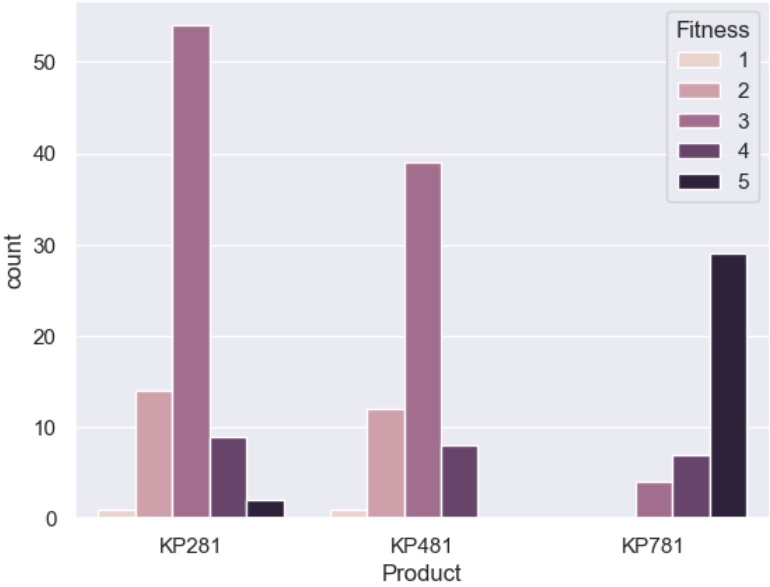


In [ ]:
```
For All 3 products,
Customers are observed to be partnered rather than single
```

Product vs Fitness

In [ ]:
```
sns.countplot(df, x='Product', hue='Fitness')
```

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

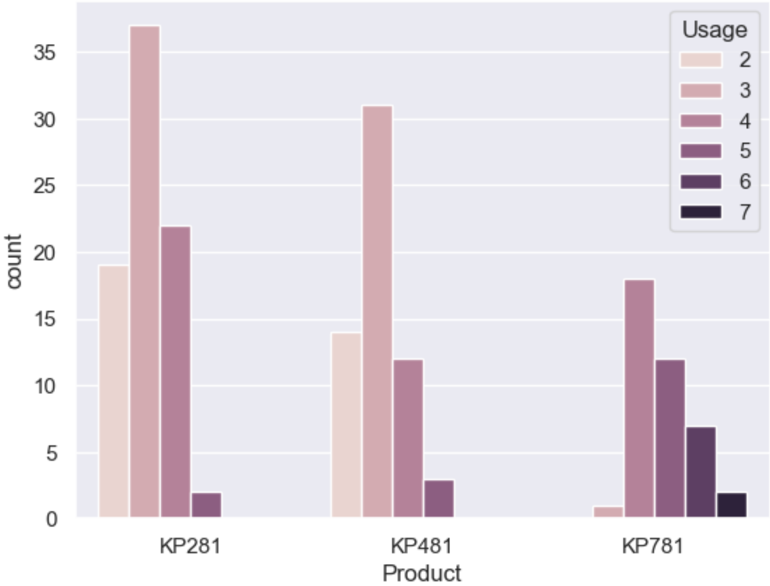


In [ ]:
```
KP281, KP481 are bought by customer who are moderately fit.
Where as KP781 is bought by customer who are very fit.
```

Product vs Usage level

In [ ]:
```
sns.countplot(df, x='Product', hue='Usage')
```

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

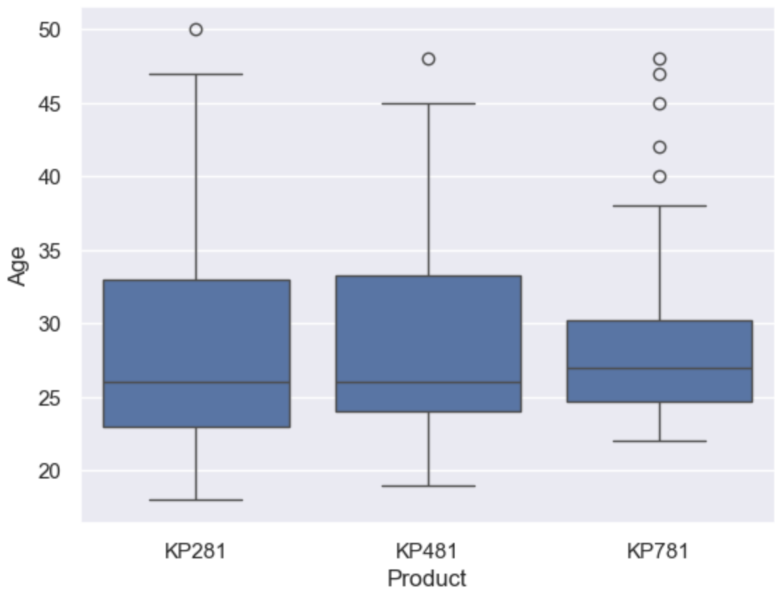


In [ ]:
```
For customers with moderate or low usage, prefer KP481 and KP281
But customer with high usage prefer KP481
```

Product vs Age

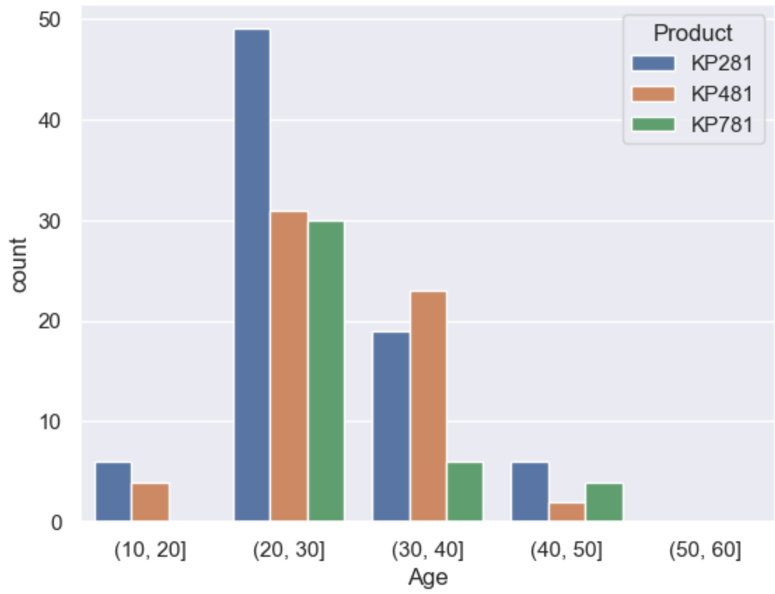
In [ ]:
```
sns.boxplot(df, y='Age', x='Product')
```

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



In [ ]:
```
sns.countplot(x=pd.cut(df['Age'], [10,20,30,40,50,60]), hue=df['Product'])
```

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

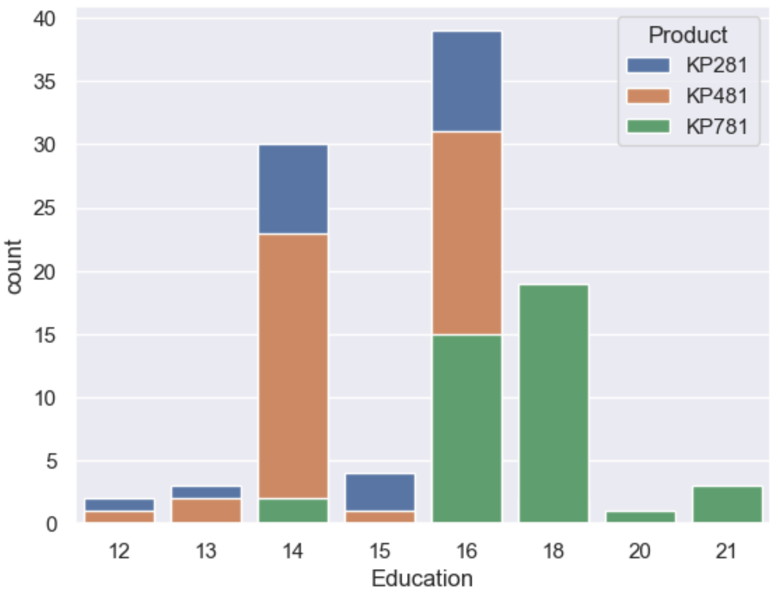


In [ ]:
```
Comments:
1. Almost all products attract age groups 25-30
2. customers in the age range 20-30 has bought KP281 more than others
```

Product vs Education

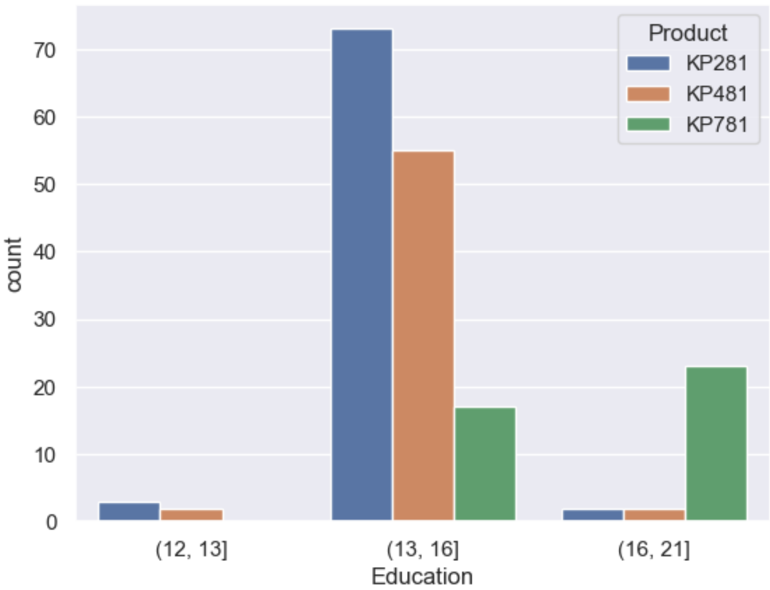
In [ ]:
```
sns.countplot(df, x='Education', dodge=False, hue='Product')
```

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



In [ ]:
```
sns.countplot(x=pd.cut(df['Education'], [df['Education'].min(), 13, 16, df['Education'].max()]), hue=df['Product'])
```

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

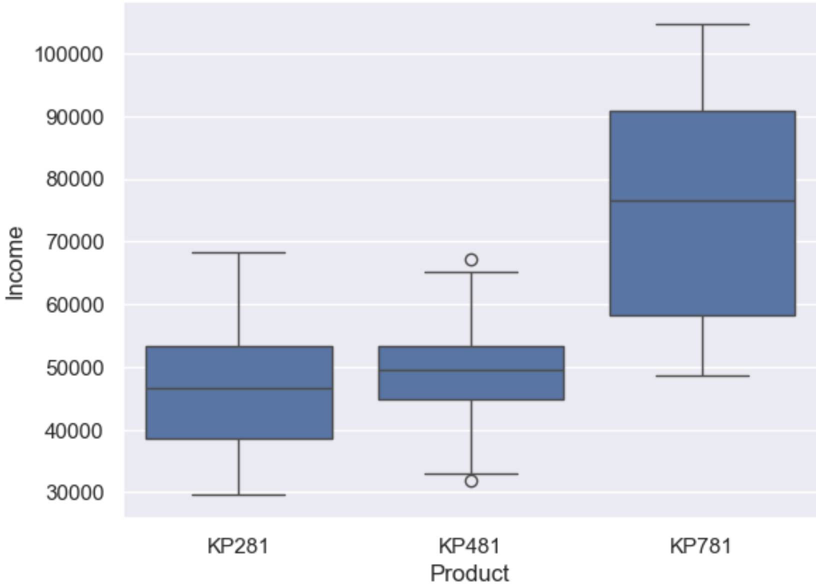


In [ ]:
```
KP481, KP281 is bought by customers with 14-16 yrs of Education
KP781 is mostly bought by customers with 16-21 yrs
```

Product vs Income

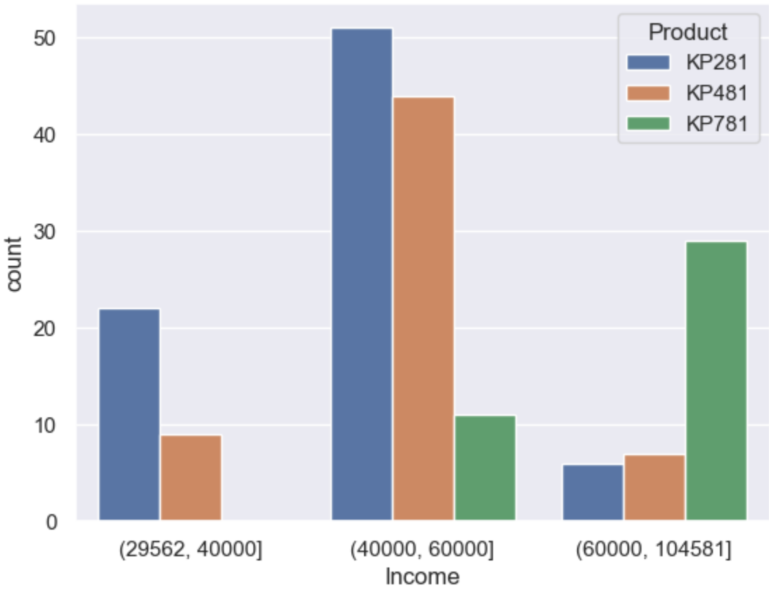
In [ ]:
```
sns.boxplot(df, y='Income', x='Product')
```

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



In [ ]:
```
sns.countplot(x=pd.cut(df['Income'], [df['Income'].min(), 40000, 60000, df['Income'].max()]), hue=df['Product'])
```

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

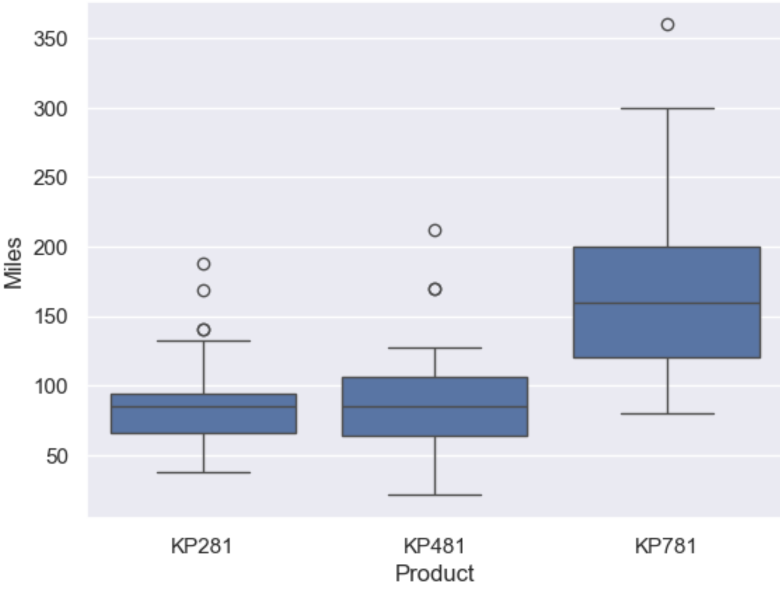


In [ ]:
```
KP781 is bought mostly by customers with high income
KP481, KP281 are bought mostly by customers with Moderate/Low income
```

Product vs Miles

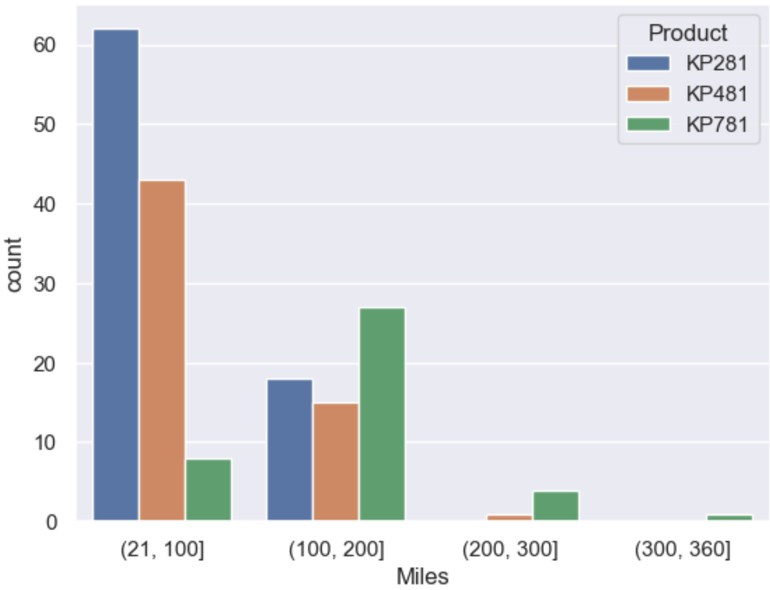
In [ ]:
```
sns.boxplot(df, y='Miles', x='Product')
```

Out[ ]: <Axes: xlabel='Product', ylabel='Miles'>



In [ ]:
```
sns.countplot(x=pd.cut(df['Miles'], [df['Miles'].min(), 100, 200, 300, df['Miles'].max()]), hue=df['Product'])
```

Out[ ]: <Axes: xlabel='Miles', ylabel='count'>



In [ ]:
```
Comment:
KP781 is bought mostly by customers with high "Miles" (Expected Walking distance)
KP481, KP281 are bought mostly by customers with Moderate/Low "Miles" value
```

Observations

In [ ]:
```
Combined Summary for Bivariate Analasis against product type:

1. On the overall, Partnered customers buy more products.

2. Product "KP781" is bought by Male customers more than Female customers
Otherwise There is not much correlation between Product Type and Gender

3. KP281, KP481 are bought by customer who are moderately fit or less fit.
Where as KP781 is bought by customer who are very fit.

4. Customer who expect to have high usage (greater than 4 days a week) tend to buy KP781
Customer who expect to have low or moderate usage (less than 4 days a week) tend to buy KP781

5. Almost all products attract age groups 25-30

6. KP781 is bought mostly by customers with high income (Above 60k USD)
KP481, KP281 are bought mostly by customers with Moderate/Low income (Below 60k USD)

7. KP781 is bought mostly by customers with high "Miles" (Expected Walking distance)
KP481, KP281 are bought mostly by customers with Moderate/Low "Miles" value
```

Customer Profiles

KP281

In [ ]:
```
Example Customer Profile for "KP281":

Fitness          : 2-4 on scale of 5
Usage            : 2-4 times a week
Age              : 20-40
Education        : 13+ years
Income           : Low, Range: [30000 to 50000]
Miles            : 50-100

NOTE:
(Product "KP281" is bought by both Male and Female customers, so Age is omitted)
(Product "KP281" is bought by both Partnered and Single customers, so MaritalStatus is omitted)
```

KP481

In [ ]:
```
Example Customer Profile for "KP481":

Fitness          : 2-4 on scale of 5
Usage            : 2-4 times a week
Age              : 20-40
Education        : 14-16
Income           : Moderate, Range: [40000 to 60000]
Miles            : 50-100

(Although Product "KP481" is bought by both Male and Female customers, Gender: Male is taken as example)
(Although Product "KP481" is bought by both Partnered and Single customers, MaritalStatus: Partnered is taken as example)
```

KP781

In [ ]:
```
Example Customer Profile for "KP781":

Gender           : Male
Fitness          : 4-5 on scale of 5 (Very fit)
Usage            : 4-6 (High Usage)
Age              : 20-30
Education        : 16-21 (High)
Income           : High, Range: [60000 to 90000]
Miles            : 100-200 (High)
```

Probability

Marginal Probabilities

In [ ]:
```
# total count of purchases by Product
df.groupby('Product')[['Product']].count()
```

Out[ ]:

	Product
Product	
KP281	80
KP481	60
KP781	40

In [ ]:
```
# divide this by total purchases (180) to get probabilities
df_MP = df.groupby('Product')[['Product']].count()/180

# string
df_MP[''] = 'Probability that the customer buys ' + df_MP.index + ' ='

# remove index, not useful
df_MP.reset_index(drop=True, inplace=True)

# present!
df_MP[['', 'Product']]
```

Out[ ]:

		Product
0	Probability that the customer buys KP281 =	0.444444
1	Probability that the customer buys KP481 =	0.333333
2	Probability that the customer buys KP781 =	0.222222

In [ ]:
```
Probability of customers buying lower end model KP281 is higher than that of other products
Probability of customers buying higher end model KP781 is lower than that of other products
```

Conditional Probabilities

In [ ]:
```
# pd.crosstab()
df_cross_PG = pd.crosstab(df['Product'], df['Gender'], margins=True)
```

```
df_cross_PG
```

Out[ ]:

Gender	Female	Male	All
Product			
KP281	40	40	80
KP481	29	31	60
KP781	7	33	40
All	76	104	180

In [ ]:
```
# Probability that a customer buys KP281 given that he is male:
df_cross_PG.loc['KP281', 'Male']/df_cross_PG.loc['All', 'Male']
```

Out[ ]: 0.38461538461538464

In [ ]:
```
# automating calculating conditional probabilities
def conditional_prob(bool1, bool2, df=df):
    col1, A = bool1.split('=')
    col2, B = bool2.split('=')
    df_cross = pd.crosstab(df[col1], df[col2], margins=True)
    return df_cross.loc[A, B]/df_cross.loc['All', B]
```

In [ ]:
```
# Probability that a customer buys KP281 given that he is male:
# testing if the above function works, As expected it should be 0.38 (As calculated 2 cells ago)
conditional_prob('Product=KP281', 'Gender=Male')
```

Out[ ]: 0.38461538461538464

In [ ]:
```
# cross product of 2 sets

def cross(arr1, arr2):
    result = []
    for i in range(len(arr1)):
        for j in range(len(arr2)):
            result.append((arr1[i], arr2[j]))
    return result

# get all possibilities
cross(df['Product'].unique(), df['Gender'].unique())
```

Out[ ]:
```
[('KP281', 'Male'),
 ('KP281', 'Female'),
 ('KP481', 'Male'),
 ('KP481', 'Female'),
 ('KP781', 'Male'),
 ('KP781', 'Female')]
```

In [ ]:
```
# give a dataframe, column-names var1, var2
# this function is for:
# calculate all probabilities P(A/B) for A in var1 and B in var2

def calculate_all_conditional_probabilities(var1, var2, df=df):
    var1_categories = np.sort(df[var1].unique())
    var2_categories = np.sort(df[var2].unique())
    groups = cross(var1_categories, var2_categories)
    data = []
    for A, B in groups:
        bool1 = var1 + '=' + A
        bool2 = var2 + '=' + B
        p_str = f'Customer buys {A} given {bool2}'
        p = conditional_prob(bool1, bool2, df)
        data.append(('Probability that:', p_str, p))
    return pd.DataFrame(data, columns=['', 'Condition', 'Probability'])
```

In [ ]:
```
pd.crosstab(df['Product'], df['Gender'], margins=True)
```

Out[ ]:

Gender	Female	Male	All
Product			
KP281	40	40	80
KP481	29	31	60
KP781	7	33	40
All	76	104	180

In [ ]:
```
calculate_all_conditional_probabilities('Product', 'Gender')
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Gender=Female	0.526316
1	Probability that:	Customer buys KP281 given Gender=Male	0.384615
2	Probability that:	Customer buys KP481 given Gender=Female	0.381579
3	Probability that:	Customer buys KP481 given Gender=Male	0.298077
4	Probability that:	Customer buys KP781 given Gender=Female	0.092105
5	Probability that:	Customer buys KP781 given Gender=Male	0.317308

In [ ]:

```
# Observations:
1. Female customers tend to buy KP281 more than KP781
```

In [ ]:

```
pd.crosstab(df['Product'], df['MaritalStatus'], margins=True)
```

Out[ ]:

MaritalStatus	Partnered	Single	All
Product			
KP281	48	32	80
KP481	36	24	60
KP781	23	17	40
All	107	73	180

In [ ]:

```
calculate_all_conditional_probabilities('Product', 'MaritalStatus')
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given MaritalStatus=Partnered	0.448598
1	Probability that:	Customer buys KP281 given MaritalStatus=Single	0.438356
2	Probability that:	Customer buys KP481 given MaritalStatus=Partnered	0.336449
3	Probability that:	Customer buys KP481 given MaritalStatus=Single	0.328767
4	Probability that:	Customer buys KP781 given MaritalStatus=Partnered	0.214953
5	Probability that:	Customer buys KP781 given MaritalStatus=Single	0.232877

In [ ]:

```
# Lets bucket age groups from the insights obtained from univariate and bivariate analysis

# create a copy of dataframe
df_bins = df.copy()
```

In [ ]:

```
# convert Fitness and Usage into strings so as to use the functions I defined
df_bins['Fitness'] = df['Fitness'].astype('string')
df_bins['Usage'] = df['Usage'].astype('string')
```

In [ ]:

```
pd.crosstab(df['Product'], df['Fitness'], margins=True)
```

Out[ ]:

Fitness	1	2	3	4	5	All
Product						
KP281	1	14	54	9	2	80
KP481	1	12	39	8	0	60
KP781	0	0	4	7	29	40
All	2	26	97	24	31	180

In [ ]:

```
calculate_all_conditional_probabilities('Product', 'Fitness', df_bins)
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Fitness=1	0.500000
1	Probability that:	Customer buys KP281 given Fitness=2	0.538462
2	Probability that:	Customer buys KP281 given Fitness=3	0.556701
3	Probability that:	Customer buys KP281 given Fitness=4	0.375000
4	Probability that:	Customer buys KP281 given Fitness=5	0.064516
5	Probability that:	Customer buys KP481 given Fitness=1	0.500000
6	Probability that:	Customer buys KP481 given Fitness=2	0.461538
7	Probability that:	Customer buys KP481 given Fitness=3	0.402062
8	Probability that:	Customer buys KP481 given Fitness=4	0.333333
9	Probability that:	Customer buys KP481 given Fitness=5	0.000000
10	Probability that:	Customer buys KP781 given Fitness=1	0.000000
11	Probability that:	Customer buys KP781 given Fitness=2	0.000000
12	Probability that:	Customer buys KP781 given Fitness=3	0.041237
13	Probability that:	Customer buys KP781 given Fitness=4	0.291667
14	Probability that:	Customer buys KP781 given Fitness=5	0.935484

In [ ]:
```
1. Customers with high fitness rating tend to buy KP781
2.
```

In [ ]:
```
calculate_all_conditional_probabilities('Product', 'Usage', df_bins)
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Usage=2	0.575758
1	Probability that:	Customer buys KP281 given Usage=3	0.536232
2	Probability that:	Customer buys KP281 given Usage=4	0.423077
3	Probability that:	Customer buys KP281 given Usage=5	0.117647
4	Probability that:	Customer buys KP281 given Usage=6	0.000000
5	Probability that:	Customer buys KP281 given Usage=7	0.000000
6	Probability that:	Customer buys KP481 given Usage=2	0.424242
7	Probability that:	Customer buys KP481 given Usage=3	0.449275
8	Probability that:	Customer buys KP481 given Usage=4	0.230769
9	Probability that:	Customer buys KP481 given Usage=5	0.176471
10	Probability that:	Customer buys KP481 given Usage=6	0.000000
11	Probability that:	Customer buys KP481 given Usage=7	0.000000
12	Probability that:	Customer buys KP781 given Usage=2	0.000000
13	Probability that:	Customer buys KP781 given Usage=3	0.014493
14	Probability that:	Customer buys KP781 given Usage=4	0.346154
15	Probability that:	Customer buys KP781 given Usage=5	0.705882
16	Probability that:	Customer buys KP781 given Usage=6	1.000000
17	Probability that:	Customer buys KP781 given Usage=7	1.000000

In [ ]:
```
# convertin age into buckets:
# Binning age into bins : 10-20, 20-30, 30-40, 40-50

age_bucket = lambda x: f'{np.int32(np.floor(x/10)*10)}-{np.int32(np.floor(x/10)*10+10)}'

df_bins['Age'] = df['Age'].apply(age_bucket)
# df_bins
```

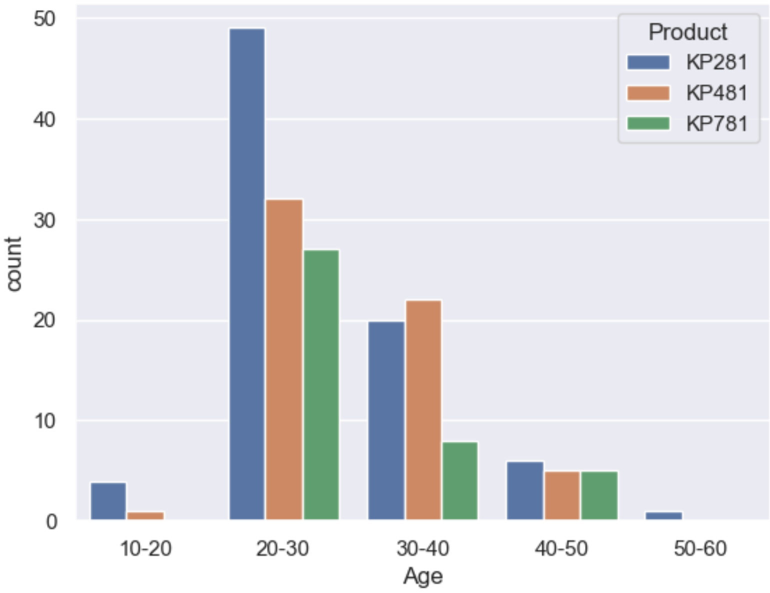
In [ ]:
```
calculate_all_conditional_probabilities('Product', 'Age', df_bins)
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Age=10-20	0.800000
1	Probability that:	Customer buys KP281 given Age=20-30	0.453704
2	Probability that:	Customer buys KP281 given Age=30-40	0.400000
3	Probability that:	Customer buys KP281 given Age=40-50	0.375000
4	Probability that:	Customer buys KP281 given Age=50-60	1.000000
5	Probability that:	Customer buys KP481 given Age=10-20	0.200000
6	Probability that:	Customer buys KP481 given Age=20-30	0.296296
7	Probability that:	Customer buys KP481 given Age=30-40	0.440000
8	Probability that:	Customer buys KP481 given Age=40-50	0.312500
9	Probability that:	Customer buys KP481 given Age=50-60	0.000000
10	Probability that:	Customer buys KP781 given Age=10-20	0.000000
11	Probability that:	Customer buys KP781 given Age=20-30	0.250000
12	Probability that:	Customer buys KP781 given Age=30-40	0.160000
13	Probability that:	Customer buys KP781 given Age=40-50	0.312500
14	Probability that:	Customer buys KP781 given Age=50-60	0.000000

In [ ]:
```
sns.countplot(df_bins, x='Age', hue='Product')
```

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



In [ ]:
```
# Education:
# Binning:
#   Less    : < 14 years
#   Moderate: 14 to 17 years
#   High    : > 18 years

edu_bucket = lambda x: 'Less' if x < 14 else ('Moderate' if x < 17 else 'High')

df_bins['Education'] = df['Education'].apply(edu_bucket)
# df_bins
```

In [ ]:
```
calculate_all_conditional_probabilities('Product', 'Education', df_bins)
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Education=High	0.074074
1	Probability that:	Customer buys KP281 given Education=Less	0.625000
2	Probability that:	Customer buys KP281 given Education=Moderate	0.503448
3	Probability that:	Customer buys KP481 given Education=High	0.074074
4	Probability that:	Customer buys KP481 given Education=Less	0.375000
5	Probability that:	Customer buys KP481 given Education=Moderate	0.379310
6	Probability that:	Customer buys KP781 given Education=High	0.851852
7	Probability that:	Customer buys KP781 given Education=Less	0.000000
8	Probability that:	Customer buys KP781 given Education=Moderate	0.117241

In [ ]:

```
# income bracket:
#   Less    :   < 40000
#   Moderate:   40000 to 60000
#   High    :   > 60000

income_bucket = lambda x: 'Less' if x < 40000 else ('Moderate' if x < 60000 else 'High')

df_bins['Income'] = df['Income'].apply(income_bucket)
# df_bins
```

In [ ]:

```
calculate_all_conditional_probabilities('Product', 'Income', df_bins)
```

Out[ ]:

		Condition	Probability
0	Probability that:	Customer buys KP281 given Income=High	0.142857
1	Probability that:	Customer buys KP281 given Income=Less	0.718750
2	Probability that:	Customer buys KP281 given Income=Moderate	0.481132
3	Probability that:	Customer buys KP481 given Income=High	0.166667
4	Probability that:	Customer buys KP481 given Income=Less	0.281250
5	Probability that:	Customer buys KP481 given Income=Moderate	0.415094
6	Probability that:	Customer buys KP781 given Income=High	0.690476
7	Probability that:	Customer buys KP781 given Income=Less	0.000000
8	Probability that:	Customer buys KP781 given Income=Moderate	0.103774

Business Insights

KP281

In [ ]:

```
1. Given that 72% of customers with low income buy KP281,
    And it has high sales in the 20-30 yrs Age groups.
This product targets the lower income groups. To help target this segment better,
we can implement flexible payment plans so that customers can pay in installments.
```

KP481

In [ ]:

```
1. Sales for all 3 products is less in the higher age bracket [40+] compared to the lower age brackets [20-30]
KP481, being a mid-level-runner models can be improved by adding features like heart-rate monitors,
personalised workout modes etc. to attract such age groups and position this product better.

2. Adding such differentiators is important also because the customer demographics of KP281 and KP481 overlap
to a significant extent.
```

KP781

In [ ]:

```
1. Only 17% of customers who buy KP781 are female, we can improve this metric
by encourage female customers to buy this product, via special promotions/discounts
targeting corresponding segment.

2. KP781 is not bought by customers with self-rated-fitness rating 1-3
it is recommended to emphasize the benifits and features of KP781 on how it can help
the segment of customers who are not in excellent shape in it's advertising campaigns.
```

In [ ]: