# SCALER AEROFIT TREADMILL CASE STUDY : [PROJECT LINK (https://www.scaler.com/academy/mentee-dashboard/class/29781/project/problems/18046?navref=cl_tt_lst_sl)](https://www.scaler.com/academy/mentee-dashboard/class/29781/project/problems/18046?navref=cl_tt_lst_sl)

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# PROBLEM STATEMENT

In [357]:

```
"""
GIVEN THE DATASET OF AEROFIT TREADMILL, DOING THE DESCRIPTIVE AND VISUAL
ANALYSIS ON THE DIFFERENT TYPES OF MODELS AND DOING VARIOUS COMAPRATIVE
ANALYSIS AND PRODUCING THE BUSINESS INSIGHTS AND RECOMMENDATION BY CREATING CUSTOMER PROFIL


"""
```

Out[357]:

```
'\nGIVEN THE DATASET OF AEROFIT TREADMILL, DOING THE DESCRIPTIVE AND VISUAL
\nANALYSIS ON THE DIFFERENT TYPES OF MODELS AND DOING VARIOUS COMAPRATIVE\nA
NALYSIS AND PRODUCING THE BUSINESS INSIGHTS AND RECOMMENDATION BY CREATING C
USTOMER PROFILES.\n\n\n'
```

In [ ]:

```

```

In [358]:

```
# IMPORTING LIBRARIES
import pandas as pd
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

In [359]:

```
# reading the dataset of treadmill dataset
df = pd.read_csv("aerofit_treadmill.txt")
```

In [360]:

```
df.head() # checking top 5 rows
```

Out[360]:

| | 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 [361]:

```
df.tail() # checking bottom 5 rows
```

Out[361]:

| | 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 |

# shape of the data

In [362]:

```
a = df.shape # checking the shape of the data
```

In [363]:

```
print("the shape of the data is ",a[0], "rows",a[1],"columns")
```

```
the shape of the data is  180 rows 9 columns
```

# duplicate rows

In [364]:

```
#Are there any duplicate values?
df.duplicated().sum()
```

Out[364]:

```
0
```

# total unique values in each row

In [365]:

```
df.nunique().reset_index()
```

Out[365]:

| | index | 0 |
|---|---|---|
| **0** | Product | 3 |
| **1** | Age | 32 |
| **2** | Gender | 2 |
| **3** | Education | 8 |
| **4** | MaritalStatus | 2 |
| **5** | Usage | 6 |
| **6** | Fitness | 5 |
| **7** | Income | 62 |
| **8** | Miles | 37 |

# dataset information

In [366]:

```
df.info() # lets see null and data types
```

```
<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
```

# data types of the dataset

In [367]:

```
#get the type of data in dataframe
df.dtypes
```

Out[367]:

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

## OBS :

ALL ARE INTEGER DATATYPES EXCEPT PRODUCT , GENDER AND MARITAL STATUS.

# summary statistics

In [368]:

```
df.describe() # let's see summary statstics
```

Out[368]:

| | 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 |

## OBS :

1. AGE OF CUSTOMER USING TREADMILL IS BETWEEN RANGE 18-50. AVERGAE AGE IS 28.78 AND MEDIAN IS 26.
2. MAXIMUN INCOME OF TREADMILL USER IS 104K, AVERGAE INCOME APPROX IS 54K. WHILE MEDIAN IS APPROX 51K.
3. EXPECTED TREADMILL USAGE IS ATLEAST ONCE MIN 1 ONCE A WEEK AND MAX IS 7 TIMES A AWEEK, WITH OVERALL AVERAGE 3 TIMES.

4. CUSTOMER EDUCATION IS BETWEEN 12-21 YEARS ,W ITH AVERAGE AND MEDIAN OF APPROX 16 YEARS AND MAXIMUM OF 21 YEARS.
5. CUSTOMER EXPECTS TO RUN ON AN AVERGAE OF 103.19 MILES PER WEEK AND MEDIAN IS 94 MILES.
6. AVERAGE SELF RATED FITNESS IS 3.

# CHECK NULL VALUES

In [369]:

```
df.isna().any() # checking null values
```

Out[369]:

```
Product          False
Age              False
Gender           False
Education        False
MaritalStatus    False
Usage            False
Fitness          False
Income           False
Miles            False
dtype: bool
```

# CHECK SUM OF NULL VALUES

In [370]:

```
df.isnull().sum()
```

Out[370]:

```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

# COULMN NAMES

In [371]:

```
df.columns
```

Out[371]:

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

# UNIQUE VALUES IN EACH COLUMNS

In [372]:

```
# This is to look at what all unique values have . Just trying to use python
list_col=['Product','MaritalStatus','Usage','Fitness','Education','Age']
# How many models we have?
# what is Martial status of customers?
# how many days people expect to use treadmill?
# what is self rated fitness of customers buying treadmill?
# what is eductaion of customer buying treadmill?
# what is eductaion of customer buying treadmill?
for col in list_col:
    print('{} :{} ' . format(col.upper(),df[col].unique()))
```

```
PRODUCT :['KP281' 'KP481' 'KP781']
MARITALSTATUS :['Single' 'Partnered']
USAGE :[3 2 4 5 6 7]
FITNESS :[4 3 2 1 5]
EDUCATION :[14 15 12 13 16 18 20 21]
AGE :[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 4
1
 43 44 46 47 50 45 48 42]
```

# VALUE COUNTS

In [373]:

```
df['Product'].value_counts().reset_index()
```

Out[373]:

| | index | Product |
|---|---|---|
| **0** | KP281 | 80 |
| **1** | KP481 | 60 |
| **2** | KP781 | 40 |

In [374]:

```
df['Usage'].value_counts().reset_index()
```

Out[374]:

| | index | Usage |
|---|---|---|
| **0** | 3 | 69 |
| **1** | 4 | 52 |
| **2** | 2 | 33 |
| **3** | 5 | 17 |
| **4** | 6 | 7 |
| **5** | 7 | 2 |

In [375]:

```
df['Fitness'].value_counts().reset_index()
```

Out[375]:

| | index | Fitness |
|---|---|---|
| **0** | 3 | 97 |
| **1** | 5 | 31 |
| **2** | 2 | 26 |
| **3** | 4 | 24 |
| **4** | 1 | 2 |

In [376]:

```
df['Education'].value_counts().reset_index()
```

Out[376]:

| | index | Education |
|---|---|---|
| **0** | 16 | 85 |
| **1** | 14 | 55 |
| **2** | 18 | 23 |
| **3** | 13 | 5 |
| **4** | 15 | 5 |
| **5** | 12 | 3 |
| **6** | 21 | 3 |
| **7** | 20 | 1 |

In [377]:

```
df['Age'].value_counts().reset_index()
```

Out[377]:

| | index | Age |
|---|---|---|
| **0** | 25 | 25 |
| **1** | 23 | 18 |
| **2** | 24 | 12 |
| **3** | 26 | 12 |
| **4** | 28 | 9 |
| **5** | 35 | 8 |
| **6** | 33 | 8 |
| **7** | 30 | 7 |
| **8** | 38 | 7 |
| **9** | 21 | 7 |
| **10** | 22 | 7 |
| **11** | 27 | 7 |
| **12** | 31 | 6 |
| **13** | 34 | 6 |
| **14** | 29 | 6 |
| **15** | 20 | 5 |
| **16** | 40 | 5 |
| **17** | 32 | 4 |
| **18** | 19 | 4 |
| **19** | 48 | 2 |
| **20** | 37 | 2 |
| **21** | 47 | 2 |
| **22** | 45 | 2 |
| **23** | 44 | 1 |
| **24** | 46 | 1 |
| **25** | 18 | 1 |
| **26** | 43 | 1 |
| **27** | 42 | 1 |
| **28** | 41 | 1 |
| **29** | 39 | 1 |
| **30** | 36 | 1 |
| **31** | 50 | 1 |

# RANGE OF DATASET

*There are 3 different treadmills products .*

There are both Partnered and single customers .

Age of customers ranges from 18 to 50 .

Education in years is from 12 -21 .

Usage is from 2 days to 7 days a week .

Fitness level of customers from 1 -5

# TREADMIL VALUE COUNTS

In [378]:

```
#Which is most sold Model?
df.Product.value_counts()
```

Out[378]:

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

## OBSERVATION :

BASE MODEL KP 281 IS THE MOST SOLD MODEL AND HIGHER END MODEL KP 781 IS THE LEAST SOLD MODEL.

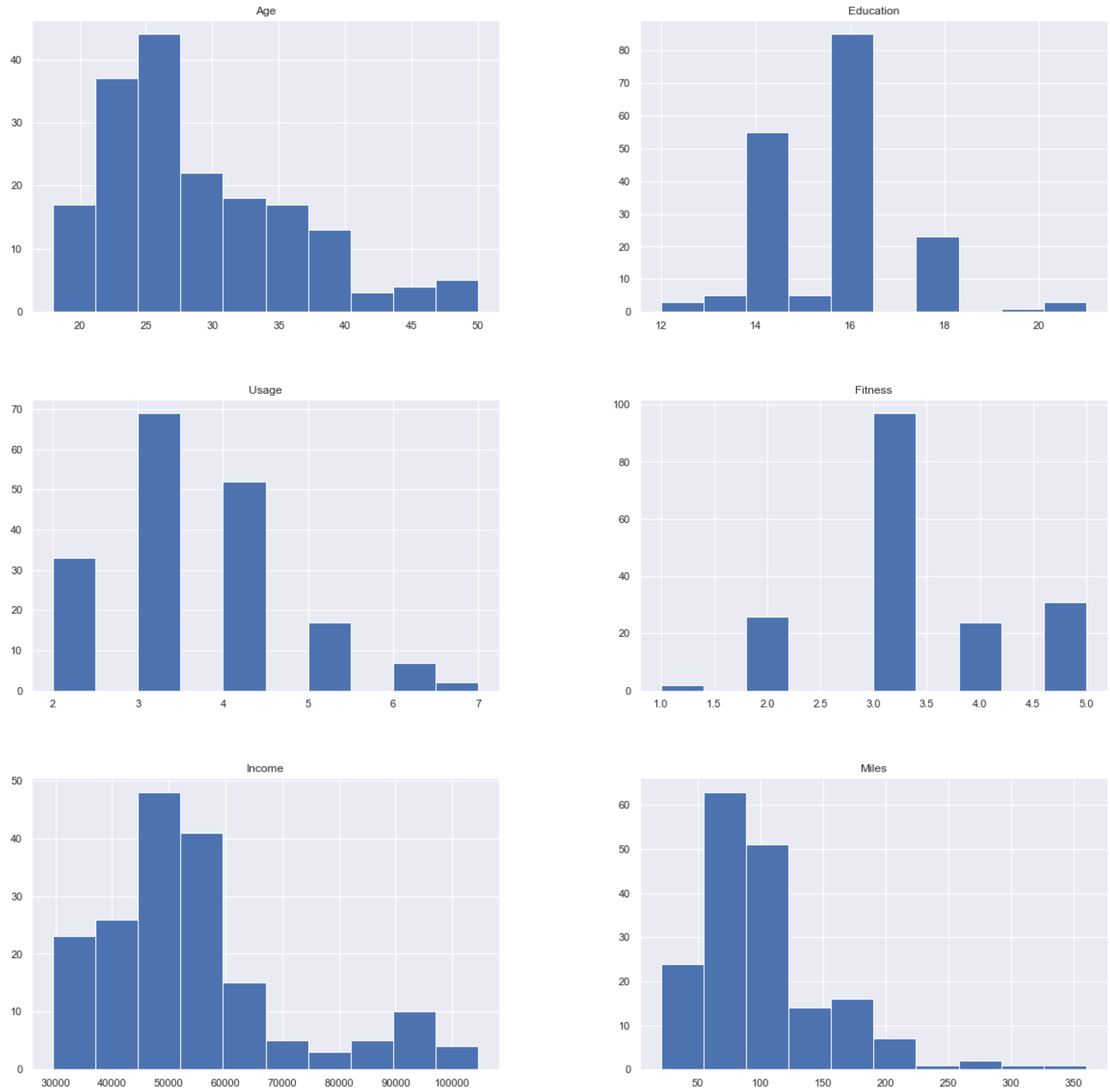
# HISTOGRAM PLOT ON ALL THE COLUMNS

In [379]:

```
df.hist(figsize=(20,20)) # plot histgram on the columns of the dataset
```

Out[379]:

```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Education'}>],
       [<AxesSubplot:title={'center':'Usage'}>,
        <AxesSubplot:title={'center':'Fitness'}>],
       [<AxesSubplot:title={'center':'Income'}>,
        <AxesSubplot:title={'center':'Miles'}>]], dtype=object)
```



# RELATIONSHIP BETWEEN PRODUCT AND GENDER USING CROSSTAB

In [380]:

```
pd.crosstab(df['Product'],df['Gender'] )
```

Out[380]:

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

# OBSERVATION :

THE LOWER END MODEL HAS THE HIGHEST NUMBER OF FEMALE CUSTOMERS THE HIGHER END MODEL HAS THE HIGHEST NUMBER OF MALE CUSTOMERS.

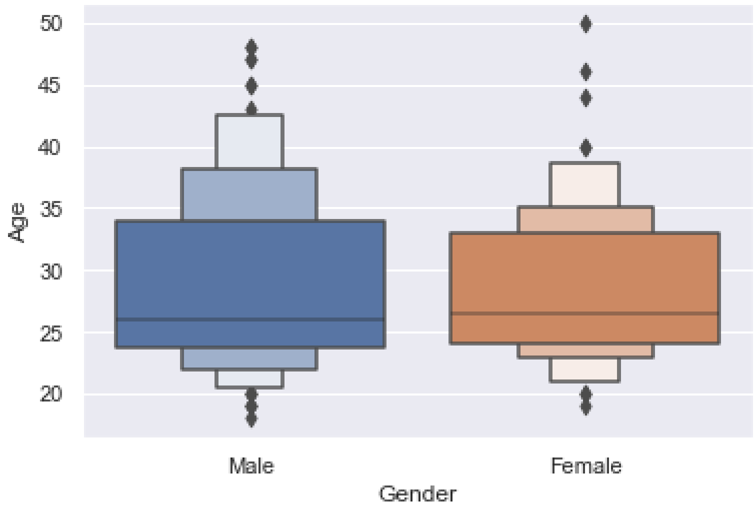
# BOX PLOT BETWEEN BOTH GENDER WITH REPSECT TO AGE

In [381]:

```
sns.boxenplot(x='Gender',y='Age',data=df)
```

Out[381]:

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




# OBSERVATION :

1. YOUNGER FEMALES BUY MORE TREADMILLS COMPARED TO MALES
2. ELDER MALES BUY MORE TREADMILLS COMPARED TO FEMALES

# RELATIONSHIP BETWEEN PRODUCT AND MARITAL STATUS USING CROSSTAB

In [382]:

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

Out[382]:

| MaritalStatus | Partnered | Single |
|---|---|---|
| **Product** | | |
| **KP281** | 48 | 32 |
| **KP481** | 36 | 24 |
| **KP781** | 23 | 17 |

# OBSERVATION :

1. ITS IS EVIDENT THAT ALL PARTNERED BUY MORE THAN SINGLE CUSTOMERS IN ALL THE TYPES OF TREADMILLS.

# VALUE COUNT OF GENDER

In [383]:

```
#Are Male customers buying treadmill more than female customers?
df.Gender.value_counts()
```

Out[383]:

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

## OBSERVATION :

1. THERE ARE 82 MALE CUSTOMER ABD 72 FEMALE CUSTOMER
2. MALES ARE HIGHEST NUMBER OF CUSTOMERS.

# VALUE COUNT OF MARITAL STATUS

In [384]:

```
#Are married customer buying Treadmill more than Single customers?
df.MaritalStatus.value_counts()
```

Out[384]:

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

## OBSERVATION :

1. THERE ATE 87 PARTERED CUSTOMERS AND 67 SINGLE CUSTOMERS
2. THERE ARE HIGH NUMBER OF PARTNERED CUSTOMERS.

# EACH TREADMILL MODEL

# KP281

In [385]:

```
df[df['Product'] == 'KP281'].describe().T
```

Out[385]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Age** | 80.0 | 28.5500 | 7.221452 | 18.0 | 23.0 | 26.0 | 33.0 | 50.0 |
| **Education** | 80.0 | 15.0375 | 1.216383 | 12.0 | 14.0 | 16.0 | 16.0 | 18.0 |
| **Usage** | 80.0 | 3.0875 | 0.782624 | 2.0 | 3.0 | 3.0 | 4.0 | 5.0 |
| **Fitness** | 80.0 | 2.9625 | 0.664540 | 1.0 | 3.0 | 3.0 | 3.0 | 5.0 |
| **Income** | 80.0 | 46418.0250 | 9075.783190 | 29562.0 | 38658.0 | 46617.0 | 53439.0 | 68220.0 |
| **Miles** | 80.0 | 82.7875 | 28.874102 | 38.0 | 66.0 | 85.0 | 94.0 | 188.0 |

# OBSERVATIONS :

1. 80 CUSTOMERS BROUGH THE KP281 MODEL.
2. AVERAGE AGE OF CUSTOMER WHO BROUGHT THIS MODEL IS 28.5 AND MEDIAN IS 26
3. AVERAGE EDUCATION IS 15 AND MEDIAN IS 16
4. EXPECTED USAGE IS 3 DAYS A WEEK.
5. EXPECTED MILES TO RUN IS ON AVERGAE 82.78 PER WEEK AND MEDIAN IS 85
6. SELF RATED FITNESS IS 3
7. AVERAGE INCOME LEVEL IS 46K DOLLAR.

# KP 481

In [386]:

```
df[df['Product'] == 'KP481'].describe().T
```

Out[386]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Age** | 60.0 | 28.900000 | 6.645248 | 19.0 | 24.0 | 26.0 | 33.25 | 48.0 |
| **Education** | 60.0 | 15.116667 | 1.222552 | 12.0 | 14.0 | 16.0 | 16.00 | 18.0 |
| **Usage** | 60.0 | 3.066667 | 0.799717 | 2.0 | 3.0 | 3.0 | 3.25 | 5.0 |
| **Fitness** | 60.0 | 2.900000 | 0.629770 | 1.0 | 3.0 | 3.0 | 3.00 | 4.0 |
| **Income** | 60.0 | 48973.650000 | 8653.989388 | 31836.0 | 44911.5 | 49459.5 | 53439.00 | 67083.0 |
| **Miles** | 60.0 | 87.933333 | 33.263135 | 21.0 | 64.0 | 85.0 | 106.00 | 212.0 |

# OBSERVATIONS :

1. THERE ARE 6O CUSTOMERS WHO PURCHASED THIS MODEL.
2. AVERAGE AGE OF CUSTOMERS WHO PURCAHSED THIS MODELIS 28.9 . MEDIAN IS 26

3. CUSTOMER RANGE IS BETWEEN 24 - 33
4. AVERAGE EDUCTAION IS 15 AND MEDIAN IS 16
5. EXPECTED USAGE IS 3 DAYS A WEEK
6. EXPECTED MILES TO RUN IS 87.9 MILES PER WEEK AND MEIDAN 85
7. AVERAG INCOME IS 48973
8. MEDIAN INCOME IS 49459

# KP 781

In [387]:

```
df[df['Product'] == 'KP781'].describe().T
```

Out[387]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Age** | 40.0 | 29.100 | 6.971738 | 22.0 | 24.75 | 27.0 | 30.25 | 48.0 |
| **Education** | 40.0 | 17.325 | 1.639066 | 14.0 | 16.00 | 18.0 | 18.00 | 21.0 |
| **Usage** | 40.0 | 4.775 | 0.946993 | 3.0 | 4.00 | 5.0 | 5.00 | 7.0 |
| **Fitness** | 40.0 | 4.625 | 0.667467 | 3.0 | 4.00 | 5.0 | 5.00 | 5.0 |
| **Income** | 40.0 | 75441.575 | 18505.836720 | 48556.0 | 58204.75 | 76568.5 | 90886.00 | 104581.0 |
| **Miles** | 40.0 | 166.900 | 60.066544 | 80.0 | 120.00 | 160.0 | 200.00 | 360.0 |

## OBSERVATIONS :

1. AVERAGE AGE OF CUSTOMER WHO PURCHASES IS 29 AND MEDIAN IS 27
2. AVERAGE EDUCATION IS 17 AND MEDIAN IS 18
3. EXPECTED USAGE IS 4-5 DAYS A WEEK
4. EXPECTED MILES TO RUN IS ON AN AVERGAE 166 MILES PER WEEK AND MEDIAN IS 160
5. AVERAGE INCOME IS 75K AND MEDIAN IS 76K

# MARGINAL RPOBABILTIES

## 1. WHAT IS THE PROBABILITY THAT A CUSTOMER IS MALE ?

## 2. WHAT IS THE PRIBABILITY THAT A FEMALE CUSTOMER IS SINGLE ?

## 3. WHAT IS THE PROBABILITY THAT A TREADMILL BROUGHT BY THE CUSTOMER IS MODEL KP 781 ?

# 1.P(MALE) = ?

## P(MALE) = NUMMBER OF MALE CUSTOMERS /TOTAL NUMBER CUSTOMER

In [388]:

```
total = df.shape[0] # total customers
mf = df
mf = mf[mf['Gender']=='Male']

m = mf.shape[0] # number of male customers

#p(male)
pmale = ( m / total)
pmale
```

Out[388]:

```
0.5777777777777777
```

## marginal probability of male is 0.5777777777777777

# 2. p(single female ) = ?

## P(SINGLE FEMALE) = TOTAL SINGLE FEMALE / TOTAL CUSTOMER

In [389]:

```
## P(SINGLE FEMALE IS CUSTOMER )


sfm = df
sfm = sfm[sfm['Gender']=='Female']
sfm = sfm[sfm['MaritalStatus']=='Single']
f = sfm.shape[0]


psingfemale = f/ total
psingfemale
```

Out[389]:

```
0.16666666666666666
```

## marginal probability of single female 0.1666666666666

# 3. P(KP781) = ?

In [390]:

```
kp = df
kp = kp[kp['Product']== 'KP781']
k = kp.shape[0]


pkp781 = k / total
pkp781
```

Out[390]:

```
0.2222222222222222
```

## Probability of KP781 is0.2222222222222

In [ ]:

```

```

# CONDITIONAL PROBABILITY

# 1. WHAT IS THE PROBABILTY THAT A CUSTOMER BROUGHT A KP 281 MODEL GIVEN THAT SHE IS SINGLE FEMALE ?

## P(A=K281/B = SINGLE FEMALE )

### P(A/B) = P(A ∩ B)/P(B)

In [391]:

```
# P(A = MODEL IS K281 / B = SINGLE FEMALE)
```

In [392]:

```
def conditional_proabaility(a, b) :
    cf= pd.crosstab(index=df["Product"], columns=[df["MaritalStatus"],df["Gender"]])
    cfnew = cf[b]
    total = cf[b].sum()
    print(total,cfnew.loc[a])
    print(cfnew.loc[a]/total)
```

In [393]:

```
conditional_proabaility(a = 'KP281', b =('Single', 'Female'))
```

```
30 13
0.43333333333333335
```

# conditional probability of model is kp281 when customer is single female is = 0.43333333333

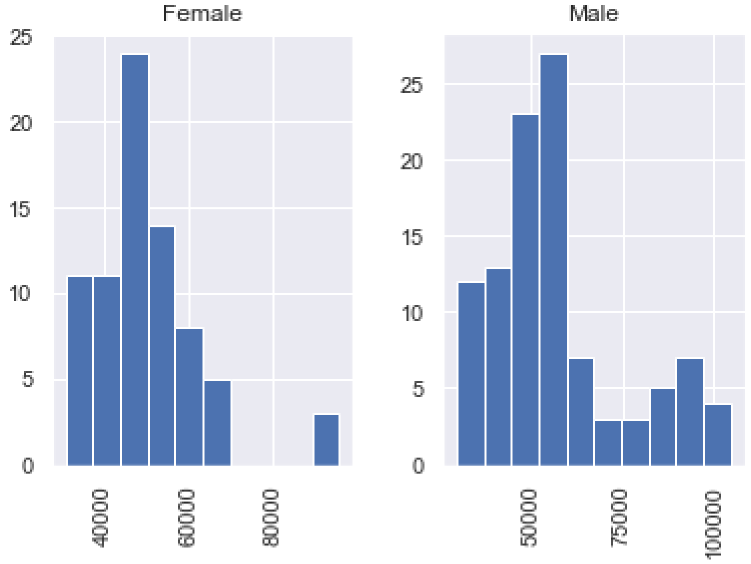
#### HISTOGRAM PLOT OF INCOME COLUMN FOR BOTH THE GENDERS

In [394]:

```
df.hist(by='Gender',column = 'Income')
```

Out[394]:

```
array([<AxesSubplot:title={'center':'Female'}>,
       <AxesSubplot:title={'center':'Male'}>], dtype=object)
```




## OBSERVATIONS :

1. THERE ARE MANY HIGH INCOME MALES AND VERY FEW HIGH INCOME FEMALES.

# MEAN MODE AND MEDIAN OF AGE COLUMNS

In [395]:

```
df['Age'].mean()
```

Out[395]:

```
28.788888888888888
```

In [396]:

```
df['Age'].mode()
```

Out[396]:

```
0    25
dtype: int64
```

In [397]:

```
df['Age'].median()
```

Out[397]:

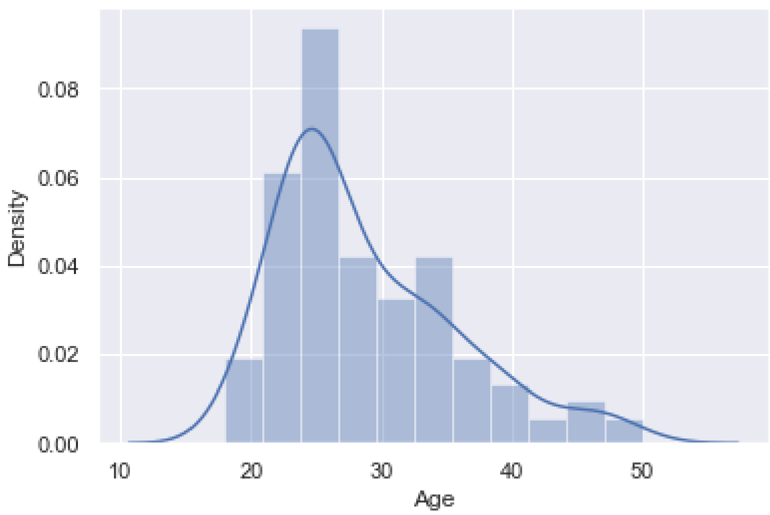
```
26.0
```

In [398]:

```
sns.distplot(df['Age'])
```

Out[398]:

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```




# OBSERVATIONS :

1. MEAN OF THE CUSTOMERS IS 28
2. MODE OF THE CUSTOMERS IS 25
3. MEDIAN OF THE CUSTOMERS IS 26.0
4. THE MAHORITY OF THE CUSTOMERS WERE BETWEEN 20 TO 30

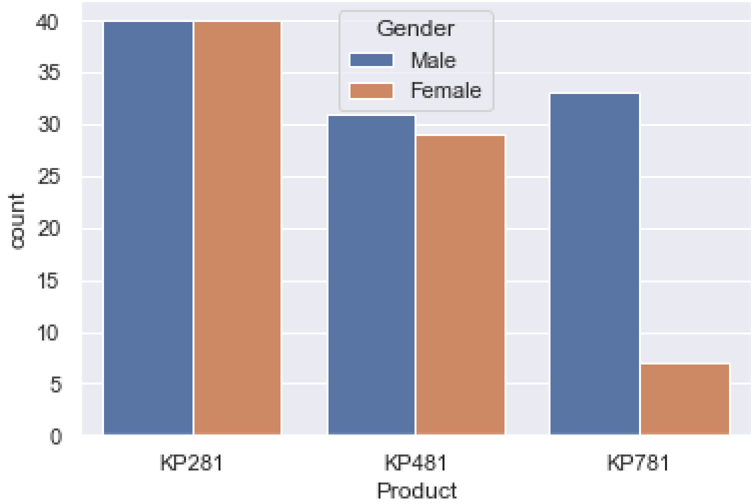
## COUNT PLOT OF DIFFERENT TREADMILLS WRT GENDER

In [399]:

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

Out[399]:

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




In [400]:

```
## OBSERVATION :
1. VERY FEW FEMALES ARE BUYING HIGH END MODELS
2. VERY HIGH NUMBER OF MALES ARE BUYING HIGH END MODELS
```

```
  Input In [400]
    1. VERY FEW FEMALES ARE BUYING HIGH END MODELS
       ^
SyntaxError: invalid syntax
```

# PAIR PLOTS OF THE COLUMNS RELATIOSHIP

In [401]:

```
sns.pairplot(df)
```

Out[401]:

<seaborn.axisgrid.PairGrid at 0x2a91e8a6790>


# CORRELATION GRAPH OF THE COLUMNS

In [402]:

```
corr=df.corr()
corr
```

Out[402]:

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

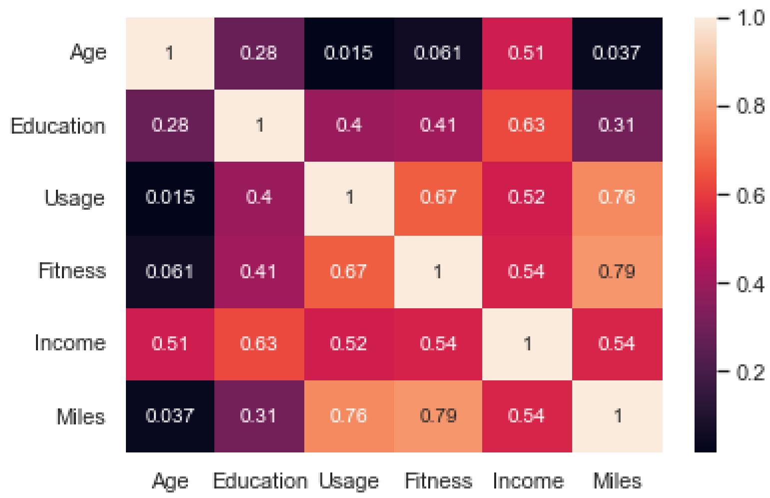
# HEATMAP OF THE COLUMNS

In [403]:

```
sns.heatmap(corr,annot=True)
```

Out[403]:

<AxesSubplot:>



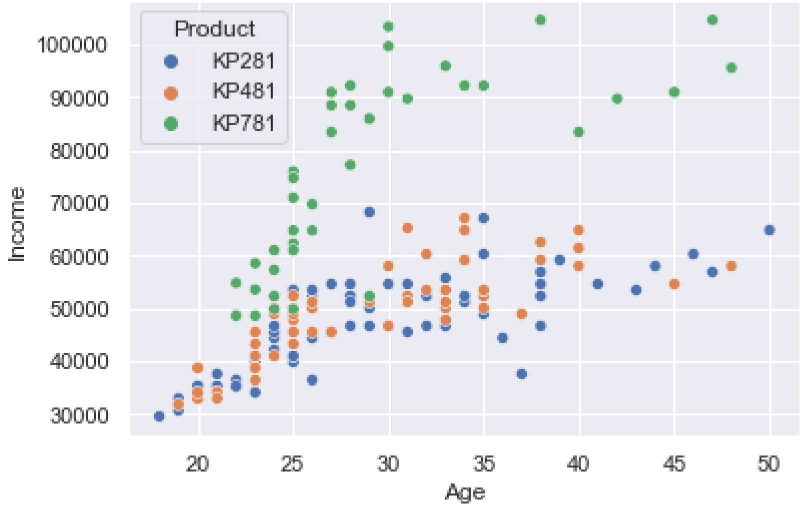

# OBSERVATIONS :

1. INCOME AND EDUCATION SHOW A GREAT REASON OF BUYING
2. USAGE AND FITNESS HAS THE GREAT CORRELATION AMONG THE REASON FOR BUYING
3. MILES RUNNED AN FITNESS LEVELS HAVE 79 PERCENT CORRELATION.

# SCATTERPLOT BETWEEN AGE AND INCOME

In [404]:

```
sns.scatterplot(x='Age', y='Income',data=df, hue = 'Product')
plt.show()
```




# OBSERVATION :

1. HIGHER END MODELA RE BROUGHT NY HIGH INCOME CUSTOMERS
2. LOWER END MODELS AREE BROUGHT BY LOW INCOME CUSTOMERS

# DATA TYPE CONVERSION

In [405]:

```
#changing it to  object dtype to category  to save memory
df.Product=df["Product"].astype("category")
df.Gender=df["Gender"].astype("category")
df.MaritalStatus=df["MaritalStatus"].astype("category")
```

# CONERVSION TO CATEGORY DATATYPE

In [406]:

```
#get the type of data in dataframe
df.dtypes
```

Out[406]:

```
Product          category
Age                 int64
Gender           category
Education           int64
MaritalStatus    category
Usage               int64
Fitness             int64
Income              int64
Miles               int64
dtype: object
```

# PLOTTING BOX PLOT ,VIOLINPLOT AND HSITOGRAM OF COLUMNS

In [407]:

```
def dist_box_violin(data):
 # function plots a combined graph for univariate analysis of continous variable
 #to check spread, central tendency , dispersion and outliers
    Name=data.name.upper()
    fig, axes =plt.subplots(1,3,figsize=(17, 7))
    fig.suptitle("SPREAD OF DATA FOR "+ Name  , fontsize=18, fontweight='bold')
    sns.distplot(data,kde=False,color='Blue',ax=axes[0])
    axes[0].axvline(data.mean(), color='y', linestyle='--',linewidth=2)
    axes[0].axvline(data.median(), color='r', linestyle='dashed', linewidth=2)
    axes[0].axvline(data.mode()[0],color='g',linestyle='solid',linewidth=2)
    axes[0].legend({'Mean':data.mean(),'Median':data.median(),'Mode':data.mode()})
    sns.boxplot(x=data,showmeans=True, orient='h',color="purple",ax=axes[1])
    #just exploring violin plot
    sns.violinplot(data,ax=axes[2],showmeans=True)
```

# INCOME

In [408]:

```
dist_box_violin(df.Income)
```

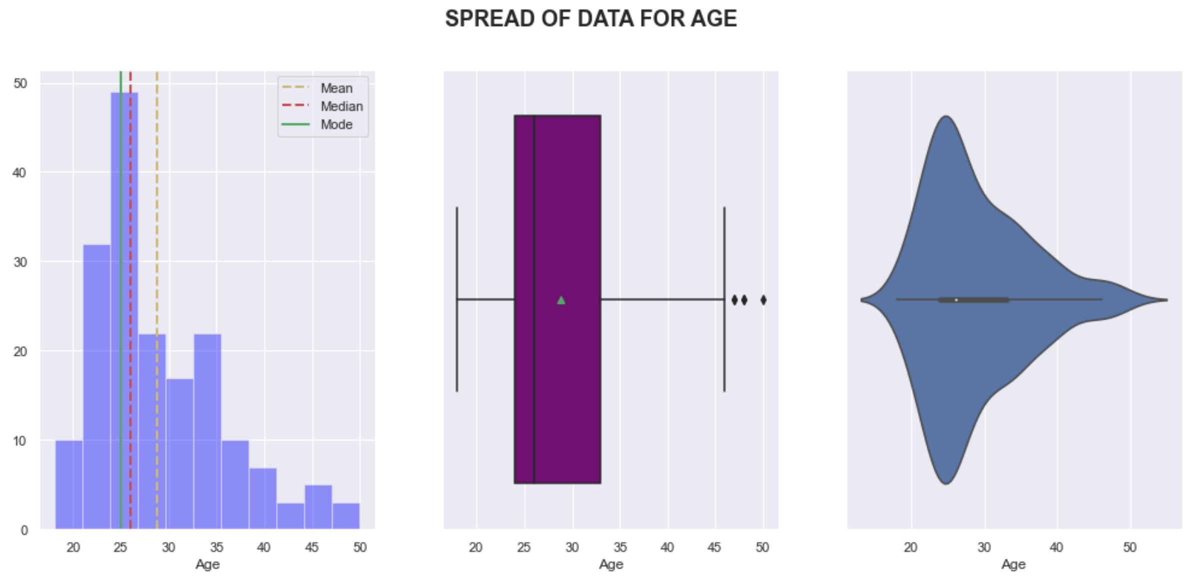

# OBSERVATIONS :

Income is skewed towards right , Median is 50K , Mean is 55k and mode is $45K. Most of the customers are in lower pay range and earn less than 70K. Income has some outliers. Few customers earn beyond 80K.

# AGE

In [409]:

```
dist_box_violin(df.Age)
```



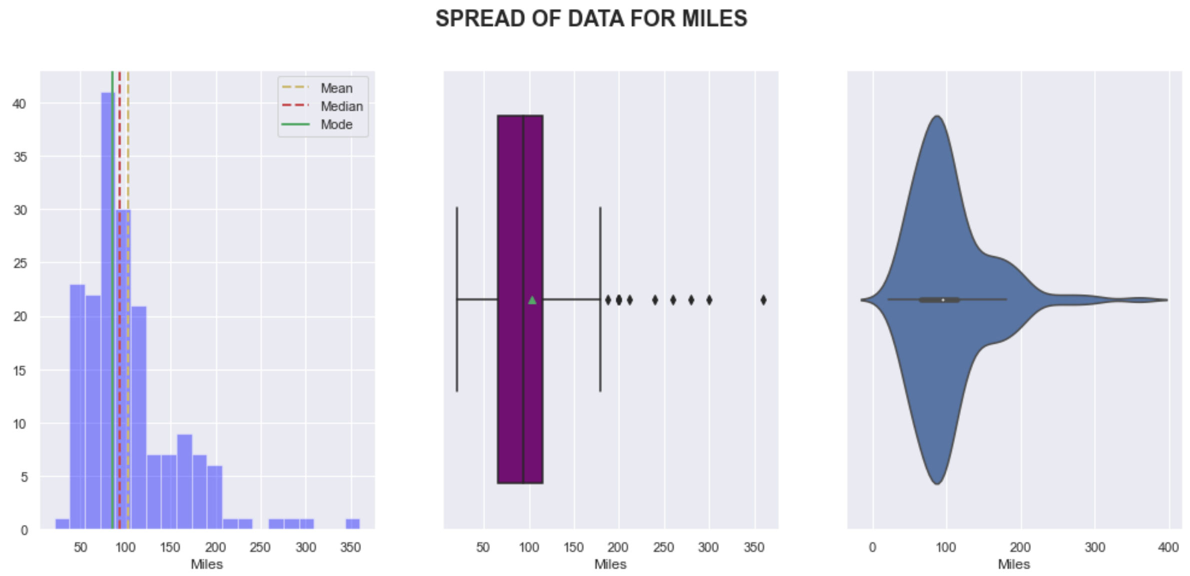

# Observations:

Age is skewed towards right. Customers buying treadmill are younger and average age of customer is 28 , median is 26 and mode is 25 Customers buying treadmill after age of 40 and before 20 are very less.

# MILES

In [410]:

```
dist_box_violin(df.Miles)
```



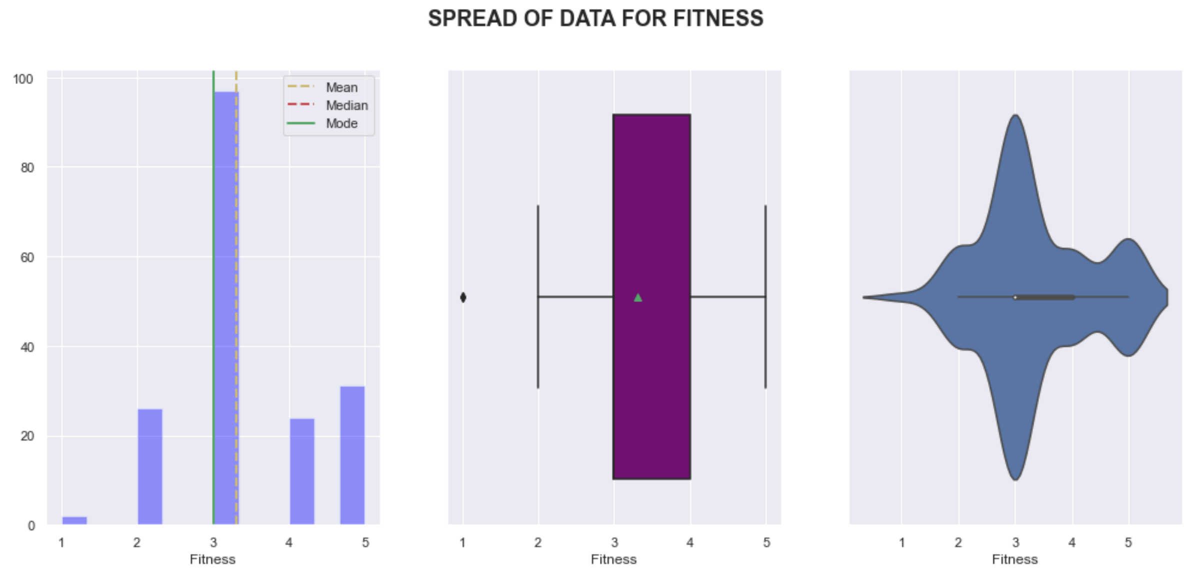

# Observations:

Miles is skewed towards right. Customers expect to run on an average 80 miles per week. There are some outliers, where customers are expecting to run more than 200 miles per weak.

# FITNESS

In [411]:

```
dist_box_violin(df.Fitness)
```



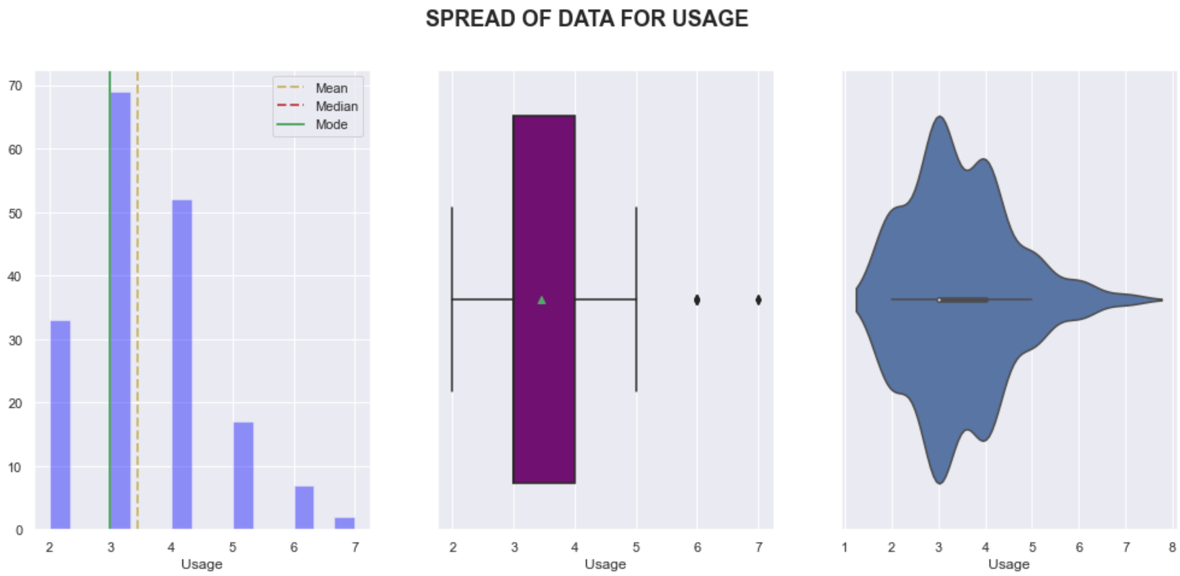

# Observations

Most of the customers have 16 year of education (assuming them to be college graduates or bachelors). There are few outliers.

# USAGE

In [412]:

```
dist_box_violin(df.Usage)
```



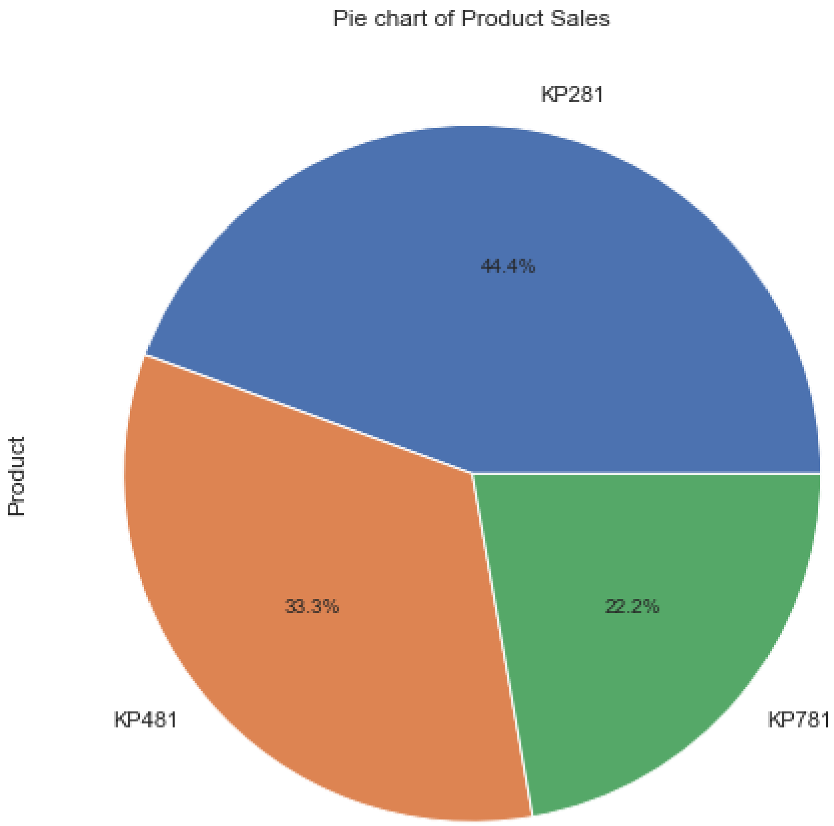

# Observations

Most of customers expect they will be using the treadmill 3-4 days per week. There are few outliers where customer are expecting to use treadmill for 6 or 7 times a week

# UNIVARIATE PIE CHART CATEGORICAL ANALYSIS

In [413]:

```
#Univariate Analysis
#categorical variables
plt.figure(figsize=(14,7))
df['Product'].value_counts().plot.pie(autopct='%1.1f%%',figsize=(8,8))
plt.title("Pie chart of Product Sales")
plt.show()
```




# OBS :

1. MOST PEOPLE BROUGHT KP281
2. NEXT PEOPLE BROUGHT KP 481
3. LEAST BROUGHT NY KP 781

# BAR PLOT FOR GENDER PRODUCT AND

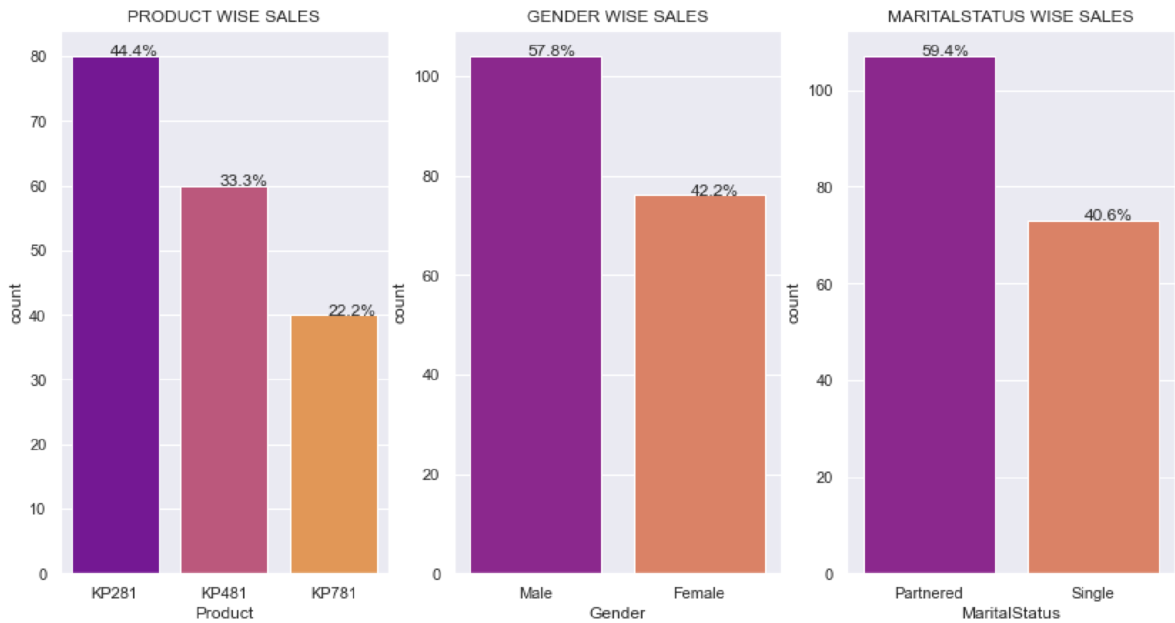
# MARITALSTATUS

In [414]:

```
# Function to create barplots that indicate percentage for each category.
def bar_perc(plot, feature):
    '''
    plot
    feature: 1-d categorical feature array
    '''
    total = len(feature) # length of the column
    for p in plot.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total) # percentage of each clas
        x = p.get_x() + p.get_width() / 2 - 0.05 # width of the plot
        y = p.get_y() + p.get_height()           # hieght of the plot
        plot.annotate(percentage, (x, y), size = 12) # annotate the percentage
```

In [415]:

```
fig1, axes1 =plt.subplots(1,3,figsize=(14, 7))
list_col=['Product','Gender','MaritalStatus']
j=0
for i in range(len(list_col)):
    order = df[list_col[i]].value_counts(ascending=False).index # to display bar in ascendi
    axis=sns.countplot(x=list_col[i], data=df , order=order,ax=axes1[i],palette='plasma').s
    bar_perc(axes1[i],df[list_col[i]])
```




# Observation:

44.4% customers brought kp 281. kp 281 model is the most purchased model. kp 481 was purchased more than kp 781. 57.8% male brought Treadmill.There are more Male customers than Female customers. 59.4% of the customers who purchased treadmill are Married.

# Bi variate Analysis

# RELATIONSHIP BETWEEN MEAN OF AGE AND PRODUCT

In [416]:

```
#Average age of customer buying each model
df.groupby('Product')['Age'].mean()
```

Out[416]:

```
Product
KP281    28.55
KP481    28.90
KP781    29.10
Name: Age, dtype: float64
```

# RELATIONSHIP BETWEEN MEAN OF INCOME AND PRODUCT

In [417]:

```
#Average Income of customer buying each model
df.groupby('Product')['Income'].mean()
```

Out[417]:

```
Product
KP281    46418.025
KP481    48973.650
KP781    75441.575
Name: Income, dtype: float64
```

# RELATIONSHIP BETWEEN MEAN OF MILES AND PRODUCT

In [418]:

```
#Average Income of customer buying each model
df.groupby('Product')['Miles'].mean()
```

Out[418]:

```
Product
KP281     82.787500
KP481     87.933333
KP781    166.900000
Name: Miles, dtype: float64
```

# RELATIONSHIP BETWEEN EACH(FEMALE AND MALE GENDER) AND PRODUCT

In [419]:

```
plt.figure(figsize=(10,10))
prd_gender=pd.crosstab(df['Product'],df['Gender'] )
print(prd_gender)
```

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


<Figure size 720x720 with 0 Axes>
```

## OBS :

1. FEMALES ARE BUYING KP 281
2. MALES ARE BUYING MORE KP 781

# GENDER PLOT

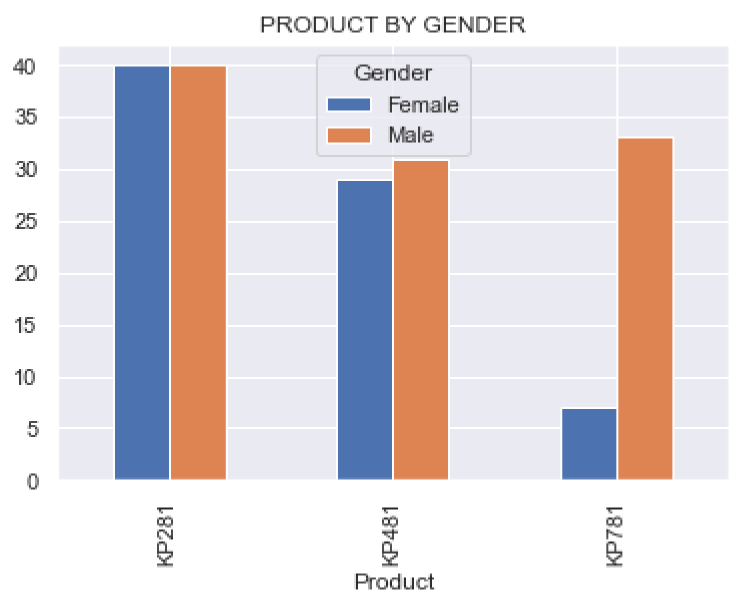
In [420]:

```
ax=prd_gender.plot(kind='bar')

plt.title("PRODUCT BY GENDER")
```

Out[420]:

```
Text(0.5, 1.0, 'PRODUCT BY GENDER')
```




# Observation

KP281 model was equally bought my Male and Female Compared to females, male bought KP481 model . KP781 model is popular in Males than in female.

# MARITAL STATUS HIST PLOT

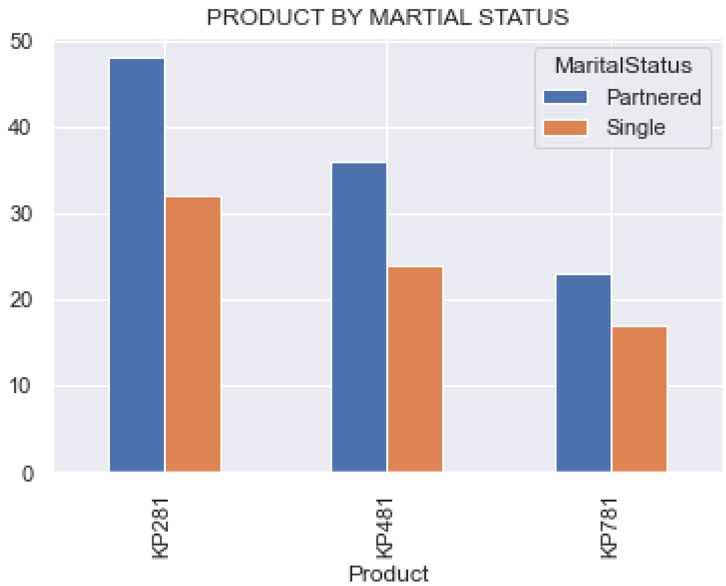
In [421]:

```
prd_mar_status=pd.crosstab(df['Product'],df['MaritalStatus'] )
print(prd_mar_status)
prd_mar_status.plot(kind='bar')
plt.title("PRODUCT BY MARTIAL STATUS")
```

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

Out[421]:

```
Text(0.5, 1.0, 'PRODUCT BY MARTIAL STATUS')
```



In [422]:

```
plt.figure(figsize=(30,10))
sns.heatmap(df.corr(), annot=True)
```

Out[422]:

```
<AxesSubplot:>
```


# CORRELATION WHRE GREATER THAN 0.5

In [423]:

```
corr_pairs = df.corr().unstack() # give pairs of correlation
corr_pairs[abs(corr_pairs)>0.5] # Gives us correlated data
```

Out[423]:

```
Age        Age          1.000000
           Income       0.513414
Education  Education    1.000000
           Income       0.625827
Usage      Usage        1.000000
           Fitness      0.668606
           Income       0.519537
           Miles        0.759130
Fitness    Usage        0.668606
           Fitness      1.000000
           Income       0.535005
           Miles        0.785702
Income     Age          0.513414
           Education    0.625827
           Usage        0.519537
           Fitness      0.535005
           Income       1.000000
           Miles        0.543473
Miles      Usage        0.759130
           Fitness      0.785702
           Income       0.543473
           Miles        1.000000
dtype: float64
```

# Observation

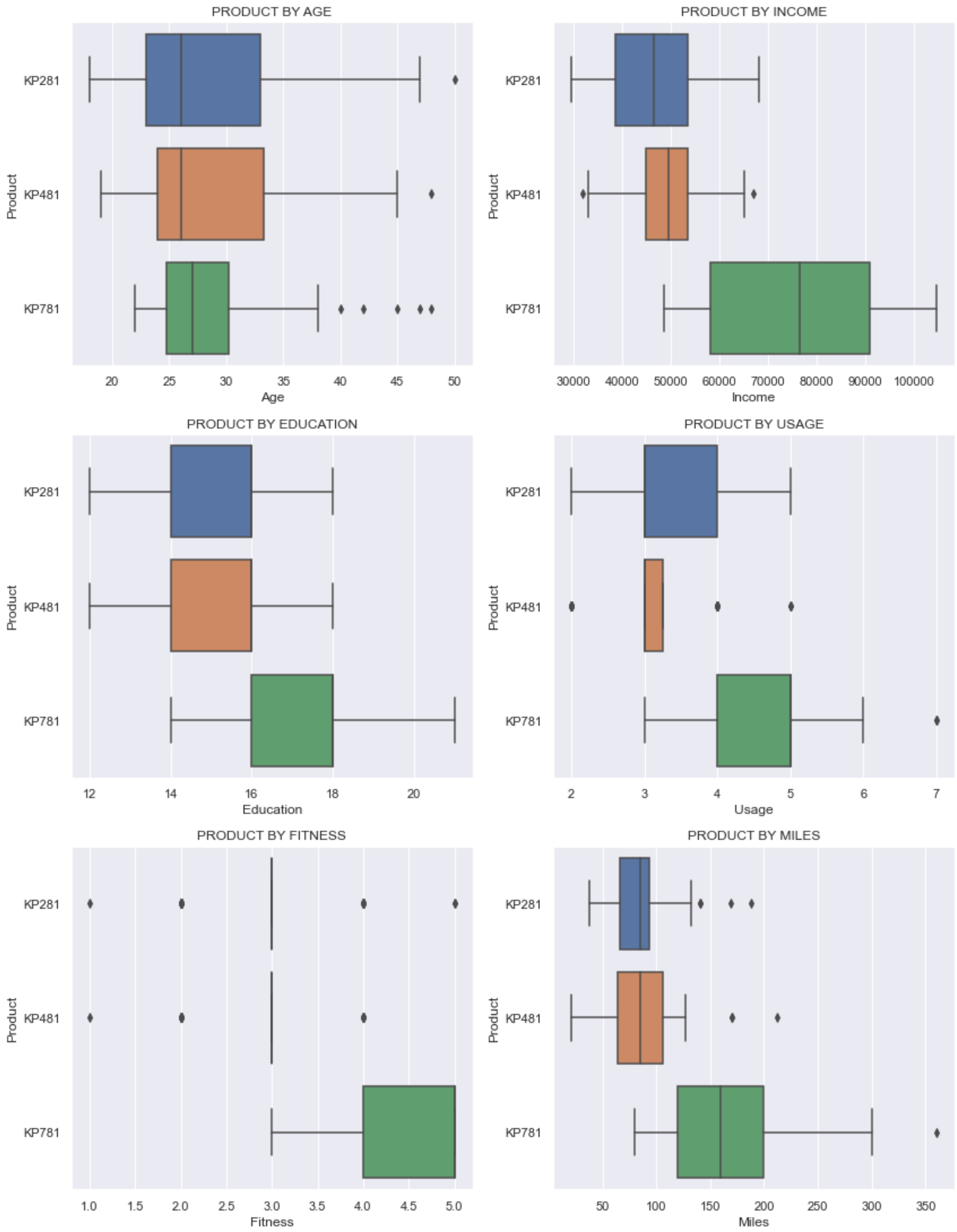
Age and Income has some in significant correlation Education and Income has very little correlation There is some corelation between Usage and Income Fitness and miles are corelated kp 781 model is correlated to Education, Usage,Fitness, Income and Miles. Miles and usage are positively correlated

# BIVARIATE ANALSYSIS FOR PRODUCT VERSUS THE REST OF THE FEATURES

In [424]:

```
#Bi Varaite Analysis for
#1.Product & Age
#2.Product & Income
#3.Product & Education
#4.Product & Usage
#5.Product & Fitness
#6.Product & Miles
fig1, axes1 =plt.subplots(3,2,figsize=(14, 19))
list1_col=['Age','Income','Education','Usage','Fitness','Miles']
#instead of writing  boxplot 6 times using for loop
for i in range(len(list1_col)):
    row=i//2
    col=i%2
    ax=axes1[row,col]

    sns.boxplot(df[list1_col[i]],df['Product'],ax=ax).set(title='PRODUCT BY ' + list1_col[i
```




# Observations:-

1. There are many outliers for KP781 ,customers are more than age of 40 .
2. Age of customers buying KP281 and KP481 is between 20-35, where as customers buying kp 781 are primarily in 25-30
3. Customers with higher income and more education have purchased kp 781 model.
4. Customers with lower income purchase KP281 and KP481 model may be because of cost of the Treadmill
5. Customer with KP281 expect to use treadmill 3-4 times a week and have average self rated fitness as 3 and some unfits.
6. Customers who bought KP481 model expecting to use Treadmill less frequently but to run more miles a week.
7. Customer buying KP781 plan to use it more frequently , run more miles and have high self rated fitness .They seem to be more health conscious or professionals.
8. KP781 model was purchased more by males customer than female customers .

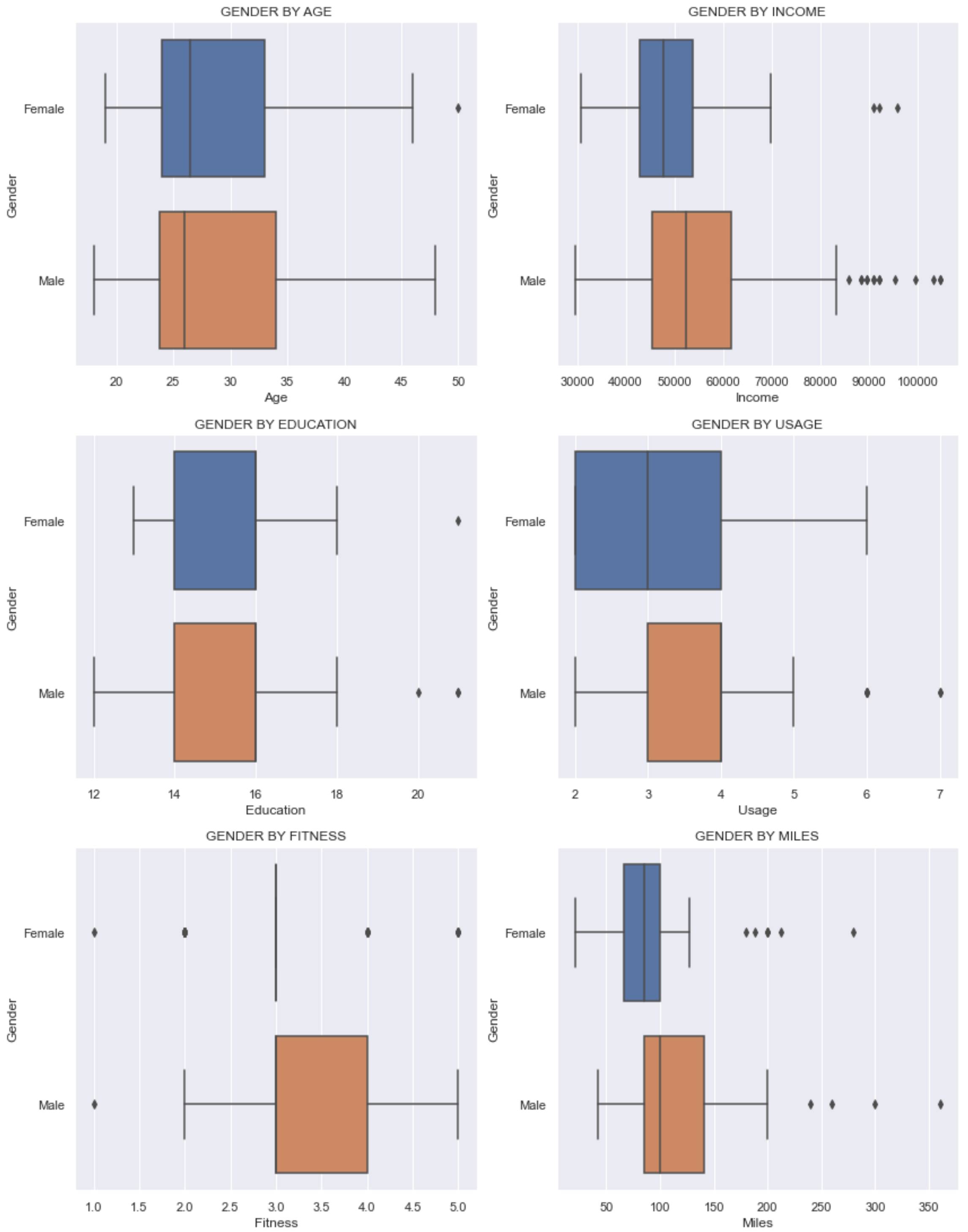
8. KP 781 model was purchased more by males customer than female customers .
9. More partnered customer tend to buy kp 781 than Single customers

# BIVARIATE ANALYSIS FOR GENDER VS REST OF THE FEATURES

In [425]:

```
#Bi Varaite Analysis for
#1.Gender & Age
#2.Gender & Income
#3.Gender & Education
#4.Gender & Usage
#5.Gender & Fitness
#6.Gender & Miles

fig1, axes1 =plt.subplots(3,2,figsize=(14, 19))
list1_col=['Age','Income','Education','Usage','Fitness','Miles']
# to plot graph side by side.
for i in range(len(list1_col)):
    row=i//2
    col=i%2
    ax=axes1[row,col]
    sns.boxplot(df[list1_col[i]],df['Gender'],ax=ax).set(title='GENDER BY ' + list1_col[i].
```




# Observations:-

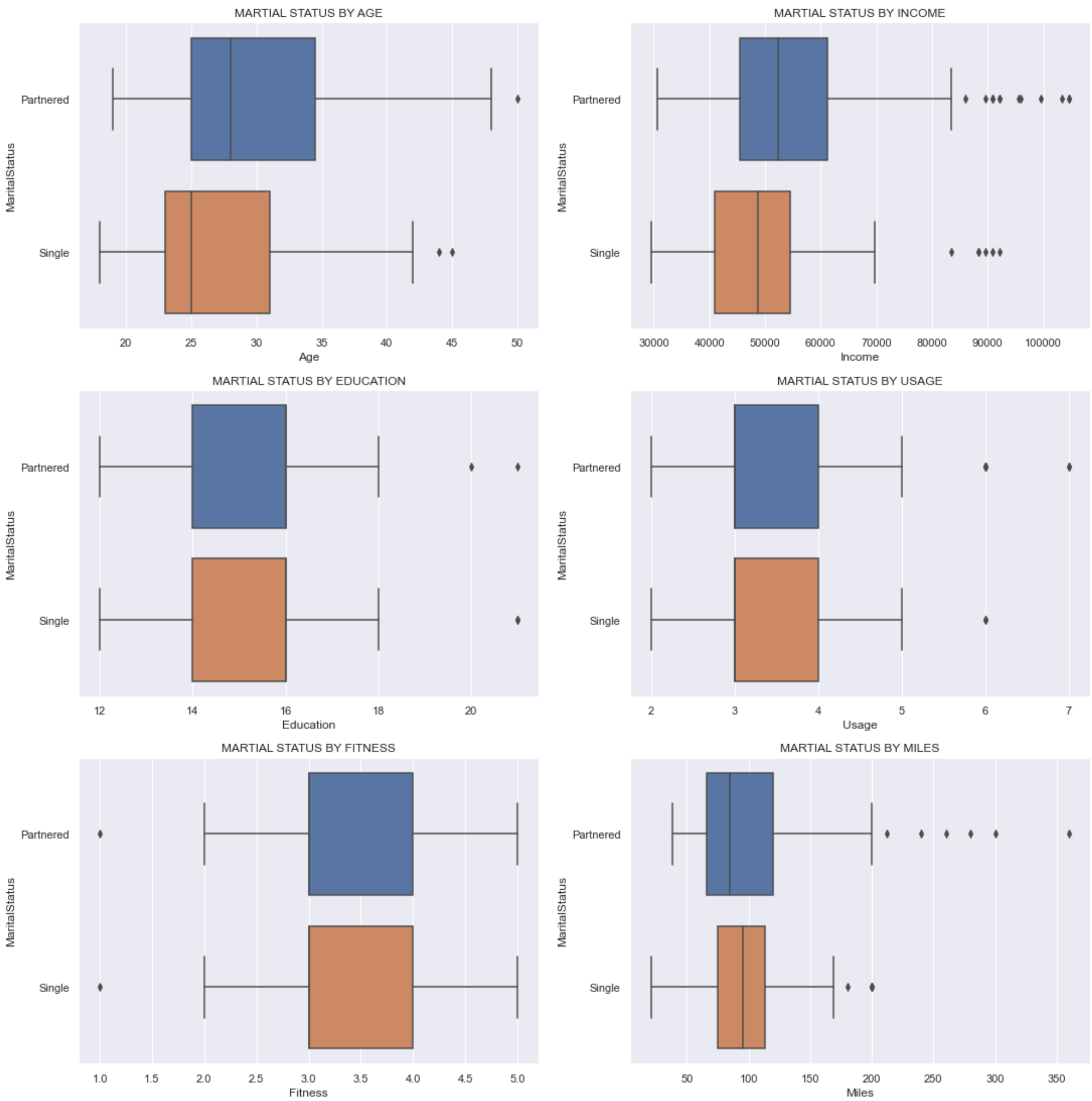
1. Male customers earn more than Female customers.
2. Males Customer have higher self rated fitness than female.
3. Expected Usage and miles covered on tread mill is less in Female customers than male customers.
4. Female in age range 23-33 purchased the treadmill.
5. Education of Male and Female customers is same.

# BIVARIATE ANALYSIS FOR MARITAL STATUS AND REST OF THE FEATURES

In [426]:

```
#Bi Varaite Analysis for
#1.Martial Status & Age
#2.Martial Status & Income
#3.Martial Status & Education
#4.Martial Status & Usage
#5.Martial Status & Fitness
#6.Martial Status & Miles
plt.figure(figsize=(7,7))
fig1, axes1 =plt.subplots(3,2,figsize=(18, 19))
list1_col=['Age','Income','Education','Usage','Fitness','Miles']
for i in range(len(list1_col)):
    row=i//2
    col=i%2
    ax=axes1[row,col]
    sns.boxplot(df[list1_col[i]],df['MaritalStatus'],ax=ax).set(title='MARTIAL STATUS BY '
```

<Figure size 504x504 with 0 Axes>

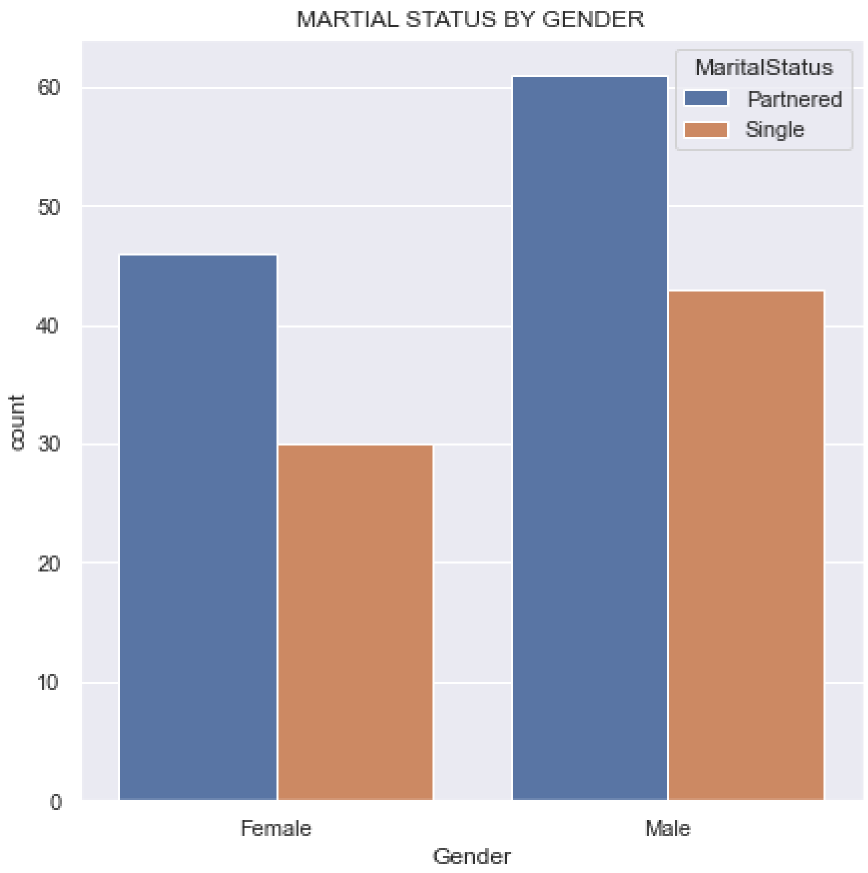


In [427]:

```
plt.figure(figsize=(7,7))
sns.countplot(df['Gender'],hue=df["MaritalStatus"]).set(title='MARTIAL STATUS BY GENDER')
```

Out[427]:

```
[Text(0.5, 1.0, 'MARTIAL STATUS BY GENDER')]
```




# Observations

1. Partnered customer expects to run more miles compared to single
2. Income of Partnered customer is more than income of single customer.
3. Age of Partnered customer is more than Age of single customer
4. There are more single males buying Treadmill than single Females
5. Self rated Fitness of both Partnered and Single customer are same.
6. Education of both Partnered and Single customer is same

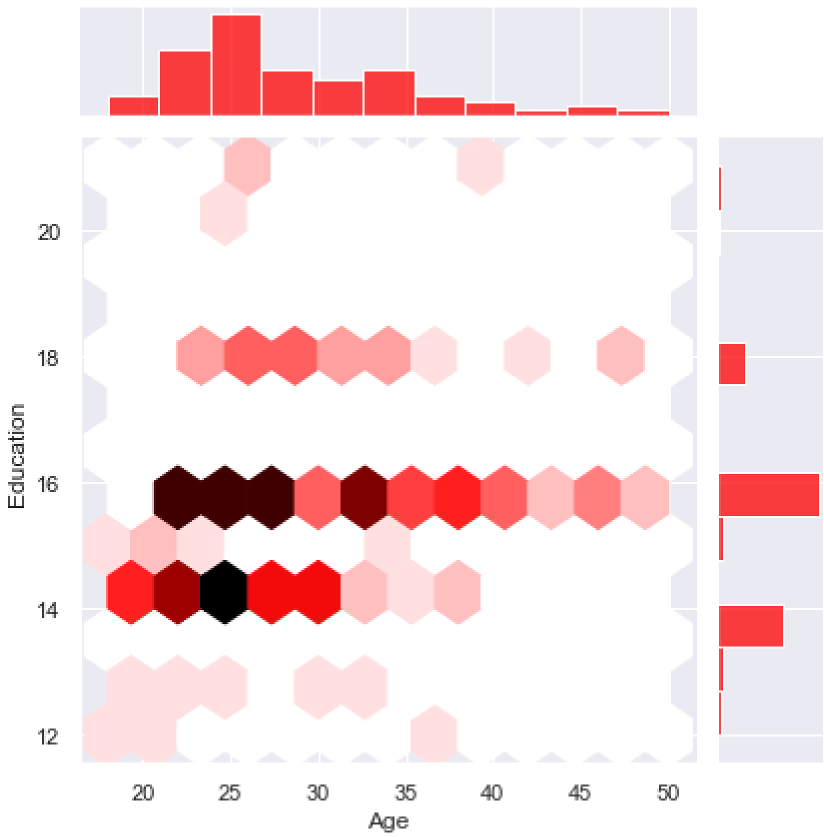
# JOINT PLOT AGE VS ECUCATION

In [428]:

```
#Bivariate Analysis Age & Education
sns.jointplot(x = 'Age',y = 'Education',data = df,color="red",kind='hex')
```

Out[428]:

```
<seaborn.axisgrid.JointGrid at 0x2a92115e820>
```




# Observation:-

1. Customer between age 20-40 have 14 -16 years of education

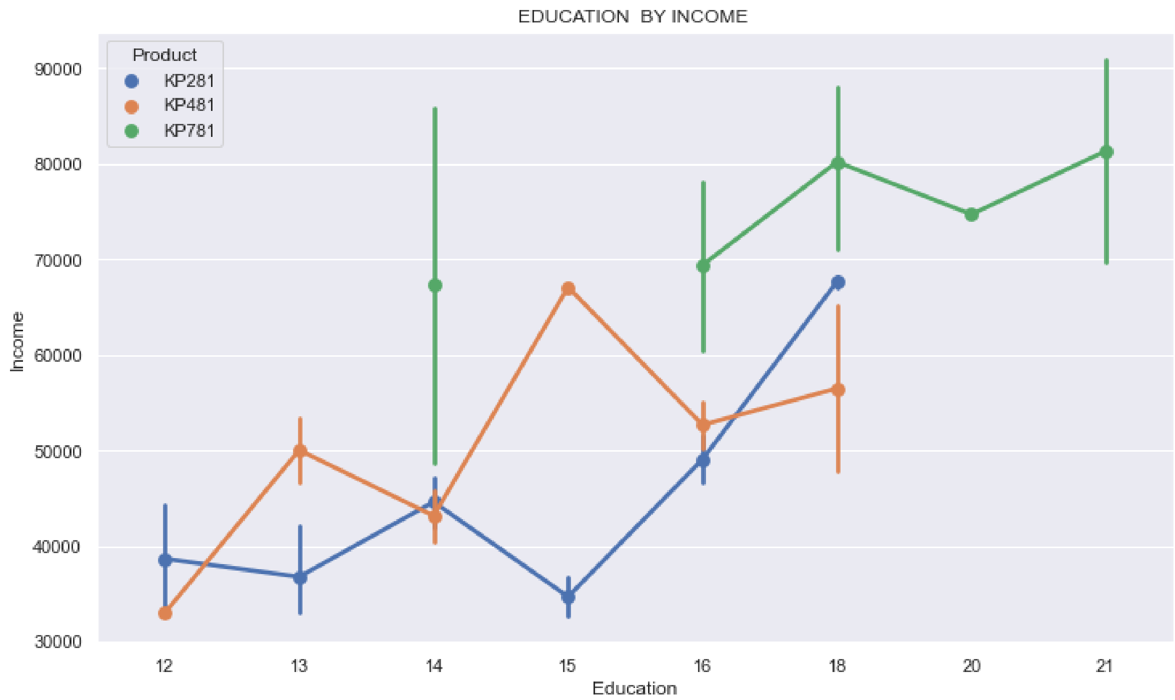
# POINTPLOT VS EDUCATION VS INCOME

In [429]:

```
plt.figure(figsize=(12,7))
sns.pointplot(x=df["Education"],y=df["Income"],hue=df['Product']).set(title='EDUCATION  BY
```

Out[429]:

```
[Text(0.5, 1.0, 'EDUCATION  BY INCOME ')]
```




# Observation:-

1. ducation and Income are correlated.
2. KP781 has higher income and higher education

# MULTIVARIATE ANALYSIS

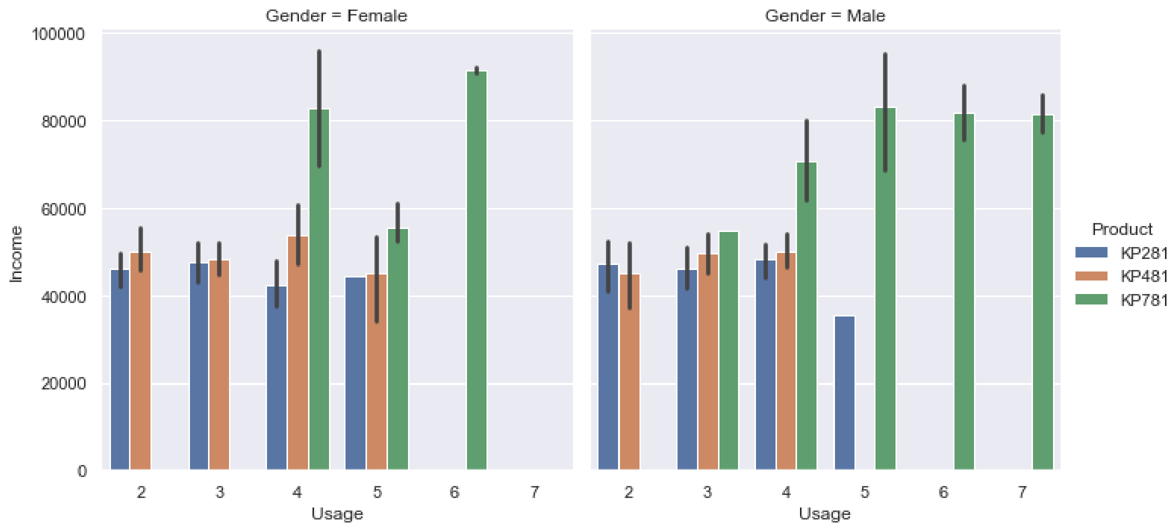
In [430]:

```
# Multivariate Analysis
plt.figure(figsize=(12,7))
sns.catplot(x='Usage', y='Income', col='Gender',hue='Product' ,kind="bar", data=df)
```

Out[430]:

```
<seaborn.axisgrid.FacetGrid at 0x2a9192575b0>
```

```
<Figure size 864x504 with 0 Axes>
```




# Observations

1. Male customer with higher income ,bought kp 781 Model and expect to use treadmill 4-6 /week
2. Customer who bought kp 281 and kp 481 are in same income range and expect to use treadmill 3-4 /week

# product vs marital status vs gender realtionship

In [431]:

```
prd_mar_gen= pd.crosstab(index=df["Product"],
                         columns=[df["MaritalStatus"],
                                  df["Gender"]] ,
                         )
prd_mar_gen
```

Out[431]:

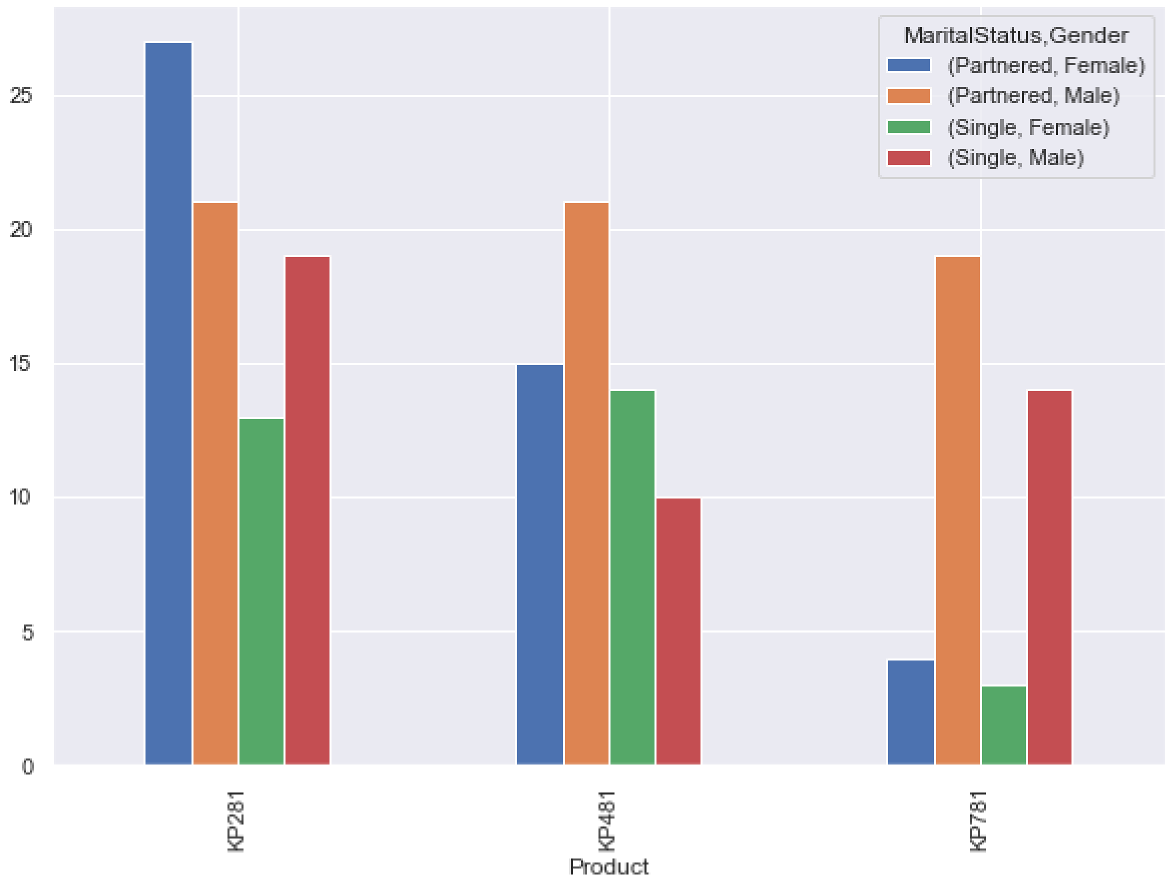
| MaritalStatus | Partnered | | Single | |
|---|---|---|---|---|
| Gender | Female | Male | Female | Male |
| Product | | | | |
| KP281 | 27 | 21 | 13 | 19 |
| KP481 | 15 | 21 | 14 | 10 |
| KP781 | 4 | 19 | 3 | 14 |

In [432]:

```
prd_mar_gen.plot(kind='bar',figsize=(10,7))
```

Out[432]:

<AxesSubplot:xlabel='Product'>




# observation :

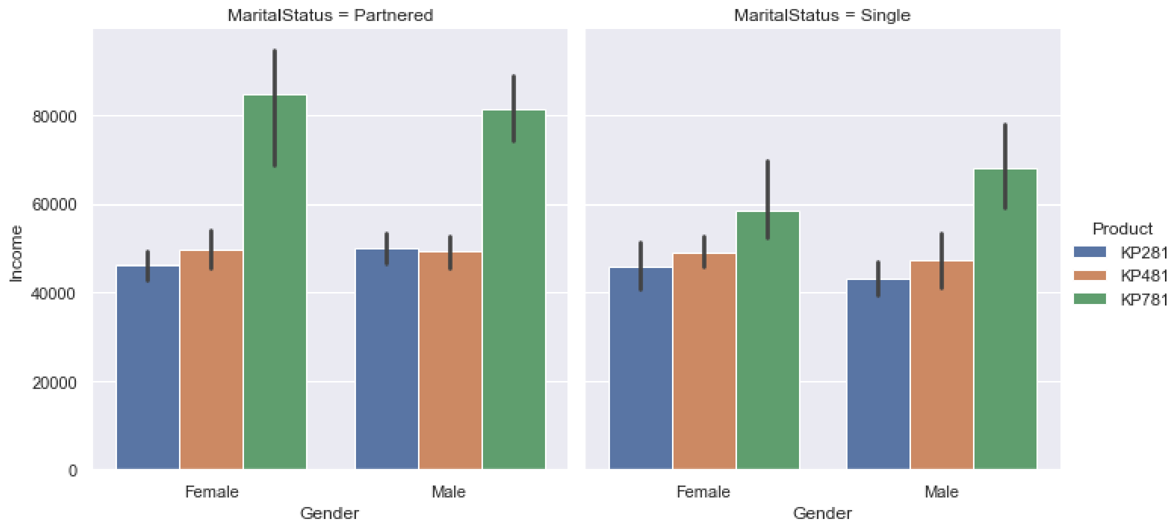
1. PARTERNED FEMALE BUYED THE KP281

2. SINGLE MALE BROUGHT THE KP781 MODEL.

# CATEGORICAL PLOT GENDER VS INCOME

In [433]:

```
# Income by gender by product and by marital status
sns.catplot(x='Gender',y='Income', hue='Product', col='MaritalStatus', data=df,kind='bar');
```




# Observations

1. Partnered Female bought kp 281 Model compared to Partnered male.
2. Single Female customers bought kp 481 model more than Single male customers.
3. Partnered Male customers bought kp 781 model more than Single Male customers.
4. There are more single males buying Treadmill than single Females.
5. Single Male customers bought kp 281 Model compared to Single Female.
6. Majority of people who buy the kp 781 are man & partnered.
7. The majority of our buyers are man.

# PRODUCT VS GENDER VS FITNESS RELATIONSHP

In [434]:

```
prod_gen_fit=pd.crosstab(index=df['Product'],columns=[df['Gender'],df['Fitness']])
prod_gen_fit
```

Out[434]:

| Gender | Female | | | | | Male | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fitness | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| Product | | | | | | | | | | |
| KP281 | 0 | 10 | 26 | 3 | 1 | 1 | 4 | 28 | 6 | 1 |
| KP481 | 1 | 6 | 18 | 4 | 0 | 0 | 6 | 21 | 4 | 0 |
| KP781 | 0 | 0 | 1 | 1 | 5 | 0 | 0 | 3 | 6 | 24 |

# OBS :

1. KP 281 HAS FEMALE WITH 3 FITNES AND MALE WITH 3 FITNESS HIGHEST
2. KP 781 HAS MALE WITH 5 FITNESS HIGHEST

# RELATIVE PLOT BETWEEN INCOME AND AGE

In [435]:

```
#scatter plot between income, age ,product and usage
sns.relplot(x="Age", y="Income", hue="Product", size="Usage",
            sizes=(40, 400), alpha=.5, palette="plasma",
            height=6, data=df).set(title='INCOME BY AGE ,PRODUCT AND USAGE');
```


# Observations:

1. Products KP281 and KP481 are bought by people with lower than 70K as income and age is concentrated more in range of 23-35
2. Product KP781 is mainly bought by people with higher than 70K income and age falls in range of 23-30.
3. Majority of people who buys the KP781 expect that they will run more than consumers of the other two products, on average.

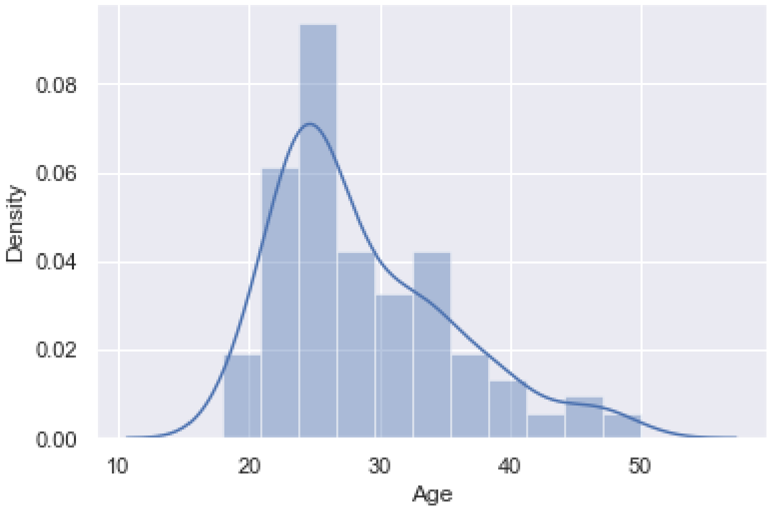
# DIST PLOT OF AGE

In [436]:

```
sns.distplot(df['Age'])
```

Out[436]:

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



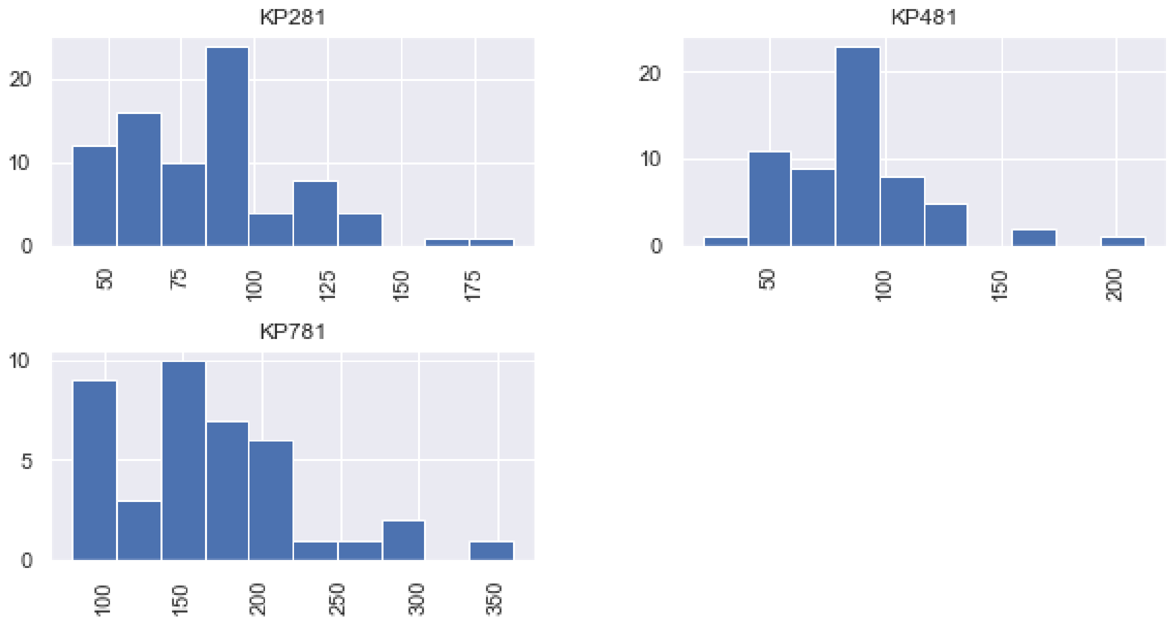

# HIST PLOT OF MODELS KP 281 KP481 AND KP 781 BY MILES

In [437]:

```
df.hist(by='Product',column = 'Miles', figsize=(10,5))
```

Out[437]:

```
array([[<AxesSubplot:title={'center':'KP281'}>,
        <AxesSubplot:title={'center':'KP481'}>],
       [<AxesSubplot:title={'center':'KP781'}>, <AxesSubplot:>]],
      dtype=object)
```




In [438]:

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

Out[438]:

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

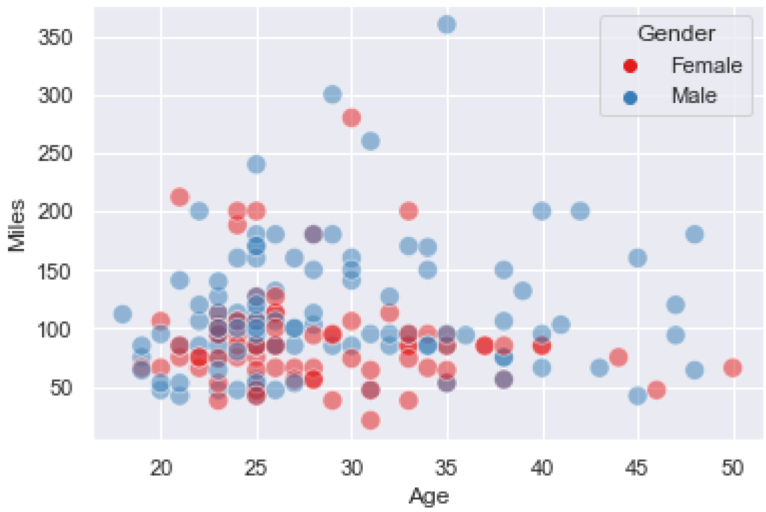
# SCATTERPLOT

In [439]:

```
sns.scatterplot(data=df,x='Age',y='Miles',hue='Gender',palette='Set1',s=100,alpha=0.5)
```

Out[439]:

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



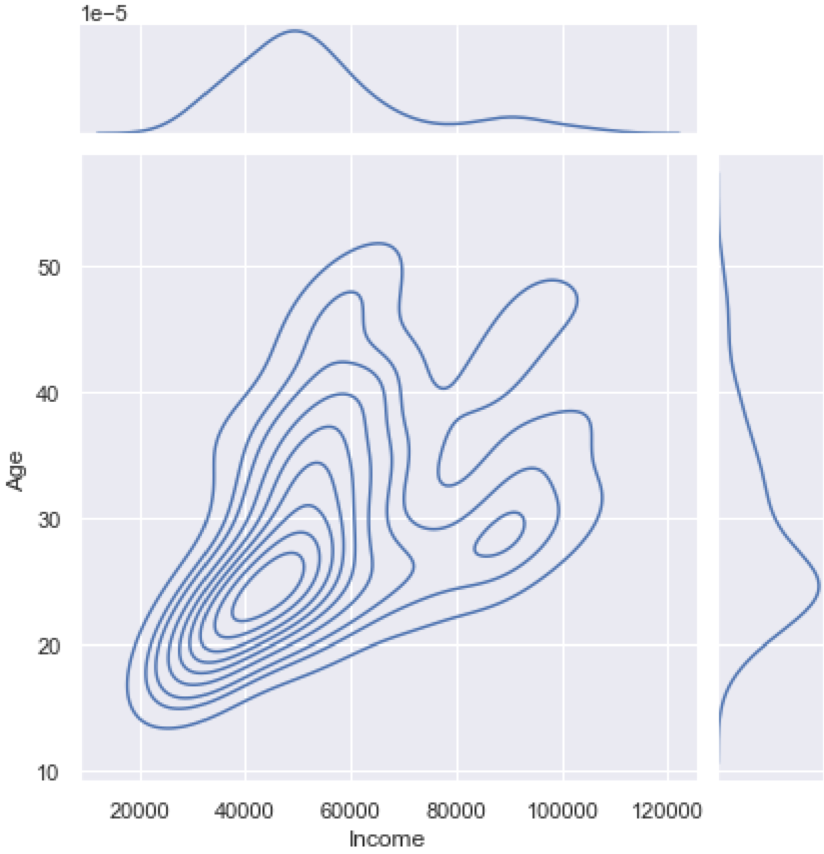

# JOINT PLOT

In [440]:

```
sns.jointplot(data=df,x='Income',y='Age',kind='kde')
```

Out[440]:

<seaborn.axisgrid.JointGrid at 0x2a925dcedc0>



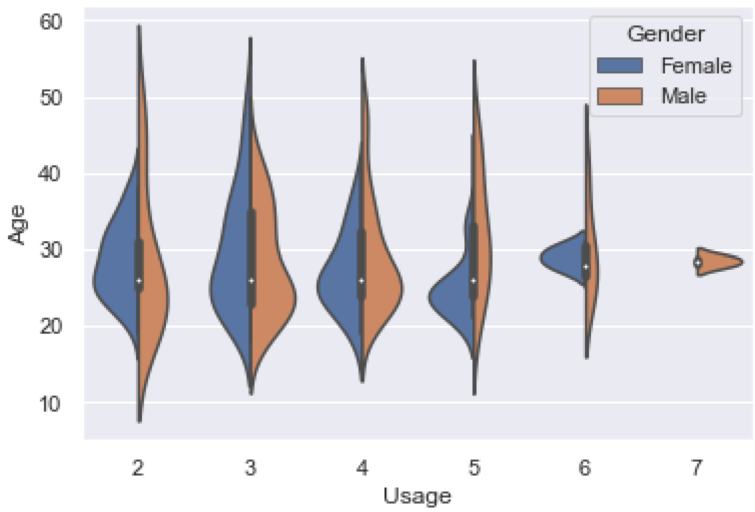
# VIOLIN PLOT

In [441]:

```
sns.violinplot(x='Usage',y='Age',data=df,split=True,hue='Gender')
```

Out[441]:

```
<AxesSubplot:xlabel='Usage', ylabel='Age'>
```

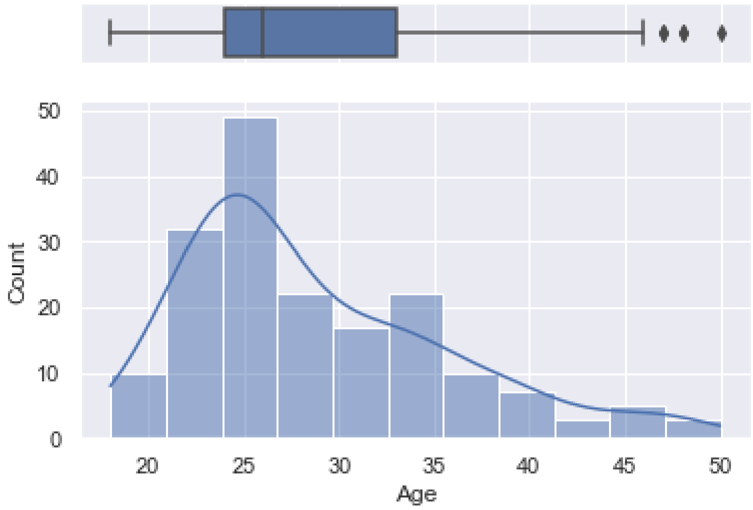



# OUTLIER DETECTION

# BOXPLOT FOR OUTLIER DETECTION OF AGE AND HISTPLOT AND DISTPLOT

In [442]:

```
sns.set(style="darkgrid")
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (.15, .85
sns.boxplot(data=df,x='Age', ax=ax_box)
sns.histplot(data=df, x="Age", ax=ax_hist,kde=True)
ax_box.set(xlabel='')
plt.show()
```




# FINDING OUTLIER BY FINDING UPPER AND LOWER LIMITS OF AGE COLUMN

In [443]:

```
# Treating Outliers
Q3 = df['Age'].quantile(0.75)
Q1 = df['Age'].quantile(0.25)
IQR = Q3-Q1
upper = Q3+(1.5*IQR)
lower = Q1-(1.5*IQR)
print(upper,lower)
```

```
46.5 10.5
```

# REMOVE AGE OUTLIERS

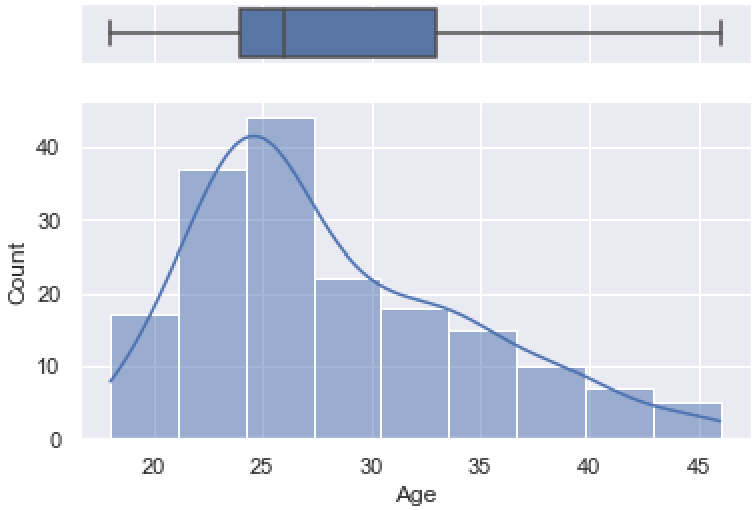
In [444]:

```
df = df[(df['Age']>lower) & (df['Age']<upper)]
```

# NEW GRAPH WITHOUT AGE OUTLIERS

In [445]:

```
sns.set(style="darkgrid")
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (.15, .85
sns.boxplot(data=df,x='Age', ax=ax_box)
sns.histplot(data=df, x="Age", ax=ax_hist,kde=True)
ax_box.set(xlabel='')
plt.show()
```



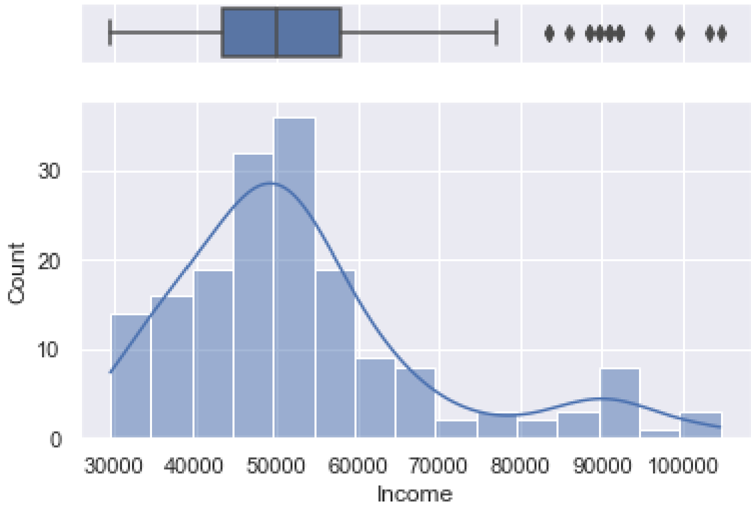

# OBSERVATIONS :

1. Mean age of the buyers is aroud 26
2. 25% of the age is around 25
3. 75% of the age is around 33

# OUTLIER DETECTION FOR INCOME

In [446]:

```
sns.set(style="darkgrid")
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (.15, .85
sns.boxplot(data=df,x='Income', ax=ax_box)
sns.histplot(data=df, x="Income", ax=ax_hist,kde=True)
ax_box.set(xlabel='')
plt.show()
```




# FINDING OUTLIER BY FINDING UPPER AND LOWER LIMITS OF INCOME COLUMN

In [447]:

```
# Treating Outliers
Q3 = df['Income'].quantile(0.75)
Q1 = df['Income'].quantile(0.25)
IQR = Q3-Q1
upper = Q3+(1.5*IQR)
lower = Q1-(1.5*IQR)
print(upper,lower)
```

```
80158.5 21034.5
```

# REMOVE AGE OUTLIERS

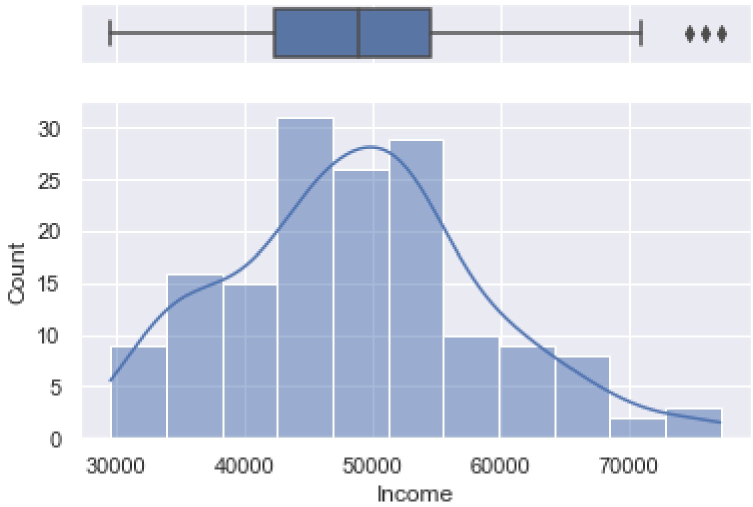
In [448]:

```
df = df[(df['Income']>lower) & (df['Income']<upper)]
```

# NEW GRAOH OF INCOME POST OUTLIER REMOVAL

In [449]:

```
sns.set(style="darkgrid")
f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (.15, .85
sns.boxplot(data=df,x='Income', ax=ax_box)
sns.histplot(data=df, x="Income", ax=ax_hist,kde=True)
ax_box.set(xlabel='')
plt.show()
```



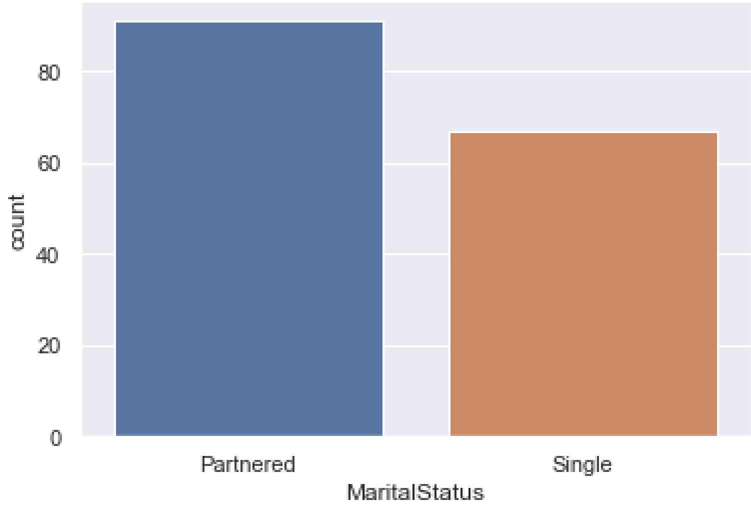

# OBSERVATIONS :

1. Mean income of the buyers is around 50000
2. 25% of the buyers earn around 42000 and 75% around 54000
3. There are few outliers having income above 70000

# COUNTPLOT OF MARITAL STATUS

In [450]:

```
sns.countplot(data=df,x='MaritalStatus')
plt.show()
```




In [ ]:

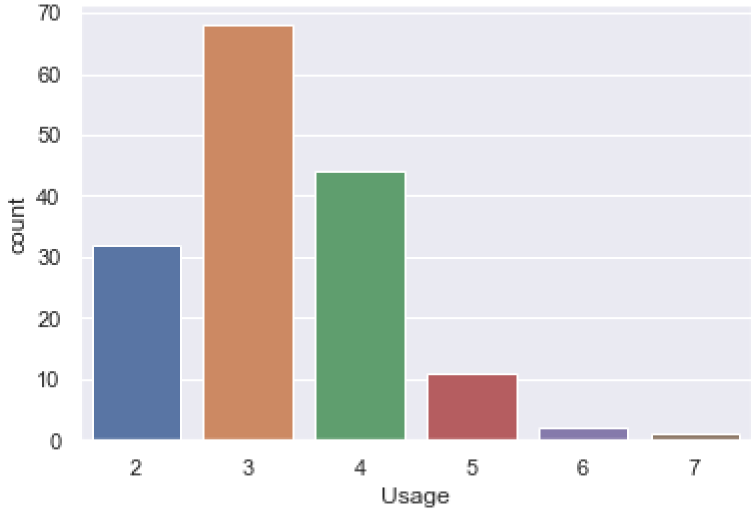
```

```

# COUNT PLOT OF USAGE

In [451]:

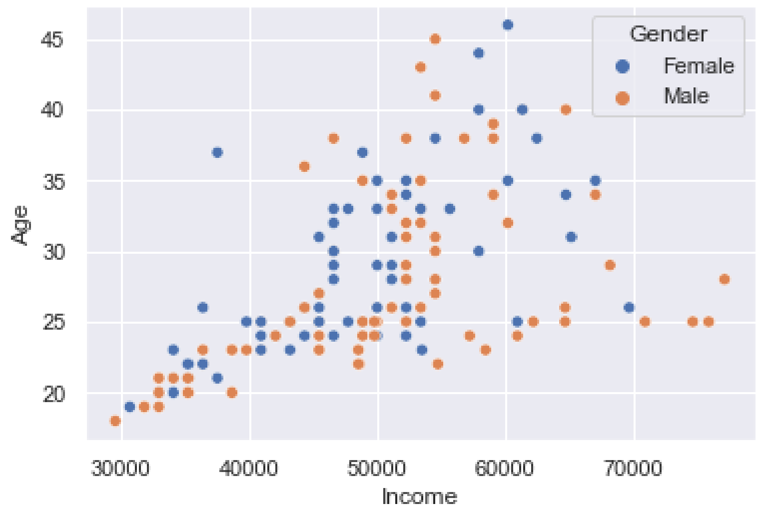
```
sns.countplot(data=df,x="Usage")
plt.show()
```




# SCATTERPLOT OF INCOME VS AGE

In [452]:

```
sns.scatterplot(data=df,x='Income',y='Age',hue='Gender')
plt.show()
```



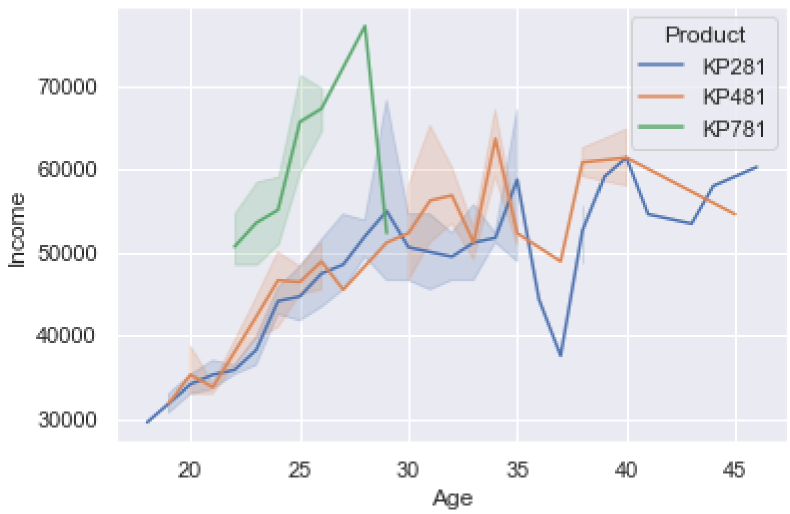

# OBSERVATION :

1. Most of the women earns less than males
2. We can see a positive trend which means as age increases the income increases

# LINE PLOT OF AGE VS INCOME

In [453]:

```
sns.lineplot(data=df,x='Age',y='Income',hue="Product")
plt.show()
```



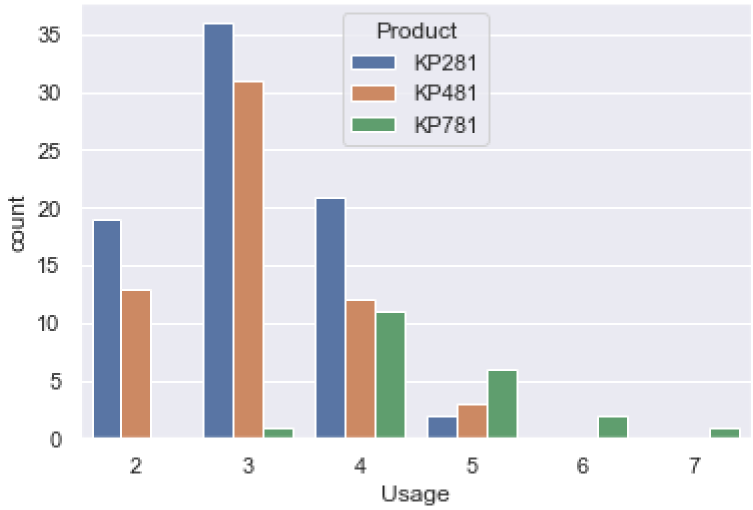
# OBSERVATIONS

1.From earlier graph we saw that persons with higher income buys more KP781 and with age income increases, but with closer look we can see that more income people with less age is buying the KP781 more KP481 and KP281 is more or the same across various buyers

# COUNT PLOT OF USAGE VS PRODUCT

In [454]:

```
sns.countplot(data=df,x="Usage",hue="Product")
plt.show()
```



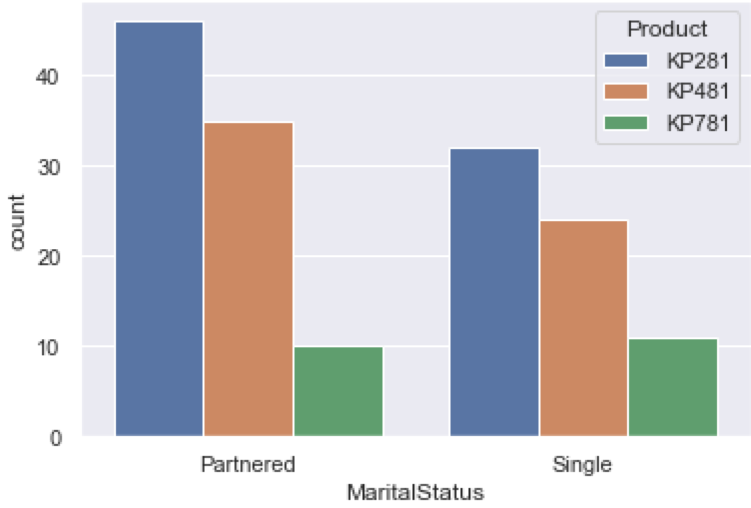

# OBSERVATIONS :

1. Most of the buyers are have a usage rating 2,3 or 4
2. KP281 is more bought by the buyers with usage rating less than 4
3. KP781 is more bought by the users with usage more than 4

# COUNT PLOT MARITAL STATUS VS PRODUCT

In [455]:

```
sns.countplot(data=df,x='MaritalStatus',hue="Product")
plt.show()
```




# OBSERVATIONS :

1. Most of the buyers are Partnered
2. And among both the Status we can see there is a same trend kp 281 most favourable and kp 781 is leastv

# NUMBER OF CUSTOMER PER MARITAL STATUS ABD GENDER AND PRODUCT

In [456]:

```
df.groupby(['MaritalStatus','Gender','Product']).Usage.count()
```

Out[456]:

```
MaritalStatus  Gender  Product
Partnered      Female  KP281      26
                       KP481      15
                       KP781       1
               Male    KP281      20
                       KP481      20
                       KP781       9
Single         Female  KP281      13
                       KP481      14
                       KP781       3
               Male    KP281      19
                       KP481      10
                       KP781       8
Name: Usage, dtype: int64
```

# NUMBER OF CUSTOMER GENDER AND PRODUCT

In [457]:

```
df.groupby(['Gender','Product'])['Usage'].count()
```

Out[457]:

```
Gender  Product
Female  KP281      39
        KP481      29
        KP781       4
Male    KP281      39
        KP481      30
        KP781      17
Name: Usage, dtype: int64
```

# OBSERVATIONS -

1. KP481 is bought more by Single females
2. KP281 remains good choice for Partnered females
3. A partnered male is equally likely to buy KP281 and KP481
4. Single male is more likely to buy either KP281 or KP481

# CUSTOMER PROFILING

# Age

1. Age is skewed towards right.
2. Customers buying treadmill after age of 40 and before 20 are very less.

# Education

3. Most customers have 16 years of Education.
4. There are few outliers (higher end).

# Usage

5. Most user loves to use Treadmills 3-4 times/week.
6. There are few outliers (higher end).

# Fitness

7. Most customer have 3-3.5 fitness rating (moderate fit).
8. Very few customers that uses treadmill have low score i.e 1. that a great news ;).

# Income

9. Income is skewed toward right.
10. Income may have outliers (higher end) as there are very few persons who earn >80k.
11. Most customers have income less than 70k.

### Miles

12. Miles is skewed towards right.
13. Customers run on an average 80 miles per week.
14. There are some outliers, where customers are expecting to run more than 200 miles per week.

# Customer Profiles MODEL WISE

## For model KP 281

1. Customers who bought this treadmill have income less than 60k with an average of 55K.
2. This model has same level of popularity in Male customers as well as Female customers as it has same numbers of Male and Female customers.
3. Average age of customer who purchases KP 281 is 28.5.
4. This model is popular among Bachelors as average years of education of customers for this product is 15.
5. Self rate fitness level of customer is average.
6. Customers expect to use this treadmill 3-4 times a week.
7. It is the most popular model (in all genders) because of its appealing price and affordability with 33.3% of sales.
8. Customers who bought this treadmill want fitness level atleast average and maybe they were looking for a basic treadmill with appealing price that also does the job.

## For model KP 481

1. This model is second most sold model with 33.3% of sales.
2. Customers with lower income purchase KP281 and KP481 model may be because of lower cost of the Treadmill.
3. Average age of customer who purchases KP481 is 29.
4. This model is popular among Bachelors as average years of education of customers for this product is 16.
5. Customers expecting KP 481 model to use less frequently but to run more miles per week on this.
6. This model is popular more in Single Female customers compare to Single male customers may be because of difference in provided features or color scheme.

## For model KP 781

1. This is the least sold product(22.2% sales) in company lineup of Treadmill may be because of it heafty price range making it Company's Premium product.
2. This model is popular with customers having high income range as average Income is 75K .
3. Average age of customer who purchases KP 781 is 29.
4. This model is popular among Customers with higher education as average education is 17 years.
5. Treadmill may have some advanced features as people with high income are ready to spend money to buy this model
6. Customers expected usage on this model is 4-5 day a week with moderate Miles to run having average 166 miles per week.
7. Male customers who are more serious about fitness or Professionals buy this mode (self fitness rating 3-5).

# OTHER OBSERVATIONS :

1. Partnered Female bought kp 281 Model compared to Partnered male.
2. Partnered Male customers bought KP 281 & KP 781 models more than Single Male customers.
3. Single Female customers bought KP 481 model more than Single male customers.
4. Single Male customers bought KP 281 & KP 781 models compared to Single females.
5. The majority of treadmill buyers are man.

## Conclusion :

6. KP 281 model is the most purchased model (44.4%) then KP 481 (33.3%). KP 781 is the least sold model (22.2%).
7. There are more Male customers (57.8%) than Female customers (42.2%).
8. Average Usage of Males is more than Average usage of Females.
9. Customers buying treadmill are younger and average age of customer is 28.
10. Most of the customers earns less than 70K and prefer KP 281 & KP 481 models.
11. 59.4% of the customers who purchased treadmill are partnered.
12. Customers average education is 16.

# RECOMMENDATIONS

1. TARGET LOW INCOME PARTNERED FEMALES AND TARGET THEM FOR KP 281 MODELS.
2. CUSTOMER HAVING 3 FITNESS RATING SHOULD BE TARGET FOR KP 281 MODELS
3. KP 781 MODELS SHOULD BE TARGERED FOR HIGH INCOME PARTENRED 5 FITNESS LEVEL MALES
4. IRRESPECTIVE GENDER SCEANRIO, KP 281 IS THE BEST MODEL TO SUIT THE MAJORITY CUSTOMERS
5. EDUCATION WITH 14 TO 16 YEARS HAVE TENDENCY TO BUY MORE OF KP 281 MODELS

# Recommendations For Better Insights:

1. Look at profit by product model to better understand sales percentages
2. Gather information on fitness goals: lose weight, better cardio health, maintain, etc.
3. Gather information on partner to gain second half of story on partnered customers.

# To Target New Customers:

1. For KP 281: Concentrate advertising broadly across gender and marital status towards individuals with annual income less than $75,000, with some college education or a bachelor’s degree, who are unfit or average fitness and in their 20s or 30s.
2. For KP 481 : Concentrate advertising broadly across gender and marital status towards individuals with annual income less than $75,000, with some college education or a bachelor’s degree, who are unfit or average fitness and in their 20s or 30s.
3. For KP 781: Concentrate advertising towards males who are average fitness to very fit, have a bachelors degree or advanced education, and are in their 20s or 30s.
4. There may be untapped potential for targeting customers in the 40s and beyond age group, which appear to be an underserved population. Analysis indicates more than just outlying purchases of KP 781 .
5. Individuals with only a high school education also appear to be an underserved population. Likely best candidates for KP 281 or KP 481 due to annual income constraints.

In [ ]:

```

```