Business Problem Statement

The market research team at AeroFit wants to identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics.

```
1.Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate  tables and charts.
2.For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.
```

In [3]:
```python
# Load  library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Create DataFrame for aerofit data

In [4]:
```python
# Load data and convert to dataframe
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmill.
```

Exploratory analysis of data

Insight :

```
- 9 Columns and 180 rows are available in the data.
- 3 Columns are with Object data type and remaining columns are with INT data type
- Data doesnt contain any null values in it
```

In [5]:
```python
df.sample(10)
```

Out[5]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
138	KP481	45	Male	16	Partnered	2	2	54576	42
108	KP481	26	Female	16	Partnered	4	3	45480	85
170	KP781	31	Male	16	Partnered	6	5	89641	260
61	KP281	34	Male	16	Single	4	5	51165	169
176	KP781	42	Male	18	Single	5	4	89641	200
72	KP281	39	Male	16	Partnered	4	4	59124	132
1	KP281	19	Male	15	Single	2	3	31836	75
29	KP281	25	Female	14	Partnered	2	2	53439	47
93	KP481	23	Male	16	Partnered	3	3	45480	64
39	KP281	26	Male	16	Partnered	4	4	44343	132

Count, NUnique value and other statistical values are available below

Observations :

```
1. Age : 50% data lie between 24 to 33 of age and with a median of 26
2. Education : 50% data lie between 14 to 16 year of education and with a median of 16
3. Usage : 50% data lie between 3 to 4 per week and with a median of 3
4. Fitness : 50% data lie between 3 to 4 self rated fitness and with a median of 3
5. Income : 50% data lie between $44058.75 to $58668.0 and with a median of $50596.5
6. Miles : 50% of data lie between 66 miles/week to 114.75 miles/week and median of 94 miles/week
7. Income and Miles column more standard deviation when compared to other columns
```

In [6]:
```python
# Exploraotory analysis of all columns
df.describe(include = 'all').T
```

Out[6]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Product	180	3	KP281	80	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Age	180.0	NaN	NaN	NaN	28.788889	6.943498	18.0	24.0	26.0	33.0	50.0
Gender	180	2	Male	104	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Education	180.0	NaN	NaN	NaN	15.572222	1.617055	12.0	14.0	16.0	16.0	21.0
MaritalStatus	180	2	Partnered	107	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Usage	180.0	NaN	NaN	NaN	3.455556	1.084797	2.0	3.0	3.0	4.0	7.0
Fitness	180.0	NaN	NaN	NaN	3.311111	0.958869	1.0	3.0	3.0	4.0	5.0
Income	180.0	NaN	NaN	NaN	53719.577778	16506.684226	29562.0	44058.75	50596.5	58668.0	104581.0
Miles	180.0	NaN	NaN	NaN	103.194444	51.863605	21.0	66.0	94.0	114.75	360.0

Null values are not available in data

In [7]:
```python
# checking for null values
df.isna().sum()
```

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

In [8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Product        180 non-null    object
 1   Age            180 non-null    int64 
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64 
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64 
 6   Fitness        180 non-null    int64 
 7   Income         180 non-null    int64 
 8   Miles          180 non-null    int64 
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

In [9]:
```python
print('Shape of dataframe is', df.shape)
print('no of elements of dataframe is', df.size)
print('dimension of dataframe is', df.ndim)
print('number of rows is ', len(df))
```

```
Shape of dataframe is (180, 9)
no of elements of dataframe is 1620
dimension of dataframe is 2
number of rows is  180
```

Conversion categorical column to category datatype

Insight :

    Product, Gender and Maritalstatus columns need to be converted to 'Category' datatype from Object datatype.

In [10]:
```python
df['Product'] =df['Product'].astype(dtype = 'category')
df['Gender'] = df['Gender'].astype(dtype = 'category')
df['MaritalStatus'] = df['MaritalStatus'].astype(dtype = 'category')
```

In [11]:
```
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    category
 1   Age            180 non-null    int64   
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64   
 4   MaritalStatus  180 non-null    category
 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: category(3), int64(6)
memory usage: 9.5 KB
```

2. Non-Graphical and Graphical Analysis

Product column

Insight :

    - Only 3 types of product are available in data - KP281, KP481, KP781
    - Out of total sales, 44% of sales are from KP281 treadmill
    - Least selling treadmill is KP781

Recommendation:

    - Most of the people prefer to buy KP281, provide attractive offer like warrantly extension ...etc and even rent
    ing these machine with monthly charges.
    - For KP781, To increase sales for this product - Experience center to added, so that user can do trial run of t
    his product and with demo can be provided to boost sales.

In [12]:
```
# Marginal Probability
np.round(df['Product'].value_counts(normalize = True)*100,2)
```

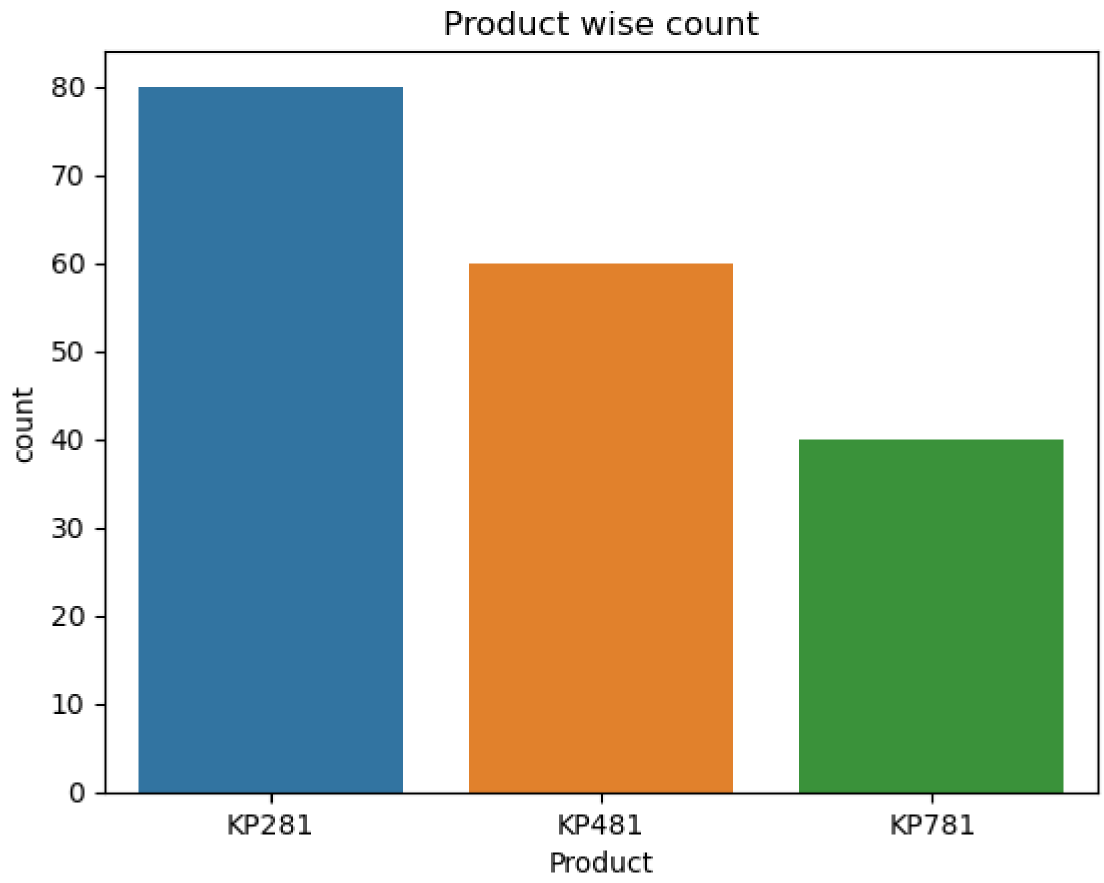
Out[12]:
```
KP281    44.44
KP481    33.33
KP781    22.22
Name: Product, dtype: float64
```

In [13]:
```
df['Product'].unique()
```

Out[13]:
```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

In [14]:
```python
# Product column
sns.countplot(data = df, x = 'Product')
plt.title('Product wise count')
```

Out[14]: Text(0.5, 1.0, 'Product wise count')



Gender Column

Insight :

```
- Out of total user buying, ~58% of sales are from Males.
- Unique values --> Male and Female
```

Recommendation:

```
- Most of the Males prefer to buy treadmill and provides goodies for completion of particular miles. This will e
ncourage user both Male and Females to use Treadmill frequency and even sales will increase.
```

In [15]:
```python
# Marginal Probability
np.round(df['Gender'].value_counts(normalize = True)*100,2)
```

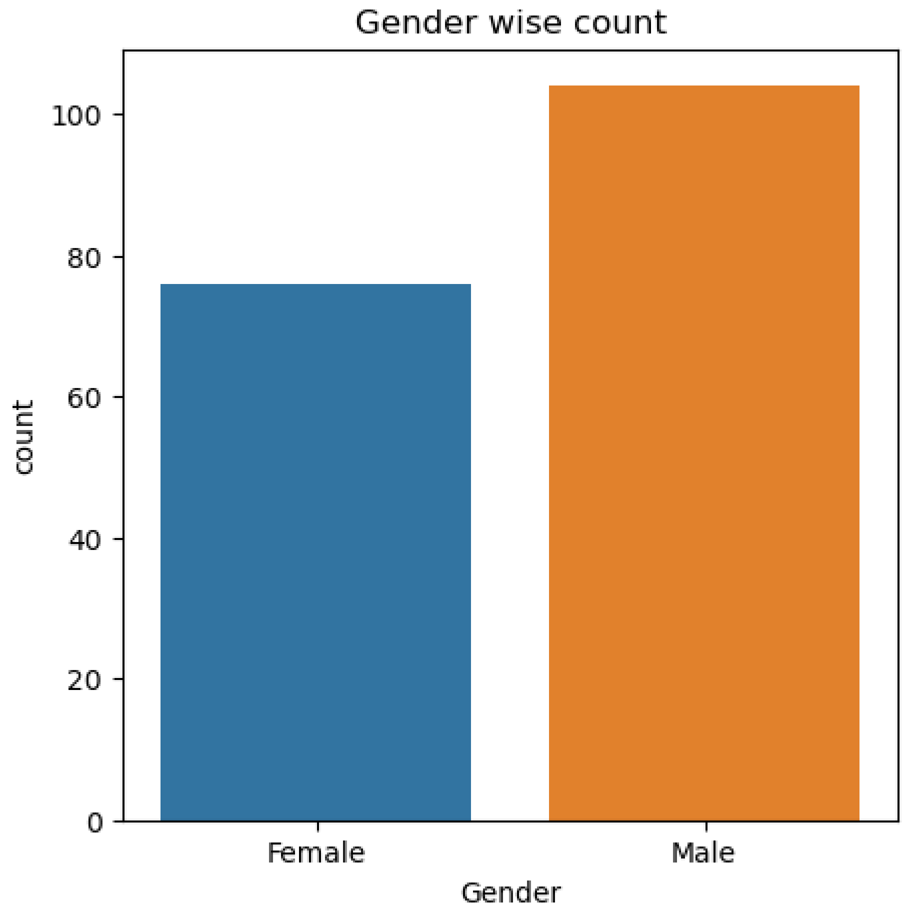
Out[15]:
```
Male      57.78
Female    42.22
Name: Gender, dtype: float64
```

In [16]:
```python
df['Gender'].unique()
```

Out[16]:
```
['Male', 'Female']
Categories (2, object): ['Female', 'Male']
```

In [17]:
```
# Gender column
plt.figure(figsize = (5,5))
sns.countplot(data = df, x = 'Gender')
plt.title('Gender wise count')
```

Out[17]: Text(0.5, 1.0, 'Gender wise count')



MaritalStatus Column

Insight :

    - Out of total user buying, 59% of sales are from Partnered.
    - Unique values --> Partnered and Single.

Recommendation:

    - Most of the Partnered prefer to buy treadmill. So, if we provide discount of 2 treadmill who will purchase at same time. Partnered users can have 2 treadmill with discount on it.

In [18]:
```
# Marginal Probability
np.round(df['MaritalStatus'].value_counts(normalize = True)*100,2)
```

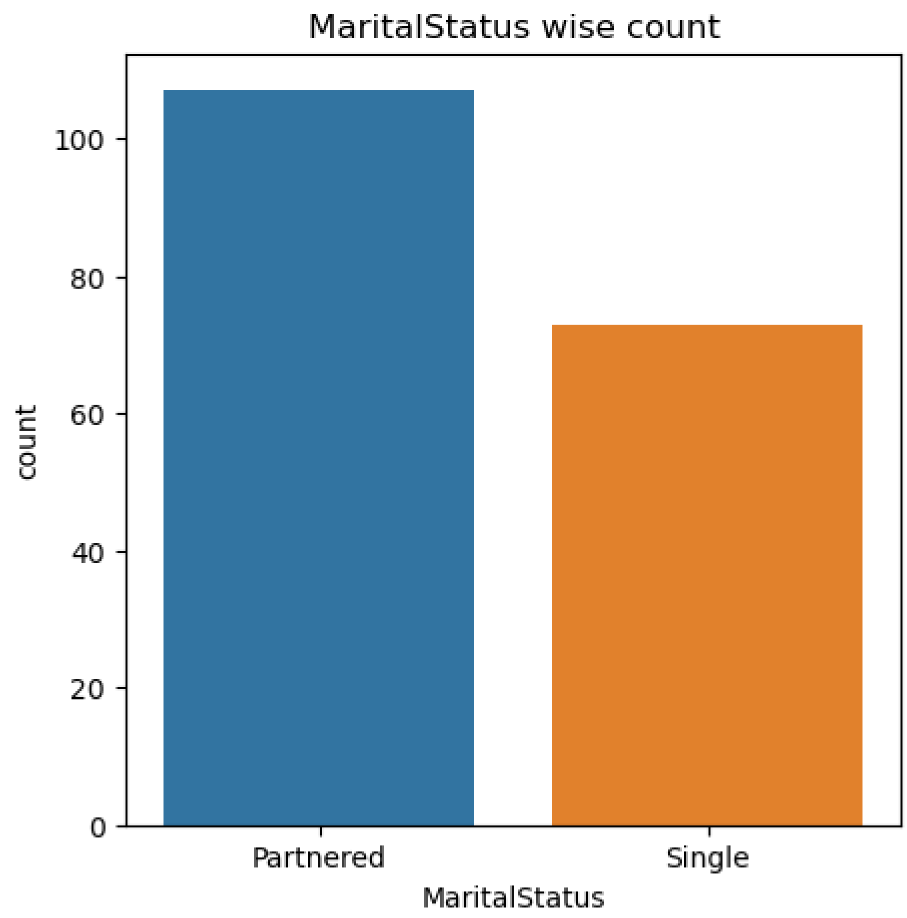
Out[18]:
```
Partnered    59.44
Single       40.56
Name: MaritalStatus, dtype: float64
```

In [19]:
```
df['MaritalStatus'].unique()
```

Out[19]:
```
['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
```

In [20]:
```
# MaritalStatus column
plt.figure(figsize = (5,5))
sns.countplot(data = df, x = 'MaritalStatus')
plt.title('MaritalStatus wise count')
```

Out[20]: Text(0.5, 1.0, 'MaritalStatus wise count')



Countious data column - like Age, Education, Usage, Fitness, Income, Miles

Exploratory analysis done in above with describe() function

Age column :

Insight :

```
- 32 are unique values in Age column out of 180 values
- min ->18 and Max --> 50
- Majority of sales are from range of 21 to 35 age
- 25 age people prefer to purchase treadmill.
- As per histogram, Data is not normal distribution and left sided plot
- Data as few outliers
```

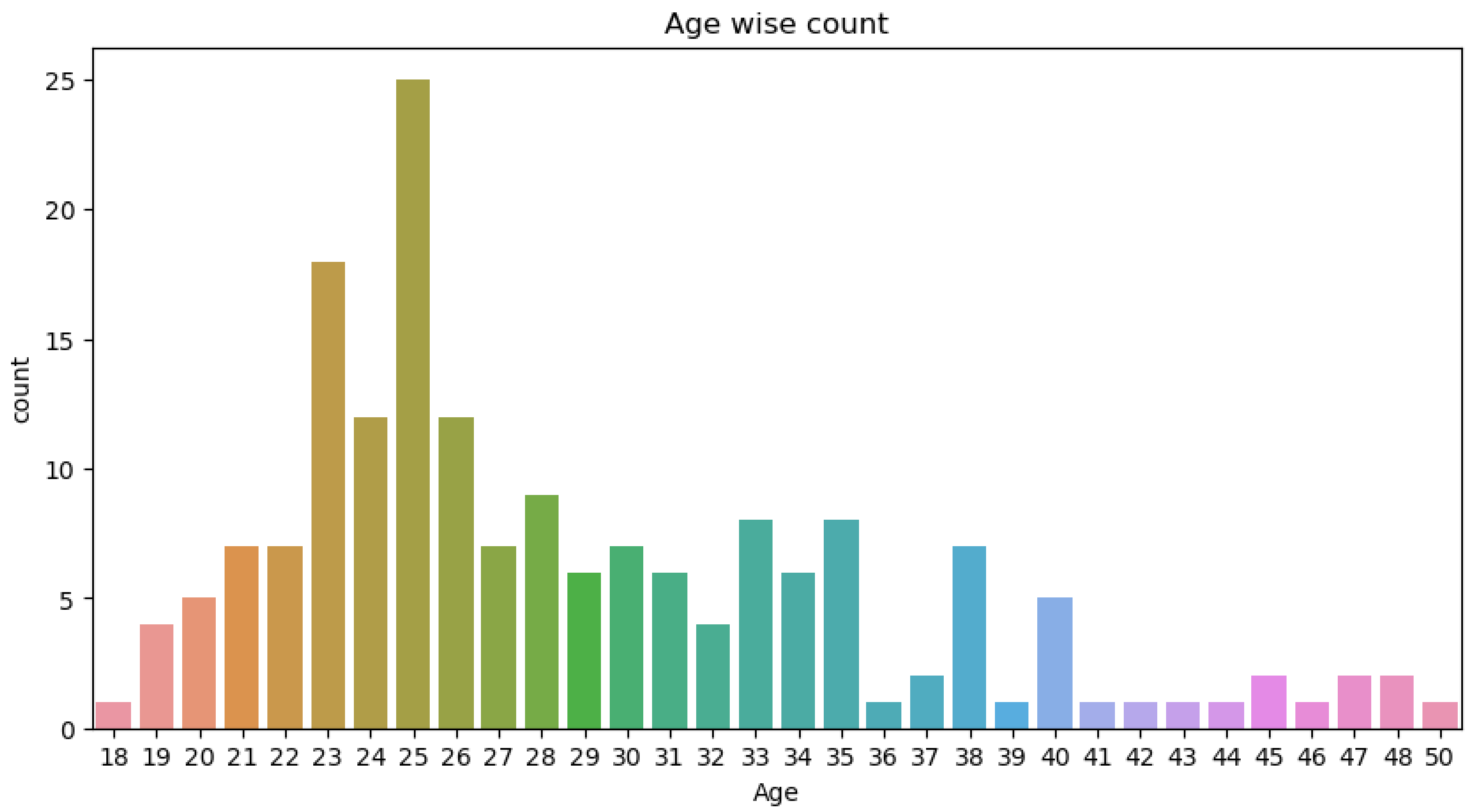
Recommendation:

```
- From 21 to 35 age, user prefer to buy treadmill, Sales excutive can put more weightage on these age group - ch
ancing of user purchasing will increase
```

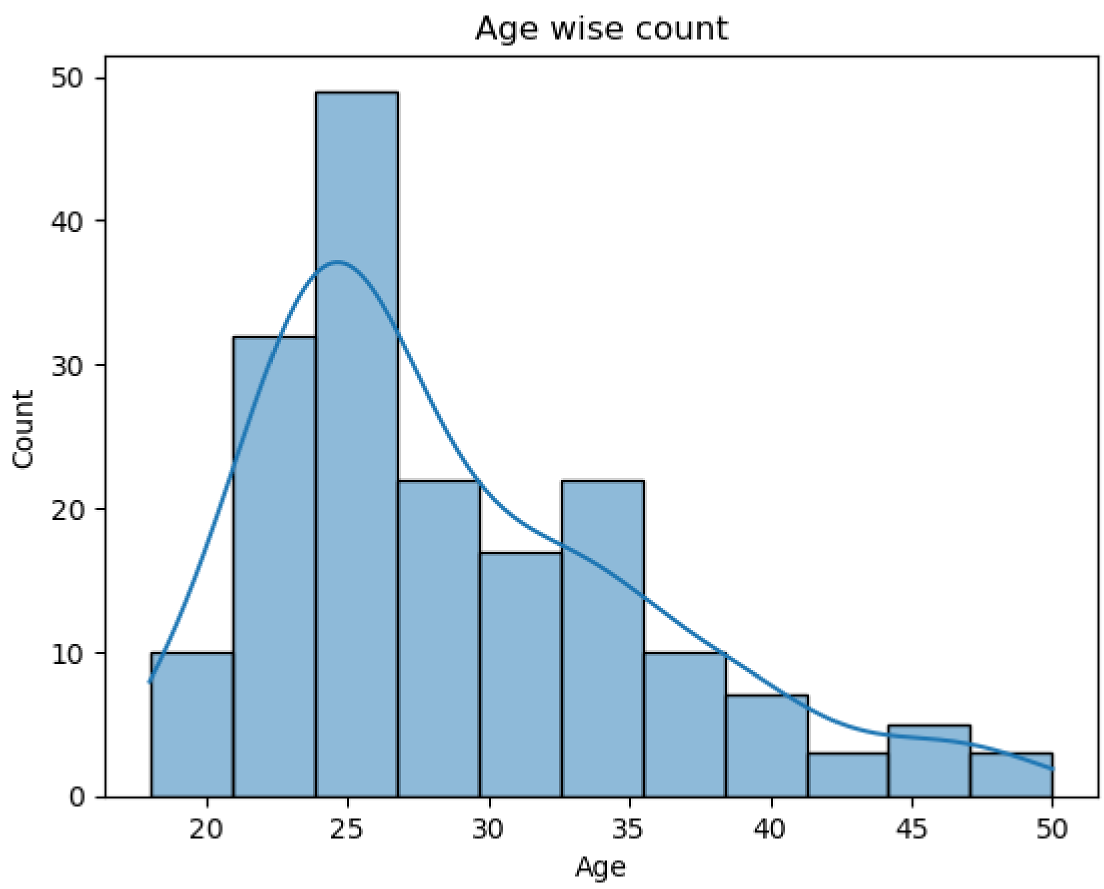
In [21]:
```
# Age column number of unique value
df['Age'].nunique()
```

Out[21]: 32

In [74]:
```
# Age column
plt.figure(figsize = (10,5))
sns.countplot(data = df, x = 'Age')
plt.title('Age wise count')
```
Out[74]: Text(0.5, 1.0, 'Age wise count')

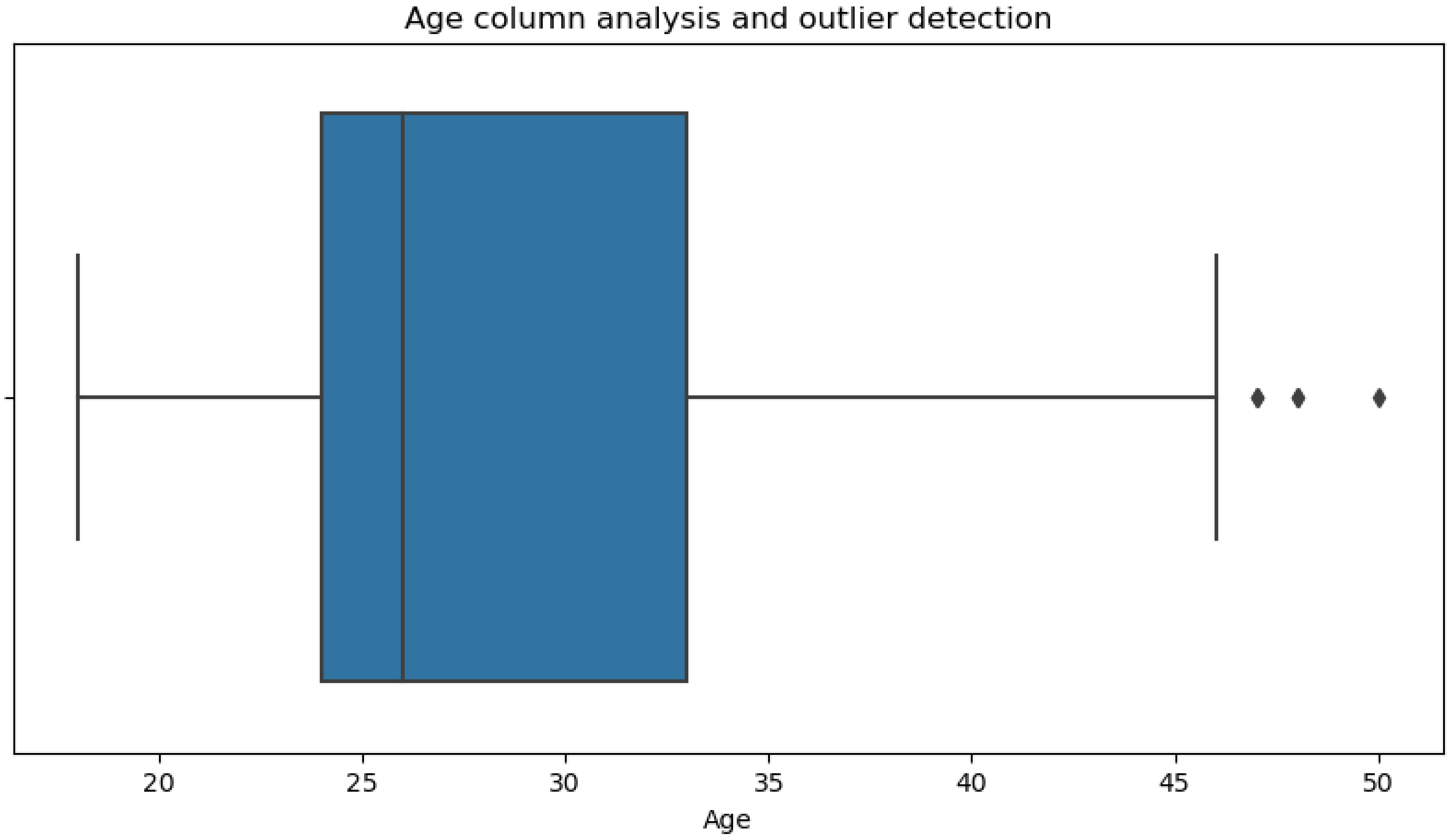


In [196]:
```
sns.histplot(data = df, x = 'Age', kde = True)
plt.title('Age wise count')
```
Out[196]: Text(0.5, 1.0, 'Age wise count')



In [23]:
```
# Age column
plt.figure(figsize = (10,5))
sns.boxplot(data = df, x = 'Age')
plt.title('Age column analysis and outlier detection')
```

Out[23]: Text(0.5, 1.0, 'Age column analysis and outlier detection')



Education column :

Insight :

```
- 8 are unique values in Education column out of 180 values
- min ->12 and Max --> 21
- Majority of sales are from range of 14 to 18 years of education
- 16 year of education people are the ones who bought most number of treadmills.
- As per histogram, Data is not normal distribution.
- Data as few outliers
```

Recommendation:

```
- From 14 to 18 years of education, these user prefer to buy treadmill, Sales excutive can put more weightage on
these years of education group - chancing of user purchasing will increase
```

In [24]:
```
# Education column number of unique value
df['Education'].nunique()
```

Out[24]: 8

In [100]:
```
df['Education'].describe()
```

Out[100]:
```
count    180.000000
mean      15.572222
std        1.617055
min       12.000000
25%       14.000000
50%       16.000000
75%       16.000000
max       21.000000
Name: Education, dtype: float64
```

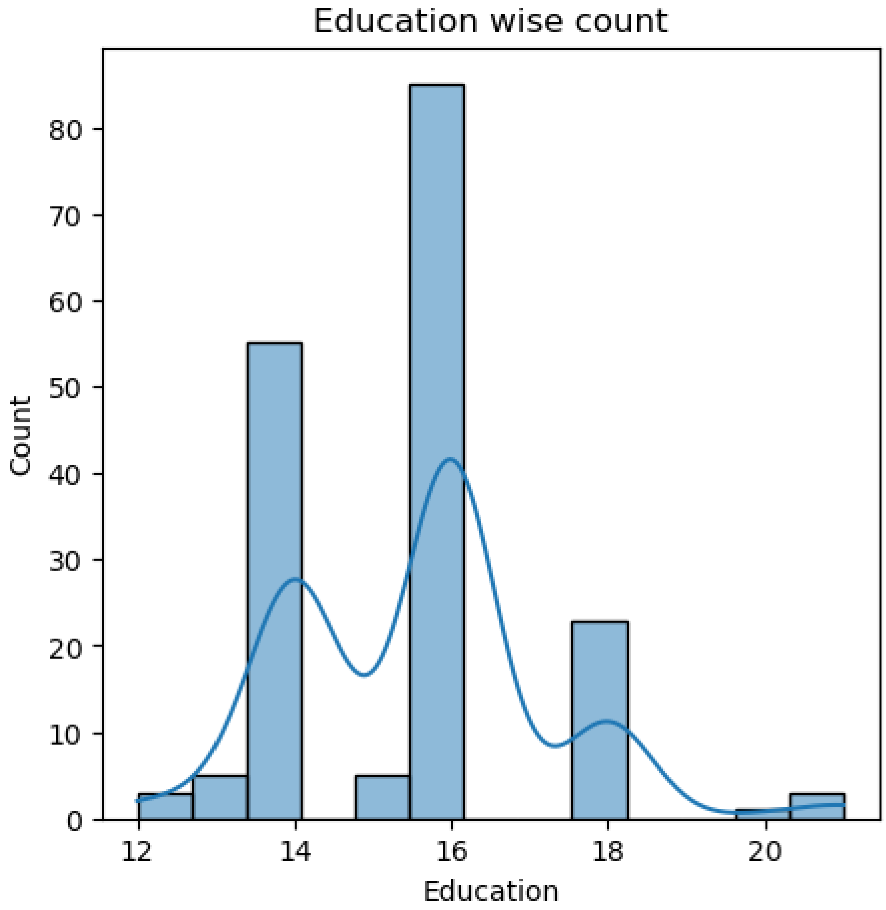
In [25]:
```
df['Education'].value_counts().reset_index().rename(columns = {'index' : 'Education', 'Education': 'count'})
```

Out[25]:

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

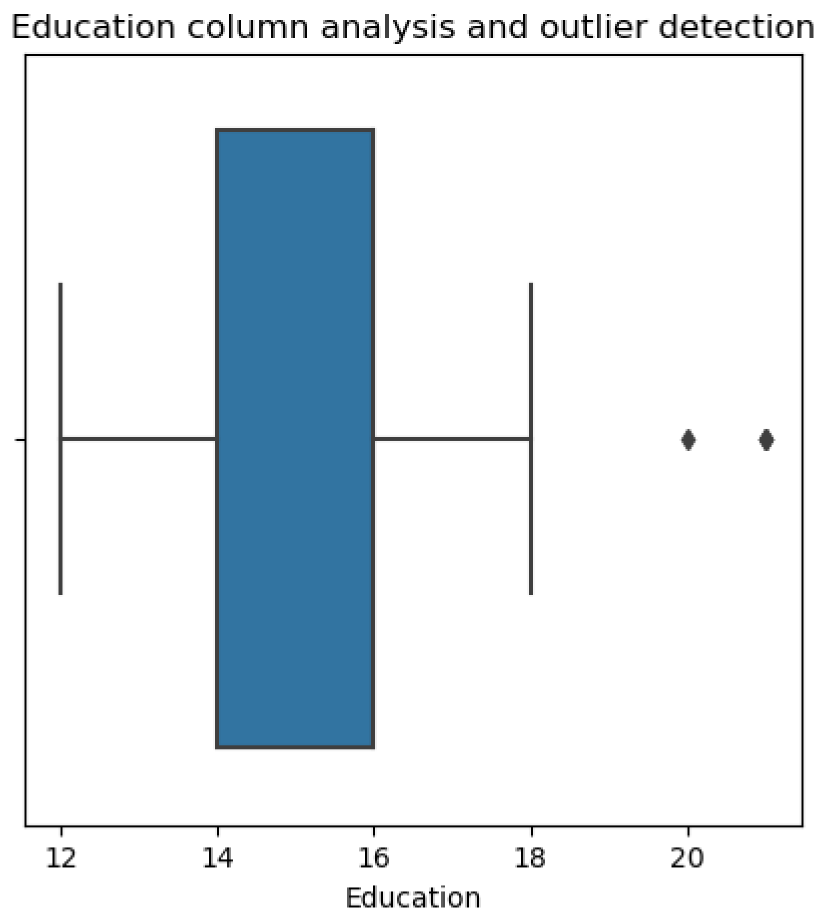
In [99]:
```
# Education column
plt.figure(figsize = (5,5))
sns.histplot(data = df, x = 'Education', kde = True)
plt.title('Education wise count')
```

Out[99]: Text(0.5, 1.0, 'Education wise count')



In [27]:
```
# Education column
plt.figure(figsize = (5,5))
sns.boxplot(data = df, x = 'Education')
plt.title('Education column analysis and outlier detection')
```

Out[27]: Text(0.5, 1.0, 'Education column analysis and outlier detection')



Usage column :

Insight :

```
- 6 are unique values in Usage column out of 180 values
- min ->2 and Max --> 7
- Majority of sales are from range of 2 to 4 times/week.
- Majority of users have usage of 3 times/week.
- As per histogram, Data is not normal distribution.
- Data as few outliers
```

Recommendation:

```
- users have usage of 2-4 times/week, these user prefer to buy treadmill, Sales excutive can put more weightage
on these group - chancing of user purchasing will increase
```

In [28]:
```
# Usage column number of unique value
df['Usage'].nunique()
```

Out[28]: 6

In [101]:
```
df['Usage'].describe()
```

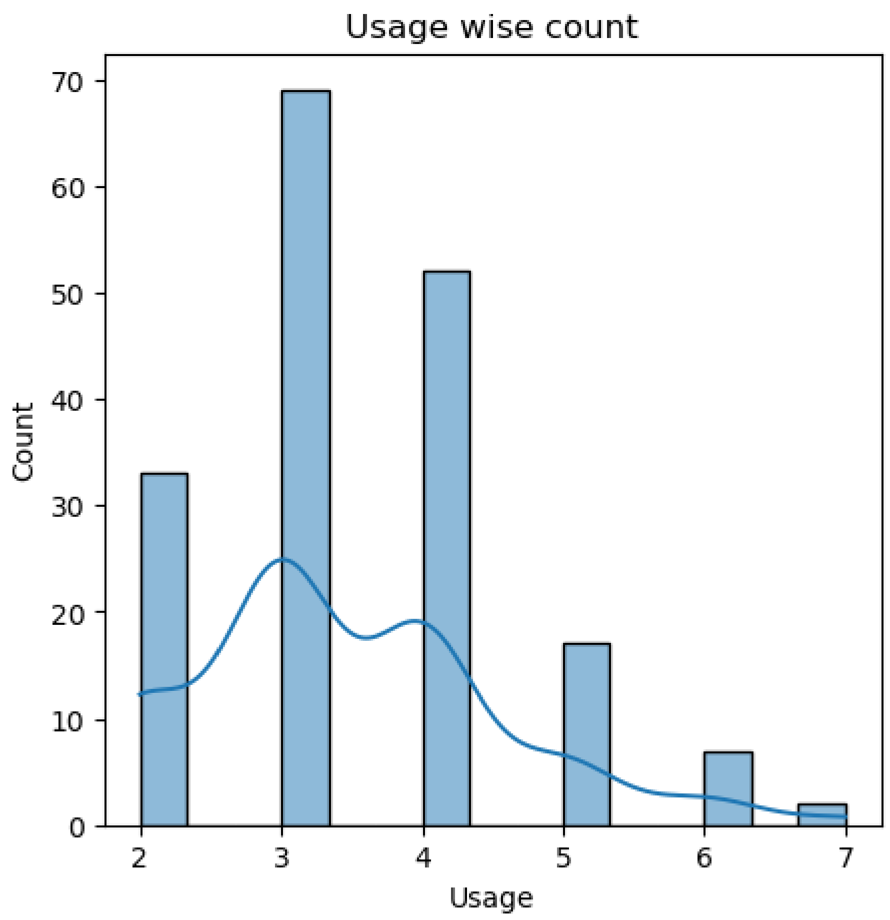
Out[101]:
```
count    180.000000
mean       3.455556
std        1.084797
min        2.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        7.000000
Name: Usage, dtype: float64
```

In [29]:
```
df['Usage'].value_counts().reset_index().rename(columns = {'index' : 'Usage', 'Usage': 'count'})
```

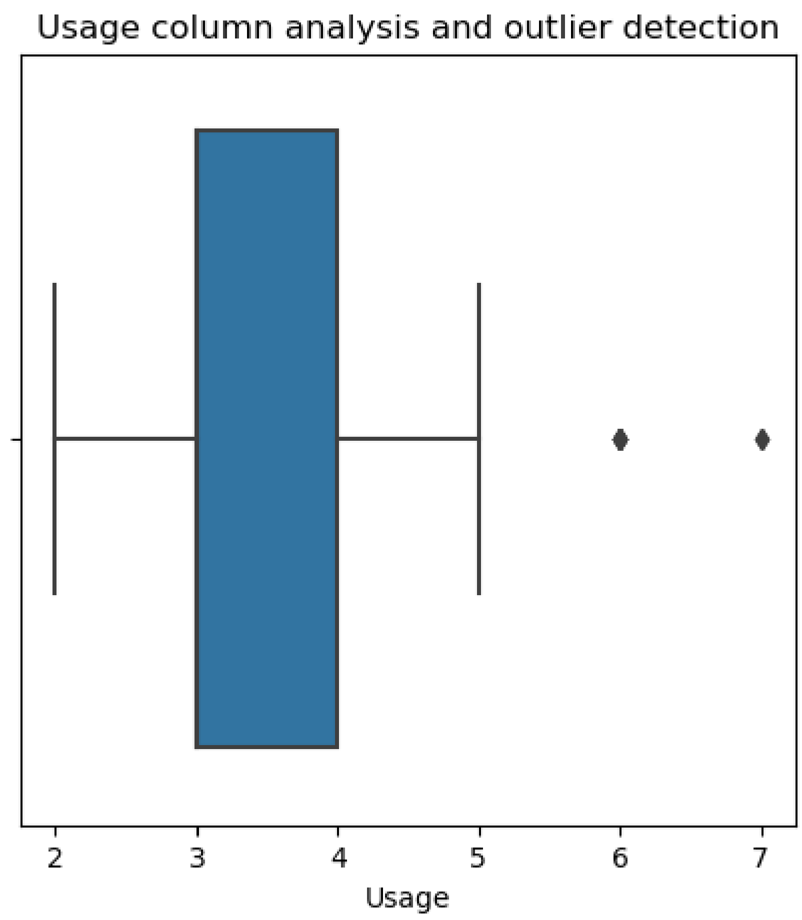
Out[29]:

	Usage	count
0	3	69
1	4	52
2	2	33
3	5	17
4	6	7
5	7	2

In [103]:
```
# Usage column
plt.figure(figsize = (5,5))
sns.histplot(data = df, x = 'Usage', kde = True)
plt.title('Usage wise count')
```
Out[103]: Text(0.5, 1.0, 'Usage wise count')



In [31]:
```
# Usage column
plt.figure(figsize = (5,5))
sns.boxplot(data = df, x = 'Usage')
plt.title('Usage column analysis and outlier detection')
```
Out[31]: Text(0.5, 1.0, 'Usage column analysis and outlier detection')



Fitness column :

Insight :

```
- 5 are unique values in Fitness column out of 180 values
- min ->1 and Max --> 5
- Majority of sales are from range of 2 to 5 Self-rated fitness.
- Majority of users have usage of 3 Self-rated fitness.
- As per histogram, Data is not normal distribution.
- Data as few outliers
```

Recommendation:

- users have 2 to 5 Self-rated fitness, these user prefer to buy treadmill, Sales excutive can put more weightage on these group - chancing of user purchasing will increase

In [32]:
```
# Fitness column number of unique value
df['Fitness'].nunique()
```

Out[32]: 5

In [106]:
```
df['Fitness'].describe()
```

Out[106]:
```
count    180.000000
mean       3.311111
std        0.958869
min        1.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        5.000000
Name: Fitness, dtype: float64
```

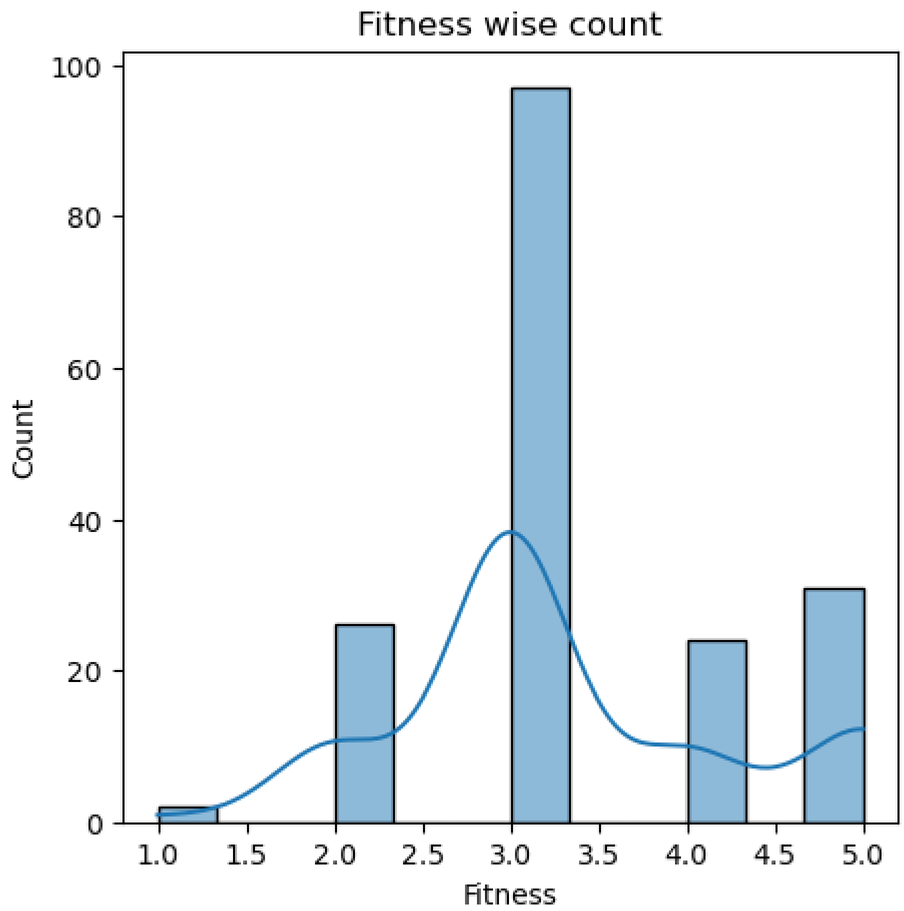
In [33]:
```
df['Fitness'].value_counts().reset_index().rename(columns = {'index' : 'Fitness', 'Fitness': 'count'})
```

Out[33]:

	Fitness	count
0	3	97
1	5	31
2	2	26
3	4	24
4	1	2

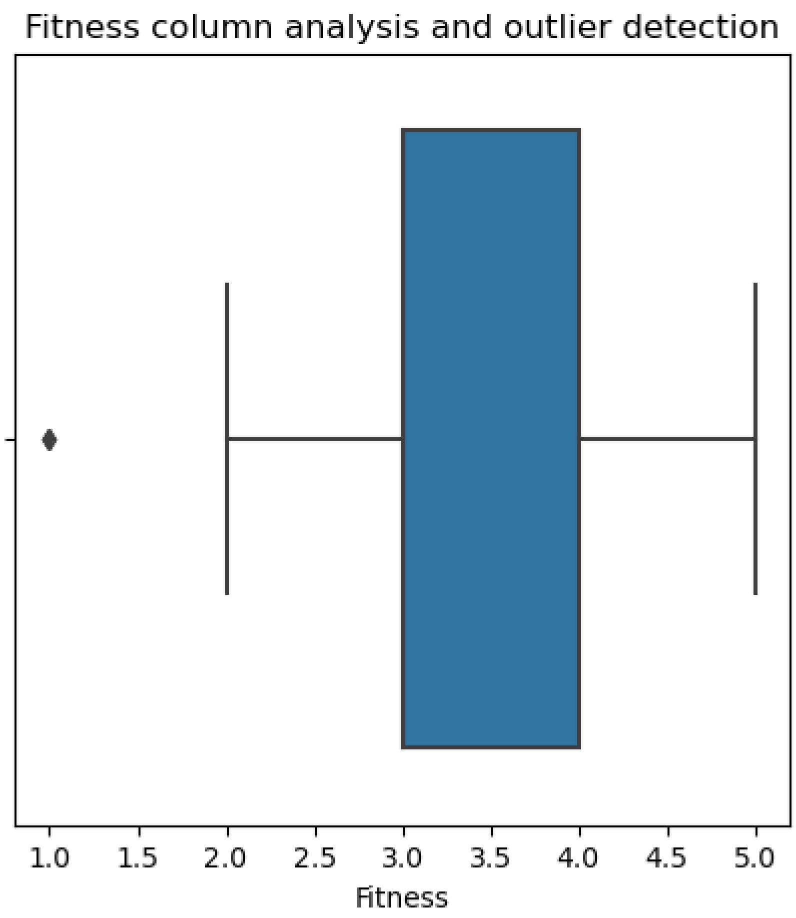
In [105]:
```
# Fitness column
plt.figure(figsize = (5,5))
sns.histplot(data = df, x = 'Fitness', kde = True)
plt.title('Fitness wise count')
```

Out[105]: Text(0.5, 1.0, 'Fitness wise count')



In [35]:
```
# Fitness column
plt.figure(figsize = (5,5))
sns.boxplot(data = df, x = 'Fitness')
plt.title('Fitness column analysis and outlier detection')
```

Out[35]: Text(0.5, 1.0, 'Fitness column analysis and outlier detection')



Income column :

Insight :

- 62 are unique values in Income column out of 180 values
- min ->$29562 and Max --> $104581
- Majority of sales are from range of $30000 to $70000 income.
- Most of users have $50,000 to $55,000 income at 35 users.
- As per histogram, Data is not normal distribution.
- Data as outliers

Recommendation:

- Users who have $30000 to $70000 income, these user prefer to buy treadmill, Sales excutive can put more weightage on these group - chancing of user purchasing will increase
- Users who have $50,000 to $55,000 income, will have highest probability of buying Treadmill

In [36]:
```
# Fitness column number of unique value
df['Income'].nunique()
```

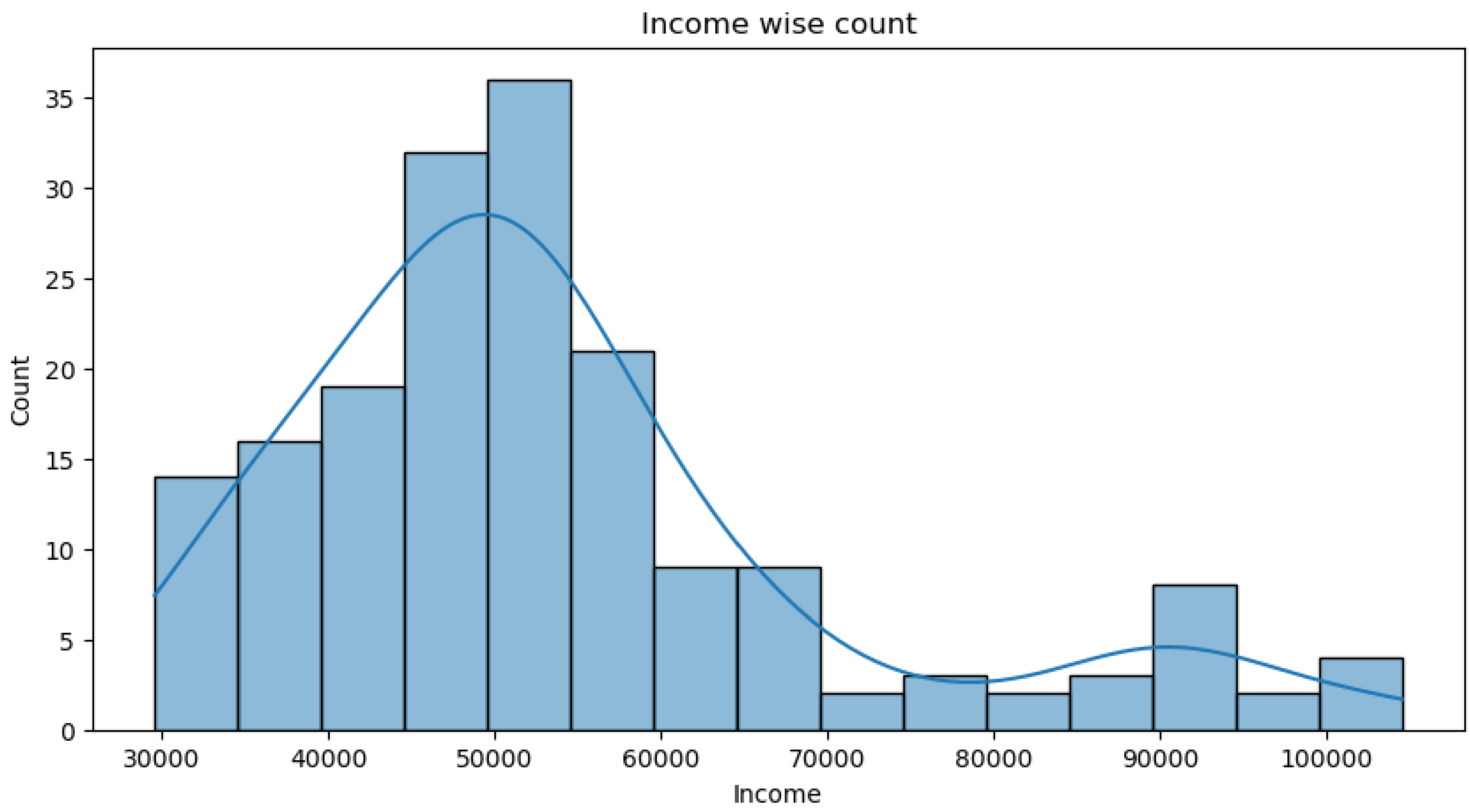
Out[36]: 62

In [108]:
```
df['Income'].describe()
```

Out[108]:
```
count       180.000000
mean      53719.577778
std       16506.684226
min       29562.000000
25%       44058.750000
50%       50596.500000
75%       58668.000000
max      104581.000000
Name: Income, dtype: float64
```

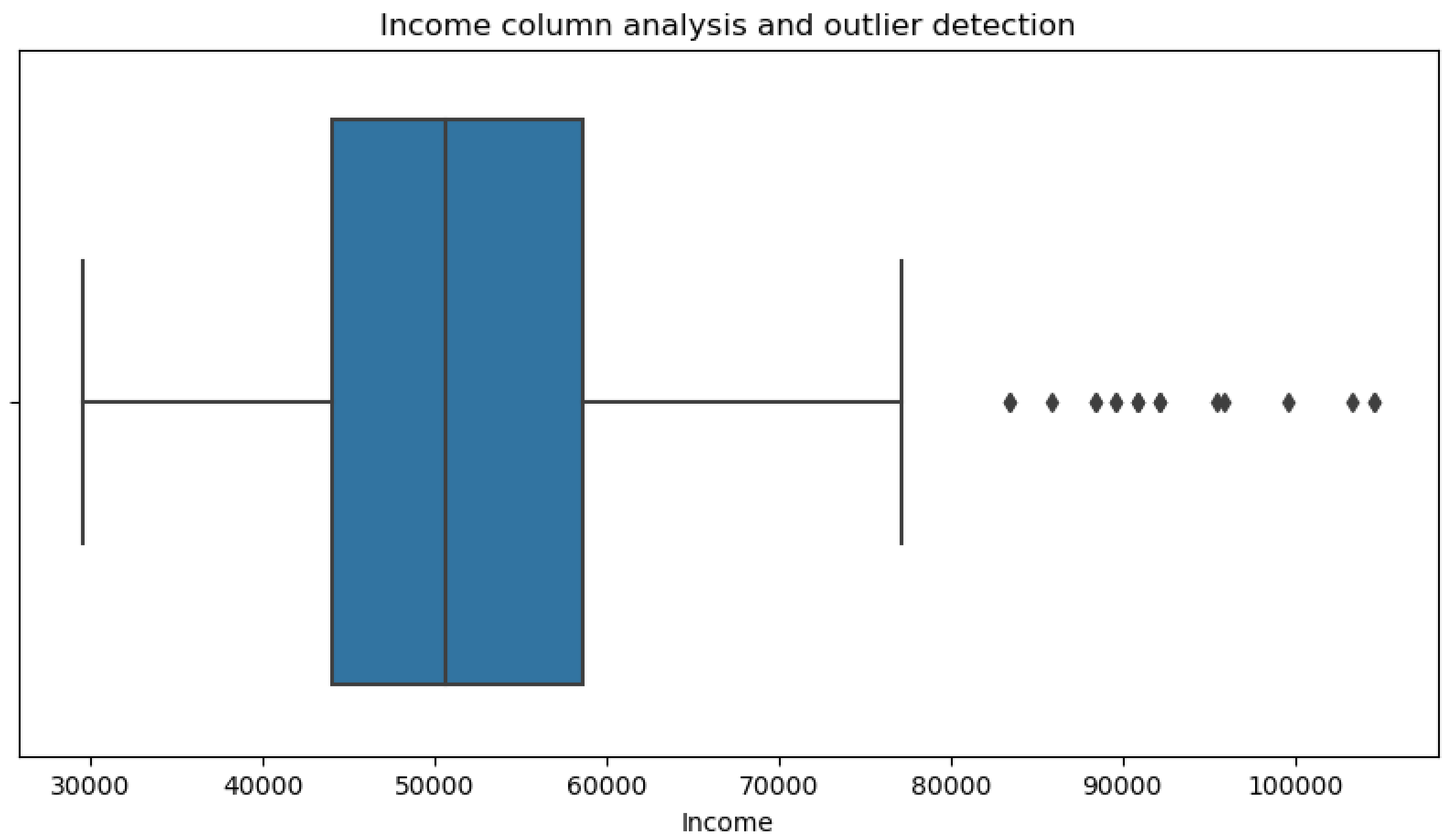
In [109]:
```
# Income column
plt.figure(figsize = (10,5))
sns.histplot(data = df, x = 'Income', kde= True)
plt.title('Income wise count')
```

Out[109]: Text(0.5, 1.0, 'Income wise count')



In [38]:
```
# Income column
plt.figure(figsize = (10,5))
sns.boxplot(data = df, x = 'Income')
plt.title('Income column analysis and outlier detection')
```

Out[38]: Text(0.5, 1.0, 'Income column analysis and outlier detection')



Miles column :

Insight :

```
- 37 are unique values in Miles column out of 180 values
- min -> 21 Avg miles/week and Max --> 360 avg miles/week
- Majority of sales are from range of 40 to 200 Avg miles/ week.
- Most of users have 70 to 80 Avg miles/week of about 40 users.
- As per histogram, Data is not normal distribution.
- Data as outliers
```

Recommendation:

- Users who have 40 to 200 Avg miles/ week, these user prefer to buy treadmill, Sales excutive can put more weightage on these group - chancing of user purchasing will increase
- Users who have 70 to 80 Avg miles/week, will have highest probability of buying Treadmill

In [39]:
```
# Miles column number of unique value
df['Miles'].nunique()
```

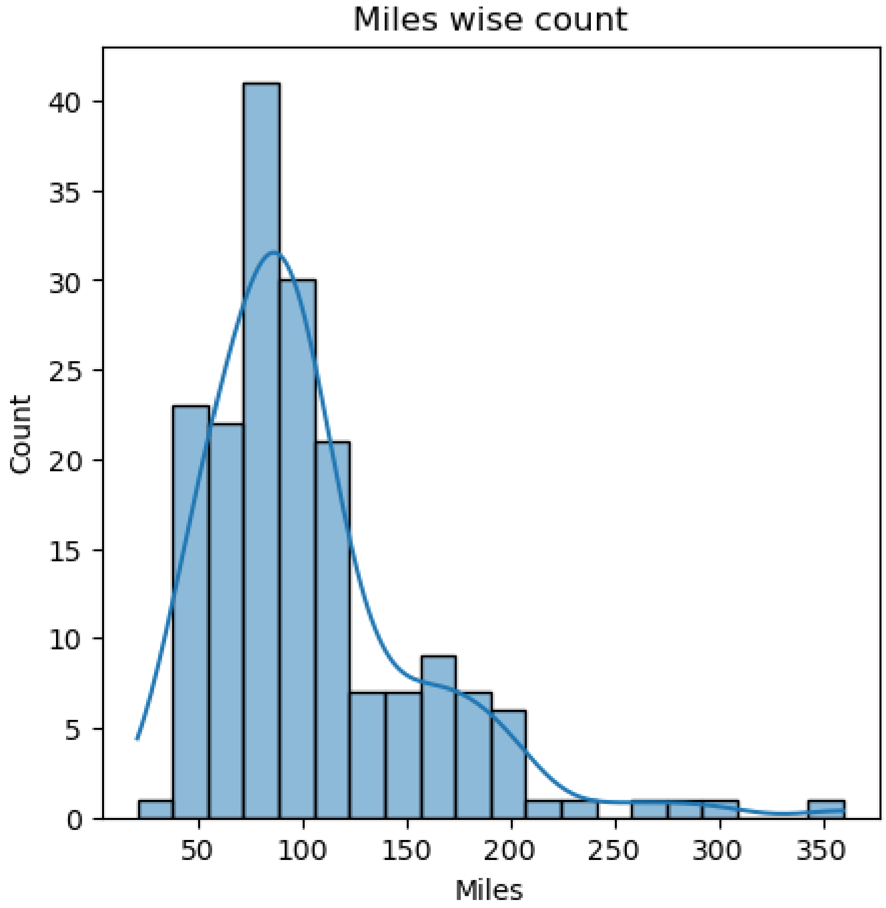
Out[39]: 37

In [110]:
```
df['Miles'].describe()
```

Out[110]:
```
count    180.000000
mean     103.194444
std       51.863605
min       21.000000
25%       66.000000
50%       94.000000
75%      114.750000
max      360.000000
Name: Miles, dtype: float64
```

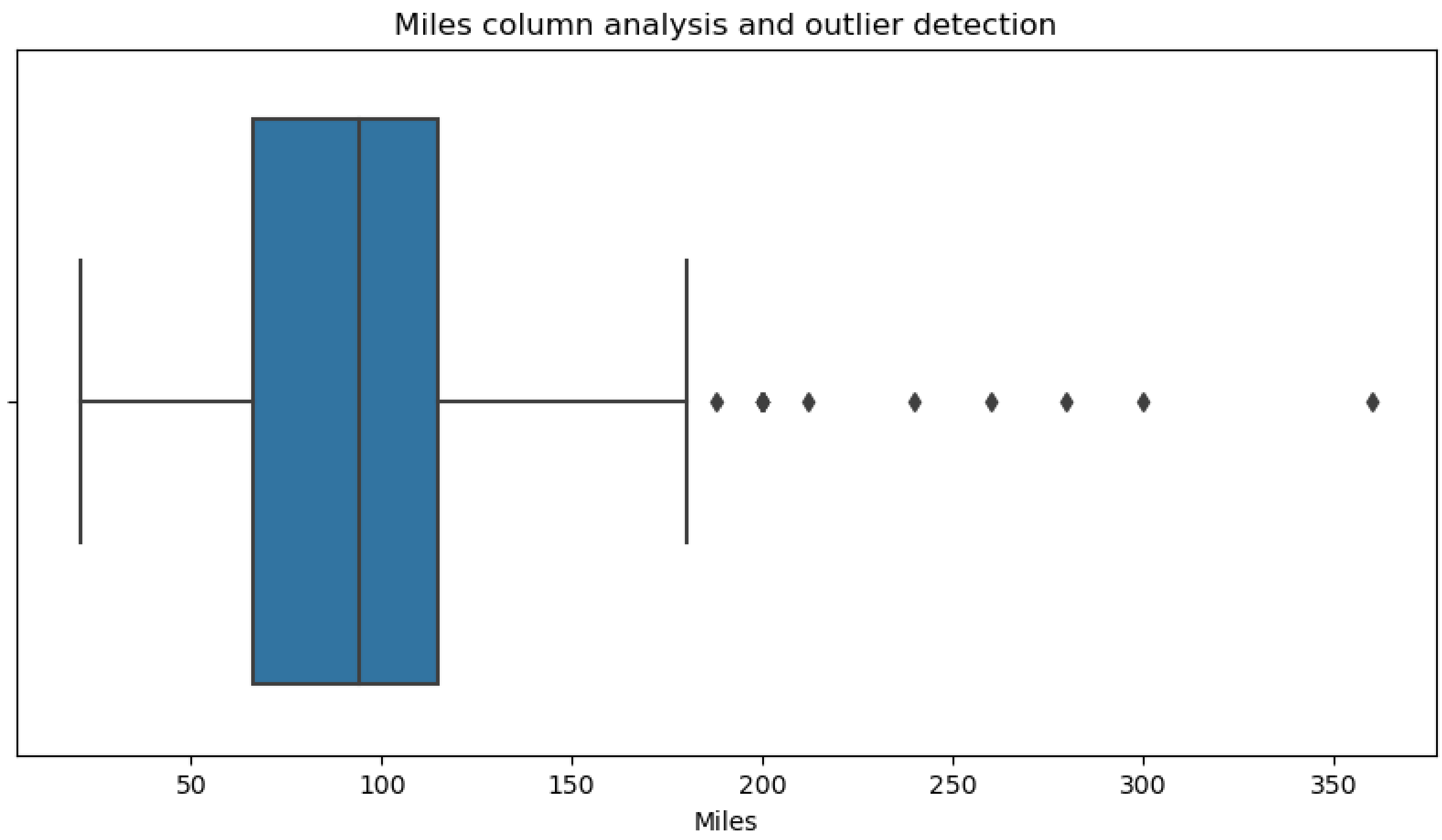
In [114]:
```
# Miles column
plt.figure(figsize = (5,5))
sns.histplot(data = df, x = 'Miles', kde = True)
plt.title('Miles wise count')
```

Out[114]: Text(0.5, 1.0, 'Miles wise count')



In [41]:
```
# Miles column
plt.figure(figsize = (10,5))
sns.boxplot(data = df, x = 'Miles')
plt.title('Miles column analysis and outlier detection')
```

Out[41]: Text(0.5, 1.0, 'Miles column analysis and outlier detection')



Bivariate plot

Bivariate analysis of Product wrt Gender and Maritalstatus

Insights :

```
- Gender Insights:
    - KP281 --> Both Male and Female user are equal who have purchased
    - KP481 --> Male user are more compared to Female and with slight difference of 2 users
    - KP781 --> Male user are more compared to Female and with very large difference of 25+ users
- Marital Status Insight:
    - In all product category, Partnered users are more.
```

Recommendataion:

```
- Target Partnered users, when compared Single. Partnered users have high chance of buying Treadmill (~60%)
- KP781, Target users will be Male and 82.5% purchased
- KP281 and KP481 --> both male and female have equal chances of buying and equal weightage can be provided.
```

In [119]:
```
pd.crosstab(df['Product'],  df['Gender'])
```

Out[119]:

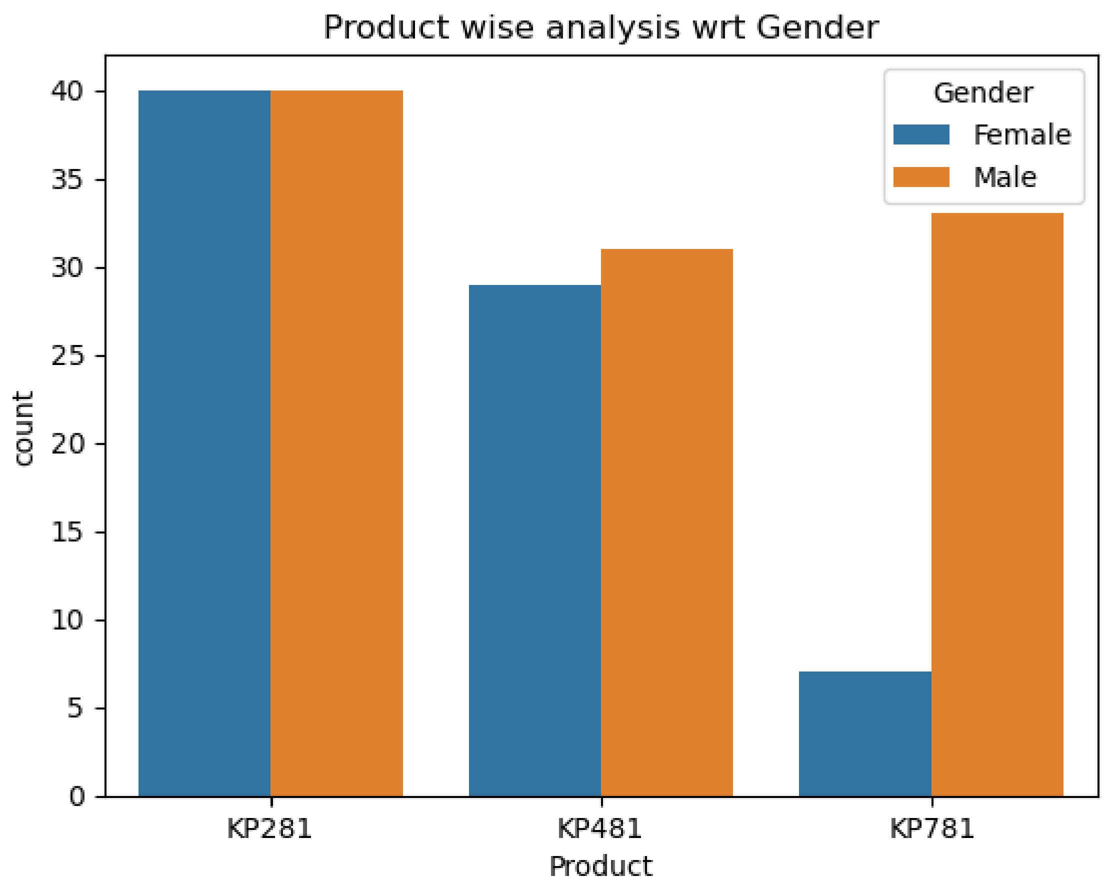
Gender Product	Female	Male
KP281	40	40
KP481	29	31
KP781	7	33

In [120]:
```
# Probability of Male users, Given they use KP781 treadmill
(33/(33+7)) * 100
```

Out[120]: 82.5

In [197]:
```
sns.countplot(data =df, x = 'Product', hue = 'Gender')
plt.title('Product wise analysis wrt Gender')
```

Out[197]: Text(0.5, 1.0, 'Product wise analysis wrt Gender')



In [123]:
```
pd.crosstab(df['Product'],  [df['MaritalStatus']])
```

Out[123]:

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

In [125]:
```
pd.crosstab(df['Product'],  [df['MaritalStatus']]).sum(axis = 0).reset_index().rename(columns = {0:'cnt'})
```

Out[125]:

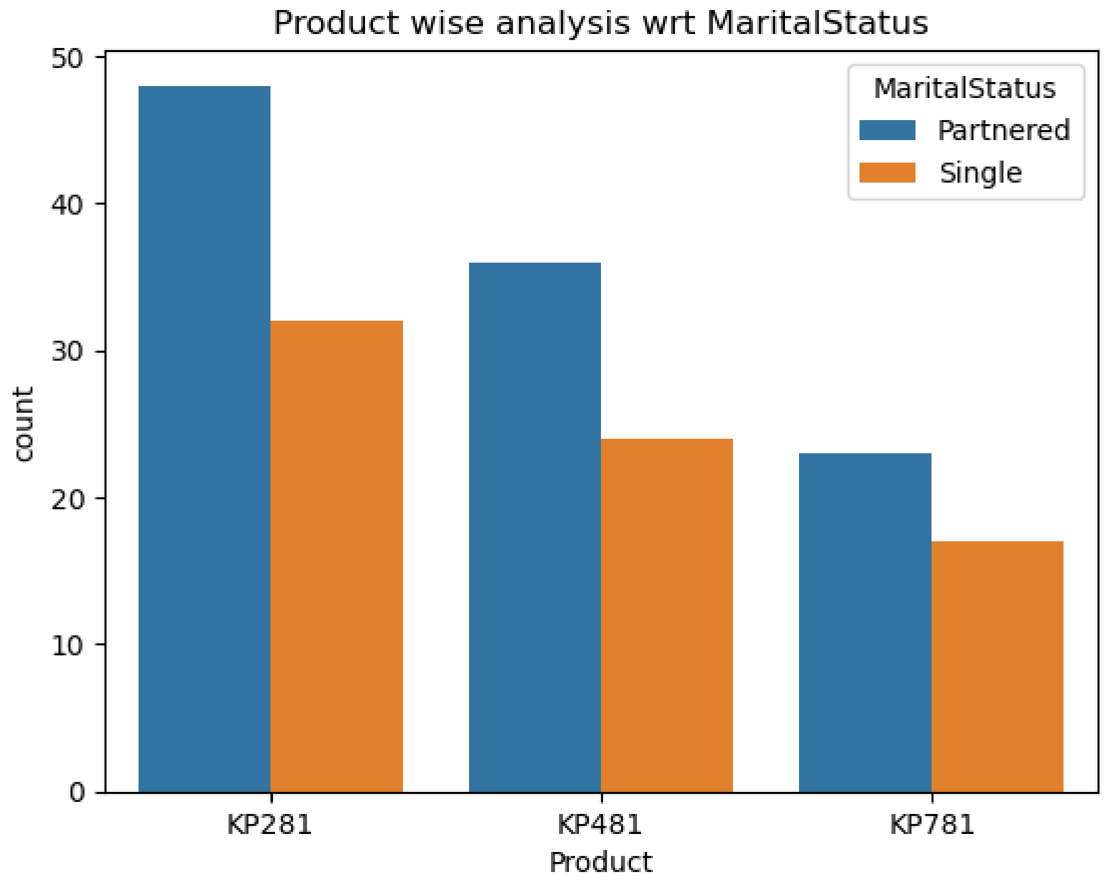
	MaritalStatus	cnt
0	Partnered	107
1	Single	73

In [126]:
```
# Percentage of share of partnered user
(107/(107+73))*100
```

Out[126]: 59.44444444444444

In [198]:
```
sns.countplot(data =df, x = 'Product', hue = 'MaritalStatus')
plt.title('Product wise analysis wrt MaritalStatus')
```

Out[198]: Text(0.5, 1.0, 'Product wise analysis wrt MaritalStatus')



Bivariate analsysis of below menttioned columns

Age, Education, Usage, Fitness, Income, Miles

Insights :

```
- Product to Age analysis
    - KP281 and KP481 --> both age median are same.
    - KP781 --> 50% of users are between 25 to 30
- Product to Education analysis
    - KP281 and KP481 --> Education below 16year, prefer to buy these product
    - KP781 --> Education above 16 year prefer to buy this product
- Product to Usage analysis
    - KP281 --> Users prefer to use more treadmill by about 3 - 4 times/week
    - KP481 --> Least used product by users
    - KP781 --> Users prefer to use more treadmill when compared to others and there 25% is at 4 times/week
- Product to Fitness analysis
    - KP281 & KP481 --> Moderate fitness users
    - KP781 --> Users have excellent shape when compared to others. Users are professional
- Product to Income analysis
    - KP781 --> Higher income users prefer this Treadmill
- Product to Miles analysis
    - KP781 --> User runs more miles in this treadmill (>=120 miles/week). User who plans to run/walk >= 120 mil
es/week prefer to buy this product.
```

Recommendation :

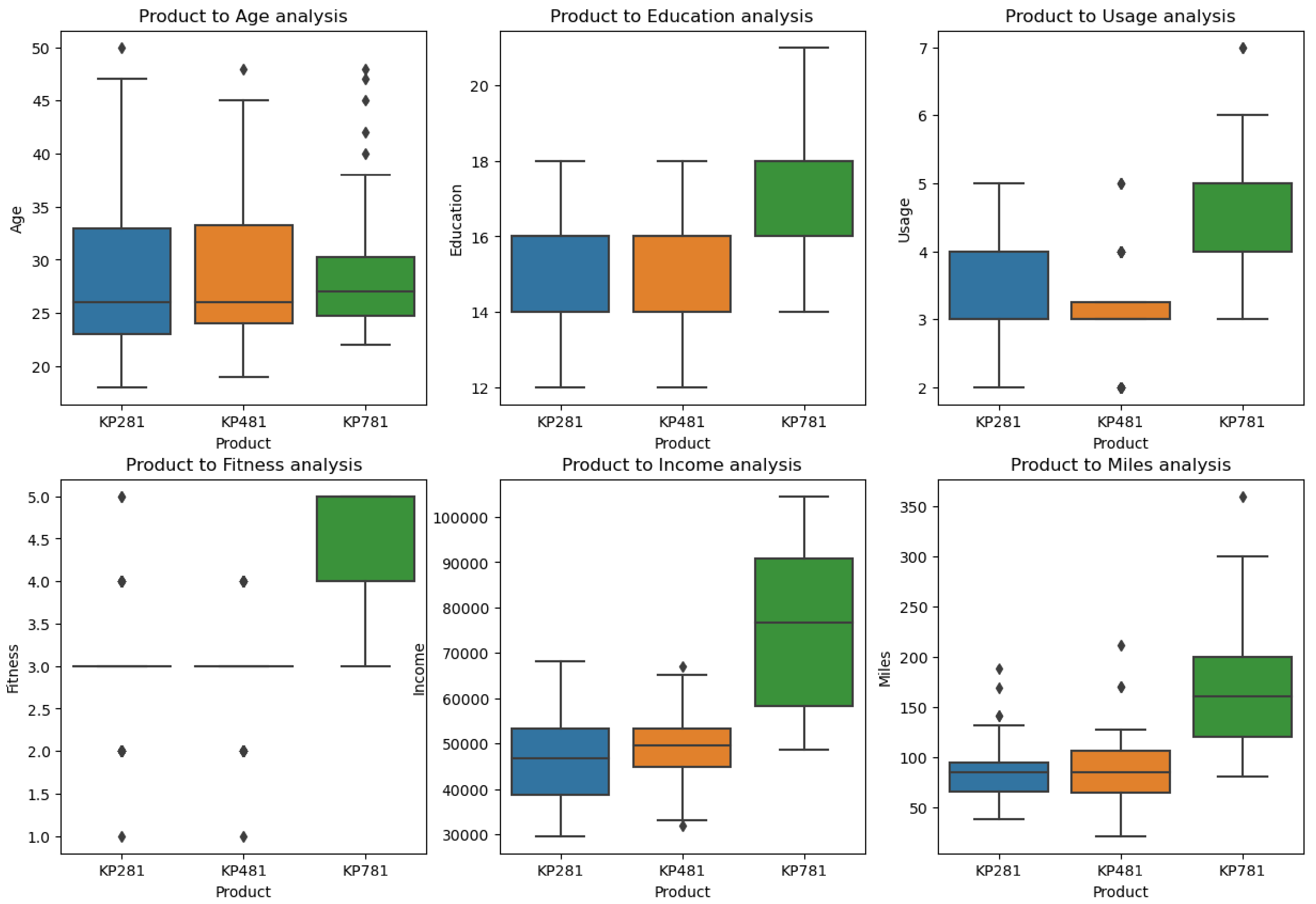
```
- KP781 --> Highter income (>= $60,000 on app.), Users who plans to run >= 12 miles/week, Professional users, Hi
gher educated >=16 years and Gender = Male. Target these matching users as they have highter chances of buying t
his product.

- KP481 --> Moderate income users ($45,000 to 53,000 app.), they prefer this product
    - KP281 --> Lower income ($40,000 to $53,000) users prefer this product, Female with Less usage
- KP281 and KP481 --> Education < 16, Fitness = 3, Both male and female prefer this product to buy
```

In [148]:

```python
plt.figure(figsize = (15,10))

plt.subplot(2,3,1)
sns.boxplot(data = df, x = 'Product', y = 'Age')
plt.title('Product to Age analysis')

plt.subplot(2,3,2)
sns.boxplot(data = df, x = 'Product', y = 'Education')
plt.title('Product to Education analysis')

plt.subplot(2,3,3)
sns.boxplot(data = df, x = 'Product', y = 'Usage')
plt.title('Product to Usage analysis')

plt.subplot(2,3,4)
sns.boxplot(data = df, x = 'Product', y = 'Fitness')
plt.title('Product to Fitness analysis')

plt.subplot(2,3,5)
sns.boxplot(data = df, x = 'Product', y = 'Income')
plt.title('Product to Income analysis')

plt.subplot(2,3,6)
sns.boxplot(data = df, x = 'Product', y = 'Miles')
plt.title('Product to Miles analysis')
```

Out[148]:

```
Text(0.5, 1.0, 'Product to Miles analysis')
```



Multivariate Analysis wrt Gender and each continous data column

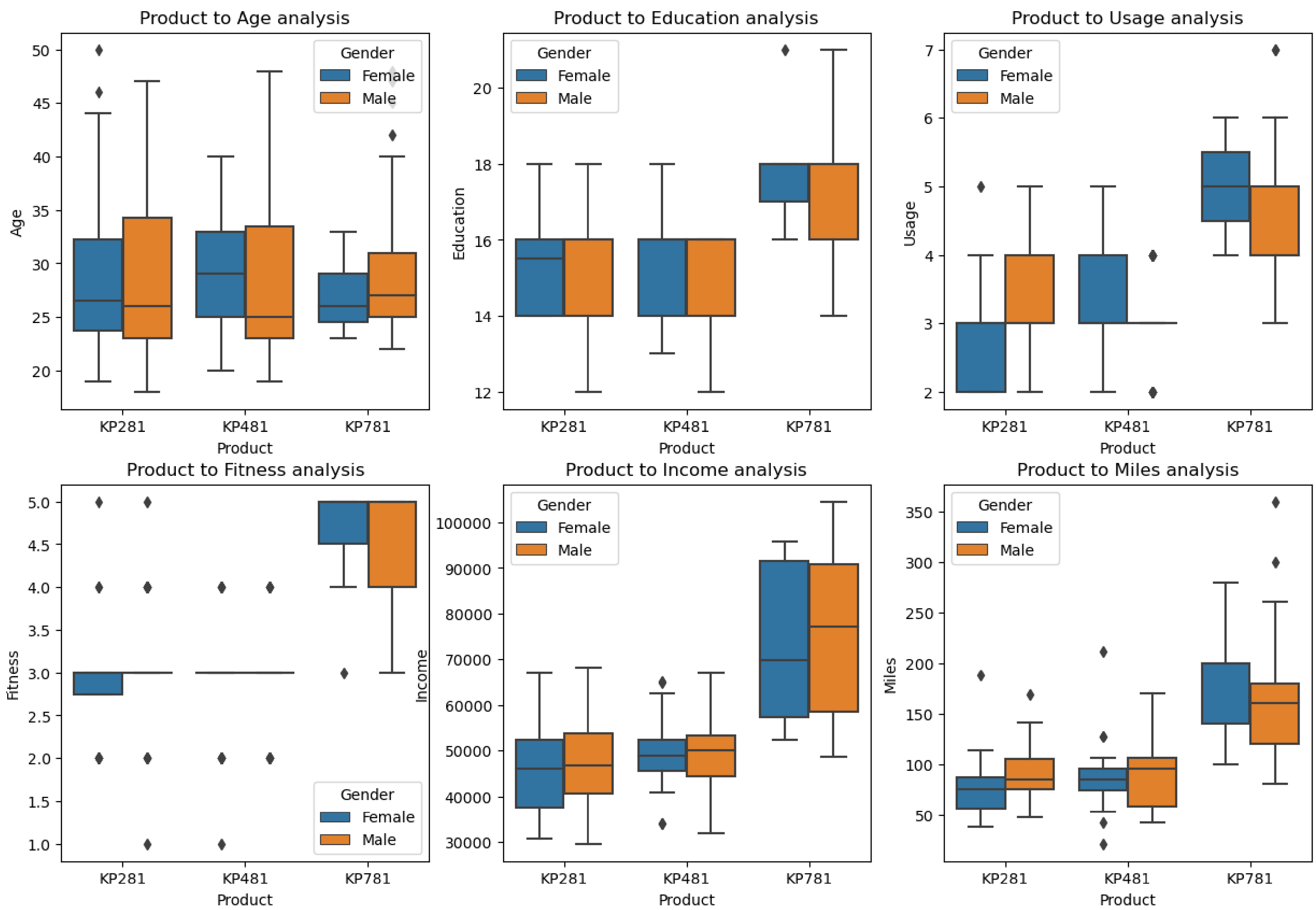
continous data column - Age, Education, Usage, Fitness, Income, Miles

In [150]:

```
plt.figure(figsize = (15,10))

plt.subplot(2,3,1)
sns.boxplot(data = df, x = 'Product', y = 'Age', hue = 'Gender')
plt.title('Product to Age analysis')

plt.subplot(2,3,2)
sns.boxplot(data = df, x = 'Product', y = 'Education', hue = 'Gender')
plt.title('Product to Education analysis')

plt.subplot(2,3,3)
sns.boxplot(data = df, x = 'Product', y = 'Usage', hue = 'Gender')
plt.title('Product to Usage analysis')

plt.subplot(2,3,4)
sns.boxplot(data = df, x = 'Product', y = 'Fitness', hue = 'Gender')
plt.title('Product to Fitness analysis')

plt.subplot(2,3,5)
sns.boxplot(data = df, x = 'Product', y = 'Income', hue = 'Gender')
plt.title('Product to Income analysis')

plt.subplot(2,3,6)
sns.boxplot(data = df, x = 'Product', y = 'Miles',hue = 'Gender')
plt.title('Product to Miles analysis')
```

Out[150]:

```
Text(0.5, 1.0, 'Product to Miles analysis')
```



Correlation

Insights :

- Fitness to miles runned are highly correlated.
- Miles to usage are highly correlated.
- Age to miles, fitness, usage are not correlated (almost tending to 0)

Recommendation :

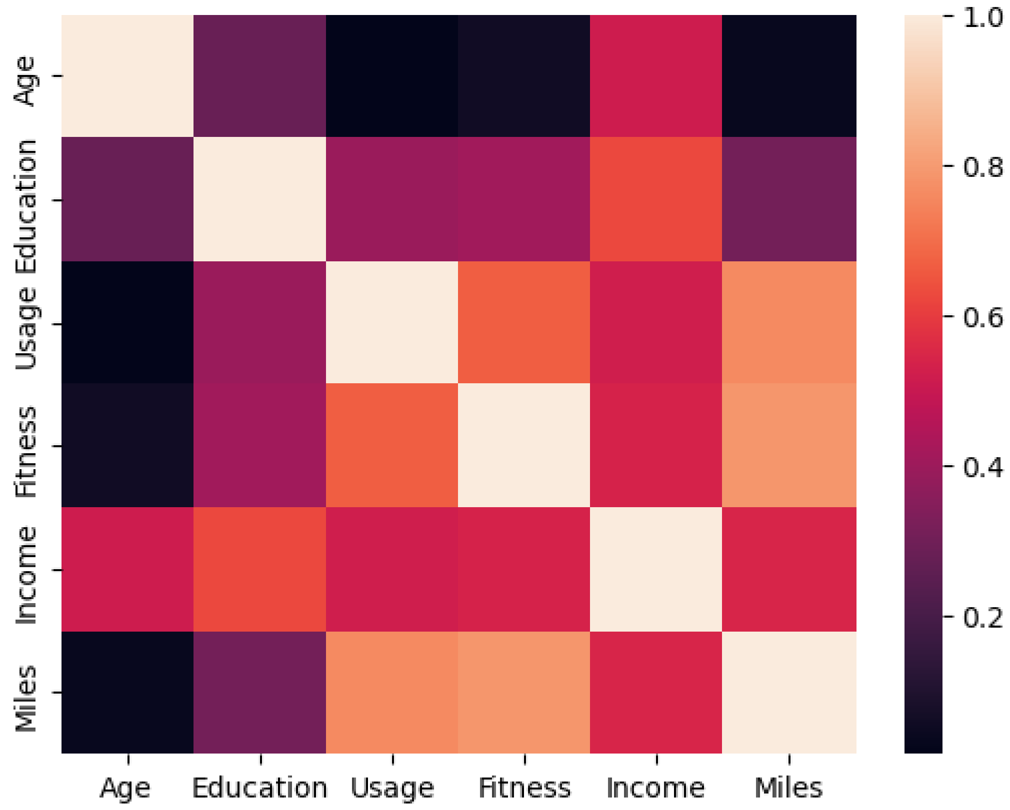
- User who are fit and they use treadmill more when compared to less fit users and they tend to cover more mile s. Target KP781 model for these type of users

In [53]:

```
sns.heatmap(df.corr())
```

```
C:\Users\trtej\AppData\Local\Temp\ipykernel_10256\58359773.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr())
```

Out[53]: <Axes: >



In [151]:

```
df.corr()
```

```
C:\Users\trtej\AppData\Local\Temp\ipykernel_10256\1134722465.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  df.corr()
```

Out[151]:

	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

Conditional Probabilities

Given Gender, what is probability of each product

```
- P(KP281 | Male)
- P(KP481 | Male)
- P(KP781 | Male)

- P(KP281 | Female)
- P(KP481 | Female)
- P(KP781 | Female)
```

Insights:

```
- Ovt of male who have purchased, probability of buying KP281 is higher and KP481, KP781 as almost of 29-30% probability
- Ovt of female who have purchased, probability of buying KP281 is higher and Female wont prefer to purchase KP781 ( probability of 9.21%)
```

Recommendation :

```
- Target user are Male or Female, They tend to buy KP281 when compared to other products.
```

In [157]:
```python
df1 = pd.crosstab(df['Gender'],  [df['Product']])
df1
```

Out[157]:

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

In [163]:
```python
#  - P(KP281 | Male)
round(df1.loc['Male','KP281'] / df1.loc['Male'].sum()*100,2)
```

Out[163]: 38.46

In [164]:
```python
#  - P(KP481 | Male)
round(df1.loc['Male','KP481'] / df1.loc['Male'].sum()*100,2)
```

Out[164]: 29.81

In [165]:
```python
#  - P(KP781 | Male)
round(df1.loc['Male','KP781'] / df1.loc['Male'].sum()*100,2)
```

Out[165]: 31.73

In [166]:
```python
#  - P(KP281 | Female)
round(df1.loc['Female','KP281'] / df1.loc['Female'].sum()*100,2)
```

Out[166]: 52.63

In [167]:
```python
#  - P(KP481 | Female)
round(df1.loc['Female','KP481'] / df1.loc['Female'].sum()*100,2)
```

Out[167]: 38.16

In [168]:
```python
#  - P(KP781 | Female)
round(df1.loc['Female','KP781'] / df1.loc['Female'].sum()*100,2)
```

Out[168]: 9.21

Given Marital Status, what is probability of each product

```
- P(KP281 | partnered)
- P(KP481 | partnered)
- P(KP781 | partnered)

- P(KP281 | Single)
- P(KP481 | Single)
- P(KP781 | Single)
```

Insights:

```
- Ovt of Partnered who have purchased, probability of buying KP281 is higher.
- Ovt of Single who have purchased, probability of buying KP281 is higher
```

Recommendation :

```
- Target user are Partnered or Single, They tend to buy KP281 when compared to other products.
```

In [169]:
```python
df2 = pd.crosstab(df['MaritalStatus'],  [df['Product']])
df2
```

Out[169]:

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

In [170]:
```python
#  - P(KP281 | Partnered)
round(df2.loc['Partnered','KP281'] / df2.loc['Partnered'].sum()*100,2)
```

Out[170]: 44.86

In [171]:
```python
#  - P(KP481 | Partnered)
round(df2.loc['Partnered','KP481'] / df2.loc['Partnered'].sum()*100,2)
```
Out[171]: 33.64

In [172]:
```python
#  - P(KP781 | Partnered)
round(df2.loc['Partnered','KP781'] / df2.loc['Partnered'].sum()*100,2)
```
Out[172]: 21.5

In [173]:
```python
#  - P(KP281 | Single)
round(df2.loc['Single','KP281'] / df2.loc['Single'].sum()*100,2)
```
Out[173]: 43.84

In [175]:
```python
#  - P(KP481 | Single)
round(df2.loc['Single','KP481'] / df2.loc['Single'].sum()*100,2)
```
Out[175]: 32.88

In [176]:
```python
#  - P(KP781 | Single)
round(df2.loc['Single','KP781'] / df2.loc['Single'].sum()*100,2)
```
Out[176]: 23.29

Given Age Bins, what is probability of each product

```
- P(KP281 | Teen)
- P(KP481 | Teen)
- P(KP781 | Teen)

- P(KP281 | Adult)
- P(KP481 | Adult)
- P(KP781 | Adult)

- P(KP281 | Mid age and old age)
- P(KP481 | Mid age and old age)
- P(KP781 | Mid age and old age)
```

Insights:

```
- Majority users who have purchased, prefer to buy KP281. Then KP481 and KP781
- KP781 users are of >40 age , with probability of 33%
```

Recommendation :

```
- Target user for KP281, Any age person
- Target user for KP781, >40 age person
```

In [195]:
```python
# Assuming Age < = 25 (Teen)
# Age <=40 (Adult)
# Age > 40 (Mid age and old age)

def age_bins(x):
    if x <= 25:
        return 'Teen'
    elif x <= 40:
        return 'Adult'
    elif x > 40:
        return 'Mid age and old age'

df3 = df[['Product','Age']].copy()
df3['bins'] = df3['Age'].apply(lambda x : age_bins(x))

age_p = pd.crosstab(df3['bins'],  [df3['Product']])
age_p
```
Out[195]:

Product	KP281	KP481	KP781
bins			
Adult	40	30	19
Mid age and old age	6	2	4
Teen	34	28	17

In [185]:
```
# p(KP281| Teen)
round(age_p.loc['Teen','KP281'] / age_p.loc['Teen'].sum()*100,2)
```
Out[185]: 43.04

In [186]:
```
# p(KP481| Teen)
round(age_p.loc['Teen','KP481'] / age_p.loc['Teen'].sum()*100,2)
```
Out[186]: 35.44

In [187]:
```
# p(KP781| Teen)
round(age_p.loc['Teen','KP781'] / age_p.loc['Teen'].sum()*100,2)
```
Out[187]: 21.52

In [188]:
```
# p(KP281| Adult)
round(age_p.loc['Adult','KP281'] / age_p.loc['Adult'].sum()*100,2)
```
Out[188]: 44.94

In [191]:
```
# p(KP481| Adult)
round(age_p.loc['Adult','KP481'] / age_p.loc['Adult'].sum()*100,2)
```
Out[191]: 33.71

In [190]:
```
# p(KP781| Adult)
round(age_p.loc['Adult','KP781'] / age_p.loc['Adult'].sum()*100,2)
```
Out[190]: 21.35

In [192]:
```
# p(KP281| Mid age and old age)
round(age_p.loc['Mid age and old age','KP281'] / age_p.loc['Mid age and old age'].sum()*100,2)
```
Out[192]: 50.0

In [193]:
```
# p(KP481| Mid age and old age)
round(age_p.loc['Mid age and old age','KP481'] / age_p.loc['Mid age and old age'].sum()*100,2)
```
Out[193]: 16.67

In [194]:
```
# p(KP781| Mid age and old age)
round(age_p.loc['Mid age and old age','KP781'] / age_p.loc['Mid age and old age'].sum()*100,2)
```
Out[194]: 33.33

In [82]:
```
age_p = pd.crosstab(df['Product'],  [df['Age']]).sum(axis = 1).reset_index().rename(columns = {0 : 'age_count'})
age_p
```
Out[82]:

	Product	age_count
0	KP281	80
1	KP481	60
2	KP781	40