Business Case: Aerofit

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

Business Problem

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

Perform descriptive analytics **to create a customer profile** for each AeroFit treadmill product by developing appropriate tables and charts.

For each AeroFit treadmill product, construct **two-way contingency tables** and compute all **conditional and marginal probabilities** along with their insights/impact on the business.

Analysing basic metrics

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
aerofit=pd.read_csv('aerofit.csv')
aerofit
```

Out[4]:

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

180 rows × 9 columns

In [8]:
```
aerofit.columns
```

Out[8]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

In [9]:
```
aerofit.shape[0] #No. of rows
```

Out[9]:
```
180
```

In [10]:
```
aerofit.shape[1] #No. of columns
```

Out[10]:
```
9
```

In [19]:
```
aerofit.ndim #returns the number of dimensions or axes
```

Out[19]:
```
2
```

In [4]:
```
aerofit.info() #it shows datatype, index info., column info and memory usage
```

```
<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 [11]:
```
aerofit.isnull()
```

Out[11]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
175	False	False	False	False	False	False	False	False	False
176	False	False	False	False	False	False	False	False	False
177	False	False	False	False	False	False	False	False	False
178	False	False	False	False	False	False	False	False	False
179	False	False	False	False	False	False	False	False	False

180 rows × 9 columns

isnull() method with True indicating missing values and False indicating non-missing values.

In [12]:
```
aerofit.isnull().any()
```

Out[12]:
```
Product          False
Age              False
Gender           False
Education        False
MaritalStatus    False
Usage            False
Fitness          False
Income           False
Miles            False
dtype: bool
```

There are no missing values in the data.

In [22]:
```
aerofit.describe()
```

Out[22]:

	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

- **Age:** The age range for individuals in this group spans from a minimum of 18 years to a maximum of 50 years, with an average age of 28.79. Additionally, 75% of the people in this group are aged 33 or younger.
- **education:** The majority of individuals possess a 16-year education, with approximately 75% of the population having an educational attainment of 16 years or less.
- **Usage:** Mean Usage per week is 3.4, with maximum as 7 and minimum as 2.
- **Fitness:** Average rating is 3.3 on a scale of 1 to 5.
- **Miles:** Average number of miles the customer walks is 103 with maximum distance travelled by most people is almost 115 and minimum is 21.
- **Income (in $):** Most customer earns around 58K annually, with maximum of 104K and minimum almost 30K

Non-Graphical Analysis: Value counts and unique attributes

In [113…
```
aerofit['Product'].unique()  #KP281, KP481, KP781 are the 3 different products
```
Out[113]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```
In [114…
```
aerofit['Age'].unique() # list of unique ages
```
Out[114]:
```
array([18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
       35, 36, 37, 38, 39, 40, 41, 43, 44, 46, 47, 50, 45, 48, 42],
      dtype=int64)
```
In [115…
```
# Number of customer againts the rating scale 1 to 5
aerofit['Fitness'].value_counts().sort_index()
```
Out[115]:
```
1     2
2    26
3    97
4    24
5    31
Name: Fitness, dtype: int64
```
In [77]:
```
unique_MaritalStatus = aerofit['MaritalStatus'].unique()
unique_MaritalStatus
```
Out[77]:
```
array(['Single', 'Partnered'], dtype=object)
```
In [119…
```
# Number of customers counts on Usage
aerofit['Usage'].value_counts().sort_index()
```
Out[119]:
```
2    33
3    69
4    52
5    17
6     7
7     2
Name: Usage, dtype: int64
```

In [92]:
```
product_counts = aerofit['Product'].value_counts()
gender_counts = aerofit['Gender'].value_counts()
marital_status_counts = aerofit['MaritalStatus'].value_counts()
```

In [93]:
```
product_counts
```

Out[93]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [94]:
```
gender_counts
```

Out[94]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [95]:
```
marital_status_counts
```

Out[95]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

In [116…
```
most_frequent_product = aerofit.groupby('Product')['Usage'].sum().reset_index()
most_frequent_product
```

Out[116]:

	Product	Usage
0	KP281	247
1	KP481	184
2	KP781	191

KP281 is the most frequent product.

In [7]:
```
product_gender_counts = pd.crosstab(aerofit['Product'], aerofit['Gender'], margins
product_gender_counts
```

Out[7]:

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

the product-wise gender **crosstab**, showing how many females and males are associated with each product.

In [10]:
```
product_usage_counts = pd.crosstab(aerofit['Product'], aerofit['Usage'], margins=T
product_usage_counts
```

Out[10]:

Usage	2	3	4	5	6	7	All
Product							
KP281	19	37	22	2	0	0	80
KP481	14	31	12	3	0	0	60
KP781	0	1	18	12	7	2	40
All	33	69	52	17	7	2	180

the product-wise usage **crosstab**, showing The average number of times the customer plans to use the individual treadmill each week.

In [11]:

```
product_fitness_counts = pd.crosstab(aerofit['Product'], aerofit['Fitness'], margi
product_fitness_counts
```

Out[11]:

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

the product-wise fitness **crosstab**, showing every fitness level with each product

In [12]:

```
fitness_usage=round(pd.crosstab(aerofit['Fitness'],aerofit['Usage'],margins=True,n
fitness_usage
```

Out[12]:

Usage	2	3	4	5	6	7	All
Fitness							
1	0.56	0.56	0.00	0.00	0.00	0.00	1.11
2	7.78	5.56	1.11	0.00	0.00	0.00	14.44
3	10.00	26.11	16.67	1.11	0.00	0.00	53.89
4	0.00	5.56	3.89	3.33	0.56	0.00	13.33
5	0.00	0.56	7.22	5.00	3.33	1.11	17.22
All	18.33	38.33	28.89	9.44	3.89	1.11	100.00

Over 53% of customers have self-rated their fitness as average (with a rating of 3), and on average, they use the product 3 to 4 times per week.

In [99]:

```
average_income_by_product = aerofit.groupby('Product')['Income'].mean()
average_income_by_product
```

Out[99]:

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

In [100…
```
gender_marital_cross_tab = pd.crosstab(aerofit['Gender'], aerofit['MaritalStatus']
gender_marital_cross_tab
```

Out[100]:

MaritalStatus	Partnered	Single
Gender		
Female	46	30
Male	61	43

relationships between two categorical variables with cross tabulation

Summary

- KP281, KP481, KP781 are the 3 different products
- Most commonly purchased treadmill product type is KP281
- There are 32 unique ages
- 104 Males and 76 Females are in the customers list
- 8 unique set of Educations (14, 15, 12, 13, 16, 18, 20, 21)
- Highest rated Fitness rating is 3
- Most customers usage treadmill atleast 3 days per week
- Majority of the customers who have purchased are Married/Partnered

Conversion of Categorical attributes to 'Category'

In [50]:
```
aerofit2=aerofit.copy()
aerofit2['Age_group']=aerofit.Age

aerofit2.Age_group = pd.cut(aerofit.Age, bins=[0,20,35,45,60],labels=['Teen','Adul
age_counts=aerofit2['Age_group'].value_counts()
age_counts
```

Out[50]:
```
Adult           142
Middle Aged      22
Teen             10
Elder             6
Name: Age_group, dtype: int64
```

count of number of individuals in each age group and Categorization of age to following categories:-

- 0-20 -> Teen
- 21-35 -> Adult
- 36-45 -> Middle Age
- 46-60 -> Elder Age

In [51]:
```
aerofit2['Fitness_Category']=aerofit.Fitness
aerofit2['Fitness_Category'].replace({1:'Poor shape',
                                      2:'Bad shape',
                                      3:'Average shape',
                                      4:'Good shape',
                                      5:'Excelent shape'}, inplace =True)
aerofit2.head()
```

Out[51]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_group	F
0	KP281	18	Male	14	Single	3	4	29562	112	Teen	
1	KP281	19	Male	15	Single	2	3	31836	75	Teen	
2	KP281	19	Female	14	Partnered	4	3	30699	66	Teen	
3	KP281	19	Male	12	Single	3	3	32973	85	Teen	
4	KP281	20	Male	13	Partnered	4	2	35247	47	Teen	

Categorization of Fitness Rating to following descriptive categories

- Poor Shape
- Bad Shape
- Average Shape
- Good Shape
- Excellent Shape

Statistical Summary

In [106…

```
cross_tab = pd.crosstab(index=aerofit['Product'], columns='Count')
marginal_probability = cross_tab / cross_tab.sum() * 100
marginal_probability.columns = ['Percentage']
marginal_probability
```

Out[106]:

Product	Percentage
KP281	44.444444
KP481	33.333333
KP781	22.222222

Representing the **marginal probability**- percent of customers have purchased **KP281**, **KP481**, or **KP781** in a table

In [129…

```
normalise_count = aerofit[['Product', 'Gender', 'MaritalStatus']].melt()
percentage=(normalise_count.groupby(['variable', 'value'])[['value']].count() / le
percentage
```

Out[129]:

variable	value	value
Gender	Female	42.22
	Male	57.78
MaritalStatus	Partnered	59.44
	Single	40.56
Product	KP281	44.44
	KP481	33.33
	KP781	22.22

Product

- **44.44%** of customers bought **KP281** product type
- **33.33%** of customers bought **KP481** product type
- **22.22%** of customers bought **KP781** product type

Gender

- **57.78%** of the customers are Male.

MaritalStatus

- **59.44%** of the customers are Partnered.

In [136…

```
#Number of days used per week (listed in %)
usage=aerofit["Usage"].value_counts(normalize=True).map(lambda calc: round(100*cal
usage.rename(columns={'index':'DaysPerWeek'}, inplace=True)
usage
```

Out[136]:

	DaysPerWeek	Usage
0	3	38.33
1	4	28.89
2	2	18.33
3	5	9.44
4	6	3.89
5	7	1.11

- Around **39%** of customers use **3 days per week**
- Less than **2%** of customers use **7 days per week**

In [154…

```
rating = aerofit['Fitness'].value_counts(normalize=True).map(lambda calc:round(100
rating.rename(columns={'index':'Rating'},inplace=True)
rating
```

Out[154]:

	Rating	Fitness
0	3	53.89
1	5	17.22
2	2	14.44
3	4	13.33
4	1	1.11

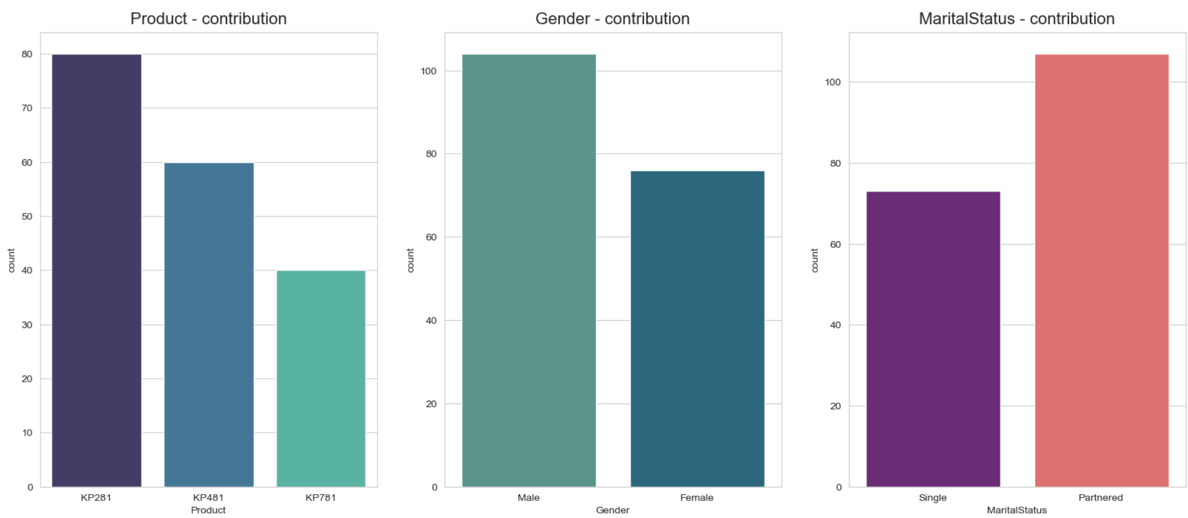
- **Approximately 53%** of customers consider themselves to have an **average fitness level**,
- while **14%** rate their fitness as **below average**.
- Additionally, **more than 17%** of customers have given themselves the **highest fitness ratings**.

Visual Analysis - Univariate & Bivariate

Univariate Analysis

In [132…

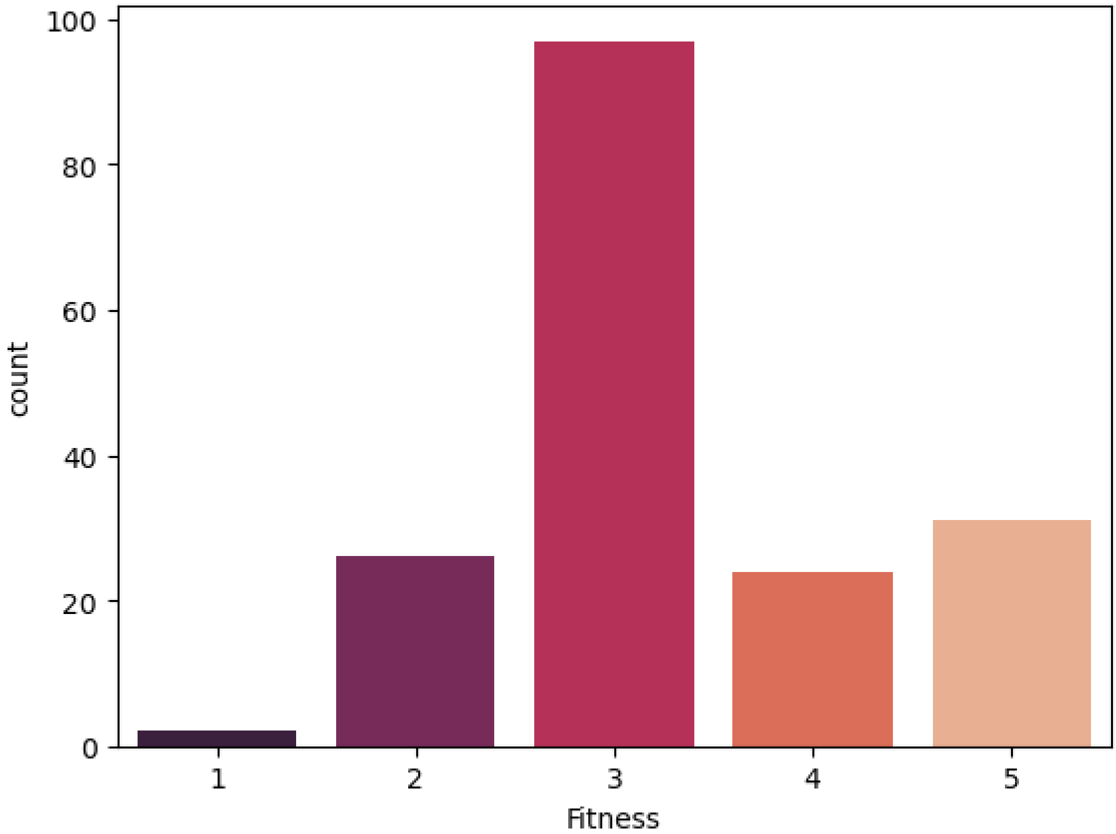
```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 8))
sns.countplot(data=aerofit, x='Product', palette="mako", ax=axs[0])
sns.countplot(data=aerofit, x='Gender', palette="crest", ax=axs[1])
sns.countplot(data=aerofit, x='MaritalStatus', palette="magma", ax=axs[2])

axs[0].set_title("Product - contribution", pad=8, fontsize=16)
axs[1].set_title("Gender - contribution", pad=8, fontsize=16)
axs[2].set_title("MaritalStatus - contribution", pad=8, fontsize=16)
plt.show()
```



- The product **"KP281"** stands out as the most commonly purchased item.
- There is a **higher number of males** in the dataset compared to females.
- The dataset contains a larger number of individuals who are in a **partnered or marital status**.

In [192…

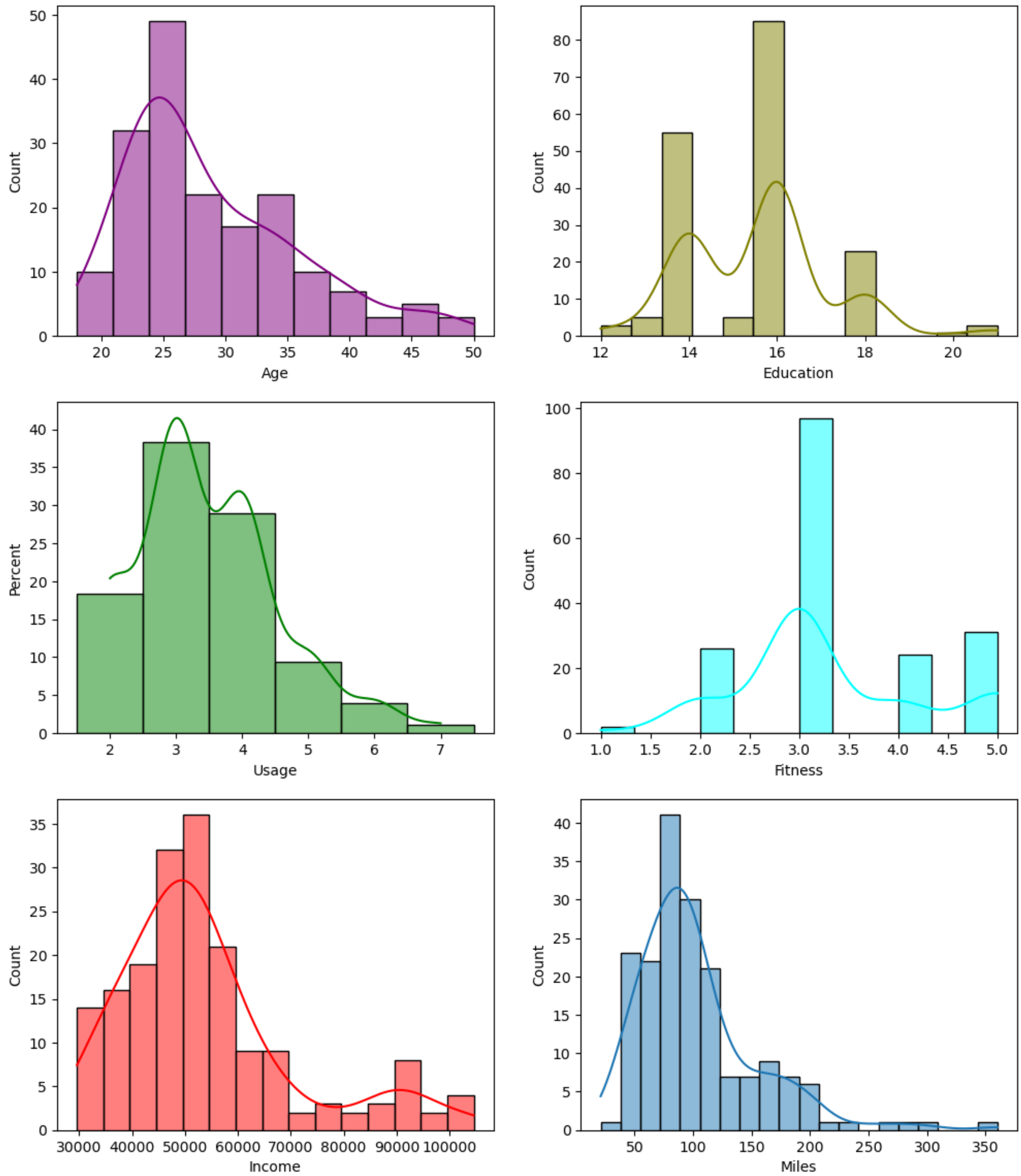
```
sns.countplot(data=aerofit,x='Fitness',palette="rocket")
plt.show()
```



- **More than 90 customers** have rated their physical fitness rating as **Average**
- **Excellent shape** is the second highest rating provided by the customers

In [15]:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.histplot(data=aerofit, x="Age",kde=True, ax=axis[0,0], color='purple')
sns.histplot(data=aerofit, x="Education", kde=True, ax=axis[0,1], color='olive')
sns.histplot(data=aerofit, x="Usage", kde=True, stat = 'percent', discrete = True,
sns.histplot(data=aerofit, x="Fitness", kde=True, ax=axis[1,1], color='cyan')
sns.histplot(data=aerofit, x="Income", kde=True, ax=axis[2,0], color='red')
sns.histplot(data=aerofit, x="Miles", kde=True, ax=axis[2,1])
plt.show()
```



- It can be evidently observed in the above plot that most customers have 16 years of Education, followed by 14 years and 18 years

- it appears that most customers use treadmills on alternate days

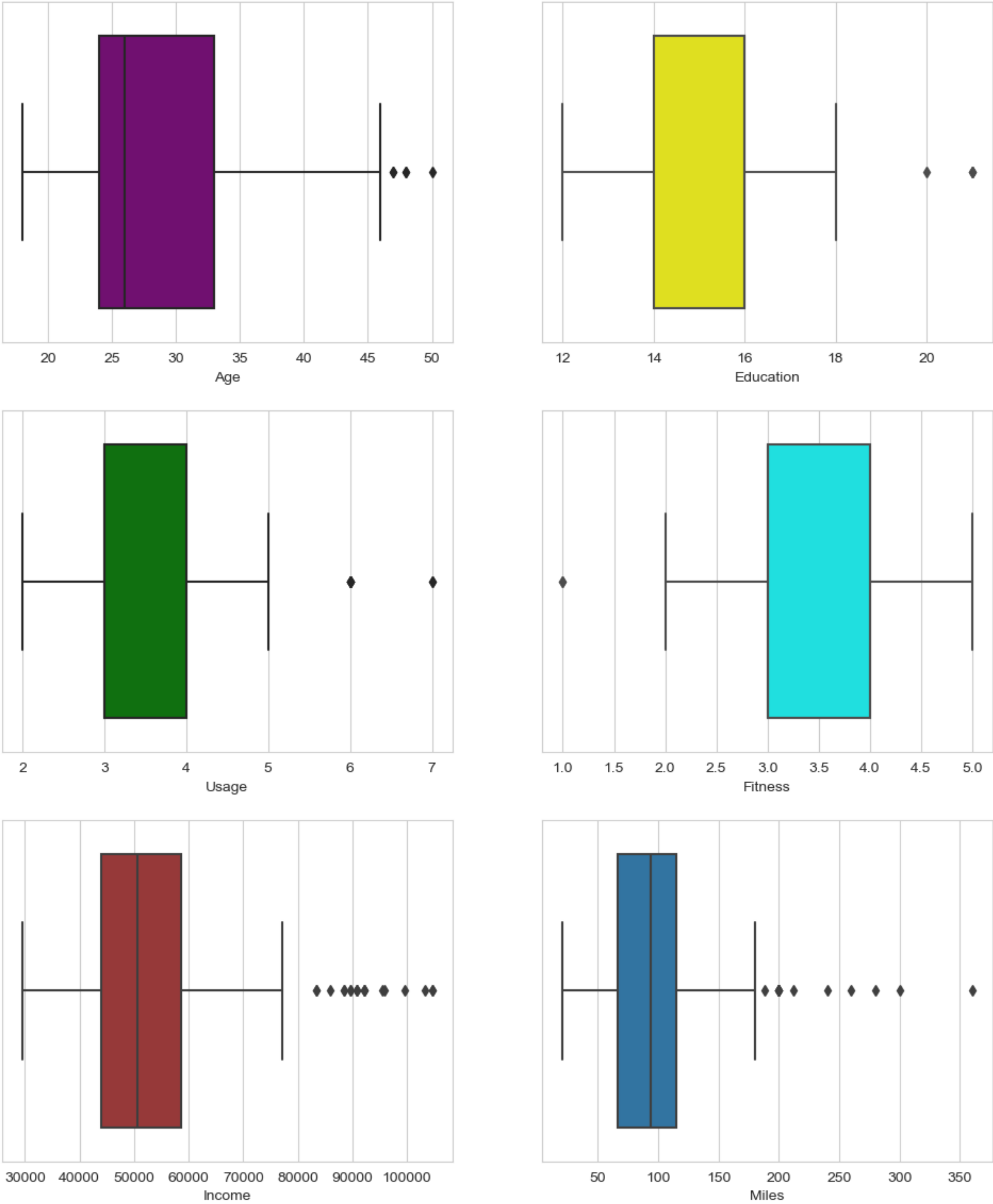
- Majority of the customers earn in between 35000 and 60000 dollars annually.

- 80 % of the customers annual salary is less than 65000$.
- most customers expect to walk or run between 40 and 120 miles a week.

In [136…

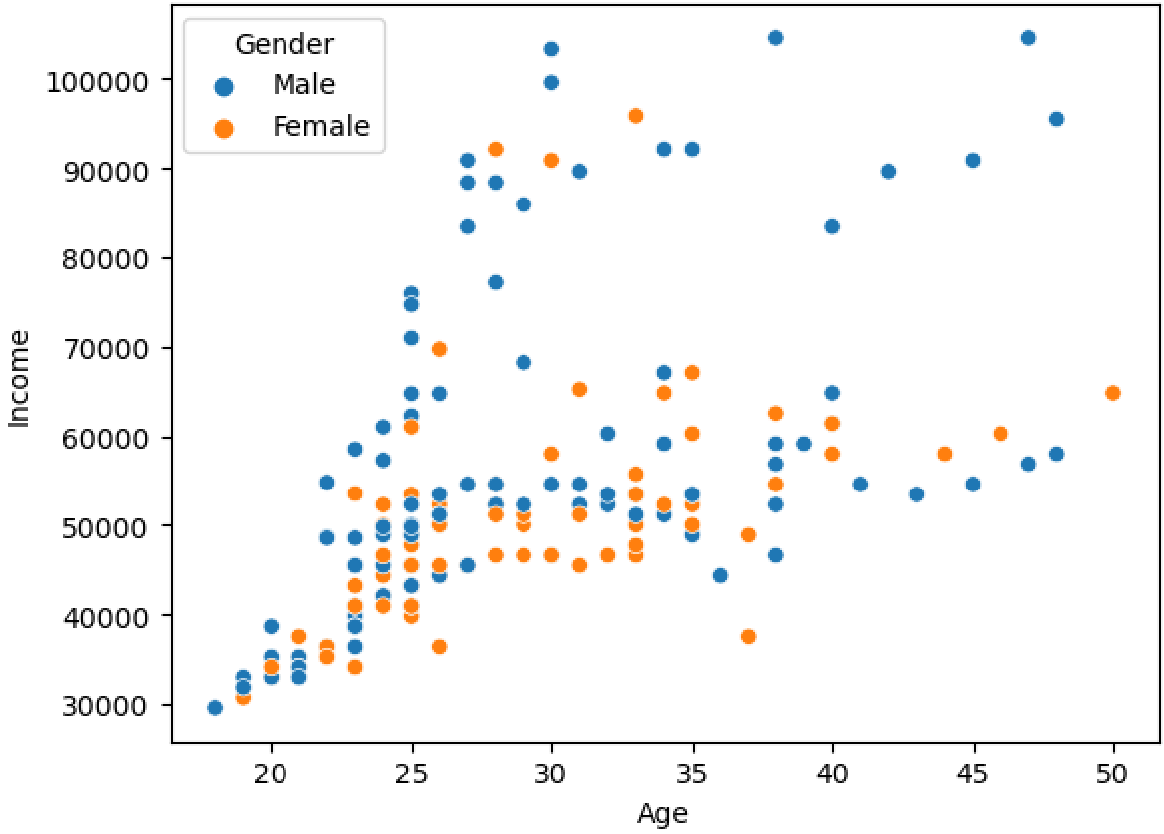
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.boxplot(data=aerofit, x="Age", ax=axis[0,0], color='purple')
sns.boxplot(data=aerofit, x="Education", ax=axis[0,1], color='yellow')
sns.boxplot(data=aerofit, x="Usage", ax=axis[1,0], color='green')
sns.boxplot(data=aerofit, x="Fitness", ax=axis[1,1], color='cyan')
sns.boxplot(data=aerofit, x="Income",  ax=axis[2,0], color='brown')
```

```
sns.boxplot(data=aerofit, x="Miles", ax=axis[2,1])
plt.show()
```



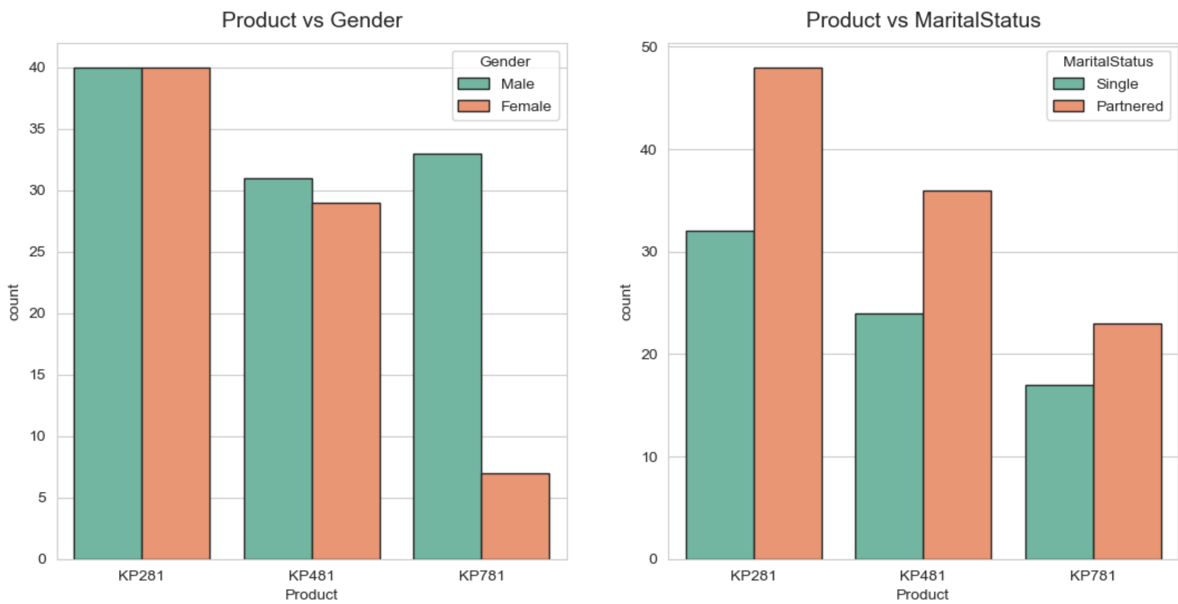
- Age, Education and Usage are having very few outliers.
- While Income and Miles are having more outliers.

In [13]:
```
age_wise_income=sns.scatterplot(data=aerofit, x='Age',y='Income', hue='Gender')
```



Bivariate Analysis

In [28]:
```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(13, 6))
sns.countplot(data=aerofit, x='Product', hue='Gender', edgecolor="0.15", palette=':
sns.countplot(data=aerofit, x='Product', hue='MaritalStatus', edgecolor="0.15", pa
axs[0].set_title("Product vs Gender", pad=10, fontsize=14)
axs[1].set_title("Product vs MaritalStatus", pad=10, fontsize=14)
plt.show()
```



Product vs Gender

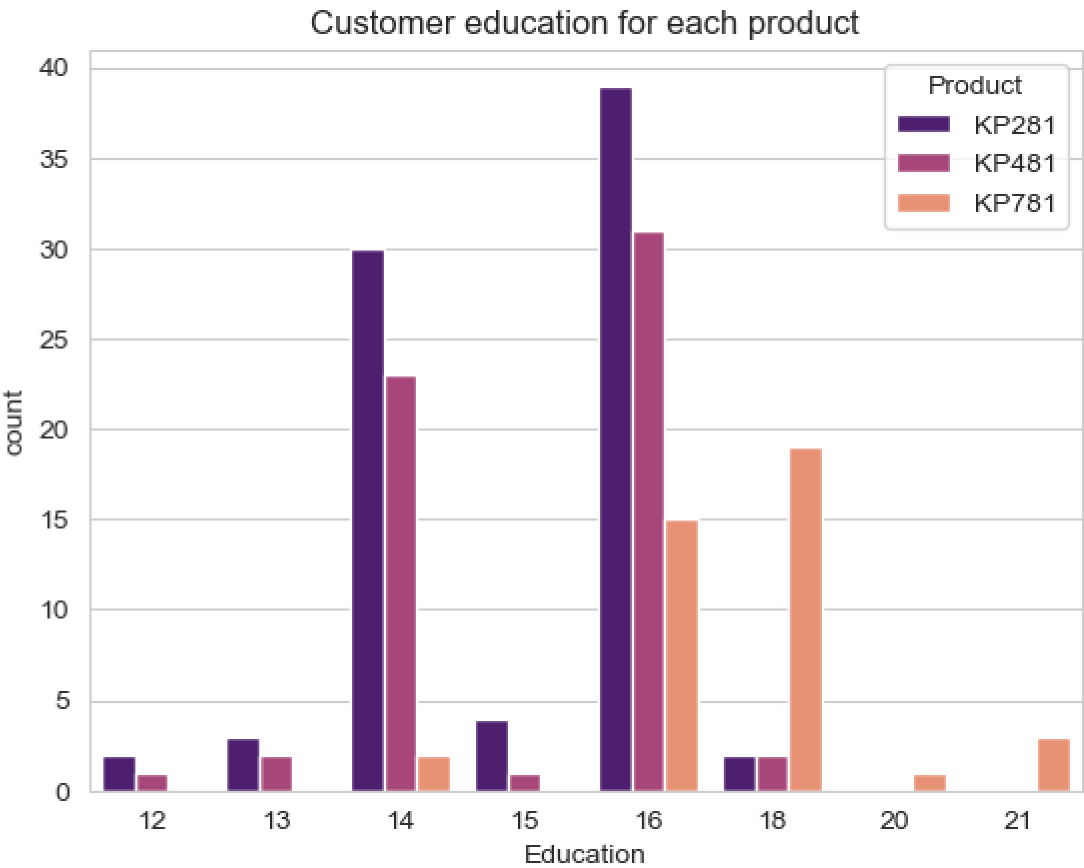
- An equal number of males and females have bought the KP281 product, and a similar pattern is observed for the KP481 product.

- The majority of male customers have opted for the KP781 product.

Product vs MaritalStatus

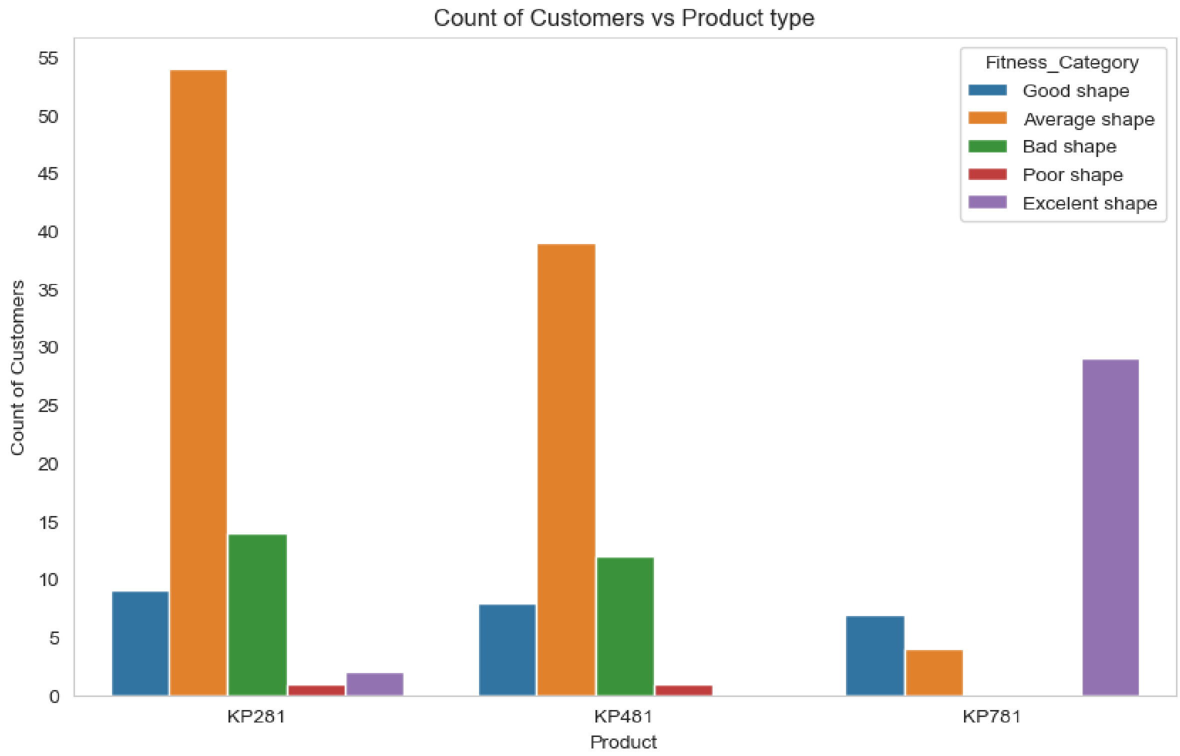
- Customer who is Partnered, is more likely to purchase the product.

In [45]:
```
sns.countplot(data=aerofit, x='Education', hue='Product', palette='magma')
plt.title('Customer education for each product')
plt.show()
```



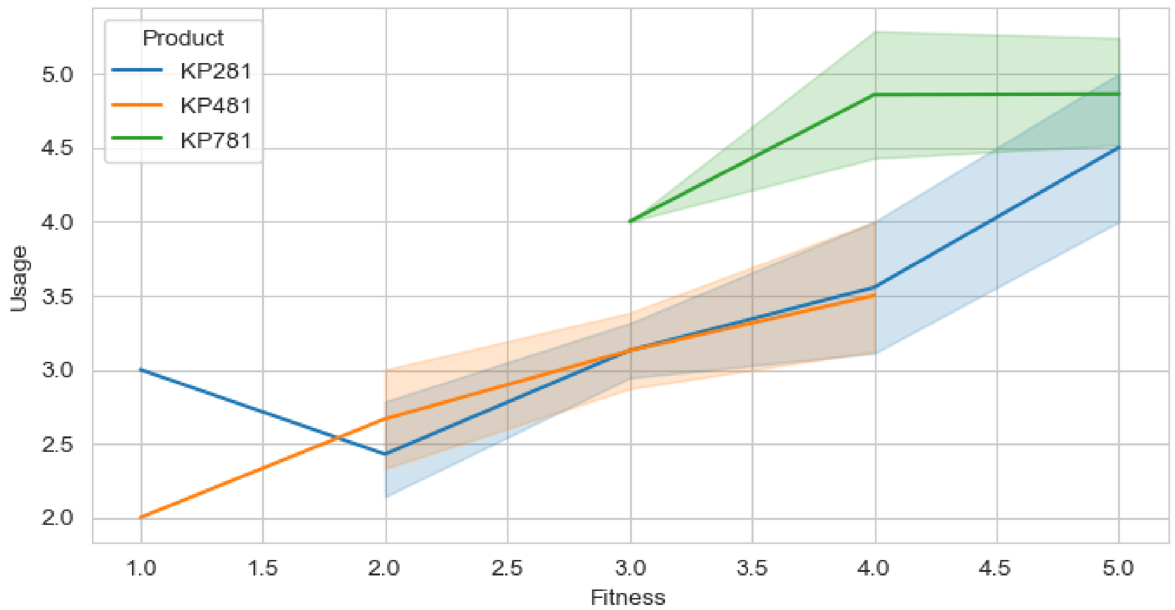
More than 16 years of Educated customer prefer KP781.

In [133…
```
plt.figure(figsize = (10, 6))
plt.title("Count of Customers vs Product type")
plt.yticks(np.arange(0, 60, 5))
sns.countplot(data = aerofit2, x = 'Product', hue = 'Fitness_Category')
plt.ylabel('Count of Customers')
plt.grid(axis = 'y')
plt.show()
```



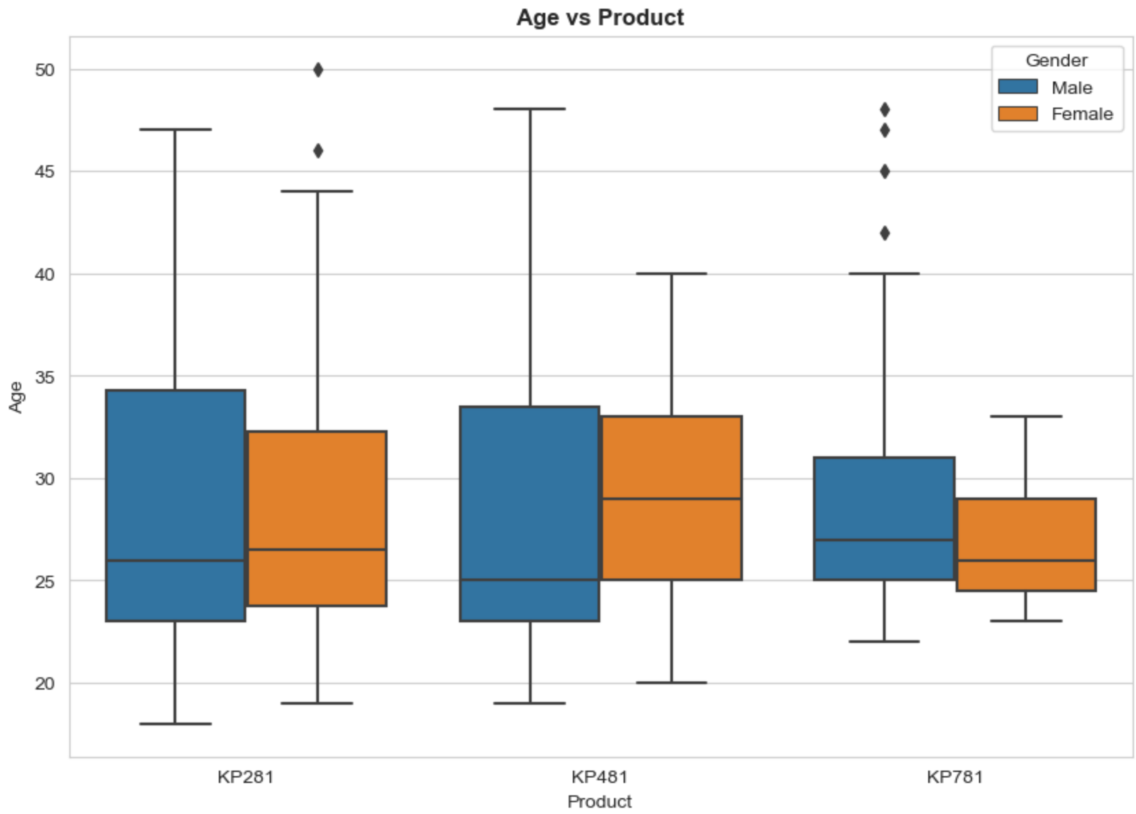
- The customers who rate themselses 3 out of 5 in self rated fitness scale are more likely to invest in the entry-level treadmills or treadmills for mid-level runners i.e., KP281 and KP481 respectively and they are more unlikey to buy the treadmill which has advanced features i.e., KP781.
- The treadmill having advanced features are mostly used by the people with high fitness levels.
- The customers who rate themselves 3 or below in the self-rated fitness scale do not buy KP781.

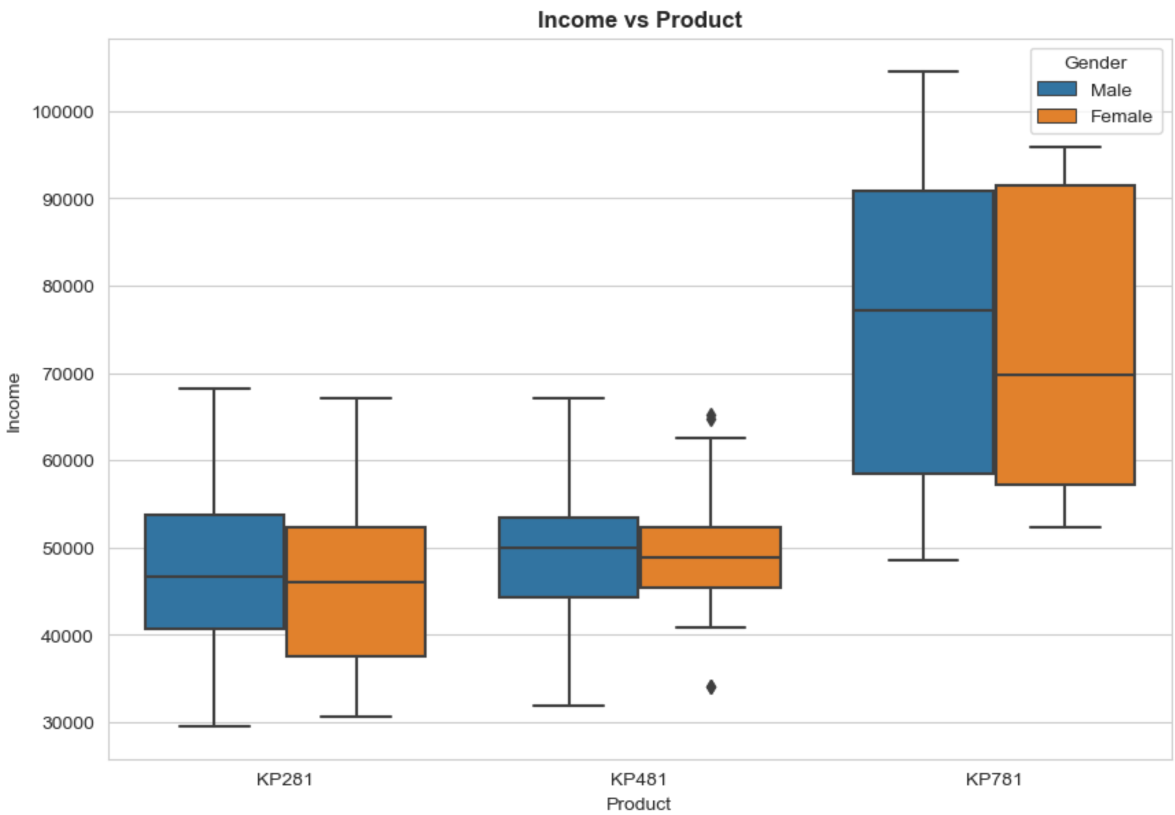
In [135…
```
plt.figure(figsize = (8, 4))
sns.lineplot(data=aerofit, x='Fitness', y='Usage',hue='Product')
plt.show()
```



In [66]:
```
fig, ax=plt.subplots(nrows=2, ncols=1, figsize=(10,15))
sns.boxplot(data=aerofit, y='Age', x='Product', hue='Gender', ax=ax[0])
```

```
ax[0].set_title('Age vs Product', fontweight='bold')
sns.boxplot(data=aerofit, y='Income', x='Product', hue='Gender', ax=ax[1])
ax[1].set_title('Income vs Product', fontweight='bold')
plt.show()
```





Age vs Product

- There is a significant difference in the median age of males and females who bought KP481.

- For any product, the age range for males is higher than that of female. The range difference is significant for the product KP781.

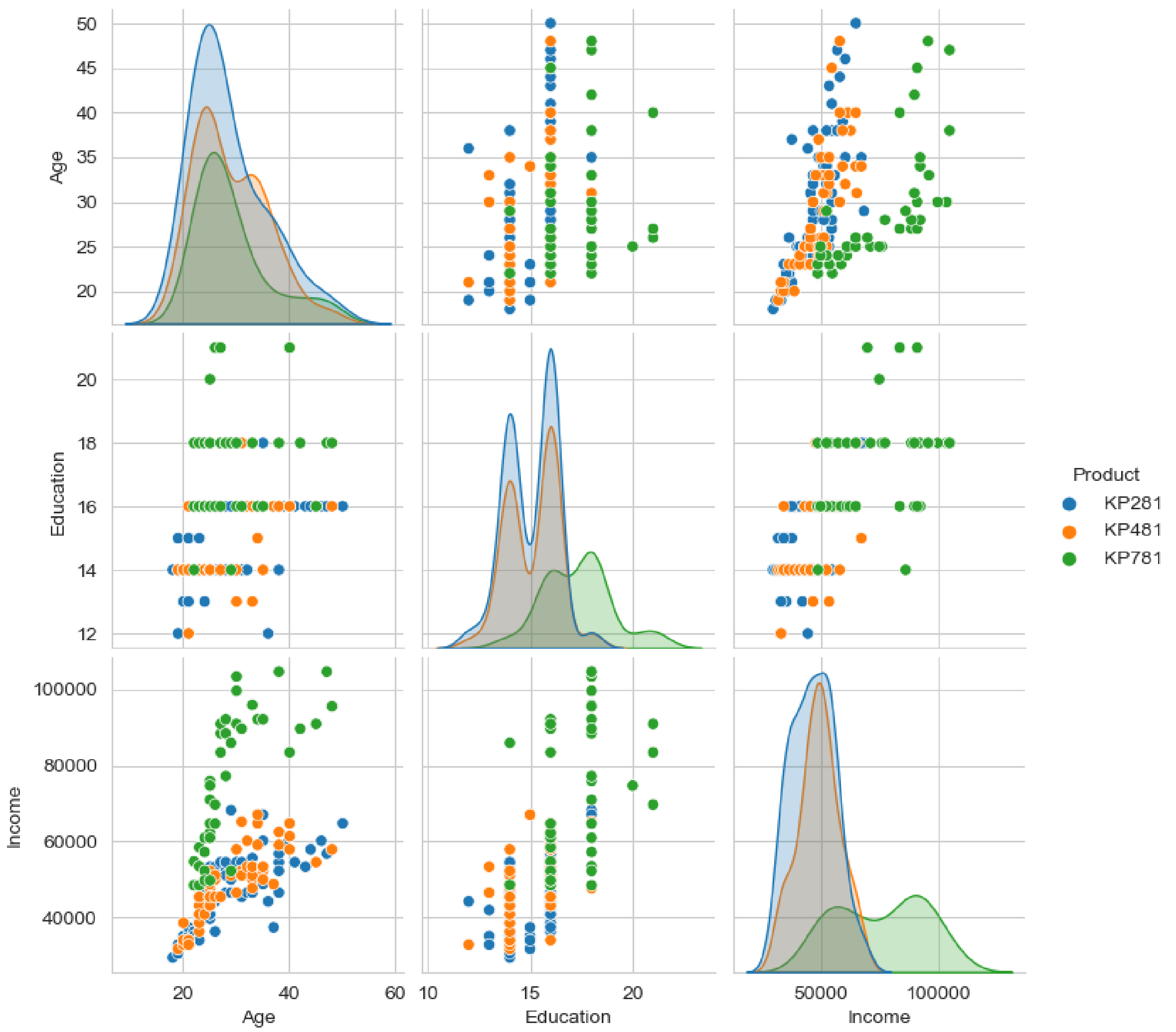
Income vs Product

- The median income of customers who bought KP781 is much higher than that of the customers who bought other two products.
- The range of income for customers buying KP781 is much higher than the same for customers buying KP281 and KP481.

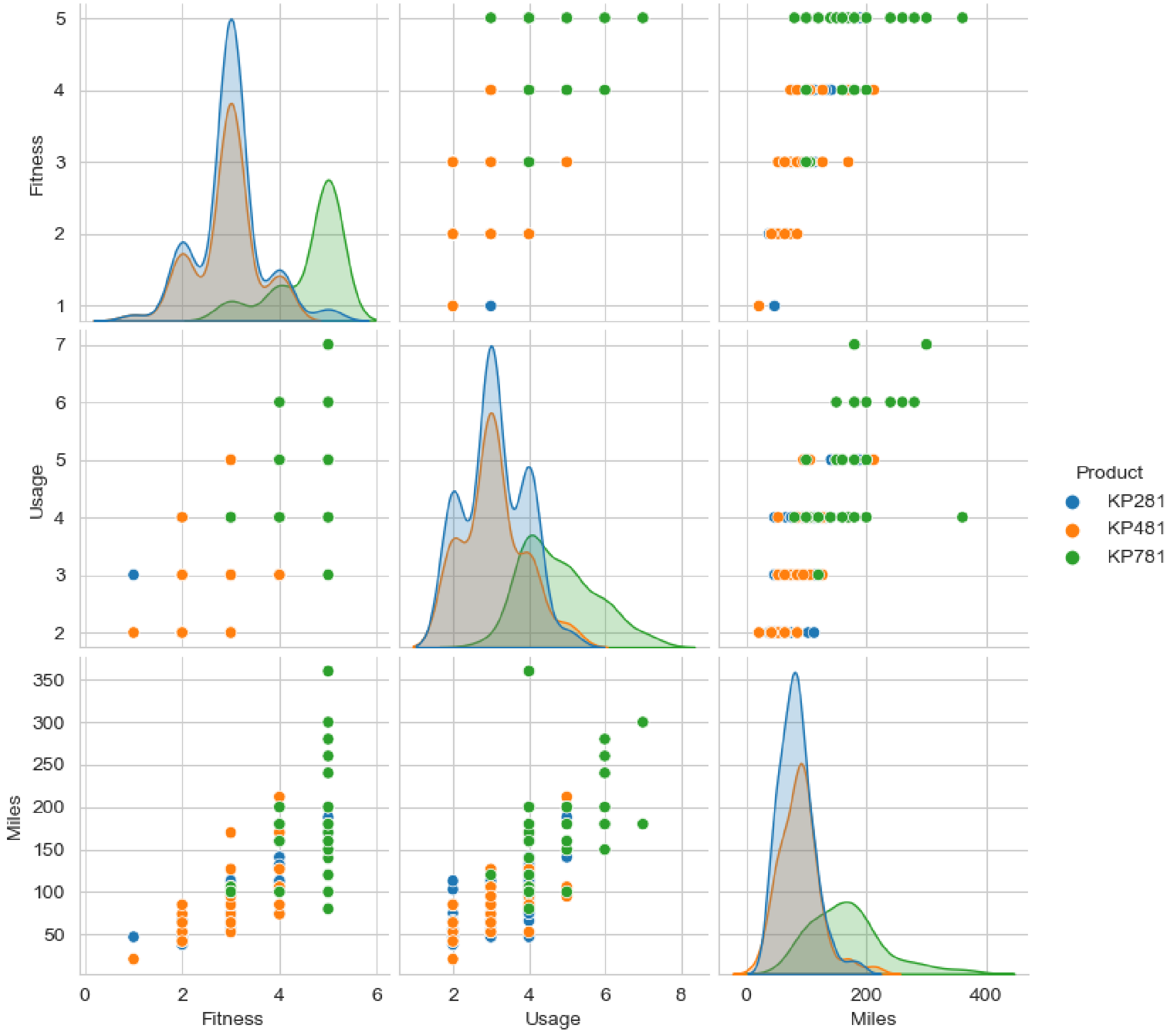
For correlation: Heatmaps, Pairplots

In [78]:
```
sns.pairplot(data = aerofit[['Product','Age','Education','Income']], hue='Product'
plt.plot()
```

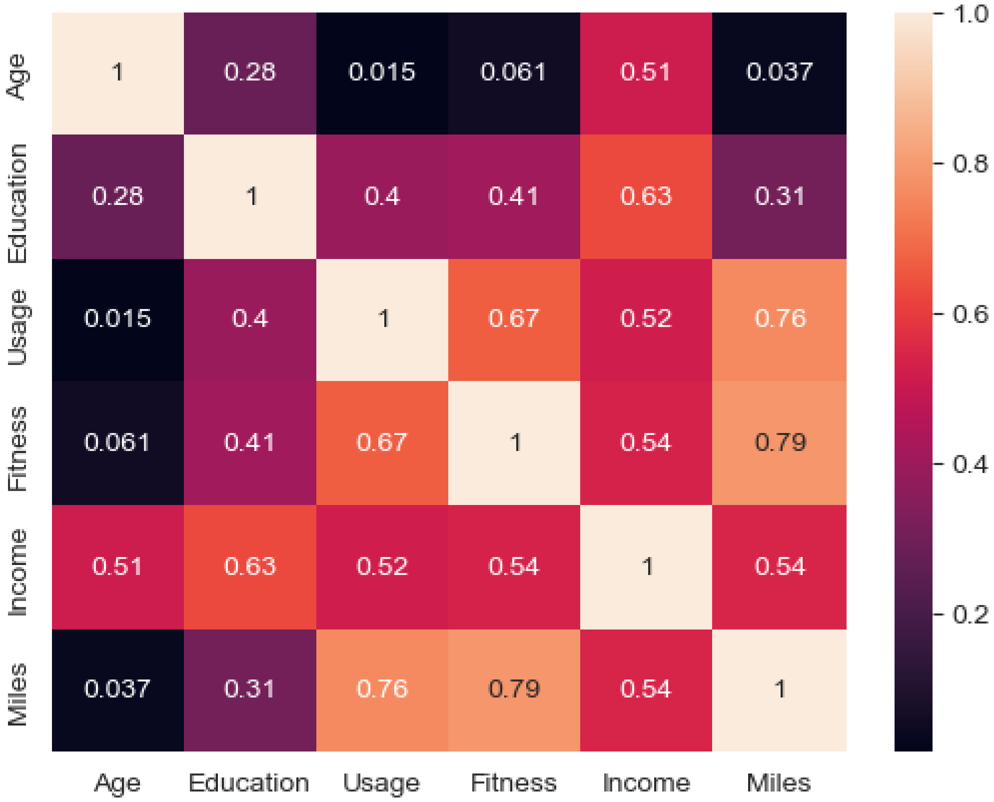
Out[78]: []



In [76]:
```
sns.pairplot(data=aerofit[['Fitness','Usage','Miles','Product']], hue='Product')
plt.show()
```




```
In [74]: sns.heatmap(aerofit[['Age','Education','Usage','Fitness','Income','Miles']].corr()
         plt.show()
```



Missing Value & Outlier Detection

Missing values

In [80]:
```
aerofit.isnull().any()
```

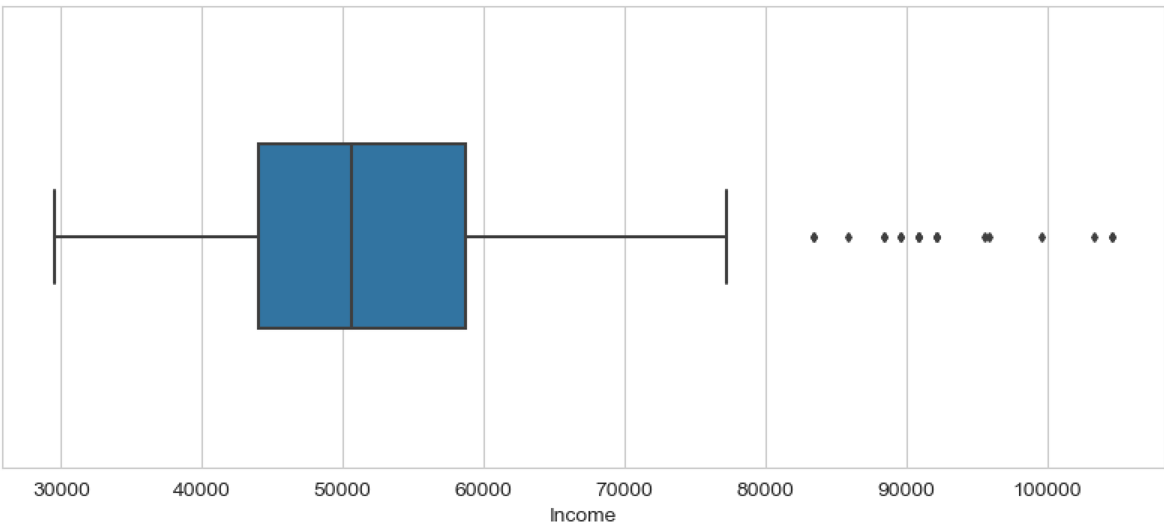
Out[80]:
```
Product          False
Age              False
Gender           False
Education        False
MaritalStatus    False
Usage            False
Fitness          False
Income           False
Miles            False
dtype: bool
```

Dataset doesn't have any null values

Outlier Detection

Detecting outliers for Annual income

In [92]:
```
plt.figure(figsize = (10, 4))
sns.boxplot(data = aerofit, x = 'Income', width = 0.4, orient = 'h',  fliersize = 
plt.show()
```



In [103…
```
data=aerofit['Income']
q1=data.quantile(.25)
q3=data.quantile(.75)
print("1st Quartile : ", q1)
print('Median : ', data.median())
print("3rd Quartile : ", q3)
iqr = q3 - q1
print('Innerquartile Range:', iqr)
upper = q3 + 1.5 * iqr
print('Upper bound:',upper)
lower=q1 - 1.5*iqr
print('Lower bound:',lower)
```

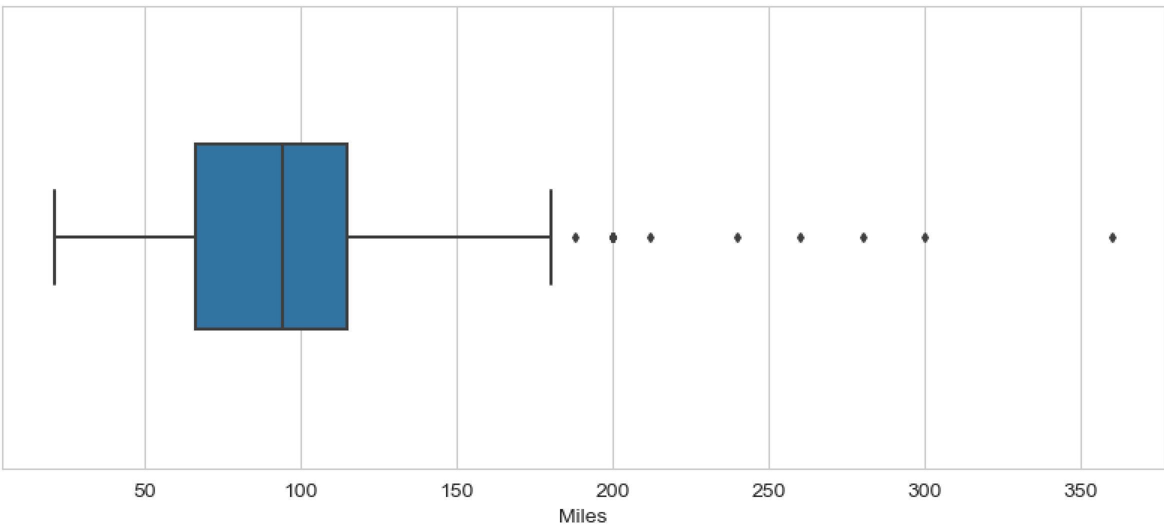
```
outliers=data[(data>upper)|(data<lower)]
print('outliers:', sorted(outliers))
outliers_count=len(data[(data>upper)|(data<lower)])
print('No. of outlier:', outliers_count)
```

```
1st Quartile :  44058.75
Median :  50596.5
3rd Quartile :  58668.0
Innerquartile Range: 14609.25
Upper bound: 80581.875
Lower bound: 22144.875
outliers: [83416, 83416, 85906, 88396, 88396, 89641, 89641, 90886, 90886, 90886, 9
2131, 92131, 92131, 95508, 95866, 99601, 103336, 104581, 104581]
No. of outlier: 19
```

we have exactly 19 outliers in the Income range.

Detecting outliers for Miles

In [97]:
```
plt.figure(figsize = (10, 4))
sns.boxplot(data = aerofit, x = 'Miles', width = 0.4, orient = 'h',  fliersize = 3
plt.show()
```



In [102…
```
data1=aerofit['Miles']
q1=data1.quantile(.25)
q3=data1.quantile(.75)
print("1st Quartile : ", q1)
print('Median : ', data1.median())
print("3rd Quartile : ", q3)
iqr= q3 - q1
print('Innerquartile Range:', iqr)
upper= q3 + 1.5 * iqr
print('Upper bound:',upper)
lower= q1 - 1.5 * iqr
print('Lower bound:',lower)
outliers=data1[(data1>upper)|(data1<lower)]
print('outliers:', sorted(outliers))
outliers_count=len(data1[(data1>upper)|(data1<lower)])
print('No. of outlier:', outliers_count)
```

```
1st Quartile :  66.0
Median :  94.0
3rd Quartile :  114.75
Innerquartile Range: 48.75
Upper bound: 187.875
Lower bound: -7.125
outliers: [188, 200, 200, 200, 200, 200, 200, 212, 240, 260, 280, 300, 360]
No. of outlier: 13
```

- we have 13 outliers in the Miles range
- While Income and Miles are having more outliers.
- Age, Education and Usage are having very few outliers.

detecting outliers in the age of males who bought KP781

In [101…

```
#as we can see some outliers in the Age vs product boxplot, so here detecting no. o

data2=aerofit.loc[(aerofit['Product']=='KP781')&(aerofit['Gender']=='Male'), 'Age'
q1=data2.quantile(.25)
q3=data2.quantile(.75)
print("1st Quartile : ", q1)
print('Median : ', data2.median())
print("3rd Quartile : ", q3)
iqr= q3 - q1
print('Innerquartile Range:', iqr)
upper= q3 + 1.5 * iqr
print('Upper bound:',upper)
lower= q1 - 1.5 * iqr
print('Lower bound:',lower)
outliers=data2[(data2>upper)|(data2<lower)]
print('outliers:', sorted(outliers))
outliers_count=len(data2[(data2>upper)|(data2<lower)])
print('No. of outlier:', outliers_count)
```

```
1st Quartile :  25.0
Median :  27.0
3rd Quartile :  31.0
Innerquartile Range: 6.0
Upper bound: 40.0
Lower bound: 16.0
outliers: [42, 45, 47, 48]
No. of outlier: 4
```

We have exactly 4 outliers in the data of age of the males who bought KP781 treadmill.

Business Insights based on Non-Graphical and Visual Analysis

Marginal Probabilities

In [126…

```
np.round(((pd.crosstab(aerofit.Product, aerofit.Gender,margins=True))/180)*100,2)
```

Out[126]:

Gender	Female	Male	All
Product			
KP281	22.22	22.22	44.44
KP481	16.11	17.22	33.33
KP781	3.89	18.33	22.22
All	42.22	57.78	100.00

- P(Male): 57.77 %
- P(Female) : 42.22 %
- 44.44% of customers bought KP281 product.
- 33.33% of customers bought KP481 product.
- 22.22% of customers bought KP781 product

Conditional Probabilities

Probability of customer purchasing particular product, when customer belongs to a specific gender.

In [119…

```
products= aerofit['Product'].unique()
genders= aerofit['Gender'].unique()
for i in products:
    for j in genders:
        prob=len(aerofit[(aerofit["Product"]==i) & (aerofit['Gender']==j)])/ len(a
        prob=np.round(prob*100, 2)
        print('P({}/{}): {}%'.format(i, j, prob))
        print()
```

```
P(KP281/Male): 38.46%

P(KP281/Female): 52.63%

P(KP481/Male): 29.81%

P(KP481/Female): 38.16%

P(KP781/Male): 31.73%

P(KP781/Female): 9.21%
```

The probability of a customer being of a specific gender, when they have purchased a particular product.

In [124…

```
for i in products:
    for j in genders:
        prob=len(aerofit[(aerofit["Product"]==i) & (aerofit['Gender']==j)])/ len(a
        prob=np.round(prob*100, 2)
        print('P({}/{}): {}%'.format(j, i, prob))
        print()
```

```
P(Male/KP281): 50.0%

P(Female/KP281): 50.0%

P(Male/KP481): 51.67%

P(Female/KP481): 48.33%

P(Male/KP781): 82.5%

P(Female/KP781): 17.5%
```

Probability of customer purchasing particular product, when customer belongs to a specific MaritalStatus.

In [125…

```
products= aerofit['Product'].unique()
status= aerofit['MaritalStatus'].unique()
for i in products:
    for j in status:
        prob=len(aerofit[(aerofit["Product"]==i) & (aerofit['MaritalStatus']==j)]).
        prob=np.round(prob*100, 2)
        print('P({}/{}): {}%'.format(i, j, prob))
        print()
```

```
P(KP281/Single): 43.84%

P(KP281/Partnered): 44.86%

P(KP481/Single): 32.88%

P(KP481/Partnered): 33.64%

P(KP781/Single): 23.29%

P(KP781/Partnered): 21.5%
```

Customer Profiling - Categorization of users.

KP281 customer's profile

- The customers who rate themselses 3 out of 5 in self rated fitness scale are more likely to invest in.
- Usage under 4days per week.
- Most of the customer who have purchased the product have rated Average shape as the fitness rating
- Income range between 39K to 53K have preferred this product.
- The customers having low fitness scale or low annual income.
- Probability increased from 44.44% to 58.7%, if customer is Female and Partnered.
- Younger to Elder beginner level customers prefer this product.
- Customers who educated under 16 years most preferable.
- Customers whose usage under 120 miles per week

KP481 customer's profile

- This is an Intermediate level Product.
- Usage under 4days per week.
- Fitness Level of this product users varies from Bad to Average Shape depending on their usage.
- Average distance covered in this product is from 70 to 130 miles per week.
- Customers Prefer this product mostly to cover more miles than fitness.
- Less to medium earning customers.
- Average Income of the customer who buys KP481 is 49K.
- Male customers who partnered prefer more than Male customers who single.
- It has almost similar customer's profile like KP281, but KP281 is wide range of customers than KP481.

KP781 customer's profile

- 82.5% of them are males rest are females.
- Among all female customers, only 9.21 % buy KP781
- Customer walk/run average 120 to 200 or more miles per week
- 90 % of them had fitness scales 4 or 5. Only 10 % of them had average body shape.
- Female Customers who are running average 180 miles (extensive exercise) , are using product KP781, which is higher than Male average using same product.
- Usage more than 4 days per week.
- Customers who educated more than 16 years.
- the customer has the annual income in range '> 80k' is 100.0%
- This product is preferred by the customer where the correlation between Education and Income is High.

Insights

- Product KP281 brings in the highest revenue, KP481 and KP781 come next in line respectively
- Highly educated customers prefer product KP781; they could be more aware of the product's typical features and its usage
- product KP781 is used more compared to others products KP281 and KP481
- Majority of the customers are in the age group of 22-33 years
- ~60-40% distribution of the male and female product buyers
- Majority of the buyers spend 14, 16, 18 years on their education
- ~60-40% distribution of the single and partnered product buyers
- Most of the users use the treadmill 3-4 times a week
- Among all the customers who bought KP281, 96.25 % of them had fitness scales of 2, 3 or 4. Only 2.5 % of them had excellent body shape, Most of the users rate themselves average in terms of their fitness levels.
- Majority of the users earn between 35000 to 60000 annually
- Majority of the users set target miles expected to be walked/ran between 53 and 132 miles

Recommendations

- A better, high-end, premium product for highly-educated, high income and active customers to increase revenue.
- Because KP781, a premium product, is favored by males who are high earners and use it more frequently, we can target this demographic with similar products and also introduce them to upcoming premium offerings.
- Female who prefer exercising equipments are very low here. Hence, we should run a marketing campaign on to encourage women to exercise more
- As KP781 provides more features and functionalities, the treadmill should be marketed for professionals and athletes. KP781 product should be promotted using influencers and other international atheletes.
- Since KP281 and KP481 also brings in significant revenue and is prefered by young & learnings individuals, added features and specialized discounts could help boost sales.
- Since KP281 is the best-selling product, we can boost the promotion of KP481 products and potentially introduce a no-cost EMI option to encourage sales.
- Research required for expanding market beyond 50 years of age considering health pros and cons.
- Provide customer support and recommend users to upgrade from lower versions to next level versions after consistent usages.
- KP781 can be recommended for Female customers who exercises extensively along with easy usage guidance since this type is advanced.