Aerofit - Case Study

Installing packages

In [1]:

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

Loading Dataset

In [2]:

```
aerofit = pd.read_csv('aerofit.csv')
```

In [3]:

```
aerofit.head(10)
```

Out[3]:

	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
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
9	KP281	21	Female	15	Partnered	2	3	37521	85

Columns and its datatypes

In [4]:

```
aerofit.shape
```

Out[4]:

```
(180, 9)
```

There are **180 datapoints** and **9 features**

In [5]:

```
aerofit.dtypes
```

Out[5]:

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

Observation

- 3 categorial features found and rest are numerical features

Let's convert the dtype of categorical feature to category

In [6]:

```
aerofit["Product"] = aerofit["Product"].astype("category")
aerofit["Gender"] = aerofit["Gender"].astype("category")
aerofit["MaritalStatus"] = aerofit["MaritalStatus"].astype("category")
```

Missing Values Detection

In [7]:

```
aerofit.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
```

In [8]:

```
aerofit.isnull().sum()
```

Out[8]:

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

Observation

- There is no missing values found

Duplicate Values Detection

In [9]:

```
aerofit.duplicated().sum()
```

Out[9]:

```
0
```

Observation

- There is no duplicates found in our dataset

Statistical Summary (Numerical)

In [10]:

```
aerofit.describe()
```

Out[10]:

	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

Insights

- There is significant difference in income of customers ranging between `$29562 - $104581`
- There is significant difference between Standard Deviation and Mean of Miles & Income. These columns might contain outliers in it

Statistical Summary (Categorical)

In [13]:

```
aerofit.describe(include = "category")
```

Out[13]:

	Product	Gender	MaritalStatus
count	180	180	180
unique	3	2	2
top	KP281	Male	Partnered
freq	80	104	107

Insights

- Top availble product `KP281`
- Most of the customer `Male & Parternered`

No. of unique count for each features

In [14]:

```
aerofit.nunique()
```

Out[14]:

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

Value counts for each features

In [15]:

```
aerofit["Product"].value_counts()
```

Out[15]:

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

Insights

- `KP281` is top available product

In [16]:

```
aerofit["Gender"].value_counts()
```

Out[16]:

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

Insights

- Most of the customers are `Male`

In [17]:

```
aerofit["MaritalStatus"].value_counts()
```

Out[17]:

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

Insights

- Most of the customers are `Partnered`

In [18]:

```
aerofit["Education"].value_counts()
```

Out[18]:

```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

Insights

- Most of the customer having 16 years of education

In [19]:

```
aerofit["Usage"].value_counts()
```

Out[19]:

```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

Insights

- Most of the customer use tredmills for 3 times

In [20]:

```
aerofit["Fitness"].value_counts()
```

Out[20]:

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

Insights

- Most of the customers self rated themselves 3 out of 5 in terms of fitness

Derived columns

1. Age -> Age Group

2. Income -> Income Slab

3. Miles -> Running Stamina

In [177]:

```
bins = [14,20,30,40,60]
labels =["Teens","20s","30s","Above 40s"]
aerofit['AgeGroup'] = pd.cut(aerofit['Age'], bins,labels=labels)

bins_income = [29000, 35000, 60000, 85000,105000]
labels_income = ['Low Income','Lower-middle income','Upper-Middle income', 'High income']
aerofit['IncomeSlab'] = pd.cut(aerofit['Income'],bins_income,labels = labels_income)

bins_miles = [0, 50, 150, 300, 400]
labels_miles = ["Low", "Medium", "High", "Freak"]
aerofit["RunningStamina"] = pd.cut(aerofit["Miles"], labels = labels_miles, bins = bins_mil

aerofit.head(5)
```

Out[177]:

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

In [22]:

```
aerofit["AgeGroup"].value_counts(normalize = True)
```

Out[22]:

```
20s          0.611111
30s          0.266667
Above 40s    0.066667
Teens        0.055556
Name: AgeGroup, dtype: float64
```

Insights

- 61% of customer is in 20's age group

In [23]:

```
aerofit["IncomeSlab"].value_counts(normalize = True)
```

Out[23]:

```
Lower-middle income    0.688889
Upper-Middle income    0.138889
High income            0.094444
Low Income             0.077778
Name: IncomeSlab, dtype: float64
```

Insights

- 68% of customer fall in `lower-middle income slab`

In [178]:

```
aerofit["RunningStamina"].value_counts()
```

Out[178]:

```
Medium    135
High       27
Low        17
Freak       1
Name: RunningStamina, dtype: int64
```

Insights

- Most of the customers run 50-150 miles on tredmill

Visual Analysis

Numerical Univariate Analysis

- We will analyse these numerical variable
  - Age

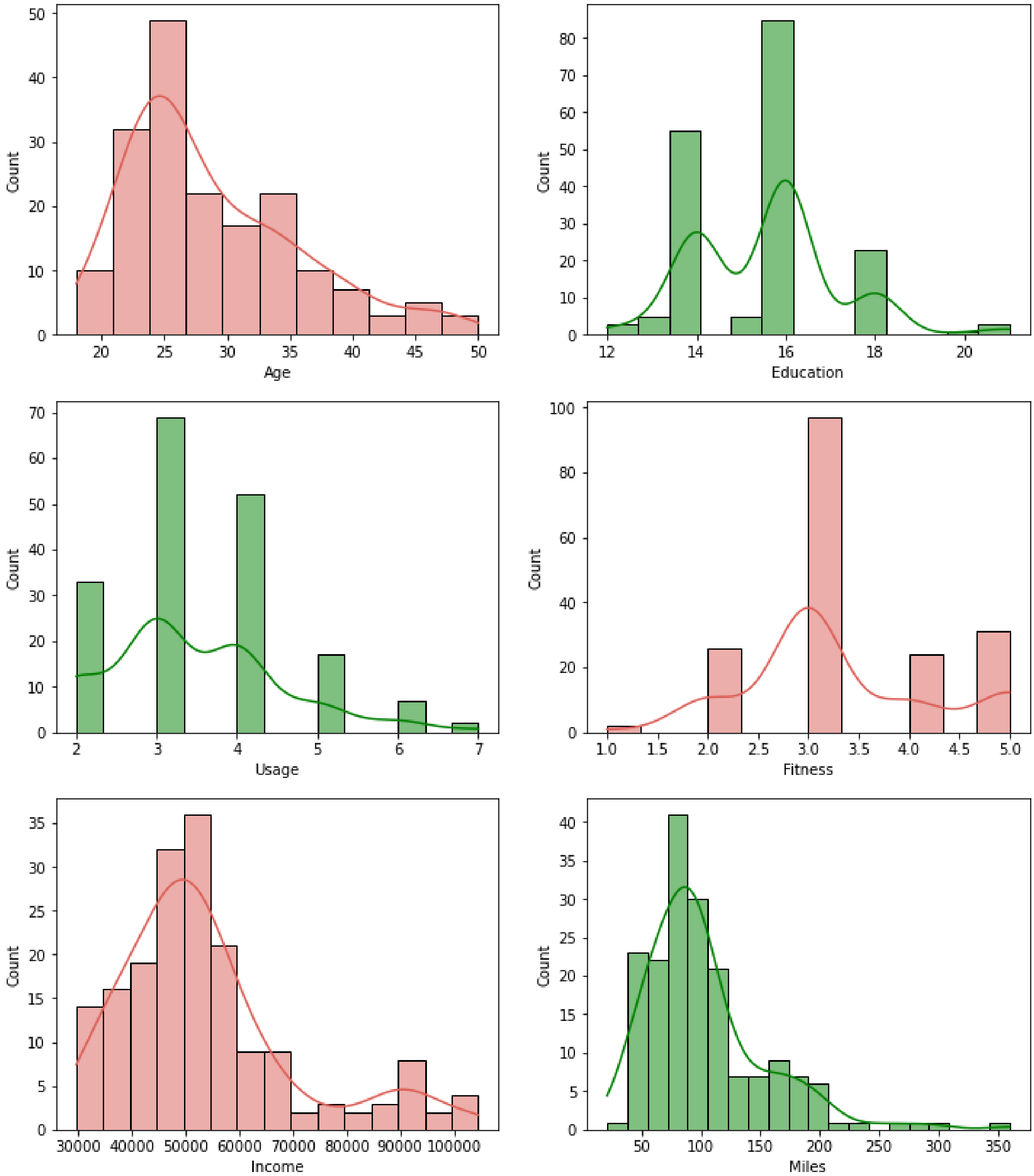
- Education
- Usage
- Fitness
- Income
- Miles

In [24]:

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

sns.histplot(data=aerofit, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=aerofit, x="Education", kde=True, ax=axis[0,1], color = "green")
sns.histplot(data=aerofit, x="Usage", kde=True, ax=axis[1,0], color = "green")
sns.histplot(data=aerofit, x="Fitness", kde=True, ax=axis[1,1])
sns.histplot(data=aerofit, x="Income", kde=True, ax=axis[2,0])
sns.histplot(data=aerofit, x="Miles", kde=True, ax=axis[2,1], color = "green")

plt.show()
```



Insights

- *Age analysis*
    - Most of the customer is in 20's

- *Education analysis*
  - Most of the customer having completed 16years of education
- *Usage analysis*
  - Most of customer rated themselves 3 out 5 in terms of fitness. Second highest rating is 5
- *Income analysis*
  - There is very significant diff. of income of customer. To significant range is between around 45000 - 55000
- *Usage analysis*
  - Most of the customer uses tredmills 3 times a week. Second highest usage is 4
- *Miles analysis*
  - Most of the customer clocks around 85-90 miles on tredmill

Categorial Univariate Analysis

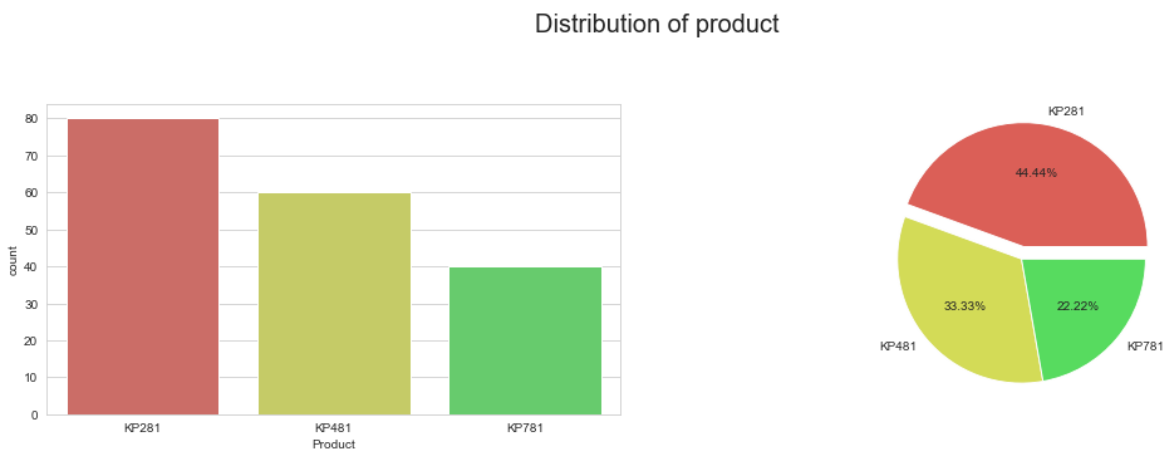
- We will analyze these categorical variables
  - Proudct
  - Gender
  - Marital Status
  - Age Group
  - Income Slab

In [25]:

```
fig = plt.figure(figsize=(18,10))
sns.set_style(style='whitegrid')
ax1 = plt.subplot2grid((2,2),(0,0))
sns.countplot(data=aerofit, x="Product")

#first row sec column
ax1 = plt.subplot2grid((2,2), (0, 1))
plt.pie(aerofit["Product"].value_counts(), explode = [0.1, 0,0], labels = aerofit["Product"
plt.suptitle('Distribution of product', fontsize = 20)

plt.show()
```



Insights

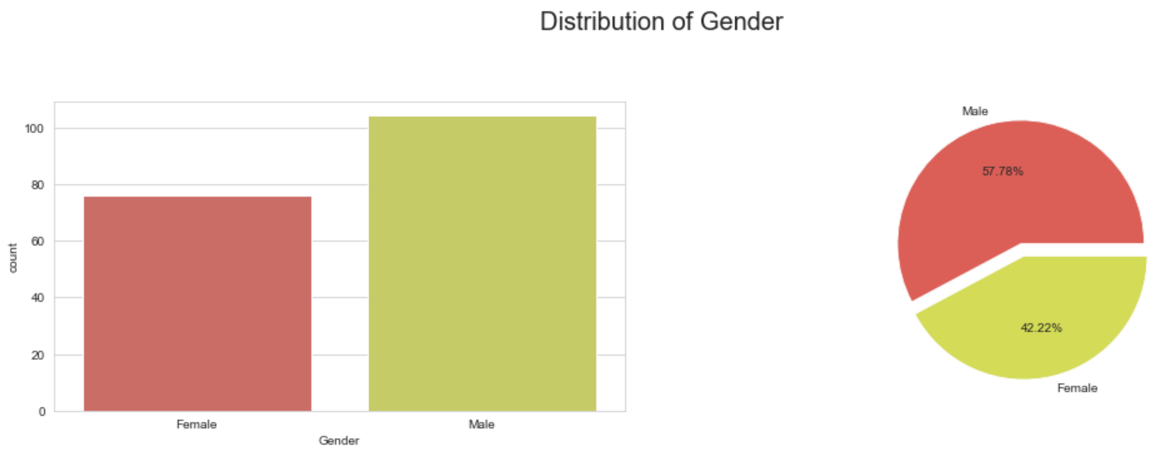
- Model KP821 is the best-selling product

In [26]:

```
fig = plt.figure(figsize=(18,10))
sns.set_style(style='whitegrid')
ax1 = plt.subplot2grid((2,2),(0,0))
sns.countplot(data=aerofit, x="Gender")

#first row sec column
ax1 = plt.subplot2grid((2,2), (0, 1))
plt.pie(aerofit["Gender"].value_counts(), explode = [0.1, 0], labels = aerofit["Gender"].va
plt.suptitle('Distribution of Gender', fontsize = 20)

plt.show()
```



Insights

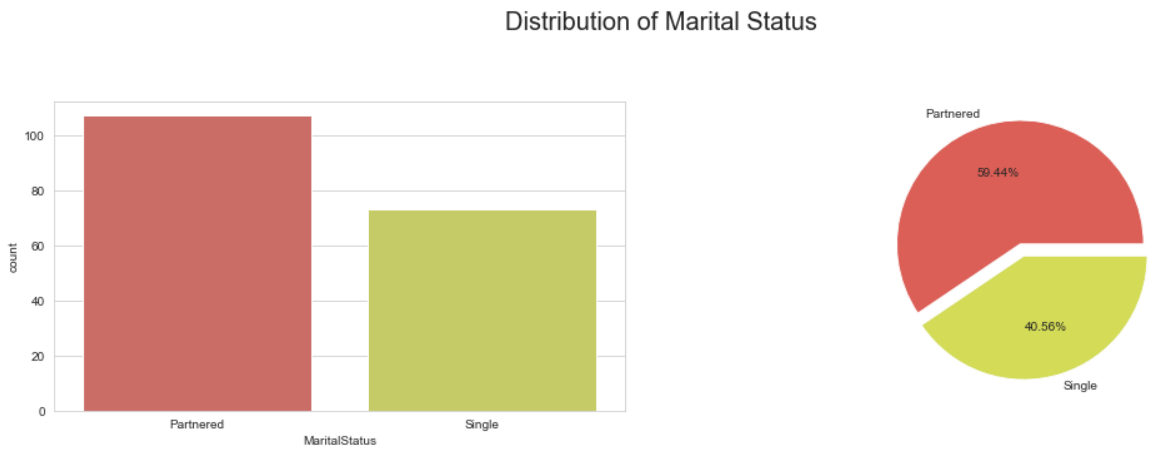
- Most of the customer are male

In [27]:

```
fig = plt.figure(figsize=(18,10))
sns.set_style(style='whitegrid')
ax1 = plt.subplot2grid((2,2),(0,0))
sns.countplot(data=aerofit, x="MaritalStatus")

#first row sec column
ax1 = plt.subplot2grid((2,2), (0, 1))
plt.pie(aerofit["MaritalStatus"].value_counts(), explode = [0.1, 0], labels = aerofit["Mari
plt.suptitle('Distribution of Marital Status', fontsize = 20)

plt.show()
```



Insights

- The treadmills are more likely to be purchased by married people

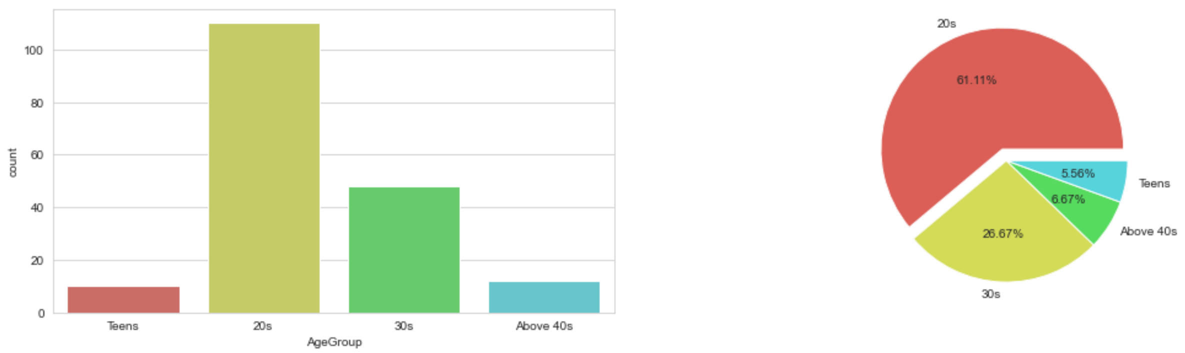
In [28]:

```
fig = plt.figure(figsize=(18,10))
sns.set_style(style='whitegrid')
ax1 = plt.subplot2grid((2,2),(0,0))
sns.countplot(data=aerofit, x="AgeGroup")

#first row sec column
ax1 = plt.subplot2grid((2,2), (0, 1))
plt.pie(aerofit["AgeGroup"].value_counts(), explode = [0.1, 0,0,0], labels = aerofit["AgeGr
plt.suptitle('Distribution of Age Group', fontsize = 20)

plt.show()
```

Distribution of Age Group



Insights

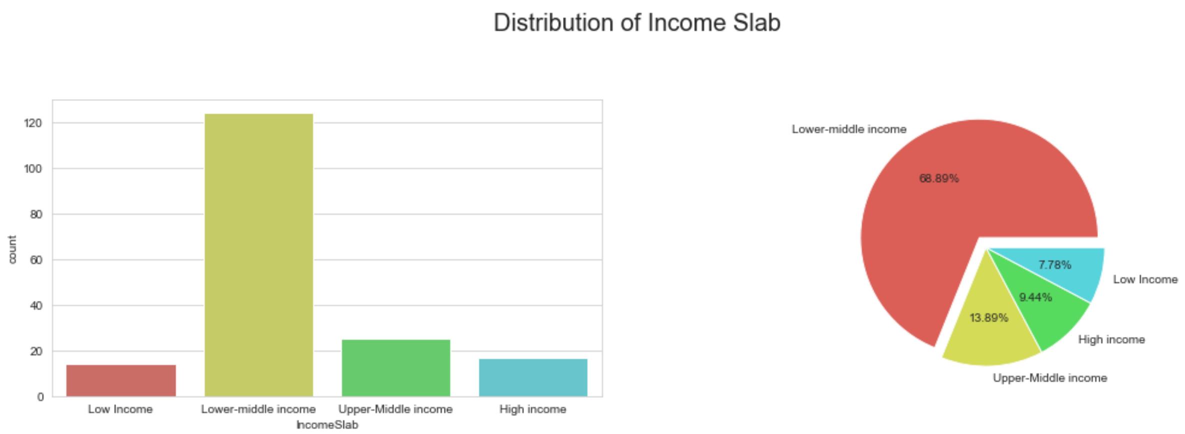
- 88% of treadmills are purchased by customers aged 20 to 40.

In [29]:

```
fig = plt.figure(figsize=(18,10))
sns.set_style(style='whitegrid')
ax1 = plt.subplot2grid((2,2),(0,0))
sns.countplot(data=aerofit, x="IncomeSlab")

#first row sec column
ax1 = plt.subplot2grid((2,2), (0, 1))
plt.pie(aerofit["IncomeSlab"].value_counts(), explode = [0.1, 0,0,0], labels = aerofit["Inc
plt.suptitle('Distribution of Income Slab', fontsize = 20)

plt.show()
```



Insights

- 83% of treadmills are bought by customers with incomes between USD dollars 35000-60000, and USD dollars 60,000-85000.

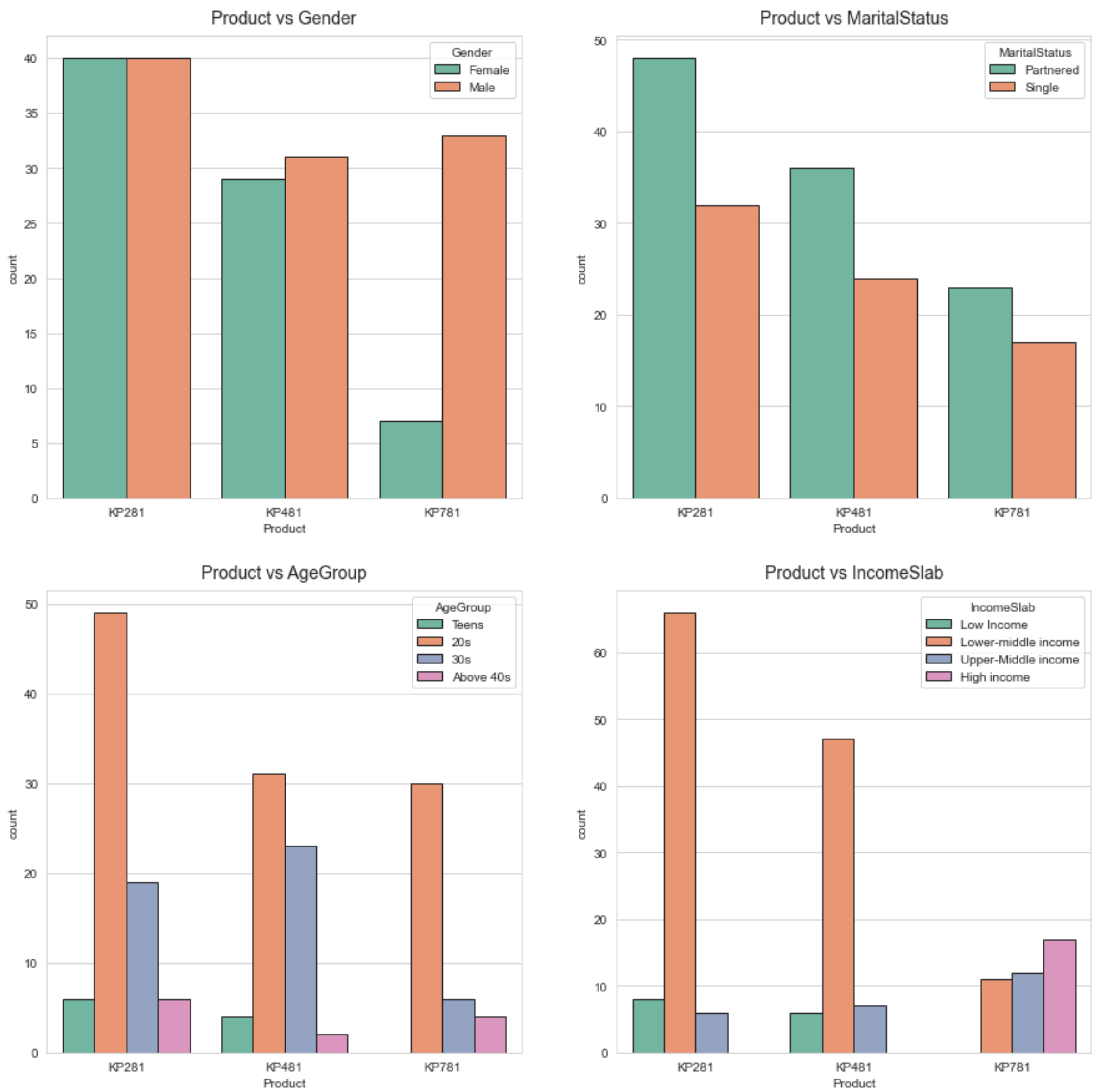
Bivariate Analysis

Categorical Bivariate Analysis

In [30]:

```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(15, 15))
columns = ["Gender", "MaritalStatus", "AgeGroup", "IncomeSlab"]

k = 0
for i in range(2):
    for j in range(2):
        sns.countplot(data=aerofit, x='Product', hue=columns[k], edgecolor="0.15", palette=
        axs[i, j].set_title("Product vs " + columns[k], pad = 10, fontsize = 14)
        k += 1
plt.show()
```



Product vs Gender

- Equal number of males and females have purchased KP281 product and Almost same for the product KP481
- Most of the Male customers have purchased the KP781 product.

Product vs MaritalStatus

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

Product vs Age Group

- Customer in 20's tends to buy more product

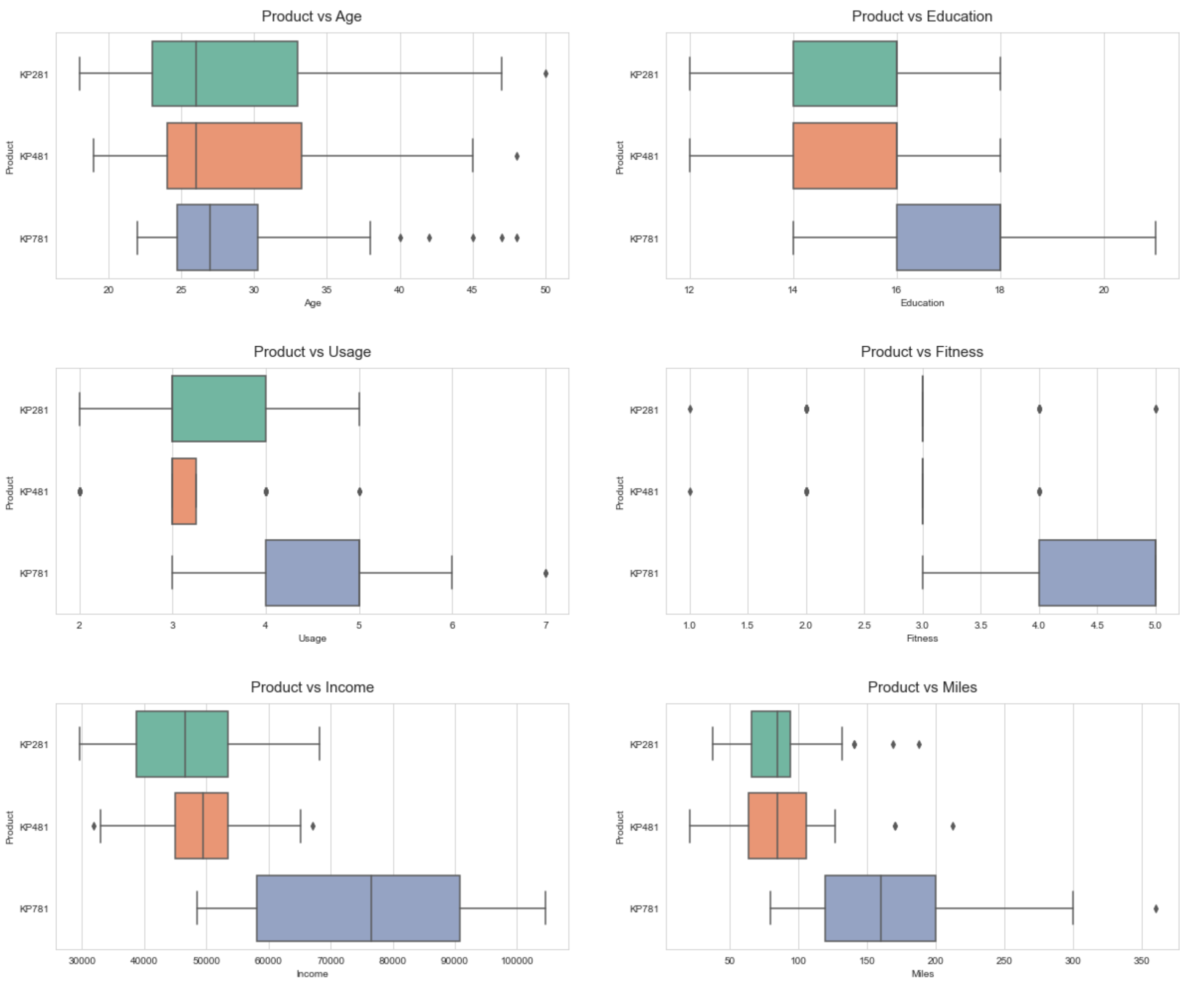
Product vs Income Slabs

- Customer with high income only buy high end model. (KP781)

Numerical Bivariate Analysis

In [31]:

```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("whitegrid")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 15))
fig.subplots_adjust(top=1.2)
fig.tight_layout(pad=7.0)
count = 0
for i in range(3):
    for j in range(2):
        sns.boxplot(data=aerofit, y='Product', x=attrs[count], ax=axs[i,j], palette='Set2')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=15)
#         axs[i, j].
        count += 1
```



Product vs Age

- Customers purchasing products KP281 & KP481 are having same Age median value.
- Customers whose age lies between 25-30, are more likely to buy KP781 product

Product vs Education

- Customers whose Education is greater than 16, have more chances to purchase the KP781 product.
- While the customers with Education less than 16 have equal chances of purchasing KP281 or KP481.

Product vs Usage

- Customers who are planning to use the treadmill greater than 4 times a week, are more likely to purchase the KP781 product.
- While the other customers are likely to purchasing KP281 or KP481.

`Product vs Fitness`

- The more the customer is fit (fitness >= 3), higher the chances of the customer to purchase the KP781 product.

`Product vs Income`

- Higher the Income of the customer (Income >= 60000), higher the chances of the customer to purchase the KP781 product.

`Product vs Miles`

- If the customer expects to walk/run greater than 120 Miles per week, it is more likely that the customer will buy KP781 product.

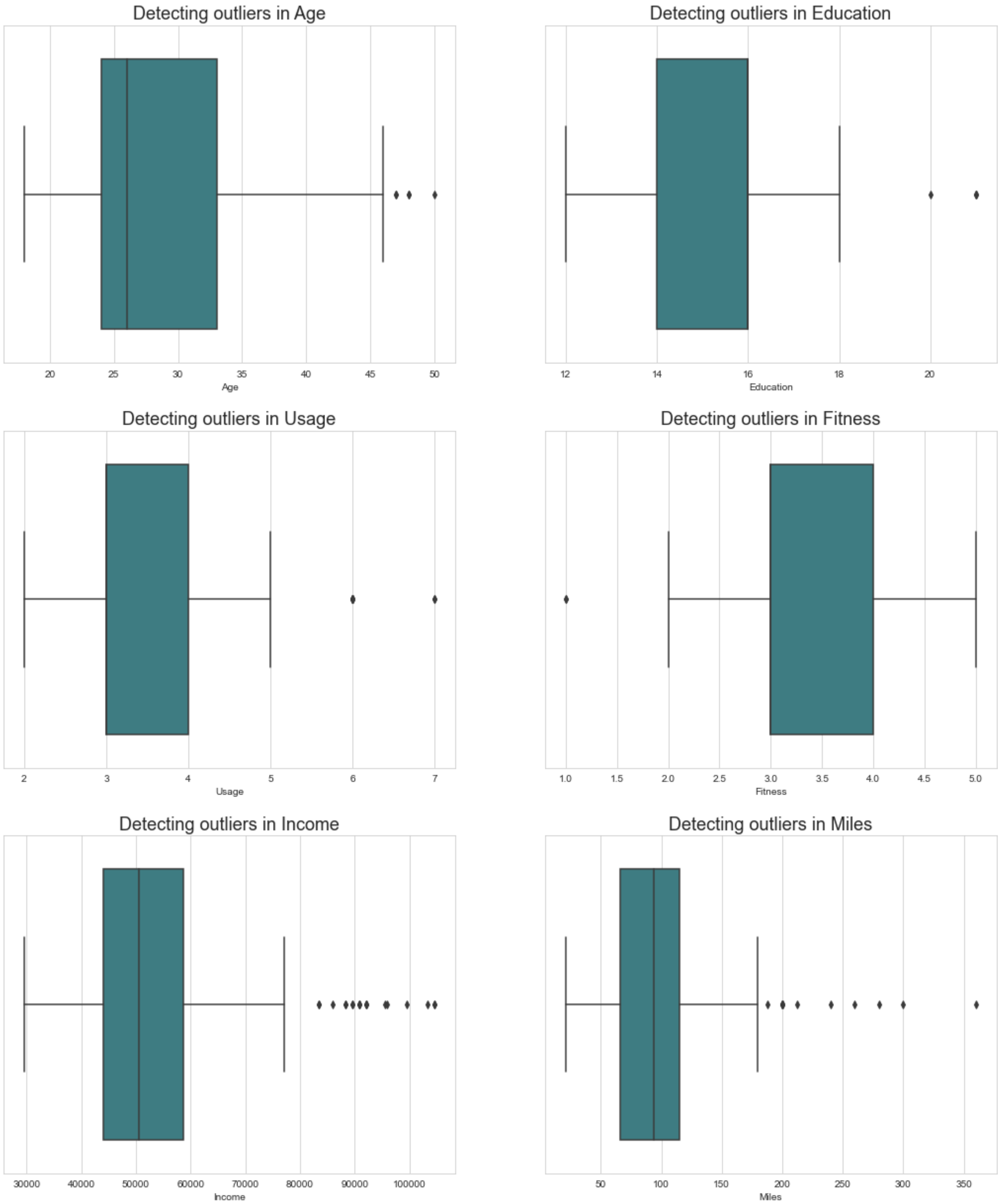
Outlier Detection using Boxplots

In [32]:

```
columns = ["Age", "Education", "Usage", "Fitness", "Income", "Miles"]

fig, ax = plt.subplots(ncols = 2, nrows = 3, figsize=(18, 15))
# fig.tight_layout(pad = 7)
fig.subplots_adjust(top = 1.2)

count = 0
for i in range(3):
    for j in range(2):
        sns.boxplot(data= aerofit, x=columns[count], ax = ax[i, j], palette = "crest", orde
        ax[i, j].set_title("Detecting outliers in " + columns[count], fontsize = 18)
        count += 1
```



Insights

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

Let's find some correlation in dataset

In [33]:

```
aerofit.corr()
```

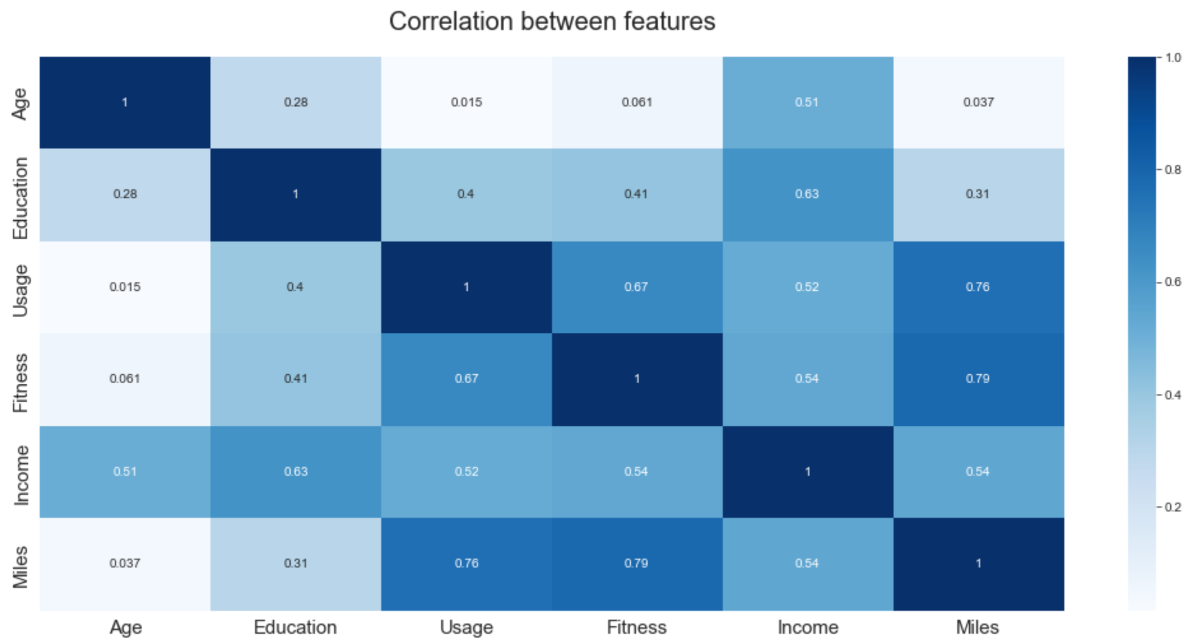
Out[33]:

	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

In [34]:

```
plt.subplots(figsize=(18, 8))

sns.heatmap(aerofit.corr(), annot = True, cmap="Blues")
plt.title("Correlation between features", fontsize = 20, pad = 21)
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.show()
```

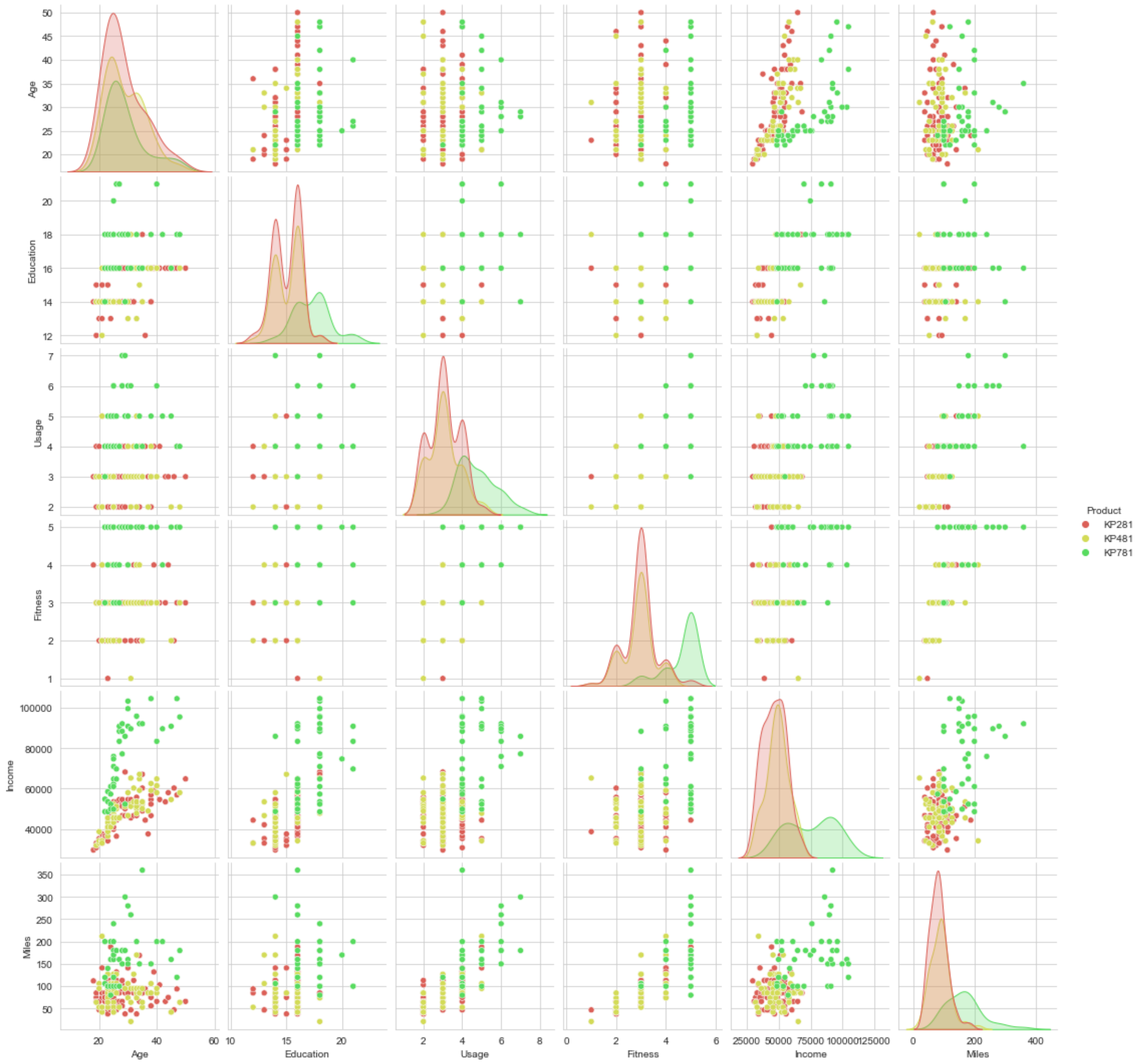


Insights

- `Miles vs Fitness` and `Miles vs Usage` are highly correlated, which means if a customer's fitness level is high they use more treadmills.
- `Income` and `Education` show a strong correlation. `High-income` and `highly educated` people prefer high-end models (KP781), as mentioned during Bivariant analysis of Categorical variables.
- There is no corelation between `Usage` & `Age` or `Fitness` & `Age` which mean `Age` should not be barrier to use treadmills or specific model of treadmills.

In [35]:

```
sns.pairplot(data=aerofit, diag_kind="kde", hue = "Product")
plt.show()
```



Lets's create contigency table to calculate probabilities

1. Contigency table for `Product - Gender`

In [61]:

```
prod_gen = pd.crosstab(columns=aerofit['Product'], index=[aerofit['Gender']], margins = Tru
prod_gen
```

Out[61]:

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

Marginal probability

In [46]:

```
aerofit["Product"].value_counts(normalize = True)
```

Out[46]:

```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

In [47]:

```
aerofit["Gender"].value_counts(normalize=True)
```

Out[47]:

```
Male      0.577778
Female    0.422222
Name: Gender, dtype: float64
```

Probability of each product given gender (conditional)

In [70]:

```
def prod_given_gender(gender):
    if gender != "Female" and gender != "Male":
        return "Invalid gender value."

    p_781 = prod_gen['KP781'][gender] / prod_gen.loc[gender]["All"]
    p_481 = prod_gen['KP481'][gender] / prod_gen.loc[gender]["All"]
    p_281 = prod_gen['KP281'][gender] / prod_gen.loc[gender]["All"]


    print(f"P(KP781|{gender}): {p_781:.2f}")
    print(f"P(KP481|{gender}): {p_481:.2f}")
    print(f"P(KP281|{gender}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Gender\n\n")


prod_given_gender('Male')
prod_given_gender('Female')
```

```
Conditional probabilities of each Product for given Gender


P(KP781|Male): 0.32
P(KP481|Male): 0.30
P(KP281|Male): 0.38

P(KP781|Female): 0.09
P(KP481|Female): 0.38
P(KP281|Female): 0.53
```

Insights

- `Females` are least probable to buy top end product `KP781`. While `Males` are almost equi-probable to buy all three products.
- 53% `Females` prefer to buy more `KP281` modal than `Males`

2. Contengency table for `Product-Income Slab`

In [60]:

```
prod_income = pd.crosstab(columns=aerofit['Product'], index=[aerofit['IncomeSlab']], margin
prod_income
```

Out[60]:

Product	KP281	KP481	KP781	All
IncomeSlab				
Low Income	8	6	0	14
Lower-middle income	66	47	11	124
Upper-Middle income	6	7	12	25
High income	0	0	17	17
All	80	60	40	180

Margin Probabilities for Income Slab

In [65]:

```
aerofit["IncomeSlab"].value_counts(normalize = True)
```

Out[65]:

```
Lower-middle income    0.688889
Upper-Middle income    0.138889
High income            0.094444
Low Income             0.077778
Name: IncomeSlab, dtype: float64
```

`Insights`

- 68% customers comes under `Lower-middle income` category who buys tredmill
- 7.7% least earning customer.

Percentage of a High-income customer purchasing KP781 treadmill (Joint Probability)

In [75]:

```
p = prod_income.loc["High income"]["KP781"] / len(aerofit)
print(f"P(KP781 | High income) = {np.round(p*100)}%")
```

```
P(KP781 | High income) = 9.0%
```

Probability of each product given income slab

In [147]:

```
def prod_given_income(income_list):
    for income in income_list:

        p_781 = prod_income['KP781'][income] / prod_income.loc[income]["All"]
        p_481 = prod_income['KP481'][income] / prod_income.loc[income]["All"]
        p_281 = prod_income['KP281'][income] / prod_income.loc[income]["All"]


        print(f"P(KP781|{income}): {p_781:.2f}")
        print(f"P(KP481|{income}): {p_481:.2f}")
        print(f"P(KP281|{income}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Income slab\n\n")

prod_given_income(list(prod_income.index))
```

```
Conditional probabilities of each Product for given Income slab


P(KP781|Low Income): 0.00
P(KP481|Low Income): 0.43
P(KP281|Low Income): 0.57

P(KP781|Lower-middle income): 0.09
P(KP481|Lower-middle income): 0.38
P(KP281|Lower-middle income): 0.53

P(KP781|Upper-Middle income): 0.48
P(KP481|Upper-Middle income): 0.28
P(KP281|Upper-Middle income): 0.24

P(KP781|High income): 1.00
P(KP481|High income): 0.00
P(KP281|High income): 0.00

P(KP781|All): 0.22
P(KP481|All): 0.33
P(KP281|All): 0.44
```

Insights

- High income earning customer only buy `KP781` (High-End modal) `100%`
- Low Income earning customer don't purchase `KP781` modal
- We can say, Majority of `KP781` modal purchased by only High Income or Upper-Middle Income earning customer

3. Contigency table for `Product - Fitness level`

In [92]:

```
prod_fitness = pd.crosstab(columns=aerofit['Product'], index=[aerofit['Fitness']], margins
prod_fitness
```

Out[92]:

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

Marginal Probabilities for self-rated fitness

In [94]:

```
aerofit["Fitness"].value_counts(normalize = True)
```

Out[94]:

```
3    0.538889
5    0.172222
2    0.144444
4    0.133333
1    0.011111
Name: Fitness, dtype: float64
```

Insights

- 53% customers rated themselves 3 out of 5
- 17% customers rated themseleve 4 out of 5
- We can say, majority of customers who purchase tredmill is somehow fit and do regular excercise

Probability of each product given fitness (Conditional)

In [146]:

```
def prod_given_fitness(fitness_list):
    for data in fitness_list:
        p_781 = prod_fitness['KP781'][data] / prod_fitness.loc[data]["All"]
        p_481 = prod_fitness['KP481'][data] / prod_fitness.loc[data]["All"]
        p_281 = prod_fitness['KP281'][data] / prod_fitness.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_given_fitness(list(prod_fitness.index[:5]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|1): 0.00
P(KP481|1): 0.50
P(KP281|1): 0.50

P(KP781|2): 0.00
P(KP481|2): 0.46
P(KP281|2): 0.54

P(KP781|3): 0.04
P(KP481|3): 0.40
P(KP281|3): 0.56

P(KP781|4): 0.29
P(KP481|4): 0.33
P(KP281|4): 0.38

P(KP781|5): 0.94
P(KP481|5): 0.00
P(KP281|5): 0.06
```

Insights

- 94% customers having fitness rated 5 purchasing `KP781` modal

4. Contigency table for `Product-Usage`

In [148]:

```
prod_use = pd.crosstab(columns=aerofit['Product'], index=[aerofit['Usage']], margins = True
prod_use
```

Out[148]:

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

Marginal Probabilitites for Usage

In [150]:

```
aerofit["Usage"].value_counts(normalize = True)
```

Out[150]:

```
3    0.383333
4    0.288889
2    0.183333
5    0.094444
6    0.038889
7    0.011111
Name: Usage, dtype: float64
```

`38% customer uses tredmill three days in week`

In [156]:

```
def prod_given_use(usage_list):
    for data in usage_list:
        p_781 = prod_use['KP781'][data] / prod_use.loc[data]["All"]
        p_481 = prod_use['KP481'][data] / prod_use.loc[data]["All"]
        p_281 = prod_use['KP281'][data] / prod_use.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_given_use(list(prod_use.index[:6]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|2): 0.00
P(KP481|2): 0.42
P(KP281|2): 0.58

P(KP781|3): 0.01
P(KP481|3): 0.45
P(KP281|3): 0.54

P(KP781|4): 0.35
P(KP481|4): 0.23
P(KP281|4): 0.42

P(KP781|5): 0.71
P(KP481|5): 0.18
P(KP281|5): 0.12

P(KP781|6): 1.00
P(KP481|6): 0.00
P(KP281|6): 0.00

P(KP781|7): 1.00
P(KP481|7): 0.00
P(KP281|7): 0.00
```

Insights

- 71% customers bought product `KP781` uses tredmill 5 days in week

5. Contigency table for `Product-Age Group`

In [157]:

```
prod_age = pd.crosstab(columns=aerofit['Product'], index=[aerofit['AgeGroup']], margins = T
prod_age
```

Out[157]:

Product AgeGroup	KP281	KP481	KP781	All
Teens	6	4	0	10
20s	49	31	30	110
30s	19	23	6	48
Above 40s	6	2	4	12
All	80	60	40	180

Marginal Probabitlites of Age Group

In [158]:

```
aerofit["AgeGroup"].value_counts(normalize = True)
```

Out[158]:

```
20s          0.611111
30s          0.266667
Above 40s    0.066667
Teens        0.055556
Name: AgeGroup, dtype: float64
```

61% customers are in 20's (21-30) age group who purchase tredmills

Probabilities of each products for given age group (conditional)

In [160]:

```
def prod_given_age(age_list):
    for data in age_list:
        p_781 = prod_age['KP781'][data] / prod_age.loc[data]["All"]
        p_481 = prod_age['KP481'][data] / prod_age.loc[data]["All"]
        p_281 = prod_age['KP281'][data] / prod_age.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_given_age(list(prod_age.index[:4]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|Teens): 0.00
P(KP481|Teens): 0.40
P(KP281|Teens): 0.60

P(KP781|20s): 0.27
P(KP481|20s): 0.28
P(KP281|20s): 0.45

P(KP781|30s): 0.12
P(KP481|30s): 0.48
P(KP281|30s): 0.40

P(KP781|Above 40s): 0.33
P(KP481|Above 40s): 0.17
P(KP281|Above 40s): 0.50
```

Insights

- 33 % customers above age 40 bought high end modal `KP781` .
- 60% Teens purchase base end modal `KP281`

6. Contigency table for `Product-Marital Status`

In [161]:

```
prod_ms = pd.crosstab(columns=aerofit['Product'], index=[aerofit['MaritalStatus']], margins
prod_ms
```

Out[161]:

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

Marginal Probability for marital status

In [163]:

```
aerofit["MaritalStatus"].value_counts(normalize = True)
```

Out[163]:

```
Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64
```

`59% customers who purchase tredmill are parterned`

Probability of each product for given marital status (conditional)

In [166]:

```
def prod_given_mar(mar_list):
    for data in mar_list:
        p_781 = prod_ms['KP781'][data] / prod_ms.loc[data]["All"]
        p_481 = prod_ms['KP481'][data] / prod_ms.loc[data]["All"]
        p_281 = prod_ms['KP281'][data] / prod_ms.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_given_mar(list(prod_ms.index[:2]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|Partnered): 0.21
P(KP481|Partnered): 0.34
P(KP281|Partnered): 0.45

P(KP781|Single): 0.23
P(KP481|Single): 0.33
P(KP281|Single): 0.44
```

Insights

- 23% customer who are single purchase hight end modal tredmill `KP781`
- for the prouct `KP281` both category show equi probable interest in purchasing tredmills

7. Contigency table for `Product-Running Stamina`

In [179]:

```
prod_miles = pd.crosstab(columns=aerofit['Product'], index=[aerofit['RunningStamina']], mar
prod_miles
```

Out[179]:

Product	KP281	KP481	KP781	All
RunningStamina				
Low	12	5	0	17
Medium	66	52	17	135
High	2	3	22	27
Freak	0	0	1	1
All	80	60	40	180

Marginal Probability for Product Running Stamina

In [180]:

```
aerofit["RunningStamina"].value_counts(normalize = True)
```

Out[180]:

```
Medium    0.750000
High      0.150000
Low       0.094444
Freak     0.005556
Name: RunningStamina, dtype: float64
```

75% customers ran 50-150 miles on tredmills

Probability of each product given running stamina

In [182]:

```
def prod_given_mile(miles_list):
    for data in miles_list:
        p_781 = prod_miles['KP781'][data] / prod_miles.loc[data]["All"]
        p_481 = prod_miles['KP481'][data] / prod_miles.loc[data]["All"]
        p_281 = prod_miles['KP281'][data] / prod_miles.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_given_mile(list(prod_miles.index[:4]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|Low): 0.00
P(KP481|Low): 0.29
P(KP281|Low): 0.71

P(KP781|Medium): 0.13
P(KP481|Medium): 0.39
P(KP281|Medium): 0.49

P(KP781|High): 0.81
P(KP481|High): 0.11
P(KP281|High): 0.07

P(KP781|Freak): 1.00
P(KP481|Freak): 0.00
P(KP281|Freak): 0.00
```

Insights

- 81% customers having higher stamina `(150-300) miles` purchasing high end modal `KP781` product

8. Contigency table for `Product-Education`

In [183]:

```
prod_edu = pd.crosstab(columns=aerofit['Product'], index=[aerofit['Education']], margins = 
prod_edu
```

Out[183]:

Product Education	KP281	KP481	KP781	All
12	2	1	0	3
13	3	2	0	5
14	30	23	2	55
15	4	1	0	5
16	39	31	15	85
18	2	2	19	23
20	0	0	1	1
21	0	0	3	3
All	80	60	40	180

Marginal probability for Education

In [184]:

```
aerofit["Education"].value_counts(normalize = True)
```

Out[184]:

```
16    0.472222
14    0.305556
18    0.127778
15    0.027778
13    0.027778
12    0.016667
21    0.016667
20    0.005556
Name: Education, dtype: float64
```

47% customers having 16 years of education

Probability of each product for given education of customers in year

In [187]:

```
def prod_give_edu(edu_list):
    for data in edu_list:
        p_781 = prod_edu['KP781'][data] / prod_edu.loc[data]["All"]
        p_481 = prod_edu['KP481'][data] / prod_edu.loc[data]["All"]
        p_281 = prod_edu['KP281'][data] / prod_edu.loc[data]["All"]


        print(f"P(KP781|{data}): {p_781:.2f}")
        print(f"P(KP481|{data}): {p_481:.2f}")
        print(f"P(KP281|{data}): {p_281:.2f}\n")

print("Conditional probabilities of each Product for given Fitness rating\n")
prod_give_edu(list(prod_edu.index[:8]))
```

```
Conditional probabilities of each Product for given Fitness rating

P(KP781|12): 0.00
P(KP481|12): 0.33
P(KP281|12): 0.67

P(KP781|13): 0.00
P(KP481|13): 0.40
P(KP281|13): 0.60

P(KP781|14): 0.04
P(KP481|14): 0.42
P(KP281|14): 0.55

P(KP781|15): 0.00
P(KP481|15): 0.20
P(KP281|15): 0.80

P(KP781|16): 0.18
P(KP481|16): 0.36
P(KP281|16): 0.46

P(KP781|18): 0.83
P(KP481|18): 0.09
P(KP281|18): 0.09

P(KP781|20): 1.00
P(KP481|20): 0.00
P(KP281|20): 0.00

P(KP781|21): 1.00
P(KP481|21): 0.00
P(KP281|21): 0.00
```

83% customers having 18 years education tends to buy high end modal KP781 modal

Insights

- **Model KP281 is the best-selling product. 44.0% of all treadmill sales go to model KP281.**
- **The majority of treadmill customers fall within the lower-middle income bracket. 63% of treadmills are bought by individuals with incomes between USD dollor 35000 and 85000.**
- **There are only 7.7% of customers with incomes below USD 35000 who buy treadmills.**
- **88% of treadmills are purchased by customers aged 20 to 40.**
- **As per the correlation table, Miles and Fitness & Miles and Usage are highly correlated, which means if a customer's fitness level is high they use more treadmills.**
- **KP281 is the only model purchased by a customer who has more than 20 years of education and an income of over USD dollor 85,000.**
- **With Fitness level 4 and 5, the customers tend to use high-end models and the average number of miles is above 150 per week**
- **Mojorily KP281 modals purchased by male customers than female one**

Recommendations

- **KP281 & KP481 are popular with customers earning USD 45,000 and USD 60,000 and can be offered by these companies as affordable models.**
- **KP781 should be marketed as a Premium Model and marketing it to high income groups and educational over 20 years market segments could result in more sales.**
- **Company should focus on the customers whose income in low around <35000 USD to increase sale in this segment of customer base**

In [ ]:

```

```