Aerofit Case Study

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Github: https://github.com/gautamnaik1994/AerofitAnalysisCaseStudy

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.

Product Portfolio:

- The KP281 is an entry-level treadmill that sells for $1,500.
- The KP481 is for mid-level runners that sell for $1,750.
- The KP781 treadmill is having advanced features that sell for $2,500.

Metric

We will use count of users, probabilities, conditional probabilities to evaluate the users.

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In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.gridspec as gridspec
import matplotlib.pyplot as plt
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
sns.set_style('darkgrid')
pd.reset_option('display.max_rows')
pd.options.display.float_format = '{:.3f}'.format
from IPython.display import display
```

In [3]:
```
df=pd.read_csv('./aerofit_treadmill.csv')
```

EDA

In [4]:
```
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 [5]:
```
df.isna().sum()
```

Out[5]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [6]:
```
df.head()
```

Out[6]:

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

In [7]:
```
df["Gender"]=df["Gender"].astype("category")
df["MaritalStatus"]=df["MaritalStatus"].astype("category")
df["Product"]=df["Product"].astype("category")
```

Using `describe()` method we can get statistics of all numerical columns

In [8]:
```
df.describe()
```

Out[8]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000	180.000	180.000	180.000	180.000	180.000
mean	28.789	15.572	3.456	3.311	53719.578	103.194
std	6.943	1.617	1.085	0.959	16506.684	51.864
min	18.000	12.000	2.000	1.000	29562.000	21.000
25%	24.000	14.000	3.000	3.000	44058.750	66.000
50%	26.000	16.000	3.000	3.000	50596.500	94.000
75%	33.000	16.000	4.000	4.000	58668.000	114.750
max	50.000	21.000	7.000	5.000	104581.000	360.000

Insights

Other than **Miles** column, the mean and median values of columns are almost identical.

In [11]:
```
variables = ["Age", "Education", "Usage", "Fitness", "Income", "Miles"]
```

In [9]:
```
df.describe(include='category')
```

Out[9]:

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

Using `groupby("Product")` function we can group the data based on the `Product` column and find statistical data of users for each product.

In [10]:
```
agg_functions = [ "mean", "median", "min", "max"]
df.groupby("Product").agg({
    "Age":agg_functions,
    "Education": agg_functions,
    "Income": agg_functions
})
print("")
df.groupby("Product").agg({
    "Miles":agg_functions,
    "Usage": agg_functions,
    "Fitness": agg_functions
})
```

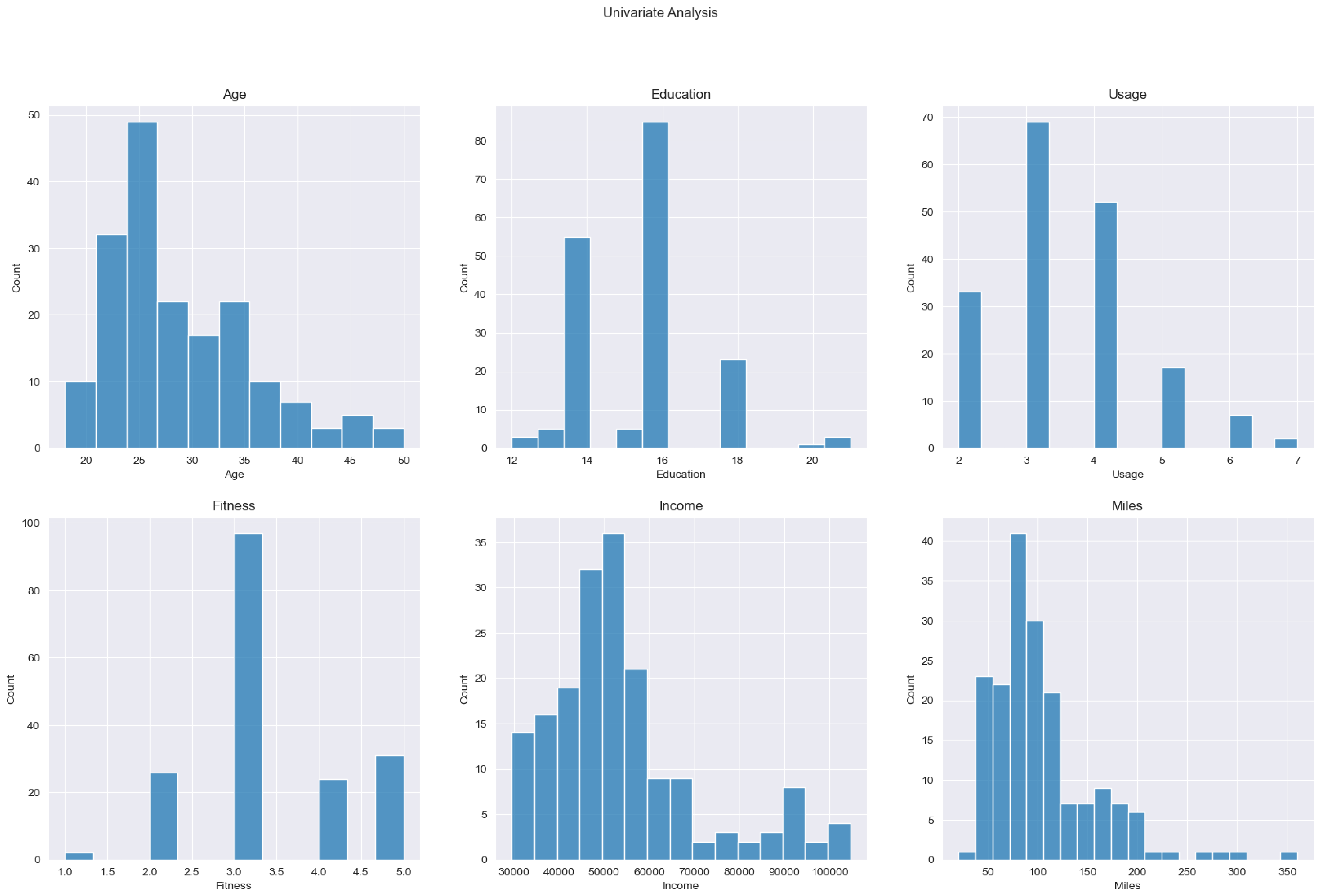
Out[10]:

	Age				Education				Income			
	mean	median	min	max	mean	median	min	max	mean	median	min	max
Product												
KP281	28.550	26.000	18	50	15.037	16.000	12	18	46418.025	46617.000	29562	68220
KP481	28.900	26.000	19	48	15.117	16.000	12	18	48973.650	49459.500	31836	67083
KP781	29.100	27.000	22	48	17.325	18.000	14	21	75441.575	76568.500	48556	104581

Out[10]:

	Miles				Usage				Fitness			
	mean	median	min	max	mean	median	min	max	mean	median	min	max
Product												
KP281	82.787	85.000	38	188	3.087	3.000	2	5	2.962	3.000	1	5
KP481	87.933	85.000	21	212	3.067	3.000	2	5	2.900	3.000	1	4
KP781	166.900	160.000	80	360	4.775	5.000	3	7	4.625	5.000	3	5

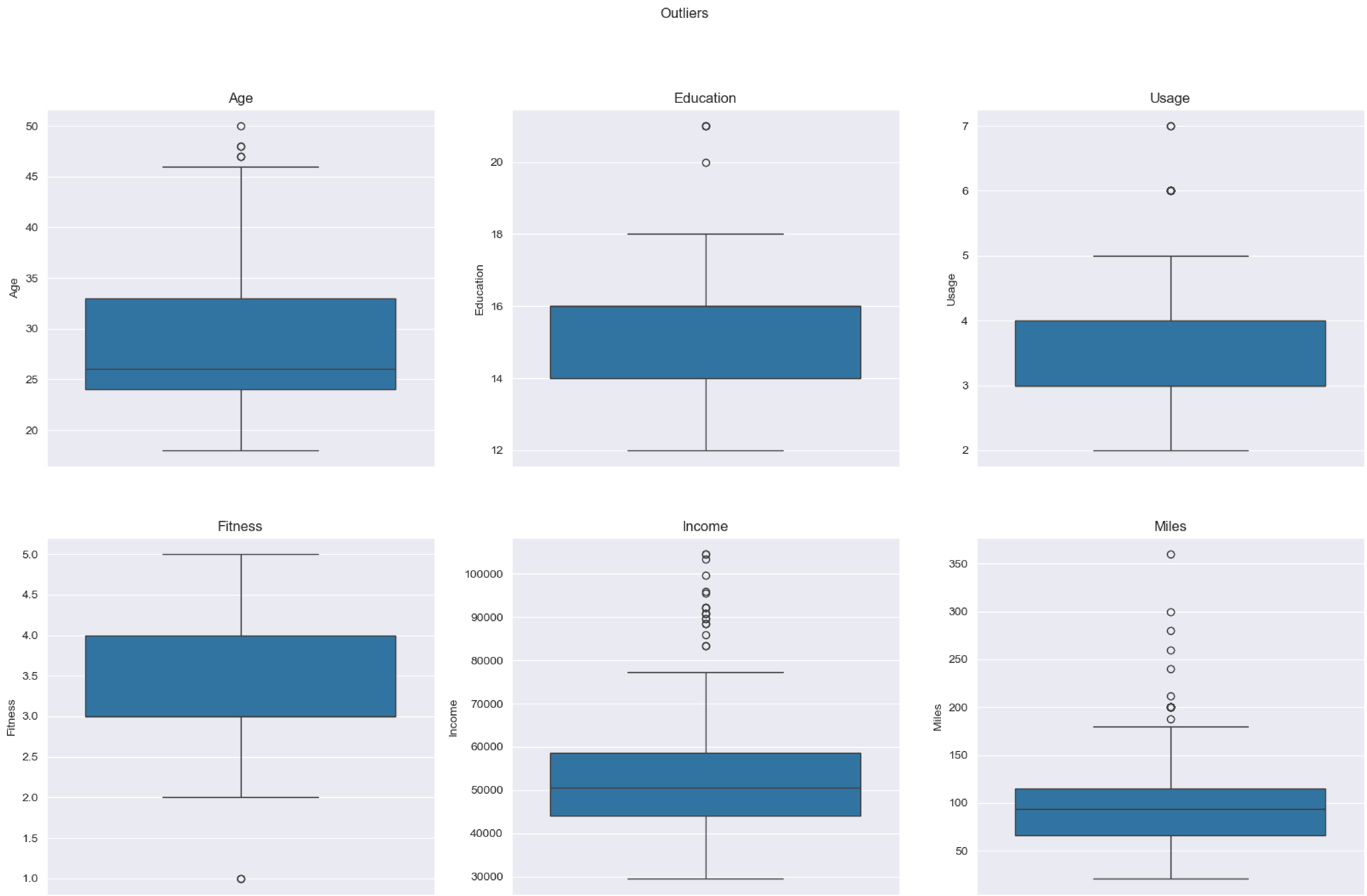
In [12]:
```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))

for i in range(2):
    for j in range(3):
        variable = variables[i * 3 + j]
        sns.histplot(ax=axes[i, j], data=df, x=variable)
        axes[i, j].set_title(variable)

plt.suptitle("Univariate Analysis")
plt.show();
```



Insights

- Most of the users are around 25 years of age, having 16 years of education with around $50000 of annual income.
- Majority of the users have fitness of level 3, use the treadmill 3 times a week and walk/run around 90 miles each week

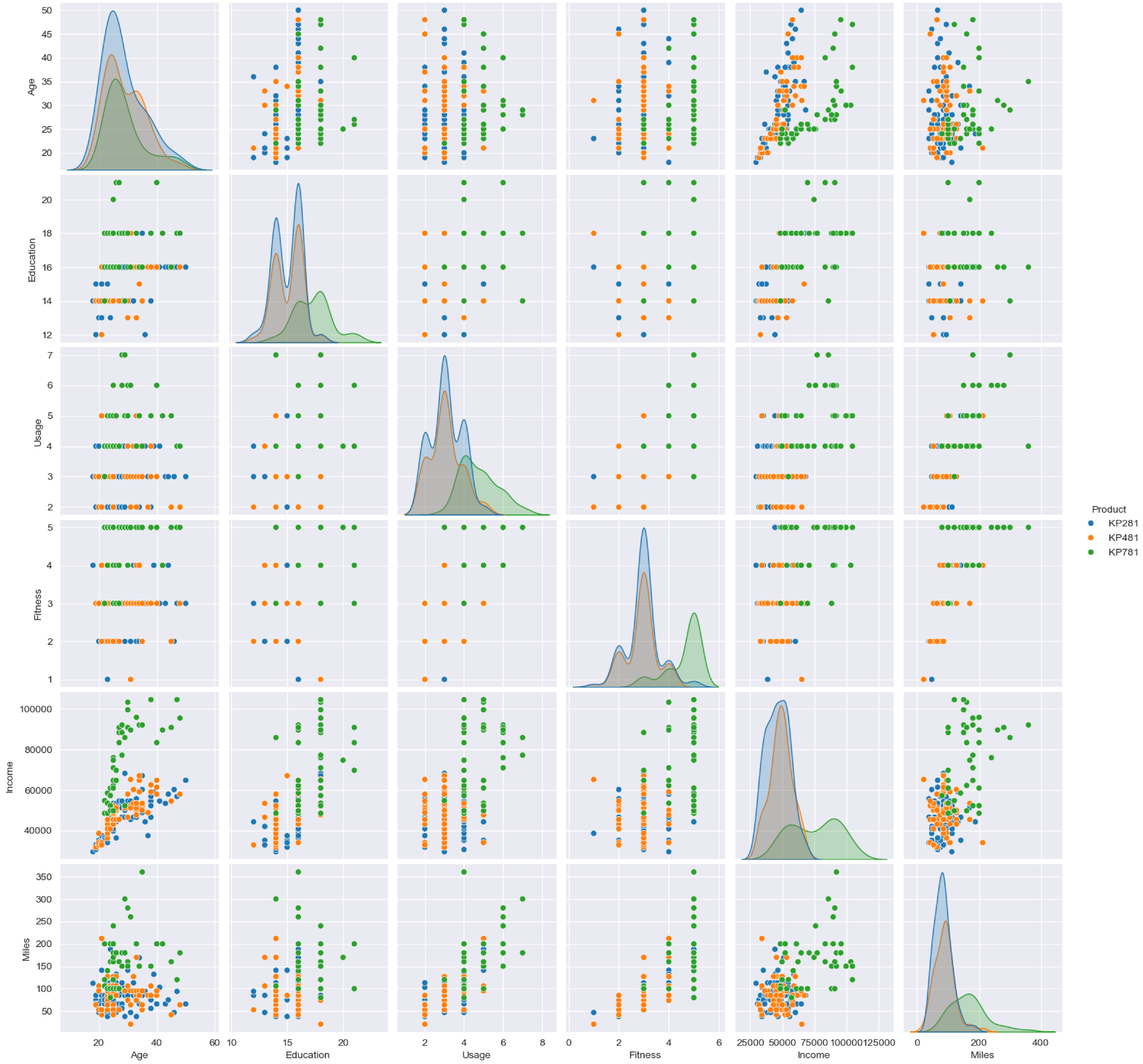
In [13]:
```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))

for i in range(2):
    for j in range(3):
        variable = variables[i * 3 + j]
        sns.boxplot(ax=axes[i, j], data=df, y=variable)
        axes[i, j].set_title(variable)

plt.suptitle("Outliers")
plt.show();
```



Insights

- There seems to be be lot of outliers for **Income** and **Miles** column

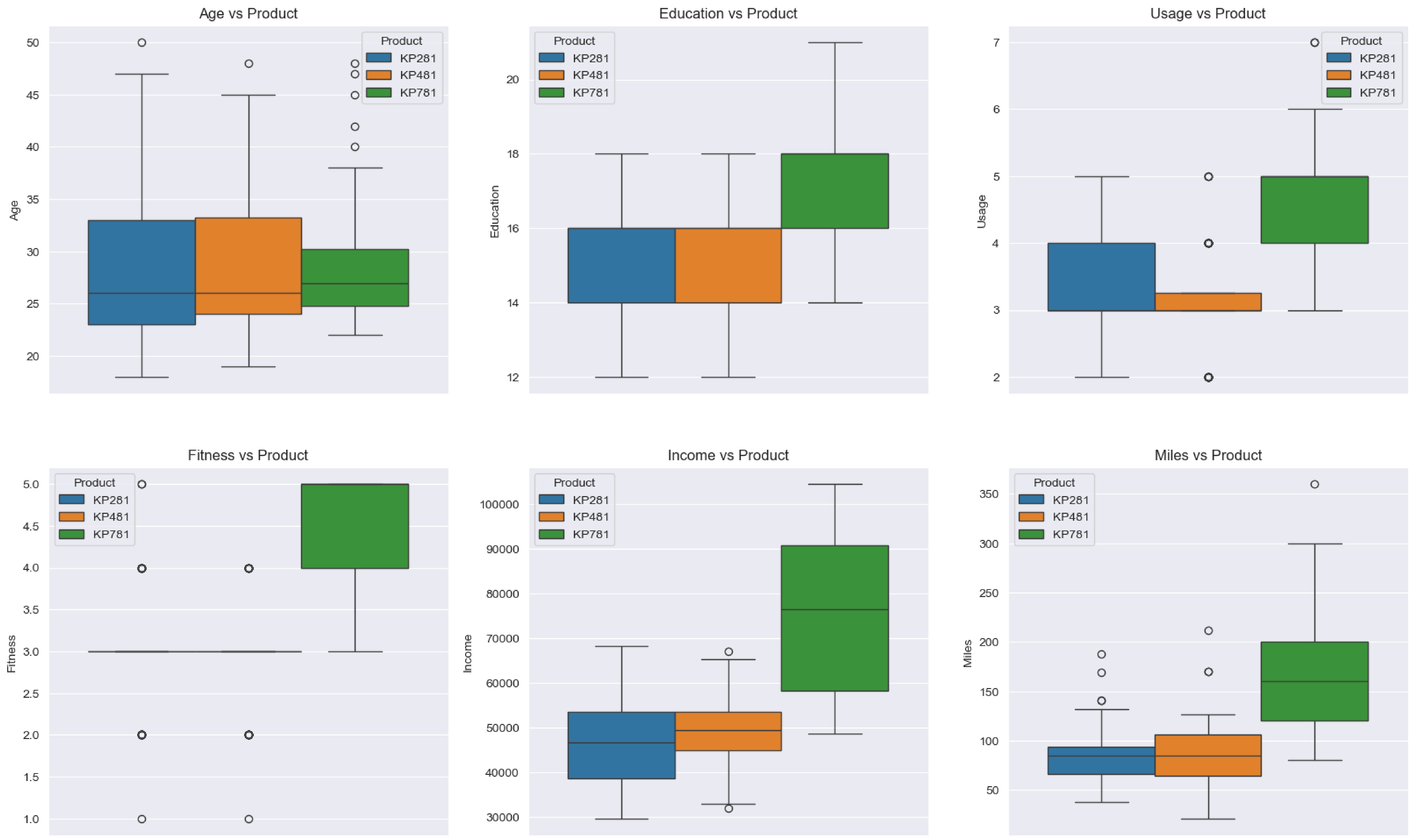
In [14]:
```
sns.pairplot(df,hue="Product");
```



Insights

- From above plots we can clearly distinguish the user of **KP781** based on **Fitness**, **Miles**, **Income** and **Usage**
- The users of **KP281** and **KP481** are similar in pattern. This will require a deeper analysis to differentiate between the two.

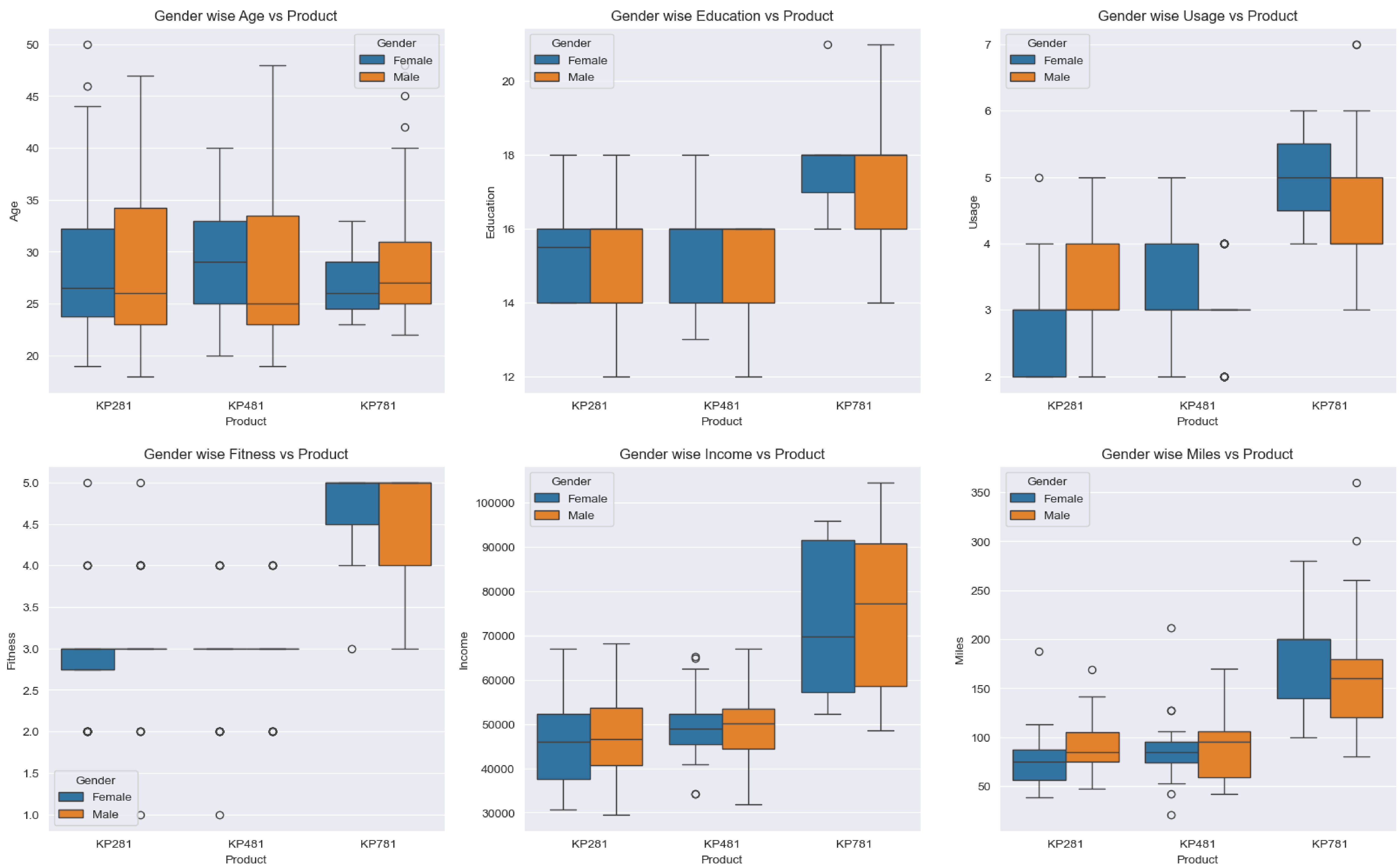
In [15]:
```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))

for i in range(2):
    for j in range(3):
        variable = variables[i * 3 + j]
        sns.boxplot(ax=axes[i, j], data=df, y=variable, hue="Product")
        axes[i, j].set_title(f"{variable} vs Product")

plt.show();
```



Insights

- Above plot shows that **Education**,**Fitness**, **Income**, **Usage**, and **Miles** have big impact on sales of KP781

In [16]:
```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))

for i in range(2):
    for j in range(3):
        variable = variables[i * 3 + j]
        sns.boxplot(ax=axes[i, j], data=df, x="Product", y=variable, hue="Gender")
        axes[i, j].set_title(f"Gender wise {variable} vs Product")

plt.show();
```

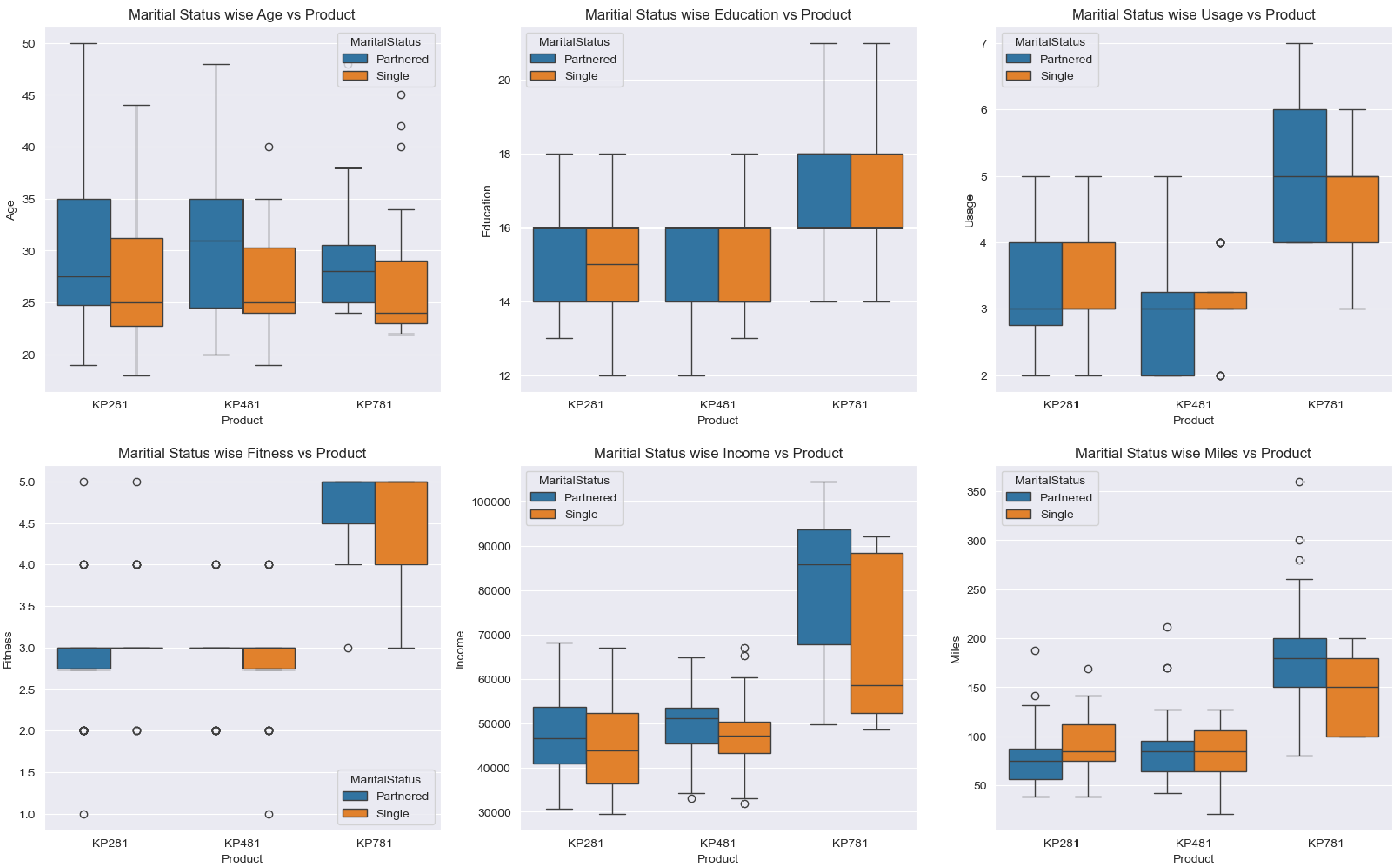


Insights

- From above plot we can see that usage of female users of KP281 is very less as compared to female users of KP781

In [17]:
```
fig, axes = plt.subplots(2, 3, figsize=(20, 12))

for i in range(2):
    for j in range(3):
        variable = variables[i * 3 + j]
        sns.boxplot(ax=axes[i, j], data=df, x="Product", y=variable, hue="MaritalStatus")
```

```
        axes[i, j].set_title(f"Maritial Status wise {variable} vs Product")
plt.show();
```



Insights

- **Partnered** users has higher usage of *KP781* as compared to **Single** KP781 users.

In [18]:
```
df_enc=pd.get_dummies(df).astype(int)
df_enc
```

Out[18]:

	Age	Education	Usage	Fitness	Income	Miles	Product_KP281	Product_KP481	Product_KP781	Gender_Female	Gender_Male	MaritalStatus_Partnered	MaritalStatus_Single
0	18	14	3	4	29562	112	1	0	0	0	1	0	1
1	19	15	2	3	31836	75	1	0	0	0	1	0	1
2	19	14	4	3	30699	66	1	0	0	1	0	1	0
3	19	12	3	3	32973	85	1	0	0	0	1	0	1
4	20	13	4	2	35247	47	1	0	0	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
175	40	21	6	5	83416	200	0	0	1	0	1	0	1
176	42	18	5	4	89641	200	0	0	1	0	1	0	1
177	45	16	5	5	90886	160	0	0	1	0	1	0	1
178	47	18	4	5	104581	120	0	0	1	0	1	1	0
179	48	18	4	5	95508	180	0	0	1	0	1	1	0

180 rows × 13 columns

In [19]:
```
cols = list(df_enc.columns.values)
cols
```

Out[19]:
```
['Age',
 'Education',
 'Usage',
 'Fitness',
 'Income',
 'Miles',
 'Product_KP281',
 'Product_KP481',
 'Product_KP781',
 'Gender_Female',
 'Gender_Male',
 'MaritalStatus_Partnered',
 'MaritalStatus_Single']
```

In [20]:
```
cols=[
    'Product_KP281',
    'Product_KP481',
    'Product_KP781',
    'Age',
    'Education',
    'Usage',
    'Fitness',
    'Income',
    'Miles',
    'Gender_Female',
    'Gender_Male',
    'MaritalStatus_Partnered',
    'MaritalStatus_Single'
]
df_enc = df_enc[cols]
```

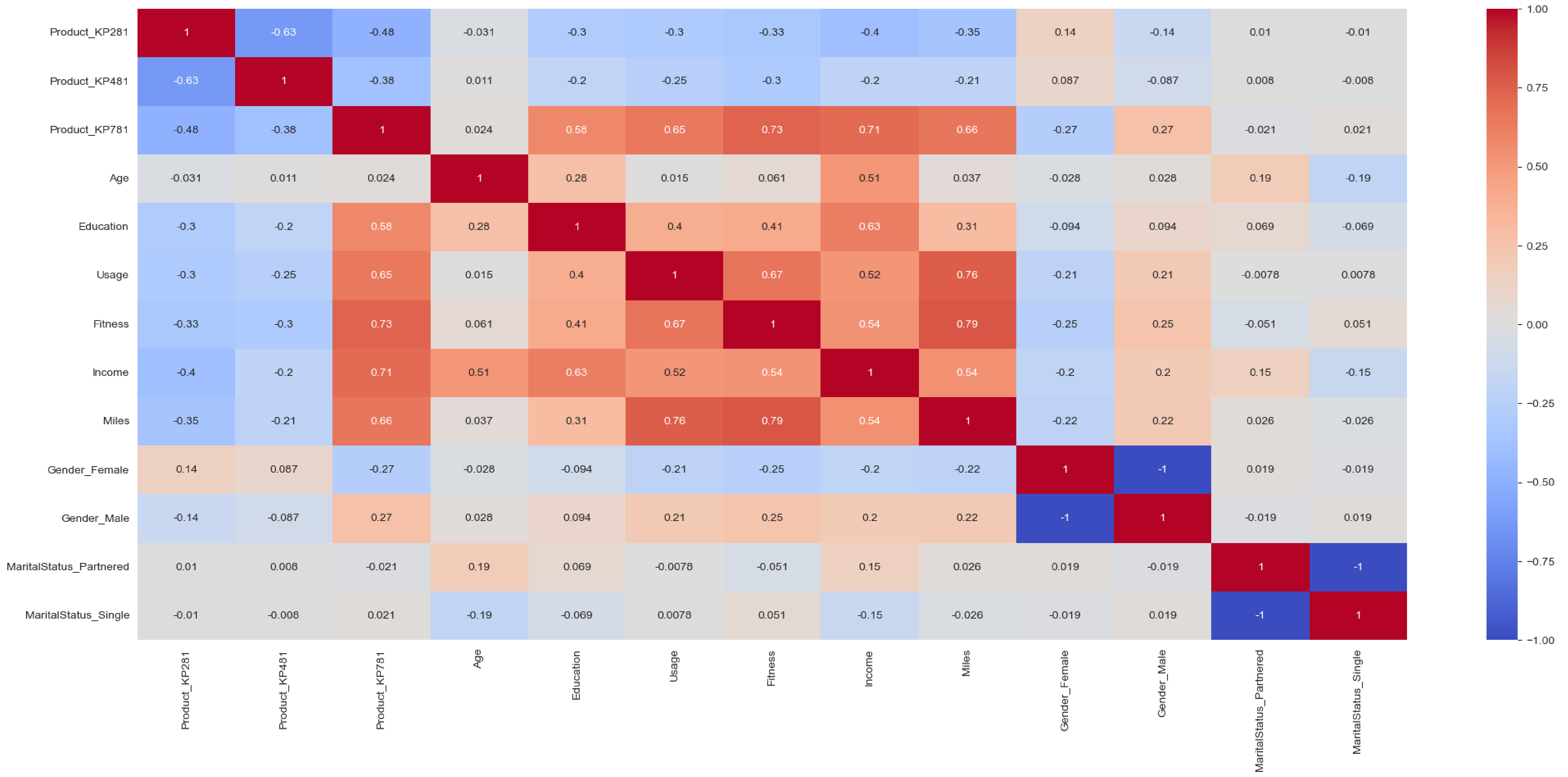
In [21]:
```
df_enc
```

Out[21]:

	Product_KP281	Product_KP481	Product_KP781	Age	Education	Usage	Fitness	Income	Miles	Gender_Female	Gender_Male	MaritalStatus_Partnered	MaritalStatus_Single
0	1	0	0	18	14	3	4	29562	112	0	1	0	1
1	1	0	0	19	15	2	3	31836	75	0	1	0	1
2	1	0	0	19	14	4	3	30699	66	1	0	1	0
3	1	0	0	19	12	3	3	32973	85	0	1	0	1
4	1	0	0	20	13	4	2	35247	47	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
175	0	0	1	40	21	6	5	83416	200	0	1	0	1
176	0	0	1	42	18	5	4	89641	200	0	1	0	1
177	0	0	1	45	16	5	5	90886	160	0	1	0	1
178	0	0	1	47	18	4	5	104581	120	0	1	1	0
179	0	0	1	48	18	4	5	95508	180	0	1	1	0

180 rows × 13 columns

In [22]:
```
plt.figure(figsize=(25, 10))
sns.heatmap(df_enc.corr(), annot=True, cmap=sns.color_palette("coolwarm", as_cmap=True))
plt.yticks(rotation=0);
```



Insights

From above heatmap we can say that :

- Fitness, Income, Miles, Usage have very high positive correlations with each KP781, but have negative correlations with each KP281 and KP481.
- Age, Maritial Status have negligible correlations with each all products
- Male user have positive correlations with KP781, but have negative correlations with other products
- Female user have positive correlations with KP281 and KP481, but have negative correlations with KP781

Probabilities

In [23]:
```
df["Product"].value_counts(normalize=True)
```

Out[23]:
```
Product
KP281    0.444
KP481    0.333
KP781    0.222
Name: proportion, dtype: float64
```

Insights

On a larger scale we can say that:

- Probability that a user will buy KP281 is 44%
- Probability that a user will buy KP781 is 22%
- KP281 is the most popular product

Using `pandas.crosstab()` function we can find probabilities of each **Category** with respect to the each **Product** item

In [24]:
```
print("Maritial Status vs Products")
pd.crosstab(index=df["MaritalStatus"], columns=df['Product'] , margins=True,  normalize=True)

print("\nGender vs Products")
pd.crosstab(index=df["Gender"], columns=df['Product'], margins=True, normalize=True)
```

```
Maritial Status vs Products
```

Out[24]:

Product	KP281	KP481	KP781	All
MaritalStatus				
Partnered	0.267	0.200	0.128	0.594
Single	0.178	0.133	0.094	0.406
All	0.444	0.333	0.222	1.000

```
Gender vs Products
```

Out[24]:

Product	KP281	KP481	KP781	All
Gender				
Female	0.222	0.161	0.039	0.422
Male	0.222	0.172	0.183	0.578
All	0.444	0.333	0.222	1.000

Insights

- 59.4% of total users are **Partnered** users
- 26.7% of total users are using **KP281** product

Conditional Probabilities

Using `conditions` inside a dataframe and `value_counts()` function, we can find conditional probabilities

In [25]:
```
print("Probability (Product | Male)")
df[df["Gender"] == "Male"]["Product"].value_counts(normalize=True)

print("\nProbability (Product | Female)")
df[df["Gender"] == "Female"]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Male)
```

Out[25]:
```
Product
KP281    0.385
KP781    0.317
KP481    0.298
Name: proportion, dtype: float64
```
```
Probability (Product | Female)
```

Out[25]:
```
Product
KP281    0.526
KP481    0.382
KP781    0.092
Name: proportion, dtype: float64
```

Insights

Above data shows that

- **Female** users are more likely to buy **KP281** and highly unlikely to buy **KP781**.
- There is almost equal distribution of **Products** between the **Male** users

In [26]:
```
print("Probability (Product | Partnered)")
df[df["MaritalStatus"] == "Partnered"]["Product"].value_counts(normalize=True)

print("\nProbability (Product | Single)")
df[df["MaritalStatus"] == "Single"]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Partnered)
```

Out[26]:
```
Product
KP281    0.449
KP481    0.336
KP781    0.215
Name: proportion, dtype: float64
```
```
Probability (Product | Single)
```

Out[26]:
```
Product
KP281    0.438
KP481    0.329
KP781    0.233
Name: proportion, dtype: float64
```

Insights

Above data shows that

- **Single** users have higher probability of buying **KP781** than **Partnered** users
- **Partnered** users have higher probability of buying **KP481**.

In [27]:
```
print("Probability (MaritalStatus | KP281)")
df[df["Product"] == "KP281"]["MaritalStatus"].value_counts(normalize=True)

print("Probability (MaritalStatus | KP481)")
df[df["Product"] == "KP481"]["MaritalStatus"].value_counts(normalize=True)

print("Probability (MaritalStatus | KP781)")
df[df["Product"] == "KP781"]["MaritalStatus"].value_counts(normalize=True)
```

```
Probability (MaritalStatus | KP281)
```

Out[27]:
```
MaritalStatus
Partnered   0.600
Single      0.400
Name: proportion, dtype: float64
```
```
Probability (MaritalStatus | KP481)
```

Out[27]:
```
MaritalStatus
Partnered   0.600
Single      0.400
Name: proportion, dtype: float64
```
```
Probability (MaritalStatus | KP781)
```

Out[27]:
```
MaritalStatus
Partnered   0.575
Single      0.425
Name: proportion, dtype: float64
```

Insights

Above data shows that

- Among users using Aerofit products, there are more **Partnered** users than **Single** users.

In [28]:
```
df[df["Product"] == "KP281"]["Gender"].value_counts(normalize=True)
df[df["Product"] == "KP481"]["Gender"].value_counts(normalize=True)
df[df["Product"] == "KP781"]["Gender"].value_counts(normalize=True)
```

Out[28]:
```
Gender
Female   0.500
Male     0.500
Name: proportion, dtype: float64
```

Out[28]:
```
Gender
Male     0.517
Female   0.483
Name: proportion, dtype: float64
```

Out[28]:
```
Gender
Male     0.825
Female   0.175
Name: proportion, dtype: float64
```

In [32]:
```python
print("\nProbability (Product | Single & Male)")
df[(df["MaritalStatus"] == "Single") & (df["Gender"]=="Male")]["Product"].value_counts(normalize=True)

print(" \nProbability (Product | Single & Female)")
df[(df["MaritalStatus"] == "Single") & (df["Gender"]=="Female")]["Product"].value_counts(normalize=True)

print("\nProbability (Product | Partnered & Male)")
df[(df["MaritalStatus"] == "Partnered") & (df["Gender"]=="Male")]["Product"].value_counts(normalize=True)

print("\nProbability (Product | Partnered & Female)")
df[(df["MaritalStatus"] == "Partnered") & (df["Gender"]=="Female")]["Product"].value_counts(normalize=True)
```

```
Probability (Product | Single & Male)
```

Out[32]:
```
Product
KP281    0.442
KP781    0.326
KP481    0.233
Name: proportion, dtype: float64
```

```
Probability (Product | Single & Female)
```

Out[32]:
```
Product
KP481    0.467
KP281    0.433
KP781    0.100
Name: proportion, dtype: float64
Probability (Product | Partnered & Male)
```

Out[32]:
```
Product
KP281    0.344
KP481    0.344
KP781    0.311
Name: proportion, dtype: float64
Probability (Product | Partnered & Female)
```

Out[32]:
```
Product
KP281    0.587
KP481    0.326
KP781    0.087
Name: proportion, dtype: float64
```

Customer Profile

KP281

- Age : Around 28, but under 35
- Income : Less than 50000
- Fitness: under 3
- Miles : Under 90
- Usage: 3-4
- Education : less than 16
- Marital Status : Both, but targeted more towards Partnered (60% Probability)
- Gender: Both

KP481

- Age: Around 28, but under 35
- Income : If Partnered then around 50000 else less than 50000
- Education : less than 16
- Fitness: under 3
- Miles : Around 100
- Usage: 3
- Marital Status : Both, but targeted more towards Partnered (60% Probability)
- Gender: Both, but targeted more towards Male (51.7% Probability)

KP781

- Age: Under 30
- Income : Above 60000
- Fitness: Above 3
- Education : Above 16
- Usage : Above 4
- Miles : Above 120
- Gender: Male (82.7% Probability)
- Maritial Status : Both, but targeted more towards Partnered (57% Probability)

Recomendations

- The data show that KP481(mid level) has almost same type of users as that of KP281(entry level).
- Some features from KP781(top level) can be added in KP481(mid level).
- This will increase the sales of KP481(mid level) as users will get better deal by paying little extra. Later on price also can be increased depending on popularity.
- Discount on KP781 can be given to female users to increase the sale.

In [ ]: