In [300…

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

Problem Statement

- **Primary Goal**
  - Recognizing **Purchase pattern** of Products wrt. Age , Education , Income , Gender etc.
  - Indentifying **customer segments,profiling and formulating markerting strategy**
  - How to **drive sales of products and revenue** , across product categories
    - Data driven discounting / offers among customer segments
- **Statistical summary**
  - More **likelihood of purchase**
  - Range / Limitation of data
- **Long term benefits** : Sales growth , Customer acquisition and retention

In [301…

```
df=pd.read_csv('aerofit_treadmill.csv')
df.head()
```

Out[301]:

	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

Basic Analysis

- **Analysing metrics** - Basic metrics
  - Observations on **shape** of data
  - **Data types** of all the attributes
  - **Conversion** of categorical attributes to 'category' (If required)
  - Statistical summary

In [302…

```
df.shape
```

Out[302]:

```
(180, 9)
```

In [303…

```
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
```

- **Conversion** - to 'category'
  - Age to Age_generation
  - Income to Income_category
  - Fitness to Fitness_level
  - Education to Education_category

In [304…

```
# Gen Z  10 - 25
# Millennials   26 - 41
# Younger millennials (25 to 32 years old)
# Older ones (33 to 40 years old)
# Gen X 42 - 57
```

In [305…

```
def age_to_generation(age):
    if age >= 10 and age <= 25:
        return 'Gen-Z'
    elif age >= 26 and age <= 32:
        return 'Younger-Millennials'
    elif age >= 33 and age <= 41:
        return 'Older-Millennials'
    else:
        return 'Gen-X'
```

In [306…

```
df["Age_generation"] = df["Age"].apply(age_to_generation)
```

In [307…

```
# Source - https://en.wikipedia.org/wiki/Education_in_the_United_States#:~:text=Students
def education_to_category(years_of_education):
    if years_of_education  <= 13:
        return 'School'
    elif years_of_education >= 14 and years_of_education <= 17:
        return 'High-School'
    elif years_of_education >= 18 and years_of_education <= 21:
        return 'Undergraduate-School'
    elif years_of_education > 21:
        return 'Graduate school'
```

In [308…

```
df["Education_category"] = df["Education"].apply(education_to_category)
```

In [309…

```
def fitness_to_category(fitness):
    if fitness  == 1:
```

```python
            return 'Poor'
        elif fitness == 2:
            return 'Below-Avg'
        elif fitness == 3:
            return 'Average'
        elif fitness == 4:
            return 'Above-Avg'
        else:
            return 'Excellent'
```

In [310…

```python
df["Fitness_category"] = df["Fitness"].apply(fitness_to_category)
```

In [311…

```python
# Source - https://money.usnews.com/money/personal-finance/family-finance/articles/where
#Poor or near-poor      $32,048 or less
#Lower-middle class     $32,048 - $53,413
#Middle class   $53,413 - $106,827
#Upper-middle class     $106,827 - $373,894
#Rich   $373,894 and up
```

In [312…

```python
def income_to_category(income):
    if income  < 32048:
        return 'Poor-Income'
    elif income >= 32048 and income < 53413:
        return 'Lower-Middle-Income'
    elif income >= 53413 and income < 106827:
        return 'Middle-Income'
    elif income >= 106827 and income < 373894:
        return 'Upper-Middle-Income'
    else:
        return 'Rich-Income'
```

In [313…

```python
df["Income_category"] = df["Income"].apply(income_to_category)
```

In [314…

```python
df.describe()
```

Out[314]:

	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

In [315…

```python
df.describe(include='object')
```

Out[315]:

	Product	Gender	MaritalStatus	Age_generation	Education_category	Fitness_category	Income_category
count	180	180	180	180	180	180	180
unique	3	2	2	4	3	5	3
top	KP281	Male	Partnered	Gen-Z	High-School	Average	Lower-Middle-Income
freq	80	104	107	79	145	97	104

Non-Graphical Analysis

- **Value counts**
  - Age to Age_group

In [316…

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

Out[316]:

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

In [317…

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

Out[317]:

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

In [318…

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

Out[318]:

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

In [319…

```
df["Age_generation"].value_counts()
```

Out[319]:

```
Gen-Z                   79
Younger-Millennials     51
Older-Millennials       39
Gen-X                   11
Name: Age_generation, dtype: int64
```

In [320…

```
df["Education_category"].value_counts()
```

Out[320]:

```
High-School              145
Undergraduate-School      27
School                     8
Name: Education_category, dtype: int64
```

In [321…

```
df["Fitness_category"].value_counts()
```

Out[321]:
```
Average      97
Excellent    31
Below-Avg    26
Above-Avg    24
Poor          2
Name: Fitness_category, dtype: int64
```

In [322…
```
df["Income_category"].value_counts()
```

Out[322]:
```
Lower-Middle-Income    104
Middle-Income           72
Poor-Income              4
Name: Income_category, dtype: int64
```

In [323…
```
df[["Product","Gender","MaritalStatus"]].value_counts()
```

Out[323]:
```
Product  Gender  MaritalStatus
KP281    Female  Partnered        27
         Male    Partnered        21
KP481    Male    Partnered        21
KP281    Male    Single           19
KP781    Male    Partnered        19
KP481    Female  Partnered        15
                 Single           14
KP781    Male    Single           14
KP281    Female  Single           13
KP481    Male    Single           10
KP781    Female  Partnered         4
                 Single            3
dtype: int64
```

- **Unique attributes**

In [324…
```
df["Product"].unique()
```

Out[324]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [325…
```
df["Gender"].unique()
```

Out[325]:
```
array(['Male', 'Female'], dtype=object)
```

In [326…
```
df["MaritalStatus"].unique()
```

Out[326]:
```
array(['Single', 'Partnered'], dtype=object)
```

In [327…
```
df["Age_generation"].unique()
```

Out[327]:
```
array(['Gen-Z', 'Younger-Millennials', 'Older-Millennials', 'Gen-X'],
      dtype=object)
```

In [328…
```
df["Education_category"].unique()
```

Out[328]:
```
array(['High-School', 'School', 'Undergraduate-School'], dtype=object)
```

In [329…
```
df["Fitness_category"].unique()
```

Out[329]:
```
array(['Above-Avg', 'Average', 'Below-Avg', 'Poor', 'Excellent'],
      dtype=object)
```

In [330…
```
df["Income_category"].unique()
```

Out[330]:
```
array(['Poor-Income', 'Lower-Middle-Income', 'Middle-Income'],
      dtype=object)
```

Visual Analysis - Univariate & Bivariate

- For **continuous variable(s)**: **Distplot**, **countplot**, **histogram** for univariate analysis
  - Age
  - Usage
  - Fitness
  - Income
  - Miles

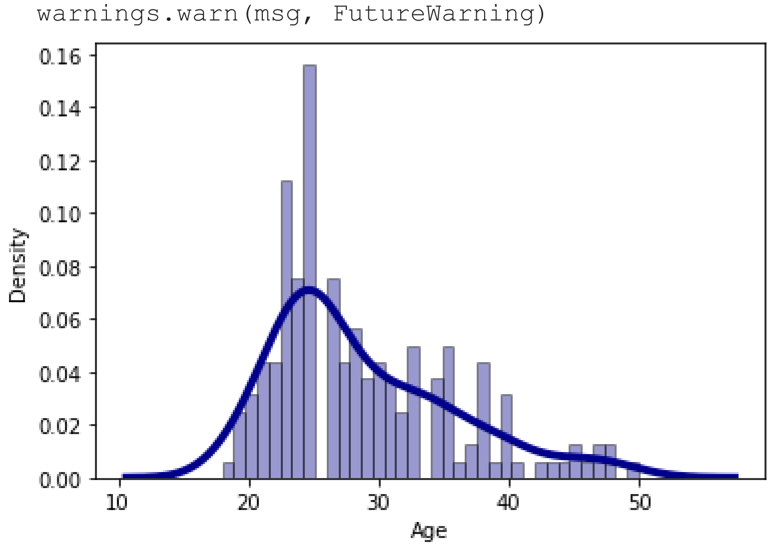
In [331…
```
def distplot_histogram_continious(colnames):
    #plt.figure()
    for feature_name in colnames:
        sns.distplot(df[feature_name], hist=True, kde=True,
        bins=int(36), color = 'darkblue',
        hist_kws={'edgecolor':'black'},
        kde_kws={'linewidth': 4})
        plt.show()
```

In [332…
```
continious_features = df.select_dtypes(include=['int64','float64']).columns
continious_features
```

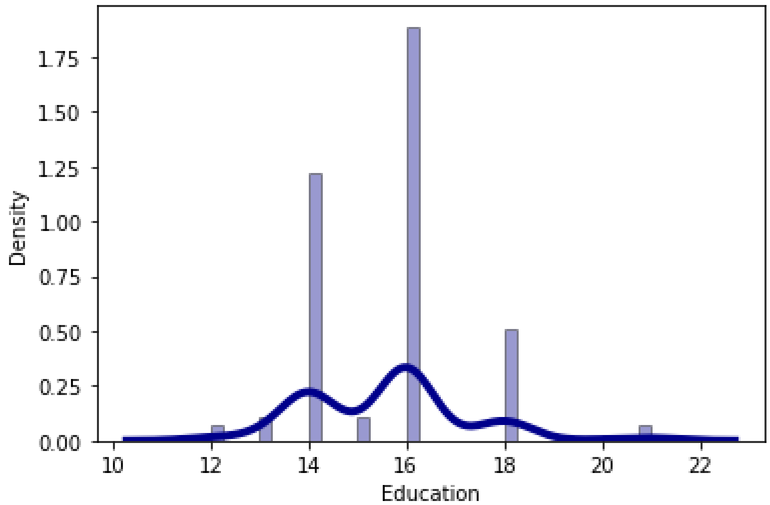
Out[332]:
```
Index(['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles'], dtype='object')
```

In [333…
```
distplot_histogram_continious(continious_features)
```

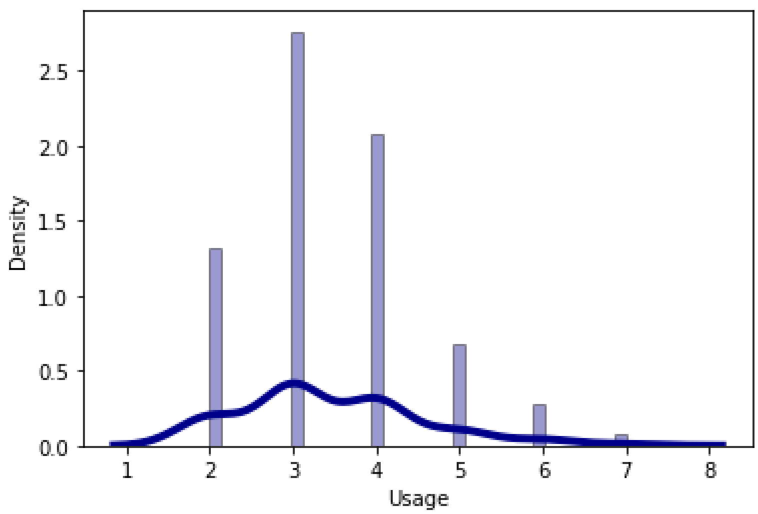
```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributi
ons.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



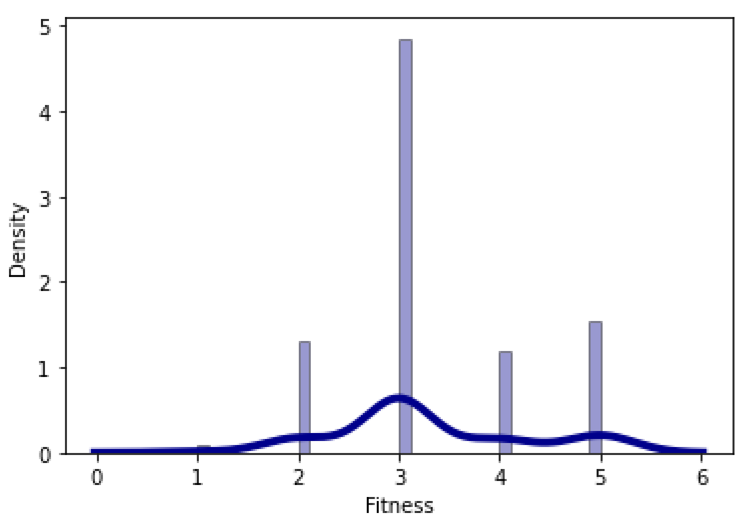
```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributi
ons.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



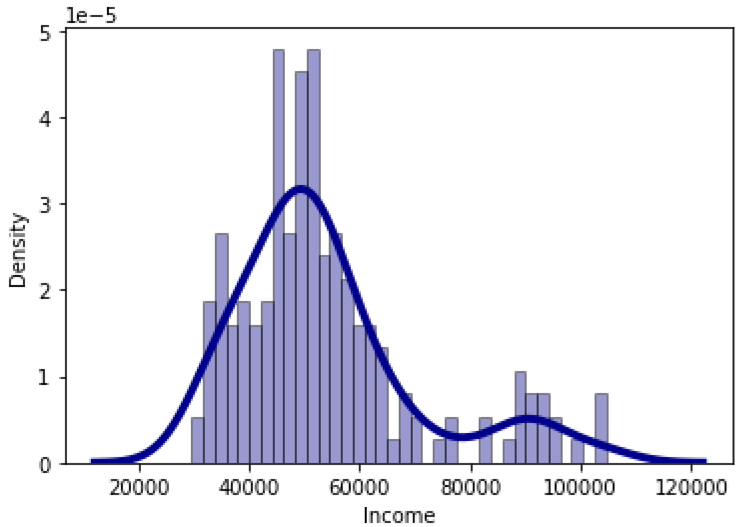

```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributi
ons.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



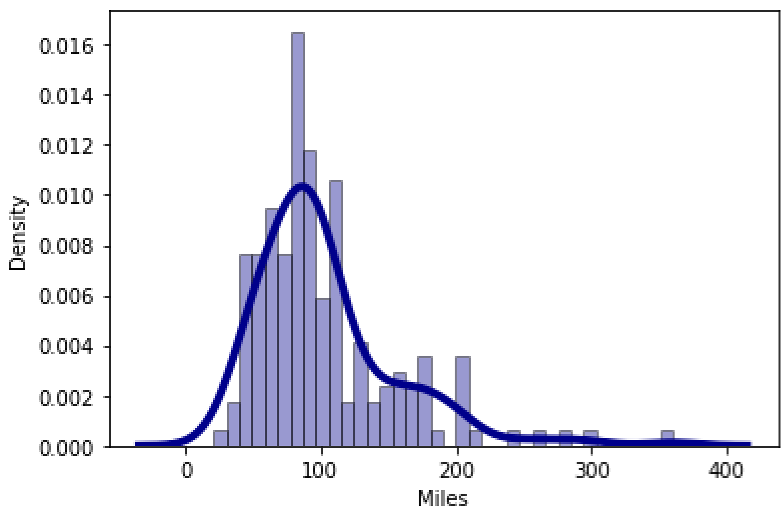

```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributi
ons.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




```
C:\Users\hp\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



- For **categorical** variable(s): **Boxplot**
  - Product
  - Gender
  - MaritalStatus
  - Age_generation
  - Education_category
  - Fitness_category
  - Income_category

In [340…

```python
categorical_features = df.select_dtypes(exclude=['int64','float64']).columns
categorical_features
```

Out[340]:

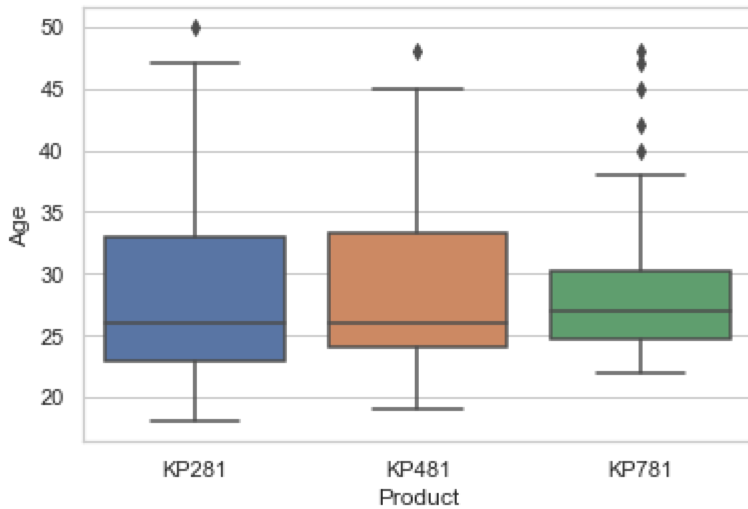
```
Index(['Product', 'Gender', 'MaritalStatus', 'Age_generation',
       'Education_category', 'Fitness_category', 'Income_category'],
      dtype='object')
```

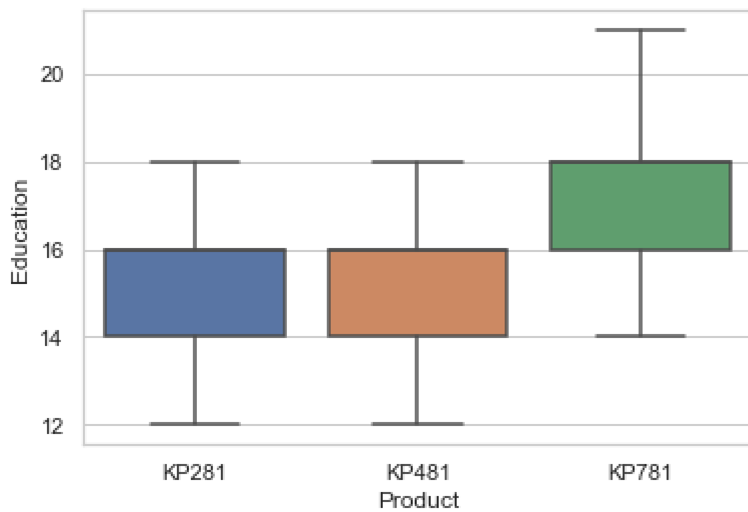
In [415…

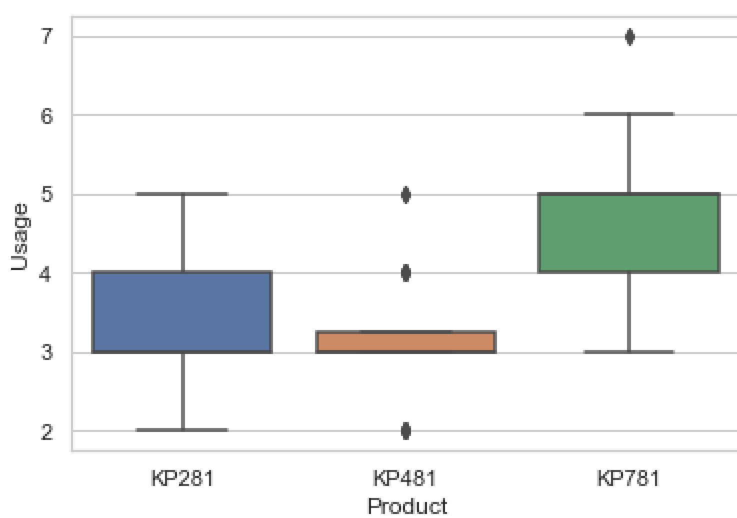
```
def boxplot_all_catogorical_vs_all_continious_features(feature_y_catg_list,feature_y_co
    plt.figure()
    for categorical_feature in feature_y_catg_list:
        for continious_feature in feature_y_contn_list:
            sns.boxplot(x = categorical_feature, y=continious_feature, data=df)
            plt.show()
```

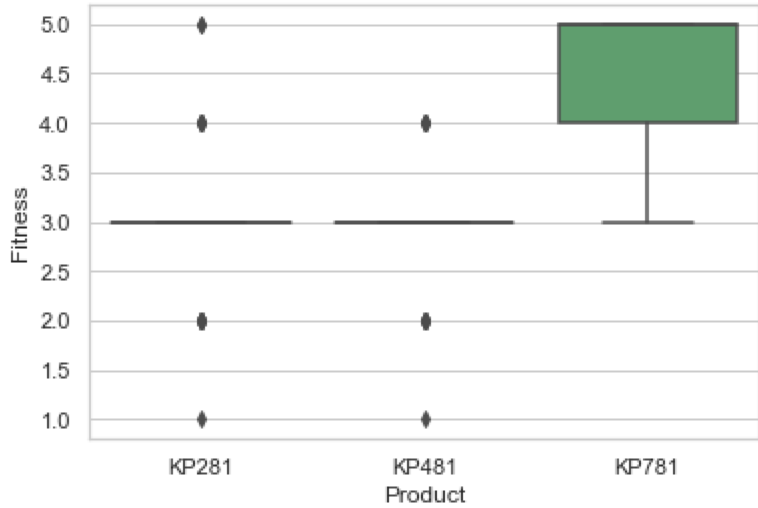
In [416…

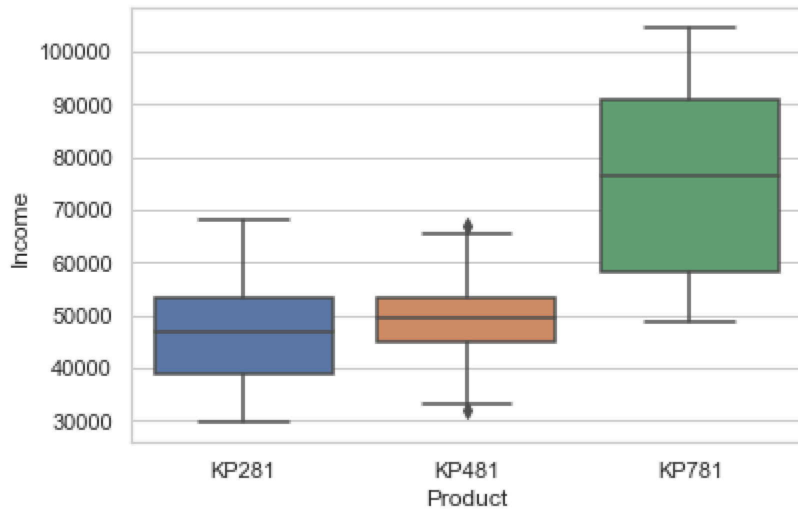
```
boxplot_all_catogorical_vs_all_continious_features(categorical_features,continious_featu
```

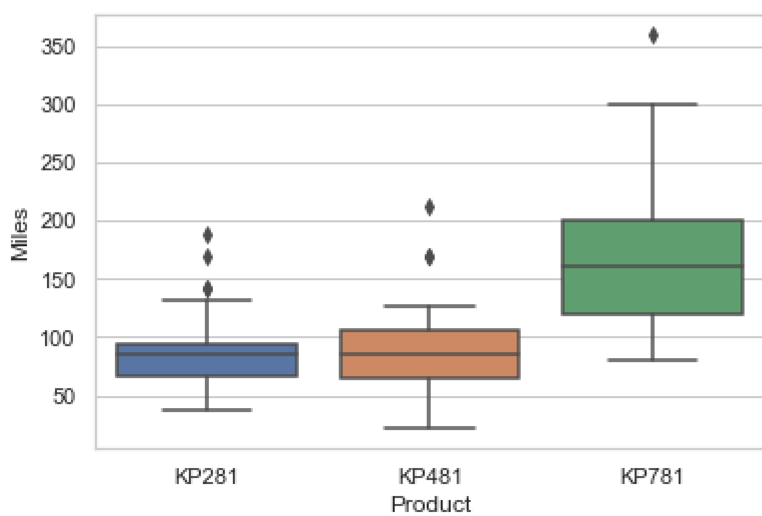


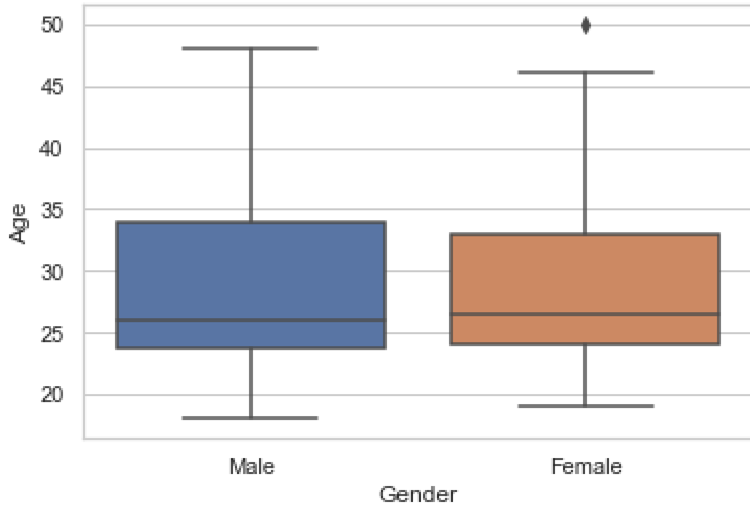




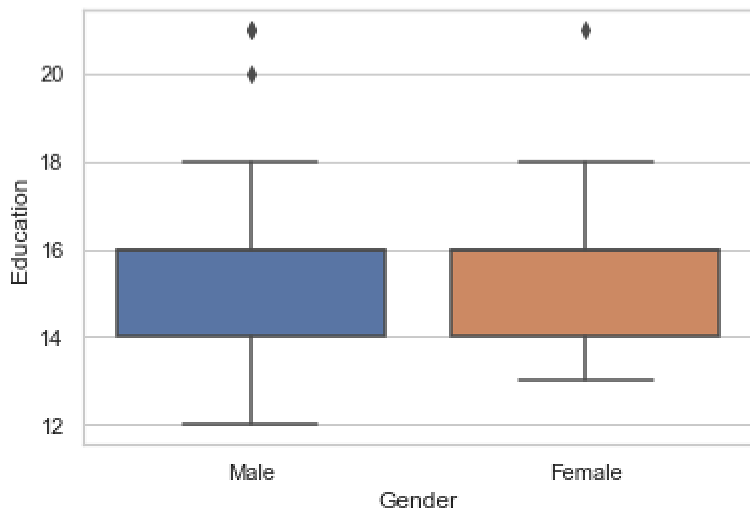

5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
KP281
KP481
KP781
Product


100000
90000
80000
70000
60000
50000
40000
30000
Income
KP281
KP481
KP781
Product

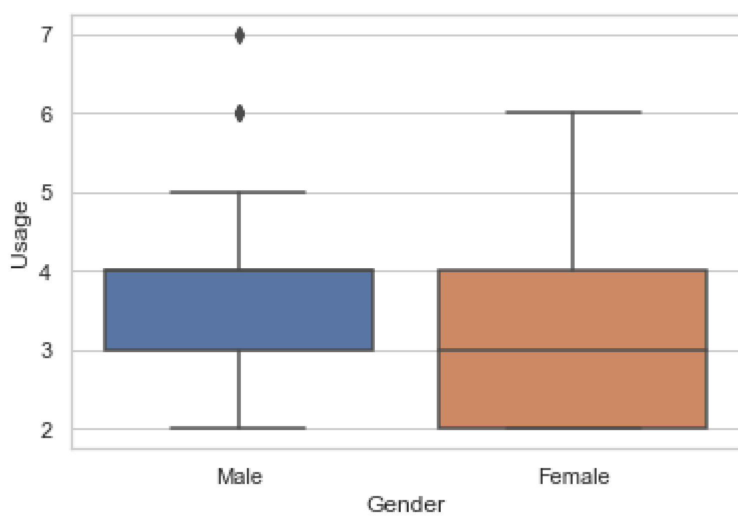

350
300
250
200
150
100
50
Miles
KP281
KP481
KP781
Product



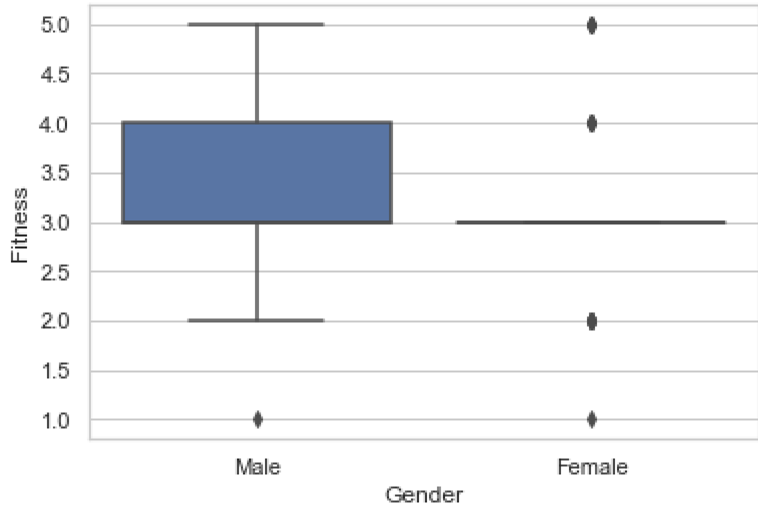
50
45
40
35
30
25
20
Age
Male
Female
Gender

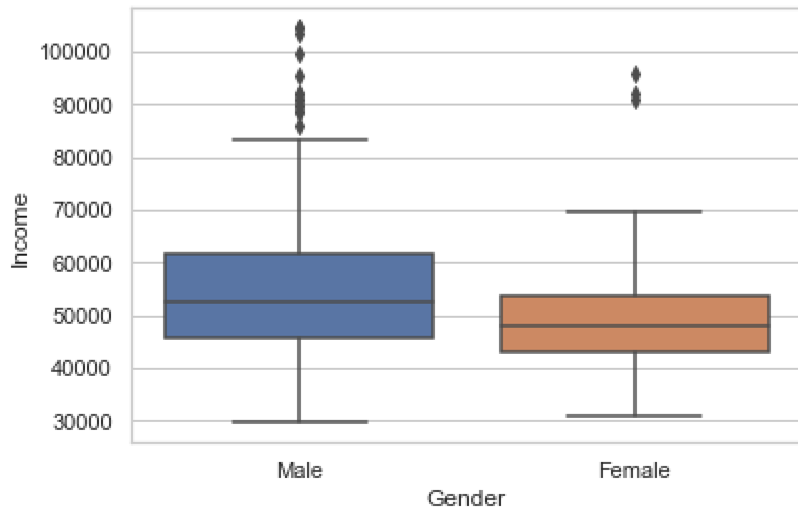


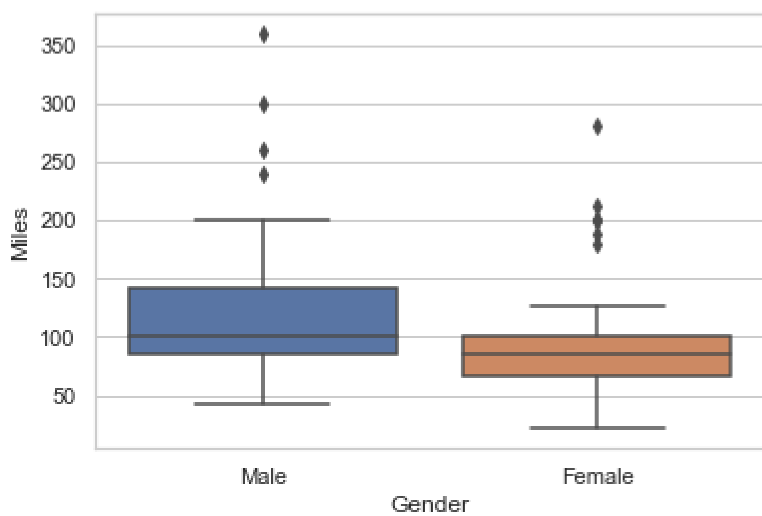
20
18
16
14
12
Education
Male
Female
Gender

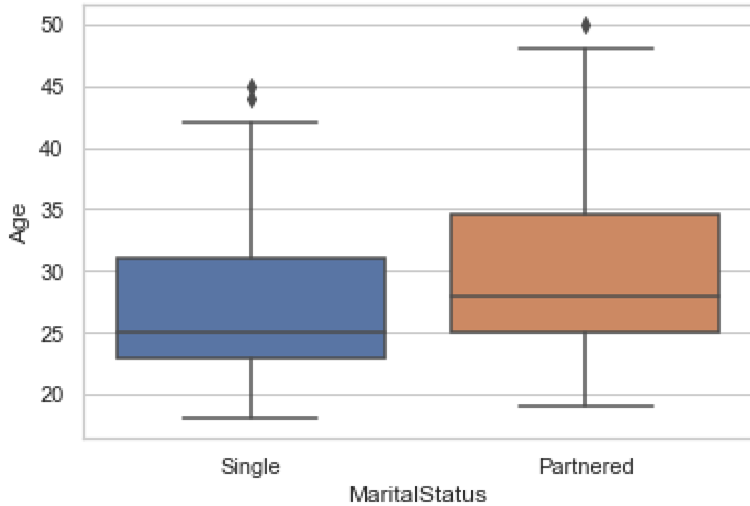


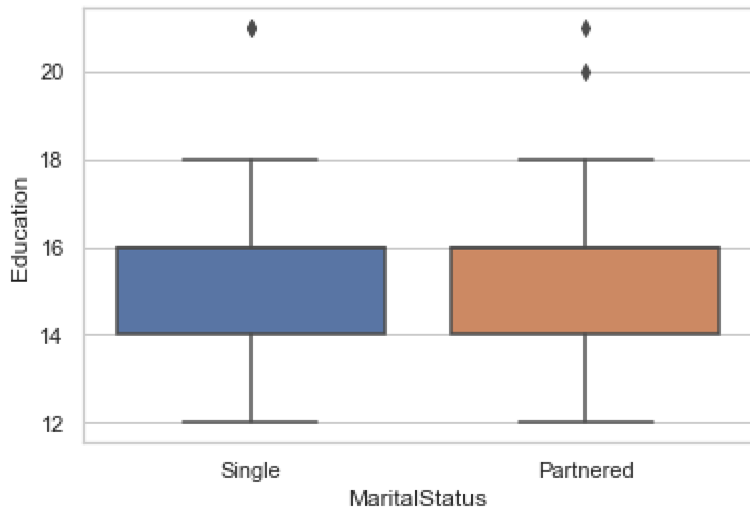
7
6
5
4
3
2
Usage
Male
Female
Gender

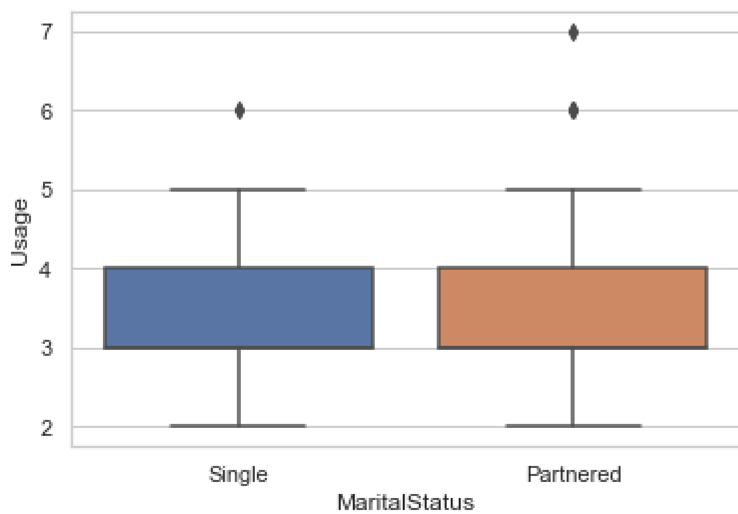

5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
Male
Female
Gender

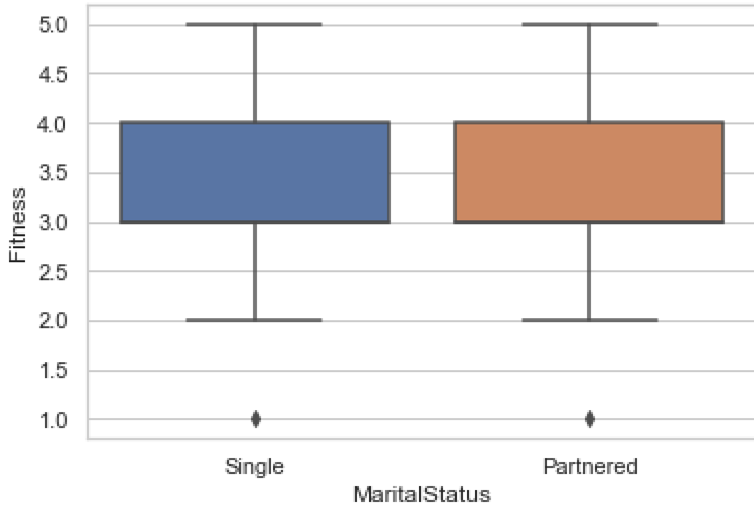

100000
90000
80000
70000
60000
50000
40000
30000
Income
Male
Female
Gender


350
300
250
200
150
100
50
Miles
Male
Female
Gender

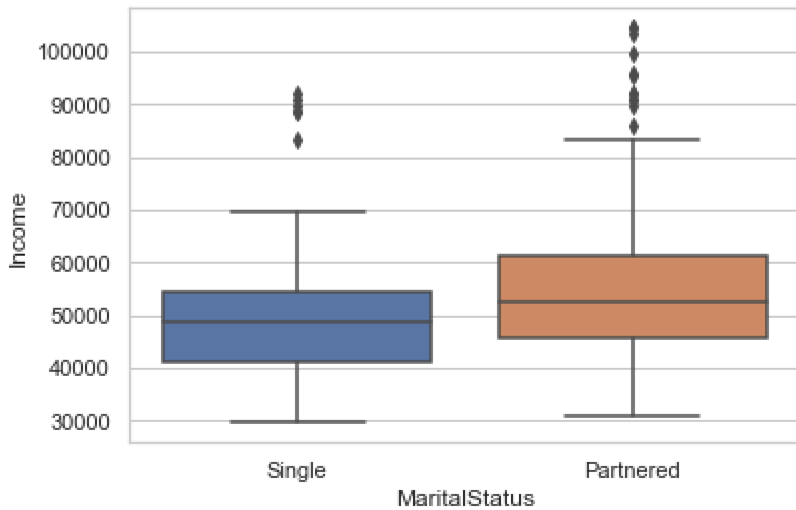

50
45
40
35
30
25
20
Age
Single
Partnered
MaritalStatus


20
18
16
14
12
Education
Single
Partnered
MaritalStatus

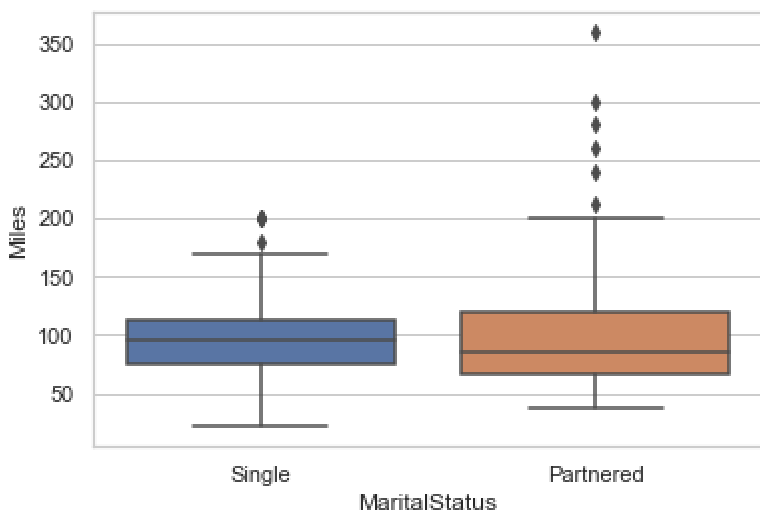

7
6
5
4
3
2
Usage
Single
Partnered
MaritalStatus



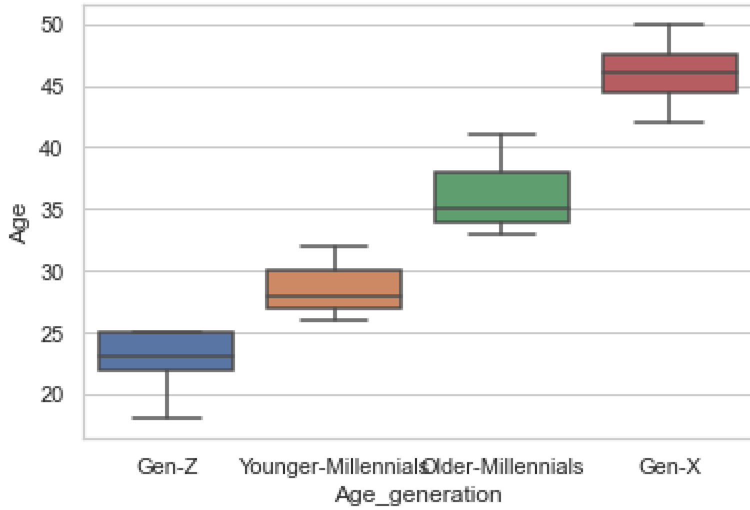
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
Single
Partnered
MaritalStatus

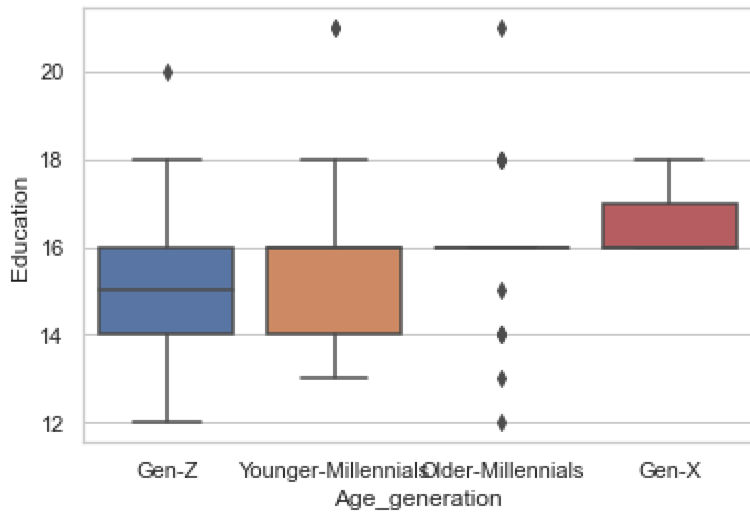


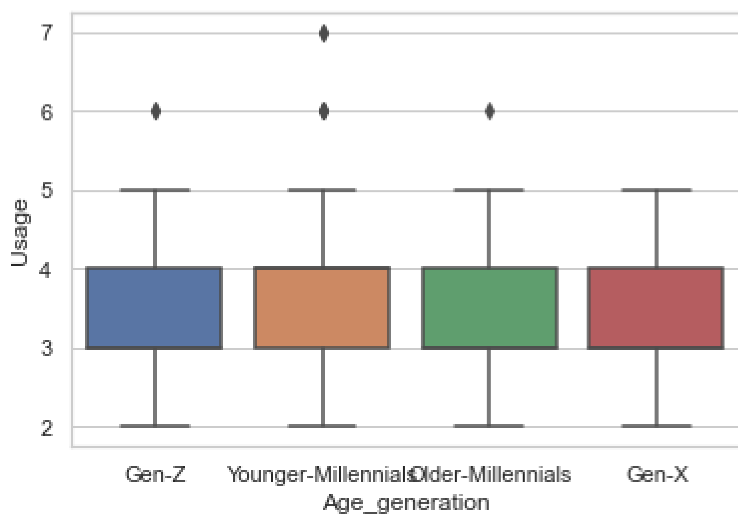
100000
90000
80000
70000
60000
50000
40000
30000
Income
Single
Partnered
MaritalStatus

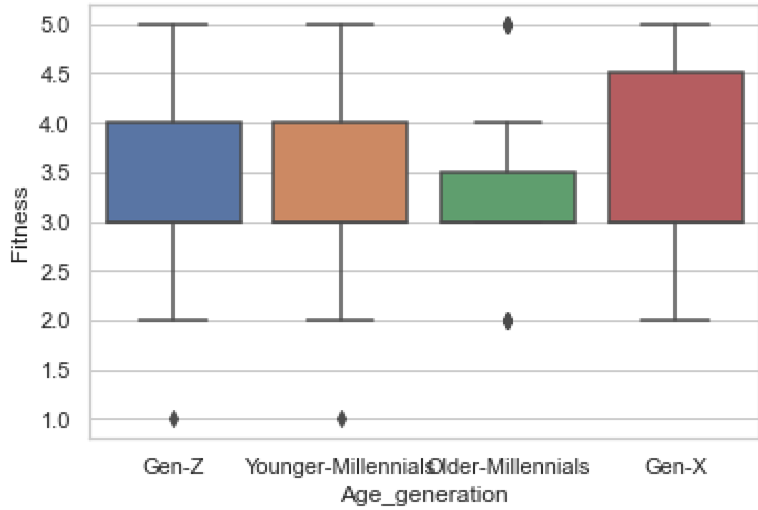


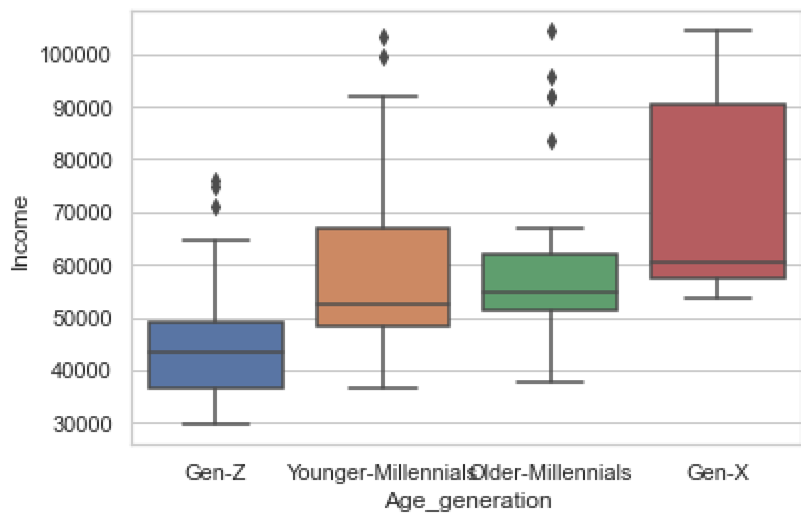
350
300
250
200
150
100
50
Miles
Single
Partnered
MaritalStatus

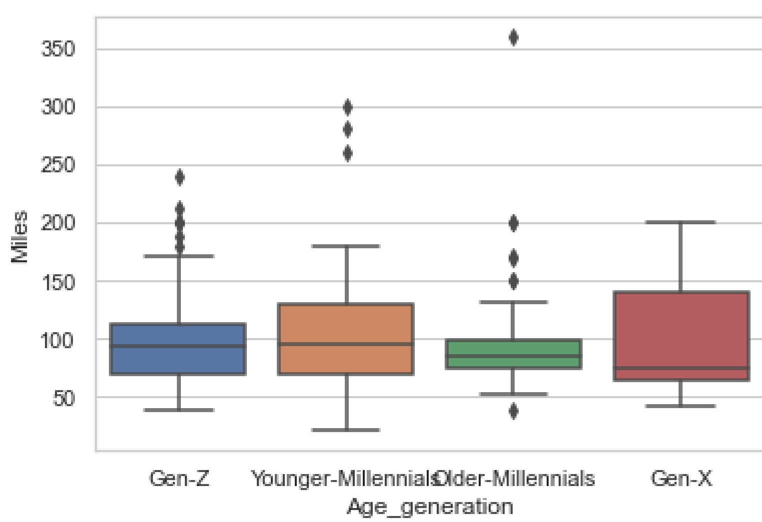

Age
50
45
40
35
30
25
20
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation

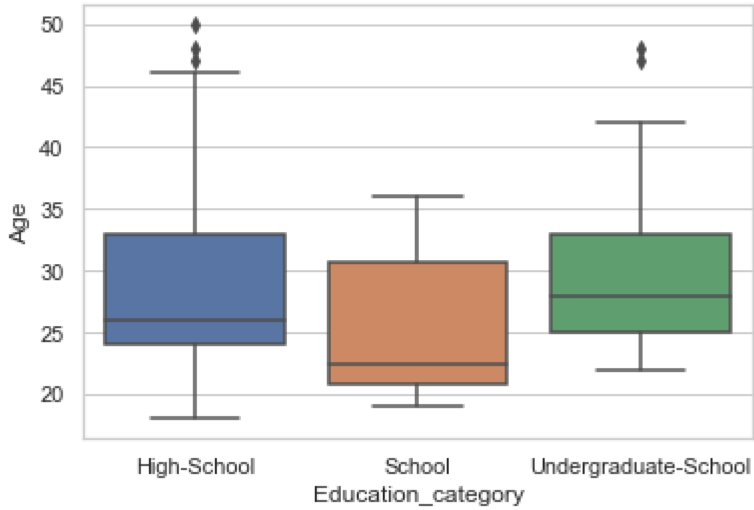

Education
20
18
16
14
12
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation

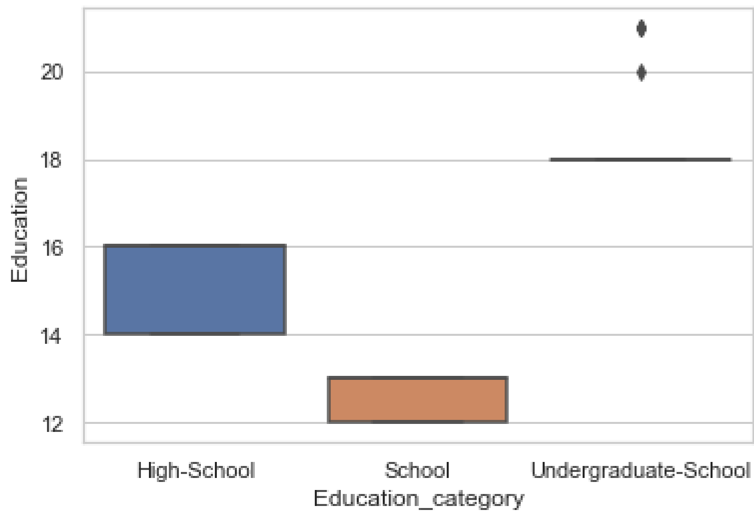

Usage
7
6
5
4
3
2
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation

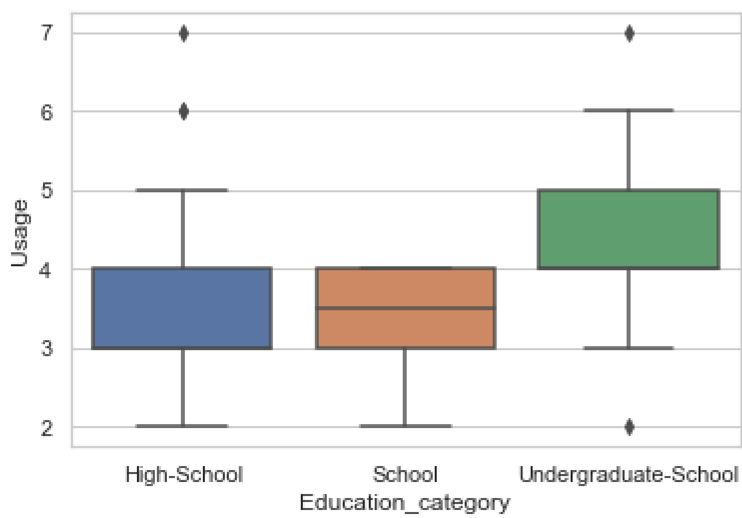

Fitness
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation

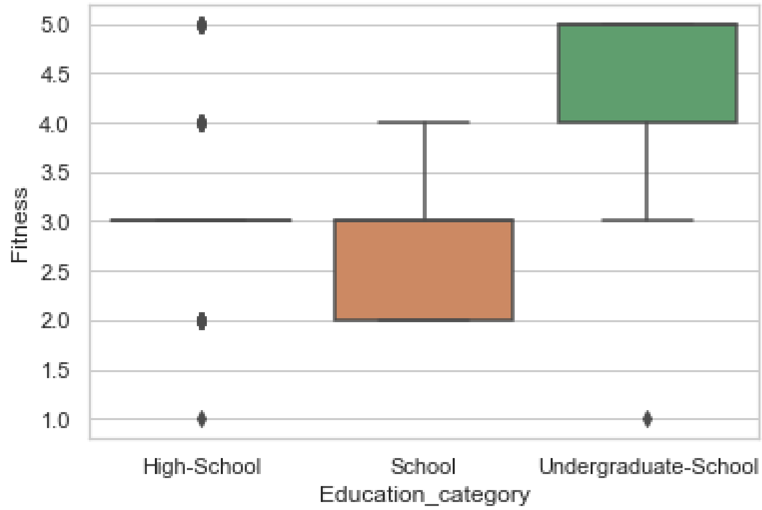

Income
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation


Miles
Gen-Z
Younger-Millennials
Older-Millennials
Gen-X
Age_generation

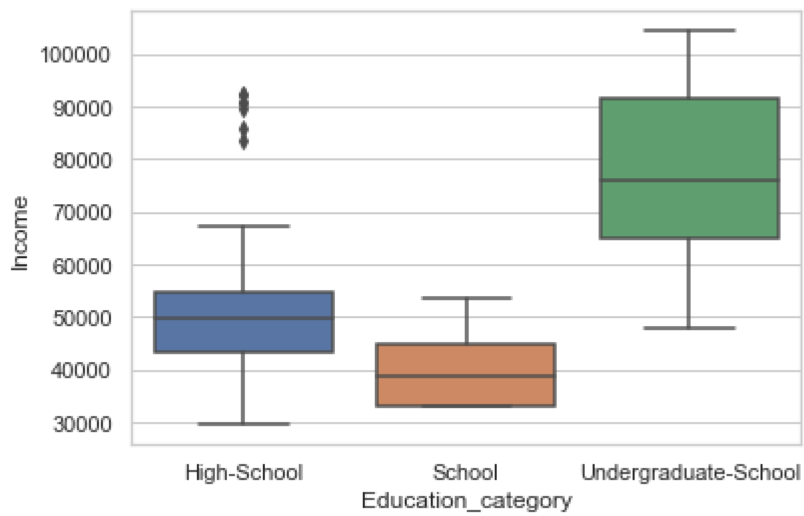

50
45
40
35
30
25
20
Age
High-School
School
Undergraduate-School
Education_category


20
18
16
14
12
Education
High-School
School
Undergraduate-School
Education_category

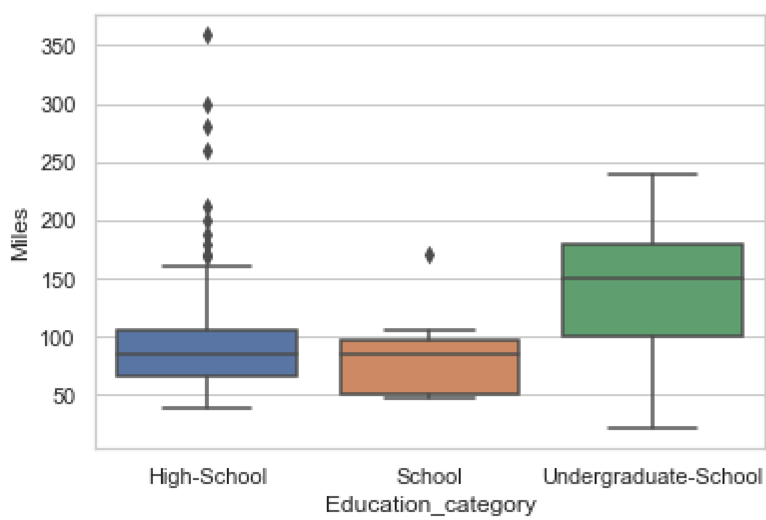

7
6
5
4
3
2
Usage
High-School
School
Undergraduate-School
Education_category



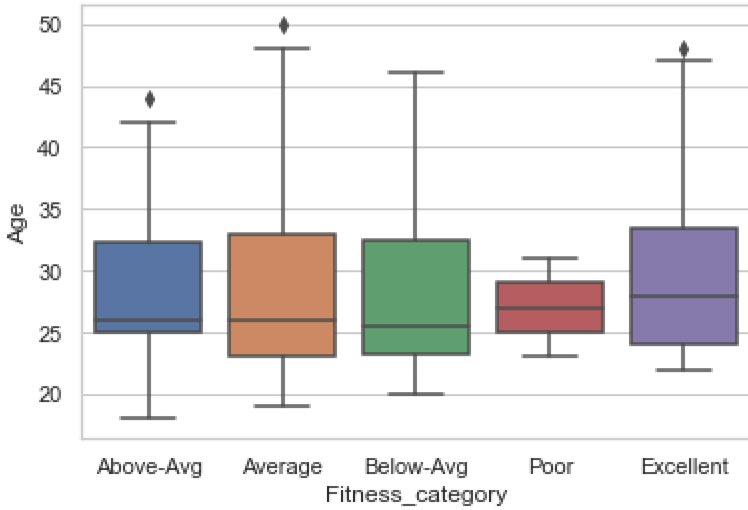
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
High-School
School
Undergraduate-School
Education_category



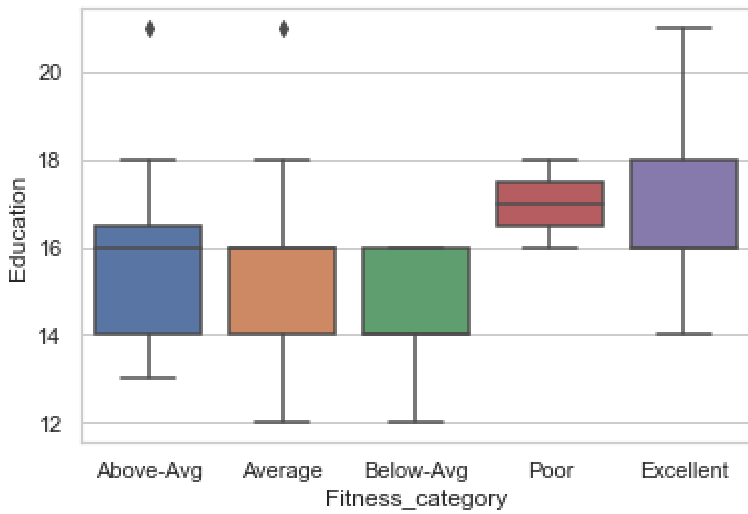
100000
90000
80000
70000
60000
50000
40000
30000
Income
High-School
School
Undergraduate-School
Education_category



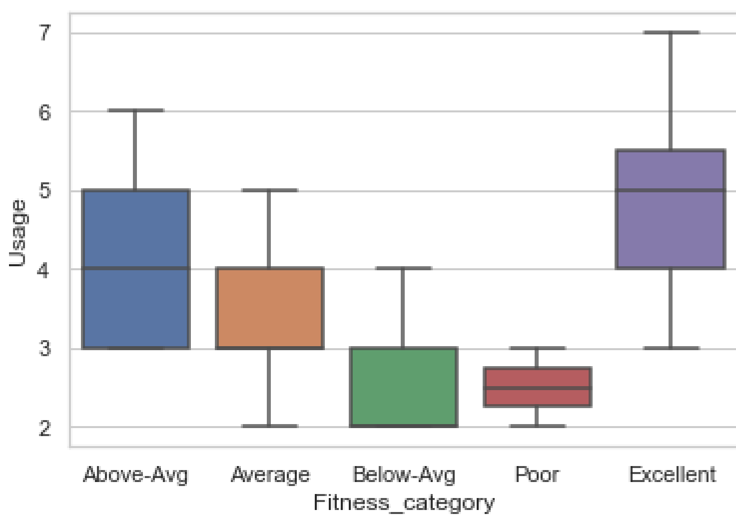
350
300
250
200
150
100
50
Miles
High-School
School
Undergraduate-School
Education_category



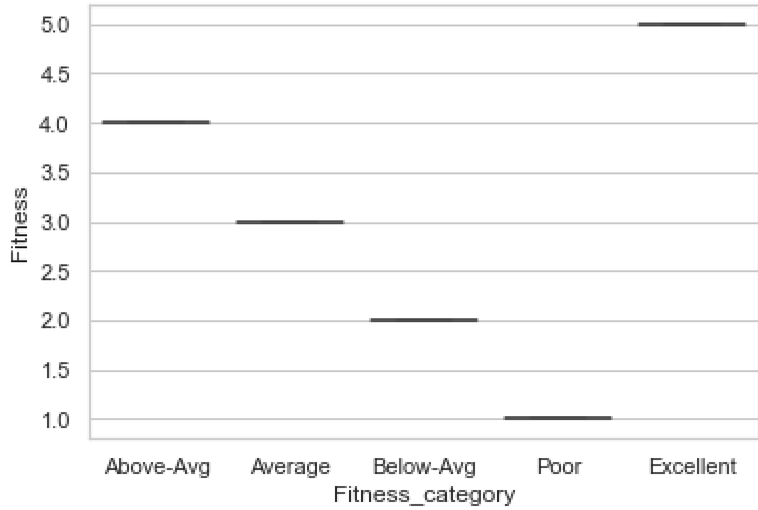
Age
50
45
40
35
30
25
20
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

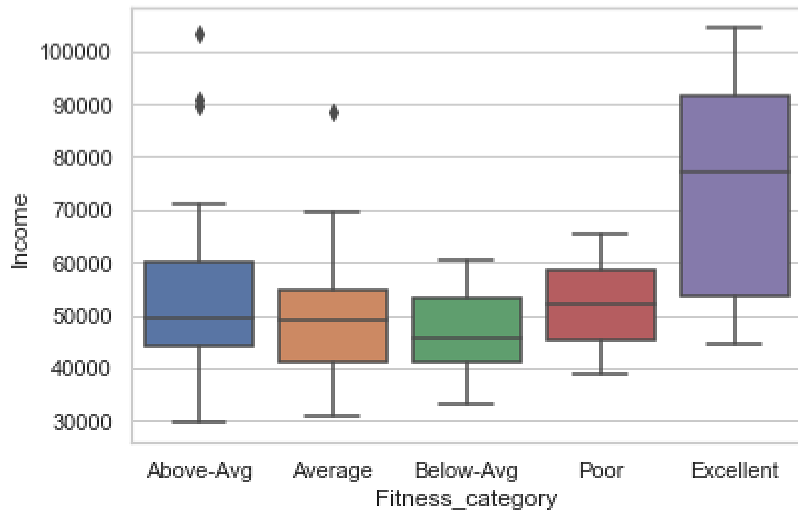


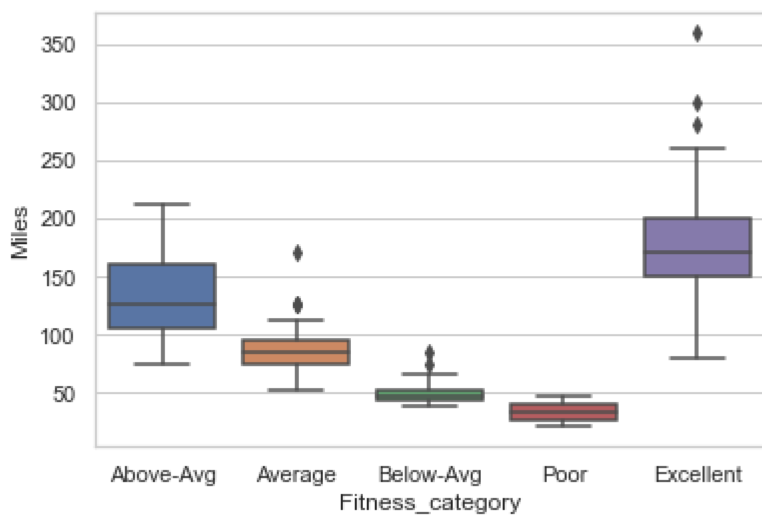
Education
20
18
16
14
12
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

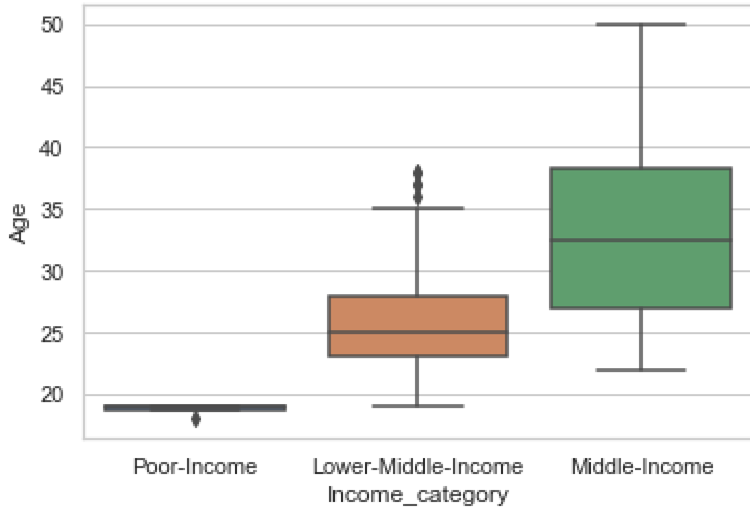


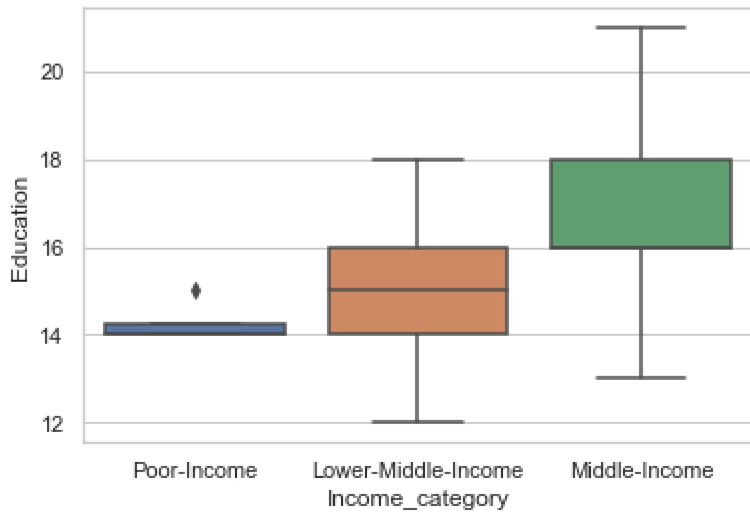
Usage
7
6
5
4
3
2
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

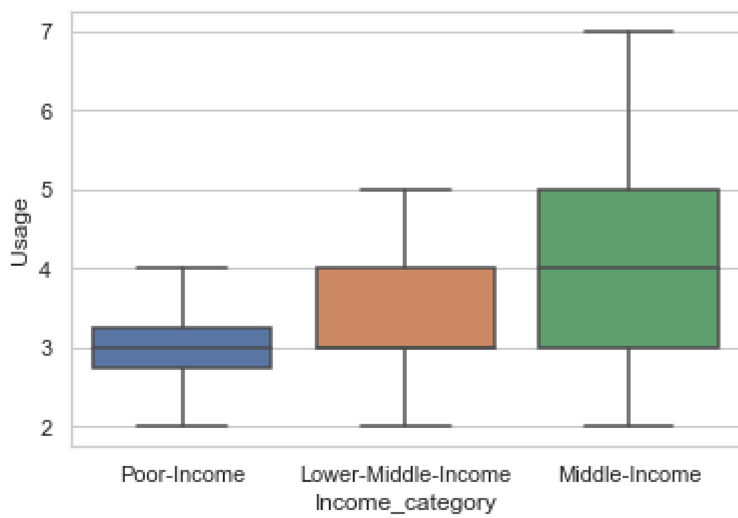

5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

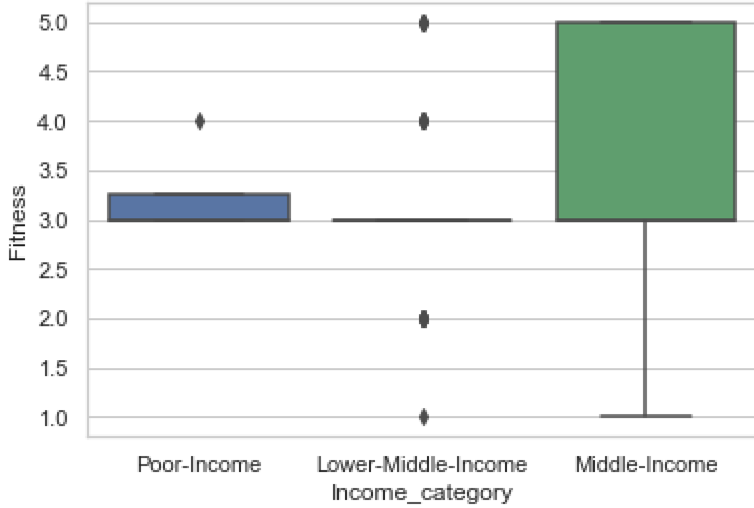

100000
90000
80000
70000
60000
50000
40000
30000
Income
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

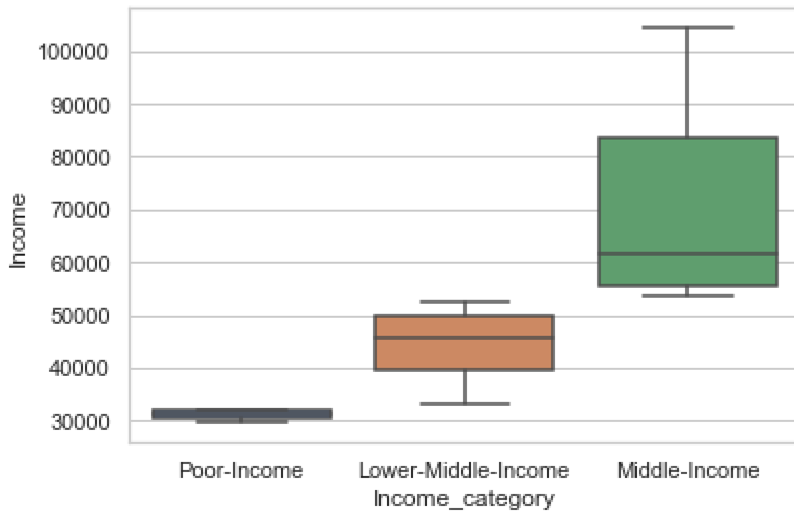

350
300
250
200
150
100
50
Miles
Above-Avg
Average
Below-Avg
Poor
Excellent
Fitness_category

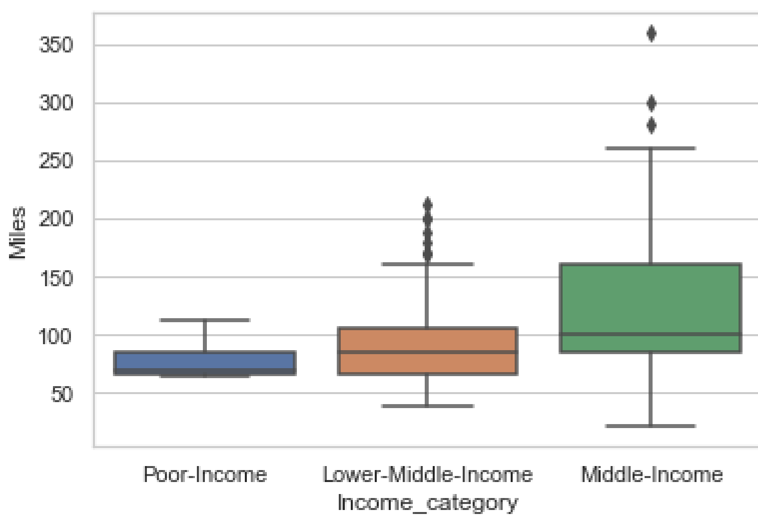

Age
50
45
40
35
30
25
20
Poor-Income
Lower-Middle-Income
Middle-Income
Income_category


Education
20
18
16
14
12
Poor-Income
Lower-Middle-Income
Middle-Income
Income_category


Usage
7
6
5
4
3
2
Poor-Income
Lower-Middle-Income
Middle-Income
Income_category







- For **categorial** variable(s): **countplot** for **Bivariate** analysis
  - Gender vs Product
  - MaritalStatus vs Product
  - Age_generation vs Product
  - Education_category vs Product
  - Fitness_category vs Product
  - Income_category vs Product

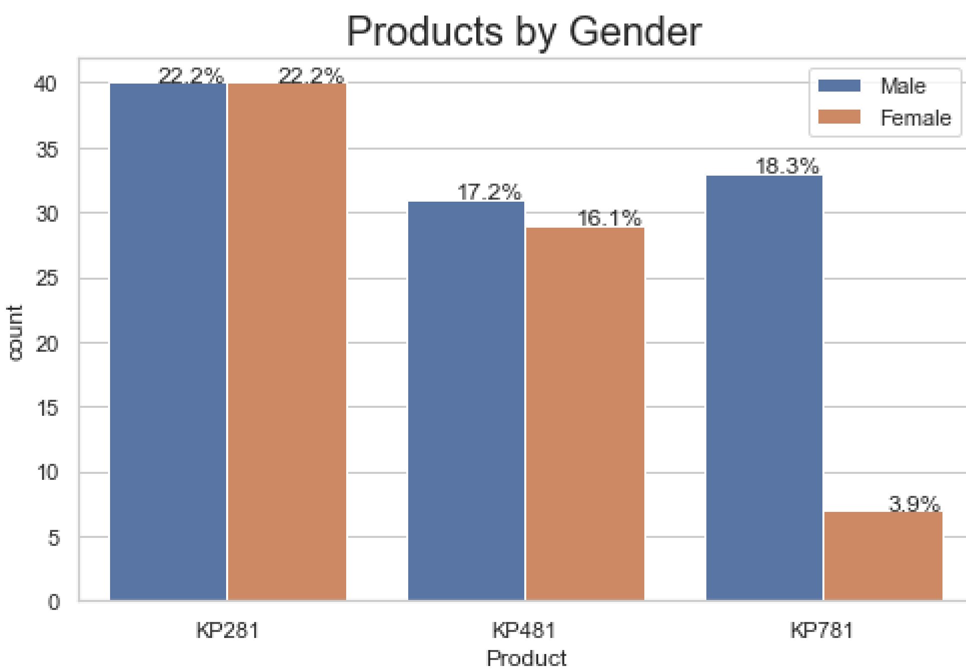
In [390…

```
def plot_products_by(feature_name):
    sns.set(style="whitegrid")
    plt.figure(figsize=(8,5))
```

```
    total = float(len(df))
    ax = sns.countplot(x="Product",  hue=feature_name, data=df)
    plt.legend(loc='upper right')
    plt.title('Products by '+feature_name, fontsize=20)
    for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width()
        y = p.get_height()
        ax.annotate(percentage, (x, y),ha='right')
    plt.show()
```

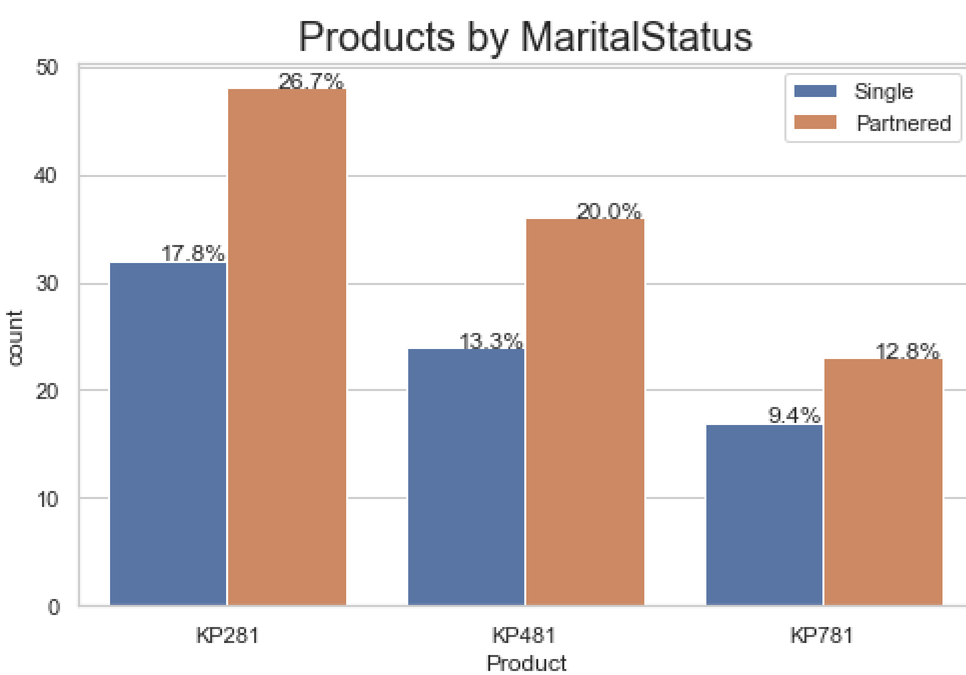
In [392…

```
plot_products_by('Gender')
```



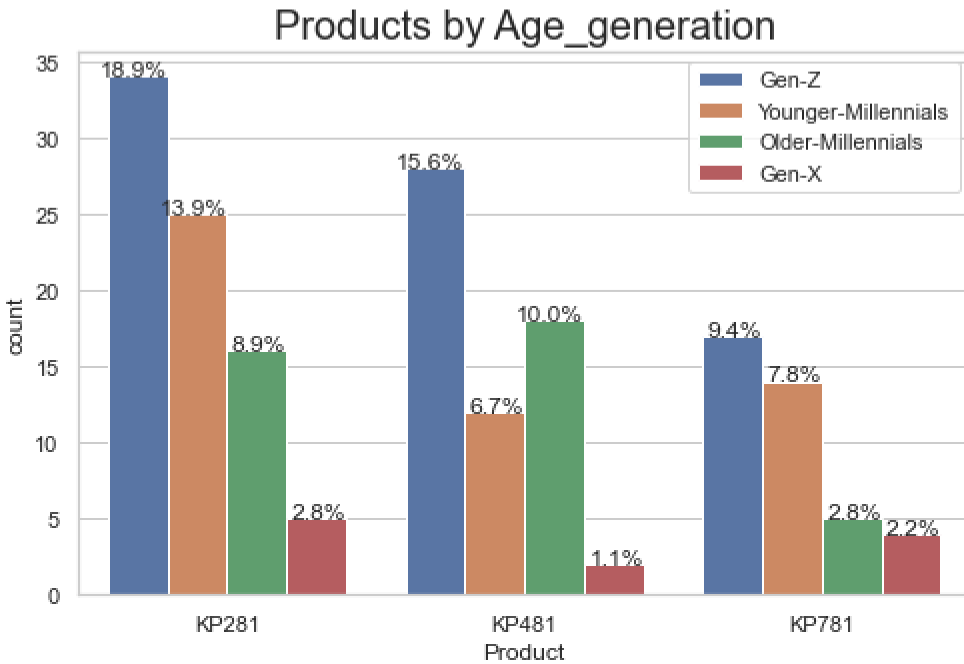
In [393…

```
plot_products_by('MaritalStatus')
```



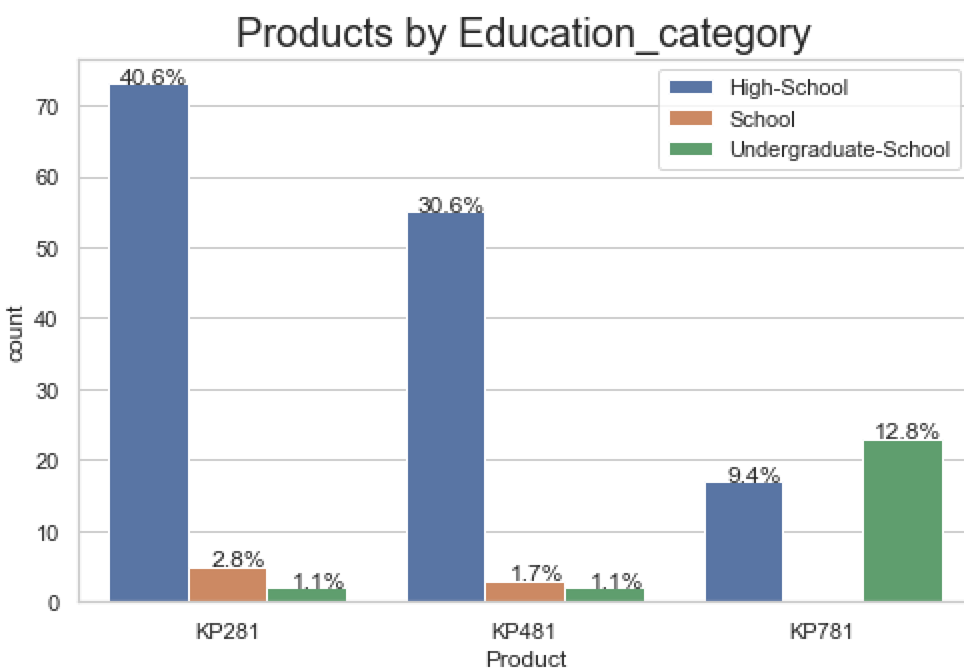
In [394…

```
plot_products_by('Age_generation')
```



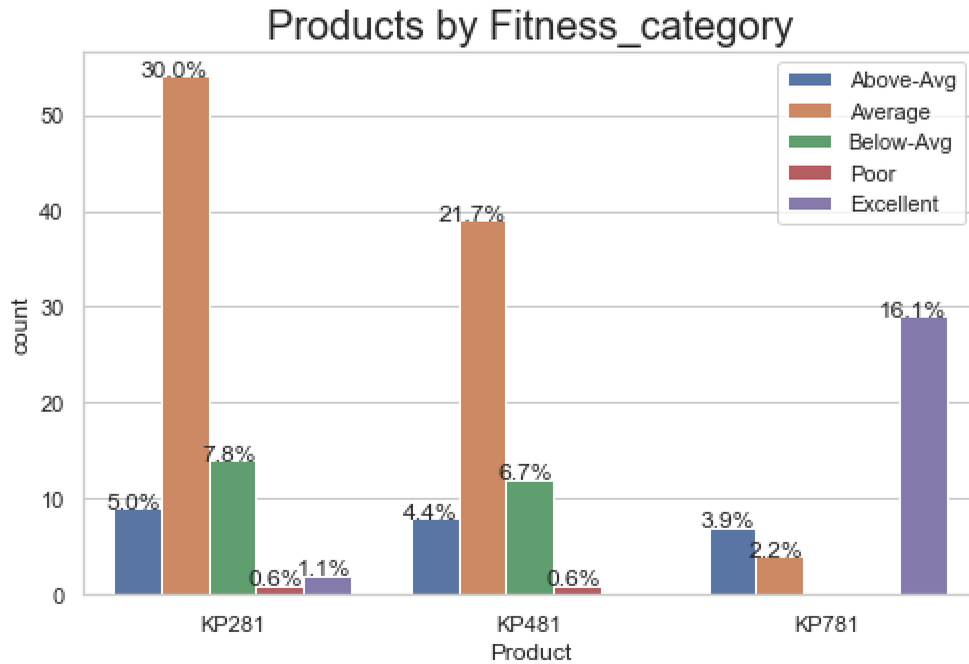
In [395…

```
plot_products_by('Education_category')
```



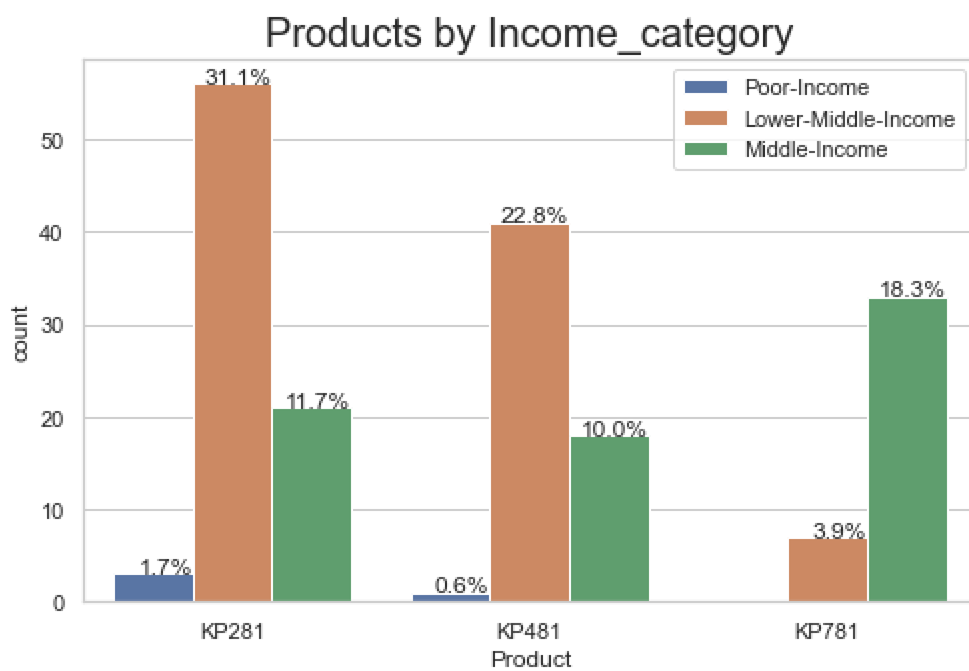
In [396…

```
plot_products_by('Fitness_category')
```



In [397…

```
plot_products_by('Income_category')
```



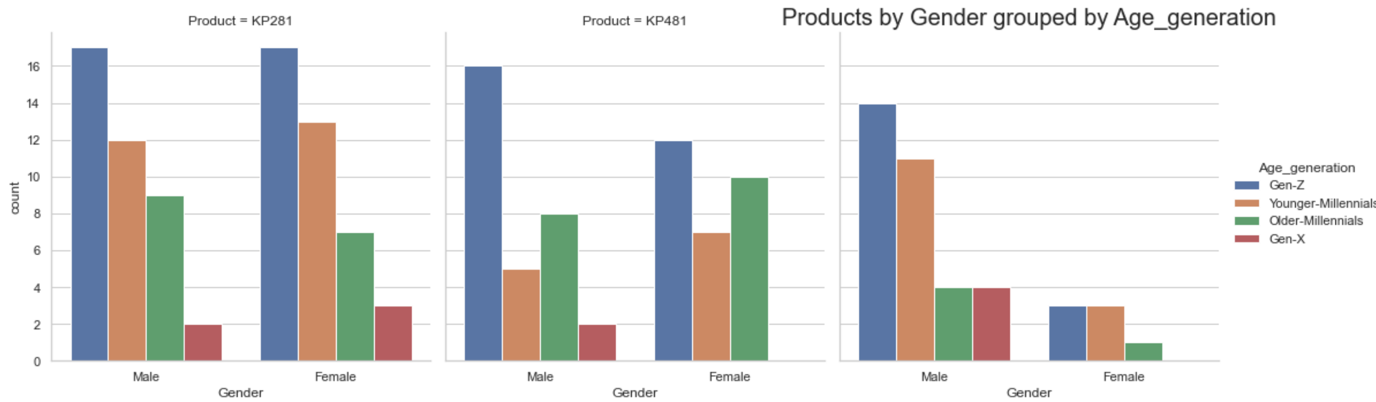
In [442…

```
def plot_products_by_multiple_categories(catg_feature_list,level_filter_name):
    for categorical_feature in catg_feature_list:
        if categorical_feature != level_filter_name and categorical_feature != "Product'
                sns.set(style="whitegrid")
                plt.figure(figsize=(8,5))
                total = float(len(df))
                ax = sns.catplot(x=categorical_feature, hue=level_filter_name, col="Proc
                plt.title('Products by '+categorical_feature +" grouped by "+level_filte
                plt.show()
```

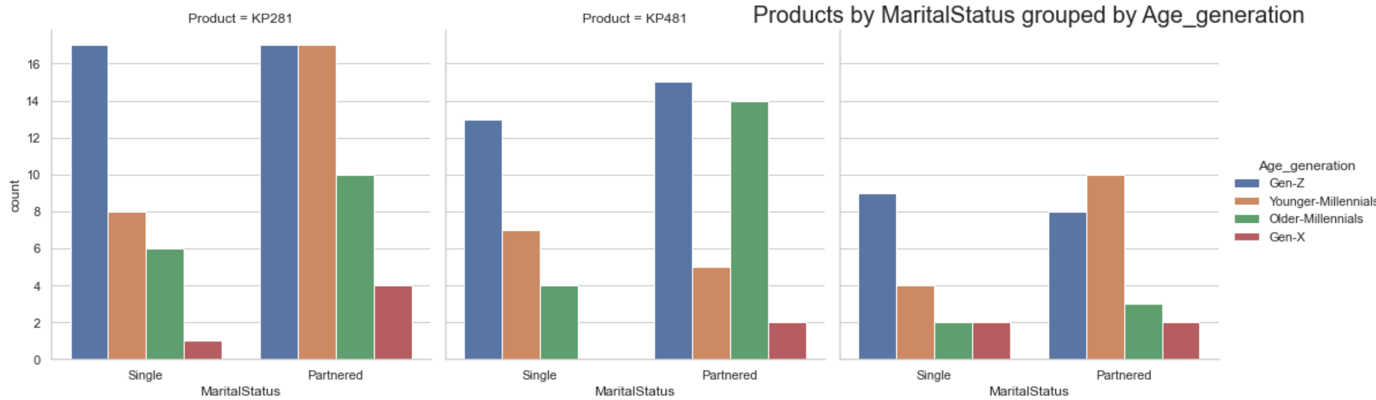
In [443…

```
plot_products_by_multiple_categories(categorical_features,"Age_generation")
```

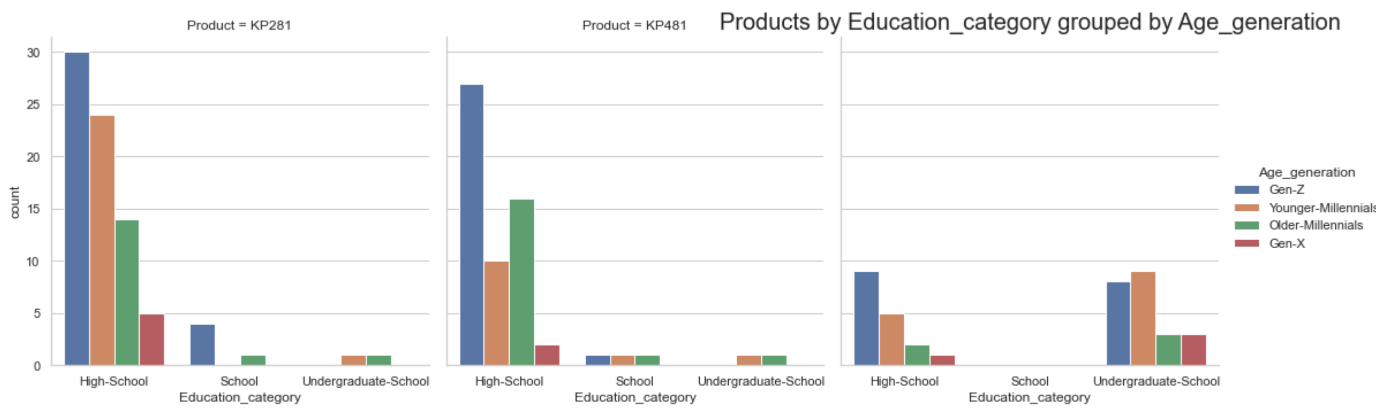
<Figure size 576x360 with 0 Axes>



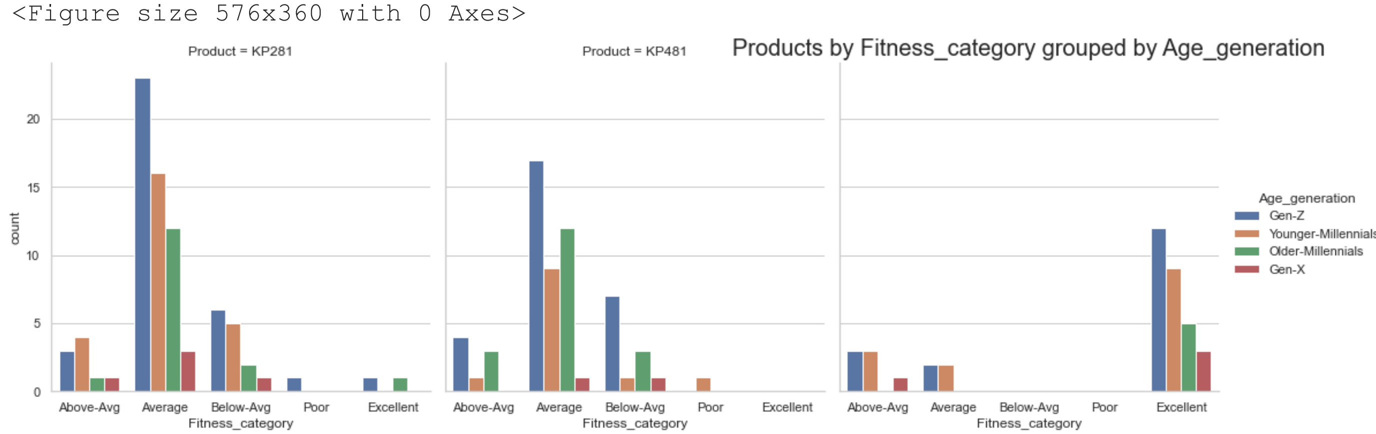
<Figure size 576x360 with 0 Axes>



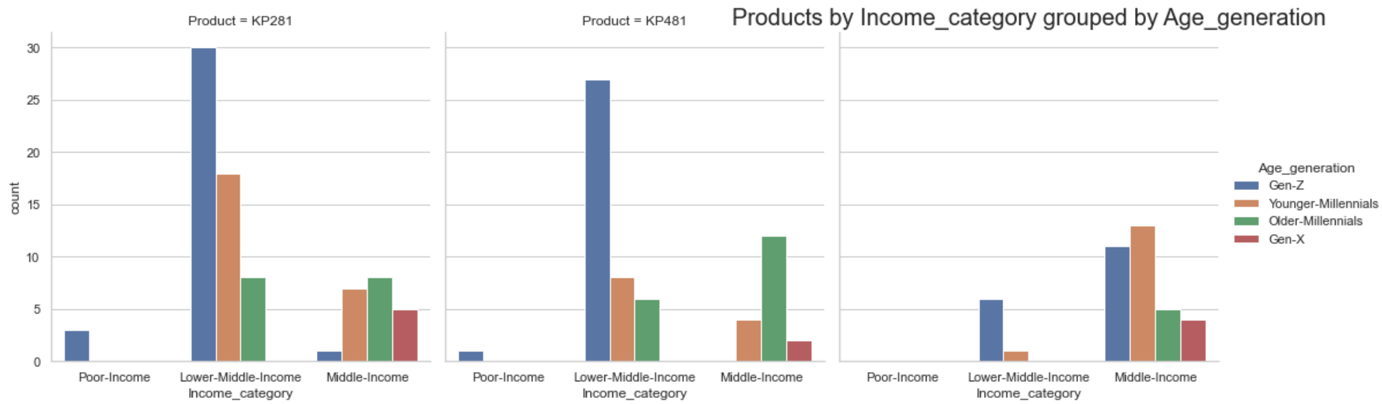
<Figure size 576x360 with 0 Axes>



<Figure size 576x360 with 0 Axes>



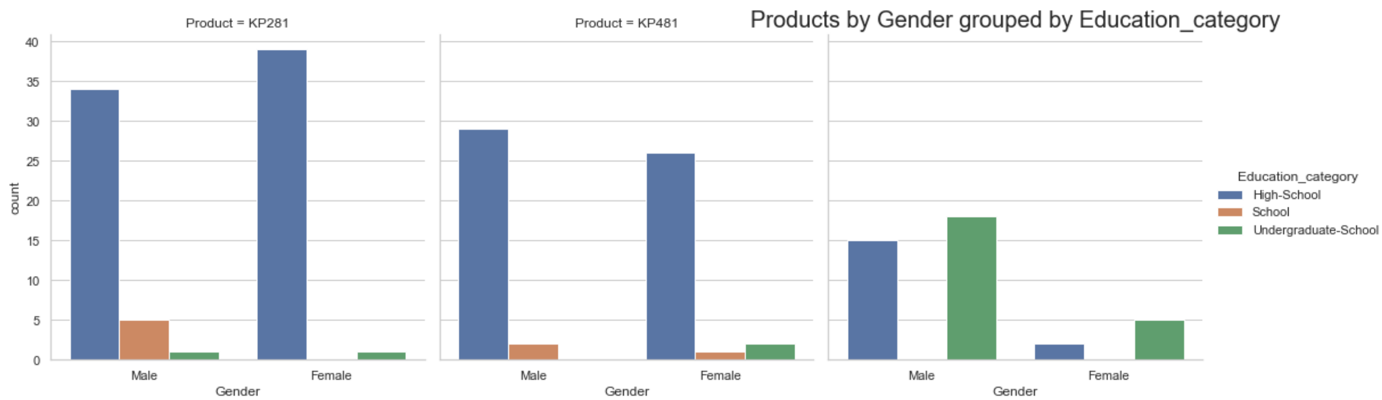
<Figure size 576x360 with 0 Axes>



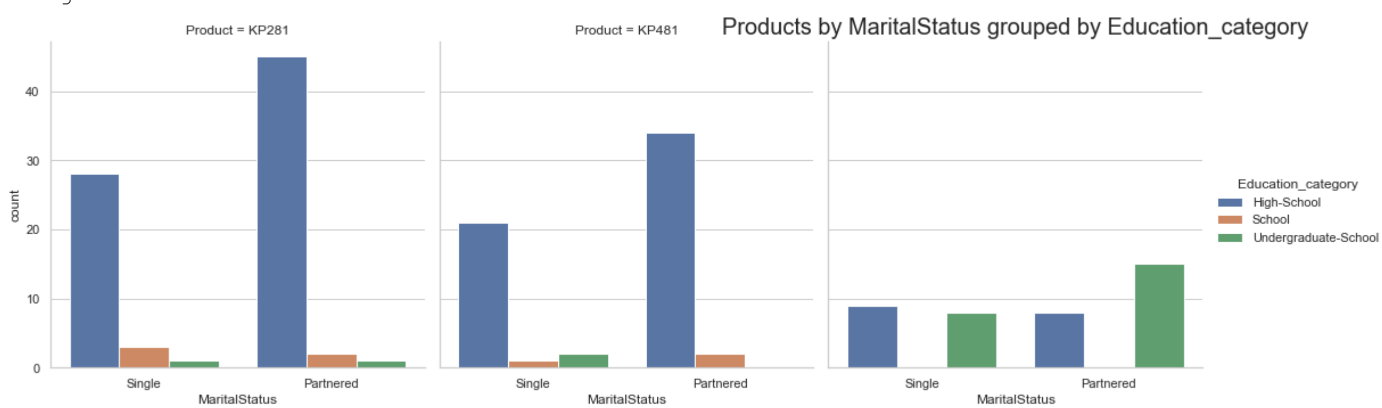
In [444…

```
plot_products_by_multiple_categories(categorical_features,"Education_category")
```

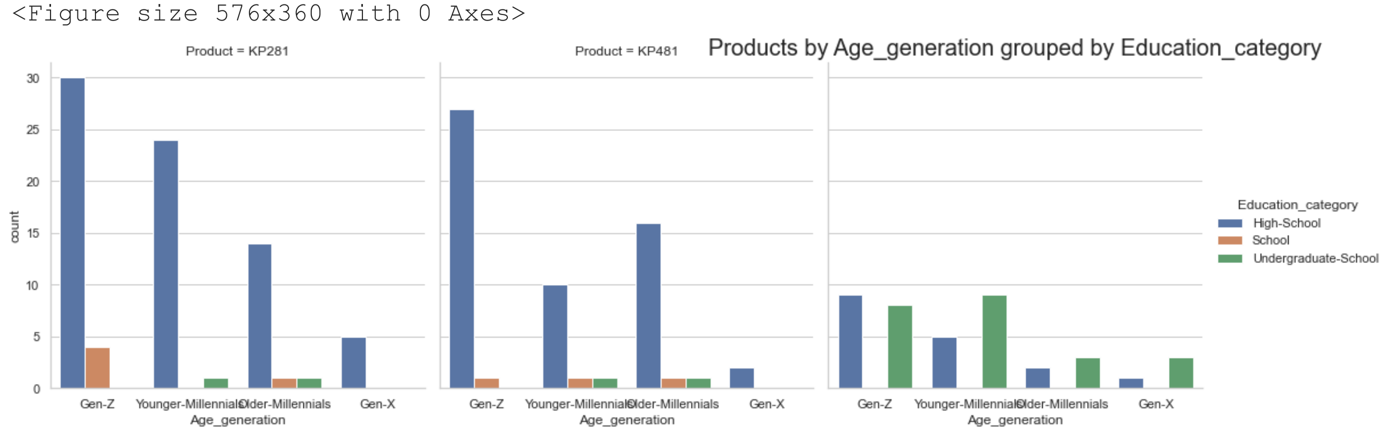
<Figure size 576x360 with 0 Axes>



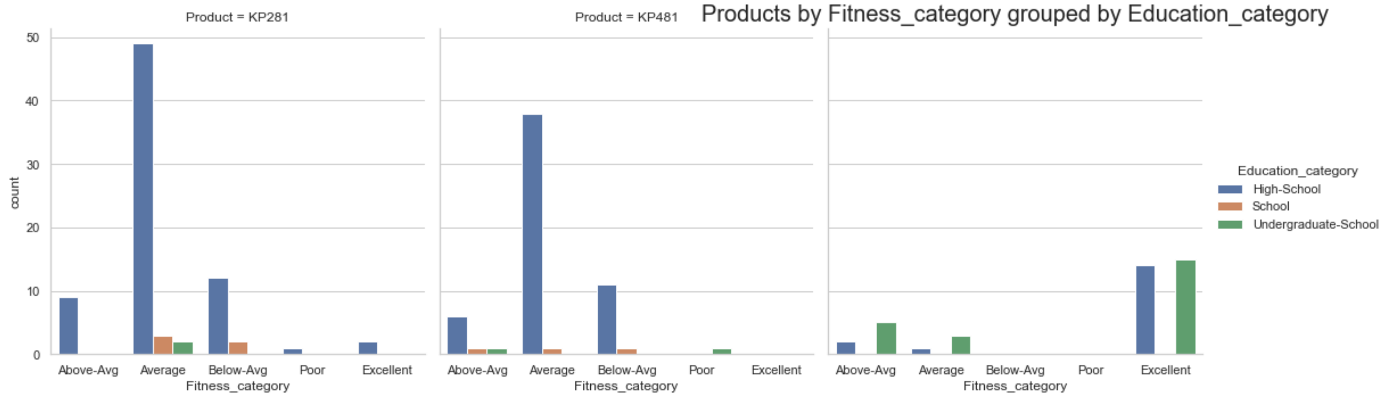
<Figure size 576x360 with 0 Axes>



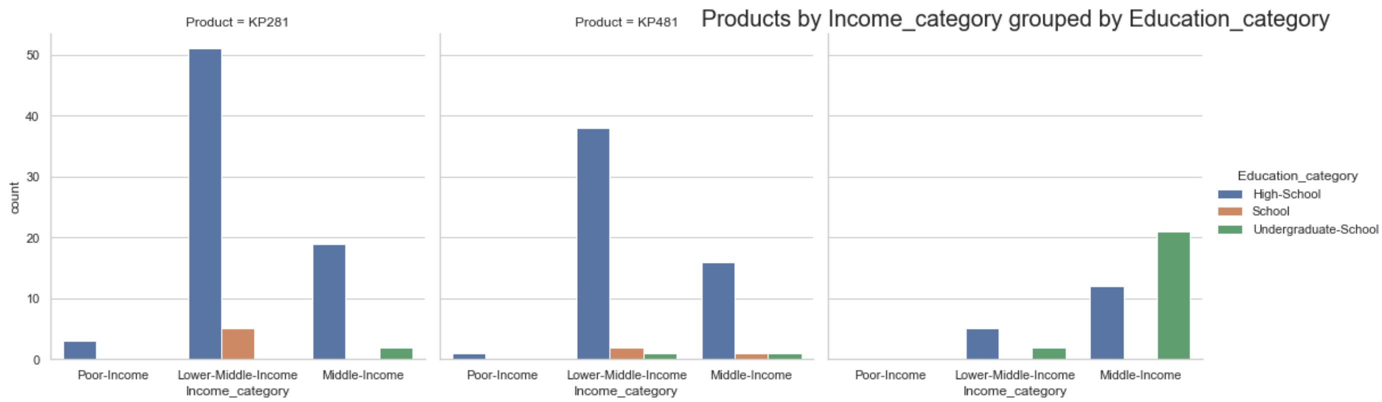
<Figure size 576x360 with 0 Axes>



<Figure size 576x360 with 0 Axes>



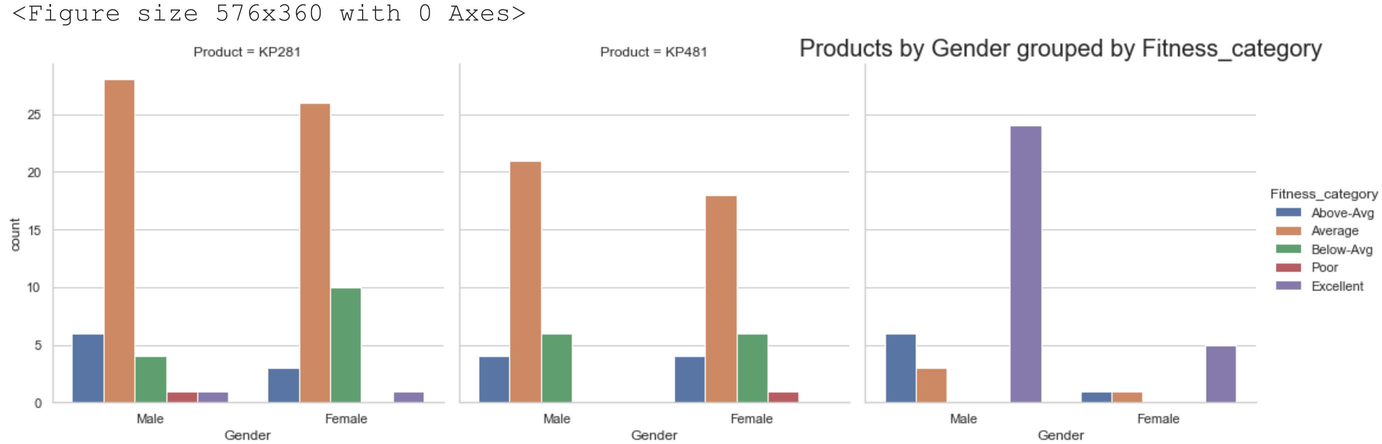
<Figure size 576x360 with 0 Axes>



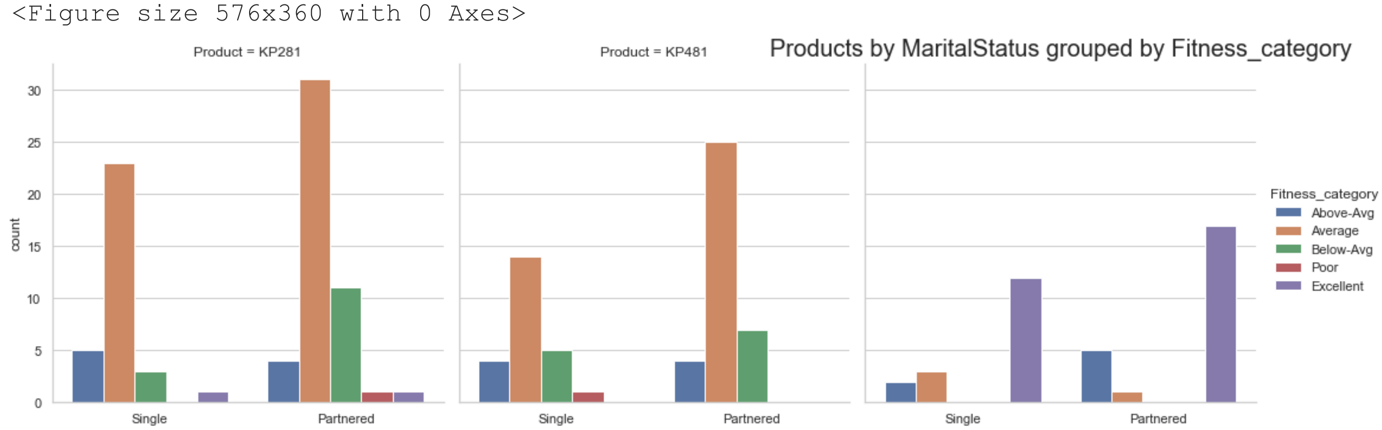
In [445…

```
plot_products_by_multiple_categories(categorical_features,"Fitness_category")
```

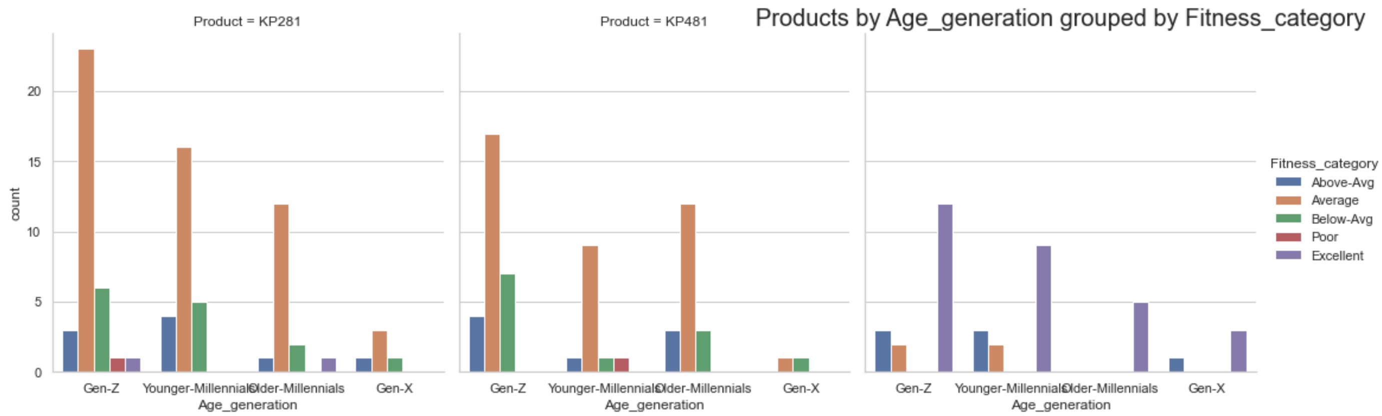
<Figure size 576x360 with 0 Axes>



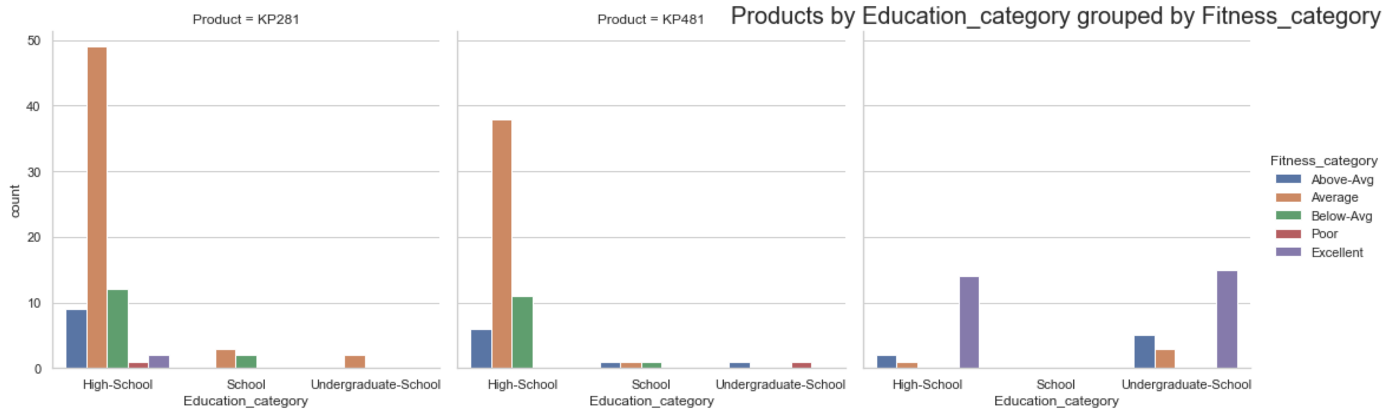
<Figure size 576x360 with 0 Axes>



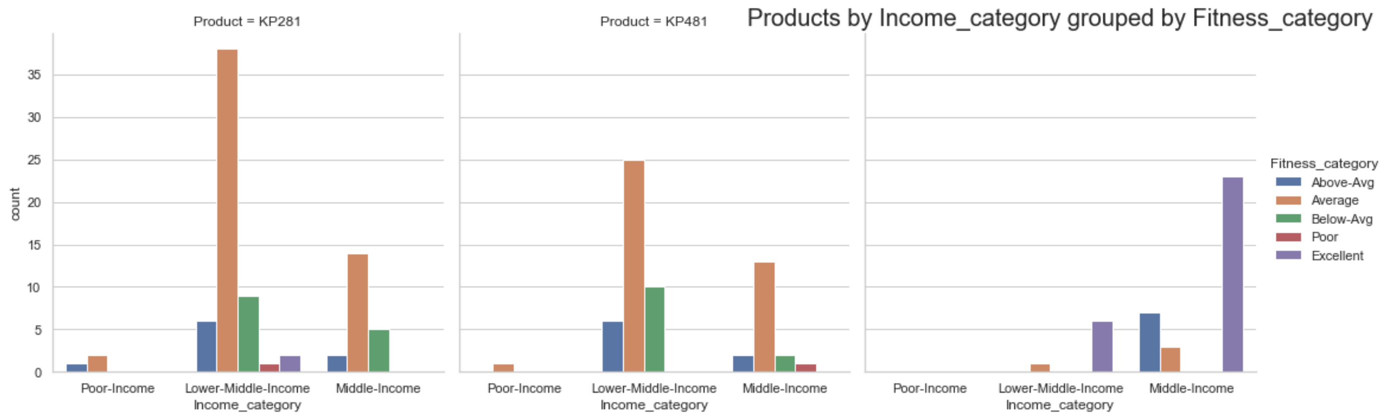
<Figure size 576x360 with 0 Axes>



<Figure size 576x360 with 0 Axes>



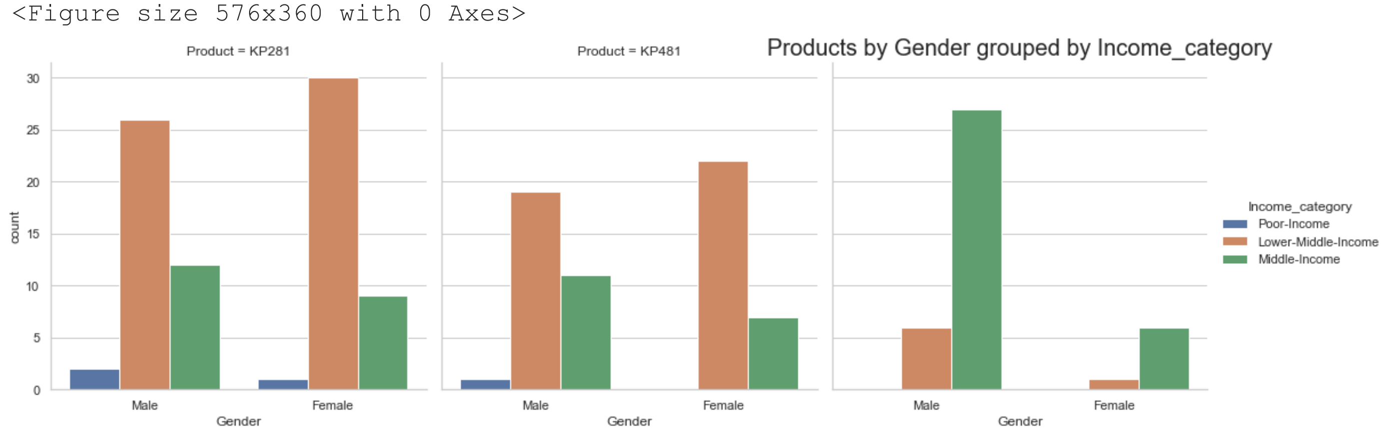
<Figure size 576x360 with 0 Axes>



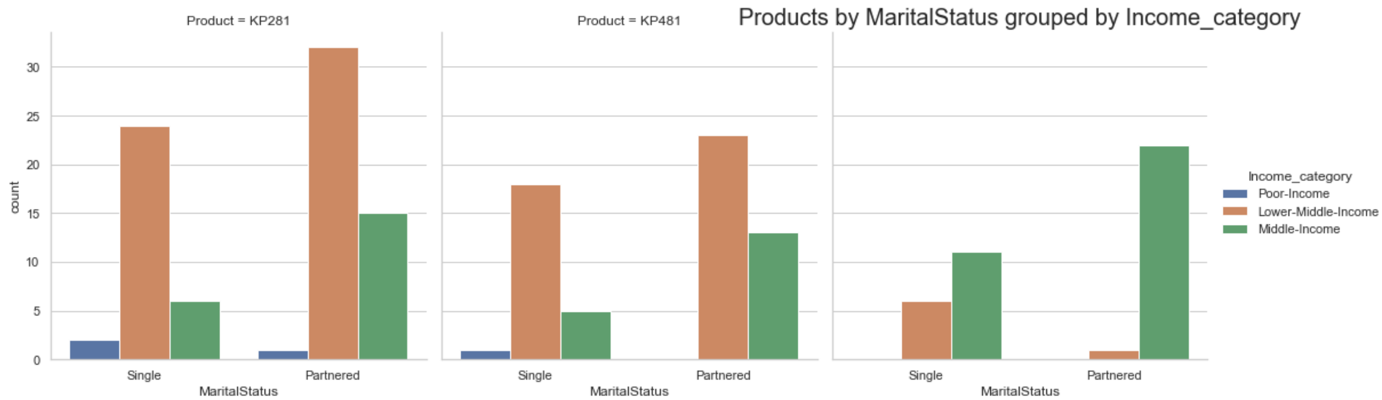
In [446…

```
plot_products_by_multiple_categories(categorical_features,"Income_category")
```

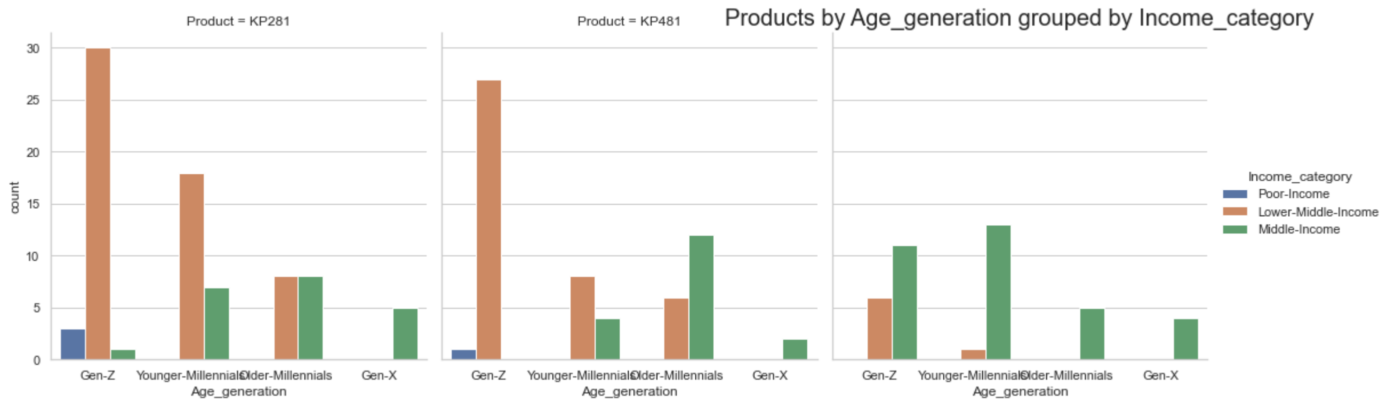
<Figure size 576x360 with 0 Axes>



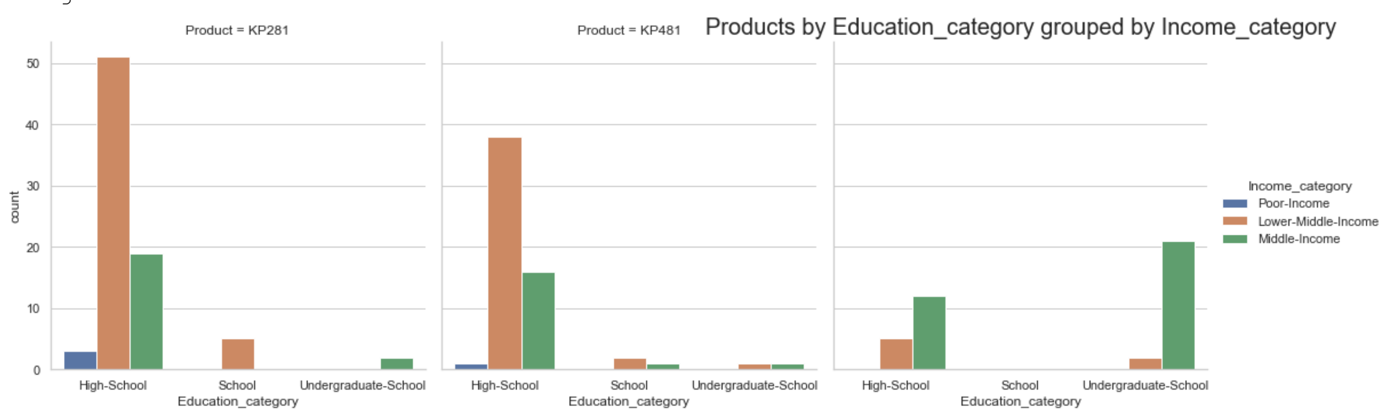
<Figure size 576x360 with 0 Axes>



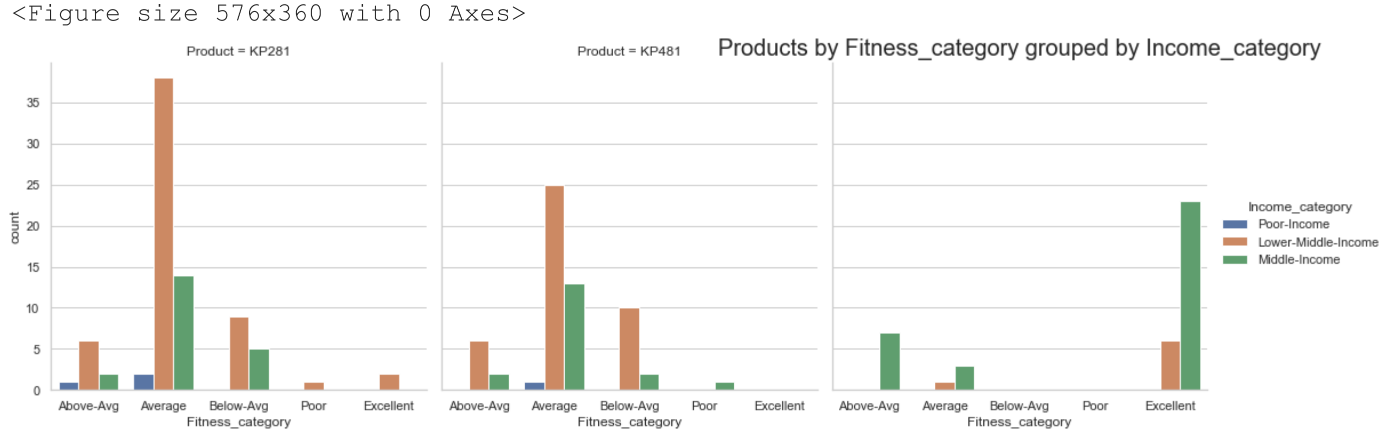
<Figure size 576x360 with 0 Axes>



<Figure size 576x360 with 0 Axes>



<Figure size 576x360 with 0 Axes>



In [417…

```
categorical_features
```

Out[417]:

```
Index(['Product', 'Gender', 'MaritalStatus', 'Age_generation',
       'Education_category', 'Fitness_category', 'Income_category'],
      dtype='object')
```

- For **correlation**: **Heatmaps**, **Pairplots**
  - Age

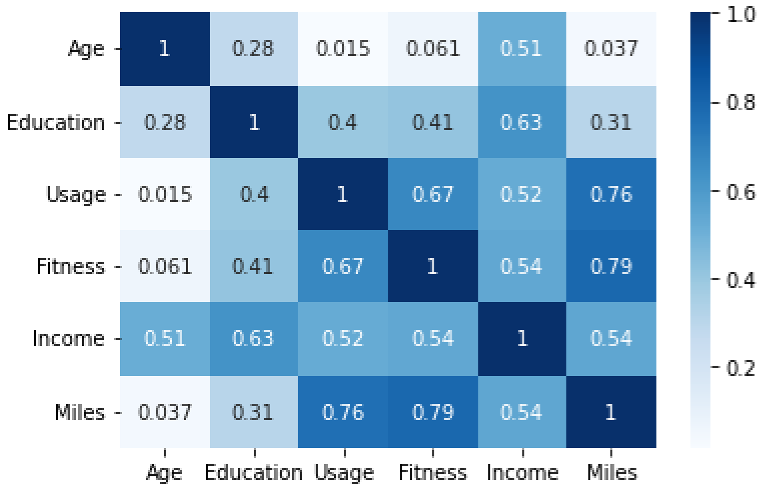
- Usage
- Fitness
- Income
- Miles

In [349…

```
sns.heatmap(df.corr(), cmap="Blues", annot=True)
```

Out[349]:

```
<AxesSubplot:>
```

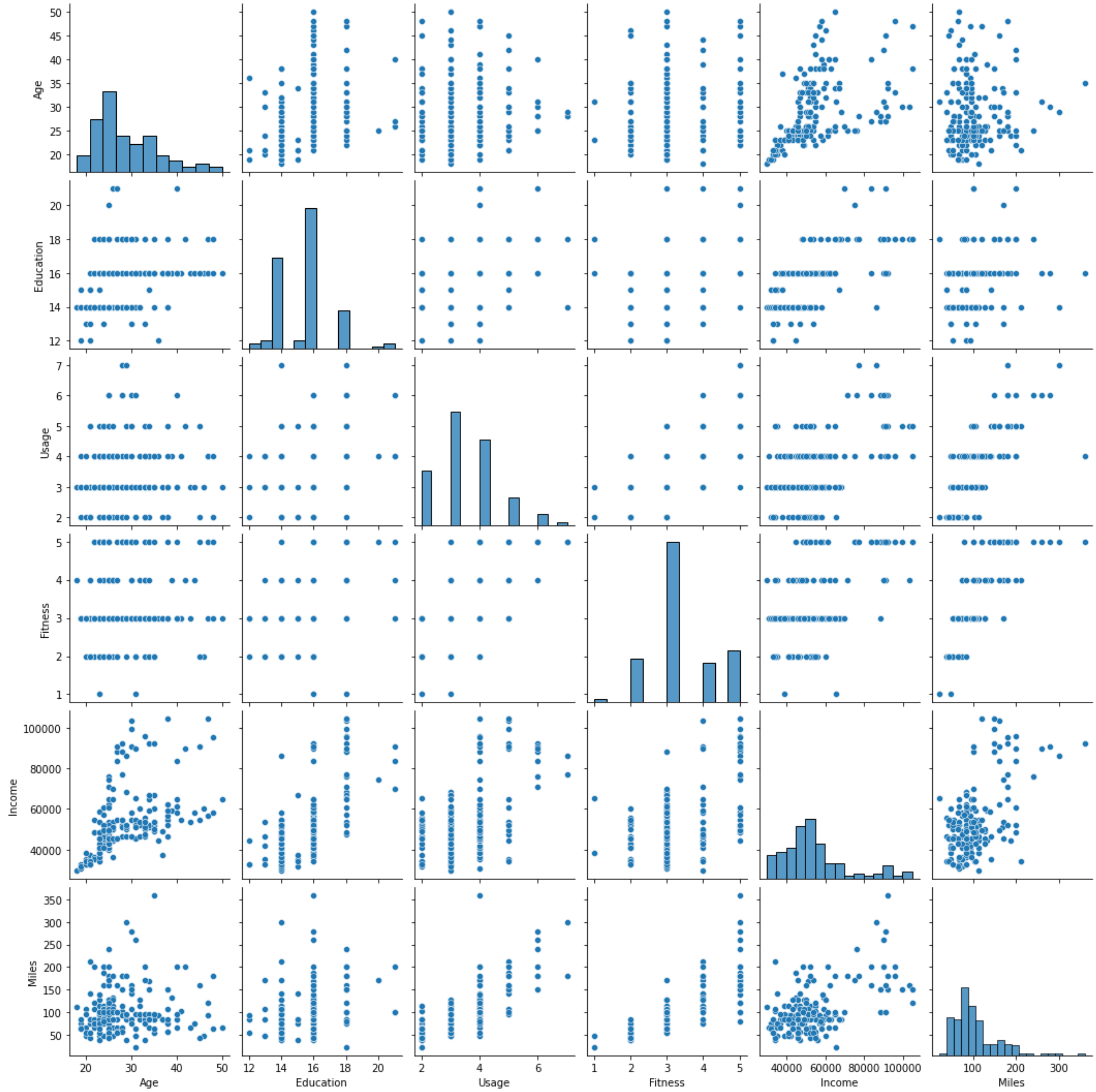


In [350…

```
sns.pairplot(data=df)
plt.plot()
```

Out[350]:

```
[]
```



Missing Value & Outlier Detection

- **Missing value detection**

In [ ]:
```
percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                 'percent_missing': percent_missing})
missing_value_df.sort_values('percent_missing', ascending=False)
```

- **Outlier detection**

In [ ]:
```
def find_outliers_IQR(column_name):
    print("Outliers by feature name --> ",column_name)
    Q1=df[column_name].quantile(0.25)
    Q3=df[column_name].quantile(0.75)

    IQR=Q3-Q1
```

```
    lower = Q1 - 1.5*IQR
    upper = Q3 + 1.5*IQR

    outliers = df[((df[column_name]<lower) | (df[column_name]>upper))]

    return outliers
```

In [ ]:

```
continious_features = df.select_dtypes(include=['int64','float64']).columns
continious_features
```

In [368…

```
outlier_df_by_age = find_outliers_IQR("Age")
outlier_df_by_age
```

```
Outliers by feature name -->  Age
```

Out[368]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education_
78	KP281	47	Male	16	Partnered	4	3	56850	94	Gen-X	Hi
79	KP281	50	Female	16	Partnered	3	3	64809	66	Gen-X	Hi
139	KP481	48	Male	16	Partnered	2	3	57987	64	Gen-X	Hi
178	KP781	47	Male	18	Partnered	4	5	104581	120	Gen-X	Under
179	KP781	48	Male	18	Partnered	4	5	95508	180	Gen-X	Under

In [369…

```
outlier_df_by_education = find_outliers_IQR("Education")
outlier_df_by_education
```

```
Outliers by feature name -->  Education
```

Out[369]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education_
156	KP781	25	Male	20	Partnered	4	5	74701	170	Gen-Z	Under
157	KP781	26	Female	21	Single	4	3	69721	100	Younger-Millennials	Under
161	KP781	27	Male	21	Partnered	4	4	90886	100	Younger-Millennials	Under
175	KP781	40	Male	21	Single	6	5	83416	200	Older-Millennials	Under

In [370…

```
outlier_df_by_usage = find_outliers_IQR("Usage")
outlier_df_by_usage
```

```
Outliers by feature name -->  Usage
```

Out[370]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education
154	KP781	25	Male	18	Partnered	6	4	70966	180	Gen-Z	Under
155	KP781	25	Male	18	Partnered	6	5	75946	240	Gen-Z	Under
162	KP781	28	Female	18	Partnered	6	5	92131	180	Younger-Millennials	Under
163	KP781	28	Male	18	Partnered	7	5	77191	180	Younger-Millennials	Under
164	KP781	28	Male	18	Single	6	5	88396	150	Younger-Millennials	Under
166	KP781	29	Male	14	Partnered	7	5	85906	300	Younger-Millennials	Hi
167	KP781	30	Female	16	Partnered	6	5	90886	280	Younger-Millennials	Hi
170	KP781	31	Male	16	Partnered	6	5	89641	260	Younger-Millennials	Hi
175	KP781	40	Male	21	Single	6	5	83416	200	Older-Millennials	Under

In [371…

```
outlier_df_by_fitness = find_outliers_IQR("Fitness")
outlier_df_by_fitness
```

```
Outliers by feature name -->  Fitness
```

Out[371]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education
14	KP281	23	Male	16	Partnered	3	1	38658	47	Gen-Z	Hi
117	KP481	31	Female	18	Single	2	1	65220	21	Younger-Millennials	Under

In [372…

```
outlier_df_by_income = find_outliers_IQR("Income")
outlier_df_by_income
```

```
Outliers by feature name -->  Income
```

Out[372]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education
159	KP781	27	Male	16	Partnered	4	5	83416	160	Younger-Millennials	Hi
160	KP781	27	Male	18	Single	4	3	88396	100	Younger-Millennials	Under
161	KP781	27	Male	21	Partnered	4	4	90886	100	Younger-Millennials	Under
162	KP781	28	Female	18	Partnered	6	5	92131	180	Younger-Millennials	Under
164	KP781	28	Male	18	Single	6	5	88396	150	Younger-Millennials	Under
166	KP781	29	Male	14	Partnered	7	5	85906	300	Younger-Millennials	Hi
167	KP781	30	Female	16	Partnered	6	5	90886	280	Younger-Millennials	Hi
168	KP781	30	Male	18	Partnered	5	4	103336	160	Younger-Millennials	Under
169	KP781	30	Male	18	Partnered	5	5	99601	150	Younger-Millennials	Under
170	KP781	31	Male	16	Partnered	6	5	89641	260	Younger-Millennials	Hi
171	KP781	33	Female	18	Partnered	4	5	95866	200	Older-Millennials	Under
172	KP781	34	Male	16	Single	5	5	92131	150	Older-Millennials	Hi
173	KP781	35	Male	16	Partnered	4	5	92131	360	Older-Millennials	Hi
174	KP781	38	Male	18	Partnered	5	5	104581	150	Older-Millennials	Under
175	KP781	40	Male	21	Single	6	5	83416	200	Older-Millennials	Under
176	KP781	42	Male	18	Single	5	4	89641	200	Gen-X	Under
177	KP781	45	Male	16	Single	5	5	90886	160	Gen-X	Hi
178	KP781	47	Male	18	Partnered	4	5	104581	120	Gen-X	Under
179	KP781	48	Male	18	Partnered	4	5	95508	180	Gen-X	Under

In [373…

```
outlier_df_by_miles = find_outliers_IQR("Miles")
outlier_df_by_miles
```

```
Outliers by feature name -->  Miles
```

Out[373]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Age_generation	Education_
23	KP281	24	Female	16	Partnered	5	5	44343	188	Gen-Z	Hi
84	KP481	21	Female	14	Partnered	5	4	34110	212	Gen-Z	Hi
142	KP781	22	Male	18	Single	4	5	48556	200	Gen-Z	Under
148	KP781	24	Female	16	Single	5	5	52291	200	Gen-Z	Hi
152	KP781	25	Female	18	Partnered	5	5	61006	200	Gen-Z	Under
155	KP781	25	Male	18	Partnered	6	5	75946	240	Gen-Z	Under
166	KP781	29	Male	14	Partnered	7	5	85906	300	Younger-Millennials	Hi
167	KP781	30	Female	16	Partnered	6	5	90886	280	Younger-Millennials	Hi
170	KP781	31	Male	16	Partnered	6	5	89641	260	Younger-Millennials	Hi
171	KP781	33	Female	18	Partnered	4	5	95866	200	Older-Millennials	Under
173	KP781	35	Male	16	Partnered	4	5	92131	360	Older-Millennials	Hi
175	KP781	40	Male	21	Single	6	5	83416	200	Older-Millennials	Under
176	KP781	42	Male	18	Single	5	4	89641	200	Gen-X	Under

Business Insights based on Non-Graphical and Visual Analysis

- **Comments Non Graphical Analysis**
  - 180 samples seems to be too less to predict behaviour of the population. Small sample size **reduces the power of the study and increases the margin of error**
  - **Overall Data spread not uniform** , very much **right skewed in age range 33-50+)** .Need to **transform the skewed data to close enough to a Gaussian distribution or Normal distribution**. This **will allow us to try more number of statistical model** to apply.
    - Less samples for age group more than 41 years of age (i.e. Generation X)
    - Less samples for High income group
    - Less samples for school students - most of the data is for Undergrad or High school students
    - Less samples for Poor income group
  - **Outliers** - Need to exclude following outliers otherwise it would **decrease normality**. It **increases the error variance** and **reduces the power of statistical tests**. They can **cause bias and/or influence estimates**. They can also **impact the basic assumption of regression as well as other statistical models**.
    - Miles - 13 samples (i.e 7% of samples) are beyond 1.5 times IQR
    - Income group - 19 samples out of 180 (i.e. ~ 10%) are outliers which can impact the analysis/prediction

- Usage - 9 outliers
- **Strong Correlation** between few independent features hence **change in one variable would cause change to another and so the model results fluctuate significantly**. The **model results** will be **unstable** and vary a lot given a small change in the data or model
  - Miles vs Usage (0.76) **[Strong correlation]**
  - Miles vs Fitness(0.79)**[Strong correlation]**
  - Miles vs Income(0.54) [Moderate correlation]
  - Education vs Income(0.63) [Moderate correlation]
  - Education vs Fitness(0.41)[Low correlation]

Recommendations

- **Key considerations**:
  - Below recommedation will be more effective when above analysis has been considered i.e. more samples are being considered ,outliers have been transformed, and apprppriate measures have been taken for skeweness/correlation treatments.

- **Actionable items for business**
  - **Gender based targeted channel** would be **more effective**
    - **Females** (across all generations **except older millennials**) like **KP281** .
    - **Undergraduate (education years 18-21) Females** prefer product **KP781**
    - **High School(education years 14-17) Males** prefer only **KP281/KP481**
  - **Generation based targeted channels** can contribute to productive sales
    - **Generation-Z**(i.e. 10-25 years of age) (including both **Single** and **Partnered**) likes product **KP281**
    - **Older Millennialls** (age 33-40) with **middle income** category should be targeted for product **KP481**
  - **Marital status** - **Partnered** clients **likely to buy more products(across categories) than** than **"Single"**
    - **Partnered & Younger millennials**(age 25 - 32) : **First choice KP281 , Second choice KP781**
    - **Partnered & Older millennials**(age 33 - 41) : **First choice KP481**
    - **Partnered & Gen-X**(age 42 - 57) : **First choice KP281**
  - **High School(education years 14-17) students, across generations** - More likely to buy a **low range product**
    - Equally likes product **KP281 and K481**
  - **Under Garduate**(education years 18-21) - More likely to buy a **high range** product
    - Both **Generation-Z(age 10-25) and Younger millennials (age 26-32)** more frequently purchase product **KP781**
  - **Fitness** level - Excellent fitness level clients should be targeted for high range products
    - **Average fitness** (across generations) - **1st choice (KP281) , Second choice KP481**
    - **Excellent fitness** - prefers **KP781**
  - **Income category** -
    - **Lower Income** - 1st choice **KP281** 2nd choice **KP481**
    - **Middle Income** - 1st choice **KP481**

In [ ]: