ScalerMart Business Case Study

Introduction

ScalerMart, a leading global electronics retailer, has experienced a significant downturn in sales, with a nearly 50% decline in revenue in 2020 compared to the previous year.

What is expected

Analyze the customer-level transactional data to identify potential reasons behind the decline in sales. The objective is to recommend data-driven strategies aimed at improving sales performance.

1. Data

The analysis was done on the data located at - \ Customers - https://drive.google.com/file/d/1qPrP3QNWjxA_JHwao44dhVapEtQtlfus/view?usp=drive_link \ Products - https://drive.google.com/file/d/1fGc33yN_yTLI-1erTwo4-KdxFMcXDjJD/view?usp=drive_link \ Sales - https://drive.google.com/file/d/1S0hQDcTlY3ZUpyD1gf50Cujfs8UTSgnt/view?usp=drive_link

2. Libraries

Below are the libraries required for analysing and visualizing data

In [1]:
```
# libraries to analyze data
import numpy as np
import pandas as pd
import scipy.stats as sps

# libraries to visualize data
import matplotlib.pyplot as plt
import seaborn as sns

import scipy.stats as stats
```

3. Data loading and exploratory data analysis

3.1. Data loading

Loading the data into Pandas dataframe for easily handling of data

In [2]:
```
# read the file into a pandas dataframe
customer_df = pd.read_csv('Customers.csv', encoding='unicode_escape')
df = customer_df
# look at the datatypes of the columns
print('*************************************************')
```

```python
print(df.info())
print('*************************************************\n')
print('*************************************************')
print(f'Shape of the dataset is {df.shape}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('*************************************************\n')
print('*************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
print('*************************************************')
```

```
*************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15266 entries, 0 to 15265
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   CustomerKey  15266 non-null  int64 
 1   Gender       15266 non-null  object
 2   Name         15266 non-null  object
 3   City         15266 non-null  object
 4   State Code   15256 non-null  object
 5   State        15266 non-null  object
 6   Zip Code     15266 non-null  object
 7   Country      15266 non-null  object
 8   Continent    15266 non-null  object
 9   Birthday     15266 non-null  object
dtypes: int64(1), object(9)
memory usage: 1.2+ MB
None
*************************************************

*************************************************
Shape of the dataset is (15266, 10)
*************************************************

*************************************************
Number of nan/null values in each column: 
CustomerKey     0
Gender          0
Name            0
City            0
State Code     10
State           0
Zip Code        0
Country         0
Continent       0
Birthday        0
dtype: int64
*************************************************

*************************************************
Number of unique values in each column: 
CustomerKey    15266
Gender             2
Name           15118
City            8258
State Code       467
State            512
Zip Code        9505
Country            8
Continent          3
```

```
Birthday       11270
dtype: int64
*************************************************

*************************************************
Duplicate entries:
False    15266
Name: count, dtype: int64
*************************************************
```

In [3]:

```python
# look at the top 5 rows
df.head()
```

Out[3]:

	CustomerKey	Gender	Name	City	State Code	State	Zip Code	Country	Continent	Birthday
0	301	Female	Lilly Harding	WANDEARAH EAST	SA	South Australia	5523	Australia	Australia	7/3/1939
1	325	Female	Madison Hull	MOUNT BUDD	WA	Western Australia	6522	Australia	Australia	9/27/1979
2	554	Female	Claire Ferres	WINJALLOK	VIC	Victoria	3380	Australia	Australia	5/26/1947
3	786	Male	Jai Poltpalingada	MIDDLE RIVER	SA	South Australia	5223	Australia	Australia	9/17/1957
4	1042	Male	Aidan Pankhurst	TAWONGA SOUTH	VIC	Victoria	3698	Australia	Australia	11/19/1965

In [4]:

```python
# read the file into a pandas dataframe
products_df = pd.read_csv('Products.csv', encoding='unicode_escape')
df = products_df
# look at the datatypes of the columns
print('*************************************************')
print(df.info())
print('*************************************************\n')
print('*************************************************')
print(f'Shape of the dataset is {df.shape}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('*************************************************\n')
print('*************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
print('*************************************************')
```

```
*************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2517 entries, 0 to 2516
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   ProductKey        2517 non-null   int64 
 1   Product Name      2517 non-null   object
 2   Brand             2517 non-null   object
 3   Color             2517 non-null   object
 4   Unit Cost USD     2517 non-null   object
 5   Unit Price USD    2517 non-null   object
 6   SubcategoryKey    2517 non-null   int64 
 7   Subcategory       2517 non-null   object
 8   CategoryKey       2517 non-null   int64 
 9   Category          2517 non-null   object
```

```
dtypes: int64(3), object(7)
memory usage: 196.8+ KB
None
**************************************************

**************************************************
Shape of the dataset is (2517, 10)
**************************************************

**************************************************
Number of nan/null values in each column:
ProductKey        0
Product Name      0
Brand             0
Color             0
Unit Cost USD     0
Unit Price USD    0
SubcategoryKey    0
Subcategory       0
CategoryKey       0
Category          0
dtype: int64
**************************************************

**************************************************
Number of unique values in each column:
ProductKey        2517
Product Name      2517
Brand               11
Color               16
Unit Cost USD      480
Unit Price USD     426
SubcategoryKey      32
Subcategory         32
CategoryKey          8
Category             8
dtype: int64
**************************************************

**************************************************
Duplicate entries:
False    2517
Name: count, dtype: int64
**************************************************
```

In [5]:

```
# look at the top 5 rows
df.head()
```

Out[5]:

	ProductKey	Product Name	Brand	Color	Unit Cost USD	Unit Price USD	SubcategoryKey	Subcategory	CategoryKey	Category
0	1	Contoso 512MB MP3 Player E51 Silver	Contoso	Silver	$6.62	$12.99	101	MP4&MP3	1	Audio
1	2	Contoso 512MB MP3 Player E51 Blue	Contoso	Blue	$6.62	$12.99	101	MP4&MP3	1	Audio

2	3	Contoso 1G MP3 Player E100 White	Contoso	White	$7.40	$14.52	101	MP4&MP3	1	Audio
3	4	Contoso 2G MP3 Player E200 Silver	Contoso	Silver	$11.00	$21.57	101	MP4&MP3	1	Audio
4	5	Contoso 2G MP3 Player E200 Red	Contoso	Red	$11.00	$21.57	101	MP4&MP3	1	Audio

In [6]:

```python
# read the file into a pandas dataframe
sales_df = pd.read_csv('Sales.csv', encoding='unicode_escape')
df = sales_df
# look at the datatypes of the columns
print('**************************************************')
print(df.info())
print('**************************************************\n')
print('**************************************************')
print(f'Shape of the dataset is {df.shape}')
print('**************************************************\n')
print('**************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('**************************************************\n')
print('**************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('**************************************************\n')
print('**************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
print('**************************************************')
```

```
**************************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62884 entries, 0 to 62883
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Order Number    62884 non-null  int64 
 1   Line Item       62884 non-null  int64 
 2   Order Date      62884 non-null  object
 3   Delivery Date   13165 non-null  object
 4   CustomerKey     62884 non-null  int64 
 5   StoreKey        62884 non-null  int64 
 6   ProductKey      62884 non-null  int64 
 7   Quantity        62884 non-null  int64 
 8   Currency Code   62884 non-null  object
dtypes: int64(6), object(3)
memory usage: 4.3+ MB
None
**************************************************

**************************************************
Shape of the dataset is (62884, 9)
**************************************************

**************************************************
Number of nan/null values in each column:
Order Number          0
```

```
Line Item           0
Order Date          0
Delivery Date   49719
CustomerKey         0
StoreKey            0
ProductKey          0
Quantity            0
Currency Code       0
dtype: int64
*************************************************

*************************************************
Number of unique values in each column:
Order Number    26326
Line Item           7
Order Date       1641
Delivery Date    1492
CustomerKey     11887
StoreKey           58
ProductKey       2492
Quantity           10
Currency Code       5
dtype: int64
*************************************************

*************************************************
Duplicate entries:
False    62884
Name: count, dtype: int64
*************************************************
```

In [7]:

```
# look at the top 5 rows
df.head()
```

Out[7]:

	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	StoreKey	ProductKey	Quantity	Currency Code
0	366000	1	1/1/2016	NaN	265598	10	1304	1	CAD
1	366001	1	1/1/2016	1/13/2016	1269051	0	1048	2	USD
2	366001	2	1/1/2016	1/13/2016	1269051	0	2007	1	USD
3	366002	1	1/1/2016	1/12/2016	266019	0	1106	7	CAD
4	366002	2	1/1/2016	1/12/2016	266019	0	373	1	CAD

Insight

- We can drop columns *State Code and Zip Code* from **Customers** table, columns *Color, SubcategoryKey and CategoryKey* from **Products** table and columns *StoreKey and Currency Code* from **Sales** table as they are redundant
- Need to convert *Gender* column to category datatype and *Birthday* column to Datetime datatype from Customers table
- Need to remove $ sign from *Unit Cost USD* and *Unit Price USD* columns and convert them to float datatype and need to convert *Brand, Subcategory and Category* to category datatype from Products table
- Need to convert *Order Date and Delivery Date* columns to Datetime datatype from Sales table

In [8]:

```
customer_df = customer_df.drop(columns = ["State Code", "Zip Code"])
products_df = products_df.drop(columns = ["Color", "SubcategoryKey", "CategoryKey"])
```

```
sales_df = sales_df.drop(columns = ["StoreKey", "Currency Code"])

customer_df['Gender'] = customer_df['Gender'].astype('category')
customer_df['Birthday'] = pd.to_datetime(customer_df['Birthday'], format='%m/%d/%Y')

# Strip '$' and convert to float
temp_series = products_df['Unit Cost USD'].str.strip('$ ')
temp_series = temp_series.str.replace(',', '')
products_df['Unit Cost USD'] = temp_series.astype('float32')

# Strip '$' and convert to float
temp_series = products_df['Unit Price USD'].str.strip('$ ')
temp_series = temp_series.str.replace(',', '')
products_df['Unit Price USD'] = temp_series.astype('float32')

products_df['Brand'] = products_df['Brand'].astype('category')
products_df['Subcategory'] = products_df['Subcategory'].astype('category')
products_df['Category'] = products_df['Category'].astype('category')

sales_df['Order Date'] = pd.to_datetime(sales_df['Order Date'], format='%m/%d/%Y')
sales_df['Delivery Date'] = pd.to_datetime(sales_df['Delivery Date'], format='%m/%d/%Y')
```

3.2. Exploratory Data Analysis

We have to calculate the revenue, for which we need the number of units sold of all the products and their corresponding unit price. This calls for merging **Sales** and **Products** table

In [9]:

```
# Merge Sales and Products table on
sales_df = pd.merge(sales_df, products_df, on='ProductKey', how='left')

# Create 'Revenue' column in Sales
sales_df['Revenue'] = sales_df['Quantity']*(sales_df['Unit Price USD'] - sales_df['Unit
sales_df['Revenue'] = sales_df['Revenue'].round(2)
```

In [10]:

```
sales_df.head()
```

Out[10]:

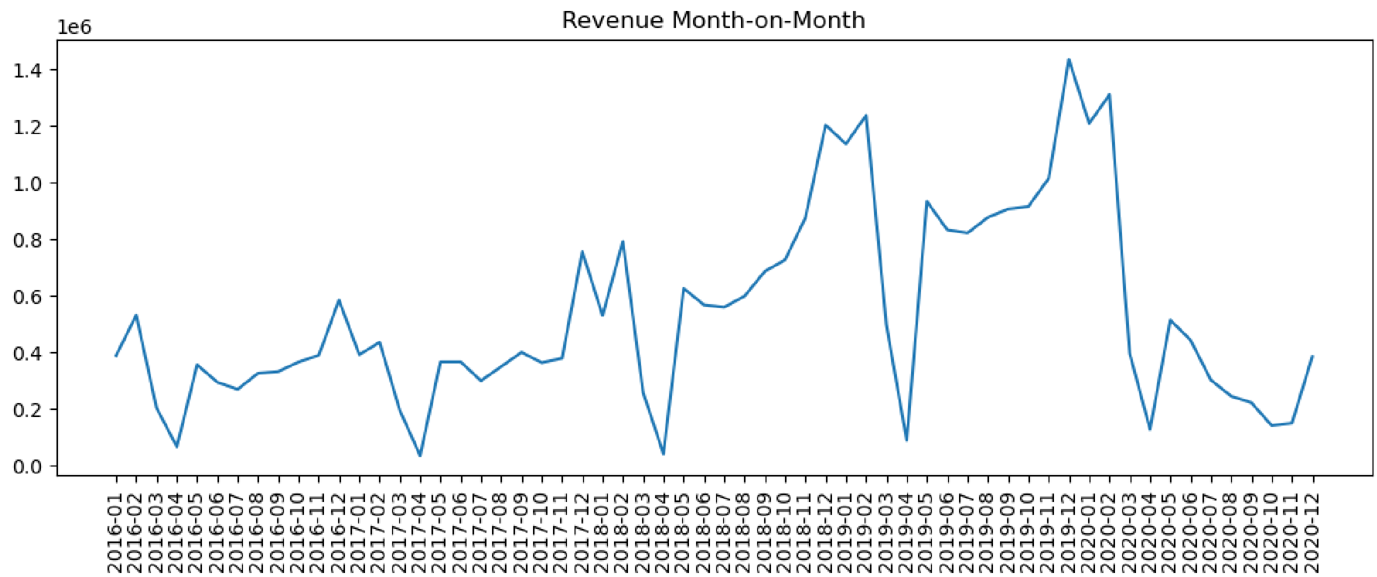
	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	ProductKey	Quantity	Product Name	Brand	Unit Cost USD	Unit
0	366000	1	2016-01-01	NaT	265598	1304	1	Contoso Lens Adapter M450 White	Contoso	31.270000	68.0(
1	366001	1	2016-01-01	2016-01-13	1269051	1048	2	A. Datum SLR Camera X136 Silver	A. Datum	141.470001	427.0(
2	366001	2	2016-01-01	2016-01-13	1269051	2007	1	Fabrikam Microwave 1.5CuFt X1100 Black	Fabrikam	220.639999	665.94
3	366002	1	2016-01-01	2016-01-12	266019	1106	7	Contoso SLR Camera M146 Orange	Contoso	148.080002	322.0(

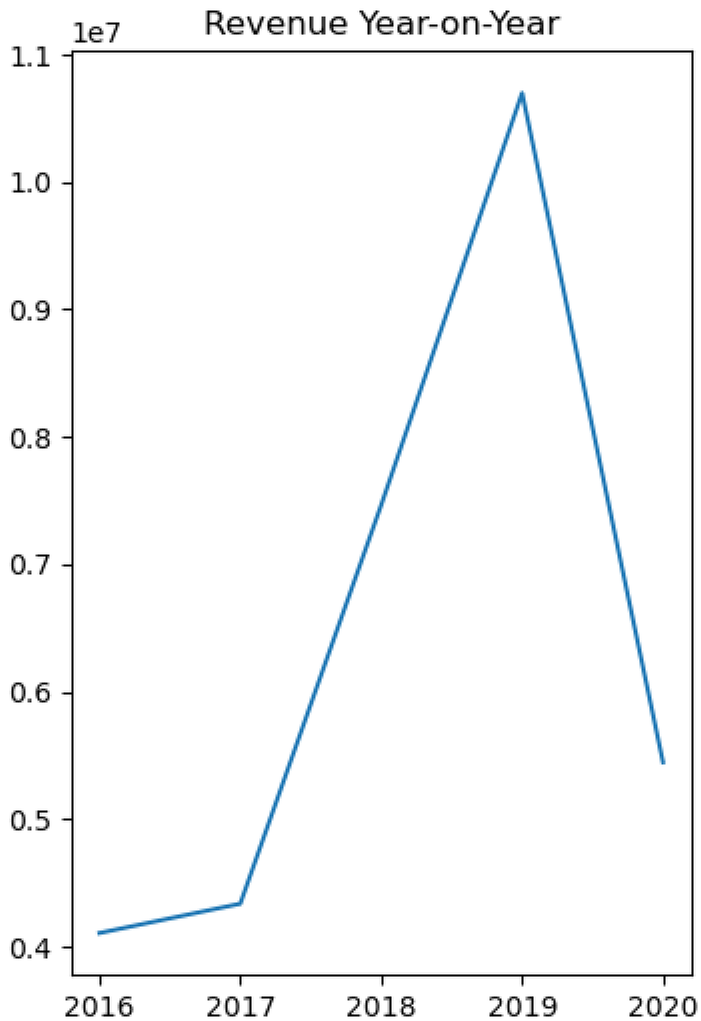
4	366002	2	2016-01-01	2016-01-12	266019	373	1	Adventure Works Laptop8.9 E0890 White	Adventure Works	166.199997	326.0

We now need to plot the *revenue* for every year. So we need to extract *Year and Month* deatils from *Order Date* and group by *Year/Month* to get total revenue for that year/month.

In [11]:

```
sales_df['Order Year'] = sales_df['Order Date'].dt.year
sales_df['Order Month'] = sales_df['Order Date'].dt.month
sales_df['Order YearMonth'] = sales_df['Order Date'].dt.strftime('%Y-%m')
# Year 2021 is incomplete with only first two months of data. So dropping Year 2021 data
sales_df.drop(sales_df[sales_df['Order Year'] == 2021].index, inplace = True)
# Revenue month-on-month
revenue_mom_df = sales_df.groupby(['Order YearMonth'], as_index=False).agg({'Revenue': '
# Revenue year-on-year
revenue_yoy_df = sales_df.groupby(['Order Year'], as_index=False).agg({'Revenue': 'sum'}
plt.figure(figsize=(12,4))
plt.plot('Order YearMonth', 'Revenue', data=revenue_mom_df)
plt.title('Revenue Month-on-Month')
plt.xticks(rotation=90)
plt.show()
plt.figure(figsize=(4,6))
plt.plot('Order Year', 'Revenue', data=revenue_yoy_df)
plt.title('Revenue Year-on-Year')
plt.show()
print(revenue_yoy_df)
```






```
   Order Year      Revenue
0        2016   4107000.47
1        2017   4337064.06
2        2018   7464961.11
3        2019  10697738.90
4        2020   5447460.15
```

In [12]:

```
revenue_2019 = revenue_yoy_df[revenue_yoy_df['Order Year'] == 2019]['Revenue'].iloc[0]
revenue_2020 = revenue_yoy_df[revenue_yoy_df['Order Year'] == 2020]['Revenue'].iloc[0]
print('Revenue in 2019: ', revenue_2019)
print('Revenue in 2020: ', revenue_2020)
print('%Change in revenue from 2019 to 2020: ', ((revenue_2020 - revenue_2019)/revenue_2
```

```
Revenue in 2019:  10697738.9
Revenue in 2020:  5447460.15
%Change in revenue from 2019 to 2020:  -49.07839683767193
```

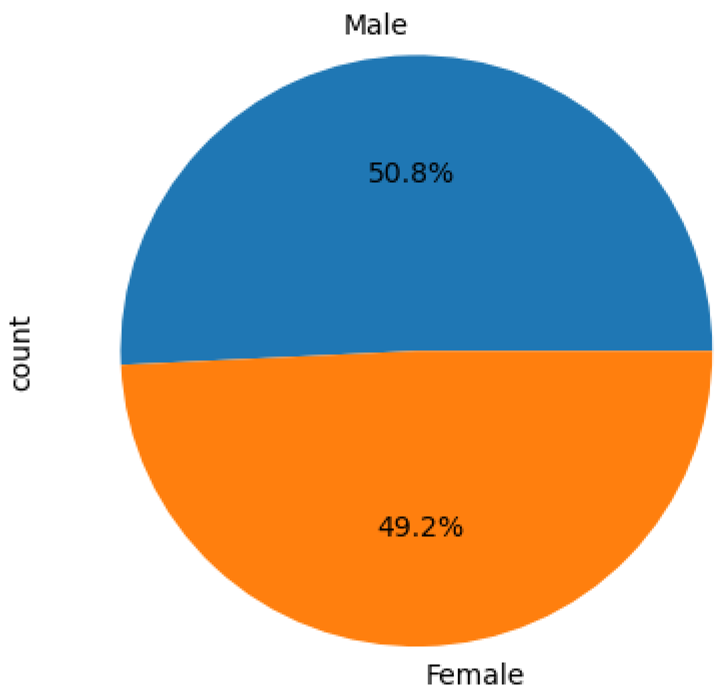
Insight

- We can see that the revenue fell by almost 50% in 2020.
- It is interesting to see from the Month-on-Month revenue graph that the revenue drops drastically every year in the month of April but shows a great recovery in the next month and eventually surpasses the previous high during December-January.
- This has been the trend since the year 2016 but the trend is broken in 2020.

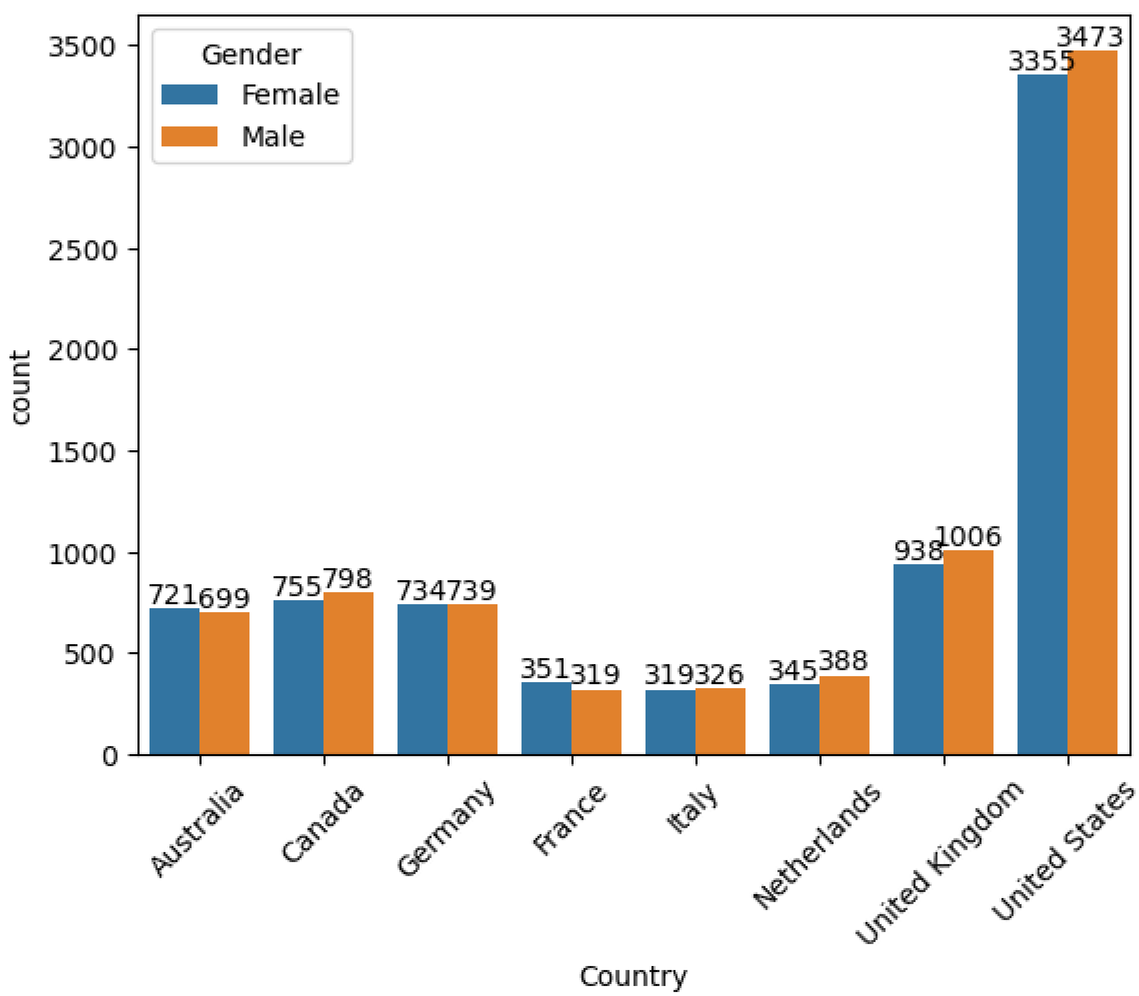
3.2.1 Customer demographics based distribution

In [13]:

```
customer_df['Gender'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.show()
```

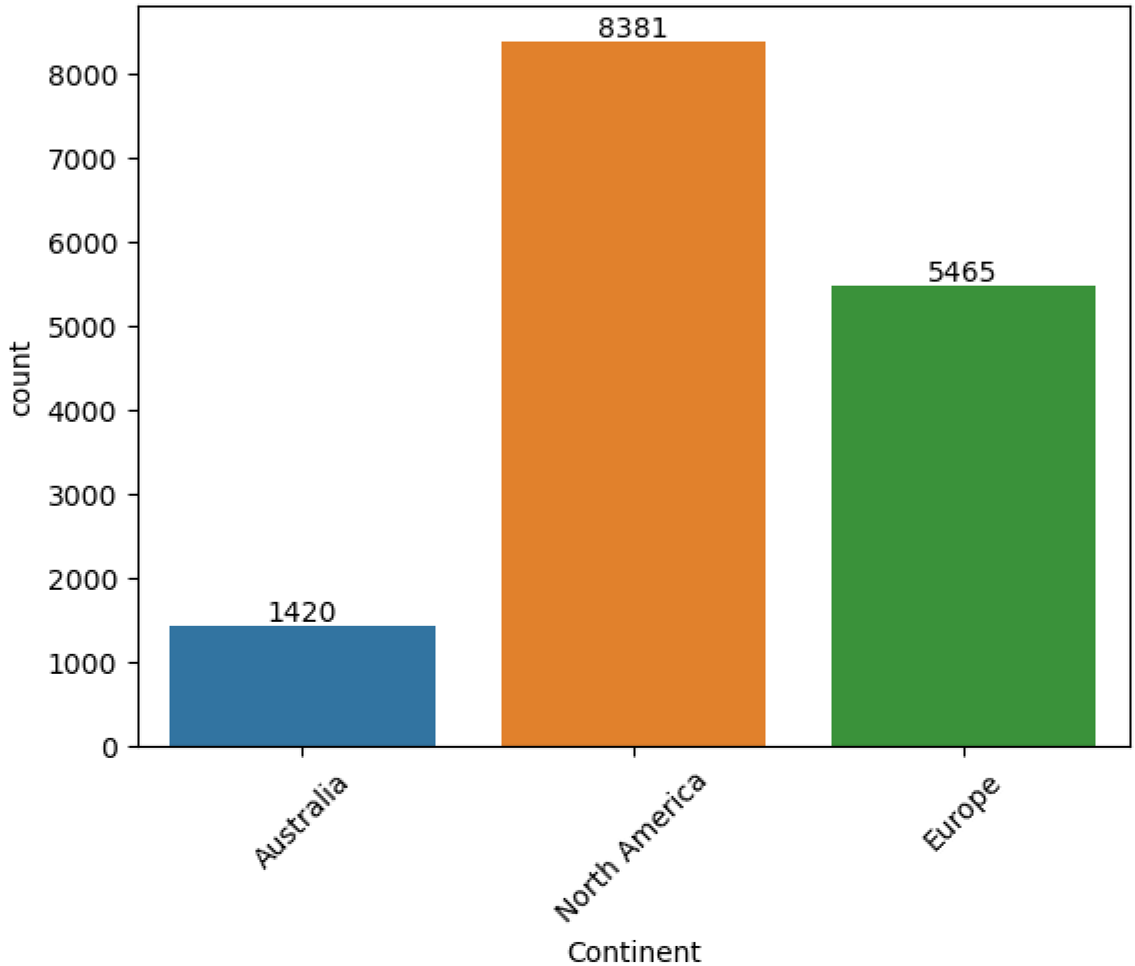


In [14]:
```
ax = sns.countplot(data=customer_df, x='Country', hue='Gender')
for container in ax.containers:
    ax.bar_label(container)
plt.xticks(rotation=45)
plt.show()
```



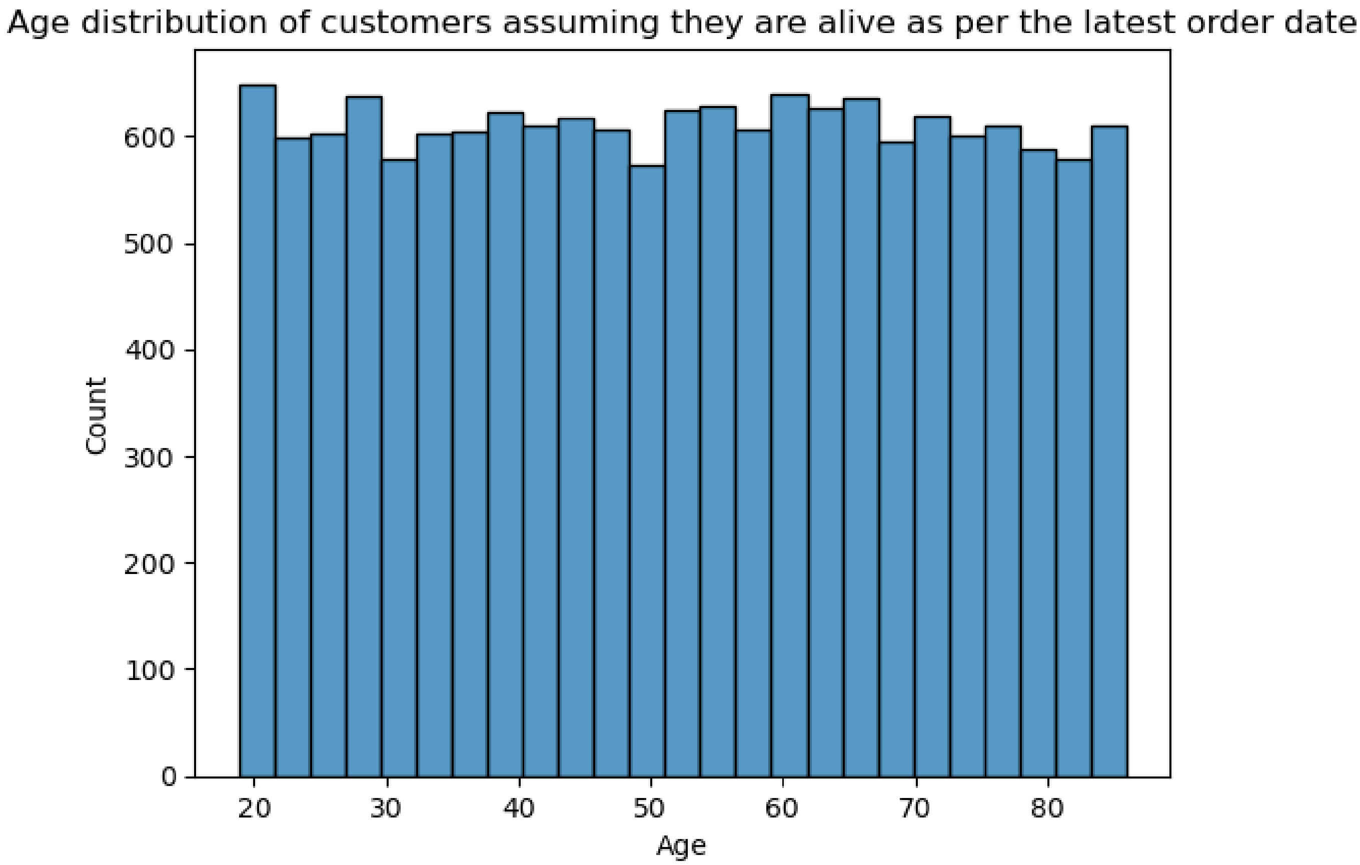
In [15]:
```
ax = sns.countplot(data=customer_df, x='Continent')
```

```
for container in ax.containers:
    ax.bar_label(container)
plt.xticks(rotation=45)
plt.show()
```



In [16]:
```
latest_order_date = sales_df['Order Date'].max()
current_age = (latest_order_date - customer_df['Birthday'])/np.timedelta64(1, 'Y')
current_age = current_age.rename('Age')
print(current_age.describe())
sns.histplot(data=current_age)
plt.title("Age distribution of customers assuming they are alive as per the latest order
plt.show()
```

```
count    15266.000000
mean        52.313487
std         19.333710
min         18.879452
25%         35.584247
50%         52.469863
75%         68.936301
max         85.967123
Name: Age, dtype: float64
```



Insight

- The **male** and **female** customer distribution is same, around **50%**
- Customers from all the countries also have the same male-female distribution. **United States** has the **highest customer** base **followed by United Kingdom**
- **North America** has the **highest** number of **customers** among continents
- Customer from **all age**, ranging from 18 to 85 are **equally present**

4. User Segmentation

Combining Customer table too

In [17]:
```
# Merge Sales(already merged with Products) and Customer table
sales_df = pd.merge(sales_df, customer_df, on='CustomerKey', how='left')
```

In [18]:
```
sales_df.head()
```

Out[18]:

	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	ProductKey	Quantity	Product Name	Brand	Unit Cost USD	...	O
0	366000	1	2016-01-01	NaT	265598	1304	1	Contoso Lens Adapter M450 White	Contoso	31.270000	...	:
1	366001	1	2016-01-01	2016-01-13	1269051	1048	2	A. Datum SLR Camera X136 Silver	A. Datum	141.470001	...	:

2	366001	2	2016-01-01	2016-01-13	1269051	2007	1	Fabrikam Microwave 1.5CuFt X1100 Black	Fabrikam	220.639999	...
3	366002	1	2016-01-01	2016-01-12	266019	1106	7	Contoso SLR Camera M146 Orange	Contoso	148.080002	...
4	366002	2	2016-01-01	2016-01-12	266019	373	1	Adventure Works Laptop8.9 E0890 White	Adventure Works	166.199997	...

5 rows × 24 columns

Creating a column defining the age group to which a customer belongs to

In [19]:
```
sales_df['Age'] = (sales_df['Order Date'] - sales_df['Birthday'])/np.timedelta64(1, 'Y')
sales_df['Age'] = sales_df['Age'].round(2)
bins = [0, 12, 20, 40, 60, 80, 100]
labels = ['Kid', 'Teenager', 'Young Adult', 'Adult', 'Senior', 'Super Senior']
# Segment the customers into groups
sales_df['Age Group'] = pd.cut(sales_df['Age'], bins=bins, labels=labels)
```

In [20]:
```
sales_df.head()
```

Out[20]:

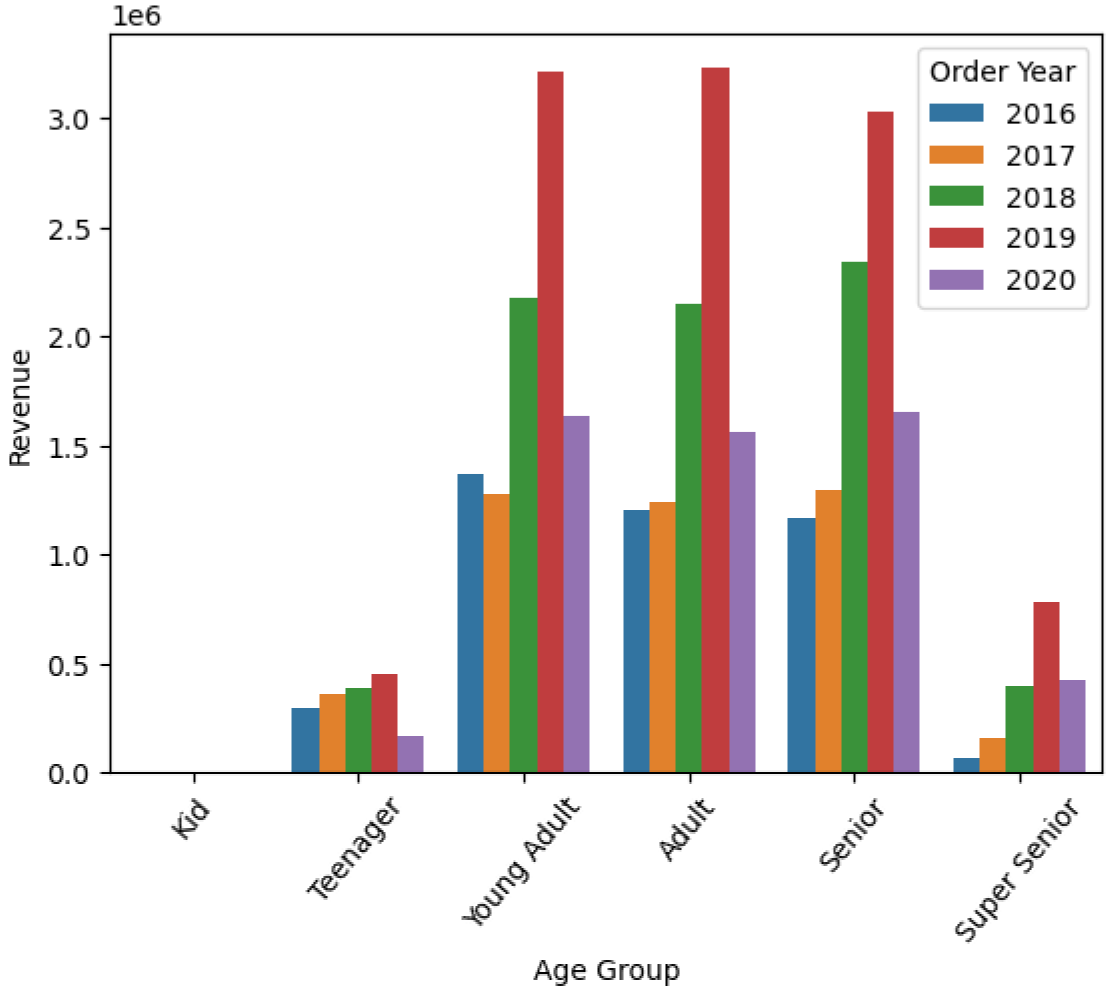
	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	ProductKey	Quantity	Product Name	Brand	Unit Cost USD	...	Ye
0	366000	1	2016-01-01	NaT	265598	1304	1	Contoso Lens Adapter M450 White	Contoso	31.270000	...	
1	366001	1	2016-01-01	2016-01-13	1269051	1048	2	A. Datum SLR Camera X136 Silver	A. Datum	141.470001	...	
2	366001	2	2016-01-01	2016-01-13	1269051	2007	1	Fabrikam Microwave 1.5CuFt X1100 Black	Fabrikam	220.639999	...	
3	366002	1	2016-01-01	2016-01-12	266019	1106	7	Contoso SLR Camera M146 Orange	Contoso	148.080002	...	
4	366002	2	2016-01-01	2016-01-12	266019	373	1	Adventure Works Laptop8.9 E0890 White	Adventure Works	166.199997	...	

5 rows × 26 columns

4.1. Segmentation based on Customer's age group

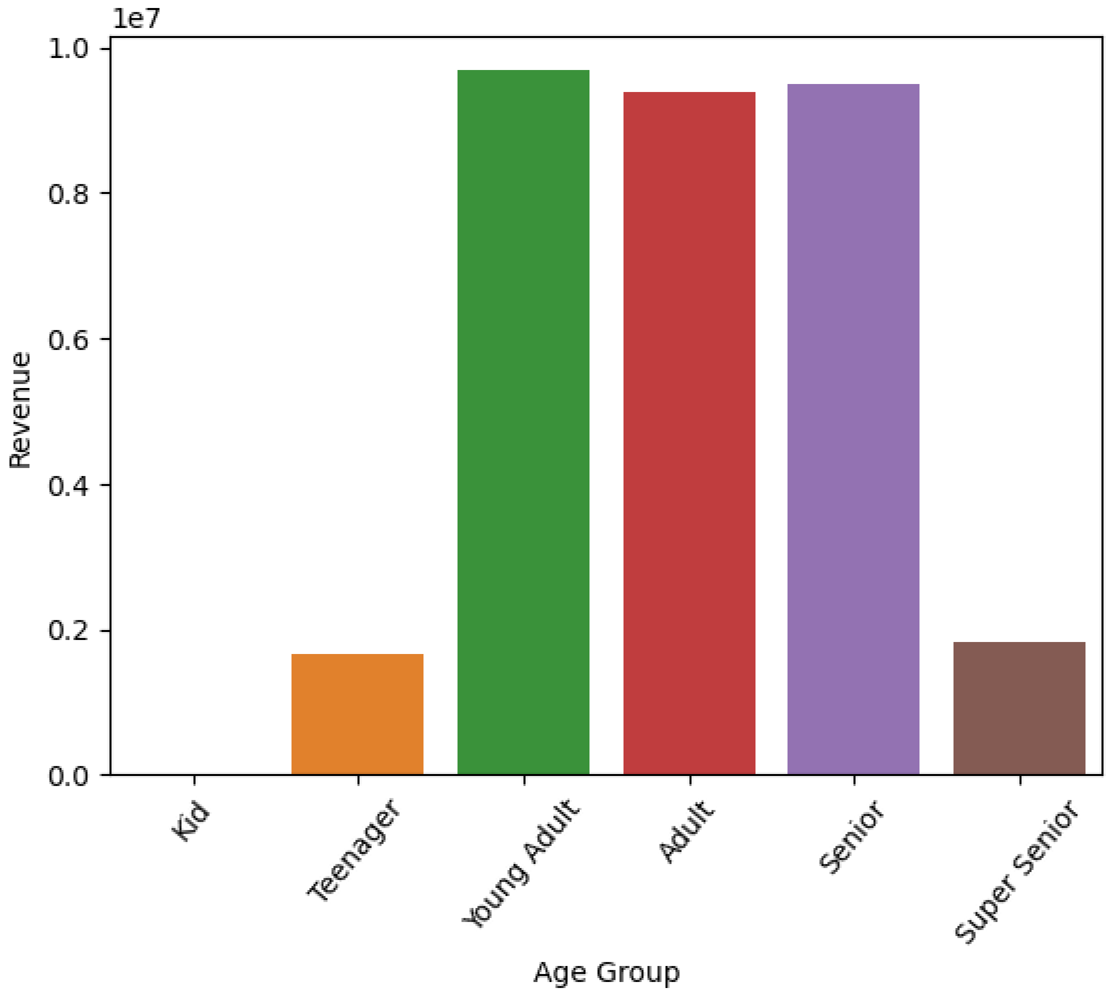
In [21]:

```
sns.barplot(data=sales_df, x = 'Age Group', y='Revenue', hue='Order Year', estimator="su
plt.xticks(rotation=50)
plt.show()
```



In [22]:

```
sns.barplot(data=sales_df, x = 'Age Group', y='Revenue', estimator="sum", errorbar=None)
plt.xticks(rotation=50)
plt.show()
```



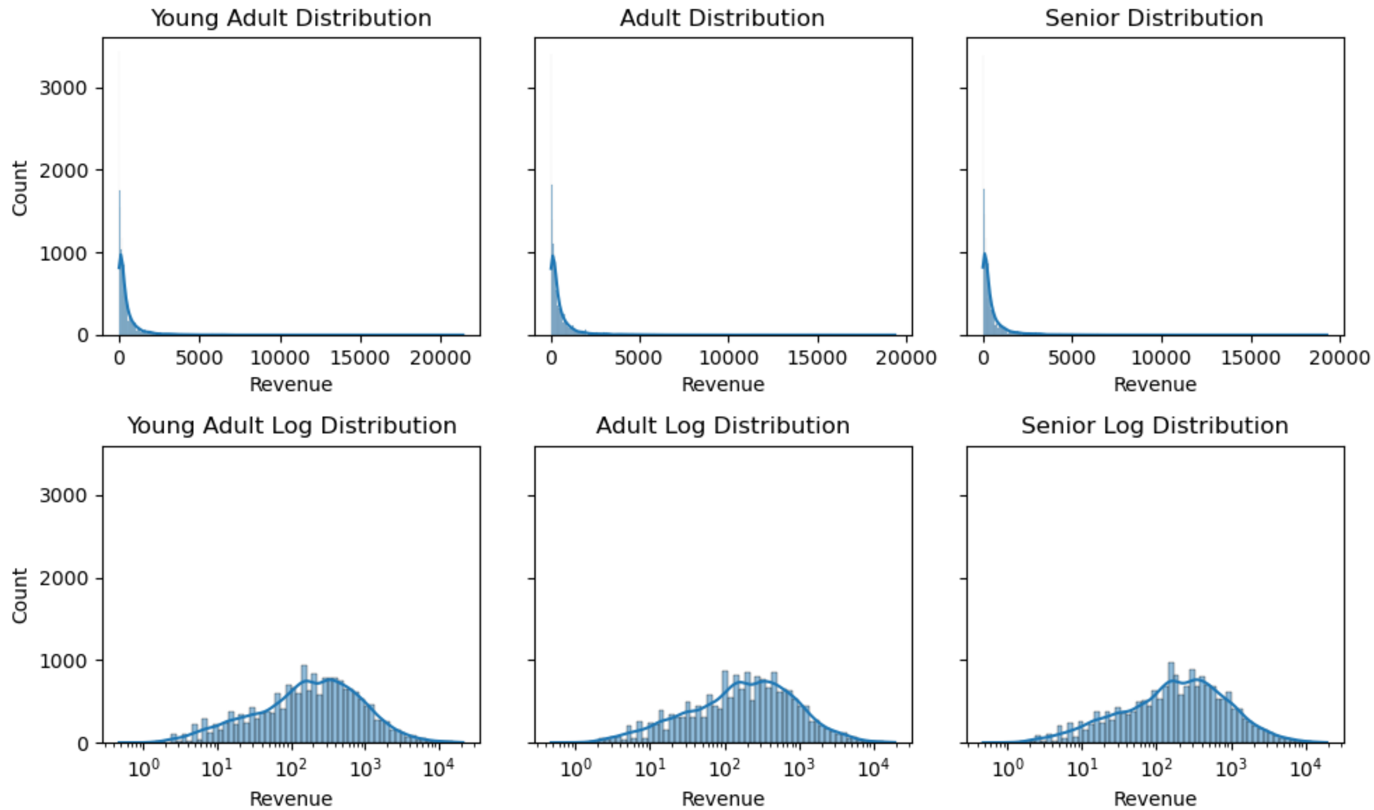
Insight

- It looks the revenue from age groups - Young Adult, Adult and Senior are similar
- Let us conduct hypothesis testing to see if that is true
- As there are three groups, let us check if we can use **one-way ANOVA test**. To use one-way ANOVA test, the samples should have normal distribution

Check for normal distribution visually and via test

In [23]:

```
young_adult_df = sales_df[sales_df['Age Group'] == 'Young Adult']
adult_df = sales_df[sales_df['Age Group'] == 'Adult']
senior_df = sales_df[sales_df['Age Group'] == 'Senior']
fig, axes = plt.subplots(2, 3, sharey=True, figsize=(10,6))
sns.histplot(ax=axes[0,0], data=young_adult_df, x = 'Revenue', kde=True).set_title('Youn
sns.histplot(ax=axes[0,1], data=adult_df, x = 'Revenue', kde=True).set_title('Adult Dist
sns.histplot(ax=axes[0,2], data=senior_df, x = 'Revenue', kde=True).set_title('Senior Di
sns.histplot(ax=axes[1,0], data=young_adult_df, x = 'Revenue', log_scale=True, kde=True)
sns.histplot(ax=axes[1,1], data=adult_df, x = 'Revenue', log_scale=True, kde=True).set_t
sns.histplot(ax=axes[1,2], data=senior_df, x = 'Revenue', log_scale=True, kde=True).set_
plt.tight_layout()
plt.show()
```



In [24]:
```
sample1 = np.log(young_adult_df['Revenue'])
sample2 = np.log(adult_df['Revenue'])
sample3 = np.log(senior_df['Revenue'])

t_stat, p_value = stats.shapiro(sample1)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Sample1 follows normal distribution')
else:
    print('Sample1 doesnt follow normal distribution')


t_stat, p_value = stats.shapiro(sample2)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Sample2 follows normal distribution')
else:
    print('Sample2 doesnt follow normal distribution')


t_stat, p_value = stats.shapiro(sample3)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Sample3 follows normal distribution')
else:
    print('Sample3 doesnt follow normal distribution')
```

```
p-value: 2.4865206748182404e-35
Sample1 doesnt follow normal distribution
p-value: 6.091784578075495e-33
Sample2 doesnt follow normal distribution
p-value: 3.404771265356769e-33
Sample3 doesnt follow normal distribution
```

```
C:\ProgramData\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning:
p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

Insight

- The Shapiro-Wilk test says that the samples are **not normally distributed** and hence we will use **Kruskal–Wallis test** instead of one-way ANOVA test

In [25]:
```
print('H0 : Revenue from Young Adults, Adults and Seniors are similar')
print('H1 : Revenue from Young Adults, Adults and Seniors are different')
t_stat, p_value = stats.kruskal(sample1, sample1, sample3)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Revenues are similar')
else:
    print('Revenues are different')
```

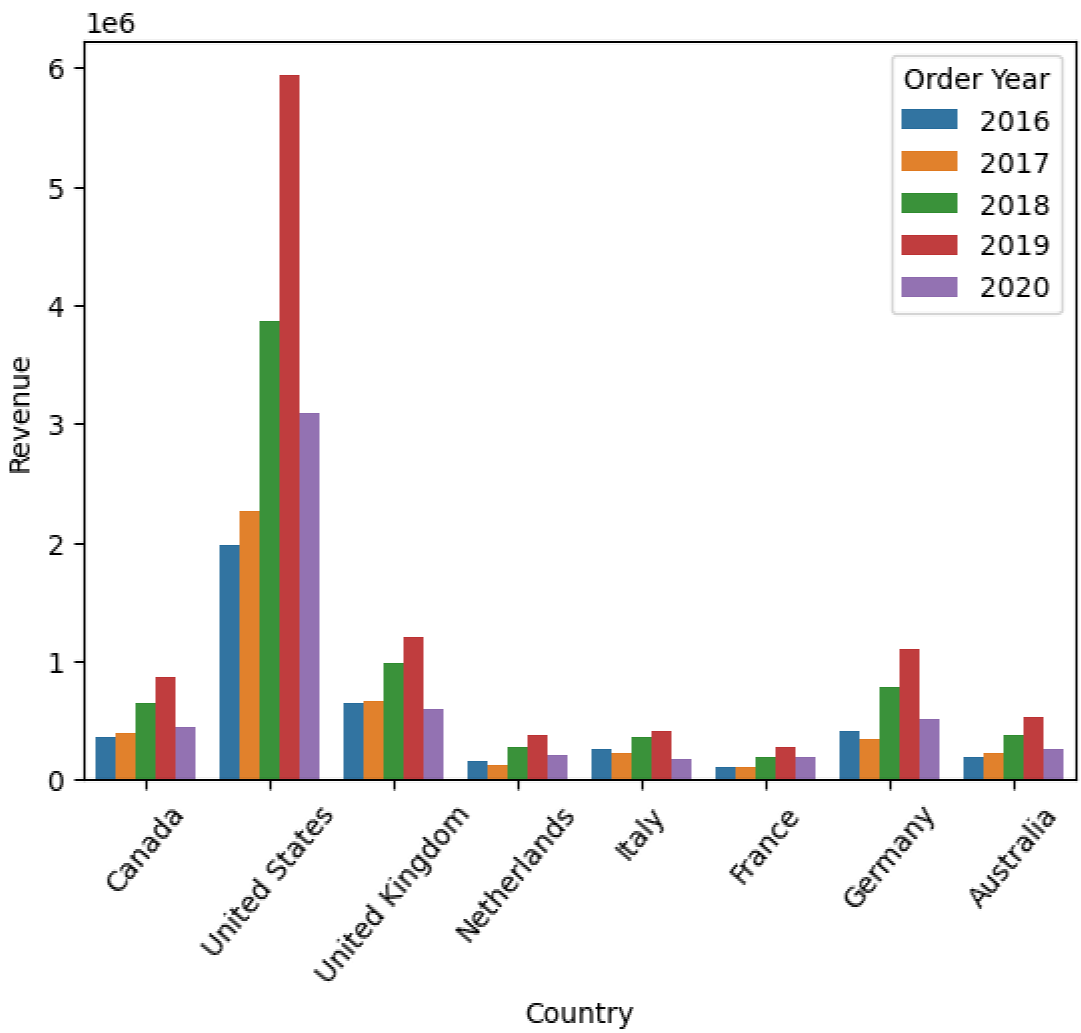
```
H0 : Revenue from Young Adults, Adults and Seniors are similar
H1 : Revenue from Young Adults, Adults and Seniors are different
p-value: 0.9867806603476335
Revenues are similar
```

Insight

- From the **Kruskal–Wallis test**, we can conclude that the **revenues** from **Young Adults, Adults and Seniors are similar**

4.2. Segmentation based on Customer's country

In [26]:
```
sns.barplot(data=sales_df, x = 'Country', y='Revenue', hue='Order Year', estimator="sum"
plt.xticks(rotation=50)
plt.show()
```

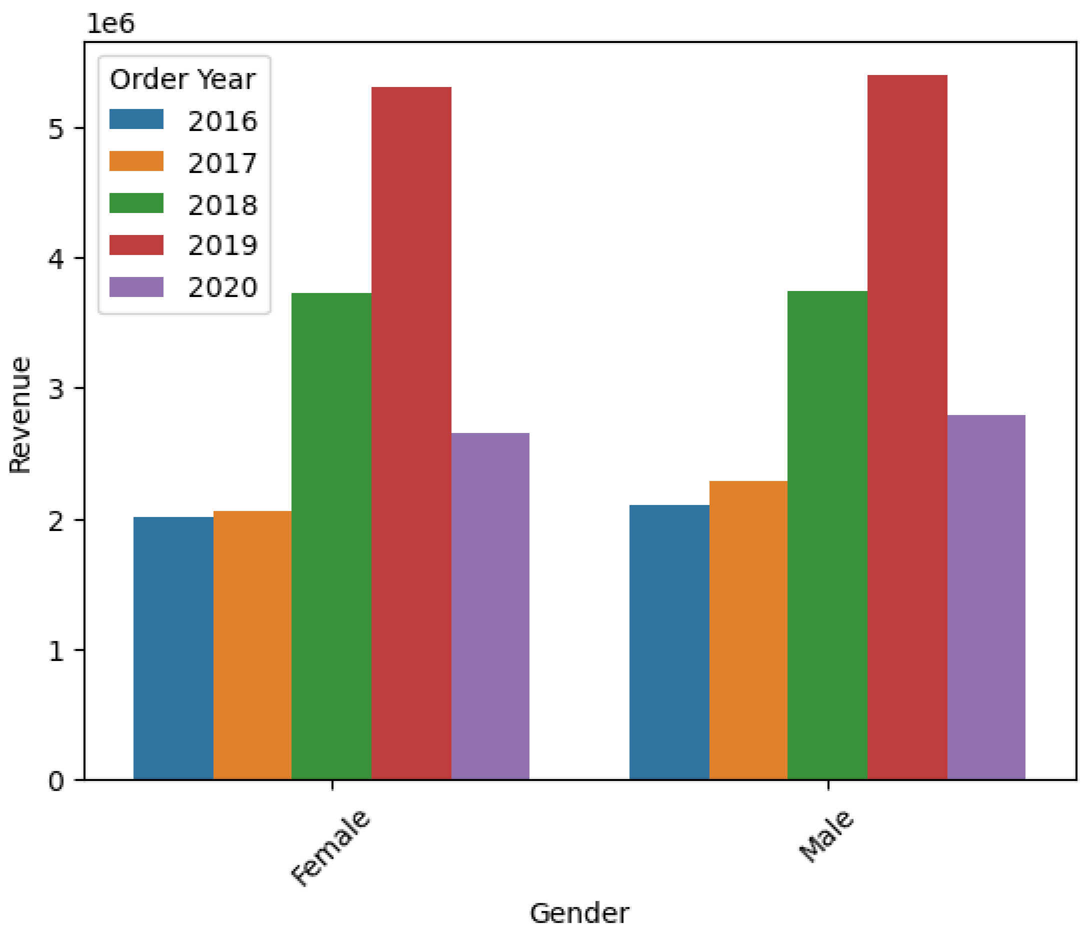


Insight

- The revenue has dropped by 50% in 2020 in allmost all countries

4.3. Segmentation based on Customer's gender

In [27]:
```
sns.barplot(data=sales_df, x = 'Gender', y='Revenue', hue='Order Year', estimator="sum",
plt.xticks(rotation=45)
plt.show()
```

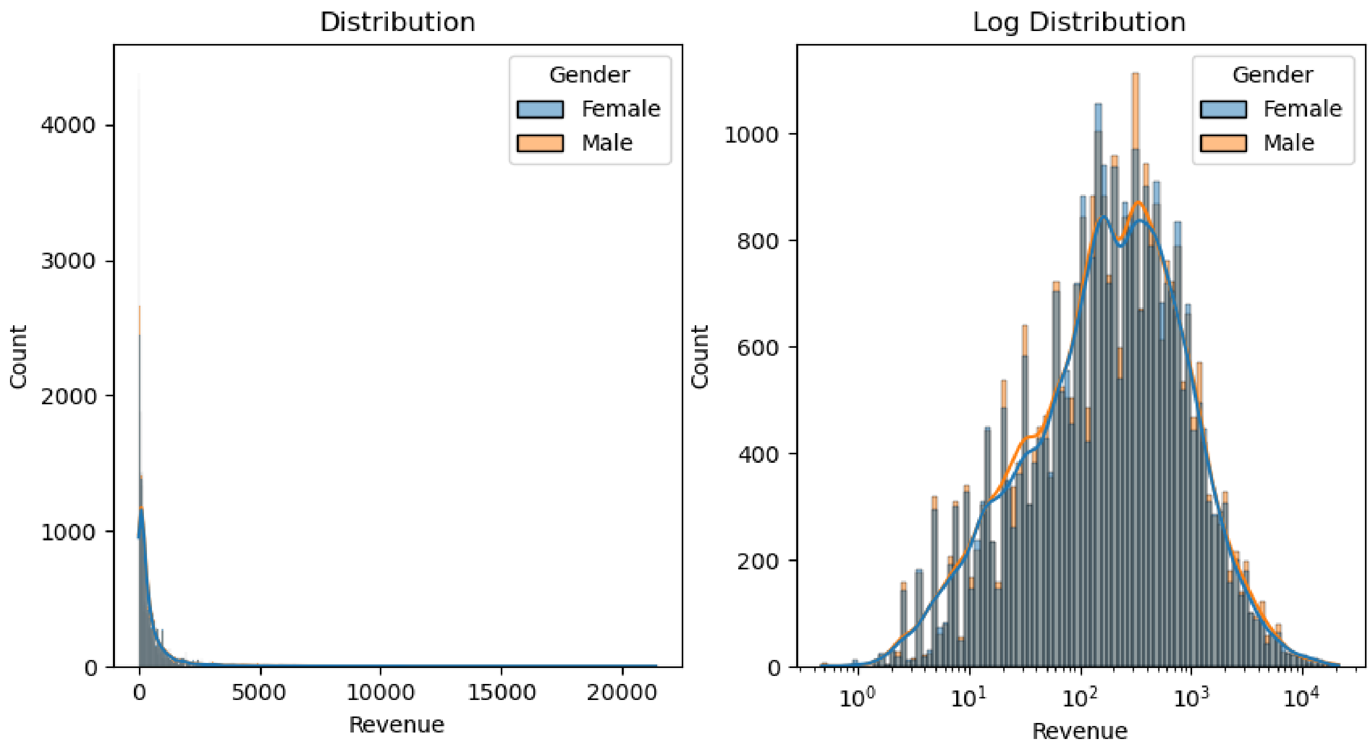


Insight

- It looks the revenue from both genders - Male and Female are similar
- Let us conduct hypothesis testing to see if that is true
- As there are 2 groups, let us check if we can use **Two-Sample T-test**. To use Two-Sample T-test, the samples should have normal distribution

Check for normal distribution visually and via test

In [28]:
```
fig, axs = plt.subplots(1, 2, figsize=(10,5))
sns.histplot(ax = axs[0], data=sales_df, x = 'Revenue', hue='Gender', kde=True).set_titl
sns.histplot(ax = axs[1], data=sales_df, x = 'Revenue', hue='Gender', kde=True, log_scal
plt.show()
```



In [29]:
```
sample1 = np.log(sales_df[sales_df['Gender'] == 'Male']['Revenue'])
sample2 = np.log(sales_df[sales_df['Gender'] == 'Female']['Revenue'])

t_stat, p_value = stats.shapiro(sample1)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Sample1 follows normal distribution')
else:
    print('Sample1 doesnt follow normal distribution')


t_stat, p_value = stats.shapiro(sample2)
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Sample2 follows normal distribution')
else:
    print('Sample2 doesnt follow normal distribution')
```

```
p-value: 1.497791876578224e-40
Sample1 doesnt follow normal distribution
p-value: 7.480131202565874e-42
Sample2 doesnt follow normal distribution
```

```
C:\ProgramData\anaconda3\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarning:
p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

Insight

- The Shapiro-Wilk test says that the samples are **not normally distributed** and hence we will use **Mann-Whitney U test** instead of Two-Sample T-test

In [30]:
```
print('H0 : Revenue from Male and Female are similar')
print('H1 : Revenue from Male and Female are different')
t_stat, p_value = stats.mannwhitneyu(sample1, sample2, alternative='two-sided')
print(f'p-value: {p_value}')
if(p_value > 0.05):
    print('Revenues are similar')
```

```
else:
    print('Revenues are different')
```

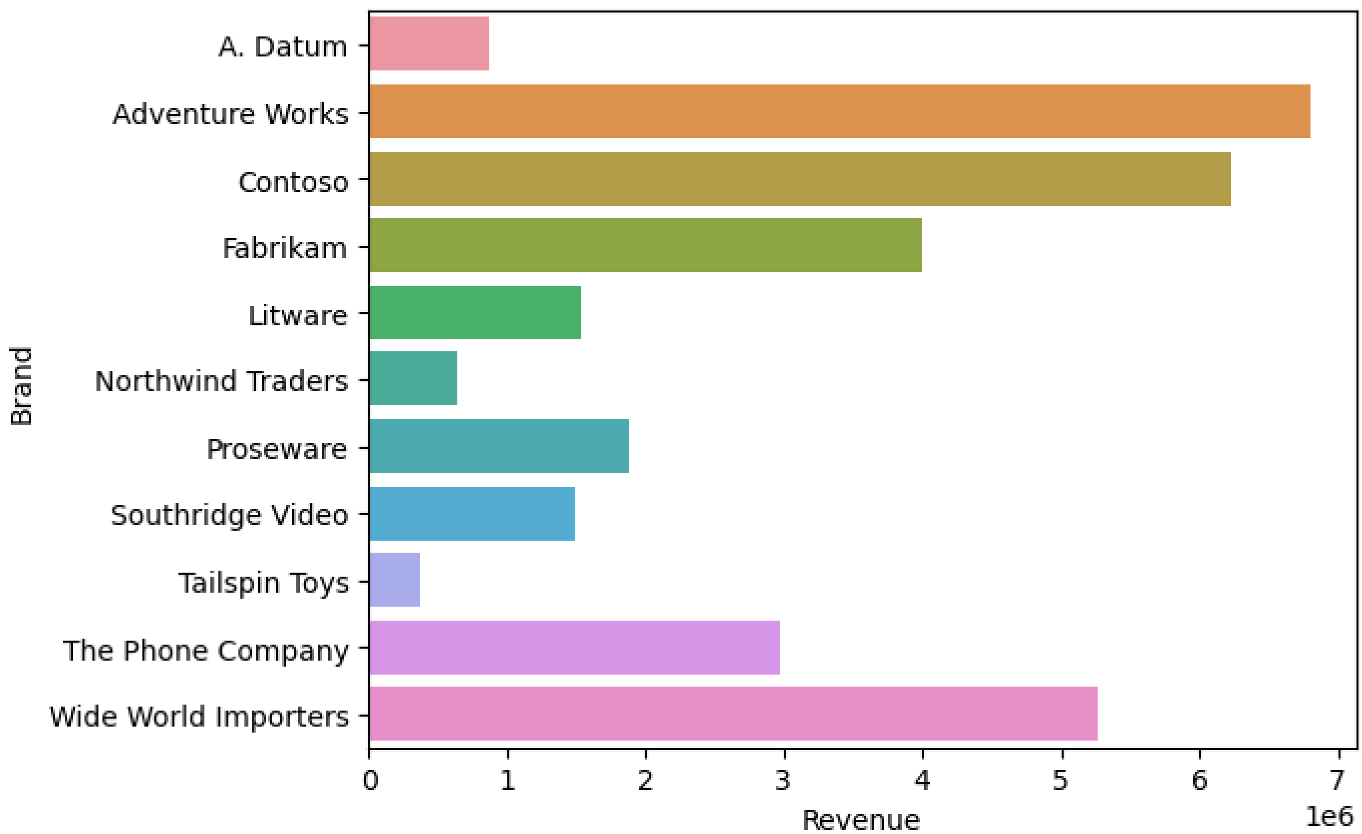
```
H0 : Revenue from Male and Female are similar
H1 : Revenue from Male and Female are different
p-value: 0.5663336950598776
Revenues are similar
```

Insight

- From the **Mann-Whitney U test**, we can conclude that the **revenues** from both **Male and Female are similar**

4.4. Segmentation based on product's brand

In [31]:
```
sns.barplot(data=sales_df, y = 'Brand', x='Revenue', estimator="sum", errorbar=None)
plt.show()
```

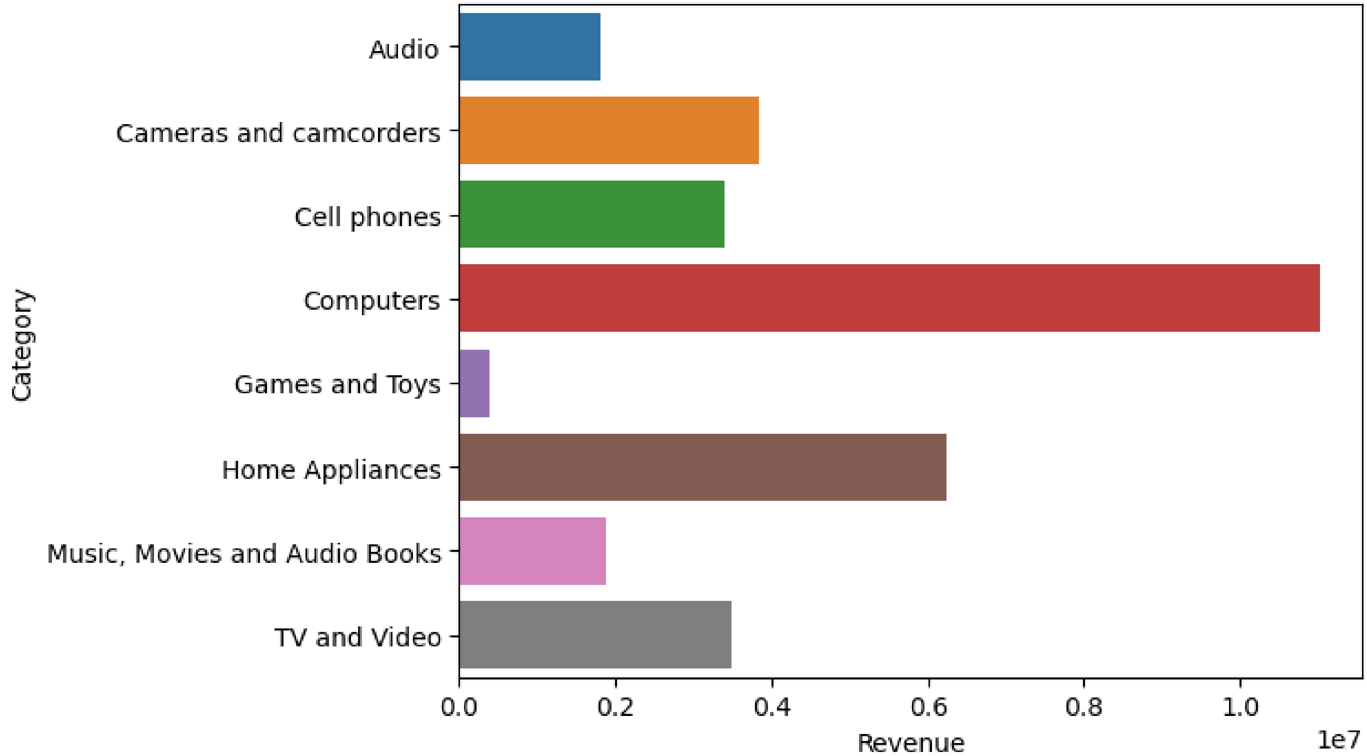


Insight

- The brand **Adventure Works** has generated **highest revenue** and **Tailspin Toys** the **least revenue**

4.5. Segmentation based on product's category

In [32]:
```
sns.barplot(data=sales_df, y = 'Category', x='Revenue', estimator="sum", errorbar=None)
plt.show()
```



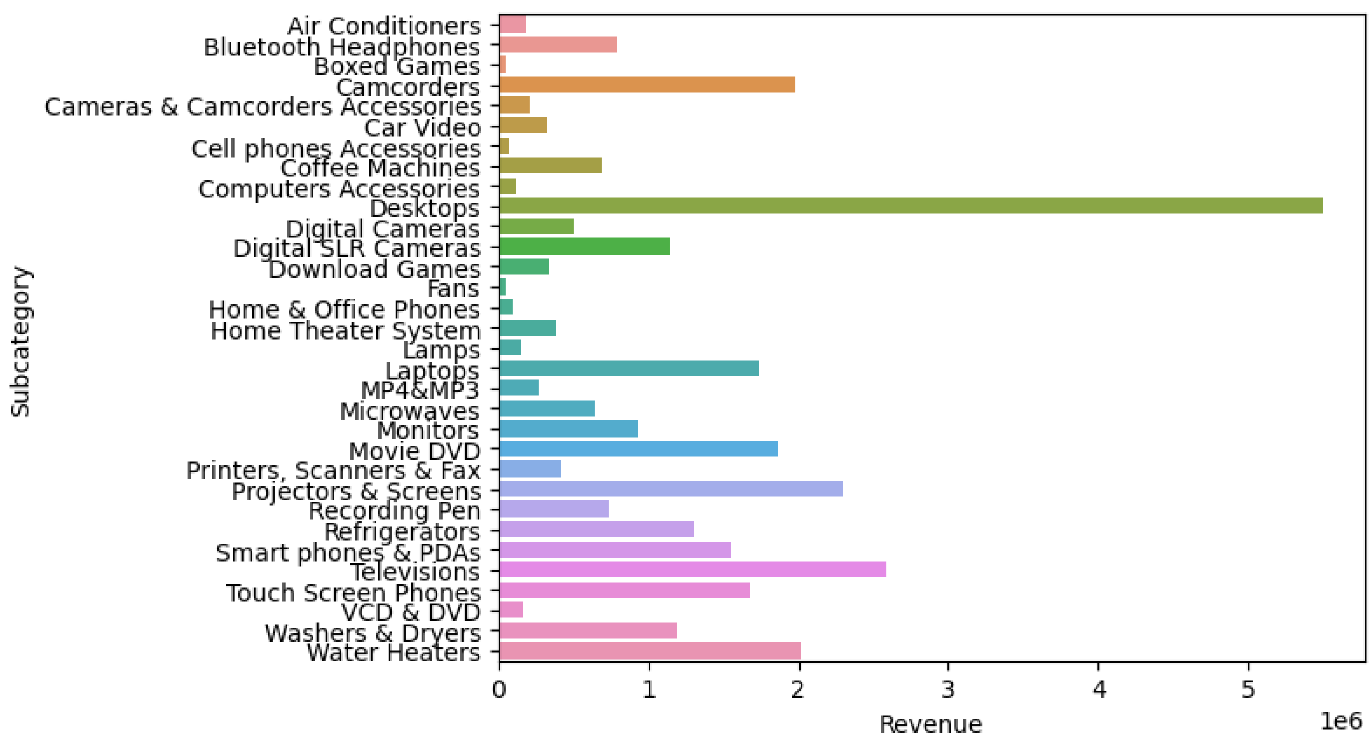
Insight

- The category **Computers** has generated **highest revenue** and **Games and Toys** the **least revenue**

4.6. Segmentation based on product's subcategory

In [33]:

```
sns.barplot(data=sales_df, y = 'Subcategory', x='Revenue', estimator="sum", errorbar=Non
plt.show()
```



In [34]:

```
sales_df.groupby('Subcategory')['Revenue'].sum().sort_values(ascending=False)
```

Out[34]:

```
Subcategory
```

```
Desktops                               5501067.69
Televisions                            2593288.33
Projectors & Screens                   2296017.80
Water Heaters                          2022457.96
Camcorders                             1979489.06
Movie DVD                              1868778.38
Laptops                                1742188.13
Touch Screen Phones                    1684685.45
Smart phones & PDAs                    1556232.22
Refrigerators                          1312095.85
Washers & Dryers                       1188974.98
Digital SLR Cameras                    1144624.65
Monitors                                938255.16
Bluetooth Headphones                    795492.59
Recording Pen                           732838.81
Coffee Machines                         687793.77
Microwaves                              644961.91
Digital Cameras                         503344.67
Printers, Scanners & Fax                421797.11
Home Theater System                     388744.24
Download Games                          337431.17
Car Video                               325615.30
MP4&MP3                                 274705.88
Cameras & Camcorders Accessories        214784.43
Air Conditioners                        185829.24
VCD & DVD                               170462.03
Lamps                                   156849.92
Computers Accessories                   116629.20
Home & Office Phones                     91368.37
Cell phones Accessories                  74227.11
Fans                                     52291.29
Boxed Games                              50901.99
Name: Revenue, dtype: float64
```

Insight

- The subcategory **Desktops** has generated **highest revenue** and **Boxed Games** the **least revenue**

4.7. RFM Segmentation

Work on a reduced dataset

In [35]:
```
sales_reduced_df = sales_df[['Order Number', 'Order Date', 'CustomerKey', 'Revenue']]
sales_reduced_df.head()
```

Out[35]:

	Order Number	Order Date	CustomerKey	Revenue
0	366000	2016-01-01	265598	36.73
1	366001	2016-01-01	1269051	571.06
2	366001	2016-01-01	1269051	445.30
3	366002	2016-01-01	266019	1217.44
4	366002	2016-01-01	266019	159.80

Calculate and add a column which shows the last order date of each customer

In [36]:
```
last_order_date_by_customer = sales_reduced_df.groupby('CustomerKey').agg({'Order Date':
last_order_date_by_customer.rename(columns = {'Order Date':'Last Order Date'}, inplace =
```

```
sales_reduced_df = sales_reduced_df.merge(last_order_date_by_customer, on='CustomerKey',
sales_reduced_df.head()
```

Out[36]:

	Order Number	Order Date	CustomerKey	Revenue	Last Order Date
0	366000	2016-01-01	265598	36.73	2019-10-15
1	366001	2016-01-01	1269051	571.06	2016-01-01
2	366001	2016-01-01	1269051	445.30	2016-01-01
3	366002	2016-01-01	266019	1217.44	2019-01-08
4	366002	2016-01-01	266019	159.80	2019-01-08

Calculate the recency of every customer

In [37]:

```
max_order_date = sales_reduced_df['Order Date'].max()
sales_reduced_df['Recency'] = max_order_date - sales_reduced_df['Last Order Date']
sales_reduced_df.head()
```

Out[37]:

	Order Number	Order Date	CustomerKey	Revenue	Last Order Date	Recency
0	366000	2016-01-01	265598	36.73	2019-10-15	443 days
1	366001	2016-01-01	1269051	571.06	2016-01-01	1826 days
2	366001	2016-01-01	1269051	445.30	2016-01-01	1826 days
3	366002	2016-01-01	266019	1217.44	2019-01-08	723 days
4	366002	2016-01-01	266019	159.80	2019-01-08	723 days

Calculate the frequency of every customer

In [38]:

```
frequency = sales_reduced_df['CustomerKey'].value_counts().reset_index()
frequency.rename(columns = {'count':'Frequency'}, inplace = True)
sales_reduced_df = sales_reduced_df.merge(frequency, on='CustomerKey', how='left')
sales_reduced_df.head()
```

Out[38]:

	Order Number	Order Date	CustomerKey	Revenue	Last Order Date	Recency	Frequency
0	366000	2016-01-01	265598	36.73	2019-10-15	443 days	8
1	366001	2016-01-01	1269051	571.06	2016-01-01	1826 days	2
2	366001	2016-01-01	1269051	445.30	2016-01-01	1826 days	2
3	366002	2016-01-01	266019	1217.44	2019-01-08	723 days	6
4	366002	2016-01-01	266019	159.80	2019-01-08	723 days	6

Calculate the monetory value of every customer

In [39]:

```
monetory_by_customer = sales_reduced_df.groupby('CustomerKey').agg({'Revenue':'sum'}).re
monetory_by_customer.rename(columns = {'Revenue':'Monetory'}, inplace = True)
sales_reduced_df = sales_reduced_df.merge(monetory_by_customer, on='CustomerKey', how='l
sales_reduced_df.head()
```

Out[39]:

	Order Number	Order Date	CustomerKey	Revenue	Last Order Date	Recency	Frequency	Monetory
0	366000	2016-01-01	265598	36.73	2019-10-15	443 days	8	768.82
1	366001	2016-01-01	1269051	571.06	2016-01-01	1826 days	2	1016.36

2	366001	2016-01-01	1269051	445.30	2016-01-01	1826 days	2	1016.36
3	366002	2016-01-01	266019	1217.44	2019-01-08	723 days	6	4929.63
4	366002	2016-01-01	266019	159.80	2019-01-08	723 days	6	4929.63

Reduce the dataset to only Recency, Frequency and Monetory of every customer

In [40]:
```
rfm_df = sales_reduced_df.groupby(['CustomerKey']).agg({'Recency':'first', 'Frequency':'
rfm_df.head()
```

Out[40]:

	CustomerKey	Recency	Frequency	Monetory
0	301	416 days	1	395.86
1	325	362 days	10	3380.07
2	554	392 days	4	504.33
3	1042	1031 days	3	732.17
4	1314	1108 days	5	1489.01

Calculate the RFM Score

In [41]:
```
# Create RFM group
rfm_df['R'] = pd.qcut(x=rfm_df['Recency'].rank(method='first'), q=5, labels = range(5,0,
rfm_df['F'] = pd.qcut(x=rfm_df['Frequency'].rank(method='first'), q=5, labels = range(1,
rfm_df['M'] = pd.qcut(x=rfm_df['Monetory'].rank(method='first'), q=5, labels = range(1,6

# RFM Score
rfm_df['R'] =  rfm_df['R'].astype(int)
rfm_df['F'] =  rfm_df['F'].astype(int)
rfm_df['M'] =  rfm_df['M'].astype(int)
rfm_df['RFM Score']  = rfm_df[['R','F','M']].sum(axis = 1)

rfm_df.head()
```

Out[41]:

	CustomerKey	Recency	Frequency	Monetory	R	F	M	RFM Score
0	301	416 days	1	395.86	3	1	1	5
1	325	362 days	10	3380.07	4	5	4	13
2	554	392 days	4	504.33	4	3	2	9
3	1042	1031 days	3	732.17	1	2	2	5
4	1314	1108 days	5	1489.01	1	3	3	7

Assign an RFM level to a customer based on the RFM Score

RFM Segmentation Image

In [42]:
```
# RFM Function
def rfm_segment(df):
    if\
    ((df['R'] == 5) and
     (df['F'] == 5) and
     (df['M'] >= 4)):
        return 'CHAMPIONS'
    elif\
    ((df['R'] >= 4) and
```

```python
       (df['F'] >= 4) and
       (df['M'] >= 4)):
          return 'LOYAL CUSTOMERS'
     elif\
      ((df['R'] >= 4) and
       (df['F'] == 3) and
       (df['M'] >= 4)):
          return 'POTENTIAL LOYALIST'
     elif\
      ((df['R'] >= 4) and
       ((df['F'] >= 1) and (df['F'] <= 2)) and
       (df['M'] >= 1)):
          return 'NEW CUSTOMER'
     elif\
      ((df['R'] >= 4) and
       (df['F'] >= 3) and
       ((df['M'] >= 1) and (df['M'] <= 3))):
          return 'PROMISING'
     elif\
      ((((df['R'] >= 1) and (df['R'] <= 2)) and
         (df['F'] >= 4) and
         ((df['M'] >= 1) and (df['M'] <= 3))) or
       ((df['R'] == 3) and
         (df['F'] >= 3) and
         ((df['M'] >= 1) and (df['M'] <= 3)))):
          return 'NEEDS ATTENTION'
     elif\
      ((((df['R'] >= 1) and (df['R'] <= 2)) and
         (df['F'] == 3) and
         (df['M'] >= 1)) or
       ((df['R'] == 3) and
         ((df['F'] >= 1) and (df['F'] <= 2)) and
         (df['M'] >= 1))):
          return 'ABOUT TO SLEEP'
     elif\
      ((df['R'] == 3) and
       (df['F'] >= 3) and
       (df['M'] >= 4)):
          return "AT RISK"
     elif\
      (((df['R'] >= 1) and (df['R'] <= 2)) and
       (df['F'] >= 4) and
       (df['M'] >= 4)):
          return "DONT LOSE THEM"
     elif\
      (((df['R'] == 1) and
         (df['F'] == 2) and
         (df['M'] >= 1)) or
       ((df['R'] == 2) and
         ((df['F'] >= 1) and (df['F'] <= 2)) and
         (df['M'] >= 1))):
          return 'HIBERNATING'
     elif\
      ((df['R'] == 1) and
       (df['F'] == 1) and
       (df['M'] >= 1)):
          return 'LOST'
     else:
          return 'UNIDENTIFIED'

#  apply RFM function
rfm_df['RFM_level'] = rfm_df.apply(rfm_segment, axis = 1)
rfm_df.head()
```

Out[42]:

	CustomerKey	Recency	Frequency	Monetory	R	F	M	RFM Score	RFM_level

0	301	416 days	1	395.86	3	1	1	5	ABOUT TO SLEEP
1	325	362 days	10	3380.07	4	5	4	13	LOYAL CUSTOMERS
2	554	392 days	4	504.33	4	3	2	9	PROMISING
3	1042	1031 days	3	732.17	1	2	2	5	HIBERNATING
4	1314	1108 days	5	1489.01	1	3	3	7	ABOUT TO SLEEP

In [43]:
```
sales_df = pd.merge(sales_df, rfm_df[['CustomerKey', 'RFM_level']], on='CustomerKey', ho
sales_df.head()
```

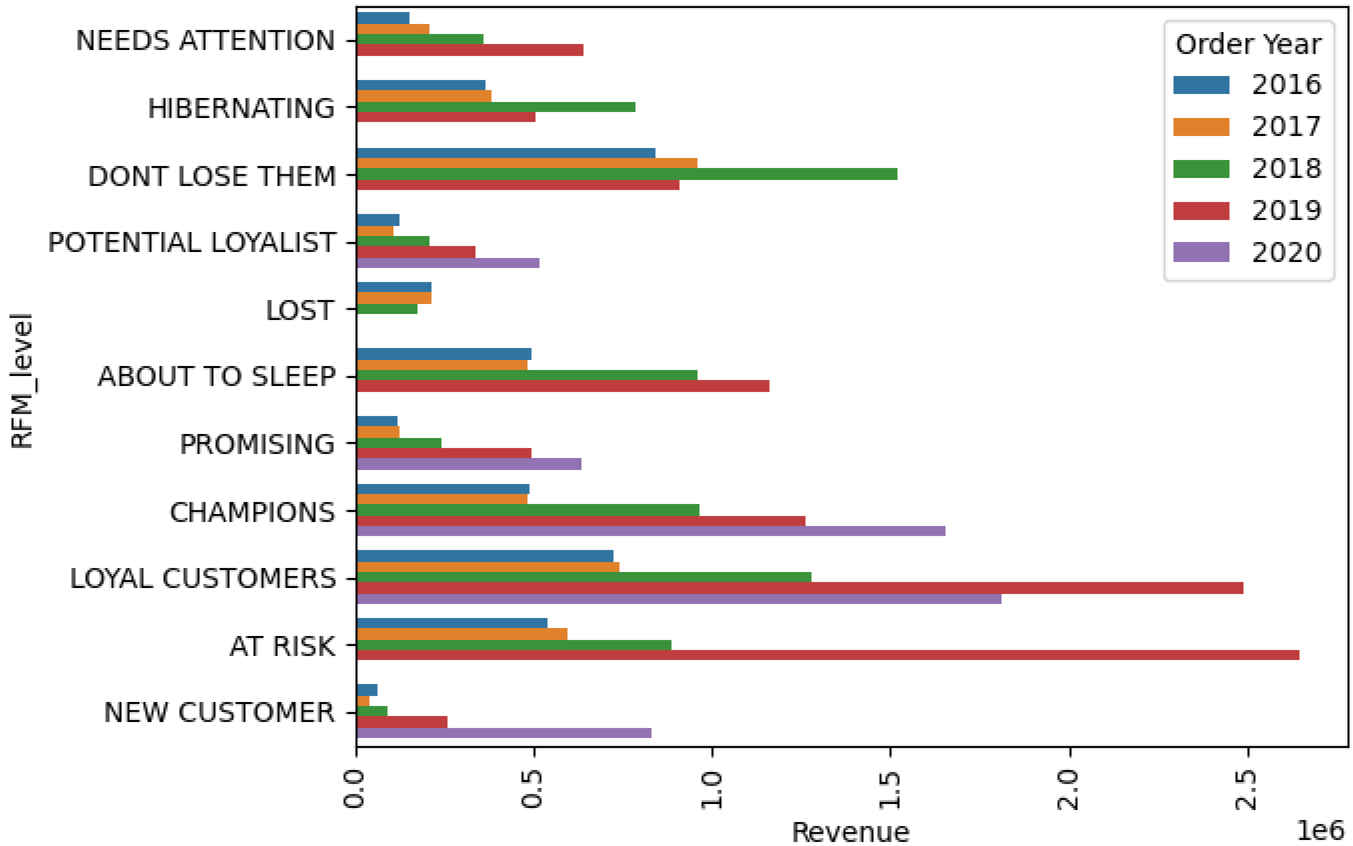
Out[43]:

	Order Number	Line Item	Order Date	Delivery Date	CustomerKey	ProductKey	Quantity	Product Name	Brand	Unit Cost USD	...	G
0	366000	1	2016-01-01	NaT	265598	1304	1	Contoso Lens Adapter M450 White	Contoso	31.270000	...	
1	366001	1	2016-01-01	2016-01-13	1269051	1048	2	A. Datum SLR Camera X136 Silver	A. Datum	141.470001	...	
2	366001	2	2016-01-01	2016-01-13	1269051	2007	1	Fabrikam Microwave 1.5CuFt X1100 Black	Fabrikam	220.639999	...	
3	366002	1	2016-01-01	2016-01-12	266019	1106	7	Contoso SLR Camera M146 Orange	Contoso	148.080002	...	F
4	366002	2	2016-01-01	2016-01-12	266019	373	1	Adventure Works Laptop8.9 E0890 White	Adventure Works	166.199997	...	F

5 rows × 27 columns

Check the revenue, over the years, from customers belonging to different RFM Level

In [44]:
```
sns.barplot(data=sales_df, y = 'RFM_level', x='Revenue', hue='Order Year', estimator="su
plt.xticks(rotation=90)
plt.show()
```



Insight

- It is clearly visible that the **revenue in 2020** is majorly due to **loyal**(Champions, Loyal Customers, Potential Loyalist) and **new customers**(New and Promising Customers)
- All the other segments of customers have not bought anything in 2020.

5. Recommendation

- The reason behind almost 50% decline in revenue in 2020 compared to previous year is due to the inability to keep the customers engaged. The company ScalerMart should **put efforts** on **converting** all customers to be in the **loyal** group - Champions, Loyal Customers, Potential Loyalist
- **Focus** should be more on customers falling under **Needs Attention, About To Sleep, At Risk** and **Dont Lose Them** group
- Especially these customers should be attracted by **providing them special discounts and offer coupons** so that they come back to purchase more and **become repeat customers**.
- ScalerMart should provide them **better offers and better service** so that these customers **become loyal customers**.