Sales Analysis

Exploratory Data Analysis (EDA) Process of analysing and summarizing data in order to gain insights and understanding of the underlying patterns and relationships.

EDA involves the following steps: - Data cleaning: Involves removing or correcting any errors or inconsistencies in the data, such as missing values or incorrect values.

```
- Data Visualization- Data visualization techniques are then used to graphicall
y represent the data and identify any trends or patterns.

- Statistical Analysis- Is used to identify any relationships between variables
and to test hypotheses about data. This may involve calculating summary statist
ics such as mean and standard deviation, and performing tests such as correlati
on analysis and hypothesis testing.
```

In [1]:
```
#pip install missingno
```

In [2]:
```
# Import libraries
import pandas as pd #Data preprocessing
import matplotlib.pyplot as plt #Data visualization
import seaborn as sns #Data visualization
import missingno as msno #Missing Data- #Data visualization
from collections import Counter #Counting
```

In [3]:
```
# Load the dataset (using pandas)

df = pd.read_csv(r"C:\Users\EZ FARMING\Desktop\Seun Personal Docs\DATA SCIENCE\PYTHON\E
# OR df = pd.read_csv("C:\\Users\\EZ FARMING\\Desktop\\Seun Personal Docs\\DATA SCIENCE
```

In [4]:
```
# Print the top rows
df.head() #Top 5 rows (by default. You can do more than 5 rows by specifying e.g df.hea
```

Out[4]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay Op
0	19-Feb-16	High	Segun	29	F	Abia	Accessories	Keyboard	O
1	20-Feb-16	High	Segun	29	F	Abia	Clothing	Polo shirts	O
2	27-Feb-16	High	Segun	29	F	Abia	Accessories	Keyboard	O
3	12-Mar-16	High	Segun	29	F	Abia	Accessories	Keyboard	O
4	12-Mar-16	High	Segun	29	F	Abia	Accessories	Keyboard	O

In [5]:
```
# Print the bottom rows
df.tail()
```

Out[5]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category
34862	7-Feb-16	High	Kenny	38	M	Ebonyi	Phones	IPhone
34863	13-Mar-15	High	Kenny	38	M	Ebonyi	Phones	IPhone
34864	5-Apr-15	High	Kenny	38	M	Ebonyi	Phones	IPhone
34865	30-Aug-15	High	Kenny	38	M	Ebonyi	Phones	IPhone
34866	NaN	NaN	NaN	38	NaN	NaN	NaN	NaN

In [6]:
```
#Dimensionality of the Data- The number of rows and columns
df.shape
```

Out[6]:
```
(34867, 12)
```

In [7]:
```
#Examine the columns/features of the data
df.columns
```

Out[7]:
```
Index(['Date', 'Customer', 'Sales Person', 'Customer_Age', 'Customer_Gender',
       'State', 'Product_Category', 'Sub_Category', 'Payment Option',
       'Quantity', 'Unit_Cost', 'Unit_Price'],
      dtype='object')
```

In [8]:
```
#Investigate the dataset for anomalies and data types (Feature also means Column)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34867 entries, 0 to 34866
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Date              34866 non-null  object
 1   Customer          34866 non-null  object
 2   Sales Person      34866 non-null  object
 3   Customer_Age      34867 non-null  int64
 4   Customer_Gender   34866 non-null  object
 5   State             34866 non-null  object
 6   Product_Category  34866 non-null  object
 7   Sub_Category      34866 non-null  object
 8   Payment Option    34866 non-null  object
 9   Quantity          34866 non-null  float64
 10  Unit_Cost         34866 non-null  float64
 11  Unit_Price        34866 non-null  float64
dtypes: float64(3), int64(1), object(8)
memory usage: 3.2+ MB
```

In [9]:
```
#object= categorical data, float=decimals, int= numbers
```

In [10]:
```
# Numerical Statistical Analysis (Showing only the numerical columns)
# i. Check if there are outliers by comparing the mean with the median values (50%)
df.describe()
```

Out[10]:

	Customer_Age	Quantity	Unit_Cost	Unit_Price
count	34867.000000	34866.000000	34866.000000	34866.000000
mean	36.382683	2.002524	349.880567	389.232473
std	11.112813	0.813936	490.015846	525.319097
min	17.000000	1.000000	0.670000	0.670000
25%	28.000000	1.000000	45.000000	53.670000
50%	35.000000	2.000000	150.000000	179.000000
75%	44.000000	3.000000	455.000000	521.000000
max	87.000000	3.000000	3240.000000	5082.000000

In [11]:
```
df.describe().astype(int)
```

Out[11]:

	Customer_Age	Quantity	Unit_Cost	Unit_Price
count	34867	34866	34866	34866
mean	36	2	349	389
std	11	0	490	525
min	17	1	0	0
25%	28	1	45	53
50%	35	2	150	179
75%	44	3	455	521
max	87	3	3240	5082

In [12]:
```
# Categorical Statistical Analysis
df.describe(include=['object', 'bool'])
```

Out[12]:

	Date	Customer	Sales Person	Customer_Gender	State	Product_Category	Sub_Category	Payment Option
count	34866	34866	34866	34866	34866	34866	34866	34866
unique	576	4	7	2	36	3	17	3
top	1-Mar-16	Low	Remota	F	Lagos	Accessories	Keyboard	Cash
freq	196	13041	6667	17439	10332	22534	11112	15911

Dealing with Missing Data

1. MCAR (Missing completely at random): These are values that are randomly missing and not opened on any other values.
2. MAR (Missing at random): These values are dependent on some additional features.
3. MNAR (Missing not at random): There is a reason behind why these values are missing.

There are several methods for imputing missing data:

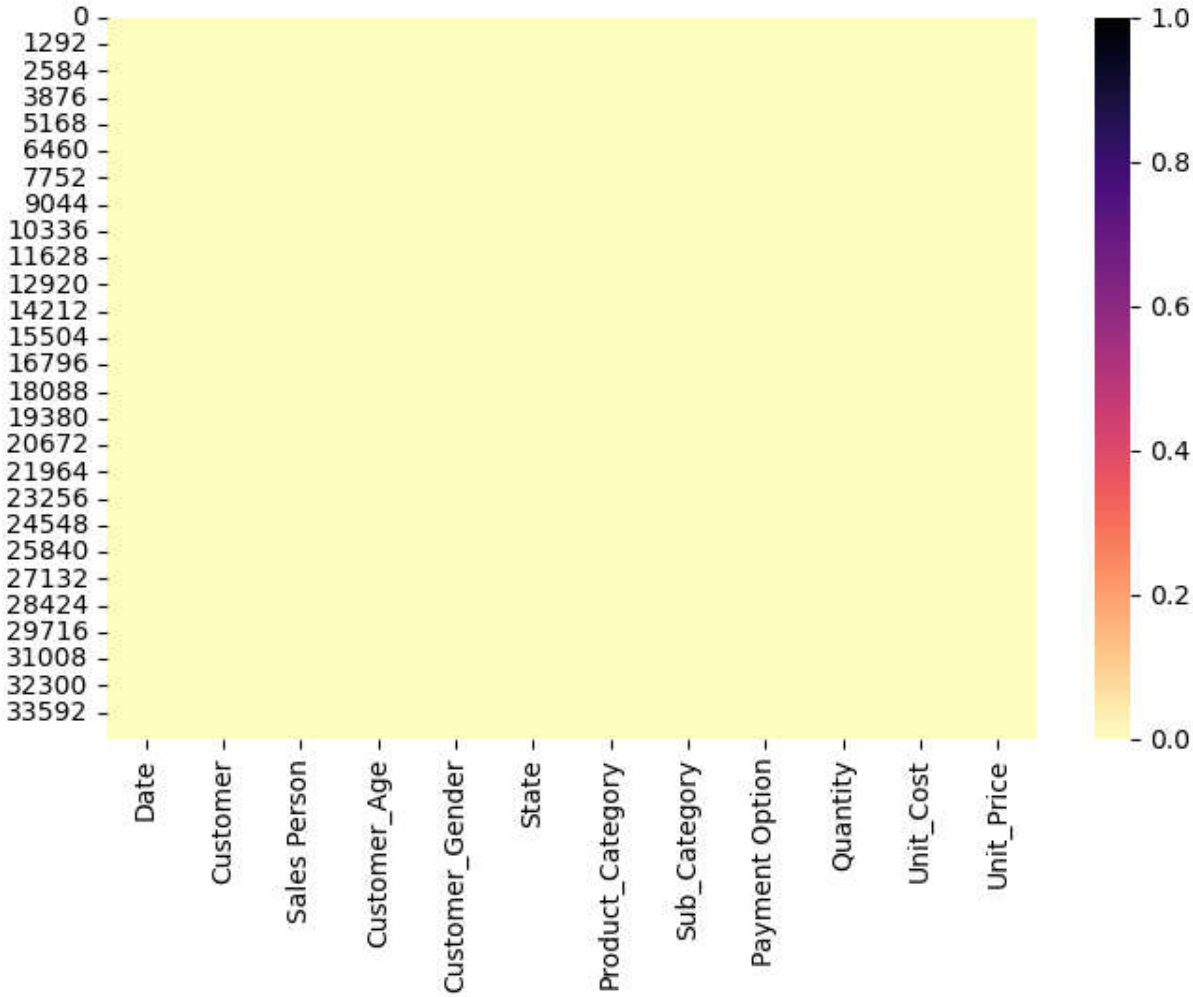
- Measure of central tendency: Involves replacing missing values with either the mean, median and mode of the variable.

- Regression imputation & Multiple imputation: Involves using other variables in the dataset to predict missing values.

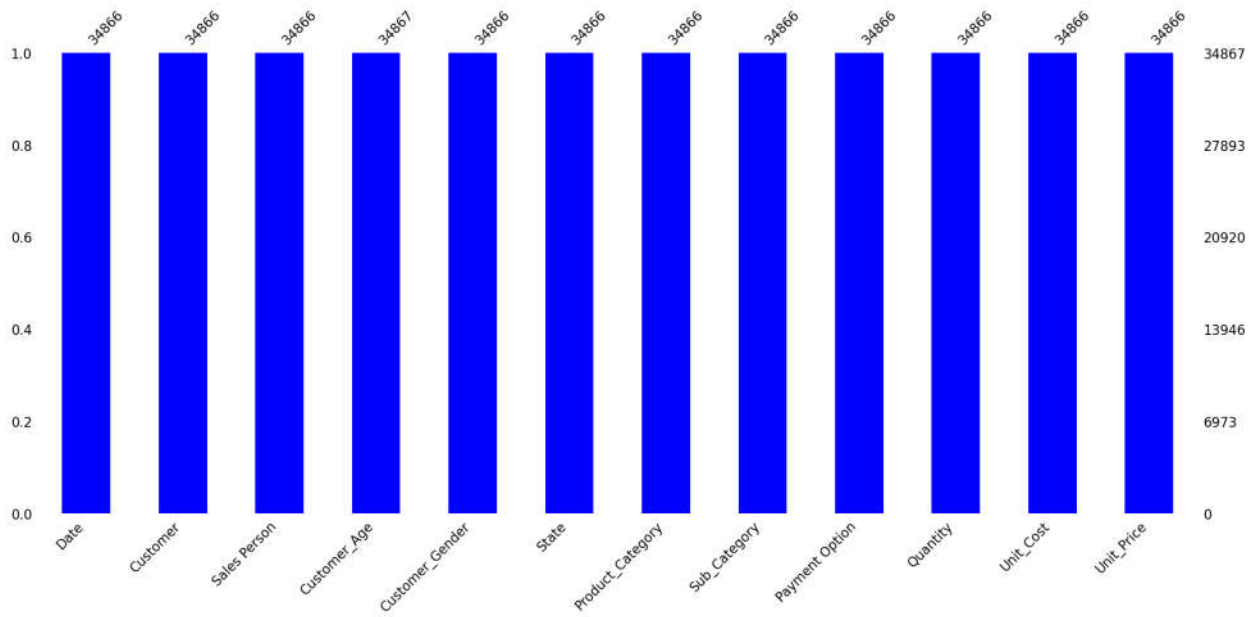
In [13]:
```
# Investigate the missing data
null_vals= df.isnull().sum()
null_vals
```

Out[13]:
```
Date                1
Customer            1
Sales Person        1
Customer_Age        0
Customer_Gender     1
State               1
Product_Category    1
Sub_Category        1
Payment Option      1
Quantity            1
Unit_Cost           1
Unit_Price          1
dtype: int64
```

In [14]:
```
# Visualize the missing data
plt.figure(figsize= (8,5))
sns.heatmap(df.isnull(), cbar= True, cmap= 'magma_r');
```



In [15]:
```
msno.bar(df, color='blue');
```



In [16]:
```
# Display where the missing data exist in the data (Rows with True is what you need)
df[df.isnull().any(axis=1)]
```

Out[16]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category
34866	NaN	NaN	NaN	38	NaN	NaN	NaN	NaN

In [17]:
```
# Drop the missing data
df.dropna(inplace=True)
```

In [18]:
```
# To confirm it was dropped,
df.isnull().sum()
```

Out[18]:
```
Date                0
Customer            0
Sales Person        0
Customer_Age        0
Customer_Gender     0
State               0
Product_Category    0
Sub_Category        0
Payment Option      0
Quantity            0
Unit_Cost           0
Unit_Price          0
dtype: int64
```

In [19]:
```
#Check for duplicates
df.duplicated().sum()
```

Out[19]: 1

In [20]:
```
#Drop the duplicates
df.drop_duplicates(inplace=True)
```

In [21]:
```
#Confirm duplicates were dropped
df.duplicated().sum()
```

Out[21]:
```
0
```

In [22]:
```
# Datatime Analysis
df.head(2)
```

Out[22]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Payı Op
0	19-Feb-16	High	Segun	29	F	Abia	Accessories	Keyboard	O
1	20-Feb-16	High	Segun	29	F	Abia	Clothing	Polo shirts	O

In [23]:
```
#Convert the Date column into a pandas datetime object
df['Date'] = pd.to_datetime(df['Date'])

df.info()

#Extract the year, month, quarter
df['year'] = df['Date'].dt.year
df['month'] = df['Date'].dt.month
df['month_name'] = df['Date'].dt.month_name()
df['quarter'] = df['Date'].dt.quarter

df.head(2)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 34865 entries, 0 to 34865
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Date              34865 non-null  datetime64[ns]
 1   Customer          34865 non-null  object
 2   Sales Person      34865 non-null  object
 3   Customer_Age      34865 non-null  int64
 4   Customer_Gender   34865 non-null  object
 5   State             34865 non-null  object
 6   Product_Category  34865 non-null  object
 7   Sub_Category      34865 non-null  object
 8   Payment Option    34865 non-null  object
 9   Quantity          34865 non-null  float64
 10  Unit_Cost         34865 non-null  float64
 11  Unit_Price        34865 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(7)
memory usage: 3.5+ MB
```

Out[23]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay O
0	2016-02-19	High	Segun	29	F	Abia	Accessories	Keyboard	(
1	2016-02-20	High	Segun	29	F	Abia	Clothing	Polo shirts	(

In [24]:
```
df['Date'] = pd.to_datetime(df['Date'], format='%d/%m/%Y')
df['Date']
```

Out[24]:
```
0       2016-02-19
1       2016-02-20
2       2016-02-27
3       2016-03-12
4       2016-03-12
           ...
34861   2015-03-22
34862   2016-02-07
34863   2015-03-13
34864   2015-04-05
34865   2015-08-30
Name: Date, Length: 34865, dtype: datetime64[ns]
```

In [25]:
```
# Group Customer Age
#Creating a function
def age_group(x):
    if x <= 25:
        return '<=25 Young Adult'
    elif x <= 40:
        return '25-40 Adult'
    elif x <= 50:
        return '41-50 Old Adult'
    else:
        return '>=51 Elders'

#Apply function to the data
df['age_group'] = df['Customer_Age'].apply(age_group)
df.head(2)
```

Out[25]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay O
0	2016-02-19	High	Segun	29	F	Abia	Accessories	Keyboard	(
1	2016-02-20	High	Segun	29	F	Abia	Clothing	Polo shirts	(

In [26]:
```
# Cost, Revenue, Profit calculations
df['Cost'] = df['Unit_Cost'] * df['Quantity']
df['Revenue'] = df['Unit_Price'] * df['Quantity']
df['Profit'] = df['Revenue'] - df['Cost']

df.head()
```

Out[26]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay O
0	2016-02-19	High	Segun	29	F	Abia	Accessories	Keyboard	(
1	2016-02-20	High	Segun	29	F	Abia	Clothing	Polo shirts	(
2	2016-02-27	High	Segun	29	F	Abia	Accessories	Keyboard	(
3	2016-03-12	High	Segun	29	F	Abia	Accessories	Keyboard	(
4	2016-03-12	High	Segun	29	F	Abia	Accessories	Keyboard	(

In [27]:
```
#Profit/Loss grouping
def PorL (x):
    if x >=0:
        return 'Profit'
    else:
        return 'Loss'
df['Profit_or_Loss_Label'] = df['Profit']. apply(PorL)
df.head()
```

Out[27]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay O
0	2016-02-19	High	Segun	29	F	Abia	Accessories	Keyboard	(
1	2016-02-20	High	Segun	29	F	Abia	Clothing	Polo shirts	(
2	2016-02-27	High	Segun	29	F	Abia	Accessories	Keyboard	(
3	2016-03-12	High	Segun	29	F	Abia	Accessories	Keyboard	(
4	2016-03-12	High	Segun	29	F	Abia	Accessories	Keyboard	(

5 rows × 21 columns

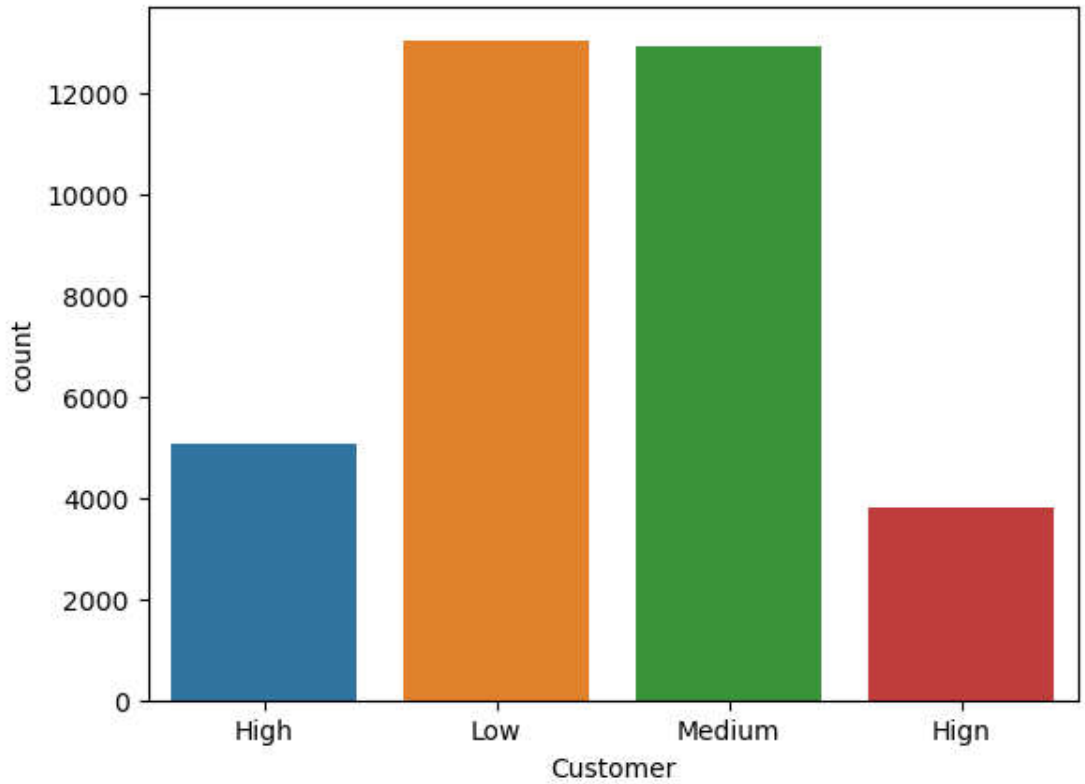
Univariate Analysis

Involves analysing the distribution and summary statistics of individual variables/Column/feature.

- Numerical Column/Feature= Numerical Visulaization Techniques
- Categorical Column/Feature = Categorical Visulaization Techniques

Categorical Data Visualization

In [28]:
```
# How customers belong to each customer spec
sns.countplot(x='Customer', data= df);
```



In [29]:
```
# Investigate the columns affected
df[df['Customer'] == 'Hign'].head(3)
```

Out[29]:

	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category
29770	2015-08-03	Hign	Derick	28	F	Lagos	Phones	IPhone
29771	2015-08-04	Hign	Derick	28	F	Lagos	Accessories	Keyboard
29772	2015-08-04	Hign	Derick	28	F	Lagos	Accessories	Keyboard

3 rows × 21 columns

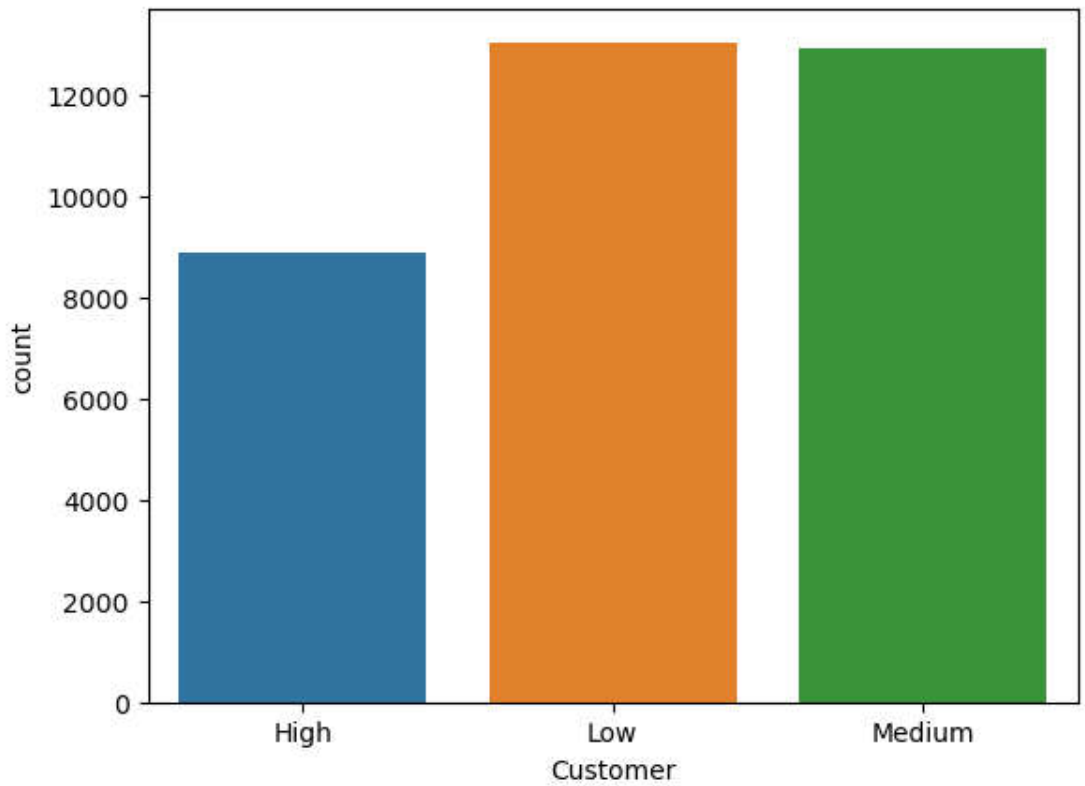
In [30]:
```
#Correct the Spelling of HIGN
df.loc[df['Customer'] == 'Hign', 'Customer'] = 'High'
df.head(2)
```

Out[30]:

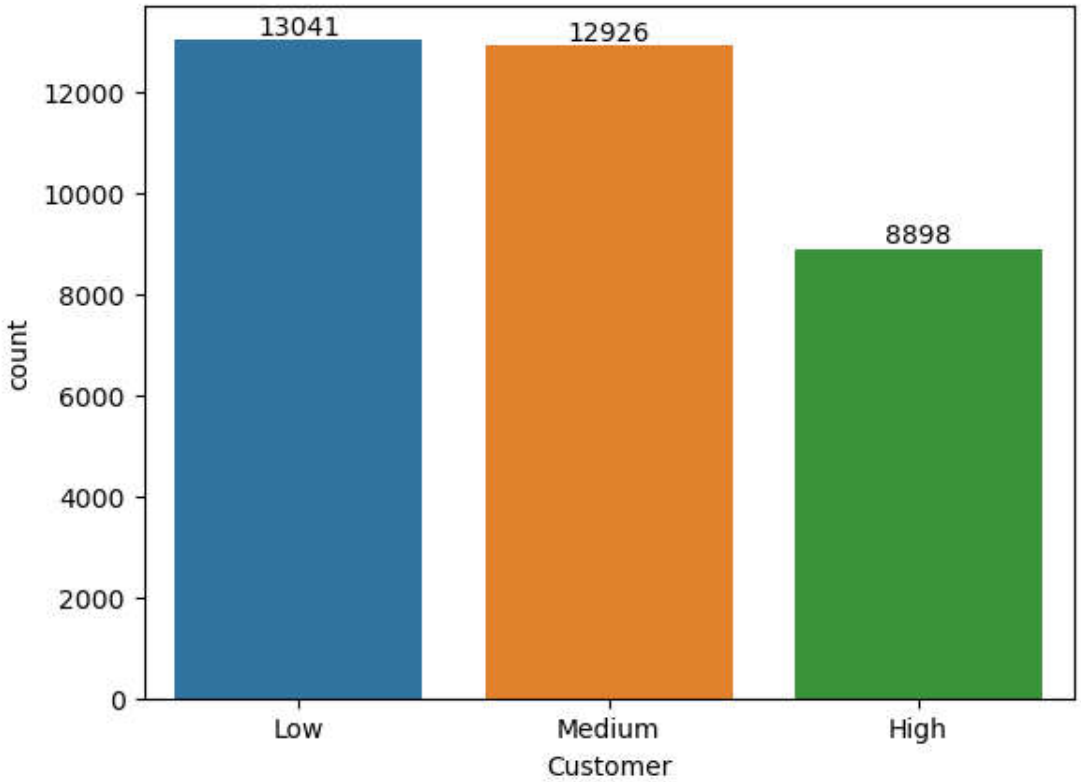
	Date	Customer	Sales Person	Customer_Age	Customer_Gender	State	Product_Category	Sub_Category	Pay O
0	2016-02-19	High	Segun	29	F	Abia	Accessories	Keyboard	(
1	2016-02-20	High	Segun	29	F	Abia	Clothing	Polo shirts	(

2 rows × 21 columns

In [31]:
```
sns.countplot(x= 'Customer', data= df);
```



In [32]:
```
ax = sns.countplot(x=df['Customer'], order=df['Customer'].value_counts(ascending=False)
ax;
values = df['Customer'].value_counts(ascending= False).values
ax.bar_label(container= ax.containers[0], labels=values);
```



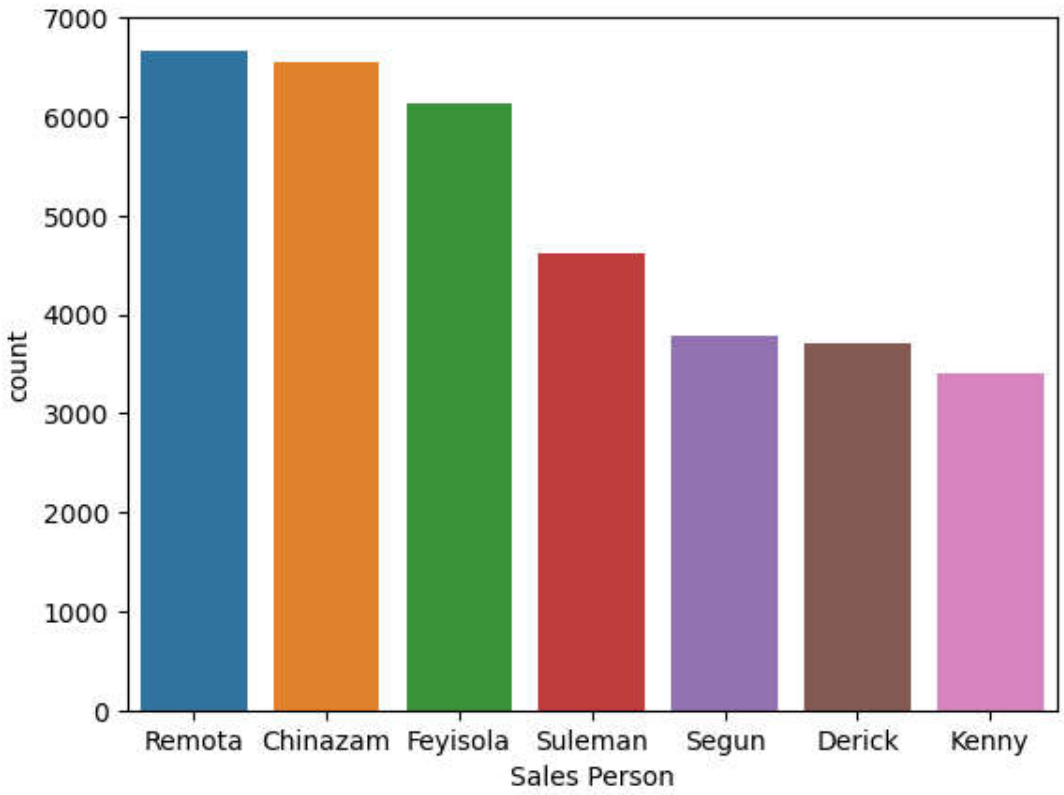
Narration about your Observations

- Looking at the bar plot, I observed that majority of the customers fall within the range of low group.

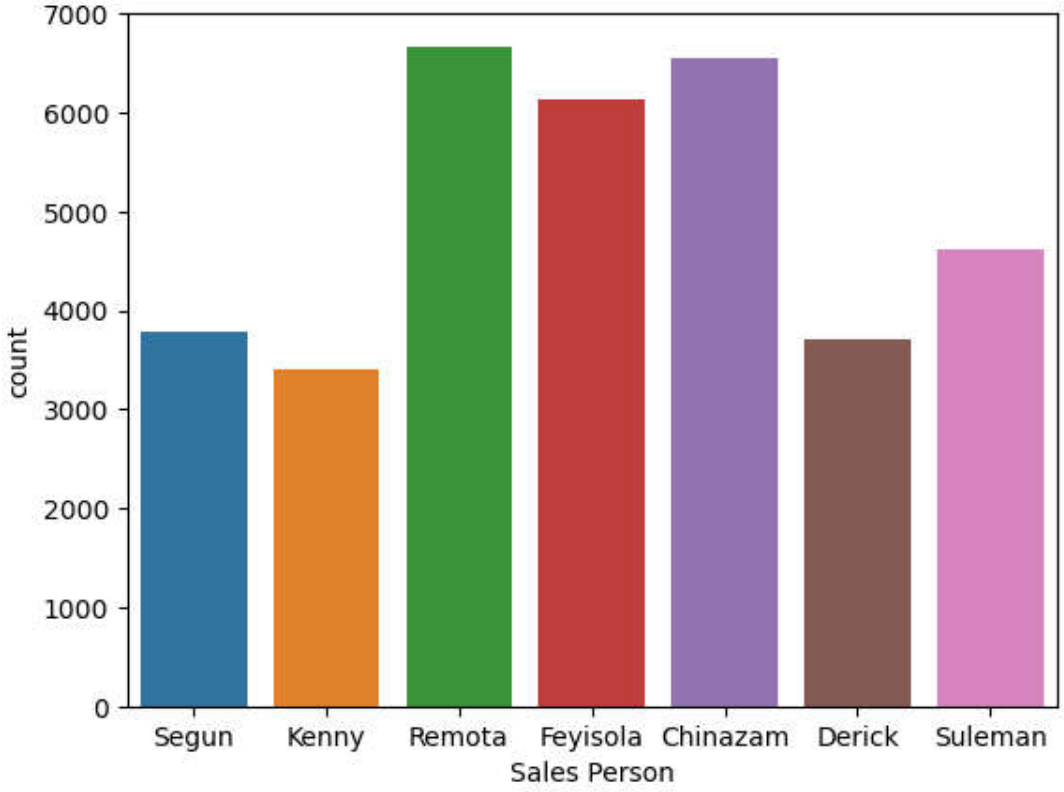
In [33]:
```
df['Customer'].value_counts()
```

Out[33]:
```
Low       13041
Medium    12926
High       8898
Name: Customer, dtype: int64
```

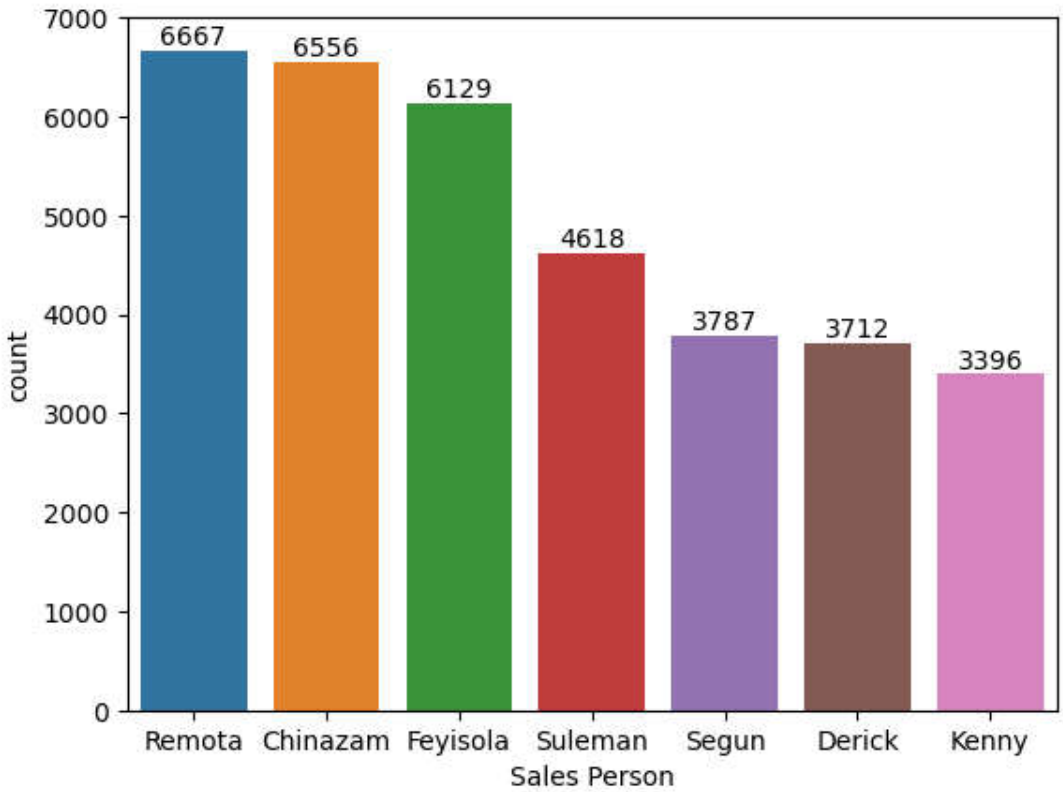
In [34]:
```
# Sales Person - How many transaction by sales person
ax = sns.countplot(x=df['Sales Person'], order=df['Sales Person'].value_counts(ascendin
ax;
```



In [35]:
```
sns.countplot(x= 'Sales Person', data= df);
```



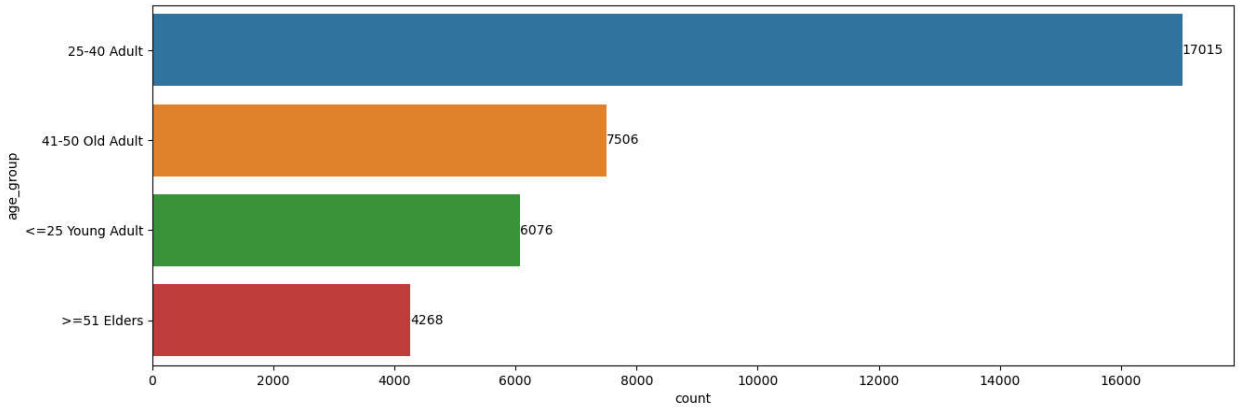
In [36]:
```
ax = sns.countplot(x= df['Sales Person'], data= df, order=df['Sales Person'].value_coun
values = df['Sales Person'].value_counts(ascending= False).values
ax.bar_label(container= ax.containers[0], labels=values);
```



Narration about your Observations

- Remota has the most transactions completed and Kenny has the least.

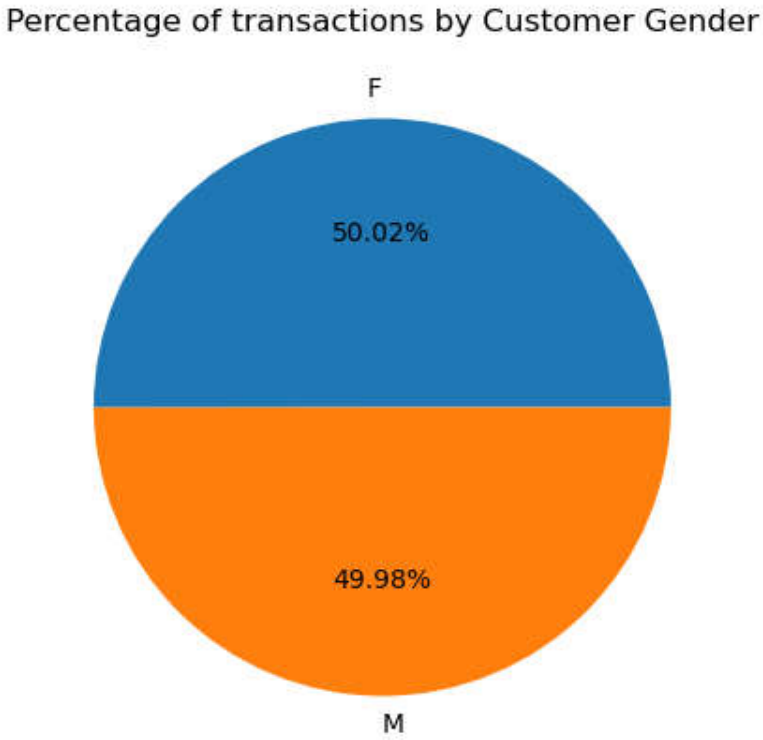
In [37]:
```
#Total transactions by customer Age Group
#to increase the size of the graph
plt.figure(figsize= (15,5))

ax = sns.countplot(y= df['age_group'], data= df, order=df['age_group'].value_counts(asc
values = df['age_group'].value_counts(ascending= False).values
ax.bar_label(container= ax.containers[0], labels=values);
```



Narration about your Observations

- Majority of the transaction are coming from the Adult between the ages of 25-40.

In [38]:
```
# Total transaction by Customer Gender

fig,ax = plt.subplots(figsize=(5,5))
count = Counter(df['Customer_Gender'])
ax.pie(count.values(), labels=count.keys(), autopct=lambda p:f'{p:.2f}%')
ax.set_title("Percentage of transactions by Customer Gender")
plt.show;
```

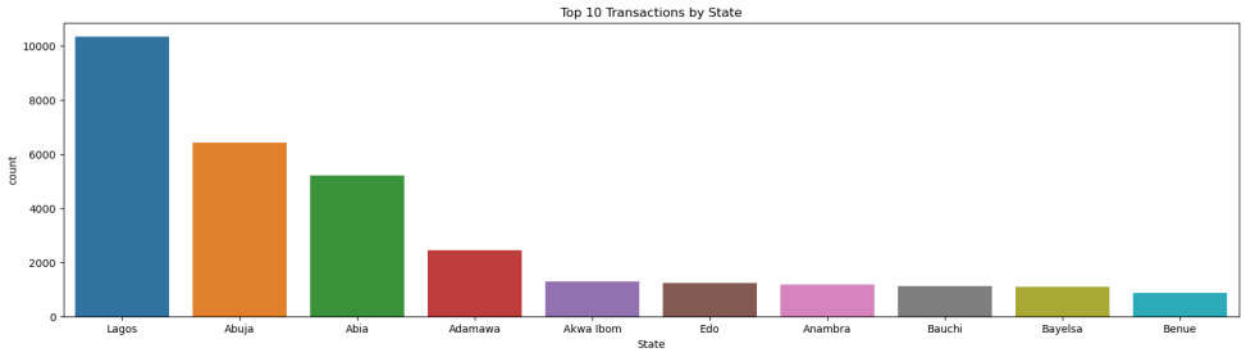


Narration about your Observations

- Majority of the transactions are coming from the Female.

In [39]:
```
# Total 10 transaction by State
plt.figure(figsize=(20,5))

topten = df['State'].value_counts().head(10)
sns.countplot(x= 'State', data=df, order=topten.index)
plt.title('Top 10 Transactions by State')
print(topten);
```

```
Lagos        10332
Abuja         6421
Abia          5206
Adamawa       2446
Akwa Ibom     1287
Edo           1229
Anambra       1171
Bauchi        1112
Bayelsa       1092
Benue          869
Name: State, dtype: int64
```



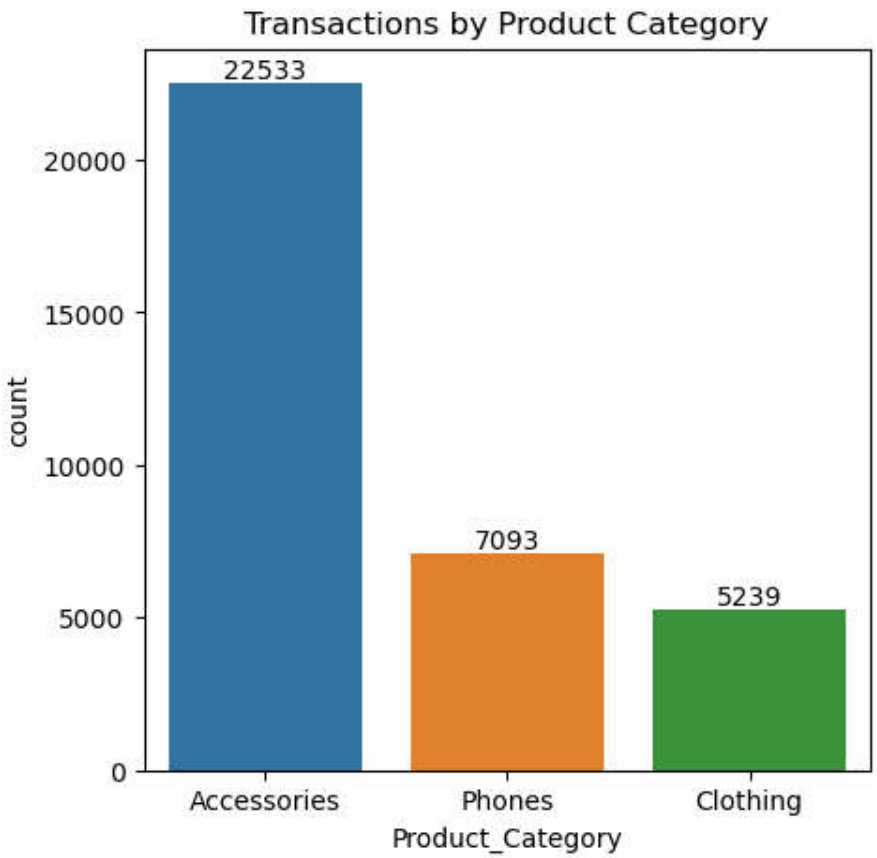
Narration about your Observations

- Majority of the transaction are coming from Lagos followed by Abuja, then Abia.

In [40]:
```
# Product Category
df['Product Category'].unique()
```

Out[40]:
```
array(['Accessories', 'Clothing', 'Phones'], dtype=object)
```

In [41]:
```
plt.figure(figsize= (5,5))

ax = sns.countplot(x= df['Product_Category'], data= df, order=df['Product_Category'].va
values = df['Product_Category'].value_counts(ascending= False).values
ax.bar_label(container= ax.containers[0], labels=values)
plt.title('Transactions by Product Category');
```



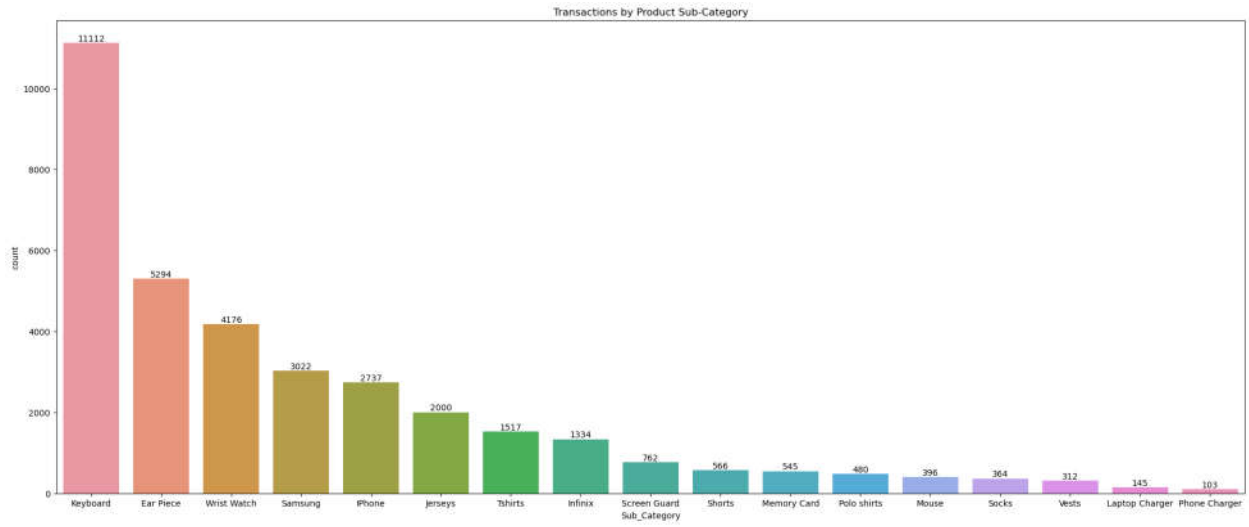
Narration about your Observations

- More accessories were purchased followed by Phones and then clothing.

In [42]:
```
#Sub Category
df['Sub_Category'].unique()
```

Out[42]:
```
array(['Keyboard', 'Polo shirts', 'Wrist Watch', 'Laptop Charger',
       'IPhone', 'Mouse', 'Jerseys', 'Screen Guard', 'Memory Card',
       'Socks', 'Tshirts', 'Infinix', 'Ear Piece', 'Vests', 'Samsung',
       'Phone Charger', 'Shorts'], dtype=object)
```

In [43]:
```
plt.figure(figsize= (25,10))

ax = sns.countplot(x= df['Sub_Category'], data= df, order=df['Sub_Category'].value_coun
values = df['Sub_Category'].value_counts(ascending= False).values
ax.bar_label(container= ax.containers[0], labels=values)
plt.title('Transactions by Product Sub-Category');
```



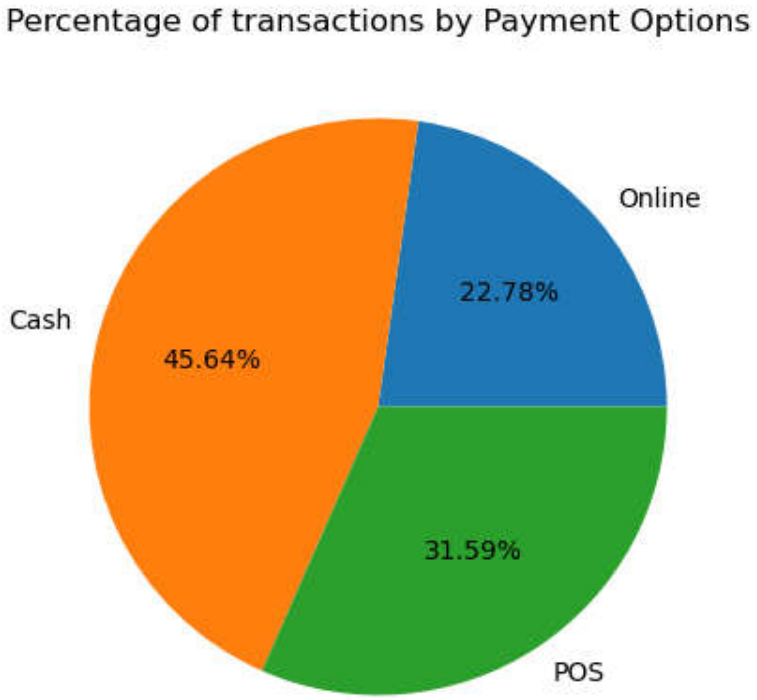
In [44]:
```
df.columns
```

Out[44]:
```
Index(['Date', 'Customer', 'Sales Person', 'Customer_Age', 'Customer_Gender',
       'State', 'Product_Category', 'Sub_Category', 'Payment Option',
       'Quantity', 'Unit_Cost', 'Unit_Price', 'year', 'month', 'month_name',
       'quarter', 'age_group', 'Cost', 'Revenue', 'Profit',
       'Profit_or_Loss_Label'],
      dtype='object')
```

In [45]:
```
#Payment Option
df['Payment Option'].unique()
```

Out[45]:
```
array(['Online', 'Cash', 'POS'], dtype=object)
```

In [46]:
```
fig,ax = plt.subplots(figsize=(5,5))
count = Counter(df['Payment Option'])
ax.pie(count.values(), labels=count.keys(), autopct=lambda p:f'{p:.2f}%')
ax.set_title("Percentage of transactions by Payment Options")
plt.show();
```

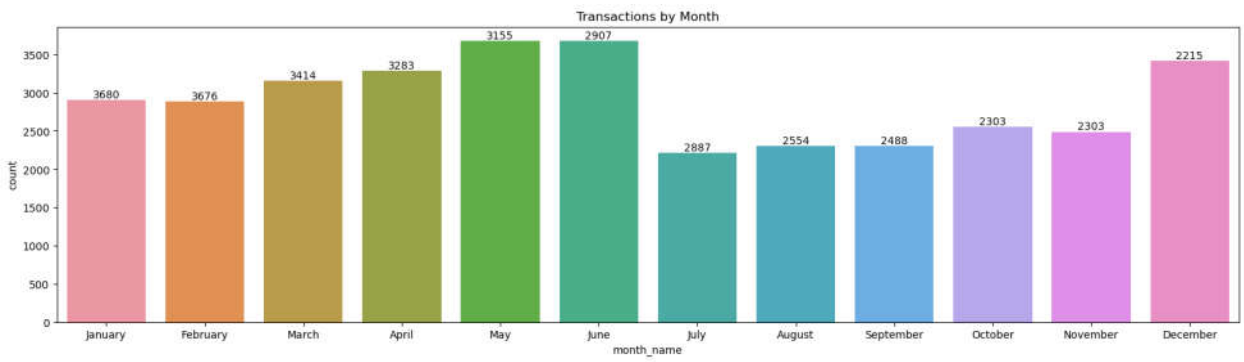


In [47]:
```
#Month Name
df['month_name'].unique()
```

Out[47]:
```
array(['February', 'March', 'April', 'June', 'July', 'August',
       'September', 'October', 'November', 'December', 'May', 'January'],
      dtype=object)
```

In [48]:
```
#Transactions by Month.
plt.figure(figsize=(20,5))

month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August'

ax= sns.countplot(x='month_name', data=df, order=month_order)
plt.title('Transactions by Month')

values = df['month_name'].value_counts().head(12)
ax.bar_label(container= ax.containers[0], labels=values)
print (values);
```

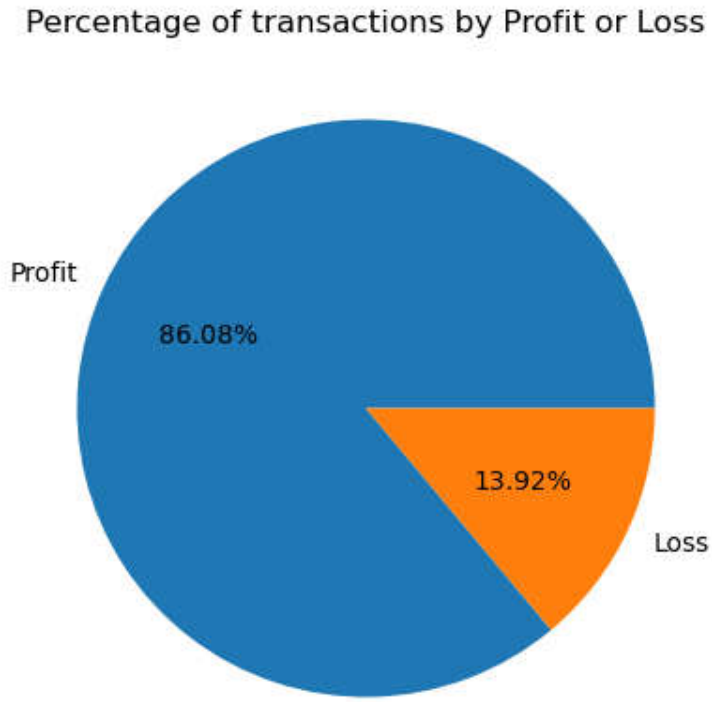
```
June         3680
May          3676
December     3414
April        3283
March        3155
January      2907
February     2887
October      2554
November     2488
August       2303
September    2303
July         2215
Name: month_name, dtype: int64
```



Narration about your Observations

- The highest transactions occured in June, followed by May, then December. The least occured in July.

In [49]:
```
# Total transaction by Profit or Loss

fig,ax = plt.subplots(figsize=(5,5))
count = Counter(df['Profit_or_Loss_Label'])
ax.pie(count.values(), labels=count.keys(), autopct=lambda p:f'{p:.2f}%')
ax.set_title("Percentage of transactions by Profit or Loss")
plt.show();
```

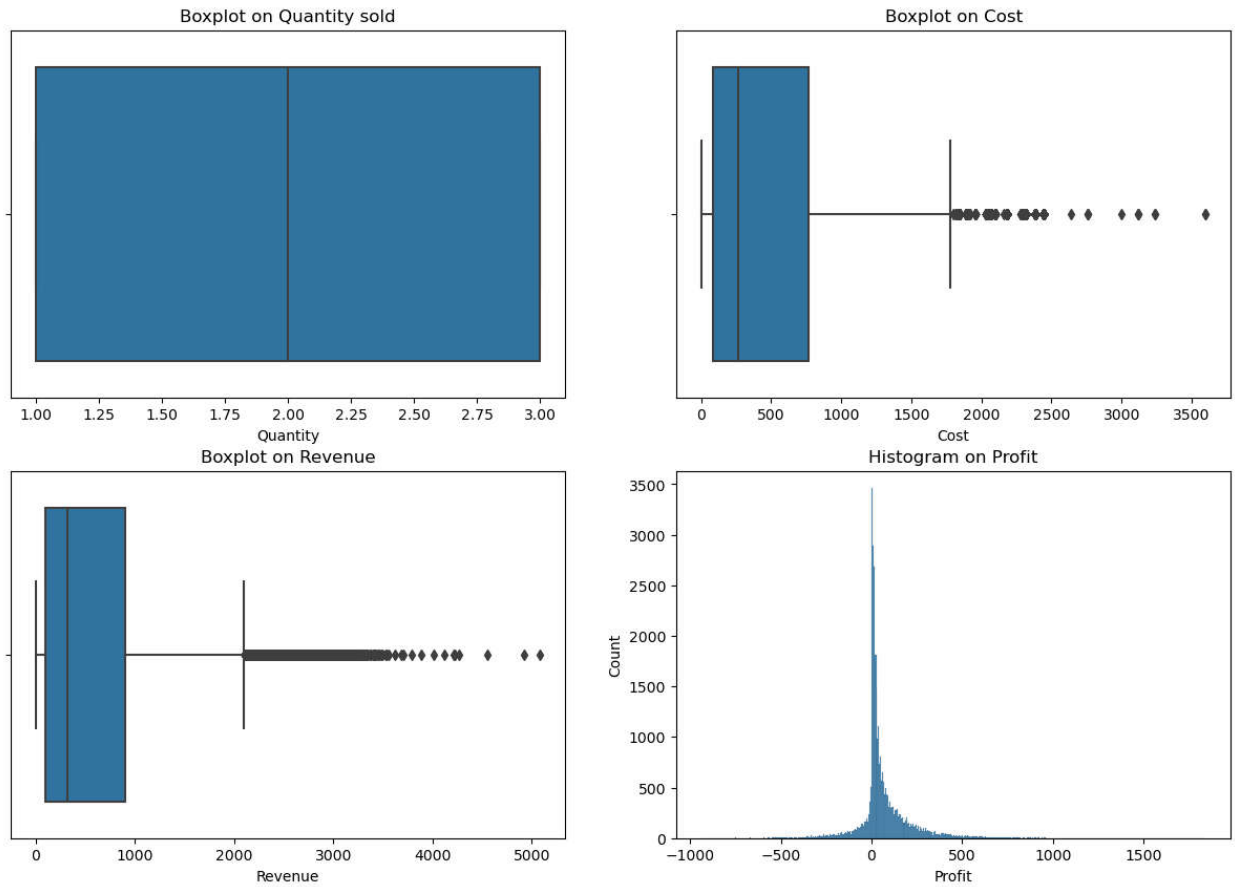


Narration about your Observations

- 86.08% of the transactions yielded into Profit while 13.92% yielded into Loss.

**** Numerical Data Visualization ***

In [50]:
```
# Quantity, Cost, Revenue and Profit - Subplot (Boxplot, scatterplot, histogram)

fig, axs= plt.subplots(nrows=2, ncols=2, figsize=(15,10))

sns.boxplot( x= 'Quantity', y=None, hue=None, data=df, ax=axs[0,0])
axs[0,0].set_title('Boxplot on Quantity sold')

sns.boxplot( x= 'Cost', y=None, hue=None, data=df, ax=axs[0,1])
axs[0,1].set_title('Boxplot on Cost')

sns.boxplot( x= 'Revenue', y=None, hue=None, data=df, ax=axs[1,0])
axs[1,0].set_title('Boxplot on Revenue')

sns.histplot( x= 'Profit', y=None, hue=None, data=df, ax=axs[1,1])
axs[1,1].set_title('Histogram on Profit');
```



Narration about your Observations

- The boxplot shows the distribution of the quantity sold in the data. From the boxplot, we can see that the median quantity sold is around 2.0. There are no outliers in the data.
- The boxplot shows the distribution of the cost price in the data. From the boxplot, we can see that the median cost price is 261. There are some outliers in the data, which indicates that there might be some extremely high cost.
- Based on the Revenue boxplot, it appears that there are several outliers in the upper range of the revenue values, suggesting that there may be a few transactions that generated a significantly higher revenue than the rest. The median revenue value appears to be around 318. Overall, the plot suggests that there is some variation in the revenue generated by transactions in the dataset, with a few transactions generating significantly higher revenue than the rest.

- The histogram plot of Profit shows the distribution of profit in the dataset. From the plot, it can be observed that there are some losses and also some profits. The majority of the profits fall between -500 and 1,000. Additionally, there seems to be some outliers on the right side of the plot, indicating that there are more profits than losses in the dataset. However, the plot does not show any information about the frequency or counts of the profits, so it is difficult to draw precise conclusions without

In [51]:
```
df['Cost'].median()
```

Out[51]:
```
261.0
```

In [52]:
```
df['Revenue'].median()
```

Out[52]:
```
318.99
```

In [ ]:
```

```

Bivariate Analysis

Bivariate analysis involves analyzing the relationship between two variables.

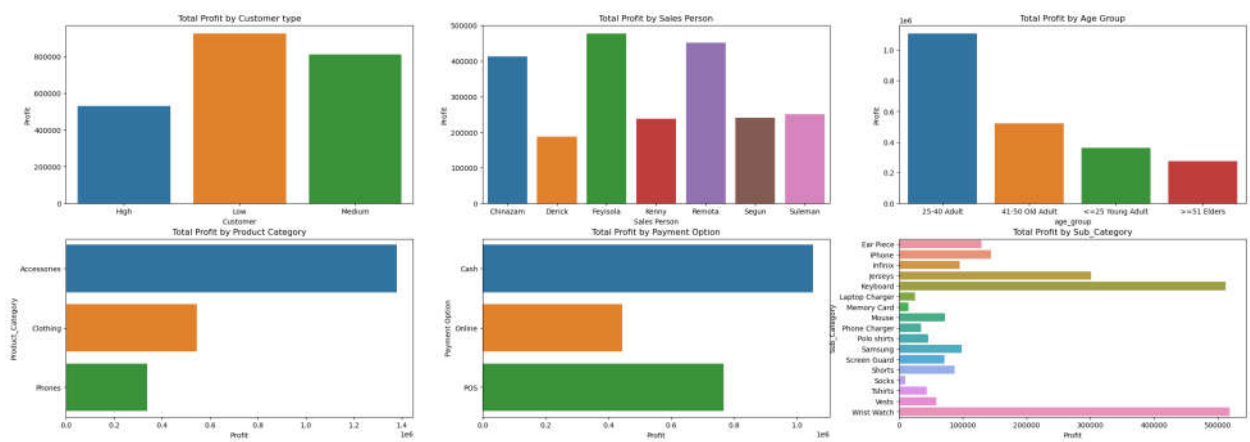
- Focus on Profit

In [53]:
```
df.columns
```

Out[53]:
```
Index(['Date', 'Customer', 'Sales Person', 'Customer_Age', 'Customer_Gender',
       'State', 'Product_Category', 'Sub_Category', 'Payment Option',
       'Quantity', 'Unit_Cost', 'Unit_Price', 'year', 'month', 'month_name',
       'quarter', 'age_group', 'Cost', 'Revenue', 'Profit',
       'Profit_or_Loss_Label'],
      dtype='object')
```

In [54]:
```
#Categorical Columns

fig, axs= plt.subplots(nrows=2, ncols=3, figsize=(30,10))

cust_prof =df.groupby('Customer')['Profit'].sum().reset_index()
sns.barplot(x='Customer', data= cust_prof, y= 'Profit', ax=axs[0,0])
axs[0,0].set_title('Total Profit by Customer type')

sp_prof =df.groupby('Sales Person')['Profit'].sum().reset_index()
sns.barplot(x='Sales Person', data= sp_prof, y= 'Profit', ax=axs[0,1])
axs[0,1].set_title('Total Profit by Sales Person')

ag_prof =df.groupby('age_group')['Profit'].sum().reset_index()
sns.barplot(x='age_group', data= ag_prof, y= 'Profit', ax=axs[0,2])
axs[0,2].set_title('Total Profit by Age Group')

pc_prof =df.groupby('Product_Category')['Profit'].sum().reset_index()
sns.barplot(y='Product_Category', data= pc_prof, x= 'Profit', ax=axs[1,0])
axs[1,0].set_title('Total Profit by Product Category')

po_prof =df.groupby('Payment Option')['Profit'].sum().reset_index()
sns.barplot(y='Payment Option', data= po_prof,x= 'Profit', ax=axs[1,1])
axs[1,1].set_title('Total Profit by Payment Option')

sc_prof =df.groupby('Sub_Category')['Profit'].sum().reset_index()
sns.barplot(y='Sub_Category', data= sc_prof, x= 'Profit', ax=axs[1,2])
axs[1,2].set_title('Total Profit by Sub_Category')
;
```

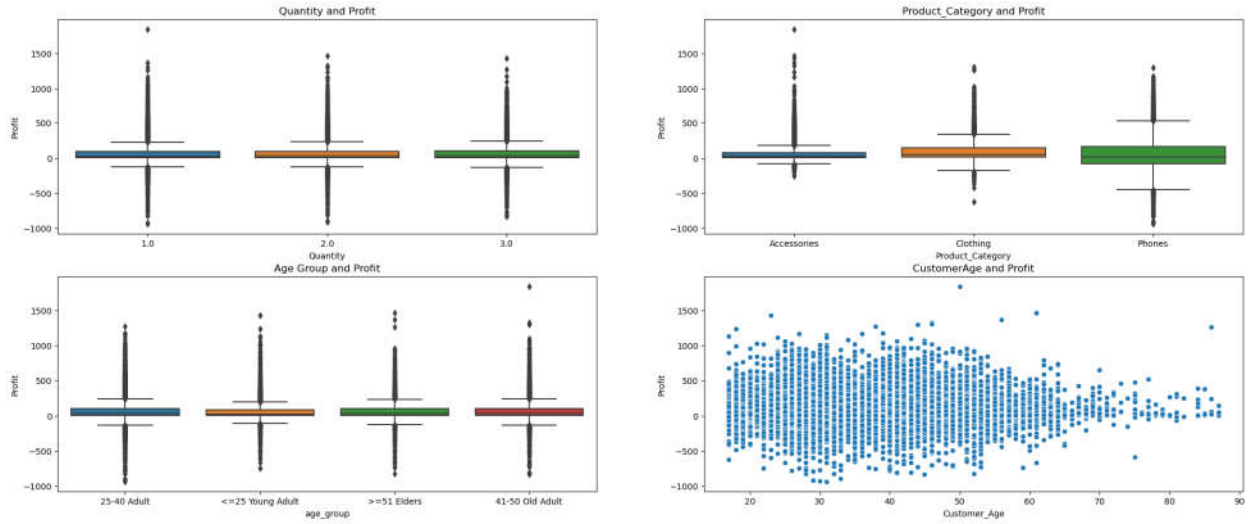
Out[54]: ''



Narration about your Observations

- .

In [55]:
```
# Numerical Columns

fig, axs = plt.subplots(nrows= 2, ncols= 2, figsize=(25,10))

sns.boxplot(x='Quantity', y='Profit', data=df, ax=axs[0,0])
axs[0,0].set_title("Quantity and Profit");

sns.boxplot(x='Product_Category', y='Profit', data=df, ax=axs[0,1])
axs[0,1].set_title("Product_Category and Profit");

sns.boxplot(x='age_group', y='Profit', data=df, ax=axs[1,0])
axs[1,0].set_title("Age Group and Profit");

sns.scatterplot(x='Customer_Age', y='Profit', data=df, ax=axs[1,1])
axs[1,1].set_title("CustomerAge and Profit");
```



The first chart (boxplot on Quantity and Profit) shows that as the quantity increases, the profit also tends to increase. There are a few outliers in the high profit region, which might be due to some special factors or reasons.

The second chart (boxplot on Product_Category and Profit) shows that some product categories have higher profits compared to others. For example, product category "Accessories" has a higher median profit compared to other categories. However, there are some outliers in the low profit region, which might need to be investigated.

The third chart (boxplot on Age Group and Profit) shows that age group does not have a significant impact on the profit. All age groups have a similar distribution of profit, with a few outliers in the high profit region.

The fourth chart (scatterplot on CustomerAge and Profit) shows that there is no strong correlation between customer age and profit. The scatterplot is evenly distributed with no clear trend or pattern.

Multivariate Analysis

It involves analyzing the relationship between three or more variables

In [56]:
```
df.columns
```

Out[56]:
```
Index(['Date', 'Customer', 'Sales Person', 'Customer_Age', 'Customer_Gender',
       'State', 'Product_Category', 'Sub_Category', 'Payment Option',
       'Quantity', 'Unit_Cost', 'Unit_Price', 'year', 'month', 'month_name',
       'quarter', 'age_group', 'Cost', 'Revenue', 'Profit',
       'Profit_or_Loss_Label'],
      dtype='object')
```

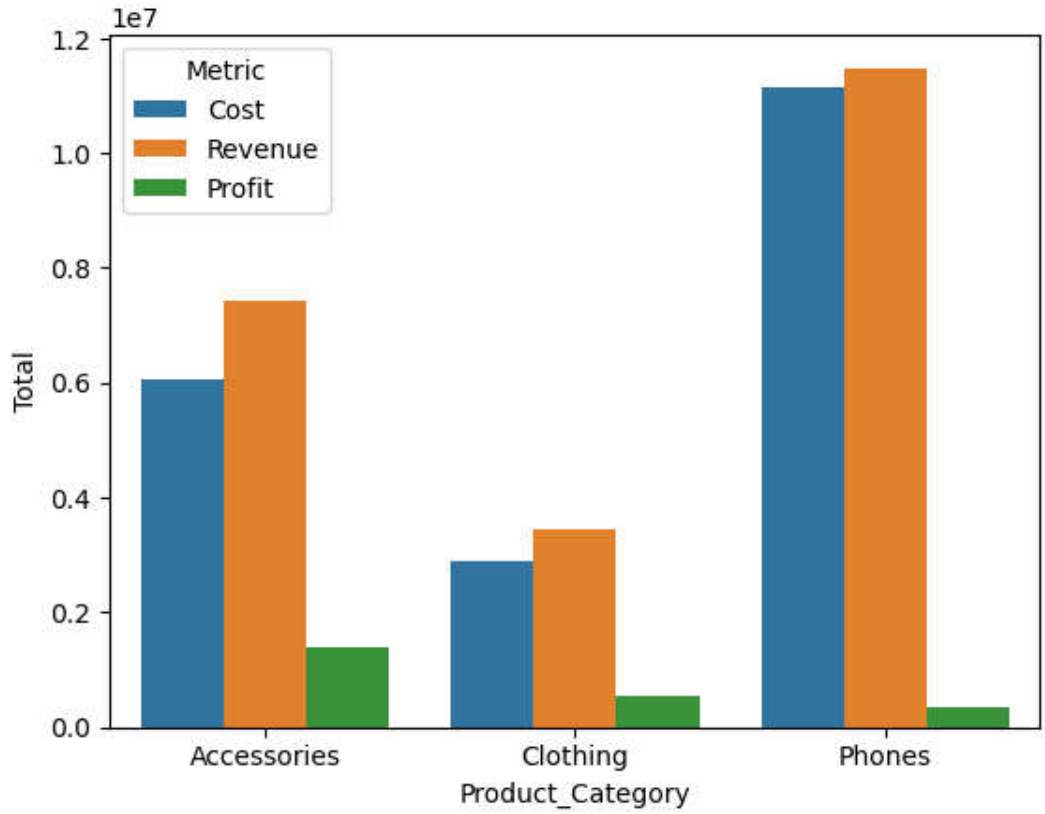
In [57]:
```
# Product category against Cost, Revenue and Profit

procat= df.groupby('Product_Category')[['Cost', 'Revenue', 'Profit']].sum().reset_index
procat1 = pd.melt(procat, id_vars= 'Product_Category', var_name= 'Metric', value_name=
```

In [58]:
```
procat1
```

Out[58]:

	Product_Category	Metric	Total
0	Accessories	Cost	6041876.06
1	Clothing	Cost	2892324.94
2	Phones	Cost	11148745.02
3	Accessories	Revenue	7420635.12
4	Clothing	Revenue	3437556.95
5	Phones	Revenue	11486354.63
6	Accessories	Profit	1378759.06
7	Clothing	Profit	545232.01
8	Phones	Profit	337609.61

In [59]:
```
sns.barplot(data=procat1, x='Product Category', y= 'Total', hue= 'Metric');
```



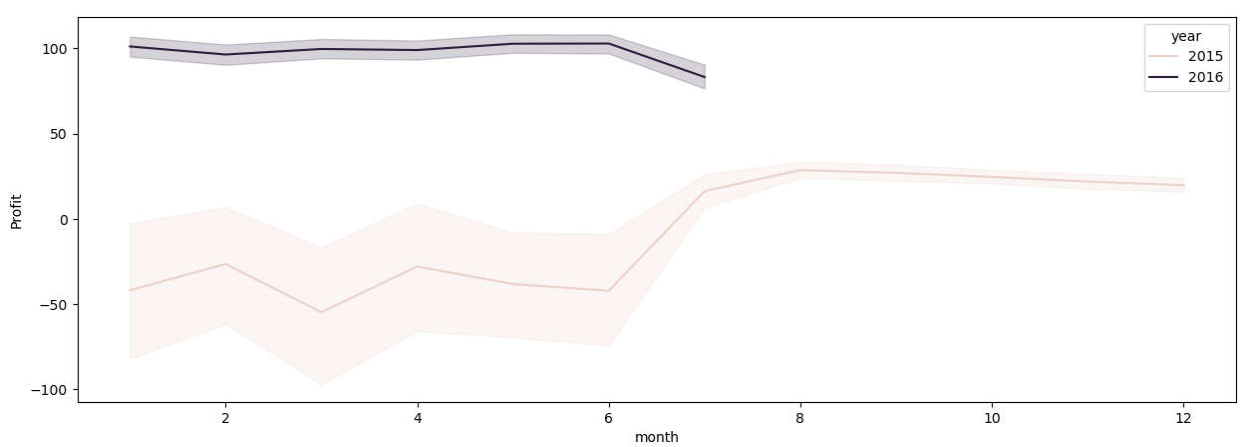
Narration about my observations

1 The largest profit made are from accessories.

2 Although, the highest cost and revenue were incurred on Phones, small profit are obtained from Phones.

3 The least cost was incurred on Clothing with a higher profit compared to Phones.

In [62]:
```
plt.figure(figsize= (15,5))
sns.lineplot(x='month', y='Profit', data=df, hue='year');
```



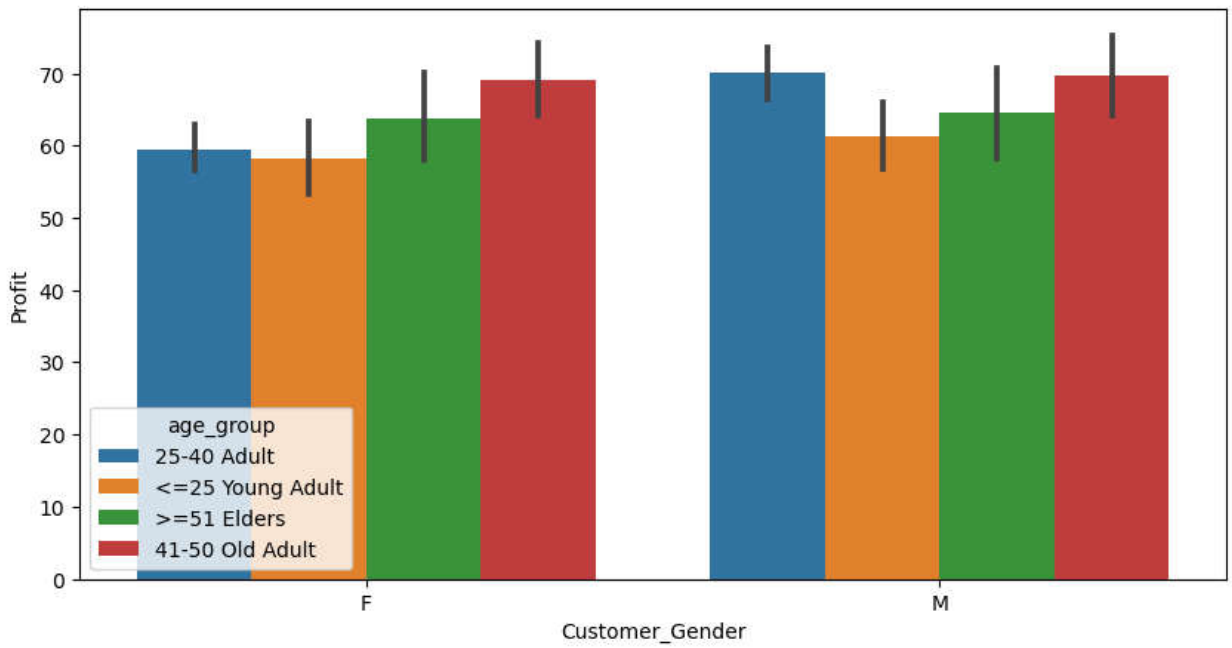
In [64]:
```
# Using pivot table
df.pivot_table(values= 'Profit', index= 'year', columns= 'month', aggfunc= 'sum')
```

Out[64]:

month	1	2	3	4	5	6	7	8	9	
year										
2015	-5778.70	-4079.65	-8163.79	-4945.69	-7801.45	-8690.61	15104.47	65918.24	62172.33	62
2016	280204.25	263640.18	299777.67	307746.51	356915.59	357549.86	107151.79	NaN	NaN	

Narration about your observations

In [75]:
```
# Customer Gender, Age Group amd Profit
plt.figure(figsize= (10,5))
sns.barplot(x= 'Customer_Gender', y= 'Profit', data=df, hue= 'age_group');
```



In [69]:
```
# Using pivot table to view the valuse for the chart above
df.pivot_table(values= 'Profit', index= 'Customer_Gender', columns= 'age_group', aggfun
```

Out[69]:

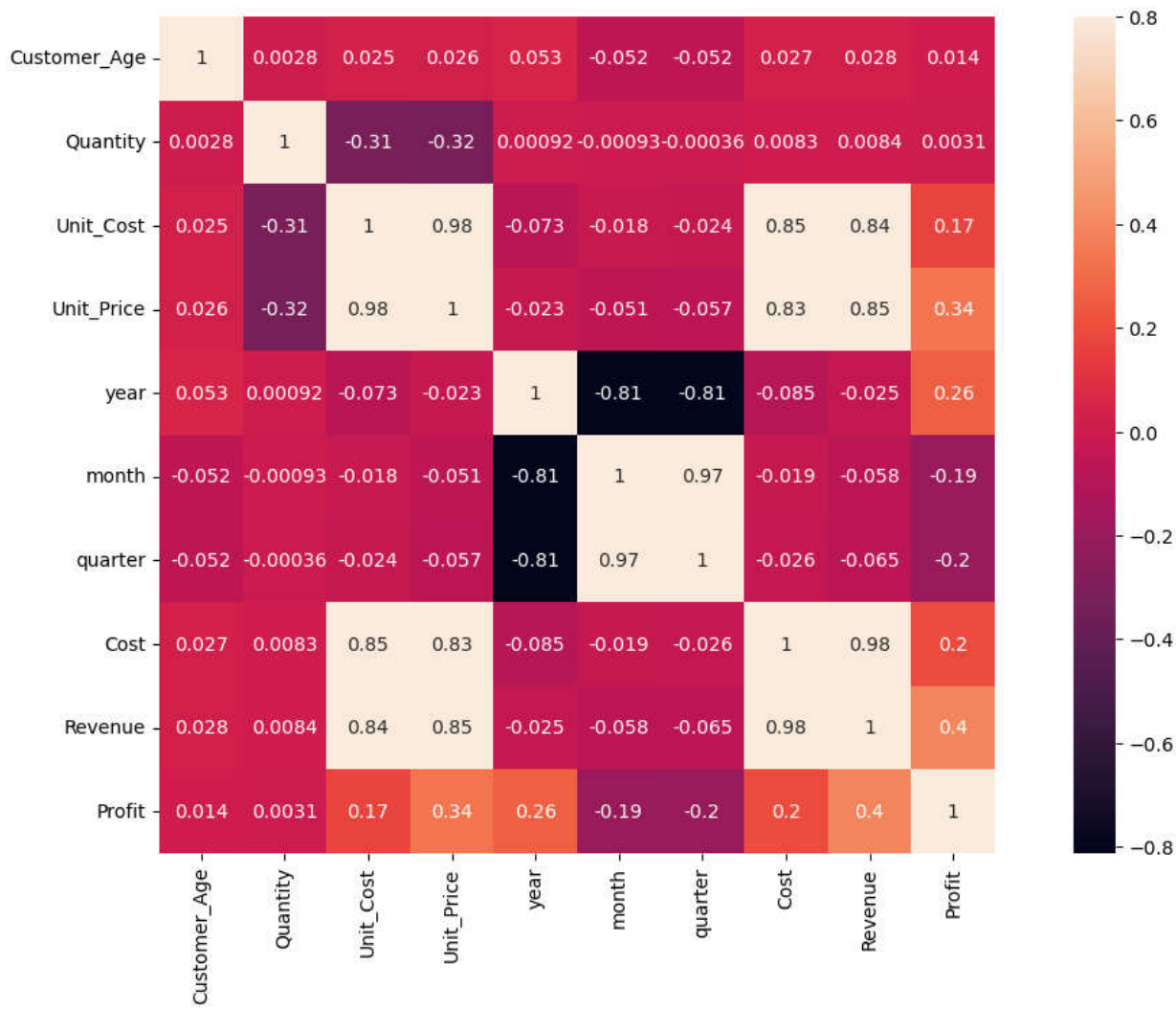
age_group	25-40 Adult	41-50 Old Adult	<=25 Young Adult	>=51 Elders
Customer_Gender				
F	509089.54	261011.12	169959.46	140191.10
M	593853.62	259447.64	194125.09	133923.11

In [70]:
```
# Correlation
a=df.corr()
a
```

Out[70]:

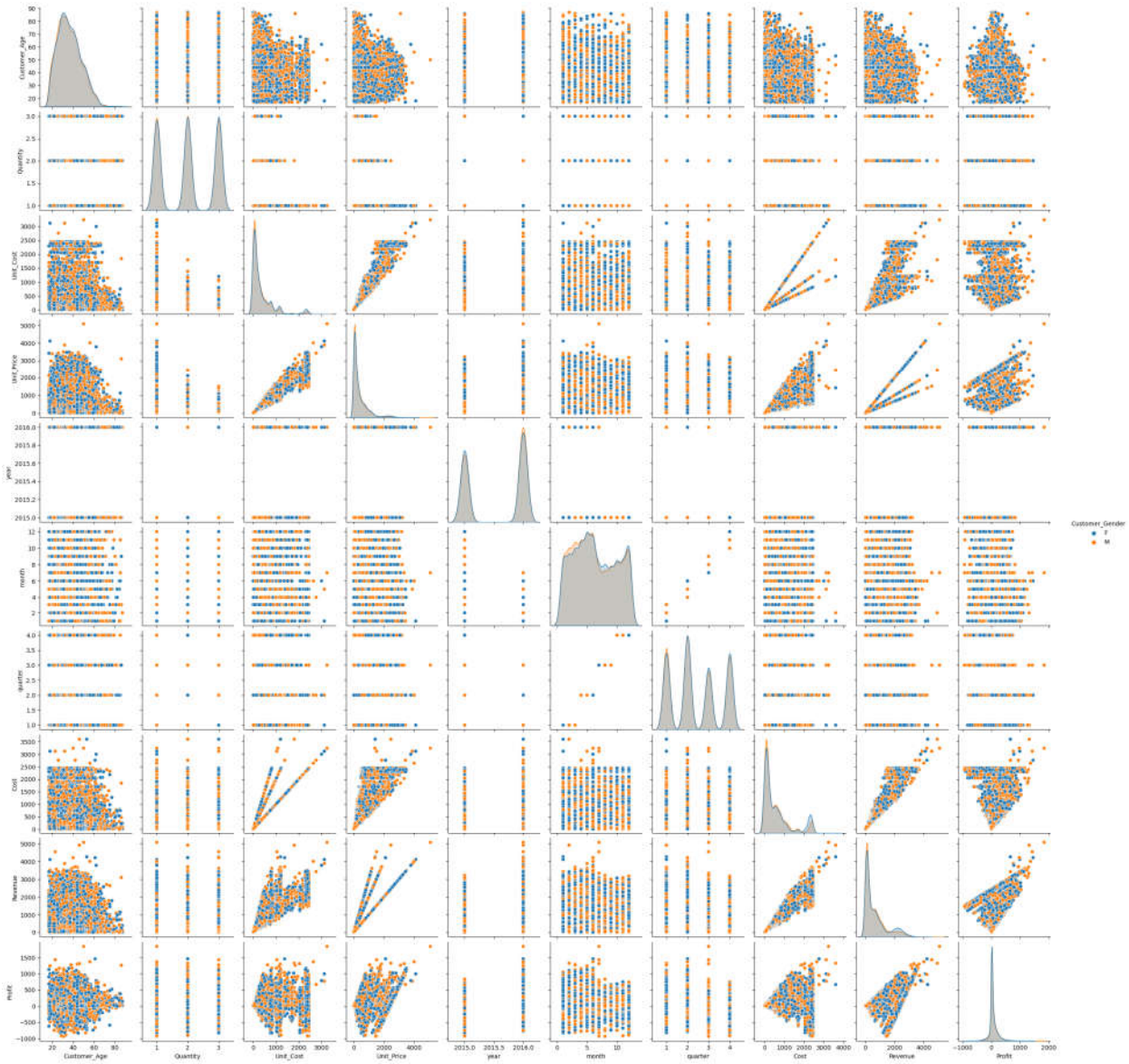
	Customer_Age	Quantity	Unit_Cost	Unit_Price	year	month	quarter	Cost
Customer_Age	1.000000	0.002801	0.025372	0.026312	0.052709	-0.051619	-0.051942	0.026551
Quantity	0.002801	1.000000	-0.312516	-0.324111	0.000918	-0.000925	-0.000358	0.008295
Unit_Cost	0.025372	-0.312516	1.000000	0.981032	-0.073270	-0.018375	-0.024215	0.854906
Unit_Price	0.026312	-0.324111	0.981032	1.000000	-0.022653	-0.051439	-0.057173	0.832966
year	0.052709	0.000918	-0.073270	-0.022653	1.000000	-0.810664	-0.812495	-0.084595
month	-0.051619	-0.000925	-0.018375	-0.051439	-0.810664	1.000000	0.971628	-0.019334
quarter	-0.051942	-0.000358	-0.024215	-0.057173	-0.812495	0.971628	1.000000	-0.026178
Cost	0.026551	0.008295	0.854906	0.832966	-0.084595	-0.019334	-0.026178	1.000000
Revenue	0.027777	0.008418	0.836954	0.851031	-0.025389	-0.058450	-0.065212	0.979119
Profit	0.013921	0.003097	0.171570	0.338494	0.259743	-0.194317	-0.195985	0.201254

In [71]:
```
a=df.corr()
plt.figure(figsize= (15,8))
sns.heatmap(a, vmax=.8, square= True, annot= True);
```



Narration about your observations

There is a high positive correlation between cost and revenue, unit price and unit cost.

In [76]:
```
#Pairplot only looks a numerical columns
sns.pairplot(df, size= 2.5, hue= 'Customer_Gender');
```

```
C:\Users\EZ FARMING\Anaconda\lib\site-packages\seaborn\axisgrid.py:2076: UserWarning:
The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```