CUSTOMER SEGMENTATION USING RFM MODELLING

In [1]:
```
### Import Libraries and Load Data
import pandas as pd
import datetime as dt
from sklearn.cluster import KMeans

# For data visualization
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_excel(r"C:\Users\ADMIN\Desktop\Customer Segmentation Project\Sterling E-Commerce Data - Customer Segmentat
df.head()
```

Out[2]:

	Category	City	County	Cust Id	Customer Since	Date of Order	Full Name	Gender	Item Id	Order Id	Payment Method	Place Name	Ref Num	Regi
0	Health & Sports	Bode	Humboldt	112285	2008-02-11	2022-08-07	Renaud, Maudie	F	880913	100547952.0	Easypay_MA	Bode	352808	Midwe
1	Men's Fashion	Belleville	St. Clair	112386	2005-06-23	2022-08-08	Shimp, Mariela	F	881493	100548328.0	Easypay_MA	Belleville	310849	Midwe
2	Men's Fashion	Belleville	St. Clair	112386	2005-06-23	2022-08-08	Shimp, Mariela	F	881492	100548328.0	Easypay_MA	Belleville	310849	Midwe
3	Computing	Young America	Carver	112501	2013-09-15	2022-08-18	Doiron, Latrina	F	886067	100551079.0	Payaxis	Young America	578056	Midwe
4	Entertainment	Young America	Carver	112501	2013-09-15	2022-08-20	Doiron, Latrina	F	886878	100551618.0	Payaxis	Young America	578056	Midwe

In [3]:
```
df.tail()
```

Out[3]:

	Category	City	County	Cust Id	Customer Since	Date of Order	Full Name	Gender	Item Id	Order Id	Payment Method	Place Name	Ref Num	Re
283078	Women's Fashion	Burkettsville	Mercer	81251	2013-10-15	2021-12-30	Kester, Apolonia	F	700522	100428972.0	cod	Burkettsville	572291	Mi
283079	Women's Fashion	Burkettsville	Mercer	81251	2013-10-15	2021-12-30	Kester, Apolonia	F	700518	100428972.0	cod	Burkettsville	572291	Mi
283080	Women's Fashion	Burkettsville	Mercer	81251	2013-10-15	2021-12-30	Kester, Apolonia	F	700520	100428972.0	cod	Burkettsville	572291	Mi
283081	Women's Fashion	Burkettsville	Mercer	81251	2013-10-15	2021-12-30	Kester, Apolonia	F	700517	100428972.0	cod	Burkettsville	572291	Mi
283082	Women's Fashion	Burkettsville	Mercer	81251	2013-10-15	2021-12-30	Kester, Apolonia	F	700519	100428972.0	cod	Burkettsville	572291	Mi

In [4]:
```
# fixing columns names
df.columns =[c.replace(" ", "_") for c in df.columns] # replace empty space between names with underscore
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 283083 entries, 0 to 283082
Data columns (total 19 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Category        283083 non-null  object
 1   City            283083 non-null  object
 2   County          283083 non-null  object
 3   Cust_Id         283083 non-null  int64
 4   Customer_Since  283083 non-null  datetime64[ns]
 5   Date_of_Order   283083 non-null  datetime64[ns]
 6   Full_Name       283083 non-null  object
 7   Gender          283083 non-null  object
 8   Item_Id         283083 non-null  int64
 9   Order_Id        283078 non-null  float64
 10  Payment_Method  283083 non-null  object
 11  Place_Name      283083 non-null  object
 12  Ref_Num         283083 non-null  int64
 13  Region          283083 non-null  object
 14  State           283083 non-null  object
 15  User_Name       283083 non-null  object
 16  Zip             283083 non-null  int64
 17  Qty_Ordered     283083 non-null  int64
 18  Total           283083 non-null  float64
dtypes: datetime64[ns](2), float64(2), int64(5), object(10)
memory usage: 41.0+ MB
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Category', 'City', 'County', 'Cust_Id', 'Customer_Since',
       'Date_of_Order', 'Full_Name', 'Gender', 'Item_Id', 'Order_Id',
       'Payment_Method', 'Place_Name', 'Ref_Num', 'Region', 'State',
       'User_Name', 'Zip', 'Qty_Ordered', 'Total'],
      dtype='object')
```

In [7]:
```
{x: len(df[x].unique())for x in df.columns}
```

Out[7]:
```
{'Category': 15,
 'City': 15668,
 'County': 2518,
 'Cust_Id': 63646,
 'Customer_Since': 11629,
 'Date_of_Order': 365,
 'Full_Name': 63610,
 'Gender': 2,
 'Item_Id': 283083,
 'Order_Id': 199330,
 'Payment_Method': 13,
 'Place_Name': 15668,
 'Ref_Num': 61505,
 'Region': 4,
 'State': 49,
 'User_Name': 63407,
 'Zip': 33440,
 'Qty_Ordered': 72,
 'Total': 23588}
```

In [8]:
```
# Statistical Analysis of the data
df.describe()
```

Out[8]:

	Cust_Id	Item_Id	Order_Id	Ref_Num	Zip	Qty_Ordered	Total
count	283083.000000	283083.000000	2.830780e+05	283083.000000	283083.000000	283083.000000	283083.000000
mean	70106.816026	741747.110628	1.004570e+08	561107.885991	49147.171374	3.008224	816.230712
std	30215.394879	95664.609013	6.090992e+04	256101.205409	27235.561738	4.565168	1986.164932
min	4.000000	574769.000000	1.003547e+08	111127.000000	210.000000	1.000000	0.000000
25%	56640.000000	659898.500000	1.004047e+08	341071.000000	26264.000000	2.000000	49.900000
50%	74320.000000	742471.000000	1.004518e+08	565623.000000	48808.000000	2.000000	149.800000
75%	92371.000000	826078.500000	1.005134e+08	782211.000000	72004.000000	3.000000	800.000000
max	115326.000000	905208.000000	1.005624e+08	999981.000000	99402.000000	501.000000	101262.590000

In [9]:
```
df.describe(exclude=["int64", "float64"]).T
```

Out[9]:

	count	unique	top	freq	first	last
Category	283083	15	Mobiles & Tablets	60954	NaT	NaT
City	283083	15668	Dekalb	2525	NaT	NaT
County	283083	2518	Jefferson	3510	NaT	NaT
Customer_Since	283083	11629	2005-11-30 00:00:00	2536	1978-11-04	2017-07-28
Date_of_Order	283083	365	2021-12-20 00:00:00	13522	2021-10-01	2022-09-30
Full_Name	283083	63610	Gonzalez, Joel	2524	NaT	NaT
Gender	283083	2	M	144295	NaT	NaT
Payment_Method	283083	13	cod	101750	NaT	NaT
Place_Name	283083	15668	Dekalb	2525	NaT	NaT
Region	283083	4	South	103482	NaT	NaT
State	283083	49	TX	17510	NaT	NaT
User_Name	283083	63407	jugonzalez	2524	NaT	NaT

In [10]:
```
df.shape
```

Out[10]:
```
(283083, 19)
```

In [12]:
```
#Customer distribution by country
country_cust_data=df[['City','Cust_Id']].drop_duplicates()
country_cust_data.groupby(['City'])['Cust_Id'].aggregate('count').reset_index().sort_values('Cust_Id', ascending=False
```

Out[12]:

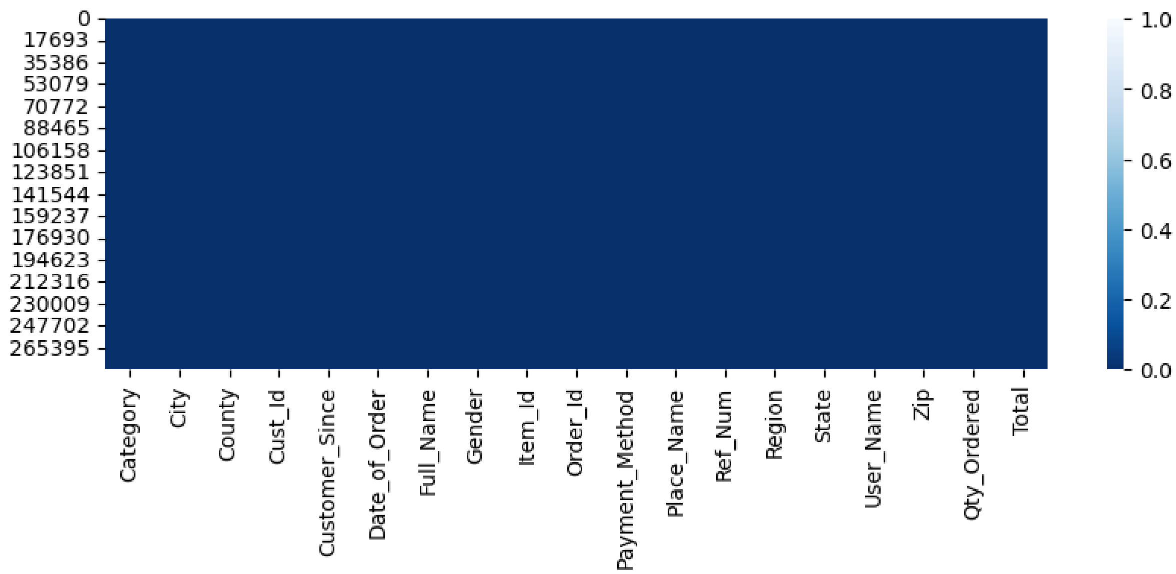
	City	Cust_Id
14750	Washington	487
6373	Houston	307
9681	New York City	257
4099	El Paso	234
3271	Dallas	199
...	...	...
11250	Pratts Hollow	1
5169	Gheens	1
11247	Prairieville	1
11246	Prairieton	1
0	True	1

15668 rows × 2 columns

In [13]:
```
# Check for missing values
print(df.isnull().sum())

# Visualization the missing data
plt.figure(figsize = (10,3))
sns.heatmap(df.isnull(), cbar=True, cmap="Blues_r")
```

```
Category          0
City              0
County            0
Cust_Id           0
Customer_Since    0
Date_of_Order     0
Full_Name         0
Gender            0
Item_Id           0
Order_Id          5
Payment_Method    0
Place_Name        0
Ref_Num           0
Region            0
State             0
User_Name         0
Zip               0
Qty_Ordered       0
Total             0
dtype: int64
```

Out[13]: <Axes: >



In [14]:
```
#dropping off missing data points
df.dropna(inplace=True)
```

In [15]:
```
#Validate if there are any negative values in Qty Required column
df['Qty_Ordered'].min()
```

Out[15]: 1

In [16]:
```
#Filter out records with negative values
df = df[(df['Qty_Ordered']>0)]
```

In [17]:
```
#Validate if there are any negative values in Total column
df.Total.min()
```

Out[17]: 0.0

In [18]:
```
df.shape
```

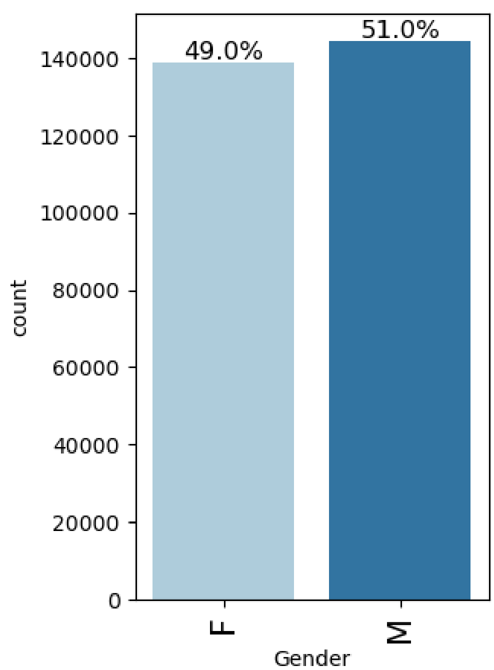
Out[18]: (283078, 19)

In [19]:
```
# function to create labeled barplots

def labeled_barplot(data, feature, perc=False, n=None):
    """

    Barplot with p[ercentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
```

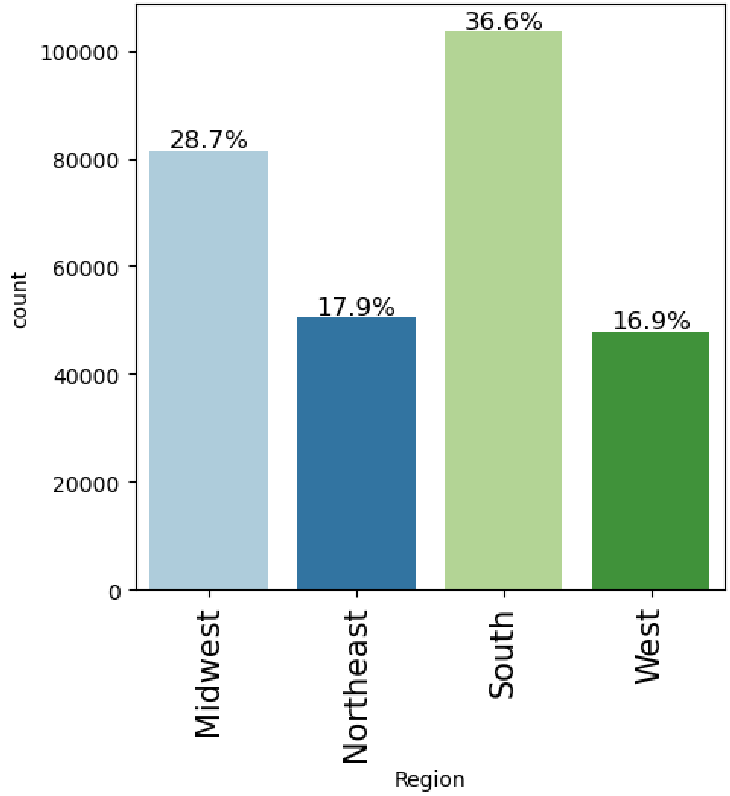
```
    n: display the top n cvategory levels (default is None, i.e., display all levels)
    """

    total = len(data[feature]) # length of the column
    count = data[feature]. nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
    x=feature,
    palette="Paired",
    order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            ) # percentage of each class of the category
        else:
            label = p.get_height() #count of each level of the category
        x = p.get_x() + p.get_width() /2 # width of the plot
        y = p.get_height() # height of the plot

        ax.annotate(
          label,
          (x,y),
          ha="center",
          va="center",
          size=12,
          xytext=(0,5),
          textcoords="offset points",
        ) # annotate the percentage
    plt.show # show the plot
```

In [ ]:

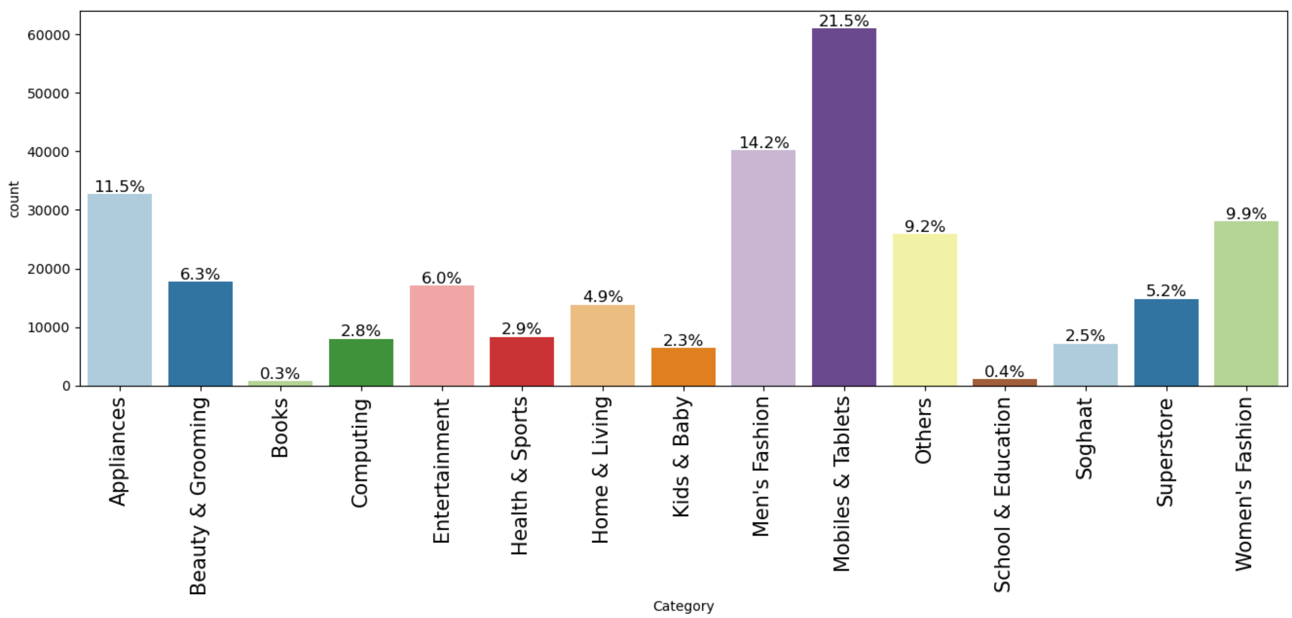
In [20]:
```
labeled_barplot(df, "Gender", perc=True)
```



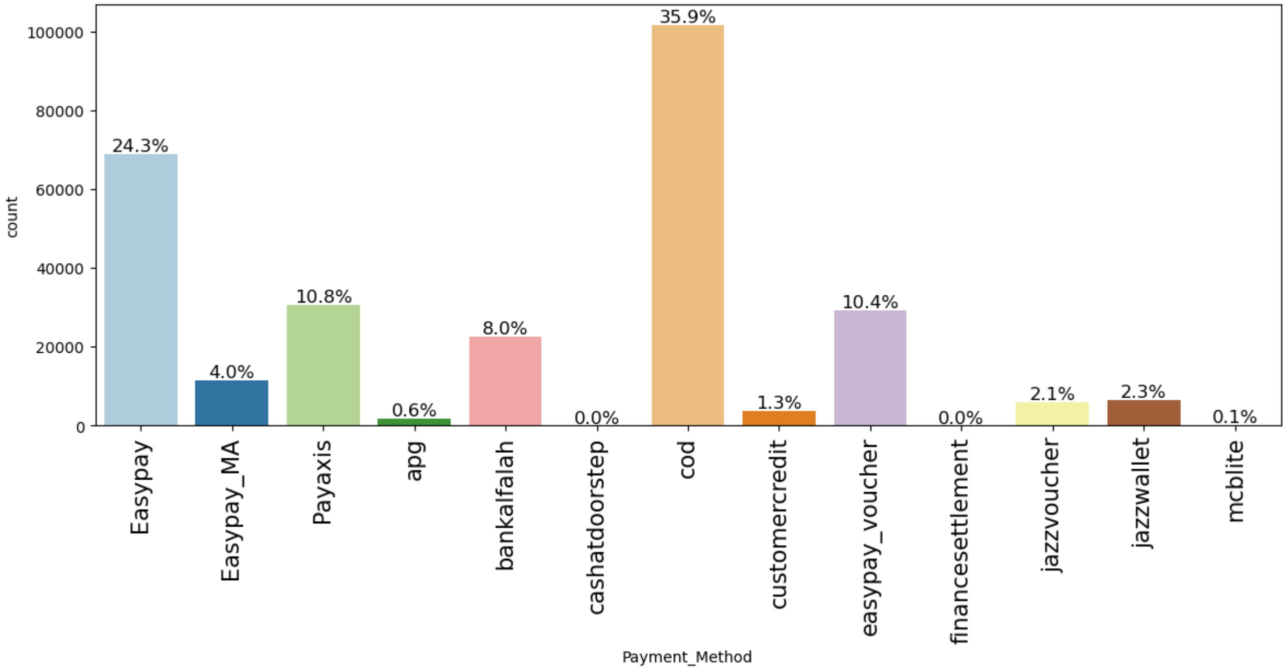
In [21]:
```
labeled_barplot(df, "Region", perc=True)
```



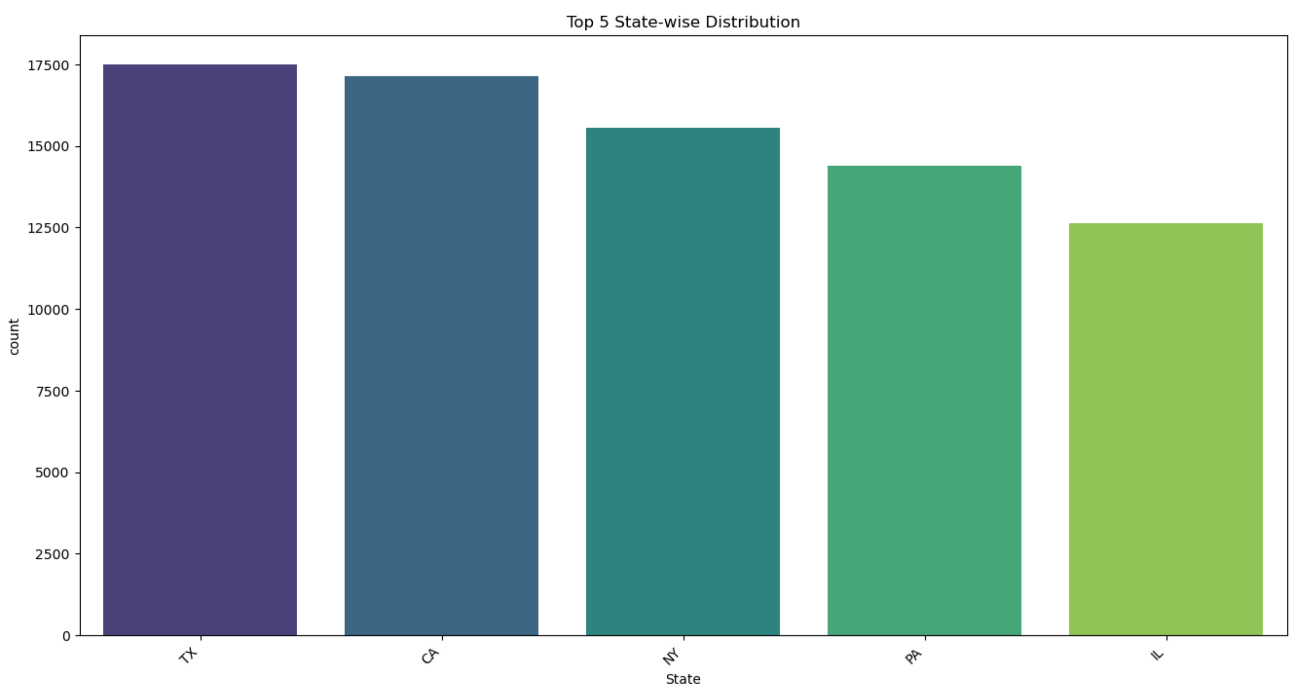
In [22]:
```
labeled_barplot(df, "Category", perc=True)
```



In [23]:
```
labeled_barplot(df, "Payment_Method", perc=True)
```

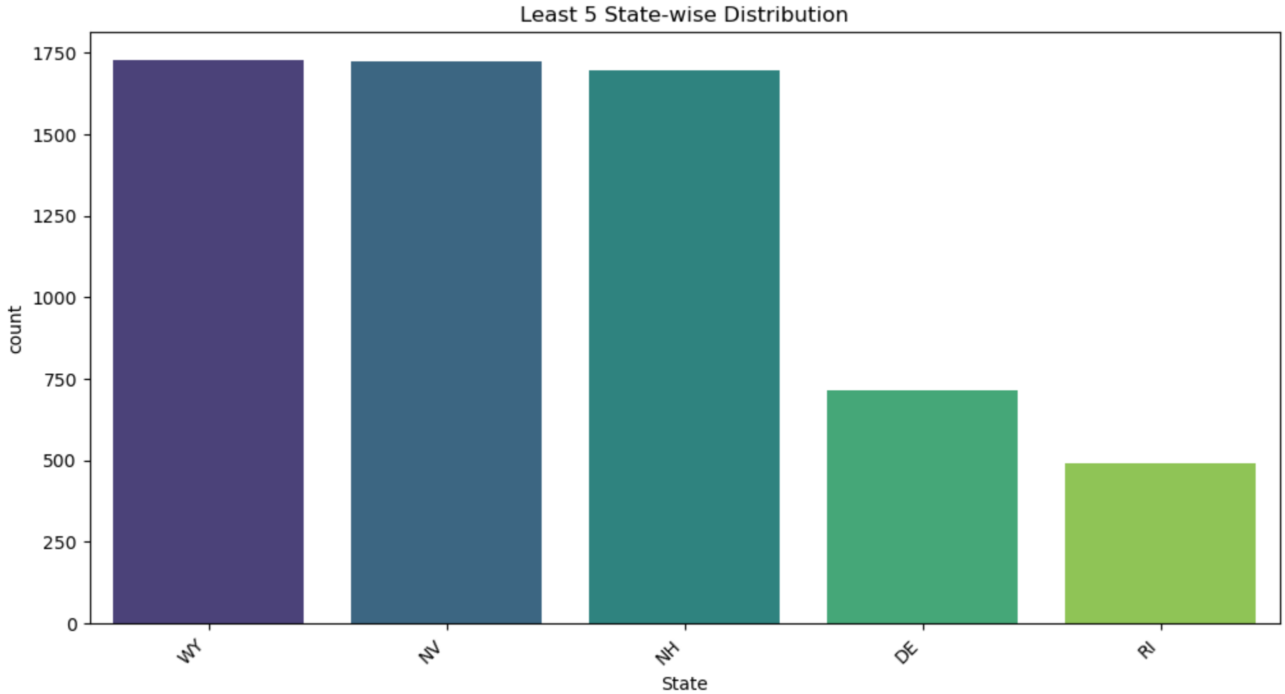


In [24]:
```python
### State-wise Distribution
# Get the top 5 states based on customer count
top_5_states = df['State'].value_counts().head(5).index

# Filter the DataFrame for the top 15 states
df_top_5_states = df[df['State'].isin(top_5_states)]

# Bar chart for top 5 state-wise distribution
plt.figure(figsize=(16, 8))
sns.countplot(x='State', data=df_top_5_states, palette='viridis', order=top_5_states)
plt.title('Top 5 State-wise Distribution')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [25]:
```python
# Get the least 5 states based on customer count
least_5_states = df['State'].value_counts().tail(5).index

# Filter the DataFrame for the least 5 states
df_least_5_states = df[df['State'].isin(least_5_states)]

# Bar chart for least 5 state-wise distribution
```

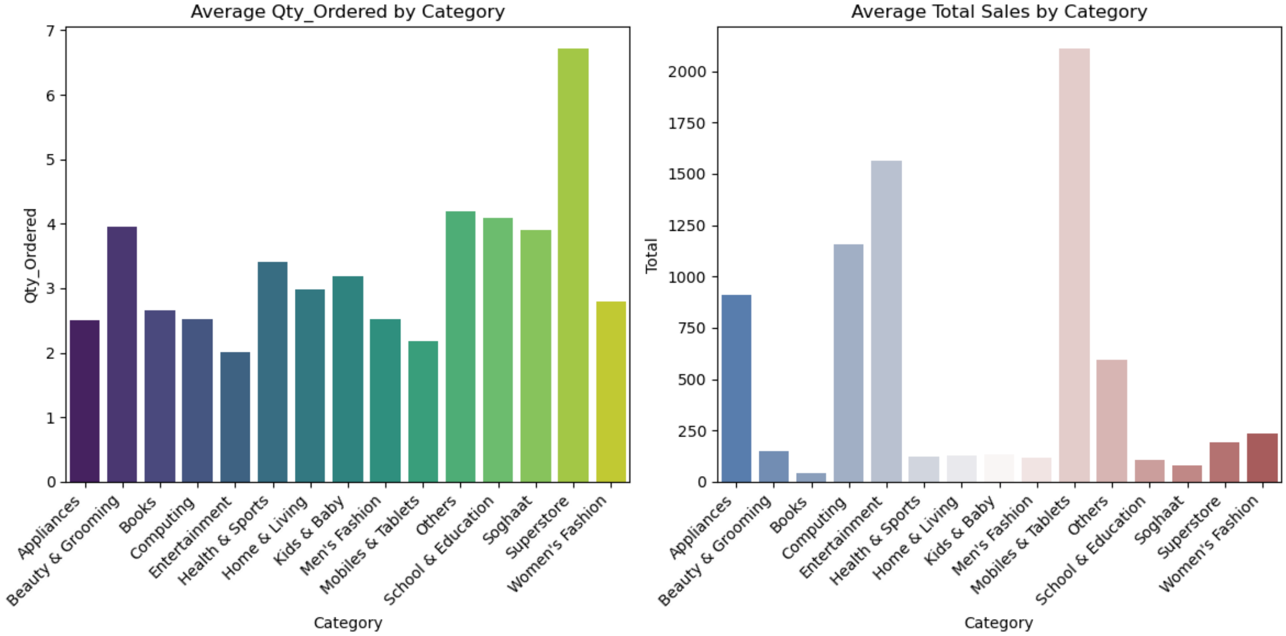
```
plt.figure(figsize=(12, 6))
sns.countplot(x='State', data=df_least_5_states, palette='viridis', order=least_5_states)
plt.title('Least 5 State-wise Distribution')
plt.xticks(rotation=45, ha='right')
plt.show()
```



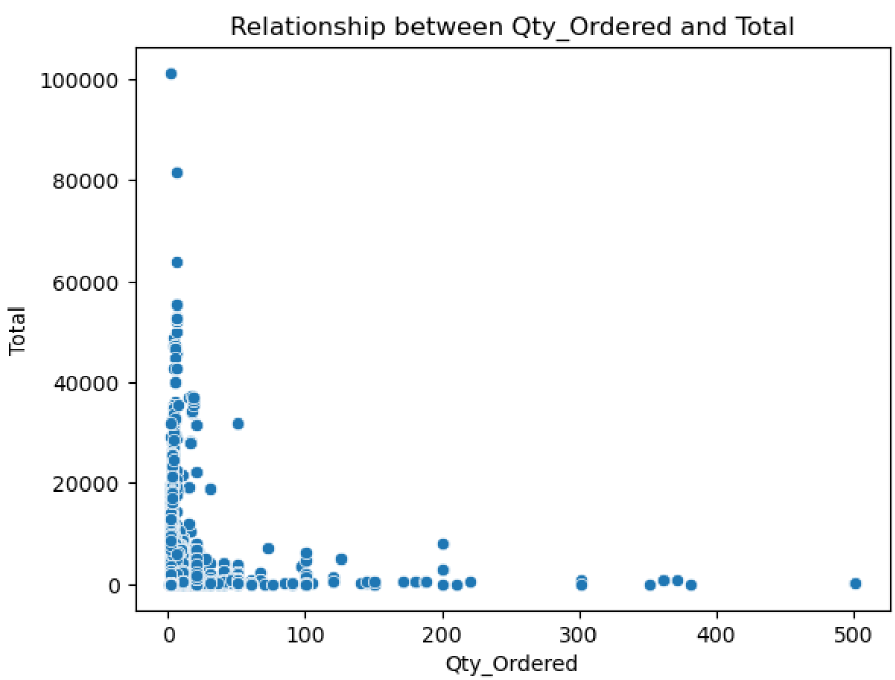
In [26]:
```
# Calculate the average of numerical variables
avg_qty_ordered = df['Qty_Ordered'].mean()
avg_total_sales = df['Total'].mean()

print(f'Average Qty_Ordered: {avg_qty_ordered}')
print(f'Average Total Sales: {avg_total_sales}')
```

```
Average Qty_Ordered: 3.0082380121379972
Average Total Sales: 816.232342064802
```

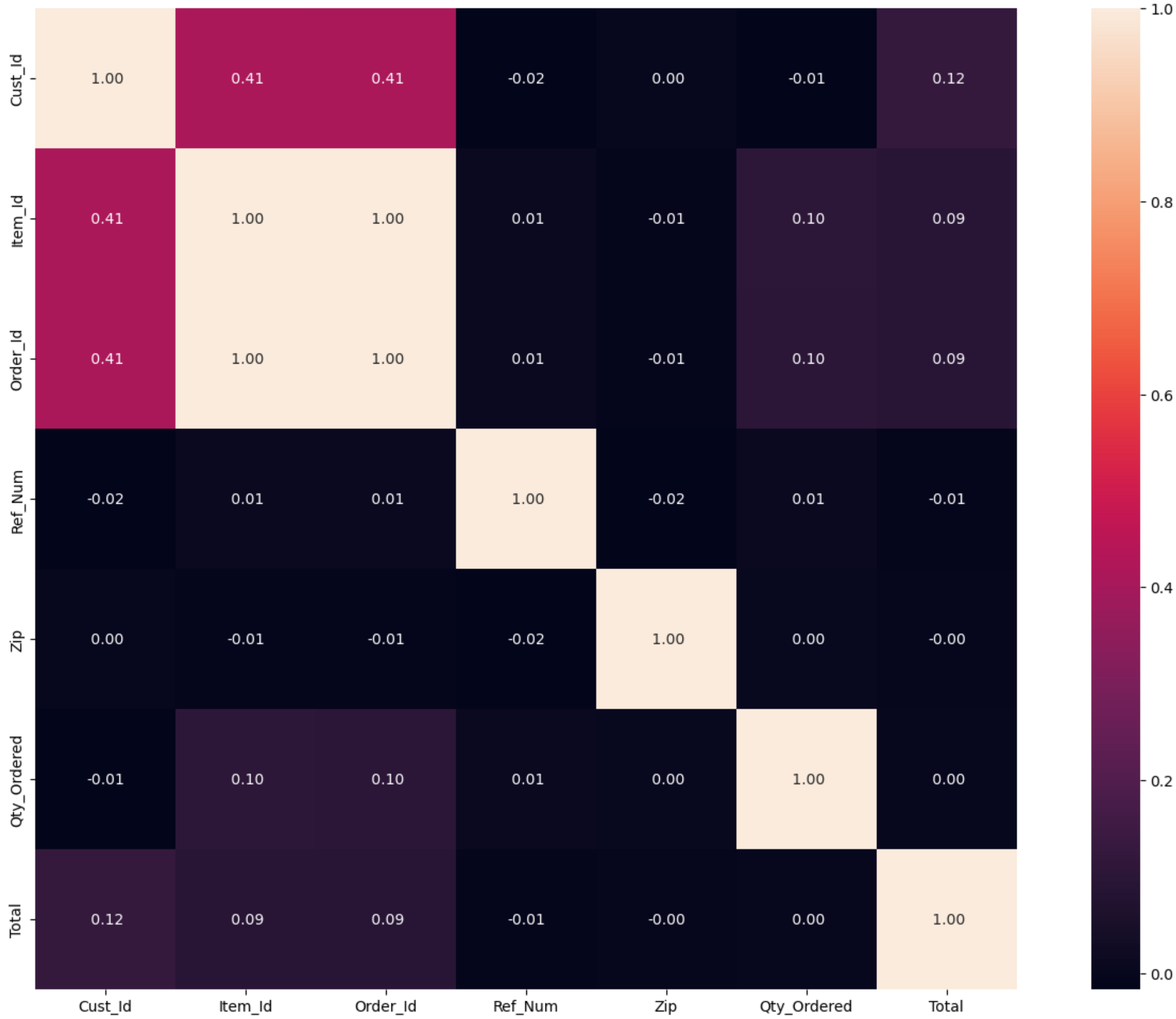
In [27]:
```
# Calculate average values by category
avg_values_by_category = df.groupby('Category')[['Qty_Ordered', 'Total']].mean().reset_index()

# Bar chart for average quantity ordered and total sales by category
plt.figure(figsize=(12, 6))

# Bar chart for Average Qty Ordered
plt.subplot(1, 2, 1)
sns.barplot(x='Category', y='Qty_Ordered', data=avg_values_by_category, palette='viridis')
plt.title('Average Qty_Ordered by Category')
plt.xticks(rotation=45, ha='right')

# Bar chart for Average Total Sales
plt.subplot(1, 2, 2)
sns.barplot(x='Category', y='Total', data=avg_values_by_category, palette='vlag')
plt.title('Average Total Sales by Category')
plt.xticks(rotation=45, ha='right')

plt.tight_layout()
plt.show()
```



In [28]:
```
sns.scatterplot(x='Qty_Ordered', y='Total', data=df)
plt.xlabel('Qty_Ordered')
plt.ylabel('Total')
plt.title('Relationship between Qty_Ordered and Total')
plt.show()
```



In [29]:
```
# Correlation between the variables in the dataset
plt.figure(figsize = (18, 12))
hm = sns.heatmap(df.corr(), cbar=True, annot=True, square=True, fmt=' .2f', annot_kws={'size': 10})
```



Data Preprocessing

Create relevant features for RFM analysis (Recency, Frequency and Monetary)

In [30]:
```
df.Date_of_Order.value_counts()
```

Out[30]:
```
2021-12-20    13522
2021-12-27    13042
2021-12-21     7154
2022-04-30     6207
2021-12-28     5284
              ...  
2022-07-20      133
2022-09-25      129
2021-10-20      122
2022-09-30       99
2022-09-24       92
Name: Date_of_Order, Length: 365, dtype: int64
```

In [31]:
```
df.Customer_Since.value_counts()
```

Out[31]:
```
2005-11-30    2536
2017-02-08     774
2015-05-17     659
2017-06-11     541
2016-12-25     491
              ... 
1981-08-01       1
1993-02-13       1
1989-01-01       1
1983-12-21       1
1992-06-10       1
Name: Customer_Since, Length: 11629, dtype: int64
```

In [33]:
```
#Recency = Latest Date - Last Date of Order, Frequency = count of Order Id of transaction(s), Monetary = Sum of Total f
import datetime as dt

#Set Latest date 10/01/2022 as last Date of Order was 09/30/2022. This is to calculate the number of days from recent p
Latest_Date = dt.datetime(2022,10,1)

#Create RFM Modelling scores for each customer
rfm = df.groupby('Cust_Id').agg({'Date_of_Order': lambda x: (Latest_Date - x.max()).days, 'Order_Id': lambda x: len(x),

#Convert Invoice Date into type int
rfm['Date_of_Order'] = rfm['Date_of_Order'].astype(int)

#Rename column names to Recency, Frequency and Monetary
rfm.rename(columns={'Date_of_Order': 'Recency',
                         'Order_Id': 'Frequency',
                         'Total': 'Monetary'}, inplace=True)

rfm.head()
```

Out[33]:

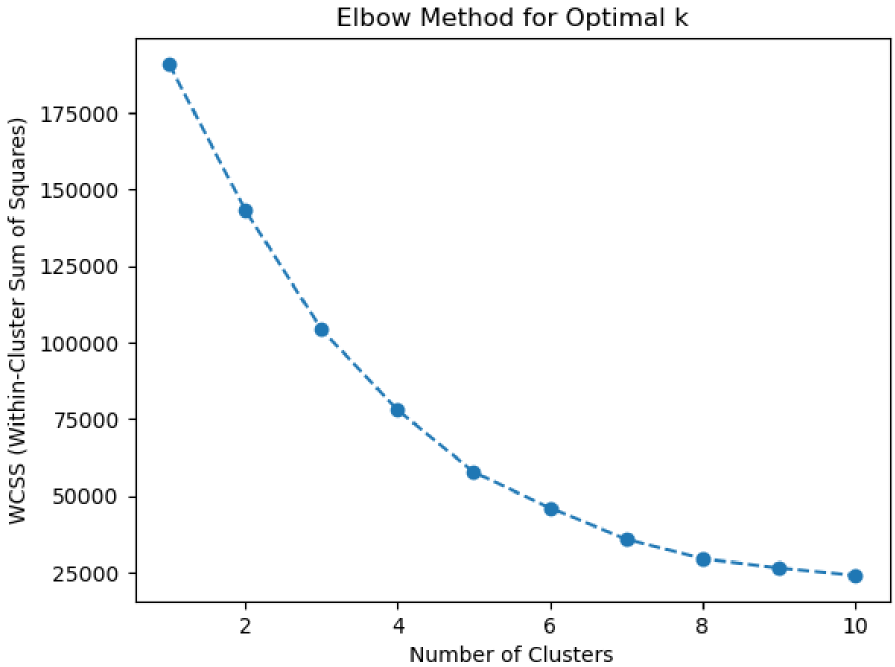
	Recency	Frequency	Monetary
Cust_Id			
4	2	41	27394.190
15	232	6	216.800
16	323	20	11868.899
20	2	11	28719.018
21	240	1	105.000

K-Means Clustering

Feature scaling

In [34]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm[['Recency', 'Frequency', 'Monetary']])
```

In [35]:
```
# Find the optimal number of clusters using the Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(rfm_scaled)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method graph
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()
```



In [36]:
```
#Perform K-Mean Clustering or build the K-Means clustering model
KMean_clust = KMeans(n_clusters= 3, init= 'k-means++', max_iter= 1000)
KMean_clust.fit(rfm_scaled)

#Find the clusters for the observation given in the dataset
rfm['Cluster'] = KMean_clust.labels_
rfm.head()
```

Out[36]:

Cust_Id	Recency	Frequency	Monetary	Cluster
4	2	41	27394.190	1
15	232	6	216.800	0
16	323	20	11868.899	0
20	2	11	28719.018	1
21	240	1	105.000	0

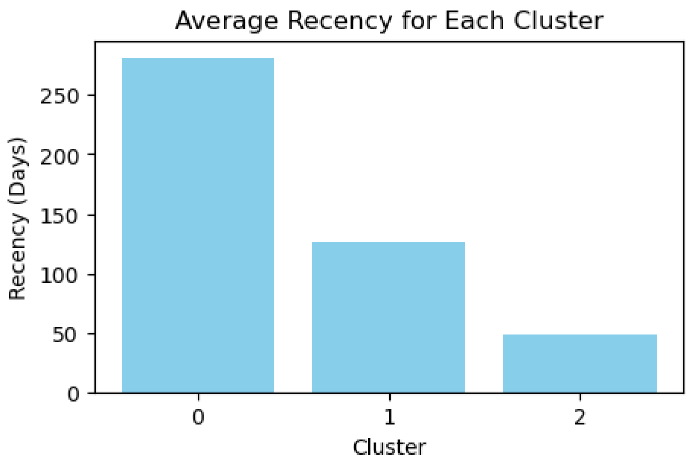
In [37]:
```
final=rfm.groupby("Cluster")["Recency","Frequency","Monetary"].mean()
final
```

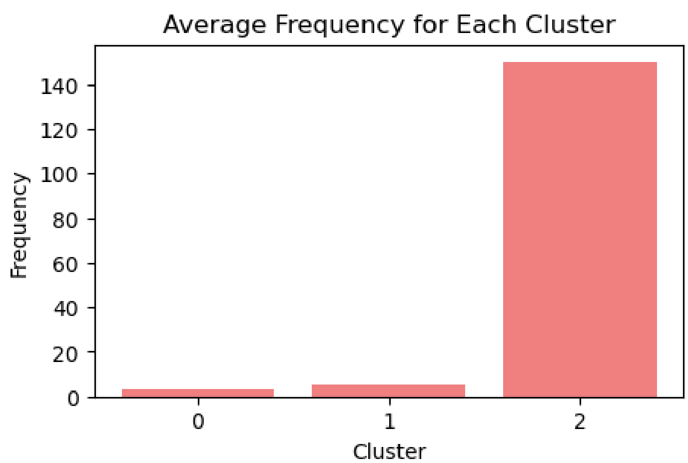
Out[37]:

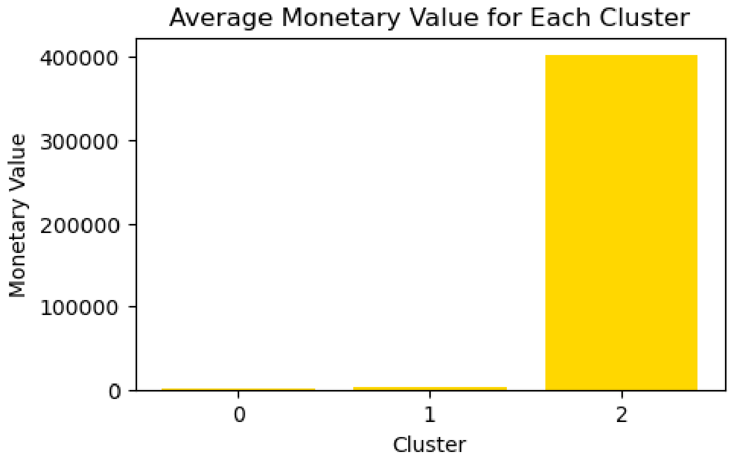
Cluster	Recency	Frequency	Monetary
0	281.528499	3.199743	1982.822826
1	125.868176	5.055269	3911.085396
2	49.311828	148.623656	393085.786848

In [38]:
```
import matplotlib.pyplot as plt
import pandas as pd

# Assuming your cluster average data is in a DataFrame named 'clusters_average_data'
data = {
    'Cluster': ['0', '1', '2'],
    'Recency': [281.53, 125.87, 47.79],
    'Frequency': [3.20, 5.07, 150.17],
    'Monetary': [1982.68, 3930.03, 403036.66]
}

cluster_average_data = pd.DataFrame(data)

# Plotting Recency
plt.figure(figsize=(5, 3))
```

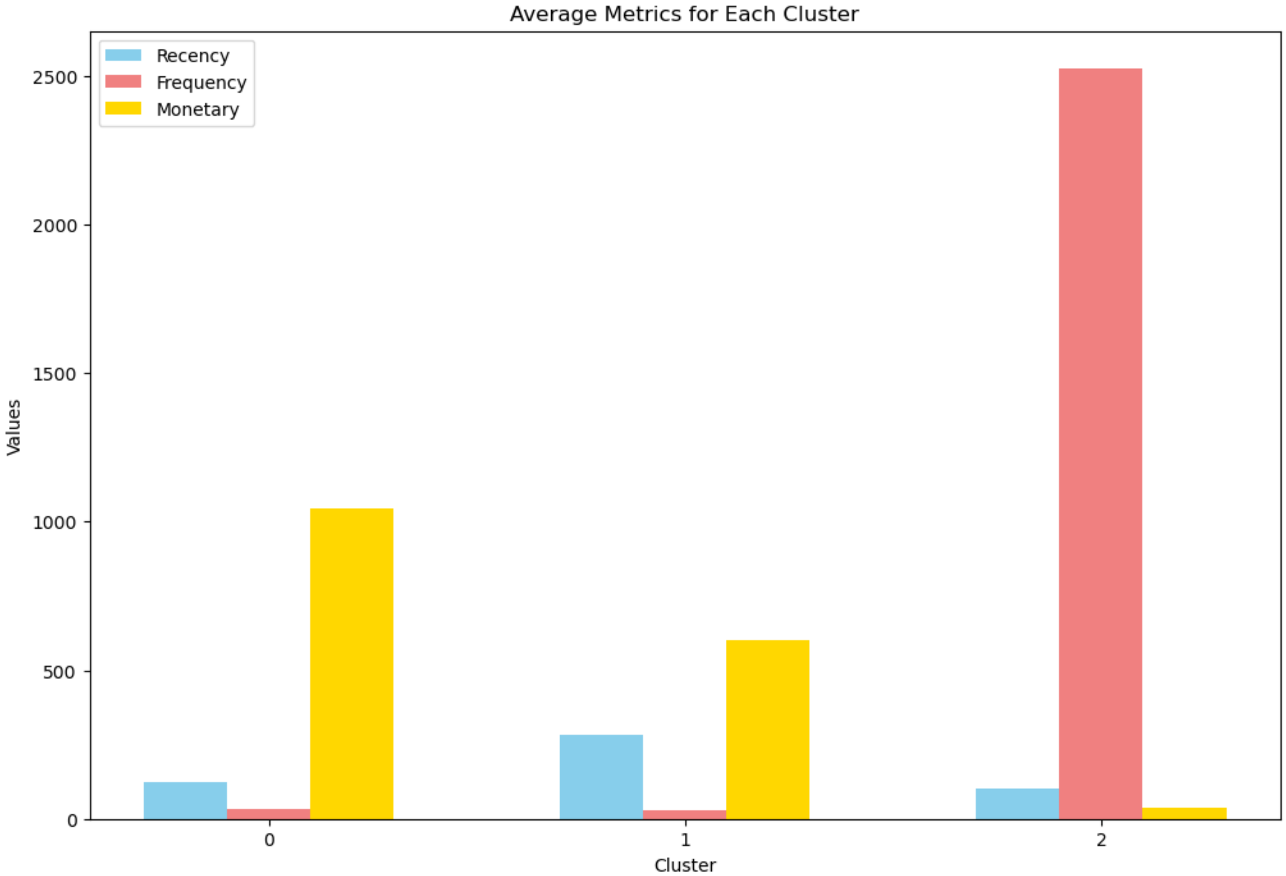
```
plt.bar(cluster_average_data['Cluster'], cluster_average_data['Recency'], color='skyblue')
plt.title('Average Recency for Each Cluster')
plt.xlabel('Cluster')
plt.ylabel('Recency (Days)')
plt.show()

# Plotting Frequency
plt.figure(figsize=(5, 3))
plt.bar(cluster_average_data['Cluster'], cluster_average_data['Frequency'], color='lightcoral')
plt.title('Average Frequency for Each Cluster')
plt.xlabel('Cluster')
plt.ylabel('Frequency')
plt.show()

# Plotting Monetary
plt.figure(figsize=(5, 3))
plt.bar(cluster_average_data['Cluster'], cluster_average_data['Monetary'], color='gold')
plt.title('Average Monetary Value for Each Cluster')
plt.xlabel('Cluster')
plt.ylabel('Monetary Value')
plt.show()
```







In [39]:
```
import matplotlib.pyplot as plt
import pandas as pd

# Assuming your cluster average data is in a DataFrame named 'cluster_average_data'
data = {
    'Cluster': ['0', '1', '2'],
    'Recency': [125, 282, 103],
    'Frequency': [35, 29, 2524],
    'Monetary': [1045.27, 601.67, 36.23]
}

cluster_average_data = pd.DataFrame(data)

# Plotting all metrics in one chart
fig, ax = plt.subplots(figsize=(12, 8))

bar_width = 0.2
bar_positions_recency = range(len(cluster_average_data))
bar_positions_frequency = [pos + bar_width for pos in bar_positions_recency]
bar_positions_monetary = [pos + bar_width for pos in bar_positions_frequency]

ax.bar(bar_positions_recency, cluster_average_data['Recency'], width=bar_width, label='Recency', color='skyblue')
ax.bar(bar_positions_frequency, cluster_average_data['Frequency'], width=bar_width, label='Frequency', color='lightcora
ax.bar(bar_positions_monetary, cluster_average_data['Monetary'], width=bar_width, label='Monetary', color='gold')

ax.set_xticks([pos + bar_width for pos in bar_positions_recency])
ax.set_xticklabels(cluster_average_data['Cluster'])
ax.set_xlabel('Cluster')
ax.set_ylabel('Values')
ax.set_title('Average Metrics for Each Cluster')
ax.legend()

plt.show()
```



In [41]:
```python
def func(row):
    if row["Cluster"]==0:
        return 'Silver'
    elif row["Cluster"]==1:
        return 'Gold'
    else:
        return 'Platinum'


rfm['group'] = rfm.apply(func, axis=1)
rfm
```

Out[41]:

Cust_Id	Recency	Frequency	Monetary	Cluster	group
4	2	41	27394.190	1	Gold
15	232	6	216.800	0	Silver
16	323	20	11868.899	0	Silver
20	2	11	28719.018	1	Gold
21	240	1	105.000	0	Silver
...	...	...	...	...	...
115322	1	2	209.600	1	Gold
115323	1	1	4419.900	1	Gold
115324	1	1	39.900	1	Gold
115325	1	2	89.900	1	Gold
115326	1	1	3559.900	1	Gold

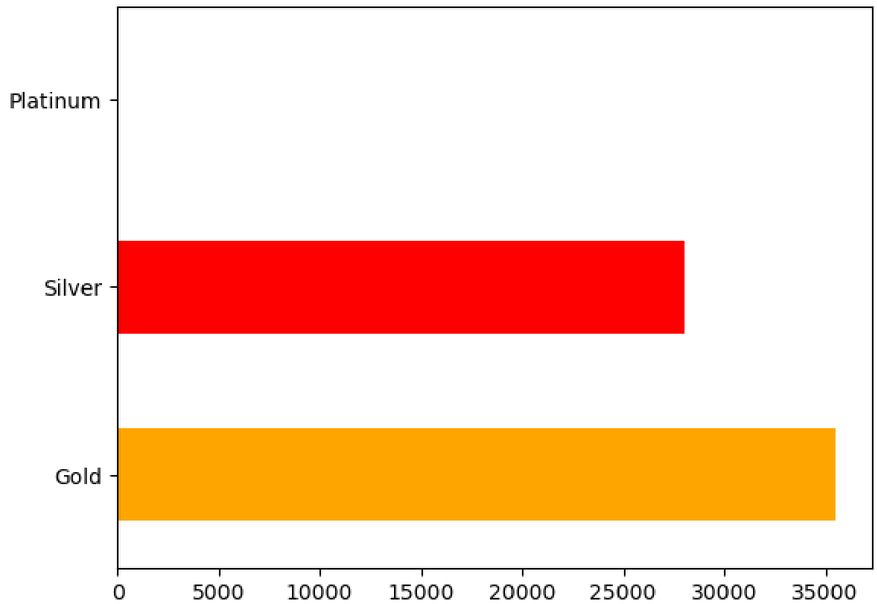
63646 rows × 5 columns

In [43]:
```python
result=rfm.group.value_counts()
result
```

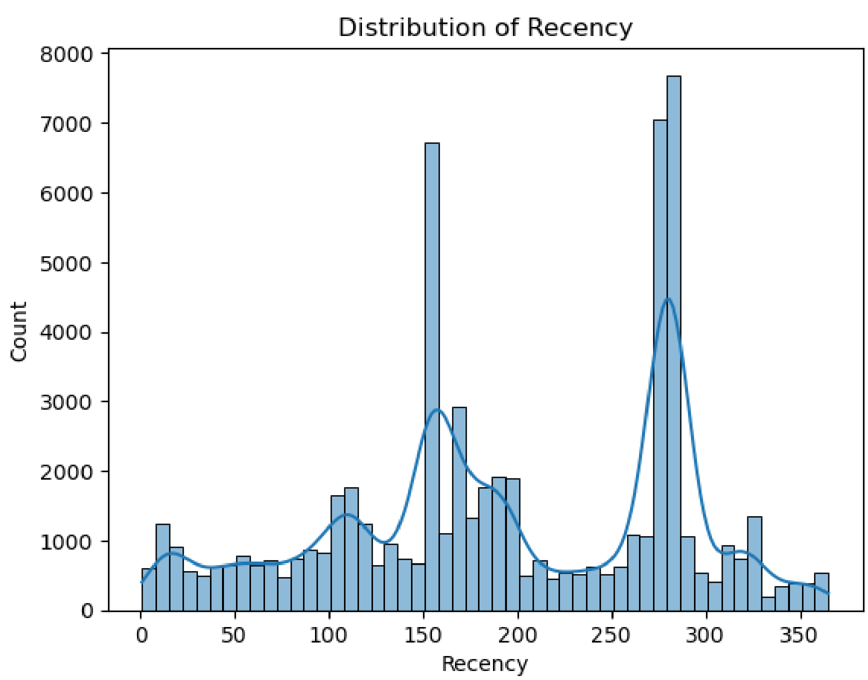
Out[43]:
```
Gold        35517
Silver      28036
Platinum       93
Name: group, dtype: int64
```

In [44]:
```
result.plot(kind="barh", color=["Orange","Red","Green"])
```

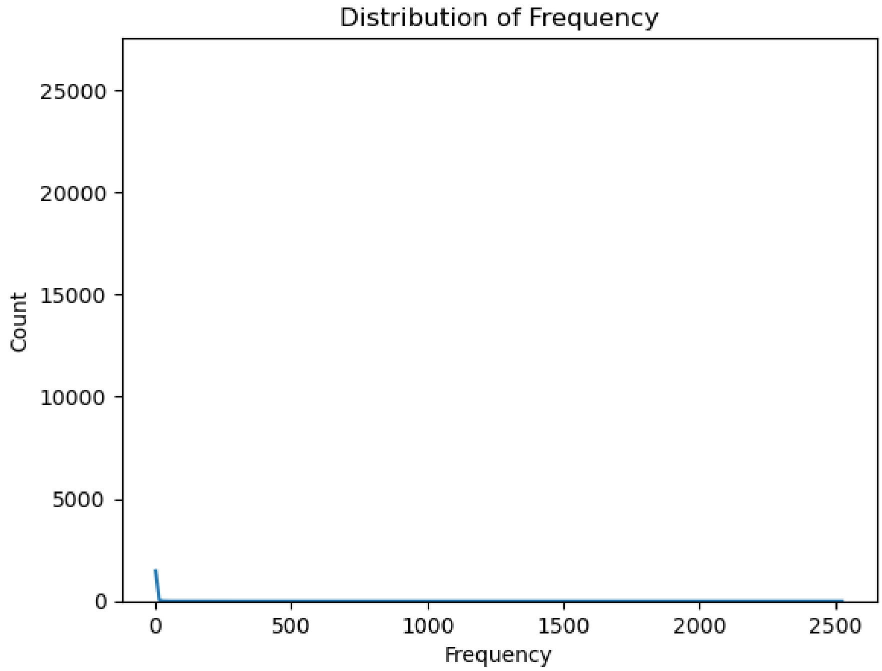
Out[44]: <Axes: >



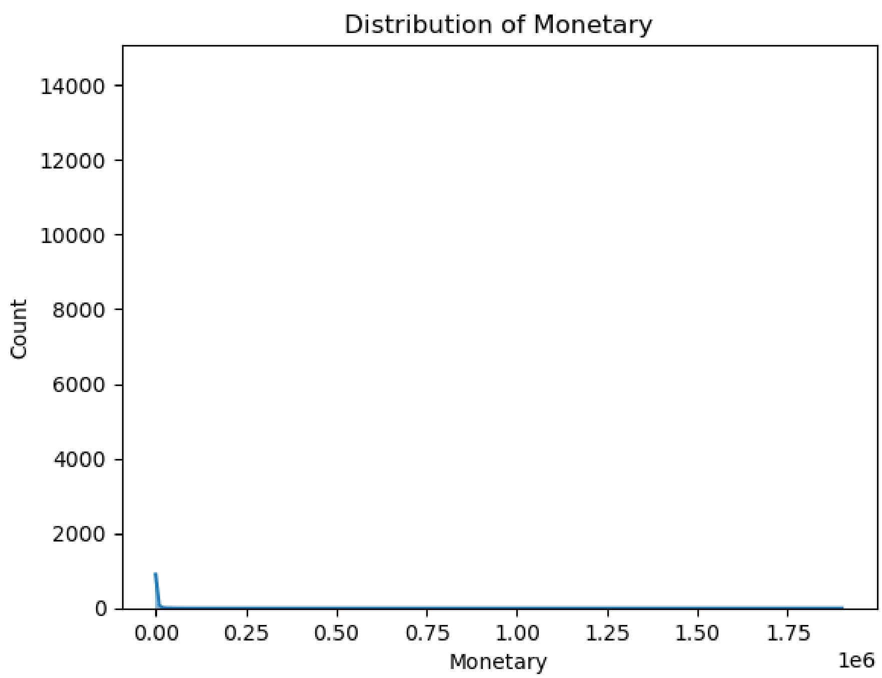
In [46]:
```
sns.histplot(rfm['Recency'], kde=True)
plt.title('Distribution of Recency')
plt.xlabel('Recency')
plt.show()
```



In [47]:
```
sns.histplot(rfm['Frequency'], kde=True)
plt.title('Distribution of Frequency')
plt.xlabel('Frequency')
plt.show()
```

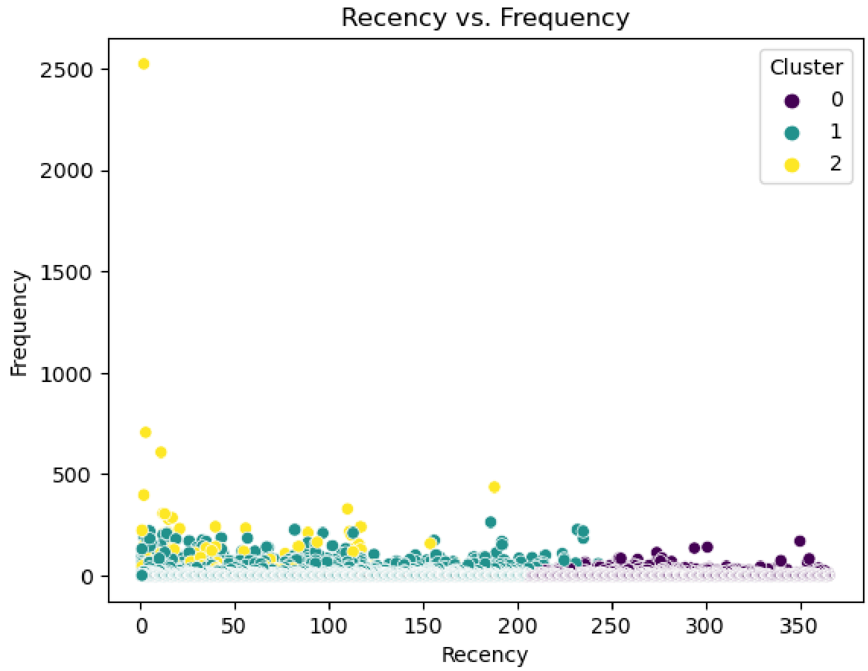


In [48]:
```
sns.histplot(rfm['Monetary'], kde=True)
plt.title('Distribution of Monetary')
plt.xlabel('Monetary')
plt.show()
```



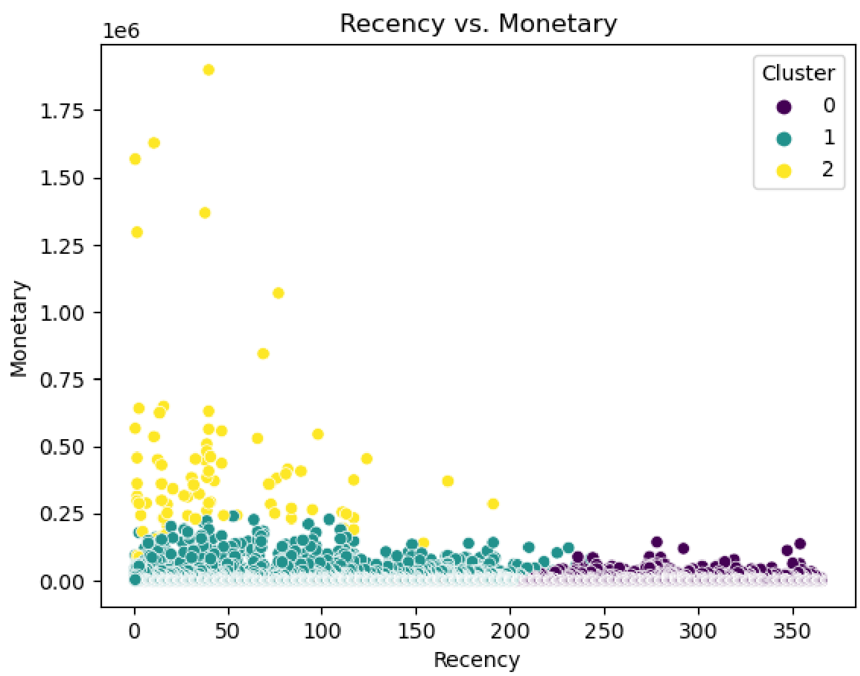
In [ ]:

In [49]:
```
sns.scatterplot(data=rfm, x='Recency', y='Frequency', hue='Cluster', palette='viridis')
plt.title('Recency vs. Frequency')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.show()
```



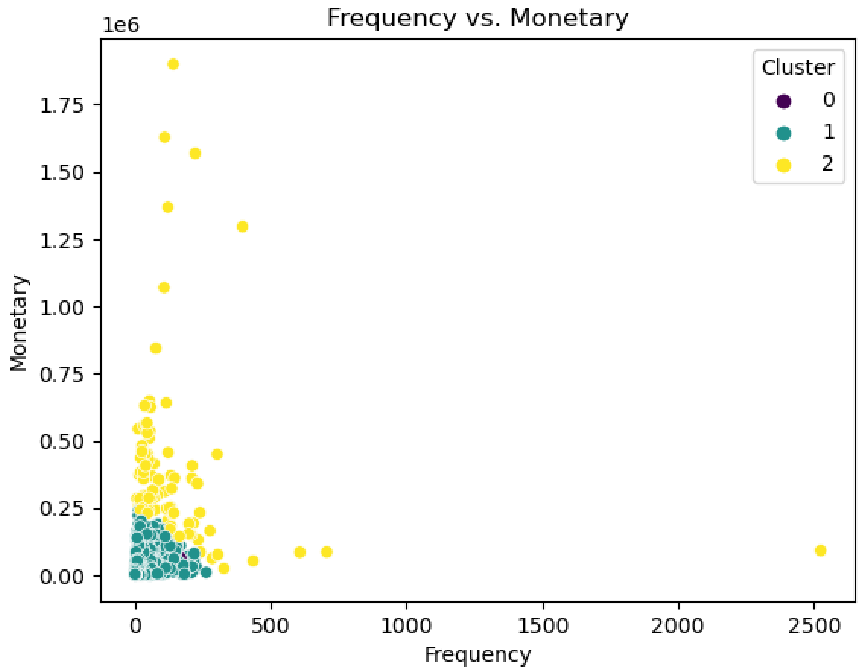
In [ ]:

In [50]:
```
sns.scatterplot(data=rfm, x='Recency', y='Monetary', hue='Cluster', palette='viridis')
plt.title('Recency vs. Monetary')
plt.xlabel('Recency')
plt.ylabel('Monetary')
plt.show()
```



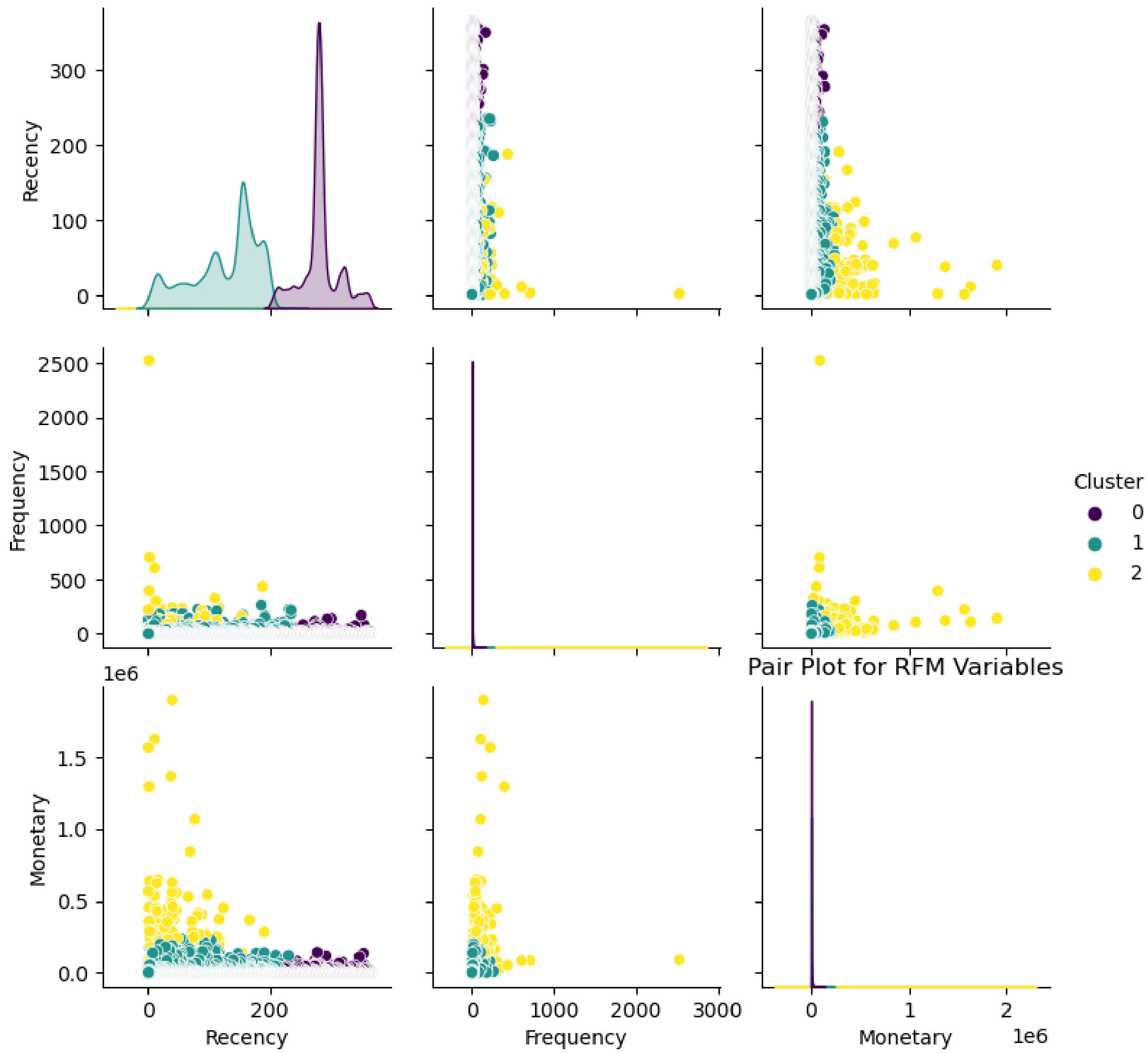
In [ ]:

In [51]:
```
sns.scatterplot(data=rfm, x='Frequency', y='Monetary', hue='Cluster', palette='viridis')
plt.title('Frequency vs. Monetary')
plt.xlabel('Frequency')
plt.ylabel('Monetary')
plt.show()
```



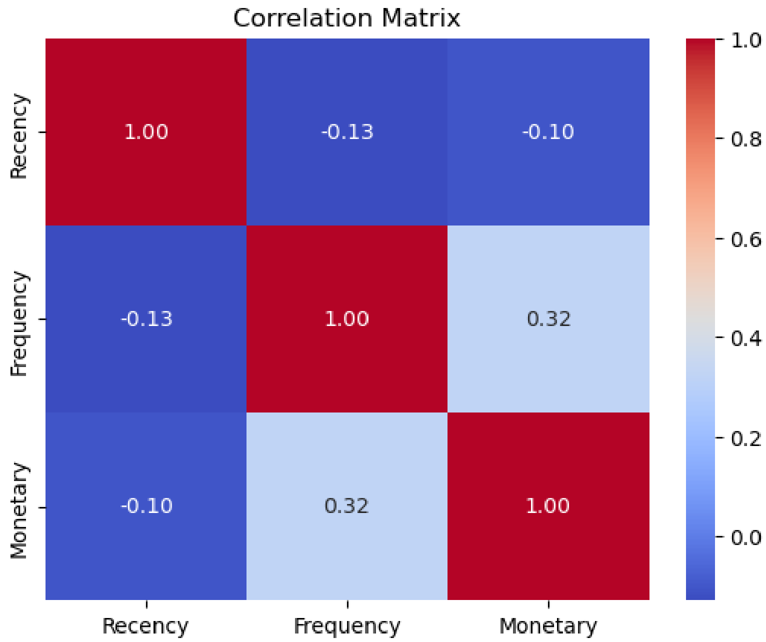
In [ ]:

In [52]:
```
sns.pairplot(rfm[['Recency', 'Frequency', 'Monetary', 'Cluster']], hue='Cluster', palette='viridis')
plt.title('Pair Plot for RFM Variables')
plt.show()
```



In [ ]:

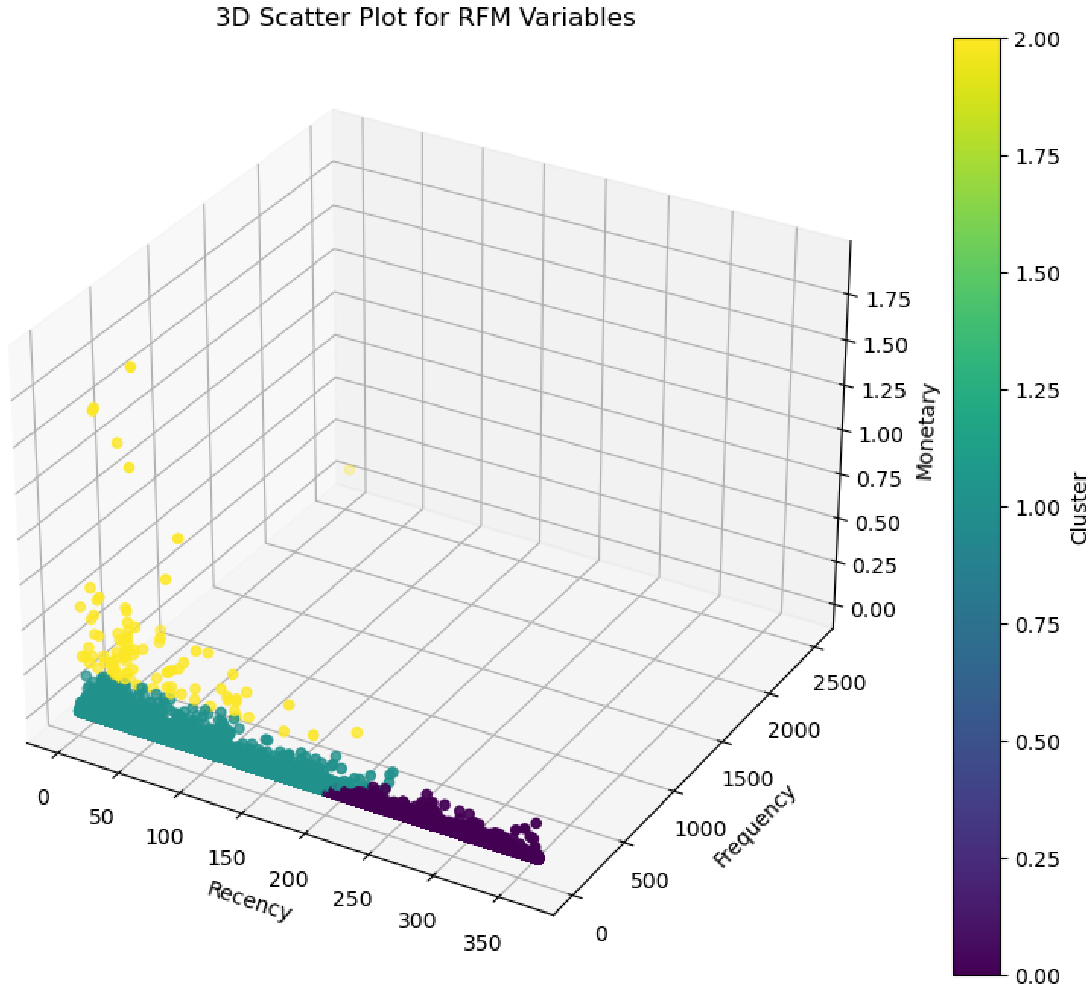
In [53]:
```
corr_matrix = rfm[['Recency', 'Frequency', 'Monetary']].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



In [ ]:

In [55]:

```
# Multivariate analysis with a 3D scatter plot
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

scatter = ax.scatter(rfm['Recency'], rfm['Frequency'], rfm['Monetary'], c=rfm['Cluster'], cmap='viridis')
ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary')
ax.set_title('3D Scatter Plot for RFM Variables')
fig.colorbar(scatter, ax=ax, label='Cluster')
plt.show()
```



In [ ]:

Key Insights:

Cluster Average

Cluster 0 (Silver):

- Recency: 282 days
- Frequency: 3 times
- Monetary: $1982.62

Cluster 1 (Gold):

- Recency: 126 days
- Frequency: 5 times
- Monetary: $3911.09

Cluster 2 (Platinum):

- Recency: 49 days
- Frequency: 149 times
- Monetary: $393,085.79

Conclusions:

This RFM customer segmentation analysis provides a roadmap for strategic decision-making, enabling organizations to tailor marketing efforts, improve customer experiences, and maximize the value of each segment. By implementing targeted strategies for Silver, Gold, and Platinum customers, you can foster customer loyalty, drive revenue growth, and position your brand as a leader in the market.

Recommendations:

Based on the key insights, we propose the following strategies for business growth:

1. Regional Targeting:

Given the regional distribution, focus marketing efforts on the South and Midwest regions, where a significant customer base exists. Tailor promotions and campaigns to resonate with the preferences of customers in these regions.

2. Payment Method Optimization:

Recognize the dominance of "cod" transactions and EasyPay. Consider incentivizing the use of other payment methods to diversify and streamline the payment process for both the business and customers.

3.Cluster-specific Marketing:

Based on the key insights and the given cluster average data, here are recommendations for each segment:

Silver Segment (Cluster 0):

Recency:

Customers in this segment have a high recency score (282 days), indicating that they haven't visited the platform recently. It's recommended to implement targeted re-engagement strategies such as personalized promotions, discounts, or reminders to encourage them to return and make a purchase. With a higher recency compared to the other segments, consider targeted promotions or loyalty programs to re-engage this group.

Frequency:

The frequency is relatively low (3 times), suggesting that they make occasional purchases. Consider offering loyalty programs, exclusive deals, or product recommendations based on their past purchases to increase their engagement and encourage more frequent transactions. Craft compelling campaigns to convert occasional customers into regular ones. Highlighting the potential benefits and value propositions can be effective.

Monetary:

The monetary value is moderate ($1,982.82), so efforts can be made to upsell or cross-sell to increase the average order value. Special promotions or bundled deals might be effective in boosting their spending.

Gold Segment (Cluster 1):

Recency:

Customers in this segment have a moderate recency score (126 days), indicating recent visits. Ensure to maintain their engagement by providing personalized recommendations, exclusive offers, or early access to new products.

Frequency:

The frequency is high (5 times), suggesting they make frequent purchases. Leverage this by introducing loyalty programs, referral bonuses, or special discounts for repeat purchases to foster customer loyalty. Focus on maintaining the loyalty of this segment through personalized offers and exclusive deals, given their moderate recency but higher frequency and monetary value.

Monetary:

The monetary value is high ($3,911.09), implying they spent a significant amount. Capitalize on this by offering premium products, VIP access, or personalized services to enhance their shopping experience.

Platinum Segment (Cluster 2):

Recency:

Customers in this segment have a very low recency score (49 days), indicating they have visited the platform recently. Implement targeted campaigns, personalized promotions, or exclusive offers to engage them.

Frequency:

The frequency is extremely high (149 times), indicating they made frequent purchases in the past. Investigate reasons for the drop in frequency and tailor marketing efforts to reignite their interest, such as personalized recommendations or special incentives for returning customers. Build a close relationship with these top-tier customers through exclusive communications, seeking feedback, and involving them in brand initiatives.

Monetary:

The monetary value is exceptionally high ($393,085.79), suggesting they have a significant lifetime value. Develop personalized loyalty programs, exclusive perks, or premium services to maintain their high spending and enhance their overall satisfaction. Prioritize VIP treatment for this high-value segment. Consider premium services, early access, or personalized experiences to enhance their loyalty further.

4. Enhanced Customer Communication:

Utilize customer segments to craft targeted and personalized communication strategies. Tailor marketing messages, promotions, and product recommendations based on the preferences and behaviors of each segment.

5. Continuous Monitoring and Adaptation:

Regularly analyze customer segments and adapt strategies based on evolving trends. Stay agile to respond to changes in customer behavior and market dynamics.

By implementing these recommendations, our company can optimize customer engagement, drive sales, and maintain a competitive edge in the e-commerce industry.

In [ ]:

```

```