online-retailer

May 12, 2025

1 Import Libraries

[49]:
```
pip install pandas numpy matplotlib seaborn scikit-learn openpyxl
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages
(2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages
(2.0.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-
packages (3.10.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-
packages (0.13.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-
packages (1.6.1)
Requirement already satisfied: openpyxl in /usr/local/lib/python3.11/dist-
packages (3.1.5)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.15.2)
```

```
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.11/dist-
packages (from openpyxl) (2.0.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

[50]:
```
# Data handling
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning & Preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans, DBSCAN
from sklearn.mixture import GaussianMixture
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score, davies_bouldin_score,␣
 ↪calinski_harabasz_score
```

2 Load the Dataset

[51]:
```
# Load the Excel dataset
file_path = 'Online Retail.xlsx'
df = pd.read_excel(file_path)

# Preview the data
df.head()
```

[51]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
```

```
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
```

3 Dataset Overview

[52]:
```python
# Check dataset structure
print("Shape of dataset:", df.shape)
print("\nColumns:\n", df.columns)

# Summary of data
df.info()
```

```
Shape of dataset: (541909, 8)

Columns:
 Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

4 Data Preprocessing

Handle Missing Data

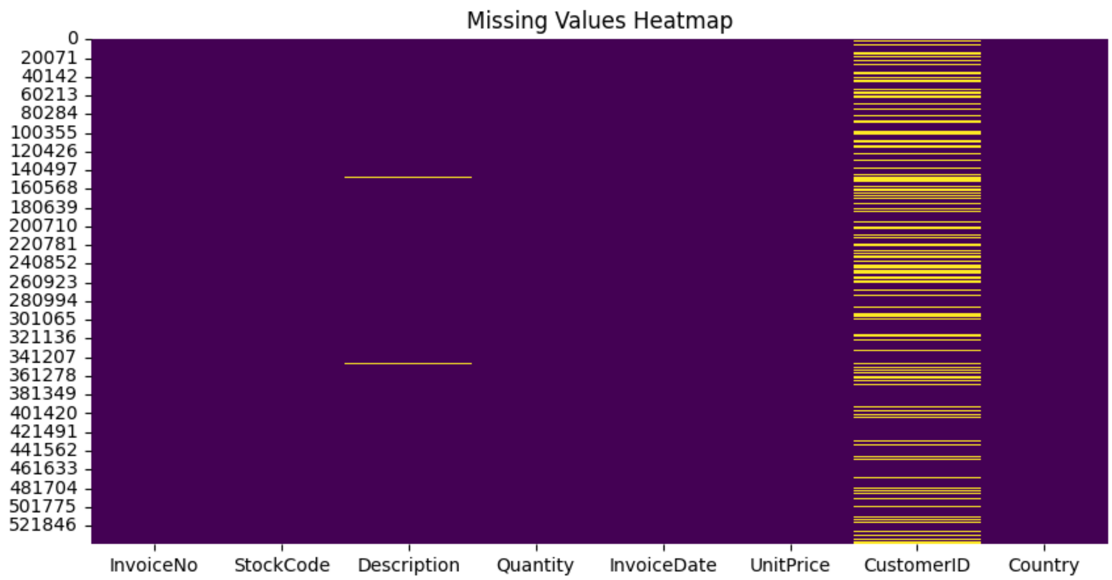
[53]:
```python
# Check missing values
df.isnull().sum()
```

[53]:
```
InvoiceNo         0
StockCode         0
Description    1454
Quantity          0
InvoiceDate       0
UnitPrice         0
```

```
CustomerID     135080
Country             0
dtype: int64
```

[54]:

```
plt.figure(figsize=(10, 5))
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.title("Missing Values Heatmap")
plt.show()
```



[55]:

```
# Remove rows with missing CustomerID
df = df.dropna(subset=['CustomerID'])

# Ensure all CustomerIDs are integers
df['CustomerID'] = df['CustomerID'].astype(int)
```

```
<ipython-input-55-23e1c83527a3>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['CustomerID'] = df['CustomerID'].astype(int)
```

Remove Canceled Transactions

[56]:

```
# Filter out canceled transactions
df = df[~df['InvoiceNo'].astype(str).str.startswith('C')]
```

[57]:
```python
print("Data shape after cleaning:", df.shape)
df.describe(include='all')
```

```
Data shape after cleaning: (397924, 8)
```

[57]:
```
          InvoiceNo StockCode                         Description  \
count      397924.0    397924                              397924
unique      18536.0      3665                                3877
top        576339.0    85123A  WHITE HANGING HEART T-LIGHT HOLDER
freq          542.0      2035                                2028
mean            NaN       NaN                                 NaN
min             NaN       NaN                                 NaN
25%             NaN       NaN                                 NaN
50%             NaN       NaN                                 NaN
75%             NaN       NaN                                 NaN
max             NaN       NaN                                 NaN
std             NaN       NaN                                 NaN

             Quantity                     InvoiceDate      UnitPrice  \
count   397924.000000                          397924  397924.000000
unique            NaN                             NaN            NaN
top               NaN                             NaN            NaN
freq              NaN                             NaN            NaN
mean        13.021823  2011-07-10 23:43:36.912475648       3.116174
min          1.000000             2010-12-01 08:26:00       0.000000
25%          2.000000             2011-04-07 11:12:00       1.250000
50%          6.000000             2011-07-31 14:39:00       1.950000
75%         12.000000             2011-10-20 14:33:00       3.750000
max      80995.000000             2011-12-09 12:50:00    8142.750000
std        180.420210                             NaN      22.096788

           CustomerID         Country
count   397924.000000          397924
unique            NaN              37
top               NaN  United Kingdom
freq              NaN          354345
mean     15294.315171             NaN
min      12346.000000             NaN
25%      13969.000000             NaN
50%      15159.000000             NaN
75%      16795.000000             NaN
max      18287.000000             NaN
std       1713.169877             NaN
```

5 Feature Engineering – RFM Analysis

Create a Reference Date

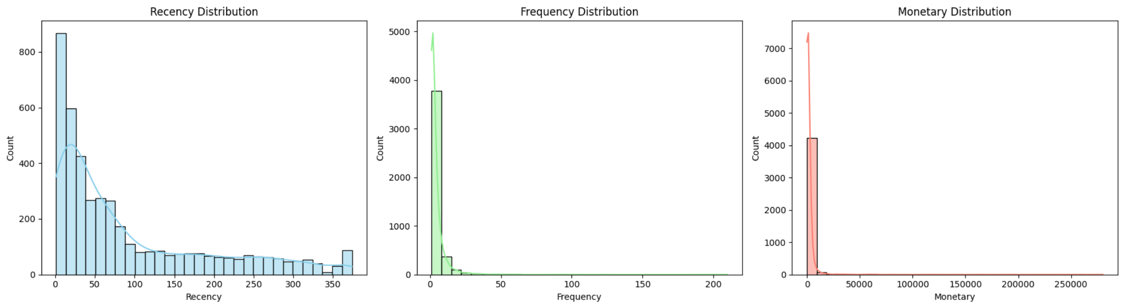
[58]:
```python
# Reference date for Recency calculation (typically the day after the last␣
↪transaction)
import datetime as dt
ref_date = df['InvoiceDate'].max() + dt.timedelta(days=1)
```

RFM Table

[59]:
```python
# Add TotalPrice column to original df first
df['TotalPrice'] = df['Quantity'] * df['UnitPrice']

rfm = df.groupby('CustomerID').agg({
    'InvoiceDate': lambda x: (ref_date - x.max()).days,  # Recency
    'InvoiceNo': 'nunique',                              # Frequency
    'TotalPrice': lambda x: x.sum() if 'TotalPrice' in x else 0  # We'll␣
↪calculate TotalPrice below
}).rename(columns={
    'InvoiceDate': 'Recency',
    'InvoiceNo': 'Frequency'
})
```

[60]:
```python
# Now recalculate Monetary (which relies on TotalPrice)
monetary = df.groupby('CustomerID')['TotalPrice'].sum()

# Merge into RFM
rfm['Monetary'] = monetary
```

[61]:
```python
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

sns.histplot(rfm['Recency'], bins=30, kde=True, ax=axes[0], color='skyblue')
axes[0].set_title('Recency Distribution')

sns.histplot(rfm['Frequency'], bins=30, kde=True, ax=axes[1],␣
↪color='lightgreen')
axes[1].set_title('Frequency Distribution')

sns.histplot(rfm['Monetary'], bins=30, kde=True, ax=axes[2], color='salmon')
axes[2].set_title('Monetary Distribution')

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



Feature Scaling

[62]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm)

# Convert back to DataFrame for readability
rfm_scaled_df = pd.DataFrame(rfm_scaled, columns=rfm.columns, index=rfm.index)
```

6 Dimensionality Reduction with PCA (Principal Component Analysis)

[63]:
```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
```

Apply PCA

[64]:
```
pca = PCA(n_components=2)  # Reduce to 2D for visualization
rfm_pca = pca.fit_transform(rfm_scaled)

# Convert to DataFrame
pca_df = pd.DataFrame(data=rfm_pca, columns=['PCA1', 'PCA2'])
```

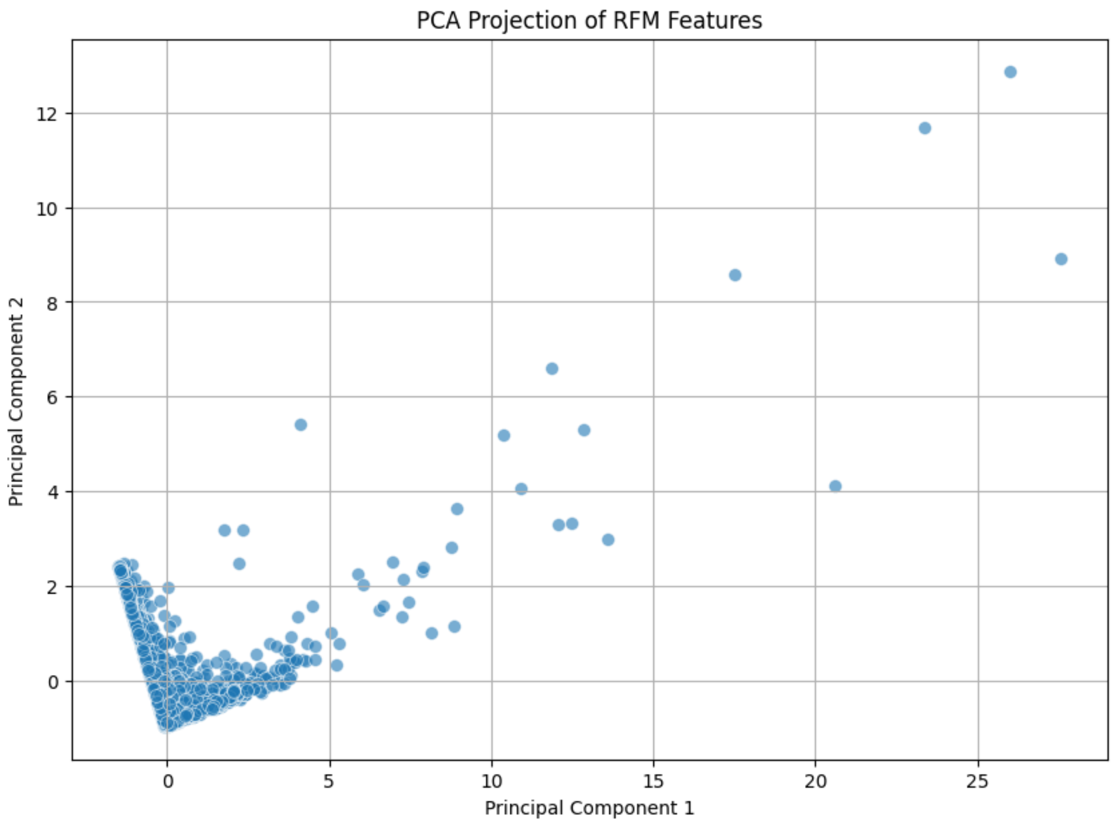
[65]:
```
print("Explained Variance Ratio (PCA):", pca.explained_variance_ratio_)
print("Total Variance Captured:", sum(pca.explained_variance_ratio_))
```

```
Explained Variance Ratio (PCA): [0.55508353 0.30254725]
Total Variance Captured: 0.857630778288257
```

Visualize the PCA Result

[66]:
```
plt.figure(figsize=(10, 7))
sns.scatterplot(x='PCA1', y='PCA2', data=pca_df, s=50, alpha=0.6)
plt.title('PCA Projection of RFM Features')
```

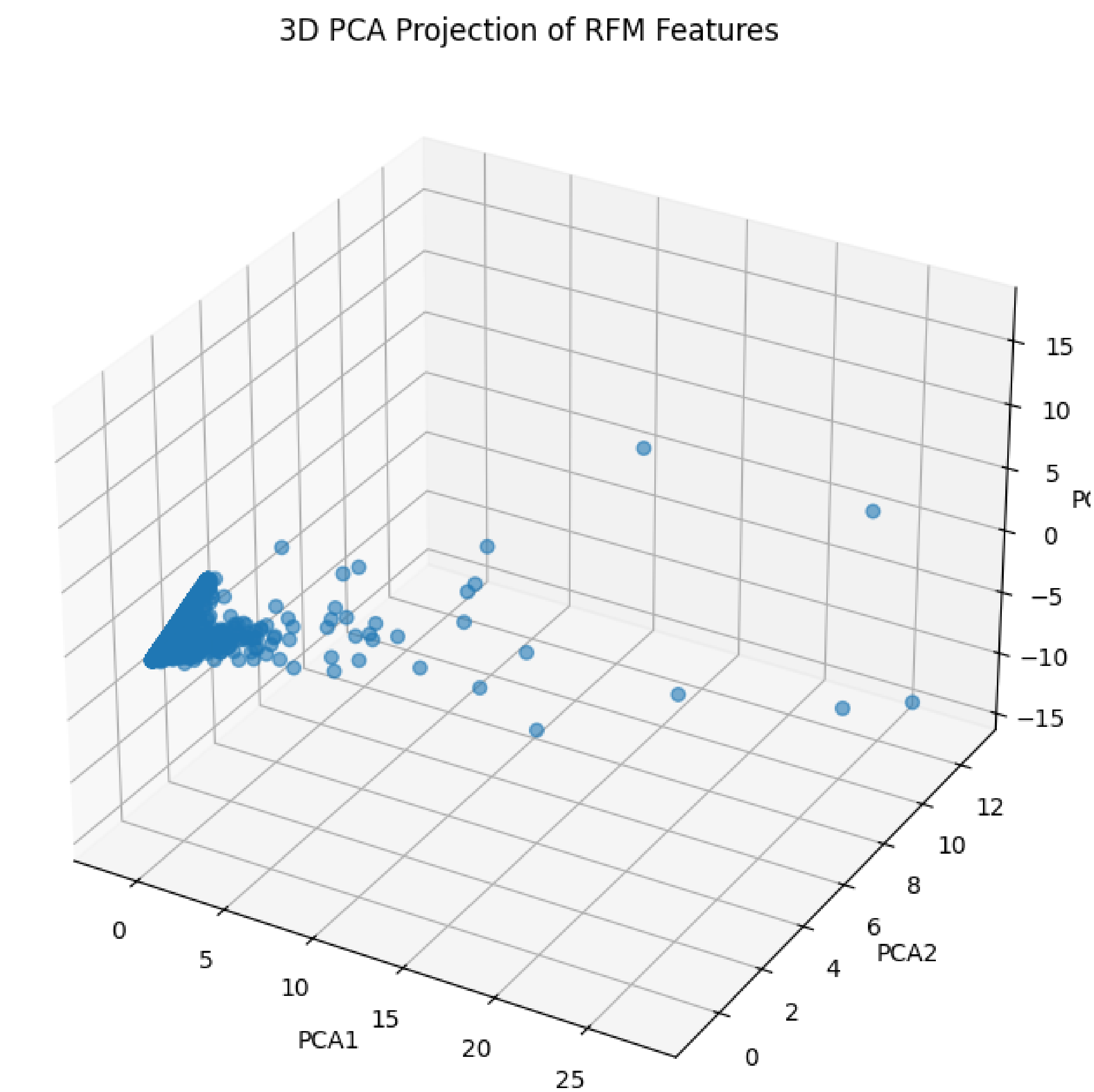
```
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.grid(True)
plt.show()
```



Use 3D PCA for Better Cluster Separation

[67]:
```
from mpl_toolkits.mplot3d import Axes3D

pca_3d = PCA(n_components=3)
rfm_pca_3d = pca_3d.fit_transform(rfm_scaled)

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

ax.scatter(rfm_pca_3d[:, 0], rfm_pca_3d[:, 1], rfm_pca_3d[:, 2], s=30, alpha=0.
  ↪6)
ax.set_title("3D PCA Projection of RFM Features")
ax.set_xlabel("PCA1")
ax.set_ylabel("PCA2")
ax.set_zlabel("PCA3")
```

```
plt.show()
```



7 K-Means Clustering

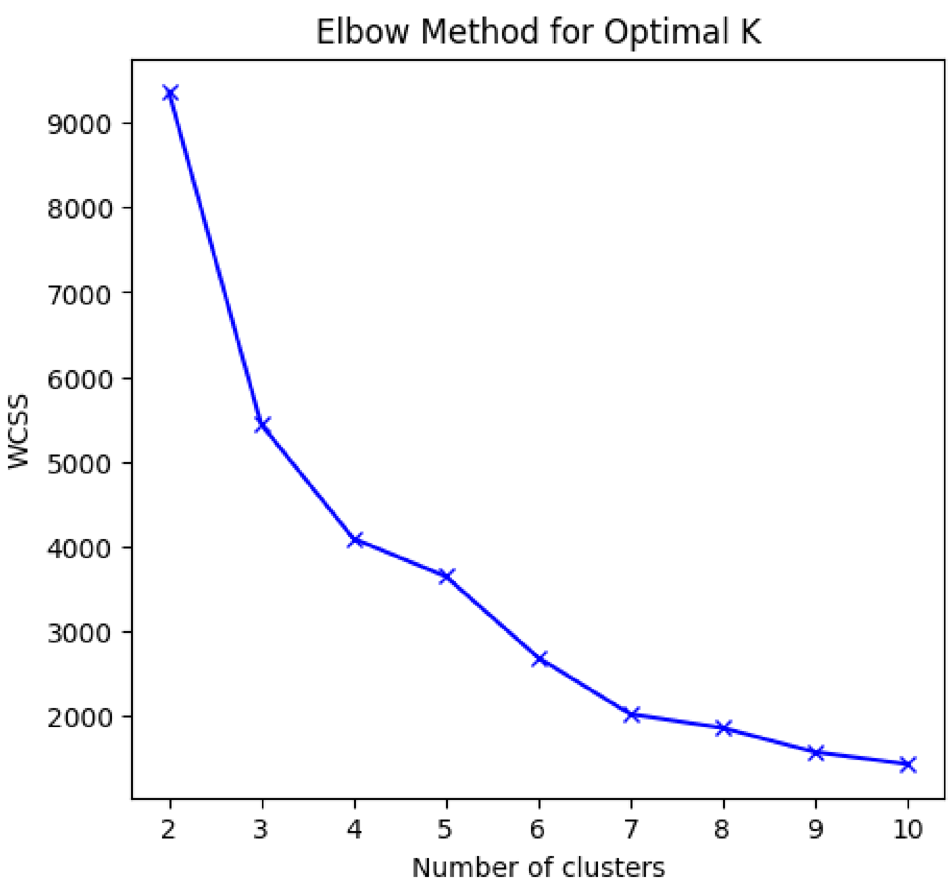
Optimal Number of Clusters (K)

[68]:
```
wcss = []
silhouette_scores = []
K = range(2, 11)

for k in K:
```

```
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(rfm_scaled)
    wcss.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(rfm_scaled, kmeans.labels_))
```

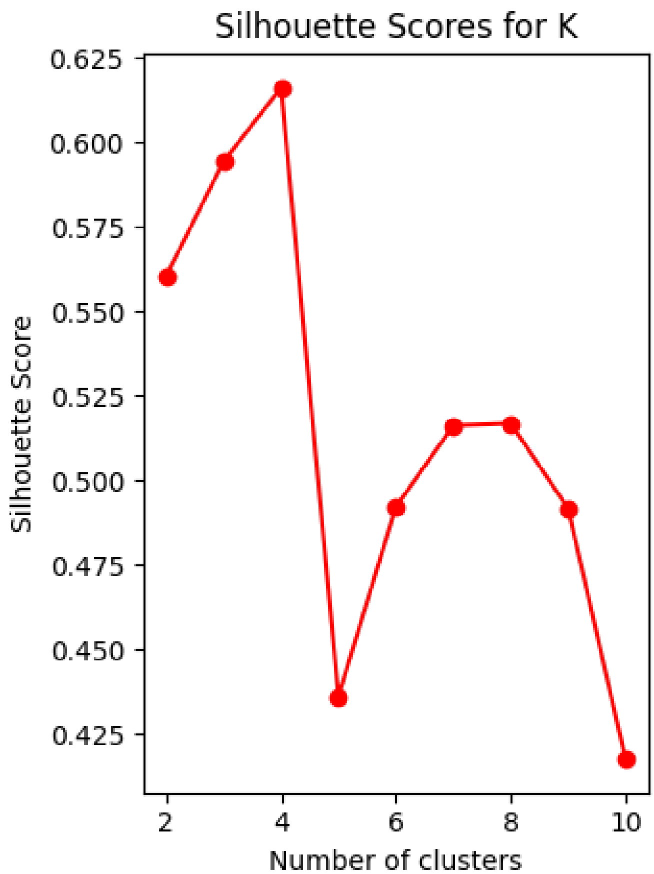
[69]:
```
# Plot WCSS (Elbow Method)
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(K, wcss, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.title('Elbow Method for Optimal K')
```

[69]:
```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```



[70]:
```
# Plot Silhouette Scores
plt.subplot(1, 2, 2)
plt.plot(K, silhouette_scores, 'ro-')
plt.xlabel('Number of clusters')
```

```
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores for K')

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



Apply K-Means Clustering

[71]:
```
kmeans = KMeans(n_clusters=4, random_state=42)
kmeans_labels = kmeans.fit_predict(rfm_scaled)

# Append cluster labels to the PCA-reduced DataFrame
pca_df['KMeans_Cluster'] = kmeans_labels

# Visualize the clusters
plt.figure(figsize=(8, 6))
sns.scatterplot(data=pca_df, x='PCA1', y='PCA2', hue='KMeans_Cluster',
 ↪palette='Set1')
plt.title('Customer Segments using K-Means')
```

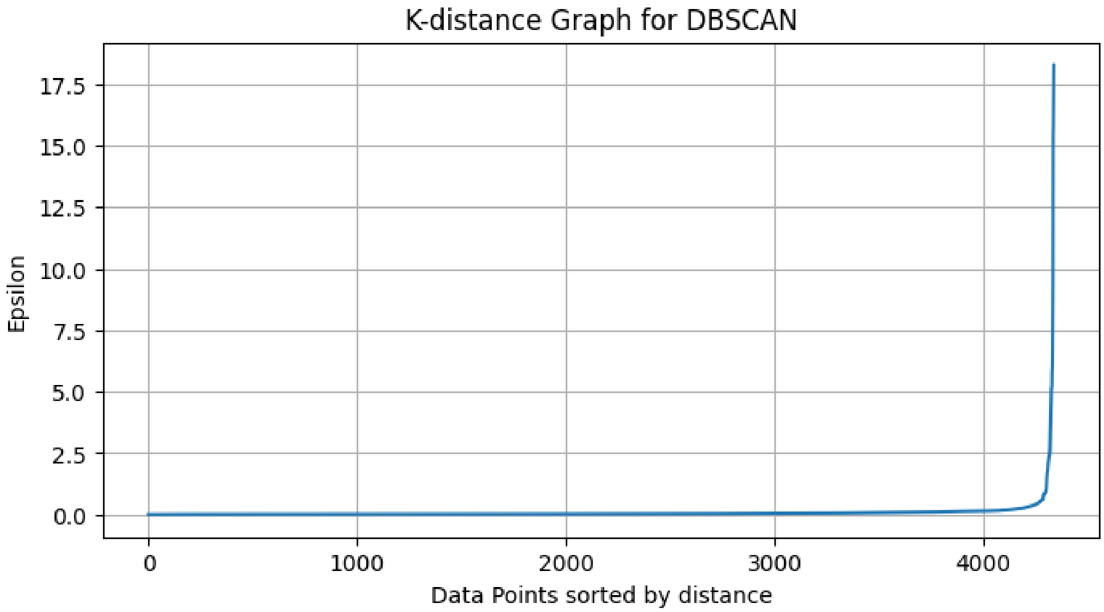
```
plt.show()
```

8 DBSCAN

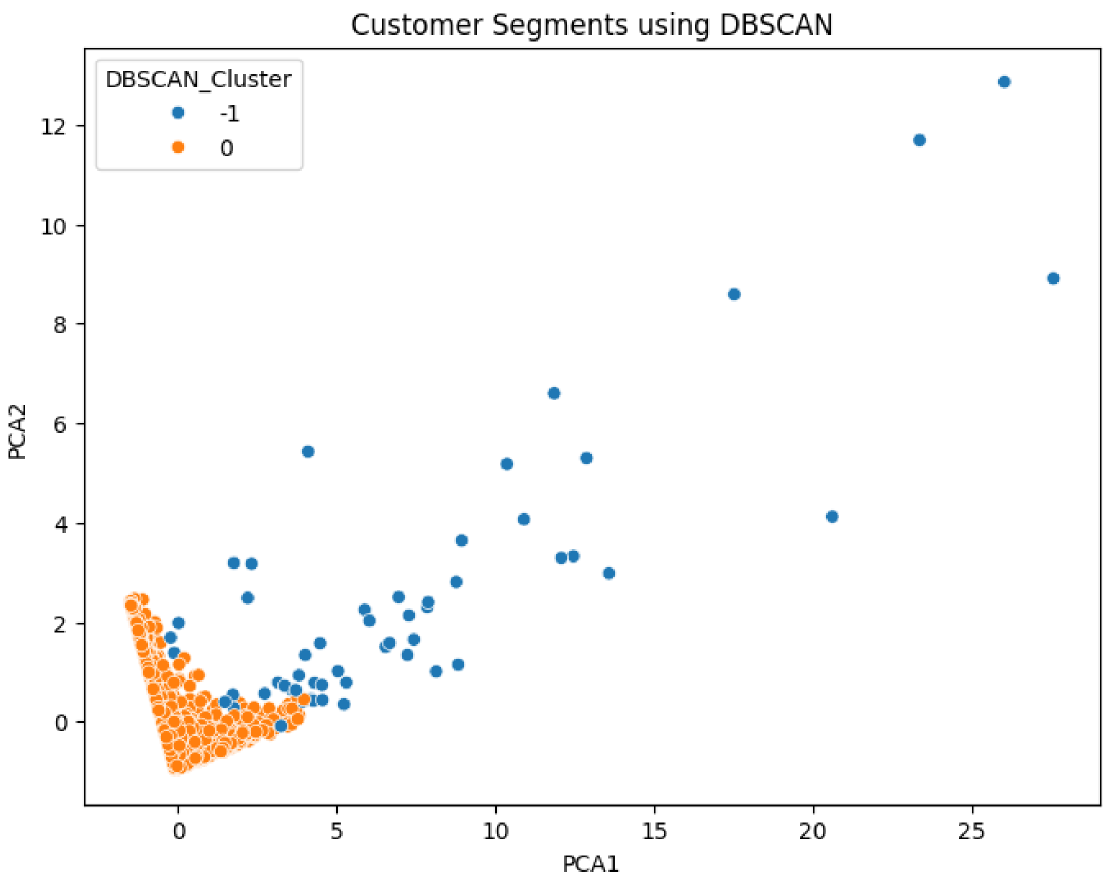
Apply DBSCAN

[72]:
```
from sklearn.neighbors import NearestNeighbors

neighbors = NearestNeighbors(n_neighbors=5)
neighbors_fit = neighbors.fit(rfm_scaled)
distances, indices = neighbors_fit.kneighbors(rfm_scaled)

# Plot the distances to estimate eps
distances = np.sort(distances[:, 4])
plt.figure(figsize=(8, 4))
plt.plot(distances)
plt.title('K-distance Graph for DBSCAN')
plt.xlabel('Data Points sorted by distance')
plt.ylabel('Epsilon')
```

```
plt.grid(True)
plt.show()
```

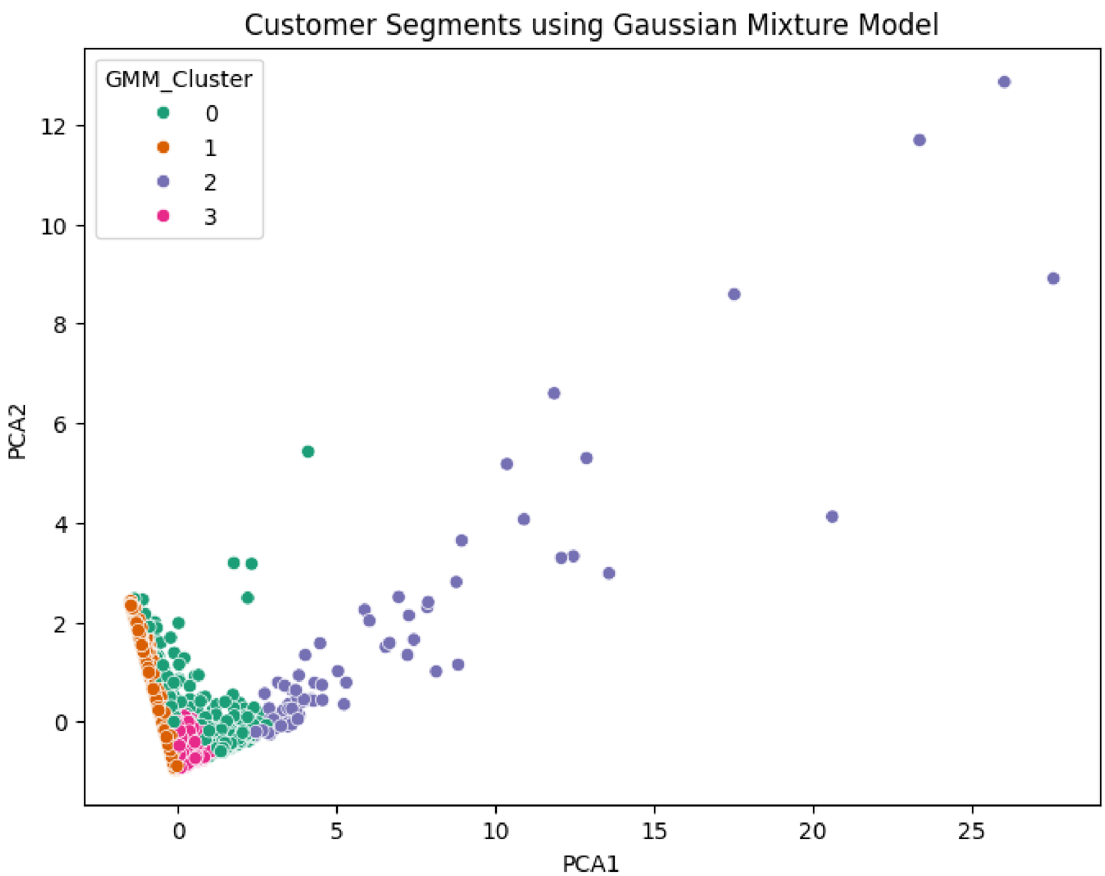


[73]:
```
dbscan = DBSCAN(eps=0.5, min_samples=5)
dbscan_labels = dbscan.fit_predict(rfm_scaled)

# Visualize DBSCAN Clusters
pca_df['DBSCAN_Cluster'] = dbscan_labels
plt.figure(figsize=(8, 6))
sns.scatterplot(data=pca_df, x='PCA1', y='PCA2', hue='DBSCAN_Cluster',␣
 ↪palette='tab10')
plt.title('Customer Segments using DBSCAN')
plt.show()
```



9 Gaussian Mixture Models (GMM)

[74]:
```
gmm = GaussianMixture(n_components=4, random_state=42)
gmm_labels = gmm.fit_predict(rfm_scaled)

# Visualize GMM Clusters
pca_df['GMM_Cluster'] = gmm_labels
plt.figure(figsize=(8, 6))
sns.scatterplot(data=pca_df, x='PCA1', y='PCA2', hue='GMM_Cluster',
  palette='Dark2')
plt.title('Customer Segments using Gaussian Mixture Model')
plt.show()
```



10 Deep Embedded Clustering (DEC)

[75]:
```
pip install tensorflow scikit-learn matplotlib seaborn
```

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-
packages (2.18.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-
packages (1.6.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-
packages (3.10.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-
packages (0.13.2)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
```

```
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (24.2)
Requirement already satisfied:
protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3
in /usr/local/lib/python3.11/dist-packages (from tensorflow) (5.29.4)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.1.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.2)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.17.2)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (3.8.0)
Requirement already satisfied: numpy<2.1.0,>=1.26.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.0.2)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (3.13.0)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.1)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-
```

```
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.11/dist-
packages (from seaborn) (2.2.2)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow)
(0.45.1)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages
(from keras>=3.5.0->tensorflow) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages
(from keras>=3.5.0->tensorflow) (0.0.9)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages
(from keras>=3.5.0->tensorflow) (0.15.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
packages (from requests<3,>=2.21.0->tensorflow) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(2.4.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(2025.4.26)
Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.8)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.1.3)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.11/dist-packages (from
```

```
werkzeug>=1.0.1->tensorboard<2.19,>=2.18->tensorflow) (3.0.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow)
(3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow)
(2.19.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-
packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->tensorflow) (0.1.2)
```

Build the Autoencoder

[76]:
```
input_dim = rfm_scaled.shape[1]
encoding_dim = 2

input_layer = Input(shape=(input_dim,))
encoded = Dense(5, activation='relu', activity_regularizer=regularizers.
↪l1(1e-5))(input_layer)
encoded = Dense(encoding_dim, activation='relu')(encoded)

decoded = Dense(5, activation='relu')(encoded)
decoded = Dense(input_dim, activation='sigmoid')(decoded)

autoencoder = Model(inputs=input_layer, outputs=decoded)
encoder = Model(inputs=input_layer, outputs=encoded)

autoencoder.compile(optimizer=Adam(learning_rate=0.01), loss='mse')
```

[77]:
```
autoencoder.fit(rfm_scaled, rfm_scaled, epochs=50, batch_size=32, shuffle=True,␣
↪verbose=1)
```

```
Epoch 1/50
136/136              2s 3ms/step -
loss: 0.7199
Epoch 2/50
136/136              0s 2ms/step -
loss: 0.5272
Epoch 3/50
136/136              1s 2ms/step -
loss: 0.4544
Epoch 4/50
136/136              0s 3ms/step -
loss: 0.4800
Epoch 5/50
136/136              0s 2ms/step -
loss: 0.6175
Epoch 6/50
136/136              0s 2ms/step -
```

```
loss: 0.4120
Epoch 7/50
136/136             1s 2ms/step -
loss: 0.5456
Epoch 8/50
136/136             1s 3ms/step -
loss: 0.5280
Epoch 9/50
136/136             1s 3ms/step -
loss: 0.4586
Epoch 10/50
136/136             1s 4ms/step -
loss: 0.3546
Epoch 11/50
136/136             1s 4ms/step -
loss: 0.7469
Epoch 12/50
136/136             1s 4ms/step -
loss: 0.5777
Epoch 13/50
136/136             1s 4ms/step -
loss: 0.5926
Epoch 14/50
136/136             0s 3ms/step -
loss: 0.4048
Epoch 15/50
136/136             1s 3ms/step -
loss: 0.6359
Epoch 16/50
136/136             1s 3ms/step -
loss: 0.5461
Epoch 17/50
136/136             0s 3ms/step -
loss: 0.3676
Epoch 18/50
136/136             0s 3ms/step -
loss: 0.3833
Epoch 19/50
136/136             0s 3ms/step -
loss: 0.5556
Epoch 20/50
136/136             1s 3ms/step -
loss: 0.4331
Epoch 21/50
136/136             0s 3ms/step -
loss: 0.5714
Epoch 22/50
136/136             0s 3ms/step -
```

```
loss: 0.4444
Epoch 23/50
136/136             0s 3ms/step -
loss: 0.4751
Epoch 24/50
136/136             1s 3ms/step -
loss: 0.4605
Epoch 25/50
136/136             1s 3ms/step -
loss: 0.7199
Epoch 26/50
136/136             1s 3ms/step -
loss: 0.4498
Epoch 27/50
136/136             1s 3ms/step -
loss: 0.4824
Epoch 28/50
136/136             1s 3ms/step -
loss: 0.5239
Epoch 29/50
136/136             1s 3ms/step -
loss: 0.3614
Epoch 30/50
136/136             1s 3ms/step -
loss: 0.6913
Epoch 31/50
136/136             1s 4ms/step -
loss: 0.6732
Epoch 32/50
136/136             1s 4ms/step -
loss: 0.4890
Epoch 33/50
136/136             1s 4ms/step -
loss: 0.5439
Epoch 34/50
136/136             1s 4ms/step -
loss: 0.3499
Epoch 35/50
136/136             0s 2ms/step -
loss: 0.5677
Epoch 36/50
136/136             1s 3ms/step -
loss: 0.5709
Epoch 37/50
136/136             0s 2ms/step -
loss: 0.5260
Epoch 38/50
136/136             1s 3ms/step -
```

```
loss: 0.6874
Epoch 39/50
136/136              1s 2ms/step -
loss: 0.6397
Epoch 40/50
136/136              1s 2ms/step -
loss: 0.5243
Epoch 41/50
136/136              1s 2ms/step -
loss: 0.4840
Epoch 42/50
136/136              1s 3ms/step -
loss: 0.4956
Epoch 43/50
136/136              1s 3ms/step -
loss: 0.5389
Epoch 44/50
136/136              1s 2ms/step -
loss: 0.4317
Epoch 45/50
136/136              0s 2ms/step -
loss: 0.3853
Epoch 46/50
136/136              1s 2ms/step -
loss: 0.7131
Epoch 47/50
136/136              1s 2ms/step -
loss: 0.5155
Epoch 48/50
136/136              1s 3ms/step -
loss: 0.5425
Epoch 49/50
136/136              1s 2ms/step -
loss: 0.3944
Epoch 50/50
136/136              0s 2ms/step -
loss: 0.4327
```

[77]:
```
<keras.src.callbacks.history.History at 0x7d84629d0090>
```

Encode the RFM Data

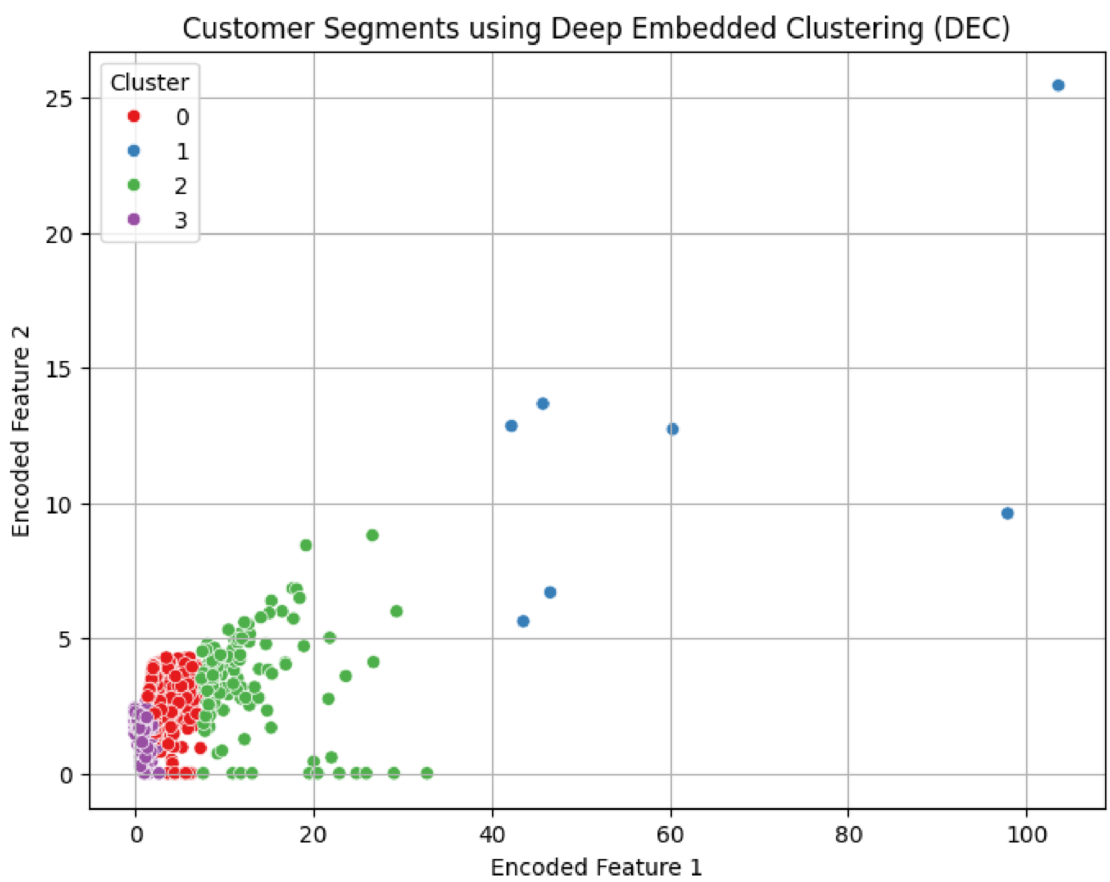
[78]:
```
encoded_data = encoder.predict(rfm_scaled)
```

```
136/136              0s 2ms/step
```

[79]:
```
kmeans = KMeans(n_clusters=4, random_state=42)
cluster_labels = kmeans.fit_predict(encoded_data)
```

Apply K-Means to the encoded data

[80]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x=encoded_data[:, 0], y=encoded_data[:, 1], hue=cluster_labels,␣
↪palette='Set1')
plt.title('Customer Segments using Deep Embedded Clustering (DEC)')
plt.xlabel('Encoded Feature 1')
plt.ylabel('Encoded Feature 2')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```



11 Evaluation Techniques

Internal Validation Metrics

[81]:
```
from sklearn.metrics import silhouette_score

silhouette_avg = silhouette_score(rfm_scaled, cluster_labels)
```

```
print(f'Silhouette Score: {silhouette_avg:.2f}')
```

```
Silhouette Score: 0.33
```

Davies-Bouldin Index

[82]:
```
from sklearn.metrics import davies_bouldin_score

db_score = davies_bouldin_score(rfm_scaled, cluster_labels)
print(f'Davies-Bouldin Index: {db_score:.2f}')
```

```
Davies-Bouldin Index: 0.89
```

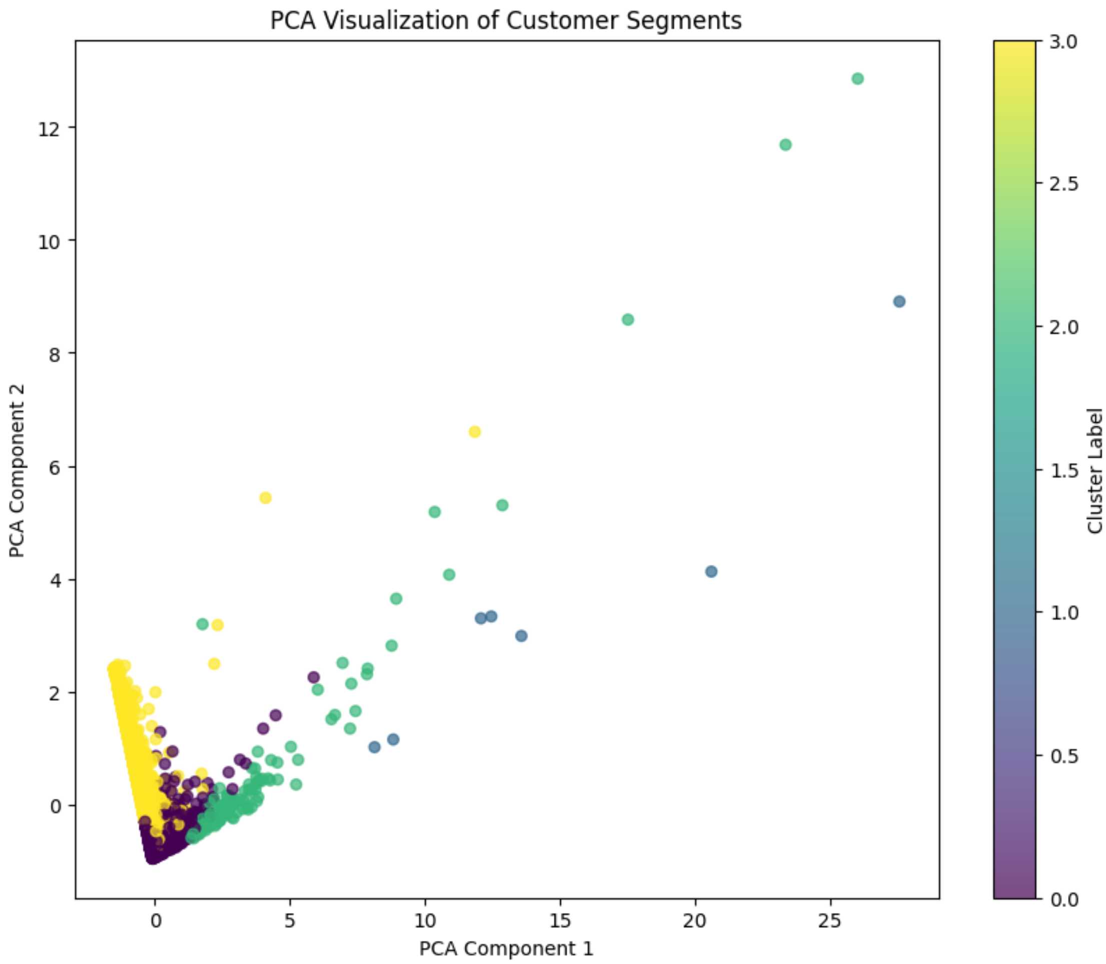
Calinski-Harabasz Index

[83]:
```
from sklearn.metrics import calinski_harabasz_score

ch_score = calinski_harabasz_score(rfm_scaled, cluster_labels)
print(f'Calinski-Harabasz Index: {ch_score:.2f}')
```

```
Calinski-Harabasz Index: 1266.98
```

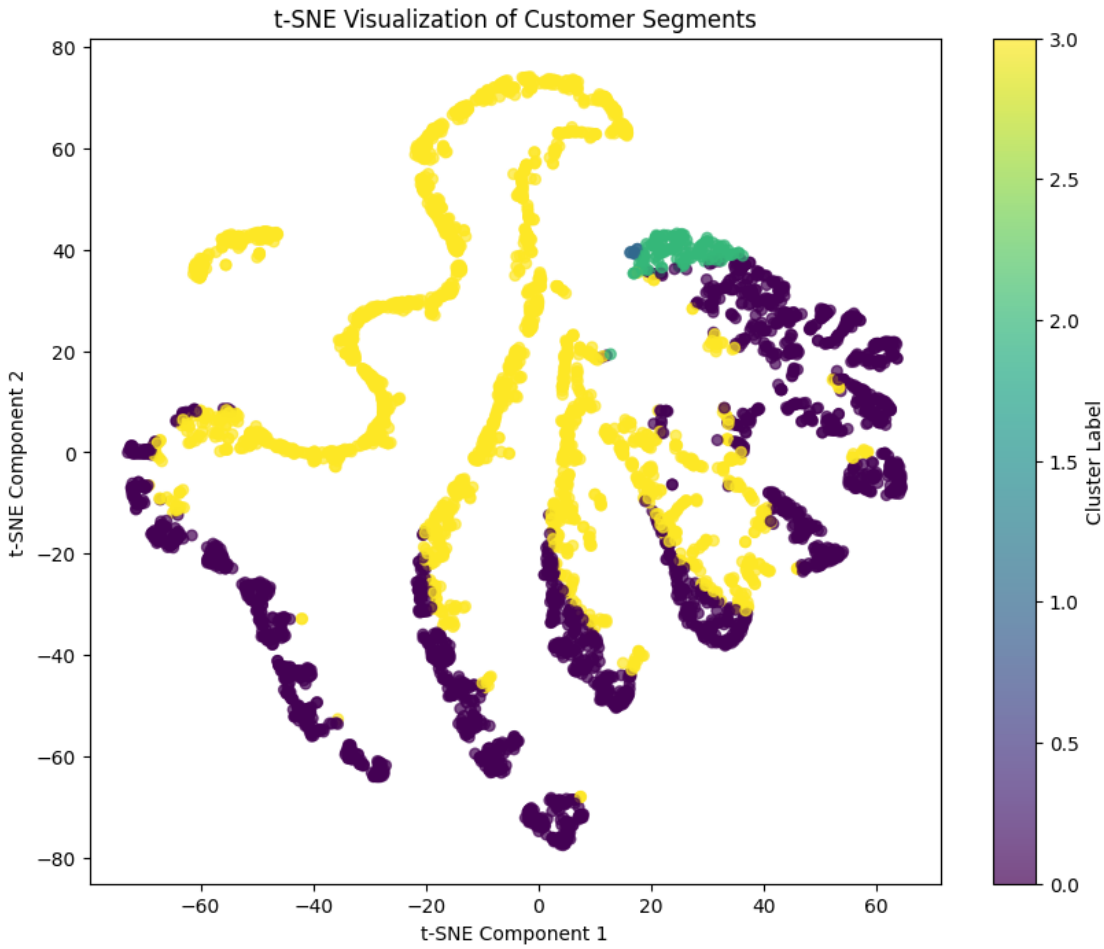
Using PCA for Dimensionality Reduction

[89]:
```
from sklearn.decomposition import PCA

# Apply PCA for 2D visualization
pca = PCA(n_components=2)
rfm_pca = pca.fit_transform(rfm_scaled)

# Visualize the clusters in 2D
plt.figure(figsize=(10, 8))
plt.scatter(rfm_pca[:, 0], rfm_pca[:, 1], c=cluster_labels, cmap='viridis',␣
 ↪s=30, alpha=0.7)
plt.title('PCA Visualization of Customer Segments')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.colorbar(label='Cluster Label')
plt.show()
```



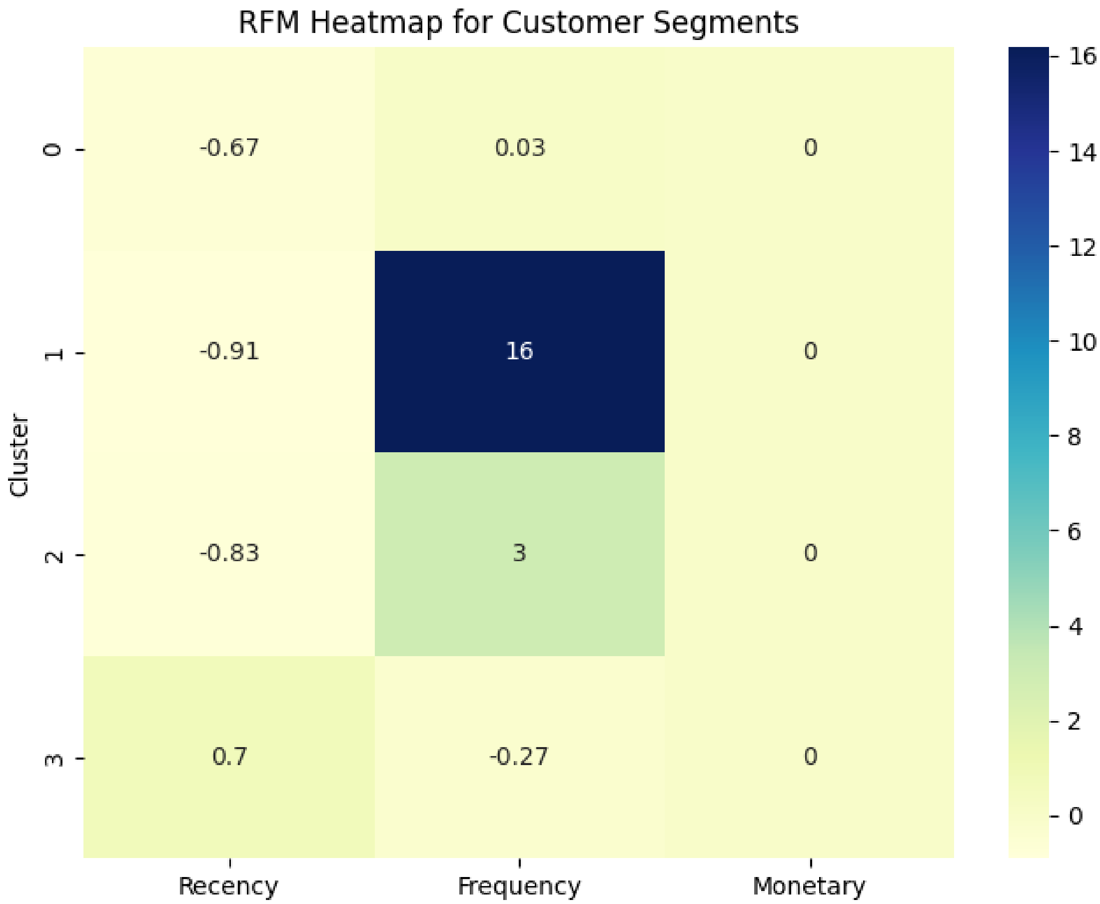
Using t-SNE for Dimensionality Reduction

[90]:
```
from sklearn.manifold import TSNE

# Apply t-SNE for 2D visualization
tsne = TSNE(n_components=2, random_state=42)
rfm_tsne = tsne.fit_transform(rfm_scaled)

# Visualize the clusters in 2D
plt.figure(figsize=(10, 8))
plt.scatter(rfm_tsne[:, 0], rfm_tsne[:, 1], c=cluster_labels, cmap='viridis',␣
↪s=30, alpha=0.7)
plt.title('t-SNE Visualization of Customer Segments')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.colorbar(label='Cluster Label')
plt.show()
```



RFM Heatmap

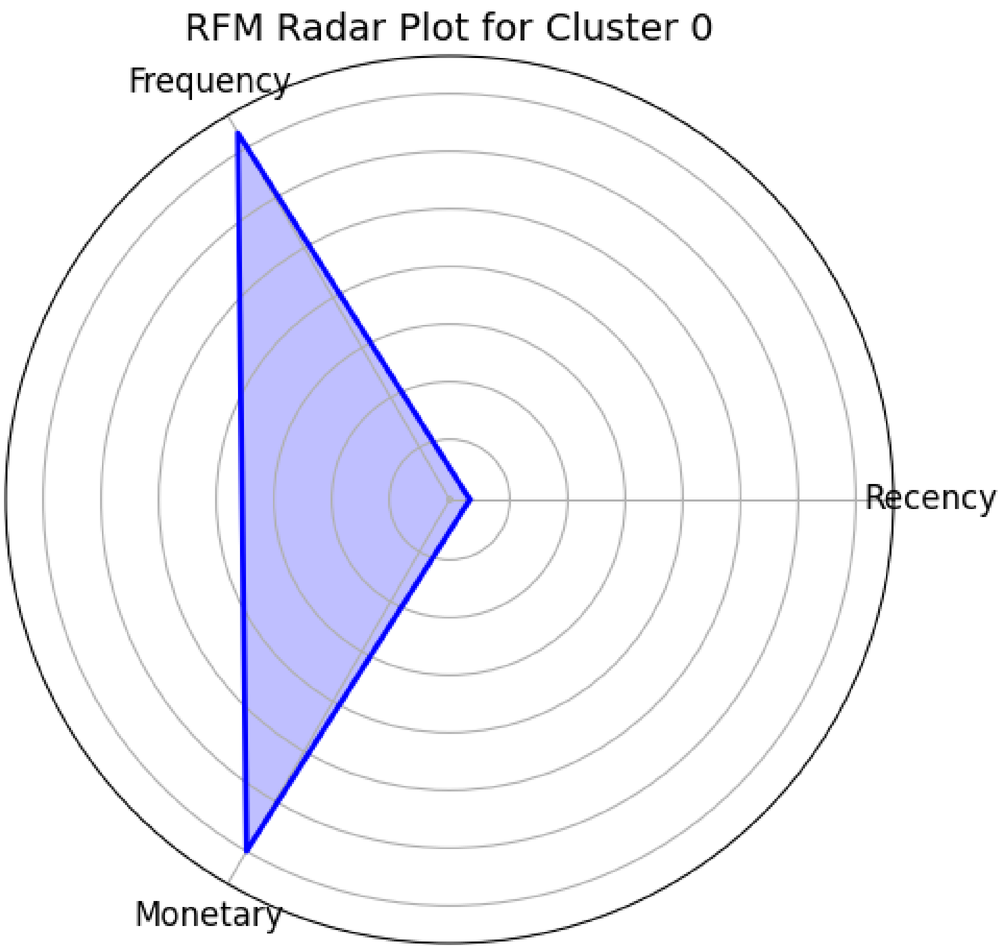
[93]:
```
import seaborn as sns

# Create a DataFrame for RFM averages per cluster
rfm_df = pd.DataFrame(rfm_scaled[:, :3], columns=['Recency', 'Frequency',␣
↪'Monetary'])
rfm_df['Cluster'] = cluster_labels

# Calculate mean values of RFM features per cluster
rfm_cluster_means = rfm_df.groupby('Cluster').mean()

# Plot heatmap for RFM features per cluster
plt.figure(figsize=(8, 6))
sns.heatmap(rfm_cluster_means, annot=True, cmap='YlGnBu', cbar=True)
plt.title('RFM Heatmap for Customer Segments')
plt.show()
```



Radar Plot for RFM Features per Cluster

[94]:
```python
import numpy as np

# Radar plot setup
def radar_plot(data, categories, cluster_num):
    angles = np.linspace(0, 2 * np.pi, len(categories), endpoint=False).tolist()
    data = np.concatenate((data, [data[0]]))  # To close the circle
    angles += angles[:1]

    fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(polar=True))
    ax.fill(angles, data, color='blue', alpha=0.25)
    ax.plot(angles, data, color='blue', linewidth=2)

    ax.set_yticklabels([])
    ax.set_xticks(angles[:-1])
    ax.set_xticklabels(categories, fontsize=12)

    ax.set_title(f'RFM Radar Plot for Cluster {cluster_num}', size=14)
```

```
    plt.show()

# Plot the radar plot for the first cluster (change cluster_num as needed)
categories = ['Recency', 'Frequency', 'Monetary']
cluster_0_mean = rfm_cluster_means.iloc[0].values
radar_plot(cluster_0_mean, categories, cluster_num=0)
```

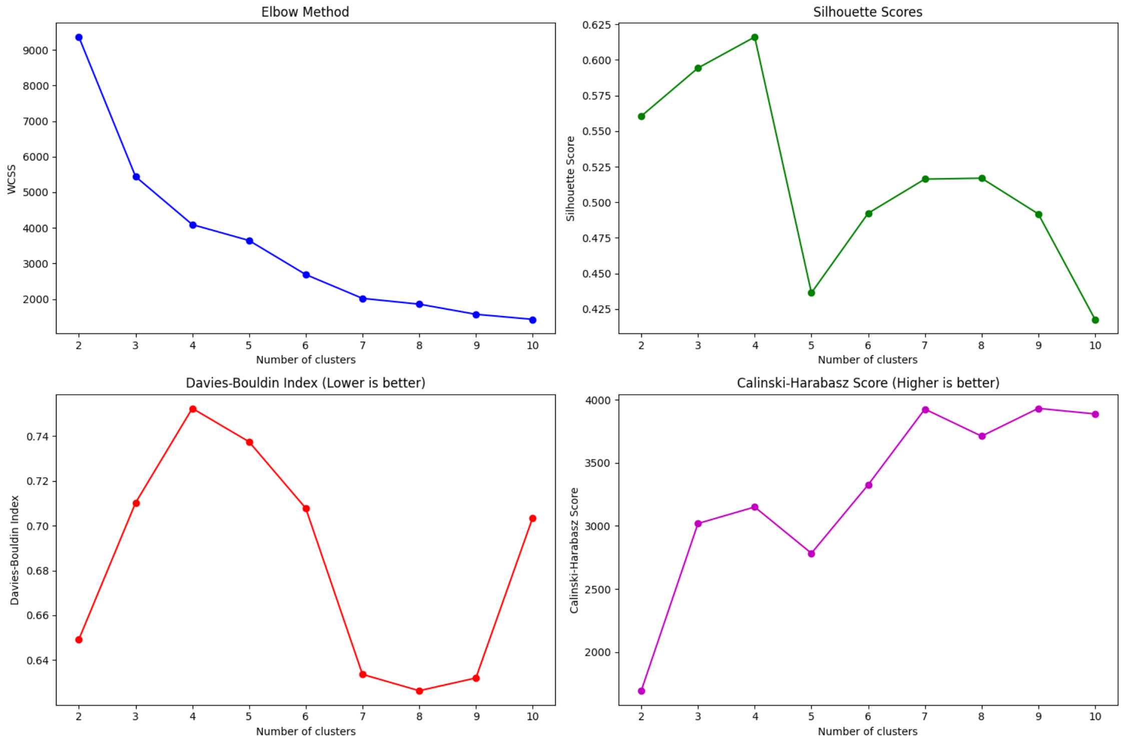


Advanced Cluster Evaluation Metrics

[107]:
```
from sklearn.metrics import calinski_harabasz_score, davies_bouldin_score,␣
↪silhouette_score
from sklearn.cluster import KMeans

def evaluate_clusters(data, max_clusters=10):
    """
    Evaluate clustering performance for different numbers of clusters
    using multiple metrics and visualize the results.
```

```python
"""
wcss = []
silhouette_scores = []
db_scores = []
ch_scores = []
k_values = range(2, max_clusters+1)

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(data)

    # Calculate metrics
    wcss.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(data, labels))
    db_scores.append(davies_bouldin_score(data, labels))
    ch_scores.append(calinski_harabasz_score(data, labels))

# Plot results
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
plt.plot(k_values, wcss, 'bo-')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.title('Elbow Method')

plt.subplot(2, 2, 2)
plt.plot(k_values, silhouette_scores, 'go-')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores')

plt.subplot(2, 2, 3)
plt.plot(k_values, db_scores, 'ro-')
plt.xlabel('Number of clusters')
plt.ylabel('Davies-Bouldin Index')
plt.title('Davies-Bouldin Index (Lower is better)')

plt.subplot(2, 2, 4)
plt.plot(k_values, ch_scores, 'mo-')
plt.xlabel('Number of clusters')
plt.ylabel('Calinski-Harabasz Score')
plt.title('Calinski-Harabasz Score (Higher is better)')

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

```
# Run evaluation on our RFM data
evaluate_clusters(rfm_scaled, max_clusters=10)
```

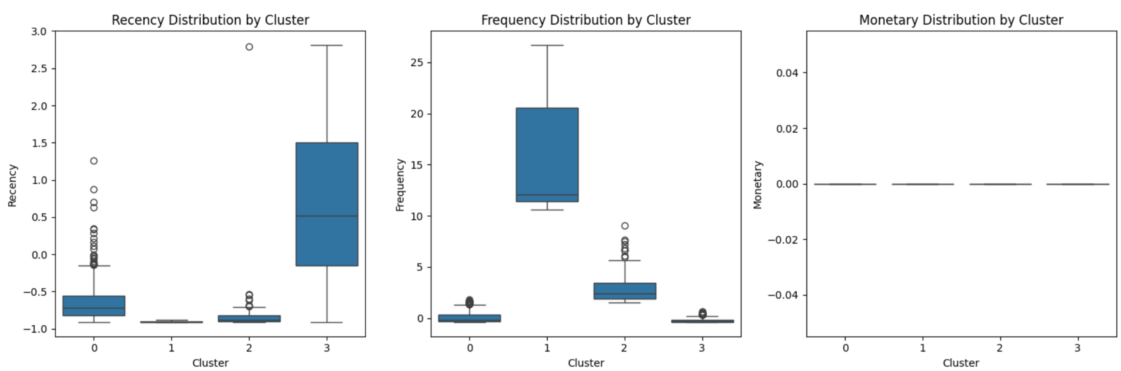


Cluster Profiling with Statistical Analysis

[108]:
```
import scipy.stats as stats

def profile_clusters(rfm_data, cluster_labels):
    """
    Create detailed statistical profiles of each cluster
    including significance testing between clusters.
    """
    # Add cluster labels to RFM data
    profiled_data = rfm_data.copy()
    profiled_data['Cluster'] = cluster_labels

    # Calculate mean values
    cluster_means = profiled_data.groupby('Cluster').mean()

    # Calculate statistical significance between clusters
    features = ['Recency', 'Frequency', 'Monetary']
    anova_results = {}
```

```
    for feature in features:
        cluster_groups = [profiled_data[profiled_data['Cluster'] == c][feature]
                          for c in profiled_data['Cluster'].unique()]
        f_val, p_val = stats.f_oneway(*cluster_groups)
        anova_results[feature] = {'F-value': f_val, 'p-value': p_val}

    # Visualize cluster profiles
    plt.figure(figsize=(15, 5))
    for i, feature in enumerate(features, 1):
        plt.subplot(1, 3, i)
        sns.boxplot(x='Cluster', y=feature, data=profiled_data)
        plt.title(f'{feature} Distribution by Cluster')

    plt.tight_layout()
    plt.show()

    return {
        'cluster_means': cluster_means,
        'anova_results': pd.DataFrame(anova_results).T,
        'cluster_stats': profiled_data.groupby('Cluster').describe()
    }

# Generate cluster profiles
cluster_profiles = profile_clusters(rfm_df, cluster_labels)
display(cluster_profiles['cluster_means'])
display(cluster_profiles['anova_results'])
```

```
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:586:
ConstantInputWarning: Each of the input arrays is constant; the F statistic is
not defined or infinite
  res = hypotest_fun_out(*samples, **kwds)
```




```
         Recency  Frequency  Monetary
Cluster
```

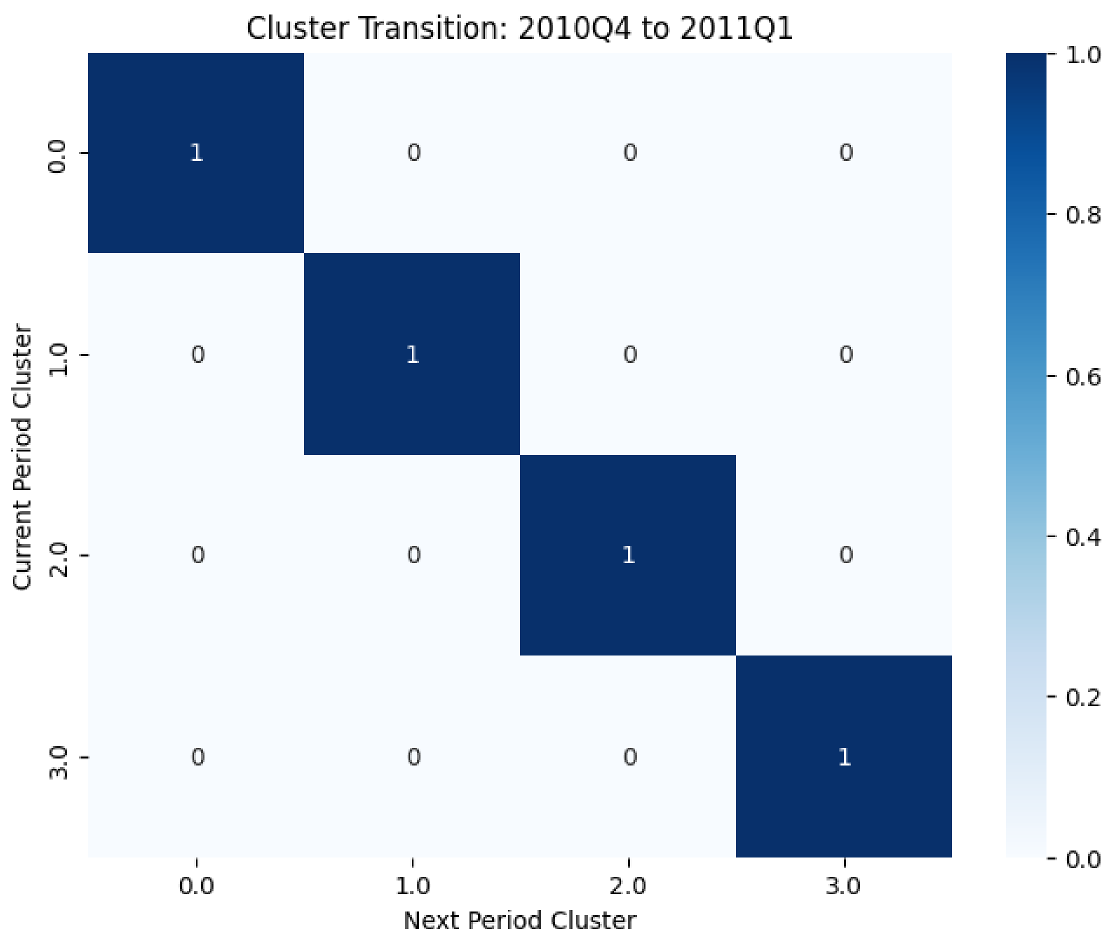
```
0       -0.669647   0.030418       0.0
1       -0.906628  16.170225       0.0
2       -0.827183   2.974744       0.0
3        0.701458  -0.271731       0.0
```

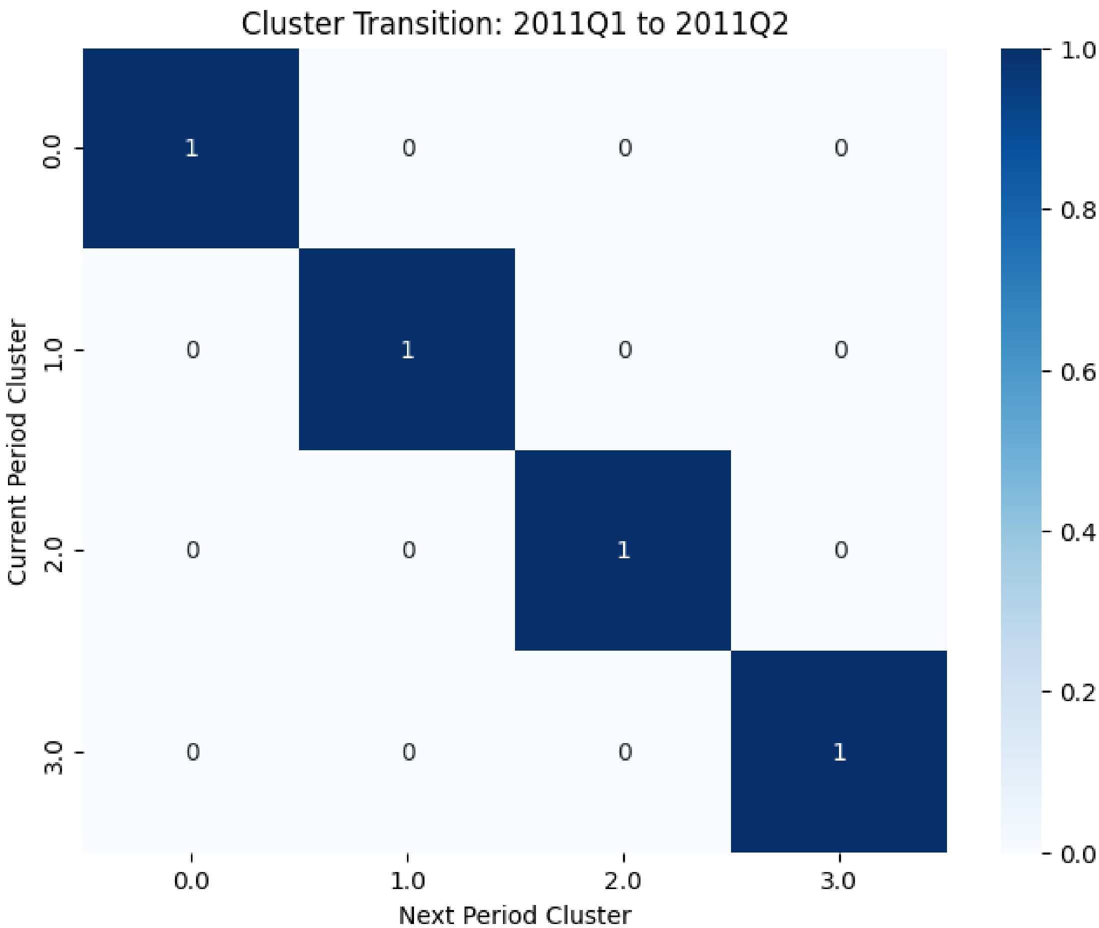
```
               F-value  p-value
Recency    1322.627362      0.0
Frequency  4028.152283      0.0
Monetary           NaN      NaN
```

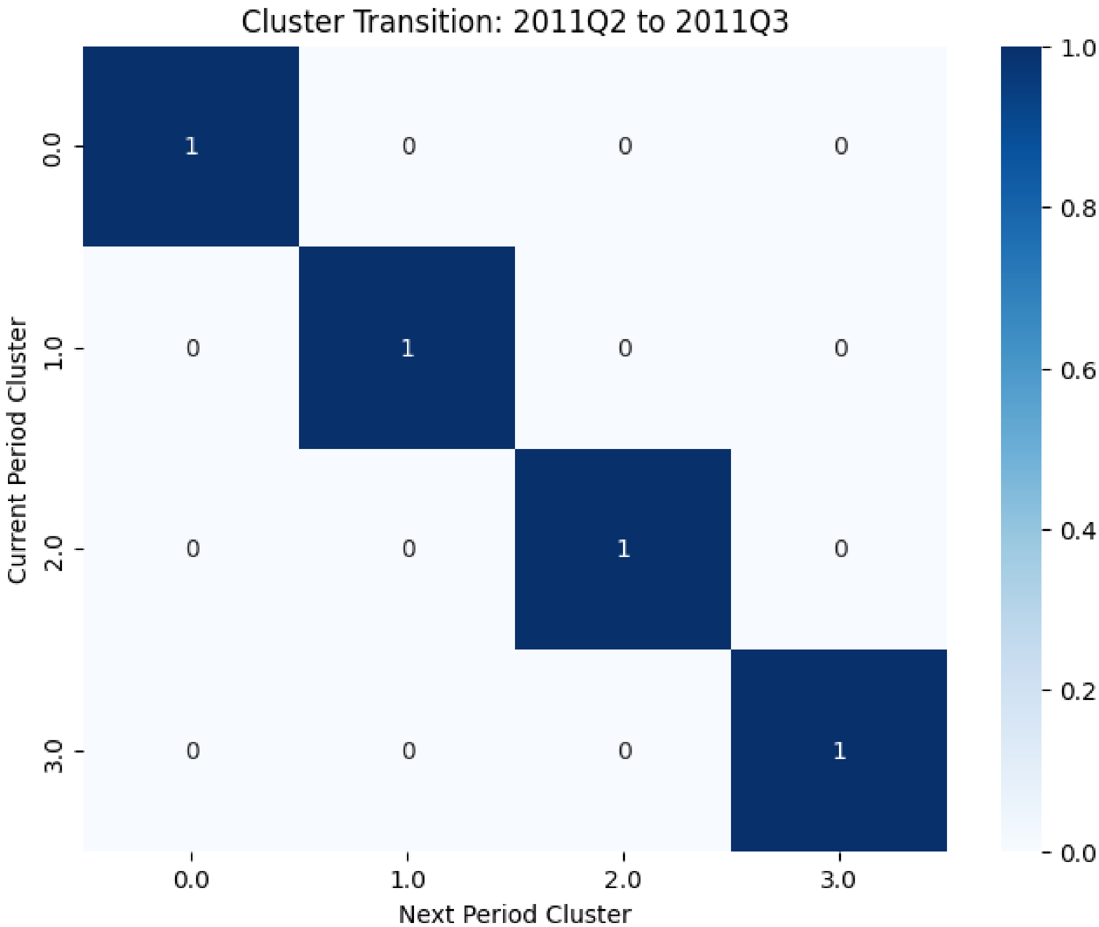
Customer Migration Analysis

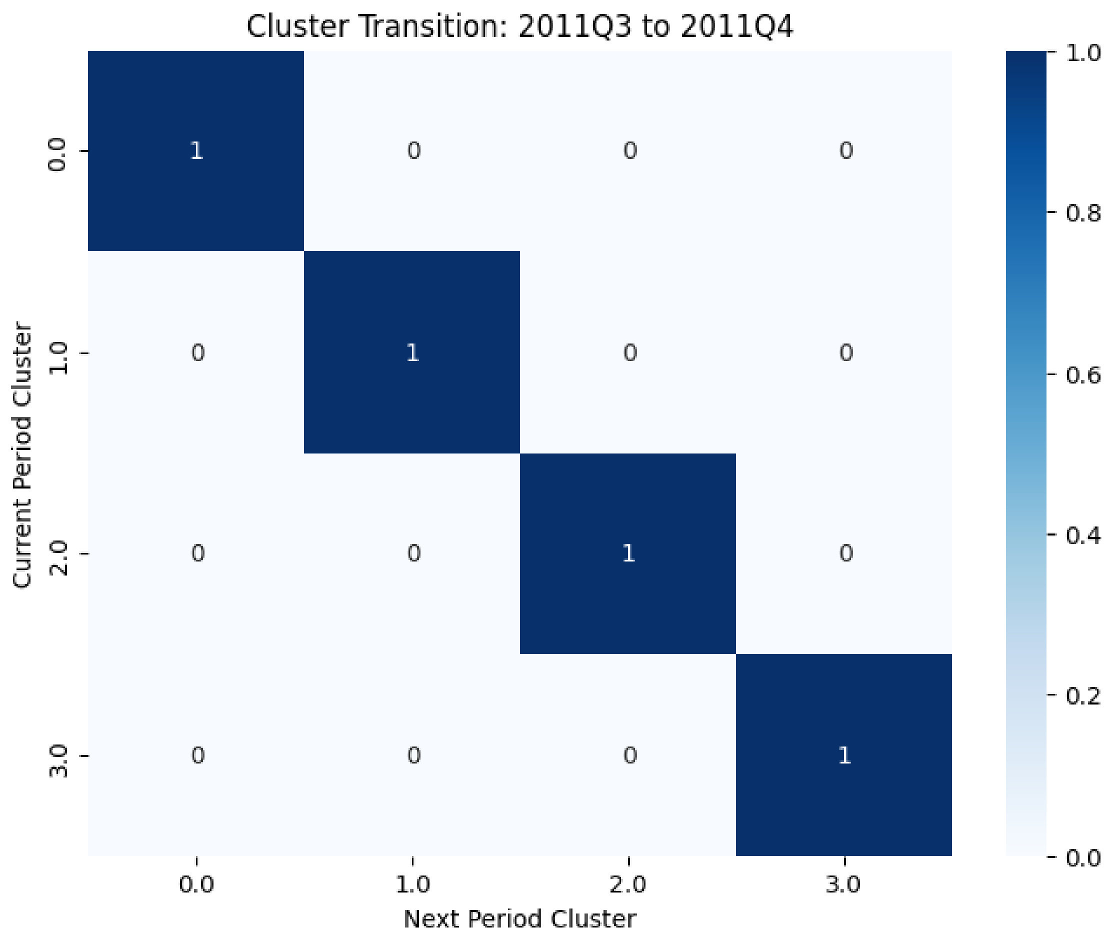
[109]:
```
from datetime import timedelta

def analyze_customer_migration(df, cluster_labels, period='Q'):
    """
    Analyze how customers move between clusters over time.
    """
    # Create time periods
    df['Period'] = df['InvoiceDate'].dt.to_period(period)

    # Get unique customers and their clusters per period
    customer_migration = df.groupby(['CustomerID', 'Period']).agg({
        'Cluster': 'last'
    }).reset_index()

    # Pivot to see cluster changes
    migration_pivot = customer_migration.pivot(index='CustomerID',
                                               columns='Period',
                                               values='Cluster')

    # Calculate transition matrix
    periods = sorted(df['Period'].unique())
    transition_matrices = {}

    for i in range(len(periods)-1):
        from_period = periods[i]
        to_period = periods[i+1]

        # Get customers present in both periods
        common_customers = migration_pivot.dropna(subset=[from_period,␣
 ↪to_period])

        if not common_customers.empty:
            # Create transition matrix
            transition_matrix = pd.crosstab(
                common_customers[from_period],
                common_customers[to_period],
```

```
                normalize='index'
            )
            transition_matrices[f"{from_period} to {to_period}"] =␣
↪transition_matrix

    # Visualize migration patterns
    for period_pair, matrix in transition_matrices.items():
        plt.figure(figsize=(8, 6))
        sns.heatmap(matrix, annot=True, cmap='Blues', vmin=0, vmax=1)
        plt.title(f'Cluster Transition: {period_pair}')
        plt.xlabel('Next Period Cluster')
        plt.ylabel('Current Period Cluster')
        plt.show()

    return transition_matrices

# Analyze quarterly customer migration
migration_results = analyze_customer_migration(df, cluster_labels, period='Q')
```




Cluster Transition: 2011Q1 to 2011Q2
Current Period Cluster
Next Period Cluster
0.0
1.0
2.0
3.0
1
0
1.0
0.8
0.6
0.4
0.2
0.0


Cluster Transition: 2011Q2 to 2011Q3
Current Period Cluster
Next Period Cluster
0.0
1.0
2.0
3.0
1
0
1.0
0.8
0.6
0.4
0.2
0.0

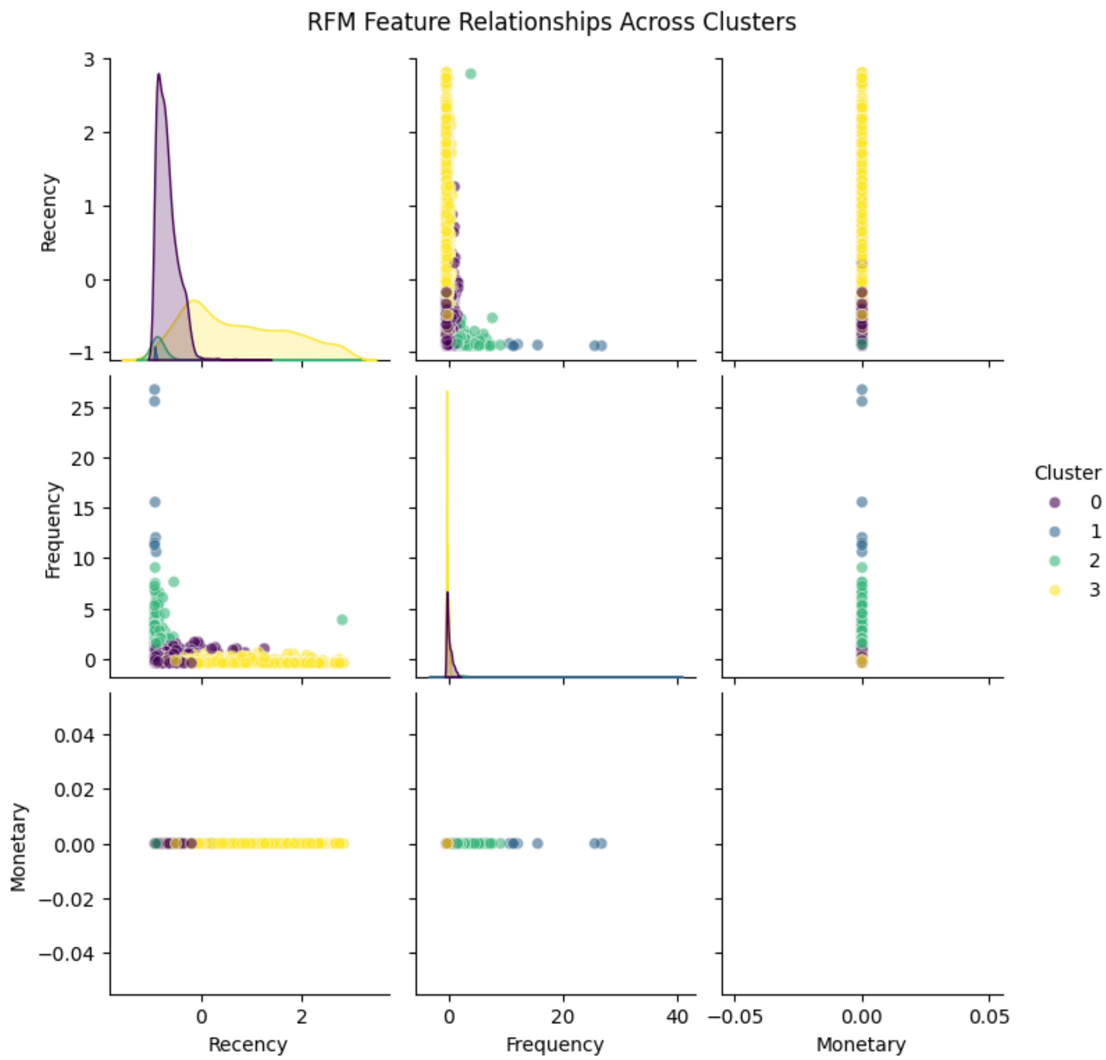


12 Conclusion and Business Impact

[97]:
```
# Visualizing the cluster characteristics
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming rfm_scaled is your scaled RFM data and cluster_labels from K-Means
# rfm_scaled likely has 4 columns now, including the cluster labels
# Select only the first 3 columns for Recency, Frequency, Monetary
rfm_df = pd.DataFrame(rfm_scaled[:, :3], columns=['Recency', 'Frequency',␣
↪'Monetary'])
rfm_df['Cluster'] = cluster_labels

plt.figure(figsize=(14, 10))

# Create pairplot to visualize relationships between RFM features
```

```
sns.pairplot(rfm_df, hue='Cluster', palette='viridis', plot_kws={'alpha':0.6})
plt.suptitle('RFM Feature Relationships Across Clusters', y=1.02)
plt.show()
```

<Figure size 1400x1000 with 0 Axes>

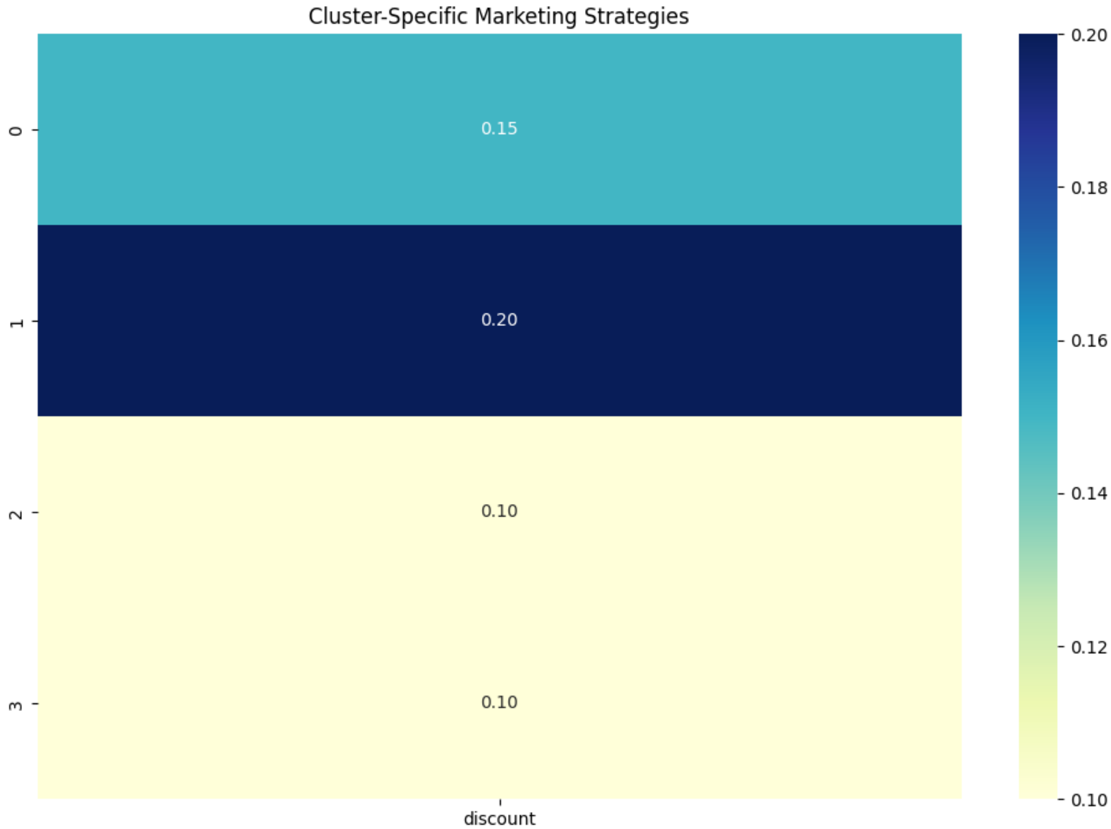


Personalized Marketing Strategies

[100]:
```
# Generate targeted marketing recommendations per cluster
cluster_profiles = {
    0: {
        'name': 'High-Value Loyalists',
        'strategy': ['Exclusive loyalty programs', 'Early access to new␣
↪products', 'Personalized high-end recommendations'],
        'channel': ['Email', 'Personalized dashboard', 'Direct mail'],
```

```
        'discount': 0.15  # Replace with a representative numerical value
    },
    1: {
        'name': 'At-Risk Customers',
        'strategy': ['Win-back campaigns', 'Limited-time offers', 'Feedback surveys'],
        'channel': ['Email', 'Retargeting ads', 'SMS'],
        'discount': 0.20  # Replace with a representative numerical value
    },
    2: {
        'name': 'Occasional Shoppers',
        'strategy': ['Bundle offers', 'Frequency incentives', 'Personalized recommendations based on past purchases'],
        'channel': ['Email', 'Social media ads'],
        'discount': 0.10  # Replace with a representative numerical value
    },
    3: {
        'name': 'New/Low-Engagement',
        'strategy': ['Welcome series', 'Educational content', 'Small incentive for first repeat purchase'],
        'channel': ['Social media', 'Email', 'Display ads'],
        'discount': 0.10  # Replace with a representative numerical value
    }
}

# Visualize strategies
strategies_df = pd.DataFrame(cluster_profiles).T.reset_index()
plt.figure(figsize=(12, 8))
# The 'strategy' and 'channel' columns contain lists of strings which cannot be used in a heatmap.
# We can replace them with a representative value for visualization.
strategies_df['strategy'] = strategies_df['strategy'].apply(lambda x: x[0] if isinstance(x, list) and len(x) > 0 else '') # Use the first strategy for representation
strategies_df['channel'] = strategies_df['channel'].apply(lambda x: x[0] if isinstance(x, list) and len(x) > 0 else '') # Use the first channel for representation

# Ensure 'discount' column is numeric
strategies_df['discount'] = pd.to_numeric(strategies_df['discount'])

sns.heatmap(strategies_df[['discount']], # Only visualize discount which is now numerical
            annot=True, fmt='.2f', cmap='YlGnBu') # Format as float with 2 decimal places
plt.title('Cluster-Specific Marketing Strategies')
```

```
plt.show()
```

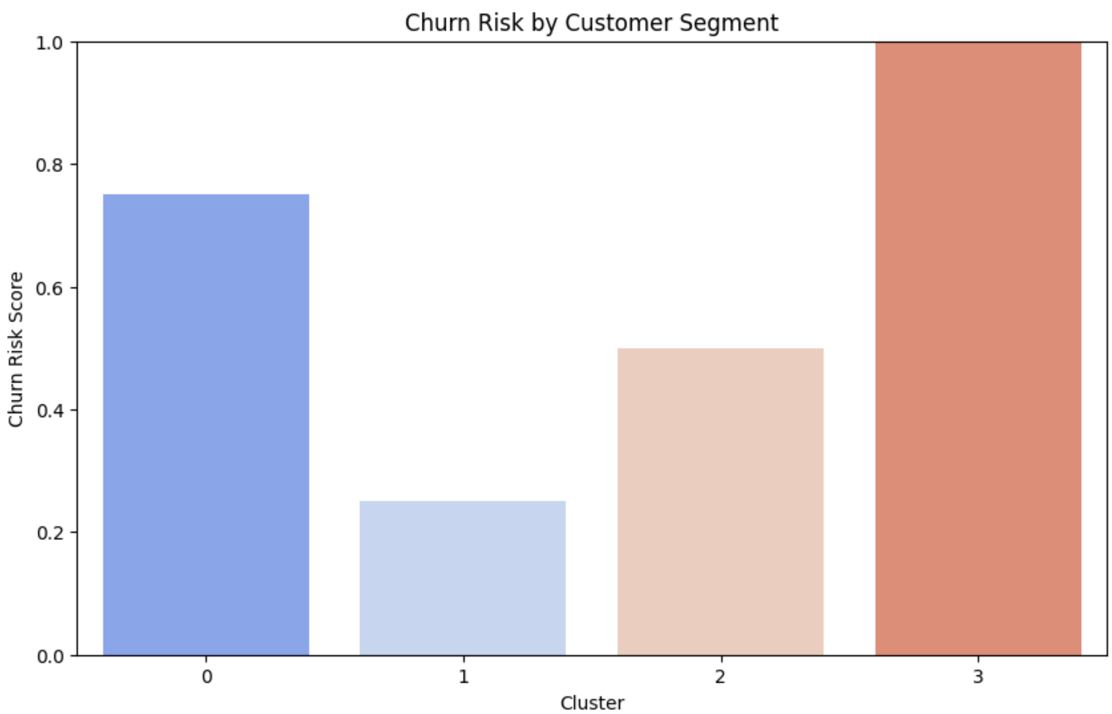


Customer Retention Optimization

[101]:
```
# Calculate and visualize churn risk by cluster
retention_metrics = rfm_df.groupby('Cluster').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': 'mean'
}).rename(columns={
    'Recency': 'Days Since Last Purchase',
    'Frequency': 'Avg Purchase Frequency',
    'Monetary': 'Avg Spend'
})

# Calculate churn risk score (higher recency = higher risk)
retention_metrics['Churn Risk Score'] = retention_metrics['Days Since Last␣
↪Purchase'].rank(pct=True)

plt.figure(figsize=(10, 6))
```

```
sns.barplot(data=retention_metrics.reset_index(), x='Cluster', y='Churn Risk␣
↪Score', palette='coolwarm')
plt.title('Churn Risk by Customer Segment')
plt.ylim(0, 1)
plt.show()
```

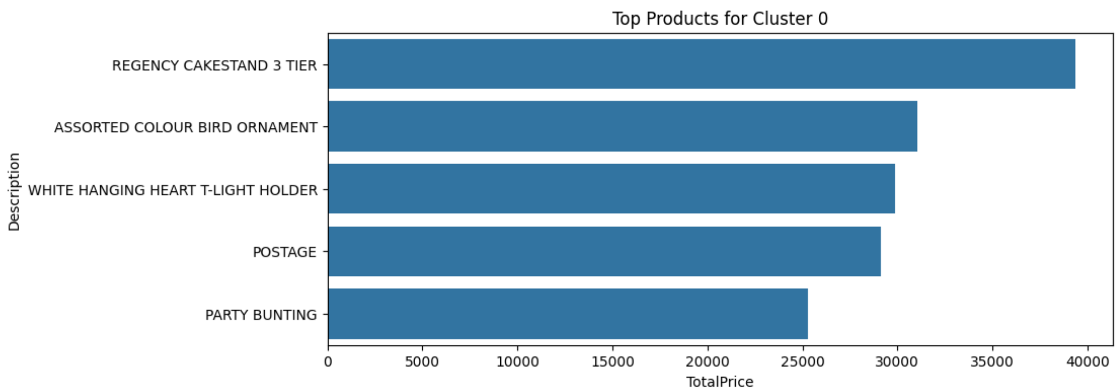
```
<ipython-input-101-a26fa7f2c538>:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=retention_metrics.reset_index(), x='Cluster', y='Churn Risk
Score', palette='coolwarm')
```

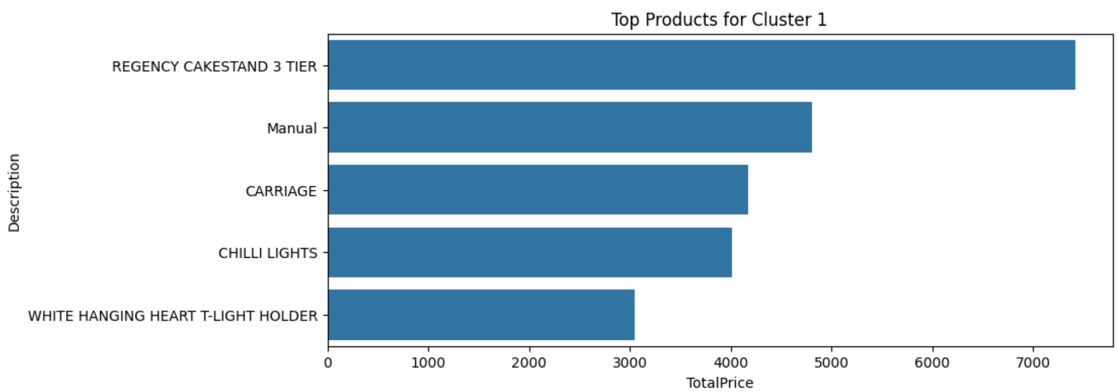


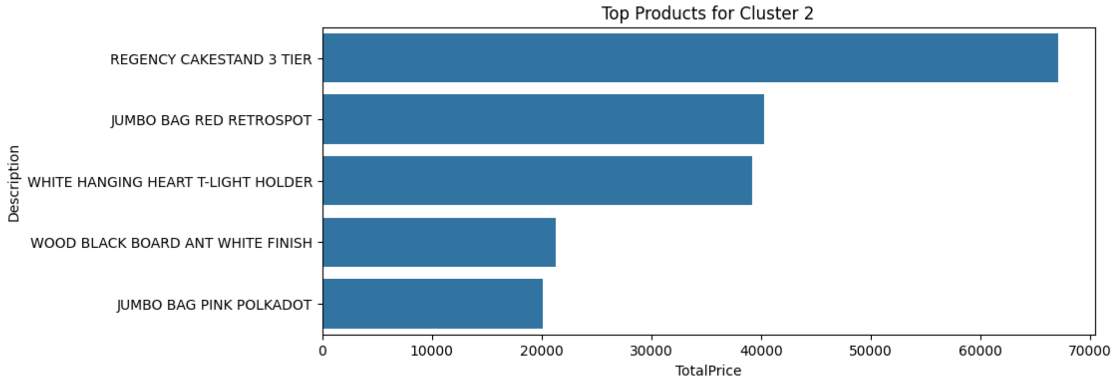
Inventory and Product Recommendations

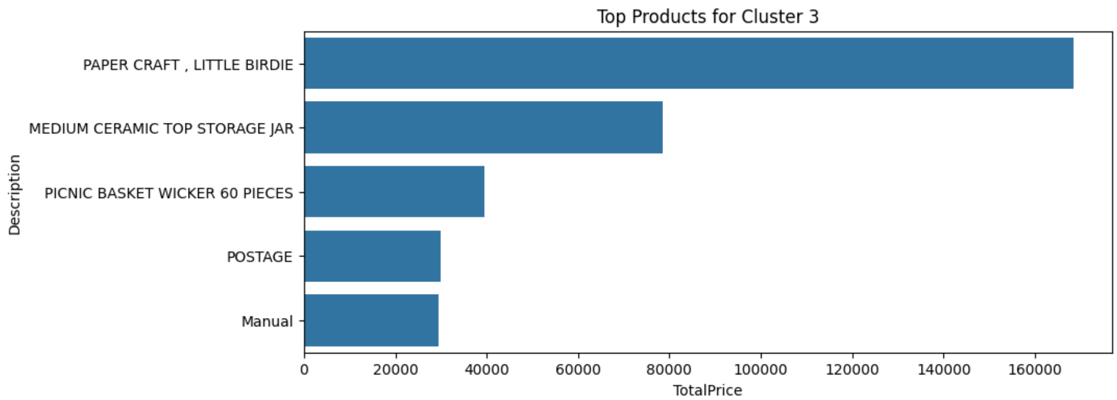
[103]:
```
# Merge cluster labels with original transaction data
df['Cluster'] = df['CustomerID'].map(pd.Series(cluster_labels, index=rfm.index))

# Analyze popular products by cluster
cluster_products = df.groupby(['Cluster', 'Description']).agg({
    'Quantity': 'sum',
    'TotalPrice': 'sum'
```

```
}).reset_index().sort_values(['Cluster', 'TotalPrice'], ascending=[True, False])

# Visualize top products per cluster
for cluster in sorted(df['Cluster'].unique()):
    top_products = cluster_products[cluster_products['Cluster'] == cluster].
    ↪head(5)
    plt.figure(figsize=(10, 4))
    sns.barplot(data=top_products, x='TotalPrice', y='Description')
    plt.title(f'Top Products for Cluster {cluster}')
    plt.show()
```



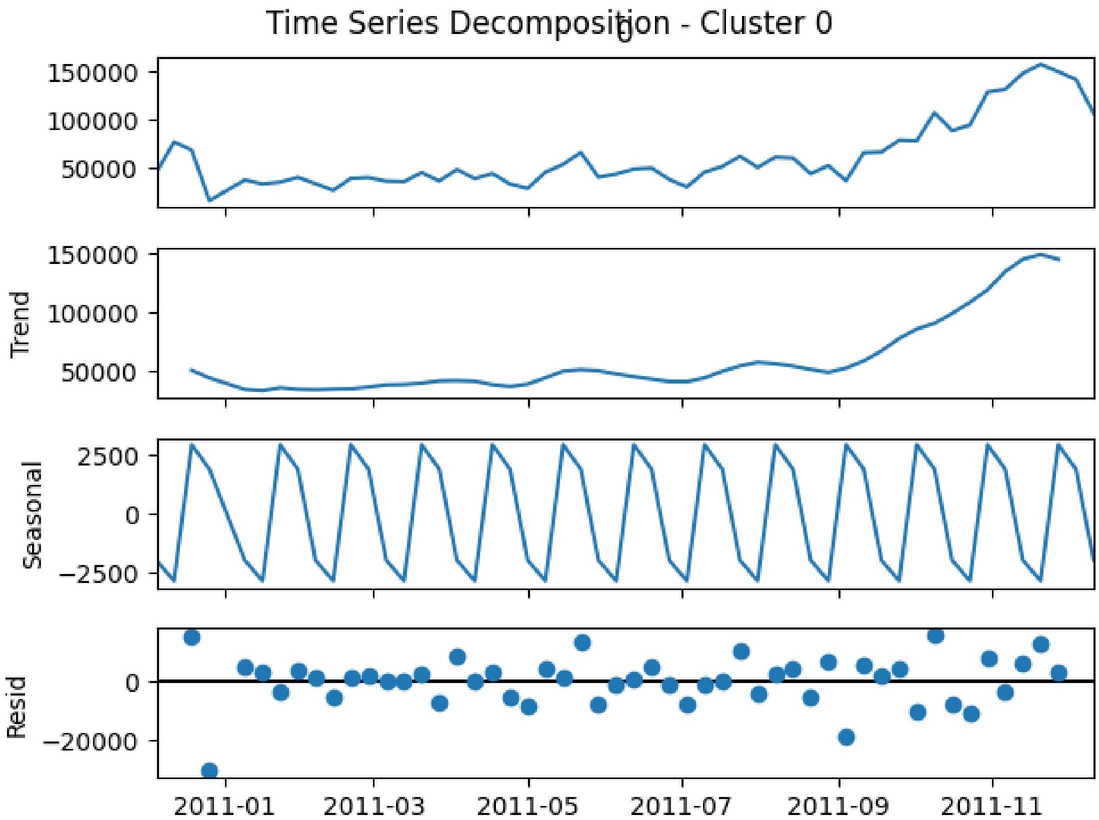


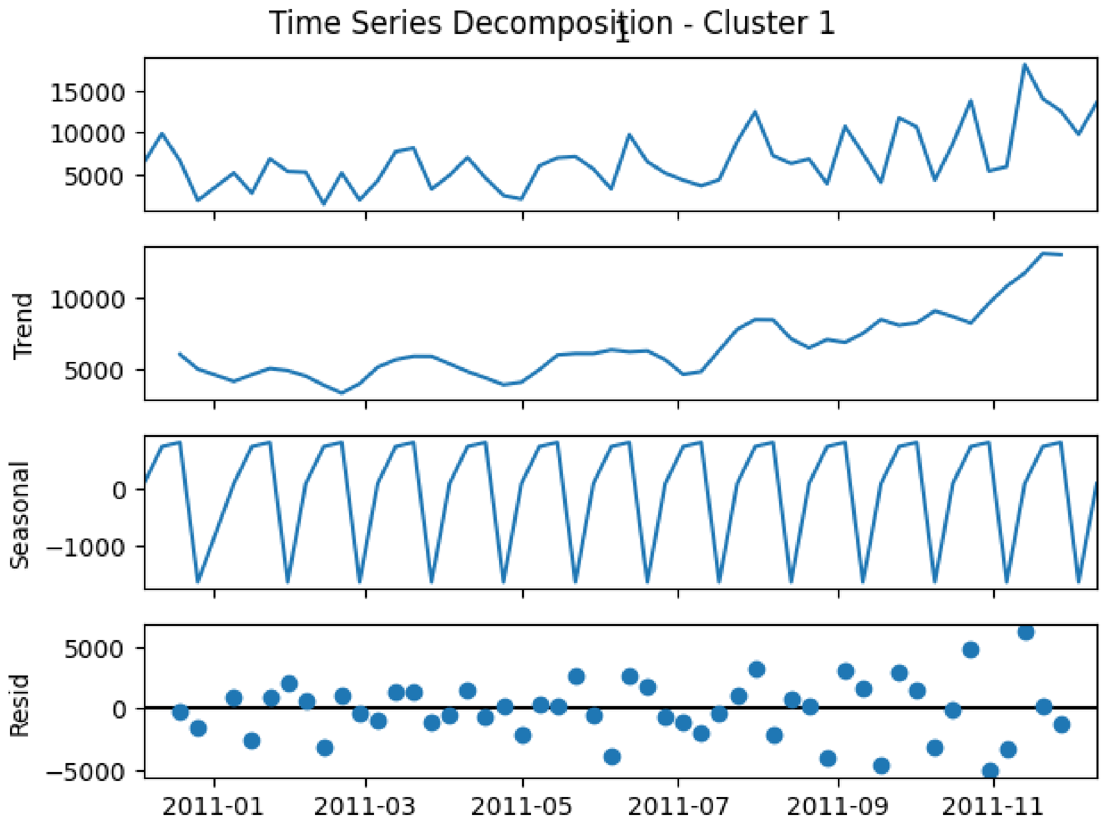


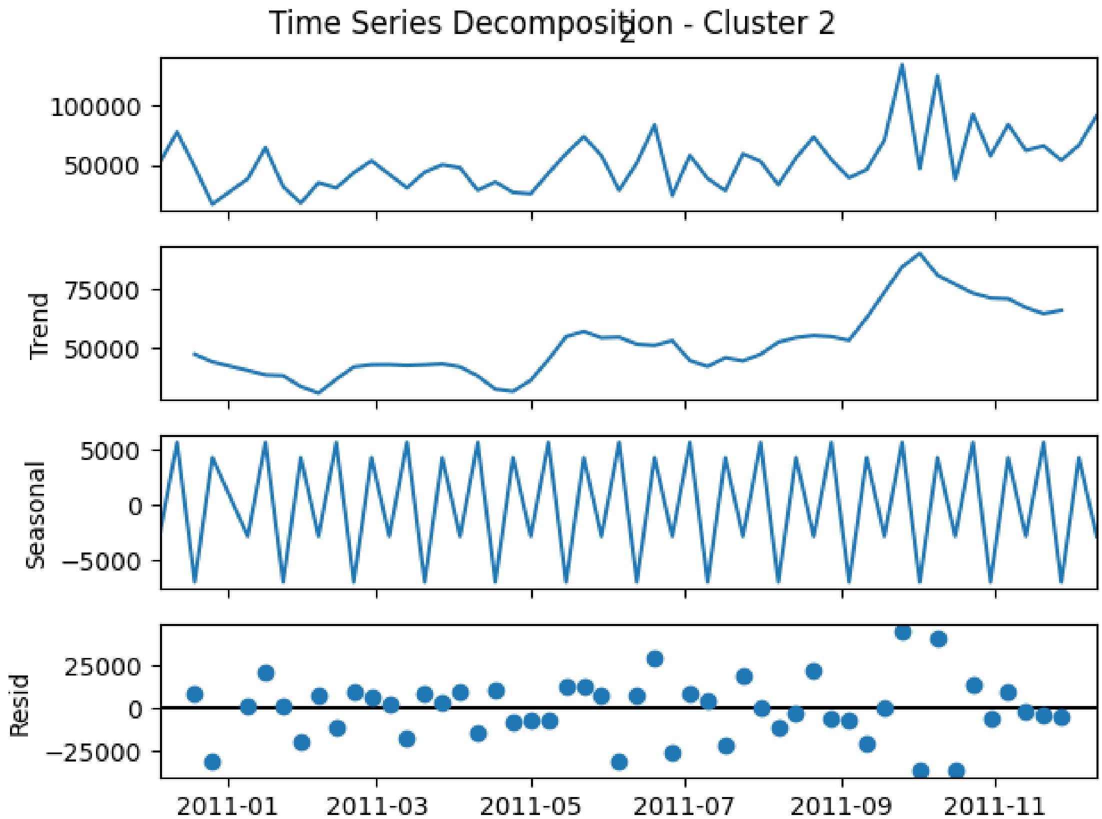


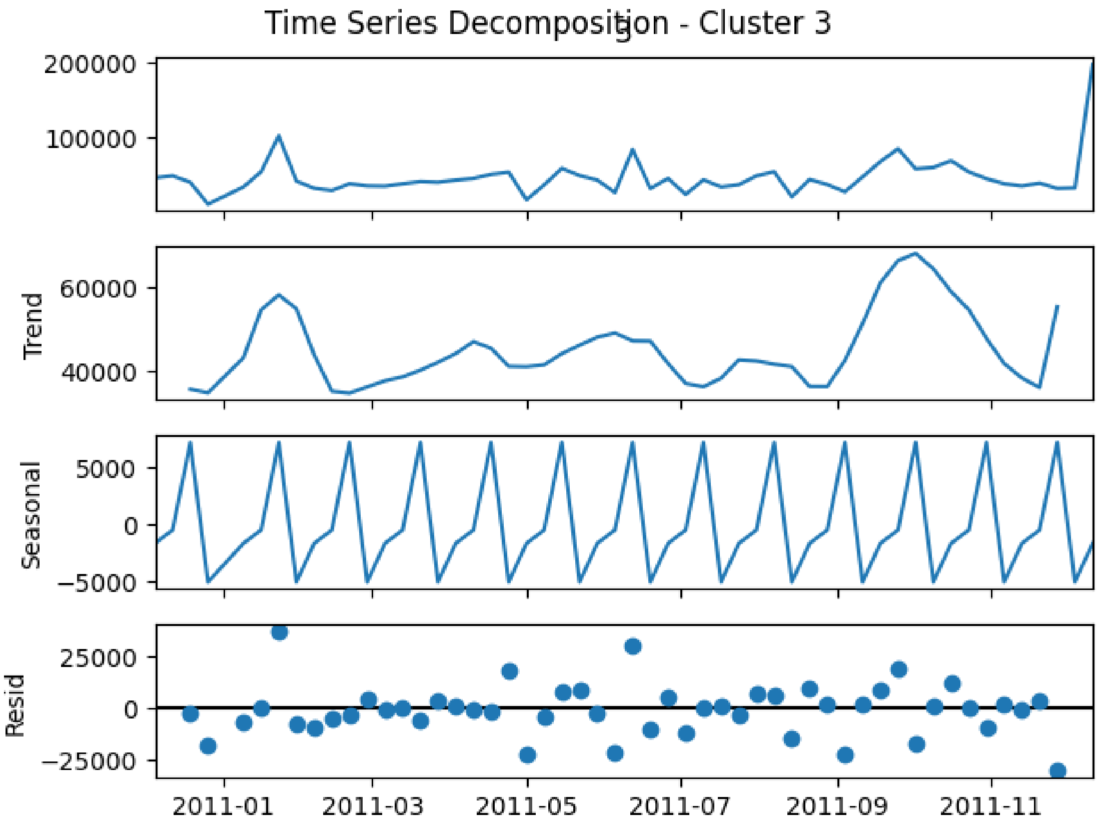
Advanced Analytics

[106]:
```
# Example code for future time-series analysis
from statsmodels.tsa.seasonal import seasonal_decompose

# Prepare time-series data by cluster
# Changed frequency to 'W' (weekly) to have more data points within the␣
↪available time range
cluster_ts = df.groupby([pd.Grouper(key='InvoiceDate', freq='W'),␣
↪'Cluster'])['TotalPrice'].sum().unstack()

# Decompose time series for each cluster
for cluster in cluster_ts.columns:
    # Set period to 4 (approximately monthly equivalent for weekly data)
    decomposition = seasonal_decompose(cluster_ts[cluster].fillna(0),␣
↪model='additive', period=4)
    decomposition.plot()
    plt.suptitle(f'Time Series Decomposition - Cluster {cluster}')
    plt.show()
```


Time Series Decomposition - Cluster 0
0
150000
100000
50000
Trend
150000
100000
50000
Seasonal
2500
0
−2500
Resid
0
−20000
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11


Time Series Decomposition - Cluster 1
1
15000
10000
5000
Trend
10000
5000
Seasonal
0
−1000
Resid
5000
0
−5000
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11


Time Series Decomposition - Cluster 2
2
100000
50000
Trend
75000
50000
Seasonal
5000
0
−5000
Resid
25000
0
−25000
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11



Time Series Decomposition - Cluster 3
200000
100000
Trend
60000
40000
Seasonal
5000
0
−5000
Resid
25000
0
−25000
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11