# Task 3: Customer Segmentation / Clustering

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score, silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
customers = pd.read_csv('Customers.csv')
# prducts = pd.read_csv('Products.csv')
transactions = pd.read_csv('Transactions.csv')
```

### Merging Customers and Transactions

In [3]:
```
merged_data = transactions.merge(customers, on='CustomerID')
```

### Aggregating features for clustering

In [4]:
```
clustering_features = merged_data.groupby('CustomerID').agg({
    'TotalValue': 'sum',
    'Quantity': 'sum',
    'ProductID': 'nunique',
    'TransactionDate': lambda x: (pd.to_datetime(x.max()) - pd.to_datetime(x.min())
}).reset_index()
```

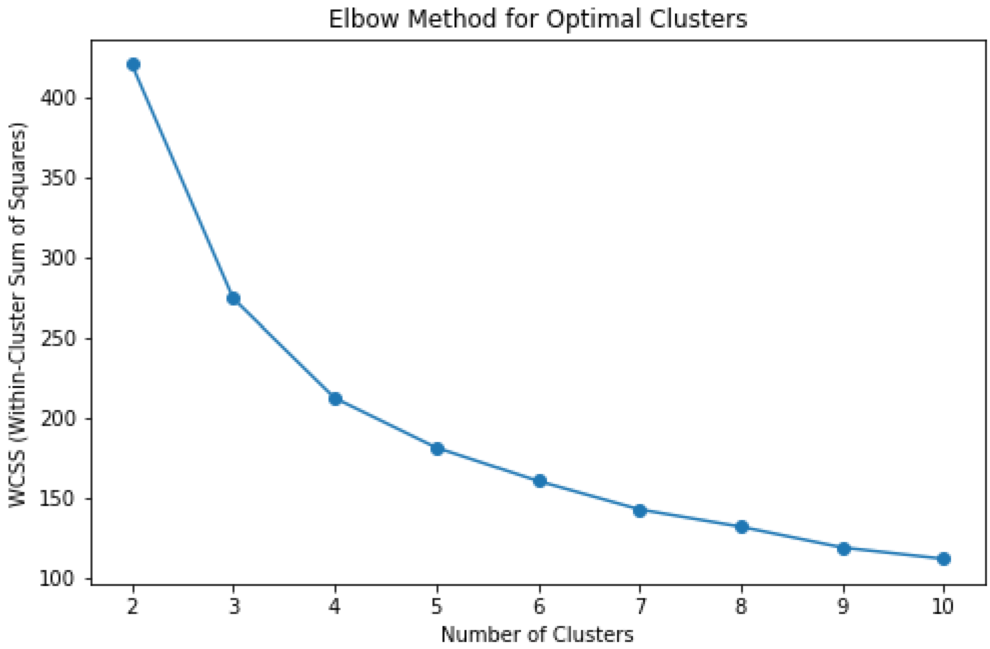
### Normalize the features

In [5]:
```
scaler = StandardScaler()
scaled_features = scaler.fit_transform(clustering_features.iloc[:, 1:])
```

### Determining the optimal number of clusters(using Elbow Method)

In [6]:
```
wcss = []
for k in range(2, 11):  # Between 2 and 10 clusters
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)
```

In [7]:
```
plt.figure(figsize=(8, 5))
plt.plot(range(2, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()
```




### Applying K-Means clustering with number of clusters

In [8]:
```
optimal_clusters = 4  # Replace with the elbow/knee point
kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
clustering_features['Cluster'] = kmeans.fit_predict(scaled_features)
```

### Evaluating clustering with Davies-Bouldin Index and Silhouette Score

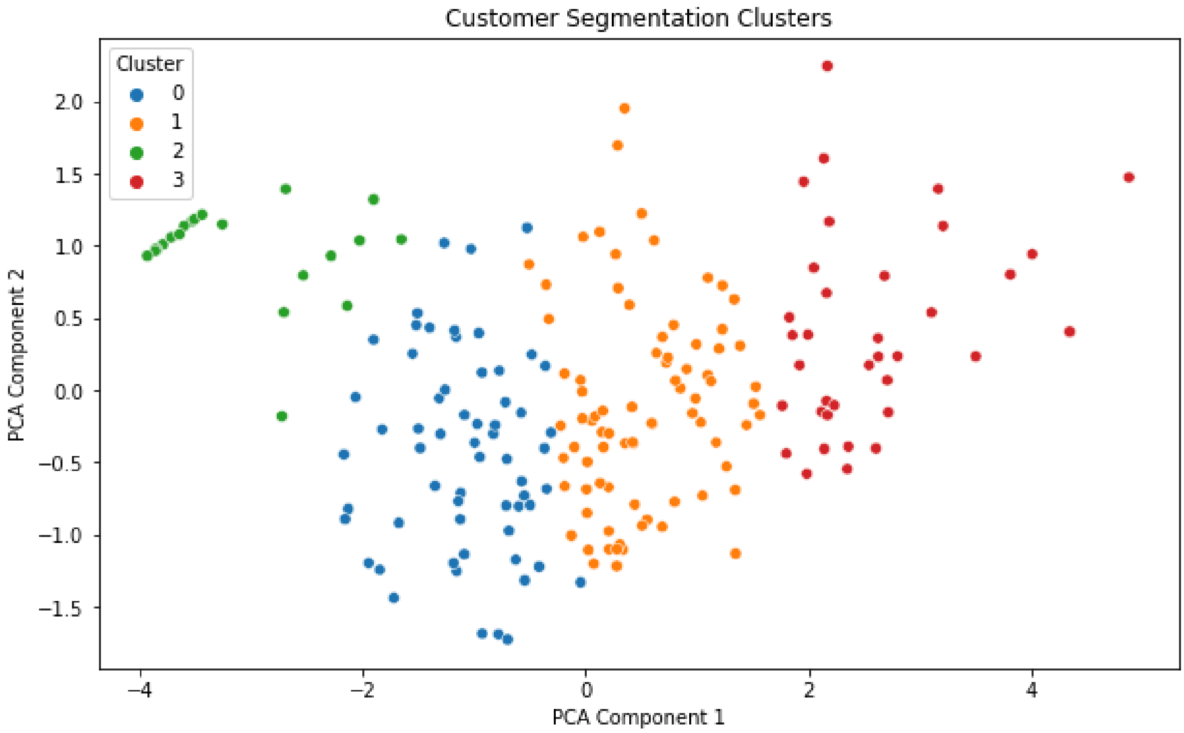
In [9]:
```
db_index = davies_bouldin_score(scaled_features, clustering_features['Cluster'])
silhouette_avg = silhouette_score(scaled_features, clustering_features['Cluster'])

print(f"Davies-Bouldin Index: {db_index}")
print(f"Silhouette Score: {silhouette_avg}")
```

```
Davies-Bouldin Index: 0.995243565164094
Silhouette Score: 0.3207724576419155
```

### Visualizing clusters using PCA

In [10]:
```
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)
clustering_features['PCA1'] = pca_result[:, 0]
clustering_features['PCA2'] = pca_result[:, 1]
```

In [11]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=clustering_features, x='PCA1', y='PCA2', hue='Cluster', palett
plt.title('Customer Segmentation Clusters')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Cluster')
plt.show()
```




## Saving the clustering results

In [13]:
```
clustering_features.to_csv('Customer_Segmentation.csv', index=False)
print("Customer_Segmentation.csv has been successfully saved!")
```

```
Customer_Segmentation.csv has been successfully saved!
```

In [14]:
```
clustering = pd.read_csv('Customer_Segmentation.csv')
print(clustering.describe())
print('\n')
print(clustering.head())
```

| | TotalValue | Quantity | ProductID | TransactionDate | Cluster | \ |
|---|---|---|---|---|---|---|
| count | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | |
| mean | 3467.314372 | 12.748744 | 4.894472 | 224.447236 | 1.165829 | |
| std | 1832.677958 | 6.151060 | 2.113908 | 91.972580 | 1.057746 | |
| min | 82.360000 | 1.000000 | 1.000000 | 0.000000 | 0.000000 | |
| 25% | 2162.040000 | 8.500000 | 3.000000 | 185.500000 | 0.000000 | |
| 50% | 3137.660000 | 12.000000 | 5.000000 | 244.000000 | 1.000000 | |
| 75% | 4770.225000 | 17.000000 | 6.000000 | 291.000000 | 2.000000 | |
| max | 10673.870000 | 32.000000 | 10.000000 | 360.000000 | 3.000000 | |

| | PCA1 | PCA2 |
|---|---|---|
| count | 1.990000e+02 | 1.990000e+02 |
| mean | -6.471652e-17 | -5.579010e-19 |
| std | 1.758316e+00 | 7.926151e-01 |
| min | -3.932953e+00 | -1.727050e+00 |
| 25% | -1.105482e+00 | -5.634270e-01 |
| 50% | 2.455155e-02 | -9.443136e-02 |
| 75% | 1.111554e+00 | 5.383232e-01 |
| max | 4.875107e+00 | 2.244023e+00 |

| | CustomerID | TotalValue | Quantity | ProductID | TransactionDate | Cluster | \ |
|---|---|---|---|---|---|---|---|
| 0 | C0001 | 3354.52 | 12 | 5 | 288 | 1 | |
| 1 | C0002 | 1862.74 | 10 | 4 | 278 | 0 | |
| 2 | C0003 | 2725.38 | 14 | 4 | 188 | 0 | |
| 3 | C0004 | 5354.88 | 23 | 8 | 299 | 3 | |
| 4 | C0005 | 2034.24 | 7 | 3 | 233 | 0 | |

| | PCA1 | PCA2 |
|---|---|---|
| 0 | 0.205374 | -0.672121 |
| 1 | -0.687542 | -0.974109 |
| 2 | -0.483137 | 0.245810 |
| 3 | 2.542390 | 0.172357 |
| 4 | -1.350826 | -0.663549 |