```python
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler

# Step 1: Load the CSV files
customers = pd.read_csv('Customers.csv')
transactions = pd.read_csv('Transactions.csv')

# Step 2: Merge data
# Merge transactions with customer information
merged_data = pd.merge(transactions, customers, on='CustomerID',
how='inner')

merged_data = merged_data.drop(columns='ProductID')

merged_data
```

```
    TransactionID CustomerID      TransactionDate  Quantity
TotalValue  \
0          T00001      C0199  2024-08-25 12:38:23         1
300.68
1          T00112      C0146  2024-05-27 22:23:54         1
300.68
2          T00166      C0127  2024-04-25 07:38:55         1
300.68
3          T00272      C0087  2024-03-26 22:55:37         2
601.36
4          T00363      C0070  2024-03-21 15:10:10         3
902.04
..            ...        ...                  ...       ...          ..
.
995        T00496      C0118  2024-10-24 08:30:27         1
459.86
996        T00759      C0059  2024-06-04 02:15:24         3
1379.58
997        T00922      C0018  2024-04-05 13:05:32         4
1839.44
998        T00959      C0115  2024-09-29 10:16:02         2
919.72
999        T00992      C0024  2024-04-21 10:52:24         1
459.86

      Price          CustomerName         Region  SignupDate
0    300.68        Andrea Jenkins         Europe  2022-12-03
1    300.68      Brittany Harvey           Asia  2024-09-04
2    300.68      Kathryn Stevens         Europe  2024-04-04
3    300.68      Travis Campbell  South America  2024-04-11
4    300.68         Timothy Perez         Europe  2022-03-15
```

```
..      ...                    ...           ...          ...
995  459.86            Jacob Holt  South America  2022-01-22
996  459.86  Mrs. Kimberly Wright  North America  2024-04-07
997  459.86          Tyler Haynes  North America  2024-09-21
998  459.86       Joshua Hamilton           Asia  2024-11-11
999  459.86        Michele Cooley  North America  2024-02-05

[1000 rows x 9 columns]
```

```python
# Step 3: Feature Engineering
# Calculate total spent by each customer
customer_total_spent = merged_data.groupby('CustomerID')
['TotalValue'].sum().reset_index()
customer_total_spent.columns = ['CustomerID', 'TotalSpent']

# Calculate the average cart value by each customer
customer_avg_cart_value = merged_data.groupby('CustomerID')
['TotalValue'].mean().reset_index()
customer_avg_cart_value.columns = ['CustomerID', 'AvgCartValue']

# Calculate the number of transactions by each customer (purchase
frequency)
customer_frequency = merged_data.groupby('CustomerID')
['TransactionID'].nunique().reset_index()
customer_frequency.columns = ['CustomerID', 'PurchaseFrequency']

customer_features = pd.merge(customer_total_spent,
customer_avg_cart_value, on='CustomerID')
customer_features = pd.merge(customer_features, customer_frequency,
on='CustomerID')

customer_features
```

```
    CustomerID  TotalSpent  AvgCartValue  PurchaseFrequency
0        C0001     3354.52    670.904000                  5
1        C0002     1862.74    465.685000                  4
2        C0003     2725.38    681.345000                  4
3        C0004     5354.88    669.360000                  8
4        C0005     2034.24    678.080000                  3
..         ...         ...           ...                ...
194      C0196     4982.88   1245.720000                  4
195      C0197     1928.65    642.883333                  3
196      C0198      931.83    465.915000                  2
197      C0199     1979.28    494.820000                  4
198      C0200     4758.60    951.720000                  5

[199 rows x 4 columns]
```

```python
scaler = StandardScaler()
scaled_features =
scaler.fit_transform(customer_features[['TotalSpent', 'AvgCartValue',
```

```
'PurchaseFrequency']])

# Step 2: Elbow Method to find the optimal number of clusters
wcss = []  # List to store WCSS for each K
for k in range(2, 11):  # Testing from 2 to 10 clusters
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)  # WCSS is stored in inertia_

# Plotting Elbow Curve
plt.figure(figsize=(8, 6))
plt.plot(range(2, 11), wcss, marker='o')
plt.title('Elbow Method For Optimal K')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()
```

```
C:\Users\revat\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on
Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
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```

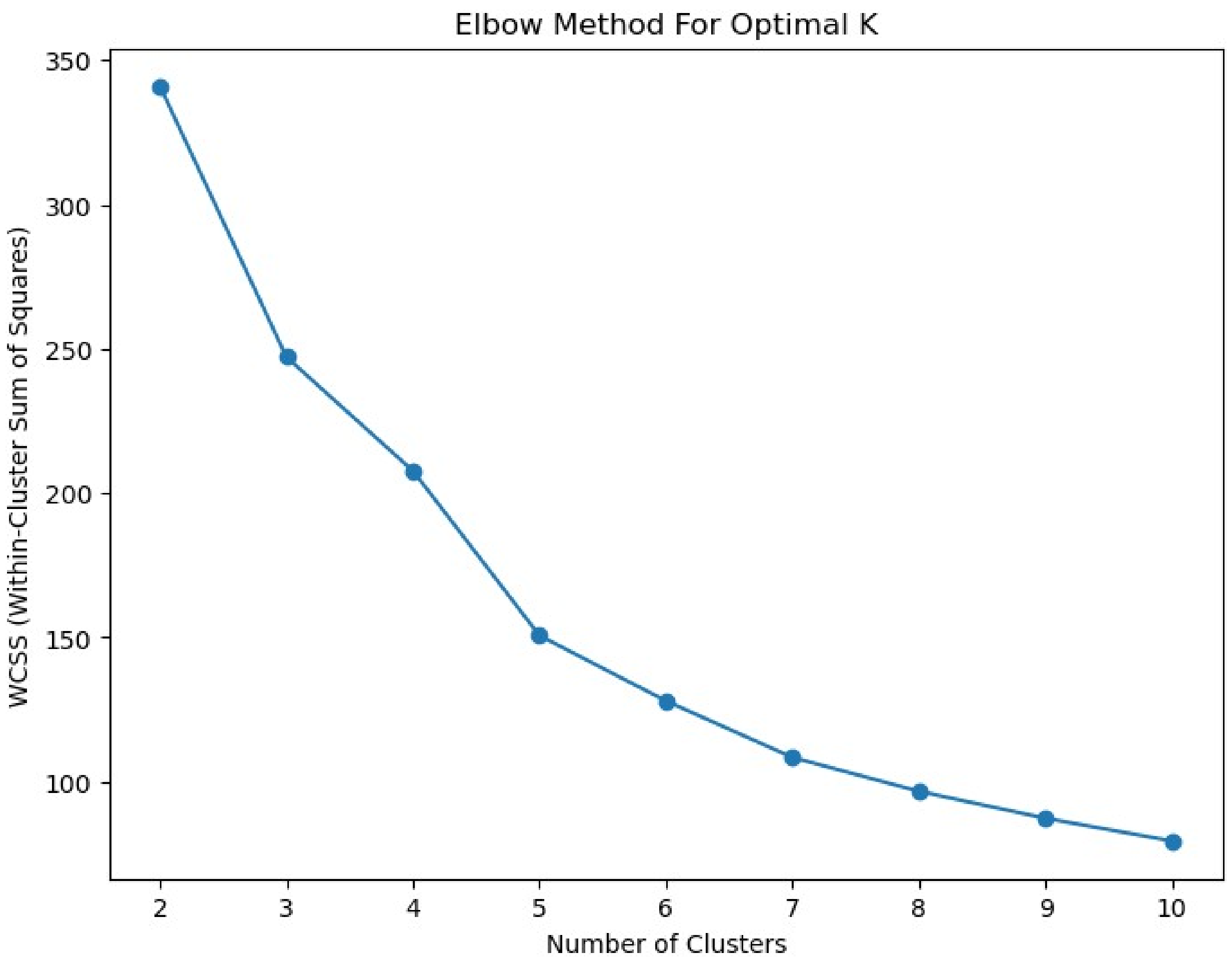


```
from sklearn.metrics import davies_bouldin_score

optimal_k = 5

# Step 4: Perform K-means clustering with the chosen number of
clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
customer_features['Segment'] = kmeans.fit_predict(scaled_features)

# Step 5: Calculate Davies-Bouldin Index and other metrics
db_index = davies_bouldin_score(scaled_features,
customer_features['Segment'])
print(f'Davies-Bouldin Index: {db_index}')

# Additional metrics (e.g., silhouette score, calinski harabasz score)
can also be calculated
from sklearn.metrics import silhouette_score, calinski_harabasz_score

sil_score = silhouette_score(scaled_features,
customer_features['Segment'])
```

```
calinski_score = calinski_harabasz_score(scaled_features,
customer_features['Segment'])

print(f'Silhouette Score: {sil_score}')
print(f'Calinski-Harabasz Score: {calinski_score}')

# Step 6: Visualizing the Clusters (2D scatter plot for better
visualization)
plt.figure(figsize=(8, 6))
sns.scatterplot(x=customer_features['TotalSpent'],
y=customer_features['AvgCartValue'], hue=customer_features['Segment'],
palette='Set1', s=100, alpha=0.7)
plt.title('Customer Segments based on Total Spent and Average Cart
Value')
plt.xlabel('Total Spent ($)')
plt.ylabel('Average Cart Value ($)')
plt.legend(title='Segment')
plt.show()
```

```
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OMP_NUM_THREADS=1.
  warnings.warn(

Davies-Bouldin Index: 0.8524813520458036
Silhouette Score: 0.3535127066812944
Calinski-Harabasz Score: 143.70464826443802
```
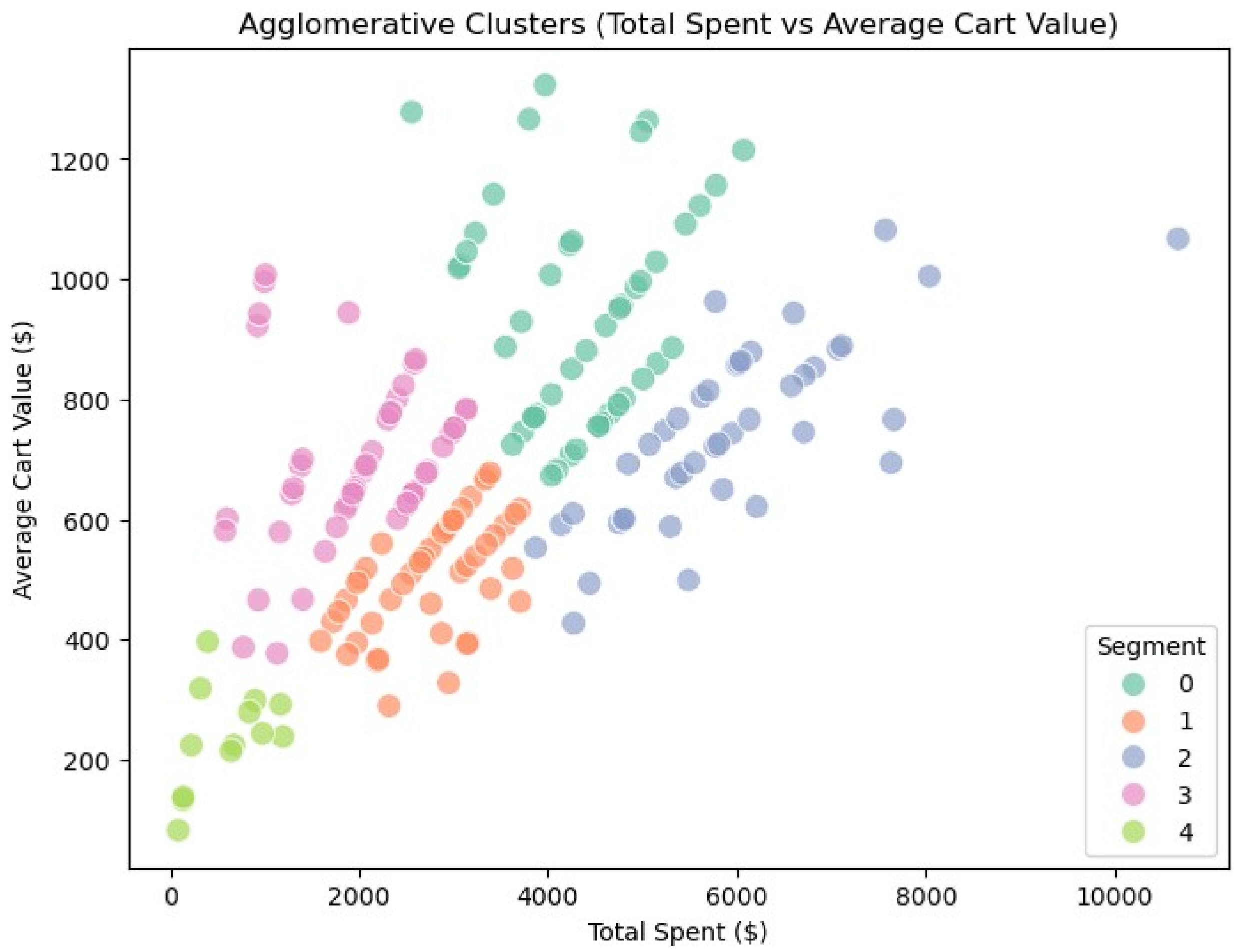


```
# Step 2: Perform K-Means Clustering (K=4 as chosen from previous
code)
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.mixture import GaussianMixture

# Step 3: Perform Agglomerative Hierarchical Clustering (using ward
linkage)
agg_clust = AgglomerativeClustering(n_clusters=5, linkage='ward')
customer_features['Agglomerative_Segment'] =
agg_clust.fit_predict(scaled_features)

agg_db = davies_bouldin_score(scaled_features,
customer_features['Agglomerative_Segment'])

print(f"Agglomerative Davies-Bouldin Index: {agg_db}")

# Additional metrics (Silhouette Score and Calinski-Harabasz Score)
print("\nAdditional Metrics:")
print(f"Agglomerative Silhouette Score:
{silhouette_score(scaled_features,
customer_features['Agglomerative_Segment'])}")
```

```python
print(f"Agglomerative Calinski-Harabasz Score:
{calinski_harabasz_score(scaled_features,
customer_features['Agglomerative_Segment'])}")


# Agglomerative Clusters
plt.figure(figsize=(8, 6))
sns.scatterplot(x=customer_features['TotalSpent'],
y=customer_features['AvgCartValue'],
hue=customer_features['Agglomerative_Segment'], palette='Set2', s=100,
alpha=0.7)
plt.title('Agglomerative Clusters (Total Spent vs Average Cart
Value)')
plt.xlabel('Total Spent ($)')
plt.ylabel('Average Cart Value ($)')
plt.legend(title='Segment')
plt.show()
```

```
Agglomerative Davies-Bouldin Index: 0.8851081906022241

Additional Metrics:
Agglomerative Silhouette Score: 0.34265137202494406
Agglomerative Calinski-Harabasz Score: 130.61439024040507
```




```
# K-Means Clustering
import os
os.environ["OMP_NUM_THREADS"] = "1"

from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
customer_features['KMeans_Segment'] = kmeans.fit_predict(
    customer_features[['TotalSpent', 'AvgCartValue',
'PurchaseFrequency']]
)

# Agglomerative Clustering
from sklearn.cluster import AgglomerativeClustering

agglomerative = AgglomerativeClustering(n_clusters=3)
customer_features['Agglomerative_Segment'] =
agglomerative.fit_predict(
    customer_features[['TotalSpent', 'AvgCartValue',
'PurchaseFrequency']]
```

```
)
print(customer_features.shape)
```

```
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(199, 7)
```