Import required libraries

In [3]:
```
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.neighbors import NearestNeighbors
from sklearn.decomposition import PCA
import seaborn as sns
import matplotlib.pyplot as plt
```

Set global plotting style

In [4]:
```
sns.set(style="whitegrid")
```

Load datasets

In [5]:
```
customers = pd.read_csv("C:/Users/PREMKUMAR BAJARU/eCommerce-Transactions-Analysis/Desktop/ZeoTape assignment/Data/Customers.csv")
products = pd.read_csv("C:/Users/PREMKUMAR BAJARU/eCommerce-Transactions-Analysis/Desktop/ZeoTape assignment/Data/Products.csv")
transactions = pd.read_csv("C:/Users/PREMKUMAR BAJARU/eCommerce-Transactions-Analysis/Desktop/ZeoTape assignment/Data/Transactions.csv")
```

In [6]:
```
customers.head()
```

Out[6]:

	CustomerID	CustomerName	Region	SignupDate
0	C0001	Lawrence Carroll	South America	2022-07-10
1	C0002	Elizabeth Lutz	Asia	2022-02-13
2	C0003	Michael Rivera	South America	2024-03-07
3	C0004	Kathleen Rodriguez	South America	2022-10-09
4	C0005	Laura Weber	Asia	2022-08-15

In [7]:
```
products.head()
```

Out[7]:

	ProductID	ProductName	Category	Price
0	P001	ActiveWear Biography	Books	169.30
1	P002	ActiveWear Smartwatch	Electronics	346.30
2	P003	ComfortLiving Biography	Books	44.12
3	P004	BookWorld Rug	Home Decor	95.69
4	P005	TechPro T-Shirt	Clothing	429.31

In [8]:
```
transactions.head()
```

Out[8]:

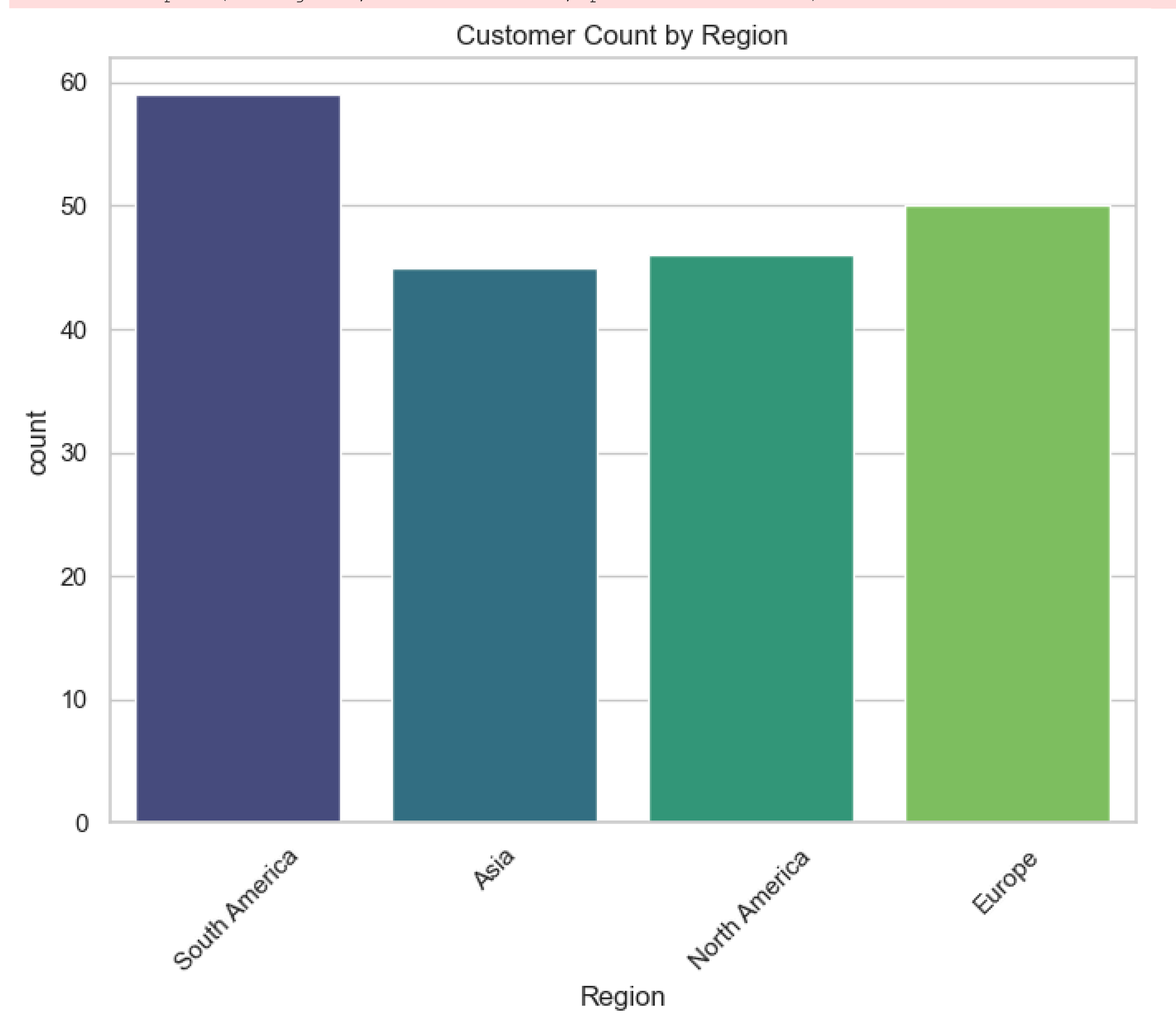
	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price
0	T00001	C0199	P067	2024-08-25 12:38:23	1	300.68	300.68
1	T00112	C0146	P067	2024-05-27 22:23:54	1	300.68	300.68
2	T00166	C0127	P067	2024-04-25 07:38:55	1	300.68	300.68
3	T00272	C0087	P067	2024-03-26 22:55:37	2	601.36	300.68
4	T00363	C0070	P067	2024-03-21 15:10:10	3	902.04	300.68

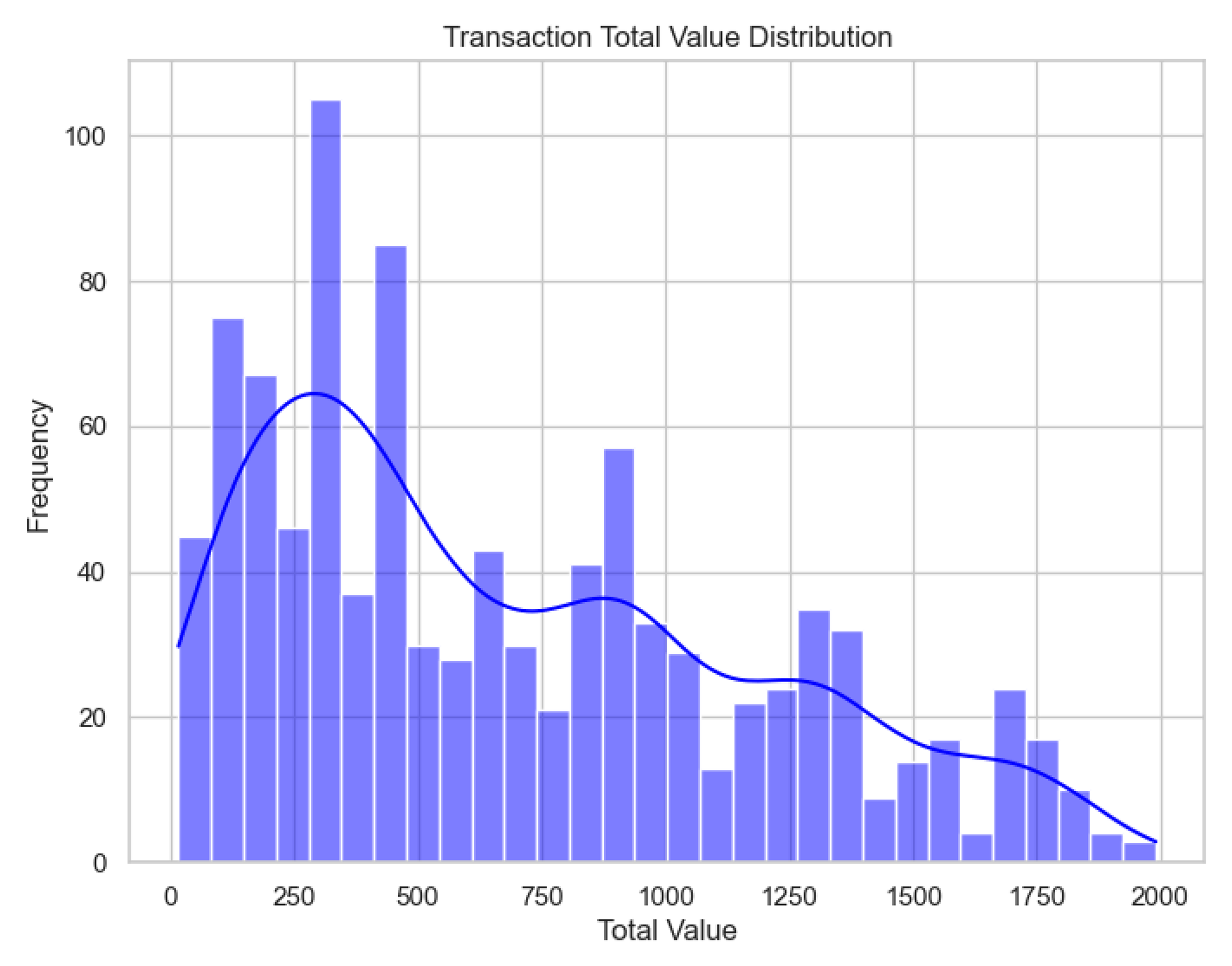
Task 1: Exploratory Data Analysis (EDA)

In [9]:
```
def perform_eda():
    print("\n--- EDA Summary ---\n")

    # Display basic info and check missing values
    for df, name in zip([customers, products, transactions], ["Customers", "Products", "Transactions"]):
        print(f"\n{name} Dataset Info:\n")
        print(df.info())
        print(f"\n{name} Missing Values:\n{df.isnull().sum()}")

    # Summary statistics for transactions
    print("\nSummary Statistics for Transactions:\n", transactions.describe())

    # Visualizations
    plt.figure(figsize=(8, 6))
    sns.countplot(x='Region', data=customers, palette="viridis")
    plt.title('Customer Count by Region')
    plt.xticks(rotation=45)
    plt.show()

    plt.figure(figsize=(8, 6))
    sns.histplot(transactions['TotalValue'], bins=30, kde=True, color="blue")
    plt.title('Transaction Total Value Distribution')
    plt.xlabel('Total Value')
    plt.ylabel('Frequency')
    plt.show()

perform_eda()
```

```
--- EDA Summary ---


Customers Dataset Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   CustomerID    200 non-null    object
 1   CustomerName  200 non-null    object
 2   Region        200 non-null    object
 3   SignupDate    200 non-null    object
dtypes: object(4)
memory usage: 6.4+ KB
None

Customers Missing Values:
CustomerID      0
CustomerName    0
Region          0
SignupDate      0
dtype: int64

Products Dataset Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   ProductID    100 non-null    object
 1   ProductName  100 non-null    object
 2   Category     100 non-null    object
 3   Price        100 non-null    float64
dtypes: float64(1), object(3)
memory usage: 3.3+ KB
None

Products Missing Values:
ProductID      0
ProductName    0
Category       0
Price          0
dtype: int64

Transactions Dataset Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   TransactionID    1000 non-null   object
 1   CustomerID       1000 non-null   object
 2   ProductID        1000 non-null   object
 3   TransactionDate  1000 non-null   object
 4   Quantity         1000 non-null   int64
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
dtypes: float64(2), int64(1), object(4)
memory usage: 54.8+ KB
None

Transactions Missing Values:
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price              0
dtype: int64

Summary Statistics for Transactions:
           Quantity   TotalValue       Price
count  1000.000000  1000.000000  1000.00000
mean      2.537000   689.995560   272.55407
std       1.117981   493.144478   140.73639
min       1.000000    16.080000    16.08000
25%       2.000000   295.295000   147.95000
50%       3.000000   588.880000   299.93000
75%       4.000000  1011.660000   404.40000
max       4.000000  1991.040000   497.76000
```

```
C:\Users\PREMKUMAR BAJARU\AppData\Local\Temp\ipykernel_17980\2423817757.py:15: 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 effe
ct.

  sns.countplot(x='Region', data=customers, palette="viridis")
```





Task 2: Lookalike Model

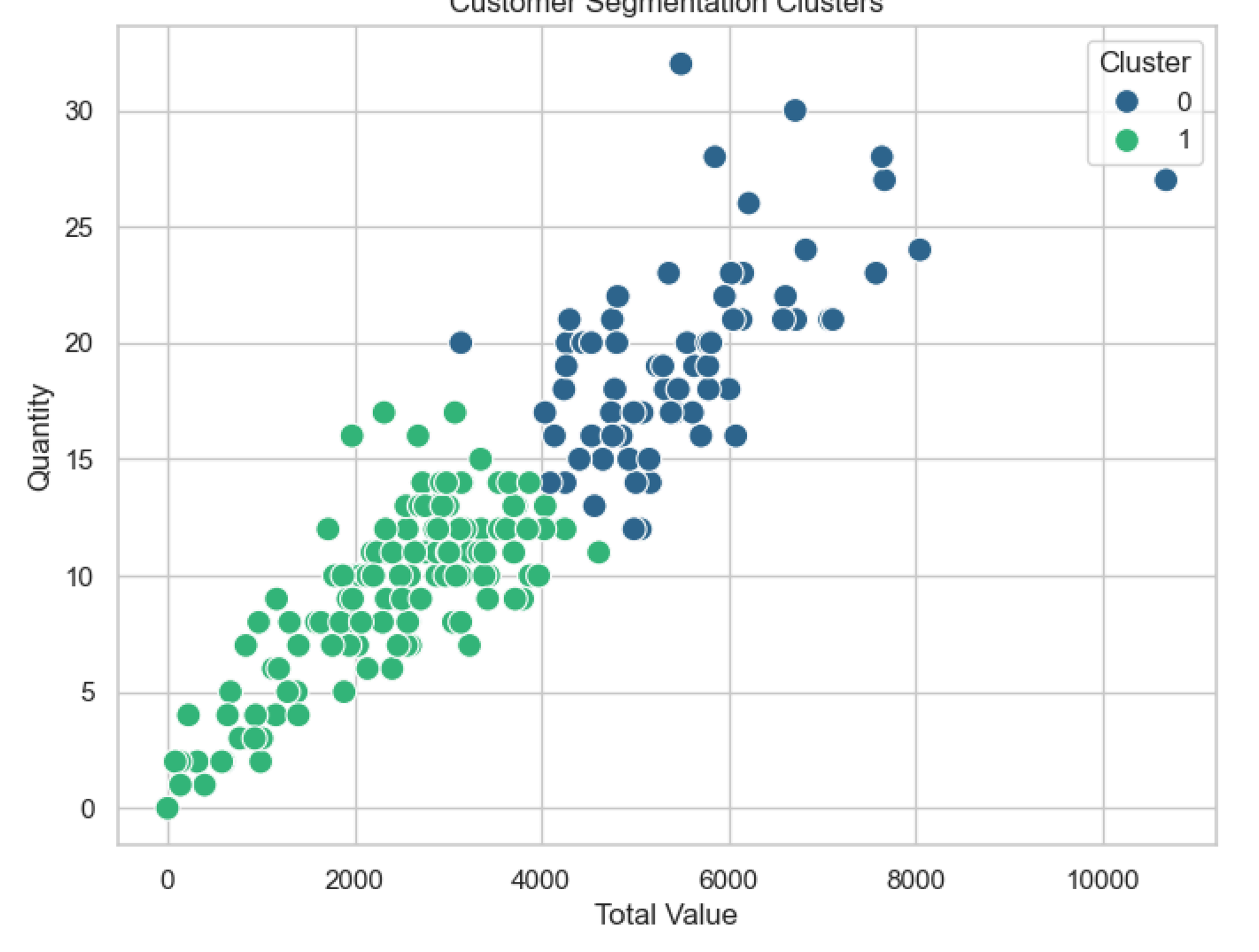
In [10]:
```
def lookalike_model():
    print("\n--- Building Lookalike Model ---\n")

    # Prepare data for similarity
    merged_data = pd.merge(transactions, customers, on='CustomerID')
    merged_data = pd.merge(merged_data, products, on='ProductID')

    pivot_table = merged_data.pivot_table(index='CustomerID', columns='ProductID', values='Quantity', aggfunc='sum', fill_value=0)

    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(pivot_table)

    # PCA for dimensionality reduction
    pca = PCA(n_components=0.95, random_state=42)
    reduced_data = pca.fit_transform(scaled_data)

    # Nearest Neighbors
    model = NearestNeighbors(n_neighbors=4, metric='cosine')
    model.fit(reduced_data)

    lookalike_results = {}
    for idx, customer_id in enumerate(pivot_table.index[:20]):
        distances, indices = model.kneighbors([reduced_data[idx]])
        similar_customers = [
            (pivot_table.index[indices[0][j]], round(1 - distances[0][j], 4))
            for j in range(1, len(indices[0]))  # Skip the first index as it's the customer itself
        ]
        lookalike_results[customer_id] = similar_customers[:3]

    # Save results to CSV
    flattened_results = [
        {
            "CustomerID": customer_id,
            "SimilarCustomerID": similar[0],
            "SimilarityScore": similar[1]
        }
        for customer_id, similars in lookalike_results.items()
        for similar in similars
    ]
    result_df = pd.DataFrame(flattened_results)
    result_df.to_csv("FirstName_LastName_Lookalike.csv", index=False)
    print("Lookalike results saved to CSV.")

lookalike_model()
```

```
--- Building Lookalike Model ---

Lookalike results saved to CSV.
```

Task 3: Customer Segmentation / Clustering

In [11]:
```
def customer_segmentation():
    print("\n--- Performing Customer Segmentation ---\n")

    # Merge and preprocess data
    customer_transactions = transactions.groupby('CustomerID').agg({'TotalValue': 'sum', 'Quantity': 'sum'}).reset_index()
    customer_data = pd.merge(customers, customer_transactions, on='CustomerID', how='left').fillna(0)

    features = ['TotalValue', 'Quantity']
    scaler = StandardScaler()
    scaled_features = scaler.fit_transform(customer_data[features])

    # Evaluate different cluster sizes for optimal clustering
    db_indices = []
    silhouette_scores = []
    for k in range(2, 11):
        kmeans = KMeans(n_clusters=k, random_state=42)
        labels = kmeans.fit_predict(scaled_features)
        db_indices.append(davies_bouldin_score(scaled_features, labels))
        silhouette_scores.append(silhouette_score(scaled_features, labels))

    optimal_clusters = db_indices.index(min(db_indices)) + 2
    print(f"Optimal Number of Clusters: {optimal_clusters}")
    print(f"Davies-Bouldin Scores: {db_indices}")
    print(f"Silhouette Scores: {silhouette_scores}")

    # KMeans Clustering
    kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
    customer_data['Cluster'] = kmeans.fit_predict(scaled_features)

    # Calculate final DB Index
    final_db_index = davies_bouldin_score(scaled_features, customer_data['Cluster'])
    print(f"Final Davies-Bouldin Index: {final_db_index:.4f}")

    # Visualize clusters
    plt.figure(figsize=(8, 6))
    sns.scatterplot(
        x=customer_data['TotalValue'],
        y=customer_data['Quantity'],
        hue=customer_data['Cluster'],
        palette="viridis",
        s=100
    )
    plt.xlabel('Total Value')
    plt.ylabel('Quantity')
    plt.title('Customer Segmentation Clusters')
    plt.legend(title='Cluster')
    plt.show()

    # Save report
    customer_data[['CustomerID', 'Cluster']].to_csv("FirstName_LastName_Clustering.csv", index=False)
    print("Clustering results saved to CSV.")

customer_segmentation()
```

```
--- Performing Customer Segmentation ---

Optimal Number of Clusters: 2
Davies-Bouldin Scores: [np.float64(0.6298644531019864), np.float64(0.6790773231366432), np.float64(0.7102764046737506), np.float64(0.7529350579420507), np.float6
4(0.8164295471714539), np.float64(0.7790991322899361), np.float64(0.8993608517663892), np.float64(0.8232396439456049), np.float64(0.8554143386495813)]
Silhouette Scores: [np.float64(0.5468050856155675), np.float64(0.4611040376839224), np.float64(0.4539109087769898), np.float64(0.4315131216122971), np.float64(0.
3982228166826936), np.float64(0.4067360036270196), np.float64(0.3687188420888175), np.float64(0.36018293105041976), np.float64(0.35816886716338303)]
Final Davies-Bouldin Index: 0.6299
```




```
Clustering results saved to CSV.
```

Done By PREMKUMAR BAJARU

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