<u>Customer Segmentation Report</u>

1. Number of Clusters Formed:
After applying the K-Means clustering algorithm, the customer data was segmented into 4 clusters. The number of clusters was chosen arbitrarily, and further tuning with methods like the Elbow Method or Silhouette Score could be explored to optimize this selection.

2. Davies-Bouldin (DB) Index Value:
The Davies-Bouldin Index (DBI), which measures the compactness and separation of clusters.A lower DB Index indicates better clustering performance, as it suggests well-separated and compact clusters.

3. Other Relevant Clustering Metrics:
Apart from the DB Index, additional cluster evaluation techniques that could be applied include:

- Inertia (Within-cluster Sum of Squares): Measures how tightly the points in a cluster are grouped.
- Silhouette Score: Evaluates how similar a data point is to its own cluster compared to other clusters.
- Calinski-Harabasz Index: Measures the ratio of the sum of between-clusters dispersion and within-cluster dispersion.

4. Visualization of Clusters:
The plot effectively demonstrates the segmentation of customers based on their purchasing behavior. The addition of features such as customer profile attributes could enhance segmentation insights further.

5. Recommendations and Insights:
Based on the clustering results, the following actions could be considered:

- Target high-value customers (clusters with high TotalValue) with exclusive promotions.
- Develop personalized marketing campaigns for each cluster based on their purchasing patterns.
- Consider further feature engineering by incorporating demographic and temporal data for better segmentation.

Conclusion:
The K-Means clustering technique provided meaningful segmentation of customers based on their transaction behavior. Further improvements can be achieved by optimizing the number of clusters and incorporating additional features from the customer profile dataset.