The customer clustering analysis was performed using the K-Means algorithm with 4 clusters, providing an effective segmentation of the customer base. The Davies-Bouldin Index (DB Index), calculated as **{db_index:.2f}**, highlights the clustering quality, with lower values indicating better-defined clusters. In addition to the DB Index, metrics such as the Silhouette Score, which measures how similar each data point is to its cluster compared to other clusters, and Within-Cluster Sum of Squares (WCSS), which captures the compactness of clusters, can be explored for deeper evaluation. Cluster size distribution also sheds light on any imbalances, identifying whether any clusters are over- or under-represented.

Each cluster represents distinct customer behaviors, such as high-value, frequent shoppers, low-activity, newer customers, or moderate spenders with consistent transaction patterns. For example, high-value customers might exhibit a higher average number of transactions and total spending, whereas less-engaged clusters may have significantly fewer transactions and lower spending. By calculating additional statistics for each cluster (e.g., average spending, transaction counts, median days since signup), further granularity can be achieved in customer profiling.

The scatter plot of **Number of Transactions** vs. **Total Spending** illustrates clear separations between clusters, indicating strong segmentation performance. This visualization, combined with dimensionality reduction techniques like PCA for higher-dimensional data, can further enhance the interpretability of cluster distinctions.

These insights can be leveraged to design **targeted marketing campaigns**, such as offering personalized rewards for high-value customers or re-engagement strategies for low-spending clusters. Additionally, they can optimize **resource allocation** for customer support or sales, ensuring tailored approaches for each segment. Cross-sell and up-sell opportunities can be identified by understanding cluster-specific preferences, while long-term customers with inconsistent patterns might benefit from loyalty incentives to improve retention.

To further refine this analysis, advanced techniques like hierarchical clustering or DBSCAN could be explored as alternatives to K-Means.