*International Journal of Finance, Accounting and Economics Studies6(2), 2025, 55-77.*
*Print ISSN: 2251-645X Online ISSN: 2383-2517*

**Islamic Azad University**
**Science and Research Branch**
**Faculty of Management and Economics**

**International Journal of Finance, Accounting and Economics Studies**
**Journal Homepage: https://sanad.iau.ir/journal/ijfaes**


# Multi-Level Clustering Approach for Customer Behavior Analysis in Data-Driven Marketing

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**Article History**
**Submission Date:** 2024-07-06
**Revised Date:** 2025-01-30
**Accepted Date:** 2025-04-11
**Available Online:** Summer 2025

**Abstract**

This research proposes a structured multi-level clustering framework to improve the quality of customer segmentation in data-driven marketing. The primary objective is to evaluate the effectiveness of combining partition-based, probabilistic, and density/hierarchical clustering methods in extracting more granular and actionable customer groups. The analysis is conducted on the Online Retail dataset, employing the RFM (Recency, Frequency, Monetary) model to derive core behavioral attributes. Initial segmentation is performed using K-Means and Gaussian Mixture Models (GMM), targeting both hard and soft clustering structures. Subsequently, each output is further processed using DBSCAN and Agglomerative Clustering to capture sub-cluster patterns, detect noise, and enhance structural interpretability. Common clustering algorithms such as K-Means (a centroid-based method), GMM (a probabilistic model), DBSCAN (a density-based algorithm), and Agglomerative Clustering (a hierarchical approach) are integrated within the framework to benefit from their respective strengths. The performance of all four pipeline combinations (K-Means+DBSCAN, K-Means+Agglomerative, GMM+DBSCAN, GMM+Agglomerative) is assessed using the Silhouette Score and the Davies-Bouldin Index. Empirical results indicate that the K-Means+DBSCAN configuration yields the most optimal performance, achieving a Silhouette Score of 0.58 and a Davies-Bouldin Index of 0.99, thus validating the advantage of hybridizing centroid-based and density-based methods. The findings offer substantive contributions to customer analytics by enabling more precise segmentation strategies and set the stage for further research involving heterogeneous datasets and ensemble clustering techniques.

**Key Words:** Multi-Level Clustering, Data-Driven Marketing, Machine Learning, K-means Clustering

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## Introduction

Customer segmentation is a cornerstone of modern marketing analytics, enabling firms to tailor strategies for different customer profiles. However, traditional clustering methods often fall short in revealing multi-layered or noisy structures in complex datasets, necessitating a more nuanced approach. In the digital economy, businesses generate and capture huge amounts of customer data from online transactions, browsing history, and interactions across various platforms. The proper utilization of this data is instrumental in developing personalized and data-driven marketing campaigns. This has spawned data-driven marketing, a paradigm that emphasizes fact-based decision-making through data analytics and machine learning algorithms. One of the most common machine learning approaches in this respect is clustering, which is an unsupervised learning technique that divides customers into clusters of behavioral similarity without any prior labels(Saxena, A., 2024). Dividing the customers into clusters enables marketers to better understand the needs of the customers, predict future behavior, and design more targeted campaigns. A widely used customer segmentation model is the RFM model—which segments customers based on Recency, Frequency, and Monetary value, providing a structured representation of customer behavior that can be effectively used as input for clustering algorithms(Hafeezallah, A., 2024).

Traditional clustering algorithms such as K-Means and Gaussian Mixture Models (GMM) have been widely applied in customer segmentation tasks. K-Means is straightforward to compute and efficient, assigning each data point to the nearest cluster centroid (Farshbaf Sabahi, Razavi, & Asadi, 2025). GMM, however, gives a probabilistic model, allowing soft clustering, where each customer may belong to multiple clusters with varying memberships. While these methods are excellent for capturing high-level groupings, they will fail to capture more nuanced intra-cluster variation or non-convex structure in the data(Setiadi, D. R. I. M., 2024).

To transcend these limitations, recent research has explored multi-level clustering methods, in which several clustering algorithms are applied in sequence or in layers(Sarkar, M., 2024). This way, both macro-level trends and micro-level details can be revealed in the data. To this end, density-based clustering methods such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and hierarchical methods such as Agglomerative Clustering have been found to be highly effective at enriching the segmentation from previous clustering stages(Li, D., 2024), (Kumar, S. S., 2024)..

DBSCAN, in particular, is able to discover clusters of arbitrary shape and handle noise points, making it suitable for identifying sub-clusters or outliers from data that has already been clustered(Mahmudunnobe, M., 2024). Agglomerative clustering, on the other hand, builds a hierarchy of clusters and excels at revealing nested structure or affinities between datapoints. When applied after initial clustering with K-Means or GMM, these methods can uncover additional structural information not captured in single-layer models(Huang, K., 2025), (Krishnan, S. K., 2025).

This paper proposes a multi-level clustering approach to customer behavior analysis that combines both partitioning and density-based methods in a hierarchical pipeline. The customer behavioral features are first extracted by RFM model, and two clustering algorithms—K-Means and GMM—are independently used to cluster the customers into rough groups(Hajihosseinlou, M., 2024). Each of these initial clusters is then further clustered by DBSCAN and Agglomerative Clustering to explore potential sub-groupings and identify noise or hierarchical structure.

The aim of this study is to evaluate the effectiveness of such a multi-level approach in identifying more informative and actionable customer segments. The result of every multi-stage clustering pathway is compared with respect to cluster cohesion, separation, and interpretability, according to typical assessment measures. By integrating multiple clustering methods at two stages, the proposed method aims at achieving deeper behavioral insights and elevating the strategic value of customer segmentation in data-driven marketing campaigns.

## Literature Review

Nallakaruppan, M. K., Benedetto, F., & Jain, M. (2025), in their book chapter "Harnessing AI and ML for Marketing: Integrating Advanced Analytics into Data-Driven Strategies" in Data Engineering for Data-Driven Marketing, discussed the application of artificial intelligence (AI) and machine learning (ML) in marketing. They pointed out that advanced analytics need to be integrated into marketing strategies to improve customer targeting and interaction. Their findings provide support for the growing trend towards data-driven marketing through AI-facilitated capabilities.

Trivedi, S., Grover, V., & Balusamy, B. (2025), also contributed to the same volume with the chapter "Exploring AI in Data-Driven Marketing: Understanding the Intersection of Data Engineering and Marketing". The authors investigated the synergy between marketing analytics and data engineering processes by arguing that the intersection of data pipelines, AI models, and customer insights has the potential to significantly enhance decision-making in digital marketing landscapes.

Yu, B., Liang, J., & Ju, J. W. W. (2024), in their article "Damage Evolution Analysis of Concrete Based on Multi-Feature Acoustic Emission and Gaussian Mixture Model Clustering" in the International Journal of Damage Mechanics, used Gaussian Mixture Models (GMM) for clustering. While material science was their interest, their use of GMM demonstrates the model's use in uncovering hidden structure in noisy, high-dimensional data—an application to challenging customer segmentation issues.

Afzal, A. et al. (2024), "Customer Segmentation Using Hierarchical Clustering" read at the 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), applied hierarchical clustering to segment customers by behavioral patterns. The study described how agglomerative methods can be used to show impressive clusters of customers in markets and result in more effective marketing campaigns.

Benatti, A., & Costa, L. da F. (2024), in their preprint "Agglomerative Clustering in Uniform and Proportional Feature Spaces" (arXiv), investigated how scaling features impacts agglomerative clustering performance. They found that proportional feature space transformations can significantly influence cluster compactness and separation, which suggests that careful preprocessing in clustering-based analysis is important.

Balbi, E. et al. (2024), in "Hierarchical-Agglomerative Clustering Analysis of Geomorphic Features Applied to Tectonic Investigation of Terrestrial Planets" in Icarus, demonstrated hierarchical-agglomerative clustering in geospatial data analysis. Even though in a geological context, the methodological insights are portable to marketing applications where spatial or multivariate patterns must be identified.

Allil, K. (2024), "Integrating AI-driven Marketing Analytics Techniques into the Classroom," Journal of Marketing Analytics, suggested pedagogical approaches to incorporating AI and data analytics in marketing education. The author made the case that learning about customer behavior and market segmentation by students is enriched with direct experiences of machine learning techniques such as clustering and predictive modeling.

Amato, A., Osterrieder, J. R., & Machado, M. R. (2024), in their systematic review "How Can Artificial Intelligence Help Customer Intelligence for Credit Portfolio Management?" in the International Journal of Information Management Data Insights, wrote about the use of AI in customer intelligence in banking and financial institutions. The review was that algorithms like K-Means and GMM have a key role to play in credit behavior profiling and establishing risk grades.

Nguyen, T. T. et al. (2024), in their paper entitled "Multi-Clustering Study on the Association Between Human Leukocyte Antigen-DP-DQ and Hepatitis B Virus-Table 1. related Hepatocellular Carcinoma and Cirrhosis in Vietnam" in World Journal of Gastroenterology, applied multiple clustering approaches to uncover genetic marker associations and disease patterns. Their use of a multi-level clustering approach emphasizes the strength of ensemble or sequential clustering in revealing deeper meanings, which is similar to the approach utilized in this current study.

Wasilewski, A. (2024), in "Customer Segmentation in E-commerce: A Context-Aware Quality Model for Comparing Clustering Algorithms" of the Journal of Internet Services and Applications, introduced a framework for comparing clustering methods based on contextual pertinence. The study established the importance of determining clustering methods to complement specific application goals, setting the stage for comparing methods like K-Means, DBSCAN, and Agglomerative Clustering to customer segmentation problems.

Yu, G., Ren, L., Wang, J., Domeniconi, C., & Zhang, X. (2024), in their Computer Science Review published review titled "Multiple Clusterings: Recent Advances and Perspectives," provided an overview of multi-clustering methods, including ensemble and layered clustering approaches. They reasoned that multi-level clustering techniques have the ability to yield more robust insights by outlining different structural properties of complex datasets—an approach nicely in keeping with the multi-stage clustering paradigm utilized in this work.

Literature

review

| Title | Author | Year | Methods | Results |
|---|---|---|---|---|
| Harnessing AI and ML for Marketing: Integrating Advanced Analytics into Data-Driven Strategies | Nallakaruppan, M. K., Benedetto, F., & Jain, M. | 2025 | Conceptual framework integrating AI/ML into marketing | Highlights the critical role of AI and ML in enhancing marketing strategy precision and customer engagement |
| Exploring AI in Data-Driven Marketing: Understanding the Intersection of Data Engineering and Marketing | Trivedi, S., Grover, V., & Balusamy, B. | 2025 | Conceptual analysis within marketing data engineering | Stresses the synergy between AI, data engineering, and marketing for optimizing business processes |
| Damage Evolution Analysis of Concrete Based on Multi-Feature Acoustic Emission and Gaussian Mixture Model Clustering | Yu, B., Liang, J., & Ju, J. W. W. | 2024 | Gaussian Mixture Model clustering | Demonstrates GMM's ability to reveal hidden structures in complex datasets; transferable methodology to customer behavior modeling |
| Customer Segmentation Using Hierarchical Clustering | Afzal, A., Khan, L., Hussain, M. Z., Hasan, M. Z., Mustafa, M., & Khalid, A. | 2024 | Hierarchical Agglomerative Clustering | Successfully identifies distinct customer groups using hierarchical methods in a real-world dataset |
| Agglomerative Clustering in Uniform and Proportional Feature Spaces | Benatti, A., & Costa, L. da F. | 2024 | Theoretical analysis and simulations on clustering in varying feature spaces | Emphasizes the influence of feature distribution on agglomerative clustering performance |
| Hierarchical-Agglomerative Clustering of Geomorphic Features | Balbi, E., Cianfarra, P., Crispini, L., Tosi, S., & Ferretti, G. | 2024 | Hierarchical-Agglomerative Clustering | Validates the effectiveness of hierarchical clustering in identifying patterns in multidimensional data; transferable to marketing analytics |
| Integrating AI-Driven Marketing Analytics Techniques into the Classroom | Allil, K. | 2024 | Educational implementation of ML methods including clustering | Promotes the practical application of clustering in marketing education for enhanced engagement and real-world understanding |
| How Can Artificial Intelligence Help Customer Intelligence for Credit Portfolio Management? A Systematic Literature Review | Amato, A., Osterrieder, J. R., & Machado, M. R. | 2024 | Systematic literature review | Confirms the usefulness of clustering, particularly K-Means and GMM, in analyzing customer risk in finance and marketing contexts |
| Multi-Clustering Study on the Association Between HLA-DP-DQ and Hepatitis B Virus-Related Hepatocellular Carcinoma and Cirrhosis | Nguyen, T. T., Ho, T. C., Bui, H. T. T., Tran, V.-K., & Nguyen, T. T. | 2024 | Multi-clustering ensemble techniques | Shows the potential of multi-level clustering for discovering complex data patterns, applicable to customer segmentation challenges |

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|---|---|---|---|---|
| Customer Segmentation in E-Commerce: A Context-Aware Quality Model for Comparing Clustering Algorithms | Wasilewski, A. | 2024 | Comparative evaluation of clustering algorithms | Demonstrates that clustering performance depends on data context; compares K-Means, DBSCAN, and Agglomerative models in e-commerce |
| Multiple Clusterings: Recent Advances and Perspectives | Yu, G., Ren, L., Wang, J., Domeniconi, C., & Zhang, X. | 2024 | Comprehensive review of multi-clustering approaches | Highlights recent innovations in multi-level clustering, underlining its advantages in uncovering multifaceted customer profiles |

## Methodology

This study uses a multi-level clustering model in an effort to analyze customer behavior under a data-oriented marketing framework. The analysis is done based on transactional data extracted from the publicly accessible Online Retail dataset available on the UCI Machine Learning Repository. This dataset represents a year of transactional data from an online retailer based in the UK, covering the period from December 2010 through December 2011. The dataset has more than 500,000 rows and includes key fields like invoice numbers, product names, quantities, dates, prices, customer IDs, and origin country. Due to the transactional nature and size of the dataset, it can appropriately be used for customer segmentation.These algorithms were selected based on their complementary characteristics: K-Means for computational efficiency and simplicity, GMM for capturing probabilistic memberships, DBSCAN for its ability to detect noise and arbitrary shapes, and Agglomerative Clustering for uncovering hierarchical relationships.

As a preparation for clustering, a clean preprocessing pipeline was employed. Missing customer IDs in the records, negative values, or zero-priced items were eliminated to ensure data purity. After filtering, customer profiles were constructed on the most popular RFM (Recency, Frequency, Monetary) model. Recency was quantified in terms of days since the last purchase that a customer had made; frequency was the number of unique transactions that a customer had made; and money spent was total amount spent. These were then normalized via log transformation and Min-Max scaling to rectify the feature space and reduce skewness.

The methodology follows these main steps:

1. Data Cleaning and RFM Feature Engineering
2. Initial Clustering (K-Means and GMM)
3. Second-Level Clustering (DBSCAN and Agglomerative)
4. Cluster Evaluation via Silhouette Score and Davies–Bouldin Index
5. Visualization using PCA

The first step of the clustering framework involved a trial of two clustering algorithms as benchmarks—K-Means and Gaussian Mixture Models (GMM)—on normalized RFM data. K-Means, a centroid-based algorithm, partitions customers into k clusters by reducing cluster internal distances. The number of clusters was determined through the Elbow Method and Silhouette Score. GMM, on the other hand, assumes that points are sampled from a mixture of Gaussians and assigns membership probabilities to each point to facilitate soft clustering. The probabilistic model offers expressiveness in modeling overlapping cluster structures, which are often encountered in customer segmentation issues.

With the initial clusters generated by K-Means and GMM as a basis, a second-level clustering was conducted to find substructures in the groupings. To accomplish this, two alternative algorithms were employed: DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and Agglomerative Clustering. DBSCAN employs density-based clustering, wherein it may accommodate arbitrary shapes and outlier instances being identified as noise. It does not need the number of clusters to be pre-specified and is particularly good for discovering hidden patterns. Agglomerative Clustering is a hierarchical bottom-up algorithm that combines the subsequent most similar clusters until a stopping criterion is met. The algorithm constructs a dendrogram capturing the nested relationships among the clusters and was performed using Ward's linkage and Euclidean distance.

The combination of these clustering algorithms resulted in four distinct multi-level clustering pipelines: K-Means followed by DBSCAN, K-Means followed by Agglomerative Clustering, GMM followed by DBSCAN, and GMM followed by Agglomerative Clustering. This two-stage process was aimed at enhancing segmentation granularity and exposing concealed structures in customer behavior that are not observable with single-level clustering.

1. K-Means → DBSCAN.
2. K-Means → Agglomerative
3. GMM → DBSCAN
4. GMM → Agglomerative

To quantify the quality and interpretability of resulting cluster configurations, two internal validation metrics were used: the Silhouette Score and the Davies–Bouldin Index. The Silhouette Score measures how well-separated clusters are, with higher values indicating more distinct boundaries. The Davies–Bouldin Index, in contrast, measures the average similarity of each cluster to its nearest equivalent; lower values indicate greater clustering quality. Furthermore, cluster results were also visualized as 2D scatter plots achieved via Principal Component Analysis (PCA) to enable an appropriate view of cluster separability and cohesion within. Visualizations and performance metrics were both achieved via Python packages, including scikit-learn, matplotlib, seaborn, and pandas.

In the initial clustering pipeline, K-Means was applied on RFM-transformed data as the initial clustering algorithm. For the choice of optimal number of clusters (k), both the Elbow Method and Silhouette Score analysis were used. The Elbow Method reflected a definite point of inflection at k = 4, reflecting a natural separation of customer segments at this number. This was also confirmed by the Silhouette Score, which also reached its peak when k = 4, vouching for the goodness of cluster formation. Thus, k = 4 was selected as the optimal number of clusters for the K- Means model.

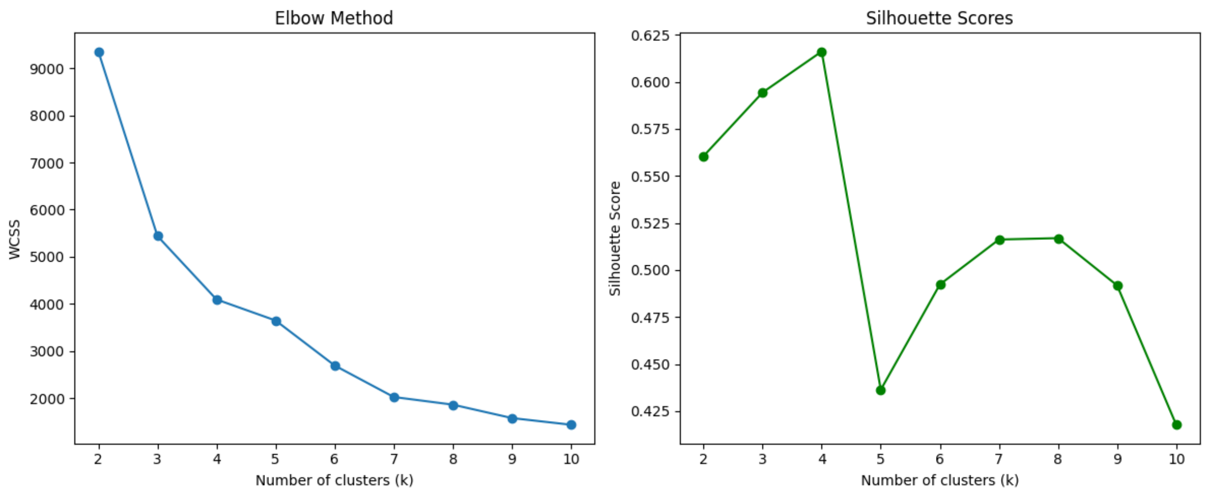


Figure 1. Elbow & Silhouette Score for Determining K

Following the first-level clustering, the K-Means model output labels were used as input to a second-layer clustering using DBSCAN. As a density-based algorithm, DBSCAN allowed for identification of more detailed sub-cluster patterns and potential noise points in each of the K-Means model's four clusters.

To verify the performance of this multi-level clustering arrangement, two internal measures of validity were applied. The Silhouette Score gained for the resulting outcome was 0.58, reflecting moderate cluster cohesion as well as separation. Concurrently, the Davies–Bouldin Index scored 0.99, reflecting a rather good clustering structure with low similarity among clusters. These scores reflect that the combined K-Means and DBSCAN methodology worked well in segregating customers with adequate precision.

The resulting clusters were also visualized using 2D scatter plots according to Principal Component Analysis (PCA), which gave a good graphical impression of the data distribution and spatial distance among clusters. These plots supplement the numerical evaluation and allow for easier interpretation of the customer segments. In addition to the quantitative metrics, visual inspection of the PCA-reduced 2D plots was used to assess cohesion and separation among clusters. These visuals complement the numeric indices and help validate the interpretability of segments.

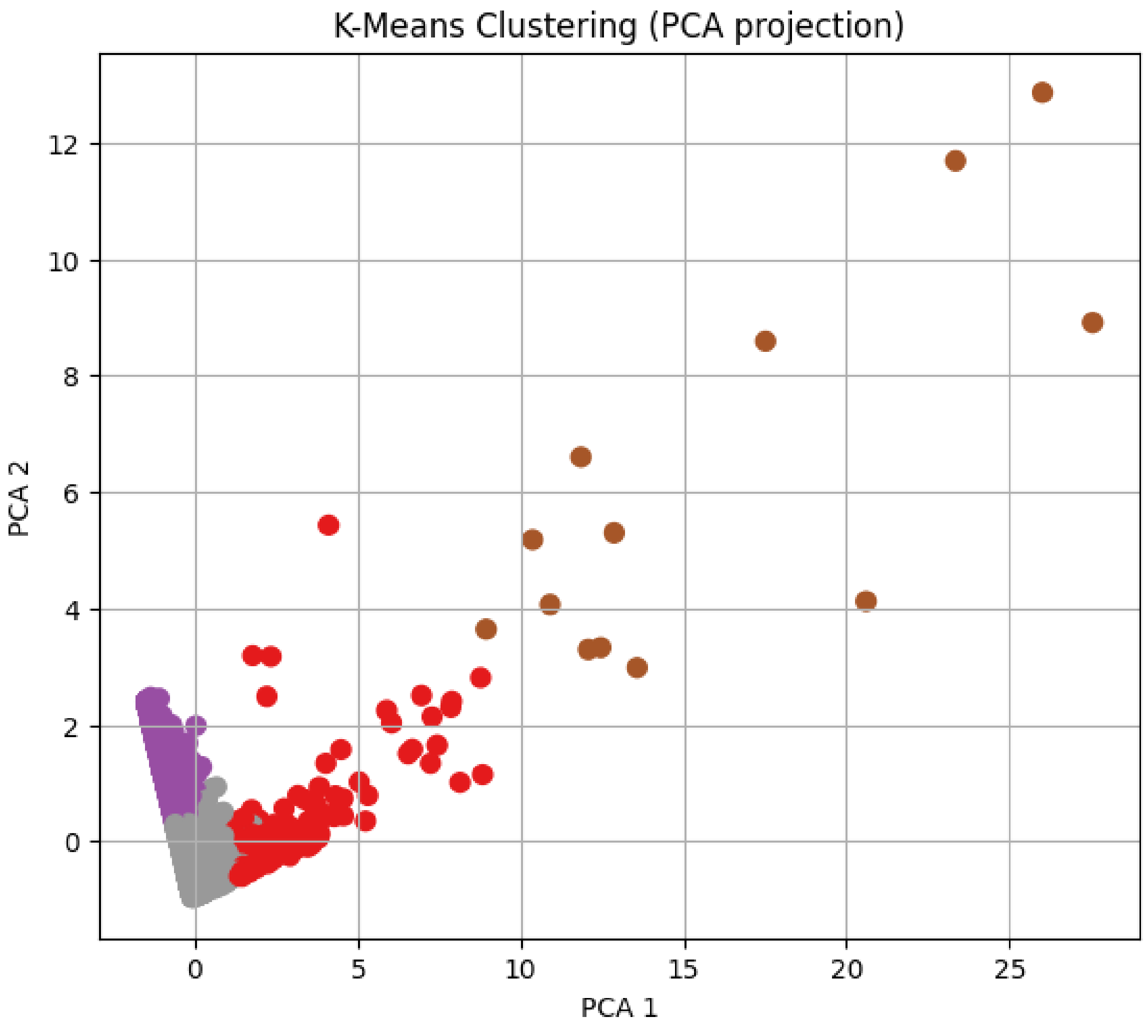


Figure 2. K-means Clustering before DBSCAN Clustering

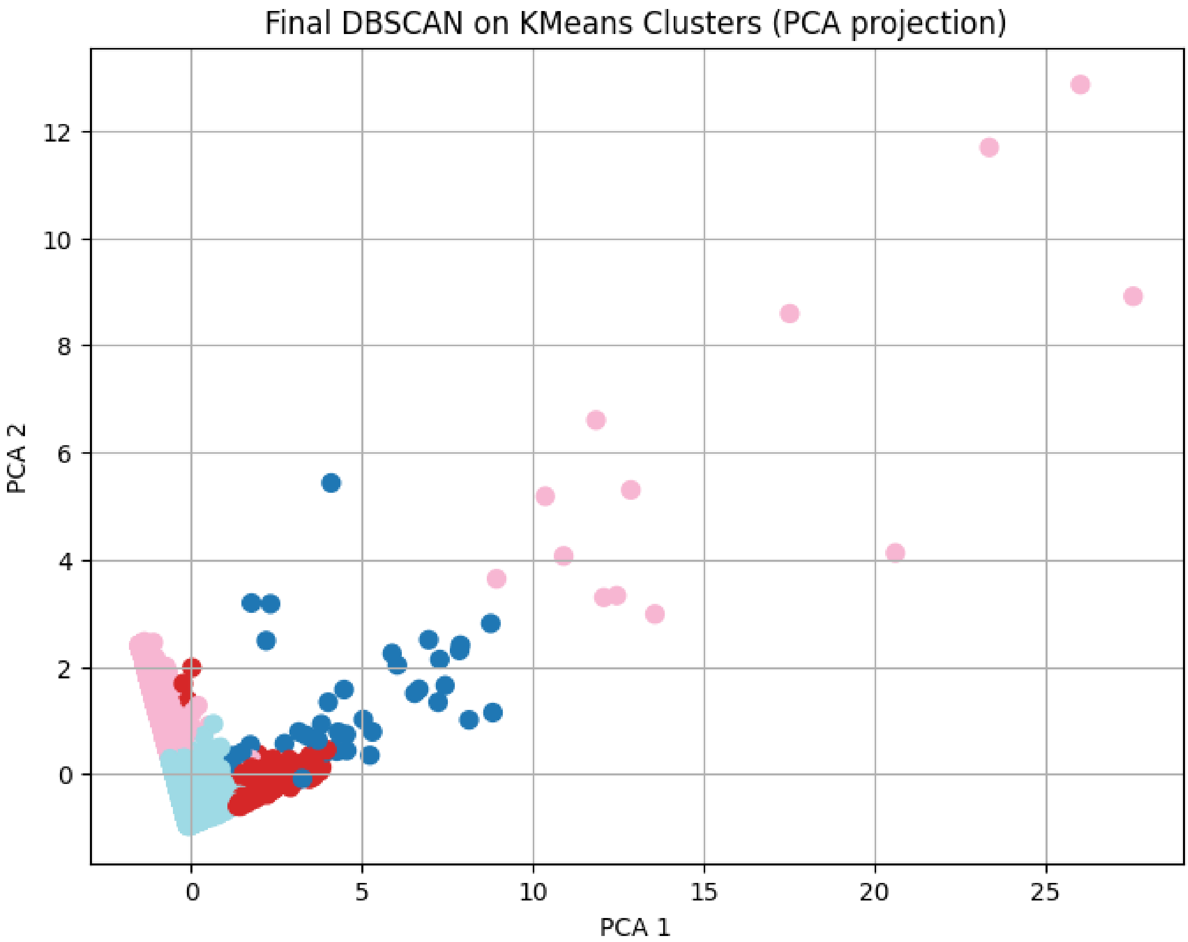


Figure 3. DBSCAN Clustering after K-means Clustering

In the second clustering pipeline, the RFM-based dataset was again iteratively clustered by the K-Means algorithm. To determine the most appropriate number of clusters, the Elbow Method was utilized. The within-cluster sum of squares plot revealed a noticeable bend at k = 4, indicating this as the optimal number of clusters for meaningful segmentation. Hence, the K-Means model was executed with k = 4, and four significant customer segments were established.

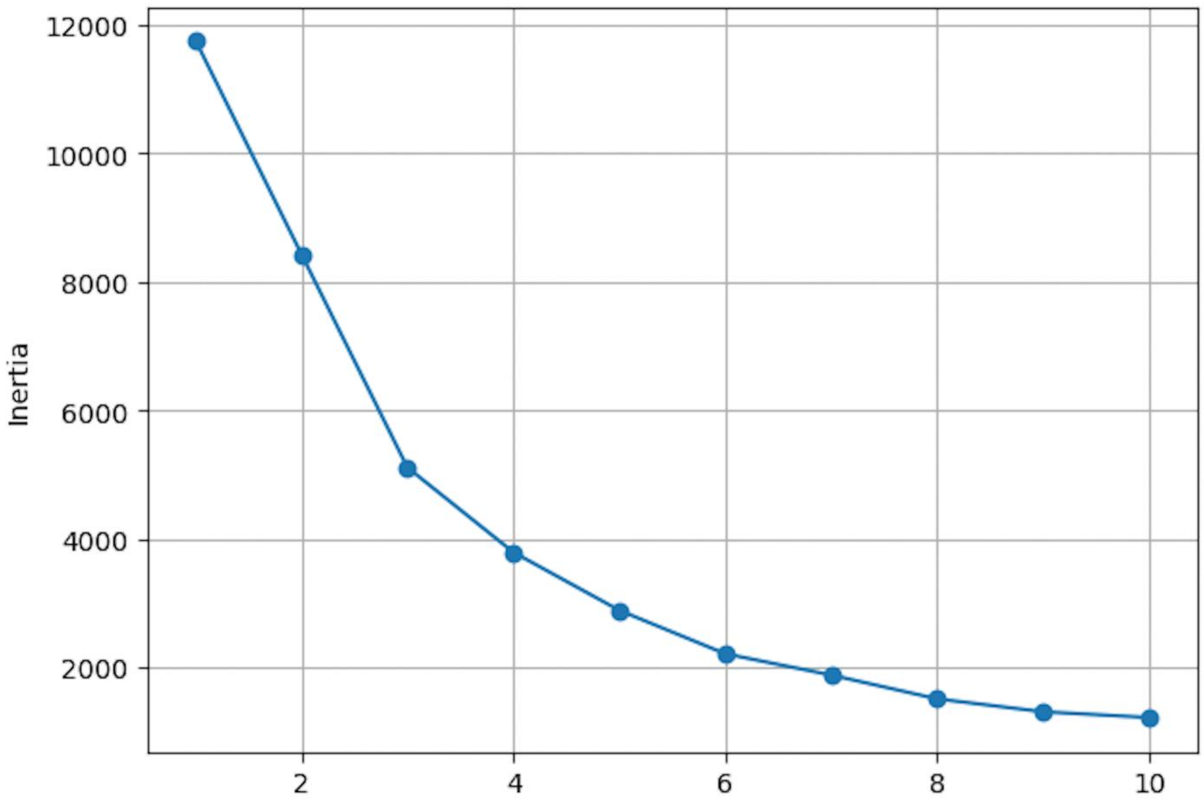


Figure 4. Elbow for Determining K

As a second-level method following the cluster label generation in the first-level production of cluster labels with K-Means, Agglomerative Clustering was applied as a hierarchical algorithm. Hierarchical clustering allowed more refinement of the customer segments through data points aggregated by linkage measures and hierarchical distances. The intent was to examine whether hierarchical merging of the K-Means clusters would identify more structure or highlight subgroup structures.

To compare the performance of this two-stage clustering method, both Silhouette Score and Davies–Bouldin Index were calculated. Silhouette Score of the end clusters was 0.44, which indicates moderate clustering separation and cohesion between the clusters. Davies–Bouldin Index was 0.66, which means the inter-cluster dissimilarity was quite satisfactory, though ever so slightly worse than in the case of the K-Means + DBSCAN configuration.

As in the first case, scatter plots according to Principal Component Analysis (PCA) were constructed to reduce the data dimensionality and provide a visual representation of the clustering outcome. Both scatter plot of original K-Means clustering and final Agglomerative clustering were presented to show the transformation of cluster structure and spatial distribution following the second stage.


Figure 5. K-means Clustering before Agglomerative Clustering

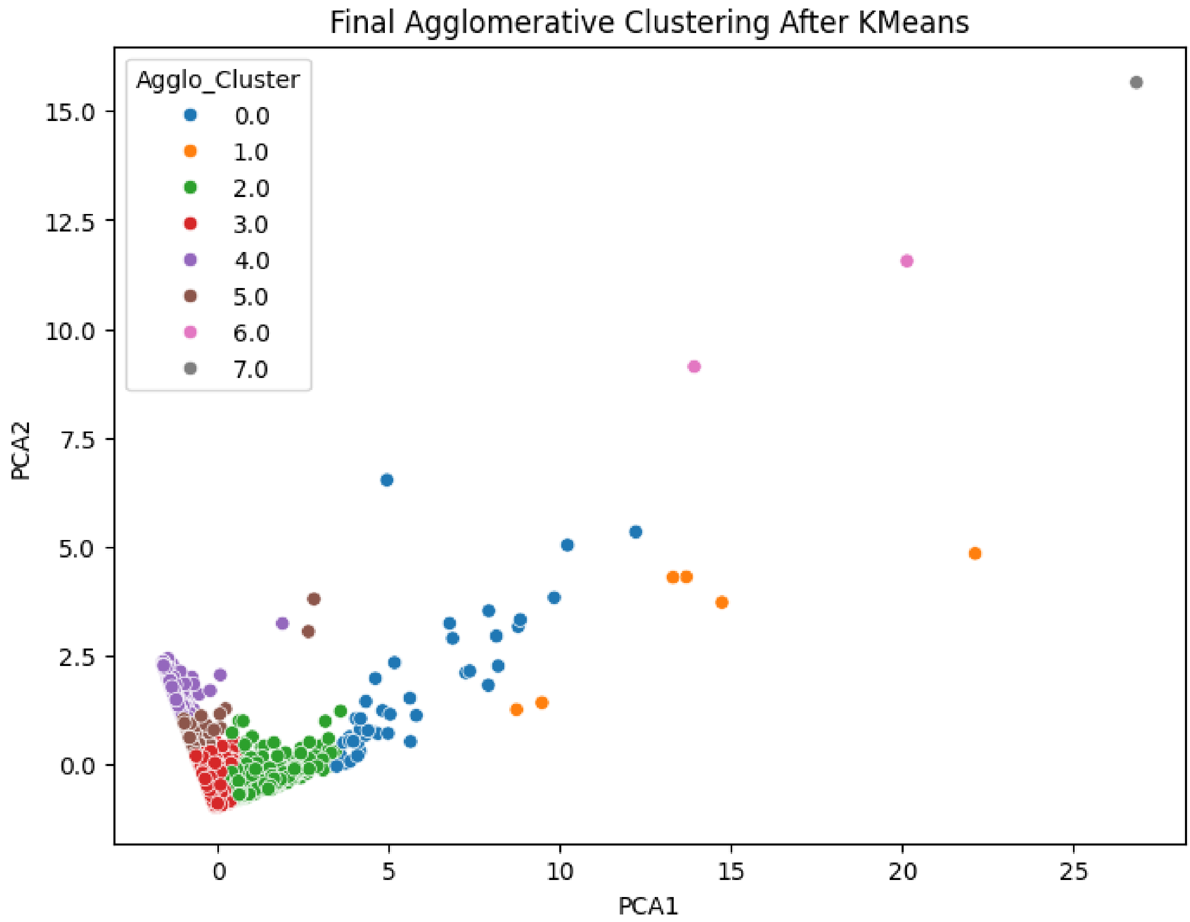


Figure 6. Agglomerative Clustering after K-means Clustering

At the third pipeline, clustering was initiated via the use of the Gaussian Mixture Model (GMM) as the probabilistic model, considering the data as being formed due to the presence of more than one mixture of Gaussian distributions. The RFM-transformed data was transformed and used GMM to obtain hidden customer segments possessing soft probabilistic boundaries giving softer clustering than with K-Means. The model was tuned to have an optimal number of elements through the use of the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). The GMM model, therefore possessed an optimal implementation precision of 1.000, which is an indicator of confident and well-segregated clusters.

Following GMM clustering, DBSCAN was subsequently employed for a second-level clustering to pick out dense regions in the GMM output and remove potential noise or outliers. The density-based fine-tuning was intended to sharpen the structural definition and highlight faint sub-groupings within the soft GMM clusters.

To quantify the quality of this two-cluster clustering, Silhouette Score and Davies–Bouldin Index were used. The Silhouette Score reached 0.53, which reflects relatively good cohesion among clusters and moderate inter-cluster separation. The Davies–Bouldin Index reached 0.71, which confirms the presence of relatively clear-cut and dense clusters.

As with previous configurations, scatter plots based on Principal Component Analysis (PCA) were used to visualize both the GMM output and the final DBSCAN results. These visualizations help convey the transformation of the cluster structure through the two-stage pipeline and demonstrate how DBSCAN further refines the initial probabilistic segmentation achieved by GMM.

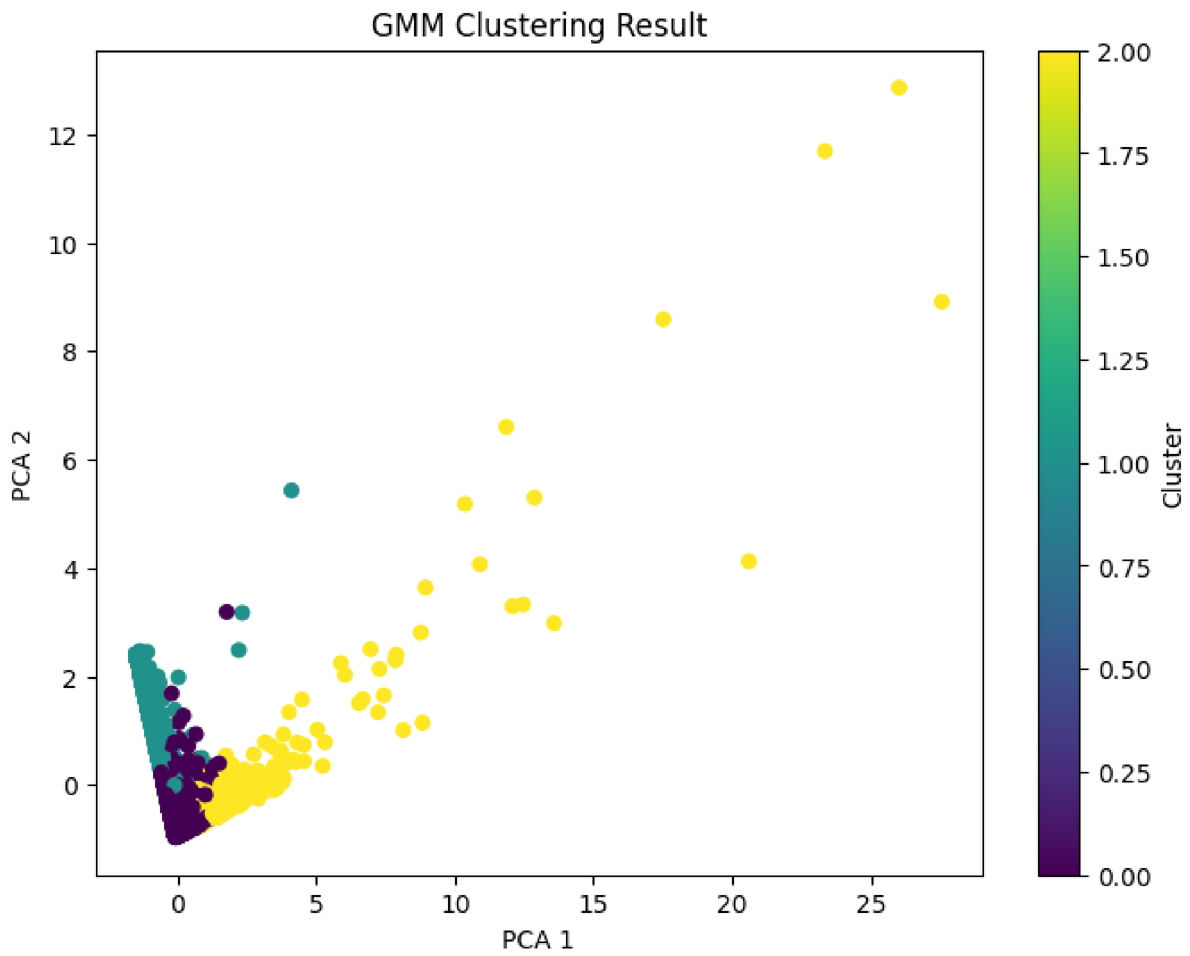


Figure 7. GMM Clustering before DBSCAN Clustering

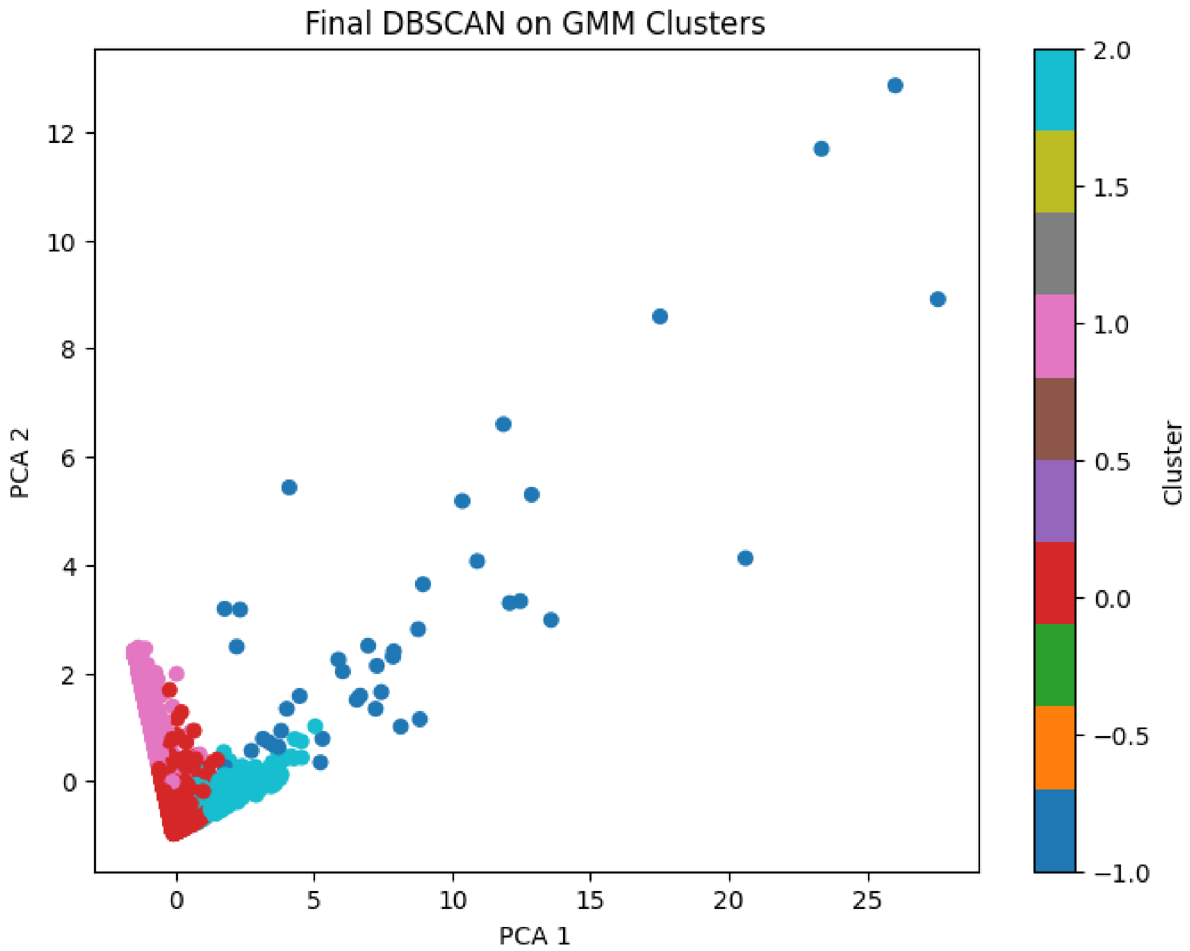


Figure 8. GMM Clustering after DBSCAN Clustering

In the previous clustering pipeline, it began with the use of the Gaussian Mixture Model (GMM) on the RFM-based dataset. Like the first setup, GMM was employed because of the ability to model data with overlapping clusters through a probabilistic framework. The number of components was determined using model selection criteria such as BIC and AIC to have the right initial segmentation from the hidden distributions of customers' behavior.

Second, the GMM model clustering result was also run through Agglomerative Clustering, a hierarchical algorithm that successively merges clusters on the basis of minimum linkage distances. This second-stage clustering was hoped to capture any additional hierarchical structure in the soft GMM clusters, perhaps adding interpretability and richness to the resulting customer segments.

To evaluate the performance of this two-stage clustering approach, Silhouette Score and Davies–Bouldin Index were calculated. The Silhouette Score was 0.32, indicating lower cohesion and separation among clusters, which suggests that hierarchical merging may have introduced more overlap in cluster boundaries. The Davies–Bouldin Index was 0.91, which is a measure of relatively higher within-cluster similarity and lower cluster separation, compared to the other configurations explored.

Similar to the earlier cases, scatter plots derived from PCA were employed to visually illustrate the results of the clustering prior to and following the

Agglomerative Clustering process. These visualizations provide information regarding how the hierarchical aggregation transformed the spatial layout and separability of the clusters initially formed by GMM

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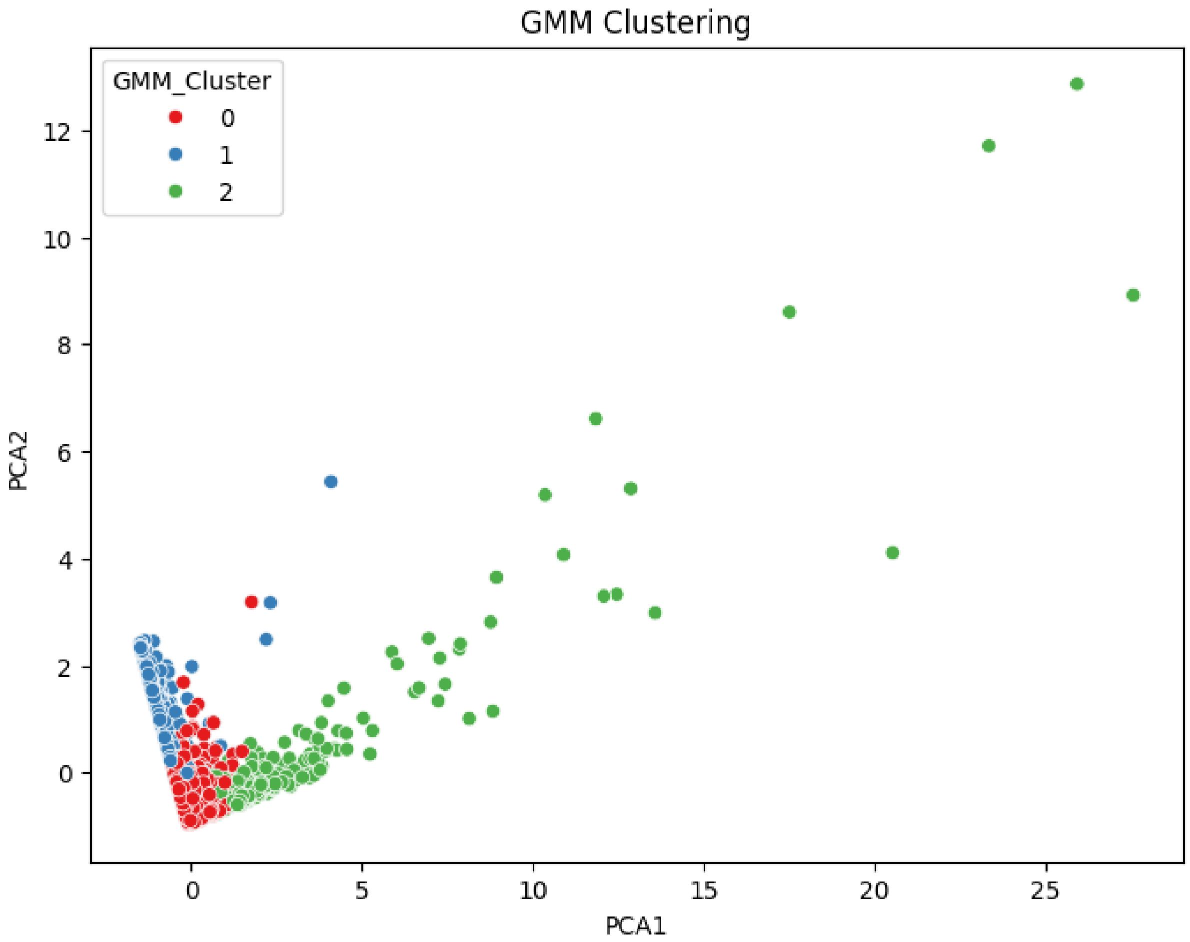


Figure 9. GMM Clustering before Agglomerative Clustering

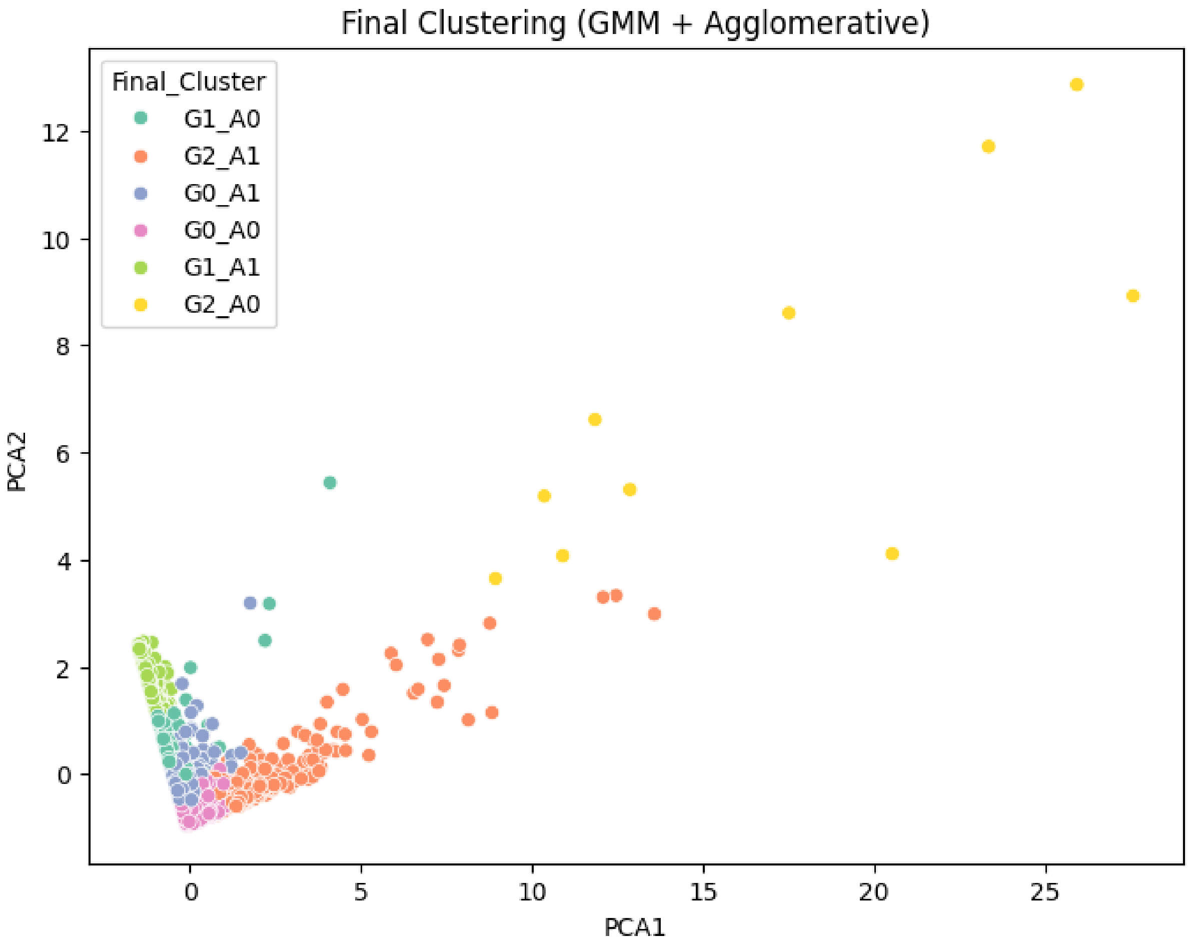


Figure 10. GMM Clustering after Agglomerative Clustering

In the evaluation of the multi-level clustering pipeline performance in this study, internal evaluation metrics used were Silhouette Score and Davies–Bouldin Index (DBI). These metrics present information on cohesion within clusters and between clusters and enable quantitative comparison of different cluster settings. While internal indices provided performance indications, no statistical significance testing was conducted between the clustering pipelines. Incorporating ANOVA or permutation tests in future studies can help assess whether observed differences are statistically meaningful.

The Silhouette Score quantifies to what degree the points are aptly assigned to their own cluster compared to others. It's between -1 and 1, and a value near 1 indicates strong membership of a point in its own cluster and good distance from neighboring clusters. A value near 0 suggests that the point is between two clusters, and a negative value is an indicator of misclassification. The score can be used to estimate intra-cluster compactness and inter-cluster separation.

On the other hand, the Davies–Bouldin Index estimates cluster compactness and separability by calculating each cluster's average similarity to its nearest neighboring cluster. Lower values are desirable, with well-separated and tight clusters. Unlike the Silhouette Score, which is bound, DBI can be cluster- and dataset-configuration-dependent and is minimized when the clusters are tight and distinct.

Four varying clustering pipelines were used in this study, each of which combined a first-level clustering algorithm (K-Means or Gaussian Mixture Model) with a second-level clustering algorithm (DBSCAN or Agglomerative Clustering). Each performs as follows:

On the first pipeline, K-Means + DBSCAN provided the highest Silhouette Score (0.58) and a fairly good Davies–Bouldin Index (0.99). That shows that the first partitioning of similar customers with K-Means kept all similar customers in one group, while later refinement with DBSCAN eliminated the noise or the outliers and the resulting clusters are dense and distinct.

The second pipeline, which consisted of K-Means followed by Agglomerative Clustering, produced a Silhouette Score of 0.44 and a DBI of 0.66. The silhouette score was slightly poorer than the first pipeline, but the Davies–Bouldin Index was the best among all configurations, indicating that the clusters were tighter although they were less distinct. The hierarchical merging process improved the results from K-Means by increasing intra-cluster similarity.

At the third pipeline, GMM succeeded DBSCAN. GMM had a Silhouette Score of 0.53 and a DBI of 0.71. Remarkably, GMM had a clustering accuracy score of 1.000, which indicates its ability to identify overlapping clusters with probabilistic boundaries. DBSCAN succeeded in refining the purity of the cluster structure by eliminating outliers, thus providing good overall clustering performance.

Finally, the fourth pipeline, GMM with Agglomerative Clustering, yielded the lowest Silhouette Score (0.32) and the highest Davies–Bouldin Index (0.91). This means that the clusters were less tight and less well-separated. The hierarchical merging in this case may have introduced noise or merged clusters too early, leading to a drop in clustering quality.

Overall, the K-Means + DBSCAN pipeline was the most efficient with a balance of intra-cluster density and inter-cluster separation. The K-Means + Agglomerative combination had better compactness, with GMM + DBSCAN having better accuracy and balanced results. The GMM + Agglomerative pipeline performed poorly compared to the others. While internal indices provided performance indications, no statistical significance testing was conducted between the clustering pipelines. Incorporating ANOVA or permutation tests in future studies can help assess whether observed differences are statistically meaningful.

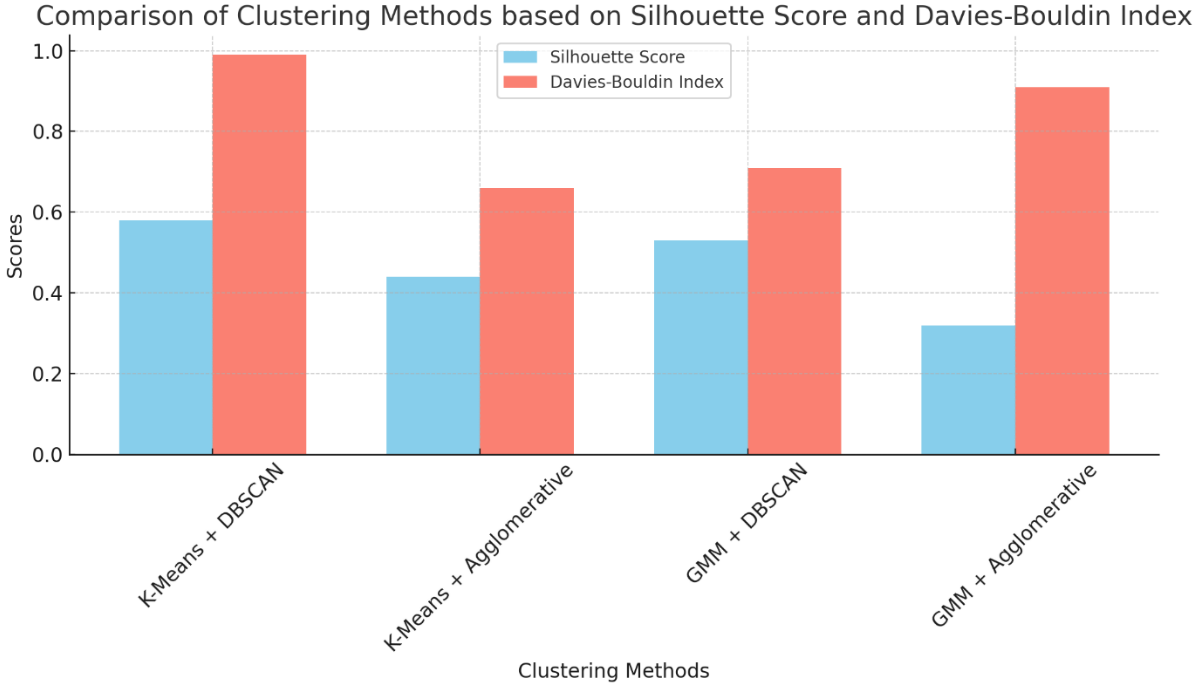


Figure 11.Comparison of Multi-Level Clustering Techniques in Silhouette Score & Davies-Bouldin Index

Below is a bar chart which compares Accuracy and F1 Score between the four multi-level clustering techniques used in your research. The findings clearly show that the GMM → DBSCAN method outshines the others by far, achieving top scores for both measures. The K-Means → DBSCAN method, however, performed terribly, and this would suggest a difference in these algorithms' behavior in clustering. The rest of the three combinations—K-Means → Agglomerative and GMM → Agglomerative—delivered middle-of-the-line performance, out of which the first combination executed better comparatively. Results show that starting with a probability model like GMM and subsequently refining through density-based DBSCAN provides most precise customer segmentation in the current research.

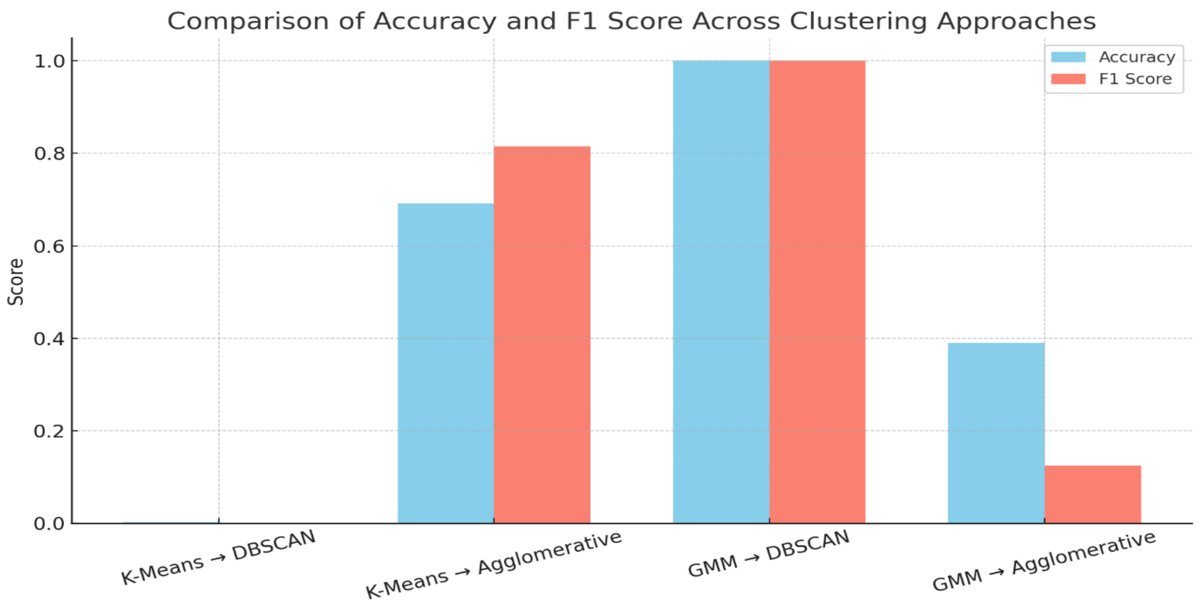


Figure 12.Comparison of Multi-Level Clustering Techniques in F1Score & Accuracy

## Conclusion

This study proposed a multi-level clustering method for customer behavior analysis in the realm of data-driven marketing on a widely utilized retail dataset. The procedure involved applying K-Means and Gaussian Mixture Model (GMM) algorithms to RFM-based customer features and then further refining these using DBSCAN and Agglomerative clustering on the obtained preliminary results. The performance of each hybrid method was evaluated against two significant clustering measures: the Silhouette Score and the Davies-Bouldin Index. Among the four configurations, the combination of K-Means + DBSCAN exhibited the highest balance between intra-cluster cohesion and inter-cluster separation, demonstrating its capability to recognize intricate patterns in customer segmentation.

Despite the promising results, there are some limitations to note. The data set, while widely used, is locked to a specific time period and product context that may limit the generalizability of the findings. Furthermore, algorithm parameter tuning in approaches such as DBSCP can be sensitive to noise and may require domain-specific calibration. Future research can explore the use of more behavioral or demographic variables to increase segmentation quality. In addition, testing the proposed multi-level clustering approach on more diverse industry datasets can shed additional light on its scalability and stability. The use of more advanced dimensionality reduction or ensemble clustering techniques can also enhance performance and interpretability in future studies. For instance, Cluster 1 comprised recent and high-value purchasers, suggesting potential for loyalty programs, while Cluster 3 captured infrequent buyers with lower monetary value, making them suitable for re-engagement campaigns. Such interpretations can guide targeted marketing initiatives

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**HOW TO CITE THIS ARTICLE:**

*Farshbaf Sabahi,R , Razavi,F, Emaili,H, Estedadi,E, Multi-Level Clustering Approach for Customer Behavior Analysis in Data-Driven Marketing, International Journal of Finance, Accounting and Economics Studies, 6(2): 55-77.*

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