iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69436

Uncovering Consumer Behavior Insights in Retail: A Data Driven Clustering-Based Approach with Distance Metrics

Neetaben Jagdishbhai Sapara[1], Dr. Hemant H. Patel[2]
[1]PG Scholar, [2]Head of the Department, Computer Science and Engineering, Dr. Subhash University, Junagadh, Gujarat, India

Abstract: In today's fast-changing business world, understanding analysis can help identify valuable customer groups. By applying the K-means clustering algorithm and using the Silhouette coefficient, this research aims to determine the ideal number of clusters for better segmentation. With the power of artificial intelligence (AI) and big data analytics, businesses can gain deeper insights into consumer behavior, allowing them to refine marketing strategies, predict sales trends, and enhance customer engagement. By analyzing both structured and unstructured data, companies can better understand shopping patterns and shifting market trends. AI-driven segmentation enables businesses to create personalized marketing campaigns, improve customer relationships, and boost retention rates. This research emphasizes the importance of data-driven strategies in optimizing customer interactions and staying ahead in a competitive market.
Keywords: Consumer Behavior, Customer Segmentation, Distance Metrics, K-means Clustering, Retail marketing

I. INTRODUCTION

In today's digital age, businesses increasingly rely on artificial intelligence (AI) and big data analytics to understand consumer behavior, refine marketing strategies, and enhance customer engagement. The field of direct marketing, in particular, has been transformed through AI-driven customer profiling and segmentation, allowing companies to create personalized campaigns tailored to individual preferences [1, 4]. By leveraging machine learning techniques and neural networks, businesses can now predict customer purchasing behavior with greater accuracy, leading to more effective decision-making and marketing strategies [2, 10].

With the rise of digital commerce and the widespread adoption of the Internet of Things (IoT) and social media, the amount of consumer data available for analysis has expanded significantly. Companies are increasingly utilizing structured and unstructured data to develop predictive models that anticipate customer needs, ultimately improving sales forecasting and retention strategies [3, 8]. Additionally, big data technologies have played a crucial role in retail marketing, enabling businesses to implement unsupervised learning techniques for better customer segmentation [14, 20]. These advancements provide deeper insights into purchasing patterns, customer loyalty, and evolving market trends [16, 29].

Research in consumer behavior analysis highlights the importance of RFM (Recency, Frequency, and Monetary) segmentation and its effectiveness in predictive analytics [11, 24]. Studies have shown that integrating AI-driven approaches with traditional segmentation methods enhances targeting precision and allows for more personalized marketing initiatives [26, 18]. Additionally, sustainable consumer behavior has gained attention as businesses focus on ethical marketing and innovation in retail [25, 12].

This research explores customer profiling, segmentation, and sales prediction in direct marketing using AI and big data analytics. By applying advanced clustering techniques and neural networks, this study aims to provide meaningful insights into optimizing marketing strategies and improving consumer engagement. The findings will contribute to the broader discourse on AI-driven marketing, offering valuable implications for businesses striving to maintain a competitive edge in today's evolving marketplace [30, 31].

II. LITERATURE SURVEY

In recent years, the application of data-driven approaches to understand consumer behavior has attracted growing interest among researchers and practitioners. A comprehensive study by Sapara and Patel [32] forms the basis of this review, as it thoroughly explores how technologies such as artificial intelligence (AI), machine learning (ML), and big data analytics are transforming retail marketing. Their work emphasizes the value of methods like RFM (Recency, Frequency, Monetary) segmentation and clustering for enhancing customer profiling and predictive performance.

Moreover, the study draws attention to critical challenges in the field, particularly those related to data privacy and ethical concerns. It also discusses evolving trends and techniques that support more personalized and effective marketing strategies.

TABLE I
LITERATURE INSIGHTS WITH METHODS, BENEFITS, AND LIMITATIONS

Author(s) & Paper	Year	Method Proposed	Benefits	Limitations
Arefin, Sydul, et al. [13]	2024	Uses RFM segmentation to analyze consumer behavior	Helps identify key customer segments	RFM may overlook certain consumer behavior complexities
Khasanah, Annisa Uswatun, Muhammad Rafly Qowi Baihaqie [19]	2024	Analyzes consumer traits for improved sales strategies	Allows better targeting of consumer needs	Requires large volumes of data to be effective
Williams, John [21]	2024	Employs big data for enhancing marketing strategies	Supports more efficient and personalized marketing efforts	Can be difficult to apply with smaller data sets
Rosário, Albérico, Ricardo Raimundo [27]	2021	Reviews marketing strategies in e-commerce	Provides insights into current e-commerce trends	Lacks actionable guidance for businesses
Chaudhary, Kiran, et al. [9]	2021	Predicts behavior based on social media data using machine learning	Improves consumer engagement with better insights	Dependent on accurate social media data
Li, Yifei [7]	2023	Analyzes the impact of social media and mobile payments on marketing strategies	Refines targeting by understanding modern consumer behavior	Relies heavily on social media and mobile data
Seyedan, Mahya, Fereshteh Mafakheri [28]	2020	Uses predictive models to optimize supply chain and inventory	Enhances efficiency in inventory management	Not always relevant to consumer behavior prediction
Aqif, Tanzeela, Abdul Wahab [6]	2022	Examines the impact of big data in reshaping retail marketing	Offers deeper insights into customer behavior patterns	May not provide solutions for smaller scale businesses
Ebrahimi, Pejman, et al. [5]	2022	Combines social media data and machine learning to predict purchase behavior	Leads to more targeted marketing strategies	Needs access to large-scale social media data
Orogun, Adebola, Bukola Onyekwelu [17]	2019	Uses machine learning for digital market consumer behavior analysis	Improves predictions of consumer preferences	Accuracy depends on the quality of data used
Raphaeli, Orit, Anat Goldstein, Lior Fink [23]	2017	Applies web usage mining to predict consumer behavior	Helps refine customer experiences through data insights	Privacy issues and data security concerns
Prasad, Aashish [22]	2019	Analyzes online	Improves the	Continuous data

		transaction data to understand consumer behavior	accuracy of marketing strategies	monitoring may be required
Akter, Shahriar, Samuel Fosso Wamba [15]	2016	Focuses on using big data to improve customer engagement and retention	Strengthens customer loyalty by understanding their preferences	Requires substantial infrastructure and resources

As outlined in Table 1, the studies reviewed highlight a range of methodologies employed in the analysis of consumer behavior. These methodologies showcase both their practical advantages and the limitations acknowledged by researchers, emphasizing the importance of advanced approaches like segmentation, predictive modelling, and the analysis of digital consumer interactions.

Taken together, the reviewed research emphasizes the growing role of sophisticated analytical techniques in enhancing the understanding of consumer behavior. Through the use of data-driven methods, businesses are better positioned to develop flexible marketing strategies that are more responsive to consumer needs. This, in turn, enables companies to refine customer targeting and engagement, ensuring they remain competitive in today's dynamic, data-rich market environment.

III. METHODOLOGY

A. *Clustering Methodology*

To segment customers accurately, different clustering techniques are applied:

1) *Different Clustering Algorithms:* Various Clustering techniques, including K-means, Agglomerative Clustering and Gaussian Mixture Models (GMM), are implemented in this study.

a) *K- means Clustering approach:*

K-Means is a widely used method for dividing data into distinct groups (clusters) based on similarity. It works by placing data points into K different clusters, where each point belongs to the group with the nearest center (called a centroid). It's best suited for situations where clusters are well-separated and roughly equal in size. K-Means is commonly used in market segmentation, customer profiling, image compression, and pattern recognition to find clear and simple groupings in data.

b) *Agglomerative Clustering approach:*

Agglomerative clustering helps in grouping similar items by measuring how close they are. It builds clusters step-by-step, starting with individual points and merging them until larger groups form. It's useful when you want to understand natural groupings or structure in your data, especially when there's no need to assume any specific data distribution. It's often applied in areas like customer grouping, pattern recognition, or organizing content.

c) *Gaussian Mixture Models (GMM):*

GMM is designed for probabilistic clustering, where each point can belong to multiple groups with certain probabilities. It's especially useful when clusters are not clearly separated or have different shapes. GMM is great for modelling complex data, such as in customer behavior analysis, detecting unusual patterns, or voice and image processing.

2) *Elbow method & Silhouette Score Method:* The optimal number of clusters is determined using the Elbow Method, ensuring balanced segmentation, also to find best clustering , we have implemented another method named silhouette score to finalize optimal number of clusters.

3) *K-Means Clustering with Distance Metrics:* This method uses distance matrices to assess similarities among customers, forming well-defined clusters.

The comparison of distance metrics used in clustering algorithms is shown in Table 2.

TABLE II
COMPARISON OF DIFFERENT DISTANCE MATRICES

Metric	Description	Formula	Best Used For
Euclidean Distance [33]	Measures the straight-line distance between two points in space.	$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$	Geometric problems, clustering, image recognition.
Manhattan Distance [33]	Adds up the absolute differences of coordinates (like moving in a grid).	$d(A,B) = \sum_{i=1}^{n} \lvert A_i - B_i \rvert$	Grid-based movement, sparse data, pathfinding in city-like layouts.
Cosine Distance [33]	Measures similarity in direction between vectors, ignoring magnitude.	Cosine Distance = 1 – Cosine Similarity $d(A,B) = 1 - \frac{A \cdot B}{\lvert\lvert A\rvert\rvert \lvert\lvert B\rvert\rvert}$	Text similarity, high-dimensional data, recommendation systems.

B. Proposed Work

Fig. 1 mentions overall system architecture for proposed research work to show flow.

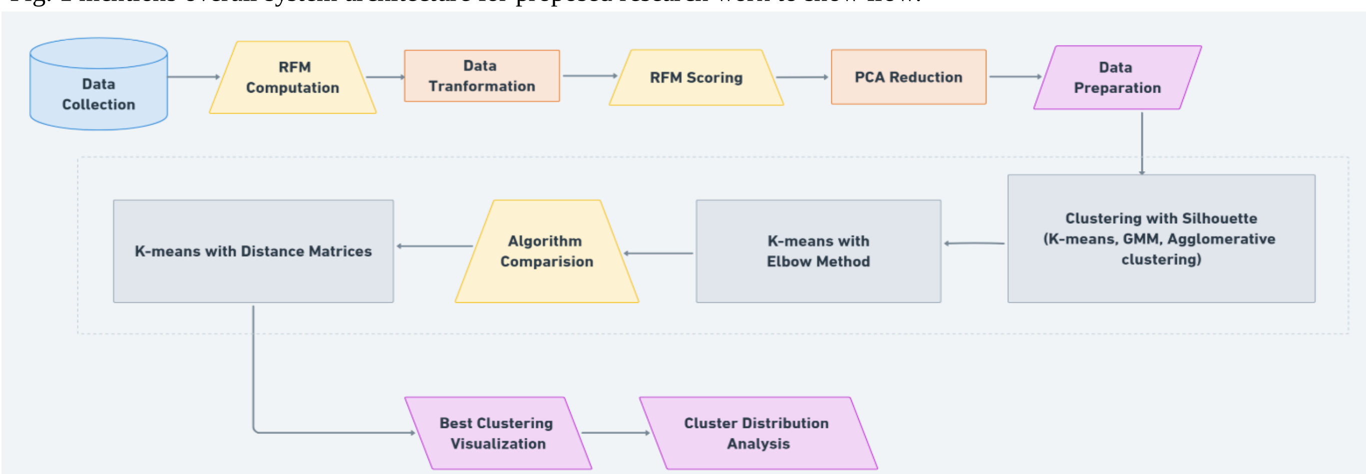


Fig. 1 Proposed System Architecture

First from finding dataset to compute RFM, to transform data and to find RFM score-based rankings. Applying PCA for dimension reduction to prepare data. Second, implementation of different clustering approach like K-means, Agglomerative and GMM with different methods like elbow method and silhouette score method & compare the different algorithms. Third, apply distinct distance matrices to k -means to get best cluster distribution.

1) Pseudocode (K-Means Algorithm with Selectable Distance Metrics):

Algorithm: K-Means with Distance Metric Choice

- Inputs:
  - Dataset D, comprising N customer data points
  - K: Desired number of clusters
  - distance_function: Chosen metric (Euclidean, Manhattan, or Cosine)
  - max_iterations: Upper limit for iterations
- Outputs:

- A set of K optimized cluster centroids
- Cluster allocation for each customer point

- Procedure:

Step 1 : Initialization Phase:
Randomly pick K data entries from D to serve as the starting centroids.
Step 2 : Clustering Loop:
Repeat until convergence or max_iterations is reached:
a. Assignment Step:
For every point in D:
- Compute its distance to each centroid using the Selected distance_function
- Assign it to the cluster with the closest centroid
b. Centroid Update Step:
For every cluster:
- Recalculate its centroid by averaging the data points assigned to it
c. Convergence Check:
If centroids have stabilized (i.e., minimal or no change):
- Terminate the loop
Step 3 : Final Output:
Return the final K cluster centers and the corresponding labels for all data points

2) Advantages of Proposed Approach over Conventional K-Means:

- *Flexibility:* Traditional K-Means only uses Euclidean Distance, which can be inaccurate for high-dimensional or sparse customer data. This algorithm allows choosing the most appropriate metric.
- *Improved Segmentation:* Different distance metrics capture different notions of similarity—offering better segmentation when customer behavior patterns are complex or directional (e.g., browsing habits).
- *Practical Utility:* Tailoring the metric improves clustering accuracy, especially in real-world marketing datasets where cluster shapes are irregular or non-convex.

IV. RESULTS AND DISCUSSION

This research focuses on improving customer profiling and segmentation in direct marketing through AI-driven clustering techniques. The approach follows a systematic methodology that includes RFM (Recency, Frequency, and Monetary) analysis, dimensionality reduction, and advanced clustering methods to create meaningful customer segments.

A. Dataset

Our research utilized the data sourced from the Marketing Campaign dataset1, which has some key demographic attributes, purchasing behavior attributes and campaign response attributes as shown in Table 3 (Table A, B and C) which contain numerical as well as categorical data values.
Dataset Source : Marketing Campaign dataset (available on Kaggle)

TABLE III
DATASET ATTRIBUTES

Table A [Demographic Attributes]		Table B [Purchasing Behaviour Attributes]		Table C [Marketing Campaign Attributes]	
Sr. No.	Attributes	Sr. No.	Attributes	Sr. No.	Attributes
1	ID	1	Dt_Customer	1	AcceptedCmp3
2	Year_Birth	2	Recency	2	AcceptedCmp4

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

3	Education	3	MntWines	3	AcceptedCmp5
4	Marital_Status	4	MntFruits	4	AcceptedCmp1
5	Income	5	MntMeatProducts	5	AcceptedCmp2
6	Kidhome	6	MntFishProducts	6	Complain
7	Teenhome	7	MntSweetProducts	7	Z_CostContact
		8	MntGoldProds	8	Z_Revenue
		9	NumDealsPurchases	9	Response
		10	NumWebPurchases		
		11	NumCatalogPurchases		
		12	NumStorePurchases		
		13	NumWebVisitsMonth		

RFM model used to calculate the value of recency, frequency and monetary based on rankings to create different segments according to their purchasing behavior.

To effectively segment customers, RFM analysis is performed. Recency, frequency, and monetary values are calculated for each customer, helping to determine engagement levels. After computing these values, data transformation techniques are applied to standardize the values, ensuring consistency across the dataset.

B. Preprocessing:

This study employs distinct algorithms to perform clustering of customers with the help of RFM analysis. Initially, this data is then preprocessed by handling missing values, normalizing numerical features, and encoding categorical variables. These preprocessing steps ensure data quality and consistency, making it suitable for analysis. After Prepocessing data is given for customer profiling approach so that the distribution of data is needed as shown in Fig. 2.

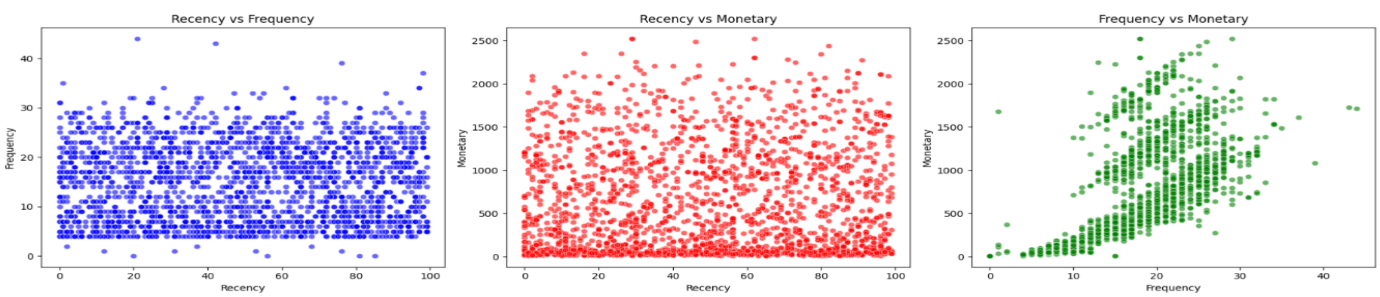


Fig. 2 Recency Vs. Frequency, Recency Vs. Monetary and Frequency Vs. Monetary

C. Feature Engineering and Dimensionality Reduction:

Once the RFM scores are generated as shown in Fig. 3. PCA (Principal Component Analysis) technique is used to reduce the dimensity of the dataset. This step eliminates redundant information while preserving the most relevant features, making clustering more efficient and effective.

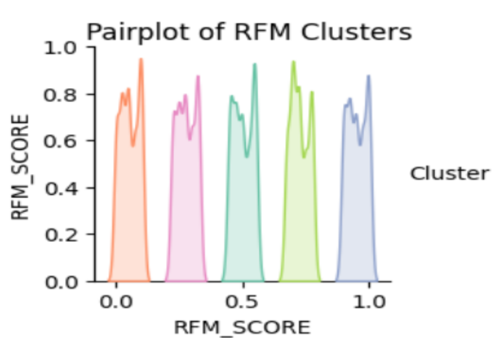


Fig. 3 Pairplot of RFM Clusters

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

D. Applying different algorithms & their Comparison and Evaluation:

The performance of different clustering methods is assessed using evaluation metrics such as silhouette scores, the elbow method, and measures of cluster cohesion is shown in Fig. 4. This comparison helps determine which algorithm provides the most accurate customer segmentation.

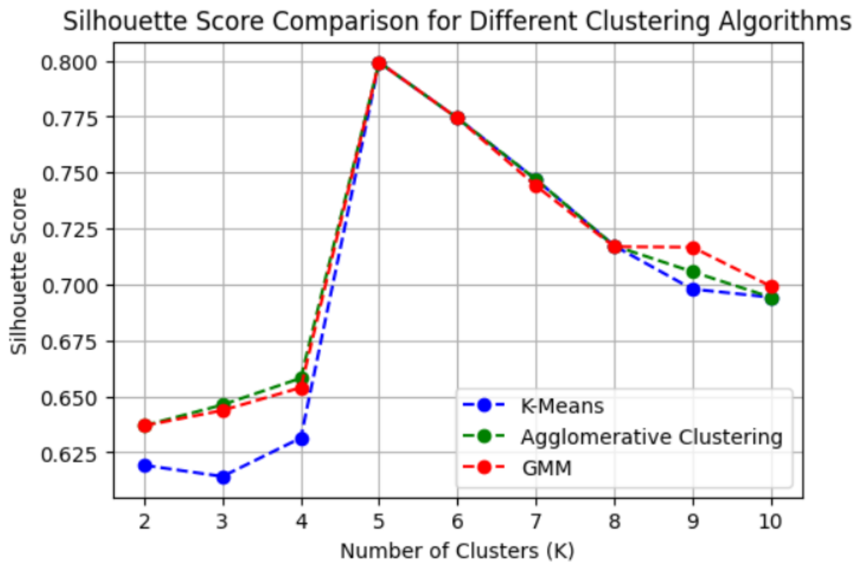


Fig. 4 Silhouette Score Comparison of K-means, Agglomerative and GMM Algorithms

E. K-Means with Elbow Method:

The optimal number of clusters is determined using the Elbow Method is demonstrated as below in Fig. 5.

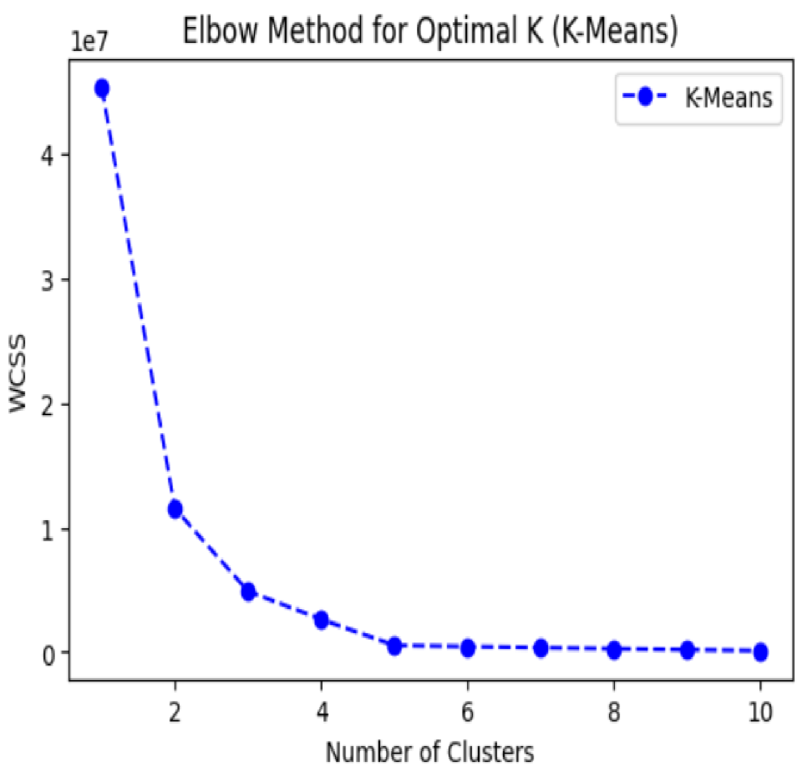


Fig. 5 Elbow method for Optimal K using K-means

F. K-means with Euclidean Distance, Manhattan Distance and Cosine Distance:

The result founded with above three different matrices is illustrated in below table named Table 4.

TABLE IV

RESULT OF DISTANCE MATRICES WITH K-MEANS

Distance Matrices	Euclidean Distance	Manhattan Distance	Cosine Distance
Value of K	5	5	2
Silhouette Score	0.80	0.80	0.93

Final silhouette score is also depicted in Fig. 6 for better visualization.

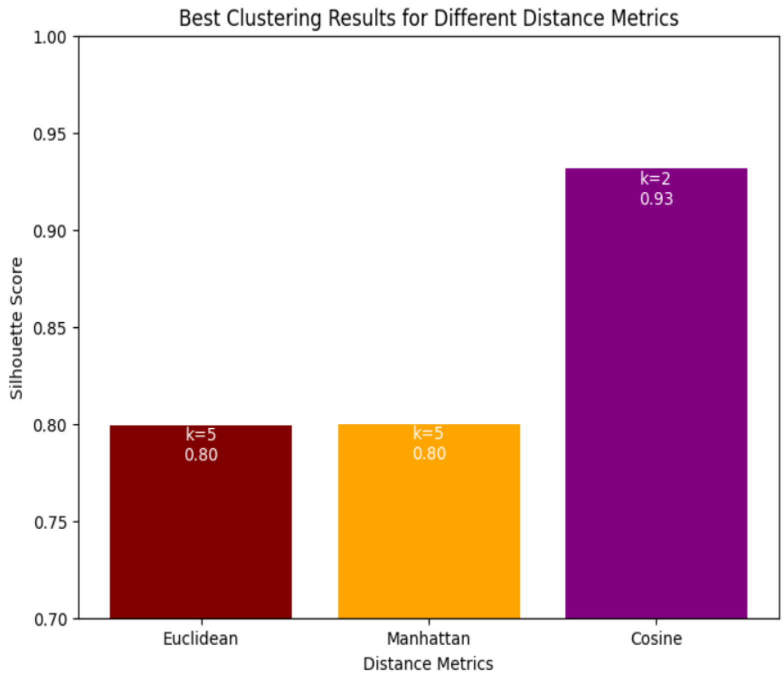


Fig. 6 Best Clustering Result with K-means

G. Visualization and Analysis for customer profiling approach:

To interpret the results, a detailed cluster distribution analysis is conducted as shown in Fig. 7. Visualization techniques such as t-SNE or UMAP are used to represent clusters graphically, providing insights into customer behavior. Additionally, the identified segments are analyzed to understand key trends and patterns, ensuring that the clustering results are meaningful and actionable.

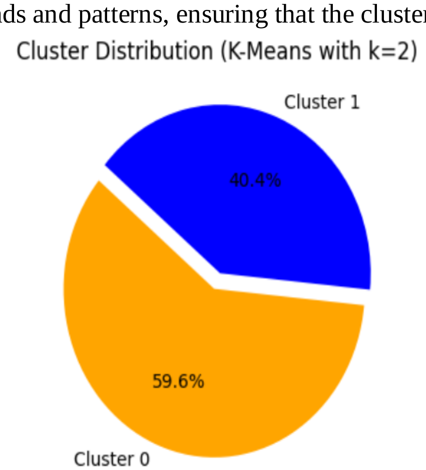


Fig. 7 Analysis of Cluster Distribution

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

H. Significance of the Research within Existing Studies:

This study enhances traditional customer segmentation methods by integrating RFM (Recency, Frequency, and Monetary) analysis with a comparative evaluation of multiple clustering algorithms. While RFM is a well-established model in direct marketing, our research advances its application by assessing and contrasting various clustering techniques—namely K-means, Agglomerative Clustering, and Gaussian Mixture Models (GMM)—across different distance measurement methods, including Euclidean, Manhattan, and Cosine distances.

Unlike many earlier works that typically rely on a single algorithm or a fixed metric, this study offers a broader and more detailed comparison, which provides deeper insight into the effectiveness of different approaches for customer profiling. This allows marketers and analysts to make more informed choices regarding segmentation strategies.

As demonstrated in Table 4 and Fig. 6, the K-means algorithm using Cosine Distance achieved the highest silhouette score of 0.93, indicating more distinct and cohesive clusters compared to the other methods. This highlights the potential of using Cosine Distance in achieving higher segmentation accuracy, thereby offering a practical improvement over traditional technique.

To support this comparison, Fig. 8 presents a visual representation using dot plot of silhouette scores across the tested clustering models and distance metrics. Table 5 shows the comparative analysis which strengthens our proposed method and underscores its value in enhancing the performance and precision of segmentation in direct marketing as well as retail marketing contexts.

TABLE V
EVALUATION OF CLUSTERING TECHNIQUES USING SILHOUETTE SCORES

Clustering Algorithms	K-means (Cosine)	K-means (Euclidean)	K-means (Manhattan)	Agglomerative	Gaussian Mixture Model (GMM)
Silhouette Score	0.93	0.80	0.80	0.79	0.79

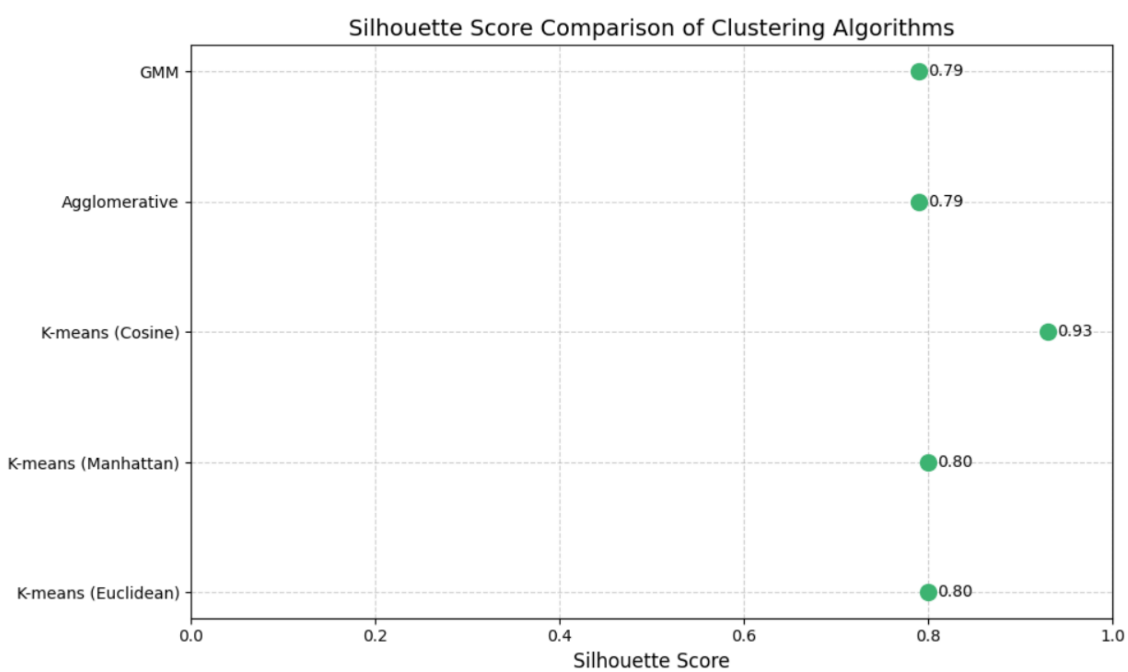


Fig. 8 Performance of Clustering Algorithms Based on Silhouette Score

V. CONCLUSIONS AND FUTURE WORK

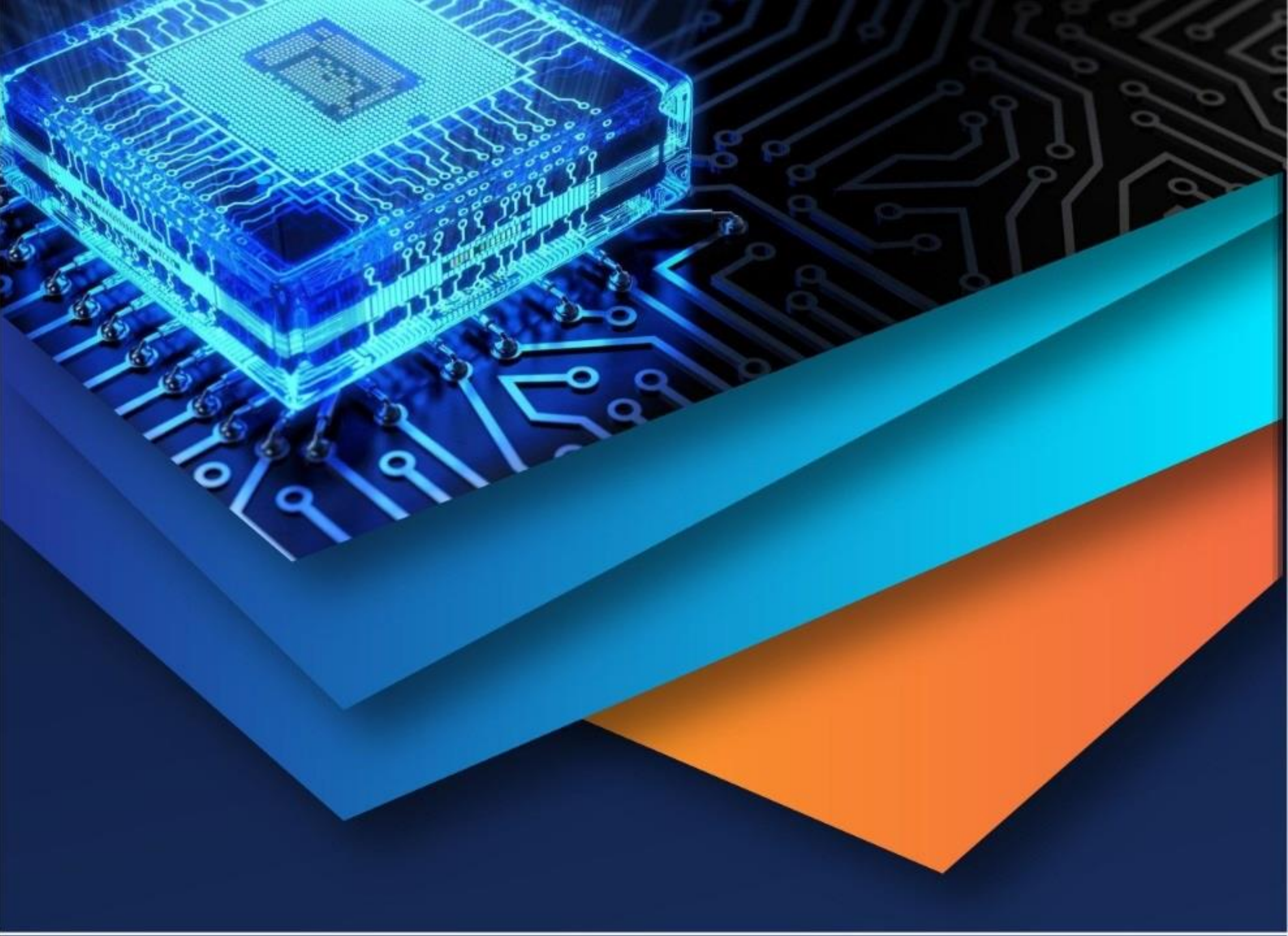
This research aims to develop an optimized clustering framework that improves the accuracy of customer segmentation in direct marketing. By applying AI-based techniques, businesses can gain deeper insights into customer behavior, allowing them to create targeted marketing strategies and enhance customer engagement. The findings will contribute to the field of AI-driven consumer analytics, offering a scalable and effective approach to personalized marketing.

In the future, better methods could be explored to predict which customers might leave, like using weighted random forests or combining different models that can work with unstructured data (like text or images). This would help in pulling out important features that can be useful for understanding and grouping customers in the retail space. As mentioned earlier in the research, these combined or hybrid models have already shown good results and could be a smart way to make predictions more accurate.

REFERENCES

[1] Kasem, Mahmoud SalahEldin, Mohamed Hamada, and Islam Taj-Eddin. "Customer profiling, segmentation, and sales prediction using AI in direct marketing." Neural Computing and Applications 36.9 (2024): 4995-5005.
[2] Pitka, Tomáš, et al. "Time analysis of online consumer behavior by decision trees, GUHA association rules, and formal concept analysis." Journal of Marketing Analytics (2024): 1-24.
[3] Rahul, Kumar, Rohitash Kumar Banyal, and Neeraj Arora. "A systematic review on big data applications and scope for industrial processing and healthcare sectors." Journal of Big Data 10.1 (2023): 133.
[4] Rane, Nitin. "Enhancing customer loyalty through Artificial Intelligence (AI), Internet of Things (IoT), and Big Data technologies: improving customer satisfaction, engagement, relationship, and experience." Internet of Things (IoT), and Big Data Technologies: Improving Customer Satisfaction, Engagement, Relationship, and Experience (October 13, 2023) (2023).
[5] Ebrahimi, Pejman, et al. "Social networks marketing and consumer purchase behavior: the combination of SEM and unsupervised machine learning approaches." Big Data and Cognitive Computing 6.2 (2022): 35.
[6] Aqif, Tanzeela, and Abdul Wahab. "RESHAPING THE FUTURE OF RETAIL MARKETING THROUGH" BIG DATA": A REVIEW FROM 2009 TO 2022." Management Research and Practice 14.3 (2022): 5-24.
[7] Li, Yifei. (2023). Big Data Analysis in Consumer Behavior: Evidence from Social Media and Mobile Payment. Advances in Economics, Management and Political Sciences. 64. 269-275. 10.54254/2754-1169/64/20231548.
[8] Moon, Nazmun Nessa, Iftakhar Mohammad Talha, and Imrus Salehin. "An advanced intelligence system in customer online shopping behavior and satisfaction analysis." Current Research in Behavioral Sciences 2 (2021): 100051.
[9] Chaudhary, Kiran, et al. "Machine learning-based mathematical modelling for prediction of social media consumer behavior using big data analytics." Journal of Big Data 8.1 (2021): 73.
[10] Reddy, Surendranadha Reddy Byrapu. "Predictive Analytics in Customer Relationship Management: Utilizing Big Data and AI to Drive Personalized Marketing Strategies." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 1-12.
[11] Gopinathan, S. "A Review on Concepts, Applications, Challenges and Future Scope in Big Data." (2018).
[12] Ducange, Pietro, Riccardo Pecori, and Paolo Mezzina. "A glimpse on big data analytics in the framework of marketing strategies." Soft Computing 22.1 (2018): 325-342.
[13] Arefin, Sydul, et al. "Retail Industry Analytics: Unraveling Consumer Behavior through RFM Segmentation and Machine Learning." 24th Annual IEEE International Conference on Electro Information Technology (eit2024). 2024.
[14] Alawadh, Monerah, and Ahmed Barnawi. "A Consumer Behavior Analysis Framework toward Improving Market Performance Indicators: Saudi's Retail Sector as a Case Study." Journal of Theoretical and Applied Electronic Commerce Research 19.1 (2024): 152-171.
[15] Akter, Shahriar, and Samuel Fosso Wamba. "Big data analytics in E-commerce: a systematic review and agenda for future research." Electronic Markets 26 (2016): 173-194.
[16] Collins, Alexis & Owen, John & Kolawole, Wayzman & Oluwaseyi, Joseph. (2024). Understanding Consumer Behavior in Retail with RFM Segmentation.
[17] Orogun, Adebola, and Bukola Onyekwelu. "Predicting consumer behaviour in digital market: a machine learning approach." (2019).
[18] See-To, Eric WK, and Eric WT Ngai. "Customer reviews for demand distribution and sales nowcasting: a big data approach." Annals of Operations Research 270 (2018): 415-431.
[19] Khasanah, Annisa Uswatun, and Muhammad Rafly Qowi Baihaqie. "Analysis of consumer characteristics on retail business with clustering analysis method and association rule for selling improvement strategy recommendations." OPSI 17.1 (2024): 249-257.
[20] Anitha, Palaksha, and Malini M. Patil. "RFM model for customer purchase behavior using K-Means algorithm." Journal of King Saud University-Computer and Information Sciences 34.5 (2022): 1785-1792.
[21] Williams, John. "Consumer Behavior Analysis in the Age of Big Data for Effective Marketing Strategies." International Journal of Strategic Marketing Practice 6.2 (2024): 36-46.
[22] Prasad, Aashish. Analysing online retail transactions using big data framework. Diss. Dissertation of National College of Ireland, 2019.
[23] Raphaeli, Orit, Anat Goldstein, and Lior Fink. "Analyzing online consumer behavior in mobile and PC devices: A novel web usage mining approach." Electronic commerce research and applications 26 (2017): 1-12.
[24] Memon, Nagma Athar. "Customer segmentation in Retail: An Experiment in Sweden." (2023).
[25] Šálková, Daniela, Aleš Hes, and Petr Kučera. "Sustainable Consumer Behavior: The Driving Force of Innovation in Retail." Sustainability 15.24 (2023): 16648.
[26] Perez-Vega, Rodrigo, et al. "Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework." Journal of Business Research 129 (2021): 902-910.
[27] Rosário, Albérico, and Ricardo Raimundo. "Consumer marketing strategy and E-commerce in the last decade: a literature review." Journal of theoretical and applied electronic commerce research 16.7 (2021): 3003-3024.
[28] Seyedan, Mahya, and Fereshteh Mafakheri. "Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities." Journal of Big Data 7.1 (2020): 53.

[29] Yoseph, Fahed, and Markku Heikkila. "Segmenting retail customers with an enhanced RFM and a hybrid regression/clustering method." 2018 International Conference on Machine Learning and Data Engineering (iCMLDE). IEEE, 2018.
[30] Chaudhuri, Neha, et al. "On the platform but will they buy? Predicting customers' purchase behavior using deep learning." Decision Support Systems 149 (2021): 113622.
[31] Liu, Hongping. ‘Big Data Precision Marketing and Consumer Behavior Analysis Based on Fuzzy Clustering and PCA Model’. 1 Jan. 2021 : 6529 – 6539.
[32] Jagdishbhai Sapara, Neetaben, and Dr. Hemant H. Patel. “Consumer Behavior Analysis through Advanced-Data Techniques: A Review for Utilities in Retail Marketing.” INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT, vol. 08, no. 10, Oct. 2024, pp. 1–5. Crossref, https://doi.org/10.55041/ijsrem37895.
[33] Han, J., Kamber, M., & Pei, J. (2011). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.



INDEX COPERNICUS

JISRA IF

TOGETHER WE REACH THE GOAL

10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY