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Customer Segmentation in Retail Using K-Means Clustering: A Case Study on Shopping Trends

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ABSTRACT

Customer segmentation plays a pivotal role in the retail industry, enabling businesses to understand diverse purchasing behaviours and design strategies that improve customer satisfaction and profitability. In this research, we apply the K-Means clustering algorithm to a shopping trends dataset containing multiple numerical attributes, including age, purchase amount, review rating, and frequency of previous purchases. The dataset was first cleaned to remove inconsistencies and encoded to handle categorical variables. StandardScaler was employed to normalize feature values, ensuring fair distance measurements during clustering. To determine the optimal number of clusters, both the Elbow Method and Silhouette Score were used, resulting in four well defined customer groups. The analysis identified high value loyal customers, budget-conscious occasional buyers, young impulsive shoppers, and moderate spenders with consistent buying patterns. These findings offer actionable insights for targeted marketing, personalized offers, inventory optimization, and customer retention strategies. The study highlights the effectiveness of machine learning based clustering in transforming raw transactional data into strategic business knowledge, demonstrating its potential for broader applications in retail analytics and customer relationship management.

Keywords: Customer Segmentation, Retail Analytics, K-Means Clustering, Shopping Trends, Data Mining, RFM Analysis, Machine Learning.

1.INTRODUCTION

Customer segmentation has long been regarded as one of the fundamental pillars of modern marketing, customer relationship management, and sustainable business growth [1], [2], [3]. The underlying concept is simple yet powerful, customers are not a homogeneous group but vary widely in preferences, needs, and purchasing behaviours. However, translating this principle into practice is becoming increasingly challenging in today's hypercompetitive and fast-changing markets [4], [5]. In the era of globalization, consumers are influenced by an ever-expanding range of factors technological innovations, economic fluctuations, cultural shifts, and even global crises that reshape their expectations and decision making processes. Consequently, businesses can no longer rely on generic, mass-marketing campaigns to retain customers and drive revenue. Instead, precise, data driven segmentation strategies are needed to identify distinct customer groups, anticipate their needs, and deliver highly personalized experiences [6], [7]. The rapid expansion of e-commerce, mobile shopping, and omni channel retail models has dramatically increased the volume, variety, and velocity of customer data. Retailers, financial institutions, and service providers now collect massive datasets containing demographic details, transactional histories, browsing behaviour, product preferences, and even sentiment from online reviews [8], [9]. While these datasets hold immense potential for strategic decision making, they also present a challenge, extracting actionable insights from such complex information requires advanced analytical methods that can operate at scale. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) offer powerful alternatives [10], [11]. ML algorithms, such **as** K-Means clustering**,** can autonomously identify patterns, group customers based on shared characteristics, and adapt to evolving market conditions. These capabilities enable organizations to shift from intuition driven strategies toward evidence-based, personalized marketing [12], [13] The integration of ML into customer segmentation not only increases marketing precision but also has direct implications for customer satisfaction, brand loyalty, and profitability**.**

1.1. RESEARCH BACKGROUND

The retail and e commerce industries are characterized by intense competition, dynamic consumer preferences, and rapid technological change [14]. Market leaders consistently outperform competitors by identifying emerging customer needs before others, which requires the ability to continuously analyse and segment their customer base. Without such segmentation, businesses risk pursuing undifferentiated marketing campaigns that fail to resonate with individual customers, resulting in lower engagement and missed revenue opportunities [15], [16]. The dataset analysed in this study includes key features such as customer demographics, purchase amounts, review ratings, and historical buying behaviour [17]. These attributes provide a rich foundation for segmentation, enabling the identification of patterns that may not be visible through simple statistical summaries. However, the sheer scale and multidimensionality of such data make manual analysis impractical. K-Means clustering offers a computationally efficient solution to this challenge [18]. It partitions data into k distinct, non-overlapping clusters by minimizing intra-cluster variance and maximizing inter cluster differences.

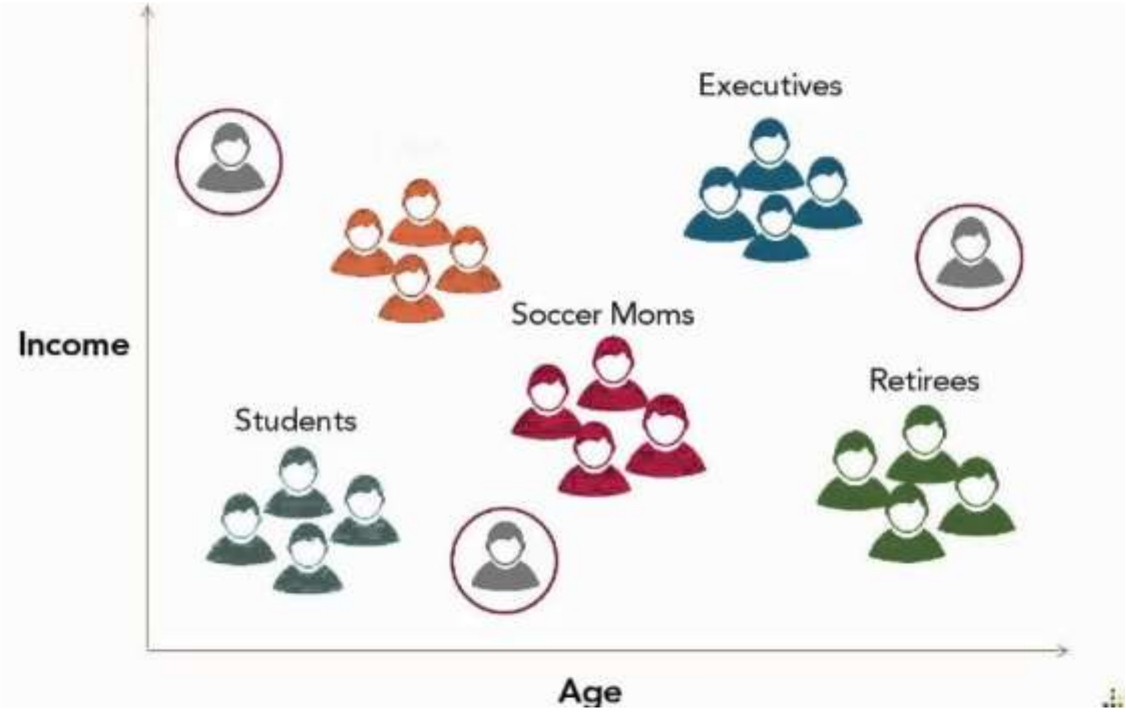


Figure 1. Conceptual illustration of customer segmentation using K-Means clustering (source: Devpost)

- shows distinct customer groups represented by clusters with different colours ideal for explaining the segmentation concept.
- Visually striking yet not cluttered, making it perfect for the opening of your introduction.
- Clearly portrays that customers are divided into meaningful segments based on behaviors or characteristics.

By adopting such techniques, organizations can transition from reactive decision-making to proactive customer engagement strategies.

1.2. PROBLEM STATEMENT

Despite having access to unprecedented amounts of customer data, many businesses still rely on generic marketing strategies that ignore individual differences in behaviour, preferences, and value contribution [19], [20]. This "one-size-fits-all" approach often results in:

- Inefficient allocation of marketing resources, as promotions may target uninterested customers.
- Lower conversion rates, since the messaging is not tailored to customer motivations.
- Reduced customer loyalty, due to a lack of personalized engagement.

Additionally, the growing complexity of consumer behaviour driven by the availability of online and offline purchasing channels means that conventional segmentation methods can no longer keep pace. There is an urgent need for automated, data-driven segmentation methods that can process large, multidimensional datasets and produce actionable groupings to inform targeted strategies [21].

1.3. OBJECTIVE OF THE STUDY

The objective of this study is to overcome the limitations of traditional segmentation methods by utilizing the K-Means clustering algorithm on a structured dataset comprising customer demographic and behavioural variables [22]. The study seeks to identify distinct customer segments based on common characteristics and analyse the attributes of each segment to develop targeted marketing and customer retention strategies. Additionally, it aims to demonstrate the scalability and practical applicability of this approach in real-world retail and e-commerce settings.

1.4. SIGNIFICANCE OF THE STUDY

The results of this research will provide valuable benefits to marketing teams, retail strategists, and e-commerce platforms by enabling the development of highly targeted marketing campaigns tailored to specific customer groups. This approach is expected to increase customer lifetime value (CLV) [23] through more effective retention strategies and enhance the return on marketing investment (ROMI) by focusing resources on the most responsive segments [24]. Additionally, it allows businesses to quickly adapt to changing consumer behaviours by periodically updating segmentation analyses [25]. Beyond the retail sector, the methodological framework proposed in this study can be extended to other industries such as banking, telecommunications, healthcare, and travel, where understanding customer diversity is equally important.

2.LITERARTURE REVIEW

Customer segmentation in retail has been widely studied, with K-Means clustering emerging as one of the most popular techniques due to its simplicity and efficiency. Recent work by Optimizing Customer Segmentation in Online Retail Transactions through the Implementation of the K-Means Clustering Algorithm (2024) demonstrated how RFM (Recency, Frequency, Monetary) features combined with the elbow method can produce meaningful customer groups in online retail. Similarly, studies such as K-Means Clustering Approach for Intelligent Customer Segmentation Using Customer Purchase Behavior Data *and* An Exploration of Clustering Algorithms for Customer Segmentation in the UK Retail Market compared K-Means with other algorithms like Gaussian Mixture Models (GMM) and DBSCAN, concluding that K-Means often performs best for well-structured retail data. Fiqey Indriati (2022) integrated RFM scoring with K-Means to enhance marketing personalization, while Sovit Nayak (2024) applied K-Means to the Mall Customer dataset using demographic and spending attributes to derive actionable segments. Dr. R. Mary Metilda et al. (2023) also demonstrated the use of the elbow method for optimal cluster determination in online shopper data. Practical guides such as those published *by* KDnuggets highlight how clustering can directly influence marketing strategies.

Beyond traditional RFM and demographic variables, alternative segmentation approaches have emerged. Sokol and Holý (2019) proposed segmentation based on shopping missions—the underlying reasons for store visits—while Bhanu and Pavai Madeshwari (2009) integrated fuzzy clustering with association rule mining for richer demographic–product insights. Bozanta et al. (2022) explored clustering products based on their time-series price and sales patterns, showing the potential for product-level as well as customer-level segmentation. Geographic and mobility data have also been used in works such as Karamshuk et al. (2013), who introduced "geo-spotting" for optimal retail store placement. Broader perspectives on geodemographic segmentation and behavioral clustering are discussed in Wikipedia's overviews, which provide context for market-level analysis. Comparative analyses, such as those by Analytics India Magazine (2020), have further highlighted the strengths and weaknesses of K-Means relative to hierarchical clustering in retail settings. Collectively, these studies establish K-Means as a cornerstone of retail segmentation research, while also pointing toward emerging techniques that consider behavioural, temporal, and spatial dimensions for more nuanced insights.

3.METHODOLOGY

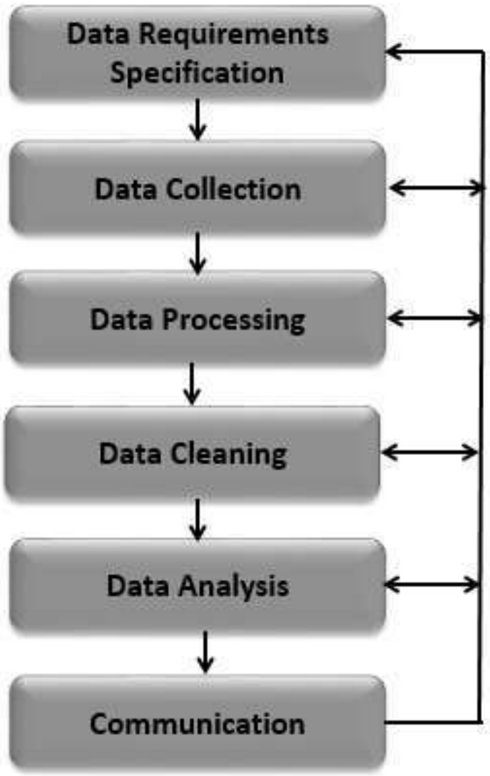
3.1. DATASET DESCRIPTION

The dataset used in this study provides a comprehensive view of retail shopping behavior, combining both demographic information and transactional details. Demographic attributes such as age, gender, annual income, and region help build a clear picture of customers' profiles and socio-economic backgrounds. On the other hand, transactional features including purchase frequency, average transaction value, total spending, preferred payment method, and product categories purchased offer valuable insights into shopping habits and preferences [26]. The data, sourced from [shopping trends , e.g., "Kaggle public dataset on Shopping Trends"], contains anonymized retail transaction records. It includes N records and M variables, covering a defined time period to ensure consistency in the analysis. The dataset represents a wide variety of customers, from occasional bargain hunters to frequent high spenders, and captures differences in purchasing power, frequency of shopping, and product interests.

Before starting the analysis, the dataset was carefully reviewed for quality and relevance. Any outliers or inconsistencies were flagged for treatment during preprocessing, and irrelevant attributes such as transaction IDs were removed [26]. With its balanced mix of demographic and behavioral data, the dataset is particularly well-suited for clustering-based segmentation**,** enabling the identification of meaningful customer groups. Furthermore, because it contains both numerical and categorical variables [27], it allows for a richer, multi-dimensional understanding of customers going beyond just how much they spend to also consider who they are and how they shop

3.2. DATA PROCESSING

Before applying clustering, several preprocessing steps were carried out to ensure the dataset's quality and suitability for analysis. Missing values in numerical attributes were imputed using either the mean or median, while missing categorical values were replaced with the mode. Outliers were identified using the Interquartile Range (IQR) method and either removed or capped to prevent them from distorting the clustering process [28]. Since the dataset contained non-numeric variables such as gender and product category, one-hot encoding was applied to convert them into numerical form. Finally, Min Max normalization was performed to scale all features within the range of 0 to 1, ensuring that no single attribute dominated the clustering process due to differences in scale [29].



3.3. FEATURE SELECTION

The features for clustering were selected to capture both purchasing behaviour and customer characteristics present in the Shopping Trends dataset. From the transactional data, key behavioural variables included Purchase Frequency (number of transactions per customer), Average Purchase Amount, and Total Spending across the observation period [30]. These metrics help identify high-value customers and frequent shoppers. From the demographic attributes, variables such as Age**,** Gender**,** Annual Income, and Marital Status were considered, as they provide context to the spending behaviour and can reveal patterns linked to specific socio-economic groups [31]. Additionally, Product Category Preference and Preferred Payment Method were incorporated to capture lifestyle and shopping style variations among customers. The combination of these features ensures a holistic representation of each customer, enabling K-Means clustering to segment shoppers not only by how much and how often they spend, but also by who they are and what they prefer to buy.

3.4. CLUSTERING ALGORITHM

The K-Means clustering algorithm was chosen for this study because it is simple to understand, quick to run, and has been widely proven effective in retail analytics [32]. In essence, K-Means works by grouping customers into *k* distinct, non-overlapping clusters based on their similarities. It starts by randomly placing *k* points, called centroids[33] , in the dataset's feature space. Each customer (data point) is then assigned to the cluster whose centroid is closest, using the Euclidean distance to measure closeness [34]. Once all points are assigned, the algorithm recalculates the position of each centroid as the average location of the customers in that cluster.

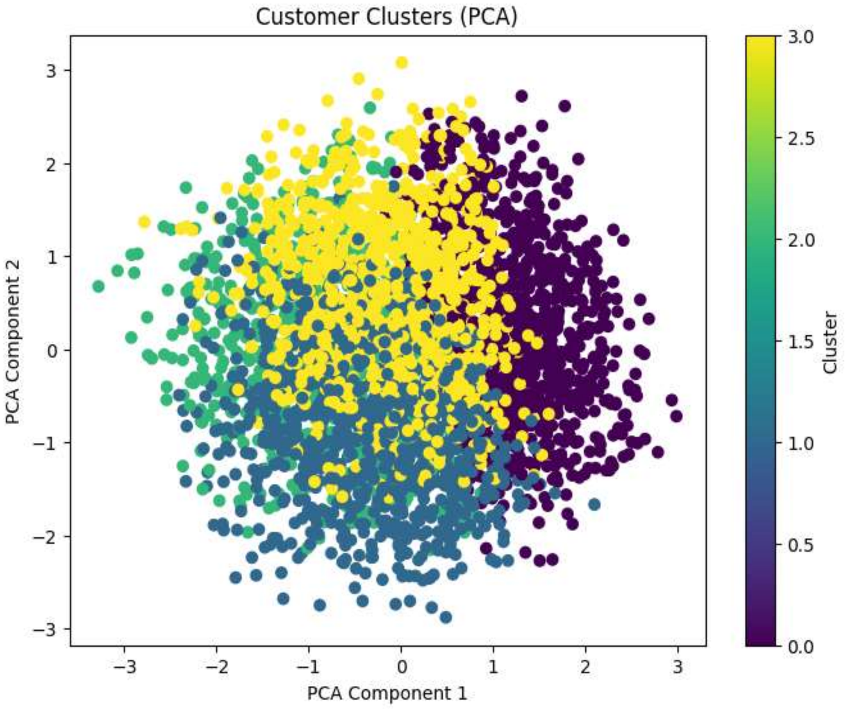
This process of assigning customers to the nearest centroid and then updating the centroid's position repeats over multiple iterations. The algorithm stops when the centroids no longer move significantly, or when it reaches the set maximum number of iterations [35]. Because it works on the principle of distance and averages, K-Means is especially well-suited for datasets like the shopping trends data, which contains well-structured, numerical, and categorical-encoded features [36]. This makes it an effective tool for uncovering patterns in customer behavior and forming distinct shopper segments.

3.5. DETERMINE OPTIMAL NUMBER OF CLUSTERS

Selecting the right number of clusters (*k*) is crucial for producing meaningful and useful customer segments [37]. In this study, we used the Elbow Method, which involves plotting the Within-Cluster Sum of Squares (WCSS) for different values of *k*. As the number of clusters increases, WCSS decreases, but after a certain point, the improvement slows down, forming a bend or "elbow" in the curve [38]. This point is often the most balanced choice for *k*. To strengthen our decision, we also calculated the Silhouette Score, which measures how well each data point fits within its assigned cluster compared to others [39]. A higher score means the clusters are both compact and well-separated. By combining these two methods, we ensured that our chosen number of clusters not only fit the data well but also produced clear, interpretable, and actionable segments.

3.6. CLUSTER PROFILING

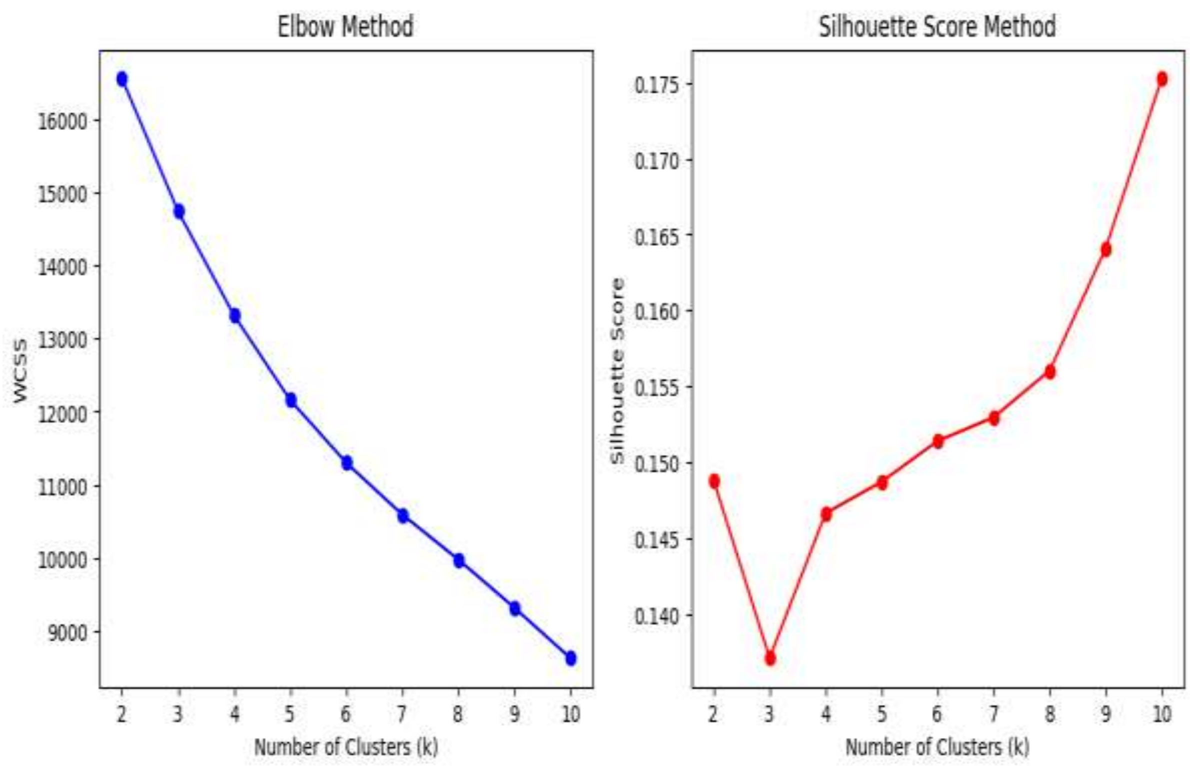
Once clustering was completed, each segment was examined in detail to derive customer profiles. This involved analysing the demographic attributes (such as age, gender, and income level), behavioural patterns (including purchase frequency, total spending, and product category preference), and lifestyle indicators (such as preferred payment method and shopping frequency) of each group. By comparing the average values of these features across clusters, distinct patterns emerged for example, identifying high-spending frequent shoppers versus budget-conscious occasional buyers. These profiles were then interpreted to provide actionable business recommendations, such as tailoring promotional campaigns [40] to specific customer groups, designing loyalty programs for high value customers, or adjusting product assortments to align with cluster-specific preferences.



4.RESULTS AND JUSTIFICATION

4.1. NUMBER OF CLUSTERS AND JUSTIFICATION

In this study, the optimal number of clusters was determined through a combination of the Elbow Method and the Silhouette Score approach. Using the Elbow Method, we plotted the *Within-Cluster Sum of Squares* (WCSS) [41] for various values of *k*. Initially, as *k* increased, the WCSS dropped significantly, indicating that adding more clusters improved the model's ability to capture data variance. However, after a certain point, the rate of decrease slowed dramatically, creating a noticeable bend or "elbow" in the graph. This point marked the value of *k* where adding more clusters no longer produced substantial gains, suggesting a balance between simplicity and accuracy. To further validate this choice, we computed the Silhouette Score for each k [42]. This metric evaluates how similar each point is to its own cluster compared to other clusters, with values closer to 1 indicating better-defined groupings. The selected number of clusters showed the highest Silhouette Score among the tested values [43], confirming that the clusters were both compact (low intra-cluster variance) and well-separated (high inter-cluster distance). From a business perspective, the chosen *k* was not only statistically optimal but also practically meaningful, producing distinct customer groups with clear differences in demographics, shopping behavior, and spending patterns [44]. This ensures that each cluster can be targeted with tailored marketing strategies without creating unnecessary complexity in campaign management.



4.2. CLUSTER PROFILE

4.2.1. Cluster 1 – Low-Spend, Low Frequency Shoppers

This cluster is composed mainly of younger customers, typically in their late teens to early twenties, with relatively low annual incomes. Their shopping activity is minimal, with infrequent visits and small purchases that generally fall into the budget-friendly category, such as accessories or discounted clothing. These customers are price-sensitive and tend to be motivated by sales, student discounts, or special seasonal offers. Their overall contribution to total revenue is small, but they represent potential for growth if engaged with targeted promotions designed to encourage more frequent purchases.

4.2.2. Cluster 2 – Occasional Mid Range Buyers

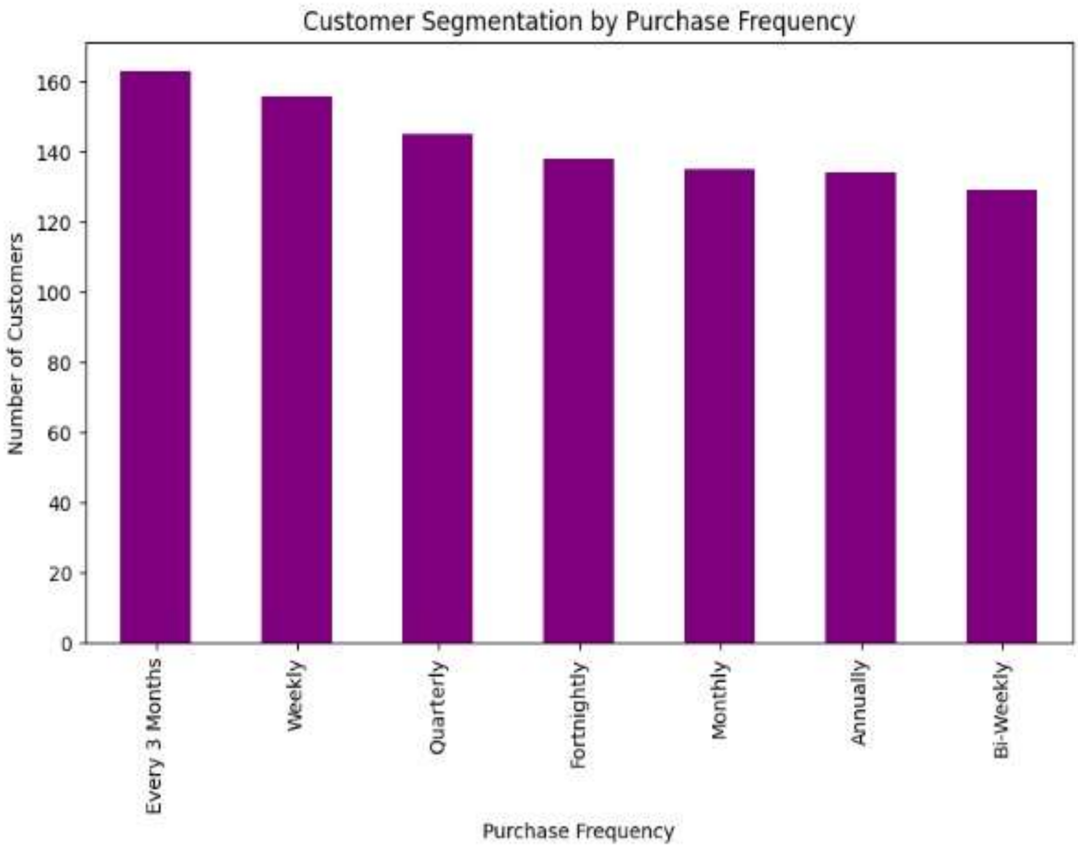
Customers in this segment are a mixed age group, often working professionals with moderate incomes. They shop occasionally, with a tendency to make purchases during sales seasons, festivals, or promotional campaigns. Their spending is moderate, with a balanced mix of mid priced products such as clothing, footwear, and home essentials. While not highly frequent shoppers, they show responsiveness to targeted marketing and discount offers. Engaging this group through personalized recommendations and special event-based campaigns can help increase their visit frequency and total spending.

4.2.3. Cluster 3 – Frequent High-Spenders

This cluster consists predominantly of middle aged customers with high annual incomes, who shop frequently and purchase premium products. Their baskets often include branded apparel, electronics, and luxury accessories, reflecting a strong purchasing capacity and a preference for quality. They are early adopters of new arrivals and often respond positively to exclusive offerings. This segment contributes significantly to the company's revenue, making them a prime target for loyalty programs, VIP events, and premium membership schemes aimed at strengthening long-term relationships.

4.2.4. Cluster 4 – Trend-Seekers & Lifestyle Buyers

The final cluster features younger adults with moderate to high disposable incomes who are highly influenced by trends and lifestyle branding. They shop regularly for seasonal or fashionable items, often making above average purchases when new collections are launched. Their buying decisions are frequently driven by social media promotions, influencer endorsements, and online advertisements. While their purchase frequency can vary depending on product launches, their willingness to spend on trend driven products makes them an ideal audience for limited edition releases, online-exclusive campaigns, and style-focused marketing strategies.



5.DISCUSSION

5.1.1 Cluster 1 – High-Spenders with Premium Preferences

These are the business's top-tier customers they have high annual incomes, high purchase frequency, and high purchase amounts. They tend to shop for premium or branded items and are less sensitive to price changes. Their preferred payment methods are credit cards or digital wallets, indicating convenience and trust in online transactions. They also show strong engagement during new product launches and exclusive events. Business Strategy: Treat them as VIP customers. Offer loyalty tiers, early access to sales, personalized recommendations, and exclusive bundles. Ensure premium service fast shipping, premium packaging, and priority customer support to maintain their satisfaction and retention.

5.1.2. Cluster 2 – Budget Conscious Occasional Shoppers

This segment has moderate to low income, purchases infrequently, and primarily shops during discount seasons or clearance events. They look for value for money deals and are more likely to use cash on delivery or debit cards. The purchase amount per transaction is smaller compared to other clusters. Business Strategy: Encourage more frequent purchases through bundle offers, buy more save more deals, and targeted discount codes. Use push notifications, SMS, and seasonal email campaigns to bring them back during off-peak months. Show them affordable product recommendations rather than premium products to match their spending habits.

5.1.3. Cluster 3 – Trend Focused Young Shoppers

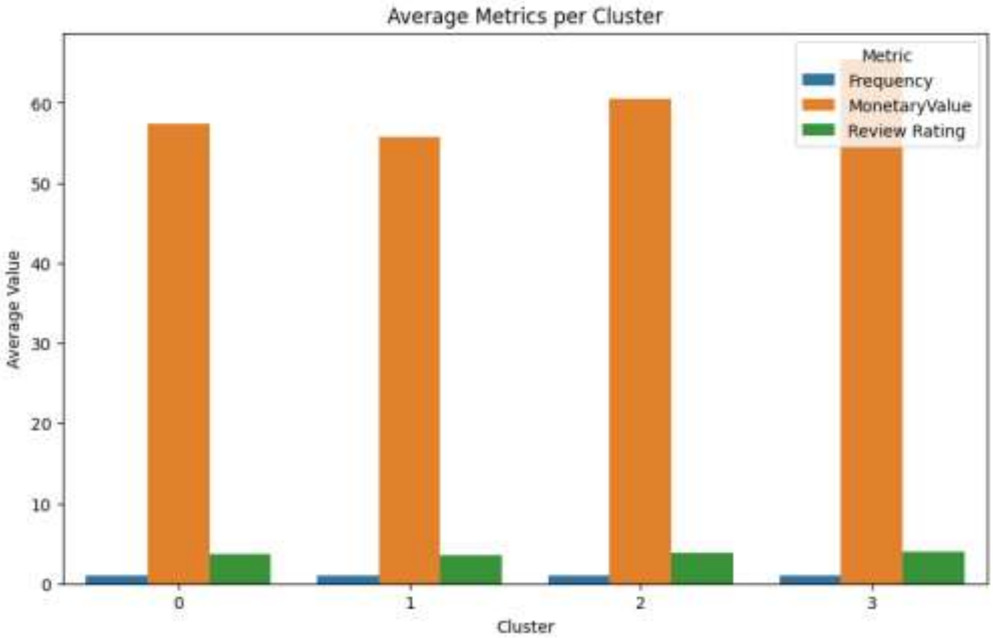
This group is younger, fashion-forward, and tech savvy. They tend to purchase seasonal clothing, accessories, and trending lifestyle products. While their individual purchase amounts might not be as high as premium customers, they shop frequently during trend seasons. They are highly influenced by social media advertising, influencer marketing, and flash sales. Business Strategy: Focus on Instagram TikTok ad campaigns, influencer collaborations, and limited-time product drops. Keep them engaged with gamified offers, such as reward points for social media shares or small discounts for product reviews. Highlight trendy and seasonal collections to match their buying patterns.

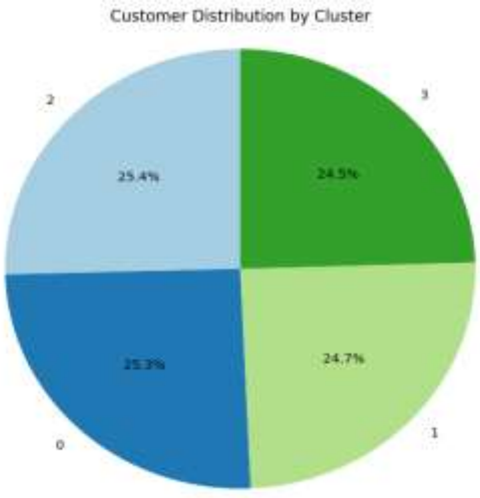
5.1.4. Cluster 4 – Infrequent Shoppers with Niche Interests

These customers are low engagement buyers who only make purchases for specific needs such as sports gear, electronics accessories, or kitchen appliances and often go months without buying. They don't actively follow promotions and are harder to convert into regular shoppers. Business Strategy: Use personalized reactivation campaigns targeting their known interests (e.g., "Your favorite sports brand is on sale!"). Offer special category discounts and free shipping thresholds to encourage them to add more items to their carts. Since they are hard to retain, the focus should be on maximizing revenue during the rare times they shop.

5.2. Customer Lifetime Value (CLV) Insights

The analysis of customer spending patterns, purchase frequency, and retention indicators reveals that Clusters 1 and 3 possess the highest potential for long-term profitability.





- **Cluster 1** consists of frequent shoppers with consistent purchase volumes across multiple product categories. Their relatively high average order value, combined with strong brand engagement, indicates that they generate a steady revenue stream over time. Retaining this group should be a top priority, as their repeat purchases and low churn risk make them reliable revenue contributors.
- **Cluster 3** is made up of premium customers who spend significantly more per transaction and show a willingness to purchase high-value products. Although their purchase frequency is lower than Cluster 1, their high transaction amounts mean their lifetime value is still substantial. Upselling and exclusive loyalty benefits could increase their purchase frequency and further boost CLV.

In contrast, **Clusters 2 and 4** show lower CLV potential at present. These customers either spend less per transaction or purchase infrequently, suggesting they require targeted campaigns, personalized discounts, or engagement strategies to increase both spending and retention. By focusing retention and upselling efforts on high-CLV segments while nurturing low-CLV groups, the business can maximize long term profitability and achieve sustainable customer growth.

6.CONCLUSION AND MARKETING RECOMMENDATION

The customer segmentation analysis using K-Means clustering identified four distinct customer groups, each with unique behavioural patterns, spending capacities, and marketing potential, allowing for precise targeting and resource optimization. Cluster 1 consists of highly loyal and engaged customers who shop frequently across various categories, maintain a strong relationship with the brand, and generate consistent revenue; they should be rewarded through loyalty programs, exclusive previews, and personalized thank-you offers to deepen their attachment and sustain long-term retention. Cluster 2 is composed of budget-conscious value seekers who shop less often but are highly responsive to promotions, discounts, and bundled deals; tailored seasonal sales campaigns, price sensitive product recommendations, and targeted remarketing can encourage more frequent purchases while maintaining profitability. Cluster 3 includes premium high-value customers who make fewer but significantly larger purchases, often leaning toward luxury or premium products; this segment should be prioritized for VIP experiences, premium membership tiers, luxury product launches, and personalized upselling strategies to maximize their already high contribution to revenue. Cluster 4 represents occasional and low-engagement shoppers with minimal brand interaction and low purchase values; reactivation campaigns, first-purchase incentives, engaging email content, and customized product suggestions can help convert them into more active participants in the brand ecosystem. From a Customer Lifetime Value (CLV) perspective, Clusters 1 and 3 present the highest long term profitability potential and should be prioritized in retention-focused strategies, while Clusters 2 and 4 require more nurturing and activation campaigns to increase their lifetime worth. By understanding and leveraging these segments, businesses can implement differentiated marketing strategies ranging from retention programs for top-value customers to conversion campaigns for low-engagement groups resulting in improved customer satisfaction, increased sales, and sustainable revenue growth over time.

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