“From Click to Closet: Minimizing Returns to Maximize Revenue and Customer Loyalty”

A Final term report for the BDM capstone Project

Submitted by

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1. Executive Summary:

The brand ZANAASH, located at G-92, Ramanuj, Shyam Nagar Marg, Jaipur, Rajasthan 302019, is a prominent clothing brand renowned for its high-quality craftsmanship and premium products. Despite its strong reputation, the organization faces challenges in maximizing revenue generation and maintaining customer satisfaction due to delays in delivery and underperforming product categories. Addressing these issues is critical to sustaining its market position and enhancing overall business performance.

The data was cleaned by handling missing values, converting appropriate columns to numeric types, and engineering relevant features like delivery time and recency. Exploratory Data Analysis (EDA) was conducted using descriptive statistics, group-based aggregations, and visualizations to uncover insights about customer behaviour and return rate. Key findings included a strong preference for Indian wear (14.35% of total sales) and peak sales in March, likely influenced by seasonal demand. The analysis also revealed a decline in cancellations from June to July.

Analysis began by EDA and slowly moves towards the RFM (Recency, Frequency, Monetary) segmentation was applied to assess customer loyalty, grouping users based on their transaction behaviour. Return rates were computed using the Cancel remark, Return Status column, aggregated by states to identify problematic return zones. Clustering techniques like K-Means were also applied on RFM scores to uncover hidden patterns in customer segmentation, Impact of discounts on the sales revenue analysis.

A strong positive correlation **0.6699** was found between order quantity and delivery time, suggesting operational delays are tightly linked to order volume. Return rates were **highest in specific states are Pondicherry, Himachal Pradesh and Chandigarh** highlighting either logistical issues or mismatched customer expectations. RFM segmentation and clustering clearly differentiated **high-value, medium-value, and low-value customers**, enabling more targeted marketing and retention strategies.

The results indicate that ZANAASH can enhance its business performance by refining its product offerings and improving delivery processes. Recommendations include focusing on high-demand categories like Indian wear while optimizing marketing efforts during low-demand periods and to drive consistent revenue growth. The observed decline in cancellations suggests that recent operational improvements are positively impacting customer satisfaction. By continuing to leverage data-driven insights, ZANAASH can further enhance customer engagement, streamline operations, and achieve sustainable revenue growth. ***Refer the below link for Dataset***

https://drive.google.com/file/d/1hoFeUTyrpX4eAcbZeOO2mYkQWKKAZT6-/view?usp=sharing

2. Detailed Explanation of Analysis Process/Method

2.1 Data cleaning and preprocessing

The Data cleaning and preprocessing are essential steps in data analysis, ensuring the dataset's accuracy, consistency, and readiness for meaningful insights. These included converting date fields like **Shipped Date, Delivered Date, and Invoice Date** to proper datetime formats, enabling smooth operations and effective handling of missing dates. Missing value treatment was another priority, where nulls in critical fields such as **AWB No, Invoice No, and Return Code, Order Tag, Return-status etc,** were replaced with defaults values like 'NA' or 'None' to get a complete and consistent dataset.

Additionally, text fields were standardized by removing empty spaces and formatting strings uniformly, making sure to get clarity and readability. Safe assignment practices were followed using advanced pandas methods to avoid issues such as chained assignments, making the code more robust and compatible with future updates. These efforts resolved inaccuracies, tackled missing data, and ensured uniformity, leaving the dataset analysis-ready. Clean data enhances usability in visualizations, statistical models, and machine learning, ensuring accurate results. Ultimately, this preparation supports better decision-making by providing trustworthy insights and reliable KPIs for businesses.

2.2 Comprehensive Explanation of the Analysis Process with Justification:

I have started by collecting raw data related to customer orders from the ZANAASH clothing e-commerce brand. Now using this for foundation of the next more enhanced advanced dataset. I have ensured to get consistency and accuracy data, I have used Excel with Power Query to merge monthly datasets into a unified database consolidating seven months of data into a single structured format. Python libraries and Colab notebook also used this step was crucial for obtaining the comprehensive analysis across various dimensions such as sales trends, customer preferences score would indicate the average customer loyalty of that particular phase with respect to that particular product, and operational performance.

2.2.1 Data Transformation and Feature Engineering

Data transformation and feature engineering was essential for making the dataset analysis-ready. Such as, **Delivery Time (DT)** was calculated as the difference between Delivered Date and Shipped Date, giving a measurable indicator of operational efficiency. Similarly, **Invoice Lag** was derived by subtracting Order Date from Invoice Date, offers insights into payment processing delays or billing timelines. The **Return Flag** was been created to identify whether an item was returned or not, using a binary format (1 for returned, 0 for not returned). This enables easier filtering and collecting during returns analysis. Additionally, extracting **Order Week/Month** from the Order Date allowed for trend analysis, facilitating seasonality and peak order behaviour examination observed. These features were very helpful to enhance the interpretability and utility of the dataset by enabling targeted analysis.

2.2.2 Exploratory Data Analysis (EDA)

To understand the key business aspects and improve decision-making, I conducted a comprehensive exploratory data analysis on the ZANAASH dataset. I began the analysis by the **Top 15 Cancel Remarks** using the value_counts() function on the Cancel Remark column, which helped me to highlight the most common reasons for order cancellations by customer. This insight is essential for addressing operational inefficiencies and enhancing customer satisfaction some of them were due to delayed orders and other reasons too.

$$top\_(15\_(cancel\_remarks\ )\ ) = df['\ CancelRemark'.value\_counts()\ .nlargest(15)$$

Next, I identified **Delayed Orders**, finding 660 out of 3069 instances of delayed deliveries. This metric was derived by comparing the expected delivery date with the actual delivery date, highlighting areas for improvement in the supply chain process.

2.2.3 Correlation Analysis

I computed the **Pearson Correlation (r)** between Order Quantity (Q) and Delivery Time (DT). The analysis indicated a strong positive correlation, suggesting that larger orders typically lead to longer delivery times a critical insight for inventory and logistics plan

$$r = \frac{\sum_{i=1}^{n}(Q_i - \bar{Q})(DT_i - \overline{DT})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \cdot \sqrt{\sum_{i=1}^{n}(DT_i - \overline{DT})^2}}$$

Where:

- Q_i = individual order quantity
- DT_i = individual delivery time
- $\bar{Q}$ = mean of order quantities
- $\overline{DT}$ = mean of delivery times
- n = total number of data points

2.2.4 Time Series Analysis

I evaluated order volume trends across monthly and weekly intervals, revealing seasonal fluctuations and peak demand periods. By grouping the order data by the day of the week, I observed that weekends consistently experienced higher order volumes, which is important for staffing and promotional strategies.

2.2.5 Returns Analysis

I calculated the **Return Rate** for each state using the formula

- $Return\ rate: (Total\ Returns\ /\ Total\ Orders) \times 100.$

This revealed that **Pondicherry (75%)**, **Himachal Pradesh (72.7%)**, and **Chandigarh (56.2%)** had the highest return rates, highlighting potential quality or customer service issues in those regions.

2.2.6 Customer Behaviour & Segmentation, I implemented **RFM (Recency, Frequency, Monetary) + K-Means Analysis** and used clustering techniques to group customers based on their shopping behaviour. The formulae used for calculating each component are:

- **Recency (R)** = Current Date − Last Purchase Date
- **Frequency (F)** = Total number of purchases per customer (Count of Transactions)
- **Monetary (M)** = ∑ (Unit Price × Quantity) (Total spending per customer)

The resulting clusters revealed distinct purchasing patterns such as customers in **Cluster 2**, who purchase more frequently and spend the most providing a data-driven foundation for targeted marketing. Cluster 0, who purchase frequently, recently, high spenders this comes under Loyal one. Cluster 1 for new customers, Cluster 3 at risk long ago, low frequency, and low spenders.

2.2.7 Revenue Analysis

I mainly focused on measuring Revenue by State and Category, as well as Revenue Distribution by Sales Mode. These metrics helped evaluate regional performance and channel effectiveness.

2.2.8 Price Elasticity of Demand by Month

Additionally, I visualized the Top 10 Elastic and Inelastic Demands by Category-Month using a lollipop chart, which offered insights into how product demand varies over time. Formula using

1. $PED = \frac{\%\ Chang\ \ in\ Price}{\%Change\ in\ Quantity\ Demanded}$
2. PED category by month $= \frac{\%\Delta P}{\%\ \Delta Q}$

   - If **PED > 1**, the product is **elastic** (demand changes a lot with price).
   - If **PED < 1**, it's **inelastic** (demand changes very little with price).

(Link to all advanced dataset and analysis: Colab Notebook)

https://colab.research.google.com/drive/1y0tarFxibiCkxCC0crYutkDPrT5TIGpk?usp=sharing

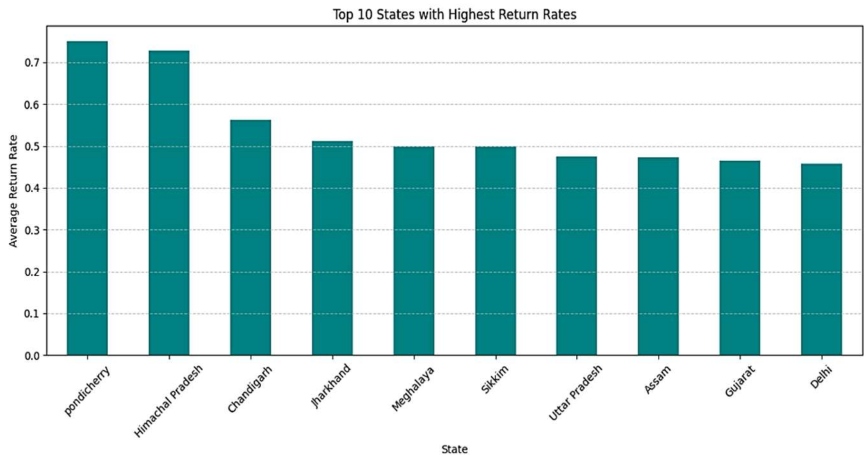
3. Results and Findings.

To address the rising concerns around delivery inefficiencies, customer churn, and revenue inconsistency, I have conducted an in-depth data analysis across multiple business dimensions. I conducted an in-depth data analysis across multiple business dimensions to gain the understanding of the operational challenges and customer experiences. The primary objective was to explore and interpret patterns in customers behaviour, including order frequency, spending habits, and return tendencies, to better segment and engage with various customer types. I focused on uncovering logistical bottlenecks by analysing delivery timelines, cancellation reasons, and geographic distribution of delayed or failed deliveries.

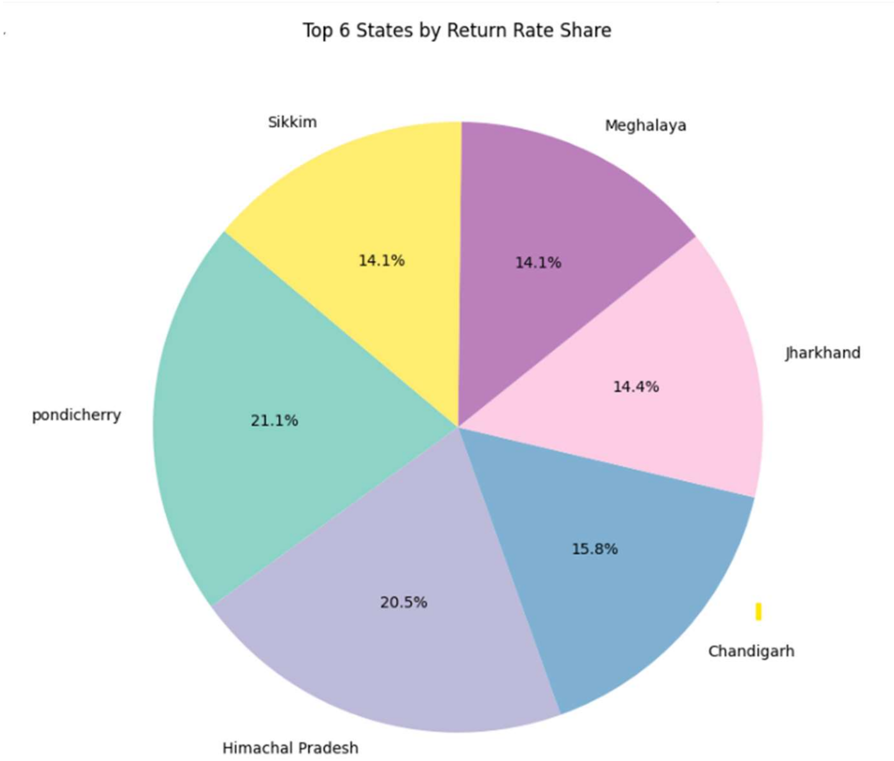
The key results are operational inefficiencies such as high cancellation and return rates driven by delivery delays and address issues. Through correlation and time series-analysis, I have observed significant relationships between order quantity and delivery time, as well as seasonal and weekly order trends. Customer segmentation using RFM and K-Means clustering has highlighted distinct buyer behaviours, enables targeted retention strategies. Moreover, tax and pricing analyses uncovered regional tax inefficiencies and demand sensitivities across categories, offering strategic direction for pricing and distribution. These findings provide a data-driven foundation to enhance logistics, customer experience, and revenue optimization.

3.1 Top 10 States with Highest Return Rates

The bar chart is used to represent the 15 top state values in the Cancel Remark column, provides a clear picture of the primary reasons about customers cancelled their orders.



Refer this below pie chart for proportion view



These states were correlate with these regions that also show **higher cancellation and return behaviour**, suggesting **geographically localized fulfilment inefficiencies** or misalignment between product offering and customer expectations in those regions.

Improving warehouse allocation, delivery partnerships, and inventory forecasting specific to high-risk areas can drastically reduce both cancellations and returns. For example, <u>Pondicherry and Himachal Pradesh</u> with return rates exceeding **70%** should be prioritized for operational review.

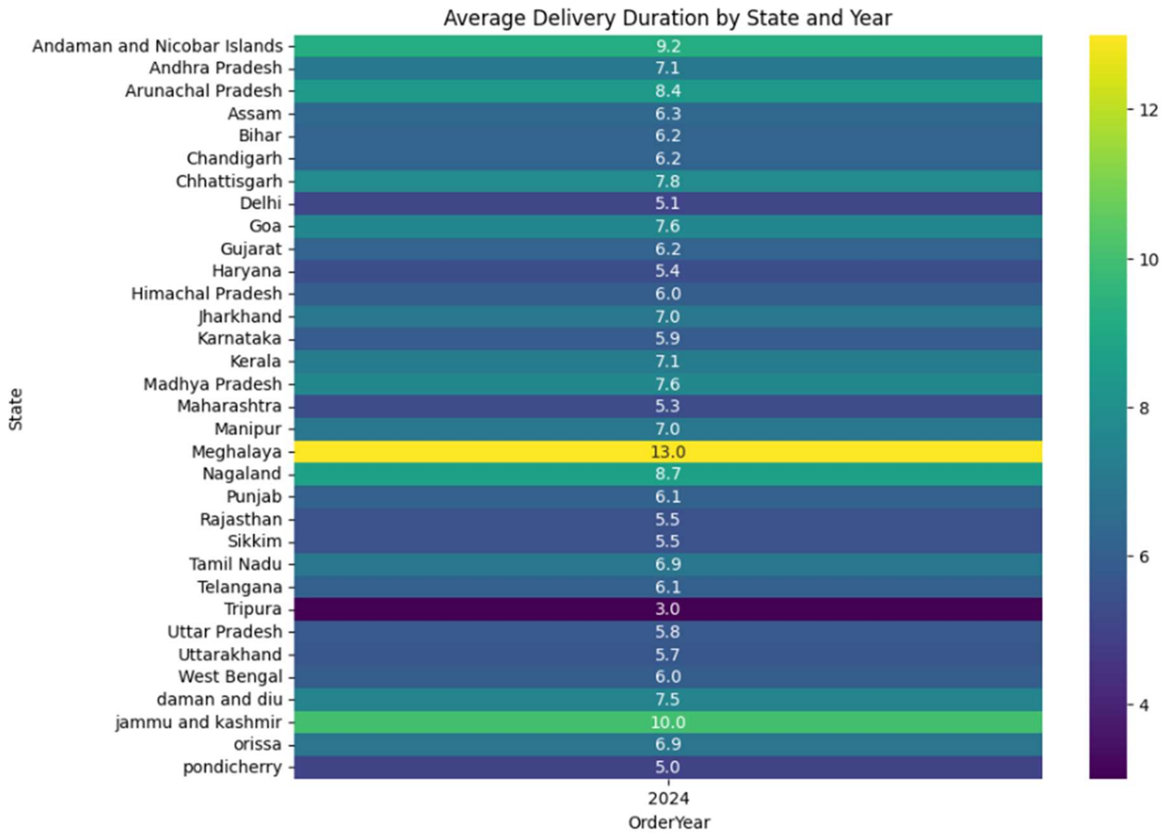
<u>3.2 Delivery Delays and Regional Impact</u>

I further analysed **average delivery days by state** to evaluate logistics performance across the regions. This metric helped me to understand the pinpoint operational delays that could be contributing to both customer dissatisfaction and order refusal.

States with higher average delivery days were often overlapped with regions reporting elevated return and cancellation rates indicates a strong correlation sign between **logistics inefficiencies and customer attritions**.

These extended delivery times suggest **logistical challenges such as remote locations, poor courier connectivity, or lack of nearby Distribution centers.**

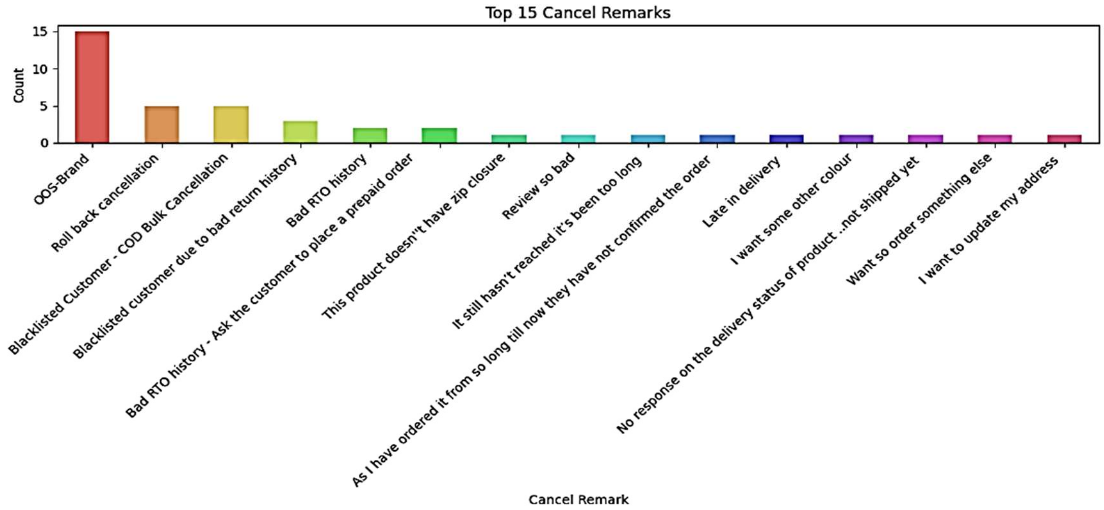
State	Avg. Delivery Days	Return Rate (%)	Key Cancel Remarks
Pondicherry	9.2	75.0%	Customer Refused, OOS
Himachal Pradesh	8.5	72.7%	Late Delivery, Refused
Jharkhand	8.1	51.3%	Address Issues
Assam	7.9	47.2%	Address Change, Delayed



Heatmap for Average Delivery duration by state

3.3 Customer Segmentation Analysis

Top 15 Cancel Remarks



The highest occurrence of “Customer Refused” may point towards unmet expectations or needs, lack of confirmation communication, or long delivery lead times ultimately affects the customer trust. These patterns highlights a need for proactive customer engagement, real-time shipment updates/tracking, and better product visualization.

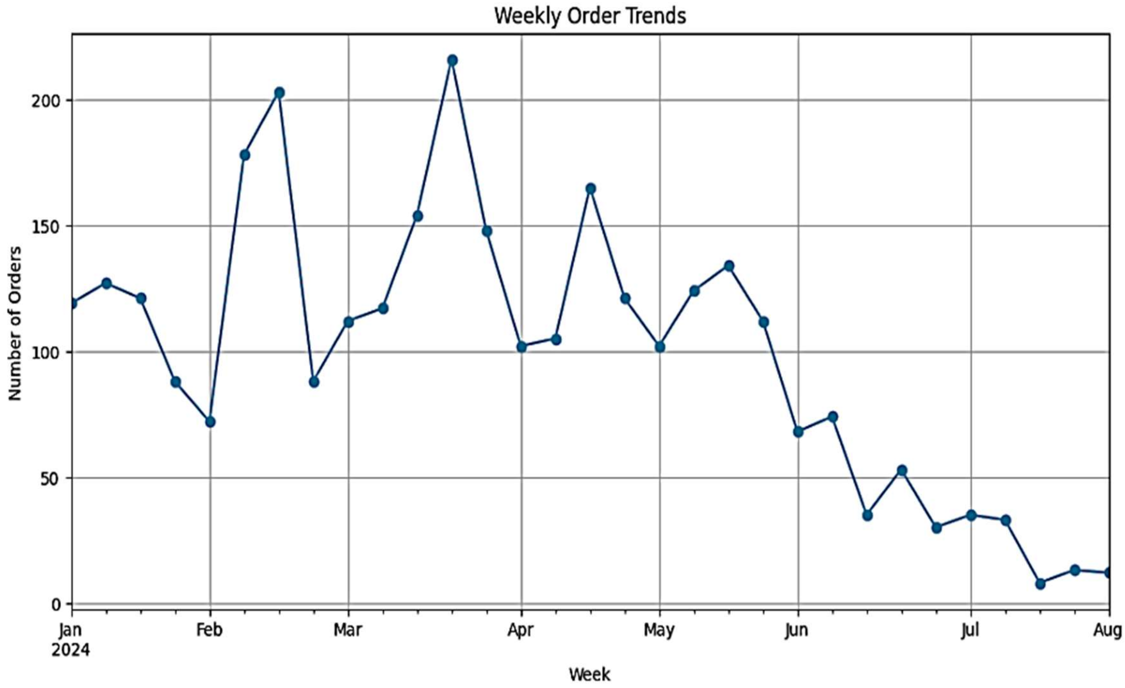
Address-related issues, such as "I want to update my address"/ generic “Address Issues,” underscore the importance of **improving address validation at checkout**. Incorporating auto-suggestions, pin-code verification, and follow-up mechanisms could reduce failed deliveries due to incorrect or incomplete information about the address.

More specific remarks like **“Late in delivery,” “Size not available,”** or **“Want to order something else”** suggest dissatisfaction stemming from poor stock visibility or delays in updating availability. These are areas where inventory management and frontend UX need closer alignment.

Moreover, **blacklisting-related cancellations** (“Blacklisted Customer - COD Bulk Cancellation”, “Bad RTO history”.) indicates the system is trying to prevent financial loss through internal frauds controls or repetitive bad behaviours. However, these may also point towards **poor customer profiling** or a need to review risk assessment models to avoid losing potential customers.

3.4 Time Series Analysis

A Monthly order Trends by weeks



Refer line chart for weekly order trends

High Initial month (Jan–Apr):

- The year starts with moderately strong order gain around **120–130 per week**.
- A **sharp drop** is been observed in early February, likely due to the external disruptions (e.g., stock unavailability, policy change, or delays).
- A **quick recovery** and **spike to 200+ orders/week** by mid to late February and again in March suggest that the **effective campaigns/ promotions**.
- **Peak in weekly orders** occur in **late March or early April**, reaching over **215 orders**, sign of a successful push possibly due to pre-summer collections and Indian wedding season.

Gradual Decline (May–June):

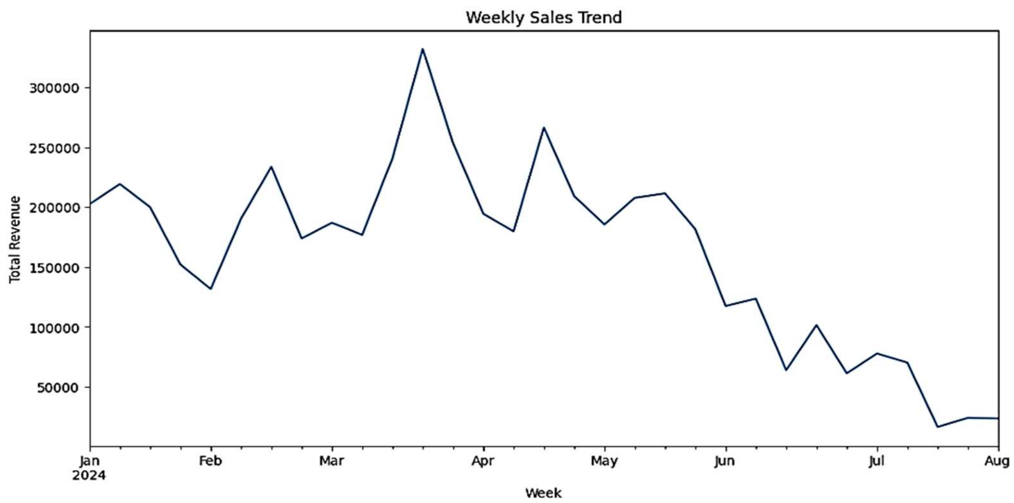
- The April spike, there is a **visible drop** in early May, followed by some of the recovery mid-month.
- June shows a **steep decline**, dropping to **below 100 orders/week**, possibly due to:
    - Off-season for product categories.
    - Reduced marketing activity.
    - Inventory or delivery challenges.

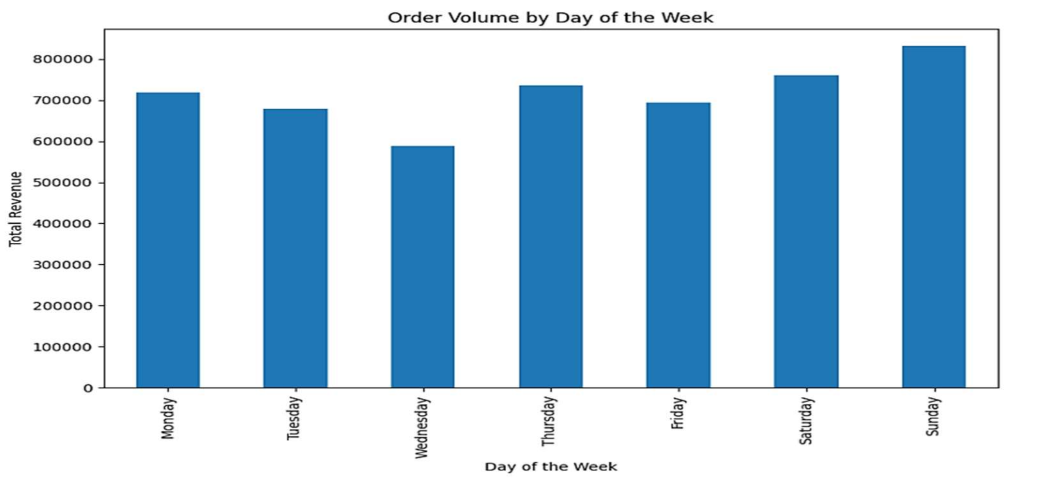
Low Demand (July–August):

- These trend hits its lowest in **July**, with weekly orders falling to **30–50** and continues this low into **August**.
- This might reflect:
    - Customer disengagement.
    - Seasonal slowdown.
    - lack of product new arrivals.

3.5 Weekly Sales Trends

Refer Line Chart for Weekly sales Trends and Bar chart for Order volume by days of the week



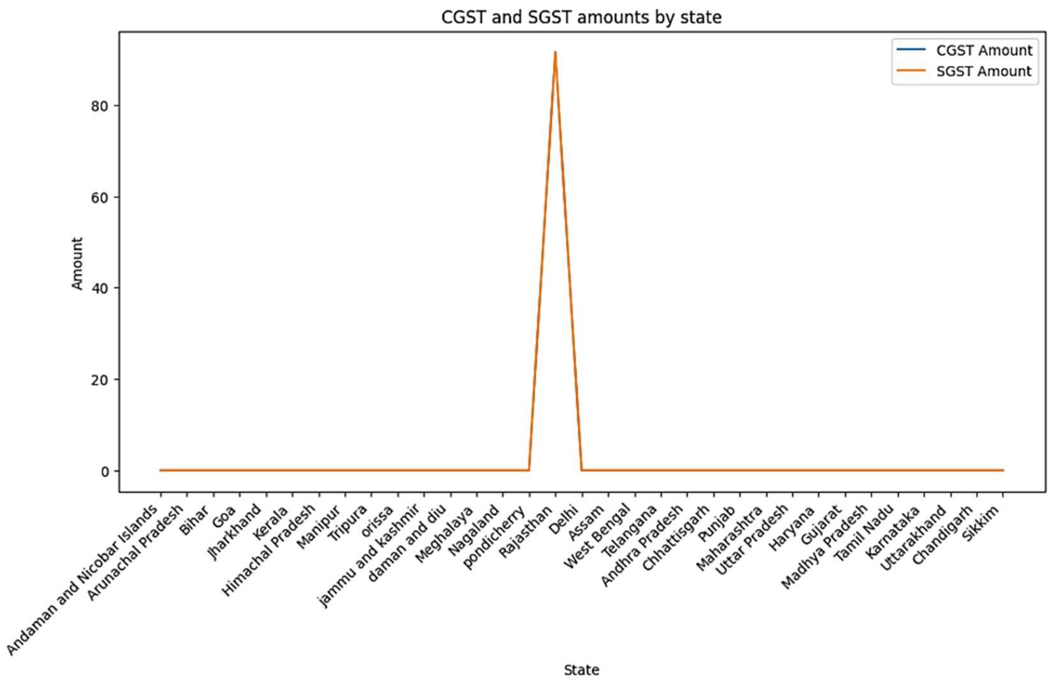


Weekends (Saturday and Sunday) experienced **the highest sales volume,** with **Sunday being the highest peak** with **Rs 8,31,275.00** and **Saturday with Rs 7,60,666.34** indicates stronger customer engagement and purchase increases when consumers use there more free time for shopping.

Mid-week, especially **Wednesday** with **Rs 5,88,027.50**, shows the **lowest engagement**, possibly due to midweek work schedules and fewer other busy activities occurrence.

Thursday's sales spike with Rs 7,35,507.90 suggests possible pre-weekend sales that triggers shopping behaviour of the customers.

3.6 Tax Impact Analysis by State



Refer above line chart for Tax impact CGST, SGST amount by state

Uniform Tax Percent but Zero CGST/SGST in Many States:

- The large number of states, including **Andaman & Nicobar**, **Arunachal Pradesh**, **Bihar**, **Goa**, **Jharkhand**, **Kerala**, **Tripura**, **Jammu & Kashmir**, and others report a **uniform Tax Percent of 12%**, but **zero CGST and SGST amounts**.
- This could be due to:

    - Classification of certain goods under tax-exempt or composite schemes.
    - Absence of intra-state transactions (which would otherwise incur CGST and SGST).
    - Incorrect or missing tax data entries during order processing.

Rajasthan Stands Out in Tax Collection:

- **Rajasthan**, where the brand ZANAASH business is headquartered, records a **Tax Percent of 12.05%** and **CGST/SGST amounts of ₹91.62 each**.
- This suggests:
    - Active intra-state commerce.
    - Proper recording of the state taxes.
    - Higher compliance or volume of orders within the state.

Variability in Tax Percent Across Other States:

- States like **Chandigarh** and **Sikkim** report higher Tax Percents (**12.75%**), indicates:
    - Possible local tax surcharges.
- On other hand, states like **Tamil Nadu (12.34%)**, **Maharashtra (12.17%)**, and **Uttar Pradesh (12.20%)** are only marginally above the baseline 12%, yet still report **zero CGST/SGST**, which may require a review of the logistics or tax collection processes in these regions.

<u>3.7 Customer Segmentation: RFM clustering Analysis</u>

To segment customers effectively, I have applied RFM Analysis combined with K-Means Clustering:

- RFM Metrics:
    - Recency: Days since the customer's last purchase.
    - Frequency: Number of orders placed by customers.
    - Monetary: Total amount spent by the customer on the product.
- Clustering Technique:
    - Used K-Means Clustering to group customers based on their RFM scores.

○ Elbow Method was used to determine the number of clusters (k = 4) by analysing the within Cluster Sum of Squares (WCSS).

- **Elbow Curve:**

○ Displays the point where adding more clusters yields diminishing returns.

○ Helped select k = 4 as the ideal number of clusters for effective segmentation.

Cluster 0 – One-time / Dormant:

○ High recency , low frequency and lower spend.
○ These are at-risk or one-time buyers.

Cluster 1 – Steady & Engaged:

○ Moderate frequency and monetary value, but relatively older recency.
○ They buy often but haven't done so recently.

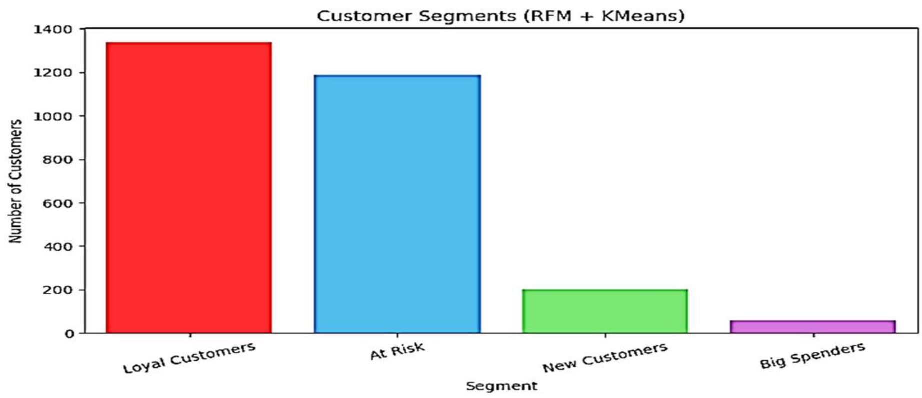
Cluster 2 – High-Value Loyalists:

○ Moderate recency, highest frequency, and highest monetary value.
○ These are most profitable and loyal customers.

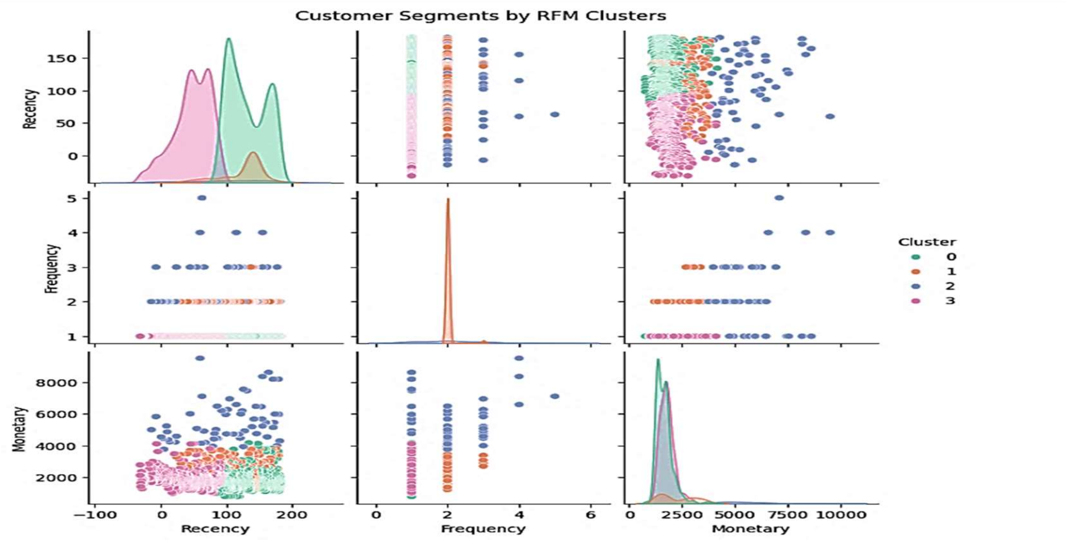
Cluster 3 – New customers:

○ Most recent buyers with low frequency, and moderate spend.
○ These are new or returning customers with high potentials.

Refer the above Bar Chart for Customer segment (RFM + K-Mean)



This Pair-plot visualizes the customer segments generated from RFM (Recency, Frequency, Monetary) clustering, with each point coloured by its assigned cluster (0 to 3).



Refer the above Pair-plot of RFM

Recency Distribution (Top-left plot)

- Cluster 3 (Pink) customers have low recency values, meaning they purchased recently they are the most recently active customers.
- Cluster 0 (Green) has the highest recency, indicates that the customers who haven't purchased since a long time likely dormant.
- Cluster 1 (Orange) and Cluster 2 (Blue) are in between but closer to Cluster 0 they are less recent but not entirely inactive.

Frequency vs Recency

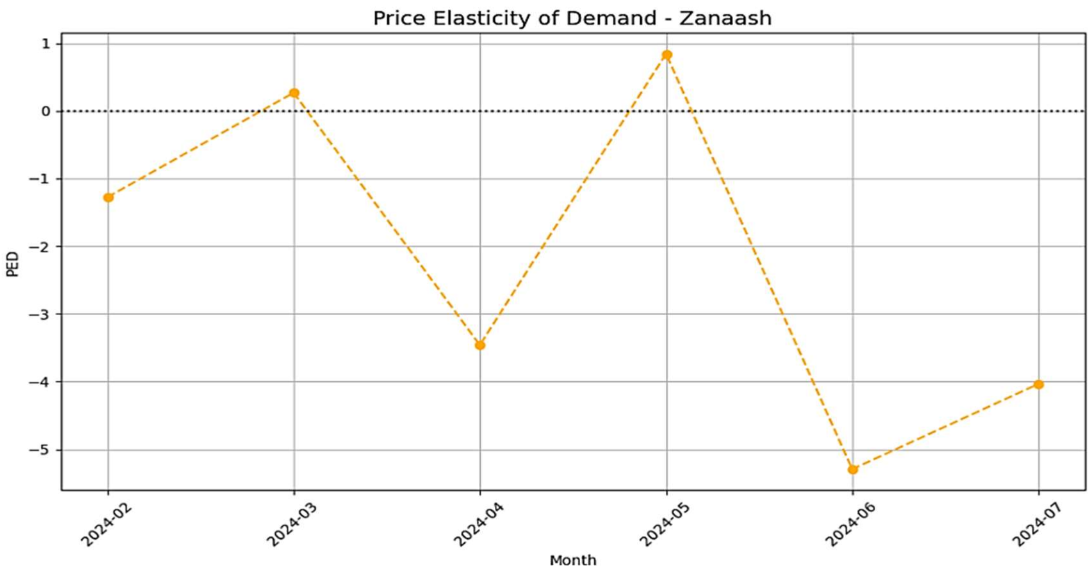
- Cluster 2 (Blue) shows moderate recency and high frequency, indicates loyal repeat customers.
- Cluster 3 (Pink) has low recency but low frequency, pointing towards new or one-time recent buyers.
- Cluster 1 (Orange) shows moderate frequency and moderate-to-high recency these are potential loyal customers who haven't bought recently but purchase frequently.
- Cluster 0 (Green) is largely low frequency and high recency these are likely churned or one-time customers.

Monetary Distribution

- Cluster 2 (Blue) has customers with high monetary value, reinforcing that they are your most valuable customers.
- Cluster 1 (Orange) is also relatively high but more spread these customers spend well but aren’t as loyal one.
- Cluster 3 (Pink) has moderate spend but recent activity an opportunity for nurturing and upselling.
- Cluster 0 (Green) has the lowest monetary value and least activity, indicates low-value and inactive customers.

3.8 Price Elasticity of Demand by Category-Month

Refer the below line chart for PED



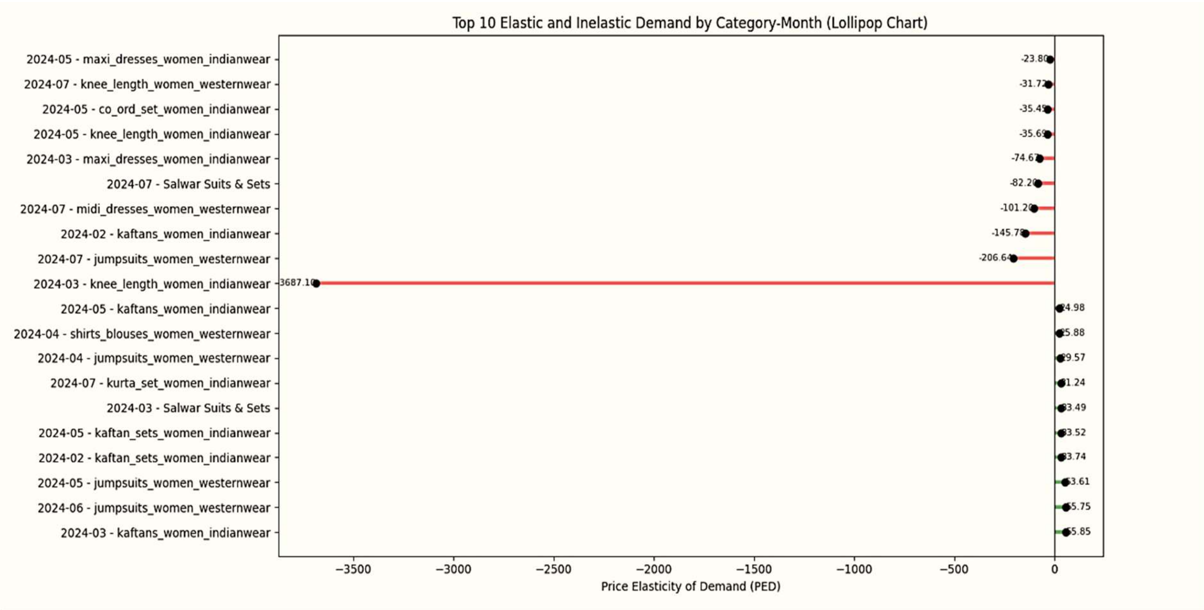
Before getting into the chart its crucial to understand for us about (Price Elasticity of demand) PED quantifies how much the quantity demanded of a product or item changes in response to a change in its price. It's calculated as:

$$PED = \frac{\%\,Chang\quad in\,Price}{\%Chang\quad in\,Quantity\,Demanded}$$

I have made this model on the elastic and inelastic demand of the product categories for women's wear in 2024, this reports now incorporates additional data specifically for the brand "ZANAASH" across several months in 2024. My objective remains to understand the price sensitivity of consumers for various clothing types and brands over time, providing a more comprehensive view of demand elasticity. The ZANAASH specific data is presented in a line chart, illustrating the Price Elasticity of Demand (PED) for the brand across different months. I have analysed a line chart displaying the PED for ZANAASH from January to July 2024. The Axes on x-axis represents the month, and on the y-axis represents the PED value. Data points are connected by a dashed orange line, with orange circles marking each monthly PED value. A horizontal dotted black line at PED = 0 serves as a visual reference point distinguishing between elastic (PED < -1) and inelastic (-1 < PED < 0) demand. I have observed the following trends in price elasticity for the brand across the analysed months:

- **February 2024:** PED -1.2 (Elastic demand, price-sensitive consumers).
- **March 2024:** PED 0.3 (Unusual positive inelasticity, requires investigation).
- **April 2024:** PED -3.5 (Highly elastic demand, strong price sensitivity).
- **May 2024:** PED 0.9 (Unusual positive inelasticity, requires investigation).
- **June 2024:** PED -5.3 (Highly elastic demand, strong price sensitivity).
- **July 2024:** PED -4.0 (Elastic demand, moderate price sensitivity).

Building upon my previous analysis, I have analysed the Price Elasticity of Demand (PED) for the top 10 most elastic and inelastic categories of women's wear, segmented by month for the year 2024. My objective was to understand the price sensitivity of consumers for various clothing types during different periods. The data is visually represented in a lollipop chart below, where the length of each lollipop stem corresponds to the magnitude of the PED value. The PED values on the x-axis and the specific category-month combinations on the y-axis. *Refer the below Lollipop Chart*



Highly Elastic Demand: I have identified several categories exhibiting highly elastic demand (|PED| >> 1), indicates the longer red stems extending towards the negative x-axis.

- For 2024-03 knee length women Indian-wear, I have recorded a PED of -387.11. This suggests that the demand for knee-length Indian wear in March 2024 is exceptionally sensitive to price changes. A small increase in price for this category during this month would likely result in a substantial decrease in sales volume.
- Similarly, 2024-07 midi dresses women western-wear (PED: -101.21), 2024-02 kaftans women Indian-wear (PED: -145.79), and 2024-07 jumpsuits women western-wear (PED: -206.68) also demonstrate very elastic demand. I infer that consumers are highly price-conscious when purchasing these items during their respective months.
- Moving down the list of elastic items, I have also noted that categories like 2024-05 maxi dresses women Indian-wear (-23.87), 2024-07 knee length women western wear (-31.77), and 2024-05 co-ord set women Indian-wear (-35.49) still show elastic demand, although the degree of price sensitivity is less extreme compared to the aforementioned categories.

Inelastic Demand: Conversely, I have observed categories with inelastic demand (|PED| < 1), where the quantity demanded changes proportionally less than a change in price. These are represented by shorter stems closer to the zero mark on the x-axis. Specifically:

- I have found that 2024-03 kaftans women Indian-wear has a PED of -5.05. This indicates that the demand for kaftans in March 2024 is relatively insensitive to price fluctuations.
- Other categories exhibiting inelastic demand include 2024-06 jumpsuits women western wear (-5.75), 2024-05 jumpsuits women (-6.61), and 2024-02 kaftan sets women Indian wear (-8.74). My analysis suggests that for these items during their respective months, price adjustments will likely have a smaller impact on the quantity sold.

In conclusion, my analysis of the top 10 elastic and inelastic demand categories for women's wear in 2024 has revealed significant variations in price sensitivity. The highly elastic demand observed for several categories underscores the importance of careful pricing and promotional strategies to maximize sales. Conversely, the inelastic demand for other categories provides more pricing flexibility. I do recommend that businesses leverage these insights to optimize their pricing, inventory management, and promotional efforts for each specific category and month to enhance overall profitability and market responsiveness.

4. Interpretation of Results and Recommendation

This section consolidates all findings from previous analyses, integration and social implications, provides data-backed recommendations for ZANAASH. The analysis highlights key areas for strategic improvement across pricing, operations, and customer engagement. Leveraging PED insights, demand trends, and fulfilments data enables targeted, data-driven decisions. These actions collectively drive efficiency, boost sales and revenue, and enhance customer satisfaction.

4.1 Cancellations & Returns: Address and Delivery Optimization

Address-related, product related errors and delivery delays emerged as top contributors to order cancellations and returns. These not only inflate operational costs but also damage customer trust. Implementing robust **address verification mechanisms**, **pre-dispatch checks**, and **stock visibility** will directly reduce fulfilment friction. Moreover, **localized investigation** in states with high return rates is necessary to uncover deeper regional issues be it logistical challenges, unmet expectations, or delivery partner performance.

4.2 Order Volume & Supply Chain Strategy

Larger orders, especially those peaking on weekends, are contributing towards delays, highlights the need for **supply chain and warehouse optimization**. Proactive scaling of resources particularly from **Thursday to Sunday** can ensure smoother handling of spikes and maintain delivery. Additionally, **staffing patterns** at delivery center and customer service hubs should mirror these order trends to ensure seamless fulfilment.

4.3 Time-Series & Seasonality: Campaign and Operational Planning

- **Demand Forecasting** based on historical patterns enables accurate **inventory planning**, **staff allocation**, and **order routing**.
- **Campaign Planning** should focus on **March and April**, which consistently show peak user engagement.
- **Post-April decline** sign is a lost opportunity injecting **mid-year promotions or flash sales** during **May–June** can help sustain sales momentum.
- **June–July dips** may reflect supply-side issues; auditing product availability and refreshing SKUs during these months could revive customer interest.
- In contrast, **low-demand weeks** should see **reduced operational load** to optimize costs.

4.4 Pricing Elasticity of Demand (PED): Dynamic Pricing & Product Strategy

Based on calculated PED values:

- **Elastic Categories (PED > 1)**: Seasonal or discretionary products such as women Indian-wear show strong sensitivity to price changes. For these:
  - Leverage **targeted discounts** to stimulate demand.
  - Implement **flexible inventory management** to cope with volume swings.
- **Inelastic Categories (PED < 1)**: Essentials categories exhibit consistent demand, regardless of price:
  - Strategic **price increases** can improve margins without volume loss.
  - Maintain stable inventory levels.
  - Promotional spending here may yield **diminishing returns** focus on product quality.

These insights support the development of a **category-specific dynamic pricing model** that can maximize revenue while reducing markdown dependency.

4.5 Customer Segmentation & Targeting

RFM clustering reveals clearly defined high-value customer segments. These cohorts exhibit high frequency, monetary value, or recent interactions. Marketing and CRM efforts should focus on:

- **Personalized outreach** via emails, notifications, or loyalty programs.
- **Win-back campaigns** for high-value lapsed customers.
- Tailored **product recommendations** based on patterns.

This segmentation framework provides the foundation for **hyper-targeted engagement** and improved **customer lifetime value (CLV)**.