Data-Driven Optimization of Inventory and Client Profitability for Medical Product Distribution

A Report for the BDM capstone Project

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CONTENTS

Executive Summary

Sarsen Surgical and Diagnostic, established in 2011, provides a wide range of surgical disposables, dressing materials, sterilization products, hospital equipment, transfusion management, and biomedical waste solutions. Led by Anand Durve, an entrepreneur with over 25 years of experience, the company operates as a contract manufacturer and distributor with setups across Maharashtra. The business is registered with government organizations such as Indian Central Railway and Mumbai Port Trust, supplying surgical products to hospitals nationwide.

This project focuses on addressing two key operational challenges: ineffective inventory management and unclear hospital-level profitability. The first problem involves solving the inconsistent restocking methods of medical products, which lead to overstocking or understocking, both of which hinder business efficiency, either in terms of profitability or customer satisfaction. The second issue concerns the lack of visibility into profit margins across hospital clients, making it difficult for the business to identify and prioritize high-value relationships.

To address the business problems mentioned above, I applied a data-driven approach using Excel and Python with the help of historical data provided from the month of January 2025 to June 2025. For inventory management, I used the Croston's Method to estimate future demand for the month of July 2025 and incorporated the modified version of buffer stock to account for late deliveries, emergencies and other unprepared events, this was done using ABC/XYZ analysis. For client profitability analysis, I calculated both total gross profits and profit margins, and then used an ABC Pareto classification on both metrics to segment clients into nine categories. This segmentation allowed me to identify high, moderate, and low-priority clients for the business.

The results of the analysis show that both product demand and client profitability are highly concentrated. In inventory management, categories AX, AY, and AZ accounted for most of the forecasted demand and expected profits, while the majority of other categories contributed little due to low volumes or unstable demand. In client profitability, a similar trend was observed: although low-profit clients such as CC made up the largest share numerically, nearly all profits and revenue came from a small group of clients in AA, AB, AC, BA, and BB categories.

Based on these findings, inventory recommendations focus on prioritizing high-demand categories (AX, AY, AZ), reducing investment in low-performing ones, and improving forecasting by incorporating procurement data. For clients, resources should be concentrated on profitable categories (AA, AB, AC), moderate contributors (BA, BB) should be developed further, and low-value clients (CA, CB, BC, CC) should be managed through revised pricing or reduced engagement to optimize returns.

Problem Statements

Inventory Management Analysis

The business faces inefficiencies in restocking due to a lack of structured demand forecasting. This results in overstocking or understocking of essential medical products, impacting working capital and readiness for urgent hospital demands. The business currently lacks a structured inventory tracking system and relies on gut instinct for restocking decisions. This results in inefficiencies, as demand patterns vary and stock decisions are not aligned with actual consumption trends. Additionally, unpredictable delays from manufacturers and sudden hospital demands exacerbate the risks of overstocking or understocking. Without data-driven forecasting or buffer planning, the business struggles to maintain product availability while managing working capital efficiently. These factors lead to missed opportunities, emergency shortages, or excess inventory, all of which directly impact the reliability and financial performance of the business.

Client Profitability Analysis

There is currently no system in place to evaluate the profitability of individual hospital clients. This makes it difficult for the business to identify which partnerships are financially sustainable. Although detailed sales data is regularly collected, it is currently used only for invoicing, with no analytical system in place to evaluate client-level profitability. This leaves the business unable to assess whether ongoing partnerships with hospitals are financially viable. Given that hospitals and manufacturers pre-determine prices, the supplier cannot adjust rates or sources. Therefore, it becomes crucial to analyse profit margins across clients to avoid continued sales at unsustainable rates or losses. A lack of this insight may result in misallocated resources and long-term financial strain on the business.

Metadata

- **File name:** Sarsen Surgical Data.xlsx
- **Tab Names (Sheet names):**
    - **New Sarsen Sale Jan – Jun 2025**: It contains the cleaned version of the provided dataset which is used for analysis.
    - **Inventory Management Analysis**: It contains the analysis of the first problem of “Inventory Management”.
    - **Client Profitability Analysis**: It contains the analysis of the second problem of “Client Profitability”.
    - **Result Sheet**: This sheet contains important data from both “Inventory Management Analysis” and “Client Profitability” including the derived result, important tables and graphs.

- **Column Names (New Sarsen Sale Jan – Jun 2025):**

Table 1: Metadata of the Dataset

Column Name	Data Type	Description
Name	String	This column consists of the Client names.
Material Given	String	This column consists of the Products sold.
Invoice Date	Date	This column shows the date at which the client bought the product.
Sell Rate (in INR)	Numeric	This column consists the selling rate (in INR.) of the product.
Quantity Sold	Numeric	This column consists the quantity of the product sold.
Cost Rate (in INR)	Numeric	This column consists of the cost rate (in INR.) of the product.
Revenue (in INR)	Numeric	This column shows the Revenue generated from each sale (Sell Rate * Quantity)
Month	String	This column was created to assign each sale into a month based on Invoice date. The month correspond to the numeric value of the month (1: January, 2: February, etc.).
Profit	Numeric	This column was inserted to calculate the gross profit generated from each sale ((Sell Rate – Cost Rate) * Quantity). The negative sale shows loss.

Descriptive Statistics

The descriptive statistics of the dataset were calculated using Python with the Pandas library. This step helped summarize the data by evaluating essential statistical measures, allowing for a better understanding of the dataset's overall structure, trends, and variability before moving forward with deeper analysis.

Table 2: Descriptive Statistics of the Dataset

	Sell Rate (In INR.)	Quantity sold	Cost Rate (In INR.)	Revenue (in INR.)	Profit (in INR.)
count	248.00	248	248.00	248.00	248.00
mean	1157.72	235	787.05	10391.80	2834.07
std	1715.43	487	1003.98	14010.75	4702.02
min	2.39	1	1.54	400.00	-300.00
25%tile	37.00	2	26.25	2776.25	580.50
50%tile	210.00	20	153.70	5140.00	1141.22
75%tile	2430.83	200	1850.63	10852.50	2898.00
max	15000.00	4000	4268.85	82250.00	35310.00

- **Count:** The dataset contains 248 transactions with recorded sell rate, quantity sold, cost rate, revenue, and profit for each entry.
- **Mean:** On average, products sell at ₹1,157.72 with 235 units sold, incurring a cost rate of ₹787.05, generating ₹10,391.80 in revenue and ₹2,834.07 in profit per transaction.
- **Standard Deviation:** The high standard deviations (e.g., sell rate ₹1,715.43 and profit ₹4,702.02) indicate substantial variability across transactions in pricing, sales volume, revenue, and profitability.
- **Minimum:** The smallest observed transaction involves a sell rate of ₹2.39, sale of 1 unit, a cost rate of ₹1.54, revenue of ₹400, and a loss of ₹300.
- **25th Percentile (Q1):** 25% of transactions have sell rates below ₹37, quantities below 2 units, cost rates under ₹26.25, revenue below ₹2,776.25, and profits below ₹580.50.
- **50th Percentile (Median):** A typical transaction sells at ₹210 with 20 units sold, a cost rate of ₹153.70, revenue of ₹5,140, and profit of ₹1,141.22.
- **75th Percentile (Q3):** 75% of transactions fall below a sell rate of ₹2,430.83, quantity of 200 units, cost rate of ₹1,850.63, revenue of ₹10,852.50, and profit of ₹2,898.
- **Maximum:** The largest transaction records a sell rate of ₹15,000, quantity of 4,000 units, cost rate of ₹4,268.85, revenue of ₹82,250, and profit of ₹35,310.

Data Preparation

- The data was taken from the Sales data of Sarsen Surgical records. The data was already stored in Excel sheet with the columns "Name", "Material Given", "Invoice Date", "Sell Rate (in INR)", "Quantity sold" and "Cost Rate (in INR)" already present. For the analysis, only the data from January to June 2025 was taken.
- The raw dataset was first examined for duplicate entries using Excel's built-in duplicate detection feature; no duplicate records were found.

- Several cells in the “Name” column were missing because clients purchasing multiple products on the same day were recorded only once. These missing values were manually filled with the appropriate client names. Rows with missing entries in either “Sell Rate (in INR)” and “Cost Rate (in INR)” were deleted to ensure data completeness.
- A new column, *Revenue*, was created using the formula:

$$Revenue = Sell\ Rate\ (in\ INR) \times Quantity\ sold$$

  This provided the total revenue generated by each sale.

- A “Month” column was added by assigning each row a numeric index (1–6) based on the “Invoice Date”. This transformation allowed aggregation and time-series analysis on a monthly basis.
- A “Profit” column was created to calculate the profit from each transaction, using the formula:

$$Gross\ Profit = (Sell\ Rate - Cost\ Rate) \times Quantity$$

  The profit used in this study represents gross profit. Fixed costs, such as logistics and administrative expenses, were not included due to data unavailability.

Detailed Analysis Process

Problem 1: Inventory Management Analysis

The objective of this analysis was to optimize inventory for July 2025 using historical data from January to June 2025. Recommended stock was determined by the formula:

$$Recommended\ Inventory = Forecasted\ Demand + Buffer\ Stock$$

This method accounts for unpredictable demand fluctuations, with buffer stock providing a safety margin against stockouts.

Forecasted Demand Calculation:

For forecasting demand, Croston’s Method[1] was employed using Python. This technique was chosen for its effectiveness with intermittent data, where frequent zero-value periods are interspersed with irregular demand. The procedure consisted of the following steps:

1) The first cell set up the environment by importing Pandas and NumPy for data handling, and scikit-learn for error calculation. The CSV file, “Croston’s Method.csv”, was then loaded into a Pandas DataFrame. The file had “Material Given” as columns and “Month” as rows.

[1] The implementation of Croston’s Method was based on the explanation provided in https://www.pmorgan.com.au/tutorials/crostons-method/

2) The second cell aimed to identify the optimal smoothing constant, α, using historical data, which determines how quickly forecasts adapt to changes in demand. Simple Exponential Smoothing (SES) was applied to the non-zero demand series, testing multiple α values between 0 and 1 with the increment of 0.1. The α that minimized Mean Absolute Error (MAE) was chosen. Formula for SES and MAE are as follows, respectively:

$$F_t = \alpha \times D_t + (1 - \alpha) \times F_{t-1}$$

Here,
F_t = forecast for the current period
D_t = actual demand in the current period
F_{t-1} = forecast of the previous period
α = smoothing constant (0 < α < 1)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |A_i - F_i|$$

Here,
A_i = actual demand
F_i = forecasted demand
n = number of observations

3) The third cell applied Croston's Method, designed for intermittent demand with frequent zero values. Demand was split into two sequences: non-zero demand sizes and the intervals between them. Both were smoothed using the optimal α, and the forecast was calculated as:

$$Forecasted\ Demand = \frac{z_t}{p_t}$$

Here,
z_t = smoothed estimate of non-zero demand size calculated using SES method
p_t = smoothed estimate of demand interval calculated using SES method

4) The fourth cell automated the entire forecasting process across all products. For each product, demand data was extracted, the optimal α was identified using SES and MAE, and Croston's Method was applied. The results were stored to generate product-wise demand forecasts efficiently. This step ensured consistency and scalability in producing inventory recommendations.
5) The fifth cell presents the forecasted demand table derived using the Croston Method, ordered ascendingly by the recommended stock levels.

Buffer Stock Calculation:

The buffer stock formula [2] used for the analysis is as follows:

$$Buffer\ Stock = k * Mean\ Absolute\ Deviation * \sqrt{LT}$$

[2] The reference taken for the formula $Buffer\ Stock = k \times M.A.D. \times \sqrt{LT}$ is taken from https://inciflo.com/blogs/safety-stock-and-importance/

Here,

- k = Service factor
- Mean Absolute Deviation, calculated as:
  - $M.A.D. = \frac{\sum |x_i - \bar{x}|}{n}$
    - x_i = the quantity of products sold per month
    - $\bar{x}$ = the average sales per product
    - n = the total number of months
- LT = Lead time

I used Excel to calculate the Buffer Stock. To determine the service factor (k), I applied an ABC/XYZ analysis, which integrates both revenue contribution (ABC analysis) and demand variability (XYZ analysis).

For the ABC analysis, I computed each product's revenue, and subsequently classified them into ABC categories according to the Pareto principle (see Table 1).

Table 3: ABC criterion of products based on item contribution

Category	**Criteria**
A	Revenue contribution ≤ 70%
B	70% < Revenue contribution ≤ 90%
C	90% < Revenue contribution ≤ 100%

For the XYZ analysis, I calculated the Coefficient of Variation (CV) using the formula:

$$Coefficient\ of\ Variation = \frac{Mean\ Absolute\ Deviation}{Mean}$$

After computing the CV for each product, I classified them into XYZ categories based on classification below (See Table 2):

Table 4: XYZ criterion of products based on demand variability

Category	**Range of Coefficient of Variation**
X	≤ 0.5
Y	0.5 < C.V. ≤ 1
Z	1 < C.V.

After categorizing each product into ABC/XYZ categories, I used the combination of VLOOKUP() and CONCAT() functions of Excel to concatenate the two grades. I calculated the service factor (k) using the service level assigned to each category (See Figure 1 and Table 3)

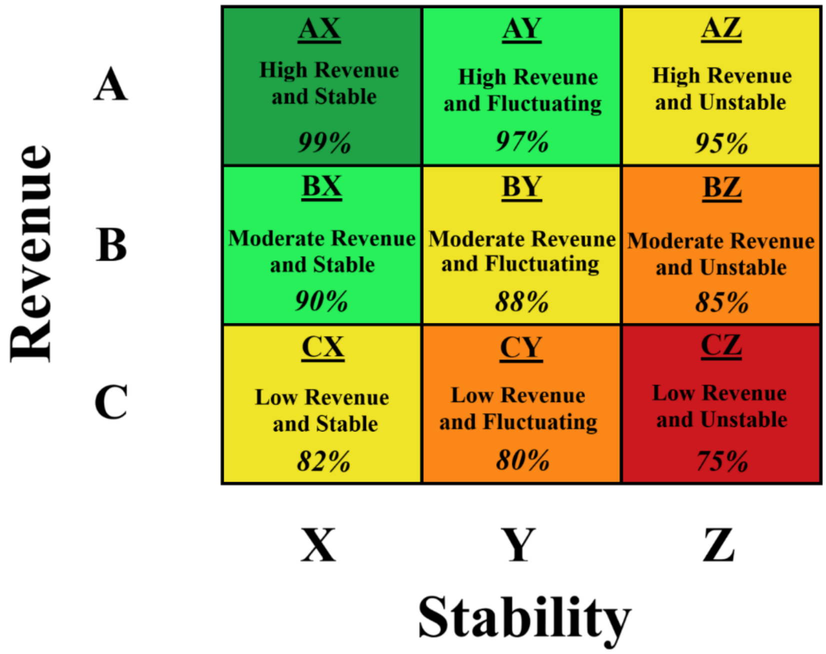

Figure 1: ABC/XYZ analysis

Table 5: Service level to Service factor conversion[3]

Service Level	Service Factor		Service Level	Service Factor
50.00%	0		90.00%	1.28
55.00%	0.13		91.00%	1.34
60.00%	0.25		92.00%	1.41
65.00%	0.39		93.00%	1.48
70.00%	0.52		94.00%	1.55
75.00%	0.67		95.00%	1.64
80.00%	0.84		96.00%	1.75
81.00%	0.88		97.00%	1.88
82.00%	0.92		98.00%	2.05
83.00%	0.95		99.00%	2.33
84.00%	0.99		99.50%	2.58
85.00%	1.04		99.60%	2.65
86.00%	1.08		99.70%	2.75
87.00%	1.13		99.80%	2.88
88.00%	1.17		99.90%	3.09
89.00%	1.23		99.99%	3.72

Mean Absolute Deviation was already available as an output from the Coefficient of Variation (CV) calculations during the XYZ analysis, thus it was used directly for the buffer stock formula. Mean Absolute Deviation was used instead of Standard Deviation in this case because it is more robust to outliers and better reflects dispersion in non-normal datasets. In contrast, standard deviation assumes normally distributed data and his outlier sensitive, making the Z-score calculation unreliable in this context.

[3] The table was taken from https://www.inventoryops.com/articles/safety-stock.html

Lead time (LT), here, was assumed to be monthly, i.e., LT = 1. This assumption was necessary due to the absence of “purchase/order date” data and as prediction is based on monthly demand.

Recommended Inventory Calculation

After calculating the Forecasted Demand and Buffer Stock for each product using the methods described above, the Recommended Inventory was determined by adding the results of Forecasted Demand and Buffer Stock using Excel.

Problem 2: Client Profitability Analysis

The objective of client profitability analysis was to identify which clients contributed most to profitability and to classify them systematically for strategic decision-making. Since client contributions often follow the Pareto principle, where a small group generates the majority of profits, Pareto-based ABC analysis was selected as the core method.

ABC analysis was applied on two dimensions: Total gross profit and profit margin. Total gross profit highlights clients generating the highest volume of profits for the business, while profit margin captures efficiency by measuring how much profit is earned per unit of revenue. Considering both provides a balanced view, ensuring that both scale and efficiency are addressed.

The analysis was carried out in the following steps:

1) A Pivot Table was created with client names and their total gross profit over six months to establish a clear view of client-level profitability.
2) Cumulative profit and cumulative profit percentage were then calculated, using the formula below, to determine the relative contribution of each client to overall profit.

$$Cumulative\ Profit\ \% = \frac{Cumulative\ Proft}{Total\ Profit\ by\ from\ Clients} \times 100$$

3) Based on these values, clients were categorized according to their gross profit contribution (See Table 4), enabling identification of high, medium, and low contributors.

Table 6: ABC criterion of clients based on Total Profits

Category	Criteria
A	Cumulative Profit % ≤ 80 %
B	80% < Cumulative Profit % ≤ 95%
C	95% < Cumulative Profit % ≤ 100%

4) A second Pivot Table was generated to summarize both total revenue and total profit for each client, ensuring consistency in the analysis.
5) Profit margin was calculated using the formula:

$$Profit\ Margin\ \% = \frac{Total\ Profit\ Generated}{Total\ Reveue} \times 100$$

This provided a relative measure of profitability independent of absolute revenue.

6) Finally, clients were classified into categories based on profit margin (See Table 5), highlighting efficiency differences among client groups.

Table 7: ABC criterion based on profit margins

Category	Criteria
A	Top 20%
B	Middle 30%
C	Bottom 50%

7) Following the ABC classification of clients based on total gross profit and profit margin, the two grades were concatenated using the combination of VLOOKUP() and CONCAT() functions of Excel. This combination formed a 3x3 matrix, providing a detailed client segmentation. Figure 2 shows the 3x3 matrix as well as the meaning of each category
8)

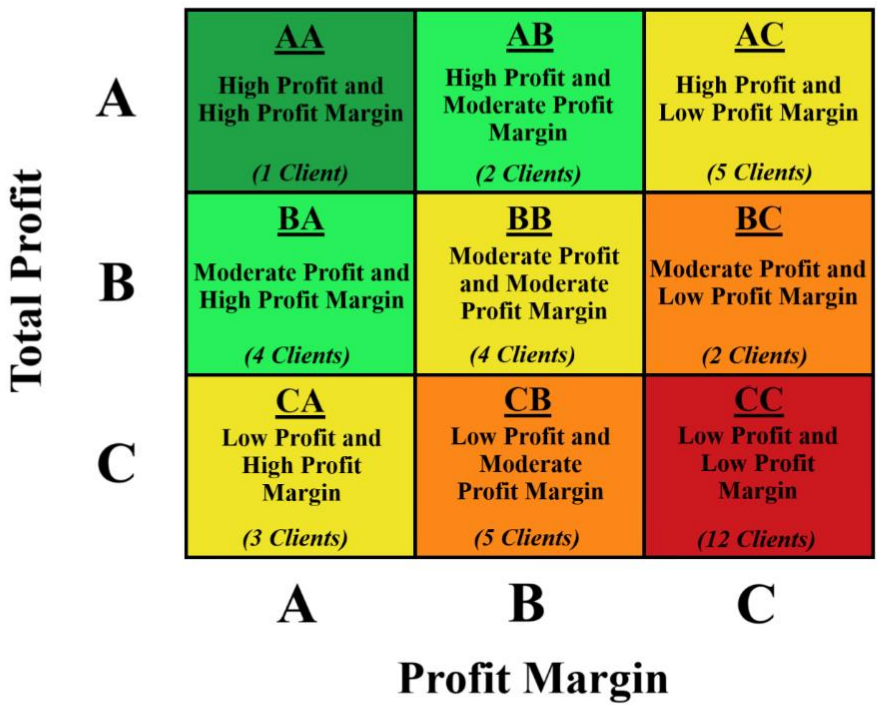

Figure 2: Categorization of Clients

Results and Interpretations

Problem 1: Inventory Management Analysis

<u>Contribution of products as per assigned Categories</u>

- **Graph and Table:**

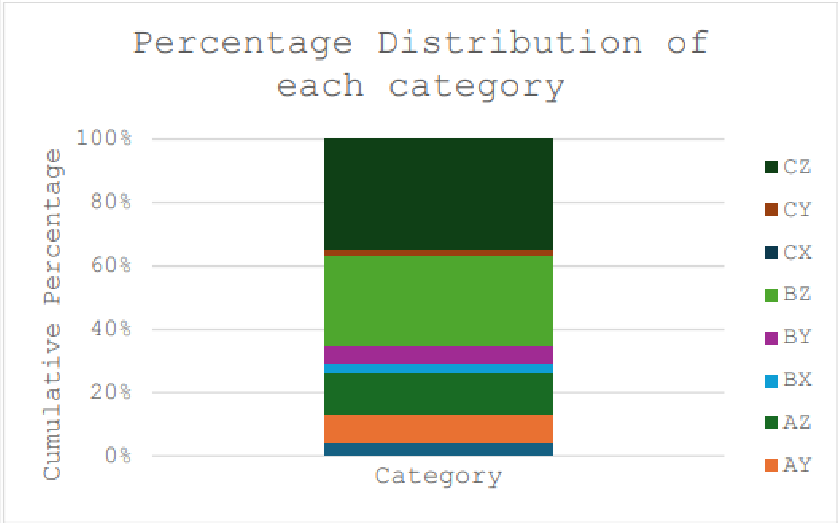

Figure 3: 100% Stacked bar chart of product categorization

- **Data Presentation:**
  The 100% stacked chart (See Figure 3) illustrates the relative share of each product category in overall sales. Each bar segment represents a category's proportional contribution. The provided table lists the exact number of unique products for each category, which totals to 92 unique products.
- **Key Findings:**
  - Categories CZ, BZ, and AZ dominate, contributing 32, 26, and 12 products respectively.
  - Categories AY, BY, and AX hold a moderate contribution, with 8, 5, and 4 products respectively.
  - Categories CX, CY, and BX contribute the least, with 0, 2, and 3 products respectively.
- **Interpretation:**
  From the 100% stacked chart (See Figure 3), categories such as CZ (32 products) and BZ (26 products) dominate the portfolio, reflecting instability in demand. This occurs because most products are ordered only when required by clients, rather than being consistently stocked, which explains the prevalence of low-volume, unstable categories.

Pareto Analysis of Recommended Stock based on ABC/XYZ Categories

- **Graph and Table:**

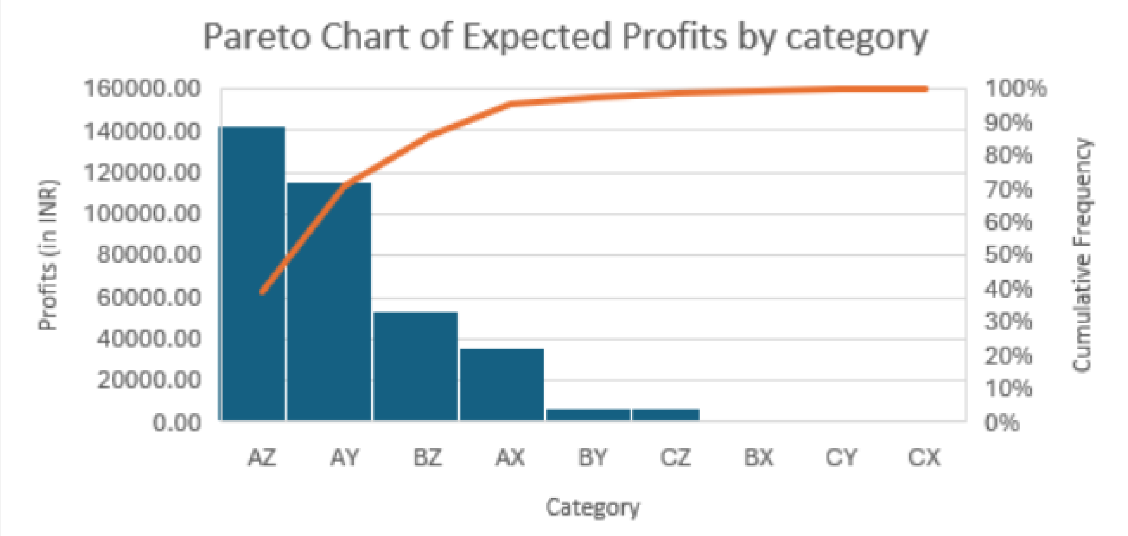

Figure 4: Pareto analysis of recommended stock

- **Data Presentation:**
  The Pareto chart (See Figure 4) visually represents the recommended stock levels for July. The bars on the chart show the absolute number of units, sorted in descending order, and the line represents the cumulative percentage. The provided table lists the exact stock levels for each category, which estimates the demand of 26,881 units across all products.
- **Key Findings:**
  - The products in AY and AX categories drive the majority of the demand, contributing nearly 60.20% (16,183 units) of the recommended stock.
  - The products in AZ, BZ and BY categories contribute nearly 36.08% (9,699 units) of the recommended stock.
  - The products in CY, CZ, BX and CX categories contribute the remaining 3.72% (999 units) of the recommended stock.
- **Interpretation:**
  From the Pareto Analysis of Recommended Stock (See Figure 4), it is clear that high-volume products (AY, AX, AZ) dominate sales regardless of their demand variability. The BX category is an exception, as it contains only a few products that, while stable, generate only moderate revenue and sell in very small absolute quantities, resulting in minimal stock recommendations.

Pareto Analysis of Expected Profits based on ABC/XYZ Categories

- **Graph and Table:**

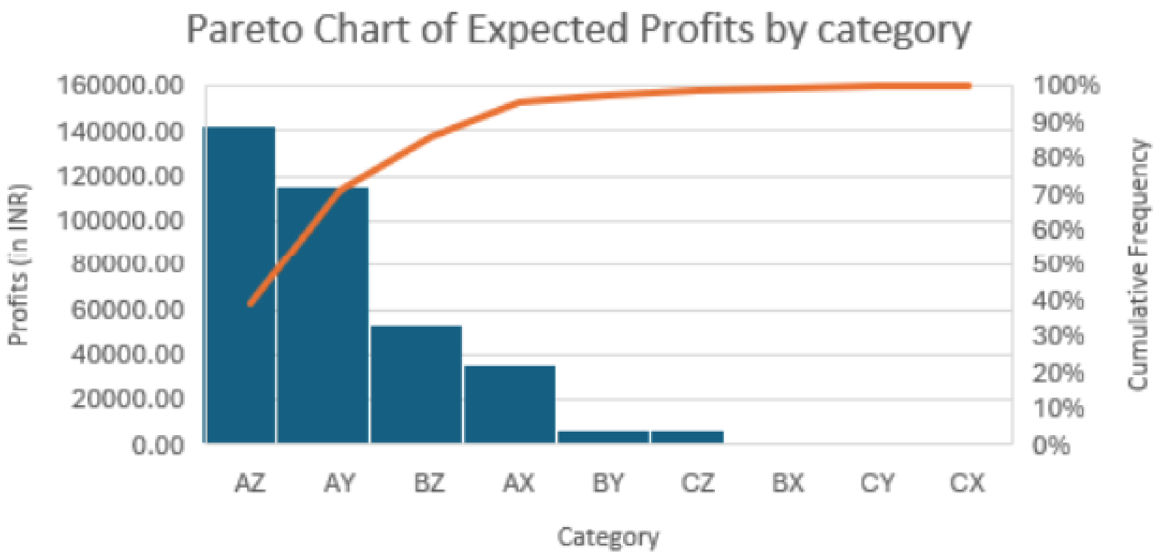

Figure 5: Pareto analysis of expected profits

- **Data Presentation:**
  The Pareto chart (See Figure 5) visually represents the expected profit contribution of each category. The bars on the chart show the profits in INR, sorted from highest to lowest, and the cumulative line shows the overall accumulation. The provided table lists the exact profit contributions for each category, estimating total of ₹ 3,62,823.46 profit.
- **Key Findings:**
  - The products in AZ and AY categories are estimated to generate the most profit, contributing nearly 71.20% (Rs. 2,58,343.83) of the estimated profits.
  - The products in BZ and AX categories are estimated to generate the moderate profits, contributing nearly 24.32% (Rs. 88,260.07) of the estimated profits.
  - The products in BY, CZ, BX, CY and CX categories are estimated to generate the least profit, contributing nearly 4.48% (Rs. 16219.56) of the estimated profits.
- **Interpretation:**
  From the Pareto analysis of expected profit (See Figure 5), categories AZ and AY alone generate 71.20% (Rs. 2,58,343.83) of projected profits. This is because expected profits are driven not only by sales volume but also by the number of products within the category, magnifying their overall contribution.

Problem 2: Client Profitability Analysis

<u>Contribution of Clients as per Assigned Categories.</u>

- **Graphs and Table:**

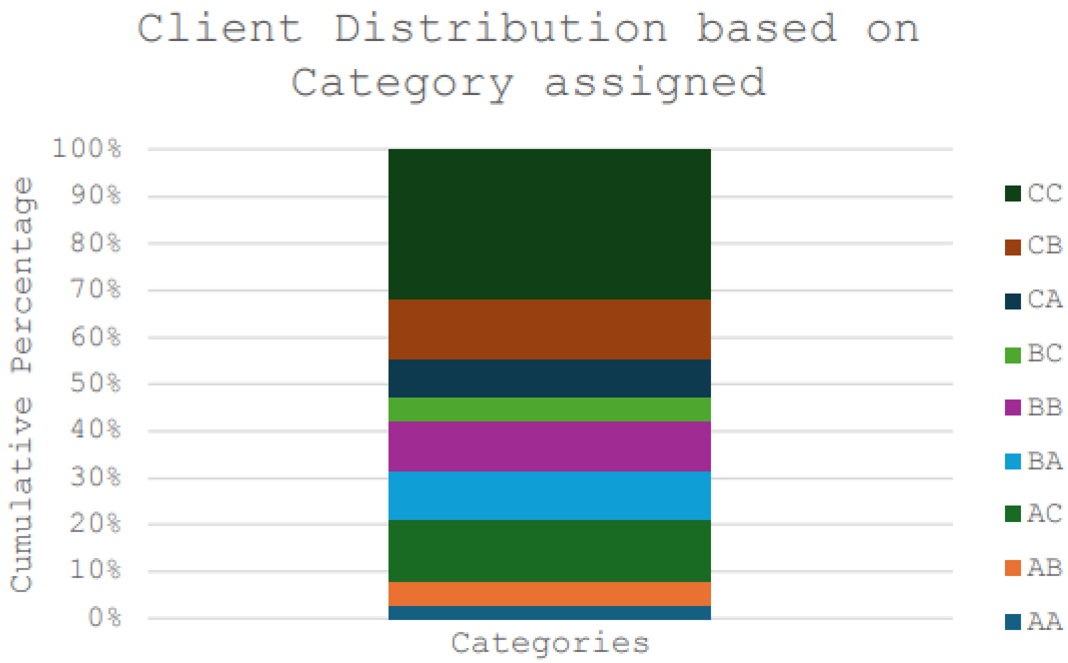

Figure 6: 100% stacked chart based on client categorization

- **Data Presentation:**
  The 100% stacked bar chart (See Figure 6) visually represents the distribution of the client base. The chart shows the proportional share of each category, with the total bar representing 100% of the client population. The provided table lists the exact number of clients for each category; the business has total of 38 clients.
- **Key Findings:**
  - The most clients fall in category CC, contributing nearly 31.57% (12 clients) of the total client base.
  - Clients in categories AC, CB, BA and BB also contribute significantly with 5, 5, 4, 4 clients respectively, contributing nearly 47.37% of the total client base.
  - The remaining client categories CA, AB, BC and AA represent a smaller client base of 3, 2, 2, 1 clients respectively, contributing nearly 21.06% of the total client base.
- **Interpretation:**

  From the 100% stacked chart (See Figure 6), categories such as CC (12 clients) dominate numerically but generate minimal profit. This is because many CC clients are one-time buyers or engage in only a few small transactions, making them low-value despite their count.

Profit Contribution as per Client Categories

- **Graph and Table:**

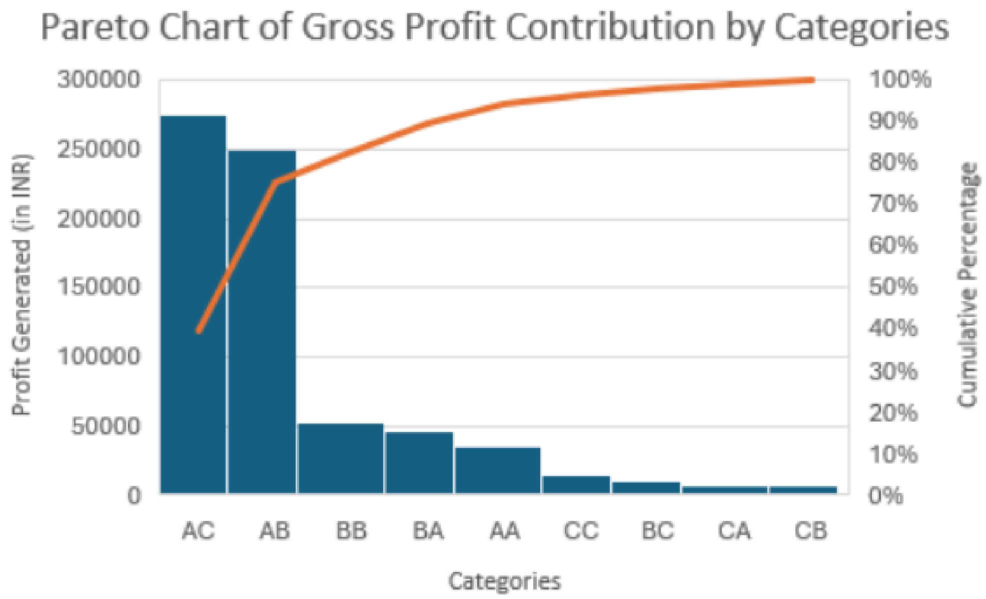

Figure 7: Pareto analysis of profit generation

- **Data Presentation:**

The provided table and Pareto chart (See Figure 7) analyse the profit contribution of different categories. The table lists the exact total profit for each category, while the Pareto chart visually represents this data. The bars show the gross profit generated (in INR) for each category, sorted from highest to lowest, and the orange line illustrates the cumulative percentage of the total gross profit. The total gross profit generated is Rs. 6,98,093.09.

- **Key Findings:**
    - The clients in categories AC and AB dominate the profit output, generating the profit of Rs. 5,24,431.06 that is 75.12 % of total profits.
    - The clients in categories BB, BA, AA contribute moderately with total profit generated by these clients is Rs. 1,34,605.55 that is nearly 19.28% of the total profits.
    - The remaining client categories CC, BC, CA, and CB are marginal contributors, generating profit of Rs. 39,056.48, that is nearly 5.6% of the total profit.
- **Interpretation:**

The profit distribution across categories (See Figure 7) shows that AC, AB, BB, BA, and AA clients, though only 16 in number (~42.1% of total), generate nearly Rs. 6,59,037 (~94.4% of profits). This concentration indicates that these clients form the core profit-generating base, combining higher volumes and/or stronger margins.

Pareto Analysis of Revenue Generated as per Categories

- **Graph and Table:**

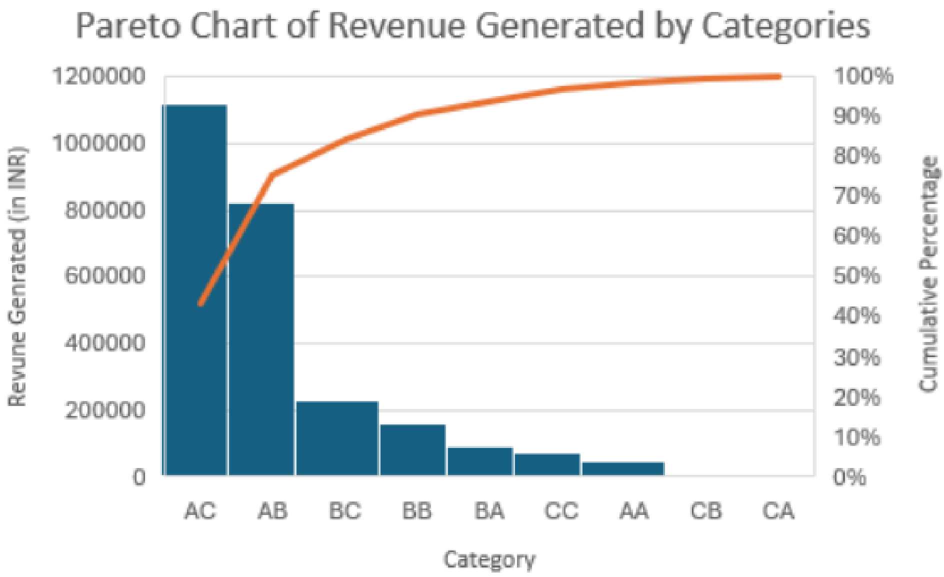

Figure 8: Pareto analysis of revenue generation

- **Data Presentation:**

The provided table and Pareto chart (See Figure 8) analyse the revenue generated by different client categories. The table lists the exact total revenue for each category, while the Pareto chart visually represents this data. The bars show the revenue generated in INR for each category, sorted from highest to lowest, and the red line illustrates the cumulative percentage of the total revenue. The total revenue generated is Rs. 25,77,166.75.

- **Key Findings:**
  - The top two client categories, AC and AB, are the dominant revenue generators, contributing Rs. 19,42,189.7, which is approximately 75.36% of the total revenue.
  - The clients in categories BC, BB and BA contribute moderately with total profit generated by these clients is Rs. 5,49,550 that is nearly 21.32% of the total profits.
  - The remaining client categories CC, AA, CB, and CA are marginal contributors, generating revenue of Rs. 1,54,444.05, contributing about 3.32% of the total revenue.
- **Interpretation:**

  The revenue generation across categories (See Figure 8) shows that client categories such as AC, AB, BC, BB and BA generate Rs. 24,22,722.7, about 94%, revenue while contributing only 17 clients, about 44.73%. This shows that frequent or high-profit generating clients disproportionately drive revenue, regardless of margin variations.

Limitations and Recommendations

Problem 1: Inventory Management Analysis

- **Limitations**
  - Lead time (LT) was assumed as 1 month due to lack of purchase date data, which reduces accuracy.
  - Forecasting with Croston's method assumes future patterns reflect past sporadic demand, which may not capture sudden structural changes.
  - The dataset spans only six months (January–June 2025), which limits trend reliability.
- **Recommendations**
  - Prioritize inventory allocation for categories AX, AY, and AZ to prevent stockouts, as they account for the majority of demand and profit generation.
  - BX products, though stable, currently contribute little due to low volumes. Expanding their product range or stimulating sales could enhance their profitability.
  - Monitor products in categories BY and CY more closely, since their demand is relatively high but profit margins remain low, making them vulnerable to inefficiencies.
  - Reduce capital tied up in low-demand categories such as CZ and BZ, where holding costs may outweigh potential returns.
  - To improve future forecasting accuracy, recording procurement dates and calculating lead times would be beneficial, as it allows for more precise buffer stock estimations.

Problem 2: Client Profitability Analysis

- **Limitations**
  - The dataset covers only six months (January–June 2025), which may not capture seasonal or long-term trends in client performance.
  - Clients were evaluated purely on financial metrics, without considering qualitative aspects such as strategic importance, growth potential, or relationship value.
  - Outliers in profit margins or revenue were not separately treated, which may distort category classifications for clients with extreme values.
- **Recommendations**
  - Prioritize AA clients, as they combine strong profit margins with meaningful profit contributions. These clients are highly valuable and should be retained through consistent engagement.
  - Strengthen relationships with AB and AC clients, who generate the highest share of profits. Maintaining loyalty and exploring opportunities to deepen transactions with this group will sustain long-term profitability.

- Monitor BA and BB clients closely. They show moderate profits but relatively strong margins, meaning they have the potential to be scaled into higher-value categories with targeted strategies.
- Reassess CA, CB, and BC clients, as they deliver weak profitability metrics. These clients should undergo periodic evaluation to ensure they do not consume resources disproportionate to their financial return.
- Rationalize CC clients, who represent the largest group but contribute minimally to profits. For one-time or infrequent buyers, pricing strategies with higher margins may be appropriate, while broader resource allocation should be minimized.