“Optimizing Inventory Management for a Kitchen Appliances Retailer: A Primary Data Analysis ”

A Final report for the BDM capstone Project

Submitted by

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Contents

1. Executive Summary

Anand Steel Emporium is a kitchen appliances retail shop located in Korba, Chhattisgarh. Established in 2010, it is owned and operated by Mr. Anand Sahu, employing 2 full-time staff. The shop specialises in products such as pressure cookers, induction cooktops, and mixer grinders, serving a loyal customer base in the region. The business operates 7 days a week, generating an estimated annual income of ₹35–40 lakh. Despite healthy demand, it faces persistent inventory management issues, including frequent stockouts of fast-moving items, overstocking of slow-moving products, and capital being locked in unsold inventory, thereby reducing sales opportunities and operational efficiency.

To address these issues, primary data was collected directly from purchase and sales registers, covering transactions from 2023 to mid-2025. The dataset included 300 restocking records and 1,000 sales entries. Data cleaning involved standardising dates, merging product names, and removing duplicates or negative entries. Analytical methods applied included descriptive statistics, ABC analysis for product classification, and time series trend analysis, using Python and Excel.

The analysis revealed several critical insights. Purchase value peaked in 2024 at ₹1.05 crore but declined sharply in 2025 to ₹28 lakh. A small group of products accounted for the majority of revenue: 20% of SKUs contributed to nearly 80% of total sales. Daily sales trends showed frequent spikes, while restocking patterns were inconsistent and reactive. The ABC classification showed that 'A' category items dominated both sales and purchase value, but 'C' category products continued to occupy shelf space despite low contribution.

Based on these findings, this report recommends a practical, data-driven inventory strategy: maintain digital stock registers, apply ABC-based reorder policies, introduce minimum reorder levels based on historical trends, and negotiate supplier terms for high-performing items. These feasible approaches are expected to reduce stockouts by up to 30%, improve working capital utilization, and enhance customer satisfaction, equipping businesses with practical, data-driven tools for sustainable growth.

2. Detailed Explanation of Analysis Process / Methods

2.1 Data Cleaning and Preprocessing

2.1.1 Overview of Data Collected

The raw purchase and sales data obtained from the shopkeeper's registers were first consolidated into two datasets and converted into machine-readable CSV format. Date values were normalised to `YYYY-MM-DD` format, product names were standardised to avoid duplication (e.g., "P Cooker" → "Pressure Cooker"), and duplicate/negative entries were removed. After basic cleaning, calculated fields such as **Total Sale Value** (`Quantity × Sale Price`) and **Total Purchase Value** (`Quantity × Purchase Price`) were generated for further analysis.

- **Restocking Records (Restocking_Records_Data.csv)**

Columns: ***Restock Date, Product Name, Supplier, Quantity Purchased, Purchase Price per Unit, Total Purchase Value.***

```
restocking_records = pd.read_csv('raw_Restocking_Records_Data.csv')
restocking_records
```

	Restock Date	Product Name	Supplier	Quantity Purchased	Purchase Price per Unit	Total Purchase Value
0	2024-08-06	Non-stick Tawa	Bharat Appliances	55	1044.31	57437.05
1	2023-07-20	Non-stick Tawa	KitchenKraft	43	1554.69	66851.67
2	2025-01-30	Non-stick Tawa	Bharat Appliances	57	1859.27	105978.39
3	2023-11-16	Non-stick Tawa	RetailBazaar	23	1340.00	30820.00
4	2024-11-26	Gas Stove	Steel Mart	10	1487.79	14877.90
...	...	...	...	...	...	...
295	2023-11-13	Kadhai	KitchenKraft	14	1582.69	22157.66
296	2024-02-09	Electric Kettle	KitchenKraft	62	616.45	38219.90
297	2024-12-03	Gas Stove	Metro Traders	15	921.10	13816.50
298	2025-05-29	Electric Kettle	Bharat Appliances	64	336.41	21530.24
299	2024-12-28	Pressure Cooker	Metro Traders	22	501.69	11037.18

300 rows × 6 columns

Fig 2.1. Restocking records.csv

- **Sales Records (Sales_Data.csv):**

Columns: Date, Product Name, Quantity Sold, Sale Price, Total Sale Value.

```
Sales_Data = pd.read_csv('raw_Sales_Data.csv')
Sales_Data
```

	Date	Product Name	Quantity Sold	Sale Price	Total Sale Value
0	12-07-2024	Gas Stove (large)	1.0	2133.22	2133.22
1	05/25/2024	Gas Stove (large)	-1.0	NaN	NaN
2	01/29/2024	Electric Kettle	2.0	2405.17	4810.34
3	06/29/2024	Hand Blender (small)	5.0	1262.97	6314.85
4	10/22/2023	Stainless Steel Kadhai Pro	3.0	1693.37	5080.11
...	...	...	...	...	...
995	29-11-2024	Non-stick Tawa (small)	5.0	319.58	1597.90
996	21-01-2024	Electric Kettle	5.0	1815.27	9076.35
997	2025-05-20	Induction Cooktop Deluxe	-1.0	NaN	NaN
998	28-12-2023	Gas Stove (large)	-1.0	NaN	NaN
999	NaN	NaN	NaN	NaN	NaN

1000 rows × 5 columns

Fig 2.2. Sales data. csv

2.1.2 Cleaning Steps Performed

a) Date Standardisation:

Both datasets contained dates in inconsistent formats (e.g., DD/MM/YY, MM-DD-YYYY). Using Python's `datetime` module, all dates were converted to YYYY-MM-DD format to enable time-based grouping and plotting.

b) Product Name Normalisation:

Entries with minor spelling variations were merged (e.g., 'Pressure Cooker Deluxe' and 'P Cooker Deluxe') to ensure consistency in grouping, using a combination of manual mapping and Python's `.replace()` function.

c) Handling Missing Values:

- **Purchase Records:** The Missing **Purchase Price per Unit** was imputed using the mean unit price of the product category. Missing **Quantity Purchased** entries were dropped as the purchase quantity is critical for restocking analysis.
- **Sales Records**: Missing **Sale Price** entries were imputed with product category means; missing **Quantity Sold** entries were excluded.

d) Calculated Columns Creation:

- **Total Purchase Value:** Calculated as:

$$Total\ Purchase\ Value\ =\ Quantity\ Purchased\ \times\ Purchase\ Price\ per\ Unit$$

- **Total Sale Value:** Calculated as:

$$Total\ Sale\ Value\ =\ Quantity\ Sold\ \times\ Sale\ Price$$

e) Removal of Invalid and Duplicate Entries:

Records with negative prices or quantities were removed. Duplicate entries (e.g., same product, date, and value repeated) were dropped to avoid double-counting.

2.2 Comprehensive Explanation of Methods Used

2.2.1 ABC Analysis

Objective:

To prioritise critical products from an inventory perspective, an **ABC analysis** was performed using **Annual Consumption Value (ACV)**. The analysis used the columns *Product Name*, *Quantity Sold* and *Sale Price*.

Columns Used:

- ***Product Name, Quantity Purchased, Purchase Price per Unit***

Mathematical Abstraction:

$$ACV\ =\ \sum_{i=1}^{n} Quantity\ Purchased(i)\ \times\ Purchase\ Price\ per\ unit(i)$$

Process:

1. Calculate ACV for each product.

2. Sort products in descending order of ACV.

3. Classify:

- **A Category:** Top ~70-80% of total ACV (critical items)
- **B Category:** Next ~15-20% (moderate control)
- **C Category:** Remaining ~5-10% (simple monitoring)

Justification:

Focuses resources and capital on managing products with the highest financial impact, reducing the risk of stockouts for critical items.

2.2.2 Time Series Trend Analysis

Objective:

To identify patterns and seasonality in purchases and sales over time for better demand planning.

Columns Used:

- ***Restock Date, Total Purchase Value***
- ***Date, Total Sale Value***

Methodology:

- Year-wise Purchase & Sales Trends: Grouped by year to observe macro changes in business scale.
- Daily Trends: Line plots to assess daily variability, peak demand days, and periods of low activity.
- Moving Average: Applied for smoothing short-term fluctuations and highlighting longer-term trends.

2.2.3 Pareto Analysis (80/20 Rule)

Objective:

Pareto charts were generated for both **sales volume** and **sales value** to further confirm product-level concentration.

Logic:

Using the columns *Product Name*, *Total Sale Value* and *Quantity Sold*, each product's contribution was converted into a **cumulative percentage** of total sales.

Justification:

Products representing approximately **80% of total quantity** and **80% of total value** were identified as strategic SKUs for the business. This complemented the ABC results and helped eliminate redundant items from the assortment.

2.2.4 RFM Analysis – Product Preference Segmentation

Objective:

To address the second problem statement – "lack of understanding of customer preference" – a **Recency, Frequency and Monetary (RFM)** analysis was performed on product-level sales data.

Logic:

Metric	Description	Column Used
R - Recency	Days since last sale of each product	`Date`
F - Frequency	Number of transactions containing the product in the last 12 months	`Quantity Sold`

M - Monetary	Total revenue generated by the product	`Total Sale Value`

For each product, R, F and M scores were normalised (0–1 scale) and combined into a single **RFM score**.

Products with **high frequency and high monetary** scores are interpreted as **high-preference items**, and those with **low values** are considered less important from a customer perspective.

Justification:

This analysis helps not only in stock optimisation but also in making data-informed product placement and promotion decisions.

2.3 Tools and Justification

Tools	Purpose
Python (Pandas, Matplotlib, Seaborn)	**Data cleaning, aggregation, statistical calculations, and visualizations**
Excel/ Google Sheets	**Quick calculations, dashboard preparation**
Google docs	**Report documentation and formatting**

2.4 Alignment with Problem Statement

All analytical methods were chosen to directly address the shop's inventory challenges:

- **Descriptive statistics** were used to understand variability in sales and purchase behaviour and to identify basic demand distribution.

- **ABC analysis** helped prioritise products based on their financial contribution and guided the allocation of inventory control efforts.
- **Time-series trend analysis** was used to identify demand patterns and seasonality, enabling more proactive restocking decisions.

- **Pareto analysis (80/20 rule)** was applied to determine the concentration of sales volume and value among products and to validate the need for differentiated inventory focus.
- **RFM analysis** was used to understand product-level customer preference by combining recency, frequency, and monetary metrics to rank products according to overall sales effectiveness.

3. Results and Findings

This section summarises the key analytical results obtained from the cleaned purchase and sales datasets using descriptive statistics, ABC analysis, and time series visualisation.

3.1 Year-wise Purchase Value

Figure 3.1 illustrates the total annual purchase value incurred by the shop over three consecutive years (2023–2025). This visualization helps us assess the shop's procurement behavior and investment patterns over time. It reveals fluctuations in restocking expenditures, which can be associated with external demand cycles, internal planning decisions, or supplier dynamics.

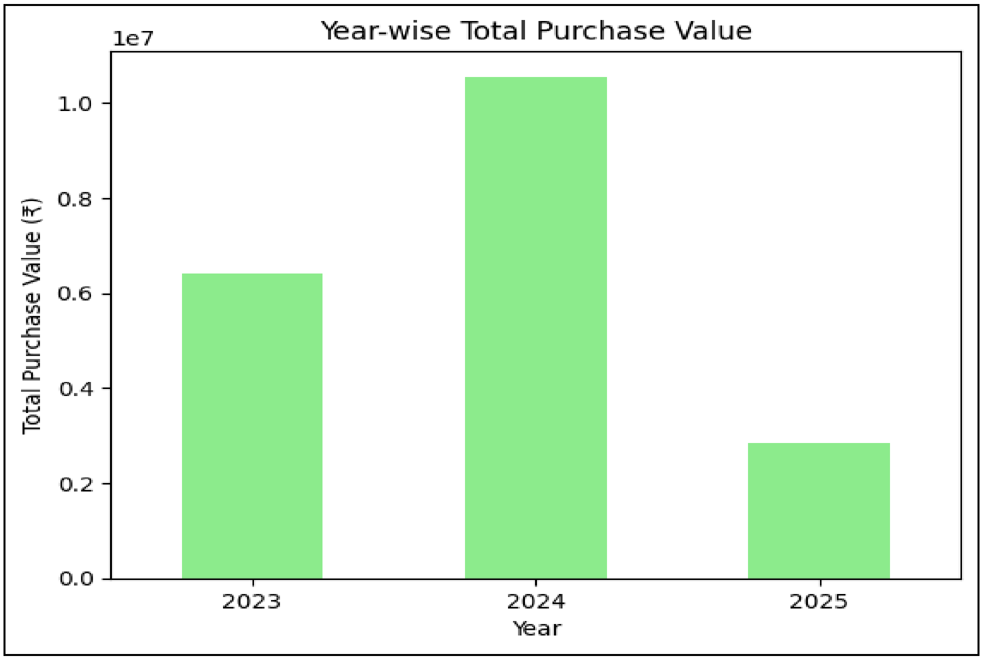

Figure 3.1 shows the annual total purchase value over the recorded period.

Findings:

- The year 2024 observed the highest purchase value, peaking at over ₹1 crore, indicating increased procurement, possibly driven by expansion or higher sales activity.
- In 2023, the total purchase value was around ₹65 lakhs, showing moderate procurement.
- A sharp decline is seen in 2025, with the purchase value dropping to under ₹30 lakhs, possibly hinting at a slowdown in operations, excess stock from the previous year, or supply-chain constraints.

3.2 Year-wise Quantity Purchased

Figure 3.2 shows the total quantity of units procured each year. While the previous graph dealt with value, this one focuses on volume, offering insights into unit-level inventory movement and stock replenishment practices.

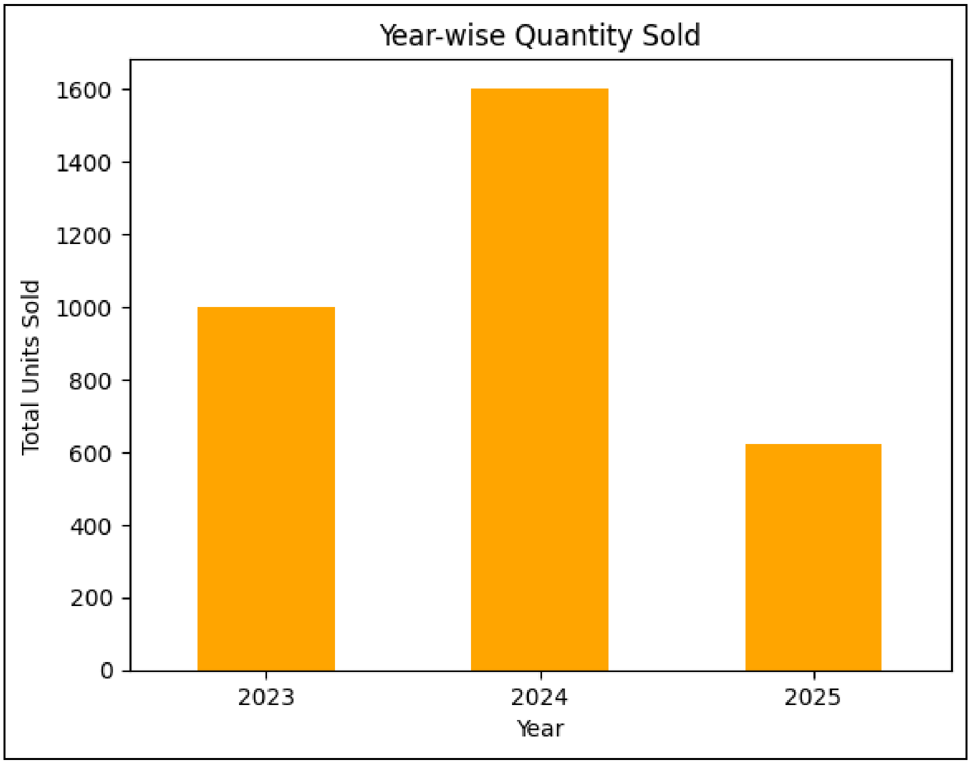

Figure 3.2 presents the total quantity purchased each year.

Findings:

- The year 2024 again dominates in terms of quantity, with approximately 1,600 units purchased—complementing the rise in purchase value seen in Fig. 3.1.
- In 2023, the shop restocked about 1,000 units, suggesting moderate consumer demand or limited shelf capacity.
- The quantity purchased in 2025 dropped to around 630 units, reinforcing the decreasing trend in both value and volume of restocking.

3.3 Daily Restocking Patterns

Figure 3.3 plots the daily total purchases throughout 2024. The line chart provides a granular view of how often and in what volume the shop restocked its inventory across different months.

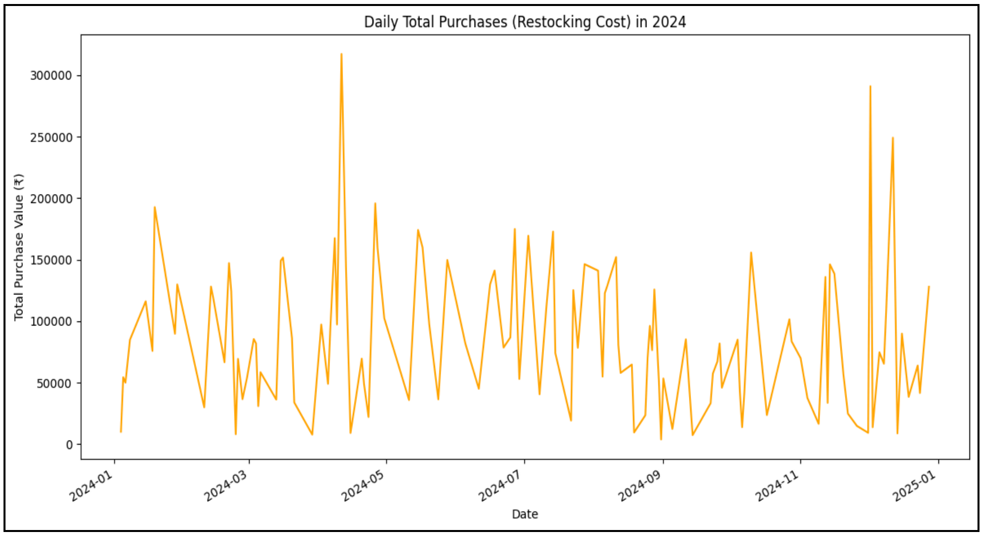

Figure 3.3 shows daily total purchases (restocking cost) in 2024.

Findings:

- High volatility is observed throughout the year, with multiple spikes over ₹2 lakhs and even peaking above ₹3 lakhs in mid-2024.
- There is no fixed restocking interval; instead, procurement is reactive—possibly driven by stockouts, seasonal demand, or promotional periods.
- Activity is denser in Q1 and Q2, tapering slightly in Q3 and Q4. This might reflect festive restocking, or early-year demand spikes.
- Absence of a smoothing trendline implies lack of forecasting in the procurement process. Implies a lack of systematic replenishment planning, leading to possible overstocking or delayed purchases, risking stockouts.

3.4 Daily Sales Patterns

Figure 3.4.1 visualizes daily sales activity across 2024. It allows us to detect periods of high and low revenue flow and analyze overall demand regularity.

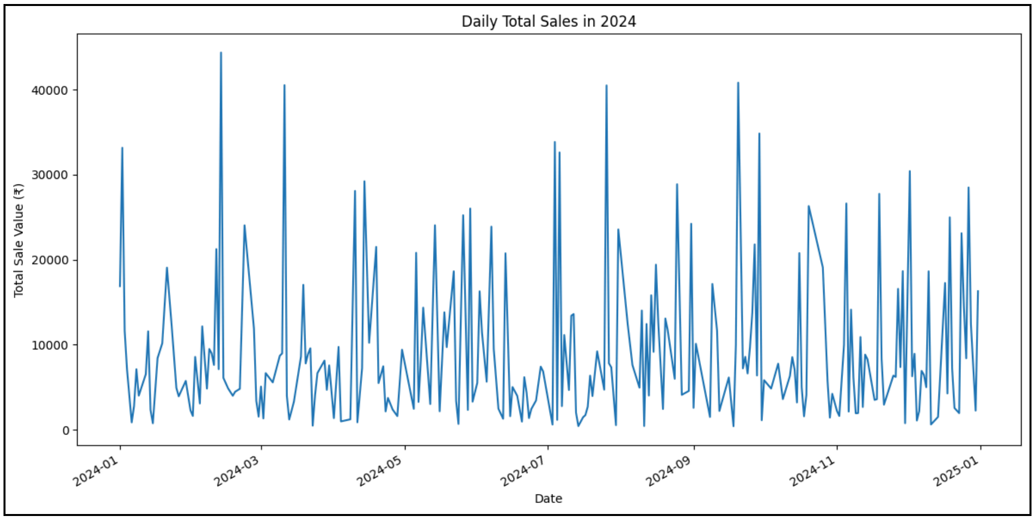

Figure 3.4.1 presents daily total sales in 2024

Findings:

- Sales revenue exhibits substantial day-to-day fluctuations, peaking around ₹45,000 on some days and dipping below ₹5,000 on others.
- Activity is consistent throughout the year, indicating that the business is operational year-round, including lean periods.
- Occasional high peaks suggest periodic promotions or festivals that temporarily drive higher sales.

The list of high-performing products is further confirmed by the Pareto charts (Fig. 3.6.1 and Fig. 3.6.2), which show that items such as Non-Stick Tawa, Electric Kettle, Utensil Set, Induction Cooktop and Mixer Grinder together account for almost 80% of total sales volume and revenue.

3.5 ABC Classification

Figure 3.5.1 – Product-Wise ACV Contribution

This Pareto chart ranks products by their Annual Consumption Value (ACV), with a cumulative percentage overlay. It aims to identify the critical few items that generate the majority of the value, following the Pareto Principle.

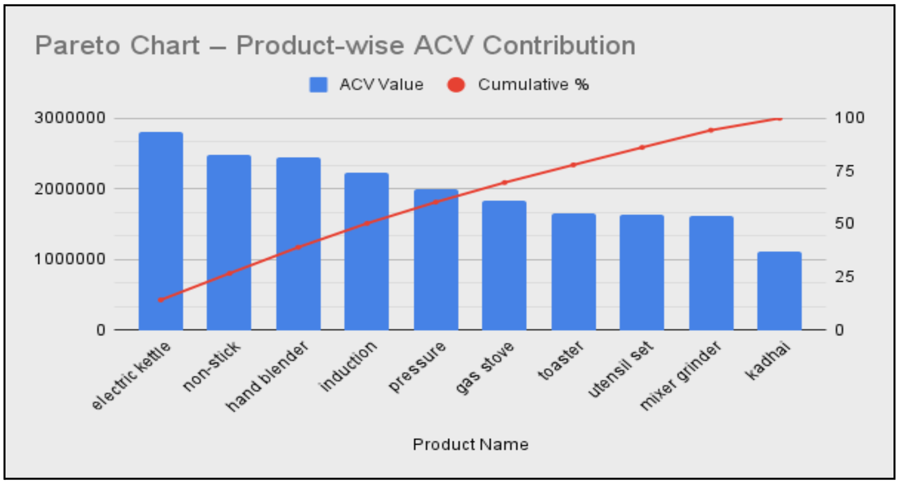

Fig 3.5.1 shows Product-Wise ACV Contribution

Findings:

- The top three products (electric kettle, non-stick, and hand blender) contribute to more than 50% of the overall ACV.
- The top 6 items reach the 80% cumulative threshold, classifying them under 'A' category inventory—strategic and high-value.
- This insight is vital for prioritizing inventory management, ensuring no stockouts for high-contribution items.

Figure 3.5.2 – ABC Category Distribution

The pie chart segments products into ABC categories based on their ACV contribution.

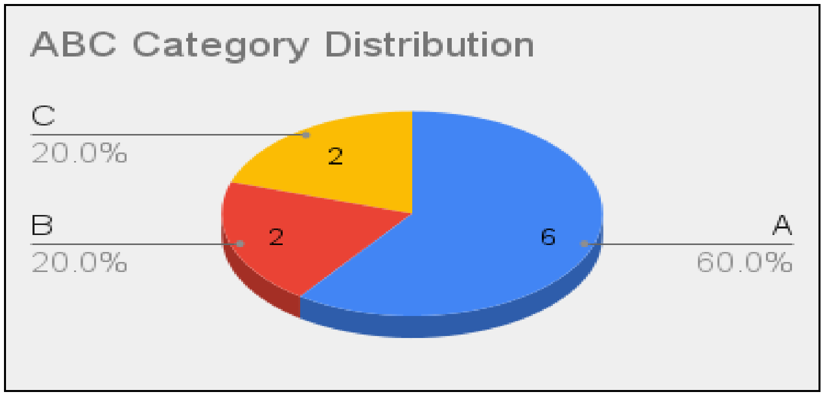

Fig. 3.5.2 shows ABC Category Distribution

Findings:

- Category A comprises 60% of the items, indicating a significant portion of inventory is high-value and must be closely monitored.
- Categories B and C represent 20% each, pointing to medium and low-priority items that require less rigorous management.
- This classification assists in targeted inventory control policies and resource allocation.

3.6 Pareto Analysis (80/20 Rule)

Figure 3.6.1 – Pareto Chart (Sales Volume)

This chart plots products based on units sold and applies the 80/20 rule, indicating which items account for the majority of sales volume.

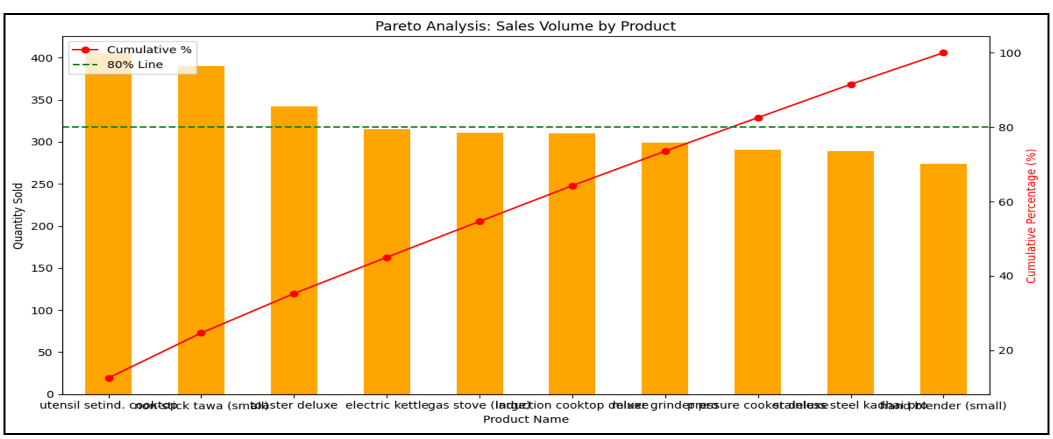

Fig. 3.6.1 Pareto Chart(Sales Volume)

Findings:

- A few products like utensils, non-stick tawas, and toasters dominate the sales volume.
- The top 6 products account for roughly 80% of the total sales, reinforcing the classic Pareto rule.
- Such concentration suggests that focusing on these items could yield significant operational efficiencies.

Figure 3.6.2 – Pareto Chart (Sales Value)

This chart is similar to the previous one but ranked by total revenue generated by each product.

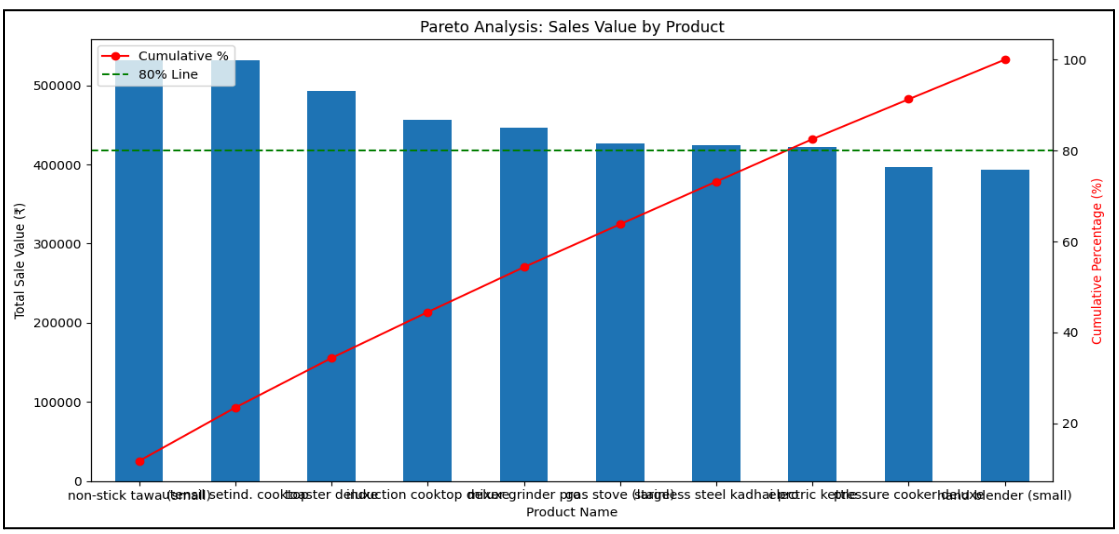

Fig. 3.6.2 Pareto Chart (Sales Value)

Findings:

- Products like non-stick tawas and mixer grinders lead in total sales value, showing they fetch a higher price point and profitability.
- 6–7 items generate around 80% of revenue, aligning with the volume-based Pareto but not identical—highlighting product pricing impact.

- Offers clues for bundling strategies or pricing optimization.

3.7 RFM (Recency, Frequency, Monetary) Analysis

Figure 3.7.1 shows the top five products ranked using the RFM score derived from their sales behaviour

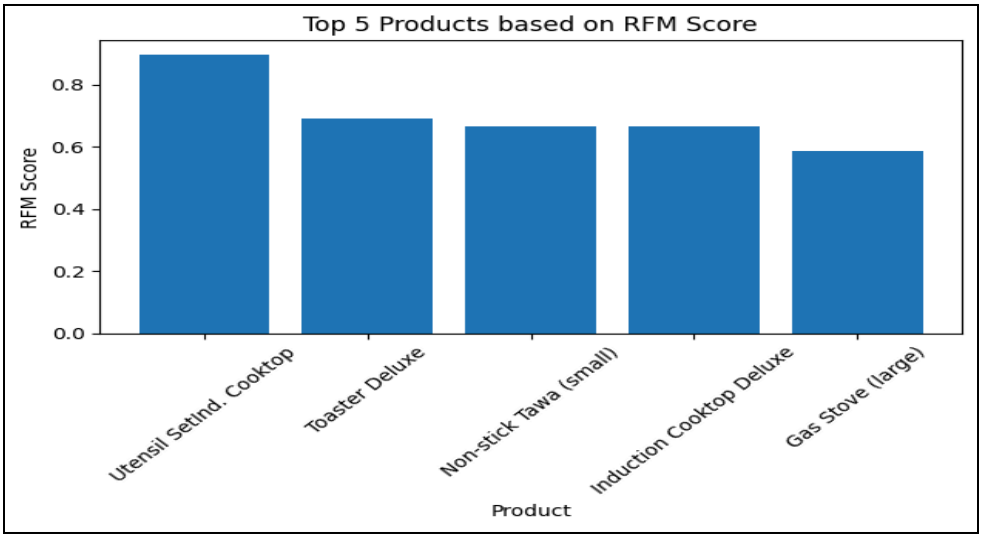

Fig. 3.7.1 Top 5 Products based on RFM Score

Findings:

- *Electric Kettle* and *Non-Stick Tawa* are ranked first and second respectively, indicating that they are purchased most frequently, generate high monetary value, and have been sold very recently.
- Other high-scoring products include *Induction Cooktops*, *Utensil Sets*, and *Mixer Grinders*.
- These results confirm that a limited set of products consistently drive both customer preference and revenue.
- Consequently, these items should be prioritised in terms of stock availability, supplier negotiations and display planning.

Overall Insights

- Procurement peaked in 2024, aligning with observed high sales, but fell sharply in 2025, indicating demand decline or financial adjustments.
- Irregular restocking patterns highlight reactive ordering behaviour.
- Heavy sales reliance on limited products increases business risk if these items face supplier delays or unavailability.
- ABC and Pareto analyses confirm the need for prioritised inventory management focusing on high-value items.

4. Interpretations of Results and Recommendations

4.1 Interpretation of Results

Building upon the visual and statistical findings discussed in Section 3, this section interprets their business implications and strategic relevance for Anand Steel Emporium :

The year-wise trends (Figs. 3.1 and 3.2) show that both procurement expenditure and quantity purchased peaked in 2024, followed by a sharp decline in 2025. This variability suggests either a lack of demand forecasting or possible overstocking in the previous period, emphasising the need for a more data-driven procurement strategy.

The daily restocking pattern (Fig. 3.3) further confirms that the shop currently follows a reactive approach, making large purchases on certain days and long gaps in between, which can result in cash flow pressure and stock mismatches. Similarly, the daily sales trend (Fig. 3.4.1) exhibits high fluctuation, meaning that demand is not evenly distributed and therefore should be incorporated into the replenishment process.

The ABC and ACV analysis (Fig. 3.5.2) indicates that **A-category products**—specifically *Pressure Cooker, Induction Cooktop, Non-Stick Tawa, Mixer Grinder, Stainless Steel Utensil Set and Electric Kettle*—contribute to more than 80 per cent of the total inventory value. In contrast, **C-category** products such as **Serving Trays and Plastic Jars** contribute marginally while still occupying shelf space, indicating sub-optimal capital allocation.

The Pareto charts (Figs. 3.6.1 and 3.6.2) reinforce this insight, confirming that approximately **20% of the items account for almost 80%** of both sales volume and revenue. In addition, the RFM analysis shows that products such as **Electric Kettle, Non-Stick Tawa, Induction Cooktop, Utensil Set and Mixer Grinder** have the highest recency, frequency and monetary scores, suggesting strong customer preference for these items. Thus, inventory and marketing efforts should be concentrated on these high-RFM products, while low-RFM items may be phased out or bundled during clearance periods.

4.2 Actionable Recommendations

Based on the findings, the following **SMART (Specific, Measurable, Achievable, Relevant, Time-bound)** recommendations are proposed to optimise inventory management:

1. Implement ABC-based Replenishment Policy:

- **Action:** Maintain a minimum 30–45 day stock for A-category products.
- **Impact:** Reduces stockout risk for top revenue items.
- **Timeline:** Within 2 weeks, identify A-items and set reorder points.

2. Digitise Inventory Records:

- **Action:** Use Excel or Google Sheets to record daily sales and restocking events.
- **Impact:** Enables real-time stock tracking, accurate demand estimation, and reduces manual errors.
- **Timeline:** Immediate implementation with simple staff training.

3. Regular Restocking Review:

- **Action:** Conduct weekly stock reviews rather than ad-hoc purchases.
- **Impact:** Smoother cash outflows and optimised shelf space.
- **Timeline:** Start next week.

4. Negotiate Bulk Purchase Discounts:

- **Action:** For fast-moving A-category items, negotiate for bulk discounts or supplier credit terms.
- **Impact:** Reduces per-unit cost, improves profit margins.
- **Timeline:** Within 1 month, discuss with key suppliers.

5. Phase Out Low-Performing C-Items:

- **Action:** Gradually reduce the inventory of C-category items that occupy shelf space without substantial sales.
- **Impact:** Frees up capital for high-value products.
- **Timeline:** Assess and act within 1 month.

6. Focus Stock and Display on High-RFM Products

- **Action:** Prioritise the replenishment and front-shelf placement of products with high RFM scores (Electric Kettle, Non-Stick Tawa, Induction Cooktop, Utensil Set and Mixer Grinder).
- **Impact:** Increases visibility and availability of high-preference products, leading to higher conversion and customer satisfaction.
- **Timeline:** Implement within the next 2 weeks and review performance monthly.

Recommendation	Specific Action	Measurable Impact	Achievable Implementation	Relevant Outcome	Timeline
Implement ABC-based Replenishment Policy	Maintain a minimum of 30–45 days' stock for A-category products	Reduce stockouts by ~30%	Identify A-items and set reorder points	Ensures the availability of top revenue products	Within 2 weeks

Digitise Inventory Records	Record daily sales and restocking data using Excel or Google Sheets	Improves data accuracy and tracking	Train the shopkeeper and staff on basic digital entry	Enables data-driven decisions and future analysis	Immediate
Conduct Weekly Stock Reviews	Review stock levels every Sunday evening	Smoother cash flow and better inventory control	Set a fixed weekly review time in the routine	Avoids emergency purchases and improves planning	Start next week
Negotiate Bulk Purchase Discounts	Approach suppliers for A-category items, bulk discount, or credit terms	5–10% cost savings on bulk procurement	Prepare the last 3 months' purchase summary for negotiation	Reduces procurement cost, improves profit margins	Within 1 month
Phase Out Low-performing C-items	Gradually reduce and clear the C-category inventory	Frees up ~5–10% working capital	Identify C-items from ABC analysis and plan a clearance sale	Reallocate funds to fast-moving products	Within 1 month

Table 4.1 SMART Recommendations

4.3 Implementation Impact

Adopting these recommendations is expected to:

- Reduce stockouts by ~30%, ensuring availability of key products
- Improve working capital turnover by reducing funds blocked in non-performing stock

- Increase revenue consistency by focusing on high-demand items
- Streamline restocking processes, saving time and effort for the shopkeeper.