# Boosting Sales at A.R Furniture through Strategic Inventory Optimization and Customer-Centric Design

## Final report for the BDM capstone Project

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# Contents

## 1. Executive Summary:

A.R. Furniture is a micro-enterprise operating in Ranchi, Jharkhand, serving both B2B carpenters and walk-in B2C customers through the sale of raw furniture frames, components, and a limited collection of finished products. The business operates entirely through manual records and owner-driven decisions, resulting in uneven purchasing patterns, inconsistent pricing, and limited visibility into product performance. The objective of this project is to transform fragmented operational data into structured insights that support inventory optimization, pricing stability, and customer-oriented improvements.

Four months of purchase, raw sales, and retail sales data were consolidated, cleaned, and analysed using Excel. The analysis framework included descriptive statistics, ABC classification, monthly trend analysis, and retail profitability assessment. These methods were selected to quantify demand patterns, identify high-value items, and highlight inefficiencies rooted in overstocking and irregular procurement.

Key findings reveal strong dependence on a small group of high-performing SKUs, significant variation in purchasing quantities, and consistent retail margins despite low transaction volume. Monthly profit patterns show rising demand through the quarter, and ABC results confirm that a limited set of A-category items drives the majority of profitability. Raw sales provide volume and steady cash flow, while retail items deliver superior margins but require better display and showroom management.

The final report converts these insights into actionable strategies covering inventory control, structured procurement, competitive pricing, and customer-centric store enhancements, positioning A.R. Furniture for improved operational stability and sustained revenue growth.

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## 2. Detailed Explanation of Analysis Process / Method:

### 2.1 Introduction:

This section documents the analytical procedures used to transform the raw transaction data (April–July 2025) into the findings presented in this final report. The analysis had three interlocking objectives:

- Establish the empirical characteristics of the transaction data (descriptive statistics) so readers understand the distribution, variability and scale of demand and prices.

- Improve the original ABC classification by integrating multi-dimensional operational metrics (profit, sales frequency, and demand stability) so inventory priorities align with both financial and operational realities.
- Add short-term demand forecasting (3-month moving average) and trend tagging (Rising / Stable / Declining) to convert static classification into actionable inventory rules (reorder frequency, safety stock, phase-out candidates).

All preprocessing and calculation steps were done in Microsoft Excel; pivot tables were used for grouping and aggregation, and column formulas were used for per-SKU computations.

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### 2.2 Data Cleaning and pre-processing

The data covers transactions dated 01-Apr-2025 through 31-Jul-2025 (4 months). Preprocessing steps:

- Standardize item codes: Correct inconsistent item-code spellings and remove trailing spaces.
- Normalize date format: Convert text dates to Excel date datatype (DD-MM-YYYY) and use Year/Month grouping in pivots.
- Remove duplicates: Identify exact-row duplicates and remove.
- Convert numeric text: Convert Qty, Rate, Total Amount fields to numeric.
- Create reliable aggregates: Build a pivot (SKU × Month) with Sum (Qty) and Sum (Total Sales) to get monthly series per SKU, then export to Raw Summary.

Rationale: clean, consistent dimensions are necessary for correct STDDEV, average and normalization calculations. These steps were performed earlier for the midterm and rechecked before the final calculations. (See dataset summary and row counts in the midterm file.)

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### 2.3 Descriptive statistics — purpose and summary tables

Purpose: Descriptive statistics establish central tendency, dispersion and shape of the data distributions so we can choose appropriate forecasting and classification methods. In particular they explain whether demand is stable or volatile, whether prices are skewed and whether outliers are present.

Below are the tables to paste into the report. (Numbers are taken from the midterm summary tables. Source: midterm report tables 4.2.1–4.3.1.)

**Table 2.3.1. Descriptive Statistics — Raw Sales**

| METRIC | QTY | SALES RATE (₹) | TOTAL SALES (₹) |
|---|---|---|---|
| MEAN | 3.35 | 2,113.97 | 5,350.03 |
| MEDIAN | 3 | 1,200 | 3,400 |
| MODE | 1 | 623 | 2,492 |
| STD. DEVIATION | 2.70 | 1,529.90 | 4,181.95 |
| RANGE | 1 – 12.55 | 623 – 5,450 | 750 – 18,000 |
| SKEWNESS | 1.79 | 0.74 | 1.37 |
| KURTOSIS | 3.85 | –0.75 | 1.06 |
| COUNT | 69 | 69 | 69 |

Interpretation: raw sales orders are generally small (mean ≈ 3 units) but have a long right tail (skewness > 1), indicating a few high-value transactions. Price and revenue distributions are right-skewed — a small set of high-price items dominate totals.

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**Table 2.3.2 Descriptive Statistics — Purchases**

| METRIC | QUANTITY PURCHASED (QTY) | PURCHASE RATE (₹) | TOTAL PURCHASE AMOUNT (₹) |
|---|---|---|---|

| | | | |
|---|---|---|---|
| MEAN | 5.72 | 1,869 | 8,889.99 |
| MEDIAN | 5 | 1,275 | 6,150 |
| MODE | 2 | 2,731 | 4,960 |
| STD. DEVIATION | 4.55 | 1,274.04 | 6,627.52 |
| SKEWNESS | 2.52 | 0.61 | 1.03 |
| RANGE | up to 25.10 | 540 – 4,330 | 1,780 – 26,355 |
| MIN / MAX | 2 / 25.10 | 540 / 4,330 | 1,780 / 26,355 |
| COUNT | 37 purchases | — | — |

Interpretation: purchases are larger and more variable than sales (higher mean and STDDEV); procurement occurs in irregular bulk sizes (outliers up to 25 units). This indicates overstocking risk from infrequent bulk buys.

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**Table 2.3.3 Monthly totals (high-level time series)**

| MONTH | RAW SALES (₹) | RETAIL SALES (₹) | TOTAL SALES (₹) | RAW PROFIT (₹) | RETAIL PROFIT (₹) | TOTAL PROFIT (₹) |
|---|---|---|---|---|---|---|
| APRIL | 55,581 | 40,600 | 96,181 | 8,625 | 5,511 | 14,136 |
| MAY | 86,578 | 35,400 | 121,978 | 11,262 | 5,465 | 16,727 |
| JUNE | 138,214 | 50,100 | 188,314 | 20,305.5 | 6,314 | 26,619.5 |
| JULY | 88,779 | 86,000 | 174,779 | 14,787 | 13,804 | 28,591 |
| TOTAL (4 MONTHS) | 369,152 | 212,100 | 581,252 | 54,979.5 | 31,094 | 86,073.5 |

Interpretation: June had highest volume and profit. Combined raw sales dominate revenue while retail yields higher margins per transaction.

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**2.4 Demand stability metric (DSI) — definition and Excel implementation**

Why DSI. Profit and sales frequency alone miss demand *predictability*. A stable SKU is easier to plan for (lower safety stock or smaller reorder frequency); a highly variable SKU requires larger safety stock or tighter review.

Metric used (Coefficient of Variation / Demand Stability Index):

For each SKU we compute:

- Monthly quantities: $q_1$, $q_2$, $q_3$, $q_4$ (April–July).
- Average monthly demand: $\mu$ = AVERAGE ($q_1$: $q_4$)
- Standard deviation: $\sigma$ = STDEV.P($q_1$: $q_4$)

Define DSI (Demand Stability Index) as the coefficient of variation:

$$\mathrm{DSI} = \frac{\sigma}{\mu}$$

Interpretation: lower DSI ⇒ more stable demand; higher DSI ⇒ more volatile demand.

The coefficient of variation is a commonly used measure in inventory and operations management to assess demand variability. In this project, it is adapted as a Demand Stability Index (DSI) to support relative comparison across SKUs rather than absolute forecasting precision.

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**2.5 Improved ABC Classification**

**2.5.1 Limitations of the Previous Approach:**

In the midterm submission, ABC classification was based solely on profit contribution, which, although financially informative, failed to consider key operational metrics like sales frequency and demand stability. This limitation was highlighted in reviewer feedback, emphasizing that effective inventory planning requires a more balanced, multi-dimensional approach.

### 2.5.2 Enhancements Implemented

To address this, we adopted an enhanced ABC classification method that integrates three weighted criteria:

- Total Profit – Reflects financial impact per SKU.
- Sales Frequency – Captures how often an item is sold, representing operational turnover.
- Demand Stability – Measures consistency of monthly demand, using an inverted version of the Demand Stability Index (DSI).

This method ensures that SKUs are evaluated not only for profitability but also for how reliably and frequently they are sold, aligning classification more closely with real-world inventory planning needs.

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### 2.5.3 Step-by-Step Methodology

The following procedure was used in Excel to calculate the improved ABC score and assign classes:

**Step 1**: Prepare Monthly Quantity Data

- Create a pivot table of SKU × Month, showing sum of quantity sold per month (e.g., April to July).
- Paste these values into a new worksheet as the raw summary.

**Step 2**: Calculate Operational Metrics for Each SKU

- Average Monthly Demand: Compute the mean of the four months' sales.
- Total Quantity Sold (4 Months): Sum of April–July quantities.
- Sales Frequency: Count the number of months with non-zero sales (or total transactions per SKU).

- Demand Stability Index (DSI): Compute as the coefficient of variation — the standard deviation of monthly sales divided by the average.

**Step 3**: Compute Profit Metrics

- Use a pivot to extract Total Profit per SKU from raw sales data.

**Step 4**: Normalize All Metrics (Min-Max Scaling)

To combine metrics on the same scale:

- Normalized Profit: (Profit − Minimum Profit) ÷ (Maximum − Minimum)
- Normalized Frequency: (Frequency − Minimum Frequency) ÷ (Maximum − Minimum)
- Normalized Stability:
    - First invert DSI: Stability Score = 1 / (1 + DSI)
    - Then normalize this inverted value using min-max scaling

**Step 5**: Compute ABC Composite Score

- Add the three normalized metrics with equal weight:

ABC Score = Normalized Profit + Normalized Frequency + Normalized Stability

**Step 6**: Rank and Classify SKUs

- Sort all SKUs in descending order of ABC Score.
- Calculate Cumulative Share of total ABC Score for each SKU.
- Assign ABC Classes based on standard Pareto thresholds:
    - A-Class: Top ~70% cumulative share
    - B-Class: Next ~20%
    - C-Class: Remaining ~10%

## 2.6 Demand Forecasting Using 3-Month Moving Average

### 2.6.1 Why We Used This Method

Since we only had four months of sales data, using complex forecasting methods like ARIMA or exponential smoothing would not give reliable results. Instead, we used a Simple Moving Average (SMA) of three months to predict future demand. This method helps smooth out random ups and downs and gives a clearer idea of the actual sales trend.

### 2.6.2 Methodology

For each product, we took the average of its sales over the last three months. This average became the estimated demand for the next month. For example, if we had sales data for April, May, and June, we averaged these to forecast July's demand. It's a quick and practical way to guess what future sales might look like, especially when data is limited.

### 2.6.3 Usage in Inventory Planning

The moving average helps in deciding how much stock to keep. It gives a baseline number that can be used to plan restocking and avoid having too much or too little inventory. It also supports better safety stock and reorder decisions.

### 2.6.4 How It Was Visualized

We used line graphs to show both the actual monthly sales and the moving average line. This made it easier to see the pattern and spot if sales were going up, down, or staying steady. As required, all charts were labelled clearly with units like "Quantity Sold" and proper month names (e.g., Apr-2025, May-2025).

## 2.7 Demand Trend Tagging

### 2.7.1 Why This Was Done

Knowing if product demand is going up, down, or staying the same helps businesses plan better. For example, products that are becoming more popular might need to be restocked more often. On the other hand, items with falling demand should be ordered less to avoid overstock.

### 2.7.2 Methodology

We used a simple method by comparing the most recent moving average with the one before it:

If the new average was more than 10% higher than the previous one → Rising

If the new average was more than 10% lower → Declining

If the change was within 10% in either direction → Stable

This method is easy to understand and works well when the data is limited to a few months.

### 2.7.3 Application in Inventory Policy

Each product was given a trend tag (Rising, Stable, or Declining). Then we combined that with its ABC classification to decide what action to take:

**Table 2.7.1: Demand Trend Classification Criteria**

| ABC CLASS | DEMAND TREND | SUGGESTED ACTION |
|---|---|---|
| **A** | Rising | Increase stock and order more often |
| **A** | Stable | Keep current stock level |
| **A** | Declining | Reduce ordering, monitor usage |
| **B** | Rising | Monitor closely; may move to A |
| **C** | Declining | Consider stopping or minimizing stock |

This approach helped us make more informed decisions based on both how important a product is and how its demand is changing.

## 2.8 Final decision table (ABC class × Demand trend → Action)

Create a compact decision table (paste into report). Example:

**Table 2.8.1: Inventory Action Matrix (ABC × Trend)**

| ABC CLASS | DEMAND TREND | ACTION |
|---|---|---|

| | | |
|---|---|---|
| **A** | Rising | Increase reorder frequency; raise safety stock; ensure supplier lead time is short. |
| **A** | Stable | Maintain optimal reorder point; periodic review; prioritize supplier reliability. |
| **A** | Declining | Reduce order size gradually; investigate demand cause; do not overstock. |
| **B** | Rising | Monitor daily/weekly; increase review frequency; consider promotional push. |
| **B** | Stable | Controlled replenishment; regular review. |
| **C** | Rising | Evaluate margin; if profitable, consider moving to B monitoring. |
| **C** | Stable/Declining | Minimize stock; order only on demand or vendor-dropship; phase out if non-profitable. |

## 3. Results and Findings

This section presents the outputs of the analytical workflow described in Section 2, including the improved ABC classification, demand trend results, short-term forecasts (3-month moving average), and the combined inventory actions derived from these findings. Each table is followed by a summary of the results and any immediate actions required.

### 3.1 Improved ABC Classification — Summary

**Table 3.1: ABC Class Counts and Profit Share (Raw Sales Profit)**

| ABC CLASS | NUMBER OF SKUS | RAW SALES PROFIT (₹) | PROFIT SHARE (OF RAW SALES PROFIT) |
|---|---|---|---|
| A | 11 | 45,526.50 | 82.8% |
| B | 5 | 4,195.00 | 7.6% |

| | | | |
|---|---|---|---|
| C | 5 | 5,258.00 | 9.6% |
| TOTAL | 21 | 54,979.50 | 100% |

**Interpretation:**

The enhanced ABC classification consolidates financial importance into a small group of SKUs. Eleven SKUs (52% of the total) account for 83% of the raw sales profit, highlighting a concentration of business revenue in a limited number of items. These high-value SKUs must be carefully managed to ensure optimal service levels and stock availability.

Immediate Action:

- Prioritize A-class SKUs in procurement and stock review cycles.
- Implement weekly or bi-weekly reviews for supplier performance and stock levels of these SKUs.

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### 3.2 Top SKUs by ABC Score

**Table 3.2: Top 6 SKUs (by ABC Score)**

| RANK | ITEM CODE | ABC SCORE (COMPOSITE) | CUMULATIVE % (ABC SCORE) | ABC CLASS |
|---|---|---|---|---|
| **1** | SSF (A) | highest (top 1) | 8.38% | A |
| **2** | SSF (D) | 2nd | 16.33% | A |
| **3** | SSF (B) | 3rd | 24.51% | A |
| **4** | Teak Sawn Timber | 4th | 32.55% | A |
| **5** | DCF (D) | 5th | 38.86% | A |
| **6** | CTF (C) | 6th | 44.07% | A |

**Interpretation:**

The top ranks are dominated by SSF family SKUs and a high-value raw material, Teak Sawn Timber. These items show a high profit contribution and stable demand patterns, justifying their A-class status.

Immediate Action:

- For these top SKUs, ensure that safety stock calculations are conservative and that reliable service-level agreements are in place with suppliers (preferably shorter lead times).

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### 3.3 Demand Trend Tagging — Summary

**Table 3.3: Demand Trend Results (by SKU)**

| ITEM CODE | APR | MAY | JUN | JUL | DEMAND TREND |
|---|---|---|---|---|---|
| BSF (A) | 1 | 0 | 1 | 0 | Stable |
| BSF (B) | 1 | 0 | 0 | 0 | Stable |
| BSF (C) | 0 | 4 | 0 | 0 | Stable |
| BSF (D) | 0 | 0 | 6 | 1 | Declining |
| BSF (F) | 0 | 1 | 2 | 0 | Stable |
| CHAIR FRAME (A) | 0 | 6 | 12 | 0 | Rising |
| CHAIR FRAME (B) | 0 | 0 | 10 | 0 | Stable |
| CTF (A) | 0 | 1 | 3 | 0 | Rising |
| CTF (B) | 0 | 2 | 4 | 0 | Rising |
| CTF (C) | 2 | 1 | 5 | 4 | Rising |
| CTSF (A) | 6 | 3 | 0 | 0 | Declining |
| DCF (A) | 4 | 0 | 0 | 8 | Rising |
| DCF (B) | 4 | 0 | 0 | 0 | Stable |
| DCF (C) | 4 | 12 | 0 | 0 | Rising |

| | | | | | |
|---|---|---|---|---|---|
| DCF (D) | 6 | 8 | 0 | 14 | Rising |
| SSF (A) | 0 | 5 | 4 | 5 | Stable |
| SSF (B) | 1 | 0 | 9 | 4 | Declining |
| SSF (C) | 2 | 3 | 0 | 0 | Stable |
| SSF (D) | 3 | 2 | 3 | 0 | Stable |
| SSF (E) | 1 | 0 | 0 | 1 | Stable |
| TEAK SAWN TIMBER | 0 | 0 | 32.43 | 19.88 | Declining |

**Interpretation:**

A number of SKUs exhibit clear trends:

- Rising Demand: Chair Frame (A), DCF SKUs, CTF SKUs, and some others.
- Stable Demand: Most SKUs fall into this category, showing consistent demand patterns.
- Declining Demand: Items like CTSF (A), SSF (B), and Teak Sawn Timber show decreasing demand over the observed months.

Immediate Action:

- For Rising SKUs, increase monitoring and raise reorder frequency or quantities.
- For Declining SKUs, reduce order quantities and investigate the causes.
- For Stable SKUs, maintain established reorder points and check supplier reliability.

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**3.4 Forecasts (3-month moving average) — Selected Examples**

**Table 3.4: Example of SMA Forecast (Selected SKUs)**

| ITEM CODE | APR | MAY | JUN | JUL | 3-MONTH SMA (LATEST) |
|---|---|---|---|---|---|
| CHAIR FRAME (A) | 0 | 6 | 12 | 0 | ≈ 6.0 |
| DCF (D) | 6 | 8 | 0 | 14 | ≈ 7.33 |
| SSF (A) | 0 | 5 | 4 | 5 | ≈ 4.67 |

| | | | | | |
|---|---|---|---|---|---|
| TEAK SAWN TIMBER | 0 | 0 | 32.43 | 19.88 | ≈ 17.44 |

**Interpretation:**

The three-month moving averages provide expected demand for the following months. For example, Chair Frame (A) has a forecasted demand of around 6 units per month. Teak Sawn Timber's forecast indicates significant demand, but with a decline compared to its June spike.

Immediate Action:

- Use the SMA figures to set reorder quantities for the next few months.
- Combine the SMA with safety stock (based on DSI) for final replenishment numbers.

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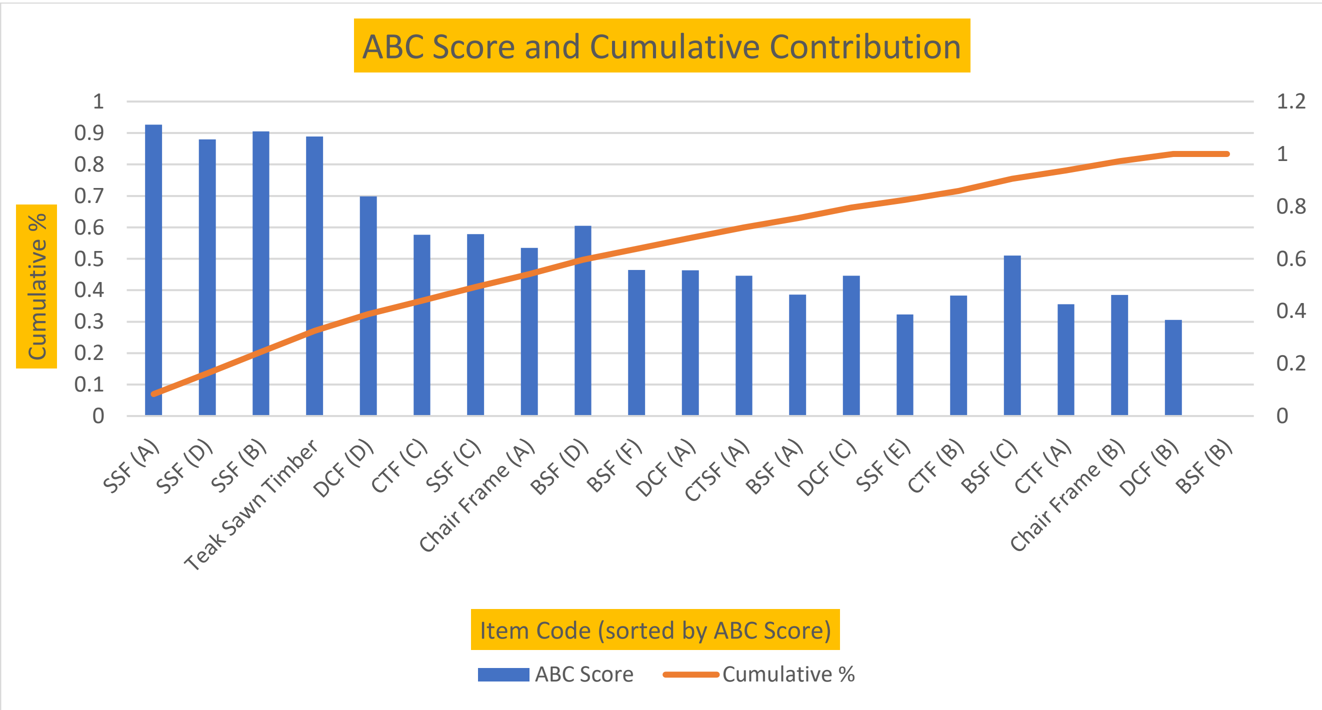
### 3.5 Visualization

Figure 3.5.1 — Pareto / ABC Chart

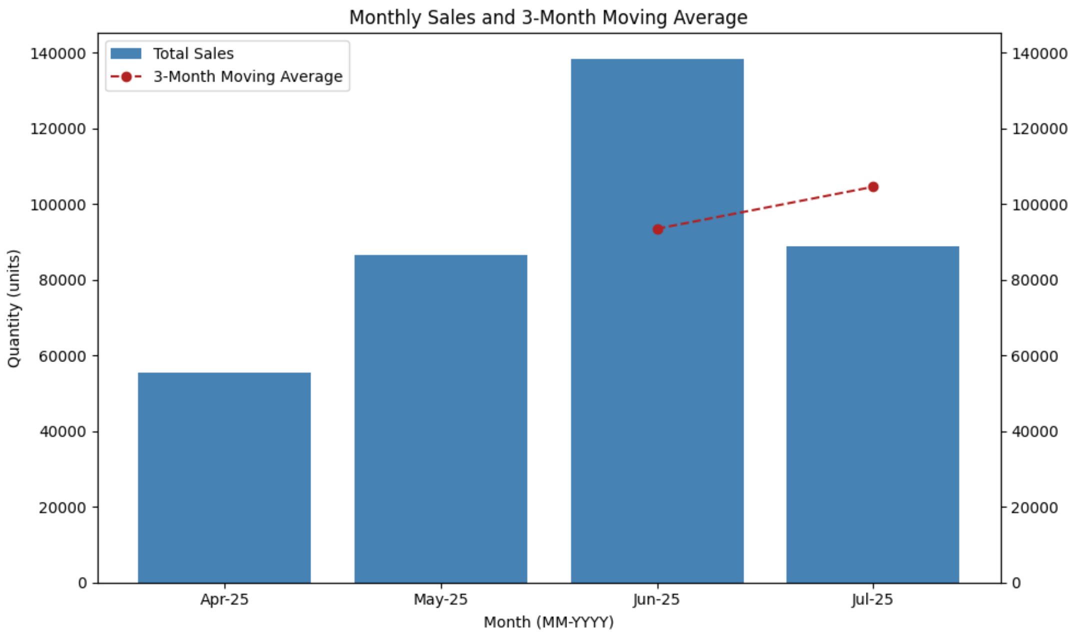



- **What it shows**: ABC Score or Profit (₹) by SKU (bar chart) with cumulative percentage (line chart)
- **Axis labels**:

1. Y-axis: "Cumulative % (%)"
2. X-axis: "Item Code (sorted)"

- **Interpretation**: The Pareto chart shows that the top 4- SKUs contribute the majority of the composite ABC score. These items must be prioritized for procurement, stock reviews, and lead time monitoring to protect revenue flow.

Figure 3.5.2 — Monthly Sales with 3-month SMA (Sample SKUs)

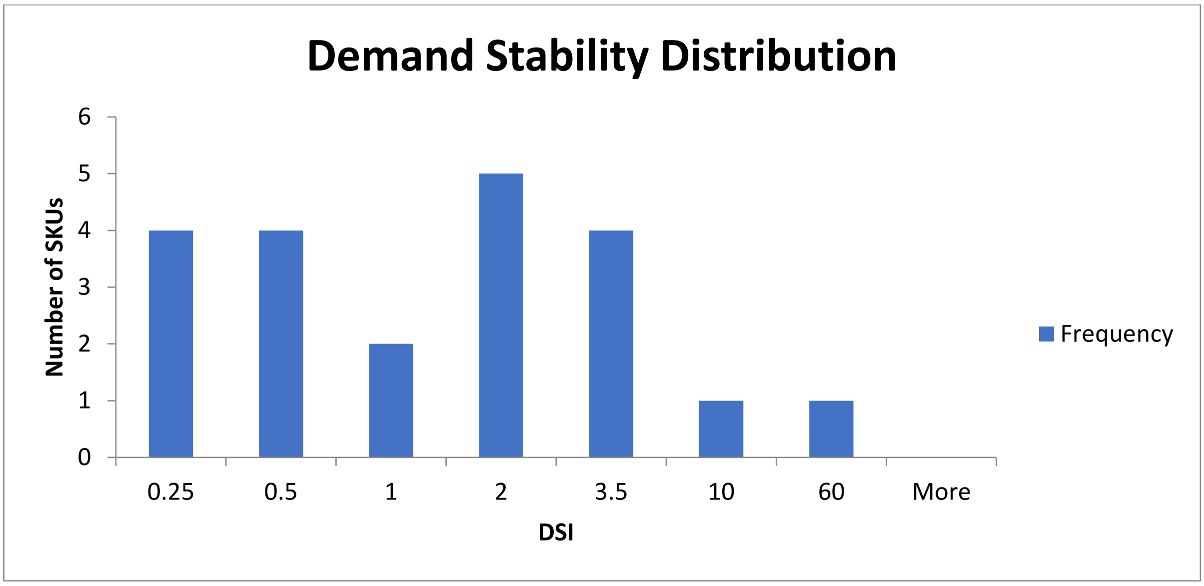



- **What it shows**: Monthly sales as bars overlaid with 3-month SMA as a trend line
- **Axis labels**:

1. Y-axis: "Quantity (units)"
2. X-axis: "Month (MM-YYYY)"

- **Caption**: *Monthly sales and 3-month moving average for representative SKUs.*
- **Interpretation**: Items like *Chair Frame (A)* display a rising demand pattern with an increasing SMA trend, signalling the need to raise reorder frequency. Conversely, other SKUs show steadiness or drops, informing procurement decisions.

Figure 3.5.3 — Demand Stability Distribution (Histogram or Boxplot)




- What it shows: Histogram of DSI (coefficient of variation) across SKUs
- Axis labels:

1. Y-axis: "Number of SKUs"
2. X-axis: "DSI (coefficient of variation)"

- Caption: *Distribution of SKU demand stability (lower DSI = more stable).*
- Interpretation: Most SKUs have low DSI values (0.1–1.5), indicating predictable demand and eligibility for scheduled restocking. A few outliers (DSI > 3.0, such as BSF (B)) show high volatility and require special ordering policies (e.g., JIT or vendor-managed inventory).

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### 3.6 Final Consolidated Action Table (SKU-Level)

Table 3.6.1: SKU → ABC Class → Demand Trend → Recommended Action

| ITEM CODE | ABC CLASS | DEMAND TREND | RECOMMENDED ACTION |
|---|---|---|---|
| SSF (A) | A | Stable | Keep high availability; weekly stock review |

| | | | |
|---|---|---|---|
| SSF (D) | A | Stable | Maintain high stock; monitor supplier lead time |
| SSF (B) | A | Declining | Reduce reorder quantity; investigate cause |
| TEAK SAWN TIMBER | A | Declining | Lower future purchase quantities; avoid bulk orders |
| DCF (D) | A | Rising | Increase reorder frequency; raise safety stock |
| CTF (C) | A | Rising | Prioritize replenishment; consider increasing MOQ |
| SSF (C) | A | Stable | Maintain established reorder point |
| CHAIR FRAME (A) | A | Rising | Increase planned orders; prepare supplier commitments |
| BSF (D) | A | Declining | Taper orders; investigate demand shift |
| BSF (F) | A | Stable | Continue current procurement cadence |
| DCF (A) | A | Rising | Raise reorder frequency; monitor stock closely |
| CTSF (A) | B | Declining | Reduce stock, consider phase-out if trend persists |
| BSF (A) | B | Stable | Controlled replenishment; monthly review |
| DCF (C) | B | Rising | Monitor for promotion to A if sustained |
| SSF (E) | B | Stable | Keep minimal safety stock; reorder on schedule |

| | | | |
|---|---|---|---|
| CTF (B) | B | Rising | Monitor closely; prepare for higher demand |
| BSF (C) | C | Stable | Reduce safety stock; reorder only as needed |
| CTF (A) | C | Rising | Monitor trend; consider targeted promotion |
| CHAIR FRAME (B) | C | Stable | Minimize inventory; reorder on demand |
| DCF (B) | C | Stable | Consider vendor-managed supply or JIT ordering |
| BSF (B) | C | Stable | Maintain minimum stock; avoid bulk purchases |

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### 3.7 Summary of Key Findings (Short Bullets)

- The enhanced ABC classification identifies 11 SKUs (approximately 52% of SKUs) as A-class, contributing 83% of raw sales profit. These items are a priority for operational management.
- Trend tagging highlights several rising SKUs, including Chair Frame (A) and multiple DCF items, suggesting that replenishment efforts should focus on these items.
- Declining demand for certain SKUs, such as Teak Sawn Timber and SSF (B), requires adjustments to order quantities to avoid overstock.
- 3-month SMA provides a robust short-term forecasting method, especially for fast-moving items with short sales cycles. This forecast can be combined with safety stock to calculate final reorder quantities.

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## 4. Interpretation of Results and Recommendations

This section draws key insights from the ABC classification, demand trend analysis, and forecast results presented earlier. The aim is to translate data-driven findings into actionable inventory and procurement strategies.

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### 4.1 Strategic Implications of ABC Classification

The updated ABC model highlights that approximately 83% of the raw sales profit is driven by just over half of the SKUs (classified as A). These high-impact SKUs are core revenue drivers and require tight monitoring. Many of these items, such as SSF (A), SSF (D), and Teak Sawn Timber, also display stable or declining trends, further reinforcing the need for close control to avoid service disruptions or unnecessary overstocking.

- Recommendation: A-class SKUs should be reviewed weekly or biweekly. Set minimum stock levels based on forecasted demand and lead time buffers. Introduce vendor performance tracking for these items.

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### 4.2 Operational Risk in Declining SKUs

Several A- and B-class SKUs (e.g., SSF (B), CTSF (A), Teak Sawn Timber) show a declining demand trend. These items, while valuable, pose a risk of overstocking if procurement patterns remain unchanged.

- Recommendation: Transition these SKUs to a controlled replenishment strategy. Reduce purchase volumes and investigate demand shifts potential causes include seasonal factors, product substitution, or pricing sensitivity.

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### 4.3 Demand Trend as a Planning Signal

Trend tagging reveals a set of Rising SKUs across multiple product lines (notably Chair Frame (A), CTF (C), DCF (D)). These trends are indicative of either seasonal spikes or latent demand growth.

- Recommendation: Adjust reorder policies for these SKUs. For example, increase order frequency and safety stock to maintain availability. Monitor closely for trend reversals and consider upgrading fast-growing B-class items to A-class if the trend sustains.

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**4.4 Reliability of 3-Month Moving Averages**

Given the limited data window (Apr–Jul), the use of 3-month SMA proved effective in smoothing monthly noise. Forecasts for SKUs such as SSF (A) and DCF (D) offer reliable short-term expectations.

- Recommendation: Base near-term reorder quantities on SMA forecasts, adjusted for stability (DSI) and safety stock requirements. Regularly update SMA values as new months are added to ensure responsiveness.

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**4.5 Integrated Action Planning**

The consolidated action table demonstrates how ABC and trend labels can jointly inform SKU-specific strategies. For instance, CTF (C) being both A-class and Rising demands priority stocking, whereas BSF (B), being C-class and Stable, can follow a just-in-time strategy.

- Recommendation: Operationalize the final action table using conditional rules in the procurement planning system. Assign review cycles based on class (A = weekly, B = biweekly, C = monthly) and trend (Rising = proactive orders, Declining = minimal reorders).

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**5. Presentation and Data**