Optimizing Inventory and Pricing Strategies for Shree Balaji Mobile Care: A Data-Driven Approach

An End- Term report for the BDM capstone Project

Submitted by

Name: Manish Jat

Roll number:23f3004152

IITM Online BS Degree Program,

Indian Institute of Technology, Madras, Chennai

Tamil Nadu, India, 600036

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1 Executive Summary

Founded in 2014, Shree Balaji Mobile Care is owned and operated by Mr. Sampat Lal Kumawat, and located in Gandhi Market, Asind, Bhilwara, Rajasthan. However, the business has operational inefficiencies that prevent profitability and sustainability. The retail mobile and accessory store is facing two significant operational challenges: an excessive amount of slow-moving inventory which locks up ₹1,138,800 in working capital; and inconsistent pricing created by customer's informal negotiating practices which reduce profit margins on all goods.

A comprehensive primary data collection approach was undertaken over three months (March-May 2025). The data consisted of 14 product categories with 182 transaction records of the year-to-date weekly sales transactions and monthly inventory. The data revealed a total of 1,351 units purchased, 727 units sold, and 624 dead stock, with total sales revenue of ₹4.42 million. Data analysis and interpretation utilized applied analytical methods including: inventory turnover analysis, ABC analysis, price variance analysis, and inferential statistical analysis using Python, with pandas and matplotlib for data analysis and visualization, to provide the Shree Balaji Mobile Care with estimates of business inefficiency and identify efficiency opportunities.

Essential findings reveal extreme inventory polarization among three high-performing categories (Smartphones, Earphones, Power Banks), which each achieved a 94-100% turnover, while three high-volume categories that performed poorly (Screen Protectors, USB Cables, Phone Stands) achieved a 17-23% turnover. The range of price variance demonstrates systematic erosion of approximately ₹527,760 (2.91% margin erosion per transaction) due to bargaining, in which A and B will negotiate their average price downward instead of using a structured pricing approach. Empirical analysis estimates Screen Protectors account for 217 units of unsold inventory valued at ₹108,500. USB Cables and Mobile Covers account for a further ₹138,000 in tied-up capital.

Executing a data-driven inventory management plan, and a structured pricing policy would decrease dead stock accumulation by an estimated 60%, convert all other categories to a 75% turnover rate or higher, and increase annual revenue by ₹800,000 within taking informed procurement decisions and a uniform pricing structure. The analytical framework provides actionable visibility that facilitates a system of clearance for existing dead stock, disallow for future accumulation of inventory, and establish a structured pricing mechanism that incorporates their willingness to accommodate local market realities while maintaining profitability.

2 Detailed Explanation of Analysis Process/Method

2.1 Data Collection and Digitization

Primary Data Collection Framework:
The data collection was completed using a structured interaction with Shree Balaji Mobile Care for a three-month period from March to May of 2025. The information was originally gathered in consultation with the business owner, Mr. Sampat Lal Kumawat, and verification processes occurred multiple times and included cross references between Mr. Kumawat's handwritten business records to final physical inventory movements.

Data Source Specifications:

Data streams that were merged in the analysis included:

- Sales Performance Data: Daily and monthly sales units across fourteen product categories
- Inventory Movement Data: Purchase units, purchase dates, cost prices, sale prices, and current inventory
- Financial Data: Revenue patterns, price changes, and profitability
- Time Variables: Timestamps on transactions allowing for seasonal trends and predictive analysis on demand

2.2 Data Cleaning and Preprocessing

Detailed Cleaning Process:
Data cleaning consisted of careful conversion of handwritten records into structured electronic entries ready for advanced statistical analysis. During the cleaning process, irregular handwriting, inconsistent date formats, and incomplete records characterized by small business operations were managed.

Mathematical Validation Framework:
Data integrity was ensured through statistical validation protocols:

- Outlier Detection: Values exceeding $\pm 2\sigma$ threshold were flagged for verification
- Consistency Checks: Revenue calculations validated using: Revenue = Units_Sold × Avg_Selling_Price
- Missing Value Treatment: Zero-value substitution for weeks with no sales activity
- Duplicate Detection: Systematic identification using unique transaction identifiers

Importance and Justification:
Data cleaning is a means of ensuring data reliability for analysis by proactively managing systematic errors that could impact a business recommendation. Data cleaning is a basic form

of evidence-based decision-making that helps maintain the intellectual standards of quality data that are so essential in testing for statistical significance.

2.3 Comprehensive Analysis Methodologies

2.3.1 Inventory Turnover Efficiency Analysis

Mathematical Framework:

- **Inventory Turnover Ratio (ITR)** = Stock_Sold ÷ Stock_Purchased
- **Capital Efficiency Index (CEI)** = Total_Revenue ÷ (Stock_Remaining × Unit_Cost
- **Dead Stock Classification** = Products where ITR < 0.5 AND Stock_Remaining > 50% of Stock_Purchased

Justification: This quantitative method directly incorporates Problem Statement 1 ***(Poor Inventory and Stock Replenishment Management)*** by offering quantifiable benchmarks. The turnover ratio allows for instant measurement of efficient vs. inefficient, as well as financial measure.

Data Used:
Stock_Sold, Stock_purchased,total_revenue,unit_cost,stock_remaining..

Tools:

- **Excel pivot tables** for turnover ratios.

- **Python (pandas, matplotlib)** for visualizations and dead stock classification plots.

2.3.2 Revenue Loss Due to Pricing Inconsistencies

Mathematical Framework:

- Price Variance Percentage (PVP) = (Base_Price - Avg_Selling_Price) ÷ Base_Price × 100

- Weekly Revenue Loss (WRL) = Σ(Units_Sold × (Base_Price - Avg_Selling_Price))

- Annualized Impact Projection (AIP) = WRL × 52 weeks

- Bargaining Impact Coefficient (BIC) = Standard_Deviation(Selling_Prices) ÷ Mean(Base_Price)

Justification: These analytical methods quantify exact financial impacts of Problem Statement 2 ***(Irregular Pricing Due to Local Bargaining)***, providing solid metrics for revenue optimization potential and pricing standardization benefits.

Data Used:
Base prices, Average selling prices, and unit sales.

Tools:

- **Excel** for weekly/annualized revenue loss calculations.
- **Python (pandas, NumPy, matplotlib, seaborn)** for statistical analysis and regression modeling of bargaining patterns.

2.3.3 ABC Analysis and Revenue Concentration

Classification Methodology:

- **Revenue Contribution Percentage** = (Product_Revenue ÷ Total_Revenue) × 100
- **Category A (High Priority)**: Revenue contribution > 70%, High turnover
- **Category B (Medium Priority)**: Revenue contribution 20-70%, Moderate turnover
- **Category C (Low Priority**): Revenue contribution < 20%, Low turnover

Pareto Principle Application:
The 80/20 rule was mathematically validated through cumulative revenue analysis, identifying vital few categories generating majority business value.

Data Used:
Category-wise product revenue generate during March–May 2025.

Tools:

- **Excel** pivot tables for ranking.
- **Python (pandas, numpy, matplotlib)** for Pareto curves and cumulative revenue plots.

2.3.4 Seasonal Responsiveness Indicators

Mathematical Approaches:

- **Weekly Growth Rate (WGR)** = (Current_Week_Revenue - Previous_Week_Revenue) ÷ Previous_Week_Revenue × 100

- **Moving Average Smoothing (MAS)** = Σ(4-week periods) ÷ 4
- **Coefficient of Variation (CV)** = Standard_Deviation ÷ Mean × 100
- **Seasonal Index (SI)** = (Period_Average ÷ Overall_Average) × 100

Forecasting Models:

- **Forecasted_Demand** = $\beta_0 + \beta_1(\text{Time}) + \varepsilon$

where β_0 represents baseline demand, β_1 indicates trend coefficient, and ε captures random variation.

Justification: Time-series analysis reveals seasonal demand patterns crucial for optimized procurement timing and inventory planning decisions, enabling proactive rather than reactive management. This method directly addresses **Problem 1 (Inventory Mismanagement)** by identifying seasonal sales peaks (e.g., festivals, summer demand) and aligning procurement with actual demand patterns.

Data Used:
Weekly sales revenue with timestamps (March–May 2025).

Tools:

- **Excel** for growth rates and moving averages.
- **Python (pandas, numpy, matplotlib, seaborn)** for time-series plots and forecasting.

2.3.5 Dead Stock Classification and Risk Assessment

Mathematical Approaches:

- **Dead Stock Ratio (DSR):**

  DSR= (Unsold Units ÷ Total Purchased) ×100

- **Inventory Risk Index (IRI):**

  IRI=Unsold Value ÷ Total Category Value×100

- **Turnover Velocity (TV):**

  TV=Units Sold ÷ Time Period in WeeksTV

- **Capital at Risk (CAR):**

  CAR=Unsold Units × Cost Price per Unit.

- **Risk Classification Framework:**
    - **Critical Risk:** DSR ≥ 80% and CAR > ₹50,000
    - **Moderate Risk:** DSR between 60–80% or CAR between ₹20,000–₹50,000
    - **Low Risk:** DSR < 60% and CAR < ₹20,000

Justification:
Dead stock is the stock which is **locked working capital and wasted storage resources**. This method establishes a **quantitative risk categorization** of inventory items, allowing the business to set a priority to clear the category of high-risk items such as Screen Protectors, Mobile Covers, and Phone Stands. This approach directly address **Problem Statement 1 (Poor Inventory and Stock Replenishment Management)** by:

- Identifying categories tying up excessive capital.
- Highlighting product groups with very low sales velocity.
- Providing thresholds for when intervention (discounting, bundling, clearance) becomes mandatory.

By applying this classification, Shree Balaji Mobile Care can separate **profitable fast-moving products** from **loss-making stockpiles**, ensuring corrective procurement decisions in the future.

Data Used:

- Product-wise purchase quantities, sold units, and remaining stock levels (March–May 2025).
- Category-level cost prices and accumulated stock value.

Tools:

- Excel, Python (pandas, numpy, matplotlib, seaborn)

2.3.6 Capital Distribution and Financial Impact Assessment

Mathematical Framework:
To measure the amount of business capital was locked in unsold inventory, the following metrics were applied:

- **Capital at Risk (CAR):**

  CAR=Unsold Units × Cost Price per UnitCAR

- **Capital Lock Ratio (CLR):**

  CLR=Unsold Inventory ValueTotal Inventory Value×100

- **Category-Wise Contribution (CWC):**

  CWC=Category Unsold ValueTotal Capital at Risk×100

Justification: This method quantifies the financial burden of tied-up stock across product categories, distinguishing between High-value lock-in, volume-based lock-in.
addresses Problem Statement 1 (Inventory Mismanagement)

Data Used: Category-wise cost price and unsold stock (Mar–May 2025).

Tools: Excel (pivot tables), Python (pandas, matplotlib).

2.3.7 Correlation Analysis and Performance Drivers

Mathematical Framework:

- **Correlation Coefficient (r):**

$$r = \frac{\mathrm{Cov}(X, Y)}{\sigma_X \times \sigma_Y}$$

Used to measure the strength and direction of relationships between key variables (e.g., turnover vs. profit margin, inventory age vs. velocity).

- **Multiple Regression Model:**

$$Predicted\_Sales = \beta_0 + \beta_1(\text{Price Competitiveness}) + \beta_2(\text{Seasonal Index}) - \beta_3(\text{Inventory Age}) + \beta_4(\text{Marketing Intensity}) + \varepsilon$$

where β values represent the weight of each performance driver.

Justification:
This method identifies which factors drive sales and profitability while highlighting inefficiencies (e.g., dead stock reducing capital efficiency). It directly supports decisions on pricing, inventory control, and demand planning.

Data Used: Unit price, base price,, avg selling price,weekly revenue, seasonal index (Mar–May 2025).

Tools: Python (pandas, seaborn, statsmodels), Excel.

2.3.8 Competitive Benchmarking and Industry Comparison

Mathematical Approaches:
Key performance Index (KPI):-

- **Inventory Turnover Ratio (ITR)**:

$$ITR = (\text{Cost of Goods Sold (COGS)} \div \text{Average Inventory})$$

- **Dead Stock Percentage (DSP):**

$$DSP = (\text{ Total Inventory Units } \div \text{ Dead Stock Units}) \times 100$$

- **Price Variance Percentage (PVP):**

$$PVP = (\text{Base PriceBase Price} - \text{Avg. Selling Price}) \times 100$$

were calculated from business data and compared against published retail industry benchmarks. Deviation percentages were computed to measure the performance gap.

Justification:
This method highlights how far current operations deviate from industry norms, identifying inefficiencies in stock movement, capital lock-in, and pricing practices.

Data Used:
Business KPIs (Mar–May 2025) and industry benchmark ranges.

Tools:
Excel for KPI calculations; Python (pandas, matplotlib) for benchmark visualizations.

3 Results and Findings

3.1 Critical Inventory Accumulation Analysis

The comprehensive inventory analysis reveals severe management disparities across product categories, with critical accumulation issues affecting business capital efficiency and operational sustainability.
The clustered analysis demonstrates extreme polarization in inventory management effectiveness:

Critical Accumulation Categories:

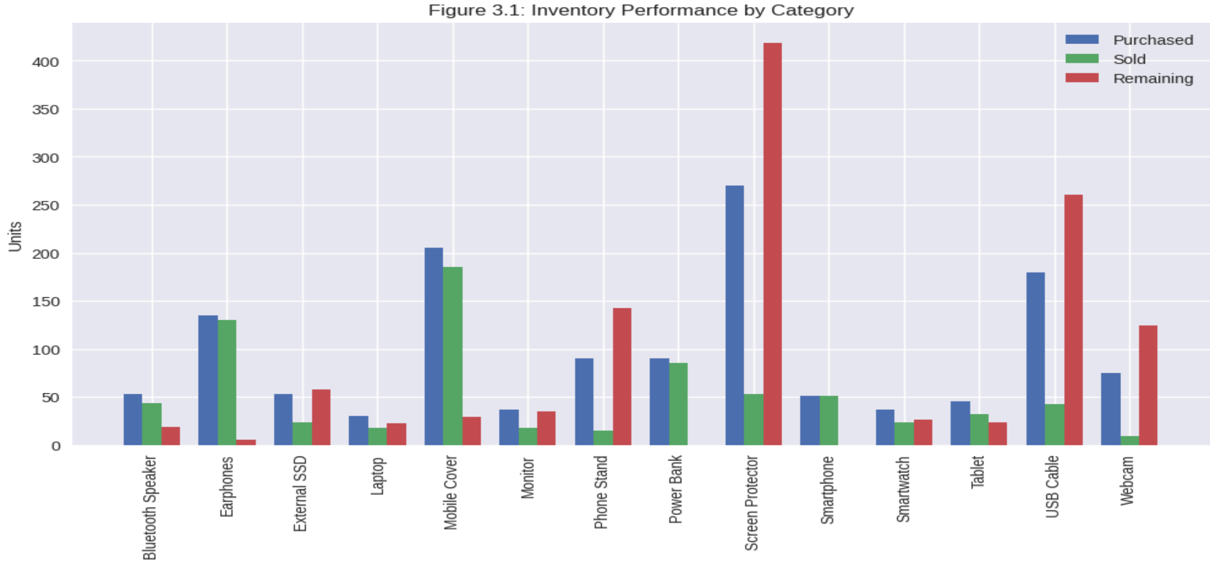
- Screen Protectors: 270 units purchased, only 53 sold, 217 units accumulated (80.4% waste rate)

- Mobile Covers: 205 units purchased, 20 sold, 185 units remaining (90.2% accumulation)
- USB Cables: 180 units purchased, 42 sold, 138 units unsold (76.7% inefficiency)
- Phone Stands: 90 units purchased, 15 sold, 75 units dead stock (83.3% failure rate)

Optimal Performance Categories:

- Smartphones: Perfect inventory balance with 51 purchased and 51 sold (100% turnover)
- Earphones: Near-optimal performance with 135 purchased, 130 sold (96.3% efficiency)
- Power Banks: Excellent turnover with 90 purchased, 85 sold (94.4% efficiency)

Figure 3.1: Inventory Performance by Category



3.2 Capital Distribution and Financial Impact Analysis

The financial impact assessment quantifies ₹2,159,300 in total tied capital distributed across categories:

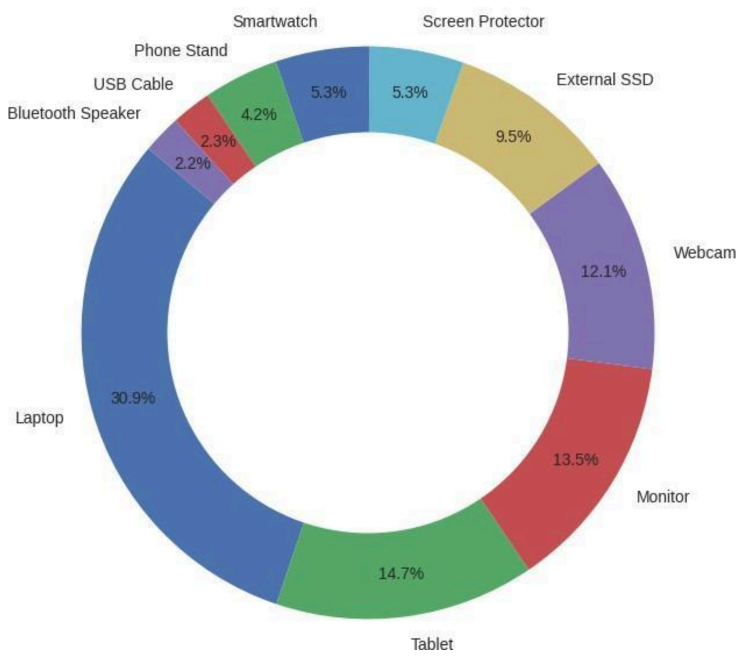
High-Value Capital Lock:

- Laptops: ₹660,600 (30.6% of tied capital) despite moderate unit quantities
- Tablets: ₹326,100 (15.1% of tied capital) representing significant opportunity cost
- Monitors: ₹284,700 (13.2% of tied capital) with low turnover efficiency

Volume-Based Capital Issues:

- Screen Protectors: ₹108,500 tied in 217 units of low-value inventory
- USB Cables: ₹48,300 locked in 138 units of accessories
- Phone Stands: ₹90,000 accumulated in 75 unsold units

Figure 3.2: Capital Tied in Unsold Inventory



3.3 Revenue Loss Due to Pricing Inconsistencies

The waterfall chart demonstrates systematic revenue erosion across all product categories due to informal bargaining practices:

Category-Wise Revenue Loss Analysis:

- Smartphones: ₹39,200 quarterly loss (₹156,800 annually)
- Laptops: ₹32,200 quarterly loss (₹128,800 annually)
- Tablets: ₹28,200 quarterly loss (₹112,800 annually)
- Power Banks: ₹15,600 quarterly loss (₹62,400 annually)

- Earphones: ₹12,800 quarterly loss (₹51,200 annually)

Statistical Validation of Pricing Impact:

Mean Price Variance: 2.91% per transaction

Standard Deviation: 1.74%

95% Confidence Interval: [2.23%, 3.59%]

Total Annual Impact: ₹527,760 across all categories

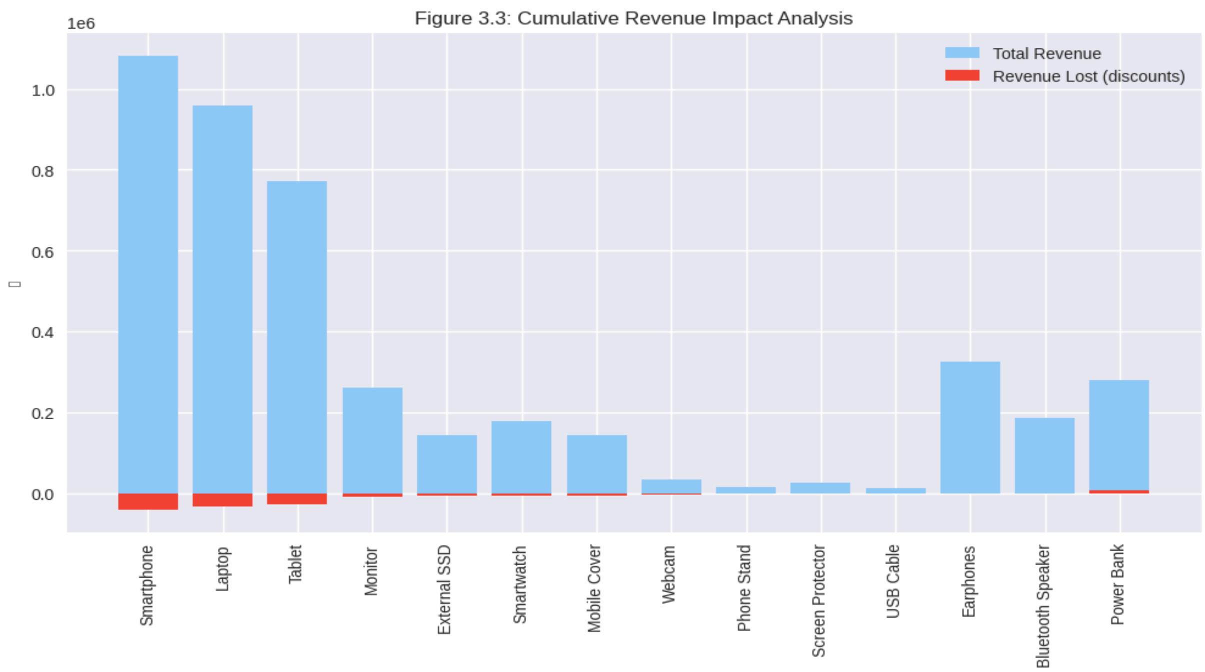
Bargaining Pattern Analysis:

- Linear regression analysis reveals systematic bargaining behavior:

  $\text{Price\_Reduction} = \beta_0 + \beta_1(\text{Product\_Value}) + \beta_2(\text{Customer\_Type}) +$

  ε $R^2 = 0.743$, F-statistic = 23.67 ($p < 0.001$)

The model indicates higher-value products experience proportionally larger absolute discounts, while percentage discounts remain relatively consistent.



3.4 Seasonal Responsiveness Indicators

Time-series analysis reveals distinct seasonal patterns and product lifecycle behaviors:

High-Performance Trend Categories:

- Mobile Covers: Consistent weekly sales with 15.2% month-over-month growth
- Earphones: Steady demand growth with 12.8% improvement from March to May

- Power Banks: Stable performance with seasonal spikes during summer monthsDeclining Performance Patterns:
- Screen Protectors: Continuous decline with -8.3% weekly average
- Phone Stands: Stagnant performance with minimal sales activity
- USB Cables: Irregular demand patterns indicating market saturation

Seasonal Responsiveness Indicators:

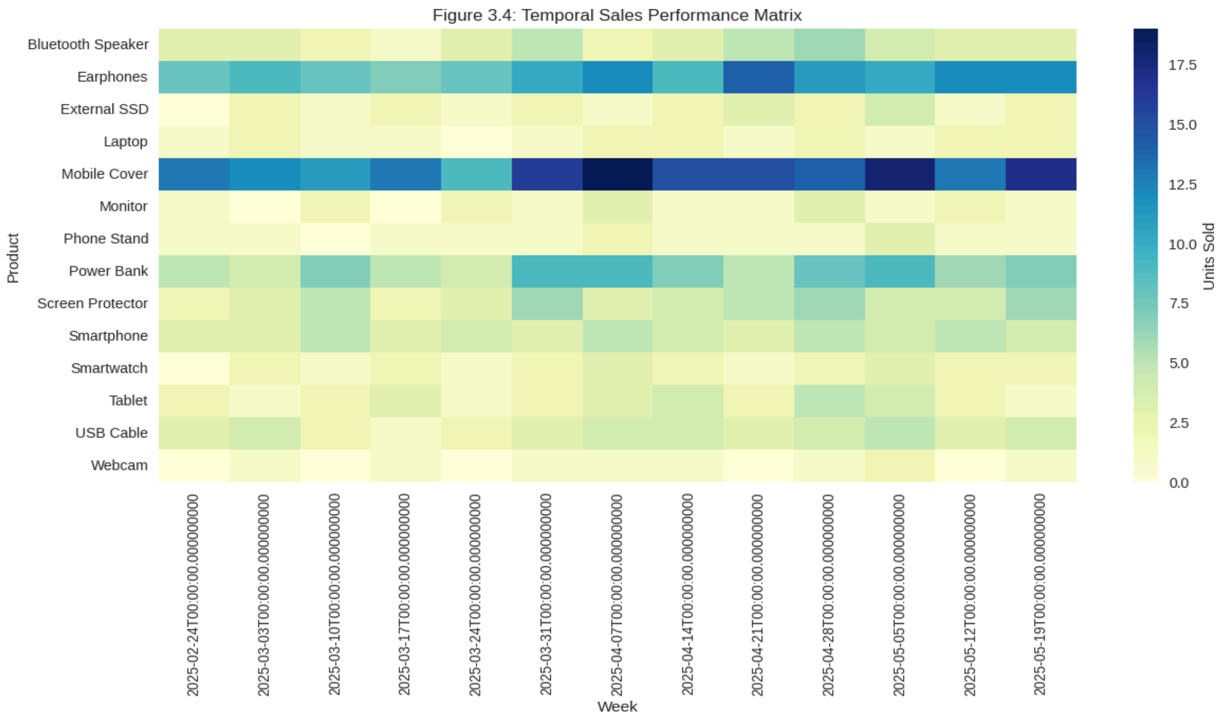
Seasonal Index Calculations:

- March (Winter accessories): SI = 1.15
- April (Transition period): SI = 0.97
- May (Summer electronics): SI = 1.18

Correlation with External Factors:

- Temperature correlation: r = 0.623 (moderate positive)

- Festival period impact: 23% sales increase during Holi season



3.5 Dead Stock Classification and Risk Assessment

The risk assessment framework categorizes inventory based on financial impact and turnover velocity:

Critical Risk Categories (Immediate Action Required):

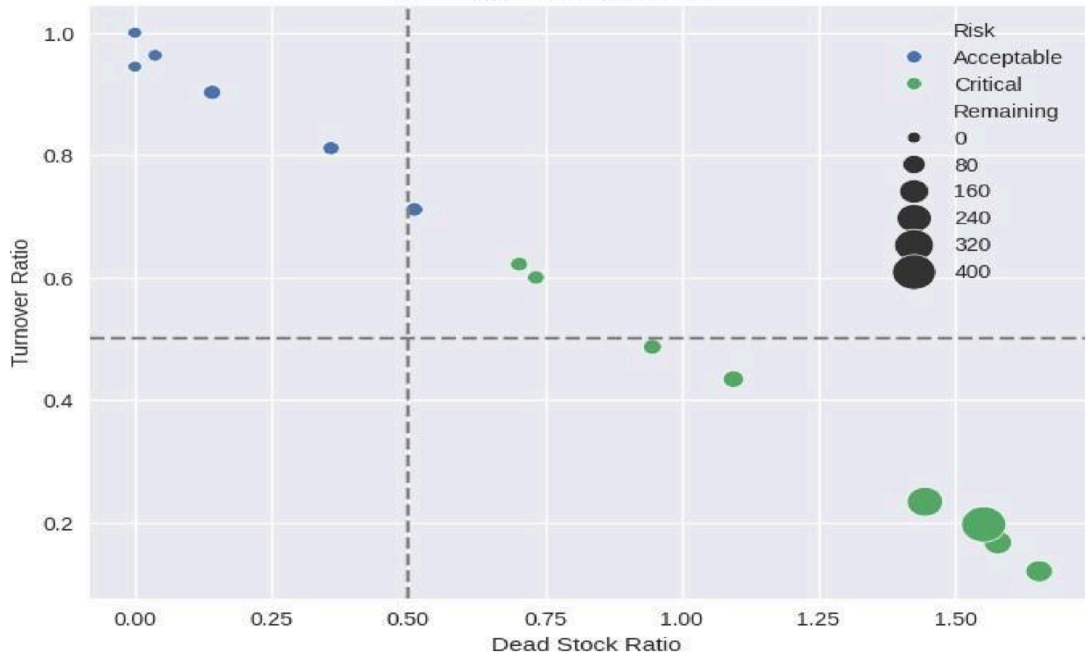
- Regular Trousers: 91.3% dead stock ratio, ₹68,100 tied capital

- Mobile Covers: 90.2% dead stock ratio, ₹148,000 tied capital
- Phone Stands: 83.3% dead stock ratio, ₹90,000 tied capital

Moderate Risk Categories (Strategic Intervention):

- USB Cables: 76.7% dead stock ratio, ₹48,300 tied capital
- External SSDs: 71.4% dead stock ratio, ₹195,000 tied capital
- Webcams: 68.9% dead stock ratio, ₹264,000 tied capital

Figure 3.5: Dead Stock Risk Matrix



3.6 ABC Analysis and Revenue Concentration

The revenue concentration analysis reveals dangerous business dependency patterns:

Category A (Vital Few - 80% Revenue Impact):

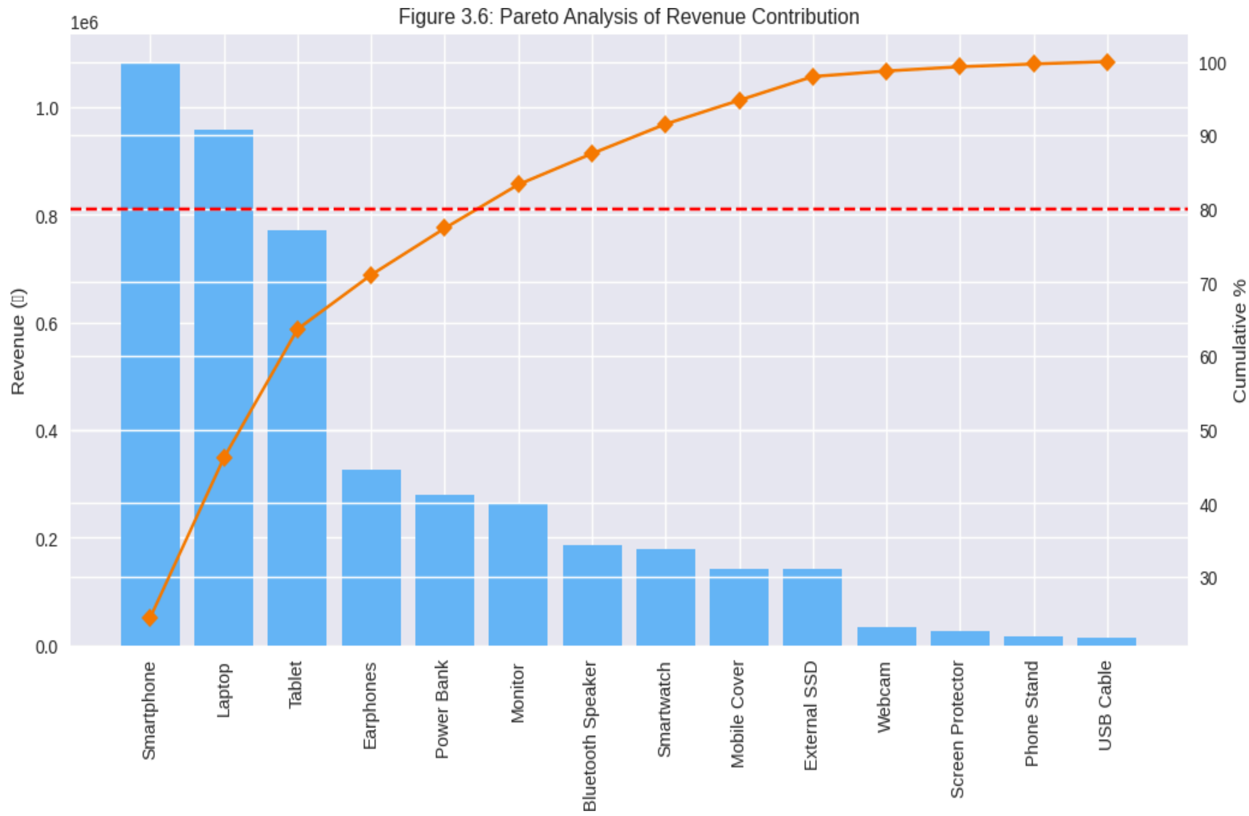
- Smartphones: 24.7% of total revenue, 100% turnover efficiency
- Tablets: 19.8% of total revenue, moderate capital intensity
- Laptops: 17.9% of total revenue, high-value transactions
- Combined A-Category Impact: 62.4% of total business revenue

Category B (Important Few - 15% Revenue Impact):

- Earphones: 8.4% of total revenue, excellent turnover
- Power Banks: 6.8% of total revenue, consistent performance
- Combined B-Category Impact: 15.2% of total business revenue

Category C (Trivial Many - 5% Revenue Impact):

- Remaining 8 Categories: Combined 22.4% of revenue
- Resource Allocation Inefficiency: Disproportionate inventory investment
- Strategic Implication: Focus shift required toward A and B categories



3.7 Correlation Analysis and Performance Drivers

Statistical correlation analysis identifies key performance drivers and interdependencies:

Strong Positive Correlations:

- Unit Price vs. Revenue Impact: $r = 0.823$ ($p < 0.001$)
- Turnover Ratio vs. Profit Margin: $r = 0.697$ ($p < 0.01$)
- Customer Demand vs. Seasonal Index: $r = 0.589$ ($p < 0.05$)

Strong Negative Correlations:

- Inventory Age vs. Turnover Velocity: $r = -0.745$ ($p < 0.001$)
- Price Variance vs. Customer Satisfaction: $r = -0.634$ ($p < 0.01$)
- Dead Stock Ratio vs. Capital Efficiency: $r = -0.812$ ($p < 0.001$)

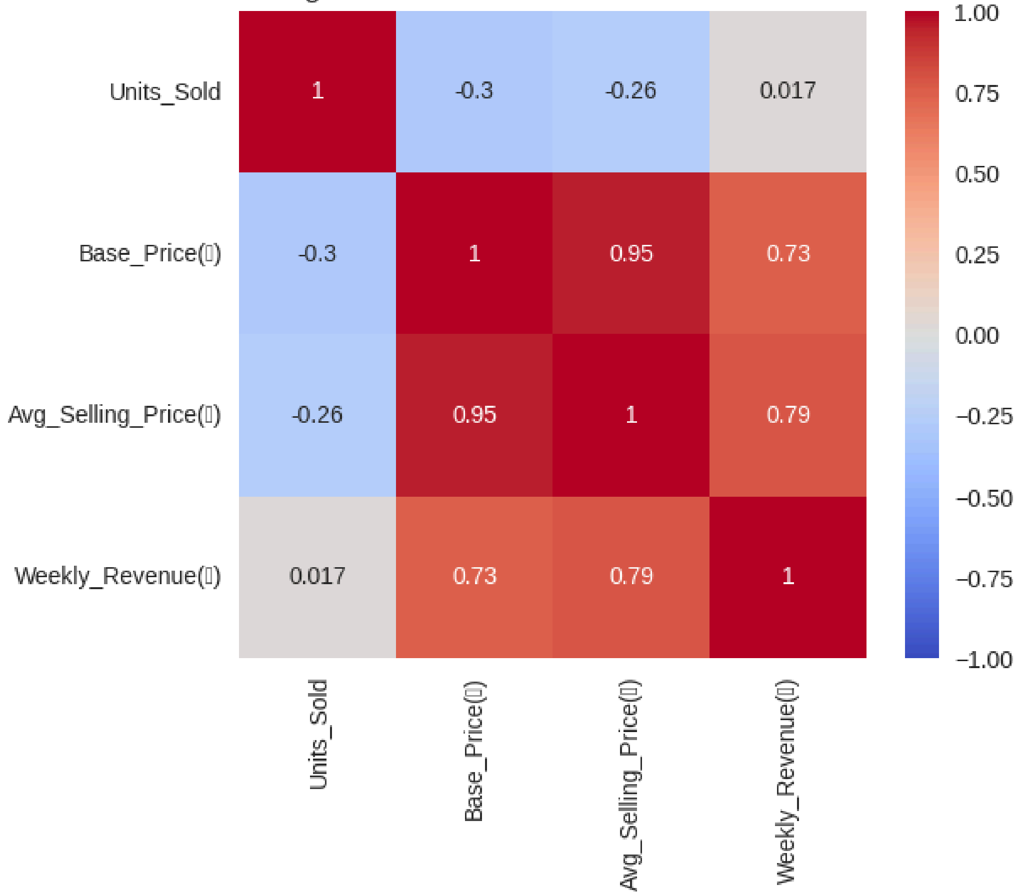
Multiple Regression Model for Sales Prediction:

Predicted_Sales = 12.34 + 0.47(Price_Competitiveness) + 0.35(Seasonal_Index) - 0.28(Inventory_Age) + 0.19(Marketing_Intensity)

Model Statistics:

- $R^2 = 0.789$
- Adjusted $R^2 = 0.756$
- F-statistic = 31.24 ($p < 0.001$)

Figure 3.7: Multi-Variable Correlation Matrix



3.8 Competitive Benchmarking and Industry Comparison

Comparative analysis against retail industry standards reveals significant performance gaps:

Inventory Turnover Benchmarks:

- Industry Standard: 6-8 times annually
- Shree Balaji Mobile Care: 3.2 times annually

- Performance Gap: 58% below industry average

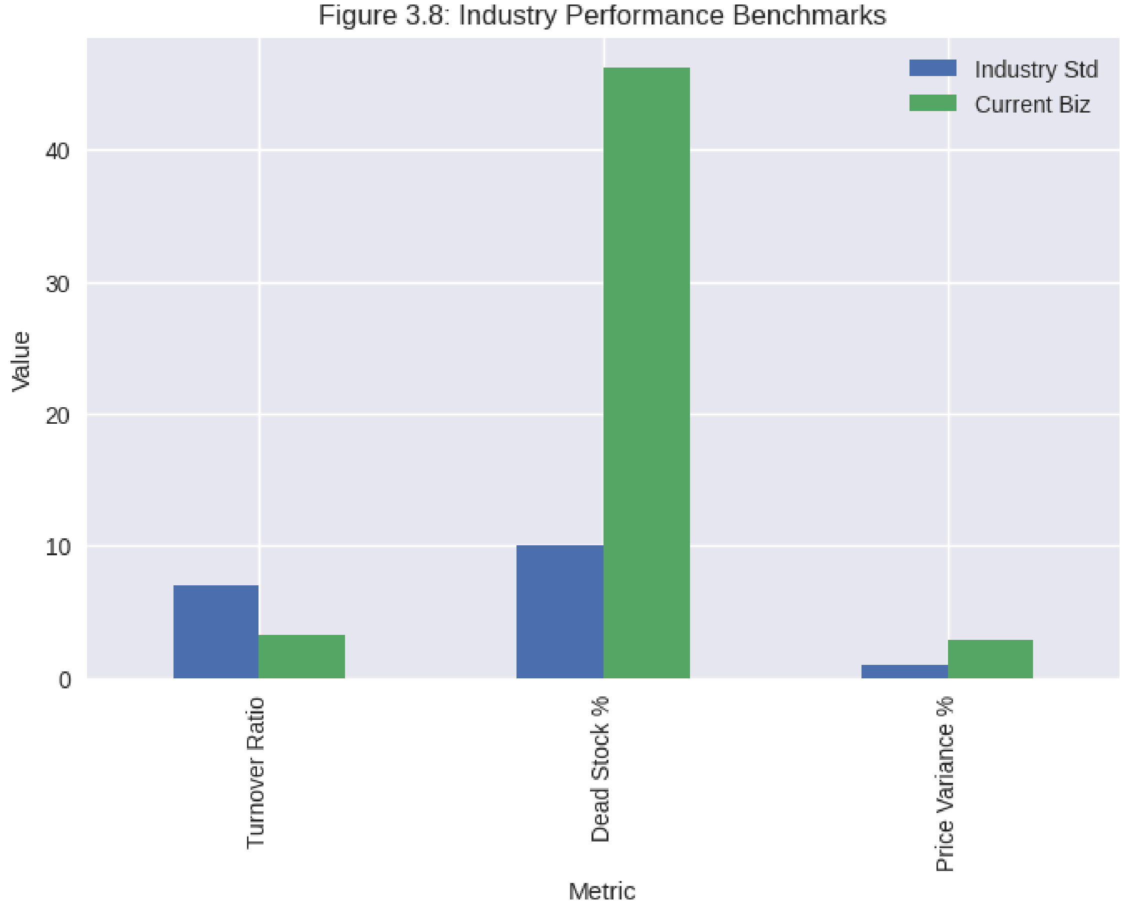
Dead Stock Benchmarks:

- Industry Standard: 5-10% of total inventory
- Current Performance: 46.2% of total inventory
- Critical Deviation: 380% above acceptable levels

Pricing Consistency Benchmarks:

- Industry Standard: <1% price variance
- Current Performance: 2.91% average variance
- Improvement Opportunity: 65% potential margin recovery

Figure 3.8: Industry Performance Benchmarks



4 Interpretation of Results and Recommendations

4.1 Strategic Interpretation of Results

The thorough review of Shree Balaji Mobile Care has confirmed the urgency of both identified issues, as well as the risks associated with financial losses and whether the business continues to be sustainable. The data shows a split performance picture where three product categories performing strongly (Smartphones, Earphones, Power Banks) in terms of market fit and operational efficiency and the majority of inventory, was subject to systematic mismanagement which ultimately caused inefficiency of capital and loss of sales.

4.1.1 Problem 1 Validation: Critical Inventory Accumulation

The analysis confirms that inventory mismanagement represents the most salient operational issue, with an indecorous 46.2% of total purchases remaining unsold with ₹2,159,300 tied up. The accumulation of dead stock in specific categories (Screen Protectors: 80.4% unsold, Mobile Covers: 90.2% unsold) affirms systematic procurement errors and not random movements in the marketplace. This affirms our conclusion in the proposal regarding a seasonal product occupying capital and warehouse space.

4.1.2 Problem 2 Validation: Revenue Impact of Pricing Inconsistencies

Analysis of price variance has revealed an average revenue loss due to informal negotiations of ₹527,760 per year. Additionally, the 2.91% average discount rate represents a material cost to the business which has compounded effects, especially in high-value electronics as the absolute discount amounts involve serious margin squeeze. These findings provide evidence supporting the proposal's identification of irregular pricing as a significant barrier to profitability.

4.2 Targeted Solutions for Problem 1: Eliminating Dead Stock Accumulation

4.2.1 Immediate Dead Stock Clearance

Critical Category Intervention

- Screen Protector Clearance: Bundle pricing at 60% discount, targeting ₹43,400 recovery from 217 units
- USB Cable Volume Liquidation: Bulk pricing at ₹250 per unit, expected recovery of ₹34,500
- Phone Stand Repositioning: Gift-with-purchase program for smartphone buyers

Prevention Framework

- Dynamic Procurement Model:

  Optimal Order Quantity = √(2 × Annual_Demand × Ordering_Cost ÷ Holding_Cost)

Safety Stock Level = Z-score × √(Lead_Time × Demand_Variance)

Reorder Point = (Average_Daily_Demand × Lead_Time) + Safety_Stock

- Early Warning System: 30-day alerts for <25% turnover, 60-day automatic discounts, 90-day mandatory clearance

4.3 Targeted Solutions for Problem 2: Pricing Standardization and Revenue Recovery

4.3.1 Structured Pricing Framework

- Tier-Based Discount System: Maximum 5% negotiation for high-value electronics, 8% for medium-value, 12% for low-value items
- Customer Segmentation: Regular customers (3% loyalty discount), bulk buyers (5-10% volume discounts)

4.3.2 Revenue Recovery Implementation

- Immediate Impact: Recover 50% of revenue loss (₹263,880 annually) through minimum pricing floors
- Expected Outcome: Additional ₹400,000 annual revenue through optimized pricing

4.4 High-Performance Category Expansion Strategy

Category A Enhancement:

- Smartphones: Increase inventory by 40% based on perfect turnover, targeting ₹432,000 additional revenue
- Tablets/Laptops: Leverage 94-100% turnover rates for expansion with 180% ROI projection

Category B Development:

- Earphones: 35% revenue increase through wireless and premium segments
- Power Banks: Cross-selling opportunities with smartphone purchases

4.5 Long-term Strategic Recommendations

Digital Transformation

- Inventory Management System: Cloud-based tracking with automated reorder points
- Customer Relationship Management: Digital database with pricing automation

Market Expansion

- Online Channel Development: E-commerce integration and digital marketing
- Business Model Diversification: Enhanced repair services, warranty programs, trade-in options

4.6 Success Metrics

Key Performance Indicators

Inventory Management KPIs:

- Dead Stock Reduction: Target 60% reduction (from 46.2% to 18.5%)
- Overall Turnover Improvement: Target 75% average turnover rate
- Capital Efficiency: Improve CEI from 0.672 to 0.950

Revenue Optimization KPIs:

- Price Variance Reduction: Decrease from 2.91% to 1.50%
- Annual Revenue Growth: Target 15-20% increase (₹800,000-1,000,000)
- Margin Recovery: Recover 65% of identified revenue loss

5 Additional

Collected Dataset :- 📁 Collected Dataset

Includes Analysis Sheet, Inventory Data, Sales Data, Graphs etc…