Understanding the Business Purview of a Grocery Firm

Final report for the BDM capstone Project

Submitted by

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Executive Summary

Moji Ram Surender Kumar & Company, established in the 1940s and located in the historic Khari Baoli market of Old Delhi, specializes in traditional Indian grocery items, including sugar and essential food products. Despite its long-standing presence, the shop faces challenges such as inefficient inventory management, material wastage, and declining profit margins due to rising competition from online platforms and mega stores

This report presents a comprehensive analysis of three major challenges faced by the grocery firm: inefficient inventory management, declining revenue and profit margins, and material wastage based on the permanent SKU's one can find throughout the year. Using detailed data analysis and visualization techniques, we have identified key issues, their business implications, and developed actionable recommendations to address these challenges.

Our analysis reveals systematic understocking across most products, with Roasted Gram and Dhampure Sugar showing the most severe inventory management problems. Revenue contribution and profit margins vary significantly across the product portfolio, indicating opportunities for pricing optimization and product mix adjustments. Material wastage is causing substantial direct costs and lost sales revenue, with Roasted Gram being the largest contributor to both.

The recommendations provided in this report include implementing data-driven forecasting, establishing SKU-specific inventory policies, strategic pricing adjustments, product mix optimization, and waste reduction strategies. By addressing these interconnected challenges in a coordinated manner, the grocery firm can improve operational efficiency, enhance financial performance, and build a more sustainable business model.

Detailed Explanation of Analysis Process/Method

This section outlines the comprehensive analytical approach used to address the three major challenges facing the grocery firm. Our methodology combines statistical analysis, data visualization, and time series forecasting to provide actionable insights for business improvement. *The approaches taken during the Mid-Term have now been refined or redefined based on the feedback received, and we have collected more data and could use more advanced analytical techniques.*

1.1 Inefficient Inventory Management Analysis

1.1.1 Data Collection and Preparation

- **Data Source**: The analysis utilized data from the grocery firm's duplicate receipt system spanning from September 14, 2024, to January 14, 2025. These receipts contained detailed records of daily sales, purchase transactions, and inventory levels for six key SKUs (Stock Keeping Units): Mawana Sugar, Dhampure Sugar, Bura, Gur, Shakkar, and Roasted Gram.

- **Data Cleaning and Structuring**: The raw receipt data was manually transcribed and cleaned in Excel to remove duplicate entries, address missing values, and correct inconsistencies. This ensured all subsequent analyses were based on accurate data. Three critical Excel tables were created:
  - **SKU Sales Tabulation**: Detailed product metrics including sales quantities and selling prices and Revenue (from the SALES sheet in the 250411_BDM Data workbook)
  - **SKU Purchase Tabulation**: Product metrics including purchase quantities and purchase prices and Purchase Value (from the PURCHASE sheet)
  - **SKU Inventory Tabulation**: Current and ideal inventory levels for each SKU (from the INVENTORY sheet)

- **Data Transformation for Advanced Analysis**: For deeper analysis in Python, we restructured the dataset from a wide format (with SKUs laid out horizontally) to a long format where each row contained:

Date | SKU | Quantity_Sold | Quantity_Purchase | Current_inventory | Ideal_inventory | Day | Selling_Price | Purchase_Price

This transformation simplified filtering, grouping, and iterative computations using pandas, enabling more sophisticated analyses.

1.1.2 Analytical Techniques for Inventory Management

Technique 1: Combined Area-Bar Plot Analysis

The first analysis employed a combined area-bar chart to visualize the relationship between purchased and sold quantities:

- **Area Layer**: Represented the aggregated quantity purchased over the period
- **Bar Layer**: Indicated the aggregated quantity sold
- **Gap Analysis**: The vertical gap between the tip of the bar and the highest point of the area visually highlighted whether a SKU was overstocked or understocked

This visualization was created using Excel's "Insert > Combo Chart" function, with the area chart representing purchase data and the bar chart displaying sales data.

Technique 2: Inventory Gap Analysis

We calculated the inventory gap as the difference between ideal and current inventory levels:

```
df['Inventory Gap'] = df['Ideal_inventory'] - df['Current_inventory']
```

This gap quantified how far off the current inventory was from the target on any given day. We then aggregated this data weekly to observe trends:

```
Weekly_gap = df.groupby(['SKU', 'Week']).agg({
    'Current_inventory': 'mean',
    'Ideal_inventory': 'mean',
    'Inventory Gap': 'mean'
}).reset_index()

# Sort by biggest gap
biggest_gaps = Weekly_gap.sort_values(by='Inventory Gap', ascending=False)

biggest_gaps.head(10) # See top 10 SKUs/months with largest gaps
```

A box-and-whisker plot was created to display the distribution of these weekly gaps for each SKU, highlighting medians, quartiles, and outliers:

```
plt.figure(figsize=(12, 6))
sns.boxplot(data=biggest_gaps, x='SKU', y='Inventory Gap')
plt.title('Inventory Gap Trends by SKU')
plt.xlabel('Week')
plt.ylabel('Inventory Gap')
```

Technique 3: Stock Cover Metric Analysis

We introduced a "Stock Cover" metric to address how quickly stock might deplete. This represented how many days' worth of product remained in inventory, assuming consistent daily sales.

```
df['Stock_cover'] = df['Current_inventory'] / df['Quantity_Sold']
df[df['Quantity_Sold']>0]['Stock_cover'].describe()
```

We analyzed days with critically low coverage (below 3 days):

```python
# First, calculate days where stock coverage is less than 3 for each SKU
coverage_analysis = df[df['Stock_cover'] != float('inf')].copy()  # Remove infinite values
coverage_analysis['Low_Coverage'] = (coverage_analysis['Stock_cover'] < 3).astype(int)

# Group by SKU and sum the days with low coverage
sku_coverage = coverage_analysis.groupby('SKU')['Low_Coverage'].sum().reset_index()

# Sort values in descending order
sku_coverage = sku_coverage.sort_values('Low_Coverage', ascending=False)
```

Technique 4: Consecutive Low Coverage Analysis

We analyzed consecutive days with low stock coverage to identify persistent understocking patterns. This analysis distinguished between SKUs with occasional 1-day coverage dips versus those with prolonged periods of understocking.

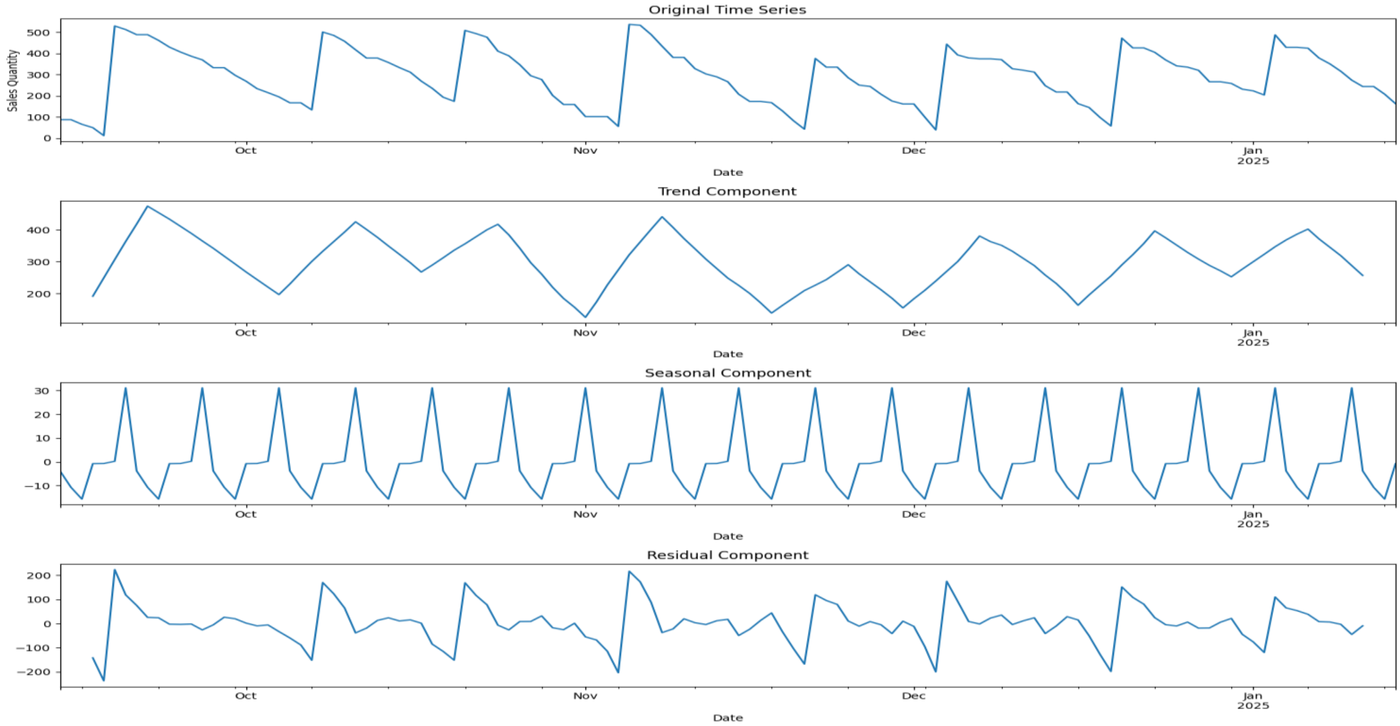
Technique 5: Time Series Forecasting

For our time series forecasting, we implemented a sophisticated SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors) model to predict future sales quantities. Below are key components of our approach:

The model incorporated seasonal decomposition to identify underlying patterns:

```python
try:
    # Perform decomposition with detected period
    decomposition = seasonal_decompose(ts_data, model='additive', period=period)

    # Plot components
    decomposition.trend.plot(ax=axes[1], title='Trend Component')
    decomposition.seasonal.plot(ax=axes[2], title='Seasonal Component')
    decomposition.resid.plot(ax=axes[3], title='Residual Component')
except Exception as e:
    print(f"Couldn't perform seasonal decomposition: {e}")
    print("This might be due to insufficient data points or irregular time series.")
```



The output of above code is shown in the Figure1: Feature Trend Seasonality & Residual Plot

We used grid search to find optimal model parameters:

```
# Define parameter grid - modified to force exploration of different p values
p = range(0, 3)  # Keeping range up to 2
d = range(0, 2)  # Limited to 0, 1 for differencing
q = range(0, 3)  # Keeping range up to 2

# Generate all combinations of p, d, q
pdq = list(itertools.product(p, d, q))

# Generate seasonal parameters
seasonal_pdq = [(x[0], x[1], x[2], seasonal_period) for x in
                list(itertools.product(range(0, 2), range(0, 2), range(0, 3)))]
```

The final forecasting step included confidence intervals to represent prediction uncertainty. This forecasting approach provided predicted sales quantities with confidence intervals, enabling more informed inventory purchasing decisions. The results are stored in the Time_series_predictions.xlsx file, which includes forecasted values along with their upper and lower confidence bounds for the next 15 days.

Technique 6: Average Inventory Comparison

We created a side-by-side bar chart comparing average current inventory with ideal inventory levels for each SKU:

```
# Create bar chart
plt.figure(figsize=(12, 6))
x = np.arange(len(avg_inventory))
width = 0.35

plt.bar(x - width/2, avg_inventory['Current_inventory'], width,
label='Current Inventory', color='skyblue')
plt.bar(x + width/2, avg_inventory['Ideal_inventory'], width, label='Ideal
Inventory', color='lightgreen')

plt.xlabel('SKU')
plt.ylabel('Average Inventory Level')
plt.title('Average Current vs Ideal Inventory by SKU')
plt.xticks(x, avg_inventory['SKU'], rotation=45)
plt.legend()
```

1.2 Declining Revenue and Profit Margins Analysis

1.2.1 Revenue Analysis Methodology

Revenue Calculation

Revenue for each SKU was calculated in Excel by multiplying the quantity sold by the selling price. This calculation was performed in the SKU sheet of the 250411_BDM Data workbook:

$$\text{Revenue} = \text{Quantity Sold} \times \text{Selling Price}$$

Revenue Share Analysis:

- The contribution of each SKU to total revenue was determined using Excel's built-in functions. The pie chart visualization ("Product Revenue Share") was created directly in Excel to provide a clear visual representation of each product's contribution to overall business revenue.

1.2.2 Cost and Profit Margin Analysis

COGS Calculation

The Cost of Goods Sold (COGS) for each SKU was calculated in Excel using the formula:
COGS=Beginning Inventory + Purchases in the Current Period−Ending Inventory

- *Beginning Inventory: The amount of inventory left over from the previous period*
- *Purchases in the Current Period: The cost of purchases made during the current period*
- *Ending Inventory: The inventory that was not sold during the current period*

Gross Margin Calculation:

Gross margin percentages were then determined:

```
Gross Margin (%) = ((Revenue-COGS) ÷ Revenue) × 100
```

The "Gross Margin by SKU" Tree Map chart was created in Excel to visualize these calculations.

Revenue vs. COGS Comparison

The comparative visualization of Revenue against COGS for each SKU ("Product wise Revenue and COGS") was created in Excel using grouped bar charts, providing a clear side-by-side comparison of these key financial metrics.

1.2.3 Online Platform Viability Analysis

An important component of our revenue and profit margin analysis was the assessment of e-commerce viability. We created an Excel sheet called " Online Platform Fee" in our workbook" to evaluate the potential of selling products through online platforms, considering the additional overhead costs associated with e-commerce.

Methodology:

1. **Platform Fee Research**: We researched the fee structures of major e-commerce platforms including Amazon and Flipkart, documenting their commission rates, fulfilment charges, and other applicable fees.

2. **SKU-Level Profitability Analysis**: For each SKU, we calculated the revised profit margins when selling through these platforms by incorporating:
   - Platform commission percentages (typically ranging from 5-15% depending on category)
   - Packaging Costs and Shipping fees
   - Payment processing fees
   - Return handling costs

3. **Break-Even Analysis**: We determined the minimum selling price required on each platform to maintain current profit margins.

4. **Comparative Assessment**: We compared the viability of different platforms for each SKU, identifying which products would be most suitable for online sales channels.

This analysis provided crucial insights into which products could successfully transition to online sales channels while maintaining acceptable profit margins, and which would require pricing adjustments or should remain exclusive to physical retail.

1.2.4 Regression Analysis

Addressing Multicollinearity: **Multicollinearity** refers to a situation where two or more predictor variables are highly correlated with one another. This can obscure how each predictor truly influences the target variable.

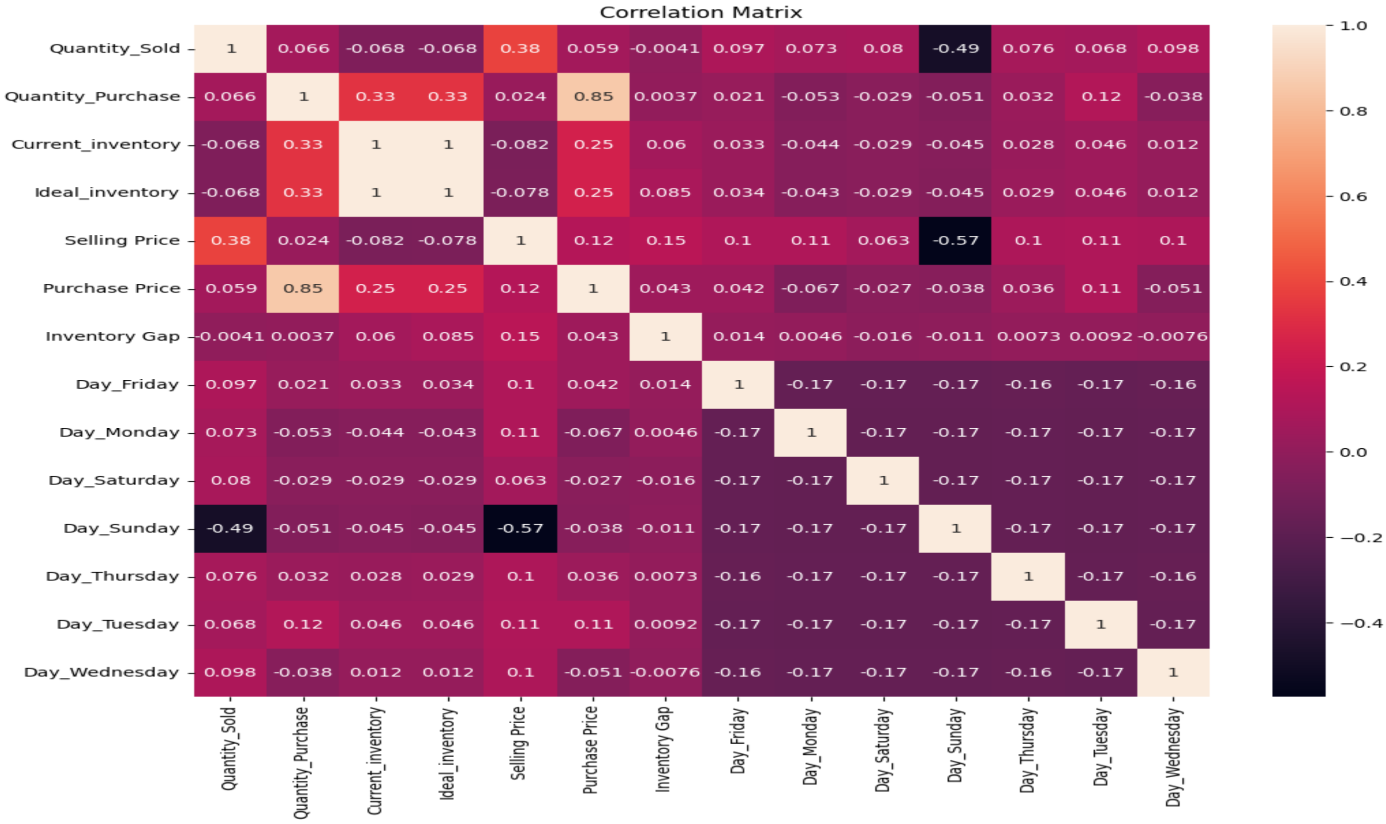


Figure 2: Correlation Heatmap of features used for regression

- **Why It Matters**: In regression, if two features are almost identical, the model can become unstable and produce misleading coefficient estimates or feature importances.
- **Approach**:
  1. **Correlation Matrix**: Created a heatmap to visually inspect correlation among features (Quantity Sold, Inventory Gap, Day encodings, etc.).
  2. **Observation**: Except for Current Inventory and Ideal Inventory, no other pairs of columns showed concerning correlations, so minimized the risk of multicollinearity.
  3. **Practical Takeaway**: Since we found minimal correlation issues, proceeded without dropping major variables (other than acknowledging Current VS Ideal Inventory overlap).

Feature Creation:

- **Inventory Gap**: Calculated as Ideal Inventory minus Current Inventory to gauge stock shortfalls or surpluses.
- **One-Hot Encoding for Day-of-Week**: Transforms categorical weekday data into individual binary features, letting the model capture daily patterns without imposing an order.
- **Days Since Last Purchase & Price Ratio Markup**: These capture the recency of replenishment and the profit margin (selling versus purchase price), respectively, providing insight into both demand urgency and pricing strategy.

Regression Implementation:

- A RandomForestRegressor model was used to predict Quantity Sold. This model provides feature importance scores that indicate how much each engineered variable (like Current Inventory, Days Since Last Purchase, etc.) influences the sales outcome. Also tested Linear Regression Model but that didn't yield satisfactory results as scores on test set were comparatively low.

Model Performance:

- The model's R^2 scores varied by SKU. Although the dataset is small (122 rows), the feature importance outputs offer actionable insights into which factors drive sales, helping the shop owner adjust inventory and pricing strategies accordingly. Refer sheet for R2 Scores of Test Set

1.3 Material Wastage Analysis

1.3.1 Inventory Gap Analysis

We analysed the inventory gap (difference between ideal and current inventory) to understand material wastage patterns: We visualized this data in two key ways:

Overall Inventory Gap Trend: We plotted the daily inventory gap alongside its 7-day moving average to identify underlying trends while smoothing out daily fluctuations. This visualization revealed a consistently negative and widening gap over time, with the 7-day moving average confirming this was not due to daily fluctuations but represented a persistent trend.

SKU-Specific Running Totals: We calculated and visualized cumulative inventory gaps by SKU to identify which products contributed most significantly to the overall problem:

```
# Calculate running total by SKU
df['Running_Total_Gap'] = df.groupby('SKU')['Inventory_Gap'].cumsum()

# Create line plot
plt.figure(figsize=(12, 6))
for sku in df['SKU'].unique():
    sku_data = df[df['SKU'] == sku]
    plt.plot(sku_data['Date'], sku_data['Running_Total_Gap'], label=sku)
plt.title('Running total Inventory Gap for SKUs')
plt.xlabel('Date')
plt.ylabel('Cumulative Inventory Gap')
plt.legend()
```

1.3.2 Wastage Cost Calculation

We calculated wastage cost by multiplying the inventory gap by the purchase price:

```
# Calculate wastage cost
df['Wastage_Cost'] = df['Inventory_Gap'] * df['Purchase Price']

# Calculate cumulative wastage cost by SKU
df['Cumulative_Wastage_Cost'] = df.groupby('SKU')['Wastage_Cost'].cumsum()
```

1.3.3 Lost Sales Revenue Analysis

We estimated lost sales revenue due to inventory shortfalls:

```
# Calculate lost sales quantity (only positive inventory gaps)
df['Lost_Sales_Qty'] = df['Inventory_Gap'].clip(lower=0)

# Calculate lost sales revenue
df['Lost_Sales_Revenue'] = df['Lost_Sales_Qty'] * df['Selling Price']
```

1.3.4 Summary Analysis

We created a summary table showing total wastage cost and lost sales revenue by SKU:

```
# Create summary table
sku_summary = df.groupby('SKU').agg({
    'Wastage_Cost': 'sum',
    'Lost_Sales_Revenue': 'sum'
}).sort_values(by='Wastage_Cost', ascending=False)
```

1.4 Integrated Analysis Approach

Our analysis methodology integrated these three problem areas to provide a holistic view of the grocery firm's challenges:

1. **Multi-dimensional Analysis**: We examined each problem from multiple perspectives (time-based, SKU-based, and financial) to provide comprehensive insights.

2. **Actionable Metrics**: We developed metrics like Stock Cover, Inventory Gap, and Lost Sales Revenue that directly connect operational issues to financial outcomes.

3. **Predictive Modelling**: We implemented time series forecasting to provide forward-looking guidance for inventory management decisions.Similaryly regression analysis was used to predict quantity sold and how it is affected by other key features.

2. Results and Findings

This section presents the key findings from our comprehensive analysis of the grocery firm's data, focusing on the three major challenges: inefficient inventory management, declining revenue and profit margins, and material wastage. The results are presented with visual representations to facilitate clear understanding of the business implications.

2.1 Inefficient Inventory Management Findings

2.1.1 Inventory-Sales Mismatch

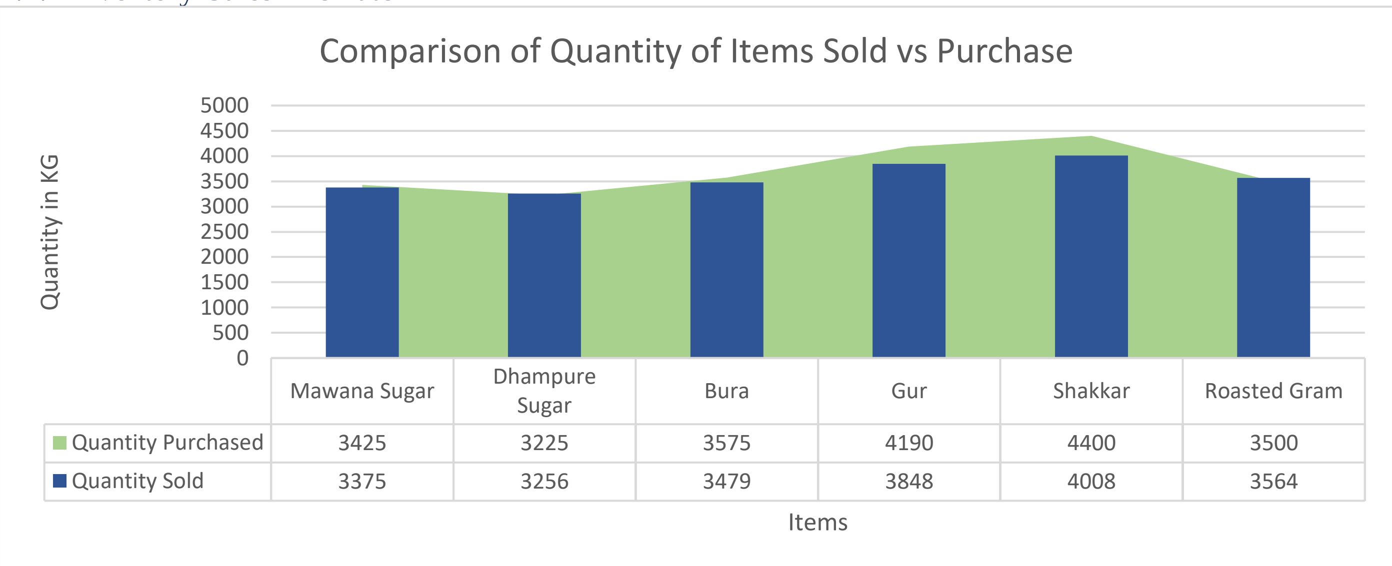


Figure 3: Comparison Of Quantity Of Items Sold Vs Purchased

Our analysis of purchase and sales quantities reveals significant inventory management inefficiencies across multiple SKUs. As shown in the combined area-bar chart above, there is a consistent mismatch between quantities purchased (area) and quantities sold (bars). Key observations include:

- **Shakkar** shows the most pronounced overstocking, with purchases significantly exceeding sales
- **Mawana Sugar**, **Dhampure Sugar**, and **Roasted Gram** demonstrate better inventory balance with smaller gaps between purchase and sales quantities

- The overall pattern indicates a systematic issue in aligning inventory procurement with actual sales demand

This mismatch ties up working capital in excess inventory for some products while potentially leading to stockouts in others, directly impacting both operational efficiency and profitability.

2.1.2 Inventory Gap Analysis

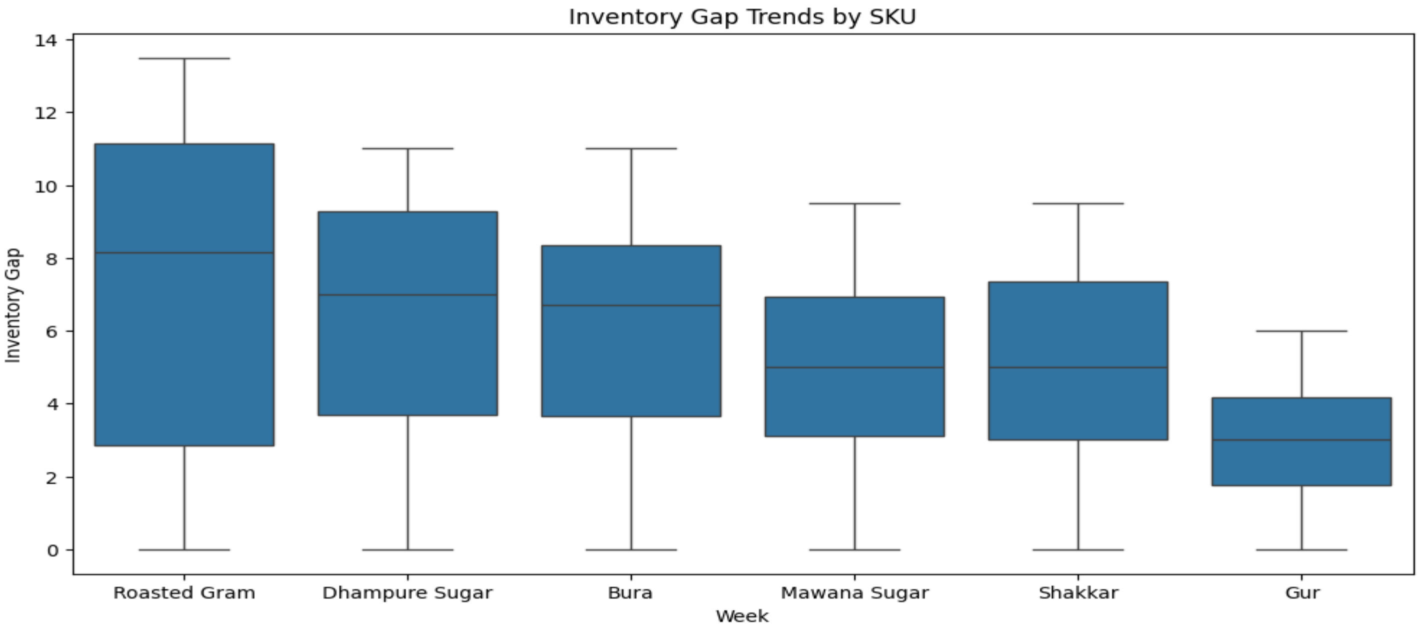


Figure 4: Inventory Gap Trends by SKU

The box-whisker plot above illustrates the distribution of inventory gaps (difference between ideal and current inventory) for each SKU. This visualization reveals:

- **Roasted Gram** exhibits the widest range of inventory gap values, indicating significant fluctuations in stock alignment with ideal levels
- **Dhampure Sugar**, **Bura**, and **Mawana Sugar** show moderate variability in their inventory gaps
- Well even though there aren't any outliers present in the visualization, the whiskers reveal there is still a high variability among minimum and maximum inventory gap across SKUs.

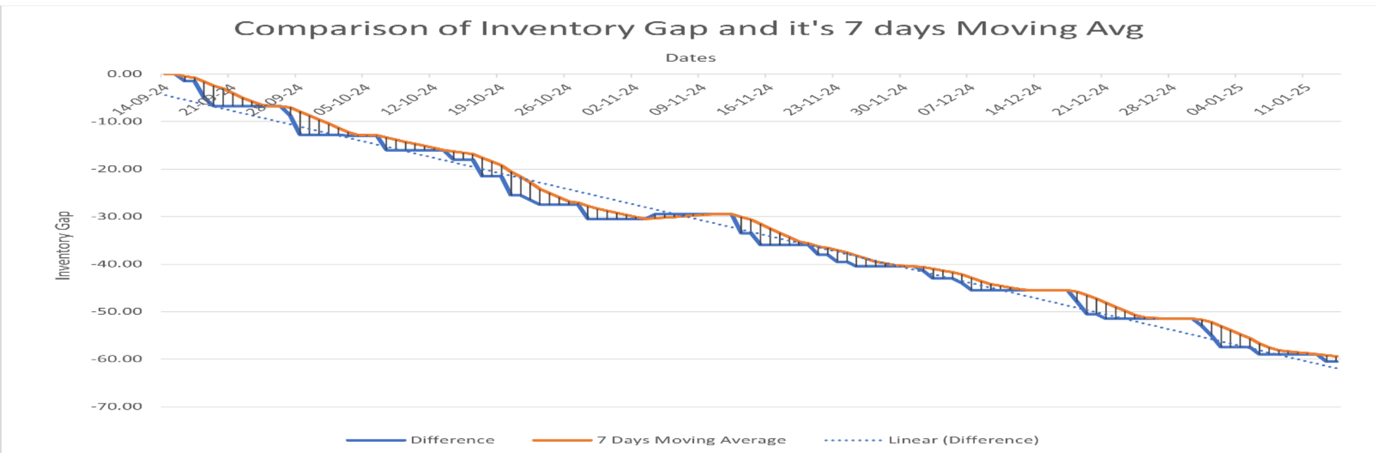


Figure 5: Comparison of Inventory Gap and it's 7 days Moving Average

The time series analysis of the overall inventory gap (blue line) and its 7-day moving average (orange line) reveals:

- A consistently negative and widening gap, reaching approximately -60KG by January 2025
- The downward trend indicates systematic understocking across products over time
- The moving average closely follows the daily values but smooths out fluctuations, confirming this is not a temporary issue but a persistent trend
- This visualization is crucial for understanding the overall trajectory of inventory management issues

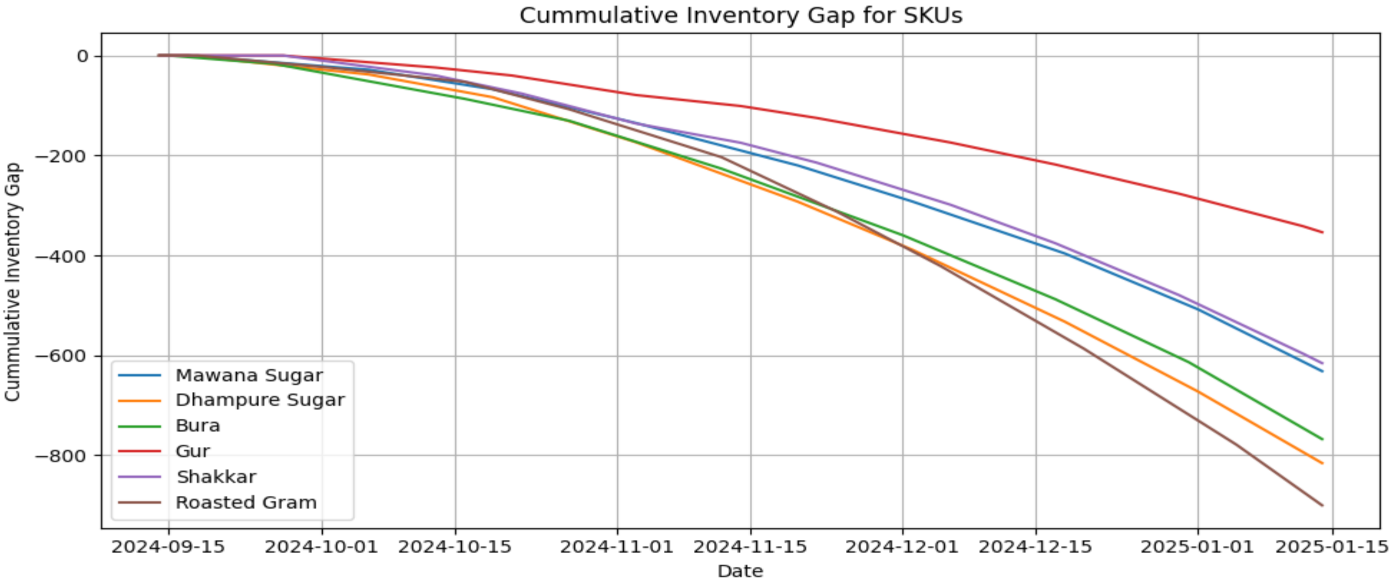


Figure 6: Running Total or Cumulative Inventory Gap by SKU

The running total inventory gap by SKU further confirms:

- All SKUs show steadily decreasing (negative) trajectories, confirming that understocking is a system-wide issue
- **Roasted Gram** and **Dhampure Sugar** have the steepest downward slopes, indicating higher cumulative understocking
- **Gur** has a relatively less sharp slope, suggesting slightly better inventory management for this product
- The cumulative view highlights the compounding effect of daily inventory mismanagement over time

2.1.3 Current vs. Ideal Inventory Comparison

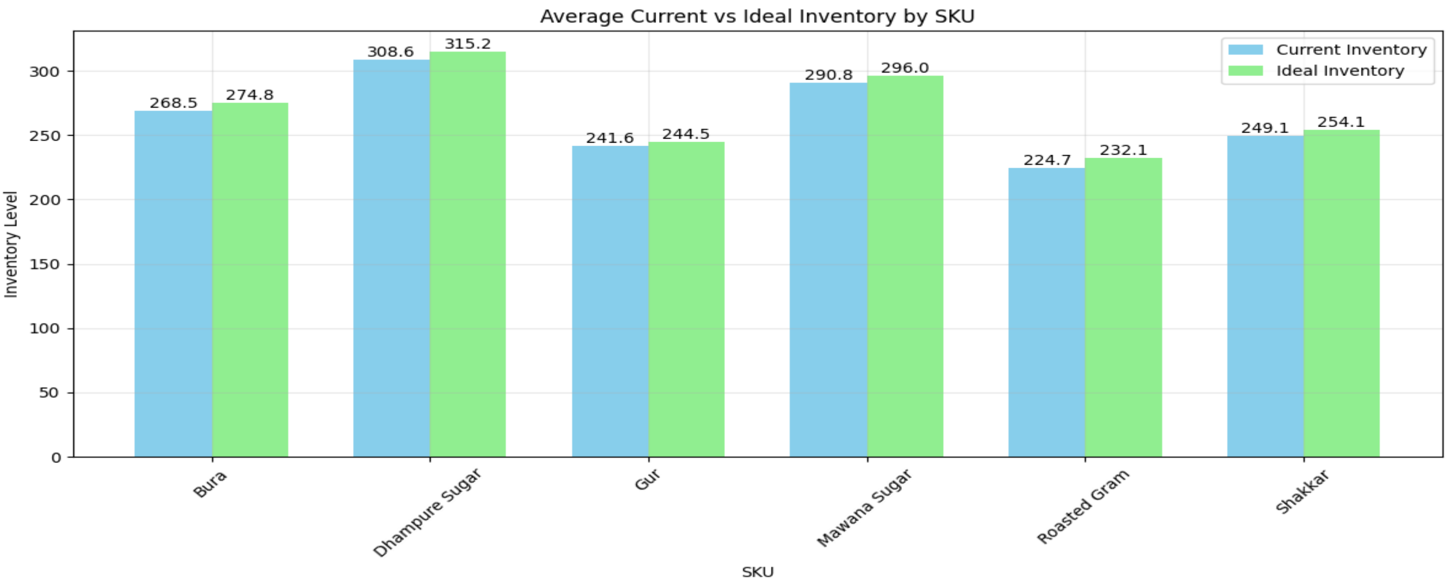


Figure 7: Average Current vs Ideal Inventory by SKU

The comparison of average current inventory (skyblue) with ideal inventory (light green) for each SKU shows:

- Most SKUs consistently maintain current inventory levels below their ideal targets
- **Roasted Gram** and **Dhampure Sugar** show the largest absolute gaps between current and ideal inventory
- **Gur** demonstrates the smallest proportional gap, indicating relatively better inventory management

This snapshot provides a clear picture of which SKUs are consistently off-balance, even if their day-to-day fluctuations weren't always the most extreme.

2.1.4 Stock Coverage Analysis

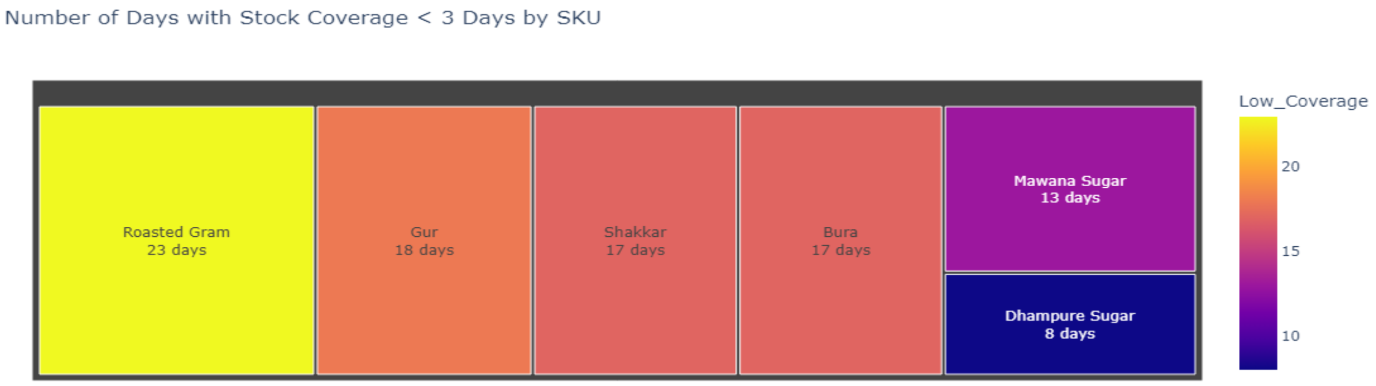


Figure 8: Treemap for Stock Coverage less than 3 by SKU

The treemap visualization shows the frequency of days with stock coverage below three days (a critical threshold) for each SKU:

- **Roasted Gram** has the highest number of days with critically low stock coverage
- The size of each rectangle represents the frequency of low coverage occurrences, providing a visual hierarchy of inventory risk by product
- This visualization highlights which products most frequently approach stockout conditions

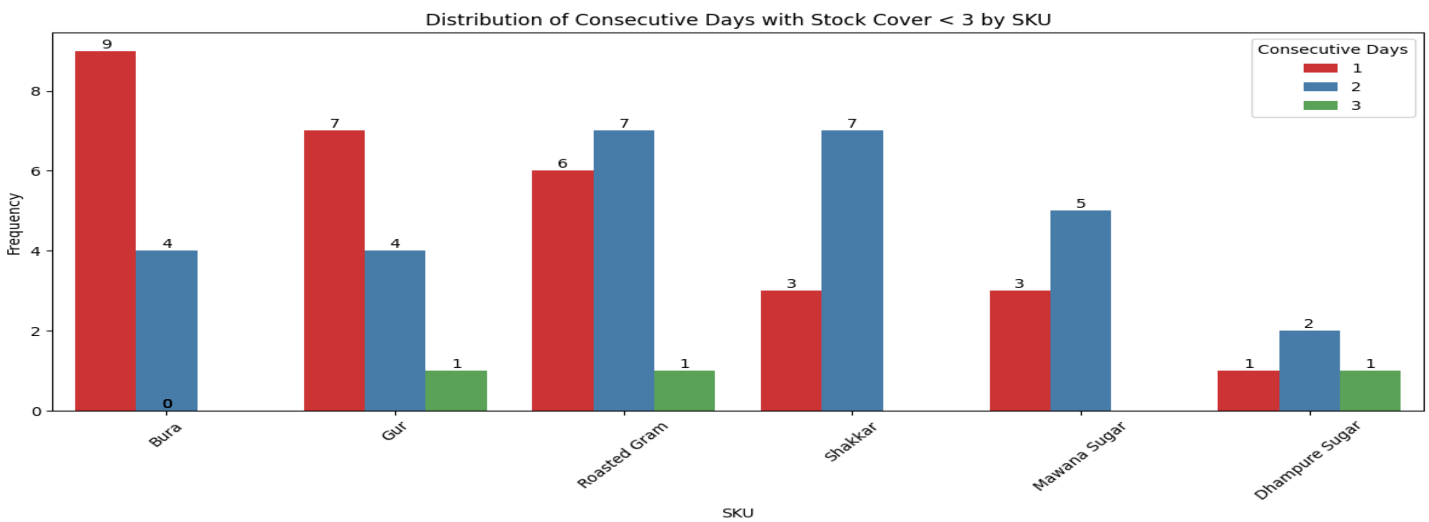


Figure 9: Distribution of Consecutive Days with Stock Cover less 3 by SKU

The analysis of consecutive days with low stock coverage reveals:
- Several SKUs experience multiple instances of 2-3 consecutive days with coverage below the critical threshold
- **Roasted Gram, Gur** and even **Dhampure Sugar** shows the highest frequency of extended low-coverage periods
- The pattern of consecutive low-coverage days indicates persistent procurement planning issues rather than isolated incidents

2.1.5 Time Series Forecasting Results

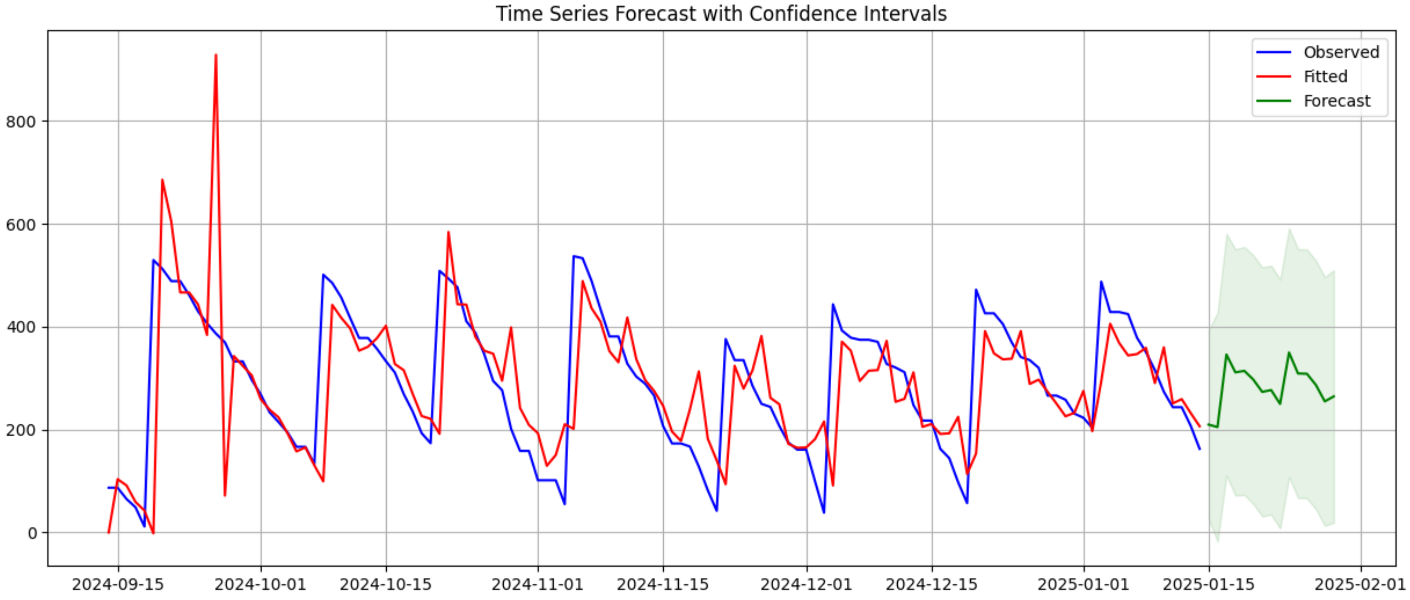


Figure 10: Time Series Forecast with Confidence Intervals

Our time series forecasting model provides:

- Predicted sales quantities (Green line) for the next 15 days with 95% confidence intervals (shaded area)
- The widening confidence interval as we move further into the future indicates increasing uncertainty in the predictions
- This forecast enables more informed inventory planning by providing expected ranges of future sales

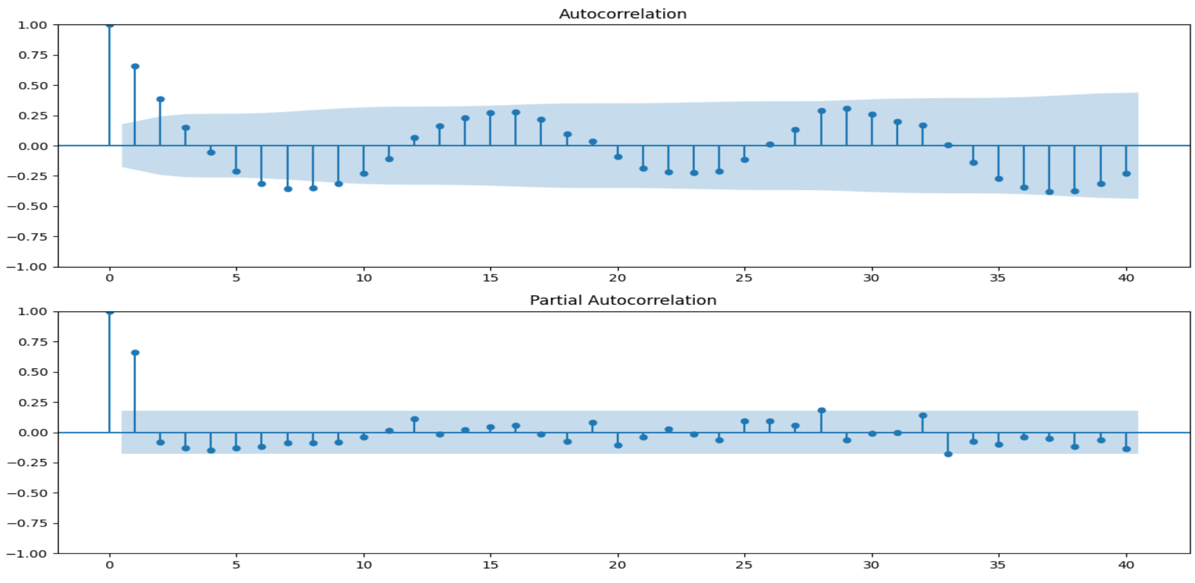


Figure 11: The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots used in our time series analysis

show:
- Significant autocorrelation at specific lags, indicating predictable patterns in sales data
- These patterns were incorporated into our SARIMAX forecasting model to improve prediction accuracy

2.2 Declining Revenue and Profit Margins Findings

2.2.1 Regression Analysis

Features\ Importance	Mawana Sugar	Dhampure Sugar	Bura	Gur	Shakkar	Roasted Gram
Current_inventory	0.2408	0.2262	0.2615	0.2709	0.2172	0.2308
Quantity_Purchase	0.0122	0.0125	0.0302	0.0059	0.0091	0.0302
Days_since_last_purchase	0.1344	0.1428	0.1378	0.1389	0.1570	0.1405
Day_Friday	0.0324	0.0226	0.0194	0.0290	0.0205	0.0223
Day_Monday	0.0323	0.0317	0.0199	0.0416	0.0184	0.0181
Day_Saturday	0.0304	0.0286	0.0158	0.0153	0.0347	0.0146
Day_Sunday	0.0118	0.0111	0.0378	0.0103	0.0479	0.0190
Day_Thursday	0.0286	0.0243	0.0309	0.0343	0.0162	0.0453
Day_Tuesday	0.0152	0.0299	0.0186	0.0299	0.0218	0.0151
Day_Wednesday	0.0356	0.0216	0.0186	0.0170	0.0243	0.0167
Selling Price	0.2948	0.3302	0.2753	0.2799	0.3188	0.3269
Price Ratio Markup	0.1316	0.1185	0.1342	0.1271	0.1140	0.1205

Table 1: Feature Importance SKU Wise for Quantity Sold

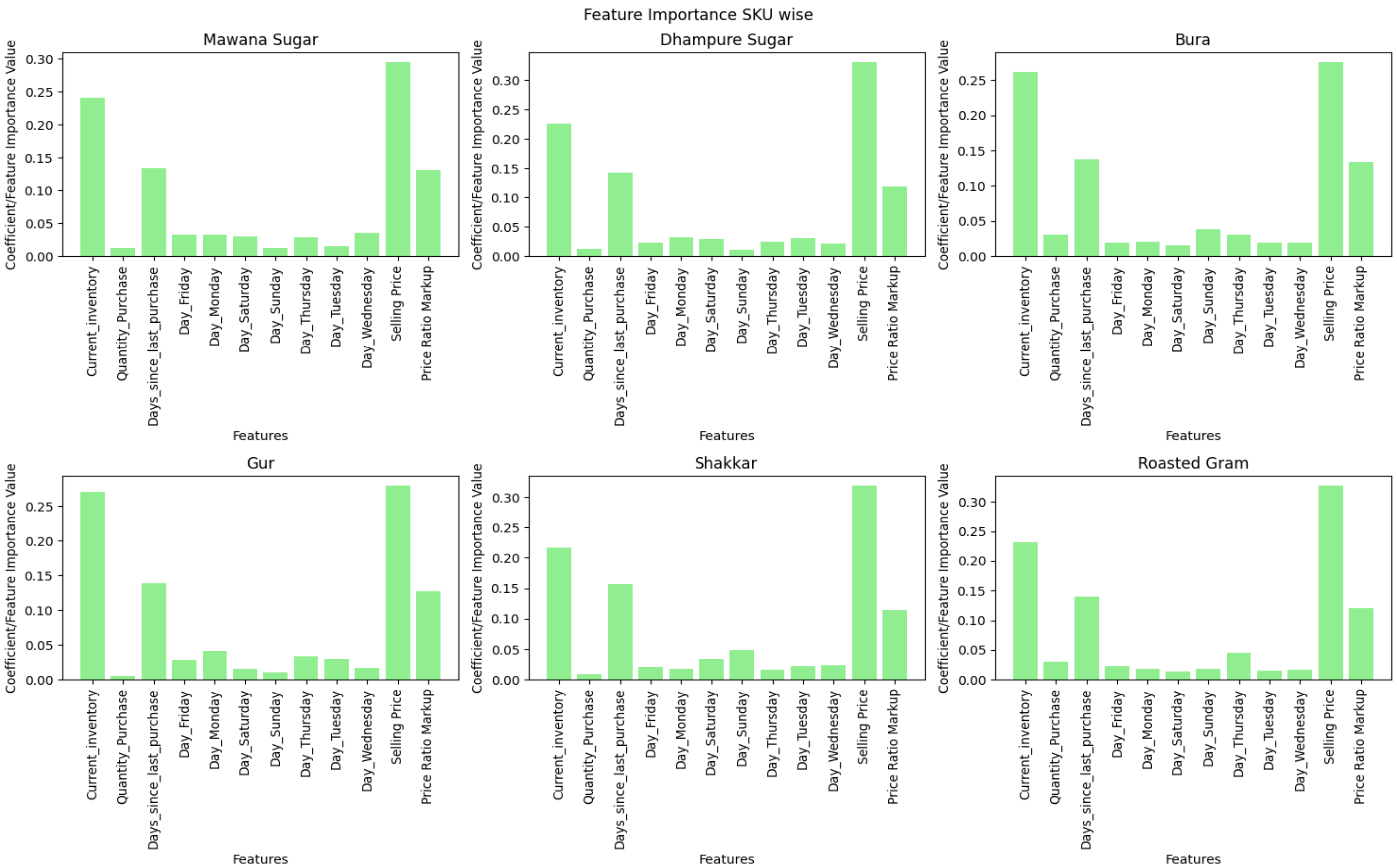


Figure 12: Feature Importance SKU Wise for Quantity Sold

- Selling price is the top feature with highest importance across SKUs, which was sort of rhetorical in a sense.
- Recency of stock updates (days since last purchase) correlates with better sales. If replenishment is too infrequent, sales suffer.
- High importance of Current_inventory across SKUs (0.21–0.27 range). Indicates that if it's not on the shelf, it doesn't sell.
- Minor but non-zero influence for certain days:
  - Gur has slightly more importance for Mondays (0.0416)
  - Shakkar shows a spike for Sundays (0.0479)

2.2.2 Revenue Analysis

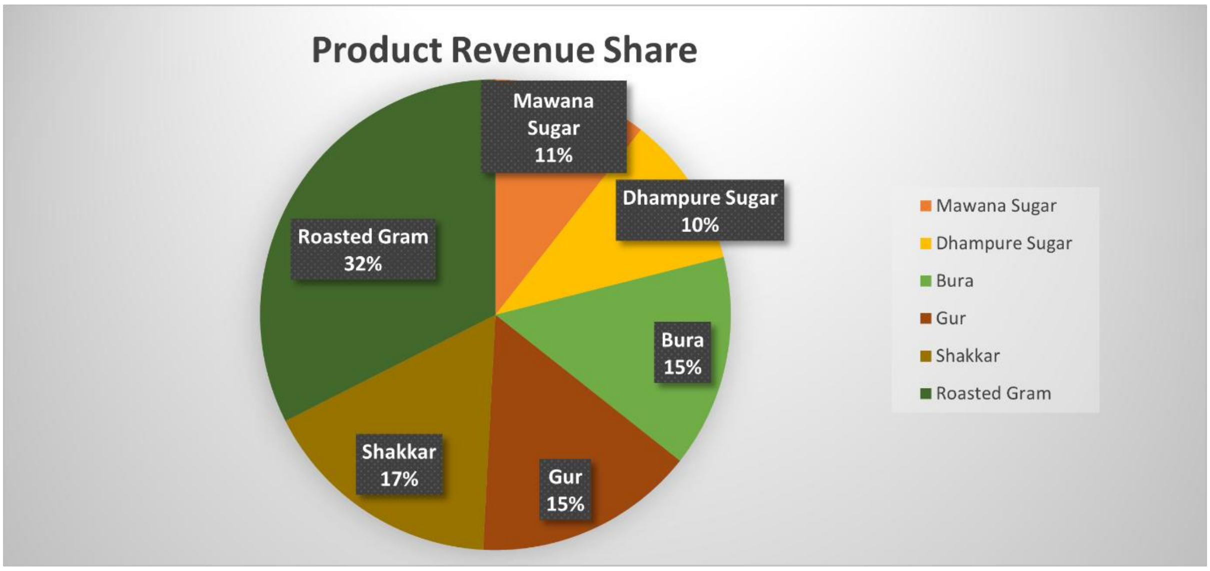


Figure 13: Revenue Share Pie Chart

The revenue share analysis, created in Excel, reveals:

- Uneven contribution of different SKUs to total business revenue
- Roasted Gram is contributing highest among all the SKUs present.
- Sugar variants have minimal contribution in the revenue.
- This visualization helps identify which products are the primary revenue drivers and which contribute less significantly

2.2.3 Revenue and Cost Analysis

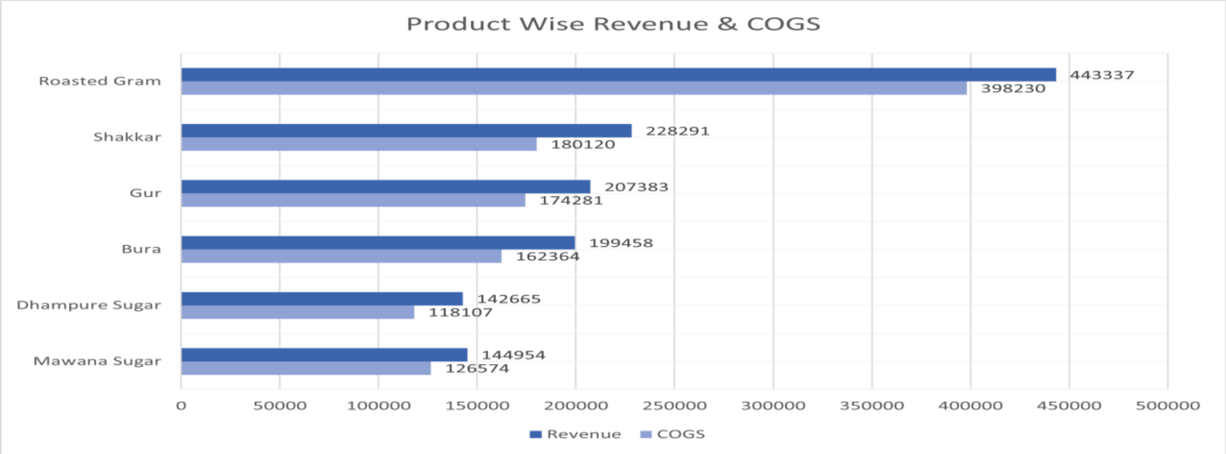


Figure 14: Product wise Revenue and COGS

The comparison of revenue (dark blue) and Cost of Goods Sold (light blue) for each SKU, calculated and visualized in Excel, shows:

- Varying profit margins across the product portfolio
- Some SKUs have wider gaps between revenue and COGS, indicating higher profit contribution
- Other SKUs show narrower gaps, suggesting potential pricing or cost issues
- This analysis directly highlights which products are most profitable in absolute terms

2.2.4 Profit Margin Analysis

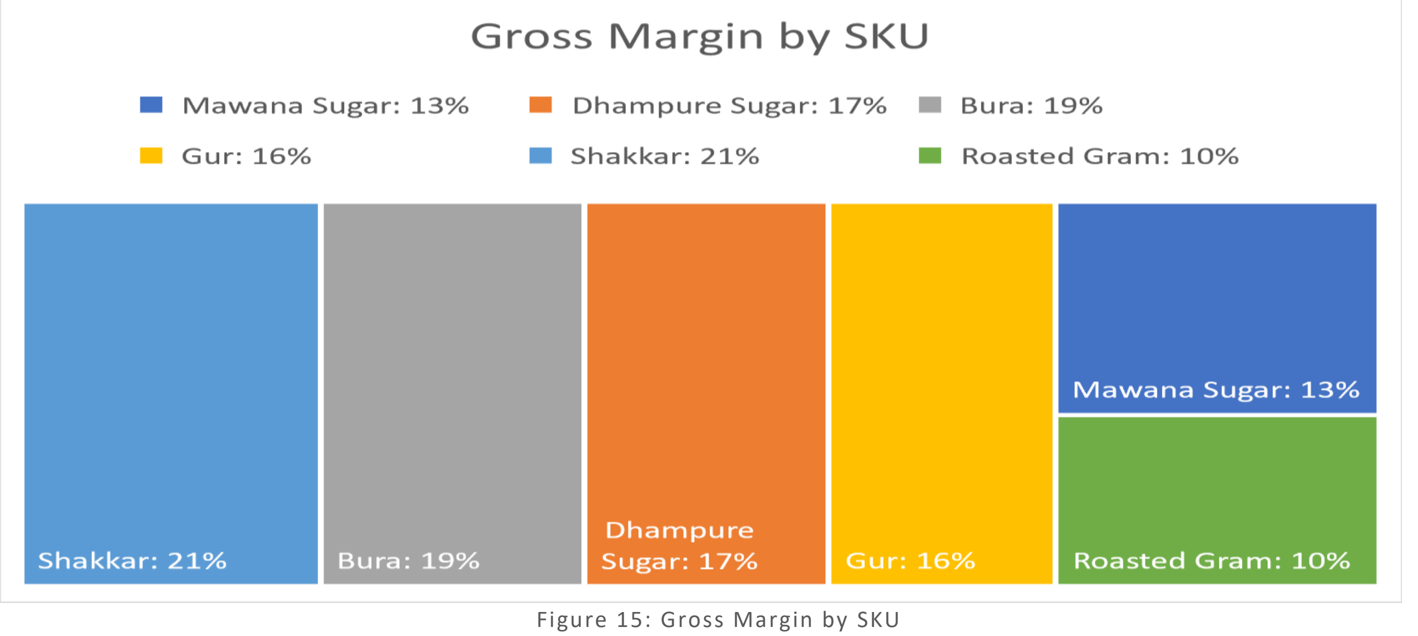


Figure 15: Gross Margin by SKU

The gross margin percentage analysis, calculated in Excel, reveals:

- Significant variation in profitability across the product range
- Some SKUs achieve healthy margins like Shakkar and Bura while others operate with minimal profitability
- This metric provides a relative measure of efficiency in converting sales into profit
- Products with lower margins may require pricing adjustments, cost reduction strategies, or reconsideration of their place in the product mix

2.2.5 Online Platform Viability Findings

Our analysis of the Online Platform Viability revealed:

Charges \ Platform	Amazon.in Seller Fees & Pricing: Calculate Your Revenue &	Fees and Commission - Low Cost of
	Amazon	Flipkart
Referral fee/Platform fee/Commission Fee:	$2.40	$ 3.00
Closing fee/Fixed/Handling Fee:	$4	$ 21.30
Shipping fee:	$42	$ 20.00
GST on Refrerral + Closing + Shipping fee	$8.71	$ 7.97
Total:	$57	52.274
Packaging Cost	₹ 5-10	₹ 5-10
Total Overhead Cost	₹ 61-67	₹ 57.27-62.27

		Product Listing Costs (Avg Purchase Price + Total Overhead Cost)		Average Costs of Product on Platform		Difference	
Product (Average Purchase Price	Average Purchase Price	Amazon	Flipkart	Amazon	Flipkart	Amazon	Flipkart
Mawana Sugar (37.75)	37.75	98.75 - 104.75	95.02 - 100.02	55-60	50-65	-43.75 : -44.75	-45.02 : -35.02
Dhampure Sugar (35)	35	96 - 102	92.27 - 97.27	55-60	50-65	-41 : -42	-42.27 : -32.27
Bura (46.5)	46.5	107.5 - 113.5	103.77 - 108.77	85-90	130-200	-22.5 : -23.5	26.23 : 91.23
Gur (44.25)	44.25	105.25 - 111.25	101.52 - 106.52	110-150	250-300 (Only Organic available)	4.75 : 38.75	148.48 : 193.48
Shakkar (45)	45	106 - 112	102.27 - 107.27	110-150	250-300 (Only Organic available)	4 : 38	147.73 : 192.73
Roasted Gram (111.25)	111.25	172.25 - 178.25	168.52 - 173.52	160-170	136-250	-12.25 : -8.25	-32.52 : 76.48

		Product Listing Costs without shipping (Avg Purchase Price + Total Overhead Cost - Shipping Fee)		Average Costs of Product on Platform		Difference	
Product (Average Purchase Price	Average Purchase Price	Amazon	Flipkart	Amazon	Flipkart	Amazon	Flipkart
Mawana Sugar (37.75)	37.75	56.75 - 62.75	75.02 - 80.02	55-60	60	-1.75 : -2.75	-25.02 : -15.02
Dhampure Sugar (35)	35	54 - 60	72.27 - 77.27	55-60	60	1 : 0	-12.27 : -12.27
Bura (46.5)	46.5	65.5 - 71.5	83.77 - 88.77	85-90	130-200	19.5 : 18.5	46.23 : 111.23
Gur (44.25)	44.25	63.25 - 69.25	81.52 - 86.52	110-150	250-300 (Only Organic available)	46.75 : 80.75	168.48 : 213.48
Shakkar (45)	45	64 - 70	82.27 - 87.27	110-150	250-300 (Only Organic available)	46 : 80	167.73 : 212.73
Roasted Gram (111.25)	111.25	130.25 - 136.25	148.52 - 153.52	160-170	136-250	29.75 : 33.75	-12.52 : 96.48

Table 2: Comparison of Product Listings Price and Feasibility of selling our products online

- **Platform Fee Impact**: E-commerce platform fees significantly impact profit margins, with commission rates varying by product category
- **SKU Suitability**: Not all SKUs are equally suitable for online sales:
  - High-margin products like Roasted Gram can better absorb platform fees while maintaining profitability
  - Low-margin products would require price increases to remain viable on online platforms
- **Platform Comparison**: Different platforms offer varying fee structures, with some more favorable for specific product categories
- **Fulfilment Considerations**: Shipping and handling costs create additional challenges for heavier items or products with lower value-to-weight ratios

This analysis provides crucial insights for developing an e-commerce strategy that selectively targets products with sufficient margin to remain profitable after accounting for platform fees and fulfilment costs.

2.3 Material Wastage Findings

2.3.1 Wastage Cost Analysis

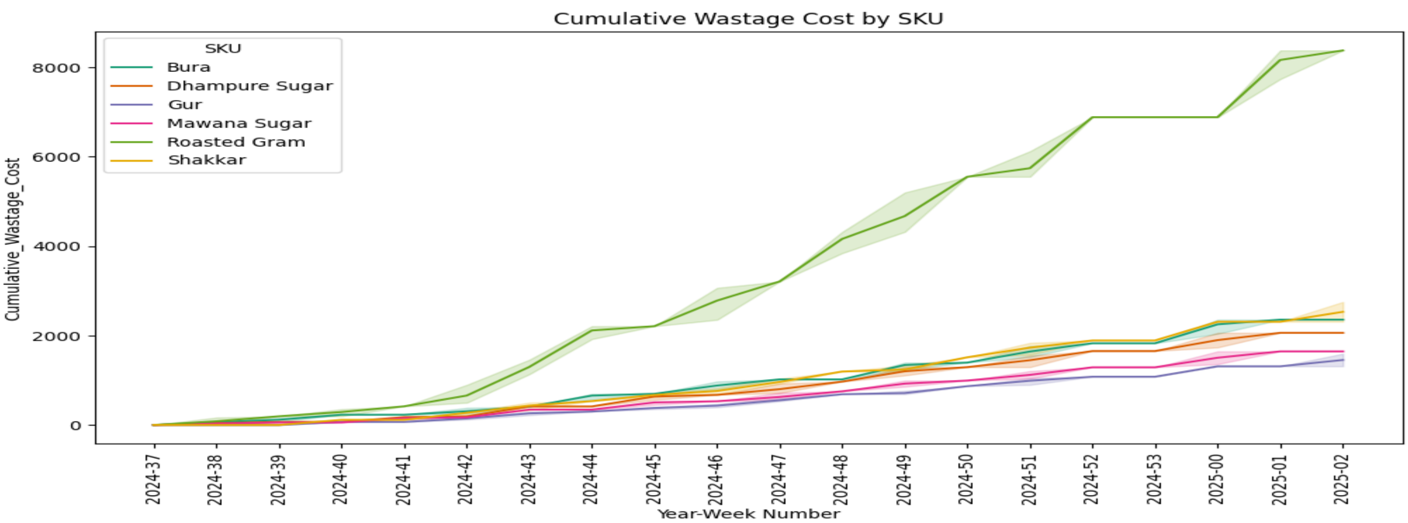


Figure 16: Cumulative Wastage Cost by SKU

The cumulative wastage cost analysis shows:

- **Roasted Gram** emerges as the main contributor to wastage costs, followed by **Bura** and **Shakkar**
- The upward trajectory for all SKUs indicates continuously accumulating wastage costs over time
- The shaded areas represent 95% confidence intervals, showing the variability in estimated costs
- This visualization quantifies the financial impact of material wastage by product

2.3.2 Lost Sales Revenue Analysis

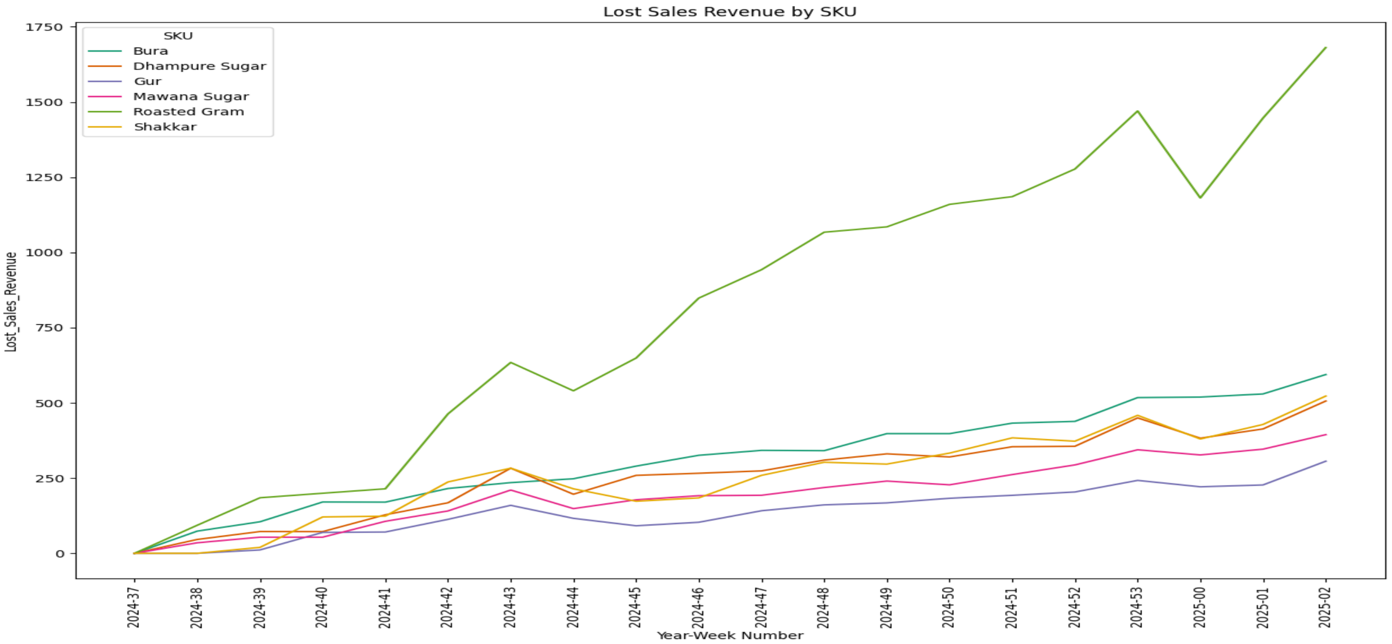


Figure 17: Lost Sales Revenue by SKU

The analysis of lost sales revenue due to inventory shortages reveals:

- Substantial potential revenue is being missed due to understocking
- **Roasted Gram** shows particularly high lost sales revenue, indicating significant opportunity cost
- The pattern over time shows that lost revenue is not sporadic but accumulative
- This metric directly connects inventory management issues to financial outcomes

2.3.3 Combined Wastage Impact

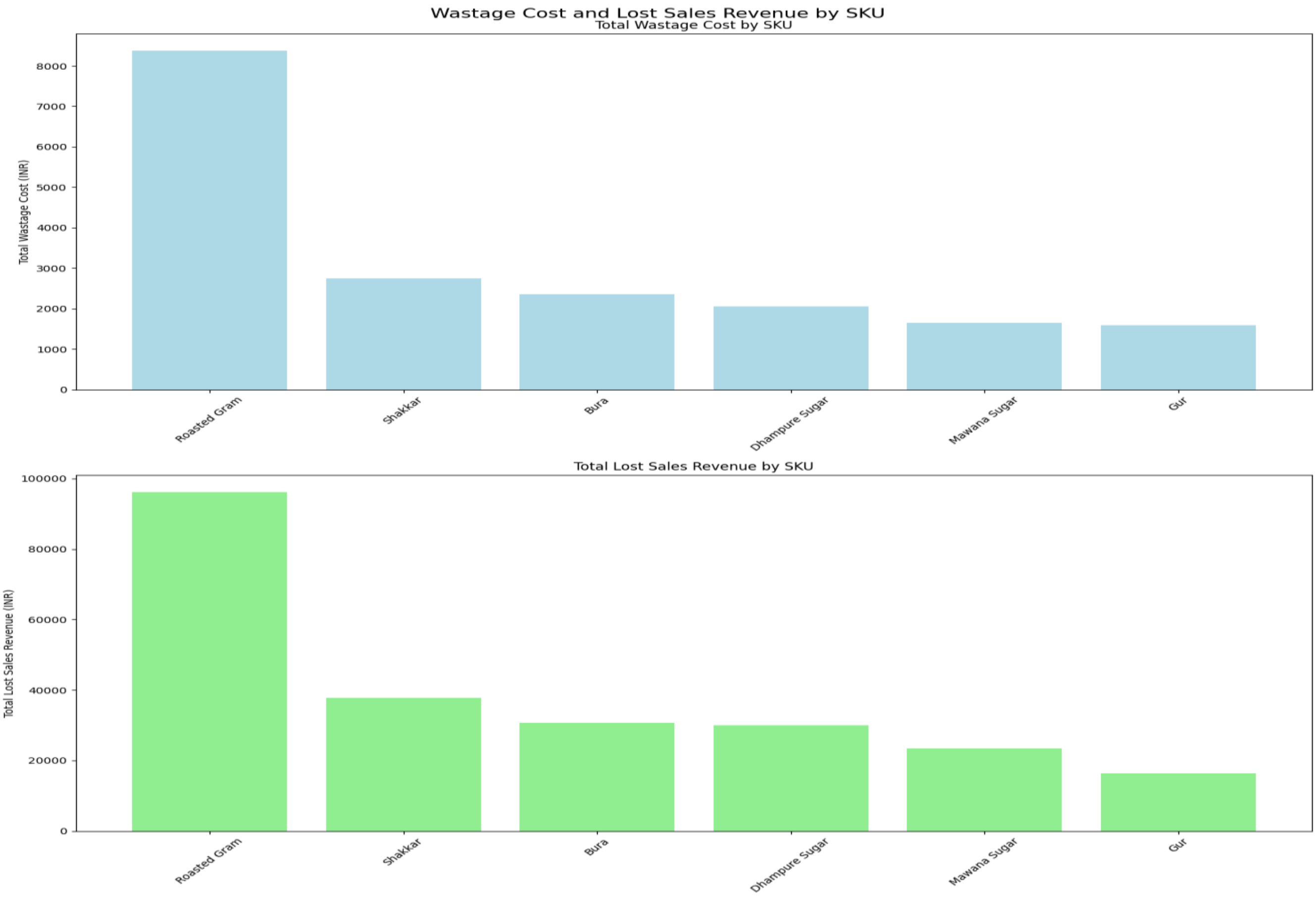


Figure 18: Wastage Cost and Lost Sales Revenue by SKU

The combined analysis of wastage cost and lost sales revenue provides:

- A comprehensive view of the total financial impact of material wastage
- Clear ranking of SKUs by their contribution to both direct wastage costs and opportunity costs
- **Roasted Gram** leads in both metrics (Wastage Cost: 8,374 INR; Lost Sales Revenue: 96,131 INR)
- This dual perspective highlights the full economic impact of inventory mismanagement

3. Interpretation of Results and Recommendations

This section interprets the findings from our analysis and provides actionable recommendations to address the three major challenges facing the grocery firm: inefficient inventory management, declining revenue and profit margins, and material wastage.

3.1 Interpretation of Inventory Management Findings

Our analysis revealed several critical insights regarding the firm's inventory management practices:

1. **Systematic Understocking**: The consistently negative and widening inventory gap across most SKUs indicates a systematic issue in maintaining adequate stock levels. This is not an isolated problem but a persistent trend affecting the entire product range.

2. **Product-Specific Vulnerabilities**: Roasted Gram and Dhampure Sugar show the most severe inventory management problems, with the steepest downward slopes in cumulative inventory gap and frequent occurrences of critically low stock coverage.

3. **Predictable Demand Patterns**: The time series analysis revealed clear seasonal patterns and trends in sales data, suggesting that demand is more predictable than current inventory practices account for.

4. **Stock Coverage Risks**: Multiple products frequently experience stock coverage below the critical threshold of 3 days, creating significant risk of stockouts and lost sales opportunities.

3.2 Interpretation of Revenue and Profit Margin Findings

Our analysis of revenue and profit margins revealed:

1. **Uneven Revenue Contribution**: The product portfolio shows significant variation in revenue contribution, with some SKUs generating substantially more revenue than others.

2. **Varying Profit Margins**: Gross margins differ considerably across products, indicating inconsistent pricing strategies or cost management.

3. **E-commerce Viability Challenges**: The Online Platform Viability analysis revealed that platform fees and fulfillment costs significantly impact profitability when selling through e-commerce channels, with some products better suited than others for online sales.

4. Regression analysis suggests Selling Price is top driver and current inventory and Minor weekday effects.

3.3 Interpretation of Material Wastage Findings

Our analysis of material wastage revealed:

1. **Significant Financial Impact**: Material wastage is causing substantial direct costs and opportunity costs through lost sales.

2. **Product-Specific Issues**: Roasted Gram stands out as the main contributor to both wastage costs and lost sales revenue.

3. **Cumulative Effect**: The wastage costs accumulate over time, indicating a persistent issue rather than isolated incidents.

4. **Inventory Gap Trends**: The 7-day moving average of inventory gaps shows a consistent downward trend, confirming that understocking is a systematic issue affecting material wastage.

4. Recommendations

Recommendations for Inventory Management

Based on our analysis, we recommend the following actions to improve inventory management:

1. **Implement Data-Driven Forecasting**
   - Utilize the SARIMAX forecasting model we've developed to predict demand for each SKU
   - Incorporate seasonal patterns and trends identified in the time series analysis
   - Set up automated alerts when actual sales deviate significantly from forecasts

2. **Establish SKU-Specific Inventory Policies**
   - Develop tailored minimum stock levels for each SKU based on its sales velocity and variability
   - Prioritize inventory management improvements for Roasted Gram and Dhampure Sugar

- Consider the "Stock Cover" metric (days of inventory) as a key performance indicator

3. **Implement Inventory Management Technology**
   - Invest in a basic inventory management system that can automate reorder alerts
   - Use barcode scanning or similar technology to improve inventory count accuracy

4. **Establish Regular Inventory Review Cycles**
   - Conduct weekly inventory reviews for high-risk SKUs (those with frequent low coverage)
   - Implement monthly comprehensive inventory audits across all products
   - Use the inventory gap visualization as a regular monitoring tool

Recommendations for Revenue and Profit Improvement

We recommend the following strategies to address revenue and profit margin challenges:

1. **Implement Strategic Pricing**
   - Review and adjust pricing for low-margin products to improve profitability
   - Consider value-based pricing for high-demand items rather than cost-plus pricing

2. **Optimize Product Mix**
   - Focus marketing and increasing shelf space on high-margin, high-revenue products
   - Consider phasing out or replacing consistently low-margin products
   - Introduce complementary products that can increase basket size for high-performing SKUs

3. **Develop Customer Loyalty Programs**
   - Implement a simple loyalty program to encourage repeat purchases
   - Use customer purchase data to offer targeted promotions
   - Create bundle offers that combine high-margin and low-margin products
   - Develop special promotions for high-value customers

4. **Implement Selective E-commerce Strategy**
   - Start with high-margin, non-perishable products that can absorb platform fees while maintaining profitability
   - Compare different platform fee structures to identify the most cost-effective options for each product category

Recommendations for Reducing Material Wastage

We recommend the following actions to address material wastage:

1. **Implement First-In-First-Out (FIFO) Inventory Management**
   - Ensure older stock is sold before newer stock to reduce spoilage
   - Clearly mark received dates on all inventory
   - For perishable items, order smaller quantities more frequently
   - Use the sales forecasting model to determine quantities for purchase

2. **Reduce Handling Damage**
   - Implement standardized procedures for unpacking and shelving products
   - Use appropriate equipment for moving and storing inventory

3. **Implement Waste Tracking System**
   - Develop a simple system to track the cause of each instance of waste
   - Categorize waste by cause (spoilage, damage, theft, etc.)
   - Set waste reduction targets for each category
   - Review waste tracking data monthly to identify trends and improvement opportunities