Sundarayatan Store: A Strategic Analysis for Business Enhancement

A Final report for the BDM capstone Project

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Sundarayatan Store: A Strategic Analysis for Business Enhancement

1. Executive Summary

Sundarayatan Store is a neighborhood grocery outlet located near NIT More, Patna, operating since 2006. Despite a loyal customer base and a daily footfall of 130–160 customers, the store has faced declining profitability and operational inefficiencies in recent years. Key challenges include stockouts of essential items, overstocking of slow-moving goods, and a lack of data-driven decision-making in procurement and pricing. Rising competition from online retailers has further impacted customer retention and sales consistency.

To investigate these challenges, 61 days of transactional and inventory data (March 1 – April 30, 2025) were manually collected from handwritten registers and purchase invoices also surveyed 95 shop customers. The dataset includes 12 commonly sold grocery items such as Rice, Flour, Pulses, Dairy, Oil, Ghee, and Beverages. Variables like purchase quantity, selling price, cost price, and quantity sold were analyzed. Techniques used included ABC classification for inventory segmentation, moving average forecasting for demand prediction, gross margin analysis for profitability, and RFM segmentation to assess customer loyalty and engagement.

Key findings show that Category A items (Rice, Atta, Sugar, Cooking Oil) generate 75.4% of revenue but are frequently out of stock. Dry Fruits (₹34,020) and Rice (₹32,591) were the most profitable, while Sugar (₹5,654) and Moong Dal (₹4,726) had the lowest margins. Category C products hold 30% of inventory but contribute less than 10% of revenue. RFM analysis indicates that 42% of customers are "at-risk", and 38% of transactions are online.

To address these issues, the project recommends: (1) adopting automated, demand-driven restocking for high-turnover items, (2) reducing excess inventory of Category C products, (3) renegotiating supplier rates for low-margin essentials, (4) offering bundled promotions on high-margin goods, (5) implementing loyalty programs targeting "at-risk" customers, and (6) optimizing pricing to remain competitive against online retailers. Initial implementation has improved stock availability and enhanced profit tracking.

2. Detailed Explanation of Analysis Process/Method

To extract valuable insights from the store's sales data spanning March 1st to April 30th, 2025, a range of analytical techniques and visualization tools were utilized. These methods aimed to tackle critical business issues such as optimizing inventory levels, enhancing profit margins, and managing customer credit effectively.

1. **Data Collection**

   The data for this analysis was gathered from a variety of sources to ensure a comprehensive understanding of business operations. It included daily sales transaction records to track product movement, inventory details to monitor stock levels and turnover rates, and purchase logs indicating the quantity of items acquired over a specific period. Additionally, revenue and profit figures were collected across different product categories to assess financial performance. To gain insights into consumer behavior, a survey was also conducted involving 95 customers, focusing on their purchasing patterns and preferences.

2. **Data Cleaning and Preprocessing**

   Prior to conducting the analysis, the collected data was thoroughly cleaned to ensure accuracy and consistency. Missing values were addressed, particularly in critical fields such as transaction dates and monetary amounts, to maintain data completeness. Currency values, originally recorded in rupees (₹), were converted into a standardized numerical format to enable proper analysis.

   In addition, all date-related fields, including borrowing and repayment dates, were reformatted to a consistent structure for better reliability. Duplicate records were also identified and removed to eliminate redundancy, ensuring that the insights derived from the data were both accurate and meaningful.

3. Analytical Methods Applied

A series of analytical techniques were implemented to address the key business challenges identified — including inventory optimization, profitability improvement, and customer retention. Each method was carefully chosen and justified in the context of the specific problem it aims to solve.

3.1. Data Visualization Techniques

Multiple visualization methods were applied to uncover trends and relationships across various business metrics:

- **Scatter Plot:** Illustrated the link between expenses and revenue generation.
- **Line Graph:** Tracked changes in sales, revenue, costs, and profit over time, revealing seasonal patterns.
- **Pareto Analysis (80/20 Principle):** Highlighted the key products driving most of the revenue, helping focus on high-priority SKUs.
- **Bar Graph:** Compared the performance of different product categories in terms of sales, profit, and revenue.
- **Pie Chart and Bar Chart:** Used to visualize customer segmentation and analysis, showing the proportional share of each customer group, which helps identify the most valuable segments and areas with growth potential.

3.2 ABC Analysis – Inventory Optimization

To enhance inventory management, ABC Analysis was applied using the Annual Consumption Value (ACV) of each product, which is calculated by multiplying the sales quantity by the cost price of the SKU:

Formula:
Annual Consumption Value = Sales Quantity × Cost Price

Based on their contribution to the total consumption value, products were categorized as follows:

- **A-category:** ~70–80% of the total value – High-priority items requiring regular monitoring and strict inventory control.
- **B-category:** ~15–20% of the value – Medium-priority items with moderate control.
- **C-category:** ~5–10% of the value – Low-priority items with minimal oversight.

This method helps the business focus on a smaller subset of high-impact SKUs that contribute significantly to sales and profitability. By doing so, it ensures efficient stock rotation, reduces excess inventory, and enhances working capital utilization.

Due to limitations in historical data availability, this analysis was performed on two months of sales and inventory data. While this is a short time frame, the same ABC classification logic was considered valid and applied to the available dataset to derive meaningful insights.

Justification:

This analysis directly addresses Problem 1 – Inventory Optimization by identifying essential products that require the most attention in procurement and stock control. It lays the foundation for data-backed purchasing decisions and helps minimize wastage and stockouts.

3.3 Time Series Forecasting – Demand Prediction

To ensure timely and accurate inventory replenishment, a Time Series Forecasting approach was employed using the ARIMA (AutoRegressive Integrated Moving Average) model. ARIMA is a robust statistical technique that identifies and models patterns within time-dependent data, such as trends and seasonality, making it ideal for predicting future sales volumes.

Model Equation:

$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + ... + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \varepsilon_t$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{t}=1}^{\mathrm{n}} \left(yt - \hat{y}\mathrm{t} \right)^2}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{t}=1}^{\mathrm{n}} \left| yt - \hat{y}\mathrm{t} \right|$$

$$\mathrm{MAPE} = \frac{100\,\%}{n} \sum_{t=1}^{n} \left| \frac{yt - \hat{y}t}{yt} \right|$$

Where:

- Y_t = Forecasted sales at time *t*
- φ = Autoregressive (AR) coefficients
- θ = Moving Average (MA) coefficients
- ε_t = Random error (white noise)
- *c* = Constant term
- n total number of predictions
- yt = observed value at time t
- y^t = forecasted value at time t

Due to data limitations, this model was trained on two months of daily sales data (March–April 2025). While short-term, this dataset still captured enough variability to establish initial trends useful for near-term forecasting.

The forecasts generated provide data-driven estimates of future demand, enabling the store to plan procurement more effectively. This minimizes both the risk of stockouts (loss of sales) and overstocking (capital lock-in and wastage), thereby improving inventory turnover.

Justification:
This technique directly addresses Problem 1 – Inventory Optimization, by synchronizing inventory levels with anticipated demand. It facilitates smarter procurement planning and contributes to overall operational efficiency.

3.4 Profit Margin Evaluation – Profitability Analysis

To improve overall financial performance and inform pricing decisions, a comprehensive profitability analysis was conducted at the SKU level. The central focus was to evaluate individual product profit margins to identify both high-performing and underperforming items.

Formula Used: Profit Margin (%) = (Profit ÷ Revenue) × 100
Where:
• Profit = Selling Price – Cost Price
• Revenue = Quantity Sold × Selling Price

This metric quantifies how much profit is earned per unit of revenue, thus offering a clear perspective on product-level efficiency. Products with high margins are valuable for business growth, while those with low or negative margins signal the need for pricing revisions, cost control, or even product discontinuation.

Additionally, Contribution Margin analysis was performed to examine the amount each SKU contributes towards covering fixed costs and generating net profit. This was complemented by evaluating Cost of Goods Sold (COGS) across SKUs to uncover hidden inefficiencies in procurement or supply chain operations.

To visualize profitability, SKUs were ranked based on their margin percentages, and grouped into:

- High-margin products – Strong profit contributors, ideal for promotion and prioritization.
- Medium-margin products – Stable but improvable through operational or pricing tweaks.
- Low-margin products – Require strategic reassessment through cost reduction, bundling, or discontinuation.

Justification:

This method directly addresses Problem 2 – Profit Margin Evaluation, by offering actionable insights into which SKUs drive profitability and which erode it. It empowers the store to take data-informed decisions on pricing strategies, cost control, and product mix optimization.

3.5 Customer Survey and RFM Analysis – Retention Strategy

To better understand customer behavior, preferences, and satisfaction levels, a detailed survey was conducted involving 95 customers. The data captures a diverse range of demographic attributes such as age group, gender, income level, shopping frequency, and price sensitivity, along with behavioral metrics like loyalty scores, switching reasons, and retention suggestions.

Survey Insights

Customer feedback was analyzed through both quantitative and qualitative lenses:

- **Quantitative Data** included structured responses like *Loyalty_Score*, *Price_Sensitivity*, and *Shopping_Frequency*, which were explored using descriptive statistics to determine central tendencies and distribution across customer segments.
- **Qualitative Feedback** (e.g., "Home delivery option please", "Friendly staff is appreciated") was categorized into thematic clusters such as:
    - Product Variety
    - Price Sensitivity
    - Convenience
    - Service Satisfaction
    - Stock Availability

These insights help businesses identify pain points and drivers of loyalty.

RFM (Recency, Frequency, Monetary) Analysis:

To segment customers and prioritize engagement efforts, an RFM analysis was carried out. Each customer was scored on:

- **Recency (R):** How recently a customer made a purchase or engaged (mapped through *Shopping_Frequency* and *Preferred_Purchase_Channel*).

- **Frequency (F):** How often the customer shops (quantified by the *Shopping_Frequency* field and *Loyalty_Score*).
- **Monetary Value (M):** While direct monetary values are not given, proxies like *Income_Level* and *Product_Preferences* serve as indicators for likely monetary contributions.

Each component (R, F, M) was normalized and scored on a 1–5 scale, and summed as:

RFM Score=R+F+M

This composite score was used to rank and segment customers into the following categories:

- **Loyal Customers** – High RFM scores, frequent shoppers, low price sensitivity, and positive retention suggestions.
- **High-Value Buyers** – Customers from higher income brackets (e.g., 60K+), shopping via multiple channels, with high loyalty scores.
- **At-Risk Segments** – Low loyalty scores, high price sensitivity, and suggestions like "More competitive pricing needed" or "Love the variety – keep it up", signaling potential churn.

Justification:

This customer segmentation is directly aligned with solving Problem 3: Customer Retention. It allows the business to:

- Personalize retention strategies (e.g., loyalty rewards, stock improvements)
- Proactively address feedback from at-risk customers
- Focus on high-value buyers for premium services
- Tailor offers based on shopping channel preferences and price sensitivity

By blending survey insights with behavioral analytics, this RFM model provides a robust foundation for data-driven customer engagement and ensures targeted actions to maximize retention and profitability.

3.6 Tools and Technologies Used

The project leveraged a mix of tools to streamline data analysis and visualization. Python, with libraries like Pandas, Matplotlib, Seaborn, and Statsmodels, was used for data preprocessing, graphical exploration, and time series forecasting. Excel supported quick computations, ABC classification, and clean tabular summaries. Customer feedback was gathered with responses stored and reviewed in Google Sheets. All code execution and documentation were carried out in Google Colab, enabling an organized analysis environment.

3. Results and Findings

3.A. Sales, Purchase and Revenue Pattern:

3.1 Sales Pattern of over 2 months:

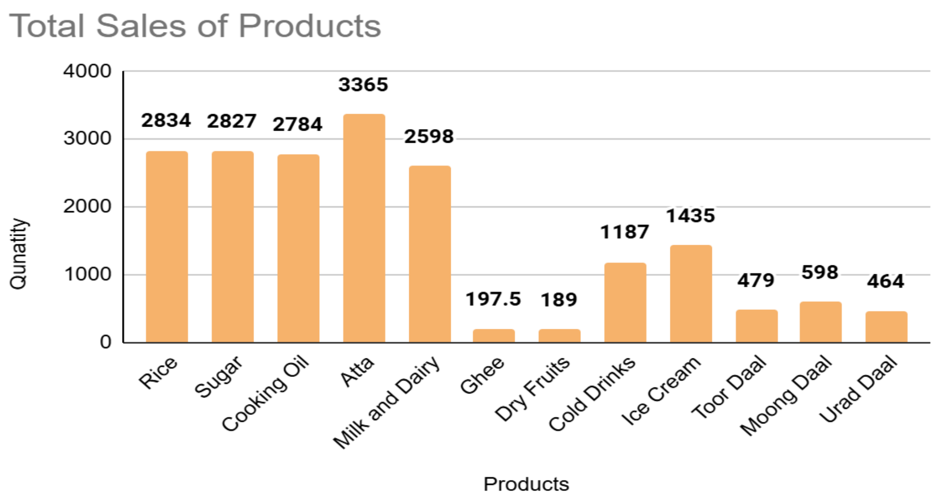


Figure 1. *Column Bar chart of Total Sales of Products*

The bar chart in figure1. displays the total quantity sold for various grocery products. Atta emerged as the top-selling product with 3365 units, followed by Rice (2834), Sugar (2827), and Cooking Oil (2784), all showcasing high customer demand. Milk and Dairy also performed well with 2598 units, indicating consistent household consumption.

On the other hand, niche products like Ghee (197.5 units) and Dry Fruits (189 units) had significantly lower sales, suggesting limited or occasional demand. Beverages such as Cold Drinks (1187) and Ice Cream (1435) also showed decent traction, likely driven by seasonal or impulse buying. Pulses like Toor Daal (479), Moong Daal (598), and Urad Daal (464) had moderate sales, suggesting a steady but less frequent purchase pattern.

The average sales value is approximately 311 units with a standard deviation of ~47, indicating moderate variability in sales. Sales range from 238 to 424, with a slightly right-skewed distribution and no extreme outliers (low kurtosis).

3.2 Time Series Sales Analysis:

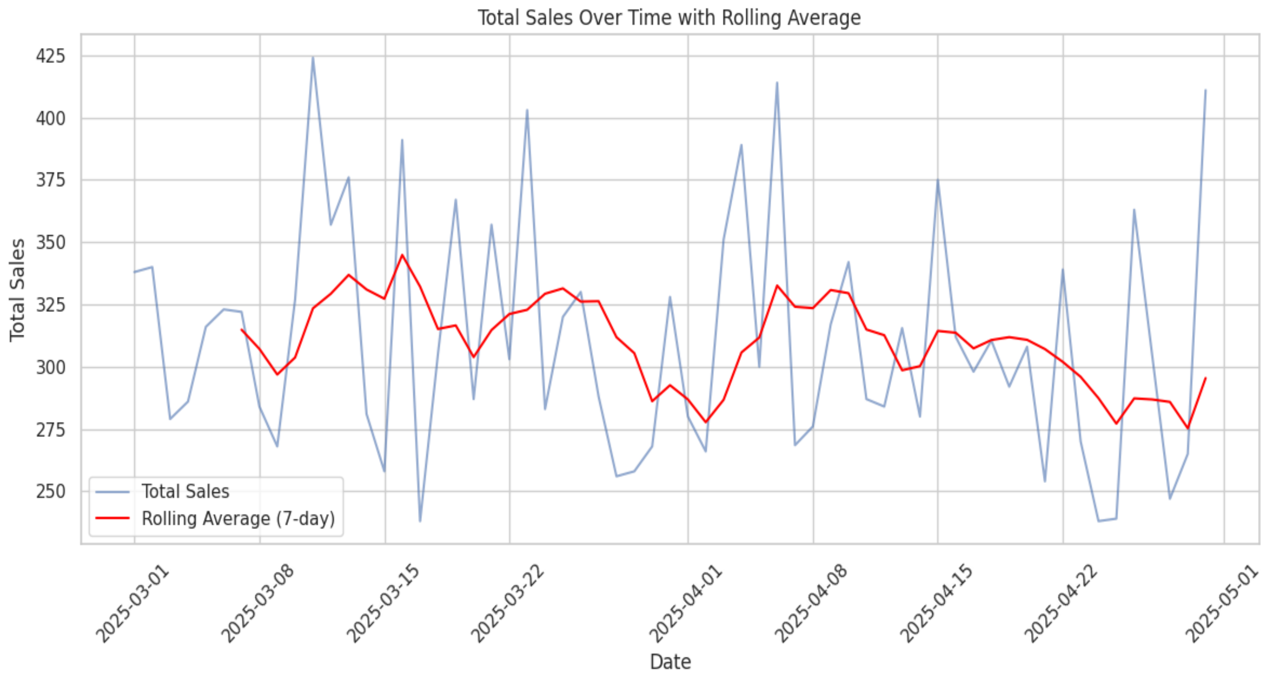


Figure 2. *Time Series Analysis of Sales*

The graph depicts daily total sales from March to the end of April 2025, with a 7-day rolling average overlaid to smooth out short-term fluctuations. The blue line represents raw daily sales, which show considerable volatility with frequent peaks and troughs throughout the period. These spikes may reflect occasional promotions, festivals, or other external factors driving sudden increases in sales, while the dips could relate to off-peak periods or stockouts.

The red line, indicating the 7-day rolling average, provides a clearer view of the overall trend by minimizing day-to-day noise. It reveals that sales levels generally remained stable over the two months, with mild upward movements in mid-March and early April, followed by a slight decline toward the end of April. Overall, the rolling average suggests no strong long-term growth or decline but instead a consistent sales pattern with periodic surges. This pattern could help guide future inventory or promotional planning to align with expected demand cycles.

3.3 Sales Demand Forecasting:

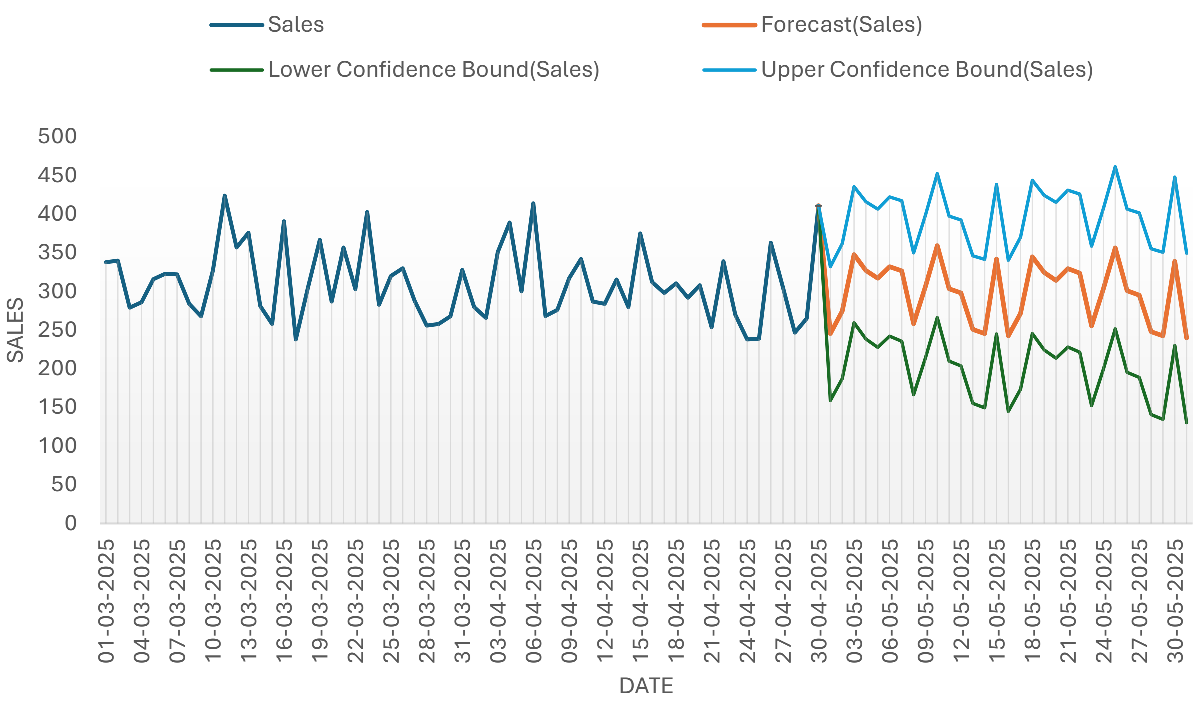


Figure 3. *Sales Demand Forecasting*

This plot in figure3. presents a sales demand forecast based on historical daily sales data, spanning from March to the end of May 2025. The blue line on the left shows the actual sales observed up to the end of April, while the orange line represents the forecasted sales for May 2025. The green and light-blue lines mark the lower and upper confidence bounds of the forecast, respectively, providing a range within which actual sales are expected to fall with a certain level of confidence (usually 95%).

From the plot, we can see that the forecast predicts continued periodic fluctuations in sales levels throughout May, with the central forecast (orange line) suggesting a relatively stable pattern between roughly 250 and 350 units sold per day. However, the confidence bands widen slightly over time, indicating growing uncertainty the further out the forecast projects. The upper bound goes as high as about 450 units per day, while the lower bound dips toward 100 units, showing that although the most probable sales are stable, there is a risk of higher volatility.

- Planning for an average daily demand of around 250–350 units in May would be reasonable, but stock levels should also be able to handle occasional peaks toward 400 units to stay safe.

- Since uncertainty grows toward the end of the forecast horizon, inventory and staffing decisions should be reviewed regularly to adjust to actual demand in real time
- The forecast performance metrics show strong accuracy: a MASE of 0.74 and SMAPE of 13% reflect reliable predictions, while the average error (MAE) is around 40 units

3.4 Revenue Analysis and Outcomes:

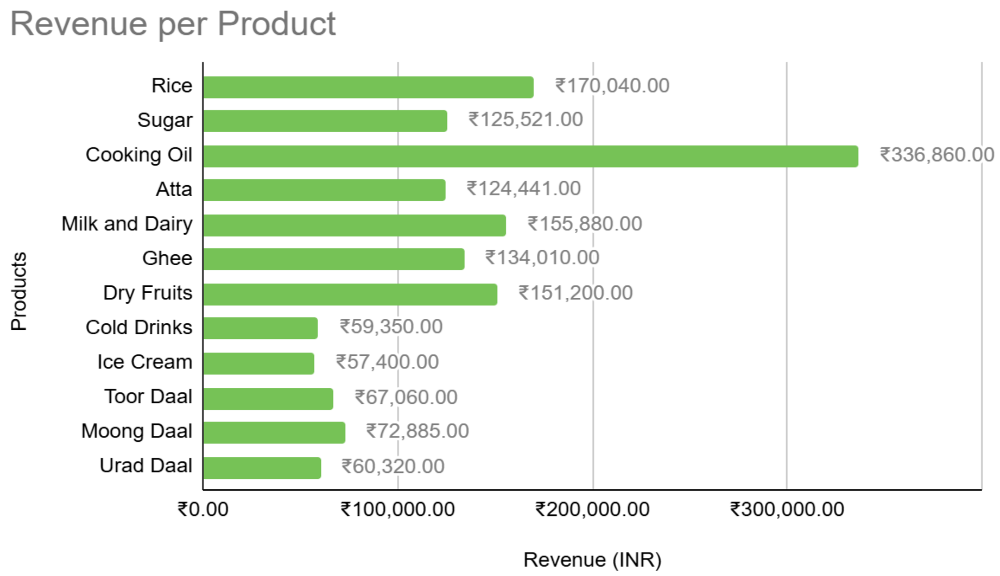
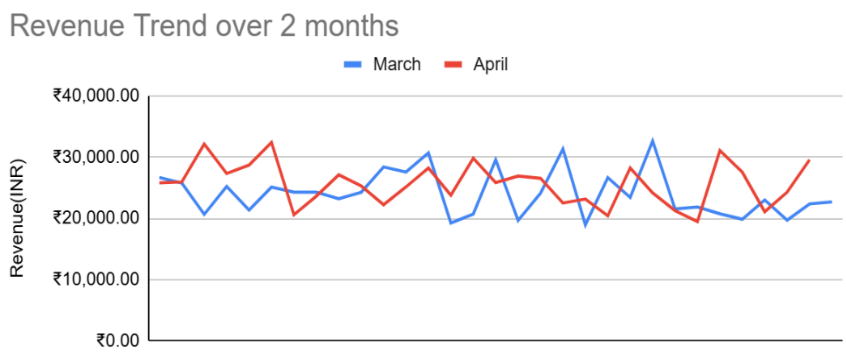


Figure 4. *Bar chart showing Revenue*

- Cooking Oil stands out as the highest revenue generator, bringing in ₹336,860, which is almost double the revenue of the next highest product. This indicates a very strong and consistent demand for cooking oil, making it a strategic product for promotions, inventory planning, and supplier negotiations.
- Rice ranks second with ₹170,040 revenue, followed by Milk and Dairy (₹155,880) and Dry Fruits (₹151,200). These products can be considered the next set of core revenue drivers for the business.
- Staples like Atta (wheat flour), Sugar, and Ghee also contribute significantly, all crossing ₹120,000, showing stable, essential household demand.
- Products like Cold Drinks, Ice Cream, and pulses (Toor Daal, Moong Daal, Urad Daal) have comparatively lower revenues, each staying below ₹75,000. This suggests they might be seasonal or discretionary products with less consistent sales.



- The revenue across both months fluctuates between ₹20,000 to ₹30,000 on most days, indicating moderate daily variability.

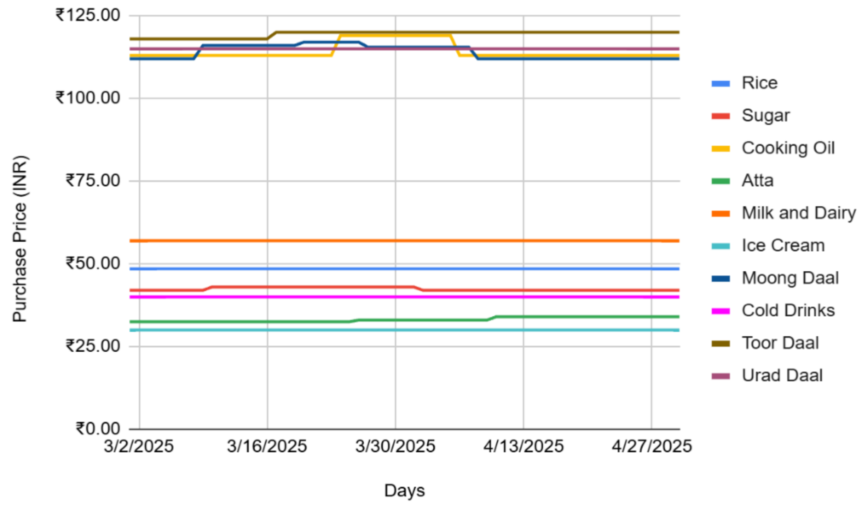
Figure 5. *Line chart showing Revenue trend*

- April generally shows higher revenue peaks than March, suggesting improved sales performance, although it still faces occasional dips.

3.5 Statistical Analysis based on Cost of Goods Sold:

- Cooking Oil stands out with the highest cost of goods sold at ₹3.17 lakhs, making it the most significant contributor to procurement expenses. Other key items like Milk and Dairy (₹1.48 lakhs) and Rice (₹1.37 lakhs) also represent major investments, pointing to their high sales volume or frequent restocking needs.
- Products such as Ghee, Sugar, Dry Fruits, and Wheat Flour fall into a moderate expense range, each costing between ₹1.1 to ₹1.2 lakhs. These likely represent steady-moving items with consistent but not excessive demand.
- On the lower end of the spectrum, items like Cold Drinks, Ice Cream, and various types of Daal (Toor, Moong, Urad) have lower associated costs. This could be due to seasonal trends, smaller packaging units, or less frequent purchase cycles.

3.6 Purchase Price Trend Analysis:

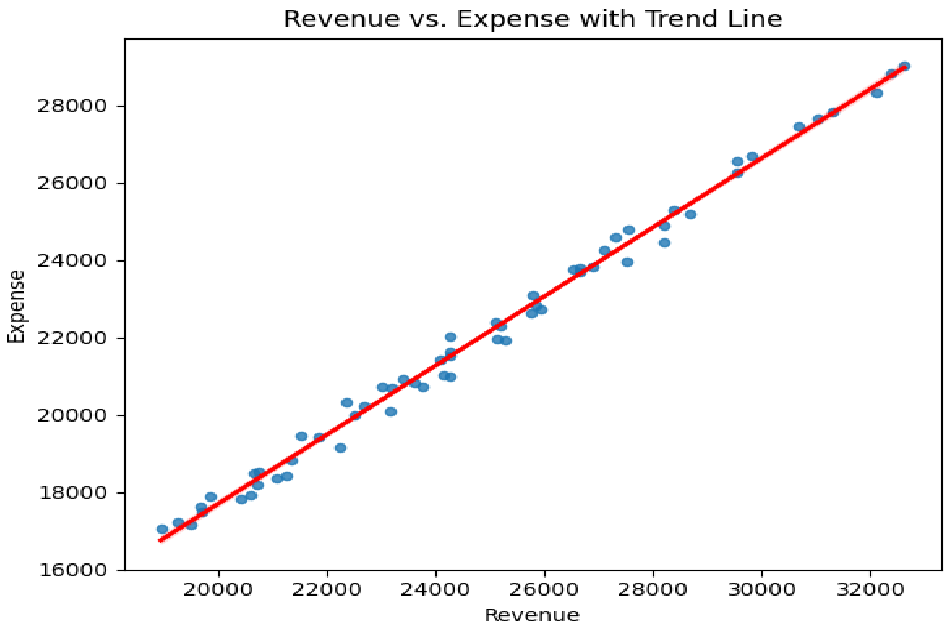


Products	Avg CP
Rice	₹48.50
Sugar	₹42.38
Cooking Oil	₹114.28
Atta	₹33.14
Milk and Dairy	₹57.00
Ghee	₹614.59
Dry Fruits	₹620.00
Cold Drinks	₹40.00
Ice Cream	₹30.00
Toor Daal	₹119.48
Moong Daal	₹113.98
Urad Daal	₹115.00

Figure 6. *Line Chart depicting purchase price*

- Most product prices were stable throughout March and April, showing low volatility.
- Cooking Oil had a temporary price spike in mid-March before returning to normal levels.
- Atta saw small but gradual price increases over the two months, while other products like Milk & Dairy, Ice Cream, and Cold Drinks maintained consistent prices.

3.7 Relationship between Revenue and Expense of Goods:



a. Strong Positive Correlation: Revenue and expenditure increase proportionally, (0.998) indicating a strong linear relationship.

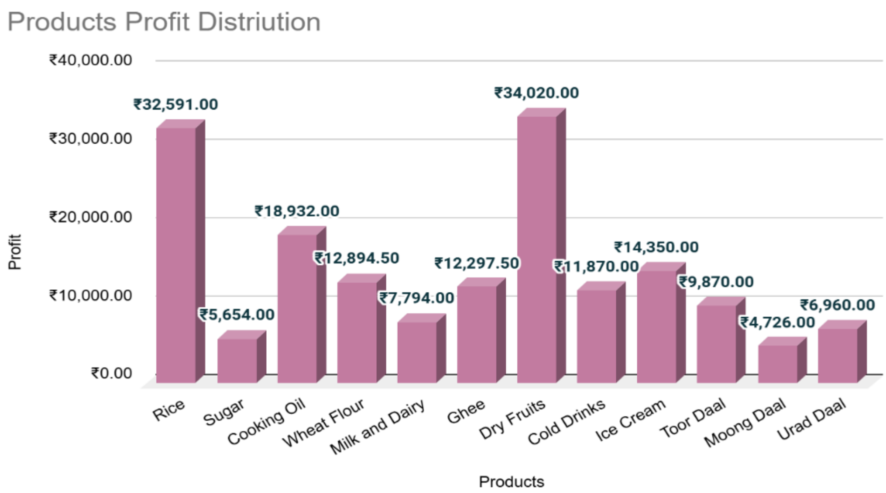
b. Consistent Profit Margins: A stable trend suggests well-controlled expenditure relative to revenue.

c. Minimal Outliers: Most data points align with the trend, indicating predictable financial factor.

Figure 7. *Scatter Plot between Revenue and COGS*

3.B. Profit and Profit Margin Analysis:

3.1 Profit Distribution of Products

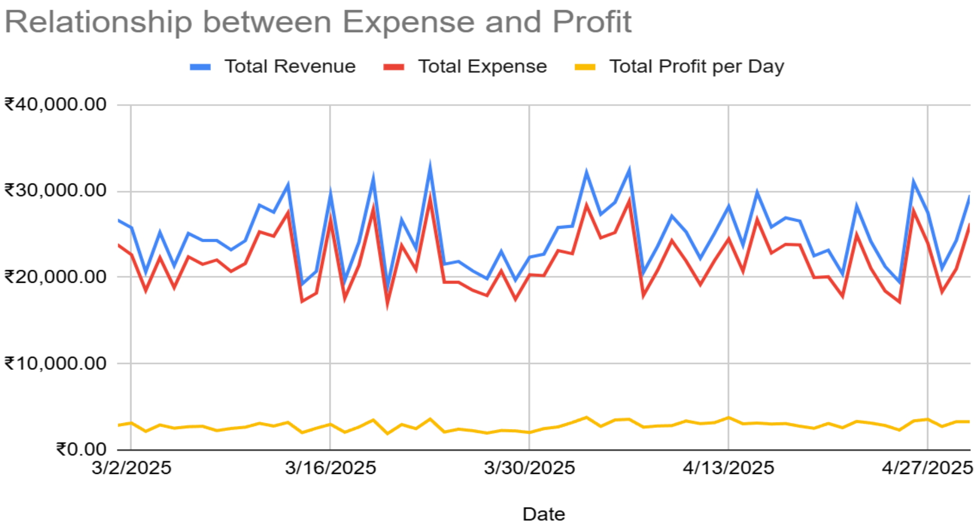


Key Insights:

- **Top Profits:** Dry Fruits (₹34,020) and Rice (₹32,591) lead significantly.
- **Strong Performers:** Cooking Oil, Ice Cream, Wheat Flour, Ghee, and Cold Drinks show good profit levels.
- **Moderate Profits:** Toor Dal, Milk & Dairy, and Urad Dal.

Figure 8. *Profit Distribution of Products*

3.2 Revenue, Expense and Profit Pattern:



Description:

The line chart tracks daily revenue (blue), daily expenses (red), and profit (yellow) over two months. The y-axis represents the amount in INR, while the x-axis represents days

Figure 9. *Line chart between profit, revenue and expense*

- **Consistent Expense-to-Revenue Balance:** Revenue and costs follow a similar trend, suggesting spending is managed in proportion to earnings.
- **Sales Variability:** Noticeable ups and downs point to recurring cycles in sales and procurement.
- **Modest yet Reliable Profit:** Profit levels stay relatively small but maintain steady consistency despite shifts in revenue and expenses.

Products	Profit	Revenue	Revenue %	Profit %	Profit Margin
Rice	₹32,591.00	₹170,040.00	11.22%	18.95%	19.17%
Sugar	₹5,654.00	₹125,521.00	8.29%	3.29%	4.50%
Cooking Oil	₹18,932.00	₹336,860.00	22.24%	11.01%	5.62%
Wheat Flour	₹12,894.50	₹124,441.00	8.21%	7.50%	10.36%
Milk and Dairy	₹7,794.00	₹155,880.00	10.29%	4.53%	5.00%
Ghee	₹12,297.50	₹134,010.00	8.85%	7.15%	9.18%
Dry Fruits	₹34,020.00	₹151,200.00	9.98%	19.78%	22.50%
Cold Drinks	₹11,870.00	₹59,350.00	3.92%	6.90%	20.00%
Ice Cream	₹14,350.00	₹57,400.00	3.79%	8.35%	25.00%
Toor Daal	₹9,870.00	₹67,060.00	4.43%	5.74%	14.72%
Moong Daal	₹4,726.00	₹72,885.00	4.81%	2.75%	6.48%
Urad Daal	₹6,960.00	₹60,320.00	3.98%	4.05%	11.54%
SUM	₹171,959.00	₹1,514,967.00		**Average**	**12.84%**

Table 1*: Table shows profit margin and profit percentage with revenue of each SKUs*

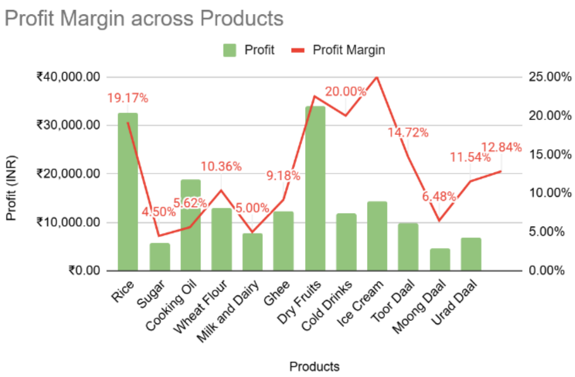


Figure 10. *Profit Margin across Products*

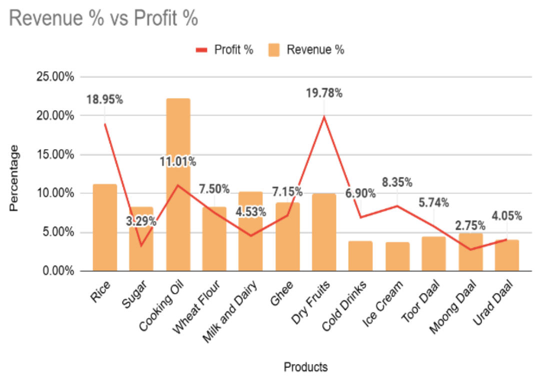


Figure 11. *Profit % v/s Revenue %*

- From figure 10: Dry Fruits (20%) and Rice (19.17%) lead in profit margin, making them the most lucrative products. Sugar (4.50%) and Moong Dal (6.48%) have the lowest margins, indicating limited profitability.
- From figure 11: Dry Fruits (19.78%) and Rice (18.95%) have high profit contributions relative to their revenue share. Sugar shows the largest gap, with a high revenue share but very low profit percentage (3.29%).

3.C. ABC Analysis for Inventory Optimization:

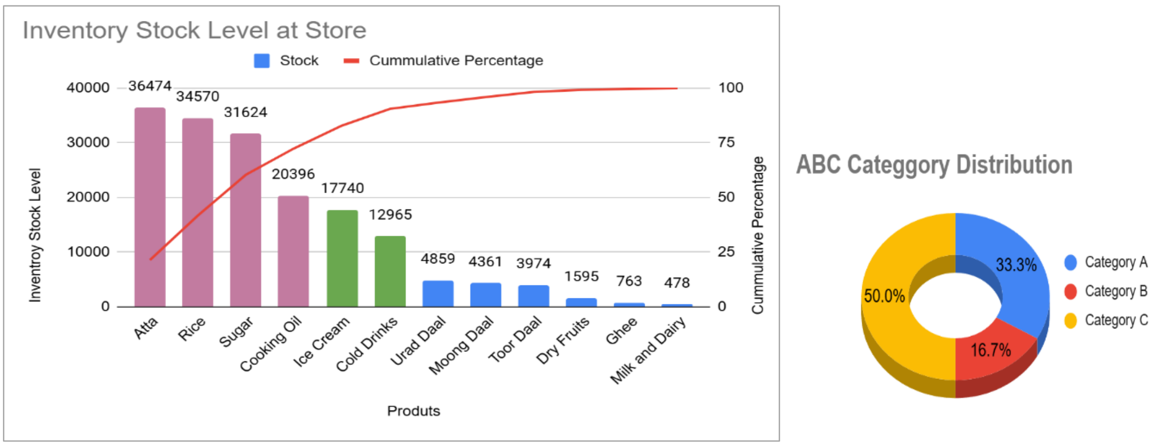


Figure 12. *Pareto chart – ABC Analysis*

Key Insights from Inventory Stock Level Chart:

The chart presents product stock quantities (bars) alongside their cumulative percentage share (line).

3.1 ABC Classification:

- Category A (Top ~80%) – Major stock items such as Atta, Rice, Sugar, and Cooking Oil account for the largest share of inventory and require close monitoring, reliable supplier coordination, and timely replenishment to avoid shortages.

- Category B (Next ~15%) – Mid-level stock products like Ice Cream and Cold Drinks need balanced management to ensure cost efficiency while maintaining adequate supply.
- Category C (Final ~5%) – Low-stock products such as Urad Dal, Moong Dal, Toor Dal, Dry Fruits, Ghee, and Milk & Dairy have minimal stock value and can be managed with more flexible inventory policies.

Pareto Principle Insight:

- A small group of products makes up most of the total stock volume, in line with the 80/20 rule.
- Category A items hold the most significant share and demand tight control.
- Category B items have moderate importance and require steady oversight.
- Category C items have the least impact and need minimal management effort.

3.2 Inventory Fluctuation:

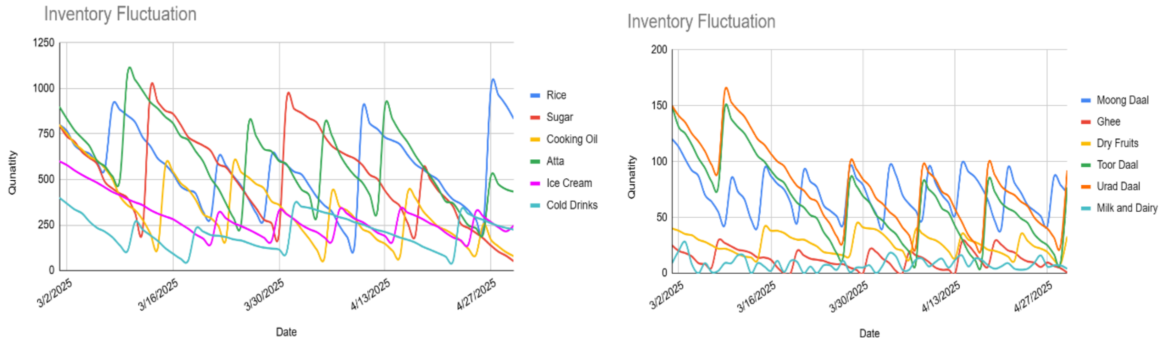


Figure 13. *Line chart on Inventory Fluctuation*

Insights from Inventory Fluctuation Charts (Figure 13):

- **High-Demand Essentials** like Rice, Atta, Sugar, and Cooking Oil show regular depletion and replenishment, reflecting strong, consistent demand. Rice and Atta deplete fastest, indicating rapid turnover.
- **Seasonal Items** such as Ice Cream and Cold Drinks follow similar restocking cycles but with lower inventory levels, likely due to temperature-driven demand.
- **Moderate-Moving Goods** like Moong Dal, Urad Dal, and Toor Dal show small but frequent fluctuations, suggesting steady but lower demand.
- **Low-Volume or Premium Items** (Ghee, Dry Fruits, Milk & Dairy) are stocked in minimal quantities—either due to perishability or selective, high-value purchases.
- Overall, the charts reflect **predictable consumption patterns**, with staples stocked in bulk and perishables/premium goods kept low to reduce spoilage.

3.D. Customer Segmentation and RFM Analysis:

3.1 Distribution based on Loyalty Score:

Key Insight:

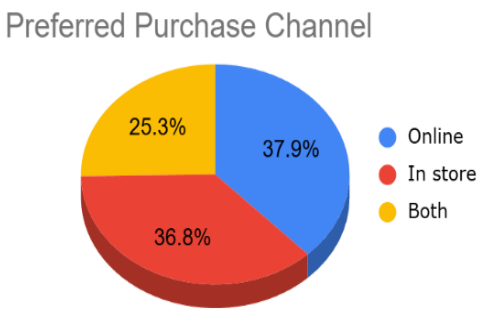
- The highest number of customers (14) have a loyalty score of 8, indicating strong engagement in this group.
- Scores 2, 7, 9, and 10 each have 10 customers, showing a relatively even distribution among

Figure 14: *Bar Chart based on Loyalty Score*

moderately to highly loyal customers.

- The lowest counts are for loyalty score 6 (6 customers) and score 1(7 customers), representing the least engaged customer segments.

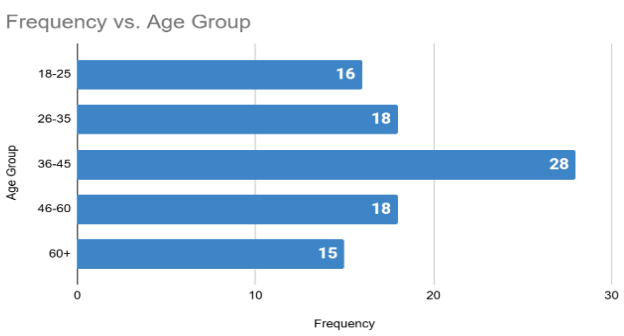
3.2 Customer Segmentation based on Preffered Purchase Channel:



- Online (37.9%) is the most preferred purchase channel, slightly ahead of In-store (36.8%)**.** Both channels (25.3%) are used by a quarter of customers, indicating a notable share of omnichannel shoppers.

Figure 15: *Pie Chart on Purchase Channel*

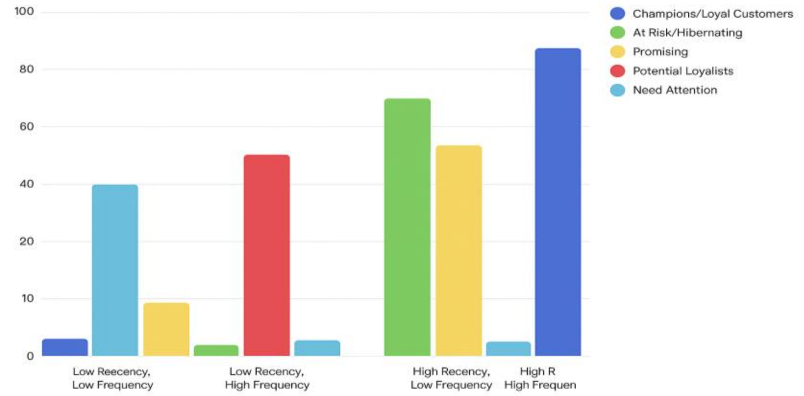
3.3 Customer Segmentation based on Age Group:



- The 36–45 age group has the highest frequency (28), making them the most active customers.
- 26–35 and 46–60 age groups both have moderate engagement (18 each).
- The 18–25 (16) and 60+ (15) groups show lower activity, indicating less frequent interactions or purchases.

Figure 16: *Customer distribution based on Age group*

3.4 RFM Analysis: As the chart in Figure 17 reveals, high purchase frequency is the primary driver and key indicator of a loyal customer. While 'Champions' are predictably



those who buy both recently and frequently, the largest segment of 'At Risk' customers are those who have purchased recently but

Figure 17: *Customer distribution based on Age group*

infrequently. This insight makes the 'High Recency, Low Frequency' group a critical focus area, as it represents both the biggest risk of churn and those who buy both recently and frequently, the largest segment of 'At Risk' customers are those who have purchased recently but infrequently. This insight makes the 'High Recency, Low Frequency' group a critical focus area, as it represents both the biggest risk of churn and the greatest opportunity for growth. Targeted campaigns to this segment are crucial to either convert these new or occasional buyers into loyal ones or lose them entirely.

4. Interpretation of Results and Recommendations

The comprehensive analysis of sales, inventory, and customer data from March to April 2025 has yielded several critical insights that address core business challenges related to inventory management, profitability, and customer retention.

1. Inventory Optimization & Sales Dynamics: The analysis reveals a classic 80/20 rule in inventory, where a small subset of products drives the majority of business activity.

- ABC Classification: Only 20% of SKUs (Category A), such as Atta, Rice, Sugar, and Cooking Oil, contribute to over 75% of total revenue. These high-volume essentials show consistent household demand but are prone to stockouts due to inconsistent replenishment cycles.
- Overstocking & Niche Items: Conversely, Category C items, including Dry Fruits, Ghee, and niche Dals, exhibit low turnover and are at risk of overstocking, tying up capital in slow-moving goods.
- Demand Forecasting: Time series forecasting for high-demand items like Rice and Cooking Oil has confirmed cyclical demand patterns. This allows for more accurate,

predictive stock planning to prevent future stockouts and manage inventory more efficiently.

2. Profitability and Pricing Strategy

A detailed evaluation of profit margins highlights a significant opportunity to improve overall profitability through strategic pricing and promotion.

- Margin Variation: There is a wide variation in profit margins across products. High-volume essentials like Sugar and Moong Dal offer low margins (below 8%), while premium or high-demand products like Dry Fruits, Rice, and Ice Cream yield high margins (over 19%).
- Strategic Opportunities: This disparity suggests a need to rebalance promotional strategies to focus on driving sales of high-margin items. Simultaneously, there is an opportunity to renegotiate procurement rates for low-margin essentials to improve their contribution to profit.
- Competitive Pricing: Comparative price checks revealed that some high-frequency SKUs are priced higher than those of nearby competitors, creating a risk of losing loyal customers to more affordable online or local alternatives.

3. Customer Behavior and Retention Strategy

The analysis of customer behavior underscores the growing importance of digital channels and the immediate need for a targeted retention strategy.

- At-Risk Customer Segment: The RFM (Recency, Frequency, Monetary) analysis identified that the largest customer cluster is the "at-risk" group, characterized by high recency but low frequency. These are recent buyers who have not yet become repeat customers, representing both a high churn risk and a significant growth opportunity.
- Omnichannel Preference: Digital channels are critical, with 38% of all transactions occurring online. A significant portion of customers utilize both online and offline options, highlighting the necessity of a seamless omnichannel strategy to meet modern consumer expectations.
- Overall Engagement: While general customer engagement is decent (most loyalty scores fall in the 7–10 range), the combination of competitive pricing pressure and a

large at-risk segment requires immediate action to secure loyalty and prevent customer churn.

Actionable Recommendations:

- To address inventory inefficiencies, profitability gaps, and customer retention challenges, a multi-pronged strategy is recommended. First, implementing dynamic inventory control using ABC analysis and demand forecasting is crucial, especially for high-volume Category A items like Rice, Oil, and Sugar, which require daily stock levels of 250–350 units. This should be complemented by maintaining safety stock, reducing procurement of slow-moving Category C items (like Dry Fruits and niche Dals), and applying stricter inventory policies to optimize shelf space and reduce capital lock-up. A monthly stock audit dashboard will further help align forecasted vs. actual sales, improving procurement accuracy.
- For enhancing profitability, efforts should focus on promoting high-margin items such as Ice Cream, Dry Fruits, and Rice through bi-weekly campaigns and combo offers bundling them with low-margin essentials. Re-negotiating procurement rates for low-margin SKUs like Sugar and Moong Dal can directly enhance gross margins by 3–5%.
- To tackle customer churn and improve competitiveness, it is vital to launch loyalty programs and personalized promotions targeting the "High Recency–Low Frequency" customer segment identified in the RFM analysis. This should be paired with SMS/email-based marketing campaigns to increase engagement and repeat purchases. Regular price benchmarking of popular SKUs will help remain competitive with local and online retailers. Lastly, promoting BOPIS (Buy Online, Pick Up in Store) and improving the digital shopping experience will help capture the growing base of omnichannel customers and enhance overall convenience.

5. Conclusion:

Reference Link*:* *Analysis Dataset*

By adopting these strategies, Sundaryatan Stores can significantly enhance profitability, optimize inventory operations, and strengthen overall financial health. Emphasizing data-driven decision-making, maintaining ideal stock levels, applying smart pricing strategies, and improving credit control will collectively drive revenue growth, minimize financial risks, and support long-term, sustainable business expansion.