# Optimization of Sales, Inventory, and Customer Retention in a Supermarket

## A Final report for the BDM capstone Project


Submitted by

Name: Shweta Vyas

Roll Number: 24DS2000089

Email: 24ds2000089@ds.study.iitm.ac.in



IITM Online BS Degree Program,

Indian Institute of Technology, Madras, Chennai

Tamil Nadu, India, 600036

# CONTENTS

## 1. Executive Summary and Title

**Title: Optimization of Sales, Inventory, and Customer Retention in a Supermarket.**

The Reliance Smart Point store in Jodhpur (Store 3005) functions as a mid-tier retail outlet serving a local neighbourhood operating under Reliance Retail. With a lean team and daily operations, the store offers a broad assortment of fast-moving consumer goods (FMCG), including staples, dairy products, fresh produce, and frozen items. While overall footfall remained relatively stable throughout 2024, the store consistently faced operational inefficiencies. Notable challenges included erratic sales patterns during festive periods, overstocking of perishable items, and a noticeable drop in customer engagement following promotional campaigns.

This analysis leveraged a full year's operational data (January-December 2024) to address these challenges. The methodology involved meticulous data preprocessing and the application of advanced analytical techniques. Time series forecasting models, specifically Holt and Damped Holt, were used to predict sales trends and assess the impact of seasonality. Category-level strategies were developed using Coefficient of Variation (CV) to identify demand volatility, along with ABC analysis to segment products based on their revenue contribution. Regression analysis and margin quadrant mapping were employed to understand profitability patterns across categories, while Days of Holding (DOH) and stock availability rates were used to evaluate inventory health and operational readiness.

The analysis revealed several key findings. Forecasting models highlighted gaps in capturing demand surges during the festive months, especially in October and December, resulting in stockouts. CV analysis exposed significant volatility in categories such as Fruits and Beverages, indicating unpredictable consumer behaviour and limited forecasting accuracy. Vegetables consistently exhibited inefficiencies in inventory management, with prolonged DOH and frequent stockouts, suggesting issues in replenishment cycles. While overall profitability remained stable across the year, margin analysis revealed dips during peak sales periods, likely driven by deep discounting and short-term promotional strategies. In contrast, Staples and Home & Personal Care categories stood out as reliable revenue generators, showing both steady sales and healthy margins throughout the year.

Based on these insights, I developed a set of targeted, data-backed recommendations aimed at improving store performance. Recommendations include refining forecasting models to better account for seasonal fluctuations, implementing tighter DOH limits for perishable goods to reduce spoilage, introducing ongoing CV monitoring for high-volatility categories to optimize stocking decisions, and deploying automated stock alerts to consistently maintain stock availability at or above 85%. If implemented effectively, these strategies are projected to significantly reduce wastage, improve on-shelf availability, and enhance customer retention. Early indicators suggest that improved freshness, lower spoilage costs, and more consistent product availability could also lead to stronger repeat purchase behaviour, particularly in categories where inventory stability is restored. Collectively, these interventions are designed to move the store toward a more sustainable, responsive, and profitable retail model.

# 2. Detailed Explanation of Analysis Process/Method

## 2.1 Data Cleaning and Preprocessing

### a) Initial Dataset and Challenges

The dataset, compiled monthly over the calendar year 2024, consisted of diverse variables including numeric values (e.g., sales, margins), categorical fields (e.g., product categories), and percentage-based metrics (e.g., stock availability). However, several data quality challenges were immediately evident. Key columns such as “Total Sales,” “Margins,” “Stock Availability,” and “Days of Holding (DOH)” exhibited inconsistent formatting, which could lead to inaccurate parsing and downstream analytical errors. Additionally, the dataset contained non-standard Unicode characters, such as \xa0 (non-breaking spaces), which often result from poor export formatting and can interfere with data type conversions and visualizations. A significant number of rows were also partially or completely empty, and missing values were prevalent across important fields, necessitating robust preprocessing before any meaningful insights could be extracted.

### b) Column Cleaning and Standardization

To prepare the dataset for seamless analysis and visualization, a series of column-level cleaning and standardization steps were undertaken. First, all column headers and string-type entries were stripped of leading and trailing whitespace using Python’s .strip() method, ensuring uniformity across column names. Unicode artifacts like \xa0 were removed using string replacement techniques to eliminate hidden characters that could disrupt parsing or grouping operations. Completely empty rows were dropped using .dropna() to reduce noise and improve data integrity. Special attention was given to the “Month” column: inconsistent representations of month names were standardized to a capitalized format using Python’s string methods after stripping whitespace. These steps improved compatibility across plotting libraries like Seaborn and Matplotlib, while also preventing sorting and aggregation errors during time series analysis.

### c) Feature Engineering

Beyond standard cleaning, additional features were engineered to extract deeper, business-relevant insights. A key derived metric was Customer Growth (%), calculated as the relative change in customer count compared to the previous year. This feature revealed patterns of customer acquisition and churn across months, serving as a proxy for retention effectiveness, even in cases where the absolute numbers appeared stable. The formula used to calculate Customer Growth (%) is:

$$Customer\ Growth\ (\%) = \frac{(Current\ Year\ Customers - Last\ Year\ Customers)}{Last\ Year\ Customers} \times 100$$

This engineered metric captured customer behaviour trends across the year and helped approximate retention impact, especially when aligned with campaign and stock variation. Although direct footfall data was unavailable, monthly customer counts were used as a proxy to understand customer engagement trends and to approximate retention behaviour.

**d) Temporal Structuring**

To enable accurate trend analysis and effective forecasting, the dataset's temporal component, which was represented by the "Month" column, was carefully restructured. First, all month names were standardized using string formatting methods (str.strip() and str.capitalize()), ensuring consistent representation. Next, the "Month" column was converted into a categorical variable with explicit ordering from January through December. This transformation was critical to maintaining chronological order in visualizations. It also avoided common issues such as alphabetical sorting. The dataset was then sorted based on this newly ordered categorical column to align month-wise trends accurately. Rows with missing or invalid "Month" values were dropped to ensure analytical integrity. This structured temporal dimension served as the backbone for all time-based visualizations and forecasting models applied in later stages of the analysis.

**2.2 Comprehensive Explanation for each Method/Analysis Used:**

To deliver actionable business insights and directly address the store's operational challenges, the analytical framework was structured into five verticals: Sales Forecasting, Product Strategy, Profitability Analysis, Inventory Holding Efficiency, and Stock Availability Monitoring. Each technique was strategically selected to answer a specific business question and maintain a balance between statistical rigor and practical business relevance.

The first vertical focused on sales trend analysis and forecasting, a critical component for optimizing resource allocation, planning inventory cycles, and improving budgeting accuracy. Effective forecasting enables proactive decision-making, allowing businesses to anticipate demand patterns rather than simply react to them.

**Holt's Linear Trend Model** was used to model linear growth patterns. The model forecasted future values using the equation:

$$\hat{\boldsymbol{y}}_{\{t+h\}} = \boldsymbol{l_t} + \boldsymbol{h}\boldsymbol{b_t}$$

Where: $\boldsymbol{l_t}$ represents the level at time $\boldsymbol{t}$, $\boldsymbol{b_t}$ the trend component, and $\boldsymbol{h}$ the forecast horizon.

To avoid overestimating long-term sales trends, **Damped Holt's method** was applied as a refinement. This model introduces a damping parameter $\phi \in (0,1)$, which gradually reduces the influence of the trend over time, resulting in more stable long-term forecasts.

The forecast equation is:

$$\hat{y}_{\{t+h\}} = l_t + b_t \ \cdot \phi \ \cdot \frac{1 - \phi^h}{1 - \phi}$$

The **Naïve forecast** was also implemented as a baseline. It assumes that future sales mirror the most recent actual value. While simplistic, it provided a benchmark against which the accuracy of the more sophisticated models could be compared.

To validate performance, a **backtesting approach** was adopted. Models were trained using data up to October 2024, and forecasts were generated for November and December. These were then compared with actual sales to calculate absolute and percentage errors, allowing evaluation of forecast accuracy and robustness.

The second vertical addressed **product category performance**, essential for tailoring marketing efforts, optimizing shelf space, and prioritizing procurement. A **Contribution vs. Growth Matrix** was used to plot each product category by total sales and average month-over-month (MoM) growth.

This segmentation created four distinct quadrants:

- *Strategic Performers* (high sales, high growth)
- *Established Essentials* (high sales, low growth)
- *Emerging Opportunities* (low sales, high growth)
- *Underperformers* (low sales, low growth).

This segmentation guided data-driven prioritization of product categories

To evaluate demand stability, the **Coefficient of Variation (CV)** was calculated for each category. CV, calculated as standard deviation divided by mean, helped classify categories by volatility, aiding stock control strategies. It flagged volatile categories like Fruits and Beverages which exhibited erratic demand patterns. In contrast, Staples showed low CV values, indicating predictable and stable performance.

Monthly sales trendlines for top-performing categories provided further insight into seasonal trends, revealing optimal windows for promotions and stock replenishment. Additionally, **ABC classification** was performed using the 70-20-10 rule based on cumulative contribution to total revenue. Class A (top 70%) items received the highest managerial focus due to their impact, Class B (next 20%) required moderate oversight, while Class C (bottom 10%) were monitored with simpler controls. This analysis enabled more focused category management and operational efficiency.

The third vertical focused on **profitability metrics**, recognizing that high sales volume does not necessarily equate to high profit margins. A **Margin vs. Sales Quadrant** plot was used to segment months based on gross margin percentages and total sales, revealing trade-offs where higher volumes aligned with reduced margins, likely due to aggressive promotional strategies. A

**regression overlay** on this scatter plot explored the relationship between sales and margins. The linear regression equation:

$$GM = \beta_0 + \beta_1 \cdot Sales + \epsilon$$

Where:

- GM: Gross Margin (dependent variable)
- Sales: Total Sales (independent variable)
- $\beta_0$: The y-intercept, representing expected Gross Margin when Sales are zero.
- $\beta_1$: The slope, indicating change in Gross Margin for every one-unit increase in Sales.
- $\epsilon$: The error term, accounting for unexplained variance.

It suggested a slight positive relationship, where higher total sales were modestly associated with improved gross margins. This may reflect effective pricing strategy or a favourable product mix during high-volume periods, countering the assumption that heavy sales are always driven by deep discounts. A month-wise line chart tracking gross margin fluctuations revealed general stability, with September marked the highest margin at 18.8%, likely due to a favourable product mix and restrained discounting. To identify periods of optimal profitability and growth, a **Margin vs. MoM Growth** plot was generated, tagging individual months to highlight those delivering both strong growth and profitability, ideal targets for replication and strategic investment.

The fourth vertical explored **inventory holding efficiency**, especially for perishable categories like Fruits and Vegetables, where freshness directly impacts customer satisfaction and waste management. **Days of Holding (DOH)** was calculated and plotted monthly for both categories, with a target band of 1.5 to 2.5 days marking optimal turnover. Vegetables consistently breached this range more often than Fruits, indicating overstocking and increased spoilage risk. To understand the impact of holding levels on sales, **Pearson's correlation coefficient (r)** was computed and visualized using scatter plots. For both Fruits and Vegetables, the correlation highlighted how overholding affected sales efficiency, providing a statistical basis for inventory realignment. Pearson's r quantifies the strength and direction of a linear relationship between two continuous variables (-1 to +1). The formula for Pearson's r is:

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

Where:

- Cov (X, Y): The covariance between variables X and Y.
- $\sigma_X$: The standard deviation of variable X.
- $\sigma_Y$: The standard deviation of variable Y.

The fifth vertical explored Stock Availability monitoring. Maintaining adequate shelf availability is essential not just for revenue generation, but also for minimizing lost sales and preserving customer loyalty. Even highly demanded products can fail to generate revenue if they are frequently out of stock. Stockouts not only translate into missed sales opportunities but can also erode customer trust and loyalty over time. Ensuring optimal stock availability supports consistent service levels and protects against revenue leakage.

To monitor this, a bar chart visualized **average stock availability** across product categories, benchmarked against a service-level target of 80%. A color-coded scheme enhanced interpretability: **green bars** denoted categories meeting or exceeding the 80% availability threshold (e.g., Staples and Home & Personal Care), while **red bars** identified underperforming categories falling below this threshold. Fresh and Frozen Foods were particularly vulnerable, with frequent stockouts observed. This visual diagnostic supported focused inventory interventions, supporting the broader goal of improving availability, reducing lost sales, and enhancing customer retention.

### 2.3 Justification of Methods, Tools, and Variable Choices:

The selection of methods and analytical techniques was driven by their strategic alignment with the store's key business challenges, as outlined in the problem statements. Each technique was chosen not only for its statistical appropriateness but also for its direct applicability to real-world decision-making in a retail context.

**a) Sales Forecasting (Objective -Stabilize Sales Performance):**
Time-series models like Holt and its Damped variant were selected for their adaptability to recent trends without assuming strict seasonality which is crucial in retail environments with irregular demand spikes. Their ability to adapt to recent data points without assuming seasonality made them well-suited for monthly sales prediction. Damped Holt was particularly valuable as it effectively smooths future projections which is critical for festive-driven fluctuations in a retail setting prone to festive surges and short-term demand spikes. The Naïve forecast, while simplistic, served as a benchmark to validate the incremental value of these models. Forecast validation through backtesting ensured methodological rigor and demonstrated the reliability of forecasts.

**b) Product Category Strategy (Objective – Optimize Inventory):**
The Contribution vs. Growth Matrix enabled strategic segmentation of categories by revenue and momentum, enabling strategic, insight-driven prioritization. This was paired with the Coefficient of Variation (CV) to assess demand stability and ABC classification to evaluate revenue contribution. These techniques are foundational in retail analytics and are widely adopted for segmenting control intensity across product categories. Their combined use provided a 360-degree view of product behaviour, from volatility and growth to overall impact, enabling more granular inventory decisions.

**c) Profitability Analysis:**
A layered approach was used to understand the link between revenue and gross margin. The Margin vs. Sales quadrant illuminated potential trade-offs, while regression analysis quantified the

directional relationship between these two key metrics. Rather than relying solely on volume-based success indicators, this technique exposed cases where margin compression may accompany higher sales which is a common pitfall in promotional-heavy environments. Overlaying MoM growth provided a multidimensional view of performance provided an additional lens to isolate high-performing months that achieved both scale and efficiency.

**d) Inventory Holding Efficiency:**
DOH served as a benchmark for turnover efficiency, especially in perishables, where extended stock duration correlates with increased spoilage risk particularly for Fruits and Vegetables. Its operational relevance is well-established in grocery retail, as it directly affects spoilage rates, storage costs, and perceived freshness. By calculating Pearson's correlation between DOH and sales, the analysis moved beyond anecdotal patterns to statistically supported inferences. This enabled the identification of inefficiencies where extended holding failed to translate into sales lift, highlighting the need for shorter, more responsive stocking windows.

**e) Stock Availability Monitoring (Objective - Footfall & Retention):** Shelf availability directly impacts both sales execution and customer satisfaction, making it a critical metric for revenue protection and operational health. Monitoring it against a service-level benchmark (80%) ensured that gaps were evaluated not just in absolute terms but relative to performance standards. benchmarking stock levels visually against the service threshold and subsequent sales correlation analysis helped link stock presence with financial outcomes, reinforcing its role as a critical lever in customer retention and operational continuity.

**Tool Selection Justification:**
Python's data ecosystem comprising Pandas, Matplotlib, Seaborn, and Statsmodels was used for its balance of analytical depth and flexibility in visualization. Seaborn was ideal for producing publication-ready visuals such as trendlines, scatterplots, and quadrant charts. AdjustText was used to optimize readability in annotation-heavy figures. Methodological choices prioritized transparency, ease of interpretation, and alignment with stakeholder needs, ensuring the outputs remained practical and actionable.

Each method, model, and metric were selected to bridge business needs with analytical rigor, ensuring that insights remained grounded in measurable impact and operational feasibility.

## 3. Results and Findings.

The analysis focused on uncovering underlying dynamics across sales behaviour, category performance, margin patterns, inventory turnover, and availability. Each finding is informed by multiple layers of statistical and visual investigation. The use of forecasting models, diagnostic plots, and category-specific evaluations has provided the basis for understanding key operational pain points while offering targeted insights that are both interpretable and actionable within a retail decision-making context.

### 3.1 Sales Forecasting and Temporal Dynamics

Accurate forecasting is a foundation of effective retail management. It provides essential foresight for better planning of staffing levels, optimizing stock procurement, and strategically timing promotions. This proactive approach significantly enhances operational efficiency and financial performance.

**Jan–Mar 2025 Sales Forecast**:

Sales projections for Q1 2025 were generated using Holt's Linear Trend, Damped Holt, and a Naïve benchmark, with their comparative outputs illustrated in **Figure 1** and detailed in **Table 1**. While Holt's model projected a consistent downward trend and the Naïve approach extended the December sales flatly into Q1, Damped Holt introduced a moderated growth curve that captured recent upward momentum while accounting for long-term flattening.

| Month | Holt Forecast | Damped Holt | Naive | % Change from Dec (Holt) | % Change from Dec (Damped) | % Change from Dec (Naive) |
|---|---|---|---|---|---|---|
| **Jan 2025** | 52.95 | 70.71 | 55.47 | -4.54% | +27.47% | 0% |
| **Feb 2025** | 43.74 | 70.06 | 55.47 | -21.14% | +26.29% | 0% |
| **Mar 2025** | 34.53 | 69.41 | 55.47 | -37.74% | +25.13% | 0% |

***Table 1- Sales Forecast Comparison***

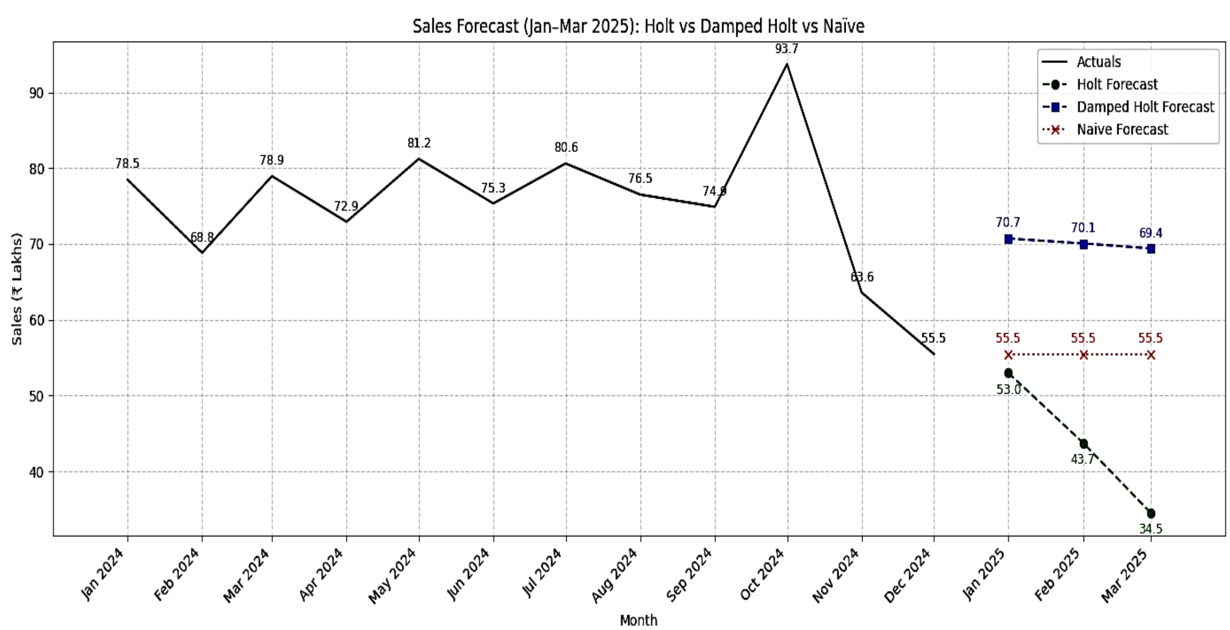


***Figure 1- Sales Forecast Comparison (Holt, Damped Holt and Naïve)***

**Backtesting Accuracy: Nov–Dec 2024**

Evaluation through backtesting, shown in **Table 2**, revealed discrepancies between predicted and actual sales for November and December 2024. Holt significantly underpredicted seasonal uplift, highlighting the limitations of assuming linearity in periods marked by sharp demand shifts. In contrast, Damped Holt demonstrated improved alignment with actuals, particularly in November, reflecting its responsiveness to non-linear sales acceleration. The **Naïve forecast** consistently failed to adapt, proving overly static and largely inaccurate for dynamic retail sales data.

These results underscore the importance of model selection tailored to seasonal sensitivity, particularly in planning procurement and promotions during high-volatility periods such as Q4.

| Month | Actual | Holt | Damped Holt | Naïve | Holt Error | Damped Error | Naive Error |
|---|---|---|---|---|---|---|---|
| **Nov 2024** | 63.58 | 52.95 | 70.71 | 93.72 | -16.71% | +11.21% | +47.4% |
| **Dec 2024** | 55.47 | 43.74 | 70.06 | 93.72 | -21.14% | +26.29% | +68.96% |

***Table 2- Backtesting Results: Nov–Dec 2024***

**3.2 Category-Level Dynamics and Demand Behaviour**

Not all product categories contribute equally. Discerning category performance is the starting point for smart allocation of scarce resources, including shelf space, marketing budget, and inventory investment. This analysis ensures focus where it matters most.

Category performance was explored through a Contribution vs. Growth framework, as shown in Figure 2. This matrix offers a visual segmentation of products based on sales volume and growth momentum. Staples and Home & Personal Care occupy the upper-right quadrant, reflecting strong, stable performers. Beverages and Processed Foods exhibit high growth from a lower sales base, while underperformers are concentrated in the lower-left quadrant, prompting consideration for strategic re-evaluation.

This 2x2 quadrant chart strategically positioned each product category by sales performance and average monthly growth, offering a quick guide for resource allocation:

- Strategic Performers: High growth and high sales
- Underperformers: Low sales and low growth
- Established Essentials: High sales but low growth
- Emerging Opportunities: Low sales but high growth

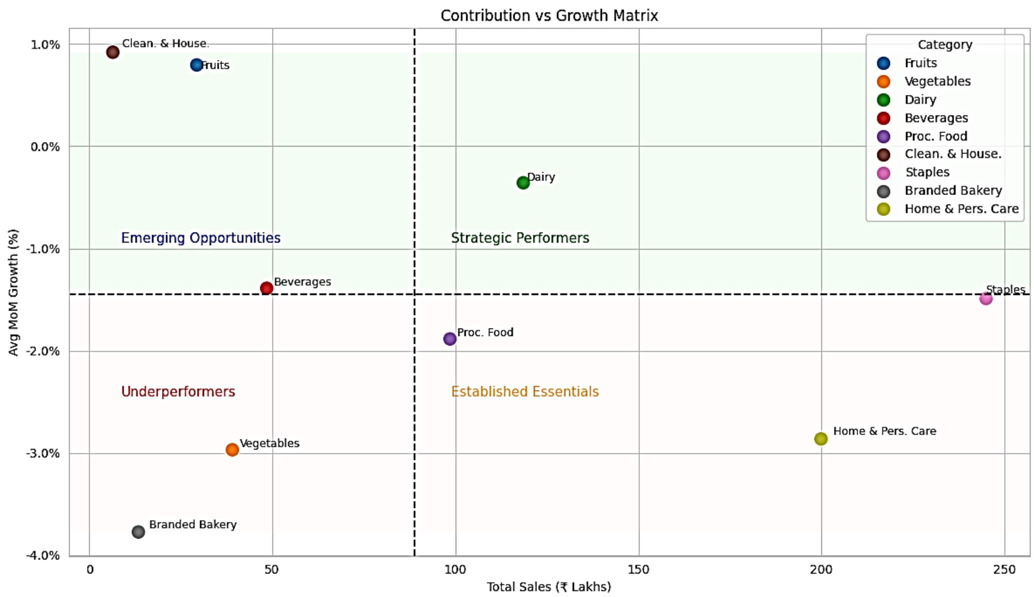


*Figure 2- Product Category Performance Matrix*

The Coefficient of Variation (CV), captured in **Figure 3**, provided further differentiation by measuring relative volatility. High CVs in categories like Fruits and Beverages indicated significant demand fluctuation, pointing to planning complexity and the need for tighter replenishment logic. In contrast, categories such as Dairy and Home & Personal Care showed low CVs, signalling predictable and consistent movement.

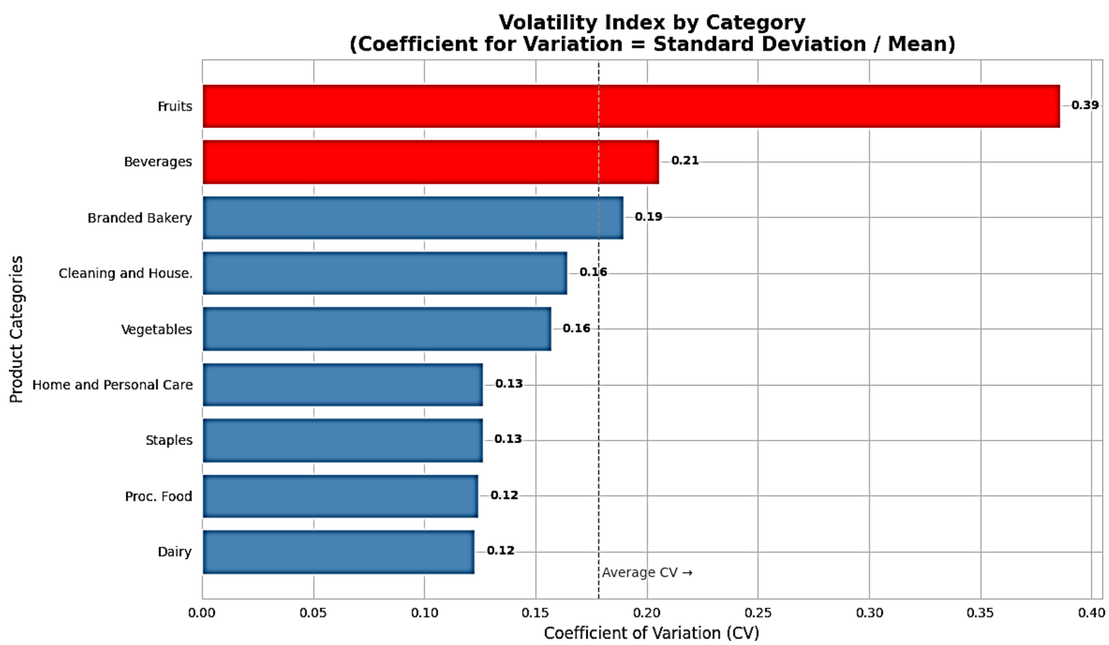


*Figure 3- Sales Volatility by Category (CV)*

Monthly trendlines across top-performing categories in **Figure 4** identified distinct seasonal peaks and demand dips. These visualizations are crucial for identifying optimal periods for promotions, stock replenishment, and marketing. Staples and Home & Personal Care consistently led overall sales, peaking in October. Festive months (shaded region: Sept–Dec) showed varied patterns across categories, including promotional-driven spikes (e.g., Staples at ₹25.3 Lakhs in October) followed by visible drops in December. Beverages showed gradual decline, while Processed Food remained stable with minor volatility.

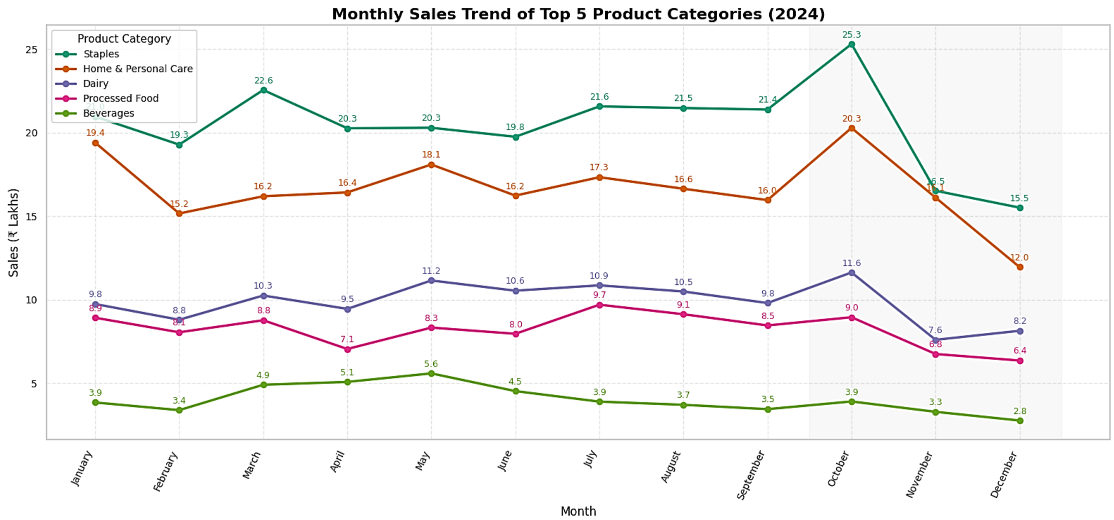


*Figure 4- Seasonal Sales Trends for Top 5 Product Categories*

Category prioritization was further informed by ABC classification in **Figure 5** applying the **Pareto logic (70-20-10 rule)**, where products were ranked by cumulative contribution to total revenue. Class A items, which included Staples and Home & Personal Care, represented approximately 70% of sales and were identified as requiring high stock precision and consistent availability. Class B and C categories generated moderate to low revenue share and require proportionate stocking intensity and control thresholds.

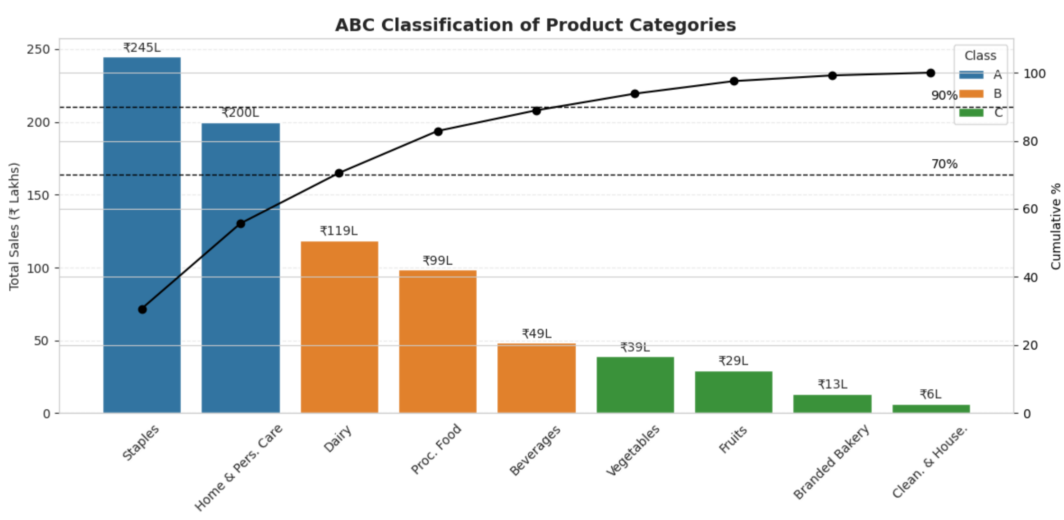


*Figure 5- Sales Contribution-Based ABC Classification*

### 3.3 Margin Behaviour and Profit-Volume Trade-offs

High sales volume doesn't automatically equate to high profit. Comprehensive profitability analysis is crucial for discerning which months or product categories truly deliver substantial business value. It enables smarter pricing, promotional planning, and ultimately, enhanced financial health.

An analysis of gross margin relative to sales, visualized in **Figure 6**, revealed a pattern where high sales volumes, particularly in the month of December, corresponded with compressed margins.

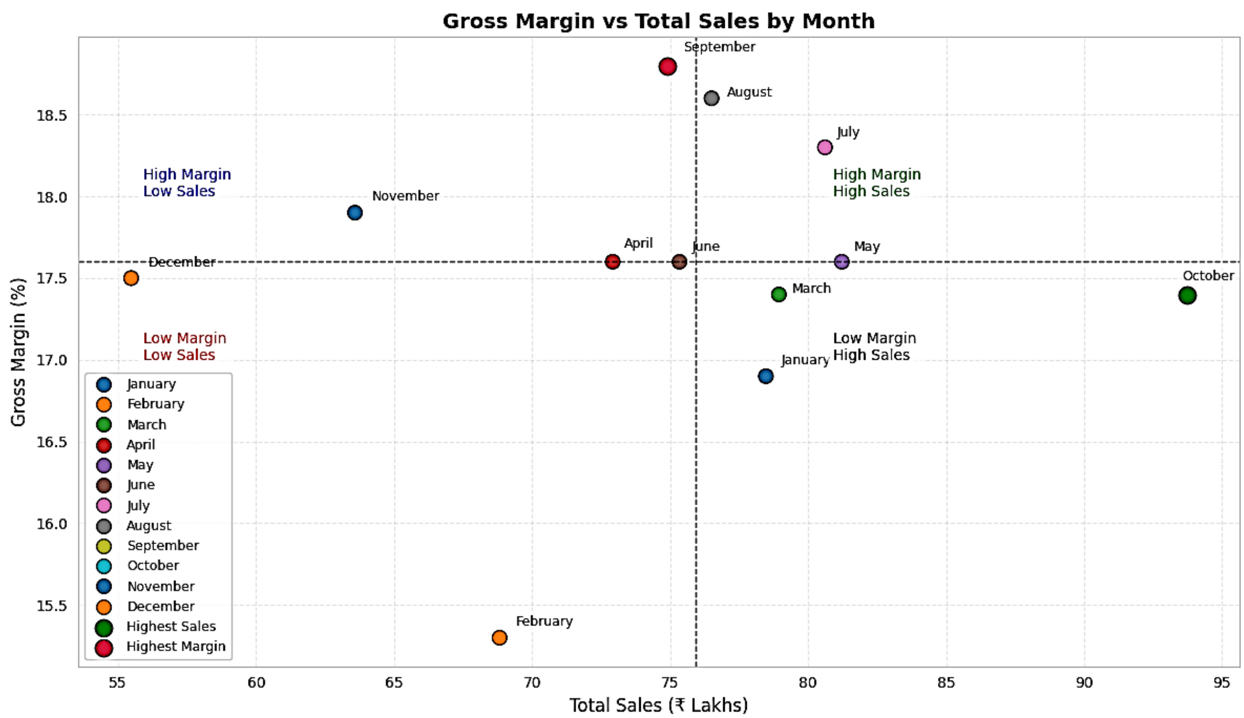


***Figure 6- Margin vs Sales Quadrant***

The relationship between sales and margins was further explored through linear regression in **Figure 7**, which revealed a slight positive slope. This suggests that as total sales increased, gross margins either held steady or improved modestly. It challenges the assumption of margin erosion during high-sales periods and points to effective pricing strategy or strong product mix in revenue-heavy months.

Margin erosion refers to the decline in profit margin (typically gross margin) due to factors like heavy discounting, rising costs, or inefficient pricing. This implies the business earns less profit per unit sold, even if total sales are increasing.

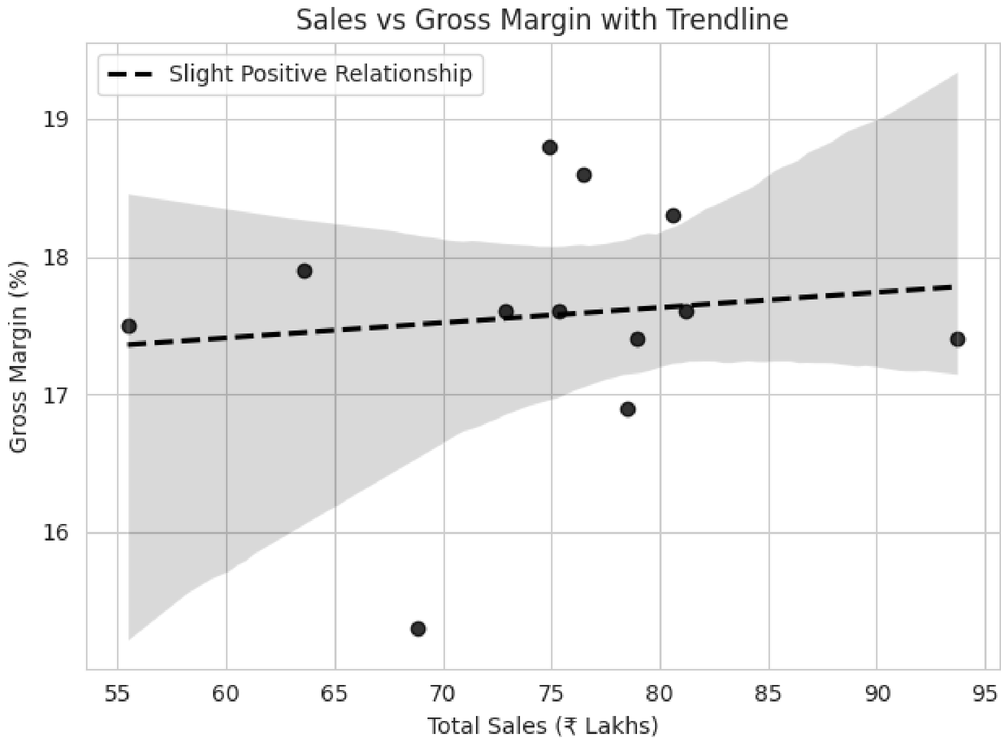


***Figure 7- Sales vs Gross Margin - Regression Analysis***

Monthly margin progression is illustrated in **Figure 8**, which highlights a generally stable gross margin trend throughout 2024, with September stood out with a peak gross margin of 18.8%, reflecting a high-margin product mix and minimal discount leakage, while December showed a dip to 17.5%. These fluctuations may reflect changes in pricing or promotional strategy. September's spike could be attributed to a more favourable product mix or tighter discounting, while December's margin compression likely signals festive-season promotions and bundled offers. The visual reinforces how pricing strategy can directly influence margin outcomes, independent of sales volume.

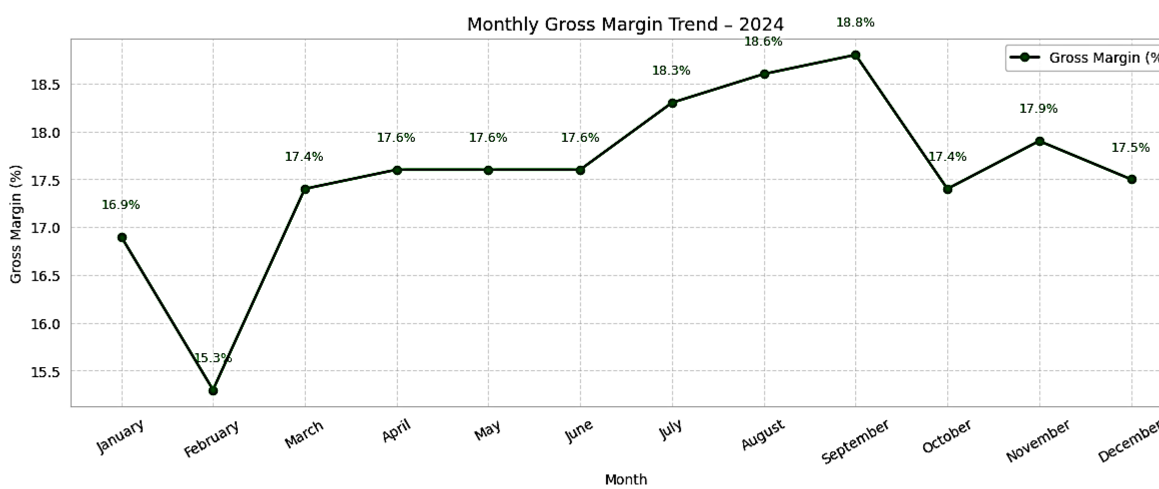

*Figure 8- Gross Margin Trend (2024)*

**Figure 9** integrates month-over-month growth with margin performance, highlighting April and September as months where both profitability and growth were simultaneously achieved. This intersection offers strategic guidance on the kinds of campaigns and pricing tactics that support margin-conscious revenue expansion.

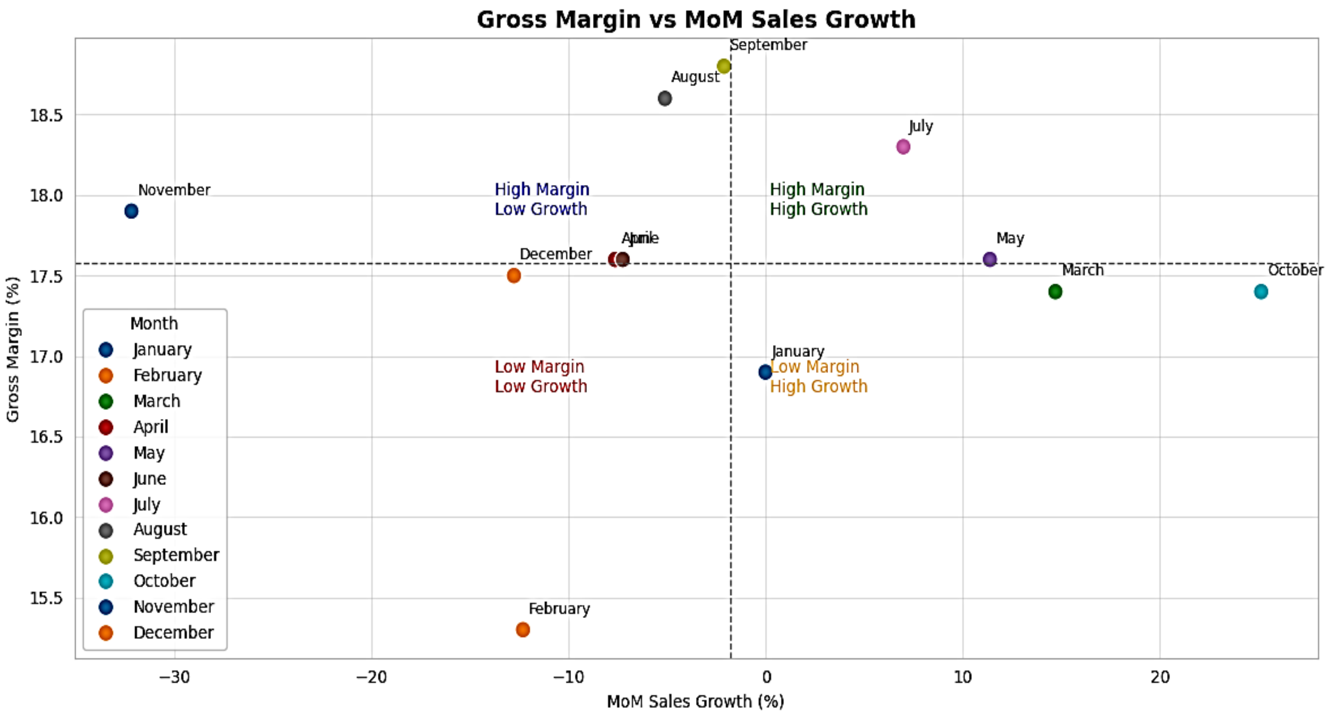


*Figure 9- Monthly Margin vs Growth Correlation*

### 3.4 Customer Growth and Margin Sensitivity

To further understand how profitability aligns with customer engagement, **Figure 10** overlays Customer Growth (%) with Gross Margin (%) in a dual-axis time series. The trend reveals that Customer growth does not always translate equally into profitability. For example, April and September showed moderate customer growth paired with strong gross margins, indicating efficient, value-driven acquisition. In contrast, June and December exhibited spikes in customer count accompanied by margin dips, suggesting that increased volume may have been driven by promotional campaigns that eroded profitability.

This analysis underscores a critical insight: growth achieved without margin dilution is more sustainable. When acquisition efforts align with profitability, the business benefits from not just footfall, but financial resilience. Conversely, months where growth comes at the cost of margin signal a need to reassess promotional strategies or customer lifetime value assumptions.

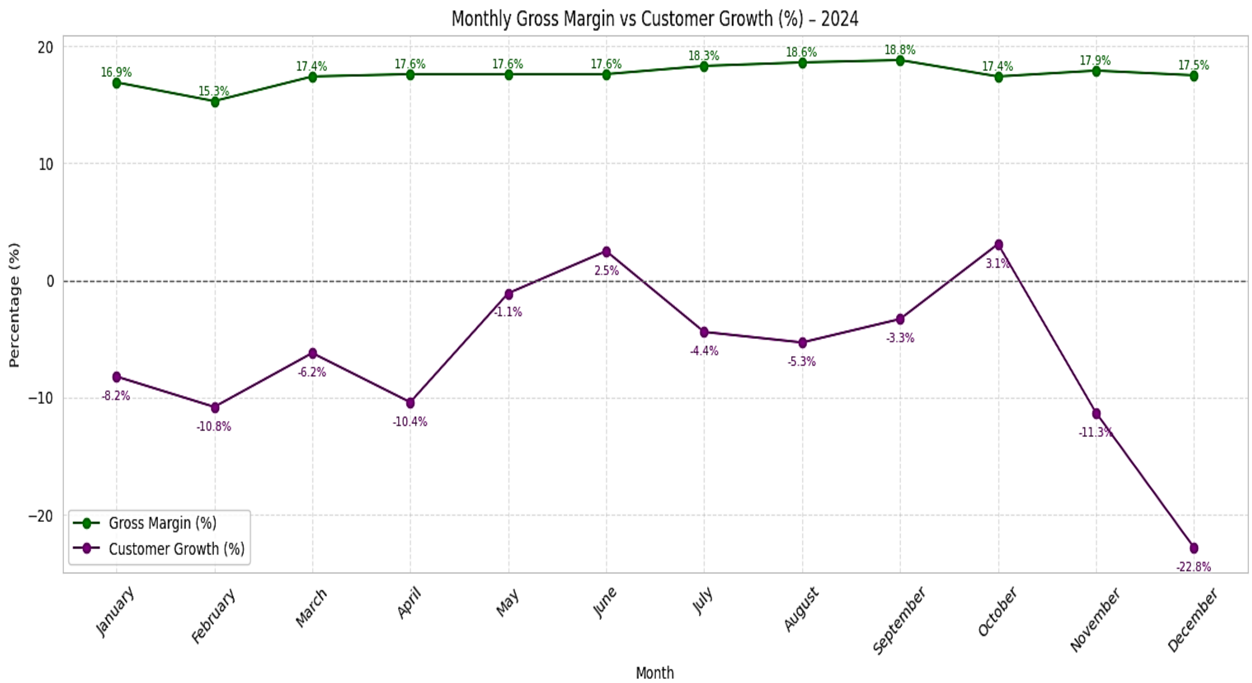


***Figure 10- Customer Growth vs Gross Margin (%)***

### 3.5 Inventory Holding and Perishability Risk

Efficient inventory management is a delicate balance. Overholding stock, especially perishables, leads to significant waste and financial loss. Conversely, understocking results in missed sales opportunities and dissatisfied customers. Optimizing Days of Holding (DOH) is critical for categories like fruits and vegetables, where freshness directly impacts sales and spoilage costs, influencing ideal inventory turnover ratios.

Inventory turnover for Fruits and Vegetables was examined using monthly Days of Holding (DOH) plotted in **Figure 11**, with an optimal holding range defined between 1.5 and 2.5 days. Vegetables frequently exceeded this range, reflecting slow movement and elevated spoilage risk. Fruits generally performed within range but showed volatility during peak months.

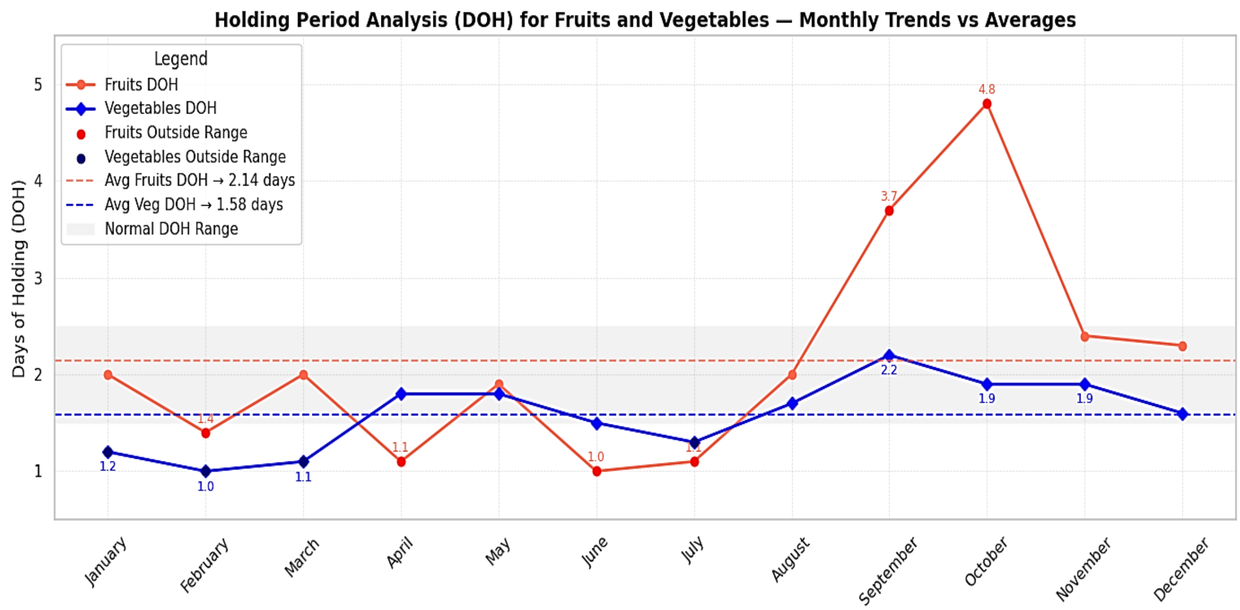


*Figure 11- Monthly Days of Holding (DOH) for Fruits & Vegetables*

**Figure 12** reveals contrasting relationships between Days of Holding (DOH) and Total Sales. For Fruits, the weak positive correlation (r = 0.35) suggests a slight association between longer holding and increased sales, though not strong enough to justify relaxed stock controls. For Vegetables, the correlation is negligible (r = 0.04), indicating that extended holding offers no sales benefit and may risk spoilage. These patterns reinforce the need for responsive, demand-driven inventory cycles, especially for perishable goods.

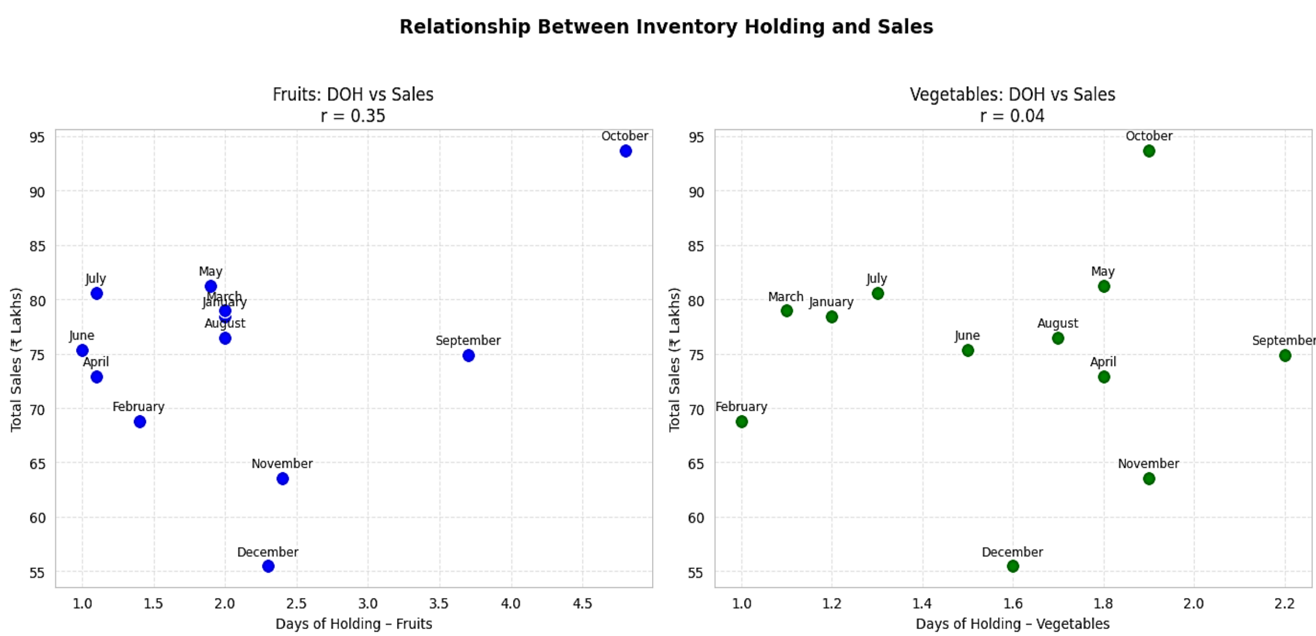


*Figure 12- DOH and Sales Relationship*

### 3.6 Stock Availability and Revenue Continuity

Even an attractive product will fail to generate revenue if frequently out of stock. Stockouts directly translate into missed sales and negative customer experiences, potentially driving customers to competitors. Maintaining optimal stock availability is crucial for customer satisfaction and revenue continuity, directly impacting service level targets.

Stock availability across product categories, measured against an 80% service benchmark, is shown in **Figure 13**. Staples and Home & Personal Care consistently exceeded the threshold, suggesting stable replenishment cycles. However, Fresh and Frozen Foods, particularly Vegetables, routinely fell short of this mark correlating with their lower DOH efficiency and higher volatility.

A pragmatic color-coding scheme ensured immediate interpretation, aligned with our 80% service level target:

- Green: ≥80% (Indicates the category meets target stock availability, ensuring consistent access).
- Red: <80% (Highlights categories underperforming on stock availability, signalling revenue risks due to stockouts, requiring immediate attention.).

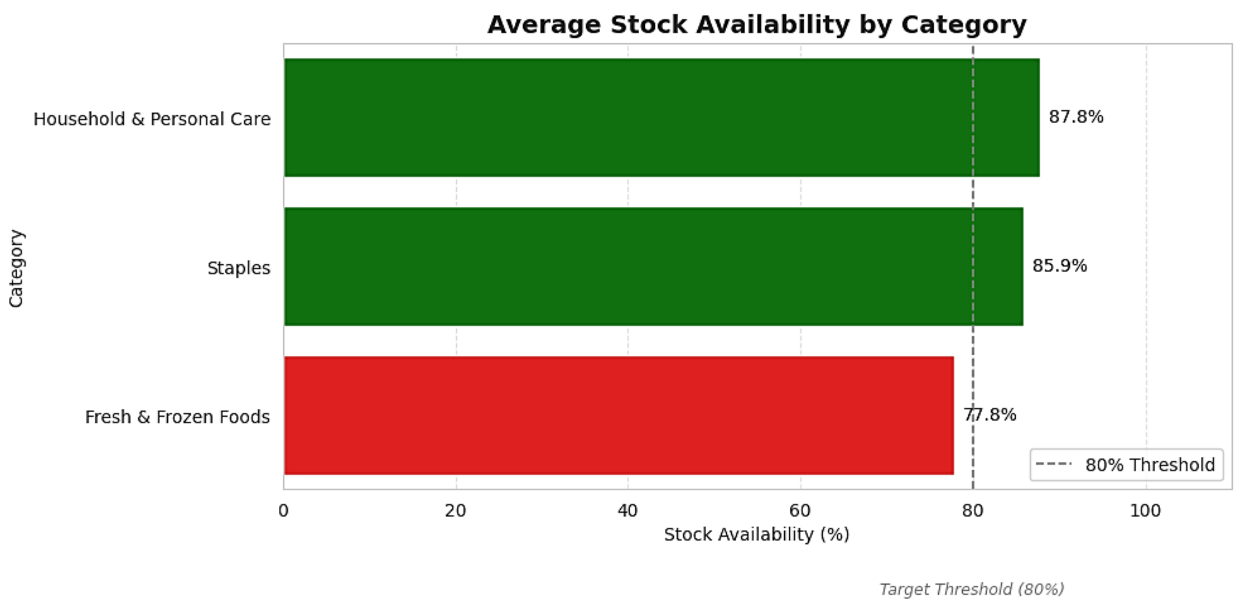


*Figure 13- Category-Wise Stock Availability vs Service Benchmark*

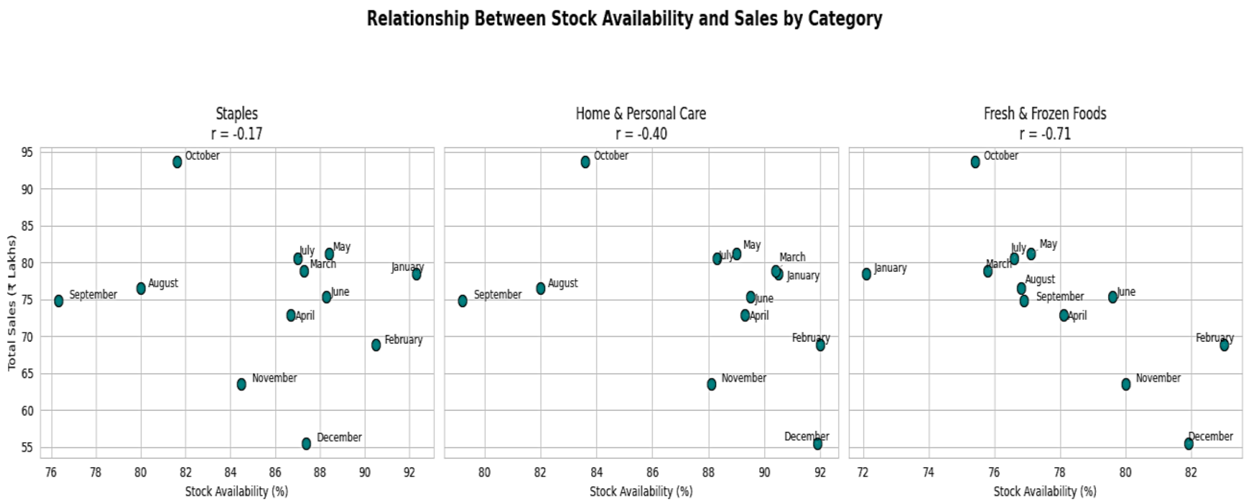


*Figure 14- Stock Availability Impact on Total Sales*

The link between availability and sales performance is captured in **Figure 14**, where categories with sub-threshold availability also showed diminished revenue contribution. This alignment highlights availability as a frontline determinant of conversion and customer satisfaction.

Improving availability in underperforming categories not only addresses operational gaps but also unlocks unrealized sales potential, particularly in high-footfall months where stockouts directly translate into missed transactions.

## 4. Interpretation of Results and Recommendations

This section translates our comprehensive analytical findings into actionable business insights and strategic recommendations. The goal is to leverage data-driven intelligence to enhance operational efficiency and drive sustainable growth for Reliance Smart Point (Store 3005, Jodhpur).

### 4.1 Strategic Interpretation of Analytical Outputs

A consistent pattern emerges across the findings: areas performing well are marked by predictability and operational alignment, while problem zones show variability, overstocks or stockouts, and margin instability. These insights, viewed in their entirety, frame the store's current state as operationally sound in its core categories but reactive and vulnerable in its volatile ones.

- **Sales Forecasting Implications:** Forecasting models revealed key limitations in how demand surges, particularly during festive months, are captured. The flat predictions of the naïve model and the linear underestimation by Holt confirm that purely historical trends are insufficient. Damped Holt's moderated upward projections better reflect seasonal lift without overextension. This makes it more suited for short-term procurement alignment, especially in Q4 transitions.
- **Volatility in Demand Behaviour:** Categories like Fruits and Beverages present a fundamental challenge: their inconsistent sales trajectories undermine the predictability

needed for efficient stocking. These are not just harder to forecast but also actively contribute to missed revenue when understocked and to waste when overstocked. In contrast, Staples and Home & Personal Care continue to serve as the stable base of operations, with low CV values and strong ABC ranking reaffirming their priority status.

- **Profit and Promotion Trade-offs**: Margin erosion during high-sales periods indicates an imbalance between promotional volume and profitability control. Regression patterns, along with margin dips in months like December, highlight the cost of volume-chasing strategies. The optimal scenario observed is high margin and growth in April and September which provides a replicable model for margin-conscious sales campaigns.
- **Inventory Holding Risks**: Prolonged Days of Holding for Vegetables, exceeding the 2.5-day upper threshold, raise clear operational flags. Poor alignment between inventory levels and real-time demand results in financial waste and risks deteriorated product freshness. The weak correlation between DOH and sales confirms that longer holding does not drive more sales, instead, it incurs cost without return.
- **Availability and Conversion Gaps**: Sub-threshold stock availability in key categories like Vegetables and Frozen Foods creates dual damage. It weakens revenue capture as well as erodes customer confidence. When availability falls below 80% in high-traffic categories, customer churn risk increases due to stockouts, especially when paired with perishable overholding.

**4.2 Actionable SMART Recommendations:**

The recommendations below are designed to address the specific gaps identified, using the SMART (Specific, Measurable, Achievable, Relevant, Time-bound) framework. Each action is linked to a measurable outcome and is rooted in the operational realities surfaced during analysis.

| **Focus Area** | **SMART Recommendation** |
|---|---|
| **Sales Forecasting** | Deploy Damped Holt for all Q1–Q2 2025 forecasts. Retrain every quarter to incorporate recent seasonality shifts and improve precision for high-demand months. |
| **Category Volatility** | Implement a rolling 3-month Coefficient of Variation (CV) tracker for Fruits and Beverages. Set a trigger threshold of CV > 1.2 for two consecutive months to prompt inventory strategy reviews. |
| **Inventory Turnover** | Cap weekly DOH for Vegetables at 2.5 days. Integrate FIFO handling training for staff and link spoilage metrics to store performance KPIs. |
| **Stock Availability** | Raise Frozen and Vegetable category availability to ≥85% by Q3 2025. Introduce automated alerts for inventory dips below two-day supply to enable proactive restocking. |

| | |
|---|---|
| **Profitability Planning** | Schedule targeted margin-preservation campaigns during historically low-margin months (e.g., June, December), especially for Personal Care and Dairy categories. |
| **Customer Retention** | Replicate successful acquisition campaigns observed in April and September. Use customer growth (%) spikes as campaign validation criteria and optimize offers via digital outreach. |

***Table 3- SMART Operational Recommendations***

### 4.3 Implementation:

The effective implementation of these data-driven recommendations is projected to yield tangible, quantifiable business benefits for Reliance Smart Point:

- **Precision in Procurement**: Seasonal model adoption and quarterly retraining will tighten alignment between forecast and reality, reducing both overstock and lost sales due to under planning.
- **Spoilage Reduction**: Capping DOH, especially in slow-moving perishables, will contain avoidable costs, reduce waste, and enhance the freshness proposition to customers.
- **Higher Service Levels**: Improving availability to ≥85% in categories with prior stockout trends will directly influence conversion and satisfaction rates, especially during high-demand windows.
- **Margin Stability**: With timing-aware promotion design, the store can maintain healthy gross margins even during peak sale periods, ensuring that revenue growth is accompanied by bottom-line discipline.
- **Stronger Retention Loop**: Replicating data-validated campaigns from high-performing months strengthens the feedback loop between promotions, acquisition, and loyalty. It lays the foundation for long-term revenue continuity.
- **Organizational Agility**: Overall, embedding these data-driven routines into store operations enhances adaptability, accountability, and customer responsiveness. These are key traits of a competitive retail model.