

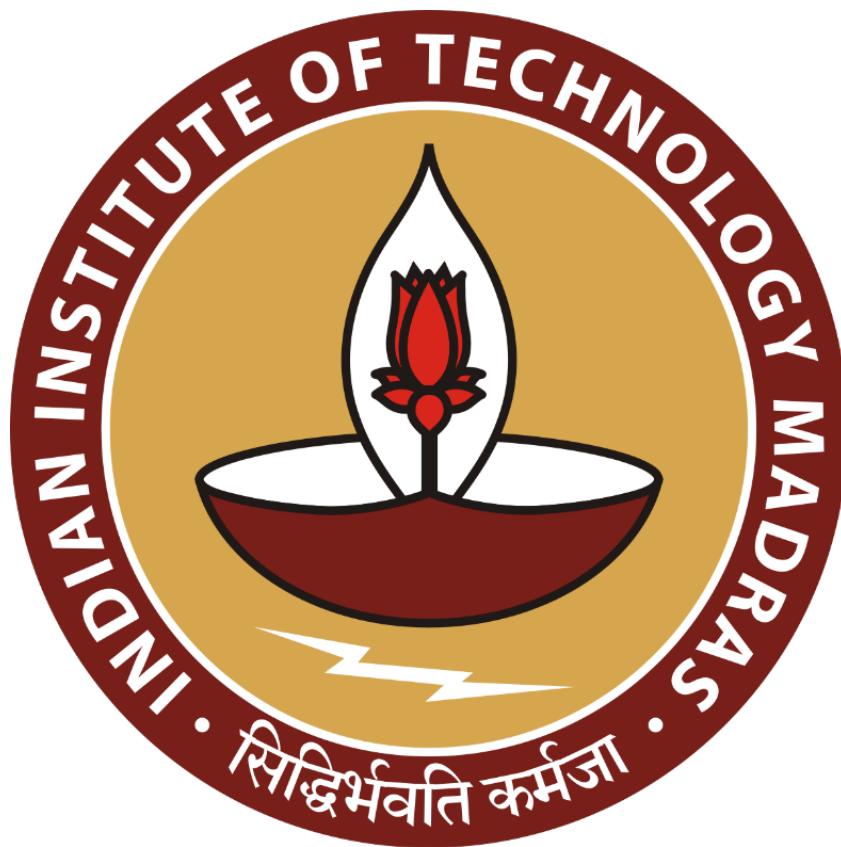
# **Smart Pharmacy Management : Leveraging Data For Efficiency & Growth**

**A Final Report For The BDM Capstone Project**

Submitted By -

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## Contents

Sr. No.	Title	Page No.
1	Executive Summary and Title	1-2
2	Detailed Explanation of Analysis Process/Method 2.1 Data Collection 2.2 Data Cleaning and Preprocessing 2.3 Comprehensive Explanation For Each Method/Analysis Used	2-7 2 2-3 3-7
3	Results and Findings 3.1 Executive summary of Results 3.2 Top-Performing Medicines (By 42-Days Revenue) 3.3 ABC (Pareto) Analysis : Inventory Prioritization 3.4 Category-Wise Medicines Sales And Revenue 3.5 Time-Series: Daily & Weekly Trends 3.6 Customer Analysis : Visits, Segmentation & ARPC	7-15 7-8 8-9 9 9-10 10-13 13-15
4	Interpretation of Results and Recommendations 4.1 High - Level Interpretation 4.2 SMART Recommendations	15-18 15-16 16-18

### The BDM Project Folder (Including All Files) Link

[https://drive.google.com/drive/folders/1erGGJXDKgA8Du09ZEYRIS\\_dyPAKIGBRd?usp=sharing](https://drive.google.com/drive/folders/1erGGJXDKgA8Du09ZEYRIS_dyPAKIGBRd?usp=sharing)

Note : The data and analysis work both are present in same excel file.

## 1. Executive Summary

'Janta Medical Store' is a small, owner-operated pharmacy located in a semi-rural area of Muradnagar, Ghaziabad, Uttar Pradesh. Established over two decades ago by Mr. Vikram Singh, the pharmacy caters to local residents with both prescription and OTC medicines. With no digital systems in place, all operations including stock tracking, billing, and accounting are done manually. The owner does not currently use any software tools or formal business practices, resulting in missed opportunities for optimisation and competitive improvement. Hence the following issues are faced by owner :

- **Inefficient Stock Management Problem**
- **Account Management Problem**
- **Customer Management Problem**

Primary data were collected on-site covering **111 medicines across 10 categories for 42 days (15 May–25 June 2025)**. The Excel dataset contains daily sales (42 columns), price and discounted price, quantity/pack, and derived revenue fields, customer daily and weekly visits. Analysis used Excel for cleaning, descriptive statistics (mean, min, max, totals), **ABC (Pareto) analysis**, weekly trend aggregation, and customer trends.

The steps involve in the project data outcomes and results are as follows :

- **Owner Discussion**
- **Problems Identification**
- **Collecting Raw Data**
- **Preprocessing & Analysing The Data**
- **Visualisation & Results**

Using tools such as Excel, the dataset was cleaned, structured, and analyzed through descriptive statistics and **ABC analysis** to classify medicines by their revenue contribution, identifying top-selling products, understanding buying patterns.

Findings indicate a clear Pareto distribution: **~20% of medicines (Category A) generate ~78% of revenue**, while Category C items contribute under 10%. Top 5 medicines produced a disproportionately large share of total revenue. Weekly revenue showed spikes corresponding to seasonal illness patterns. Around **28.60% of customers were regular buyers**, showing strong loyalty, while occasional customers presented untapped growth potential.

**Interpretation :** Prioritizing Category A items for restocking and reducing purchases of C items will free working capital and reduce expiries.

Some recommendations are given below :

- **Implement an Excel-based or Python-Flask Dashboard**
- **Weekly re-order the Category-A medicines / items**
- **Phase out the lower turn-over medicines / items**
- **Periodic Demand Forecasting**

## 2. Detailed Explanation of Analysis Process/Method

### 2.1 Data Collection

The data was collected from the pharmacy store through primary data collection methods. The observation period spanned **42 consecutive days**, from **15 May to 25 June 2025**, ensuring a comprehensive view of both product sales and customer behavior across weekdays and weekends. Data were manually recorded in the Microsoft Excel and later organized for analysis.

**Medicines Data :** It included information on **111** different medicines spread across **10** product categories, such as analgesics, antibiotics, supplements, and personal care items.

**Customer Data :** It is a separate customer log that is maintained, capturing daily customer visits classified into *regular* and *occasional* customers to study buying frequency and loyalty trends.

### 2.2 Data Cleaning and Preprocessing

Before performing any statistical or visual analysis, extensive data cleaning and preprocessing were carried out to ensure the dataset's accuracy, consistency, and usability. The original workbook contained multiple sheets, including *Medicines Price*, *Daily Sales Data*, *Category-wise Sales*, *Daily Revenue*, *Weekly Revenue*, *Daily Customers Data*, *Daily Customers Trends*, *Weekly Customers Trends* and *ABC Analysis*, which were consolidated into a single structured Excel file. Each sheet was inspected for completeness and proper column alignment.

- All numerical fields such as price, discounted price, quantity, and daily sales were converted to numeric data types to facilitate computation.

- Blank or missing daily sales entries were replaced with zeros, as these represented genuine instances of no sale rather than missing data.
- No missing price values were found.
- However, any anomalies or unexpected spikes in sales were verified with the store owner and noted as context-specific events (for example, a rise in respiratory medicine sales during the early-monsoon period).
- Inconsistent or abbreviated names were standardized (for instance, “Betadine Sol.” was renamed “Betadine Solution”) to maintain uniform grouping across categories.
- Derived fields were created to support quantitative analysis, e.g.,

**Discounted Price = Price × 0.9**

**Daily Revenue = Discounted Price × Daily Sales**

**Regular Customers = Customers with (Total Visits >= 4)**

**Occasional Customers = Customers with (Total Visits < 4)**

- To integrate customer behavior, two supplementary datasets were prepared, the first one is *Daily Customers Data*, recording total, regular, and occasional visitors, and another one is *Weekly Customers Trend*, summarizing weekly averages.

Date	Total Customers Visited	Regular Customers	Occasional Customers
15-May-2025	43	15	28
16-May-2025	28	8	20
17-May-2025	44	14	30
18-May-2025	38	16	22
19-May-2025	31	13	18
20-May-2025	31	15	16
21-May-2025	23	14	9
22-May-2025	34	8	26
23-May-2025	31	12	19
24-May-2025	27	9	18

Week	Total Customers Visited	Regular Customers	Occasional Customers
Week-1 (15/05/2025 - 21/05/2025)	238	95	143
Week-2 (22/05/2025 - 28/05/2025)	236	80	156
Week-3 (29/05/2025 - 04/06/2025)	187	65	122
Week-4 (05/06/2025 - 11/06/2025)	164	53	111
Week-5 (12/06/2025 - 18/06/2025)	143	54	89
Week-6 (19/06/2025 - 25/06/2025)	154	54	100

- Each dataset was cross-checked for logical consistency and verified through manual inspection and owner feedback.

**Importance :** This rigorous data cleaning and preprocessing ensured data quality, reduced redundancy, and established a reliable foundation for all subsequent descriptive, ABC, and correlation analyses that guide the business recommendations.

## 2.3 Comprehensive Explanation For Each Method/Analysis Used

The analytical framework for this study combined descriptive statistics, ABC (Pareto) analysis, time-series evaluation, and correlation techniques to derive actionable business insights from the pharmacy's sales and customer data. All computations and visualizations were performed in **Microsoft Excel**, chosen for its accessibility, transparency, and suitability for small-scale business datasets. The methodological design followed a structured, stepwise approach beginning with data summarization and progressing toward advanced relationship analysis.

The first phase involved **descriptive statistical analysis**, used to summarize the essential characteristics of the dataset. Measures such as mean, minimum, maximum, average, and total revenue were computed to understand the overall distribution of sales values and price ranges across 111 medicines.

Let  $R_i$  is the Revenue on  $i^{\text{th}}$  day where  $i = [1, 2, 3, \dots, 42]$

$P_i$  is the discounted price of medicine

$Q_i$  is the total units sold of medicine

$$\textbf{Minimum Revenue} = \text{MINIMUM}(R_1, R_2, R_3, \dots, R_{42})$$

$$\textbf{Maximum Revenue} = \text{MAXIMUM}(R_1, R_2, R_3, \dots, R_{42})$$

$$\textbf{Average Revenue} = \text{AVERAGE}(R_1, R_2, R_3, \dots, R_{42}) = (R_1 + R_2 + R_3 + \dots + R_{42}) / 42$$

$$\textbf{Total Revenue} = \sum P_i * Q_i$$

Total	446
Maximum Weekly Revenue	₹ 92,305.36
Minimum Weekly Revenue	₹ 57,382.35
Average Weekly Revenue	₹ 67,384.41
Overall 6-Weeks Revenue	404,306.47

This helped quantify product performance and served as input for subsequent ABC classification.

Next, an **ABC (Pareto) analysis** was conducted to identify key inventory drivers. Medicines were first sorted in descending order of revenue, followed by computation of cumulative revenue

and its proportion to the grand total, using the expression

$$\text{Cumulative \% Revenue} = \frac{\text{Cumulative Revenue}}{\text{Total Revenue}} \times 100$$

Items were classified into three categories based on their contribution to total revenue: *Class A* (top 70–80%), *Class B*(next 15–20%), and *Class C* (bottom 5–10%). This step enabled prioritization of fast-moving, high-value products and detection of underperforming stock that could be rationalized.

Simultaneously, a customer analysis framework was developed using four dedicated datasets: *Daily Customers Data*, *Customers Visits Analysis*, *Daily Customers Trend*, and *Weekly Customers Trend*. Each entry recorded **Total Visits**, **Regular Customers**, and **Occasional Customers**, enabling segmentation and behavioral trend study. Total visits representing the total customer footfall per day were computed as

$$\text{Total Visits} = \text{COUNT}(\text{Visits in 42 Days})$$

From these values, *the regular customers and occasional customers were identified as*

<i>If (Total Visits &gt;= 4)</i>	$\rightarrow$	<i>Customer is ‘Regular’</i>
<i>If (Total Visits &lt; 4)</i>	$\rightarrow$	<i>Customer is ‘Occasional’</i>

Unique Customers	Emails	Office on the web Frame	Total Visits in 6 Weeks	Customers Category
Prisha Naik	prisha.naik@example.com		5	Regular
Kabir Chatterjee	kabir.chatterjee@example.com		4	Regular
Mahi Nair	mahi.nair@example.com		1	Occasional
Ishaan Singh	ishaan.singh@example.com		3	Occasional
Aarohi Iyer	aarohi.iyer@example.com		1	Occasional
Riya Nair	riya.nair@example.com		1	Occasional
Shruti Menon	shruti.menon@example.com		4	Regular
Charvi Bose	charvi.bose@example.com		2	Occasional
Advika Das	advika.das@example.com		1	Occasional
Anay Mahajan	anay.mahajan@example.com		2	Occasional

Now the Total Regular Customers and Total Occasional Customers were calculated as

$$\text{Total Regular Customers} = \text{COUNT}(\text{Regular Customers})$$

$$\text{Total Occasional Customers} = \text{COUNT}(\text{Occasional Customers})$$

The Min, Max & Average Regular Customers and Occasional Customers were calculated as :

Let  $CR_i$  is the total regular customers visited on  $i^{\text{th}}$  day, where  $i = [1, 2, 3, \dots, 42]$

And  $CO_i$  is the total occasional customers visited on  $i^{\text{th}}$  day, where  $i = [1, 2, 3, \dots, 42]$

$$\text{Total \% of Regular Customers Per Day} = \text{Regular Customers} * 100 / \text{Total Customers}$$

$$\text{Minimum Regular Customers Per Day} = \text{MINIMUM}(CR_1, CR_2, CR_3, \dots, CR_{42})$$

$$\text{Maximum Regular Customers Per Day} = \text{MAXIMUM}(CR_1, CR_2, CR_3, \dots, CR_{42})$$

$$\text{Average Regular Customers Per Day} = \text{AVERAGE}(CR_1, CR_2, CR_3, \dots, CR_{42})$$

$$= (CR_1 + CR_2 + CR_3 + \dots + CR_{42}) / 42$$

<b>Total Regular Customers Visited in 42 Days</b>	<b>401</b>
<b>Minimum Regular Customers Visited Per Day</b>	<b>3</b>
<b>Maximum Regular Customers Visited Per Day</b>	<b>19</b>
<b>Average Regular Customers Visited Per Day</b>	<b>10</b>

$$\text{Total \% of Occasional Customers Per Day} = \text{Regular Customers} * 100 / \text{Total Customers}$$

$$\text{Minimum Occasional Customers Per Day} = \text{MINIMUM}(CO_1, CO_2, CO_3, \dots, CO_{42})$$

$$\text{Maximum Occasional Customers Per Day} = \text{MAXIMUM}(CO_1, CO_2, CO_3, \dots, CO_{42})$$

$$\text{Average Occasional Customers Per Day} = \text{AVERAGE}(CO_1, CO_2, CO_3, \dots, CO_{42})$$

$$= (CO_1 + CO_2 + CO_3 + \dots + CO_{42}) / 42$$

<b>Total Occasional Customers Visited in 42 Days</b>	<b>721</b>
<b>Minimum Occasional Customers Visited Per Day</b>	<b>5</b>
<b>Maximum Occasional Customers Visited Per Day</b>	<b>33</b>
<b>Average Occasional Customers Visited Per Day</b>	<b>17</b>

Office on the

A **time-series analysis** was then conducted on both sales and customer data to identify demand cycles and growth trends. Weekly averages and moving averages were plotted to observe recurring footfall peaks. Finally, **correlation analysis** quantified relationships among key performance metrics using Pearson's coefficient :

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

This helped measure associations such as *Customers vs. Revenue*, *Price vs. Sales*, and *Regular vs. Occasional Visits*, revealing how customer flow and pricing strategies impacted revenue.

The chosen methods—descriptive statistics, ABC classification, customer trend evaluation, and correlation—were justified by their interpretability and practical relevance. They provided a balanced analytical structure that could be easily maintained by the pharmacy owner while ensuring statistical rigor. Together, these analyses created a unified model for **inventory optimization**, **demand forecasting**, and **customer retention**, aligning quantitative insights with actionable business strategy.

### 3. Results and Findings

#### 3.1 Executive summary of Results

Metric	Value
Total Revenue in 42-Days or 6-Weeks	₹4,04,306.47
Estimated Monthly Revenue	₹2,98,416.68
Total Customer Visits	1122
Total Regular Customer Visits	401 (35.74%)
Total Occasional customer Visits	721 (64.26%)
Total Unique Customers	451
Total Unique Regular Customers	128 (28.38%)

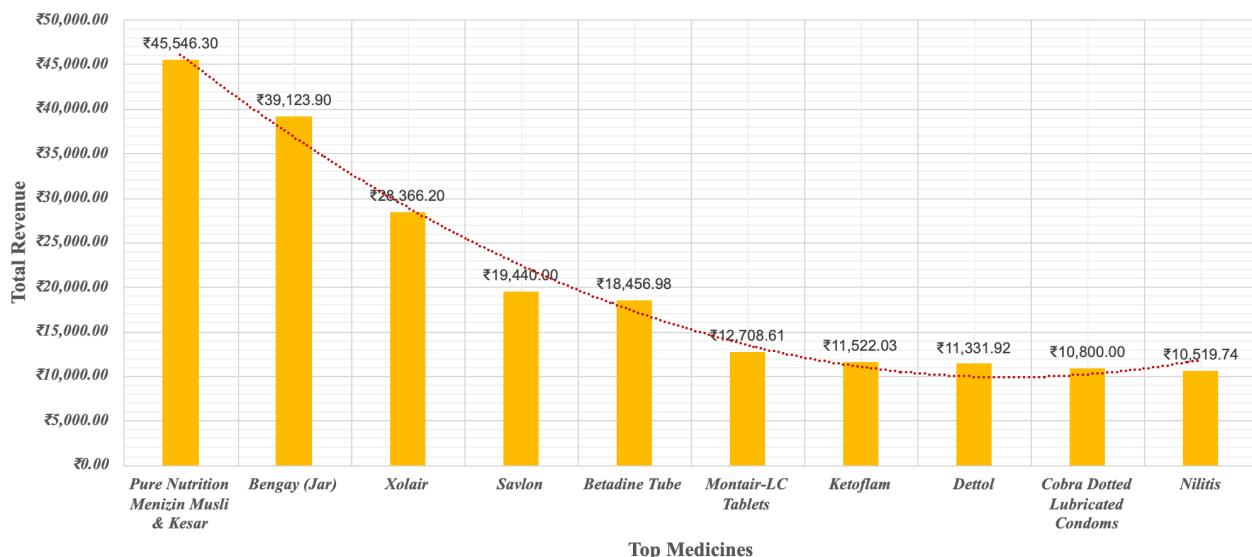
Metric	Value
Total Unique Occasional customer Visits	323 (71.62%)
Mean ARPC (Average Revenue Per Customer, Daily Mean)	₹360.34
Mean ARPC (Average Revenue Per Regular Customer, Daily Mean)	₹1,008.25
Mean ARPC (Average Revenue Per Occasional Customer, Daily Mean)	₹721
Correlation Between Price & Sales (Per SKU)	0.03733167
Correlation Between Regular Customers & Revenue	0.137298292
Correlation Between Occasional Customers & Revenue	0.162477275

**Note :** Mean ARPC is influenced by occasional high-ticket purchases (specialty medicines)

### 3.2 Top-Performing Medicines (By 42-Days Revenue)

Medicines	Total Revenue	% Contribution To Total Revenue
Pure Nutrition Menizin Musli & Kesar	₹45,546.30	11.27%
Bengay (Jar)	₹39,123.90	9.68%
Xolair	₹28,366.20	7.02%
Savlon	₹19,440.00	4.81%
Betadine Tube	₹18,456.98	4.57%
Montair-LC Tablets	₹12,708.61	3.14%
Ketoflam	₹11,522.03	2.85%
Dettol	₹11,331.92	2.80%
Cobra Dotted Lubricated Condoms	₹10,800.00	2.67%
Nilitis	₹10,519.74	2.60%

**Bar Chart For Top-10 Highest Revenue Generated Medicines**



**Interpretation :** A handful of products generate a large share of revenue — both high-volume OTC items (e.g., Bengay, Savlon) and a few high-priced specialty/ supplement SKUs (e.g., Xolair, Pure Nutrition).

### 3.3 ABC (Pareto) Analysis : Inventory Prioritization

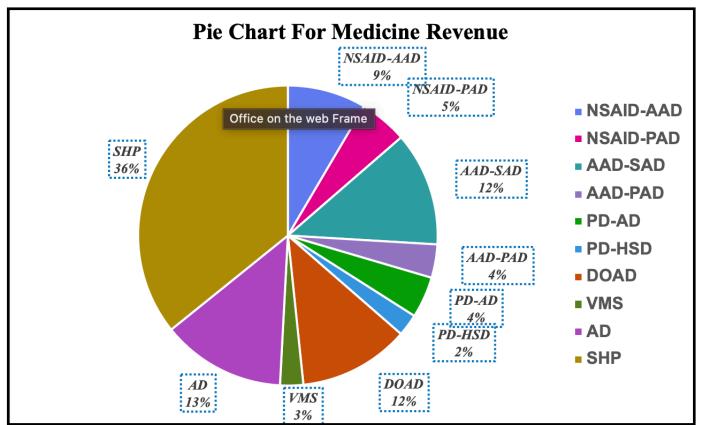
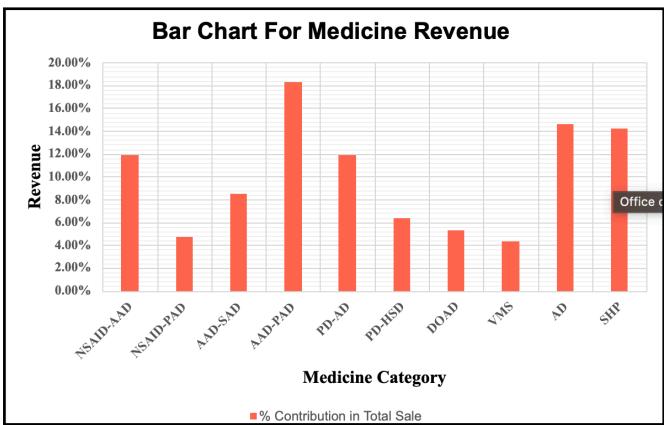
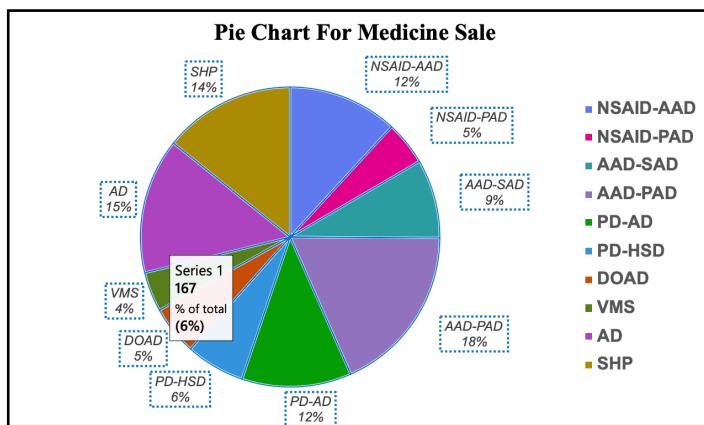
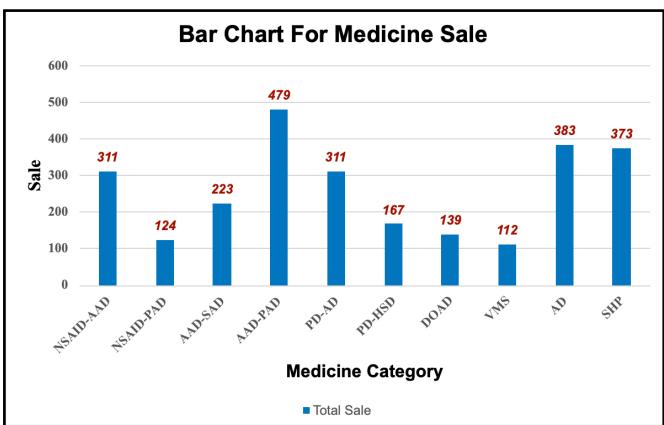
ABC Category	No. of SKUs	% of SKUs	Revenue Contribution (₹)	% of Revenue
A	32	28.83%	₹323,371.83	79.98%
B	28	25.23%	₹59,846.00	14.80%
C	51	45.95%	₹21,088.65	5.22%
<b>Total</b>	<b>111</b>	<b>100.00%</b>	<b>₹404,306.47</b>	<b>100.00%</b>

**Key Insight :** Class A items (~28.83% of SKUs) produce ~79.98% of the revenue, which is a stronger-than-usual Pareto concentration. Class C items (~45.96% of SKUs) account for just ~5.22% of revenue and are prime candidates for purchase rationalization or delisting.

**Action Implication :** Prioritize A items for safety stock and weekly reorders, review B items fortnightly and reduce purchase frequency or discontinue C items.

### 3.4 Category-Wise Medicines Sales And Revenue

Medicine Category	Total Sale	% Contribution in Total Sale	Total Revenue	% Contribution in Total Revenue
NSAID-AAD	311	11.86%	₹ 34,307.57	8.49%
NSAID-PAD	124	4.73%	₹ 20,860.03	5.16%
AAD-SAD	223	8.50%	₹ 49,733.19	12.30%
AAD-PAD	479	18.27%	₹ 14,545.24	3.60%
PD-AD	311	11.86%	₹ 18,027.76	4.46%
PD-HSD	167	6.37%	₹ 9,645.12	2.39%
DOAD	139	5.30%	₹ 48,351.88	11.96%
VMS	112	4.27%	₹ 10,112.46	2.50%
AD	383	14.61%	₹ 54,044.62	13.37%
SHP	373	14.23%	₹ 144,678.60	35.78%
<b>All Categories Total (In 42 Days)</b>	<b>2622</b>	<b>100.00%</b>	<b>₹ 404,306.47</b>	<b>100.00%</b>

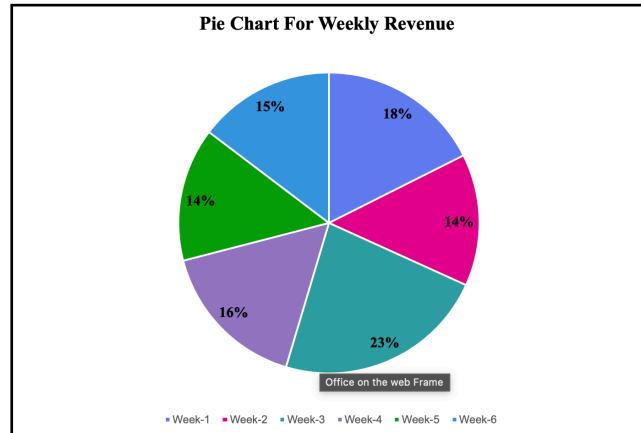
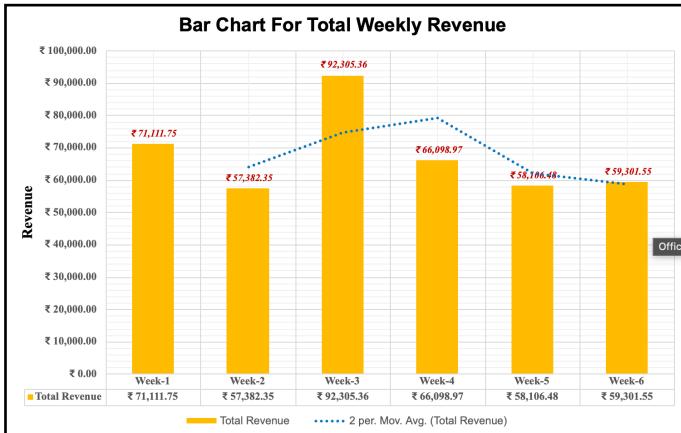


**Interpretation:** Category contributions are dispersed; *Sexual Health Products (SHP-36%)*, *Analgesic & Disinfection (AD-13%)*, and *Drugs For Observatory Airway Disease (DOAD-12%)* are important revenue contributors. However, overall revenue is heavily skewed toward certain high-price SKUs.

### 3.5 Time-Series: Daily & Weekly Trends

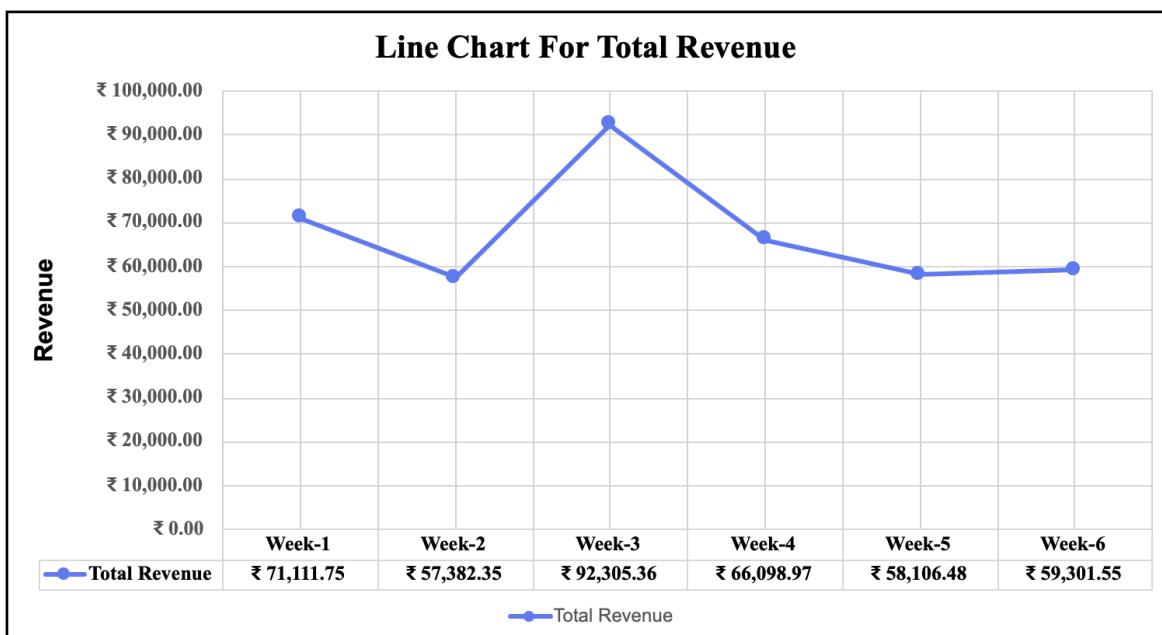
**Maximum Revenue Generating Week :** By the analysis and visualisation, the week-3 generates the maximum revenue of ₹92,305.36 which is the 22.83% of total revenue.

Week	Total Revenue	% Contribution in Total Revenue
Week-1	₹ 71,111.75	17.59%
Week-2	₹ 57,382.35	14.19%
Week-3	₹ 92,305.36	22.83%
Week-4	₹ 66,098.97	16.35%
Week-5	₹ 58,106.48	14.37%
Week-6	₹ 59,301.55	14.67%



**Fluctuations in Weekly Revenue :** The line chart is showing the fluctuations in revenue of each week, and it is showing that the *week-3* revenue is at peek while *week-2* has the lowest revenue.

Total revenue shows several peaks; two strong weekly peaks correspond to weeks with larger specialty purchases.

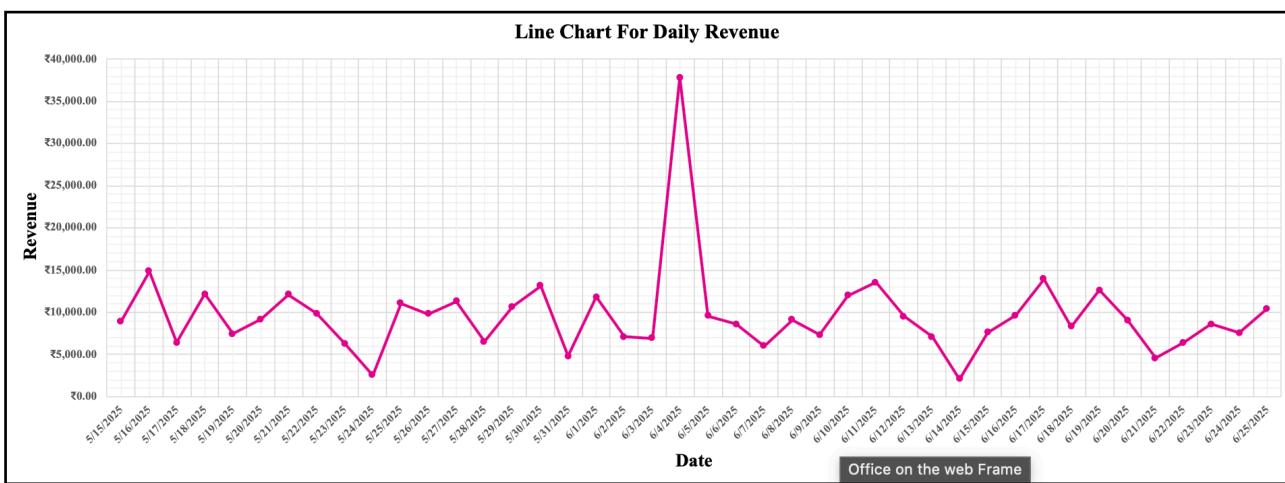
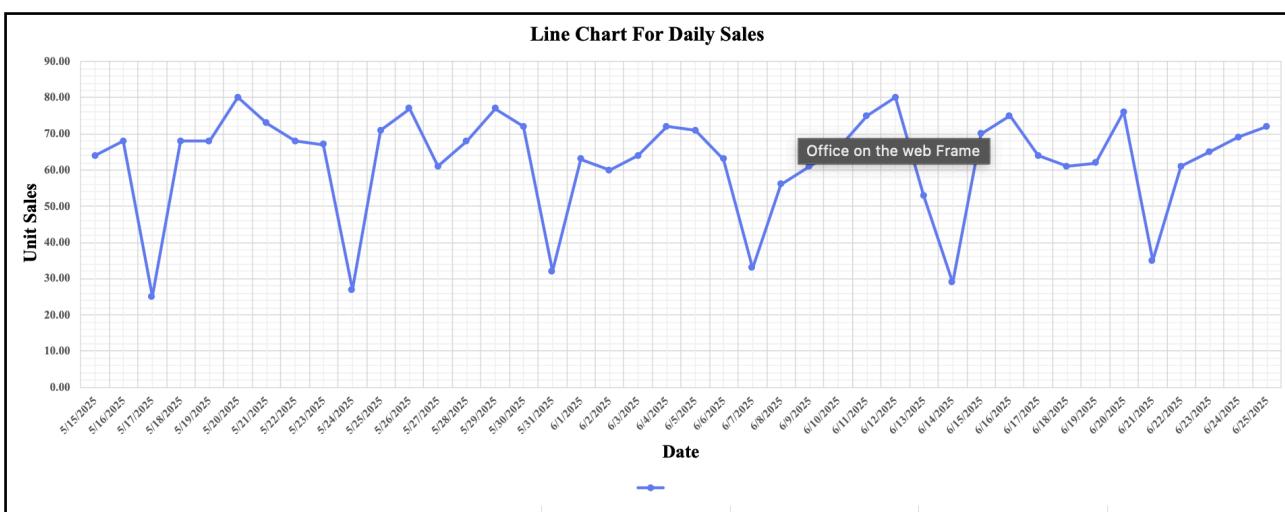


**Daily Series Analysis :** The daily time series of total revenue and customer visits shows noticeable short-term variability, reflecting real-world purchasing dynamics influenced by customer flow, product availability, and local health conditions.

The maximum per day revenue is ₹37,813.74 on the other hand the minimum per day revenue is just only ₹2,102.17. The average per day revenue is ₹9,626.34 which describe the per day revenue more concisely due to huge difference in max. and min. Per day revenue.

<b>Maximum Per Day Revenue</b>	₹ 37,813.74
<b>Minimum Per Day Revenue</b>	₹ 2,102.17
<b>Average Per Day Revenue</b>	₹ 9,626.34
<b>Estimated Monthly Revenue (Average Per Day Revenue x 31)</b>	₹ 298,416.68
<b>Overall 42-Days Revenue</b>	₹ 404,306.47

**Daily Trend Observation :** The daily data display short-term oscillations in both revenue and footfall. The revenue fluctuates sharply day-to-day. The daily data display short-term oscillations in both revenue and footfall. The *Weak Positive Correlation ( $r = 0.2054$ ) indicates that as the number of customers visit increases, revenue tends to increase slightly, but the relationship is not very strong.*



**Managerial Insight & Justification :** Combining the daily and weekly time-series patterns provides a predictive rhythm for pharmacy operations. Using a 7- days moving average smooths daily volatility and supports forecasting for inventory and staffing. Implementing this analysis as an Excel or Python-Flask dashboard will enable the owner to anticipate peak days, pre-order critical items, and maintain optimal stock levels for high-footfall weekends.

### **3.6 Customer Analysis : Visits, Segmentation & ARPC**

Total Unique Customers	451	
Total Unique Regular Customers	128	28.38%
Total Unique Occasional Customers	323	71.62%

**Notes On Customer Definitions :** Customers Visits Analysis provides customer-level aggregation (Total Visits in 6 Weeks and a category label Regular/Occasional). In our computations, “Regular” refers to customers categorized as such in that sheet.

#### **Customer Trend Observations :**

- *Regular customers* provide a stable baseline; converting occasional visitors into repeat buyers is a high-leverage opportunity.
- *ARPC* is relatively high, driven by intermittent purchases of premium items — focus on maintaining availability of A-class premium SKUs to capture these revenue spikes.

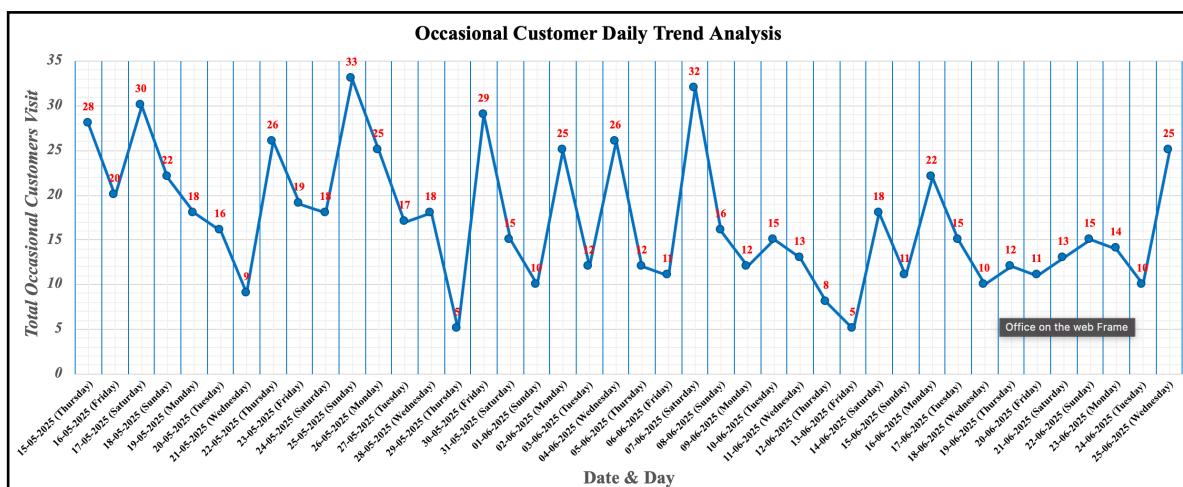
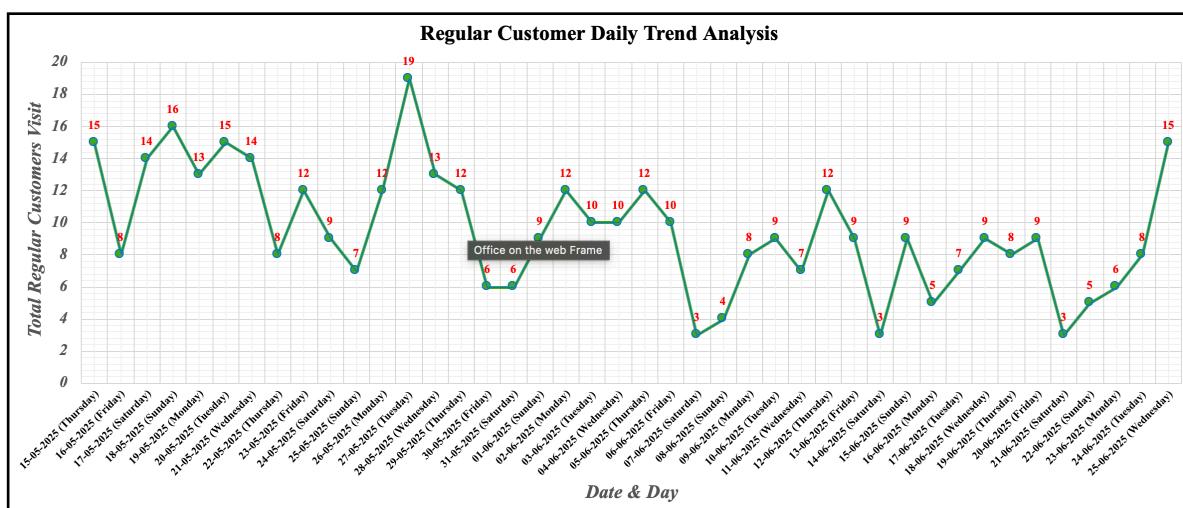
Total Customers Visited in 42 Days	1122
Total Revenue Generated in 42 Days	₹ 404,306.48
Mean ARPC (Average Revenue Per Customer)	₹ 360.34
Total Regular Customers Visited in 42 Days	401
Minimum Regular Customers Visited Per Day	3
Maximum Regular Customers Visited Per Day	19
Average Regular Customers Visited Per Day	10
Mean ARPC (Average Revenue Per Regular Customer)	₹ 1,008.25
Total Occasional Customers Visited in 42 Days	721
Minimum Occasional Customers Visited Per Day	5
Maximum Occasional Customers Visited Per Day	33
Average Occasional Customers Visited Per Day	17
Mean ARPC (Average Revenue Per Occasional Customer)	₹ 560.76

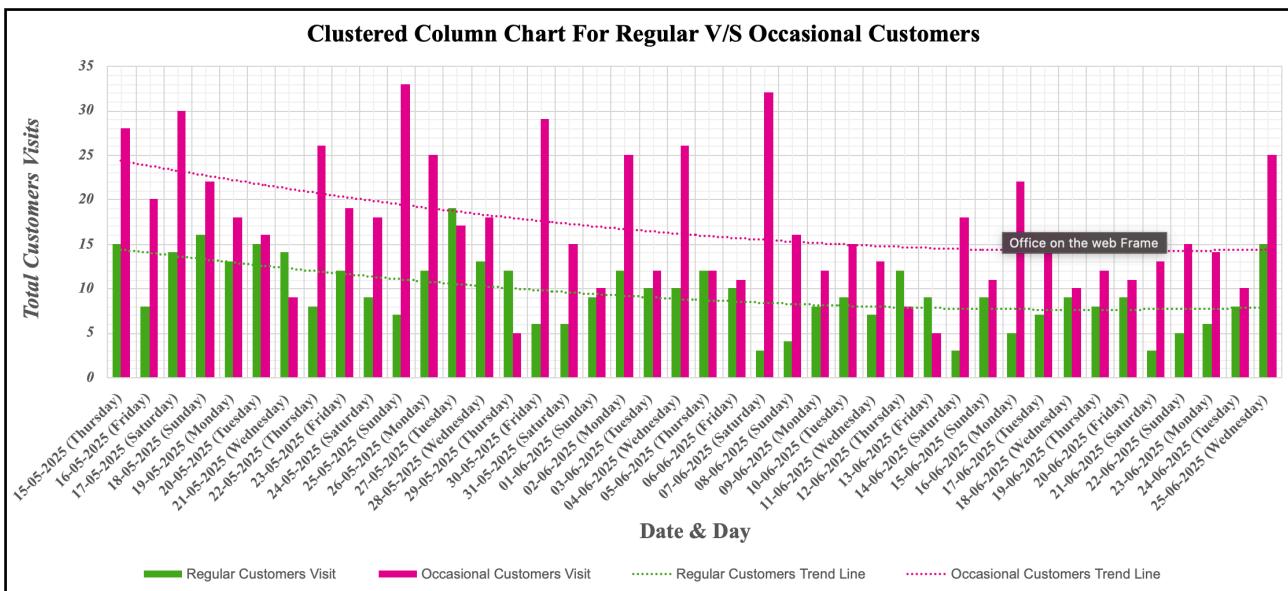
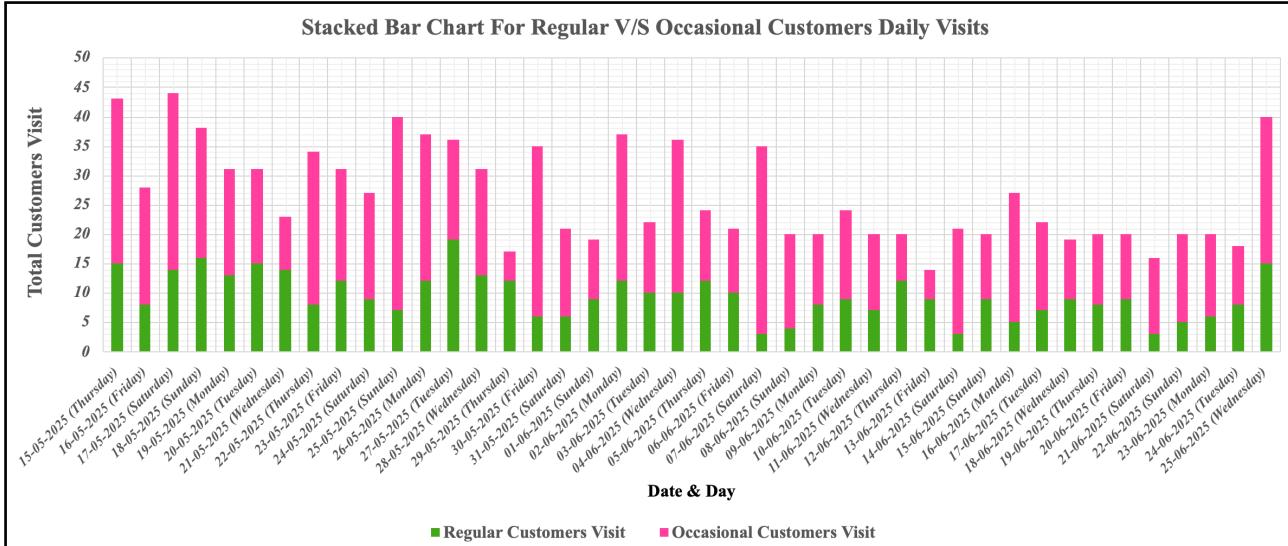
Segment	Total Visits	% Share	Average Daily Visits	Mean ARPC
Regular Customers	401	35.7%	10	₹1,008.25
Occasional Customers	721	64.3%	17	₹560.76

■ Regulars make up roughly one-third of all visitors but contribute more than half of total revenue, indicating high value and loyalty.

■ Occasional Customers form the majority but generate comparatively less per visit.

- **Daily Footfall** : Between 20–45 visits per day on average.
- **Peak Regular Visits** : 19 customers/day (strong retention pattern).
- **Peak Occasional Visits** : 33 customers/day (likely promotional or weekend-driven).
- **Lowest Visit Days** : Around 6–9 regulars, often midweek (Wednesday slump).





## 4. Interpretation of Results & SMART Recommendations

This section links the analytical results above directly to business actions. Each recommendation is SMART (Specific, Measurable, Achievable, Relevant, Time-bound).

### 4.1 High - Level Interpretation

- **Revenue Concentration :** ~29% of SKUs (A class) produce ~79% of revenue - Janta Medical Store's revenue is highly concentrated. Ensuring availability of these SKUs reduces revenue risk.

- **Customer Base** : 451 unique customers over 42 days with 1123 visits indicates many single/occasional visitors. Converting occasional shoppers to repeat buying behavior increases predictability.
- **Volatility Drivers** : Weekly revenue spikes are attributable to a combination of footfall increases and infrequent high-value purchases. Inventory policy must cover both steady-moving items (to keep regulars satisfied) and specialty items (to capture high-ticket sales).

## 4.2 SMART Recommendations

### **Recommendation-1 : ABC-Driven Reorder & Safety Stock (Immediate / 2-Months)**

**Specific** : Configure Excel reorder tables and conditional alerts for all Class-A SKUs to maintain a safety stock equal to 2 weeks' average demand and set automatic weekly reorder reminders.

**Measurable** : Reduce stock-out events for A items by 25% within 2 months.

**Why** : A items generate ~79% of revenue; stock-outs create outsized revenue loss.

**How** : Use ABC Analysis sheet + Weekly Revenue to compute average weekly demand per SKU; set reorder points in dashboard.

### **Recommendation-2 : Rationalize Class-C Inventory (Short Term / 2-Months)**

**Specific** : Reduce purchase frequency for Class C SKUs by **50%** or delist the bottom 30% C-SKUs with zero sales in the 42-day window.

**Measurable** : Cut dead stock value by 15% within 3 months.

**Why** : C items account for only ~5% of revenue while occupying shelf space and tie-up capital.

**How** : Mark-C SKUs for reduced order cycles; negotiate smaller minimum-order quantities with suppliers.

### **Recommendation-3 : Loyalty & Conversion Program (Customer-Focused; 1–3 Months)**

**Specific** : Introduce a simple loyalty program (Excel-based), e.g., “*Health Points*”: 1 point per ₹100 spent; 200 points → ₹50 coupon. Track by customer email.

**Measurable** : Increase the percentage of repeat visits among occasional customers by 10 percentage points (e.g., convert 10% of occasional visitors into regulars) within 3 months.

**Why** : Repeat customers correlate strongly with steady revenue and are cheaper to retain than acquire.

**How** : Use *Customers Visits Analysis* sheet to identify top occasional visitors and send SMS/call promos; record points in Excel.

#### **Recommendation-4 : Weekend & Seasonal Pre-Stocking (Immediate and Ongoing)**

**Specific** : Pre-stock 2 days before weekends and seasonal demand weeks (monsoon) based on Weekly Customers Trend and Daily Customers Trend.

**Measurable** : Increase the percentage of repeat visits among occasional customers by 10 percentage points (e.g., convert 10% of occasional visitors into regulars) within 3 months.

**Why** : Increase weekend revenue by **10%** and reduce emergency purchases by **30%** in 2 months.

**How** : Weekend footfall is higher; monsoon weeks show respiratory / skin-care spikes.

#### **Recommendation-5 : Monitor ARPC & Target High-Margin Bundles (2–4 Months)**

**Specific** : Create promotional bundles combining fast-moving B-items with complementary A-items (e.g., analgesic + antiseptic). Track ARPC and conversion.

**Measurable** : Increase B-item turnover by 12% and ARPC by 8% in 4 months.

**How** : Use historical basket data in Daily Customers Data to design bundles.

#### **Recommendation-6 : Weekly KPI review & owner training (Immediate)**

**Specific** : 30-minute weekly meeting to review dashboard, top-10 SKUs, stock-outs, weekly revenue, weekly visits, and pending supplier lead times.

**Measurable** : KPI compliance reports for each week; aim for 10% improvement in working capital turnover in 6 months.

**How** : Use the Python-Flask or HTML-JS Dashboard as the meeting agenda.

\*\*\*\*\* **Finished** \*\*\*\*\*