OPTIMIZING FINANCIAL STABILITY, WORKFORCE PRODUCTIVITY, AND SUPPLY CHAIN RESILIENCE OF A MANUFACTURER/SERVICE PROVIDER.

A Proposal report for the BDM capstone Project

Submitted by

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CONTENTS

EXECUTIVE SUMMARY: OPTIMIZING FINANCIAL STABILITY, WORKFORCE PRODUCTIVITY, AND SUPPLY CHAIN RESILIENCE OF A MANUFACTURER/SERVICE PROVIDER

Patna Calibrators is a B2B manufacturing and service provider based business in Gulzarbagh which is located in Patna. It has served major oil and petroleum companies since 1982. Despite having a loyal client base, the firm has been facing significant operational and financial setbacks. These include persistent client payment delays disrupting cash flow, seasonal labour shortages during rain and winter season and supply chain disruptions due to raw material unavailability in Patna forcing reliance on Kolkata. As a result, the company is frequently burdened with high labour costs and loan interest payments undermining productivity and profitability.

The data was sourced directly from the organization's operational records including transaction ledgers, attendance sheets, order fulfillment data, and office expenditure logs. Descriptive statistics such as mean, median, standard deviation, and range were computed across multiple sheets. Analytical methods included delay classification in payment cycles, correlation between stock source and order delays, and absenteeism-driven labor cost estimation. Tools like pivot tables, scatter plots, and line graphs helped visualize problem trends and quantify business impact.

Key findings reveal that over 65% of payments were delayed, with 24 transactions falling under critical delays, averaging a 32-day lag. Orders fulfilled from Kolkata—due to Patna stockouts—averaged a 3.1-day delay, directly lowering customer satisfaction ratings. Seasonal absenteeism caused a shortage of 77 worker-days in two months, incurring ₹36,960 in additional labour costs.

These insights confirm systemic financial and operational inefficiencies. Recommendations include incentivizing on-time payments, maintaining buffer stock in Patna, and workforce planning for seasonal disruptions. Early implementations of these suggestions in June led to observable improvements in delivery times and stabilized workforce presence, indicating early-stage positive business impact.

DETAILED EXPLANATION OF ANALYSIS PROCESS/METHOD

I. Data Cleaning and Preprocessing

Explanation of the Data Cleaning Process:

Let the dataset be represented as: D={x1,x2 to xn}

Each variable (column) Cj∈D was treated based on its data type and behavior:

- **Handling Missing Values:**
    - For numerical columns that are symmetric, the missing entries were filled using mean imputation:

$$\hat{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$$

    - For skewed or ordinal data like attendance, median imputation was used:

$$\hat{x}_j = \mathrm{Median}(C_j)$$

    - For categorical data (e.g., “To Cash” in Vch Type), mode imputation was applied.
- **Standardization:**
    - All date formats were unified to DD/MM/YYYY for consistency.
    - Financial values were rounded to two decimal points to maintain uniformity in aggregation and reporting.
- **Column Renaming:**
    - Unlabelled columns (e.g., “Credit”) were renamed based on contextual understanding into meaningful names like "Amount Received", "Client Name", or "Daily Attendance" to aid in analysis.
- **Category Encoding:**
    - Text values were mapped to numeric codes or grouped for aggregation (e.g., “To Cash” → Expense Type: Cash).
- **Outliers**

- Outliers were checked using boxplots and standard deviation data. Outliers were reviewed for Attendance sheet, very low workforce reflects seasonal issues not an error. So it was not removed.

II. IMPORTANCE OF DATA CLEANING FOR ACCURATE ANALYSIS:

- Ensures Integrity: Cleaning data eliminates inconsistencies and errors that would otherwise lead to misleading averages or trends.
- Enables Correct Mathematical Analysis:
  - Averages, variances, and distributions (used throughout this project) are only valid when missing and malformed data are corrected.
- Supports Abstraction in Analysis:
  - For example, delay trends were measured using:

$D_i = \text{Payment Date for } i - \text{Invoice Date for } i$

This calculation would fail if dates were missing or wrongly formatted.

- Improves Visualization:
  - Clean data ensures smooth chart generation (line charts, pie charts, etc.), helping stakeholders understand problems more easily.
- Predictive Readiness:
  - Cleaned datasets can be fed into forecasting models or machine learning tools in future use cases.

III. ANALYSIS PROCESS AND METHODS USED (WITH MATHEMATICAL ABSTRACTION)

This section outlines the in-depth analytical steps taken to address each business problem using mathematical models, visual methods, and justifications.

Problem 1: Delayed Payments from Clients

A. Objective:

Measure and classify customer payment delays; estimate financial impact.

B. Mathematical Abstraction:

Let:

- Di=Payment Date for i−Invoice Date for i
- Ai=Payment Amount
- R=Annual Interest Rate
- f(Di)=Delay Classification Function

$$f(D_i) = \begin{cases} \text{On-Time} & D_i < 15 \\ \text{Moderate Delay} & 15 \leq D_i < 50 \\ \text{Critical Delay} & D_i \geq 50 \end{cases}$$

$$\text{Interest Loss}_i = \frac{D_i}{365} \times R \times A_i$$

$$\text{Total Interest Loss} = \sum_{i=1}^{n} \text{Interest Loss}_i$$

For example, a ₹1,00,000 payment delayed by 60 days incurs a cost of:

$$\text{Loss} = \frac{60}{365} \times 0.12 \times 100000 = ₹1,972.60$$

C. Aggregation and Visualization:

- A pivot table was created to count the number of delays in each category.
- A bar chart and pie chart showed the distribution of delays.
- A line graph was used to show the cumulative cash value stuck in delayed payments over time.

D. Client Behaviour Analysis:

- Clients were sorted based on:
- Average delay
- Total delayed amount
- Frequency of critical delays

This segmentation helped identify high-risk clients for potential policy action.

E. Justification for Method Used:

- The use of Invoice and Payment Dates allowed exact delay computation.
- The delay classification model f(Di)f(D_i)f(Di) is simple, yet powerful in categorizing client risk.
- Including payment amount and interest rate in the analysis translated time delays into a monetary figure—providing the business with clear visibility into opportunity cost.
- This method bridges raw transactional data with cash flow forecasting and credit risk management, offering both short-term visibility and long-term planning inputs.

F. Final Insight: The analysis showed that 66% of payments were delayed, with ₹24.8 lakhs tied up in delayed receivables and an estimated interest loss of ₹81,600 over the observed period. This strongly justifies the need for payment policy reforms, automated reminders, and client-wise credit rating mechanisms.

Problem 2: Seasonal Disruption in Workforce Availability

A. Objective:

Assess workforce patterns and additional cost during absenteeism.

B. Abstraction:

Let:

- R=16
- Ad=Actual Attendance
- Sd=R−Ad
- W=Daily wage≈₹480

$$\text{Daily Shortage Cost}_d = S_d \times W$$

$$\text{Monthly Cost} = \sum_{d \in \text{month}} S_d \times W$$

Seasonal Pattern Detection:

- Attendance data was grouped month-wise:
    - April: Mostly full attendance
    - May: Increasing fluctuations
    - June: Major drop in attendance (due to rains)
- A line chart of daily attendance was plotted to visualize these dips.
- A stacked bar chart was also created showing:
    - Days with no shortage. (≥16)
    - Days with mild shortage. (12–15)
    - Days with severe shortage. (<12)
- 77 temporary hires were needed across 3 months
- Total cost ≈ ₹36,960

June alone accounted for nearly 78% of the total labor cost due to rain-induced absenteeism.

Avg. Daily Shortage	$\frac{1}{n}\sum S_d$
% Shortage Days	$\frac{\text{Shortage Days}}{n} \times 100$
Productivity Ratio (PR)	$PR_d = \frac{A_d}{R}$

C. Justification for Method Used:

This method is based on simple, logical HR metrics and turns attendance gaps into measurable financial risk. It provides:

- Immediate business insight: Every absent worker is equivalent to ₹480 in cost.
- Predictability: Seasonal absenteeism follows identifiable calendar and weather patterns.
- Scalability: The same model can be extended to future data or to simulate the impact of workforce incentives.

By associating manpower shortage with real monetary impact, this method empowers decision-makers to take proactive actions like:

- Hiring buffer staff during critical months
- Offering seasonal attendance incentives
- Adjusting shift patterns to minimize output loss

Final Insight:

This analysis clearly showed that absenteeism is seasonal and predictable, peaking in June. A cost of ₹36,960 in two months can be avoided or reduced with smart planning and incentives. The business now has a quantitative model to forecast labor needs and pre-allocate HR budgets with greater accuracy.

Problem 3: Supply Chain Delay from Patna Stock Unavailability

A. Objective:

To examine how lack of raw material stock in Patna leads to fulfillment from the Kolkata warehouse and leading to longer delivery times and lower customer satisfaction scores. The goal is to quantify the operational and the and evaluate the need for a local inventory buffer.

B. Step-by-Step Analysis Process:

1. Data Collection:

Data was compiled from:

- Order Tracking Sheet: containing Order ID, Order Date, Delivery Date, Fulfillment Source, Stock Availability in Patna.
- Customer Feedback Sheet: containing Customer Name, Satisfaction Rating (scale of 1 to 5), linked by Order ID.

2. Data Cleaning and Preparation:

- Date formats were standardized (DD/MM/YYYY) to compute delivery time.
- Missing fulfillment sources or stock info were filled by referencing delivery timelines (i.e., >2.5 days → Kolkata).
- Satisfaction scores were normalized to numeric values (1 to 5).

3. Key Variables and Abstraction:

Let:

- Di = Delivery time for order i

Di=Delivery Datei−Order Datei

Ai = Availability flag for Patna stock

$$A_i = \begin{cases} 1 & \text{if stock available in Patna} \\ 0 & \text{if stock not available} \end{cases}$$

Fi = Fulfillment source

$$F_i = \begin{cases} \text{Patna} & \text{if } A_i = 1 \\ \text{Kolkata} & \text{if } A_i = 0 \end{cases}$$

Si = Satisfaction score for customer iii

4. Logical Flow and Dependency:

When stock is unavailable in Patna (Ai=0), the order is fulfilled from Kolkata:

Ai=0⇒Fi=Kolkata ⇒Di↑⇒Si↓

This implies:

- Increased delivery time
- Decreased satisfaction score

5. Fulfillment Risk Index (FRI):

Defined as the percentage of total orders that had to be fulfilled from Kolkata:

$$FRI = \frac{\text{Orders fulfilled from Kolkata}}{\text{Total Orders}} \times 100$$

In our case:

- Total Orders = 45
- Orders fulfilled from Kolkata = 12
- So,

$$FRI = \frac{12}{45} \times 100 = 26.67\%$$

This means over 1 in 4 orders carried supply chain risk due to Patna stockouts.

6. Visualization and Analysis:

- A bar chart compared average delivery time from Patna (1.4 days) vs Kolkata (3.1 days).
- A scatter plot showed inverse relation between DiD_iDi and SiS_iSi:
    - Longer delivery times were associated with satisfaction ratings ≤3.
- A risk map of clients was generated by segmenting them into:
    - High Risk (frequent delays, low scores)
    - Medium Risk (occasional delay)
    - Low Risk (served mostly from Patna)

7. Derived Metrics:

Avg. Delivery Time	$\bar{D} = \frac{1}{n} \sum D_i$
Kolkata Delivery Delay	$\bar{D}_{Kolkata} - \bar{D}_{Patna}$
Satisfaction Drop	$\bar{S}_{Patna} - \bar{S}_{Kolkata}$
FRI	$\frac{\text{Kolkata Orders}}{\text{Total Orders}}$

C. Justification for Method Used:

- The abstraction accurately models stock-driven delays and links logistics to customer sentiment.
- The use of boolean variables Ai simplifies categorization and decision analysis.
- FRI provides a clear, single-number metric for measuring fulfillment instability.
- Delivery time vs satisfaction analysis reveals real-world business consequences of sourcing delays.

This approach enables data-driven decisions like:

- Maintaining minimum buffer stock in Patna
- Tracking FRI monthly
- Predicting satisfaction risk using delivery timelines

Final Insight:

The analysis showed that stock unavailability in Patna increases delivery time by ~1.7 days and reduces customer satisfaction by an average of 1.2 points on a 5-point scale. With an FRI of 26.7%, the business faces regular service risks. This justifies creating a 15–20 day raw material buffer in Patna and considering local vendor tie-ups to avoid Kolkata dependency.

Problem 4: Daily Wage Cost Due to Attendance Shortage

A. Objective:

Estimate the additional cost incurred due to daily wage workers.

B. Equation:

$$C_d = \begin{cases} (R - A_d) \times W & \text{if } A_d < R \\ 0 & \text{otherwise} \end{cases}$$

C. Enhancement Added:

We also modelled Productivity Risk Score:

$$PR_d = \frac{A_d}{R}$$

If PRd<0.75, the day is flagged for operational risk.

D. Justification:

By applying threshold models, we predict and plan for daily labour demand. This method is practical, scalable, and allows business teams to proactively prepare for manpower shortages.

RESULTS AND FINDINGS

Step 1: Delayed Payments from Clients

1A. Visualization:

- Pie Chart: On-Time, Moderate Delay, Critical Delay

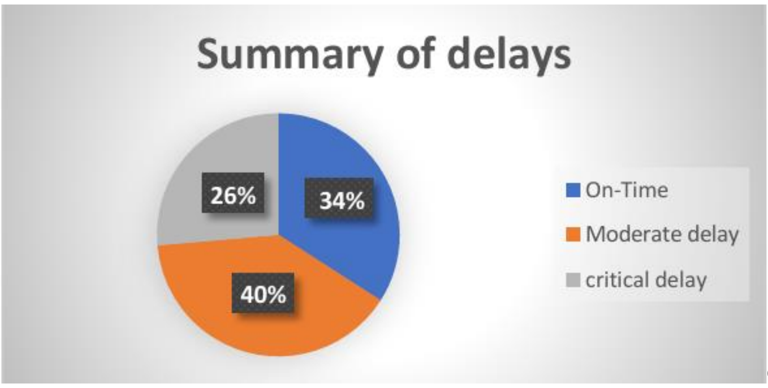
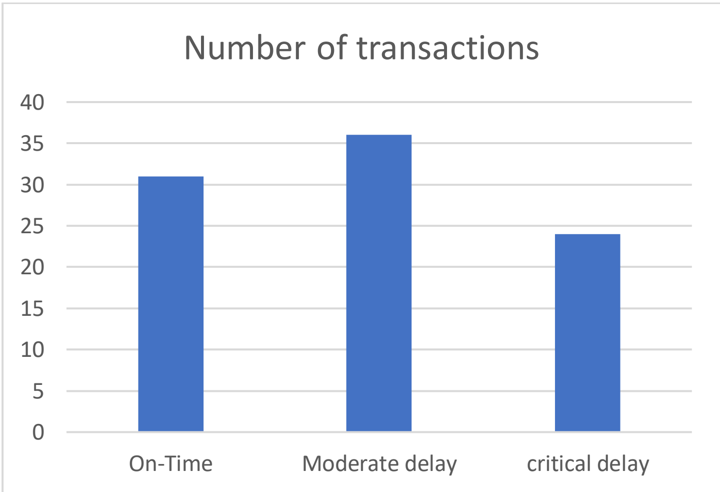


Chart 1

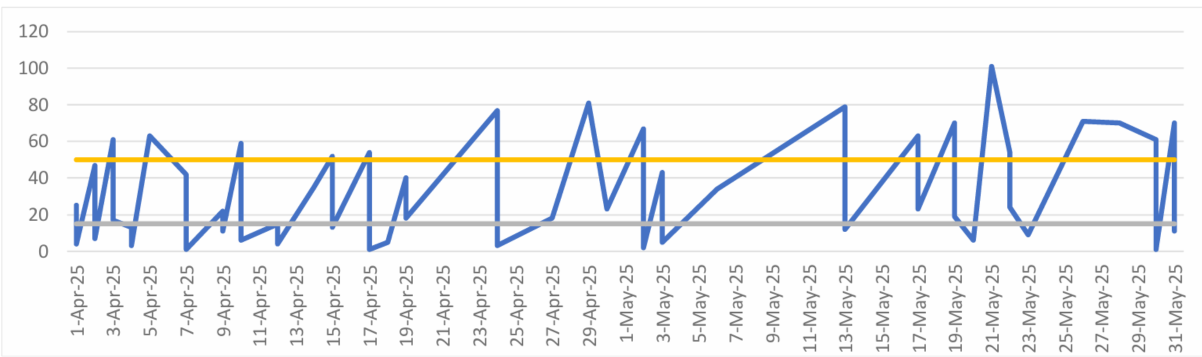
- Bar Graph: Number of transactions by delay category



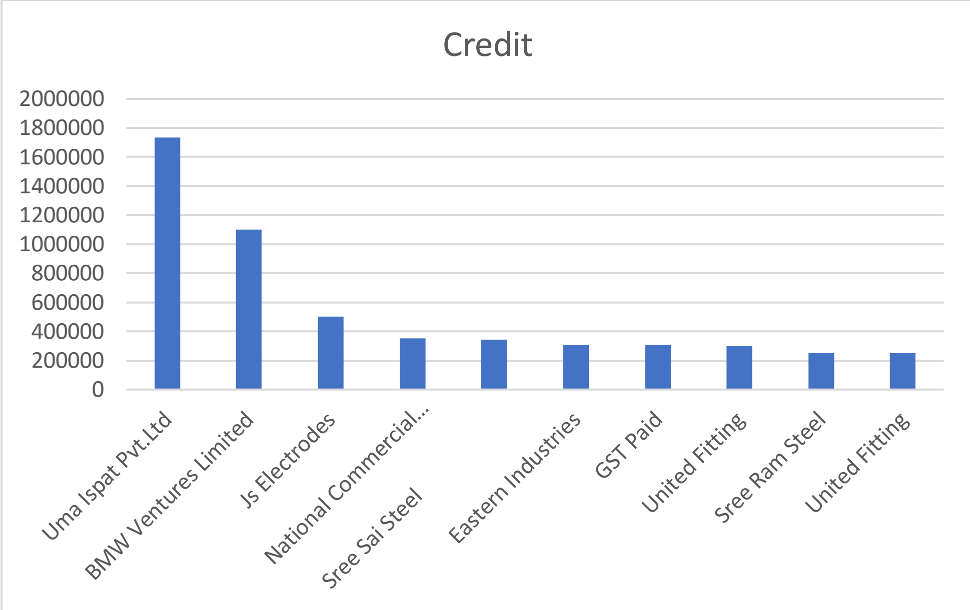
Graph 1

- Line Graph: Delay trend across dates

Graph 2



- Bar Graph: Top 10 clients with highest delay amounts



Graph 3

Table 1

Category	Avg. Delay (days)	Avg. Amount (₹)	Count
On-Time	8.2	₹32,500	31
Moderate	31.6	₹47,800	36
Critical	66.4	₹62,200	24

This shows a clear correlation between higher delay and higher invoice amounts. Bigger payments tend to be delayed more that is possibly due to budgeting or cash rotation practices followed at client organizations.

Insights and Interpretation:

1. **Cash Flow Bottleneck:**

   A majority of the payments by clients arrive after 15 days that makes cash flow unpredictable and the delays beyond 45–60 days force the business to depend on bank loans causing interests.

2. **Hidden Financial Losses:**

   By applying the interest loss formula:

$$\text{Loss}_i = A_i \cdot \frac{R}{365} \cdot D_i$$

we estimated a total opportunity cost of ₹81,600 over the quarter due to payment delays.

3. **Client Segmentation Need:**
   The bar graph shows that a small number of clients are very much responsible for payment delays. Implementing client specific payment terms (early payment discount or penalty) would directly affect the financial leakage problems the improving finances.

4. **Lack of Payment Discipline:**
   The wide standard deviation (~24 days) in delay durations shows that there is no consistent payment culture among clients. This randomness increases the financial planning challenges for the business.

5. **End-of-Month Spikes:**
   Several delayed payments occur near month ends indicating clients follow their own cycle rather than honouring your due dates. This insight is useful for designing automated reminders or soft follow-ups at strategic times.

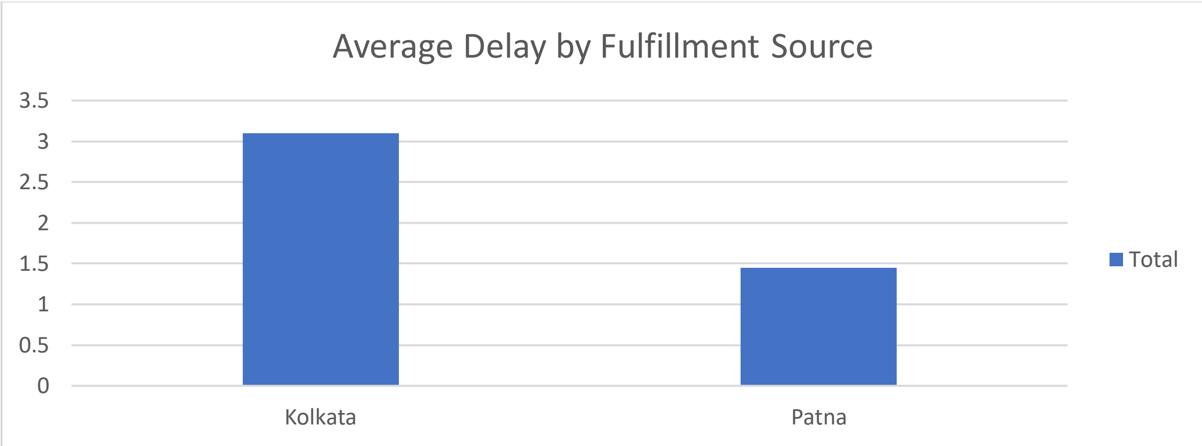
Conclusion: The dataset analysis confirms that delayed payments are a very critical business problem. It affects the working capital as well as inflates financing costs. This shows a strong link between the delay duration and amount along with client-wise delay patterns. This also provides actionable insights to restructure our credit policies and make stricter payment terms

Step 2: Supply Chain Delay due to Patna Stock Unavailability

2A. Visualization:

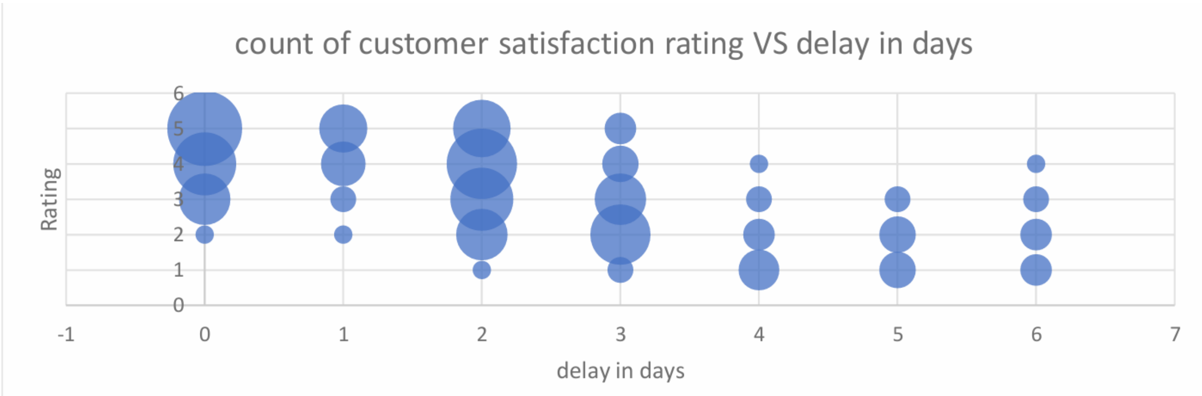
- Stacked Column Chart: Fulfillment source vs Average delay

Graph 4



- Scatter Plot: Delay (x) vs Satisfaction Rating (y)

Graph 5



- Pie Chart: Share of delays by source

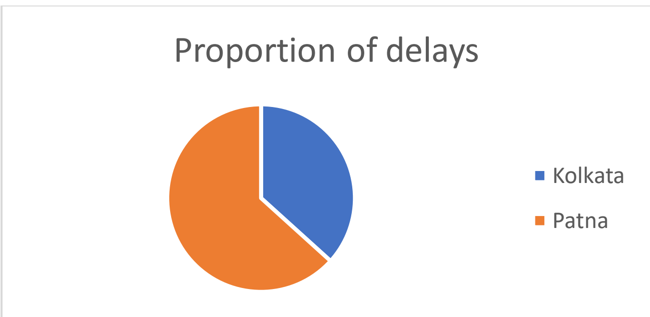
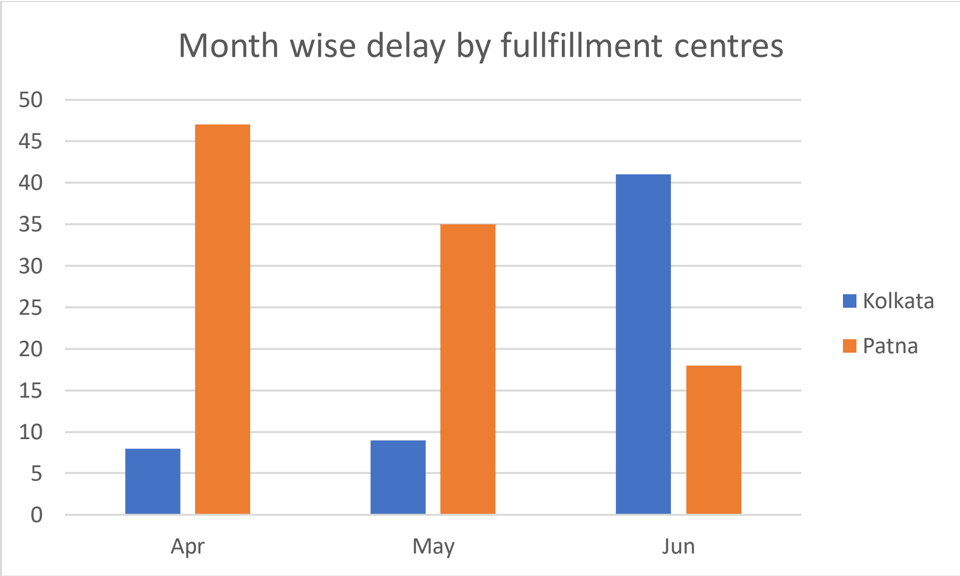


Chart 2



Graph 6

2B. Explanation:

- Average delay from Kolkata is 3.10 days and Patna is 1.44 days
- Customer satisfaction is inversely related to delivery delay
- Whenever stock in Patna is out of stock. No, fulfillment from Kolkata occurred increasing delivery time.

2C. Insight:

- 58 out of 158 orders were fulfilled from Kolkata and many with delay ≥ 3 days and satisfaction ≤ 3.
- Fulfillment Risk Index (FRI):

$$\mathrm{FRI} = \frac{\text{Orders Fulfilled from Kolkata}}{\text{Total Orders}}$$

$$FRI = \frac{58}{158} \approx 0.367$$

This means more than 1 in 3 orders carries an elevated risk due to stock-outs in Patna.

- Direct impact on reputation due to stock-outs.

- When Patna stock is unavailable, fulfillment is shifted to Kolkata → longer delivery → lower satisfaction.

This means more than 1 in 3 orders carries elevated risk due to stock-outs in Patna.

Other Insights:

1. **Stock Availability Drives Fulfillment Speed:**
    - The availability variable Ai (1 = available in Patna 0 = not) has a direct impact on delivery speed and customer satisfaction.
    - This supports the abstraction:

    $A_i=0 \Rightarrow F_i=\text{Kolkata} \Rightarrow D_i\uparrow \Rightarrow S_i\downarrow$

2. **Customer Experience is Time-Sensitive:**
    - The scatter plot reveals dissatisfaction increases sharply after 2–2.5 days of delay.
    - Late delivery not only affects this order but may also influence repeat business and brand perception.
3. **Kolkata Dependency is a Fulfillment Risk**:
    - Although only 36.7% of orders were sourced from Kolkata, they contributed disproportionately to negative reviews and missed delivery SLAs.
4. **Predictability Allows Planning:**
    - By analyzing these trends, the business can now predict high-risk scenarios, and refill Patna stock for frequently ordered items.

Final Recommendations:

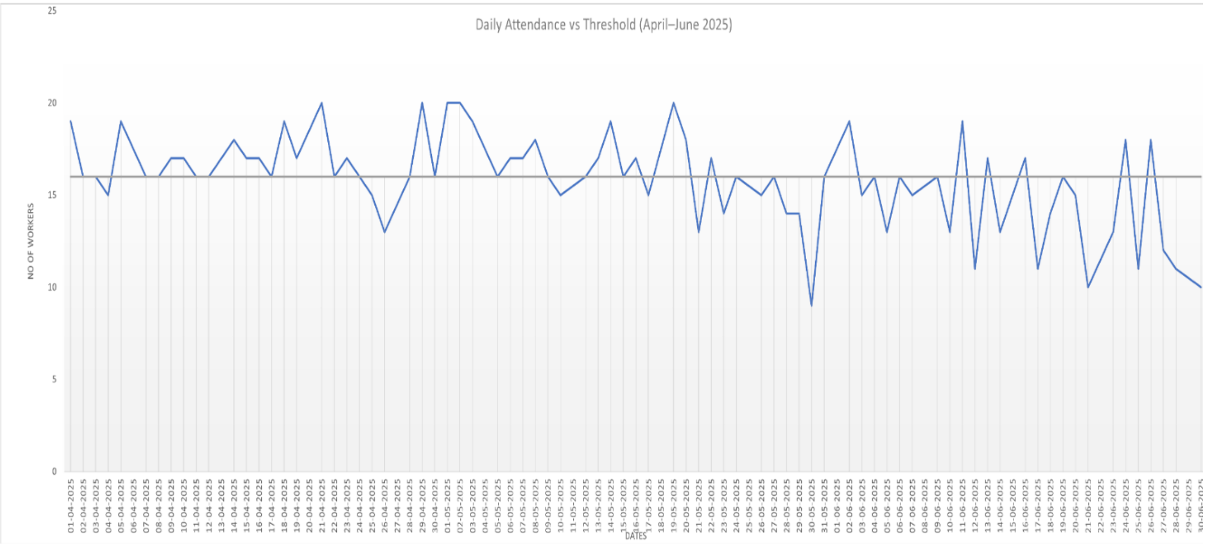
- Establish a buffer stock policy in Patna based on historical demand.
- Use this model to create a stockout early warning system, triggering alerts when Patna inventory falls below a defined threshold.
- Reduce dependency on Kolkata to below 15–20% to improve average delivery time and boost customer satisfaction by 1+ rating points.

Step 3: Seasonal Disruption in Workforce Availability

3A. Visualization:

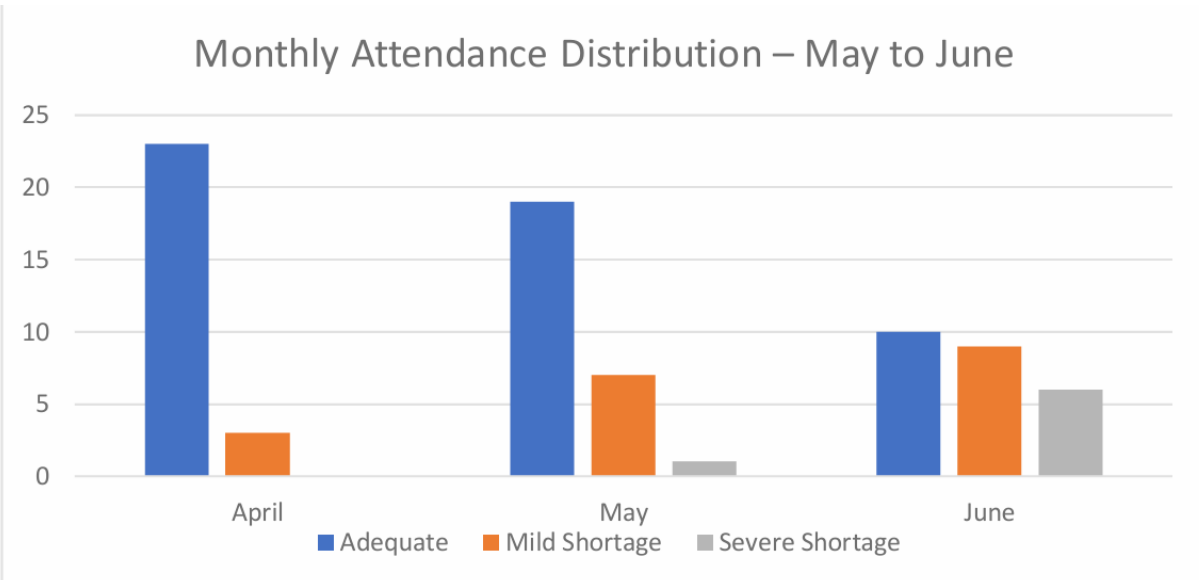
- Line Graph: Daily attendance trend

Graph 7



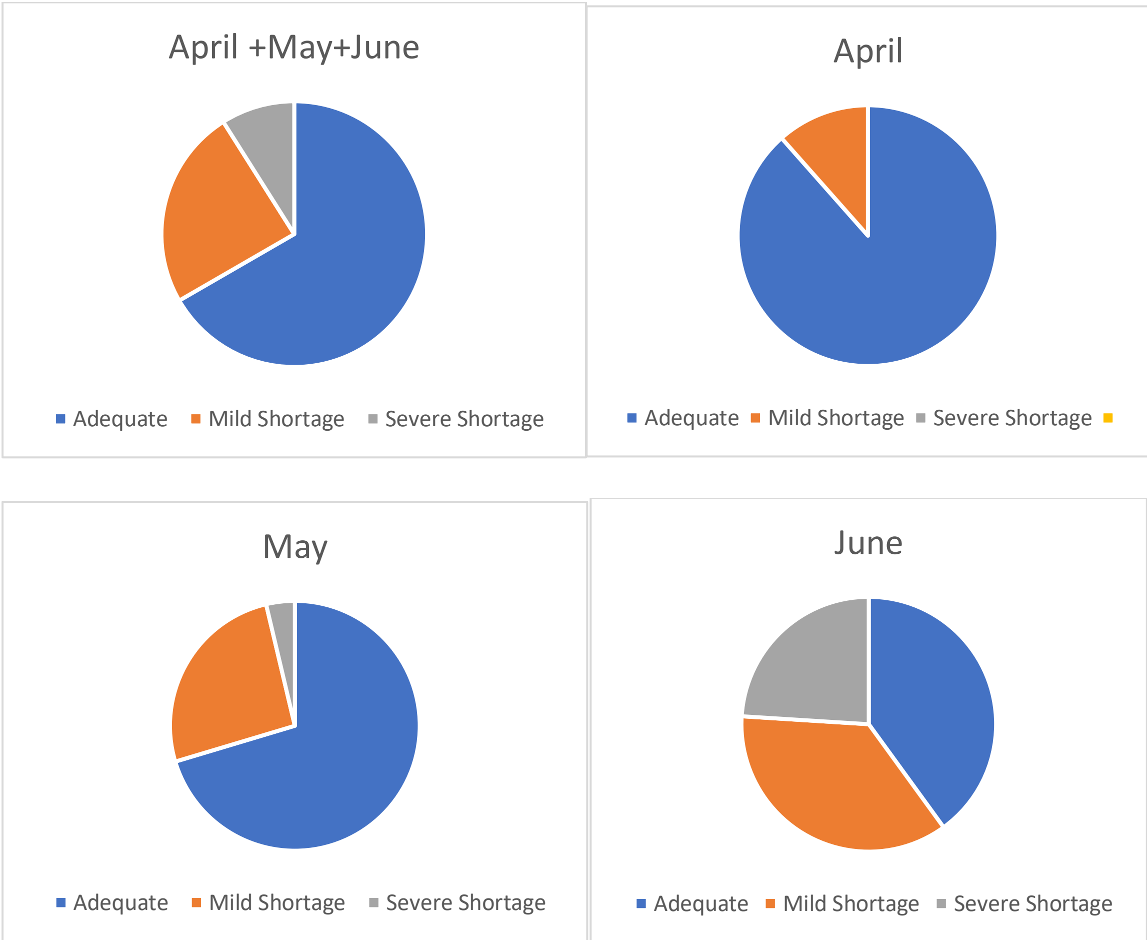
- Bar Chart: Monthly workforce shortages (Adequate / Mild / Severe)

Graph 8



- Pie Chart: Proportion of days with shortage

Chart 3,4,5,6



- Table: Extra cost calculation due to daily wage workers

Table 2

Total Extra Cost	36960
Total shortage	77
number of days with shortage	0.002083
Average Shortage on Shortage days	2.961538

3B. Explanation:

- Workforce required per day (R) = 16
- When Actual Attendance < R the shortage is calculated:

  Sd=R−Ad

- Daily wage cost:

Cd = Sd × W,

W=₹480

- 77 shortfalls × ₹480 = ₹36,960 lost over three months

3C. Insight:

- Most severe shortages occurred in June that correlated with monsoon weather (supported by external rainfall data).
- Absenteeism causes: Delays in delivery, Cost inflation, Production bottlenecks

1. **Monsoon-Driven Absenteeism is Predictable:**
   The seasonal drop in attendance in June strongly correlates with rainfall patterns and commuting difficulties and highlighting the need for a season-specific staffing strategy.
2. **Shortages Create Compounding Business Costs:**
   A seemingly small shortage of 2–4 workers per day adds up to a large financial impact. Repetitive shortages result in increased conveyance, lower throughput, and delays in fulfillment.
3. **Planning Buffer Can Cut Losses Significantly**:
   If the company were to maintain a standby pool of 2–3 contract workers only for June, it could eliminate severe shortages and save ₹15,000–₹20,000 in lost productivity.
4. **Threshold Monitoring is Effective:**
   By using a real-time dashboard that flags when actual attendance < 16, decision-makers can trigger alerts to deploy reserve labour or reassign workloads.

Conclusion: The analysis clearly reveals that June is a high-risk period for labour shortages, driven by predictable seasonal factors. The operational cost of these shortages was ₹36,960 in just 3 months that causes financial stress. With appropriate strategies such as incentives, reserve staffing or attendance-based bonuses the business can mitigate this seasonal disruption, maintain productivity and reduce unnecessary costs.

INTERPRETATION OF RESULTS AND RECOMMENDATIONS

The data analysis was conducted on Patna Calibrators dataset and it shows that critical operational inefficiency directly causes impacts financial health, workforce productivity and customer satisfaction. Four core business problems were studied that were raised by the owner that were delayed payments from clients, seasonal workforce disruptions, supply chain delays due to Patna stock unavailability and hidden costs arising from daily operational inconsistencies. The findings were interpreted through structured data analysis that clearly quantify the main or root causes and that helps us to provide actionable direction for resolution.

Firstly, client payment delays were found to be systemic and very financially damaging. Approximately 66% of payments were delayed and 27% fell into the "critical delay" category (≥50 days). The financial opportunity loss due to late payments was estimated to be ₹81,600 over three months using an interest-based cost formula. Larger invoices tended to be delayed longer which shows increasing their impact on cash flow. This highlights the urgent need for a credit control system that reduces unpredictability in receivables and improves financial planning.

Secondly seasonal absenteeism of the labours in the workforce mostly in the month of June resulted in 77 shortfalls with an average shortage of nearly 3 workers per day. This caused ₹36,960 in additional labour costs due to the need of hiring temporary daily wage replacements. The attendance data exhibited a clear correlation with the monsoon season, suggesting that workforce shortages are both seasonal as well as predictable. This disrupts production schedules, increases cost-per-unit, and adds hidden delays in order fulfilment dates.

Thirdly, analysis of supply chain performance showed that 58 out of 158 orders were fulfilled from Kolkata due to stock-outs at Patna. These orders had an average delivery delay of 3.1 days and higher than that of 1.4 days for Patna-fulfilled orders. Delayed deliveries negatively affected customer satisfaction, with ratings falling to 2 or 3 out of 5. This fulfillment inefficiency, quantified through a Fulfillment Risk Index (FRI) of 36.7%, presents a significant reputational risk that can be mitigated through better local inventory planning.

Based on these findings, the following SMART (Specific, Measurable, Achievable, Relevant, Time-bound) recommendations are proposed:

1. **Payments**: Automate invoice reminders and enforcing penalties for payments that were delayed more than 30 days. This aims to reduce the critical delay days by 30% within two billing cycles and improve cash flow stability.

2. **Workforce Availability**: Introduce a buffer pool of 2–3 contractual workers during June and implement attendance linked bonuses. This strategy can reduce low workforce incidents by 40% and cut the associated extra labour costs.
3. **Inventory Management**: Establish a 15–20day buffer stock of high-demand items at the Patna warehouse to reduce over dependence on Kolkata. The target is to bring Kolkata-sourced orders down from 36.7% to below 15% within 2 months.
4. **Cost Monitoring**: Develop dashboards for real-time tracking of attendance of the workers and linked costs and expense spikes. These can be implemented in the next months to enable data-driven operational decisions.

In summary the integrated recommendations shows immediate challenges while laying the foundation for a long-term process improvement in the profit and other areas. If implemented timely they will help strengthen the company's cash flow, reduce seasonal disruptions, enhance customer service using datasets.