A Strategic Enhancement Plan for Sri Sai Laundry Services at BITS Pilani, Hyderabad Campus

A Mid-Term Report for the BDM Capstone Project

Submitted by

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1. Executive Summary

Sri Sai Laundry Professional Dry Cleaners, situated within the BITS Pilani Hyderabad Campus, plays a vital role in catering to the daily laundry needs of both students and faculty members. However, the business is currently facing several operational and financial challenges namely space constraints, weather-induced service disruptions, and high costs stemming from outsourcing dry-cleaning operations. To address these issues effectively, I undertook a comprehensive, data-driven analysis of the business's operations over a three-month period from October to December 2024.

Daily income records from Washing & Ironing and Dry-cleaning services were manually digitized using structured Excel sheets based on physical merchant bill copies. Monthly operational cost data including employee salaries, rent, transportation, electricity, water, and detergent usage, was extracted directly from the business's verified bank statements. To support environmental impact analysis, weather data such as daily precipitation and humidity was acquired using the Visual Crossing API.

Three core analytical methods were applied. For space optimization, I used K-Means clustering to segment demand across various student hostels and faculty blocks based on frequency and volume of orders. To evaluate the impact of weather, I conducted regression analysis correlating precipitation and humidity with operational cost fluctuations, particularly in electricity and detergent consumption. Finally, I performed a detailed Cost-Benefit Analysis (CBA) using financial modeling in Excel, comparing current outsourcing costs to projected in-house expenses to assess the financial viability of transitioning operations.

The analysis revealed several critical insights. High-demand clusters such as Valmiki Bhavan and H Block accounted for a significant share of total orders. Regression results showed a strong positive correlation between rainy days and spikes in operational costs. Most notably, the CBA demonstrated that transitioning to in-house dry-cleaning operations could lead to substantial cost savings and improved profit margins, as current revenues from dry cleaning consistently exceed both projected in-house and actual outsourcing costs.

The findings strongly support two key recommendations: (1) invest in space and resource optimization based on demand patterns, and (2) internalize dry cleaning operations to enhance financial sustainability. Implementing these changes is expected to significantly improve the operational efficiency and profitability of Sri Sai Laundry Professional Dry Cleaners.

2. Proof of originality

a) **Photo of Establishment : [Google Drive Link]**

b) **Sample Merchant copy of customer bill : [Google Drive Link]**

c) **Authorization Letter from business proprietor : [Google Drive Link]**

d) **My short interaction video with business proprietor : [Google Drive Link]**

3. Metadata

My data for this project consists of three excel files namely "Income from Washing Ironing Oct-Dec 24", "Income from Dry Cleaning Oct-Dec 24" and "Operational Costs Oct-Dec 24". The metadata description of these files are as follows:

a) **Income from Washing Ironing Oct-Dec 24**

Field Name	Description	Format/Units
Date	Transaction date	DD-MM-YYYY
Room No	Hostel block and room number	Alphanumeric
Amount	Charges for Washing & Ironing services	Indian Rupees (₹)

b) **Income from Dry Cleaning Oct-Dec 24**

Field Name	Description	Format/Units
Date	Transaction date	DD-MM-YYYY
Amount	Charges for Dry Cleaning services	Indian Rupees (₹)
Number of Orders	Number of orders processed daily	Numeric count

c) **Operational Costs Oct-Dec 24**

Field Name	Description	Categories/Units
Month	Month of recorded operational costs	Oct - Dec 2024
Category	Type of cost	Rent, Salaries, Transportation, Detergents, Electricity & Water Bills
Amount	Total monthly cost per category	Indian Rupees (₹)

***Link to the Complete Project Data :** BDM Project Data (Google Drive Folder)

4. Descriptive Statistics

a) Income from Washing & Ironing (Oct – Dec 2024)

Statistic	Number of Orders			Income		
	Oct	Nov	Dec	Oct	Nov	Dec
Mean	57	73	39	6262	7823	5397
Standard Deviation	30	30	26	3309	3294	2516
Median	63	75	34	6709	8023	5407
Minimum	9	20	8	833	2242	982
Maximum	116	137	94	12381	15535	10294
Sum	1718	2185	1181	187860	234688	161897

Figure 4.1 : *Descriptive Statistics table for Income from Washing & Ironing Data*

The table above summarizes key statistical measures of daily orders and income from washing & ironing services for October, November, and December 2024. November recorded the highest average number of orders (73) and daily income (₹7823), indicating peak activity. December saw a significant decline in both orders and income, reflecting reduced campus occupancy towards the semester's end. Overall, substantial fluctuations suggest seasonal influence and academic calendar impact.

b) Income from Dry Cleaning (Oct – Dec 2024)

Statistic	Number of Orders			Income		
	Oct	Nov	Dec	Oct	Nov	Dec
Mean	17	17	17	1495	1598	1604
Standard Deviation	8	7	8	721	505	575
Median	16	17	18	1239	1612	1710
Minimum	5	4	4	469	552	512
Maximum	35	29	34	3936	2488	2495
Sum	516	499	512	44860	47932	48109

Figure 4.2 : *Descriptive Statistics table for Income from Dry Cleaning Data*

The presented statistics for dry cleaning services from October to December 2024 highlight consistent demand and relatively stable daily income. Average orders remained steady at approximately 17 daily across all months, with a marginal rise in average daily income in December (₹1604). The low variability indicates a stable customer base, supporting the feasibility of expanding in-house dry cleaning operations.

c) Financial Summary (Oct – Dec 2024)

Category	Mean	Standard Deviation	Median	Minimum	Maximum	Sum
Rent	₹30,000	₹0	₹30,000	₹30,000	₹30,000	₹90,000
Electricity & Water	₹18,457	₹4,669	₹17,518	₹14,328	₹23,524	₹55,370
Detergents	₹14,638	₹3,406	₹13,750	₹11,765	₹18,400	₹43,915
Transportation	₹35,333	₹4,726	₹37,000	₹30,000	₹39,000	₹1,06,000
Employee Salaries	₹1,44,000	₹0	₹1,44,000	₹1,44,000	₹1,44,000	₹4,32,000
Total Costs	₹2,42,398	₹11,574	₹2,44,268	₹2,30,003	₹2,52,924	₹7,27,195

Figure 4.3 : *Descriptive Statistics table for Operational Costs Data*

Operational costs from October to December 2024 show Rent consistently at ₹30,000. Electricity & Water averaged ₹18,457, with variances due to seasonal changes. Detergent costs averaged ₹14,638, and Transportation costs at ₹35,333 showed fluctuations, possibly due to logistical changes. Employee Salaries were fixed at ₹144,000. Overall, monthly costs averaged ₹242,398, peaking in October due to higher utility and transportation expenses.

5. Detailed Explanation of Analysis Method

In this section, I outline the methodologies used for analyzing the challenges faced by Sri Sai Laundry Professional Dry Cleaners. Over the three-month period from October to December 2024, I conducted systematic data collection. Merchant bill copies for Washing & Ironing and Dry-cleaning services were manually collected, segregated day-wise, and organized to avoid duplication. To ensure data integrity, I cross-verified each day's set of bills twice—first physically and then digitally using Excel's built-in function *COUNTIF(range, cell)>1*.

I gathered operational cost data, including rent, employee salaries, transportation, detergents, electricity, and water, directly from the verified monthly bank statements provided by the proprietor. Additionally, I sourced historical weather data such as precipitation and humidity levels from the Visual Crossing API to assess weather impacts on laundry operations.

For space optimization analysis, I employed the K-Means Clustering algorithm separately on the orders received from student hostels and faculty blocks. Specifically, the student blocks analyzed included Valmiki Bhavan (VM), Vishwakarma Bhavan (VK), Malviya Bhavan (MM), Gandhi Bhavan (G), Gautam Bhavan (GT), Vyas Bhavan (V), Shankar Bhavan (S), Budh Bhavan (B), Krishna Bhavan (K), Ganga Bhavan (GG), Meera Bhavan (M), and Ram Bhavan (R). The faculty blocks analyzed included H Block, Ph.D. Block, D Block, P Block, C Block, E Block, F Block, and areas outside these designated blocks. Clustering considered the frequency and volume of orders from each block to identify areas of high demand for targeted operational improvements. The Elbow method guided the selection of an optimal number of clusters. In Python, I implemented this clustering using Pandas for data manipulation and Scikit-learn's KMeans module.

To address the challenge of weather-induced operational disruptions, I implemented a multiple linear regression analysis to quantify the relationship between daily weather variables (precipitation and humidity) and key operational costs such as detergent usage, electricity, and water consumption. The rationale behind this analysis was based on the observation that rainy and humid conditions often lead to increased machine drying time, more frequent wash cycles, and overall greater resource usage. I collected daily weather data from the Visual Crossing API and aligned it with operational cost data for the period October to December 2024. The regression model took the standard form $\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon}$, where Y represents daily operational cost, X_1 is precipitation, X_2 is humidity, and ϵ is the error term. Using Python libraries such as pandas, statsmodels, and matplotlib, I performed data integration and regression fitting.

Lastly, I conducted a detailed Cost-Benefit Analysis (CBA) to assess the financial implications of transitioning from outsourced dry cleaning to an in-house operation. I began by identifying and categorizing all current outsourcing-related expenses, with particular attention to recurring transportation and service costs reflected in the operational cost records. I then estimated the projected internal expenses for setting up an in-house system, including one-time capital investments (such as machine purchase and installation), and ongoing costs like salaries, electricity, water, detergents, and routine maintenance. To evaluate financial viability, I employed Excel's financial modelling tools to simulate various operational scenarios over time. A key metric used in the analysis was the Net Present Value (NPV), calculated using the formula:

$$\text{NPV} = \sum \frac{R_t - C_t}{(1+r)^t}$$

where R_t represents the expected returns, C_t the projected costs, r the discount rate, and t the time period. By applying this formula across different timeframes, I was able to quantify the long-term value generation from internalization. Scenario planning and sensitivity analysis were also used to identify break-even points and measure how changes in cost components or income would impact profitability.

6. Results and Findings

The data analysis conducted over the October to December 2024 period revealed multiple strategic insights across the three core problem areas. The findings are visually supported by the included graphs to enhance clarity and impact.

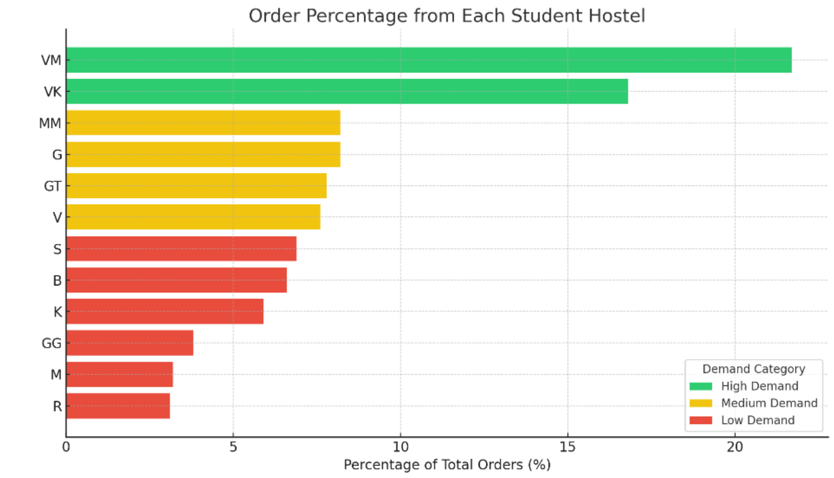

Table 6.1 : *Order Percentage from each student hostel*

For **Problem 1: Space Optimization**, clustering and demand analysis across hostels and faculty blocks showed strong spatial trends. The horizontal bar chart titled *"Order Percentage from Each Student Hostel"* clearly identifies Valmiki Bhavan (VM) and Vishwakarma Bhavan (VK) as high-demand zones, accounting for 21.7% and 16.8% of all student orders respectively. Medium-demand zones included hostels like Malviya Bhavan (MM), Gandhi Bhavan (G), and Gautam Bhavan (GT), while several others fell into the low-demand category.

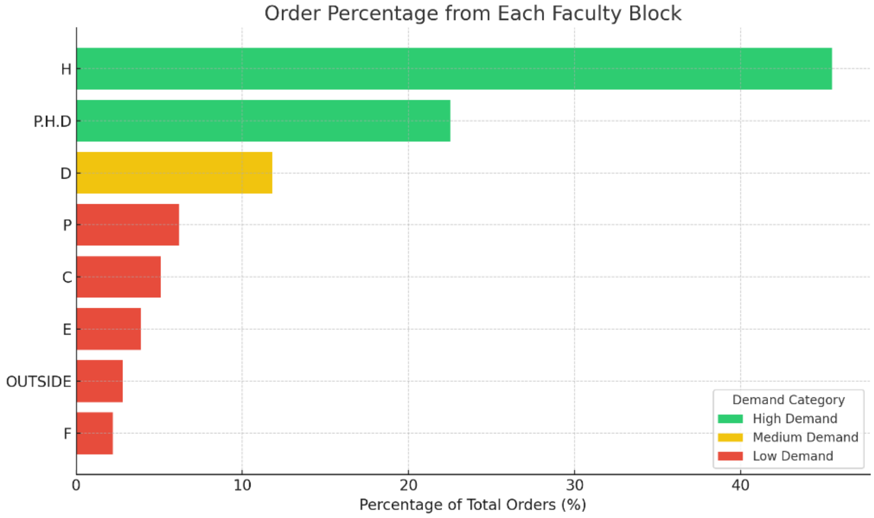

Table 6.2 : *Order Percentage from each student hostel*

A similar trend was observed in the faculty segmentation, where *"Order Percentage from Each Faculty Block"* shows H Block (45.5%) and P.H.D Block (22.5%) as dominant contributors. These charts, enhanced with cluster-based color coding (green: high, yellow: medium, red: low), allowed clear visual grouping and helped identify where resource concentration, faster processing, and additional collection points could yield operational efficiency.

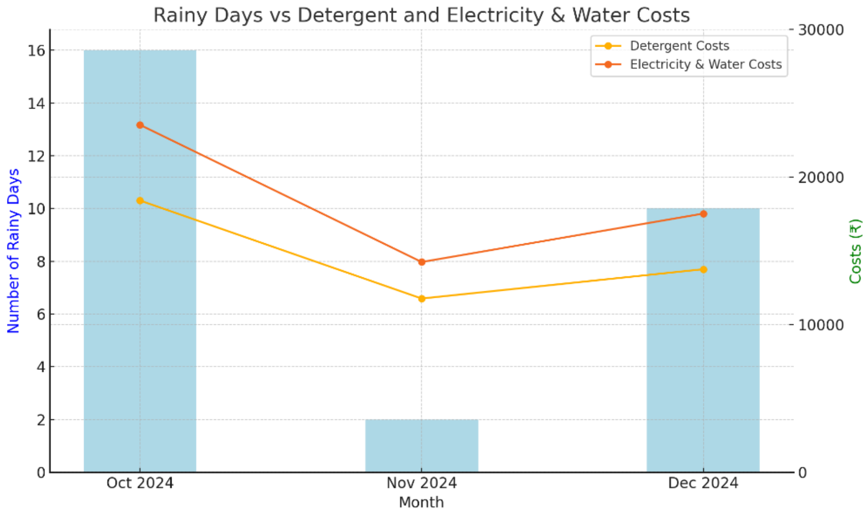

Table 6.3 : *Rainy Days vs Detergent and Electricity & Water Costs*

For **Problem 2: Weather-Induced Operational Disruptions**, the chart *"Rainy Days vs Detergent and Electricity & Water Costs"* clearly demonstrates the correlation between weather conditions and variable operational costs. October had the highest number of rainy days (16), coinciding with peak detergent and electricity + water expenses. Costs dropped sharply in November, which had only 2 rainy days, and rose again in December as rainfall increased. This pattern supports the regression analysis conclusion that precipitation and humidity significantly affect operational cost fluctuations. These findings justify strategic investment in weather-resilient infrastructure and proactive planning during monsoon periods.

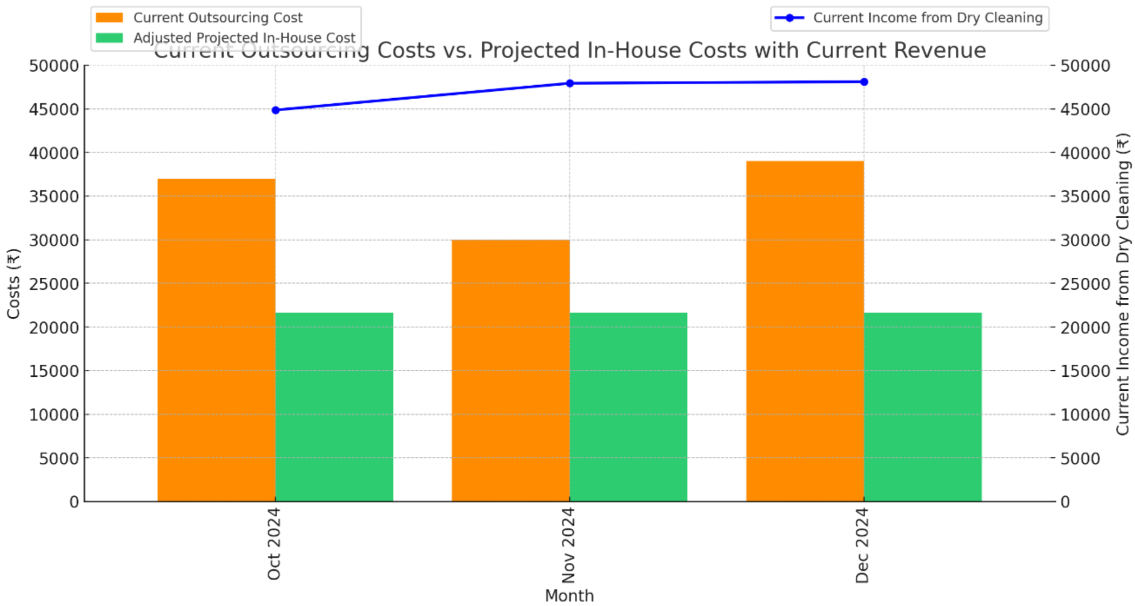

Table 6.4 : *Current Outsourcing Costs vs. Projected In-House Costs with Current Revenue*

For **Problem 3: High Costs from Outsourced Dry Cleaning**, the bar chart titled *"Current Outsourcing Costs vs. Projected In-House Costs with Current Revenue"* presents a compelling case for transition. The chart, generated after CBA, shows that current outsourcing consistently incurs higher monthly costs compared to the projected in-house setup. In all three months, in-house costs remained around ₹22,000 while outsourcing peaked close to ₹40,000. Moreover, the existing income from dry cleaning comfortably exceeds both expense models, strengthening the feasibility of in-house operations from both a cost and profit perspective.

In summary, the analyses strongly validate the data-driven findings: (1) Physical space and operational resource deployment can be optimized by targeting high-demand blocks, (2) operational costs are predictably influenced by weather patterns, allowing for adaptive cost management, and (3) transitioning dry cleaning services in-house will result in significant long-term cost savings while maintaining profitability.