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

A Final Report for the BDM Capstone Project

Submitted by

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1. Executive Summary

Sri Sai Laundry Professional Dry Cleaners has been serving the students and faculty of BITS Pilani Hyderabad Campus since 2010, offering essential laundry services such as washing, ironing, and dry cleaning. Currently, we are facing significant operational and financial challenges, primarily due to constrained operational space, disruptions caused by weather conditions, and the high financial costs associated with outsourcing dry-cleaning services.

To effectively tackle these problems, I meticulously collected detailed operational and financial data from October to December 2024. I collected merchant copies of bills, entered the respective transaction details (Date, Customer Location, and Amount) into Excel, and performed preprocessing to remove duplicate entries (same date and customer location) using the Excel formula: =IF(COUNTIFS($A$2:A2, A2, $B$2:B2, B2)>1, "Duplicate", "Unique"). Monthly expenses were directly obtained from verified bank statements. Additionally, weather-related data (precipitation and humidity) were gathered via the Visual Crossing API. I applied descriptive statistical methods, K-Means clustering to optimize space management, regression analysis to identify the impact of weather on operational costs and conducted a comprehensive Cost-Benefit Analysis (CBA) to assess the financial feasibility of in-house dry-cleaning operations.

My analysis revealed high-demand zones, notably Valmiki Bhavan and H Block, significantly influencing service allocation strategies. Regression analysis confirmed a strong relationship between rainy days and increased operational costs, notably in utilities and detergent consumption. Importantly, the CBA clearly demonstrated the financial advantage of transitioning from outsourced to in-house dry-cleaning operations.

Based on these findings, I recommend optimization of space according to identified demand clusters and a strategic long-term investment in in-house dry-cleaning facilities. Implementing these recommendations is expected to significantly enhance operational efficiency and profitability of Sri Sai Laundry Professional Dry Cleaners.

2. Detailed Explanation of Analysis Process/Method

2.1) Data Cleaning and Pre-processing

I regularly collected weekly merchant bills for washing, ironing, and dry-cleaning services, and entered the transaction details—Date, Room No. (Customer Location), and Amount—into structured Excel sheets. I continued this process for three months: October, November, and December 2024. At the end of every month, I recorded the operational costs from the proprietor's verified bank statements. These expenses included salaries, rent, electricity and water, detergents, and transportation.

For preprocessing, I eliminated duplicate entries based on the same date and location using Excel: = *IF(COUNTIFS($A$2:A2, A2, $B$2:B2, B2)>1, "Duplicate", "Unique").* Additionally, I removed entries where critical data like Room No. or Amount was missing or bills were torn.

2.2) Comprehensive Explanation for Each Method/Analysis Used

Problem 1: Space Optimization Using K-Means Clustering

To identify areas with high, medium, and low demand, I began by segmenting the dataset into two categories based on the location prefixes found in the "Room No" field. These prefixes indicate the customer’s residence block: **Student Hostels**: VM (Valmiki Bhavan), VK (Vishwakarma Bhavan), MM (Malviya Bhavan), G (Gandhi Bhavan), GT (Gautam Bhavan), V (Vyas Bhavan), S (Shankar Bhavan), B (Budh Bhavan), K (Krishna Bhavan), GG (Ganga Bhavan), M (Meera Bhavan), R (Ram Bhavan) and **Faculty Blocks**: H Block, P.H.D, D Block, P Block, C Block, E Block, F Block, OUTSIDE

One complication with faculty data was the inclusion of room numbers like C1, C2, D3, P5, etc., which represent different floors or sections of the same building. To maintain uniformity, I implemented a normalization step, wherein all alphanumeric prefixes representing the same base block were standardized. For example, both "C1" and "C5" were mapped to "C". The normalization logic was implemented as follows :

```python
# Extract prefix from Room No and normalize for faculty block types
df['Prefix'] = df['Room No'].astype(str).str.split(' ').str[0]
faculty_blocks_base = ['C', 'D', 'P', 'E', 'F', 'H', 'P.H.D', 'OUTSIDE']
df['Normalized Prefix'] = df['Prefix'].apply(
    lambda x: ''.join([char for char in x if not char.isdigit()]) if any(x.startswith(fac) for fac in faculty_blocks_base) else x)
```

Next, I classified the data into two segments (Student and Faculty) using the cleaned prefixes:

Student Block Summary:

	Normalized Prefix	Total_Amount	Total_Transactions
0	B	34426.0	326
1	G	44295.0	403
2	GG	20731.0	188
3	GT	43065.0	383
4	K	32387.0	290
5	M	21284.0	159
6	MM	48179.0	404
7	R	17226.0	151
8	S	39418.0	337
9	V	38413.0	374
10	VK	92974.0	823
11	VM	116109.0	1066

Faculty Block Summary:

	Normalized Prefix	Total_Amount	Total_Transactions
0	C	872.0	7
1	CP	344.0	2
2	D	6513.0	21
3	E	2664.0	7
4	F	534.0	4
5	H	14290.0	81
6	J	112.0	1
7	OUTSIDE	748.0	5
8	P	1341.0	11
9	P.H.D	8520.0	40

After cleaning and classification, I used K-Means Clustering to identify patterns in demand. K-Means is an unsupervised learning algorithm that partitions a dataset into K distinct clusters based on feature similarity. It aims to minimize intra-cluster variance. Input features for the K-Means clustering are Amount (Total revenue from the block) and Frequency (Number of orders from the block). The code for K-Means model is as follows

```python
from sklearn.cluster import KMeans

# function for clustering input
def prepare_cluster_input(data):
    return data.groupby('Normalized Prefix').agg({
        'Amount': 'sum',
        'Room No': 'count'
    }).rename(columns={'Room No': 'Frequency'}).reset_index()

# Prepare and cluster student data
student_cluster_input = prepare_cluster_input(student_df)
kmeans_student = KMeans(n_clusters=3, random_state=42)
student_cluster_input['Cluster'] = kmeans_student.fit_predict(student_cluster_input[['Amount', 'Frequency']])

# Prepare and cluster faculty data
faculty_cluster_input = prepare_cluster_input(faculty_df)
kmeans_faculty = KMeans(n_clusters=3, random_state=42)
faculty_cluster_input['Cluster'] = kmeans_faculty.fit_predict(faculty_cluster_input[['Amount', 'Frequency']])
```

Code Block 2

Code Explanation: groupby() and agg() are used to prepare the input data by summarizing the amount and frequency per block. KMeans(n_clusters=3) initializes the model to divide data into three clusters (representing low, medium, high demand).random_state=42 ensures consistent results across multiple runs. fit_predict() runs the K-Means algorithm and assigns a cluster label to each row in the dataset. This process was repeated separately for student and faculty segments to better tailor the optimization strategies based on their respective demand characteristics.

Problem 2: Impact of Rainy Weather on Operational Costs Using Linear Regression

To investigate whether weather conditions affect utility-related operational expenses, I performed a regression analysis using daily weather data obtained via Visual crossing API and Operational costs data collected from the verified bank statements. First, I used pandas and datetime libraries in Python to convert the weather excel file into a daily log. From this, date converted to proper datetime format, extracted the Month and Year from each row and created a binary column Rainy_Day set to True if precipitation > 0. This allowed me to group the dataset by month and count the total number of rainy days for each month from October to December 2024.

Next, I attempted to extract the monthly utility costs directly from the Excel sheet using filters. However, due to formatting inconsistencies and merged cells, I opted for manual entry based on verified monthly totals for the two categories of interest – Electricity + Water and Detergent costs. These were added up for each month:

- October 2024: ₹23,524 + ₹18,400 = ₹41,924
- November 2024: ₹14,238 + ₹11,765 = ₹26,003
- December 2024: ₹17,518 + ₹13,750 = ₹31,268

This data was entered into a Data Frame using Python code and merged with the rainy day counts by the corresponding month. I used the statsmodels package to run an Ordinary Least Squares (OLS) regression. The code included: add_constant ensures the model estimates both intercept and slope, OLS(y, X).fit() trains the model and summary() provides key statistics like coefficients, R-squared, standard error, t-values, and p-values.

```
import statsmodels.api as sm

X = sm.add_constant(regression_df['Rainy_Days'])  # Independent: Rainy days
y = regression_df['Relevant_Cost']                # Dependent: Utility cost

model = sm.OLS(y, X).fit()
model.summary()
```

Code Block 3

The regression model was used to analyze the relationship:

$$\text{Relevant Costs} = \beta_0 + \beta_1(\text{Rainy Days})$$

Problem 3: Cost-Benefit Analysis of In-House Dry-Cleaning Setup

To analyze the economic impact of moving dry-cleaning operations from an outsourced model to an in-house facility, I applied the Cost-Benefit Analysis (CBA) framework using both revenue and cost data.

First, I manually entered monthly revenue from dry cleaning and the outsourced vendor costs based on transaction records:

- Revenues: ₹44,860 (Oct), ₹47,932 (Nov), ₹48,109 (Dec)
- Outsourced Costs: ₹37,000 (Oct), ₹30,000 (Nov), ₹39,000 (Dec)

After speaking with the proprietor, I obtained the estimated cost for running an in-house dry-cleaning facility: ₹22,500 per month. This amount covers labor, machinery operation, and materials required.

The analysis was performed in Python with the following logic:

- Step 1: Store monthly revenue and outsourced cost values in lists.
- Step 2: Calculate net benefit for each month by subtracting the in-house cost from the monthly revenue.
- Step 3: Use the Net Present Value (NPV) formula to discount future benefits at a monthly rate of 0.008 (10% annual rate).

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

This was implemented with the following code:

```python
months = ['October', 'November', 'December']
revenues = [44860, 47932, 48109]
outsourced_costs = [37000, 30000, 39000]
inhouse_cost = 22500
discount_rate = 0.008  # monthly (10% annually)

net_benefits = [rev - inhouse_cost for rev in revenues]
npv = sum(benefit / ((1 + discount_rate) ** (i + 1)) for i, benefit in enumerate(net_benefits))

import pandas as pd
df = pd.DataFrame({
    'Month': months,
    'Revenue': revenues,
    'Outsourced Cost': outsourced_costs,
    'In-House Cost': [inhouse_cost]*3,
    'Net Benefit': net_benefits
})
```

Code Block 4

2.3) Justification

Excel was selected as the primary tool for data entry and cleaning because of its intuitive interface, widespread use, and ability to perform simple yet powerful operations such as duplicate detection and data aggregation. It enabled consistent documentation of transactions and monthly expenses with minimal training overhead.

To accurately segment the customer data, I relied on prefix identification within the Room No. entries. This method was simple yet effective in distinguishing between student and faculty locations, which was necessary for independent analysis of different user groups.

For identifying clusters of demand and optimizing space allocation, K-Means clustering was ideal because it allowed classification of continuous variables like revenue and order frequency into meaningful clusters without prior labeling. This unsupervised learning method provided insights into high, medium, and low demand zones across student and faculty demographics.

Rainfall data was included in the analysis after observing operational disruptions caused by precipitation, particularly in drying activities and increased water usage. Linear regression was the appropriate tool to quantify the impact of such weather patterns on utility expenses. Although the dataset was limited in time span, the regression model provided valuable direction for seasonal cost planning.

Where automation failed due to formatting limitations, I used manually verified cost entries for sensitive variables like electricity, water, and detergent expenses. This ensured accuracy and eliminated the risk of false assumptions. The Cost-Benefit Analysis (CBA) method was justified for evaluating the viability of shifting to an in-house dry-cleaning setup. It is widely used in operations and finance to compare future gains against upfront or ongoing costs. Incorporating Net Present Value (NPV) further strengthened the financial projection by accounting for the time value of money, an essential concept in long-term investment planning.

Lastly, I chose Python along with the pandas and statsmodels libraries for all computational tasks due to their flexibility, reproducibility, and professional-grade analytical power. Python allowed dynamic data manipulation, clear visualizations, and robust model evaluation, making the analysis both reliable and scalable for future business decisions.

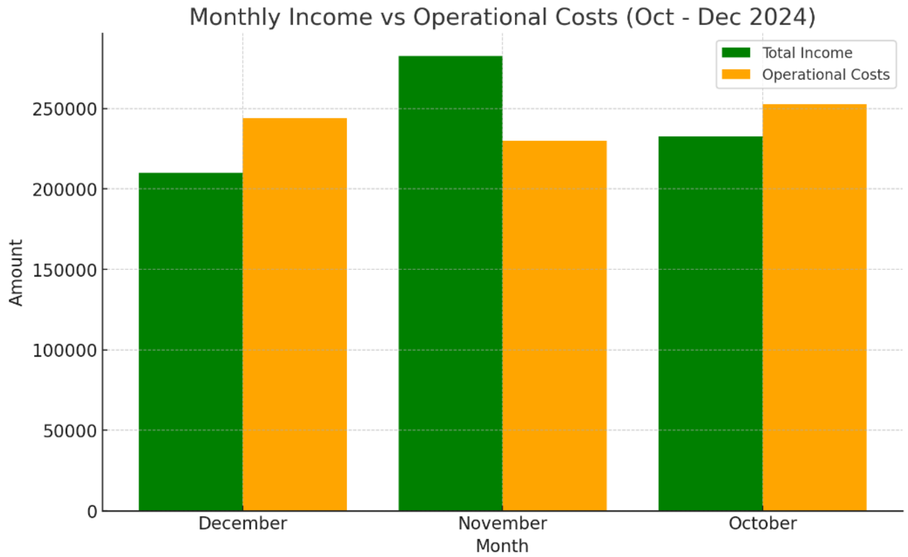
*** Link to Complete Project Data:** G-Drive Link for Data Folder

*** Link to Analysis Folder:** G-Drive Link for Codes Folder

3. Results and Findings

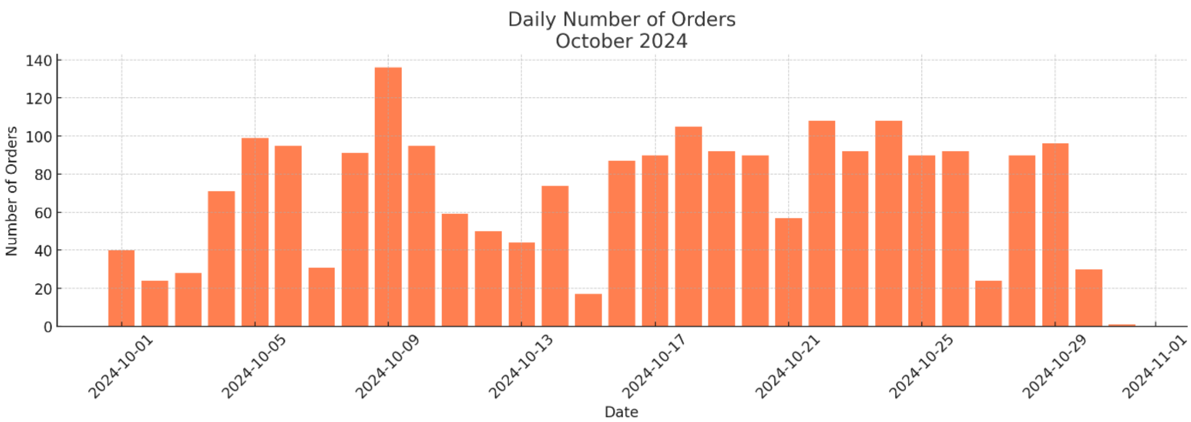
The insights drawn from the analysis of the data are the following:

- The bar chart below compares total income with total operational costs for October, November, and December 2024. While November shows a strong profitability margin, October's expenses are nearly on par with income, and December shows a slight dip in income due to reduced demand toward the semester's end.



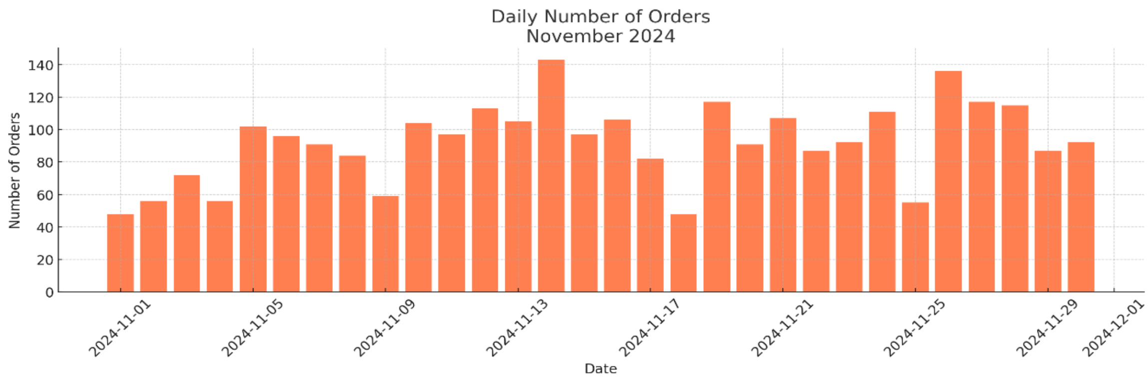
Graph 1 : Monthly Income vs Operational Costs (Oct-Dec 2024)

- Three bar charts below show day-to-day order volumes for each of the three months.



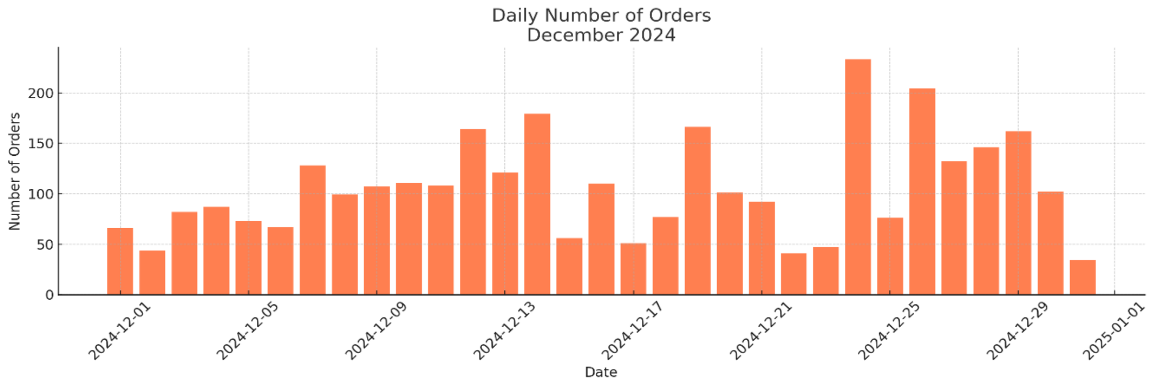
Graph 2: Daily trend for number of orders – October 2024

In October, the number of orders steadily increased after the first week, with peak order activity seen around mid-month. There was a notable spike between the 9th and 20th of the month, likely to correspond increased usage before academic deadlines or festival-related breaks. The beginning and end of the month saw relatively lower order volumes, pointing to transitional demand patterns.



Graph 3: Daily trend for number of orders – November 2024

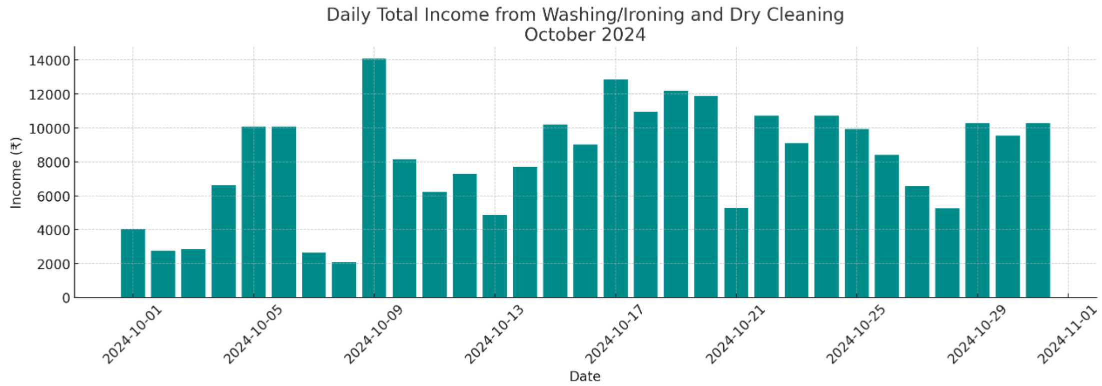
November experienced the highest and most consistent order volume throughout the month. Several days surpassed the 100+ order mark, indicating steady laundry usage across the student and faculty base. This consistency affirms the operational strength of the business during this month and aligns with the peak revenue period captured in the financial charts.



Graph 4: Daily trend for number of orders – December 2024

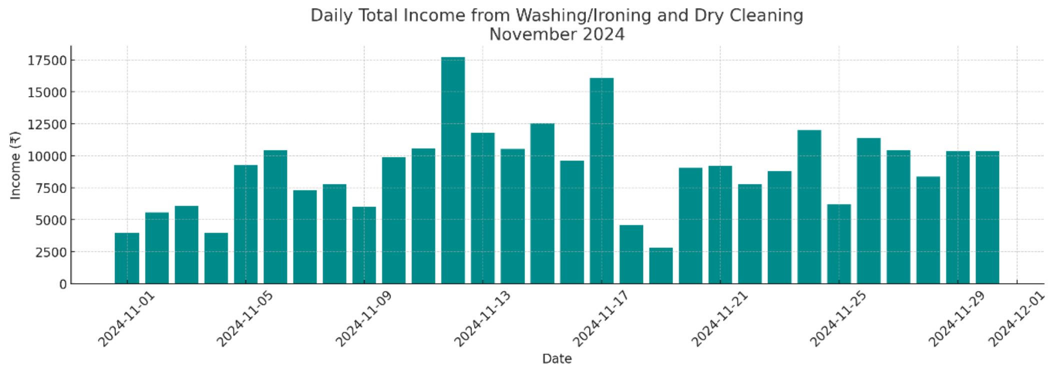
In December, the chart reveals a fluctuating pattern with a pronounced mid-month peak. The first half of the month showed healthy activity, but there was a sharp decline in orders toward the last week. This drop coincides with the academic calendar, where students begin leaving campus for the winter break, reducing service demand.

- The charts below show the total income (Washing/Ironing + Dry Cleaning) on a day-to-day for each of the three months.



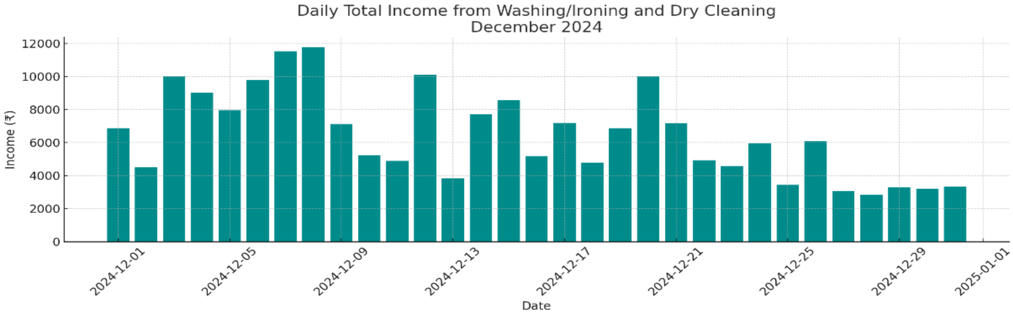
Graph 5 : Daily trend for total income – October 2024

Income trends in October mirrored the order volumes. The mid-month days delivered strong revenue, particularly between October 9th and 20th. These revenue peaks support the strategy of increasing manpower or machine availability during such windows.



Graph 6 : Daily trend for total income – November 2024

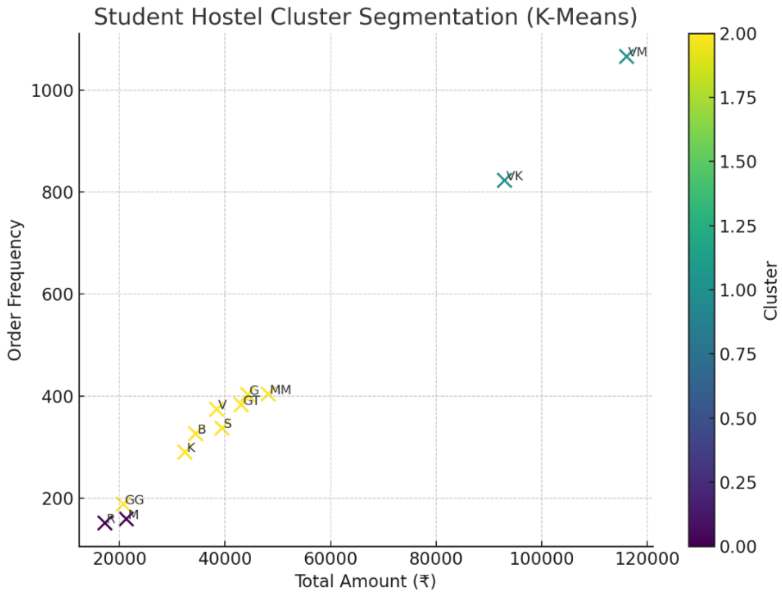
November saw the most stable and highest income days across the three-month period. The data clearly shows that this was the peak month for Sri Sai Laundry Services in terms of both order volume and financial returns. Nearly every day reflected high productivity and utilization.



Graph 7 : Daily trend for total income – December 2024

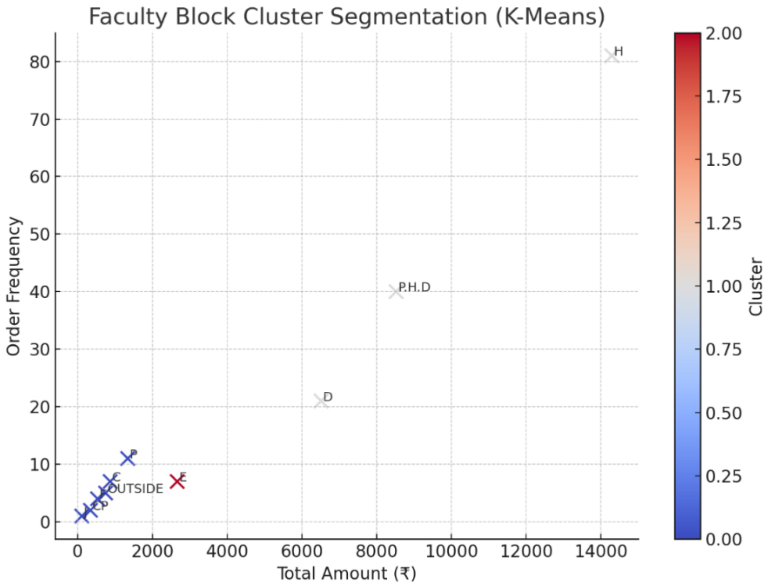
While December began strong, there was a steady decline in income after the 20th of the month. This is consistent with the pattern seen in the order chart and is attributed to the reduced campus population toward semester-end. Despite this, some mid-December dates still saw good spikes in income, suggesting urgent services before departure.

- The scatter plot below presents a segmentation of student hostels using the K-Means clustering technique, which groups locations based on their total revenue generated and the frequency of laundry transactions over the three-month analysis period. This visualization effectively uncovers three distinct demand patterns among student residences. At the top tier, VM (Valmiki Bhavan) and VK (Vishwakarma Bhavan) stand out prominently as high-demand clusters. With a combined total revenue of over ₹2 lakh and more than 1,800 transactions between them, these hostels consistently generated the highest volume of orders. Their strategic importance to daily operations cannot be overstated—they serve as the backbone of the student customer base and must be prioritized in terms of manpower allocation, pick-up timing, and resource availability. The medium-demand segment includes hostels such as MM (Malviya Bhavan), G (Gandhi Bhavan), and GT (Gautam Bhavan). These hostels showed solid engagement with over 350–400 orders each and contributed significant income in the range of ₹40,000–₹48,000. Although not as dominant as VM and VK, they remain important for maintaining overall service balance and should be considered for inclusion in route optimization and semi-prioritized delivery mechanisms. On the lower end of the spectrum, hostels such as M (Meera Bhavan), R (Ram Bhavan), and GG (Ganga Bhavan) fell into the low-demand cluster. These residences recorded under 200 transactions and generated less than ₹22,000 each in income across the quarter.



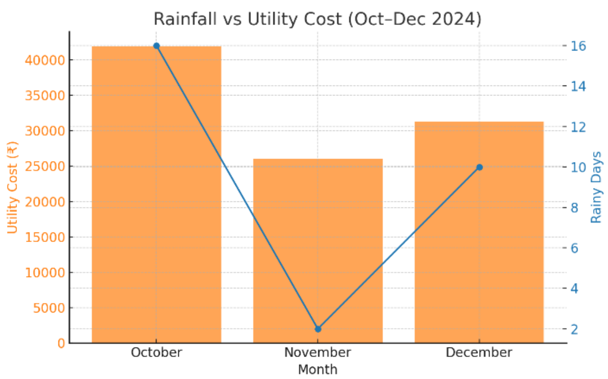
Graph 8 : Student Hostel Cluster Segmentation (K-Means)

- Similarly, the K-Means clustering applied to faculty block data revealed clear distinctions in service demand across the different residential blocks. Blocks such as H Block and P.H.D Quarters emerged as high-demand zones, both in terms of the number of transactions and total revenue generated. H Block recorded the highest number of orders among faculty areas (81 orders), with a corresponding revenue of ₹14,290, while P.H.D Quarters followed with 40 orders and ₹8,520 in revenue. These metrics indicate strong and consistent usage patterns from faculty residing in these areas, suggesting that they are both aware of and reliant on the laundry services provided. A second tier of medium-demand areas includes D Block (21 orders, ₹6,513), which also contributes reasonably to monthly income. These zones, while not as active as the top-tier blocks, show potential for further engagement through targeted outreach, such as reminder messaging or loyalty incentives. On the other end of the spectrum, blocks such as J Block, OUTSIDE customers, CP, F Block, and C Block displayed minimal engagement. These areas had extremely low transaction volumes, ranging from just 1 to 7 orders over the entire three-month period, with revenues below ₹900 in most cases. The reasons could range from geographic inaccessibility to lack of awareness or simply alternative arrangements by the residents. These insights present an opportunity for the business to investigate specific challenges faced in these blocks, be it physical delivery limitations, lack of promotional reach, or service timing mismatches—and address them accordingly to unlock untapped revenue potential.



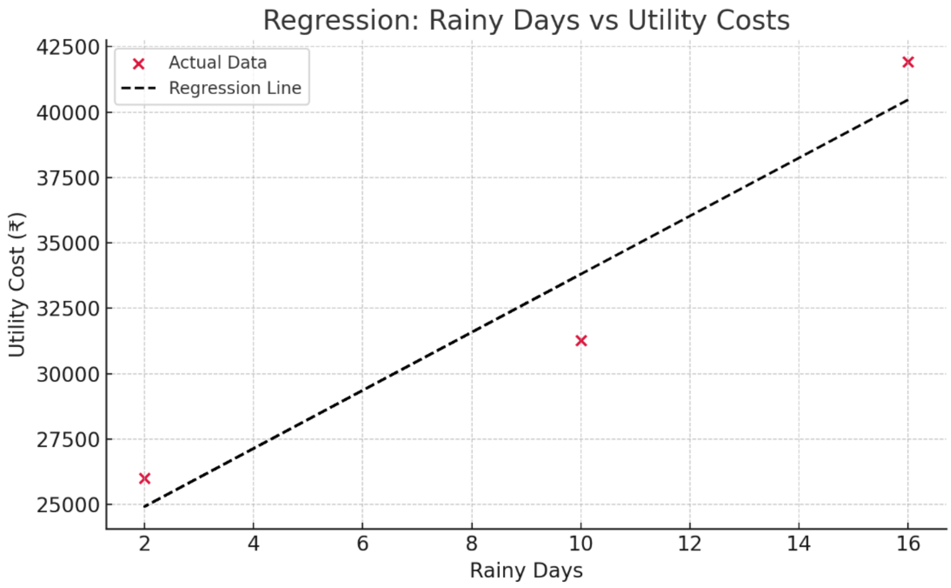
Graph 9 : Cluster Segmentation (K-Means)

- The dual-axis chart compares the number of rainy days with monthly utility costs, highlighting how weather conditions influence operational expenses. In October, there were 16 rainy days, and utility-related costs (electricity, water, and detergents) spiked to ₹41,924, the highest among the three months. This increase is attributed to extended use of dryers, repeated washes due to dampness, and overall inefficiencies caused by high moisture levels. In November, with only 2 rainy days, utility costs dropped significantly to ₹26,003, representing a more efficient operational environment under dry weather conditions. December, with 10 rainy days, saw moderately elevated costs at ₹31,268, reaffirming the trend. This visual clearly indicates a strong correlation between precipitation and rising utility expenses. The pattern suggests a need for weather-adaptive infrastructure such as improved drying facilities or preemptive planning for rainy periods to reduce cost overheads and maintain consistent service quality.



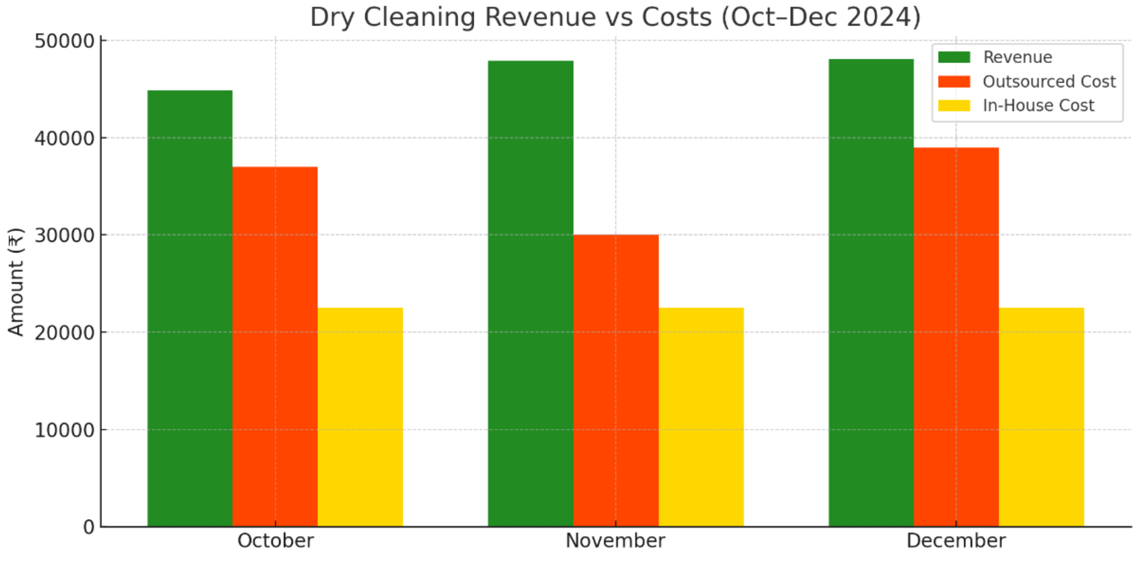
Graph 10: Rainfall vs Utility cost (Oct-Dec 2024)

- The scatter plot with an overlaid regression line illustrates the relationship between the number of rainy days and the utility-related operational costs incurred during October to December 2024. A simple linear regression model was applied using Python's statsmodels library to quantify this relationship. The results showed a strong positive correlation, with an R-squared value of 0.926, meaning that approximately 92.6% of the variance in utility costs can be explained by the number of rainy days. The regression output revealed a slope coefficient (β_1) of ₹1,111.32, which signifies that for every additional rainy day in a month, utility costs are expected to increase by ₹1,111.32. The intercept (β_0) was ₹23,975.13, representing the baseline utility cost in a month with zero rainfall. While the p-value for the slope was 0.175, which is above the typical 0.05 threshold for statistical significance, this can be attributed to the small sample size (n=3 months). Despite this, the regression trend aligns with operational insights and cost data observed across the months. This model reinforces the operational impact of weather on laundry service efficiency. Increased precipitation leads to higher electricity use for drying, greater detergent consumption, and occasional rewashing of damp clothes—all contributes to elevated monthly costs. These insights support the need for infrastructure investment to mitigate weather-related cost fluctuations.



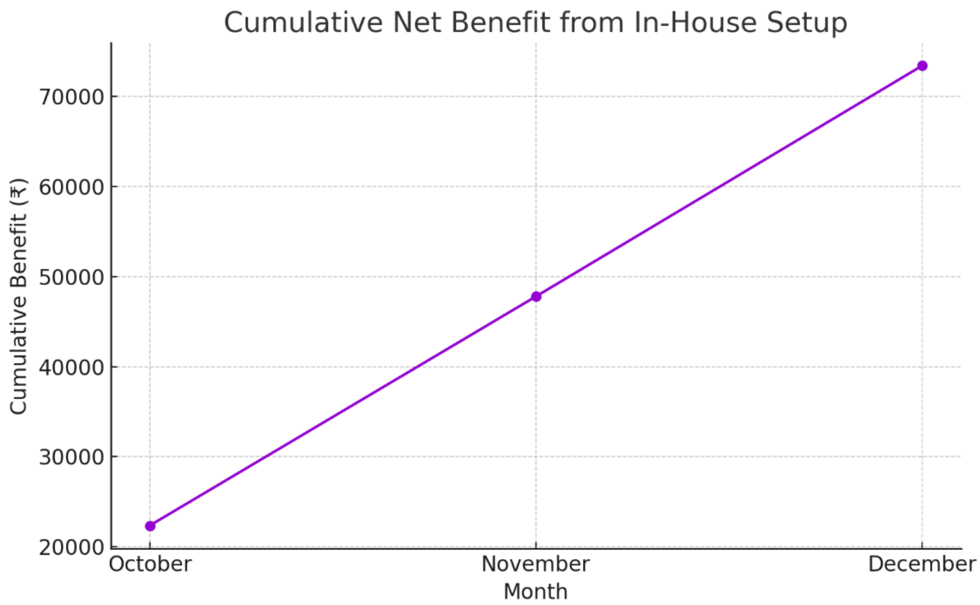
Graph 11: Regression Line Plot for Rainfall vs Utility cost

- The grouped bar chart provides a clear comparison between the monthly revenue earned from dry cleaning services and the associated costs under two models: the current outsourced arrangement and the proposed in-house setup. Across October, November, and December 2024, the in-house operational cost remains stable at ₹22,500 per month, based on estimates provided by the proprietor, whereas outsourced costs vary significantly—₹37,000 in October, ₹30,000 in November, and ₹39,000 in December. Dry cleaning revenue remains relatively stable, with ₹44,860 in October, ₹47,932 in November, and ₹48,109 in December, consistently surpassing both cost structures. However, the difference between revenue and cost is notably greater in the in-house model, indicating a much healthier profit margin. For instance, in October, the profit under outsourcing would be just ₹7,860, whereas switching to in-house would yield ₹22,360—a net benefit of ₹14,500. Similar advantages appear in November and December, with respective savings of ₹7,500 and ₹16,500. These consistent margins make a strong case for transitioning to an in-house setup, not only to enhance profitability but also to reduce reliance on external vendors. This visualization effectively communicates the financial efficiency and predictability of operating dry-cleaning services internally and supports the recommendation for an immediate shift in the business model.



Graph 12: Dry Cleaning Revenue vs Costs (Oct-Dec 2024)

- The line chart visualizes the cumulative monthly savings that would be realized if Sri Sai Laundry Services were to transition from outsourced to in-house dry-cleaning operations. Over the course of three months, the projected net savings—calculated as the difference between monthly revenue and the fixed in-house operational cost—were ₹22,360 in October, ₹25,432 in November, and ₹25,609 in December. These monthly savings are not only individually significant but also show a steady upward trend, culminating in a total cumulative profit of ₹73,401 by the end of December. This progressive growth indicates that the financial advantages of the in-house model are both consistent and compound over time. Importantly, the chart demonstrates the long-term value of adopting a fixed-cost model in a service environment with stable income. By maintaining a constant operational expense of ₹22,500 per month, the business can lock in predictable costs while capturing the full revenue from its dry-cleaning services. This reduces dependency on external vendors and minimizes cost volatility. Overall, visualization reinforces the strategic and financial viability of internalizing dry-cleaning services, showcasing the clear profit trajectory achievable with this operational shift.



Graph 13: Cumulative Net Benefit from In-House setup

4. Interpretation of Results and Recommendation

The results derived from the analysis across all three core problem statements offer strong and actionable insights into the operational health and financial potential of Sri Sai Laundry Services. The problems identified in the proposal—space constraints, weather-related inefficiencies, and excessive dry-cleaning outsourcing costs—have been carefully interpreted based on clustering, regression, and cost-benefit methodologies.

4.1) Interpretation of Results

The K-Means clustering analysis for space optimization provided a clear and data-driven perspective on the distribution of demand across the campus. It revealed that a significant majority of both income and transaction volume was concentrated in a small number of student hostels—particularly VM (Valmiki Bhavan) and VK (Vishwakarma Bhavan)—along with high-performing faculty blocks such as H Block and P.H.D Quarters. Despite their disproportionate contribution to overall business activity, these zones were being handled with the same operational procedures as lower-demand areas. This uniform approach has resulted in inefficiencies, particularly in logistics and turnaround time. By restructuring collection routes, allocating dedicated storage or sorting space, and prioritizing high-frequency areas with express service counters, the business could significantly enhance daily throughput and customer satisfaction without requiring any major infrastructure expansion.

The regression analysis focusing on the relationship between rainfall and utility costs further supported a critical operational insight—that weather conditions directly influence cost behavior. October, which had the highest number of rainy days (16), also incurred the highest utility expenses (₹41,924). In contrast, November, with only 2 rainy days—saw costs drop to ₹26,003, and December, with 10 rainy days, incurred ₹31,268 in utility costs. Using Python’s statsmodels library, a linear regression model was developed, which yielded an R^2 value of 0.926, indicating that over 92% of the variation in utility expenses can be explained by rainfall patterns. The regression slope of ₹1,111.32 per rainy day quantifies the financial burden of wet weather on laundry operations. While the p-value of 0.175 falls slightly above conventional thresholds of significance, the strong trend and operational experience confirm its practical relevance. These findings strongly tells that investment in weather-resilient infrastructure, such as advanced dryers, semi-covered drying zones, or moisture-control procedures, particularly in the pre-monsoon period.

The Cost-Benefit Analysis (CBA) for transitioning dry-cleaning operations from outsourced to in-house delivery provided the most compelling case for financial reform. The current outsourcing model, with variable monthly expenses of ₹37,000 in October, ₹30,000 in November, and ₹39,000 in December, is both unpredictable and high in cost. In contrast, the proposed in-house model fixes the monthly cost at ₹22,500, offering financial stability and scalability. With consistent dry-cleaning income ranging from ₹44,860 to ₹48,109 per month, the business would realize net monthly savings of ₹22,360 in October, ₹25,432 in November, and ₹25,609 in December. When these monthly gains are evaluated using Net Present Value (NPV) methodology at a 10% annual discount rate, the total benefit across the three months adds up to ₹72,216.55. This not only establishes the immediate financial viability of the in-house setup but also signals strong long-term profitability and resilience to market fluctuations—a strategic upgrade that reduces dependency on external vendors and improves quality control.

4.2) Recommendations

1. **Optimize Storage and Workflow Based on Demand Segments**

   The K-Means clustering analysis clearly indicated that VM (Valmiki Bhavan) and VK (Vishwakarma Bhavan) among student hostels, along with H Block and P.H.D Quarters among faculty residences, are the most active and high-revenue clusters. These few zones alone contribute close to 40% of the overall income and order volume, yet they are currently being treated uniformly with all other locations. To address this imbalance and increase efficiency, it is recommended to implement demand-based operational zoning. This includes allocating dedicated collection and delivery routes, using separate bins or labeled sacks for sorting, and possibly assigning time-specific pickups. These adjustments can significantly reduce the turnaround time, minimize sorting errors, and increase daily processing capacity—all without requiring additional physical space or staffing. This recommendation can be implemented immediately using the existing workforce and infrastructure.

2. **Invest in Weather-Adaptive Infrastructure**

   The regression analysis between rainy days and utility costs provided strong evidence of a direct correlation: months with more rain saw a noticeable rise in electricity, water, and detergent expenses. For example, October, with 16 rainy days, incurred utility costs of ₹41,924 compared to ₹26,003 in November with only 2 rainy days. To mitigate these effects, the business should invest in weather-resilient infrastructure, such as commercial-grade electric dryers, semi-covered drying sheds, or improved ventilation systems. These upgrades will reduce the need for rewashing due to poor drying conditions, thus lowering electricity and detergent use. The goal should be to reduce weather-related utility costs by at least 25% within six months. To maximize efficiency and returns, these investments should be planned and implemented before the monsoon season (June to September), ensuring the business is fully equipped to handle peak weather-related stress.

3. Transition to In-House Dry-Cleaning Facility

With a stable dry-cleaning income ranging between ₹44,000 and ₹48,000 per month, and an in-house setup costing only ₹22,500 monthly (as opposed to ₹30,000–₹39,000 in outsourced costs), the financial case for bringing dry-cleaning operations in-house is clear and compelling. The Cost-Benefit Analysis projected monthly savings of ₹22,360–₹25,609 and a three-month Net Present Value (NPV) of ₹72,216.55 at a 10% discount rate. Beyond cost savings, transitioning in-house allows for greater control over service quality, scheduling, and turnaround time, while also reducing the dependency on external vendors. A basic in-house setup can be procured quickly, and the investment can be fully recovered within 3–4 months based on projected cash flows.

4.3) Implementation Impact

If these recommendations are implemented, Sri Sai Laundry Services can expect improvements in both operational efficiency and financial performance. Specifically, the business stands to gain a 20–25% increase in daily throughput and workflow efficiency, particularly by prioritizing high-demand clusters and optimizing collection and delivery logistics. Investments in weather-adaptive infrastructure, such as commercial dryers and semi-covered drying spaces, are projected to yield up to a 30% reduction in utility expenses during peak monsoon months, thereby cushioning the business against seasonal fluctuations. Most notably, the shift from outsourced to in-house dry-cleaning services is projected to generate a net profit of over ₹75,000 within just three months, based on consistent monthly savings and income patterns. These operational gains come without the need for significant physical expansion or additional manpower. Instead, they are the direct result of data-informed decision-making and targeted resource allocation.