SALES AND OPERATIONS ANALYSIS

1. Project Overview

This project analyzes and optimizes the sales pipeline, focusing on lead management, conversion efficiency, customer satisfaction, and operational bottlenecks. The goal is to enable data-driven decisions for increasing conversion rates, reducing turnaround times, and improving customer experiences across multiple stores.

2. Dataset Summary

- Rows: 1,000
- Columns: 14

Key Features:

- Lead journey details (Lead ID, Store Name, Lead Type, Lead/Pre-Booking/Booking/Delivery Dates)
- Cancellation info (Status, Reason)
- Customer service (Service Follow-up Date, Customer Rating)
- Operational metrics (TAT Pre-Booking Days, TAT Booking Days, TAT Delivery Days)
- Segmentation available: by Store, Lead Type, Date

3. Dataset Cleaning

1. Handling Missing Values

- Checked the number of nulls in each column.
- Filled missing values in Cancellation Reason with "Not Cancelled" for non-cancelled leads.
- Left missing dates and ratings as-is so that conversion rates, TAT, and satisfaction calculations use only available data.

2. Standardizing Date Formats

- Converted all columns containing dates (Lead Date, Pre-Booking Date, Booking Date, Delivery Date, Service Follow-up Date) to datetime format using pd.to_datetime(), ensuring correct ordering and calculations.

3. Standardizing Categorical Values

- Cleaned up Lead Type and similar columns to have consistent formatting by applying .str.title().str.strip() (e.g., ensures "hot", "Hot ", and "HOT" all become "Hot").

4. Cleaning Numeric Data
- Converted TAT Pre-Booking Days, TAT Booking Days, TAT Delivery Days, and Customer Rating to numeric type (floats).

5. Removing Duplicates
- Dropped rows with duplicate Lead ID to guarantee each lead is represented only once.

4. Exploratory Data Analysis using Python

1. Basic Overview
- Checked the shape and columns of the dataset (1,000 rows, 14 columns after cleaning).
- Displayed the first and last few rows to visually inspect data variety and structure.

2. Missing Values
- Counted missing values in each column.
- Noticed most missingness in stage dates, Customer Rating, and Service Follow-up Date.
- Found no duplicate Lead IDs.

3. Value Counts & Distributions

Examined value counts for:
- Lead Type (Hot, Warm, Cold):Warm: 509, Hot: 303, Cold: 188
- Cancellation Status:Not Cancelled: 729, Cancelled: 271
- Store Name: Four stores-Bangalore, Chennai, Delhi, Mumbai MBC distributed nearly evenly.

4. Descriptive Statistics
- Calculated mean, min, max, median, and spread for numeric columns:
- Customer Rating:Range: 0 to 10; Mean: ~4.85
- TAT (Turnaround Times) in Days:Pre-Booking, Booking, Delivery stages analyzed for average and range.

5. Calculations & Analysis

1. Conversion Rates

- Calculated what percent of leads reached each stage: Pre-Booking, Booking, Delivery.

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Conversion Rates (Overall):
Lead → Pre-Booking: 81.20%
Pre-Booking → Booking: 100.00%
Booking → Delivery: 100.00%
```

2. Store-wise Analysis

- Broke down lead counts, conversion rates, and operational metrics store-by-store.

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Conversion Rates by Store (%):
       Store Name  Lead → Pre-Booking (%)  Pre-Booking → Booking (%)  \
0  Bangalore MBC               80.608365                      100.0
1    Chennai MBC               81.603774                      100.0
2      Delhi MBC               80.608365                      100.0
3     Mumbai MBC               82.061069                      100.0

   Booking → Delivery (%)
0                   100.0
1                   100.0
2                   100.0
3                   100.0
```

- Computed average Turnaround Time (TAT) for Pre-Booking, Booking, and Delivery stages per store.

```
Average TAT for each stage per store:
               TAT Pre-Booking (Days)  TAT Booking (Days)  TAT Delivery (Days)
Store Name
Bangalore MBC                3.117925            3.033019             4.514151
Chennai MBC                  3.121387            3.202312             4.387283
Delhi MBC                    3.028302            3.018868             4.283019
Mumbai MBC                   2.976744            3.046512             4.627907
```

- Compared which stores are fastest and which have slower processes, helping identify best practices and bottlenecks.

3. Cancellation Analysis

- Grouped cancellations by store and by cancellation reason.
- Identified top reasons for lost leads:

```
Cancellation patterns by store and reason:
        Store Name Cancellation Reason  Count
0   Bangalore MBC        Changed Mind     13
1   Bangalore MBC     Financing Issue     14
2   Bangalore MBC   Model Unavailable     13
3   Bangalore MBC               Other     22
4   Bangalore MBC               Price     10
5     Chennai MBC        Changed Mind     15
6     Chennai MBC     Financing Issue     10
7     Chennai MBC   Model Unavailable      8
8     Chennai MBC               Other      8
9     Chennai MBC               Price     18
10      Delhi MBC        Changed Mind     14
11      Delhi MBC     Financing Issue     21
12      Delhi MBC   Model Unavailable     13
13      Delhi MBC               Other     13
14      Delhi MBC               Price     16
15     Mumbai MBC        Changed Mind      9
16     Mumbai MBC     Financing Issue     14
17     Mumbai MBC   Model Unavailable      9
18     Mumbai MBC               Other     14
19     Mumbai MBC               Price     17
```

- Compared patterns across stores to see if certain stores or customer profiles are driving cancellations.

4. Lead Type Segmentation

- Showed the distribution and share of Hot, Warm, Cold leads—both overall and per store.

```
Overall breakdown of Hot/Warm/Cold leads:
Lead Type
Warm    509
Hot     303
Cold    188
Name: count, dtype: int64

As percentages:
Lead Type
Warm    50.9
Hot     30.3
Cold    18.8
Name: proportion, dtype: float64

Breakdown by store (counts):
Lead Type      Cold  Hot  Warm
Store Name
Bangalore MBC    51   80   132
Chennai MBC      39   70   103
Delhi MBC        51   70   142
Mumbai MBC       47   83   132

Breakdown by store (percentages):
Lead Type           Cold        Hot       Warm
Store Name
Bangalore MBC  19.391635  30.418251  50.190114
Chennai MBC    18.396226  33.018868  48.584906
Delhi MBC      19.391635  26.615970  53.992395
Mumbai MBC     17.938931  31.679389  50.381679
```

- Helps target follow-up efforts and monitor quality of incoming leads.

5. Net Promoter Score (NPS)

- Defined Promoters (Customer Rating 9–10) and Detractors (0–6).
- Calculated NPS for each store using: NPS= %Promoters−%Detractors

```
              Promoters  Detractors  Total Ratings  Promoter %  Detractor %  \
Store Name
Bangalore MBC       23.0       134.0          191.0   12.041885    70.157068
Chennai MBC         28.0        99.0          153.0   18.300654    64.705882
Delhi MBC           30.0       123.0          186.0   16.129032    66.129032
Mumbai MBC          23.0       138.0          199.0   11.557789    69.346734

                  NPS
Store Name
Bangalore MBC -58.115183
Chennai MBC   -46.405229
Delhi MBC     -50.000000
Mumbai MBC    -57.788945
```

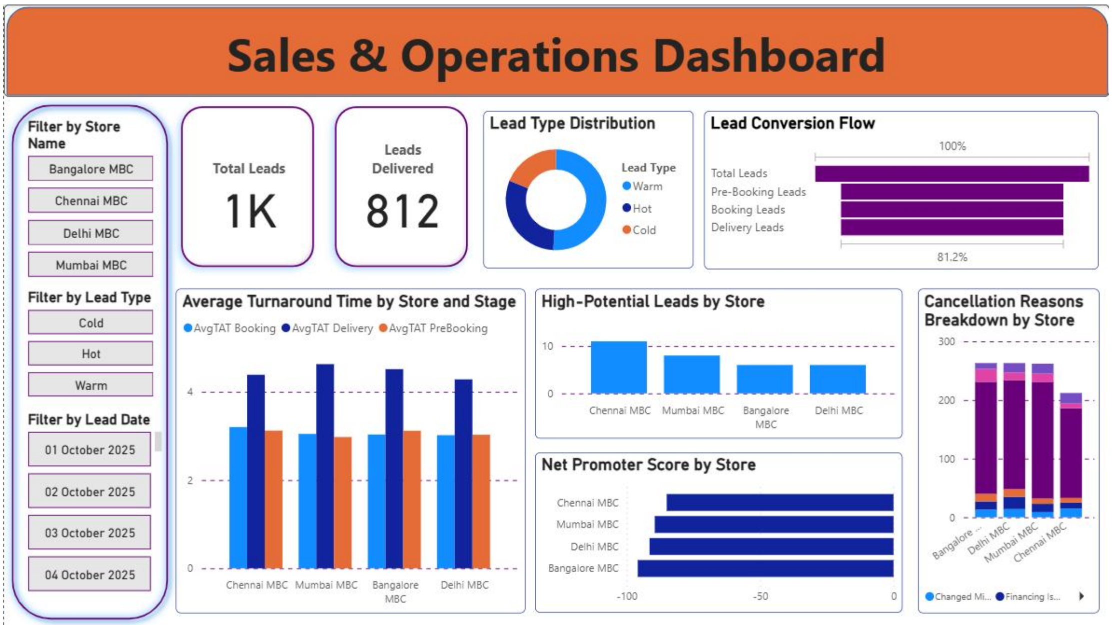
- All NPS scores are negative, showing more dissatisfied than satisfied customers overall.

6. High-Potential Lead Extraction

- Filtered for “high-potential" leads:Hot,Not Cancelled,High Customer Rating (≥9),Fast Delivery (≤5 days)
- Flagged these leads for priority follow-up.

6.Dashboard in PowerBI

Finally,built an interactive dashboard in PowerBI to present insights visually



7. Business Recommendations

1. Reduce Cancellations:
- Target the top cancellation reasons (“Changed Mind”, “Price”, “Financing Issue”, “Model Unavailable”).
- Offer stronger follow-up for undecided customers.
- Provide transparent financing options and clear product availability to minimize lost leads.

2. Improve Negative NPS Stores:
- Stores with the lowest customer satisfaction (negative NPS) should review customer service, post-sale engagement, and delivery experience.
- Conduct detailed feedback sessions with customers.

3. Accelerate Delivery Times:
- Fast TAT stores outperform slow ones.
- Identify bottlenecks in longest delivery stages.
- Implement best practices from quickest locations in slower stores.

4. Focus on High-Potential Leads:
- Leads flagged as “Hot”, not cancelled, with high ratings and fast delivery should be prioritized.
- Design targeted outreach campaigns to close these leads rapidly.

8. Conclusions

This analysis of sales and operations data highlights both strengths and areas needing improvement within the organization’s lead management pipeline. The dashboard and underlying analytics bring clear visibility to store-wise performance, customer satisfaction, cancellation issues, and high-potential sales opportunities.

By tracking pipeline conversions, operational speed, lead quality, and customer feedback, the business is now positioned to:
- Reduce cancellations by addressing targeted causes,
- Increase conversions by focusing on high-potential leads,
- Enhance customer experience in stores with low NPS,
- Shorten turnaround times by learning from top-performing locations.