“Optimizing Operational Efficiency and Inventory Management for Tim Hortons”

Authors: Nilesh Kokulwar, Hashwanth Adapa, Jaspreet Singh Saini, Priyankaben Sukhdevbhai Kaloliya, Sree Keerthi Kandula, Kaival Kiran Patel

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Summary/Abstract

This project focuses on optimizing operational efficiency and inventory management for a Tim Hortons store by analyzing waste, sales, and labor-related data. The study aims to identify patterns in waste and variance metrics to propose actionable strategies for improving resource utilization.

Using real-world data from the store, such as waste variance reports, sales per labor hour, and cost per labor hour, we employed exploratory data analysis and visualization techniques to uncover inefficiencies.

This report presents our methodology, key insights, and recommends enhancing the store's operational processes while minimizing waste.

Introduction

Efficient inventory and labor management are critical for businesses like **Tim Hortons**, where profitability and sustainability depend heavily on minimizing waste and optimizing workforce utilization.

This project aims to address the following research objectives:

- Analyze the underlying causes of waste across different product categories.
- Examine the relationship between sales and labor costs to determine efficiency.
- Propose strategies to improve overall operational efficiency.

The motivation stems from the need for better inventory control and cost reduction in a competitive quick-service restaurant industry.

Methodology

Data Sources:

- Waste Variance Report: Includes data such as product descriptions, units, waste costs, and variance percentages.
- Sales Per Labor Hour (SPLH) and Cost Per Labor Hour (CPLH): Data related to workforce utilization and cost efficiency.
- Account Summary Reports: Contains sales and labor cost details.

Steps in Analysis:

1. Data Cleaning: Addressed missing values, corrected inconsistencies, and prepared datasets for merging.
2. Data Integration: Combined SPLH and Account Summary files on the 'Date' field for comprehensive analysis.
3. Exploratory Data Analysis (EDA): Analyzed features such as variance percentages, waste costs, and labor efficiencies.
4. Visualization: Created informative dashboards in Tableau to showcase trends and key insights.

Research Conducted:

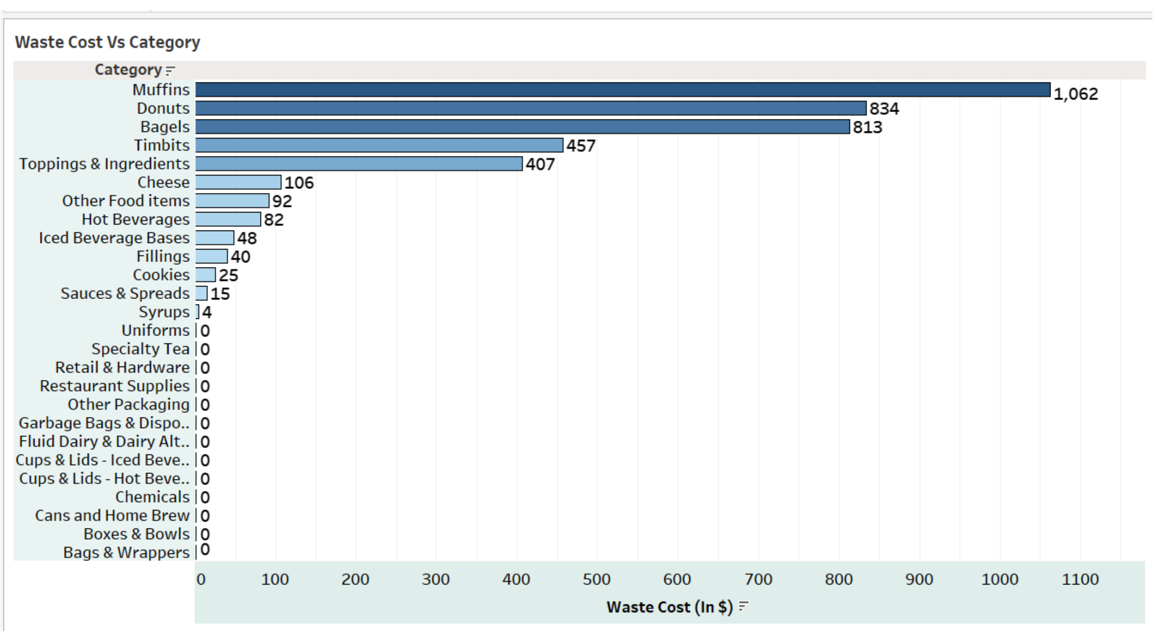
Documented research on inventory management and operational efficiency, particularly in quick-service restaurants, to frame the study contextually.

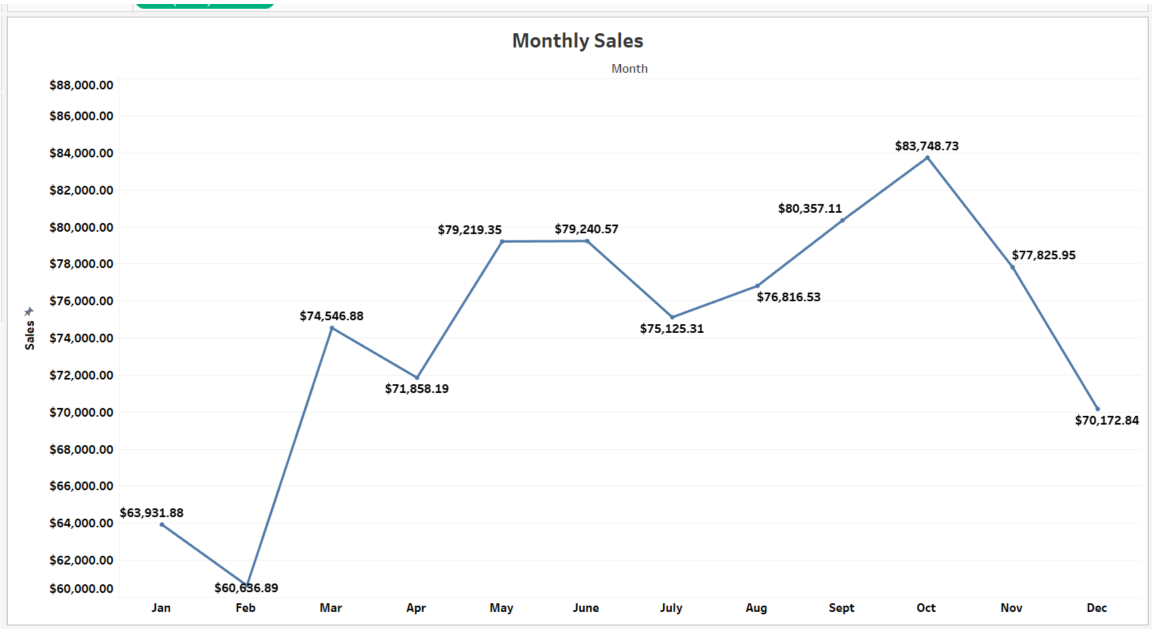
Data Analysis

Key Findings:

1. **Waste Analysis**:
- High waste costs in specific categories such as baked goods and beverages.
- A consistent pattern of variance between actual and theoretical inventory counts.
2. **Labor Efficiency**:
- CPLH often exceeded SPLH, indicating inefficiencies in workforce utilization during low-sales periods.
3. **Trends Identified**:
- Seasonal spikes in waste during holidays and high customer traffic periods.
- Variance percentage trends showing a strong correlation with inventory mismanagement.

Visualizations:




Monthly Sales
Month
Sales
$88,000.00
$86,000.00
$84,000.00
$82,000.00
$80,000.00
$78,000.00
$76,000.00
$74,000.00
$72,000.00
$70,000.00
$68,000.00
$66,000.00
$64,000.00
$62,000.00
$60,000.00
$63,931.88
$60,636.89
$74,546.88
$71,858.19
$79,219.35
$79,240.57
$75,125.31
$76,816.53
$80,357.11
$83,748.73
$77,825.95
$70,172.84
Jan
Feb
Mar
Apr
May
June
July
Aug
Sept
Oct
Nov
Dec


Net Sales By Day
Day
Net Sales
$150,000
$140,000
$130,000
$120,000
$110,000
$100,000
$90,000
$80,000
$70,000
$60,000
$50,000
$40,000
$30,000
$20,000
$10,000
$0
$81,368
$127,958
$138,567
$141,223
$146,868
$146,117
$110,173
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Day
Sun
Mon
Tue
Wed
Thu
Fri
Sat

Interpretations and Limitations:

Findings Interpretation:

- High variance percentages suggest inadequate forecasting and inventory control measures.
- The mismatch between labor costs and sales indicates scheduling inefficiencies.
- Some products have consistently high waste rates, requiring reevaluation of stocking practices.

Limitations:

- Data granularity is restricted to store-level reports, limiting insights at the itemized or regional level.
- External factors like supplier delays or sudden demand spikes were not accounted for.
- The analysis focuses on historical data, making predictions subject to untested assumptions.

Recommendations and Future Work

Actionable Recommendations:

1. Implement real-time inventory tracking to reduce manual errors and improve forecasting.
2. Use predictive models to anticipate high-demand periods and adjust staffing schedules accordingly.
3. Revisit supplier contracts to ensure timely and accurate deliveries.
4. Introduce employee training programs focused on reducing waste and improving efficiency.

Future Work:

- Develop machine learning models for demand forecasting and waste reduction.
- Conduct similar analyses across multiple Tim Hortons stores for a broader perspective.
- Incorporate external data (e.g., weather, holidays) to refine predictive analytics.

Appendix

Python EDA Script:

Importing Libraries and Loading the Dataset:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

# Loading Dataset
df = pd.read_excel('Complete_Variance_Report_Waste_2022.xlsx')
df.head()
df.info()
df.isnull().sum()
df.describe()
```

Univariate Analysis:

```
# Plotting distributions of numerical columns

sns.set(style="whitegrid")

numerical_columns = ['Actual_Cost', 'Theoretical_Cost', 'Waste_Cost',
'Variance_Percentage']

fig, axes = plt.subplots(2, 2, figsize=(12, 10))

for i, col in enumerate(numerical_columns):

    ax = axes[i // 2, i % 2]

    sns.histplot(df[col], kde=True, ax=ax)

    ax.set_title(f"Distribution of {col}")

plt.tight_layout()

plt.show()


# Checking for outliers using boxplots

fig, ax = plt.subplots(2, 2, figsize=(12, 8))

ax = ax.flatten()

for i, col in enumerate(numerical_columns):

    sns.boxplot(x=col, data=df, ax=ax[i])

    ax[i].set_title(f"Boxplot of {col}")

plt.tight_layout()

plt.show()
```

Outlier Detection and Capping:

```
# Outlier detection using IQR

def detect_outliers_iqr(column):
```

```
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return lower_bound, upper_bound

columns_to_check = ['Actual_Cost', 'Theoretical_Cost', 'Waste_Cost', 'Variance_Percentage']
for col in columns_to_check:
    lb, ub = detect_outliers_iqr(df[col])
    print(f"{col}: Lower Bound = {lb}, Upper Bound = {ub}")

# Capping outliers
for col in columns_to_check:
    lb, ub = detect_outliers_iqr(df[col])
    df[col] = np.where(df[col] > ub, ub, np.where(df[col] < lb, lb, df[col]))
```

Bivariate Analysis:

```
# Scatterplot: Actual Cost vs Theoretical Cost
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='Theoretical_Cost', y='Actual_Cost')
plt.title("Actual Cost vs Theoretical Cost")
plt.xlabel("Theoretical Cost")
plt.ylabel("Actual Cost")
plt.show()
```

```
# Barplot: Variance % by Category

plt.figure(figsize=(12, 6))

sns.barplot(data=df, x='Category', y='Variance_Percentage', ci=None,
palette="magma")

plt.title("Average Variance % by Category")

plt.xticks(rotation=45)

plt.xlabel("Category")

plt.ylabel("Variance_Percentage")

plt.show()
```

Advanced EDA:

```
# Grouping by 'Category' and calculating the sum for each cost column

top_categories = df.groupby('Category')[['Waste_Cost', 'Actual_Cost',
'Theoretical_Cost']].sum()


# Sorting each column in descending order and selecting the top 10

top_waste_cost = top_categories.sort_values(by='Waste_Cost',
ascending=False).head(10)

top_actual_cost = top_categories.sort_values(by='Actual_Cost',
ascending=False).head(10)

top_theoretical_cost = top_categories.sort_values(by='Theoretical_Cost',
ascending=False).head(10)


# Plotting Top 10 Categories for Each Cost Type

def plot_top_categories(data, column, title, color):

   plt.figure(figsize=(10, 6))

   data[column].plot(kind='bar', color=color, alpha=0.7)

   plt.title(title, fontsize=16)

   plt.xlabel('Category', fontsize=14)
```

```
    plt.ylabel(column, fontsize=14)

    plt.xticks(rotation=45, ha='right')

    plt.grid(axis='y', linestyle='--', alpha=0.7)

    plt.tight_layout()

    plt.show()


plot_top_categories(top_waste_cost, 'Waste_Cost', 'Top 10 Categories by Waste Cost', 'red')

plot_top_categories(top_actual_cost, 'Actual_Cost', 'Top 10 Categories by Actual Cost', 'blue')

plot_top_categories(top_theoretical_cost, 'Theoretical_Cost', 'Top 10 Categories by Theoretical Cost', 'green')
```

References

- Internal Tim Hortons store data provided with permission.
- Research articles on inventory and labor management.
- Documentation for libraries and tools used (e.g., Python, Tableau).