# DOWNTIME SHIELD

MANUFACTRING DOWNTIME ANALYSIS





# OUR PROJECT TEAM



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- 1-Introduction
- 2-WORKFLOW
- 3-Objective
- 4-Methodology

- 5-Insights
- 6- Recommended Solutions



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# 1-INTRODUCTION

- •Downtime impacts productivity and increases costs.
- •This project analyzes real factory data to track and classify downtime events.
- •Uses data analysis to identify root causes and inefficiencies.
- •Aims to support better maintenance and operational decisions.
- •Focused on boosting efficiency and reducing unplanned stops.

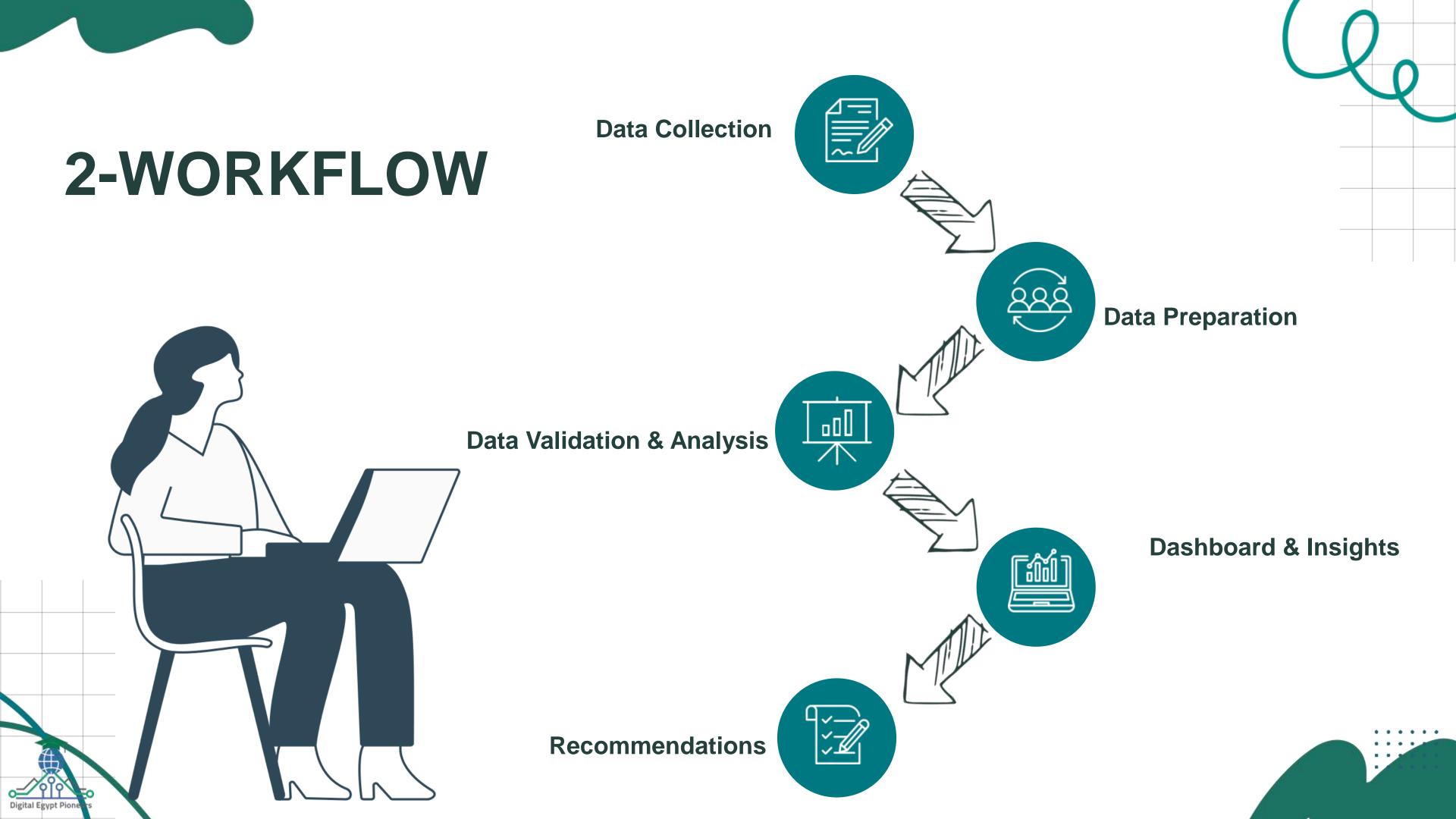




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### 3-OBJECTIVE

- •Track and classify downtime events accurately.
- •Identify root causes and impact on productivity.
- •Analyze trends and patterns in downtime data.
- •Provide insights to reduce unplanned stoppages.
- •Support predictive maintenance and efficiency improvements.





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# 4-Methodology

- □ Dataset
  - about dataset
  - dataset description
- **□** Data preprocessing
  - Data preparation
  - Data cleaning & preprocessing
  - Data modeling
- **□** Data Visualization
  - Key Insights from Downtime Patterns





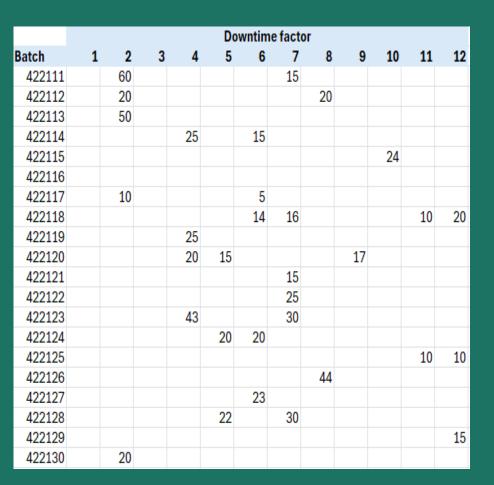
### ☐ Dataset

#### about dataset

- •Downtime sheet: Logs errors per batch 40 rows × 12 columns
- •Factors sheet: Describes and categorizes error types
- •Manufacturing Data sheet: Includes operator, batch date, start/end time 40 rows × 6 columns
- •Product sheet: Lists product information linked to each batch

#### dataset description

- •Downtime Contains information on various types of errors (factors) that caused downtime, recorded per batch.
- •Factors (Errors) Lists and categorizes the different types of errors that can occur in the production process.
- •Manufacturing Data Includes detailed batch-level data such as:
- Operator responsible for the batch
- Date of the batch
- •Start and end times for each batch
- •**Product** Provides information related to the products being manufactured.



Factor	Description	Operator Error
1	Emergency stop	No
2	Batch change	Yes
3	Labeling error	No
4	Inventory shortage	No
5	Product spill	Yes
6	Machine adjustment	Yes
7	Machine failure	No
8	Batch coding error	Yes
9	Conveyor belt jam	No
10	Calibration error	Yes
11	Label switch	Yes
12	Other	No

Date	Product	Batch	Operator	Start Time	End Time
2024-08-29	OR-600	422111	Mac	11:50:00	14:05:00
2024-08-29	LE-600	422112	Mac	14:05:00	15:45:00
2024-08-29	LE-600	422113	Mac	15:45:00	17:35:00
2024-08-29	LE-600	422114	Мас	17:35:00	19:15:00
2024-08-29	LE-600	422115	Charlie	19:15:00	20:39:00
2024-08-29	LE-600	422116	Charlie	20:39:00	21:39:00
2024-08-29	LE-600	422117	Charlie	21:39:00	22:54:00
2024-08-30	CO-600	422118	Dee	04:05:00	06:05:00
2024-08-30	CO-600	422119	Dee	06:05:00	07:30:00
2024-08-30	CO-600	422120	Dee	07:30:00	09:22:00
2024-08-30	CO-600	422121	Dennis	09:22:00	10:37:00
2024-08-30	CO-600	422122	Dennis	10:37:00	12:02:00
2024-08-30	CO-600	422123	Dennis	12:02:00	14:15:00
2024-08-30	CO-600	422124	Dennis	14:15:00	15:55:00
2024-08-30	CO-600	422125	Charlie	15:55:00	17:15:00

Product	Flavor	Size	Min batch time
OR-600	Orange	600 ml	60
LE-600	Lemon lime	600 ml	60
CO-600	Cola	600 ml	60
DC-600	Diet Cola	600 ml	60
RB-600	Root Berry	600 ml	60
CO-2L	Cola	2 L	98



# ☐ Data preprocessing

#### Data preparation

The original dataset had only 40 rows, which limited analysis. To extract deeper insights, we expanded it to 10,000 rows by following the same patterns. This synthetic data simulates a larger manufacturing setup for better analysis of shifts, downtime, and operator performance

#### Main Goals of the Code:

- Expand the data to 10,000 rows using random sampling with replacement.
- Convert Start and End Time columns to datetime using a fixed reference date.
- Define 3 shifts: Morning, Afternoon, Night
- Randomly assign shifts and adjust batch start times accordingly.
- Set realistic batch durations based on product type:
- Make sure End Time stays within shift limits
- Calculate batch duration in minutes.



```
import pandas as pd
import numpy as np
file_path = (r"C:\Users\Haridy\Downloads\Manufacturing_data.xlsx")
df_original = pd.read_excel(file_path)
# Expand the dataset to 10,000 rows
target_rows = 10000
expanded_df = pd.DataFrame()
# Randomly sample from original data with replacement
while len(expanded_df) < target_rows:</pre>
   temp_df = df_original.sample(n=min(1000, target_rows - len(expanded_df)), replace=True).copy()
   expanded_df = pd.concat([expanded_df, temp_df], ignore_index=True)
# Use fixed reference date
default_date = "2024-01-01"
# Convert start/end times to datetime using fixed date
expanded_df['Start Time'] = pd.to_datetime(default_date + " " + expanded_df['Start Time'].astype(str))
expanded_df['End Time'] = pd.to_datetime(default_date + " " + expanded_df['End Time'].astype(str))
# Define shift time ranges
morning_shift_start, morning_shift_end = 6, 14
afternoon_shift_start, afternoon_shift_end = 14, 22
night_shift_start, night_shift_end = 22, 6 # Night shift spans midnight
def adjust_shifts(index, row):
   # Duration constraints based on product type
   if row['Product'] == "CO-2L":
       min_duration, max_duration = 98, 110
   else:
       min_duration, max_duration = 60, 72
   # Randomly assign a shift
    shift = np.random.choice(["morning", "afternoon", "night"])
       start_hour = np.random.randint(morning_shift_start, morning_shift_end)
   elif shift == "afternoon":
       start_hour = np.random.randint(afternoon_shift_start, afternoon_shift_end)
       start_hour = np.random.choice(list(range(22, 24)) + list(range(0, 6)))
   # Set new start time
   start_time = row['Start Time'].replace(hour=start_hour, minute=0, second=0)
   duration = np.random.randint(min_duration, max_duration + 1)
    end_time = start_time + pd.Timedelta(minutes=duration)
```

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# □ Data preprocessing

#### Data preparation

- •Scale downtime values proportionally for each batch using a defined function.
- •Ensure realistic total downtime per batch (between 5–30 minutes).
- •Adjust all downtime columns proportionally while preserving their relative weights.
- •Recalculate total downtime for each batch after adjustment.
- •Save the cleaned and adjusted dataset to a new Excel file for further analysis.

```
shift_end_hour = morning_shift_end if shift == "morning" else afternoon_shift_end if shift == "afternoon" else night_shift_end
   shift_end_time = start_time.replace(hour=shift_end_hour, minute=0, second=0)
   # Adjust for night shift crossing midnight
   if shift == "night" and start_hour >= 22:
       shift_end_time += pd.Timedelta(days=1)
   if end_time > shift_end_time:
       end_time = shift_end_time
   row['Start Time'] = start_time
   return row
# Apply shift adjustments
expanded_df = expanded_df.apply(lambda row: adjust_shifts(row.name, row), axis=1)
# Calculate duration in minutes
expanded_df['Duration'] = (expanded_df['End Time'] - expanded_df['Start Time']).dt.total_seconds() // 60
# Save final expanded dataset
final_file_path = r"C:\Users\Haridy\Downloads\Manufacturing_data_expanded.xlsx"
expanded_df.to_excel(final_file_path, index=False)
print(f"Expanded dataset saved to: {final_file_path}")
```

```
import pandas as pd
# Load the dataset
file_path = (r"C:\Users\Haridy\Downloads\adjusted_downtime_data.xlsx")
# Function to reduce downtime while maintaining proportionality
   total_downtime = row["total"]
   # If already within range, keep as is
   if 5 <= total_downtime <= 30:
   # Compute the scaling factor to bring downtime within range
   scale_factor = 30 / total_downtime if total_downtime > 30 else 5 / total_downtime
   downtime_columns = df.columns[1:-1] # Excluding 'Batch' and 'total'
   row[downtime_columns] = (row[downtime_columns] * scale_factor).round().astype(int)
   # Recalculate total downtime after adjustment
   row["total"] = row[downtime_columns].sum()
   return row
# Apply the adjustment function to each row
df_adjusted = df.apply(reduce_downtime, axis=1)
adjusted_file_path = "reduced_downtime_data.xlsx"
df_adjusted.to_excel(adjusted_file_path, index=False)
print(f"Updated file saved as: {adjusted_file_path}")
```



# □ Data preprocessing

#### Data cleaning & preprocessing

- •Preprocessing and cleaning: The data was cleaned and preprocessed.
- •No outliers: There were no outliers in the dataset since we made adjustments.
- •Expanded dataset: The number of operators was increased from 4 to 9.
- •Shifts adjustment: Each shift now includes 3 operators.
- •Duration constraint: The duration was constrained to a range of 60 to 110 minutes, aligning with the global standard for soft drink factories.
- •More realistic data: After these adjustments, the data is now more realistic and closer to reality.

operator id 🔻	operator 🔻	shift -
1001	Mac	night
1002	Dee	night
1003	Dennis	morning
1004	Charlie	morning
1005	Michael	night
1006	Emily	morning
1007	David	evening
1008	Sarah	evening
1009	John	evening

2024-01-01	Diet Cola	420000	10:00 AW	11:08 AIVI	1:08	80	1.1	morning	1005
2024-01-01		420001	11:00 PM	12:07 AM	1:07	67	1.1	night	1001
2024-01-01	Orange	420002	12:00 PM	1:09 PM	1:09	69	1.2	morning	1004
2024-01-01	Cola	420003	3:00 PM	4:03 PM	1:03	63	1.1	evening	1007
2024-01-01	Lemon Lime	420004	8:00 PM	9:02 PM	1:02	62	1.0	evening	1008
2024-01-01	Orange	420005	6:00 PM	7:09 PM	1:09	69	1.2	evening	1009
2024-01-01	Root Berry	420006	11:00 AM	12:09 PM	1:09	69	1.2	morning	1006
2024-01-01	Cola_2L	420007	2:00 PM	3:40 PM	1:40	100	1.7	evening	1007
2024-01-01	Orange	420008	11:00 PM	12:02 AM	1:02	62	1.0	night	1002
2024-01-01	Cola_2L	420009	6:00 AM	7:39 AM	1:39	99	1.7	morning	1003
2024-01-01	Orange	420010	10:00 PM	11:09 PM	1:09	69	1.2	night	1005
2024-01-01	Root Berry	420011	4:00 PM	5:06 PM	1:06	66	1.1	evening	1008
2024-01-01	Cola_2L	420012	10:00 PM	11:38 PM	1:38	98	1.6	night	1001
2024-01-01	Cola	420013	7:00 AM	8:00 AM	1:00	60	1.0	morning	1004
2024-01-01	Cola	420014	11:00 PM	12:07 AM	1:07	67	1.1	night	1002
2024-01-01	Cola_2L	420015	6:00 PM	7:44 PM	1:44	104	1.7	evening	1009
2024-01-01	Lemon Lime	420016	10:00 AM	11:04 AM	1:04	64	1.1	morning	1006
2024-01-01	Cola	420017	4:00 AM	5:06 AM	1:06	66	1.1	night	1005
2024-01-01	Lemon Lime	420018	2:00 PM	3:09 PM	1:09	69	1.2	evening	1007
2024-01-01	Cola_2L	420019	3:00 PM	4:47 PM	1:47	107	1.8	evening	1008
2024-01-01	Orange	420020	8:00 PM	9:02 PM	1:02	62	1.0	evening	1009
2024-01-01	Cola	420021	4:00 AM	5:12 AM	1:12	72	1.2	night	1001
2024-01-01	Cola	420022	8:00 AM	9:05 AM	1:05	65	1.1	morning	1003
2024-01-01	Lemon Lime	420023	2:00 PM	3:06 PM	1:06	66	1.1	evening	1007
2024.04.04	~ !	100001	7.00.444	0.00.444	• • • •		4.0		4004

▼ Product ▼ Batch ▼ Start Time ▼ End Time ▼ duration ▼ Duration (m) ▼ Duration(h) ▼ shift ▼ operator id ▼

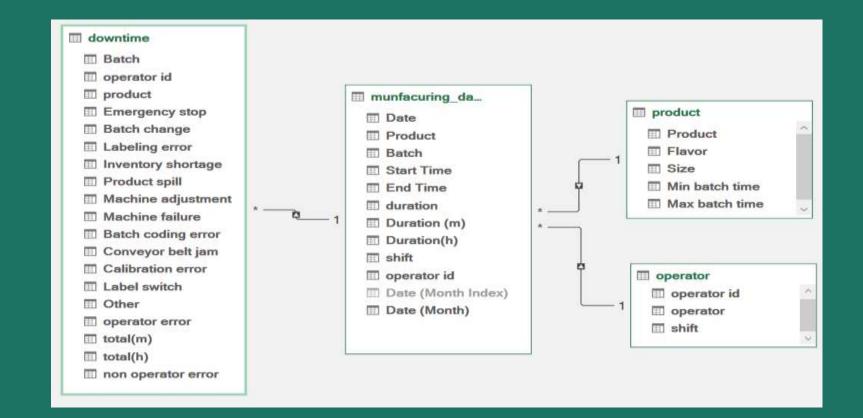
Batcl *	operator *	product *	Emergency stc *	Batch chang *	Labeling err *	Inventory shortag 🔻	Product sp *	Machine adjustmer	Machine failur *	Batch coding ern 7	Conveyor belt ja 🔻	Calibration err *	Label swits *	Othe *	operator err *	total(m) *	total(h) *	non operator en 💌
42000	1003	Diet Cola	2	5	1	2	3	1	1	4	6	2	2	0	.0.28	30	0.50	0.22
42001	1001	Roat Berry	1	6	1	5	4	0	6	0	1	5	1	0	0.27	30	0.50	0.23
42002	1004	Orange	3	4	2	3	0	1	4	3	4	3	2	0	0.22	29	0.48	0.27
42003	1007	Cola	4	4	3	4	2	3	2	3	2	2	2	1	0.27	32	0.53	0.27
42004	1008	Lemon Lime	3	1	3	3	1	0	6	4	4	3	2	1	0.18	31	0.52	0.33
42005	1009	Orange	3	4	4	1	2	0	1	3	4	6	2	- 1	0.28	32	0.53	0.25
42006	1005	Root Berry	5	3	4	-1	2	1	5	:4	1	5	0	. 0	0.25	31	0.52	0.27
42007	1007	Cola_2L	1	2	1	5	0	2	2	2	5	2	- 2	0	0.17	24	0.40	0.23
42008	1002	Orange	3	4	0	6	0	5	1	3	4	2	1	2	0.25	32	0.53	0.28
42009	1003	Cola_2t	3	3	2	0	0	4	9	1	3	2	3	0	0.22	30	0.50	0.28
42010	1005	Orange	0	4	2	3	2	4	. 6	1	4	2	2	1	0.25	31	0.52	0.27
42011	1008	Root Berry	2	1	3	3	3	1	6		5	1	3	1	0.18	31	0.52	0.33
42012	1001	Cola_2L	7	8	1	0	3	0		3	0	1	6	3	0.35	32	0.53	0.18
42013	1004	Cola	5	1	0	4	0	3	1	0	5	5	1	- 1	0.17	26	0.43	0.27
42014	1002	Cola	2	1	2	- 4	1	.5	9	14	1	0	- 1	0	0.20	30	0.50	0.30
42015	1009	Cola_2L	1	5	2		3	5			4	3	- 1	1	0.28	30	0.50	0.22
42016	1006	Lemon Lime	1	3	2	3	1	1	7	24		0	3	1	0.20	29	0.48	0.28
42017	1005	Cola	2	3	1	3	1	3	5	3	6	2	2	. 1	0.23	32	0.53	0.30
42018	1007	lemon Lime	2	2	2	3	0	0	8	U4	2	3	2	2	0.18	30	0.50	0.32



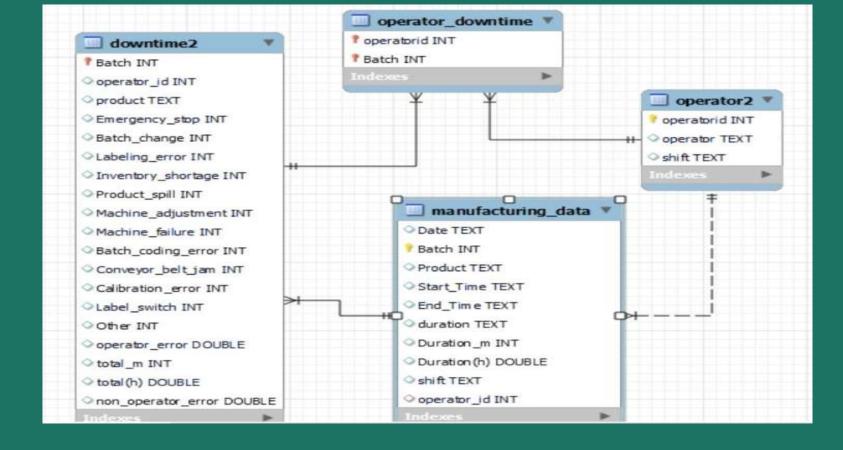
# ☐ Data preprocessing

#### **Data Modeling**

- •Modular Design Separates downtime tracking, batch manufacturing data, and operator details for clarity
- •Comprehensive Downtime Tracking 12+ categories (e.g., machine failures, labeling errors) with operator vs. non-operator error differentiation.
- •Batch Process Monitoring Records batch start/end times, durations (in minutes/hours), and links to operators and shifts.
- •Operator Performance Analysis Tracks operator-shift assignments and ties them to downtime events.
- •Structured Relationships Uses Batch and Operator\_Id to connect downtime, manufacturing, and operator tables.
- •Analysis-Ready Metrics Includes pre-calculated durations (minutes/hours) and supports time-based reporting.



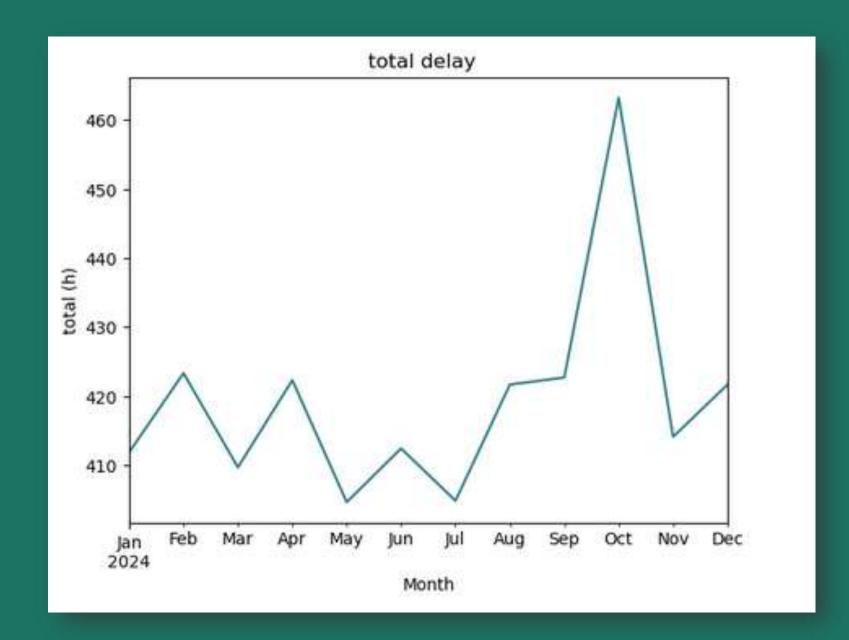
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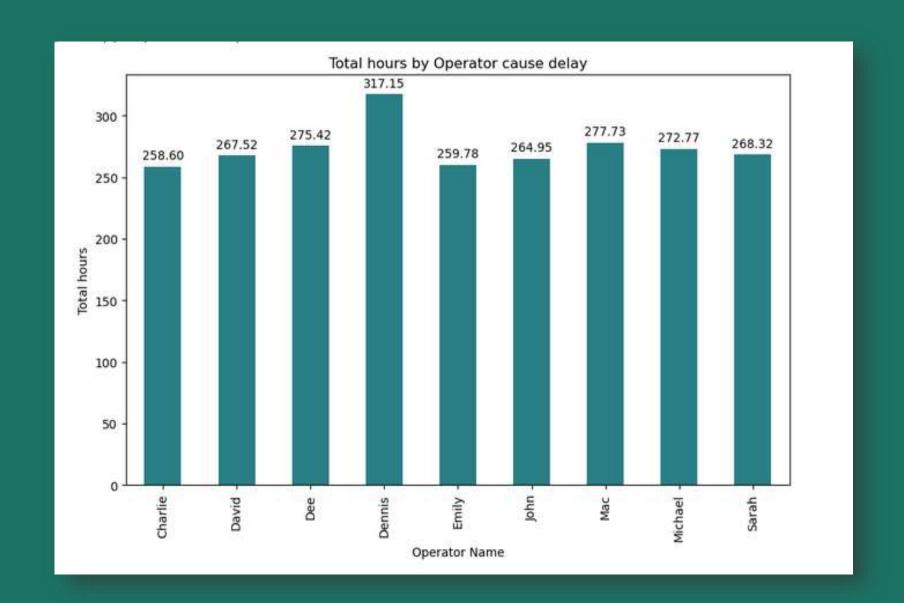
**New Insights from Downtime Patterns** 

 Which months had the most/least downtime?



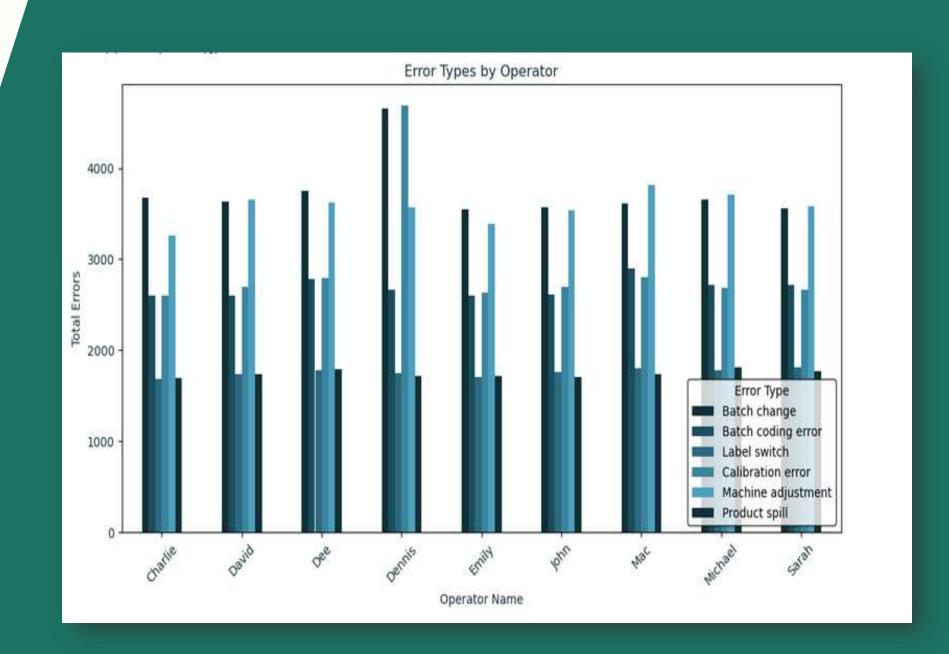


- **New Insights from Downtime Patterns**
- Which operator caused the most delays?
- Who needs the most urgent training based on delay hours?





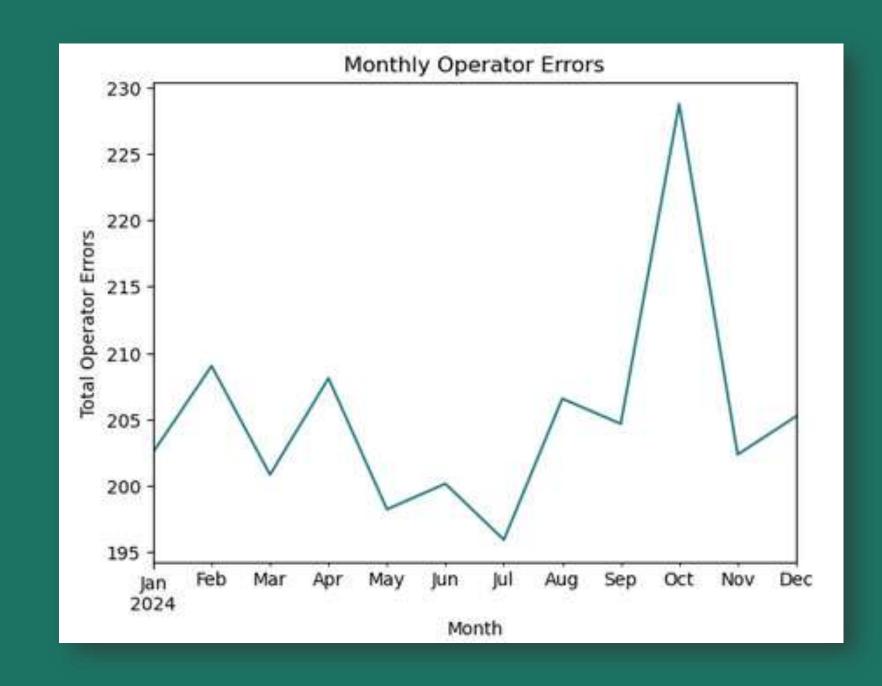
- **New Insights from Downtime Patterns**
- Which operator has the highest total errors, and which error type is their biggest problem?
- Which operator needs targeted training for a specific error ('Calibration error')?





- **New Insights from Downtime Patterns**
- Which month had the highest operator errors?

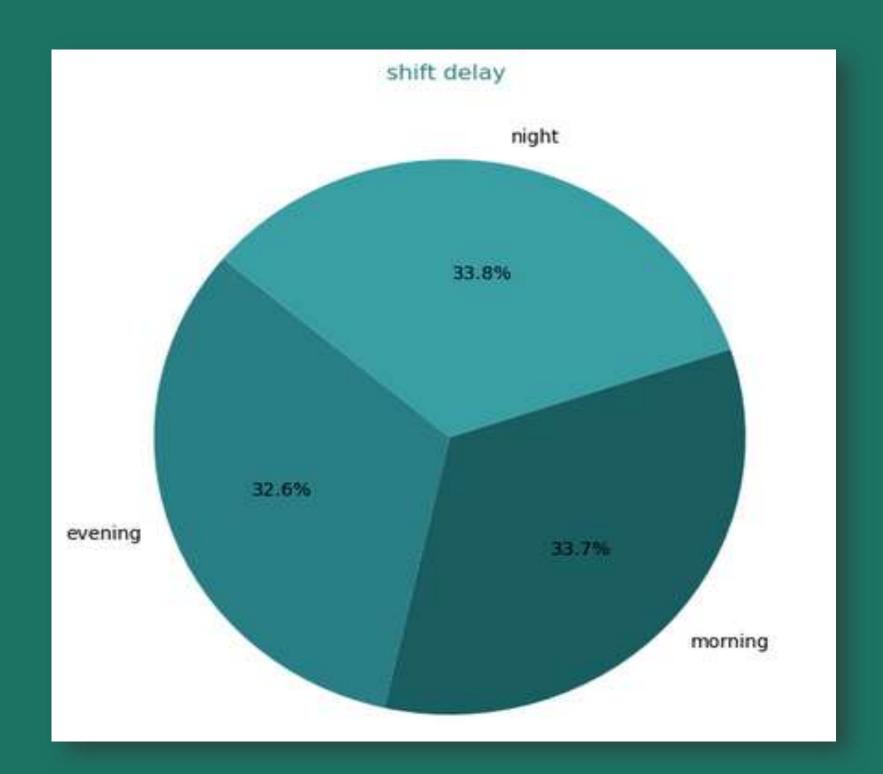
 Are operator errors improving over time?





- **New Insights from Downtime Patterns**
- Which shift has the highest downtime hours?

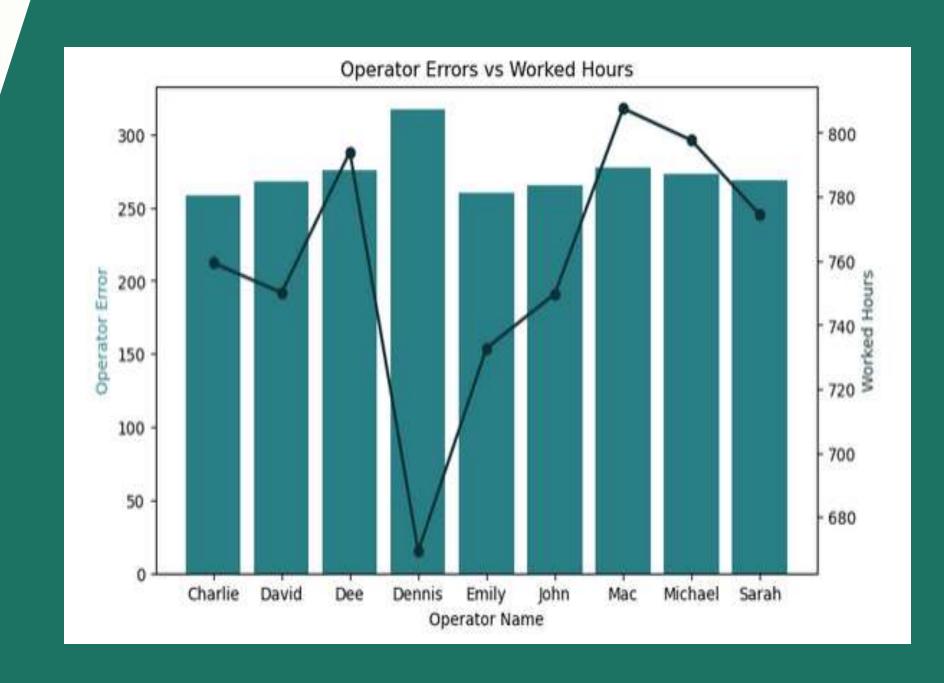
 How much longer are night shift delays compared to morning shift?





- **New Insights from Downtime Patterns**
- Does working more hours lead to more errors?

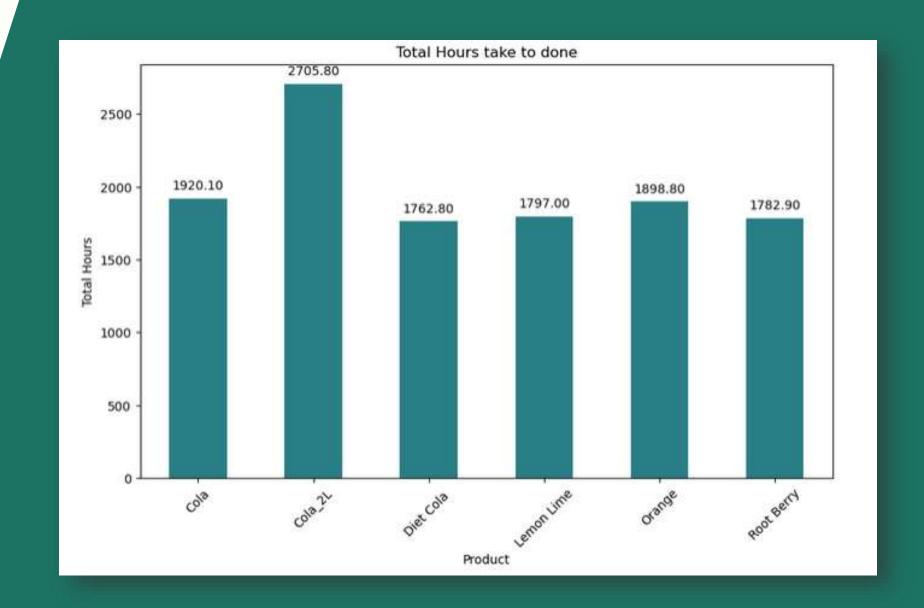
 Which operator stands out for either good or bad performance?





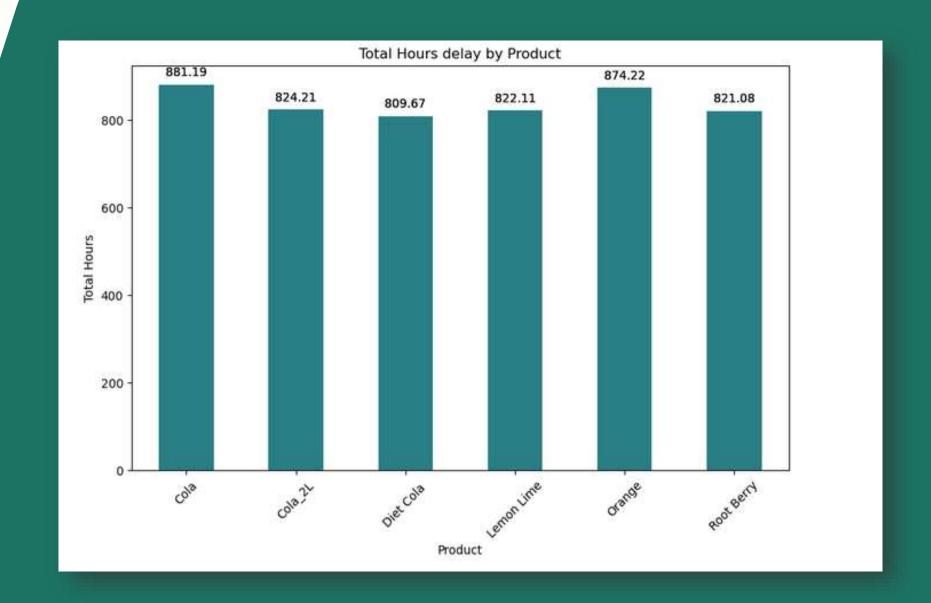
**New Insights from Downtime Patterns** 

Which product takes the longest to produce ?





- **New Insights from Downtime Patterns**
- Which product causes the most production delays?





Total Batches 10,000

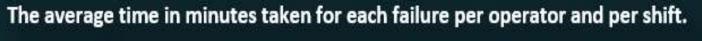


### **OVERVIEW DASHBOARD**



#### AVEARAGE DWONTIME 30 min/B

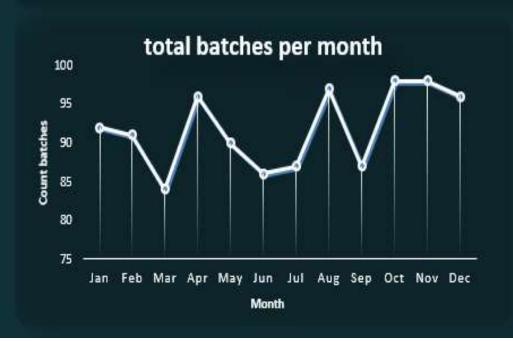




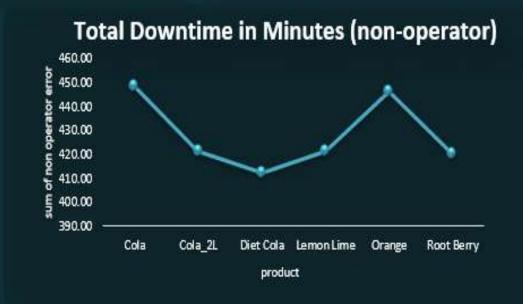














The Leading Cause of Downtime Machine Failure (813.8 hr)

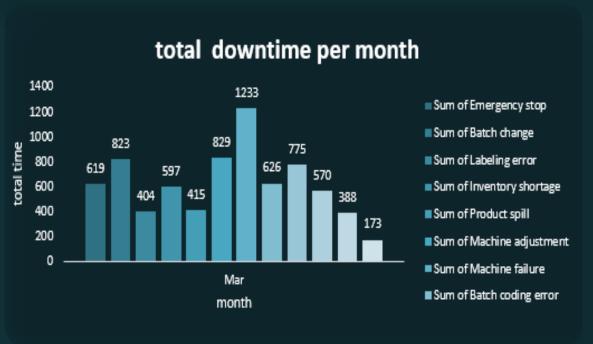


### **DOWNTIME DASHBOARD**



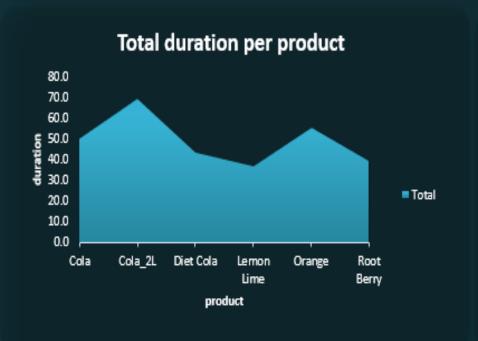
The Most Downtime-Shift Night Shift (1698.9 hr)

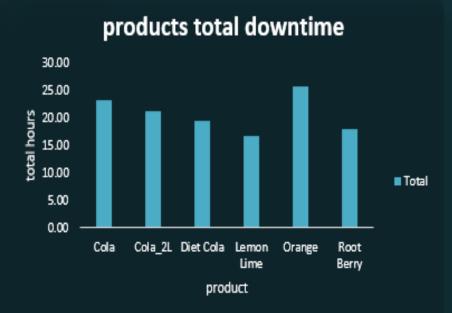


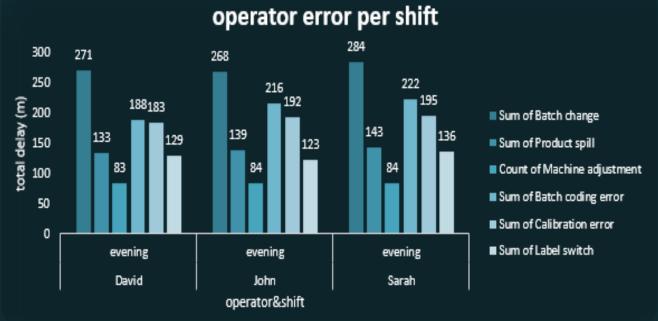














Highest Downtime operator Dennis (317 min)

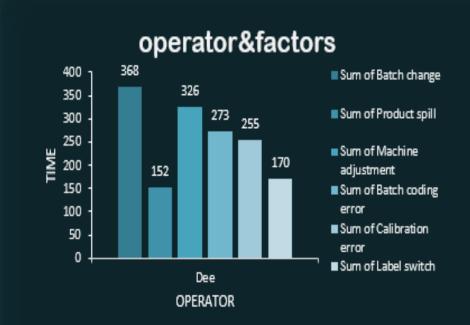


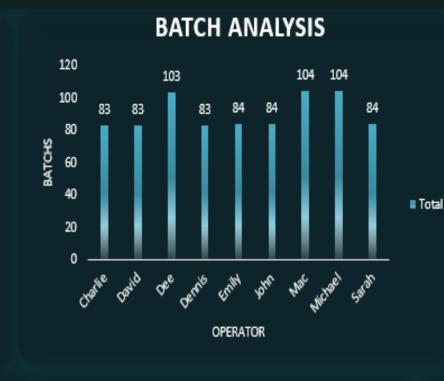
### **OPERATOR DASHBOARD**

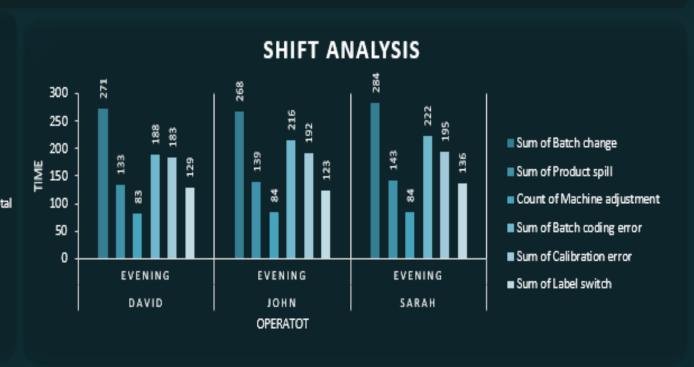


The Least Downtime Contributor
Charlie ( 258 min )



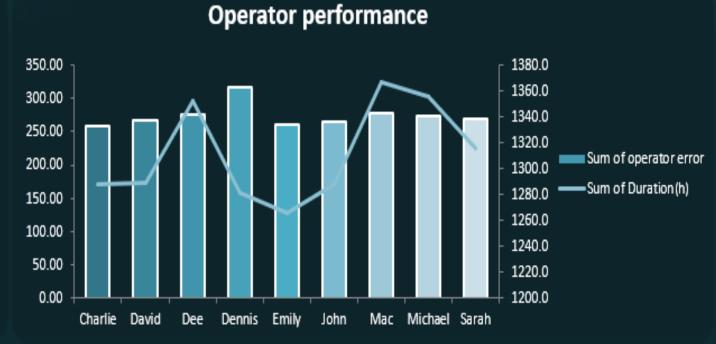














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# 5-Insights

#### Operator Performance Issue

- Dennis is the worst-performing operator with:
  - Exceptionally high error rates
  - Low working hours
  - Significant outlier compared to shift peers

#### **\*** Error Pattern Analysis

- ❖ Most frequent operator-related failure: Machine Failure
- Least common issue: Other miscellaneous errors
- Shift-specific patterns:
  Night/Evening Shifts: Machine Adjustment errors dominate
  Morning Shift: Calibration Errors are most prevalent

#### Production Bottlenecks

- Cola product requires the longest production time
- Appears to be the most time-intensive product in the lineup

#### **Shift Performance Trends**

- Consistent error rates among all operators except Dennis
- ❖ Night shift shows particular vulnerability to equipment issues





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# 6- Recommended Solutions

#### 1. For Dennis' Performance Issues

#### **Immediate Actions:**

- •Conduct one-on-one performance review with Dennis to identify root causes
- •Implement a 30-day probation period with clear KPIs
- Pair with a high-performing operator for mentoring

#### **Training Solutions:**

- •Mandatory machine operation certification
- Error simulation training for most frequent mistakes
- •Weekly performance monitoring with HR

#### 2. Machine Failure Reduction

#### **Preventive Measures:**

- Daily machine inspection checklist for all shifts
- Predictive maintenance program for critical equipment
- Spare parts inventory optimization

#### **Operator-Specific:**

- Machine operation refresher courses quarterly
- Visual troubleshooting guides at each station
- •Error reporting incentive program





# 6- Recommended Solutions

#### 3. Shift-Specific Solutions

#### **Night/Evening Shifts:**

- Dedicated adjustment technician during peak hours
- •Pre-shift machine calibration verification
- Enhanced lighting for precision work areas

#### **Morning Shift:**

- •Weekly calibration equipment certification
- Digital calibration tracking system
- Vendor-managed calibration services

#### 4. Cola Production Optimization

#### **Process Improvements:**

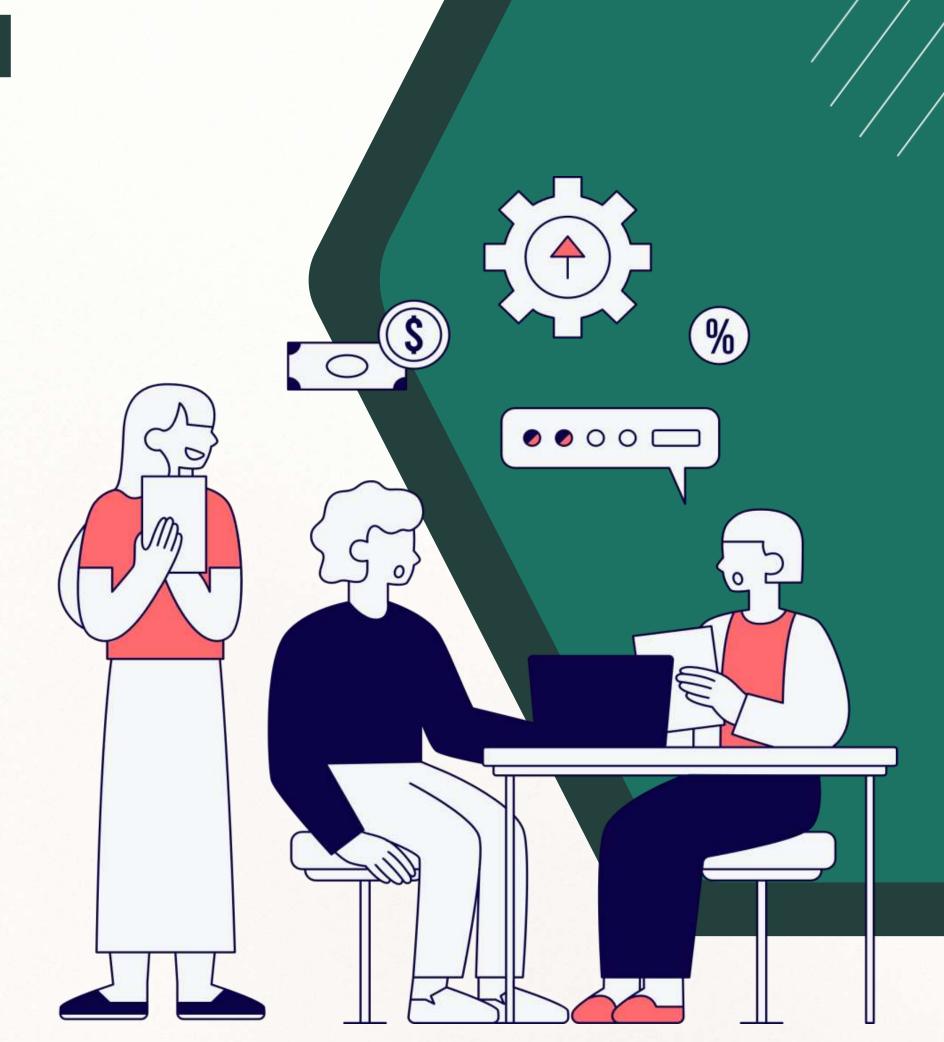
- •Time-motion study for Cola production line
- Bottleneck analysis with Pareto charts
- Parallel processing implementation

#### **Equipment Upgrades:**

- •High-speed filling heads for Cola line
- Automated quality control checkpoints
- •Predictive maintenance for Cola-specific machines

#### **5. Systemic Improvements**

- Cross-shift knowledge sharing sessions
- •Digital performance dashboards for real-time monitoring
- Root cause analysis team for recurring issues
- •Reward system for error-free shifts





# Thank You

