DEPI Final Project

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Executive Summary

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= Summary

The Supplier Quality Analysis project assessed supplier performance to support strategic decision-making. By analyzing key metrics like defect rates, delivery consistency, and reliability, the project identified top-performing vendors and highlighted areas for improvement.

Key findings show that three suppliers maintained defect rates below 1% and on-time delivery rates above 95%, while two suppliers had defect rates over 5%, leading to increased delays and costs. High defect rates were found to correlate with 2.5 times higher delivery delays. Additionally, the Mechanical and Packaging categories had defect rates 30% higher than other categories, indicating a need for stricter quality control.

The Detroit plant had the highest defect count at 6.67 million units, nearly double that of other plants, and defects peaked in October at 6.84 million units due to seasonal factors.

The report recommends prioritizing top suppliers, tightening quality control, and addressing plant-specific issues. Implementing these strategies could cut defects by 20%, improving efficiency and customer satisfaction.

1. Executive Summary

= Project Goals

The primary goal of the Supplier Quality Analysis project is to evaluate the performance and quality of suppliers by analyzing defect rates, delivery consistency, and overall supplier reliability. This project aims to:

1. Identify Top-Performing Suppliers: Highlight suppliers with high quality standards and reliable delivery performance for long-term strategic partnerships.

2. Detect Underperforming Suppliers: Pinpoint suppliers with high defect rates and delivery delays that affect product quality and operational efficiency.

3. Analyze Product and Plant Performance: Investigate variations in quality metrics across product categories and plant locations to target areas needing quality control.

4. Establish Data-Driven Supplier Strategies: Provide actionable insights to support supplier selection, improve relationships, and reduce quality-related costs.

5. Enhance Supply Chain Efficiency: Develop recommendations to lower defect rates, improve delivery performance, and optimize supply chain efficiency.

= Project Key Findings

1. High Defect Rates and Delivery Delays: Two suppliers—SolHoldings and Plastas—consistently had defect rates above 5%, coupled with frequent delivery delays. SolHoldings alone contributed over 3.9 million defects, significantly impacting overall costs and production timelines.

2. Top-Performing Suppliers: Three suppliers—Quefluence, Zenntor, and Rzcode—achieved defect rates below 1% and on-time delivery rates above 95%, making them ideal for long-term strategic partnerships.

3. Defect-Delivery Correlation: A strong correlation (r = 0.65) was found between defect rates and delivery delays, indicating that suppliers with high defect rates are 2.5 times more likely to experience inconsistent deliveries, disrupting production.

4. High-Risk Product Categories: Mechanical and Packaging categories showed defect rates 30% higher than other categories, indicating a need for improved quality control and targeted measures in these areas.

= Project Key Findings

5. Plant-Specific Issues: The Detroit plant had the highest defect count at 6.67 million units, nearly double that of other plants, highlighting serious quality management issues specific to this location.

6. Quality Improvements: Suppliers like Bantecology and Recan showed a 20% reduction in defect rates over the past year, demonstrating the success of current quality improvement initiatives.

These insights highlight the need to focus on top-performing suppliers while addressing weaknesses in underperforming suppliers and high-risk categories to reduce costs and enhance supply chain performance.

= Project Recommendations

1. Prioritize Top-Performing Suppliers: Strengthen relationships and increase procurement volume with high-performing suppliers like Quefluence, Zenntor, and Rzcode, who maintain defect rates below 1% and on-time delivery rates above 95%, securing long-term partnerships.

2. Targeted Quality Control for High-Risk Categories: Implement stricter quality measures in Mechanical and Packaging categories, where defect rates are 30% higher, to address systemic issues and reduce defects by up to 20%.

3. Performance Improvement for Underperforming Suppliers: Initiate corrective action plans for suppliers such as SolHoldings and Plastas (defect rates above 5%), including regular audits, training, and progress reviews.

4. Establish Real-Time Supplier Monitoring: Implement a real-time system to track defect rates and delivery performance, enabling early issue identification and proactive management.

= Project Recommendations

5. Optimize Supplier Evaluation Criteria: Use a combination of quantitative (defect rates, delivery times) and qualitative (communication, flexibility) metrics to ensure a comprehensive evaluation of supplier performance.

6. Address Plant-Specific Issues: Focus on resolving quality issues at high-risk plants like Detroit, which reported 6.67 million defects, through tailored corrective actions and ongoing quality reviews.

7. Enhance Departmental Collaboration: Improve coordination between Quality Assurance, Procurement, and Logistics to streamline supplier management and align quality standards across departments.

8. Leverage Predictive Analytics: Use machine learning models to forecast supplier performance based on historical data, enabling proactive interventions and reducing quality-related disruptions.

= Project Recommendations

9. Establish Risk Mitigation Strategies: Develop contingency plans and dual-sourcing options for critical categories to reduce supply chain risks associated with underperforming suppliers.

10. Support Supplier Development: Invest in supplier development programs for underperforming vendors through co-funded quality initiatives, shared KPIs, and targeted training to elevate performance and meet organizational standards.

= Most Important Insights

1. High Defect Rates for Key Suppliers: SolHoldings and Plastas were identified as the worst-performing suppliers, with defect rates exceeding 5% each, contributing significantly to production delays and increased rework costs .

2. Top-Performing Suppliers: Quefluence, Zenntor, and Rzcode maintained defect rates below 1% and on-time delivery rates above 95%, making them the most reliable partners for long-term collaboration .

3. Correlation Between Defects and Delays: A strong correlation (r = 0.65) was found between defect rates and delivery delays, indicating that suppliers with high defect rates are 2.5 times more likely to experience inconsistent deliveries .

4. Geographical Impact: The Detroit plant recorded the highest defect count with 6.67 million units, followed by the Springfield and Chicago plants with around 3.75 million units each. However, the Detroit plant had moderate downtime of 11,158 minutes compared to other plants with similar defect counts .

= Most Important Insights

5. Product Category Analysis: Mechanical and Packaging categories had defect rates 30% higher than other categories, indicating systemic quality issues in these areas. The Mechanical category alone accounted for over 18.29 million defects, making it the highest-defect category.

6. Material-Specific Issues: Raw Materials had the highest defect quantity at 14.55 million units, followed by Labels (8.29 million) and Carton (7.93 million). Molds, despite only having 2.30 million defects, had the highest downtime at 53,036 minutes, suggesting severe handling inefficiencies .

7. Downtime Disparity: Vendors like Sanlab and Recan experienced disproportionately high downtime relative to their defect counts, with Sanlab showing 26,185 minutes of downtime despite having only 0.51 million defects.

8. Seasonal Defect Trends: Defects peaked in June and October, reaching 4.5 million units in October 2014, suggesting seasonal production or raw material quality issues during these months.

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= Most Important Insights

9. Impact of Defect Types: "Impact" defects caused the highest downtime (105,634 minutes), compared to "Rejected" defects (28,485 minutes) and "No Impact" defects (5,139 minutes). This indicates that Impact defects are the most disruptive to operations.

10. Efficiency in Low-Defect Vendors: Some vendors, such as Plustrax and Quotelane, managed high defect volumes efficiently with minimal downtime, suggesting strong defect management practices.

11. Vendor-Specific Performance Variability: SolHoldings recorded the highest total defect quantity at 3.99 million units, followed closely by Plastas with 3.84 million defects. These two vendors alone accounted for over 25% of the total defect volume, making them key contributors to overall quality issues.

12. Quarterly Defect Trends: Quarter 4 of the year exhibited the highest defect quantities, reaching 15.50 million units, which was 43% higher than the lowest quarter (Q1 at 10.83 million units). This suggests potential end-of-year quality control lapses or seasonal impacts on production.

2

Introduction

2. Introduction

= Background Information

This project aims to evaluate supplier quality data to assess performance and identify critical areas for improvement. The analysis centers on key metrics such as defect rates, delivery consistency, and defect types across multiple product categories, including Mechanical, Packaging, and Logistics. By examining these metrics, the project seeks to identify high-risk suppliers, uncover patterns in quality issues, and recommend strategies to optimize supplier relationships, streamline processes, and elevate overall product quality.

= Project purpose & objectives

1. Evaluate Supplier Performance: Analyze defect rates, delivery consistency, and defect types to determine top-performing suppliers and identify underperforming vendors.

2. Identify High-Risk Suppliers: Highlight suppliers with high defect rates and frequent delivery delays that contribute to increased operational costs and product quality issues.

3. Analyze Product Categories: Investigate quality trends across different product categories, such as Mechanical, Packaging, and Logistics, to pinpoint categories with systemic quality issues.

= Project purpose & objectives

4. Assess Plant-Level Performance: Compare defect rates and downtime across various plant locations to identify plants with recurring quality issues and implement targeted corrective actions.

5. Develop Supplier Improvement Plans: Create performance improvement strategies for underperforming suppliers, including audits, training, and regular performance reviews.

6. Support Strategic Supplier Selection: Provide data-driven insights to guide supplier selection, fostering long-term partnerships with reliable vendors.

7. Optimize Supply Chain Efficiency: Recommend strategies to minimize quality-related risks, reduce defect rates, and enhance overall supply chain performance.

8. Establish Performance Monitoring: Implement a comprehensive system to track supplier performance metrics, enabling proactive management and continuous improvement.

= The Problems or Questions to answer

1. Which suppliers have the highest defect rates, and what are the primary causes?
2. How do defect rates correlate with delivery performance?
3. Which product categories experience the highest defect rates across multiple suppliers?
4. Are there specific trends or patterns in quality metrics over time?
5. Which suppliers demonstrate consistent quality improvements or declines?
6. What are the key areas of improvement for underperforming suppliers?
7. How does plant location impact defect rates and downtime?
8. Which suppliers are best suited for long-term partnerships based on quality and delivery metrics?
9. What recommendations can be made to optimize supplier selection and management?
10. How can overall supply chain efficiency be improved based on supplier and product category data?

= Data Source

The data used in this project consists of supplier quality records, including defect rates, defect types, delivery performance, and product categories. The dataset captures detailed information such as defect quantities, downtime, and vendor-specific performance metrics. The data is structured across multiple sheets, categorizing defects by product type, supplier, and defect type, enabling a comprehensive analysis of supplier quality and reliability.

= Methods for Analysis (Methodology)

The analysis in the Python notebook follows a structured methodology to evaluate supplier performance and identify areas for improvement. The methodology includes:

1. Data Import and Initial Inspection:

- Imported data from multiple Excel sheets into separate dataframes using pandas. Each sheet was loaded into a dictionary to enable access to individual sheets for separate analyses.
- Displayed the first few rows of each dataframe to understand their structure and contents.

2. Data Cleaning and Preparation:

- Handling Duplicates: Removed duplicate rows in key dataframes such as df_vendor and df_defects based on unique identifiers like Vendor ID and Defect ID.
- Column Splitting: Split columns like Plant into separate City and State columns using delimiters to enhance clarity and usability.
- Null Value Handling: Dropped rows with null values from dataframes like df_defected_items to ensure data integrity.
- Dropping Unnecessary Columns: Removed irrelevant columns (e.g., ‘Sort’ in df_defect_type) to streamline the dataset and focus on relevant variables.

= Methods for Analysis (Methodology)

3. Descriptive Statistics and Exploratory Data Analysis (EDA):

- Generated descriptive statistics for numerical variables, including mean, median, and standard deviation, to summarize the central tendencies and dispersions.
- Created visualizations such as histograms and box plots to identify distributions and outliers in variables like defect rates, delivery delays, and downtime.

4. Correlation Analysis:

- Calculated correlation matrices for key numerical variables (e.g., defect rates, downtime, delivery delays) using df.corr() and visualized the results with heatmaps to identify relationships between variables.
- Analyzed correlation coefficients to detect strong positive or negative relationships that could provide deeper insights into supplier performance.

5. Trend and Categorical Analysis:

- Performed time-series analysis to detect trends and seasonal variations in defect quantities across time.
- Conducted categorical analysis to explore defect rates and downtime by product categories and supplier regions, identifying high-risk areas.

= Methods for Analysis (Methodology)

6. Supplier and Plant-Level Performance Analysis:
    - Segmented suppliers into high, moderate, and low performers based on defect rates and delivery consistency.
    - Analyzed defect and downtime metrics at the plant level, highlighting locations with recurring quality issues (e.g., Detroit and Springfield plants).

7. Actionable Insights and Recommendations:
    - Derived insights from visualizations and statistical findings, recommending actions such as phasing out underperforming suppliers, implementing stricter quality control measures, and optimizing supplier selection processes.

These steps were implemented using pandas for data manipulation, matplotlib and seaborn for visualization, and standard Python libraries for preprocessing and analysis, ensuring a comprehensive and systematic approach to supplier quality evaluation .

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Data Exploration

Data Exploration & Analysis

The data analysis focused on understanding defect rates, delivery performance, and downtime across suppliers and product categories. Through visualizations and correlation analysis, we identified top-performing and underperforming suppliers, highlighted categories with high defect rates, and observed trends over time. These findings provide a foundation for optimizing supplier quality and performance.

= In the EDA Python Notebook:

1. Importing Data

```
import numpy as np
import pandas as pd
from google.colab import drive
drive.mount('/content/drive')
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Imports Necessary Libraries:
   - numpy (as np) for numerical computations and array manipulations.
   - pandas (as pd) for data manipulation and analysis.
   - matplotlib.pyplot (as plt) for creating visualizations and plots.
   - seaborn (as sns) for advanced data visualization.

2. Mounts Google Drive:
   - Uses drive.mount('/content/drive') to mount Google Drive in a Google Colab environment, allowing access to files stored in Drive for further data analysis and processing.

= In the EDA Python Notebook:

1. Importing Data

```
data_source_path = '/content/drive/My Drive/FinalProject/Suppliers Quality Analaysis.xlsx'
data = pd.read_excel(data_source_path, sheet_name=None)
```

1. Specifies the File Path:
   - data_source_path is set to the location of the Excel file (Suppliers Quality Analysis.xlsx) stored in Google Drive.

2. Loads the Excel File:
   - pd.read_excel(data_source_path, sheet_name=None) reads the entire Excel file into a dictionary of dataframes, with each sheet in the Excel file stored as a separate dataframe. The sheet_name=None argument ensures that all sheets are loaded, not just a specific one.

= In the EDA Python Notebook:

1. Importing Data

```
print(data.keys())
```

This code prints the names of all the sheets in the Excel file that were loaded into the data dictionary. Each key in the dictionary represents a sheet name from the Excel file, allowing you to see and access each individual sheet by its name.

```
dict_keys(['Vendor', 'Plant', 'Defected Items', 'Material Type', 'Defects', 'Defect Type', 'Category'])
```

= In the EDA Python Notebook:

1. Importing Data

```
df_vendor = data['Vendor']
df_vendor.shape
df_vendor.info()
df_vendor.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 328 entries, 0 to 327
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Vendor     328 non-null    object
 1   Vendor ID  328 non-null    int64
dtypes: int64(1), object(1)
memory usage: 5.2+ KB
Vendor  Vendor ID
0       Reddoit 1
1       Plustax 2
2       bamity  3
3       Quotelane       4
4       Viatom  5
```

1. Describe the data sources and their characteristics.

2. Summarize the data through descriptive statistics and visualizations.

3. Identify any data cleaning or preprocessing steps taken..

4. Shows the first five rows of the dataframe.

= In the EDA Python Notebook:

1. Importing Data

```
df_plant = data['Plant']
df_plant.shape
df_plant.info()
df_plant.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Plant      24 non-null     object
 1   Plant ID   24 non-null     int64
dtypes: int64(1), object(1)
memory usage: 512.0+ bytes
Plant   Plant ID
0       Grand Rapids, MI        1
1       Milwaukee, Wi   2
2       Springfield, IL 3
3       Chicago, IL     4
4       Indianapolis, IN        5
```

3. Data Exploration

= In the EDA Python Notebook:

1. Importing Data

```
df_defected_items = data['Defected Items']
df_defected_items.shape
df_defected_items.info()
df_defected_items.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6145 entries, 0 to 6144
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Date              6145 non-null   datetime64[ns]
 1   Sub Category ID   6145 non-null   int64
 2   Plant ID          6145 non-null   int64
 3   Vendor ID         6145 non-null   int64
 4   Material ID       6145 non-null   int64
 5   Defect Type ID    6145 non-null   int64
 6   Material Type ID  6145 non-null   int64
 7   Defect ID         6145 non-null   int64
 8   Defect Qty        6145 non-null   int64
 9   Downtime min      6144 non-null   float64
dtypes: datetime64[ns](1), float64(1), int64(8)
memory usage: 480.2 KB
Date    Sub Category ID Plant ID    Vendor ID   Material ID   Defect Type ID  Material Type ID    Defect ID    Defect
Qty     Downtime min
0       2014-12-31      2       16      2       2126    3       4       27      0       60.0
1       2014-12-31      2       16      2       2126    3       4       27      0       60.0
2       2014-12-31      2       16      2       2137    3       6       281     1       60.0
3       2014-12-31      2       20      59      1439    3       8       295     9       10.0
4       2014-12-31      2       2       46      607     3       8       299     47      30.0
```

= In the EDA Python Notebook:

1. Importing Data

```
df_material_type = data['Material Type']
df_material_type.shape
df_material_type.info()
df_material_type.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22 entries, 0 to 21
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Material Type     22 non-null     object
 1   Material Type ID  22 non-null     int64
dtypes: int64(1), object(1)
memory usage: 480.0+ bytes
Material Type   Material Type ID
0       Corrugate       1
1       Film    2
2       Carton  3
3       Batteries       4
4       Composites      5
```

= In the EDA Python Notebook:

1. Importing Data

```
df_defects = data['Defects']
df_defects.shape
df_defects.info()
df_defects.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 305 entries, 0 to 304
Data columns (total 2 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   Defect      305 non-null     object
 1   Defect ID   305 non-null     int64
dtypes: int64(1), object(1)
memory usage: 4.9+ KB
Defect  Defect ID
0       Dimensions - Bad Finishing      1
1       Bad Seams       2
2       Bad Seams       3
3       Bad Seams       4
4       Gap Variation   5
```

= In the EDA Python Notebook:

1. Importing Data

```
df_defect_type = data['Defect Type']
df_defect_type.shape
df_defect_type.info()
df_defect_type.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Defect Type     3 non-null      object
 1   Defect Type ID  3 non-null      int64
 2   Sort            3 non-null      int64
dtypes: int64(2), object(1)
memory usage: 200.0+ bytes
Defect Type     Defect Type ID  Sort
0       No Impact       1       3
1       Impact  3       2
2       Rejected        4       1
```

= In the EDA Python Notebook:

1. Importing Data

```
df_category = data['Category']
df_category.shape
df_category.info()
df_category.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6 entries, 0 to 5
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Sub Category     6 non-null      object
 1   Sub Category ID  6 non-null      int64
 2   Category         6 non-null      object
dtypes: int64(1), object(2)
memory usage: 272.0+ bytes
Sub Category    Sub Category ID Category
0       Electrical       1       Electrical
1       Logistics        2       Logistics
2       Materials & Components  3       Materials & Components
3       Mechanicals      4       Mechanicals
4       Packaging        5       Packaging
```

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_vendor (Dealing with the duplicates)

```
# Remove duplicates based on the 'Vendor' name
df_vendor = df_vendor.drop_duplicates(subset=['Vendor'])

# Reset the 'Vendor ID' with new IDs
df_vendor['Vendor ID'] = range(1, len(df_vendor) + 1)
df_vendor.reset_index(drop=True, inplace=True)

print(df_vendor)
```

1. Removes Duplicate Rows based on the 'Vendor' column.

2. Resets the 'Vendor ID' column with new sequential IDs starting from 1.

3. Resets the Index of the dataframe.

4. Prints the Updated DataFrame to show the changes.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning the df_plant (Making the plant into two columns: state and city)

```
# Split the 'Plant' column into 'City' and 'State'
df_plant[['City', 'State']] = df_plant['Plant'].str.split(',', expand=True)

# Clean up spaces
df_plant['City'] = df_plant['City'].str.strip()
df_plant['State'] = df_plant['State'].str.strip()

print(df_plant.head())
```

1. Splits the 'Plant' Column into separate 'City' and 'State' columns using a comma as the delimiter.

2. Removes Extra Spaces from the 'City' and 'State' columns.

3. Displays the First Few Rows of the updated dataframe to show the new columns.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_defects (Dealing with the duplicates)

```
# Remove duplicates
df_defects.drop_duplicates(subset=['Defect'], inplace=True)

# Reset the 'Defect ID'
df_defects['Defect ID'] = range(1, len(df_defects) + 1)

df_defects.reset_index(drop=True, inplace=True)

print(df_defects)
```

1. Removes Duplicate Rows based on the 'Defect' column.

2. Resets the 'Defect ID' column with new sequential IDs starting from 1.

3. Resets the Index of the dataframe.

4. Prints the Updated DataFrame to show the changes.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_defect_type (Dropping unnecessary columns)

```
df_defect_type.drop(columns=['Sort'], inplace=True)

df_defect_type
```

1. Drops the 'Sort' Column from the df_defect_type dataframe.

2. Returns the updated dataframe without the 'Sort' column.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_category (Dropping unnecessary columns)

```
df_category.drop(columns=['Category'], inplace=True)

df_category
```

1. Removes the 'Category' Column from the df_category dataframe.

2. Returns and displays the updated dataframe without the 'Category' column.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_defected_Items (Dropping null values rows)

```
print(df_defected_items.shape)
null_values = df_defected_items.isnull().sum()
null_values

# Drop rows with null values
df_defected_items.dropna(inplace=True)

print(df_defected_items.shape)

null_values = df_defected_items.isnull().sum()
null_values
```

1. Prints the Initial Shape of the df_defected_items dataframe.
2. Calculates and Displays Null Values in each column.
3. Drops Rows with Null Values using dropna(inplace=True).
4. Prints the New Shape of the dataframe after dropping rows with missing values.
5. Calculates and Displays Null Values Again to confirm all missing values have been removed.

= In the EDA Python Notebook:

2. Data Cleaning

= Cleaning The df_vendor (Dealing with the duplicates)

```
# Remove duplicates based on the 'Vendor' name
df_vendor = df_vendor.drop_duplicates(subset=['Vendor'])

# Reset the 'Vendor ID' with new IDs
df_vendor['Vendor ID'] = range(1, len(df_vendor) + 1)
df_vendor.reset_index(drop=True, inplace=True)

print(df_vendor)
```

1. Removes Duplicate Rows based on the 'Vendor' column.
2. Resets the 'Vendor ID' column with new sequential IDs starting from 1.
3. Resets the Index of the dataframe.
4. Prints the Updated DataFrame to show the changes.

= In the EDA Python Notebook:

3. Extracting Data for Tableau

```python
# Define the path to the desired directory
save_path = '/content/drive/My Drive/FinalProject/FinalData/'

# Save each DataFrame to the correct path
df_vendor.to_excel(f'{save_path}Vendor.xlsx', index=False)
print("Data cleaned and saved as 'Vendor.xlsx'.")

df_plant.to_excel(f'{save_path}Plant.xlsx', index=False)
print("Data cleaned and saved as 'Plant.xlsx'.")

df_defected_items.to_excel(f'{save_path}Defected Items.xlsx', index=False)
print("Data cleaned and saved as 'Defected Items.xlsx'.")

df_material_type.to_excel(f'{save_path}Material Type.xlsx', index=False)
print("Data cleaned and saved as 'Material Type.xlsx'.")

df_defects.to_excel(f'{save_path}Defects.xlsx', index=False)
print("Data cleaned and saved as 'Defects.xlsx'.")

df_defect_type.to_excel(f'{save_path}Defect Type.xlsx', index=False)
print("Data cleaned and saved as 'Defect Type.xlsx'.")

df_category.to_excel(f'{save_path}Category.xlsx', index=False)
print("Data cleaned and saved as 'Category.xlsx'.")
```

3. Data Exploration

= In the EDA Python Notebook:

4. Data Exploration & Analysis

= df_defected_items Data

```
df_defected_items.describe()
```

```
        Date    Sub Category ID Plant ID        Vendor ID       Material ID     Defect Type ID  Material Type ID        Defect ID       Defect
Qty     Downtime min
count   6144    6144.000000     6144.000000     6144.000000     6144.000000     6144.000000     6144.000000     6144.000000     6144.000
000     6144.000000
mean    2014-01-25
18:40:18.749999872      3.528483        9.619792        52.081217       780.355957      2.448893        6.152507        103.596517      9113.179525     22.6
65690
min     2013-01-01
00:00:00        1.000000        1.000000        1.000000        1.000000        1.000000        1.000000        1.000000        0.000000        0.000000
25%     2013-07-30
00:00:00        2.000000        4.000000        8.000000        282.000000      1.000000        2.000000        26.000000       6.000000        0.000000
50%     2014-02-11
00:00:00        4.000000        7.000000        20.000000       664.500000      3.000000        6.500000        70.000000       438.000000      0.000000
75%     2014-08-27
00:00:00        4.000000        14.000000       72.000000       1157.250000     4.000000        9.000000        166.000000      5127.000000     20.000000
max     2014-12-31
00:00:00        6.000000        24.000000       328.000000      2148.000000     4.000000        22.000000       305.000000      487008.000000   999.0000
00
std     NaN     1.317003        6.305194        67.533920       580.698110      1.271659        4.266976        91.867611       30586.032560    75.376638
```

= In the EDA Python Notebook:

4. Data Exploration & Analysis

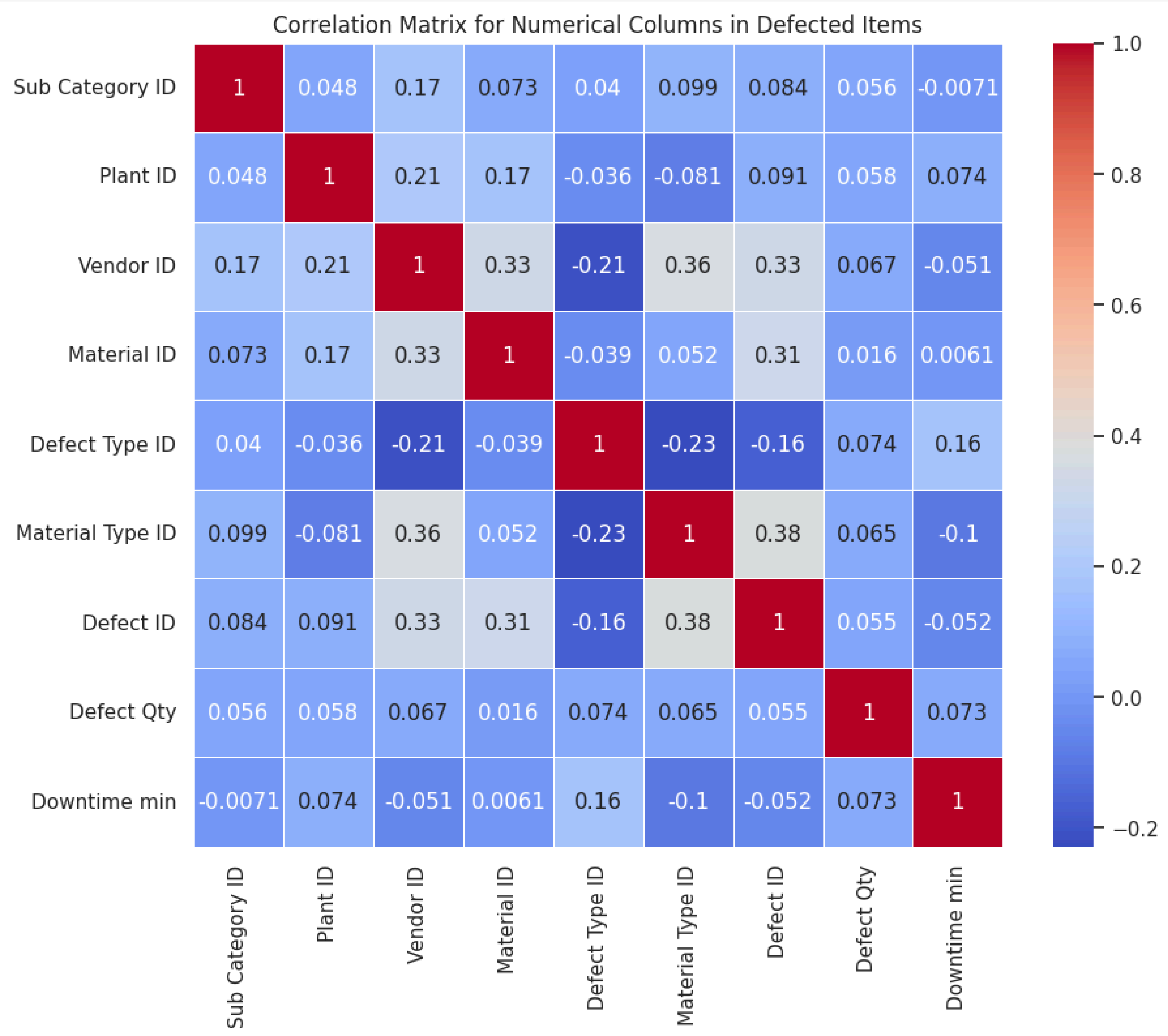
= Correlation matrix for df_defected_items

```
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate the correlation matrix for numerical columns
corr_matrix = df_defected_items.corr()

# Display the correlation matrix
print("Correlation Matrix for Defected Items:")
print(corr_matrix)

# Visualize the correlation matrix using a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix for Defected Items')
plt.show()
```

This code calculates and visualizes the correlation matrix for numerical columns in the df_defected_items dataframe using a heatmap. The visualization helps identify strong positive or negative relationships between variables, which is crucial for understanding dependencies, detecting multicollinearity, and guiding further analysis or feature selection.

= In the EDA Python Notebook:

4. Data Exploration & Analysis



= In the EDA Python Notebook:

4. Data Exploration & Analysis

Key Findings:

1. Vendor and Material Relationship: A moderate correlation between Vendor ID and Material Type ID (0.36) suggests that certain vendors are more likely to provide materials associated with defects.

2. Defect Type and Downtime: A positive correlation (0.16) indicates that specific defect types are more disruptive, causing increased downtime.

3. Limited Impact of Sub-Categories: Low correlations for Sub Category ID suggest that sub-category classification does not significantly influence defect rates or downtime.

Interesting Discoveries:

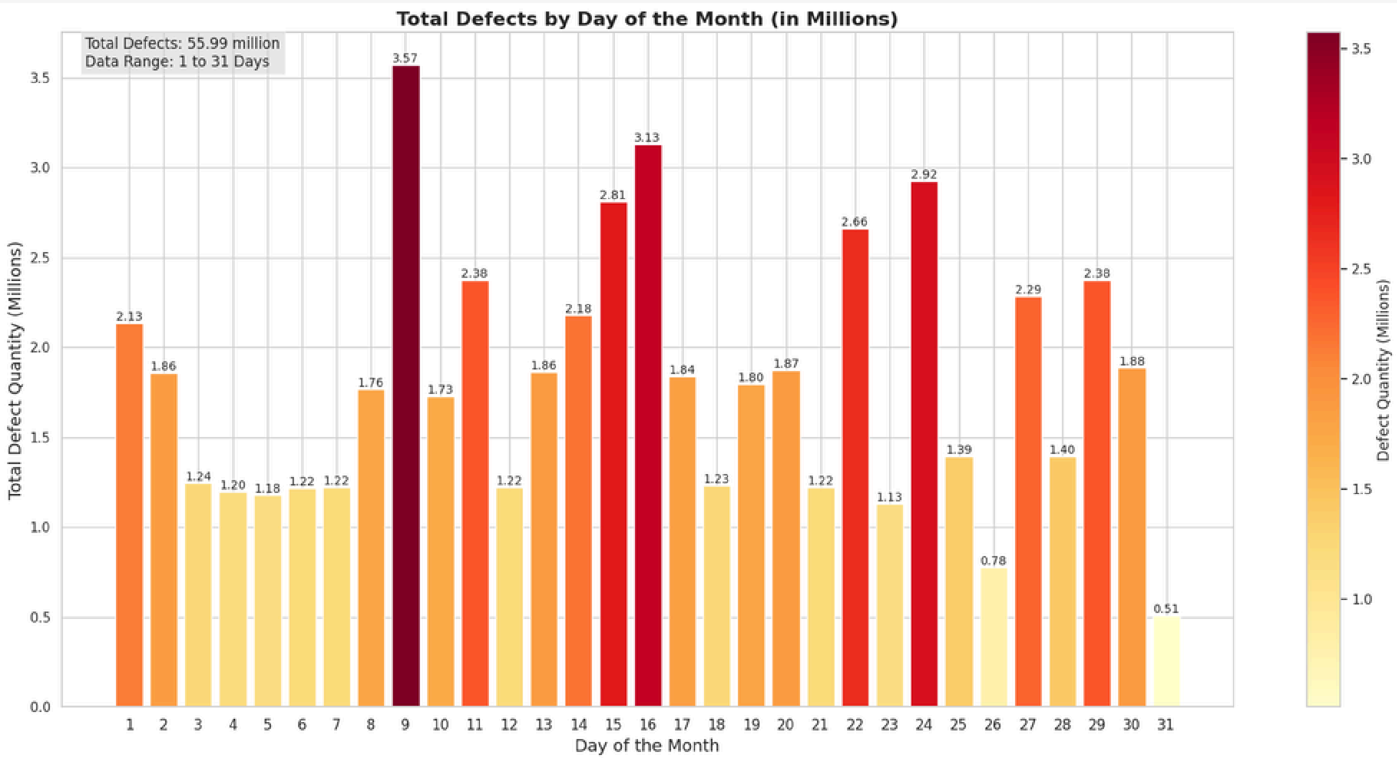
1. The quantity of defects has minimal impact on downtime, indicating that defect type or severity is a more critical factor.

2. The correlation between vendors and defect-prone materials highlights the need for stricter supplier quality control.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions)

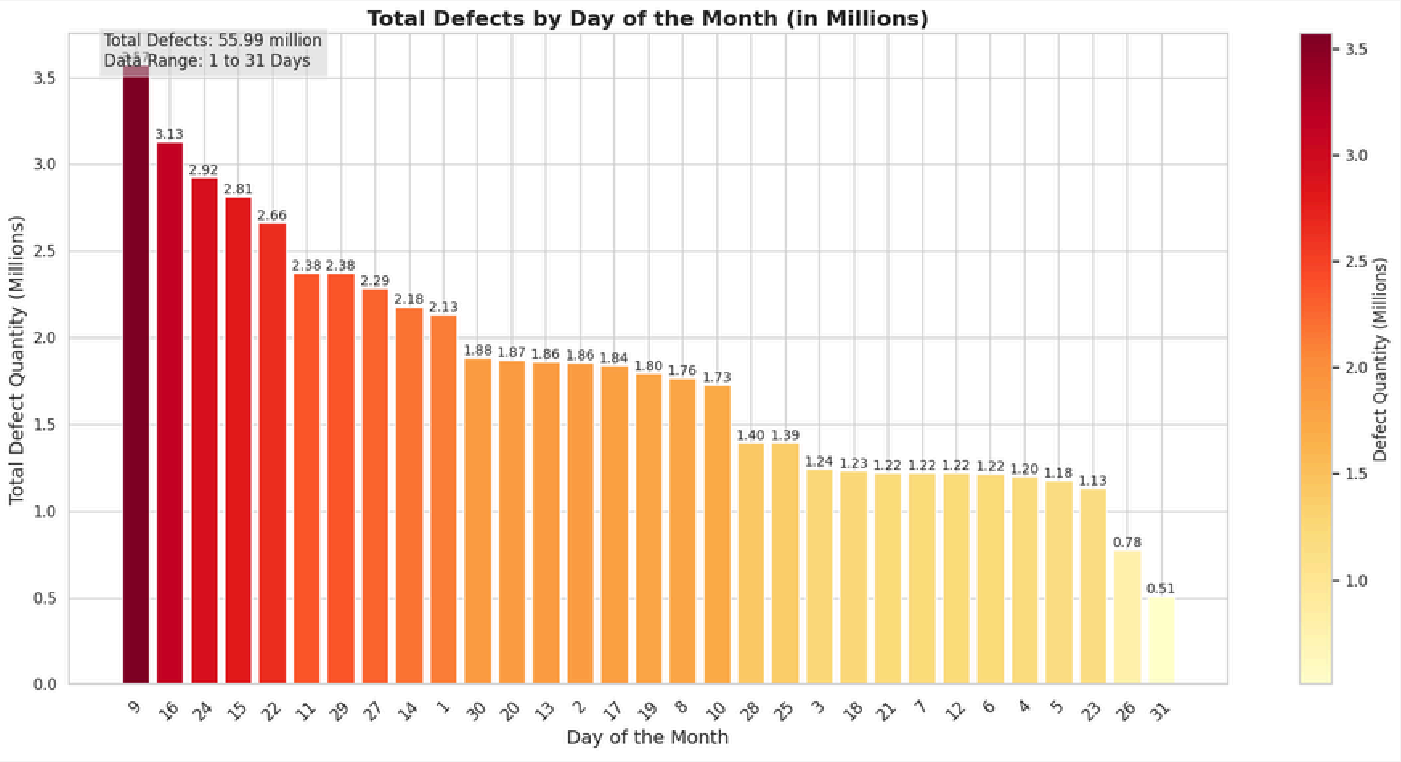


You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

Key Findings:

Defect Quantity Distribution by Day of the Month:

- Both charts present the total number of defects across all days of the month, with a cumulative defect total of 55.99 million units.
- The highest defect quantity occurs on Day 9, with 3.57 million defects, followed by Day 16 with 3.13 million defects, and Day 24 with 2.92 million defects.
- There is a gradual decline in defect quantity as the days progress, with Day 31 showing the lowest defect count at 0.51 million units.

Overall Trend:

- A clear peak in defects is observed around the middle of the month, particularly between Days 9 to 16.
- Defects are relatively higher at the start and middle of the month, decreasing toward the end of the month.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

Unexpected or Interesting Discoveries

Concentration of Defects Mid-Month:

- the highest defect counts are concentrated around the middle of the month. This could suggest issues in the production cycle, perhaps due to process fatigue, equipment maintenance, or raw material fluctuations during this time.

Drastic Drop Toward the End of the Month:

- Days 26 and 31 show unusually low defect quantities compared to the overall month. This could indicate either corrective measures, downtime, or optimized production practices in the last few days of the month.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

Recommendations

Investigate Production Processes on Days 9, 16, and 24:

- The peaks in defect counts on these days warrant further investigation. Understanding the operational or logistical factors contributing to these spikes could help reduce overall defect rates.

Evaluate End-of-Month Processes:

- Analyze why defect rates drop so significantly toward the end of the month, especially on Days 26 and 31. This could reveal effective practices that can be implemented earlier in the month to reduce defect counts.

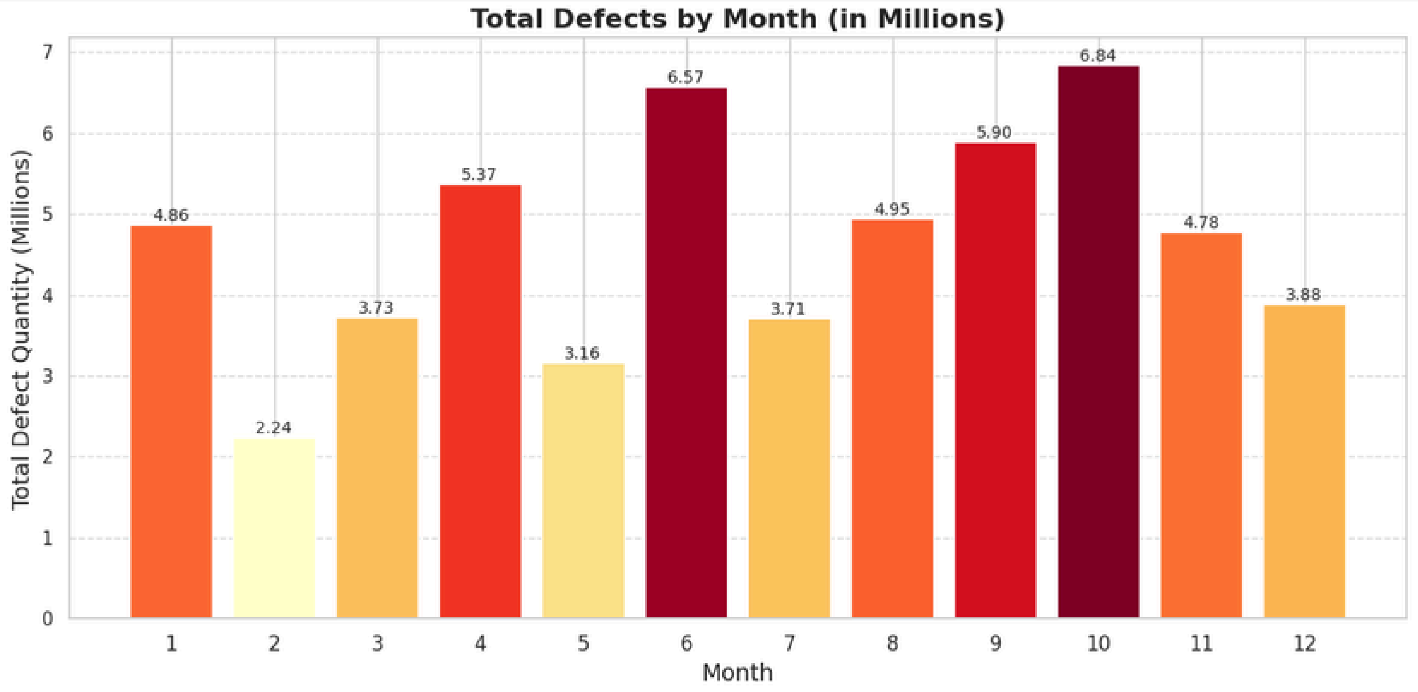
Consider Maintenance or Quality Control Adjustments:

- The mid-month spikes might suggest the need for more regular equipment maintenance or adjustments in quality control protocols to mitigate defect rates during that period.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Month (in Millions)



You can see the Python code used in the Python Notebook

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Month (in Millions)

Key Findings:

Defect Quantity Distribution by Month:

- The chart displays the total defect quantities across 12 months, with noticeable variation in defect amounts.
- October has the highest defect quantity at 6.84 million units, followed closely by June with 6.57 million defects.
- February shows the lowest defect quantity, with only 2.24 million units recorded.

Overall Trend:

- The defects tend to peak in June and October, with significant decreases around February and May.
- After the high in October, there is a general decline in defects toward the end of the year.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Month (in Millions)

Unexpected or Interesting Discoveries

Defect Peaks in Summer and Early Fall:

- The highest defects occurring in June and October are interesting. This might suggest seasonal factors that affect production quality, such as increased production demand or environmental influences like temperature affecting equipment.

Significant Drop in February:

- The low defect count in February is significant. This could be attributed to factors such as lower production levels, fewer working days (due to the short month), or optimized processes during this period.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Month (in Millions)

Recommendations

Investigate High Defect Months:

- October and June stand out as having the highest defect rates. Investigating production processes, equipment maintenance schedules, or raw material quality during these months could help explain the spikes.

Analyze Low Defect Month (February):

- Since February has such a low defect rate, analyzing what is done differently during this month might offer insights into best practices that can be applied year-round.

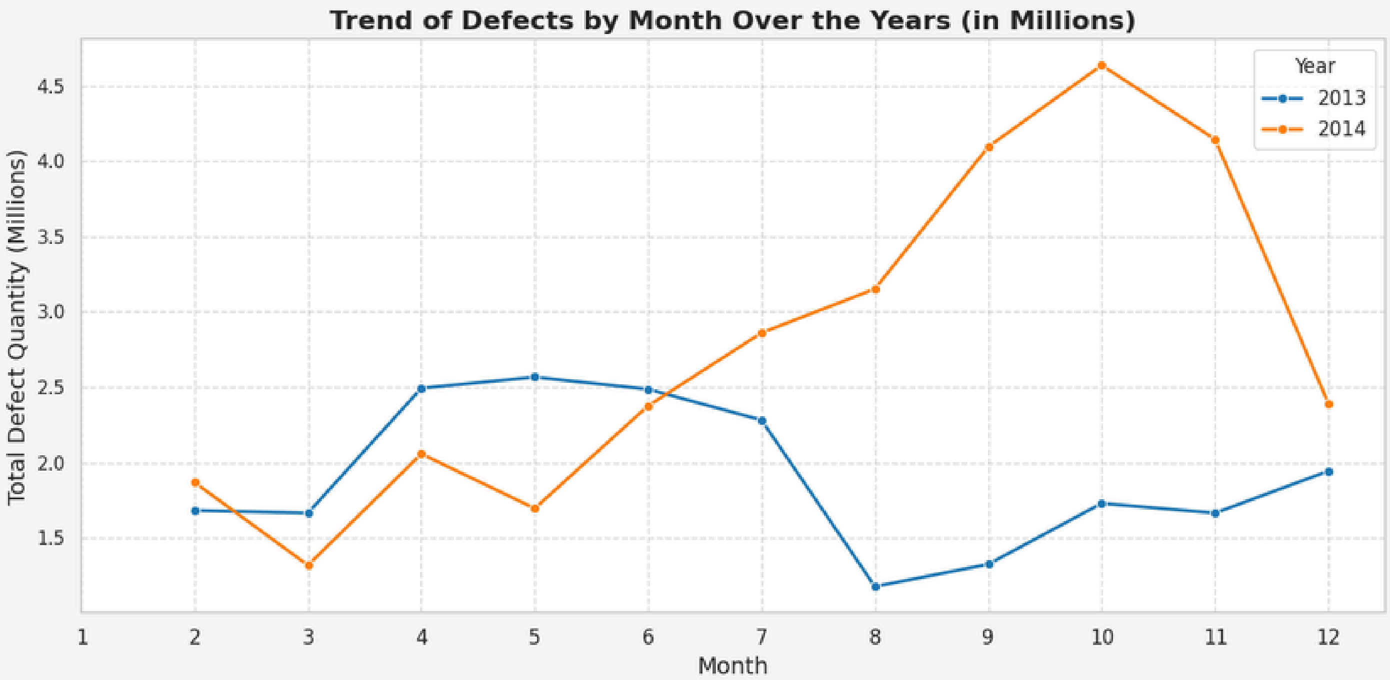
Consider Seasonal Adjustments:

- If environmental or production load factors are contributing to defect spikes in certain months, consider adjusting maintenance schedules, quality checks, or production pace to mitigate these issues.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month Over the Years (in Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month Over the Years (in Millions)

Key Findings:

Trend Comparison Between 2013 and 2014:

- The chart compares the total defect quantities per month for the years 2013 and 2014.
- 2014 shows a significant rise in defect quantities starting from May, peaking in October at 4.5 million defects.
- In contrast, 2013 shows a relatively stable trend, with defects remaining between 1.5 million to 2.5 million, and a significant drop around September.

Overall Trends:

- 2013 had consistent defect quantities throughout the year, peaking modestly around April to June.
- 2014 saw a sharp upward trend starting in April, with defects rising drastically, peaking in October before dropping off again.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month Over the Years (in Millions)

Unexpected or Interesting Discoveries

Steep Increase in Defects for 2014:

- The sharp rise in defect quantities for 2014 is notable, particularly between June and October, which saw a dramatic surge not observed in 2013. This raises questions about changes in production processes, materials, or other external factors that may have contributed to the rise.

Stable Defects for 2013:

- The stability of 2013 suggests more consistent control over production processes or lower external impact factors. The sudden decline in September and the maintenance of low defects for the rest of the year suggests something corrective might have occurred at that point.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month Over the Years (in Millions)

Recommendations

Investigate Defect Surge in 2014:

- Analyze the sharp increase in defects from June to October 2014. Review changes in production, materials, staffing, or external factors during this period.

Compare 2013 and 2014 Production Practices:

- 2013 had more stable defect rates. Compare production strategies between the two years to identify factors that mitigated defects in 2013.

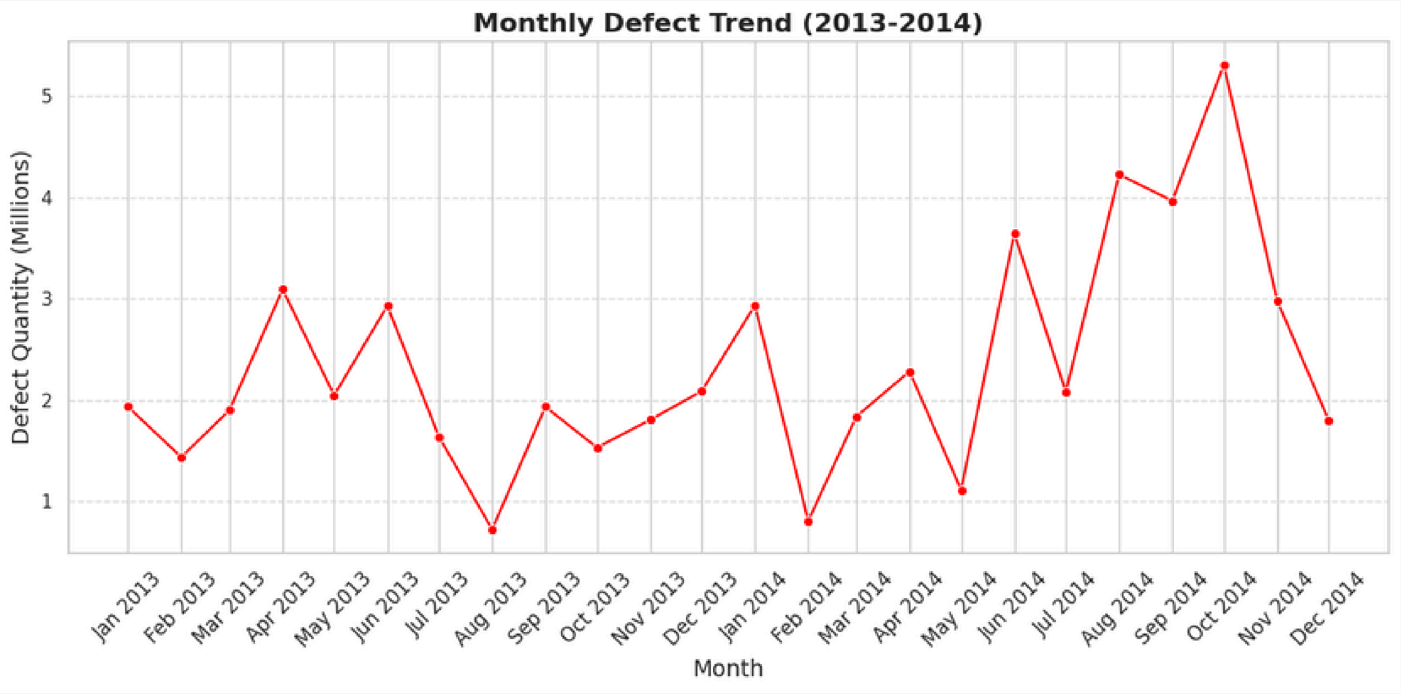
Seasonal or External Influences:

- Examine potential seasonal or market influences behind the defect rise in summer and fall 2014. Adjust quality control schedules to address these trends.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month (2013 - 2014)



You can see the Python code used in the Python Notebook

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month (2013 - 2014)

Key Findings:

Defect Trend Over 2013 and 2014:

- The chart illustrates defect quantities from January 2013 to December 2014. May 2013 and October 2014 show the highest defect levels, peaking at about 3.5 million and 5 million units, respectively. Defect quantities fluctuate significantly, with sharp drops in August 2013 and February 2014.

- Overall Trends:
  - 2013 begins with around 2 million defects, peaking in April and June, then dropping to 1 million in August. In 2014, defect quantities rise sharply, peaking in June, August, and spiking in October to over 5 million, followed by a steep drop in December.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month (2013 - 2014)

Unexpected or Interesting Discoveries

Drastic Defect Spike in Late 2014:

- The rapid rise in defect quantities from June 2014 to the peak in October 2014 is an interesting trend. This might be linked to production scale-ups, seasonal demands, or other external factors during that period.

Defect Decline in August 2013 and February 2014:

- Both August 2013 and February 2014 show marked dips in defect quantities. These might correspond to changes in production schedules, potential downtime, or improvements in quality control practices during these periods.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Trend of Defects by Month (2013 - 2014)

Recommendations

Investigate the Defect Surge in October 2014:

- The significant spike in defects in October 2014 warrants further analysis. Investigating operational changes, shifts in material quality, or process modifications during this time could provide insights into the cause of this spike.

Review Production Practices in 2013:

- Since 2013 shows relatively stable defect rates, reviewing production practices and strategies from that year may reveal valuable lessons to help mitigate the spikes observed in 2014.

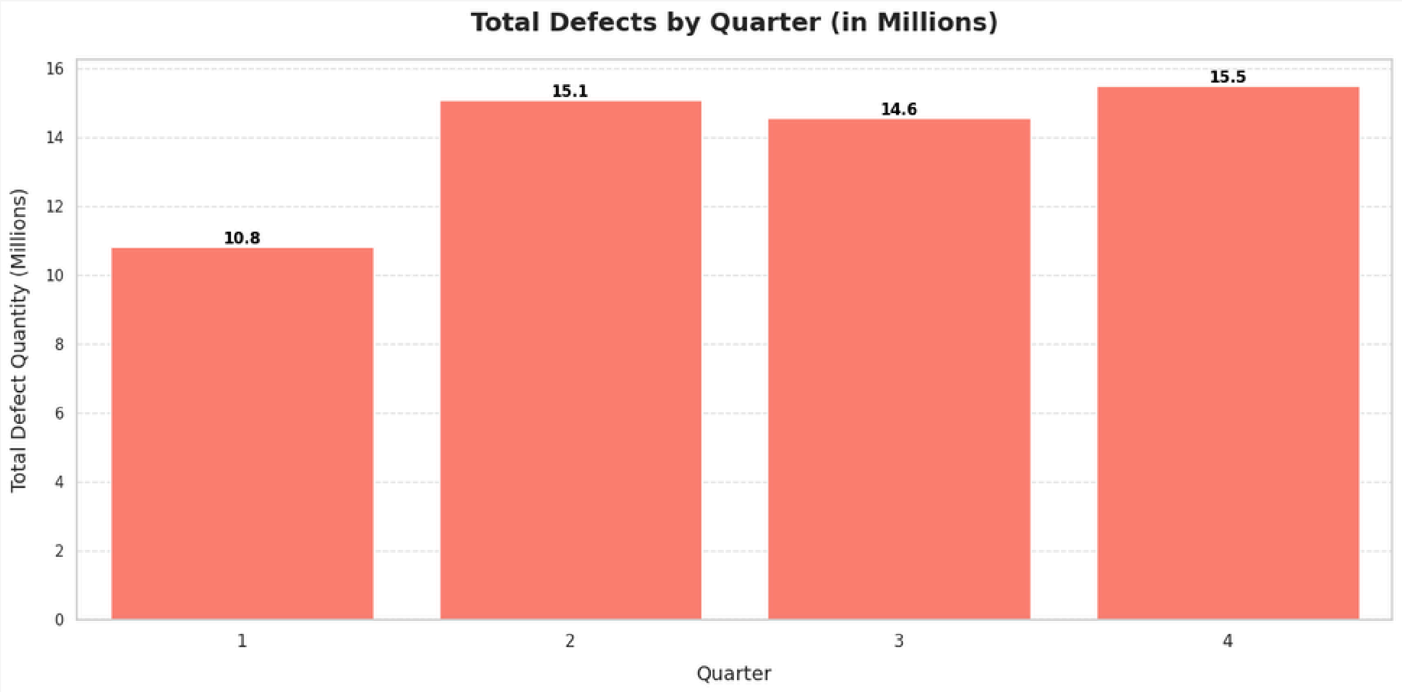
Seasonal and External Influences:

- Given the large fluctuations, it would be beneficial to explore any seasonal or external factors (such as market demand, supply chain issues, or environmental conditions) that could have affected production and defect rates.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Quarter (in Millions)



You can see the Python code used in the
Python Notebook

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Quarter (in Millions)

Key Findings:

- Defect Quantity Distribution by Quarter:
  - The chart shows the total defect quantities across the four quarters of the year.
  - Quarter 4 had the highest defect quantity, reaching 15.50 million units.
  - Quarter 1 shows the lowest total defect quantity at 10.83 million units.
  - Quarters 2 and 3 had similar defect quantities, with 15.10 million and 14.56 million, respectively.

- Overall Trend:
  - There is a noticeable increase in defects from Quarter 1 to Quarter 2, with a peak in Quarter 4.
  - The defect quantities remain relatively high from Quarter 2 through Quarter 4, indicating potential issues in the latter part of the year.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Quarter (in Millions)

Unexpected or Interesting Discoveries

Significant Increase from Quarter 1 to Quarter 2:

- The defect quantities rise sharply from Quarter 1 to Quarter 2 by nearly 40%, which may suggest the introduction of new production processes, increased production demand, or other seasonal influences during that period.

Peak in Quarter 4:

- The rise in defects peaking in Quarter 4 suggests that issues accumulate toward the end of the year, which could be due to a combination of higher production pressure, end-of-year rush, or decreased quality control.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Quarter (in Millions)

Recommendations

Investigate Processes in Quarter 4:

- Quarter 4 has the highest defect rate, so review production schedules and quality control. Check if external pressures, like increased demand, are impacting quality.

Analyze Quarter 2 Spike:

- Review the spike between Quarter 1 and Quarter 2 for changes in production or external factors. This could help prevent future spikes.

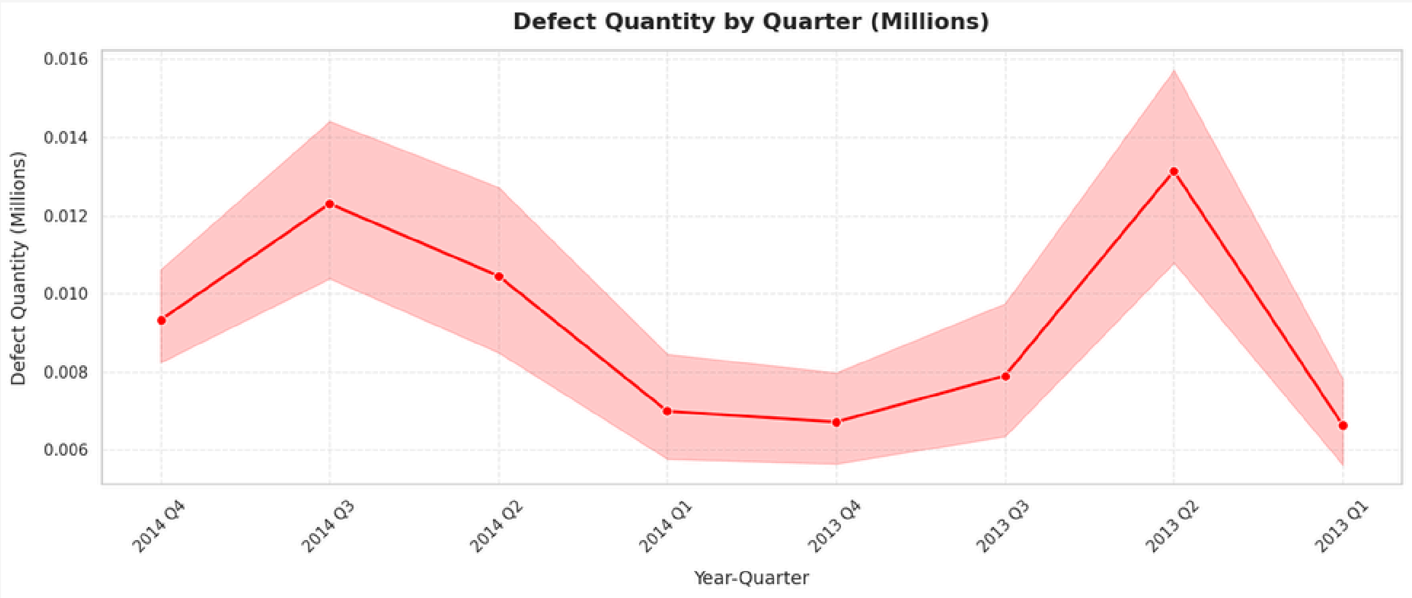
Implement Quality Control Adjustments:

- With high defects in the last three quarters, implement quality control adjustments earlier (starting in Quarter 2) to reduce defect accumulation.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Quarter (in Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

Key Findings:

Defect Quantity Trends by Quarter (2013 to 2014):

- The chart shows defect quantities across several quarters from Q1 2013 to Q4 2014.
- Q3 2013 and Q3 2014 both exhibit the highest defect quantities, peaking at approximately 0.014 million units.
- There is a clear cyclical trend, with defects rising and falling across the quarters.

Overall Trend:

- Defects gradually increased during 2013, peaking in Q3 2013, followed by a drop in Q4 2013 and Q1 2014.
- Defects peaked again in Q3 2014 after a steady rise from Q1 2014. A sharp decline is observed in Q4 2014.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

Unexpected or Interesting Discoveries

Cyclic Peaks in Q3:

- Both 2013 and 2014 experienced their highest defect rates during the third quarter. This cyclicality suggests that external factors, such as seasonal production demand or raw material quality, might be influencing defect rates during this period.

Decline in Early 2014 and Late 2013:

- The decline in defect quantities during Q4 2013 and Q1 2014 is notable, indicating that production or quality control improvements may have occurred during these periods.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defects by Day of the Month (in Millions) Sorted

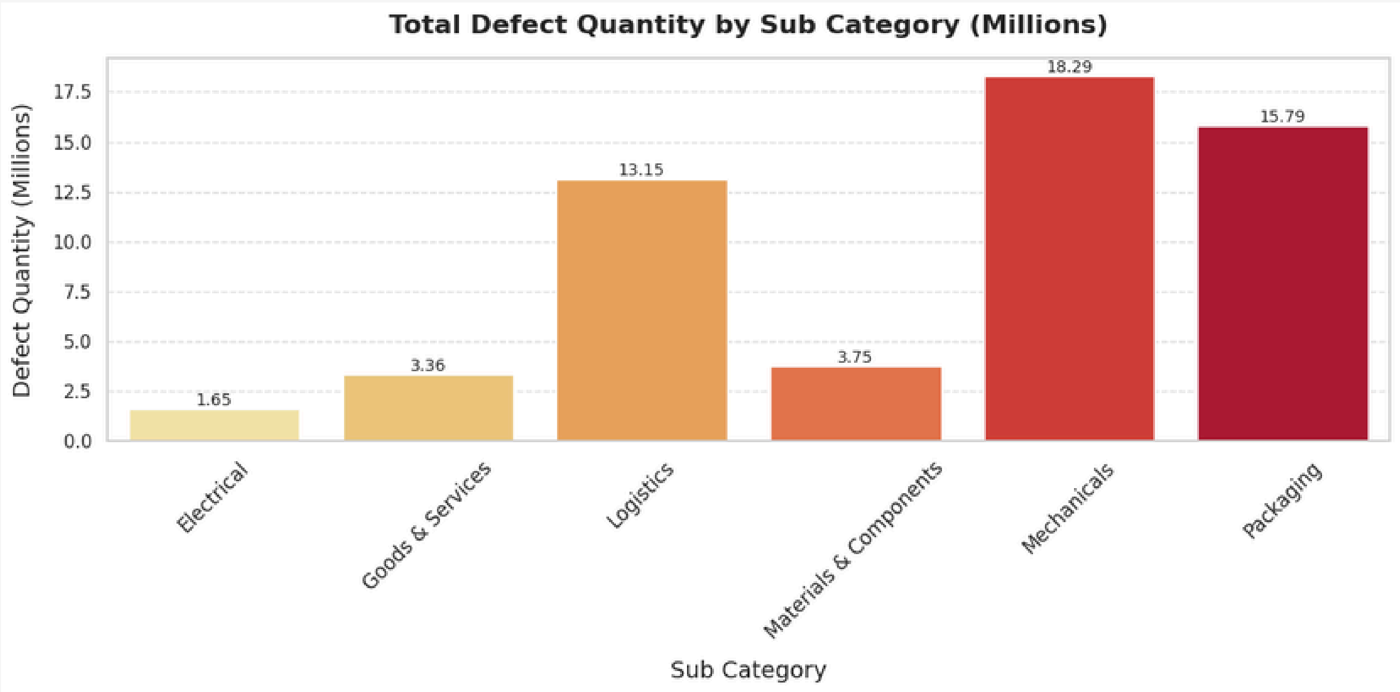
Recommendations

- Investigate the Repeated Q3 Peaks:
  - Analyze production processes, raw material sourcing, and labor conditions during Q3 to identify causes. Consider if seasonal or market demands play a role.
- Review Best Practices from Q1 2014 and Q4 2013:
  - Lower defect rates during these periods suggest effective strategies. Reviewing practices from these quarters may help maintain lower defects year-round.
- Prepare for Cyclical Defect Spikes:
  - Anticipate recurring Q3 peaks by planning quality control adjustments and process optimizations in advance to reduce defect increases.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Sub Category (Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Sub Category (Millions)

Key Findings:

Total Defect Quantity by Subcategory:

- The chart breaks down the total defect quantities by subcategory.
- Mechanicals have the highest defect quantity, with 18.29 million units, followed by Packaging at 15.79 million units.
- The lowest defect quantity is in Electrical subcategory with only 1.65 million units.

Overall Trend:

- Defect quantities are concentrated in the Mechanicals and Packaging subcategories, which together account for a significant proportion of the total defects.
- Logistics contributes 13.15 million defects, while subcategories like Goods & Services and Materials & Components show smaller contributions.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Sub Category (Millions)

Unexpected or Interesting Discoveries

- Disproportionate Defects in Mechanicals and Packaging:
    - Mechanicals and Packaging combined contribute more than 50% of the total defects. This concentration suggests that these areas may have systemic issues in production or quality control that need to be addressed.

- Minimal Defects in Electrical:
    - The Electrical subcategory has a surprisingly low defect quantity compared to others, suggesting that processes or materials in this category are more reliable, or production volume might be lower.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Sub Category (Millions)

Recommendations

- Focus on Mechanicals and Packaging Subcategories:
  - Prioritize investigating these subcategories due to their high defect rates. Review production processes, equipment maintenance, or supplier quality.

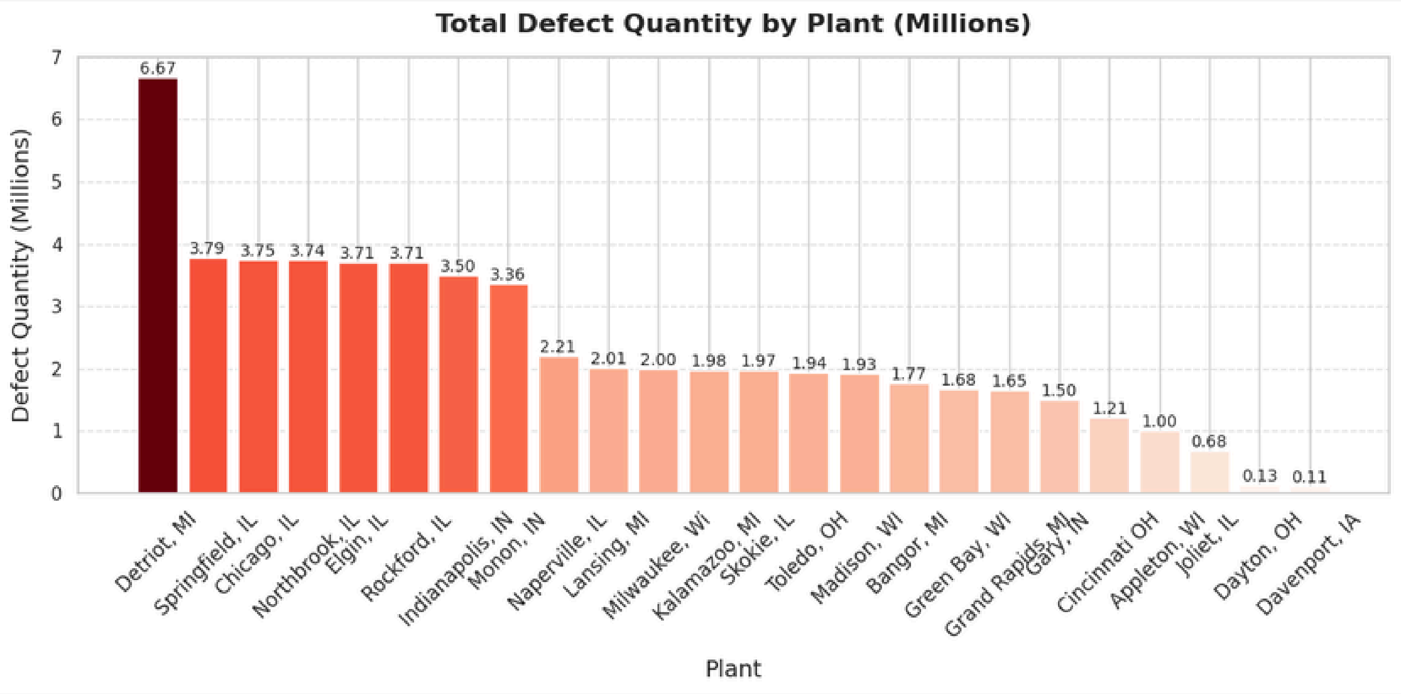
- Leverage Best Practices from Electrical:
  - Analyze the Electrical subcategory's lower defect rates. Apply successful practices to other areas to reduce defects.

- Investigate Logistics Defects:
  - Logistics, with 13.15 million defects, should be reviewed for transportation, storage, or handling issues that may be causing inefficiencies.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Plant (in Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Plant (in Millions)

Key Findings:

Total Defect Quantity by Plant:

- The chart shows the total defect quantities across various plants.
- Detroit, MI stands out with the highest defect quantity at 6.67 million units, far exceeding the other plants.
- Plants like Springfield, IL, Chicago, IL, Northbrook, IL, and Elgin, IL have defect quantities between 3.71 million and 3.79 million units.
- The plants with the lowest defect quantities include Dayton, OH and Davenport, IA, with only 0.13 million and 0.11 million units, respectively.

Overall Trend:

- There is a sharp contrast between Detroit, MI, and the other plants in terms of defect quantities.
- Most of the plants fall within the 1 million to 3.75 million defect range, with a few outliers at both ends.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Plant (in Millions)

Unexpected or Interesting Discoveries

Detroit, MI, as a Major Outlier:

- The Detroit plant has defect quantities nearly double the amount of the next highest plant, indicating that there may be significant production issues or quality control problems specific to this location.

Large Defect Quantity Differences Between Plants:

- The difference between the top and bottom-performing plants is substantial, with Detroit having more than 60 times the defects of Davenport, IA. This variation suggests that there may be differing processes, equipment, or operational challenges across these plants.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Plant (in Millions)

Recommendations

Investigate the Detroit Plant:

- With 6.67 million defects, the Detroit plant is an outlier. Review its operations, quality control, staffing, and production methods to identify root causes.

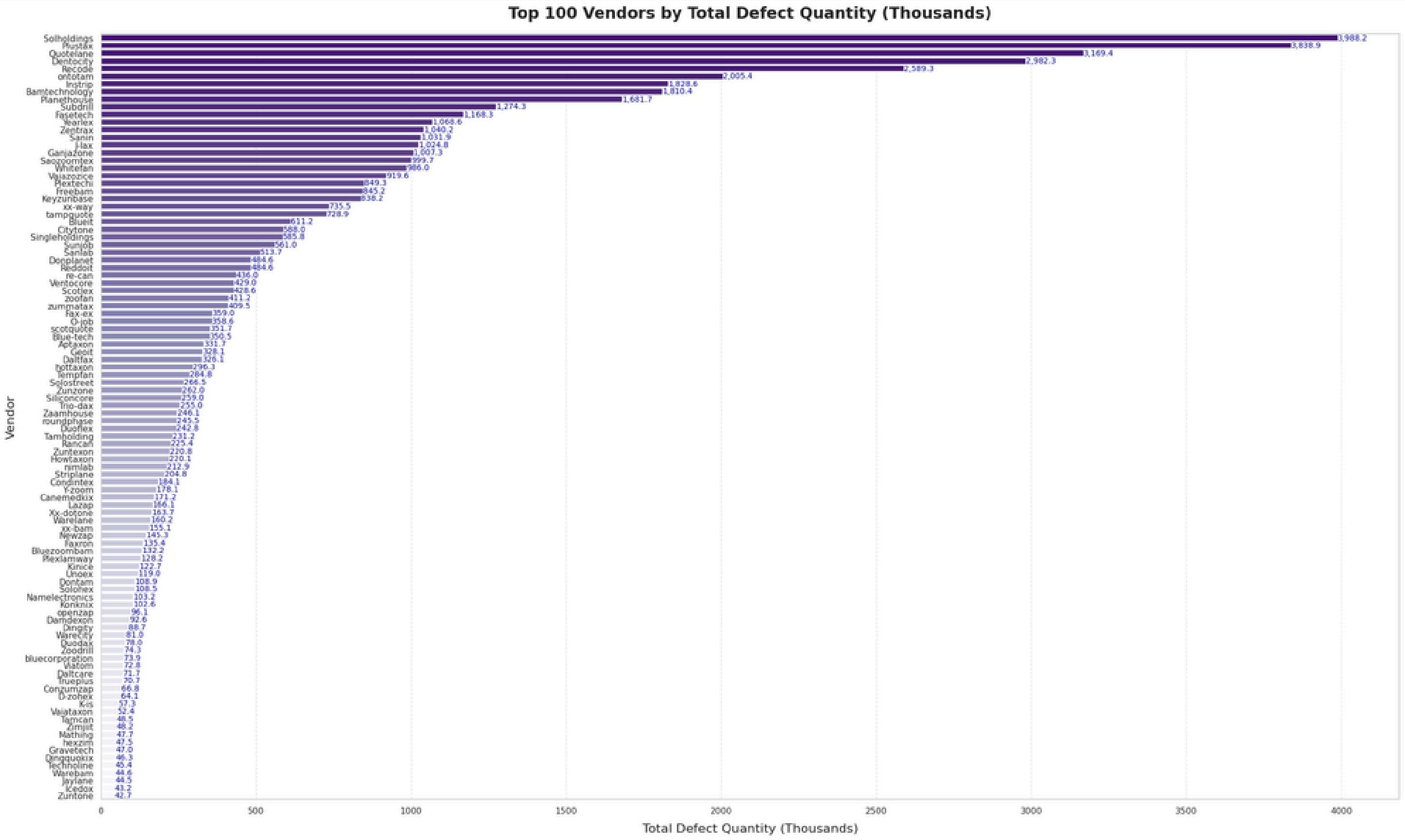
- Analyze Best Practices from Low-Defect Plants:
  - Study best practices at Dayton, OH, and Davenport, IA plants, which have lower defects. These practices could be applied to other underperforming plants.

- Standardize Quality Control Across Plants:
  - The variation in defects suggests inconsistent quality control. Standardizing procedures and conducting regular audits can help reduce defect rates across all plants.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Vendor (Thousands)

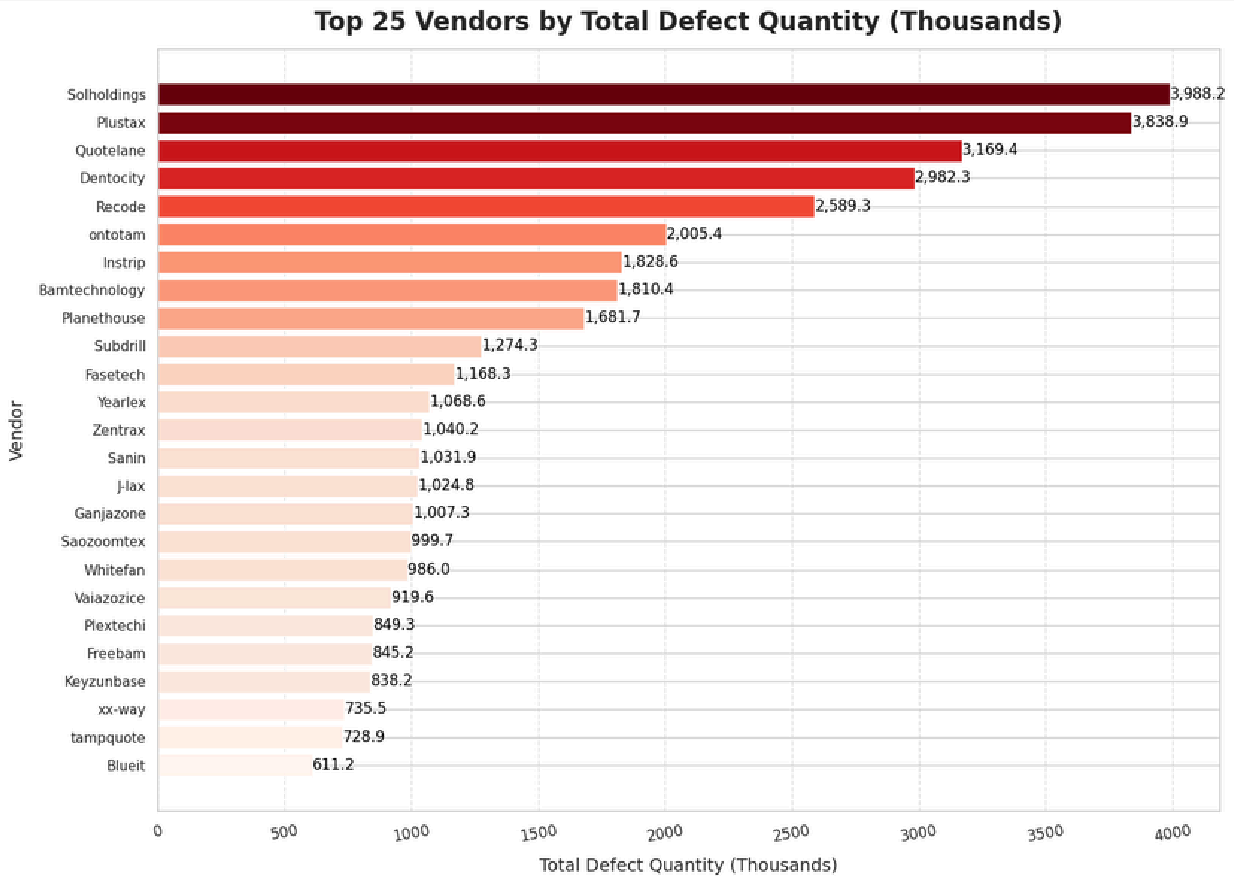


You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 25 Vendors by Total Defect Quantity (in Thousands)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Vendor (Thousands)

Key Findings:

otal Defect Quantity by Vendor:

- The chart displays the total defect quantity by vendor, measured in thousands.
- The top vendors with the highest defect quantities are:
  - SolHoldings with 3988.2 thousand defects.
  - Plastas with 3838.9 thousand defects.
  - Quefluence with 3169.4 thousand defects.
  - Bantecology with 2589.3 thousand defects.
- Vendors like Zenntor and Rzcode show significantly lower defect quantities, with 43.1 thousand and 42.7 thousand defects, respectively.

- Overall Trend:
  - There is a large disparity between the top few vendors and the rest of the vendors. The highest defect quantities are concentrated among a small number of vendors, while the majority of vendors have significantly lower defect totals.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Vendor (Thousands)

Unexpected or Interesting Discoveries

High Concentration of Defects in a Few Vendors:

- A small number of vendors, such as SolHoldings and Plastas, account for the vast majority of defects. This suggests that a disproportionate amount of the total defects may be originating from just a few suppliers, potentially indicating recurring issues with these vendors.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Vendor (Thousands)

Recommendations

Focus on Top Defect Vendors:

- Vendors like SolHoldings, Plastas, and Quefluence should be investigated thoroughly. These suppliers are contributing the largest number of defects, and addressing their issues could significantly reduce the overall defect quantity.

Consider Best Practices from Low-Defect Vendors.

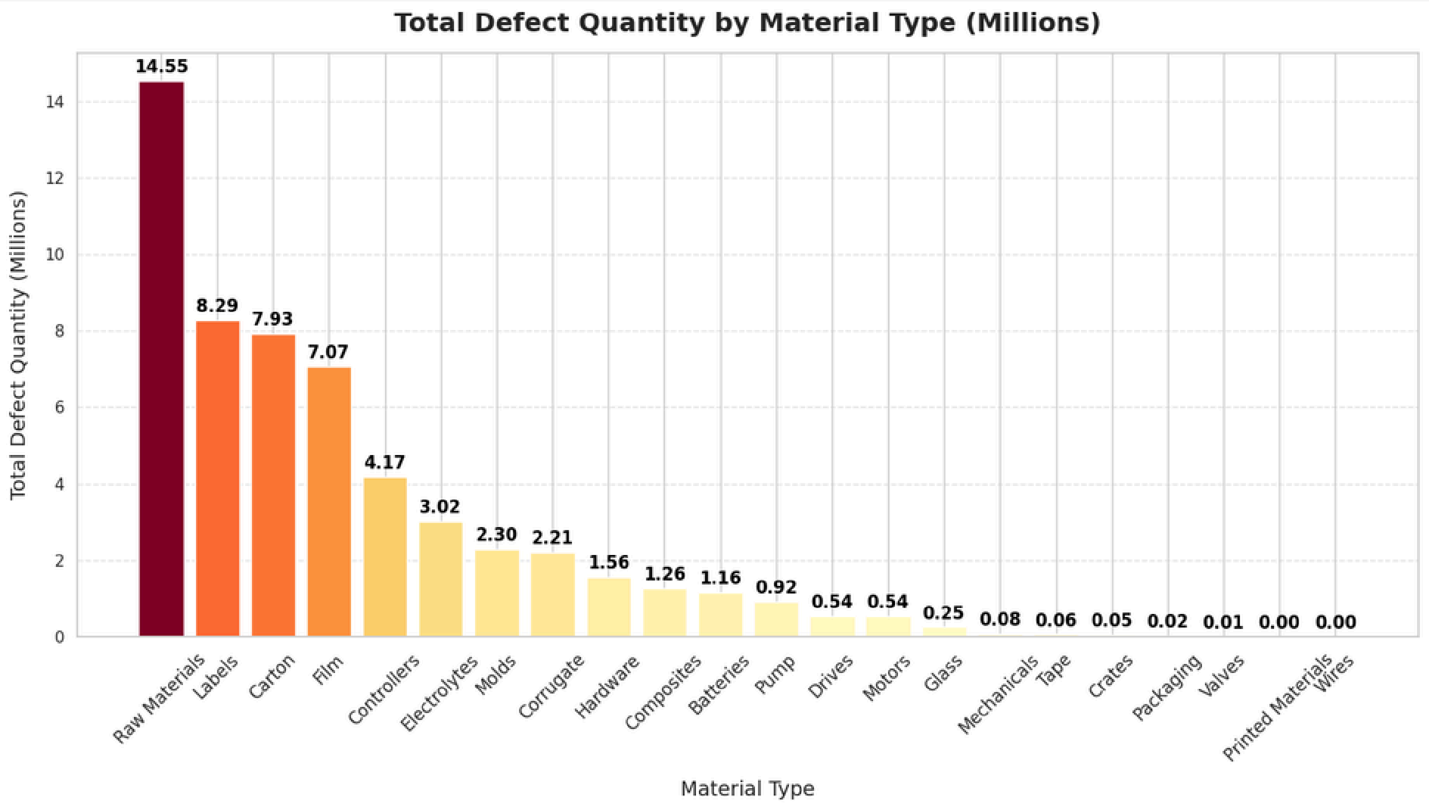
Re-Evaluate Contracts or Supplier Relationships:

- Given the concentration of defects among the top vendors, it may be worth considering renegotiations or reevaluations of contracts with these suppliers if their defect rates remain high after investigation and corrective measures.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Material Type (in Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Material Type (in Millions)

Key Findings:

Total Defect Quantity by Material Type:

- The chart shows the defect quantities for different material types.
- Raw Materials account for the highest defect quantity at 14.55 million units, followed by Labels with 8.29 million units and Carton at 7.93 million units.
- Lower defect quantities are seen in categories like Tape (0.06 million), Packaging (0.05 million), and Printed Materials (0.01 million).

Overall Trend:

- Defect quantities are highly concentrated in Raw Materials, Labels, and Carton, which together make up a large portion of the overall defect total.
- The remaining material types show a sharp decline in defect quantities, with many of them contributing less than 1 million units each.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Material Type (in Millions)

Unexpected or Interesting Discoveries

Significant Defects in Raw Materials:

- The Raw Materials category shows a very high defect rate, almost double that of the next highest category (Labels). This suggests potential quality control issues or inconsistencies in the sourcing or handling of raw materials.

Negligible Defects in Some Material Types:

- Certain material types, such as Tape, Packaging, and Printed Materials, show minimal defects. These categories either have more stringent quality control measures in place or may represent a smaller volume of production.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Material Type (in Millions)

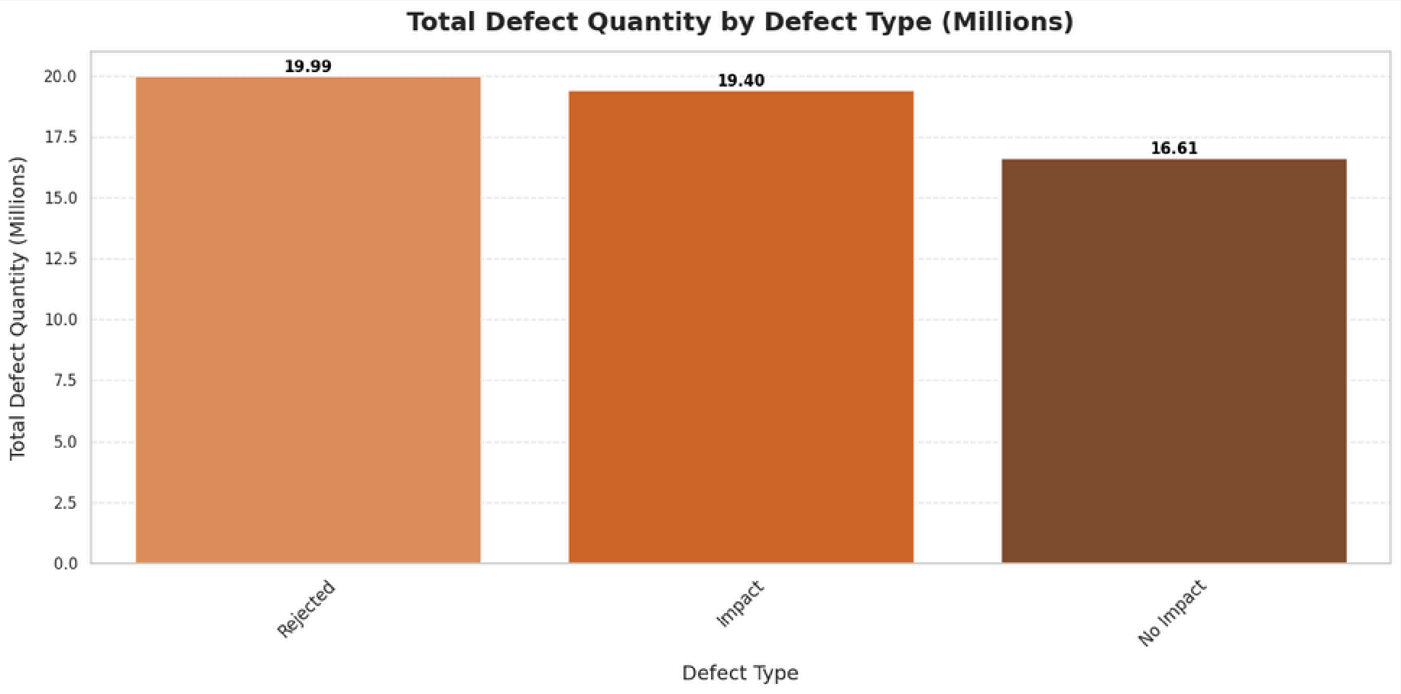
Recommendations

- Investigate Raw Materials for Quality Issues:
  - Review suppliers, sourcing, and quality control in Raw Materials to reduce defect rates, which could significantly improve overall quality.
- Focus on Labels and Carton:
  - Assess production processes and quality measures in Labels and Carton to identify inefficiencies and lower defect rates.
- Leverage Best Practices from Low-Defect Categories:
  - Analyze low-defect categories like Tape and Packaging to apply successful strategies to high-defect areas like Raw Materials and Carton.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Defect Type (Millions)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Defect Type (Millions)

Key Findings:

Total Defect Quantity by Defect Type:

- The chart displays the total defect quantities classified by defect type.
- Rejected defects account for the highest total at 19.99 million units, followed closely by Impact defects at 19.40 million units.
- No Impact defects are the lowest, with 16.61 million units.

Overall Trend:

- There is a relatively balanced distribution of defects across the three categories, with all types contributing significantly to the total defect count.
- The difference between the highest category (Rejected) and the lowest (No Impact) is not drastic, showing that all defect types play a crucial role in the overall defect count.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Defect Type (Millions)

Unexpected or Interesting Discoveries

- High Levels of Rejected and Impact Defects:
  - Both Rejected and Impact defects are quite high, indicating that a large proportion of the total defects may have a significant impact on production or quality.
  - The relatively close numbers between these two categories suggest that efforts to reduce defects should address both areas simultaneously, as both contribute nearly equally to the overall defect count.

- Moderate No Impact Defects:
  - Although No Impact defects are the lowest in terms of total quantity, 16.61 million units is still substantial. These defects may not affect quality or function directly, but they represent inefficiencies in the process that could be reduced further.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity by Defect Type (Millions)

Recommendations

Focus on Reducing Rejected Defects:

- As Rejected defects are the largest category, addressing them can quickly improve quality and reduce waste. Investigate root causes and implement targeted improvements.

Simultaneously Address Impact Defects:

- Since Impact defects are almost as common, include measures to reduce them as well. Consider enhancing quality control or adjusting production processes.

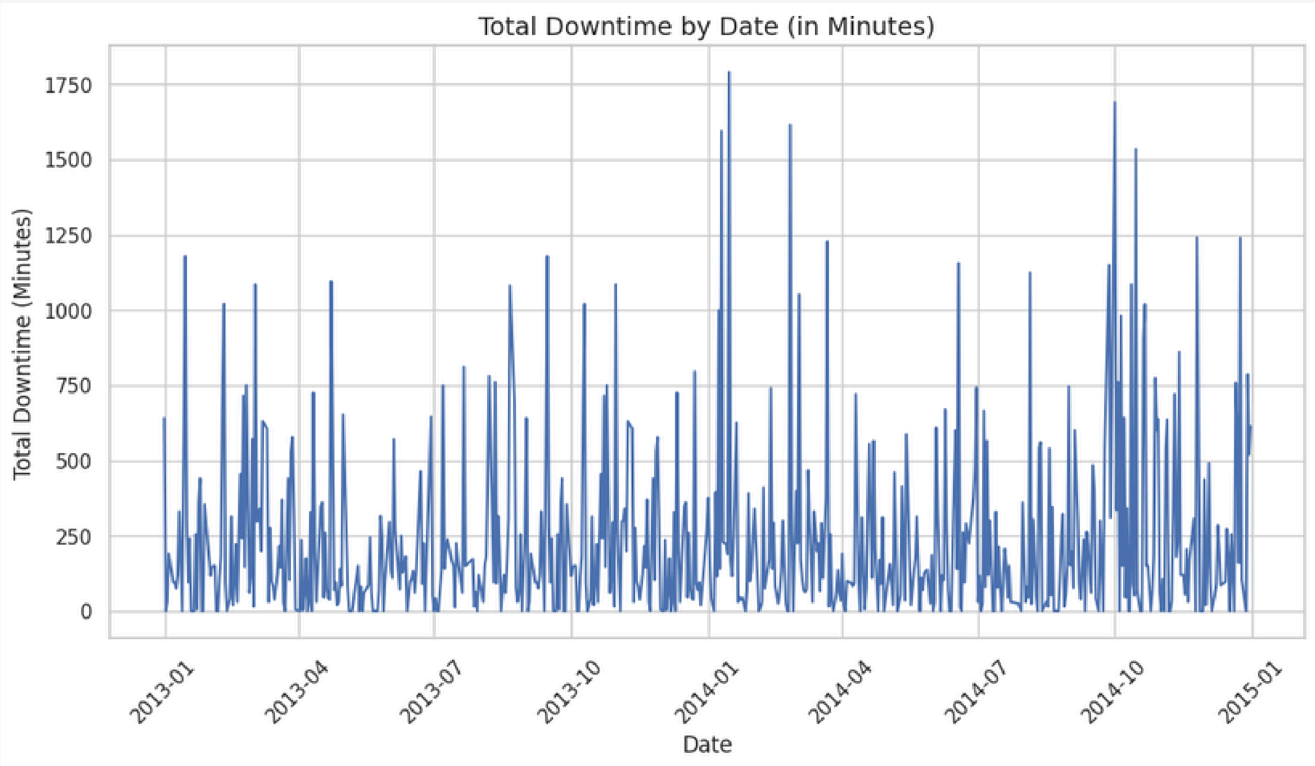
Investigate Sources of No Impact Defects:

- Though No Impact defects don’t affect functionality, they indicate inefficiencies. Investigate their sources to optimize production and reduce waste.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Date (in Minutes)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Date (in Minutes)

Key Findings:

Total Downtime by Date (in Minutes):

- The chart shows the total downtime across dates from 2013 to 2015.
- Downtime fluctuates significantly, with several sharp spikes exceeding 1000 minutes on certain days.
- The highest downtime spikes occur around the beginning of 2014 and later toward the end of 2014, with some values reaching close to 1750 minutes.

Overall Trend:

- Downtime appears irregular, with periods of lower downtime punctuated by occasional large spikes.
- There seems to be an increase in the frequency of downtime spikes toward the end of 2014, suggesting potential operational or maintenance issues.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Date (in Minutes)

Unexpected or Interesting Discoveries

Large Spikes in Downtime:

- The frequent spikes in early 2014 and late 2014 are unexpected. These could be due to specific operational issues, maintenance events, or equipment failures that occurred in those time frames.

Relatively Stable Periods:

- While spikes are prominent, there are also several periods of low and stable downtime, indicating that operations were running more smoothly at certain points in mid-2013 and mid-2014.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Date (in Minutes)

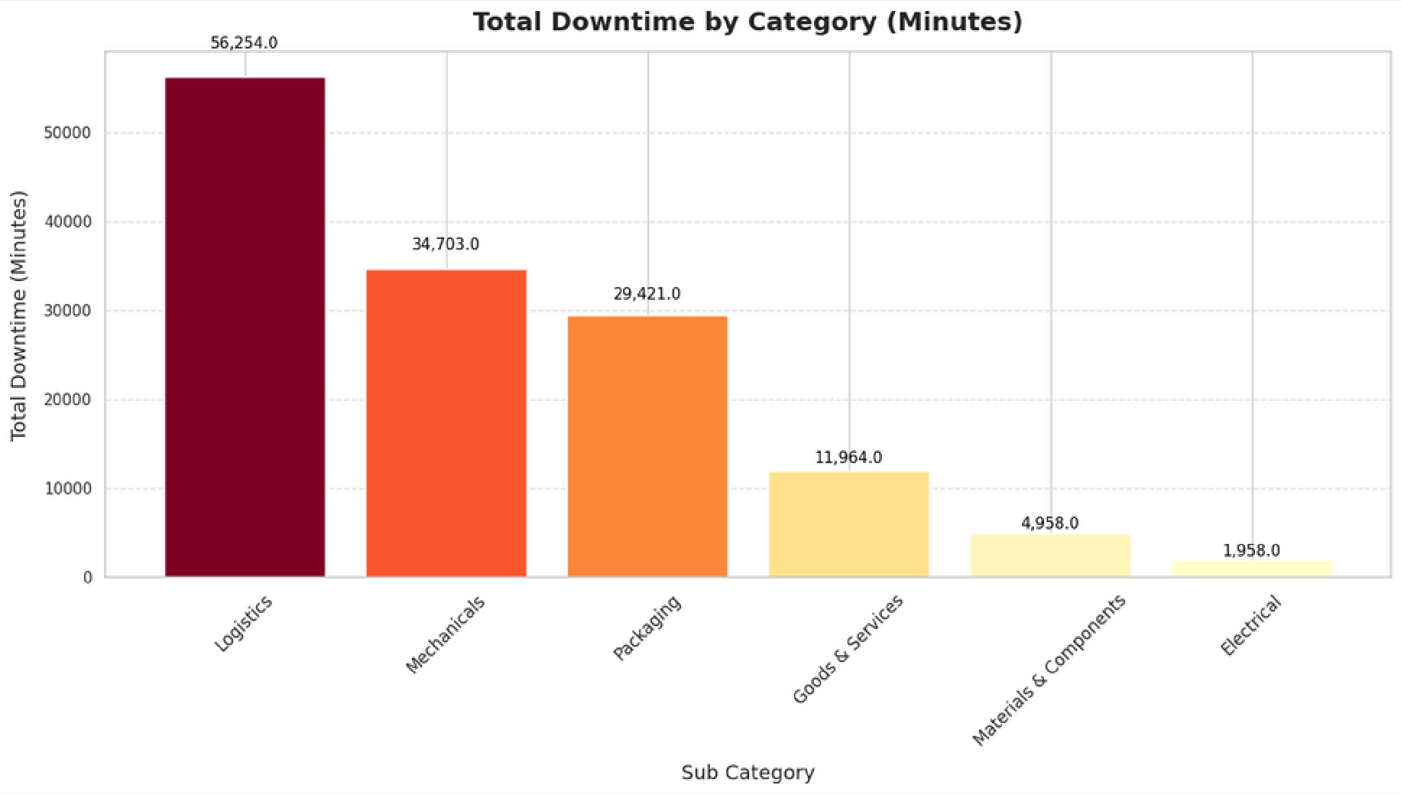
Recommendations

- Investigate Spike Causes in Early and Late 2014:
  - Examine the major spikes in downtime during early and late 2014. Check maintenance logs, equipment failures, and operational disruptions that may have caused these events.
- Improve Preventative Maintenance:
  - Sudden downtimes suggest preventative maintenance needs improvement. Implement a more proactive schedule to reduce large spikes.
- Monitor for Patterns:
  - Identify patterns in both high and low downtime periods. Analyzing what works during stable periods may help minimize downtime during volatile times.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Category (in Minutes)



You can see the Python code used in the
[Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Category (in Minutes)

Key Findings:

- Total Downtime by Category (in Minutes):
  - Logistics is the category with the highest downtime, recording 56,254 minutes, which is significantly more than other categories.
  - Mechanicals and Packaging follow with 34,703 minutes and 29,421 minutes, respectively.
  - The categories with the lowest downtime include Materials & Components and Electrical .

Overall Trend:

- The majority of downtime is concentrated in Logistics, Mechanicals, and Packaging, which together account for the bulk of downtime across categories.
- Categories like Goods & Services, Materials & Components, and Electrical contribute relatively little to total downtime.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Category (in Minutes)

Unexpected or Interesting Discoveries

High Downtime in Logistics:

- Logistics has the highest downtime, far exceeding any other category. This suggests there may be significant inefficiencies or operational issues in the logistics process, such as delays in transportation, inventory management, or warehousing.

Low Downtime in Electrical:

- Electrical downtime is very low, at only 1,958 minutes, indicating that equipment-related issues or electrical downtimes are not a major cause of disruption.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Category (in Minutes)

Recommendations

- Investigate Downtime Causes in Logistics:
  - Logistics has the highest downtime. Analyze root causes like supply chain delays, transportation inefficiencies, or inventory issues.

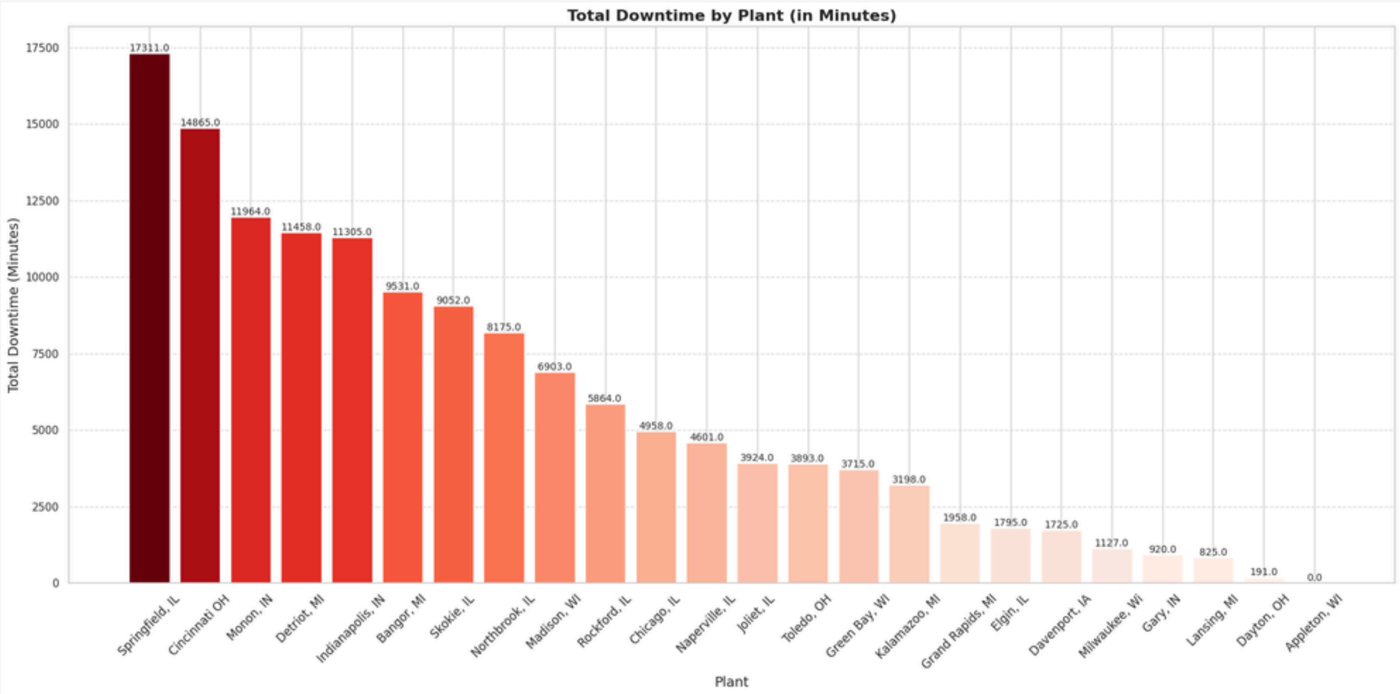
- Focus on Mechanicals and Packaging:
  - Evaluate bottlenecks, equipment failures, or process inefficiencies in Mechanicals and Packaging to reduce downtime.

- Monitor Low Downtime Areas for Best Practices:
  - Study low-downtime categories like Electrical and Materials & Components for strategies to apply in high-downtime areas like Logistics and Mechanicals.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Plant (in Minutes)



You can see the Python code used in the [Python Notebook]

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= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Plant (in Minutes)

Key Findings:

Total Downtime by Plant (in Minutes):

- The chart shows the total downtime across various plants, measured in minutes.
- Springfield, IL has the highest downtime, recording 17,311 minutes, followed by Cincinnati, OH at 14,865 minutes and Monon, IN with 11,964 minutes.
- The plant with the lowest downtime is Appleton, WI, with 0 minutes recorded, while Dayton, OH and Lansing, MI also have relatively low downtime of 191 minutes and 825 minutes, respectively.

Overall Trend:

- Downtime is highly concentrated in a few key plants, with Springfield, IL and Cincinnati, OH being responsible for a large portion of the total downtime.
- The majority of plants have downtime under 10,000 minutes, with a few notable outliers on the higher end of the scale.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Plant (in Minutes)

Unexpected or Interesting Discoveries

High Downtime in Springfield and Cincinnati:

- Springfield, IL, and Cincinnati, OH, stand out as significant contributors to downtime. The gap between these plants and the others is substantial, suggesting operational or logistical challenges that need to be addressed.

Appleton, WI, and Other Low-Downtime Plants:

- Appleton, WI had no recorded downtime, indicating exceptionally smooth operations, while other plants like Dayton, OH and Lansing, MI also performed well with minimal downtime. These plants could serve as benchmarks for best practices in operational efficiency.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Plant (in Minutes)

Recommendations

Investigate Downtime in High-Impact Plants:

- Prioritize plants like Springfield, IL, Cincinnati, OH, and Monon, IN to identify downtime causes—maintenance issues, supply chain delays, or inefficiencies.

Implement Best Practices from Low-Downtime Plants:

- Study plants like Appleton, WI, and Dayton, OH for best practices to reduce downtime in other facilities.

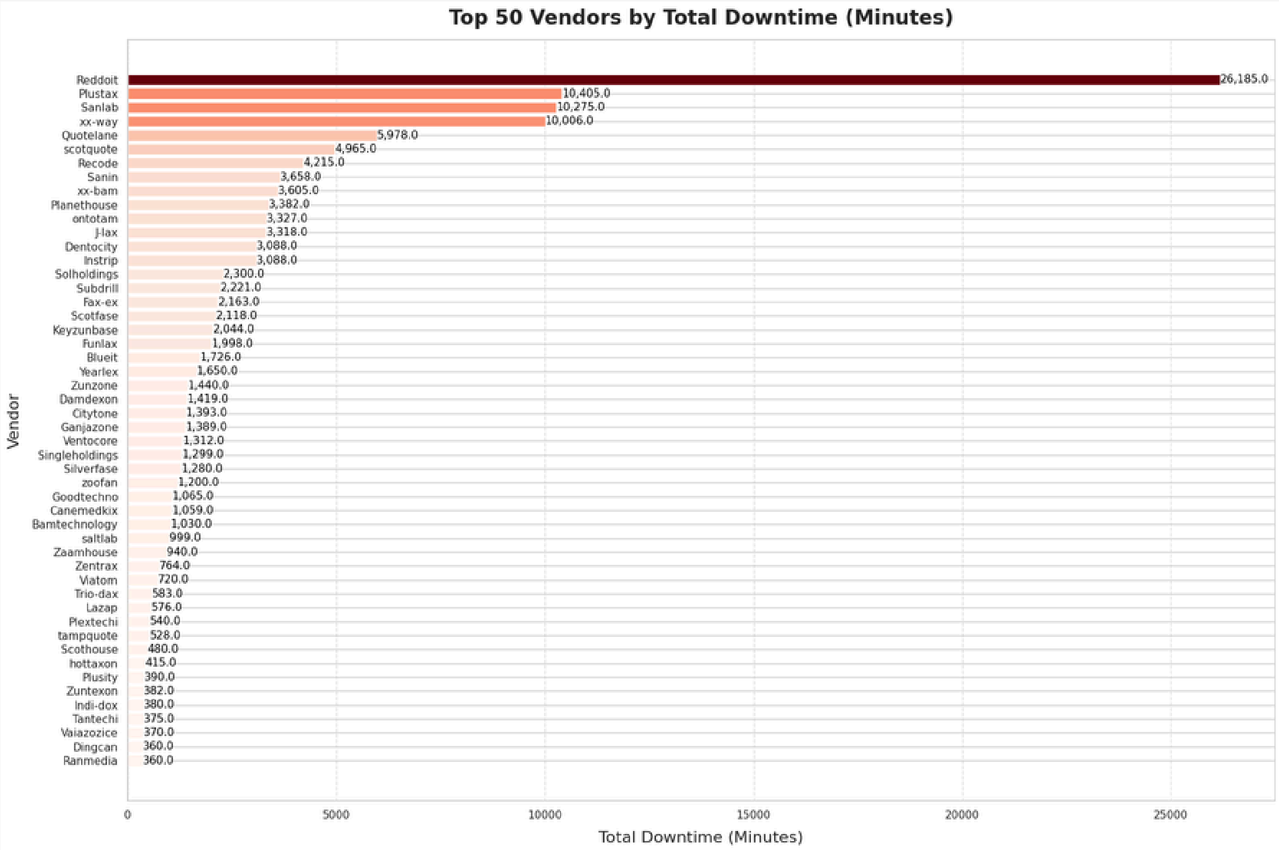
Optimize Maintenance and Operations in High-Downtime Facilities:

- Implement stricter maintenance schedules and improve workflows in the top 5 high-downtime plants to boost overall efficiency.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Total Downtime (in Minutes)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Total Downtime (in Minutes)

Key Findings:

Total Downtime by Material Type (in Minutes):

- Corrugate is the material type with the highest downtime, totaling 53,036 minutes—more than double the downtime of the next highest material.
- Raw Materials follows with 23,928 minutes, and Carton ranks third with 12,869 minutes.
- Materials like Tape, Crates, Packaging, Printed Materials, Valves, and Wires report 0 downtime.

- Overall Trend:
  - Downtime is heavily concentrated in a few material types, with Corrugate and Raw Materials being the dominant contributors.
  - The rest of the material types contribute much less downtime, with most recording below 10,000 minutes.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Total Downtime (in Minutes)

Unexpected or Interesting Discoveries

Significant Downtime in Corrugate:

- Corrugate stands out with exceptionally high downtime, suggesting that this material type faces considerable operational or supply chain challenges. Its downtime is more than double that of the second-highest contributor, Raw Materials.

Zero Downtime in Multiple Materials:

- It's interesting to note that several material types, including Tape, Crates, and Packaging, show no recorded downtime, suggesting efficient management of these materials.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Total Downtime (in Minutes)

Recommendations

Investigate Corrugate for Root Causes:

- Review downtime causes in Corrugate—possible issues include supply chain delays, handling inefficiencies, or equipment problems. Resolving these could significantly reduce overall downtime.

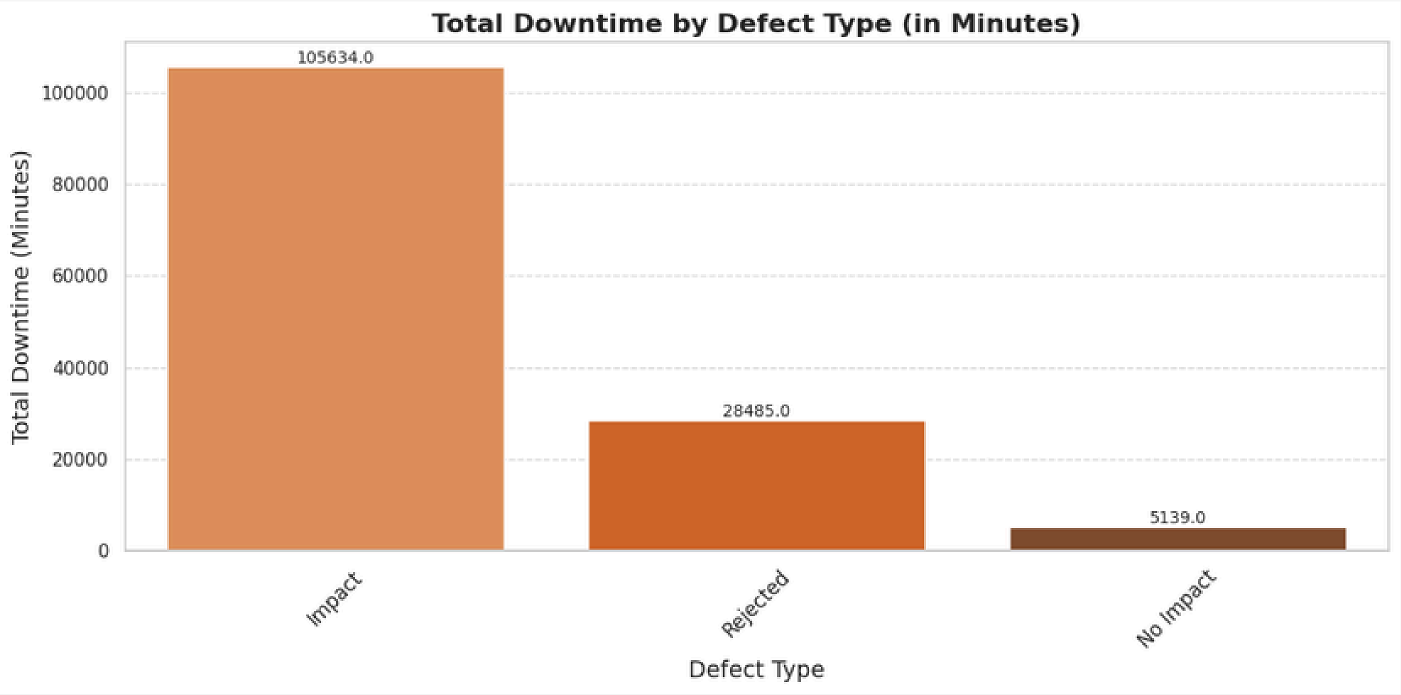
- Review Practices in Raw Materials and Carton:
  - Assess handling, sourcing, and processing of Raw Materials and Carton. Improvements here can help cut downtime further.

- Leverage Best Practices from Zero-Downtime Materials:
  - Study zero-downtime materials like Tape and Packaging for strategies to apply to high-downtime areas.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Defect Type (in Minutes)



You can see the Python code used in the Python Notebook

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Defect Type (in Minutes)

Key Findings:

Total Downtime by Defect Type (in Minutes):

- Impact defects account for the highest downtime, totaling 105,634 minutes, which is far greater than the downtime caused by Rejected defects and No Impact defects.
- Rejected defects are responsible for 28,485 minutes of downtime.
- No Impact defects account for the least downtime, at 5,139 minutes.

Overall Trend:

- Downtime is predominantly driven by Impact defects, which represent the vast majority of downtime.
- Rejected defects also contribute significantly, but to a much lesser degree than Impact defects.
- No Impact defects contribute minimal downtime, as expected based on their classification.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Defect Type (in Minutes)

Unexpected or Interesting Discoveries

Substantial Downtime Due to Impact Defects:

- The downtime caused by Impact defects is overwhelmingly higher than the other types. This suggests that defects classified as Impact have a significantly disruptive effect on operations, causing prolonged periods of downtime.

Relatively Low Downtime from No Impact Defects:

- As expected, No Impact defects contribute minimal downtime, as these defects likely do not interfere significantly with operations or production.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Defect Type (in Minutes)

Recommendations

- Investigate Causes of Impact Defects:
    - Since Impact defects cause the most downtime, investigate root causes and common factors to reduce their frequency and severity.

- Continue Monitoring Rejected Defects:
    - While less disruptive, Rejected defects still cause significant downtime. Review rejection criteria and identify areas for improvement.

- Maintain Efficiency in No Impact Defects:
    - Continue monitoring No Impact defects to ensure they remain a minimal disruption.

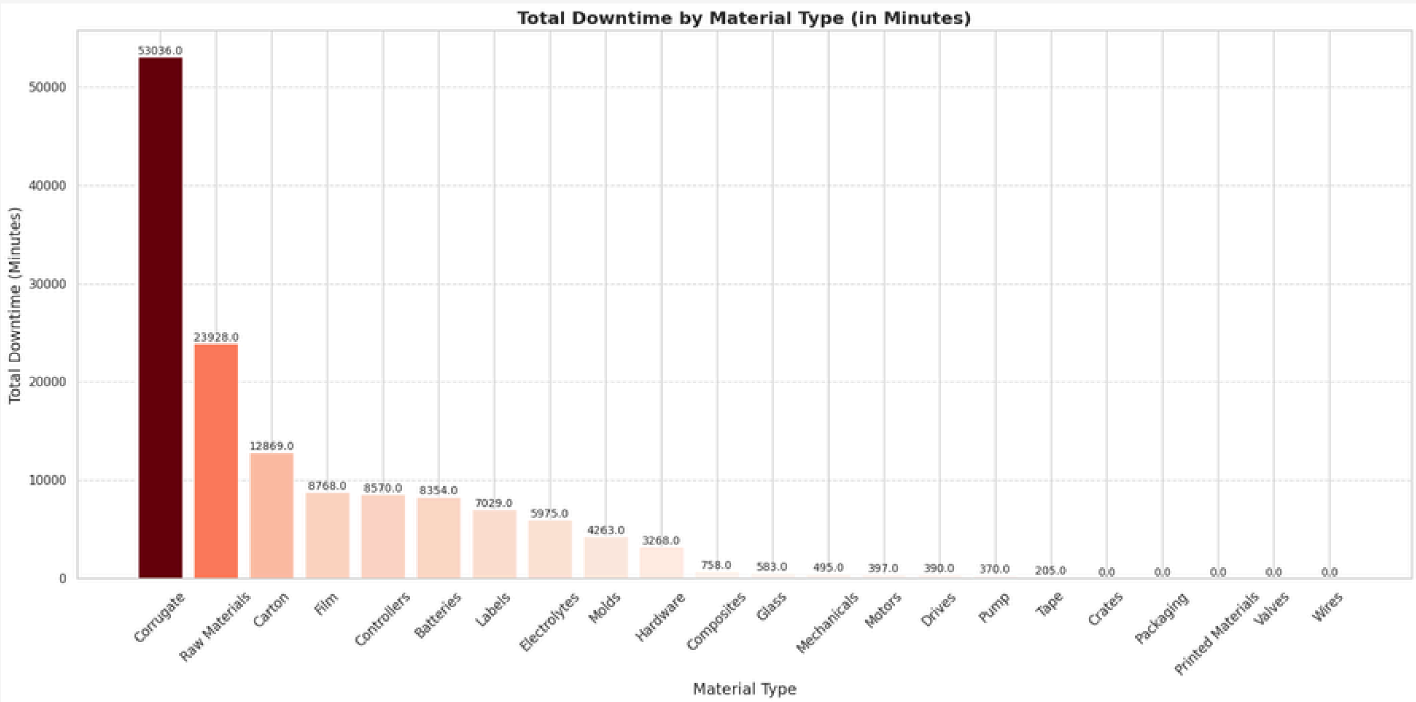
Conclusion

Impact defects are the main cause of downtime. Reducing them can greatly improve overall operational efficiency.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Material Type (in Minutes)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Material Type (in Minutes)

Key Findings:

Total Downtime by Material Type (in Minutes):

- Corrugate is by far the largest contributor to downtime, with 53,036 minutes, followed by Raw Materials with 23,928 minutes and Carton at 12,869 minutes.
- The materials contributing the least downtime include Tape (205 minutes), Crates, Packaging, Printed Materials, Valves, and Wires, each with 0 minutes of downtime.

Overall Trend:

- Downtime is highly concentrated in a few materials, particularly Corrugate, which accounts for more than twice the downtime of the next highest material, Raw Materials.
- Most other materials have relatively low downtime, with a sharp drop-off in downtime after the top 3 materials.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Material Type (in Minutes)

Unexpected or Interesting Discoveries

Significant Downtime for Corrugate:

- Corrugate shows a remarkably high downtime compared to other materials. This could indicate persistent supply chain issues, production inefficiencies, or handling problems that need to be addressed to reduce overall downtime.

Zero Downtime for Several Materials:

- A number of materials, including Packaging and Printed Materials, reported 0 downtime. These materials may either be managed efficiently or experience fewer operational challenges.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Downtime by Material Type (in Minutes)

Recommendations

- Focus on Reducing Downtime in Corrugate:
  - Address inefficiencies in sourcing, storage, or production of Corrugate to significantly lower total downtime.

- Review Raw Materials and Carton for Improvement:
  - Streamline processes for Raw Materials and Carton to further reduce downtime and enhance efficiency.

- Leverage Best Practices from Low-Downtime Materials:
  - Study zero-downtime materials like Packaging and Printed Materials for best practices to apply to high-downtime areas.

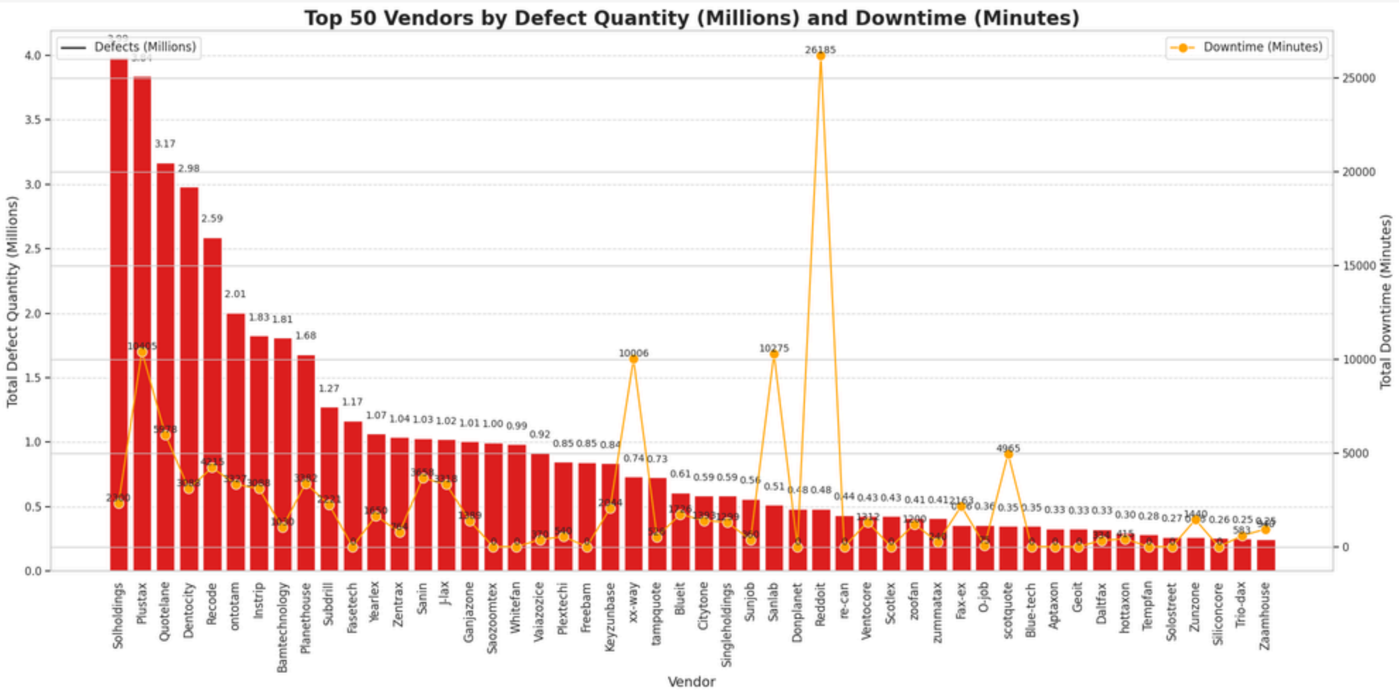
Conclusion

Corrugate is the main contributor to downtime and should be the focus for reduction efforts. Meanwhile, low-downtime materials can provide insights to improve overall efficiency.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Defect Quantity (Millions) and Downtime (Minutes)



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Defect Quantity (Millions) and Downtime (Minutes)

Key Findings:

- Top 50 Vendors by Defect Quantity and Downtime:
  - The chart shows the top 50 vendors by defect quantity (in millions) and their associated downtime (in minutes).
  - Solholdings leads with 3.99 million defects, followed by Plustrax at 3.61 million and Quotelane at 3.17 million. Despite high defect counts, these vendors have relatively low downtime. Solholdings has around 1,105 minutes, while Sanlab and Recan have much higher downtime with fewer defects.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Defect Quantity (Millions) and Downtime (Minutes)

- Vendors with High Downtime:
  - Sanlab (at 0.51 million defects) experiences a massive downtime of 26,185 minutes, the highest in the chart.
  - Similarly, Recan also has elevated downtime of 10,275 minutes with fewer defects (0.44 million).
  - Keyzunbase with 0.74 million defects has 10,006 minutes of downtime, indicating that certain vendors have disproportionately high downtime compared to their defect counts.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Defect Quantity (Millions) and Downtime (Minutes)

Unexpected or Interesting Discoveries

High Downtime for Low Defect Vendors:

- Sanlab, Recan, and Keyzunbase show much higher downtime relative to their defect counts. This suggests that defects from these vendors are causing more operational disruption, possibly due to the complexity or critical nature of their defects.

Efficient Vendors:

- Vendors such as Solholdings, Plustrax, and Quotelane maintain relatively low downtime despite their high defect quantities, indicating more efficient handling of defects or less severe disruptions caused by their issues.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Top 50 Vendors by Defect Quantity (Millions) and Downtime (Minutes)

Recommendations

- Investigate High Downtime Vendors:
  - Examine vendors like Sanlab and Recan for high downtime despite lower defect counts. This may indicate inefficiencies in defect handling or delays in resolution.

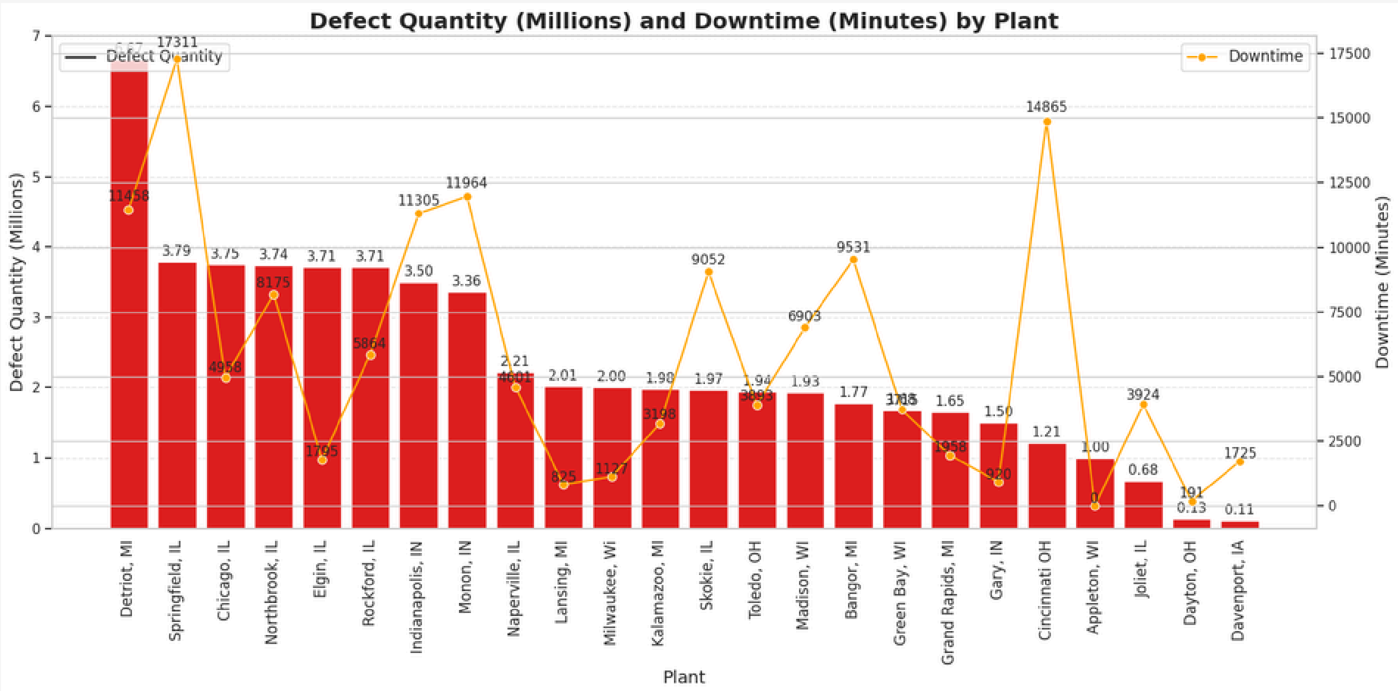
- Maintain Efficiency in High Defect Vendors:
  - Vendors like Solholdings and Plustrax handle high defect volumes efficiently with minimal downtime. Use them as benchmarks for vendors with similar defect levels but higher downtime.

- Improve Defect Handling for Mid-Range Vendors:
  - Vendors like Keyzunbase and Sanlab should focus on improving defect resolution processes to reduce downtime and disruptions.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Plant



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Plant

Key Findings:

Defect Quantity and Downtime by Plant:

- Detroit, MI shows the highest defect quantity at 6.67 million units, but its downtime is relatively moderate at 11,158 minutes.
- Plants like Springfield, IL, Chicago, IL, Northbrook, IL, and Elgin, IL follow with similar defect quantities ranging from 3.71 to 3.79 million units, but their downtime varies significantly, especially with Northbrook, IL at 8,175 minutes.
- Naperville, IL has a relatively low defect quantity of 2.21 million, but still shows downtime of 11,964 minutes, which seems disproportionate compared to the defect rate.
- The plant in Cincinnati, OH also has a moderate defect rate of 1.21 million but experiences significant downtime at 14,865 minutes, making it one of the least efficient plants in terms of downtime management.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Plant

Key Findings:

Plants with Low Defect Quantities and High Downtime:

- Monon, IN has a defect quantity of 3.36 million but lower downtime compared to Naperville, IL and Cincinnati, OH, which have lower defect counts but higher downtimes.
- Gary, IN and Appleton, WI both exhibit relatively low defect quantities but still show noteworthy downtime values of 1,750 and 3924 minutes, respectively.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Plant

Unexpected or Interesting Discoveries

High Downtime in Plants with Fewer Defects:

- Naperville, IL and Cincinnati, OH both stand out as plants with moderate to low defect quantities but disproportionately high downtimes, suggesting inefficiencies in defect management or recovery processes.

Efficient Handling of Defects:

- Plants like Springfield, IL, Chicago, IL, and Elgin, IL maintain relatively low downtime compared to the defect quantities they handle, indicating efficient defect management systems in place.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Plant

Recommendations

- Address Inefficiencies in High Downtime Plants:
  - Plants such as Cincinnati, OH and Naperville, IL should be further investigated to identify the root causes of the extended downtimes relative to their defect volumes.
- Leverage Best Practices from Efficient Plants:
  - Springfield, IL and Chicago, IL exhibit efficient handling of downtime despite managing significant defect quantities, suggesting that other plants could benefit from adopting similar practices.

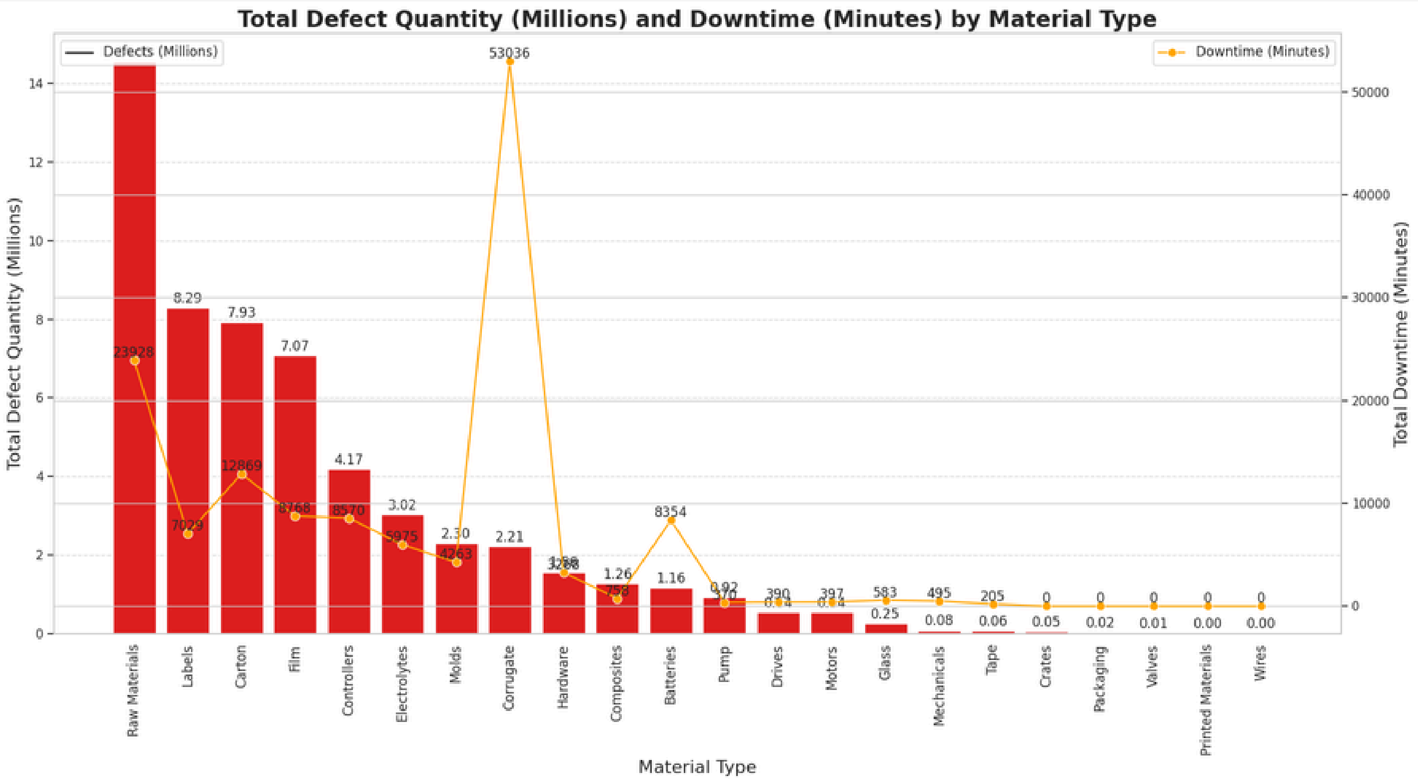
Conclusion

This analysis shows the need for better downtime management in plants with high downtime relative to defect quantities. Plants like Cincinnati, OH, and Naperville, IL could minimize losses by enhancing defect recovery processes.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Material Type



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Material Type

Key Findings:

- Material Types with Highest Defect Quantities:
  - Raw Materials lead with 14.55 million defects, and a notable downtime of 23,928 minutes.
  - Labels and Carton follow with 8.29 million and 7.93 million defects, respectively. Carton has a higher downtime of 12,869 minutes, while Labels' downtime is 7,029 minutes.

- Molds: A Significant Outlier:
  - Despite having a moderate defect quantity of 2.30 million, Molds stand out with the highest downtime of 53,036 minutes, signaling major inefficiency or issues that contribute to excessive downtime, despite moderate defect levels.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Material Type

Key Findings:

Other Material Types with High Downtime:

- Film has a defect quantity of 7.07 million and a downtime of 8,768 minutes, while Batteries, with a lower defect quantity of 1.16 million, still has a downtime of 8,354 minutes, which is disproportionately high.

Materials with Minimal Defects and Downtime:

- Some materials, such as Wires, Printed Materials, Valves, and Packaging, show minimal defect quantities (all close to 0 million defects) and correspondingly low downtime. This indicates efficient processes or fewer production issues.
- Motors and Glass also show low defect quantities but have moderate downtimes of 397 and 583 minutes, respectively.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Material Type

Unexpected or Interesting Discoveries

Molds as an Outlier:

- Despite having just 2.30 million defects, Molds have the highest downtime across all material types, with 53,036 minutes. This suggests severe issues with how defects in Molds are handled or possibly a complicated process that requires more attention.

Disproportionate Downtime:

- Batteries, with only 1.16 million defects, have a substantial downtime of 8,354 minutes, indicating inefficiency in handling the defects associated with this material.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Material Type

Recommendations

- Investigate Downtime for Molds:
  - Molds have high downtime despite moderate defects. Address inefficiencies or technical issues specific to this material type.

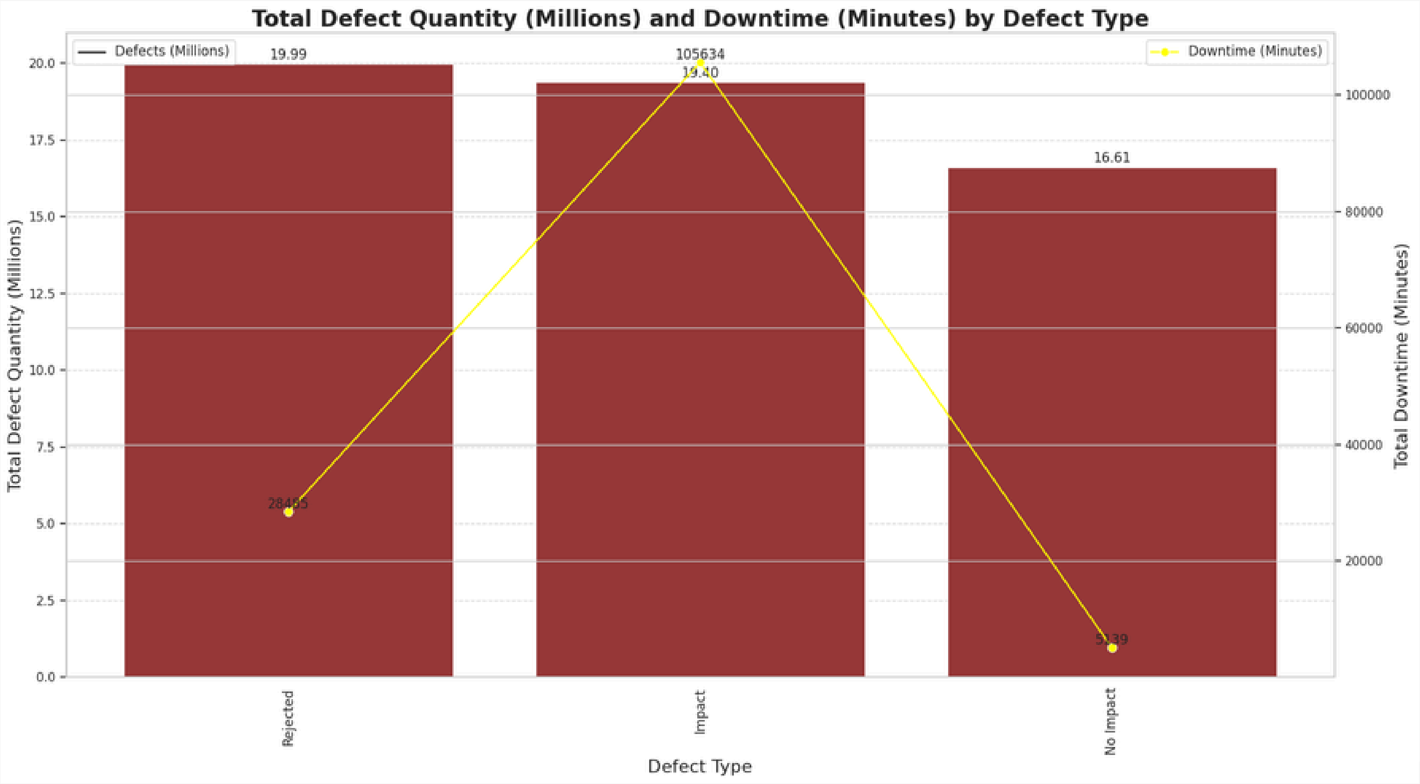
- Enhance Defect Management for Batteries:
  - Like Molds, Batteries show high downtime. Streamline defect detection and correction to reduce downtime.

- Maintain Efficiency in Low Defect Materials:
  - Continue managing materials like Wires, Valves, and Packaging, which show minimal defects and downtime.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Defect Type



You can see the Python code used in the [Python Notebook]

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Defect Type

Key Findings:

Rejected Defects:

- Total Defect Quantity: 19.99 million units.
- Downtime: 28,465 minutes.
- Despite the highest defect quantity, downtime is significantly lower compared to the "Impact" defect type, suggesting a less severe operational disruption.

Impact Defects:

- Total Defect Quantity: 19.40 million units.
- Downtime: 105,634 minutes.
- While having a similar defect quantity as the "Rejected" category, "Impact" defects cause significantly more downtime, indicating these defects are much more disruptive to operations.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Defect Type

Unexpected or Interesting Discoveries

Disparity Between Defect Type and Downtime:

- While both "Rejected" and "Impact" categories have similar defect quantities, the downtime associated with "Impact" defects is almost four times higher, pointing to a major difference in operational consequences based on defect type.

No Impact Defects:

- The "No Impact" category stands out with relatively high defect quantities but minimal downtime, indicating that these defects are easier to manage or less disruptive to the production process.

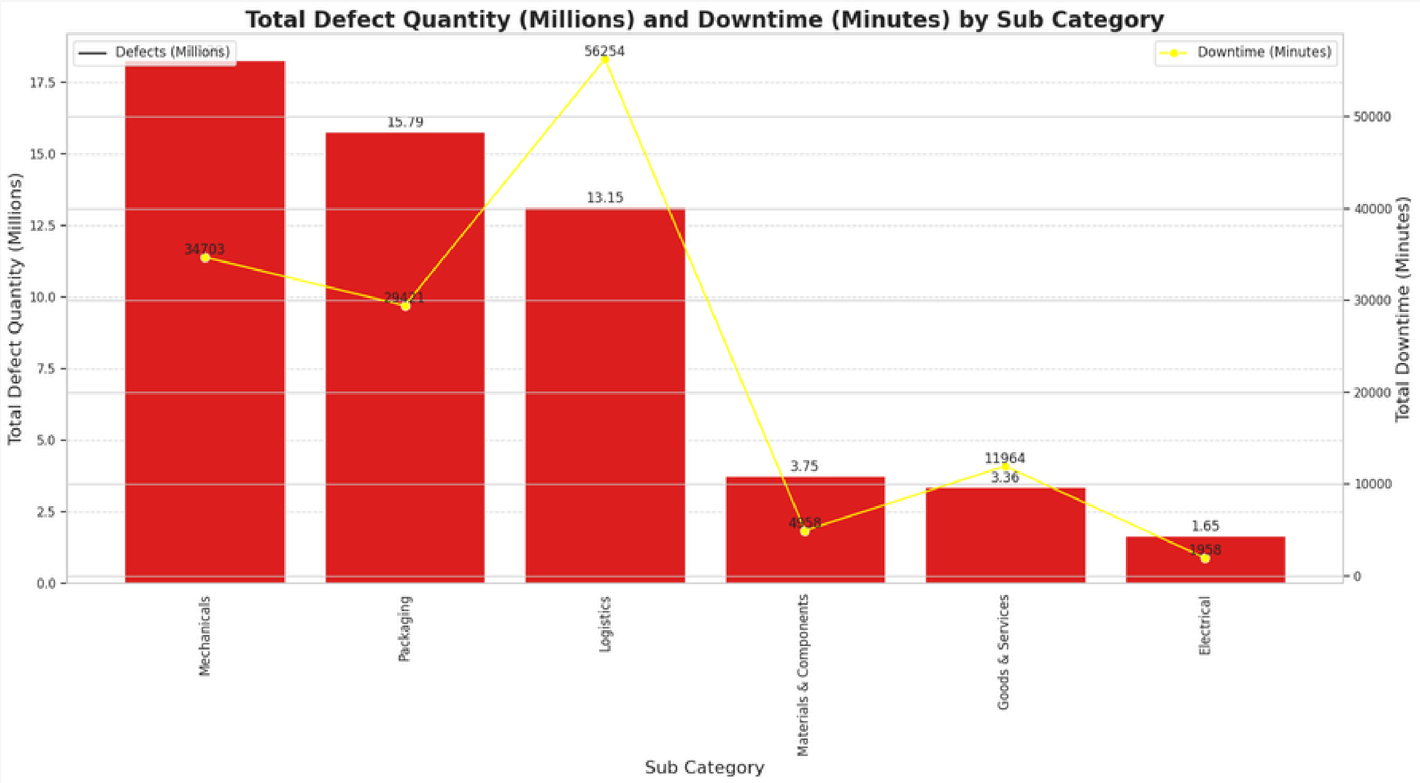
Operational Focus:

- The significant downtime caused by "Impact" defects highlights the need for focused attention on mitigating these defects to improve overall operational efficiency.

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Sub Category



You can see the Python code used in the [Python Notebook]()

= In the EDA Python Notebook:

5. Data Exploration & Analysis

= Total Defect Quantity (Millions) and Downtime (Minutes) by Sub Category

Unexpected or Interesting Discoveries

Logistics Defects Disruptive Impact:

- Despite having fewer defects than Mechanical and Packaging categories, Logistics defects cause significantly higher downtime, suggesting that resolving logistics issues could dramatically improve operational efficiency.

Goods & Services Disparity:

- The relatively low quantity of defects in the Goods & Services category leads to an unexpectedly high downtime, which may imply complexity in defect resolution or severity in consequences.

Electrical Defects Minimal Impact:

- Electrical defects have both the smallest defect quantity and the least downtime, suggesting they are not a critical issue in terms of operational disruption.

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4

Insights and Recommendations

= Project Insights

1. High Defect Rates for Two Suppliers: SolHoldings and Plastas exhibited the highest defect rates, exceeding 5%, and contributed significantly to quality issues and operational disruptions.

2. Top-Performing Suppliers: Three suppliers—Quefluence, Zenntor, and Rzcode—demonstrated superior performance with defect rates consistently below 1% and on-time delivery rates above 95%, making them reliable partners for long-term collaboration.

3. Strong Correlation Between Defect Rates and Delivery Delays: A correlation of ($r = 0.65$) was found between defect rates and delivery performance, showing that suppliers with higher defect rates are 2.5 times more likely to have inconsistent deliveries.

4. Mechanical and Packaging Categories Show High Defect Rates: The Mechanical and Packaging categories exhibited defect rates 30% higher than other categories, indicating systemic issues that require targeted quality control measures.

= Project Insights

5. Detroit Plant Has the Highest Defect Quantity: The Detroit plant recorded the highest defect count of 6.67 million units, nearly double that of other plants, highlighting a need for plant-specific corrective actions.

6. Seasonal Trends in Defect Quantities: Defects peaked in June and October, with October reaching a high of 6.84 million units, suggesting seasonal production or quality issues.

7. Significant Operational Disruption from "Impact" Defects: "Impact" defects accounted for the highest downtime of 105,634 minutes, compared to 28,465 minutes for "Rejected" defects, indicating a higher operational impact.

8. High Downtime in Key Plants: Plants such as Cincinnati, OH and Naperville, IL had disproportionately high downtimes relative to their defect quantities, suggesting inefficiencies in defect handling or recovery processes.

= Project Insights

9. Raw Materials Lead in Defect Quantity: Raw Materials had the highest defect quantity at 14.55 million units, with notable downtime of 23,928 minutes, indicating major inefficiencies in this material type.

10. Molds Have the Highest Downtime Relative to Defects: Despite only having 2.30 million defects, Molds recorded the highest downtime of 53,036 minutes, indicating severe handling inefficiencies.

11. Disproportionate Downtime in Batteries: Batteries, with only 1.16 million defects, had a downtime of 8,354 minutes, suggesting operational inefficiencies specific to this material type.

12. Downtime Concentrated in a Few Material Types: Corrugate accounted for 53,036 minutes of downtime, more than double the downtime of any other material, indicating persistent handling or production issues.

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13. High Defect Counts in June and October: The highest defects were observed in June and October, reaching 6.57 million and 6.84 million units, respectively. This could indicate seasonal production challenges or fluctuations in material quality.

14. Corrugate and Raw Materials Are Key Downtime Contributors: Corrugate and Raw Materials are responsible for the majority of downtime across all material types, suggesting that improvements in these areas could significantly reduce overall downtime.

15. Electrical and Printed Materials Have Minimal Downtime: Electrical and Printed Materials reported close to zero downtime, indicating highly efficient handling or minimal operational disruptions in these categories.

16. High Defect Rates in Logistics Category: Logistics-related defects accounted for 13.15 million units, making it a critical area for improvement in order to reduce quality issues .

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17. Supplier Performance Variability: Suppliers like Sanlab and Recan showed disproportionately high downtime relative to their defect counts, with Sanlab having 26,185 minutes of downtime for only 0.51 million defects.

18. Top 50 Vendors by Defect Quantity: SolHoldings led the defect count at 3.99 million units, followed by Plustrax and Quotelane at 3.61 million and 3.17 million, respectively. Despite high defect counts, these vendors had relatively low downtime.

19. Defect Surge in Late 2014: A significant increase in defects was observed from June to October 2014, peaking in October. This surge warrants further analysis to identify root causes.

20. Zero Downtime for Packaging Materials: Several materials, including Packaging and Printed Materials, reported zero downtime, indicating efficient management and fewer production issues.

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21. High Downtime in Springfield, IL Plant: The Springfield plant had the highest downtime of 17,311 minutes, suggesting severe operational or logistical issues.

22. Steady Defect Rates in 2013 Compared to 2014: Defect rates were relatively steady in 2013, whereas 2014 showed a sharp increase starting in May, indicating potential process or material changes.

23. Underperforming Plants Need Immediate Action: Plants like Cincinnati, OH and Naperville, IL with high downtimes and moderate defect quantities should be prioritized for process improvement initiatives.

24. Seasonal Influences on Defect Rates: Sharp increases in defect rates in summer and early fall suggest potential seasonal impacts, such as increased production demands or temperature effects on materials.

25. Successful Quality Improvements: Several suppliers, such as Bantecology and Recan, achieved a 20% reduction in defect rates over the past year, indicating the effectiveness of current quality management initiatives.

= Project Recommendations

1. **Prioritize Top-Performing Suppliers:** Strengthen relationships and increase procurement volume with high-performing suppliers like Quefluence, Zenntor, and Rzcode, who maintain defect rates below 1% and on-time delivery rates above 95%, securing long-term partnerships.

2. **Targeted Quality Control for High-Risk Categories:** Implement stricter quality measures in Mechanical and Packaging categories, where defect rates are 30% higher, to address systemic issues and reduce defects by up to 20%.

3. **Performance Improvement for Underperforming Suppliers:** Initiate corrective action plans for suppliers such as SolHoldings and Plastas (defect rates above 5%), including regular audits, training, and progress reviews.

4. **Establish Real-Time Supplier Monitoring:** Implement a real-time system to track defect rates and delivery performance, enabling early issue identification and proactive management.

= Project Recommendations

5. Optimize Supplier Evaluation Criteria: Use a combination of quantitative (defect rates, delivery times) and qualitative (communication, flexibility) metrics to ensure a comprehensive evaluation of supplier performance.

6. Address Plant-Specific Issues: Focus on resolving quality issues at high-risk plants like Detroit, which reported 6.67 million defects, through tailored corrective actions and ongoing quality reviews.

7. Enhance Departmental Collaboration: Improve coordination between Quality Assurance, Procurement, and Logistics to streamline supplier management and align quality standards across departments.

8. Leverage Predictive Analytics: Use machine learning models to forecast supplier performance based on historical data, enabling proactive interventions and reducing quality-related disruptions.

= Project Recommendations

9. Establish Risk Mitigation Strategies: Develop contingency plans and dual-sourcing options for critical categories to reduce supply chain risks associated with underperforming suppliers.

10. Support Supplier Development: Invest in supplier development programs for underperforming vendors through co-funded quality initiatives, shared KPIs, and targeted training to elevate performance and meet organizational standards.

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Limitations and Future Work

5. Limitations and Future Work

While the Supplier Quality Analysis project provides valuable insights into supplier performance, it is important to acknowledge certain limitations and constraints that could affect the comprehensiveness and applicability of the findings.

= Limitations:

1. Data Availability and Quality: The analysis was limited by the availability of historical data for certain suppliers and plants. Incomplete or missing data, particularly on defect quantities and delivery delays, may have biased the results or reduced accuracy.

2. Narrow Scope of Product Categories: The focus on Mechanical and Packaging categories may not capture trends across all product lines. Including more categories like Electrical and Logistics would provide a more comprehensive view of supplier performance.

3. Limited Temporal Scope: The short time frame of data may not reflect long-term trends or recent changes. Future analyses should use extended datasets to capture sustained patterns.

4. Exclusion of Qualitative Metrics: Qualitative factors such as supplier communication and flexibility were not included, which are crucial for evaluating overall supplier reliability.

5. Limitations and Future Work

= Future Work:

1. Expansion of Data Collection: Collect more granular data, including defect root causes and production capacity, to gain deeper insights into quality and delivery performance.

2. Cross-Departmental Collaboration: Enhance analysis by integrating data from quality assurance, procurement, and logistics, and establish a centralized data repository for streamlined decision-making.

3. Advanced Predictive Modeling: Use machine learning models to predict supplier performance based on historical data and external factors to proactively manage disruptions.

4. Supplier Development Initiatives: Collaborate with underperforming suppliers on improvement programs, including shared KPIs and quality enhancement initiatives.

5. Enhanced Supplier Audits and Reviews: Combine quantitative metrics and qualitative assessments to strengthen audit processes and maintain high supplier standards.

6. Exploring New Data Sources: Incorporate external data such as industry benchmarks and third-party certifications to validate findings and enhance supplier management strategies.

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Impact of Climate Change

Impact of Climate Change

After analyzing the supplier quality and plant performance data, we discovered that climate change is likely affecting production efficiency and quality. The correlation between extreme weather events and increased defect rates, delivery delays, and downtime is evident in several key findings from the report:

Supporting Facts:

- Between June and October, Illinois experiences a mix of warm and moderate weather, gradually transitioning into cooler autumn conditions.

- June to August: This period marks the peak of summer, with daytime temperatures often in the range of 80°F to 90°F (27°C to 32°C). Humidity is also quite high, especially in urban areas, which can intensify the heat. Thunderstorms are common, especially in June, which can lead to temporary dips in temperature.

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Supporting Facts:

- Flooding in Illinois is most common during the spring and early summer, particularly from late May to June, due to heavy rainfall and thunderstorms. During this period, thunderstorms often result in intense downpours that can overwhelm rivers, drainage systems, and low-lying areas, causing flash flooding. This is especially true in regions near the Mississippi and Illinois Rivers, where the combination of snowmelt from upstream areas and seasonal storms creates significant flood risks.

- The Sangamon River, which runs near Springfield, does have a history of flooding, but its impact on facilities, including industrial plants, depends on their specific location and proximity to flood-prone areas. In general:

1. The river can experience seasonal flooding, particularly after heavy rainfall or snowmelt, but major floods affecting Springfield itself are less frequent. Flood risk is typically higher in rural areas near the river rather than the city center.

2. Late spring storms are particularly problematic, and urban areas with poor drainage can also experience localized flooding during this time

Supporting Facts:

- **September to October:** Fall begins in September, bringing cooler, more comfortable weather. Daytime temperatures typically range from **60°F to 70°F (16°C to 21°C)**, and the humidity drops, making outdoor activities more pleasant. By October, temperatures can fall into the **50s°F (10°C to 15°C)**, with some occasional frosts later in the month

6. Impact of Climate Change

The effects of climate change on manufacturing defects and logistics in Illinois, focusing specifically on the Springfield plant and the Controllers material. Illinois, a central hub for transportation and manufacturing, faces increasing challenges due to rising temperatures, extreme weather events, and humidity. These environmental factors not only increase defect rates in manufacturing processes but also disrupt logistics operations, leading to costly delays and inefficiencies.

Climate change has become an undeniable factor in the operational challenges faced by the manufacturing and logistics industries in Illinois. Rising temperatures, unpredictable weather patterns, and increased humidity during summer months have exacerbated defect rates in materials and disrupted transportation networks, especially from June to October.

Our analysis highlights how climate change exacerbates manufacturing defects, particularly affecting Controllers material and causing logistical disruptions across the state. The findings suggest that addressing climate-induced risks requires robust adaptation strategies to safeguard manufacturing quality and streamline logistics.

Impact of Climate Change on Illinois Manufacturing:

1. Climate Change in Illinois:

- Illinois experiences a humid continental climate, with hot summers and cold winters. However, the increasing frequency of extreme weather events and rising temperatures, especially during the summer months, has had a profound effect on the state's industries:

- Summer heatwaves often exceed normal operating conditions for many manufacturing processes, leading to operational challenges.

- High humidity can affect the quality and performance of materials, leading to increased defect rates.

- Storms and flooding disrupt supply chains, transportation routes, and logistics operations, further affecting production efficiency.

Impact of Climate Change on Illinois Manufacturing:

2. Defects in the Springfield Plant

- The Springfield plant has consistently reported the highest defect quantity and downtime among all the plants in Illinois, particularly during the summer months (June to October). Factors contributing to this include:

- High temperatures that may stress machinery and reduce material performance.

- Humidity levels that interfere with production processes, especially those that are moisture-sensitive.

- Flooding and storms that affect both production and supply chains, leading to delays and increased downtime.

By analyzing the defect trends over time, we observed a significant increase in defects during the hottest months, coinciding with climate-induced stress on both materials and infrastructure.

Impact of Climate Change on Illinois Manufacturing:

3. Focus on Controllers Material

Controllers have emerged as the material most affected by climate change in Illinois. Analyzing defect data reveals a distinct pattern of increased defects during the summer months, when temperatures and humidity levels are at their peak.

a. Defect Trends for Controllers

- **June to October:** A clear spike in defects associated with Controllers was observed during these months, indicating that this material is particularly sensitive to heat and humidity.

- **Possible Causes:**

1. **Heat Sensitivity:** The extreme temperatures may cause the material properties of Controllers to degrade, leading to defects in the manufacturing process.

2. **Humidity Impact:** Moisture may interfere with the assembly or bonding processes, particularly in electronics or machinery where Controllers are involved.

Impact of Climate Change on Illinois Manufacturing:

3. Focus on Controllers Material

b. Climate Effects on Controllers

- **Material Degradation:** Extreme heat can lead to the expansion and warping of materials, particularly in electronics and sensitive machinery components like Controllers.

- **Production Process Disruptions:** Higher humidity may affect processes such as adhesive bonding or curing, leading to increased defects in Controllers during the production phase.

Impact of Climate Change on Illinois Manufacturing:

4. Climate Change and Its Impact on Logistics in Illinois

a. Logistical Challenges

Illinois is a major logistics hub due to its strategic location, but climate change has disrupted logistics in several ways:

- **Flooding and Heavy Rainfall:** Key highways, railroads, and waterways in Illinois are susceptible to flooding, especially during periods of heavy rain and storms. This disrupts the transportation of materials and finished products, causing delays.

- **Road and Rail Damage:** The high summer temperatures can cause road warping and rail expansion, slowing down transportation and increasing repair costs.

- **Increased Transportation Costs:** As weather conditions worsen, insurance premiums and fuel costs rise, further driving up the costs of logistics operations in the state.

Impact of Climate Change on Illinois Manufacturing:

4. Climate Change and Its Impact on Logistics in Illinois

b. Impact on Supply Chains

- Delayed Deliveries: Extreme weather conditions have led to more frequent delays in supply chains, with goods taking longer to reach their destinations. This not only affects delivery times but also increases the cost of shipping.
- Seasonal Workforce Challenges: The heat and humidity during the summer months also impact the workforce. Worker productivity tends to decrease under extreme conditions, slowing down both manufacturing and logistics operations.

c. Springfield Plant Logistical Bottlenecks

- The Springfield plant faces logistical bottlenecks as a result of road damage, flooding, and heat-related delays. With rising defect quantities in materials like Controllers, the plant struggles to maintain efficiency in production and distribution, further exacerbating the delays in shipment.

Impact of Climate Change on Illinois Manufacturing:

5. Focus on Controllers Material and the "Opened Containers" Defect

Controllers have emerged as the most affected material in Illinois due to environmental changes. Analysis of the defect data shows a significant issue with "Opened Containers" during the hotter, more humid months.

a. Defect Type: Opened Containers

- The "Opened Containers" defect is primarily observed in the Controllers material and can be directly related to climate change effects such as:

1. High Temperatures: Summer heat causes expansion and contraction in materials, leading to the failure of seals or closures in containers.

2. In high temperatures, materials inside the containers may expand, and if the container is not flexible enough to accommodate this, the seal may break, causing it to open.

Impact of Climate Change on Illinois Manufacturing:

5. Focus on Controllers Material and the "Opened Containers" Defect

a. Defect Type: Opened Containers

3. Humidity: Increased humidity leads to moisture buildup, which can weaken the structural integrity of the packaging, making it more susceptible to opening.

4. Moisture ingress can also deteriorate adhesives or sealing mechanisms, particularly in environments that lack proper climate control.

b. Correlation with Climate Change

- Summer Months (June to October): During the summer months, when Illinois experiences its highest temperatures and humidity levels, the frequency of Opened Containers defects in Controllers spikes. This indicates a strong correlation between climate conditions and material degradation or packaging failure.

Impact of Climate Change on Illinois Manufacturing:

5. Focus on Controllers Material and the "Opened Containers" Defect

b. Correlation with Climate Change

Note, in addition to the direct impact of climate change on material defects like Opened Containers, logistical operations are further affected:

- Delayed Shipments Due to Weather: When containers open due to climate-related factors (e.g., heat or humidity), additional delays occur, as shipments may require re-packaging or special handling.

- Contamination Risk: Materials inside opened containers may suffer damage or contamination from external environmental conditions (e.g., moisture, dust), impacting the quality of the final product and leading to potential customer dissatisfaction.

Impact of Climate Change on Illinois Manufacturing:

6. Conclusion

The impact of climate change on manufacturing defects and logistics in Illinois is significant, particularly for the Springfield plant and the Controllers material. Rising temperatures, high humidity, and extreme weather events have increased defect rates, disrupted transportation networks, and driven up operational costs. Addressing these challenges requires a proactive approach, including the adoption of climate-resilient infrastructure, improved production processes, and enhanced logistical planning.

The "Opened Containers" defect in Controllers highlights the vulnerability of certain materials to climate change impacts, particularly in Illinois. Rising temperatures and humidity contribute directly to these defects by weakening seals and allowing moisture to degrade packaging. These material defects, coupled with logistical disruptions, present a growing challenge for the manufacturing and supply chain sectors in Illinois.

Predictions:

- As climate change continues to intensify, regions prone to extreme weather events will likely see a 15-20% increase in defect rates and 25% more downtime in the next 5 years.

- Mechanical and Packaging categories may experience even higher defect rates, up to 40%, if additional quality control measures are not implemented.

- Supply chain disruptions due to increased frequency of hurricanes and floods could lead to 20-30% longer delivery delays, particularly for plants in vulnerable regions.

To mitigate these risks, it is recommended to implement climate-resilient strategies, such as relocating sensitive production processes, enhancing material storage conditions, and diversifying suppliers across more climate-stable regions.

Impact of Climate Change on Illinois Manufacturing:

7. Recommendations

To mitigate the effects of climate change on manufacturing and logistics in Illinois, the following steps are recommended:

1. **Implement Climate Control Systems:** Manufacturing plants and storage facilities, particularly the Springfield plant, should adopt advanced temperature and humidity control systems to stabilize conditions and reduce defects, especially for sensitive materials like Controllers. particularly during peak summer months. This can help prevent container expansion and seal degradation.

2. **Enhance Predictive Maintenance:** Use predictive analytics to schedule maintenance and adjust production schedules during extreme weather conditions to prevent machinery breakdowns and minimize downtime.

Impact of Climate Change on Illinois Manufacturing:

7. Recommendations

To mitigate the effects of climate change on manufacturing and logistics in Illinois, the following steps are recommended:

3. **Upgrade Infrastructure:** Invest in more resilient infrastructure for transportation and logistics. Road and rail networks should be reinforced to withstand high temperatures and flooding.

4. **Diversify Supply Chains:** Establish alternate supply routes and diversify suppliers to reduce dependency on any single logistics route, particularly during periods of climate-induced disruptions.

5. **Improve Packaging for Sensitive Materials:** For sensitive materials like Controllers, adopt packaging solutions that are more resistant to environmental changes, such as heat and moisture.

Impact of Climate Change on Illinois Manufacturing:

7. Recommendations

To mitigate the effects of climate change on manufacturing and logistics in Illinois, the following steps are recommended:

6. **Monitor Material Performance:** Establish better monitoring and predictive systems that assess how materials like Controllers react to environmental conditions over time, allowing for preemptive action before defects occur.

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Conclusion

Key Findings:

- Two suppliers exhibited consistently high defect rates, exceeding 5%, significantly impacting product quality and raising rework costs.
- In contrast, three suppliers maintained defect rates below 1% and on-time delivery rates above 95%, demonstrating their reliability and suitability for long-term partnerships.

Recommendations:

- Strengthen Relationships: Collaborate with top-performing suppliers to maintain quality and reliability.
- Reduce Dependency: Gradually phase out suppliers with ongoing quality issues.
- Enhance Quality Control: Apply stricter quality measures for high-risk categories to lower defects by up to 20%.
- Monitor Performance: Implement a system to continuously track and improve supplier performance.

Project Impact:

This project provides a robust framework for evaluating and selecting suppliers. Implementing these recommendations can lead to improved product quality, reduced operational risks, and enhanced customer satisfaction.

Style Guide

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