BeerBo Printing - Analysis Summary Document

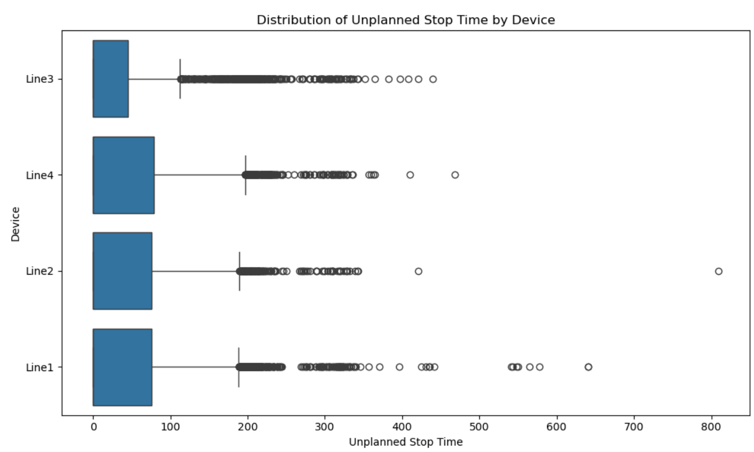
1. Overview of Analysis Process

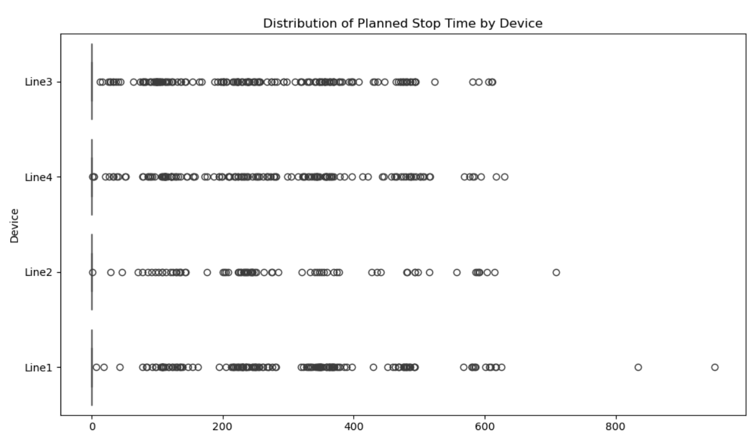
This analysis examined downtime patterns, production & quality metrics, and performance comparison using data from BeerBo Printing's production and quality logs. In this analysis, SQL was used for data extraction and aggregation, and Python was used for statistical analysis and visualization. The more in-detail analysis is in the jupyter notebook titled "manufacturing_analytics.ipynb", and this report aims to provide key findings and recommendations.

2. Downtime Analysis

Downtime Breakdown

In this analysis, **downtime** is defined as periods when production is halted, as captured by the unplanned_stop_time and planned_stop_time variables (distinct from the "Down" category in process_state_display_name). **Unplanned downtime** made up **75.99%** of total stop time, while **planned downtime** accounted for **24.01%**. Median unplanned downtime across all lines was **0 seconds**, but distributions were right-skewed with many high outliers.



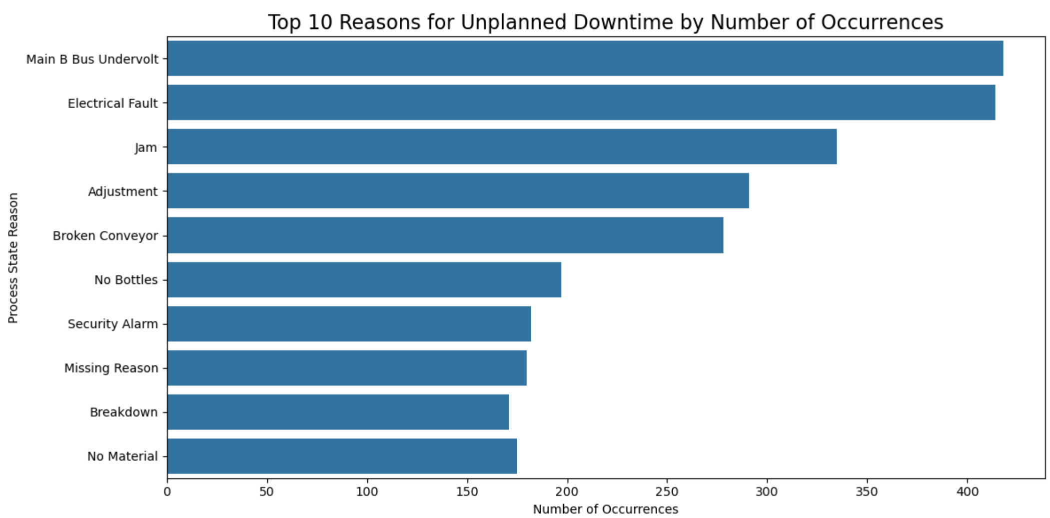


Downtime across Production Lines

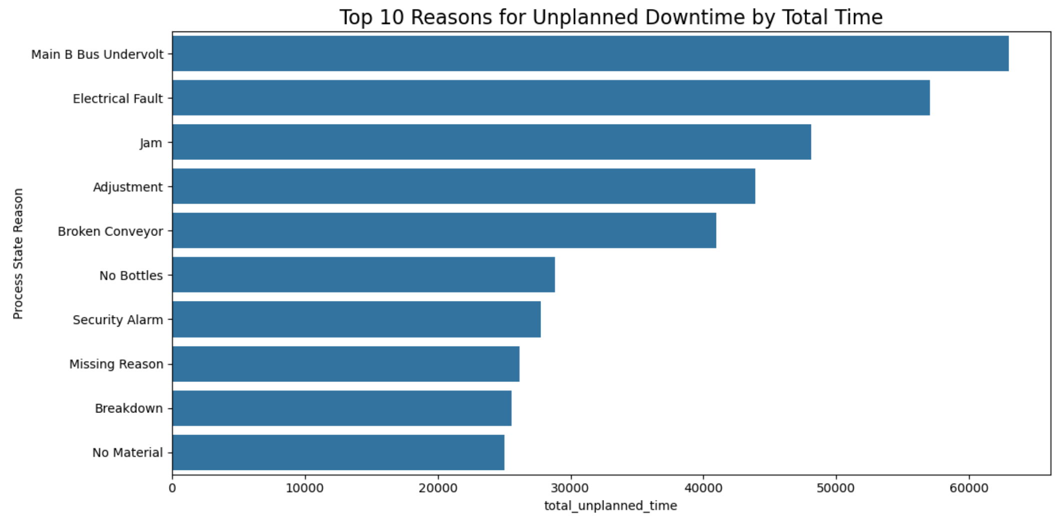
When comparing downtime across the production line, **Line 3** had the **lowest average unplanned downtime** (**41.30s**), while **Line 1** had the **highest max unplanned stop** (**640.2s**), which is a little over 10 mins. Although downtime metrics vary slightly by line, differences in **mean, minimum, and maximum** values are relatively small, indicating similar downtime behavior across all production lines. Therefore, no individual production line appears to require immediate attention based on downtime alone.

deviceKey	Line1	Line2	Line3	Line4
unplanned_stop_time_mean	51.576421	49.172053	41.300305	49.006807
unplanned_stop_time_median	0.0	0.0	0.0	0.0
unplanned_stop_time_std	89.929091	84.25179	78.060467	81.67703
unplanned_stop_time_min	0.0	0.0	0.0	0.0
unplanned_stop_time_max	640.208119	809.164892	439.728239	468.443734
planned_stop_time_mean	16.732938	15.078125	13.842797	14.394469
planned_stop_time_median	0.0	0.0	0.0	0.0
planned_stop_time_std	79.98716	74.095999	67.710112	70.585941
planned_stop_time_min	0.0	0.0	0.0	0.0
planned_stop_time_max	951.0	709.0	612.0	630.0

Downtime Causes

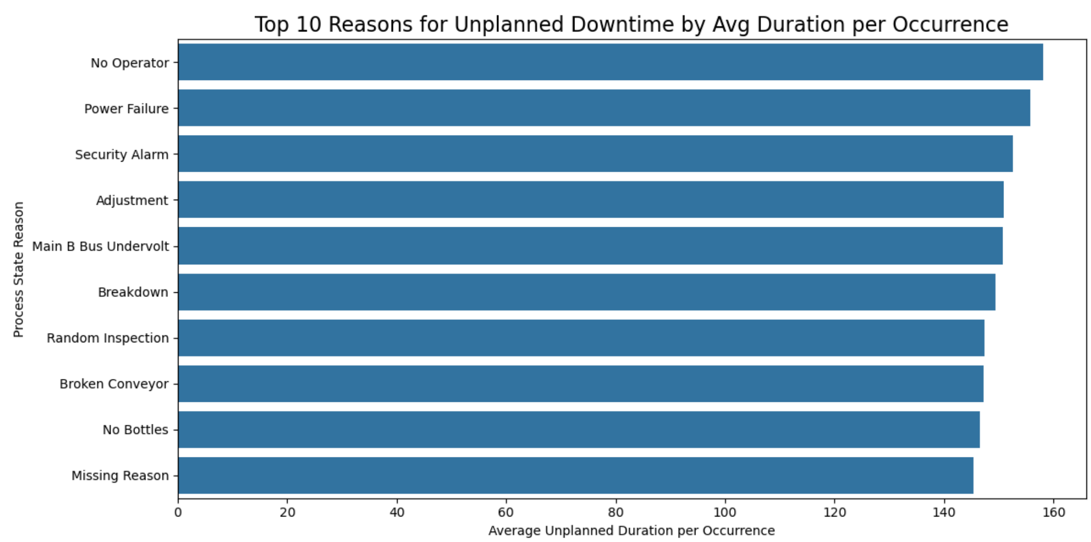


All top 10 reasons have similar average durations, ranging from ~137s to ~153s per occurrence. This consistency suggests these events follow known patterns (e.g., standard repair/reset procedures).



The top causes of unplanned downtime were **Main B Bus Undervolt** (418 occurrences, 62,983s total), **Electrical Fault** (414 occurrences, 57,034s), and **Jam** (335 occurrences, 48,106s). Among the top 10 reasons for unplanned downtime—both in terms of total duration and number of occurrences—**No Bottles** and **No Material** stand out. These causes may indicate supply chain disruptions or staging inefficiencies and present actionable opportunities for improvement from a logistics and inventory management perspective.

While the top 10 reasons for unplanned downtime align closely in both **frequency** and **total time**, assessing the **average unplanned stop duration per occurrence** will reveal which reasons are the most disruptive on a per-event basis. This view helps identify high-severity downtime drivers that may otherwise be overlooked due to their lower frequency.



As shown in the bar chart, the average unplanned duration per occurrence is relatively consistent across the top 10 reasons, indicating that their overall impact stems more from frequency than severity—highlighting opportunities for process optimization. Notably, **No Operator**, though not among the top causes by frequency, has the highest average duration (158s), pointing to potential staffing or handover issues. **Power Failure** and **Security Alarm** also rank high in severity, suggesting system-level or safety-related delays. Meanwhile, frequent issues like **Broken Conveyor**, **Adjustment**, and **Breakdown** consistently require recovery time in the 147–151s range. While frequent issues such as **Broken Conveyor**, **Adjustment**, and **Breakdown** present opportunities for improvement, any changes should be evaluated by technical experts with domain knowledge to assess feasibility and ensure that proposed optimizations are both practical and sustainable.

Recommendations

Here is the recommendations based on the Downtime Analysis:

- Prioritize investigation into **frequent and high-duration** issues like **Main B Bus Undervolt, Electrical Fault, and Jam.**
- Work with maintenance and logistics teams to reduce recurring causes such as **Broken Conveyor**, **No Material**, and **No Bottles**.
- For future analysis, **Missing Reason** entries need to be addressed by reviewing system data capture or operator reporting processes.
- Investigate **No Operator** events further — they combine moderate frequency with the highest impact per occurrence.
- Consider preventive strategies for **Power Failures** and **Security Alarms**, as their durations suggest significant system-level interruptions.

It is also important to note that while these metrics highlight areas for potential improvement, any recommended changes should be carefully evaluated by technical experts with relevant domain knowledge to assess their feasibility and ensure that proposed optimizations are both practical and sustainable in the context of BeerBo Printing's operations.

3. Production & Quality Analysis

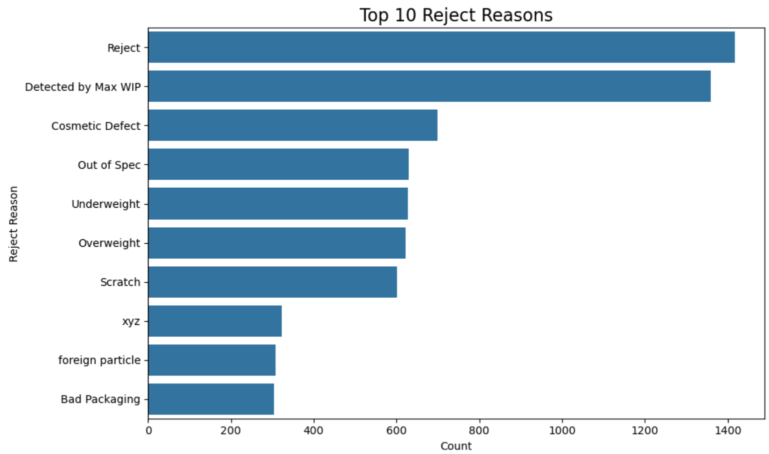
Reject Rate and Quality Issues

The overall reject rate across all production lines was **4.20%**, calculated as the total number of rejected units divided by the sum of good and rejected units. This rate provides a high-level measure of production quality and offers a baseline for future comparisons.

As shown in the bar chart below, the most common reject reasons from the **Quality** table revealed that the top three were:

- **Reject** (1,418 instances),
- **Detected by Max WIP** (1,359 instances), and
- **Cosmetic Defect** (699 instances).

While "Reject" and "Out of Spec" are frequently recorded, their generic nature limits diagnostic value. These labels may reflect incomplete classification or default inputs, suggesting that a refinement in how reject reasons are captured could enable more targeted quality improvements.



Production Efficiency Across Lines

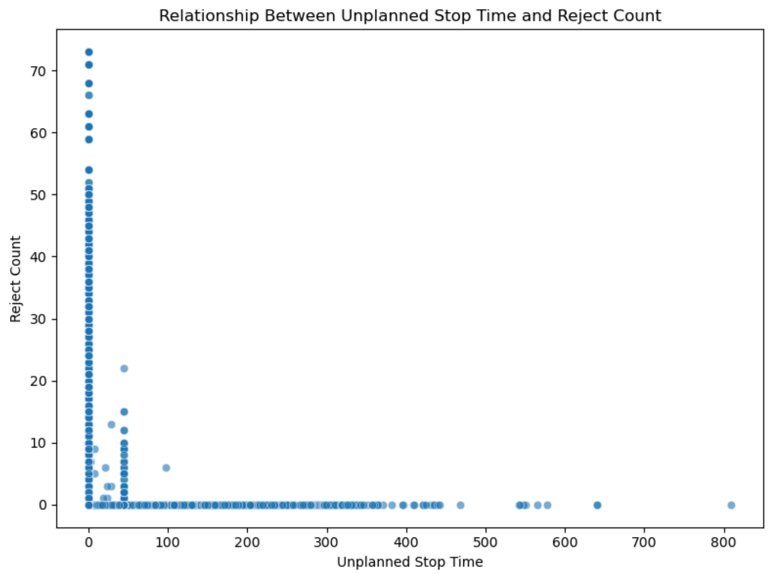
	deviceKey	avg_good_count_per_hour
0	Line1	1150.001746
1	Line2	1093.887610
2	Line3	944.072069
3	Line4	933.982512

When comparing production efficiency, **Line 1** achieved the highest throughput with an average of **1,150 good units per hour**, followed closely by **Line 2** at **1,093 units per hour**. In contrast, **Line 4** averaged just **934 units per hour**, highlighting a **~23% performance gap** that may signal underlying inefficiencies. Furthermore, there is enough statistical evidence that there is a difference between Line 1 and Line 4 in average good count per hour. These differences suggest that Lines 3 and 4 may benefit from further investigation into process design, operator workflows, or equipment performance.

Correlation Between Downtime and Rejects

To explore whether downtime contributes to product quality issues, we analyzed the relationship between unplanned_stop_time and reject_count. The **Pearson correlation coefficient** was **-0.35**, indicating a weak negative linear relationship. However, visual analysis via a scatter plot revealed a clearer, **non-linear pattern**: when unplanned_stop_time was greater than zero, reject_count was typically zero. This suggests that most rejects occur **only during active production**, and that unplanned stops generally **coincide with halted production**, not defective output.

This insight underscores the importance of separating downtime and quality as distinct but interconnected operational concerns. While downtime affects overall throughput, quality issues appear more closely linked to production conditions rather than disruptions themselves.



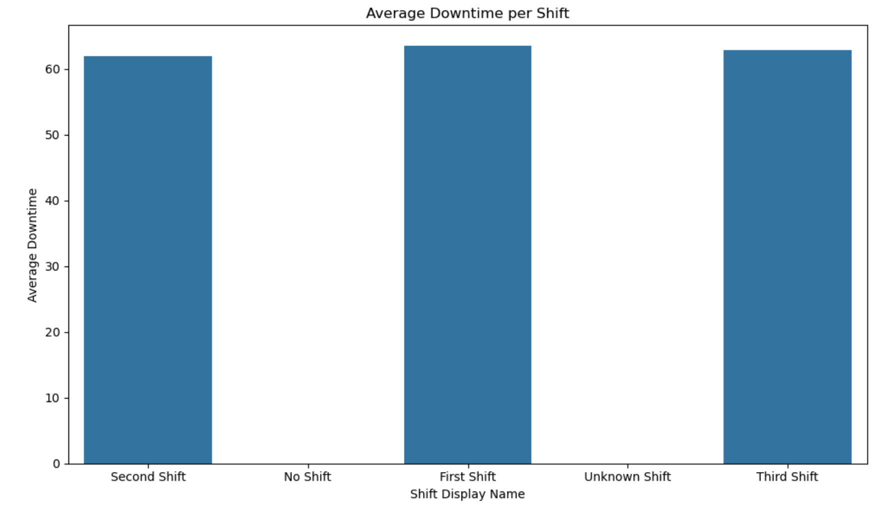
Recommendations

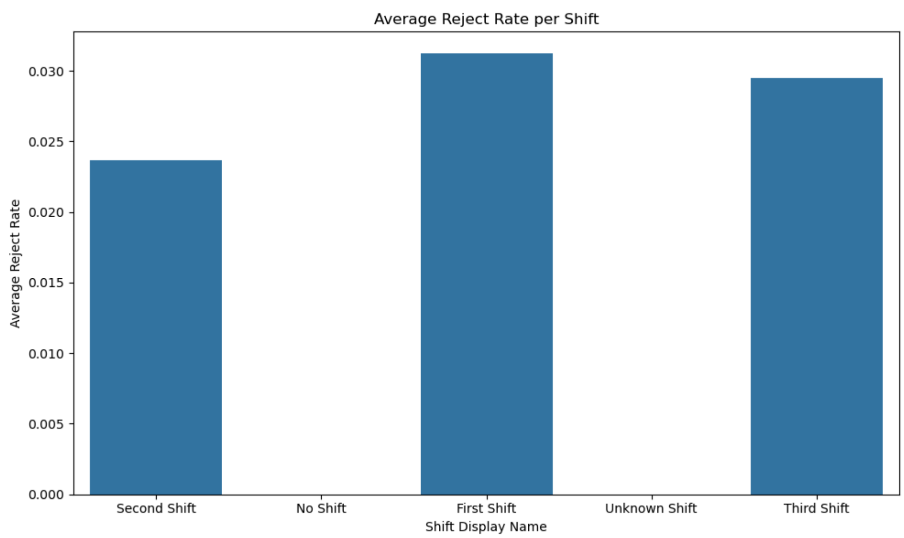
Here is the recommendations based on the Production & Quality Analysis:

- **Refine rejects reason labeling**, particularly for generic categories like **Reject** and **Out of Spec**. Introduce clearer subcategories or structured input options to improve diagnostic precision through **training operators and quality staff** on proper labeling practices to ensure consistency and enable more targeted root cause analysis.
- Consider implementing **context-aware quality KPIs**—such as **reject rate per run_time**—to more accurately reflect production performance during active periods, ensuring that quality metrics align with actual operational conditions.
- Although downtime and reject count are not directly correlated, setting up **alerts for abnormal reject rates within short production windows** is highly recommended if it has not been implemented. Even if unplanned stops don't directly cause defects, sudden spikes in reject rates during active production may indicate emerging issues—such as equipment wear, material defects, or operator error—that require immediate attention. Monitoring reject rates in near-real time enables quicker responses, minimizes waste, and helps maintain consistent product quality.

4. Performance Comparison

<u>Shifts</u>

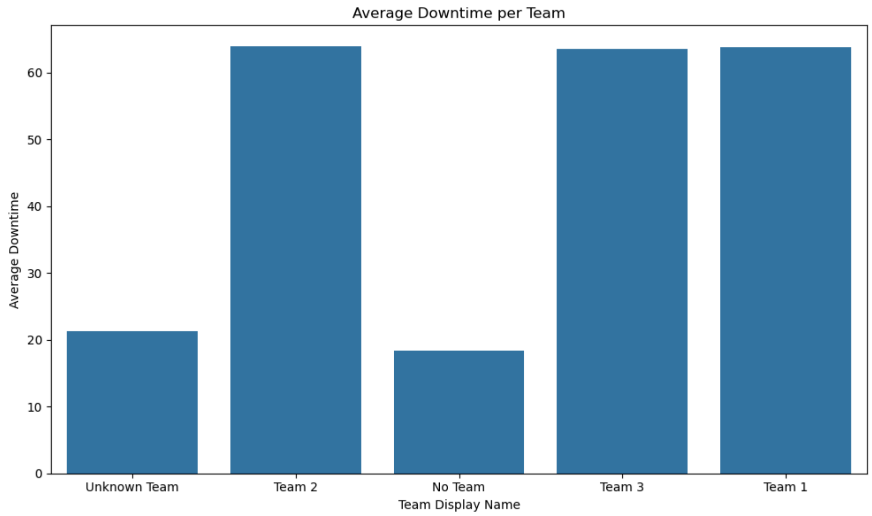


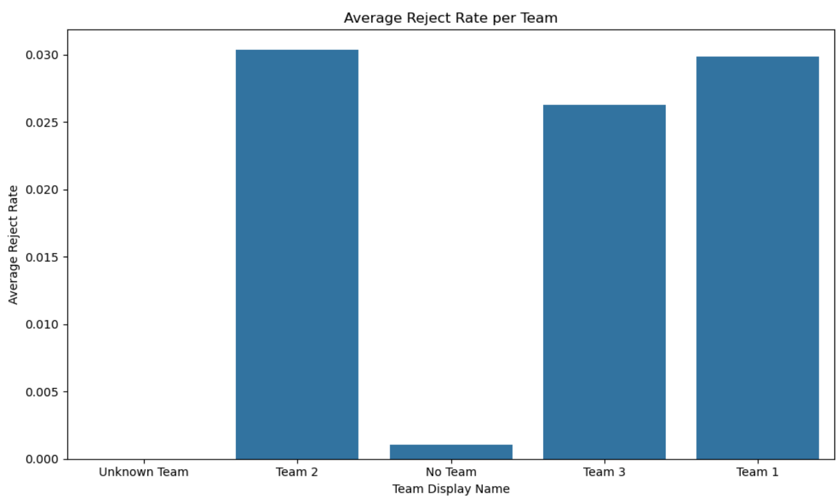


When analyzing performance across different shifts, the **First Shift** recorded the **highest average reject rate (3.12%)** and **highest average downtime (63.4 seconds)**. In contrast, the **Second Shift** outperformed others with both the **lowest reject rate (2.37%)** and **lowest average downtime (61.87 seconds)**, suggesting more consistent production quality and fewer interruptions. These differences may be influenced by factors such as staffing, process adherence, or operational load.

However, while the performance variation is observable, the differences in downtime and quality across shifts are relatively small, and there is not enough statistical evidence to indicate the difference is significant. Therefore, the data we have **do not indicate significant performance gaps**. Further monitoring over time may help determine whether these patterns are consistent or situational.

Teams





Team-level analysis revealed that **Team 2** experienced the **highest average reject rate (3.03%)** and **highest average downtime (63.89 seconds)**, while **Team 3** demonstrated better quality outcomes with the **lowest reject rate (2.62%)**. Teams labeled as **"No Team"** or **"Unknown Team"** showed significantly lower downtime and reject rates, though these entries likely reflect missing or improperly recorded team assignments and should be interpreted with caution. Similar to the shift analysis, the difference is not statistically significant.

Nevertheless, these comparisons underscore the importance of monitoring performance at the shift and team levels to identify potential training, coordination, or leadership gaps that may affect operational outcomes.

Recommendations

- **Support underperforming teams, such as Team 2**, which recorded the highest reject rate (3.03%) and average downtime (63.89s). Conduct targeted reviews of workflows, equipment usage, and communication practices to identify areas for improvement and provide additional training where necessary.

- **Leverage Team 3's best practices**, as it achieved the lowest reject rate (2.62%). Explore contributing factors—such as team structure, leadership, or process discipline—that may be scalable across other teams to enhance overall performance.
- **Establish regular performance reviews** at the shift and team levels, using metrics like reject rate and downtime to track progress, recognize high performers, and proactively address operational issues.

5. Conclusion

Overall, the analysis did not uncover any critical performance issues, but it did highlight several **opportunities for operational improvement**. While production lines performed within a similar range in terms of downtime and efficiency, there were **notable differences at the shift and team levels**, particularly in reject rates and downtime patterns.

One recurring challenge across datasets was the presence of **missing or generic labels**—such as **Reject, Unknown Team, and No Shift**—which limit the ability to draw precise insights. Improving the consistency and specificity of labeling will be essential for more accurate root cause analysis and continuous improvement efforts.

Although there was **no strong direct correlation** between unplanned downtime and reject count, frequent stops may still influence quality outcomes. This is especially evident in the **team-level analysis**, where teams with higher downtime also tended to have higher reject rates. However, due to limited statistical depth, it is unclear whether these differences are statistically significant.

Moving forward, **establishing benchmarks and implementing real-time monitoring** of key performance indicators—such as reject rates, throughput, and downtime—will be valuable for identifying emerging issues early, supporting decision-making, and fostering a culture of continuous improvement.