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RMIT BUSINESS ANALYTICS CHAMPION SEASON 6

ROUND 2: CASE STUDY

TEAM NAME: THE TORTURED ANALYST DEPARTMENT

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EXECUTIVE SUMMARY

OVERVIEW

- Analysis of **production & maintenance data** (Jan–Jun 2025) to **identify key OEE loss drivers**, quantify impact, and propose data-driven improvements.
- Dataset: **168K logs**, 194 maintenance orders, 158 equipment mappings — providing a full view of performance across lines and product types.

PROBLEMS

- **OEE averages ≈81%**, mainly limited by Availability (≈0.85).
- Unplanned downtime (~15%) dominates losses — mostly from Material Handle & Filament (~90%)
- Found **1,161 hours** of **No-Production runtime**, plus several low-availability lines.

IMPACTS

Total quantified loss:

- **21,196 hours downtime** (~15.5% of available time)
- **7.2M units lost** (~1.6% total output)
- **19.8% effective capacity loss**

→ Addressing these key causes could recover up to **+10% OEE**, improving both capacity and cost efficiency.

SOLUTIONS

- Applied **statistical testing** (Chi-square, Cramér's V) to **isolate line-, product-, and process-related factors**.
- Built **Error–Product frequency matrices** to pinpoint **recurring downtime drivers**.
- Quantified business impact from downtime, rejection, and untracked runtime.

→ **Findings**: most efficiency losses stem from **material handling**, feeding systems, and calibration precision rather than operator performance.

RECOMMENDATIONS

- **Anomaly Detection Dashboard** – track OEE and detect early degradation.
- **AI-based Monitoring** – identify micro-stops and runtime anomalies.
- **Predictive Maintenance (DDPM)** – forecast failures and minimize downtime.

DATA OVERVIEW

Dataset Summary

Data Source: Production & Maintenance Recording System
Period: 01/01/2025 – 30/06/2025

Data	Description	Record Count
production log (main)	*Records production time, quantity, and downtime by shift, product, and line*	*167946*
maintenance order	*Maintenance work orders by machine and order type*	*194*
cross reference	*Mapping between equipment and operation line*	*158*

Description of Key Analytical Data

Each record in the production log represents a unique combination of **LINE_NAME**, **SHIFT_NAME**, **PRODUCTION_DATE**, and **SIZE_TYPE**, along with the corresponding **UTIL_REASON_DESCRIPTION** that specifies the machine's operational state during that period.

– Several columns contain **NULL** values but remain contextually meaningful.
– Columns with constant or zero values (e.g., **WAITING_TIME**) were excluded
– Each downtime reason (**UTIL_REASON_DESCRIPTION**) corresponds to a distinct operational category, which was reclassified into higher-level groups for analysis.

HOW WE PROCESS DATA...

1

Exclude records where **AE_MODEL_CATEGORY** = "**Business External**"
→ **External** or **uncontrollable** events.

Remove column **WAITING_TIME** (all zero values)

2

UTIL_MODEL_DESCRIPTION ≠ NULL
→ represents time-related information only

UTIL_MODEL_DESCRIPTION = NULL
→ represents product-related information only

→ **Combine all** to create **unified records** that capture each machine's **full production activity** by product and shift.

3

Cluster the **UTIL_REASON_DESCRIPTION** categories
→ Group similar downtime reasons into higher-level clusters

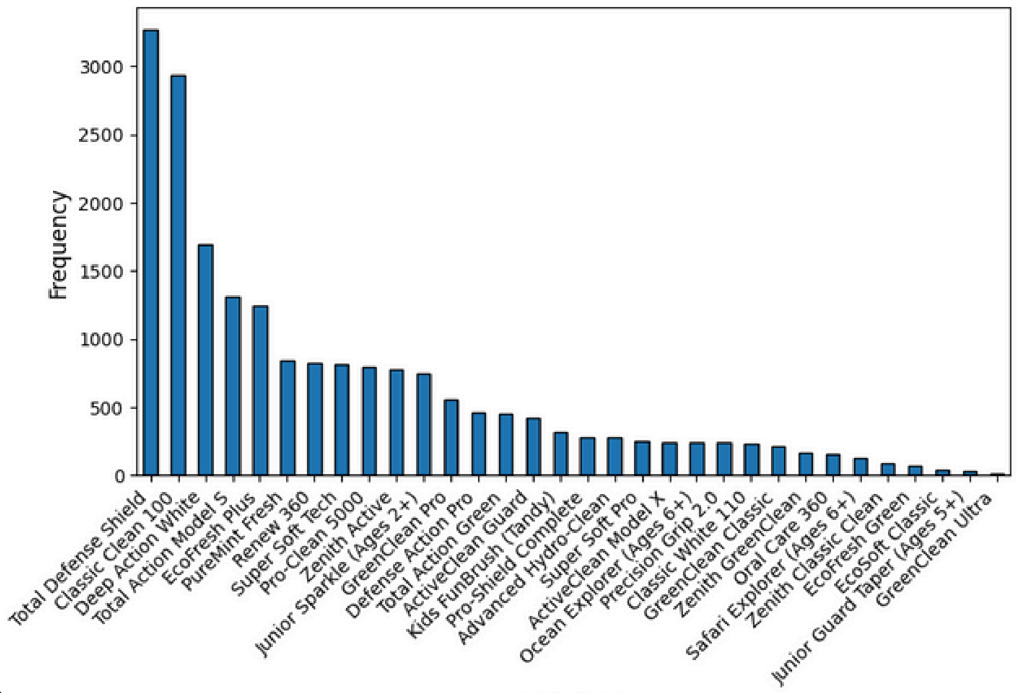
FEATURE ENGINEERING

New calculated variables were created to measure efficiency:

Overall Equipment Effectiveness = Availability x Performance x Quality

$$= \frac{\text{Runtime}}{\text{Production Available Time}} \times \frac{\text{Effective Runtime}}{\text{Runtime}} \times \frac{\text{Good Production Quantity}}{\text{Total Production Quantity}}$$

CATEGORY OVERVIEW

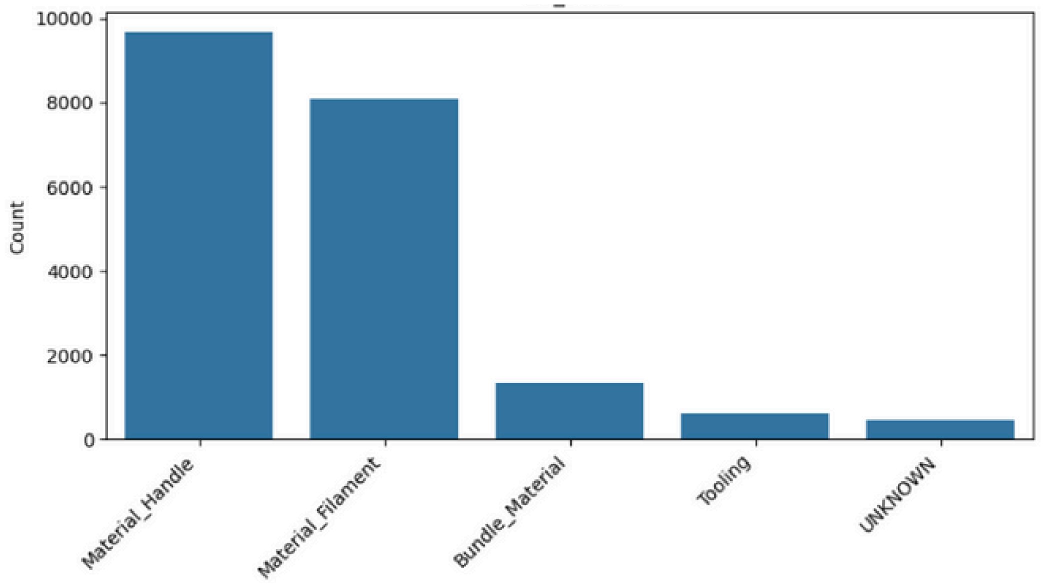


Distribution of "Size_Type"

The product portfolio is **diverse**, with production volumes **skewed** toward a few high-volume SKUs

Uneven product volumes suggest **output normalization** is required when **comparing** performance or error frequency

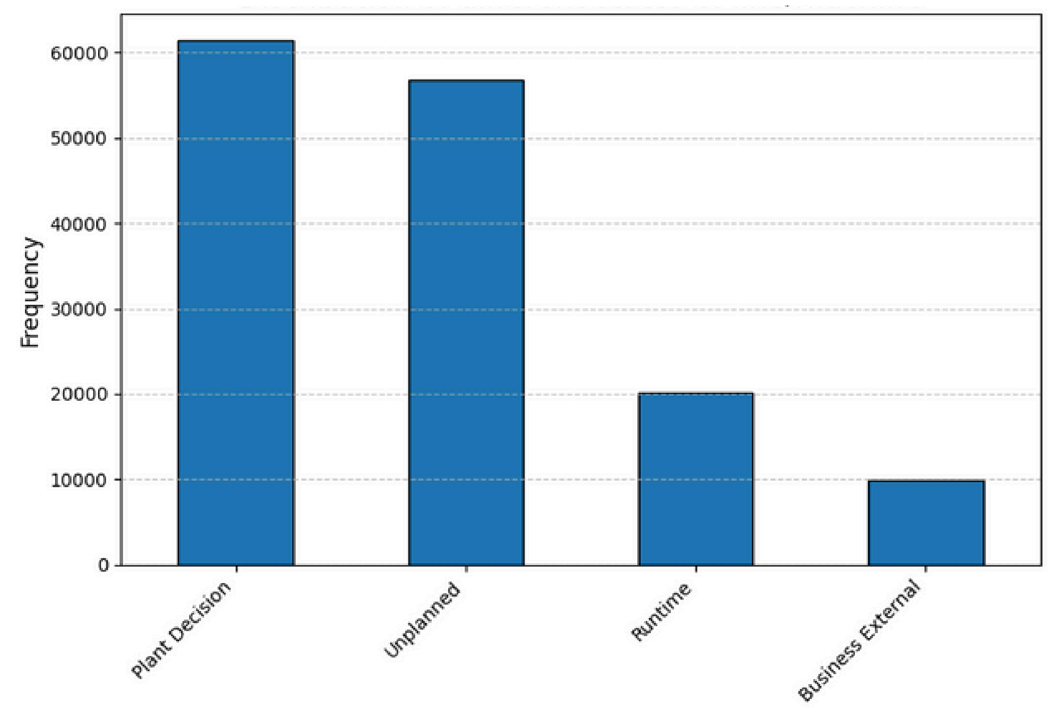
The category of the production changeover/activity type (Co_Type)



"**Material Handle**" and "**Material Filament**" represent key operational phases where material transfer and feeding occur — the most **error-prone stages** identified in later analysis.

General Insight

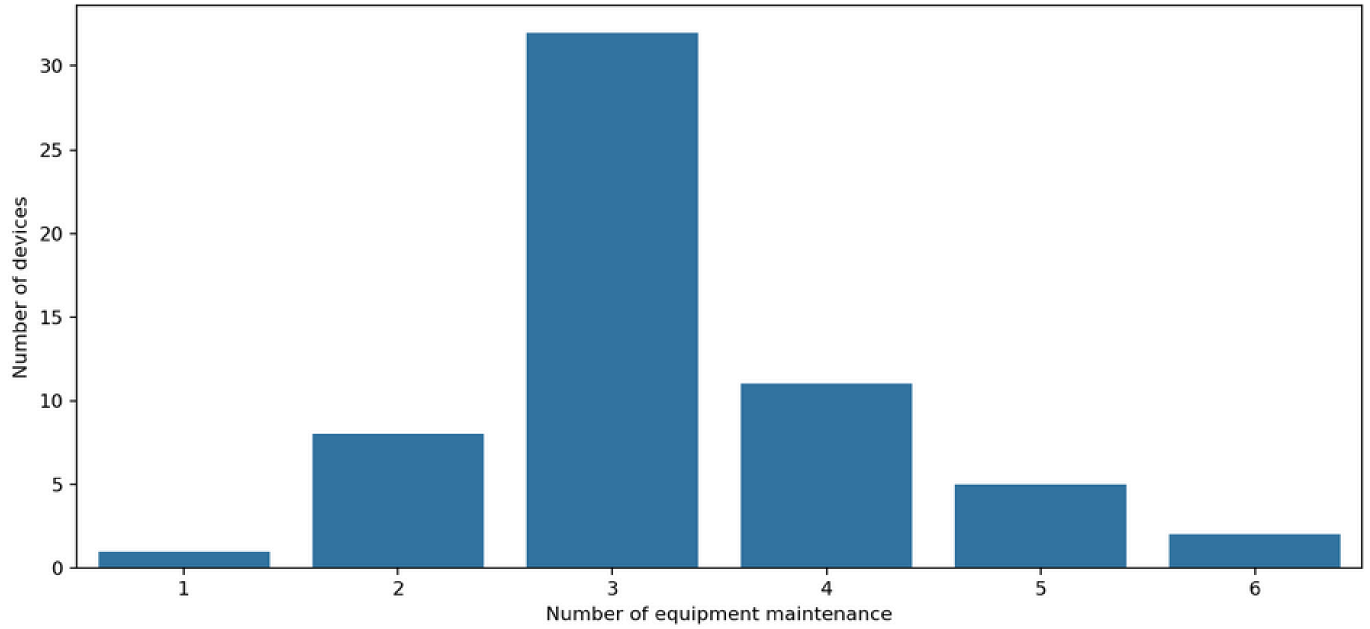
The dataset captures **production activities** across multiple product types and lines, reflecting the **plant's operational diversity**. Data validation shows **no waiting time** and **balanced maintenance**, suggesting a **stable** supply flow and well-coordinated planning.



The different states of line/machine

The dominance of **"Plant Decision"** and **"Unplanned"** categories highlights the balance between planned stops and sudden downtime, setting the baseline for **subsequent impact quantification** and **root cause identification**

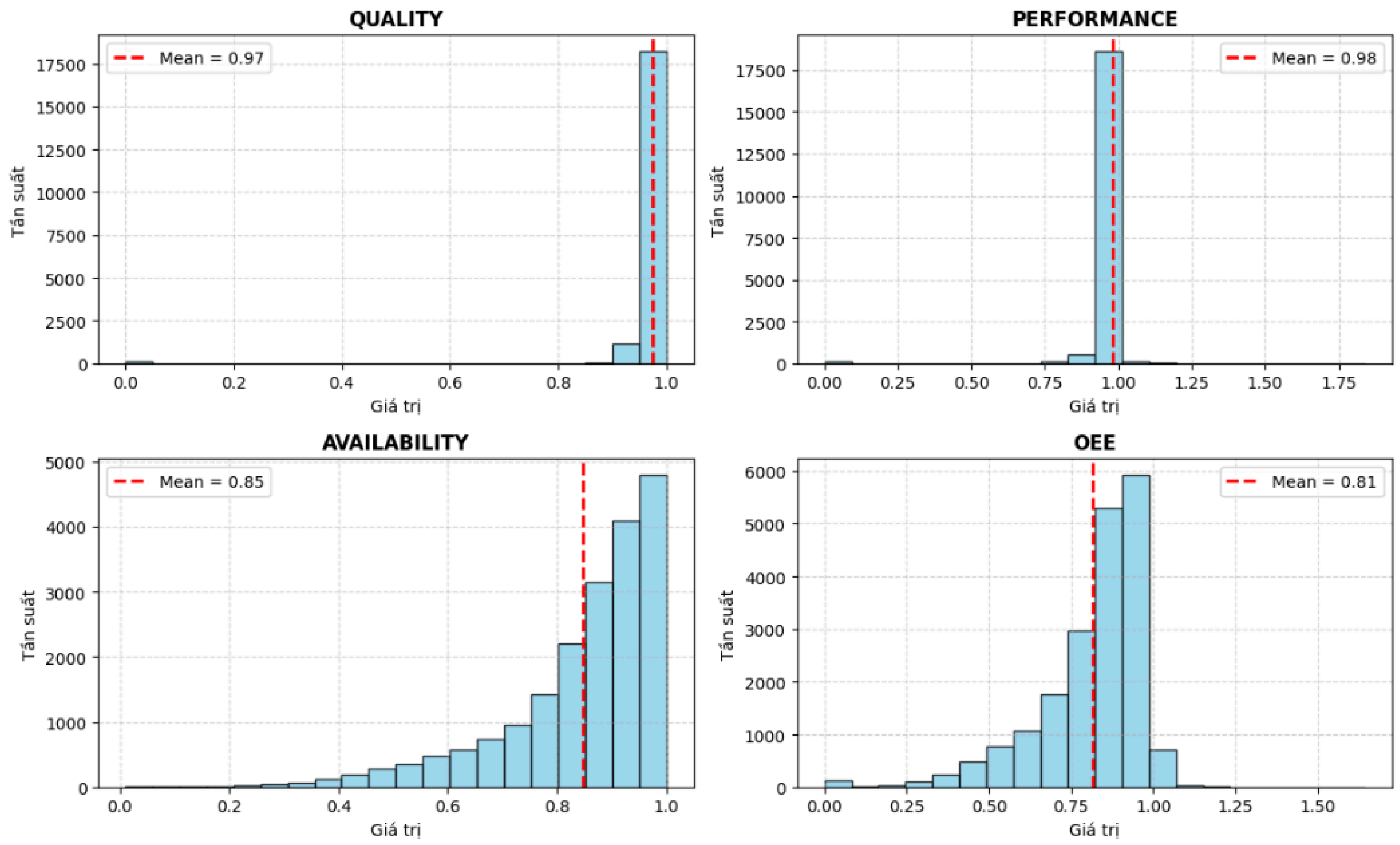
Unplanned = machine idle
(Runtime = 0, no output)



Equipment maintenance

Maintenance frequency clusters around **three services per asset** in the period, indicating a **steady** PM cadence

OVERALL EQUIPMENT EFFECTIVENESS



Key Insights

- **Performance** and **Quality** remain close to the ideal value (≈1.0)
- **Availability** shows a broader, **left-skewed distribution** (mean ≈ 0.85)
- Consequently, OEE (mean ≈ 0.81) inherits this left-skewed pattern and is **mainly limited by Availability**, while the other two components are near optimal.

Detail Observation

Availability

- Average = **0.85**, **wide distribution** skewed left.
- Strongly affected by downtime — several lines show long stops or frequent micro-stops, leading to high variation across shifts.

Performance

- Average = **0.98**, highly **concentrated near 1.0**
- Machines almost at ideal speed, with minimal loss.

Quality

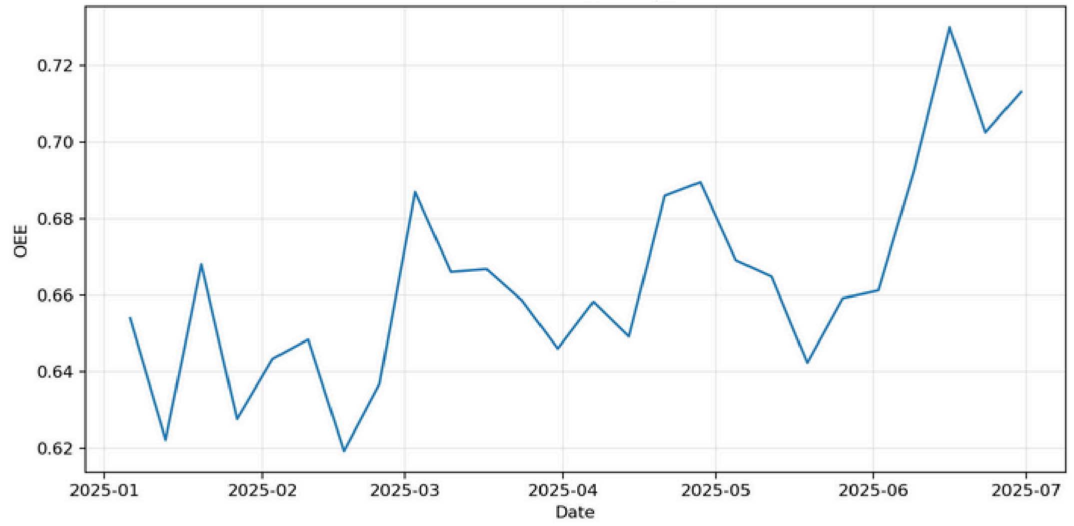
- Average = **0.97**, also tightly **clustered near 1.0**
- Most products meet quality standards with few defects
- A small number of records have **Quality = 0**, which requires further investigation.

CONCLUSION

- The plant maintains **high speed** and **product quality**, but **time losses** are the main factor limiting overall OEE.
- The variation in **Availability** across lines or shifts suggests process instability — **potential causes** may include setup delays, or material issues.
- Overall OEE ≈ 81% is above the industry average
- A few cases with **Performance** or **Quality** = 0 should be reviewed for data accuracy or operational abnormalities.

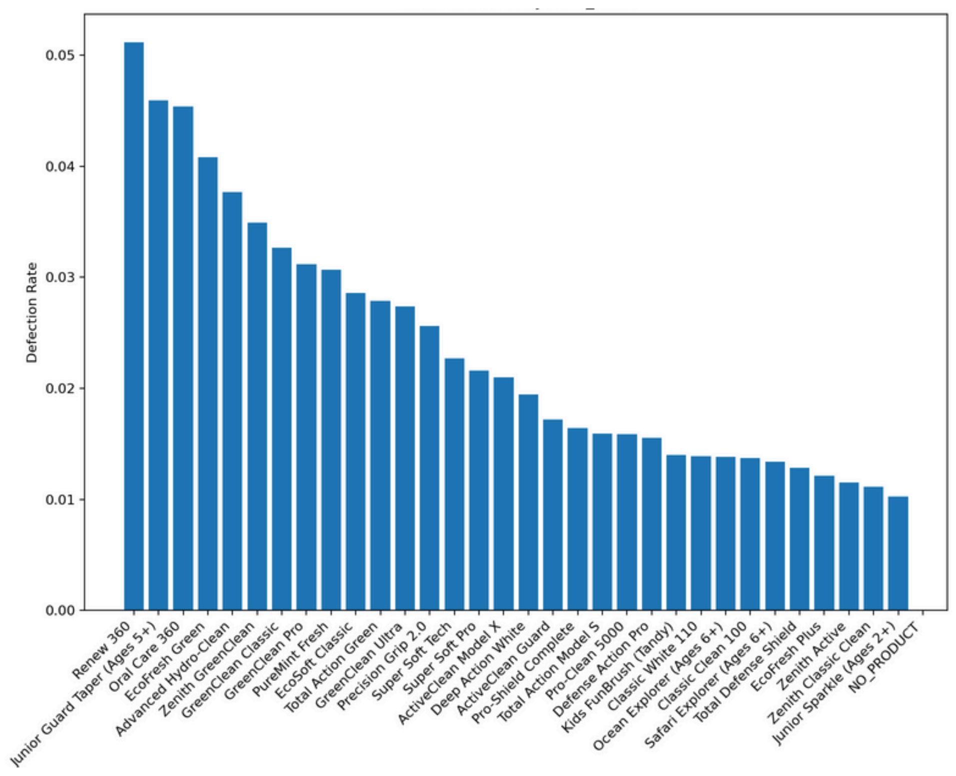
DATA OVERVIEW | **PERFORMANCE OVERVIEW** | ROOT CAUSE ANALYSIS | IMPACT QUANTIFICATION | ACTIONABLE RECOMMENDATION

OEE PERFORMANCE BREAKDOWN BY LINE & PRODUCT



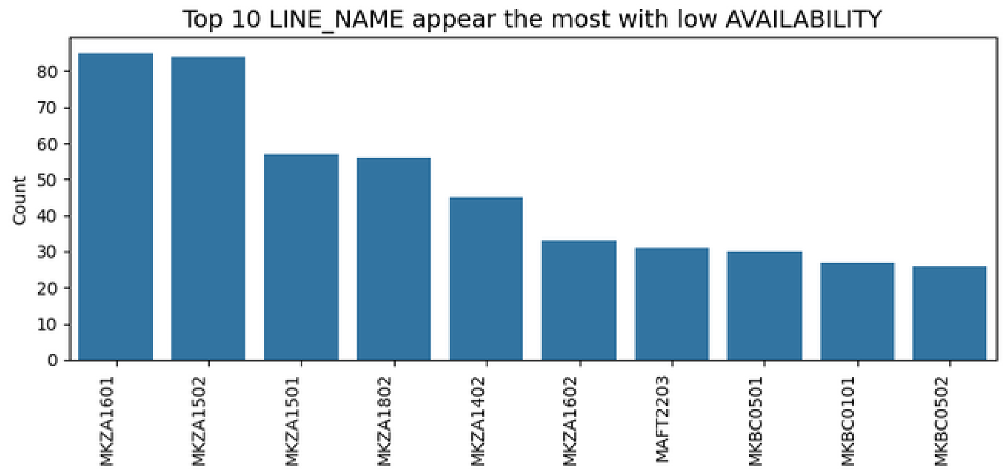
OEE BY WEEKS

The overall OEE **fluctuates** across weeks but shows a clear **upward trend**, indicating **gradual improvement** in equipment performance and process stability.
→ Continuous **monitoring** and short-term actions appear effective.



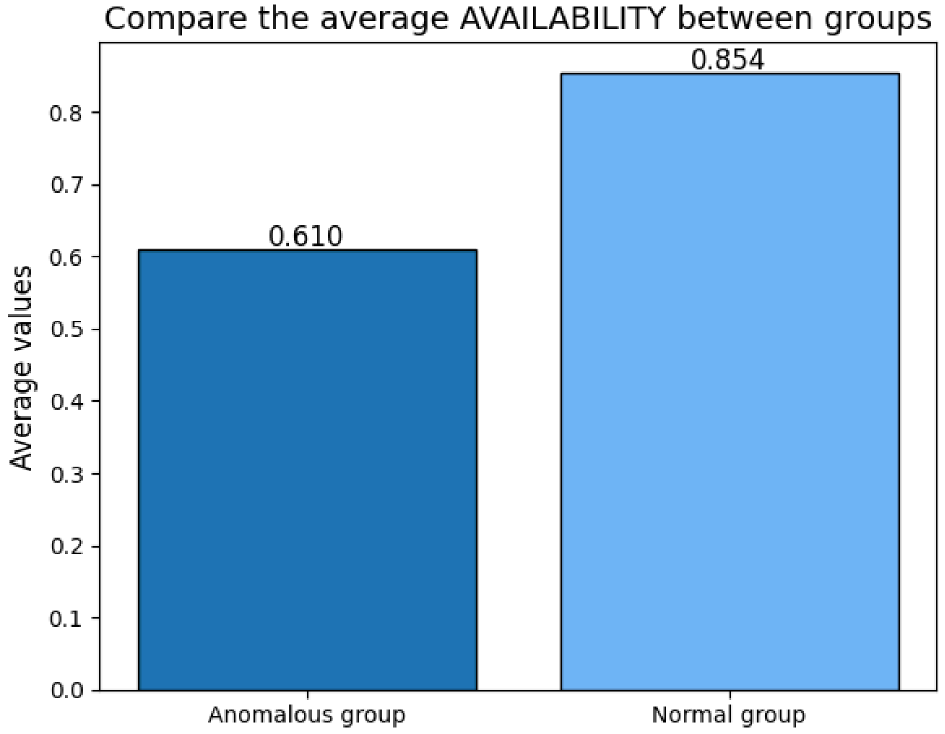
DEFECTION RATE OVERVIEW BY PRODUCTS

Some product types show slightly **higher Defection Rates**, but overall quality remains **stable** — defect rates stay **below 5%**, indicating consistent quality control.



AVAILABILITY ANALYSIS

Certain **LINE_NAMEs** appear significantly more frequently among records with low Availability, marking these lines as anomalous groups.



- Certain lines appear most frequently among **low-availability records**, marking them as **anomalous groups**.
- Statistical testing **confirms** a significant difference in Availability between normal and anomalous lines (**0.854** vs **0.610**), suggesting **setup delays** or **frequent changeovers** as potential causes.

Plant speed and quality remain **strong**, but **time losses** (availability gaps) are the main constraint. Addressing these will yield the largest OEE gain.

ANALYSIS OF RELATIONSHIPS BETWEEN FACTORS AND PRODUCTION ERRORS

Methodology

1. Group errors types by **ID** and summarize frequent types.
2. Apply **Chi-square Test** of Independence to evaluate the relationship between the **LINE_NAME**, **SIZE_TYPE**, **CREW_ID**, and the **error**.

Relationship strength is measured by **Cramér's V**:
0.1 < V < 0.2 → Weak link; V ≥ 0.2 → Strong link.

Cramér's V Result

Error ID	Occurrences	LINE_NAME	SIZE_TYPE	CREW_ID
11	*14564*	*0.2226*	*0.1796*	*0.0314*
17	*8220*	*0.2217*	*0.2492*	*0.0311*
13	*5220*	*0.1491*	*0.1184*	*0.0319*
03	*3830*	*0.2858*	*0.2061*	*0.0165*
14	*3822*	*0.1266*	*0.1592*	
06	*3809*	*0.1685*	*0.1339*	*0.0101*
18	*3391*	*0.2750*	*0.1856*	*0.0107*
02	*3335*	*0.1753*	*0.1761*	*0.0159*
12	*3138*	*0.1622*	*0.1950*	
16	*2184*	*0.1508*	*0.1473*	*0.0186*

*Values are shown only when **p-value < 0.05***

Findings

Machine/Line-based pattern

Errors cluster by **LINE_NAME**, especially older or complex lines

→ Suggests that equipment condition or technical setup is a key driver of recurring issues

Product/SKU-based pattern

Significant link with **SIZE_TYPE**

→ Errors likely stem from product design or material characteristics (e.g., handle thickness, filament stiffness).

Human factor

Cramér's V for CREW_ID is very low (**~0.03**) → Confirms that errors **are not operator-related**, allowing focus on equipment and process improvements instead of training or skills.

Operational Implications

Results show that errors are systematically **linked to machine lines** and **product types**, not operators.

Machine-related

Lines with higher Cramér's V likely have mechanical instability or wear.

→ Prioritize **preventive maintenance**, **calibration**, and **tooling optimization**

Product-related

Certain **SIZE_TYPEs** show recurring errors, suggesting design or material sensitivity.

→ Collaborate with **Product Engineering** to **adjust tolerances** and **setup parameters.**

UNPLANNED DOWNTIME ANALYSIS

Description

Identify the main root-cause groups contributing the most to unplanned downtime

Approach

After filtering data where **Ae_Model_Category = 'Unplanned'**, the **Material_Handle** group was identified as accounting for around 50% of total downtime.

This group is **directly** related to material feeding and handle replacement activities, therefore **selected** for **deeper analysis**.

After creating a **separate dataframe**, frequency statistics were calculated as follows:

CO_TYPE		
Material_Handle	27422	48.2%
Mateiral_FIlament	22422	39.5%
Bundle_Material	3347	5.89%
Tooling	1967	3.46%
NULL	1678	2.95%

TARGET GROUP: CO_TYPE = "MATERIAL HANDLE"

Methodology

1. Create a dedicated dataframe for the group **CO_TYPE = 'Material_Handle'**

2. Calculate the frequency of each failure (**UTIL_REASON_DESCRIPTION**)

3. Analyze distribution by **SIZE_TYPE** and **LINE_NAME** → to identify variations across machines and product types

4. Cluster similar **UTIL_REASON_DESCRIPTION** values to form major root-cause categories

5. Examine error distribution across machines and product types (SIZE_TYPE)

6. Record the **top 5 most frequent causes** into an Error–Product Frequency Matrix to detect specific error tendencies

Preliminary Findings

- The Material_Handle group is **fairly evenly distributed** across lines and does not focus on a single area.
- However, when **segmented by product** (SIZE_TYPE), clear **correlations** begin to **emerge** between certain error types and specific products
- Some errors occur **more frequently** with **particular products**, suggesting a possible incompatibility between material type and operating parameters.

ERROR–PRODUCT FREQUENCY MATRIX: MATERIAL HANDLE

Matrix Explanation

Each cell shows the error rate (%) for each product (Size_Type).
Highlighted cells indicate errors that occur more frequently than average.
The matrix helps identify product–error relationships for root cause analysis and improvement.

Clustered Util_Reason_Description	Lines with High Frequency	Renew 360	Oral Care 360	Deep Action White	Total Action Model S	Green Clean Pro	EcoFresh Plus	Junior Sparkle (Age 2+)	Super Soft Tech	PureMint Fresh	Total Action Green
Average Production Frequency (%)		*4.07*	*0.82*	*8.59*	*6.64*	*2.83*	*5.77*	*3.84*	*3.63*	*4.22*	*2.29*
Mechanical Adjustment	*MAFT (87%)*	*70.8*	*16.2*								
Material Change	*MHPT (67%)*	*14.5*		*44.5*	*23.4*						
Rework				*14.5*	*17.8*	*13.9*					
Handle stuck / FM stuck				*16.0*	*18.8*		*19.8*				
Robot / Welding / Conveyor adjustment		*10.0*		*15.7*	*21.2*		*12.9*				
Cleaning mechanical parts	*MHPT (76%)*			*62.2*	*17.0*						
Jammed handle on chain				*9.3*			*38.5*	*16.0*			
Adjust printing/logo/supply box position		*23.7*		*20.9*					*13.1*		
Adjust fiber picker gap/position				*10.0*		*19.5*	*10.6*			*13.4*	*11.0*
Lack of handle on chain							*36.1*				
Adjust sparepart / parameters	*MHPT(66%)*			*52.9*	*24.2*						

Some specific **SKUs** and **lines** (such as **MAFT** and **MHPT**) show **repeated errors** with **high frequency**, indicating that the root causes are product-specific rather than purely operational.

INSIGHTS

Some products: **Deep Action White**, **Total Action Model S**, and **Renew 360** show higher-than-average error rates across multiple categories: Mechanical Adjustment, Material Change, Cleaning Mechanical Parts...

→ This suggests that the issues may be **related to material characteristics** of the **handle** or the material feeding process.

It's **important** to review the relationship between SKU, handle type, and machine setup, especially in feeding systems, robot areas, and sensor calibration.

→ Focus **improvement** on:

- Optimizing material feeding and setup process
- Checking material compatibility across SKUs

Implementing these actions will **help reduce repeated downtime** and **increase overall line availability** across the plant.

TARGET GROUP: CO_TYPE = "MATERIAL FILAMENT"

Methodology same approach as used for 'Material Handle'

ERROR-PRODUCT FREQUENCY MATRIX: MATERIAL FILAMENT

Clustered Util_Reason_Description	Lines with High Frequency	Renew 360	Classic Clean 100	Total Defense Shield	Pro-Shield Complete	Pro-Clean 5000	ActiveClean Guard	Super Soft Tech
Average Production Frequency (%)								
Mechanical adjustment	*MAFT*	*49.0*	*15.3*			*14.1*		
Stuck handle on chain	*MKBC*		*39.7*	*33.6*				
Adjust sparepart	*MHPT*		*36.7*	*55.5*				
Change material	*MHPT*		*18.9*	*71.9*				
Double handle on chain	*MKBC*		*25.8*	*23.6*	*17.2*	*14.6*		
Adjust robot position	*MKBC*		*25*	*41.5*		*12.6*		
Jammed handle on chain	*MKBC*		*23.5*	*30.3*		*27.7*		
Adjust fiber picker gap / position			*36.0*	*31.8*				
Rework	*MKZA*		*21.2*			*22.7*	*18.7*	*15.1*
Handle stuck on FM	*MKBC*		*24.8*	*28.7*		*22.1*		
Repair laser/Jam conveyor/Lack of handle	*MKBC*		*34.5*	*22.1*		*13.9*		
Replace/adjust mechanical parts	*MKBC*		*40.5*	*23.1*				
Adjust welding parameters	*MKBC*		*31.6*	*23.3*		*16.7*		

Findings

Compared with **Material Handle**, the **Material Filament** group shows a more **concentrated pattern** — affecting **fewer products** (7 SKUs) but with significantly higher error frequency.

Key issues include **mechanical adjustment**, **stuck or double handles**, and **spare-part or parameter adjustments**, mainly related to filament alignment and precision.

Lines such as **MKBC** appear **repeatedly**, indicating that mechanical calibration and filament tension control are the main influencing factors.

INSIGHTS

Products such as **Total Defense Shield**, **Classic Clean 100**, **Pro-Clean 5000** show above-average error rates

These SKUs feature **complex filament or handle structures**, making them more sensitive to feeder alignment and filament tension.

→ **Focus improvement on**: standardizing filament tension and feeder setup, performing regular calibration, and monitoring mechanical adjustments to detect early drift.

TARGET GROUP: CO_TYPE = NULL

Methodology

1. Use dataframe with **AE_MODEL_CATEGORY** = **'Unplanned'** → focus on subgroup where **CO_TYPE = NULL**.
2. Examine runtime characteristics.
3. Count frequency by **SIZE_TYPE** and **MACHINE_ID**
4. Analyze **UTIL_REASON_DESCRIPTION** to identify true root causes.

Findings

All 1,678 records with **CO_TYPE = NULL** are concentrated on **a single SKU — "Total Defense Shield" — and appear only on machine MHPT2307**.

RUNTIME = 0 while **PRODUCTION_AVAILABLE_TIME > 0**
→ confirming these are true downtime events.

Average downtime ≈ 17.5 minutes/stop
Total accumulated downtime ≈ 490 hours
Mostly micro-stops (8–20 mins), few major stops (>60 mins)

→ **This significantly impacts line availability**

Observation

After analyzing the frequency of **UTIL_MODEL_DESCRIPTION** within the Unplanned group **(CO_TYPE = NULL)**:

Description	*%*
Change material	21.04
Stuck handle on chain	16.98
Adjust sparepart	12.34
Double hadle on chain	7.27
Cleaning Jaw	5.66

The **top 5 unplanned reasons** account for **63%** of total downtime, dominated by Change Material, Stuck Handle on Chain, and Adjust Sparepart.

Most of these are related to material feeding and equipment setup, suggesting that **the unplanned stops** were **not random**, but stemmed from **material handling** and **mechanical adjustment issues**.

Insight

The records with **CO_TYPE = NULL reflect actual unplanned machine stops** that occurred during operation — on machine **MHPT2307** producing **Total Defense Shield**.

These events are strongly linked to **material feeding** and **mechanical handling**.

Because the stops are **short** and **repetitive**, they accumulate significant downtime **(~490 hours)**, reducing line availability and throughput.

→ **Implication:** Improving **material supply consistency**, **feeder calibration**, and **early detection of jams** could substantially reduce these micro-stops.

NO PRODUCTION

Summary

Machine shows **Runtime > 0** but both **Good = 0** and **Reject = 0** → indicating the machine was **running without producing** any products.

This is an operational anomaly that is currently **not recorded as a fault**, and thus **easily overlooked**.

Methodology

1. Filter records with **Util_Reason_Description = 'Runtime'**
2. Select records where both **Good_Production_Qty = 0** and **Reject_Production_Qty = 0**
3. Analyze by **Line_Name** and **Size_Type**; perform statistical tests to verify differences in frequency (p-value < 0.05)

Evidence

619 records met the **No-Production** condition ~ **2.84%** rate across all records

Average runtime **≈ 145 minutes** per record while no products were produced

IDLE RUNNING

Statistics show all **Production quantity = 0** while **Runtime > 0**

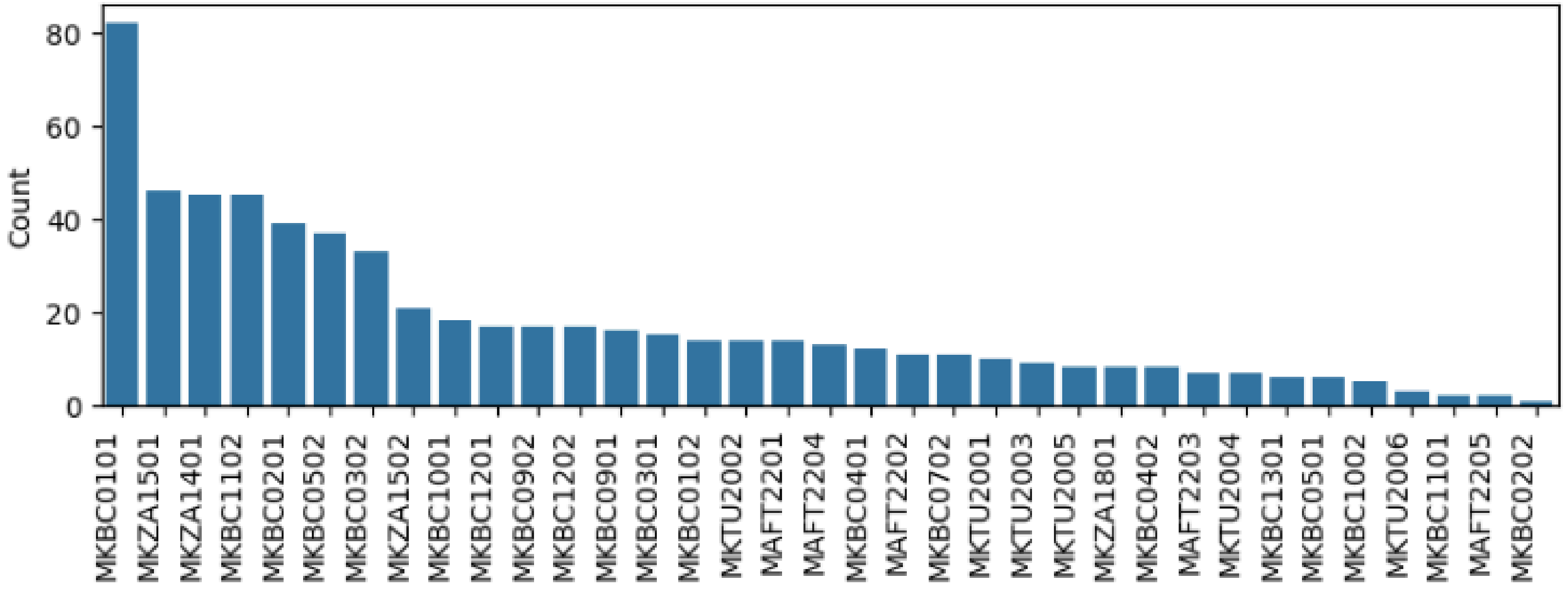
Key Issue

I. This runtime period was not labeled as a downtime event, meaning these losses are currently **untracked** in the OEE system.

II. Total runtime without production: **≈ 1,161 hours** during the analyzed period, resulting in reduced Availability and Throughput, even though these periods are not logged as downtime.

NO PRODUCTION

By Line Name



– The line **MKBC0101** has the highest occurrence of No-Production events. (Estimated No-Production rate for this line **~13.25%**)

– Hypothesis testing **confirms** this line's frequency is **statistically significant** (p-value < 0.05).

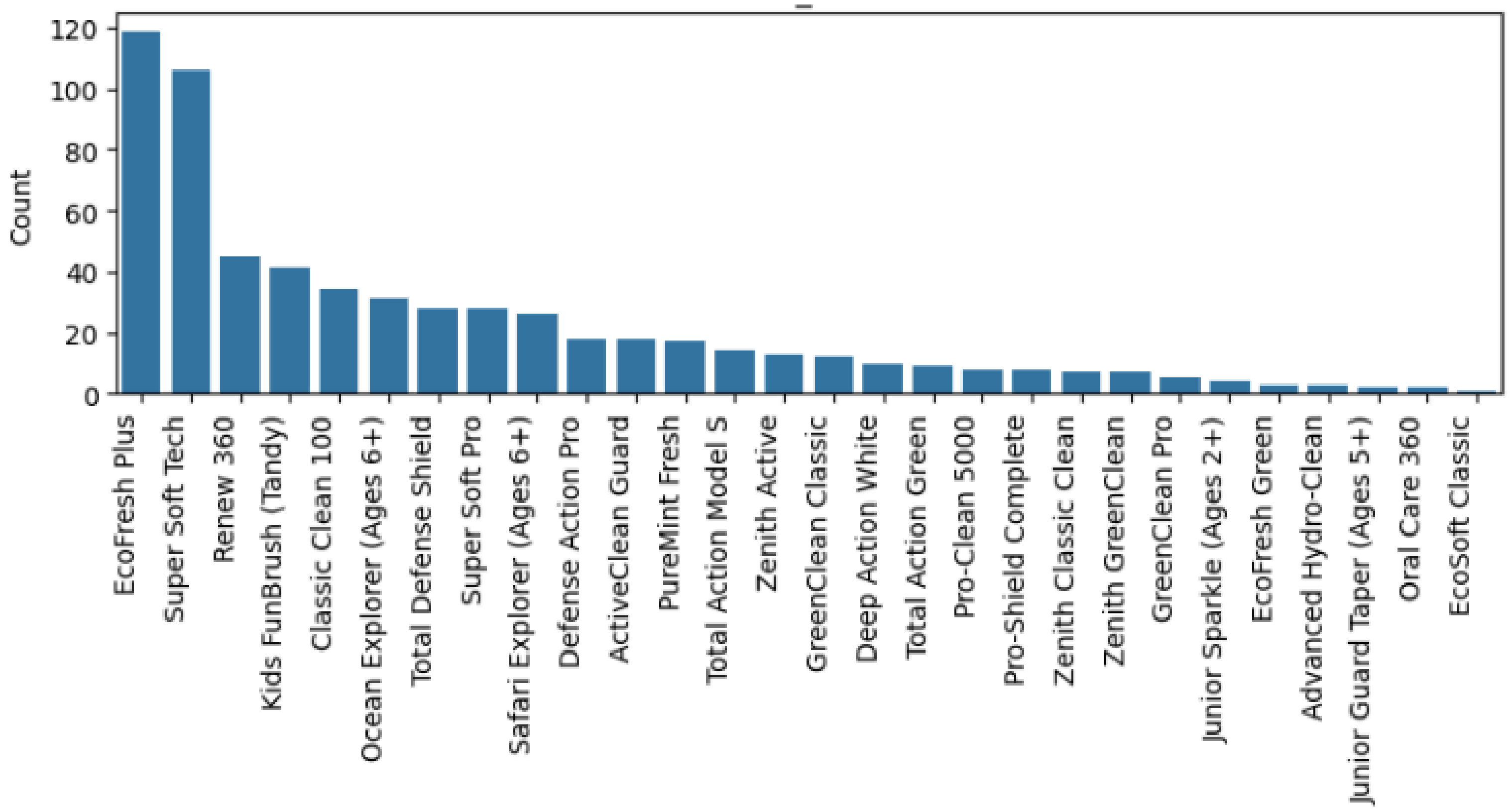
→ This line **(MKBC0101)** should be considered a **primary focus** for root-cause investigation

Insight

These cases are not data errors but represent **empty running** caused by **process**/equipment behavior.

Potential root causes include **material feeding**, robot pick/place, **sensor failure**, or **PLC** logic during start-up or product changeover.

Patterns are concentrated on line **MKBC0101** and the two **SKUs** above, suggesting issues related to setup at shift start/batch start or material characteristics



By Size Type

Two product types most frequently associated with this issue: **EcoFresh Plus** and **Super Soft Tech**.

Statistical testing confirms the relationship is significant (p-value < 0.05).

Implementation Approach

Automate Detection: Flag and track cases where Runtime > 0 but no output is recorded.

Verify Process Logic: Review material feeding, robot operation, and PLC setup to prevent "run-empty" conditions.

Standardize Setup: Apply consistent pre-run checks for EcoFresh Plus and Super Soft Tech.

Improve Control: Introduce auto-stop or slowdown when no product is detected within a defined time.

Overall Loss

Total Downtime	Total number of products lost due to Downtime	Total number of defective products
21196 hours	**80,495,591 units**	**7,232,022 units**
accounting for **15.46%** of total Production Available Time	accounting for the majority of total product losses	accounting for **1.6%** of total produced units

→ Downtime is **the major contributor** to OEE loss, more than quality defects

Representative Loss by Line Name

Line Name (Top 5)	Error occurrence rate	Total Downtime	Total products lost due to Downtime	Total defective products
MKZA1501	80.33%	48497	3271850	163400
MKBC0202	82.33%	40023	3257872	176310
MKZA1502	82.16%	47431	3239302	147701
MKZA1601	78.01%	44610	3000394	98967
MKBC0102	82.10%	36008	2931051	137452

*Losses are **fairly consistent** across lines, implying that **improvement should focus on process-wide optimization** rather than isolated lines.*

Representative Loss by Size Type

Size Type	Error occurrence rate	Total Downtime	Total products lost due to Downtime	Total defective products
Renew 360	76.9%	83899	2024832	309785
Deep Action White	74.4%	102168	5207058	626588
Total Action Model S	74.5%	109548	7675192	502823
EcoFresh Plus	74.3%	67407	5790438	433147
Total Defense Shield	75.3%	153220	10855882	1135655
Classic Clean	72.0%	141657	10828558	1156630
Super Soft Tech	77.8%	86692	5984921	330353
Other		527217	32128710	2737041

No Production Loss

During certain periods, **machines were running** but **produced no output**, leading to untracked losses.

- Total unrecorded runtime: **~1,161** hours (≈2.8% of total records)
- Concentrated on Line **MKBC0101** (No-Production ≈13.25%), mainly **EcoFresh Plus** and Super Soft Tech

→ Reduced actual **Availability** and **Throughput**.

Root causes: material feeding, robot pick/place, or sensor issues during start-up or changeover.

Key Takeaway

- Downtime loss dominates → focus on Availability improvement.
- “Material Handle” – related stops explain nearly half of total downtime → biggest impact lever.
- Product-specific patterns (**Total Defense Shield**, **Model S**) → collaboration with Product Engineering required.
- These findings **quantify** and **confirm** where improvements will yield the largest OEE gain.

Business Impact Interpretation

- Total quantified loss: **≈19.8%** of effective capacity (Total Good Product Quantity)
- Directly affects efficiency, delivery reliability, and cost control
- Addressing **top-impact causes** could **recover up to 10% OEE**, yielding clear financial benefits

RECOMMENDATION #1 & #2. ANOMALY DETECTION USING DASHBOARD & MODEL

Aspect	Short-Term Approach	Long-Term Approach
Purpose	*Detect abnormal performance trends (drift) over time in **KPIs** such as **Availability** and **Performance**. Trigger alerts when a **line or SKU** is gradually **degrading** even before it crosses **error thresholds.***	***Early detection** of abnormal patterns before they lead to major downtime or defects.* *Typical targets:* • ***Gradual drift** in Availability / Performance / Quality* • ***Micro-stop anomalies** (frequency and clustered patterns)* • ***No-production runtime** (machines running idle with intermittent rejects)* • ***Includes Explainable AI (XAI)** to show operators why an alert was triggered.*
Operating Principle	*Data is **aggregated by line/SKU** over **short time intervals** (adjustable by project scale). The system calculates:* • ***Rolling Mean (moving average)*** • ***Slope of the time series:** If the slope remains negative for multiple periods or exceeds control limits, the dashboard will highlight that line/SKU.*	• ***Data Preparation:** Collect, clean, and generate features → Transform **raw logs** into quantitative inputs* • ***Model Training:** Learn **normal behavioral** patterns → Define a **"safe zone"** per line/SKU* • ***Anomaly Scoring:** Compute anomaly score for new data → Identify **unusual machine behavior*** • ***Alerting & Visualization:** Apply **thresholds** and show **dashboard** → Provide clear **early warnings** to engineers* • ***Feedback Loop:** Capture operator feedback & refine model → **Reduce false alarms, improve accuracy***
Dashboard Architecture / Feature Groups	• ***Trend Line Chart** – Time series of **OEE / Availability** by week* • ***EWMA Chart** – Exponentially Weighted Moving Average chart with **±2σ** control limits* • ***Drift Heatmap** – (Line × Week) matrix showing **drift intensity** via **color scale*** • ***Alert Table** – **Top 10 lines** with the strongest negative trend (worst slopes)* • ***KPI Summary** – **Average** of 4 main KPIs + **overall** trend direction*	• ***Level & Trend** (OEE / Components): OEE, Availability, Performance, Quality — values and volatility* • ***Throughput & Yield:** Good rate, Reject rate, short-term % change, spike indicators* • ***Downtime Shape:** Total downtime minutes, stop counts, **micro-stop ratio (5–20 min)**, p95 stop duration* • ***No-Production Runtime: Idle run flag** (runtime > 0 & output = 0), idle ratio, consecutive idle periods*
Feedback Loop	***Capture operator feedback & refine model***	***Reduce false alarms, improve accuracy***

RECOMMENDATION #3. PREDICTIVE MAINTENANCE MODEL (DDPM)

Purpose

Predict potential unplanned downtime due to **equipment failure** — especially recurrent mechanical issues (e.g., Mechanical Adjustment, Handle Stuck, Material Change).
Enable preventive maintenance before actual breakdowns occur.

Initial Feature Groups

DDPM uses **historical production** and **maintenance data** to learn machine behavior.
Typical variables include:

- **Production Log**: runtime, downtime reasons (UTIL_REASON_DESCRIPTION), micro-stop frequency, production speed.
- **Maintenance Order**: count of maintenance events, error types (mechanical, material, tooling).
- **Line & Product Features**: LINE_NAME, SIZE_TYPE (SKU), CO_TYPE (Material_Handle, Filament, etc.).

Derived Metrics: MTBF (Mean Time Between Failures), MTTF (Mean Time To Failure), downtime ratio, operating hours since last maintenance.

Operating Principle

Stage	*Main Activity*
1. Data Integration	*Combine data from production (MES) and maintenance (CMMS) systems*
2. Feature Engineering	*Build features like time between failures, common failure types, runtime before next downtime*
3. Model Training	*Train model to predict failure probability in the next shift (classification/regression)*
4. Prediction & Scheduling	*Estimate failure risk per machine → automatically propose maintenance 24–48 hours in advance*
5. Feedback & Continuous Learning	*Compare predictions with actual results and periodically retrain models*

Evaluation Metrics

Category	*Description*
Model Accuracy	*Correctly identifies machines at risk*
Maintenance Efficiency	*Increased mean time between failures*
Downtime Reduction	*Fewer unexpected stoppages*
OEE Improvement	*Better availability and reliability*
Cost Optimization	*Fewer emergency repairs and replacements*

Model Outputs

- **Time_to_Failure** – Estimated hours/minutes before next failure
- **Expected_Downtime_Duration** – Predicted duration if failure occurs
- **Next_MTBF** – Forecasted Mean Time Between Failures for the machine

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