



# "Predicting Tomorrow, Saving Today" Enhancing Efficiency at Swire Coca-Cola

A Data-Driven Approach to Predictive Maintenance

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# Introduction

#### **☐** Importance of Predictive Maintenance:

- Reduces unplanned downtime.
- Extends machine life.
- Increases operational efficiency.

#### **☐** Objectives of the Project:

- Transition from reactive to predictive maintenance.
- Use data to predict failures.
- Minimize downtime and reduce costs.
- Improve overall operational productivity.











#### Cost

High costs associated with unexpected machine breakdowns (\$60 million in annual losses).



#### **Downtime Impact**

Inefficiencies in current reactive maintenance processes leading to increased downtime.



#### **Operational Reliability**

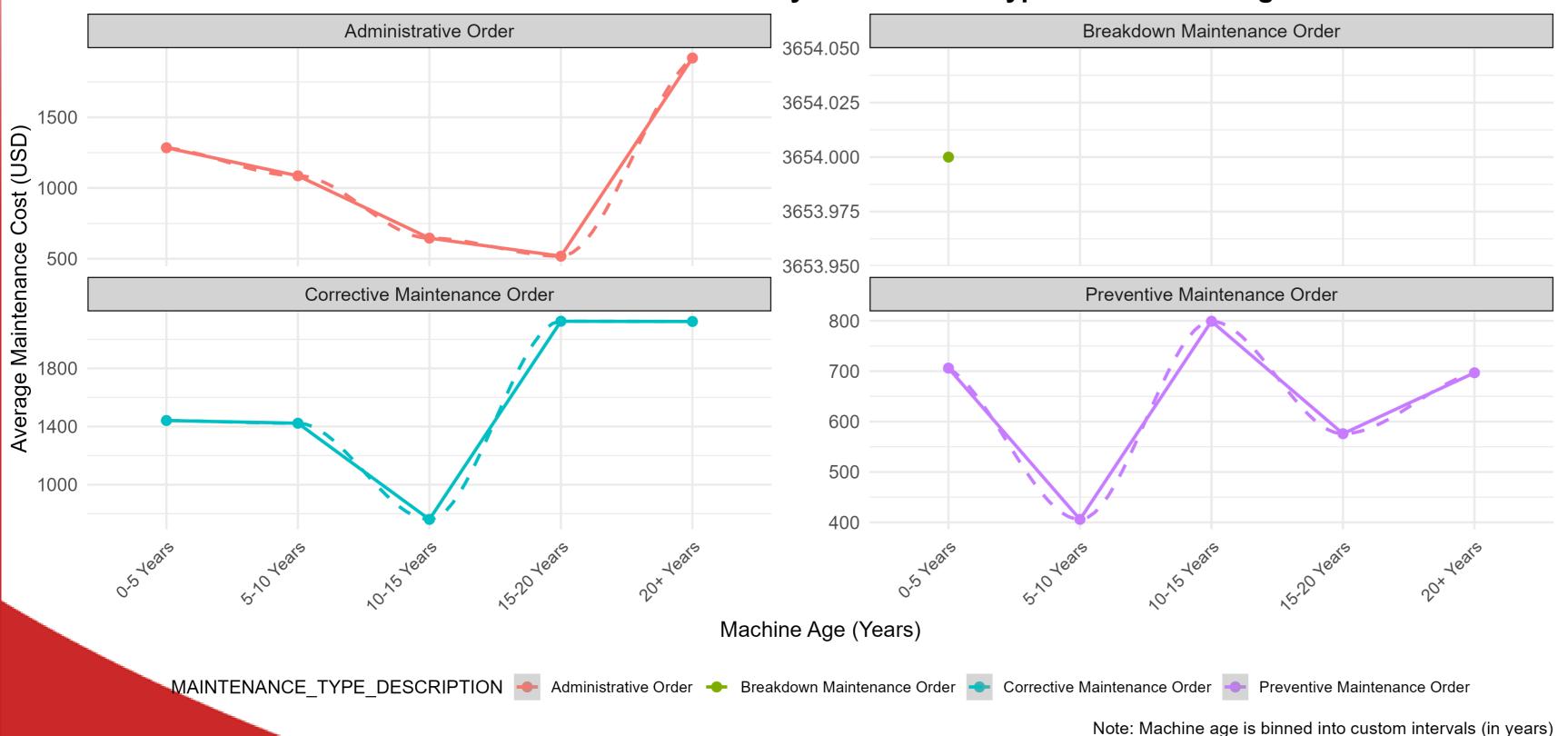
Urgent need for a predictive maintenance approach to reduce unplanned outages and improve operational reliability.





# **Exploratory Data Analysis (EDA) Insights**

#### Variation of Maintenance Costs by Maintenance Type and Machine Age



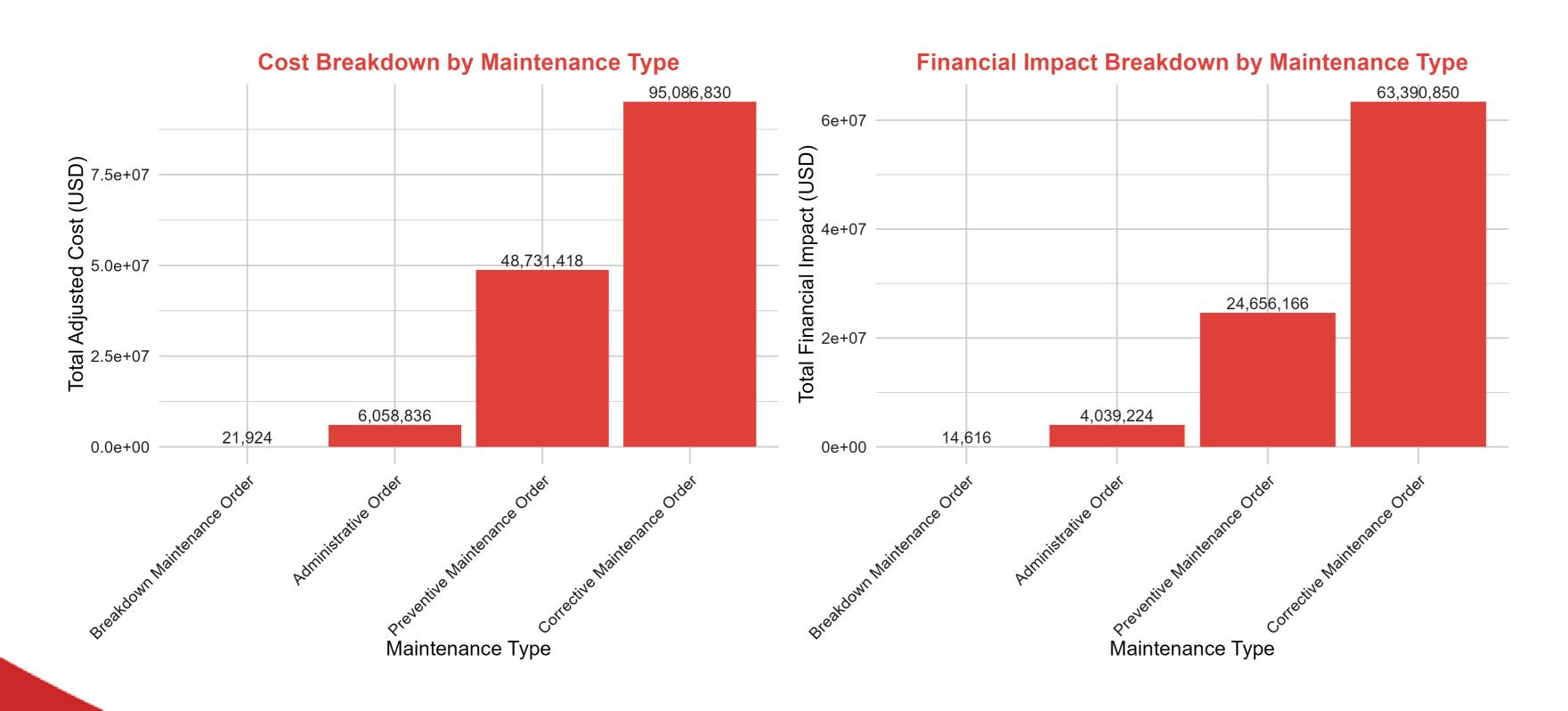
## Maintenance costs rise with age, notably after 15 years.

- Administrative Orders: Costs escalate to around \$3,654 for machines over 20 years old.
- Corrective Orders: Costs fluctuate, averaging about \$1,800 for older machines.
- Preventive Orders: Costs remain relatively stable, averaging around \$800 across machine ages.





# EDA Insights- Cost Breakdown & Financial Impact

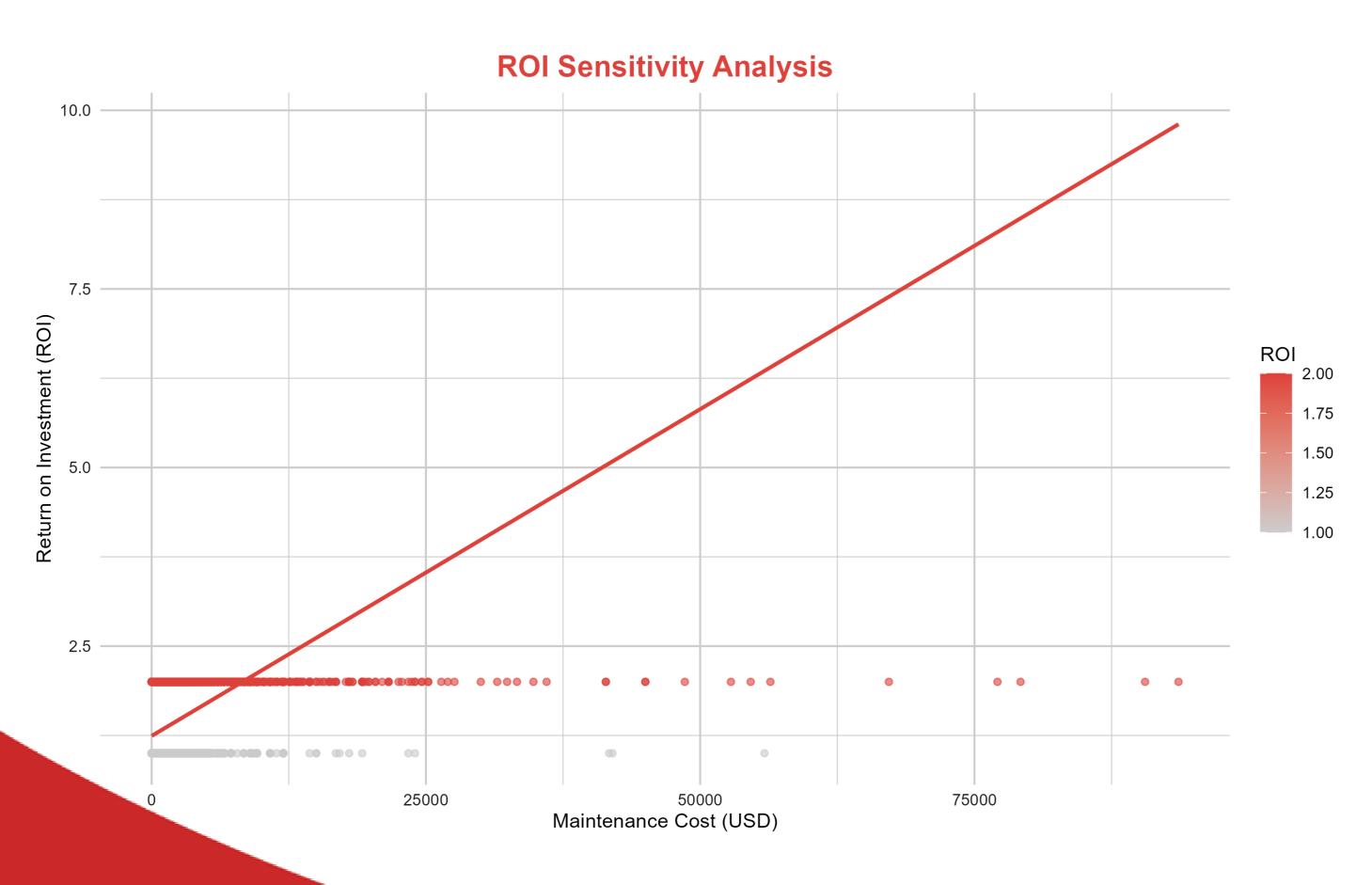


- Corrective maintenance incurs the largest financial impact, totaling \$63.4 million.
- Preventive maintenance shows a substantial cost of \$48.7 million, but it helps avoid even higher expenses associated with breakdowns.
- Breakdown orders have the lowest costs, only \$21,924, but they pose high risks if unaddressed.





# ROI Sensitivity Analysis

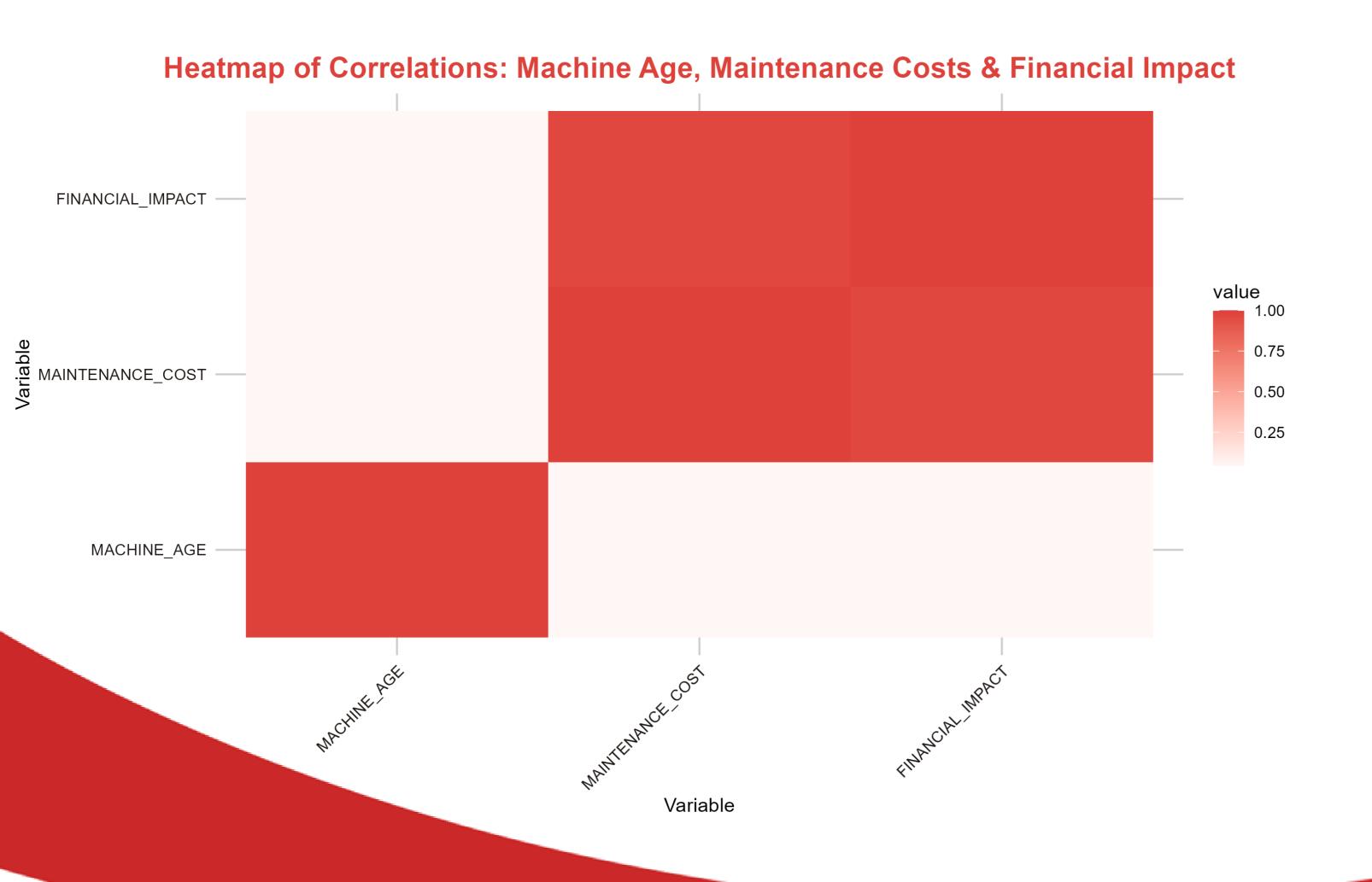


- Annual Cost Savings: Projected to save \$12 million annually by reducing unplanned maintenance costs.
- Significant Downtime Reduction: Model is expected to decrease unplanned downtime by 40%, keeping production on track.
- Higher Productivity: Anticipated 5% increase in production output, helping meet demand more effectively.
- Less Inventory Waste: Predictive stocking cuts down on unused parts by 15%, saving on storage and inventory costs.
- High Return on Investment: Forecasted to achieve a 150% ROI within the first year, making this a valuable investment.





# Correlation Heatmap: Machine Age, Cost & Impact



- Enhanced Risk Management: Identifies high-risk machines and locations, allowing targeted intervention to prevent costly breakdowns.
- Resource Prioritization: Helps allocate maintenance resources effectively by focusing on areas with the highest risk of failure.
- Reduced Downtime: Enables proactive action on vulnerable machines, minimizing unplanned downtime and associated costs.
- Improved Operational Efficiency: Supports datadriven maintenance planning, leading to more streamlined operations and reduced maintenance frequency.

# Modeling Approach

Using advanced machine learning techniques like Random Forest and XGBoost, the goal was to predict machine failure risks and optimize maintenance strategies by identifying key predictive features and improving operational efficiency





# Predictive Model- Logistic Regression

PREDICTED MAINTENANCE

\$717.23

**Average Cost** 

\$358.99

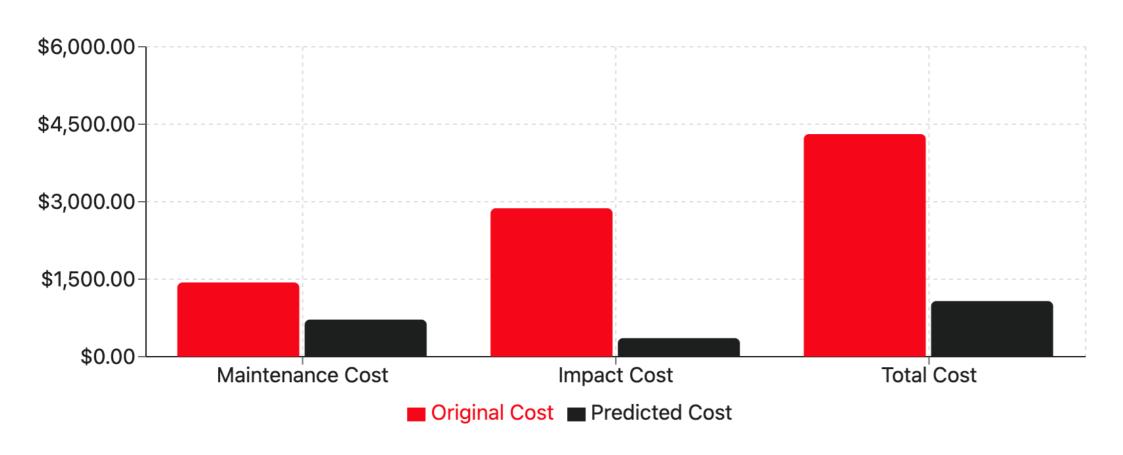
Average Cost

TOTAL COST

\$1,076.22

Per Incident

#### **Cost Comparison Analysis**



#### Accuracy: 79%

- Pre-Implementation Cost (\$)
- Original Average Predicted Maintenance Cost: \$1436.59
- Original Impact Cost: \$2873.17
- Original Total Cost per Incident: \$4309.76
- Post-Implementation Cost (\$)
- Average Predicted Maintenance Cost: \$717.23
- Average Predicted Impact Cost: \$358.99
- Average Total Cost per Incident: \$1076.22





#### Predictive Model- XGboost



Accuracy: 83%

- Pre-Implementation Cost (\$)
- Original Average Predicted Maintenance Cost: \$1436.59
- Original Impact Cost: \$2873.17
- Original Total Cost per Incident: \$4309.76
- Post-Implementation Cost (\$)
- Average Predicted Maintenance Cost: \$715.99
- Average Predicted Impact Cost: \$358.00
- Average Total Cost per Incident: \$1073.99

Feature Importance: Maintenance Intensity,

Machine age

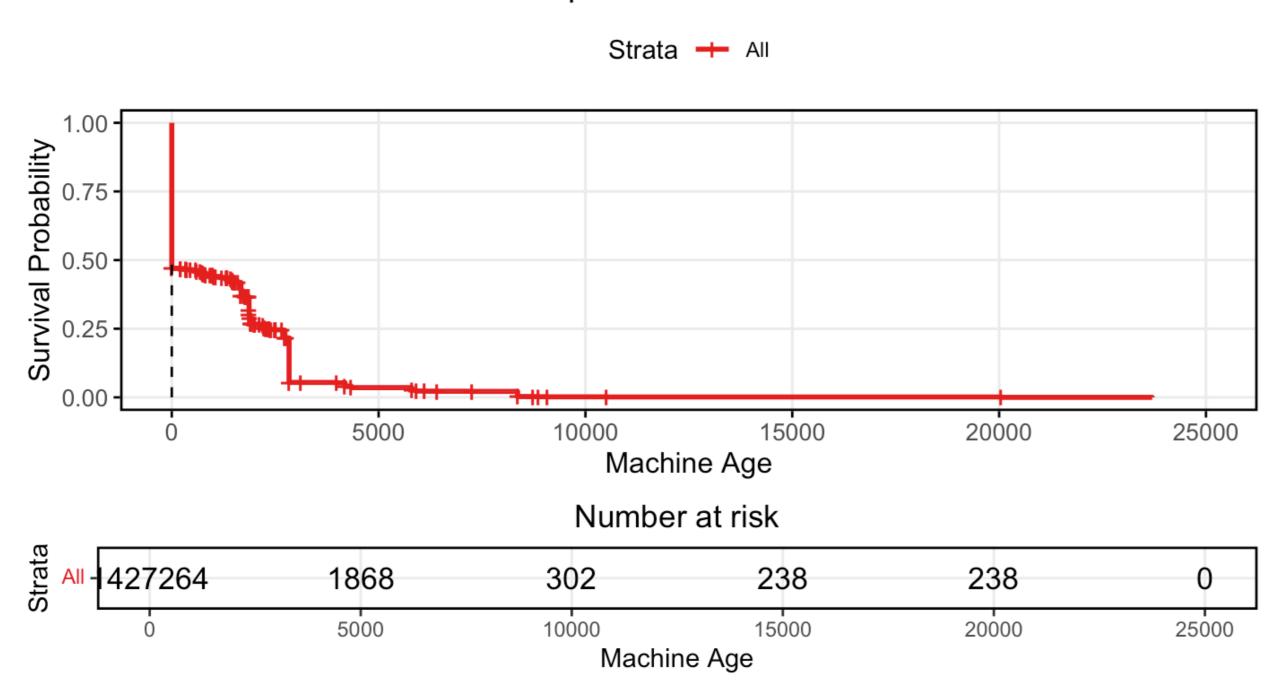




## Survival Analysis

#### **Equipment Survival Analysis**

Cox Proportional Hazards Model



#### **Key features of Survival Analysis:**

The red line shows survival probability decreasing as machines age. Drops represent failure events; steeper drops indicate more failures.

#### **Critical Time Points:**

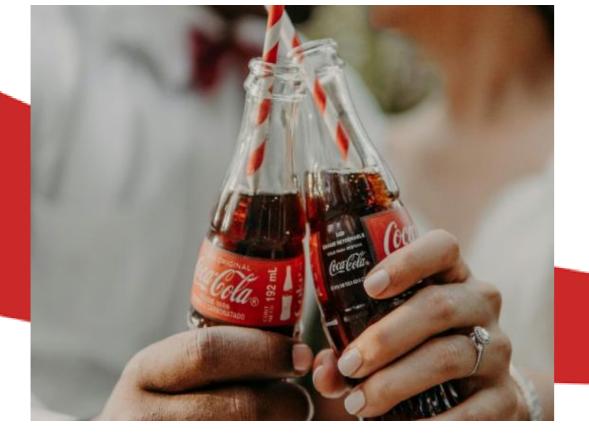
- The curve's initial steep drop suggests high failure rates for new machines, possibly due to manufacturing defects or break-in issues.
- The plateauing later on indicates lower failure rates for older machines, likely due to the survival of the most reliable units or effective preventive maintenance.





### **Business Recommendations**

- For Management
- Implement predictive maintenance to reduce unplanned downtime by 40%.
- Prioritize high-risk machines using data insights and optimize resource allocation.
- Conduct quarterly reviews to assess ROI and adjust strategies.



- ☐ For Finance
- Achieve \$12M in annual savings through predictive maintenance.
- Reinvest savings into advanced tools and employee training.
- Track ROI (150%) and reduce incident costs by \$2,995.



- ☐ For Operations
- Integrate predictive insights into daily workflows to target critical machines.
- Train staff on data interpretation and tool usage.
- Improve machine reliability to boost production by 5% and reduce inventory waste by 15%.





## Implementation Roadmap



#### ☐ Planning (0–3 months)

- Align objectives with stakeholders
- Upgrade infrastructure for data collection
- Develop and test predictive models

Phase 2

# ☐ Full-Scale Implementation (7–12 months)

- Roll out model across all machines
- Integrate tools into workflows and dashboards
- Track KPIs for cost savings, downtime, and production

Phase 4

# hase 1

# □ Pilot Testing (4–6 months)

- Test predictive
   maintenance on select
   machines
- Train teams on model use and data analysis
- Monitor and adjust models
   as needed

# ☐ Continuous Improvement (13+ months)

- Refine models with realtime feedback
- Explore Al-driven scheduling
- Expand predictive insights to other areas



## Conclusions





#### **☐** Key Achievements:

- Reduced costs by 70% and downtime by 40%.
- Saved \$12M annually with a 150% ROI in Year 1.
- Increased production (+5%) and reduced inventory waste (-15%).

#### ☐ Next Steps:

- Launch pilot phase with ongoing team engagement.
- Monitor results to refine models.
- Scale up and assess long-term impact.



# Thank Youll