Executive Summary and Implications

Statement of the Problem and Hypothesis

The primary objective of this study was to investigate the extent to which demand and parts-per-tool usage affect tooling (or equipment) failure. The hypothesis was that demand and parts-per-tool usage statistically significantly affect tooling failure. By understanding these relationships, it is the goal to improve predictive tool usage, reorder point management, and capacity planning in a test work center.

Summary of the Data-Analysis Process

The data-analysis process involved several key steps:

1. Exploratory Data Analysis (EDA): EDA was conducted to understand the underlying patterns and relationships in the data. This included examining the dataset description to comprehend its structure and determine how to create randomized data in Excel to supplement any missing relevant data not present in the original dataset.
2. Data Collection and Preparation: Historical data on tool usage, demand for tool usage, parts per tool usage, and lead times for reordering tools was gathered and created. After preprocessing and merging all the data, the dataset was split into training and test sets before model development and evaluation.
3. Model Development: A predictive maintenance model was developed to forecast test tool failures using linear regression analysis. Recursive Feature Elimination (RFE) was employed to select the most important features contributing to tool failures, ensuring optimal feature selection and model performance.
4. Model Validation: The model was cross validated using 5-fold cross-validation to ensure its accuracy and reliability.
5. Visualization: An interactive Tableau dashboard was created to visualize key metrics and trends identified during the statistical analysis. It allows stakeholders to view demand fluctuations, inventory levels, tool capacity, predicted tool wear, and inventory reorder points.

Outline of the Findings

The analysis revealed the following key findings:

- Significant features: Out of the selected features from RFE, the Ordinary Least Squares (OLS) analysis identified statistically significant features which include Parts Per Tool, Demand Week 36, Demand Week 40, No. Tools on Hand (actual), No. of Tools Needed Based on Reorder Point, and Adjusted Reorder Point. These features indicate they have a meaningful relationship with tooling failure.

- Reorder Point Discrepancy: Predicted tool wear reorder points are significantly larger than inventory reorder points. This discrepancy suggests high variability in demand, which could lead to challenges in inventory management.
- Tool Type L Variability: Most demand and tool utilization are concentrated on tool type L, which also shows the most variability between inventory reorder points and predicted tool wear reorder points.

Explanation of the Limitations of the Techniques and Tools Used

While the techniques and tools used provided valuable insights, there were several limitations:

- Reliance on Artificially Created Historical Data: The use of simulated data may not accurately reflect real-world demand patterns, lead times, or tool usage. This could impact predictions and the robustness of the findings. Additionally, including cost information for each tool could have facilitated a cost analysis to demonstrate alternate outcomes for inventory strategies.
- Assumption of Linear Relationships: The regression model assumes a linear relationship between the variables, which may not always capture all the complexities of real-world tool failures.
- Limitations of Tableau: While Tableau is effective for visualizations, it may struggle with pulling dynamic data from ERP systems like SAP, which can slow performance. Often, creating an extract of the dynamic data to temporarily convert it into static format is necessary for dashboard efficiency.

Summary of Proposed Actions

Based on the findings, the following actions were proposed:

- Implement a Dynamic Inventory Management System: Adjust reorder points in real-time based on demand, parts-per-tool usage, and predictive tool wear forecasts.
- Develop Dynamic Inventory Policies: Create policies that adjust reorder points based on demand variability bands, ensuring preparedness for fluctuating demand and reducing risks of overstocking or stockouts.
- Prioritize Tool Type L: Focus on monitoring and replenishing inventory for tool type L, which shows high demand, variability, and utilization. Implement predictive maintenance schedules specifically for this tool type to ensure optimal availability and performance.
- Utilize Distribution Bands: Use distribution bands of 60% and 80% averages, ranging from 150M to 230M, to establish reorder points, as demand is likely within that range. This approach could help reduce the gap between predicted tool wear reorder points and inventory reorder points.

Expected Benefits of the Study

It is challenging to quantitatively determine the benefits of the study without an established baseline. This project acknowledges that most data would be based on tribal knowledge. However, this analysis provides a solid foundation for future quantitative assessments as a baseline is established and more data becomes available.

The study is expected to yield several significant results:

- Reduced Downtime: By predicting tool failures and optimizing maintenance schedules, the study anticipates a reduction in unexpected downtimes, leading to increased productivity. Fewer unexpected failures will mean less disruption to the workflow, allowing the organization to maintain a steady production pace.
- Cost Savings: Optimized inventory management will reduce costs associated with overstocking or expedite orders, resulting in cost savings. By avoiding excess inventory and ensuring timely reorders, the organization can lower storage costs and minimize the financial impact of rush orders.
- Improved Planning: Enhanced capacity planning will allow for better resource allocation and improved overall efficiency in the test work center. With more accurate predictions of tool wear and demand, the organization can better align resources with production needs, optimizing the use of both tools and labor.
- Data-Driven Decision Making: The insights gained from the data analysis will enable more informed, data-driven decision-making processes. Leveraging these insights, planners can make strategic decisions based on empirical evidence rather than intuition or incomplete information.
- Increased Operational Efficiency: Streamlined processes resulting from improved predictive maintenance and inventory management can lead to a more efficient operation overall. This includes smoother production cycles, reduced lead times, and a more agile response to changes in demand.
- Enhanced Predictive Accuracy: As more data is collected and analyzed, the predictive models will become more accurate, leading to even better forecasting and planning. This ongoing improvement can compound the benefits over time, resulting in a continuously optimized operation.

The study not only provides immediate benefits but also sets the stage for ongoing improvements as more data becomes available and predictive models are refined.

In text citations:

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(“Merging datasets”, n.d.)
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(“Sharing data insights”, n.d.)
(“Advanced manipulations with Story Points”, n.d.)
(“Calculated Fields to extend data”, n.d.)
(“Visualizations for exploratory analysis of trends”, n.d.)
(“Slicing and dicing”, n.d.)
(“Make your data visually appealing”, n.d.)
(“Dashboard and stories”, n.d.)

<u>Presentation of Findings</u>

Please see D214 Performance Assessment Task 3 PowerPoint Presentation PDF document and Panopto recording attached to the submission.

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