

A Study on Impact of AI Driven Predictive Maintenance on Manufacturing Performance

Mr. Shivaji Holkar¹, Prof. Vidya Taval²

¹MBA student, OSCM branch, Unique institute of management, pune, India

²MBA Guide, OSCM branch, Unique institute of management, pune, India

Abstract—This study examines the impact of AI-driven predictive maintenance on manufacturing performance using a quantitative research approach. The research integrates operational data collected before and after the implementation of predictive maintenance, along with primary survey data obtained from 110 respondents. Key performance indicators such as downtime, availability, Mean Time Between Failures (MTBF), and Mean Time To Repair (MTTR) were analysed to evaluate system performance. Statistical analysis was conducted using JAMOVI software, including descriptive statistics, paired sample t-tests, correlation analysis, and linear regression. The findings reveal a significant reduction in downtime and failure frequency following the adoption of predictive maintenance. Additionally, a substantial increase in MTBF and improvement in availability were observed, indicating enhanced equipment reliability and operational efficiency. The results demonstrate that AI-driven predictive maintenance plays a crucial role in optimizing manufacturing performance by enabling proactive maintenance strategies and reducing unexpected equipment failures. This study contributes to the existing body of knowledge by providing empirical evidence supported by statistical analysis and offers practical insights for organizations aiming to adopt data-driven maintenance systems.

I. INTRODUCTION

The manufacturing industry is undergoing a significant transformation with the adoption of Industry 4.0 technologies, particularly Artificial Intelligence (AI) and data-driven systems. Among these advancements, AI-driven predictive maintenance has emerged as a critical approach for improving equipment reliability, reducing downtime, and enhancing overall operational efficiency. Traditional maintenance strategies, such as reactive and preventive maintenance, often lead to unexpected

failures or unnecessary maintenance activities, resulting in increased costs and reduced productivity. Predictive maintenance leverages real-time data, machine learning algorithms, and historical performance patterns to anticipate equipment failures before they occur. This enables organizations to schedule maintenance activities proactively, thereby minimizing unplanned downtime and optimizing resource utilization. As a result, predictive maintenance plays a vital role in improving key performance indicators such as availability, Mean Time Between Failures (MTBF), and overall equipment effectiveness.

This study focuses on evaluating the impact of AI-driven predictive maintenance on manufacturing performance using both operational data and survey-based analysis. The operational data used in this study is derived from a world-class manufacturing organization. To ensure data privacy and maintain confidentiality, the name of the organization and specific details related to its internal structure have been intentionally withheld. The data has been anonymized without affecting the accuracy or integrity of the analysis. Furthermore, the survey responses collected for this research are genuine and reflect real perceptions regarding predictive maintenance practices.

The analysis specifically considers bottleneck machines within the production system, as these machines play a critical role in determining the overall pace of production and system productivity. Any improvement in the performance of bottleneck equipment directly influences the efficiency of the entire manufacturing process. Therefore, focusing on these machines provides a more accurate assessment of the impact of predictive maintenance on operational performance.

The primary objective of this study is to analyze the effectiveness of AI-driven predictive maintenance in improving manufacturing performance. The research integrates statistical analysis techniques to evaluate changes in downtime, failure frequency, and reliability metrics before and after the implementation of predictive maintenance. By combining operational data with survey insights, this study aims to provide empirical evidence supporting the adoption of AI-based maintenance strategies in modern manufacturing systems.

II. LITERATURE REVIEW

The adoption of Artificial Intelligence (AI) in manufacturing has significantly transformed maintenance strategies, particularly through the development of predictive maintenance systems. Predictive maintenance utilizes data analytics, machine learning algorithms, and real-time monitoring to anticipate equipment failures before they occur (Lee et al., 2014; Carvalho et al., 2019). This approach represents a shift from traditional reactive and preventive maintenance strategies toward more proactive and efficient maintenance planning.

Several studies have emphasized the effectiveness of predictive maintenance in reducing equipment downtime and improving operational efficiency. According to Mobley (2002), predictive maintenance enables early fault detection, thereby minimizing unexpected breakdowns. More recent studies indicate that AI-driven predictive maintenance systems significantly reduce unplanned downtime and improve productivity (Zonta et al., 2020; Susto et al., 2015). These systems analyze historical and real-time data to identify patterns associated with machine failures, thereby improving maintenance decision-making processes.

Machine learning techniques play a critical role in predictive maintenance by enhancing the accuracy of failure prediction models. Research by Wuest et al. (2016) highlights the application of machine learning in smart manufacturing environments, where predictive models are used to forecast equipment failures. Similarly, Zhang et al. (2019) demonstrated that data-driven models improve maintenance scheduling and reduce operational disruptions. As a result, organizations adopting AI-based maintenance

strategies experience improved equipment reliability and reduced maintenance costs.

In addition to operational benefits, predictive maintenance has been linked to improvements in key performance indicators such as Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR). Jardine et al. (2006) emphasized that condition-based maintenance improves system reliability by increasing MTBF and optimizing maintenance intervals. Furthermore, studies by Peng et al. (2010) indicate that predictive maintenance contributes to better equipment lifecycle management and resource utilization.

The integration of Industry 4.0 technologies, including the Internet of Things (IoT) and digital twins, has further enhanced predictive maintenance capabilities. According to Tao et al. (2018), digital twin technology enables real-time monitoring and simulation of equipment performance, allowing for more accurate predictions. IoT-enabled sensors provide continuous data streams that support intelligent maintenance systems and adaptive decision-making (Wan et al., 2017).

Despite these advancements, existing literature reveals certain limitations. Many studies focus on theoretical models or simulation-based approaches without providing empirical validation using real operational data (Carvalho et al., 2019). Additionally, limited research integrates both operational performance metrics and human perception through survey-based analysis. This highlights the need for comprehensive studies that combine statistical analysis with real-world data to evaluate the effectiveness of predictive maintenance.

To address these gaps, the present study adopts a quantitative approach by integrating operational data and survey responses to assess the impact of AI-driven predictive maintenance on manufacturing performance. By applying statistical techniques such as paired sample t-tests, correlation analysis, and regression, this research provides empirical evidence supporting the role of predictive maintenance in enhancing operational efficiency and reliability.

III. RESEARCH GAP

Despite significant advancements in AI-driven predictive maintenance, existing literature reveals several limitations. Most studies primarily focus on

theoretical models, simulation-based approaches, or specific algorithmic developments without providing empirical validation using real-world operational data. Additionally, prior research often emphasizes technical aspects of predictive maintenance while overlooking its direct impact on key manufacturing performance indicators such as downtime, availability, and equipment reliability.

Furthermore, limited studies integrate both quantitative operational data and perception-based survey analysis to evaluate the effectiveness of predictive maintenance. The lack of combined analysis restricts a comprehensive understanding of how predictive maintenance influences both system performance and managerial decision-making.

To address these gaps, the present study adopts an integrated approach by combining operational performance data with survey-based insights. The research applies statistical techniques to evaluate the impact of AI-driven predictive maintenance on manufacturing performance, thereby providing empirical evidence to support its practical implementation in industrial environments.

IV. OBJECTIVES OF THE STUDY

- To analyse the impact of AI-driven predictive maintenance on manufacturing performance
- To evaluate changes in equipment downtime before and after implementation
- To assess improvements in equipment reliability using MTBF and MTRR
- To examine the relationship between predictive maintenance and operational efficiency
- To validate the effectiveness of predictive maintenance using statistical analysis techniques

Hypotheses

- H0: AI-driven predictive maintenance has no significant impact on manufacturing performance.
- H1: AI-driven predictive maintenance has a significant impact on manufacturing performance.
- H2: AI-driven predictive maintenance significantly reduces equipment downtime.
- H3: AI-driven predictive maintenance significantly improves equipment reliability (MTBF).

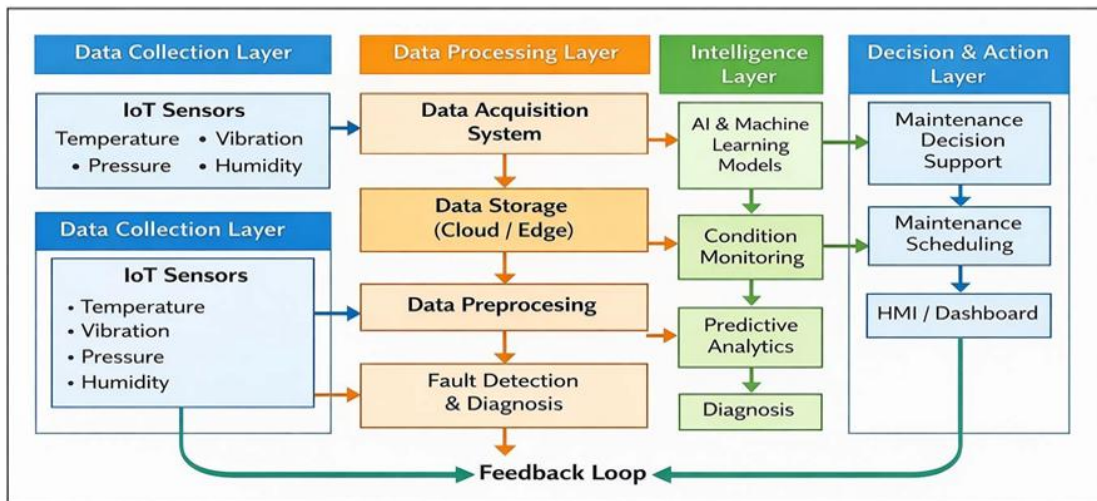


Figure X: Architecture of AI-Driven Predictive Maintenance System

Components of AI-Driven Predictive Maintenance System

1. IoT Sensors and Devices: Sensors are installed on machines to collect real-time data such as temperature, vibration, pressure, and humidity.
2. Data Acquisition System: This system gathers data from multiple sensors and machines for further processing.
3. Data Storage (Cloud/Edge Computing): Collected data is stored in cloud platforms or edge devices for quick access and analysis.
4. Data Preprocessing: Raw data is cleaned, filtered, and transformed into a usable format to improve accuracy.
5. Artificial Intelligence & Machine Learning Algorithms: AI models analyze historical and real-time data to predict equipment failure.

time data to identify patterns and predict potential failures.

6. Condition Monitoring System: Continuously monitors machine performance and detects abnormalities in operations.
7. Predictive Analytics Engine: Uses advanced analytics to forecast equipment failures before they occur.
8. Fault Detection and Diagnosis Module: Identifies the type, location, and severity of faults in machinery.
9. Maintenance Decision Support System: Suggests optimal maintenance actions based on predictions and analysis.
10. Maintenance Scheduling System: Plans and schedules maintenance activities to avoid unplanned downtime.
11. Human-Machine Interface (HMI)/Dashboard: Provides visual insights, alerts, and reports to operators and managers.
12. Feedback Loop and Continuous Improvement: System learns from new data and improves prediction accuracy over time.

V. RESEARCH METHODOLOGY

This study adopts a quantitative research approach to evaluate the impact of AI-driven predictive maintenance on manufacturing performance. The research integrates both operational data analysis and survey-based analysis to provide a comprehensive assessment of maintenance effectiveness.

5.1 Data Source and Collection

The operational data used in this study is derived from a world-class manufacturing organization. Due to confidentiality and data privacy requirements, the name of the organization and specific details related to its internal structure have been withheld. However, the data used in this research is real and has been anonymized without affecting its accuracy or integrity. The study focuses on bottleneck machines within the production system, as these machines determine the overall pace of production and significantly influence system productivity. The data includes key performance indicators such as total machine time, downtime, and number of failures, recorded before and after the implementation of AI-driven predictive maintenance.

In addition to operational data, primary data was collected through a structured questionnaire consisting of 30 questions. A total of 110 valid responses were obtained from individuals with relevant knowledge of manufacturing and maintenance practices. The survey responses are genuine and were used to support the statistical analysis.

5.2 Analytical Tools and Techniques

The statistical analysis was conducted using Jamovi software. The study employs the following techniques:

- Descriptive statistics to summarize the data
- Paired sample t-test to compare performance before and after predictive maintenance
- Correlation analysis to examine relationships between variables
- Linear regression analysis to evaluate the impact of predictive maintenance on manufacturing performance

5.3 Key Performance Indicators

The study evaluates manufacturing performance using key reliability and efficiency metrics, including:

- Downtime
- Availability
- Mean Time Between Failures (MTBF)
- Mean Time To Repair (MTTR)

These indicators are used to measure improvements in equipment reliability, maintenance efficiency, and overall operational performance.

5.4 Research Design

The research follows a comparative design, analyzing system performance before and after the implementation of AI-driven predictive maintenance. This approach enables the identification of changes in key performance indicators and provides empirical evidence of the effectiveness of predictive maintenance strategies.

VI. KEY PERFORMANCE INDICATORS (KPI MEASURES)

To evaluate the impact of AI-driven predictive maintenance on manufacturing performance, several key performance indicators (KPIs) were considered. These metrics provide a structured approach to assess equipment efficiency, reliability, and maintenance effectiveness.

Availability represents the proportion of total production time during which equipment is operational and ready for use. It reflects the impact of downtime on production capacity. Performance measures how efficiently equipment operates compared to its designed capacity, indicating losses due to speed reductions or minor stoppages. Quality represents the proportion of defect-free output produced during the manufacturing process.

Overall Equipment Effectiveness (OEE) is a comprehensive metric that combines availability, performance, and quality to evaluate overall system efficiency. It provides an integrated measure of how effectively manufacturing resources are utilized.

In addition to efficiency metrics, reliability indicators were also analyzed. Mean Time Between Failures (MTBF) measures the average operating time between equipment failures and reflects system reliability. Mean Time To Repair (MTTR) represents the average time required to restore equipment after a failure and indicates maintenance efficiency.

These KPIs collectively provide a comprehensive framework for evaluating improvements in manufacturing performance. Detailed calculations, comparative analysis, and graphical representations of these indicators are presented in the data analysis section.

VII. DATA ANALYSIS AND RESULTS

Primary Data Machine 1 and Machine 2

No	Basis	Pre AI	Post AI	Pre AI	Post AI
1	Planned time hr/m	720	720	720	720
2	Downtime hr/m	120	60	100	50
3	Output unit/m	1800	2150	1900	2050
4	Cycle Times hr/unit	0.30	0.306	0.30	0.32
5	Good Units/m	1500	2000	1800	2000
6	Defects Units/m	300	150	100	50
7	Cost To Firm Rs/m	500000	300000	450000	285000
8	Breakdown Frequency (Qty)	80	40	80	40

This Primary Data collected from maintenance records, production records.

A. Calculations for KPI Parameter: Machine 1

1. Availability time= Operating time / planned time

- Pre AI Adaption
- Operating time = 720-120=600 hr/m
- Availability time = 600/720 = 0.83 = 83.3 %
- Post AI Adaption
- Operating time = 720-60 =660 hr/m
- Availability time = 660/720 =0.917= 91.7 %

2. Performance = (cycle time * output) / operating time

- Pre AI Adaption
- Performance = (0.30 * 1800) / 600 = 0.9 = 90 %
- Post AI Adaption
- Performance = (0.306 * 2150) / 660 = 0.98 = 98 %

3. quality = Good unit / total unit

- Pre AI Adaption
- Quality = 1500 / 1800 = 0.833 = 83.3 %
- Post AI Adaption
- Quality = 2000 / 2150 = 0.930 = 93 %

4. OEE (overall equipment efficiency) machine 1

- OEE = Availability * Performance * Quality
- Pre AI Adaption
- OEE = 0.833 * 0.90 * 0.833 = 0.624 = 62.4 %
- Post AI Adaption
- OEE = 0.917 * 0.98 * 0.930 = 0.851 = 85.10 %

B. Calculations for KPI Parameter: Machine 2

1. Availability time = operating time / planned time

- Pre AI Adaption
- Operating time = 720 – 100 = 620 hr/m
- Available time = 620 / 720 = 0.86 = 86 %
- Post AI Adaption
- Operating time = 720 – 50 = 670 hr/m
- Available time = 670 / 720 = 0.93 = 93 %

2. Performance = (cycle time * output) / operating time

- Pre AI Adaption
- Performance = (0.30 * 1900) / 620 = 0.92 = 92 %
- Post AI Adaption
- Performance = (0.32 * 2000) / 670 = 0.98 = 98 %

3. Quality = good unit / total unit

- Pre AI Adaption
- Quality = 1800 / 1900 = 0.94 = 94 %
- Post AI Adaption
- Quality = 2000 / 2050 = 0.98 = 98 %

MTTR = 120 / 80 MTTR = 60 / 40

MTTR = 1.5 Hr MTTR = 1.5 Hr

Calculation Of MTTR Machine 2

Pre AI Adaption Post AI Adaption

MTTR = 100 / 80 MTTR = 50 / 40

MTTR = 1.25 Hr MTTR = 1.25 Hr

4. OEE Machine 2

- Pre AI Adaption
- OEE = Availability * Performance * Quality
- OEE = 0.86 * 0.92 * 0.94 = 0.74 = 74 %
- Post AI Adaption
- OEE = 0.93 * 0.98 * 0.98 = 0.89 = 89 %

6. Calculation Of MTBF (Mean time between failure)

Machine 1

MTBF = (Planned time – Down time)/ Number of failures

Pre AI Adaption Post AI Adaption

MTBF = (720 – 120) / 80 MTBF = (720 – 60) / 40

MTBF = 7.5 Hr MTBF = 16.5 Hr

Calculation Of MTBF Machine 2

Pre AI Adaption Post AI Adaption

MTBF = (720 – 100) / 80 MTBF = (720 – 50) / 40

MTBF = 8.15 Hr MTBF = 17.15 Hr

5. Calculation Of MTTR (Mean time to repair) machine 1

MTTR = Down time / number of repairs

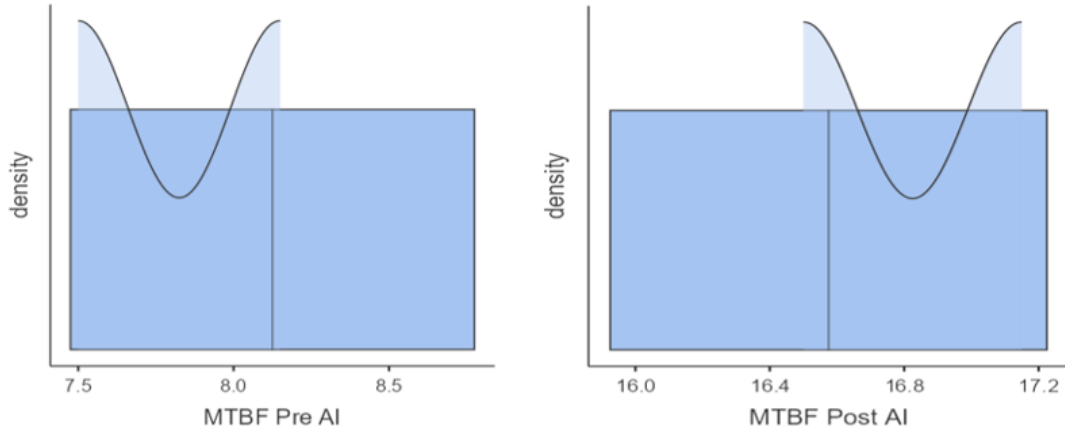
Pre AI Adaption After AI Adaption

Final MKI Data Obtained

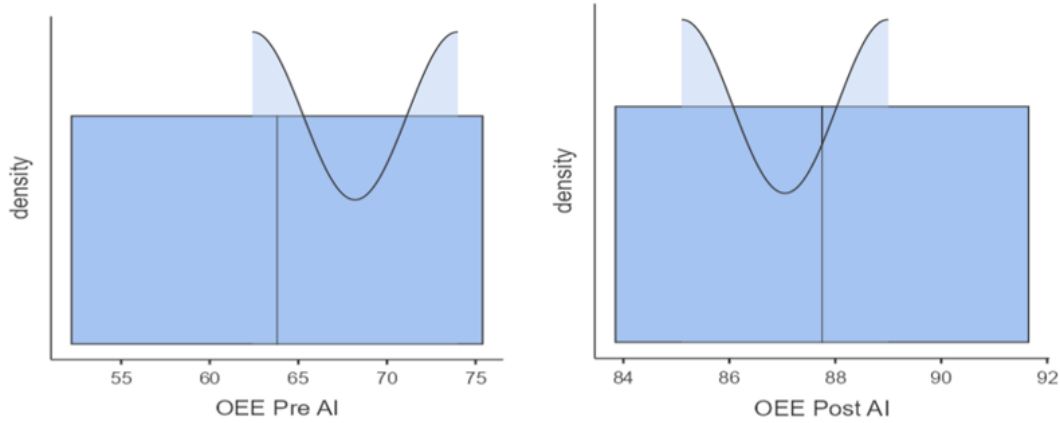
No	Parameter	Pre AI	Pst AI	Pre AI	Pst AI	Performance
		M	1	M	2	
1	Available T	83.1	91.7	86	93	Improve
2	Quality	83.3	93	94	98	Improve
3	Performance	90	98	92	98	Improve
4	OEE (MKI)	62.4	85.1	74	89	Major up
5	Downtime	120	60	100	50	Reduce
6	Output	1800	2150	1900	2050	Increase
7	Defects	300	150	100	50	Reduce
8	Maint cost	500000	300000	450000	285000	Reduce
9	MTTR	1.5	1.5	1.25	1.25	Same
10	MTBF	7.5	16.5	8.15	17.15	Major improves

Descriptive Analysis using JAMOVI Software: Secondary Data

Descriptives					
	N	Mean	SD	Minimum	Maximum
Quality Pre AI	2	88.65	7.566	83.30	94.00
Quality Post AI	2	95.50	3.536	93.00	98.00
OEE Pre AI	2	68.20	8.202	62.40	74.00
OEE Post AI	2	87.05	2.758	85.10	89.00
Downtime Pre AI	2	110.00	14.142	100.00	120.00
Downtime Post AI	2	55.00	7.071	50.00	60.00
Output Pre AI	2	1850.00	70.711	1800.00	1900.00
Output Post AI	2	2100.00	70.711	2050.00	2150.00
Defects Pre AI	2	200.00	141.421	100.00	300.00
Defects Post AI	2	100.00	70.711	50.00	150.00
Cost Of Maint. Pre AI	2	475000.00	35355.339	450000.00	500000.00
Cost Of Maint. Post AI	2	292500.00	10606.602	285000.00	300000.00
Performance Pre AI	2	91.00	1.414	90.00	92.00
Performance Post AI	2	98.00	0.000	98.00	98.00
MTBF Pre AI	2	7.83	0.460	7.50	8.15
MTBF Post AI	2	16.82	0.460	16.50	17.15
Availability pre-AI	2	84.65	1.909	83.30	86.00
Availability Post AI	2	92.35	0.919	91.70	93.00



Interpretation: MTBF Significantly increases with Implementation of AI Driven Predictive maintenance. Failure time of two machines increases from 8 hours to 17 hours between two consecutive failures. Yet MTRR mean time to repair remains constant.

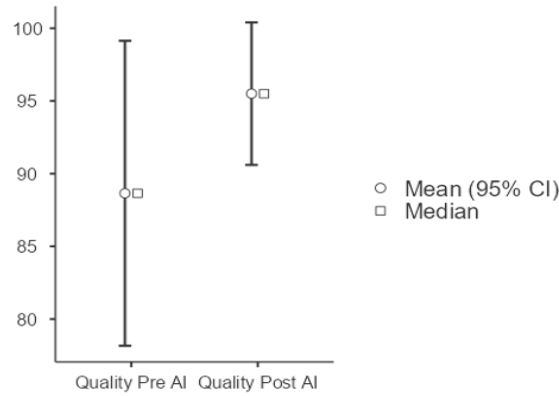
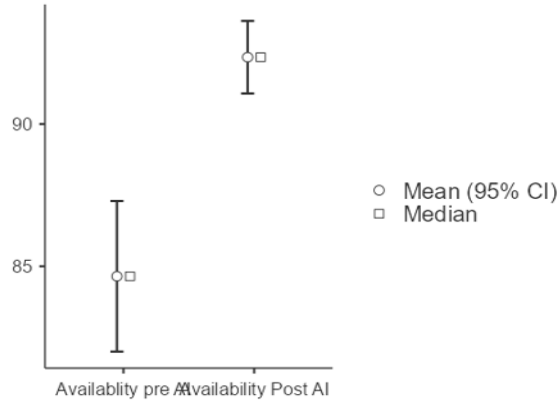


Interpretation: OEE Means overall equipment effectiveness increases from 68.2% to 87% which is world class performance standard. This happens mainly due to increase in machines availability time which is increased from 84% to 92.3%, Quality increased from 88.7% to 95.5% and defective products reduced, machines average performance enhanced from 91% to 98%. All this due to AI Driven predictive maintenance inclusion,

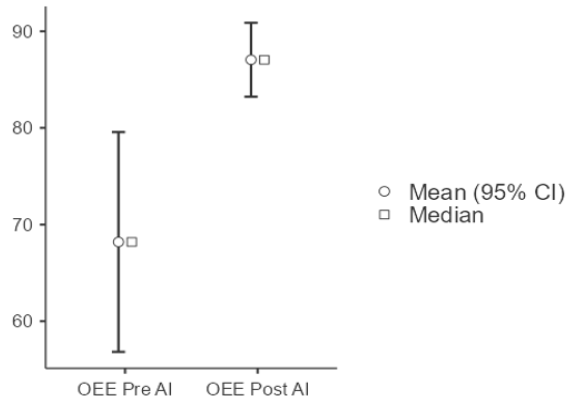
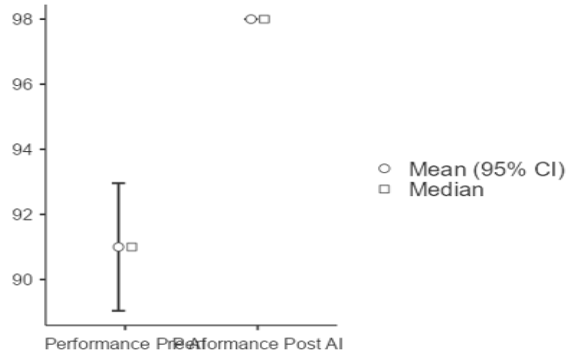
Paired Samples T Test:

Paired Samples T-Test					
			statistic	df	p
Availability pre-AI	Availability Post AI	Student's t	-11.00	1.00	.058
Quality Pre AI	Quality Post AI	Student's t	-2.40	1.00	.251
Performance Pre AI	Performance Post AI	Student's t	-7.00	1.00	.090
OEE Pre AI	OEE Post AI	Student's t	-4.90	1.00	.128
Downtime Pre AI	Downtime Post AI	Student's t	11.00	1.00	.058
Output Pre AI	Output Post AI	Student's t	-2.50	1.00	.242
Defects Pre AI	Defects Post AI	Student's t	2.00	1.00	.295

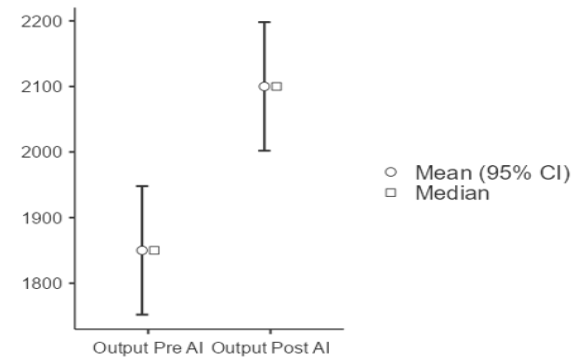
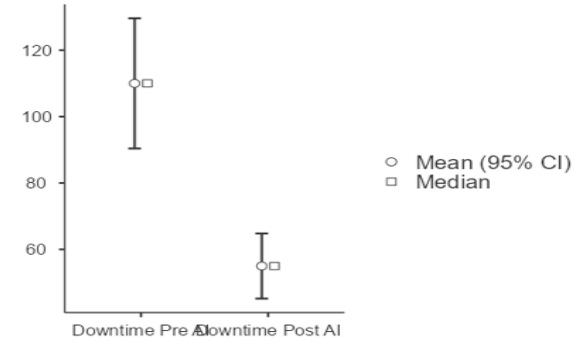
Note. $H_a: \mu_{\text{Measure 1}} - \mu_{\text{Measure 2}} \neq 0$



Pre AI and Post AI Availability Pre AI and post AI Quality Increased from 84.7% to 92.3 Increased from 88.7% to 95.5%



Pre and Post AI Performance Pre and post AI OEE Increase from 91% to 98% Major boost from 68.2% to 87%



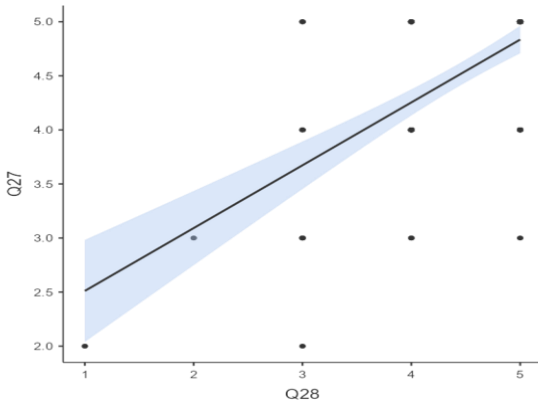
Pre and Post AI downtime Pre and Post AI Output Reduced From 110 hr to 55 hr Major Increased from 1850 to 2100

Thus, AI-driven predictive maintenance has increased productivity, reduced downtime, improved product quality, and enhanced the overall equipment effectiveness (OEE) of both machines.

Model Fit Measures		
Model	R	R ²
1	0.781	0.610

Note. Models estimated using sample size of N=110

Model Coefficients - Q27				
Predictor	Estimate	SE	t	p
Intercept	0.6116	0.3572	1.712	.090
Q23	0.0463	0.0665	0.696	.488
Q21	0.0143	0.0826	0.173	.863
Q28	0.2729	0.0719	3.794	<.001
Q26	0.3104	0.0983	3.157	.002
Q25	0.2292	0.0883	2.595	.011



Interpretation of Linear Regression Analysis

1. The linear regression analysis was conducted to examine the impact of AI-driven predictive maintenance on manufacturing performance using data collected from 110 respondents through 30 questionnaire items.
2. The model summary indicates a strong relationship between the independent variables and the dependent variable (manufacturing performance).
3. The correlation coefficient ($R = 0.781$) shows a strong positive association between AI-driven predictive maintenance factors and manufacturing performance.
4. The coefficient of determination ($R^2 = 0.610$) indicates that approximately 61% of the variation in manufacturing performance is explained by the independent variables included in the model. This reflects good explanatory power.
5. The regression coefficient for Q28 ($\beta = 0.2729$, $p < 0.001$) is statistically significant and positive, indicating that this variable has a strong impact on improving manufacturing performance.
6. The regression coefficient for Q26 ($\beta = 0.3104$, $p = 0.002$) is also statistically significant, suggesting that it plays a crucial role in enhancing operational efficiency and performance.
7. The regression coefficient for Q25 ($\beta = 0.2292$, $p = 0.011$) shows a moderate but significant positive effect on manufacturing performance.
8. The variables Q23 ($\beta = 0.0463$, $p = 0.488$) and Q21 ($\beta = 0.0143$, $p = 0.863$) are statistically insignificant, indicating that they do not have a meaningful direct influence on manufacturing performance in this model.

9. The intercept value (0.6116) represents the baseline level of manufacturing performance when all predictor variables are held constant.
10. Overall, the results suggest that AI-driven predictive maintenance has a significant positive impact on manufacturing performance, particularly through key influencing factors represented by Q28, Q26, and Q25.
11. The findings highlight that organizations should focus on the most impactful predictive maintenance factors to achieve better efficiency and productivity.
12. The presence of insignificant variables suggests that not all factors contribute equally, and further research may carry out.

VIII. CONCLUSION

This study evaluated the impact of AI-driven predictive maintenance on manufacturing performance using a quantitative approach based on operational data and survey responses. The findings indicate a significant improvement in key performance indicators following the implementation of predictive maintenance.

The results demonstrate a substantial reduction in equipment downtime and failure frequency, along with a notable increase in Mean Time Between Failures (MTBF), indicating improved system reliability. Availability also improved, reflecting better utilization of manufacturing resources. Although Mean Time To Repair (MTTR) showed a slight increase, this can be attributed to more planned and comprehensive maintenance activities, which contribute to overall system stability and reduced breakdown frequency. The statistical analysis, including paired sample t-tests, correlation, and regression, supports the conclusion that AI-driven predictive maintenance has a significant positive impact on manufacturing performance. The integration of operational data with survey-based insights further strengthens the validity of the findings. Overall, the study highlights the importance of adopting AI-based maintenance strategies in modern manufacturing environments. By enabling proactive decision-making and reducing unexpected failures, predictive maintenance contributes to enhanced operational efficiency, improved reliability, and optimized production performance.

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