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The Evaluating the Financial Impact of Predictive Maintenance in Manufacturing: An Integrative Literature Review

Feresane Matthew Sibeko [1 *]

[1] Graduate School of Business Leadership, University of South Africa, Pretoria, South Africa
*** Corresponding Author:** FticksM@outlook.com

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ABSTRACT

Even if measuring the ROI (Returns-on-Investment) of predictive equipment maintenance is essential for discerning whether the manufacturing entity is overspending or underspending on equipment maintenance, most manufacturing executives often do not bother to measure the ROI of their equipment maintenance. This affects decisions on the improvement initiatives that can be adopted. To address such a problem, this study used integrative review to evaluate insights from the existing studies about the techniques, values, and limitations of measuring the ROI of predictive manufacturing equipment's maintenance. The research was a qualitative study based on content analysis of articles retrieved primarily through Google searches as the major search engine. After predictive maintenance, findings from the analysis indicated the financial metrics to measure the financial gains obtained since the introduction of predictive machine maintenance. It evaluates the benefits and advantages so far attained as compared to the costs incurred in the application of predictive maintenance. Apart from ROI, some of the commonly used financial metrics were found to encompass cost-benefit analysis and net present value (NPV). ROI analysis seeks to evaluate the benefits gained against the costs incurred in the use of predictive machine maintenance. However, findings indicated the major inhibitors of measuring the ROI of predictive machine maintenance to often arise from cost, poor data utilization culture, and ignoring predictive maintenance. Unless management is able to deal with such challenges, they may never get to understand the returns on investment generated from the expenditure on predictive equipment maintenance. From these findings, this study has contributed to changing the general perception of predictive maintenance as an expenditure rather than an investment.

Keywords: Predictive Maintenance, Equipment Maintenance, Preventive Maintenance, Reactive Maintenance

INTRODUCTION

In order to guarantee responsibility, openness, and moral conduct in the banking industry, independent directors are essential. The rules, procedures, and practices that regulate how businesses are run are referred to as corporate governance. In order to guarantee openness, responsibility, and efficient decision-making within the company, it includes the interactions between shareholders, the board of directors, management, and other stakeholders (Zubair, Adams & Aniagolu 2022). Fundamentally, corporate governance seeks to create a structure that upholds moral conduct, safeguards the interests of shareholders, encourages strong financial results, and advances the company's long-term viability and prosperity. Both public and private firms must prioritize governance since it has a significant impact on how well they function overall and how they are perceived. It protects the interests of shareholders and other stakeholders by ensuring that businesses are run ethically and responsibly (Adams & Balogun, 2020).

Even if most manufacturing entities are increasingly using predictive maintenance, measuring ROI to understand the return on investment being generated from the dollars expended on each equipment's maintenance is still a challenge (Keller & Owen, 2025). Most manufacturing executives spend on equipment's investment without evaluating the generated returns. If ROI analysis is being done, it is often integrated as part of the overall ROI analysis. This affects the evaluation of how the maintenance costs must be controlled and managed to lower operational costs and improve on the operating profit margins. Equipment maintenance is the strategic process of evaluating and undertaking repairs and upgrade that improve the equipment's overall effective performance (Zhong, Xia, Zhu, & Duan, 2023). Equipment maintenance may take the form of preventative, proactive or reactive equipment maintenance. Preventive or proactive equipment maintenance refers to the approach where the equipment is diagnosed and repaired or upgraded before it fails to affect manufacturing processes. This contrasts with the reactive approach that takes the approach of waiting for the machines to fail before the necessary repairs or upgrades are made(Siemens, 2025).

Some high-performing manufacturing entities spend and spend on equipment's maintenance with the motive of attaining and maintaining the highest level of operational efficiency (West, Siddhpura, Evangelista, & Haddad, 2024). Others also spend and spend on equipment maintenance as part of the stringent cost control initiatives aimed at lowering the costs of equipment's downtime and redundancies to bolster the manufacturing firm's overall cost competitiveness. However, without usage of the appropriate techniques for measuring the ROI of equipment's maintenance, the risk of overspending or underspending becomes quite imminent.

Underspending implies limited resources are invested in predictive maintenance (Oxmaint, 2025). This causes risks of frequent machine failure that affect operational efficiency, productivity, and the achievement of the desired returns on investment. Manufacturing entities that underspend on equipment's maintenance use a dual equipment's maintenance system reflecting aspects of predictive and preventive equipment's maintenance. In contrast, overspending on equipment's maintenance causes risks of poor cost controls and wastes that affect operating profit margins and the overall profitability of the business (Siemens, 2025). Yet as some manufacturing entities overspend on predictive equipment's maintenance, others tend to avoid it completely. Some manufacturing enterprises opt for the use of preventive equipment's maintenance.

In such initiatives, predictive maintenance approaches are completely avoided in favour of the preventive maintenance approach. Because of such business philosophy, preventive equipment's maintenance is perceived as more cost-effective. Because preventive equipment's maintenance waits for equipment to fail and then spends on repairs, maintenance, upgrade, or purchase of new equipment, it is often construed as more cost-effective (Reliable Plant, 2025). Preventive equipment's maintenance is construed to improve cost savings. No maintenance or repair expenditures are incurred unless the equipment breaks down or fails to signify there is actually a need for the money to be spent.

To some or even most manufacturing executives, this often makes a lot of business sense. It releases pressure for money to be spent and used in the other areas as the management waits for the equipment to breakdown and respond. In the highly competitive global manufacturing business space where most of the manufacturing entities are struggling to lower operational costs and improve cost competitiveness, most of the manufacturing executives often find such business approach quite convenient (Sankar, 2025). Unfortunately, even if that is so, frequent and sudden machine breakdowns must be some of the incidents that the manufacturing executives must be prepared to deal with. Frequently disrupted operational processes and manufacturing processes are some of the incidents that the operational managers must be prepared to deal with. This affects operational efficiency, productivity, throughput, and effective cost management (Zhong, Xia, Zhu, & Duan, 2023).

Yet as most manufacturing executives adopt such business approaches, empirical facts imply the increasing competition in the global manufacturing business ecosystem is driving most manufacturing executives to adopt various predictive equipment's maintenance approaches. This changing business behaviour contrasts with the previous approaches where most manufacturers used the preventive equipment's maintenance approaches. It is the quest to respond to such dynamics that drove this study to evaluate the concept of predictive manufacturing machine maintenance as well as the techniques for measuring and improving the ROI of predictive equipment maintenance. Through such analysis, the study aims to discern the major limitations of equipment maintenance and the improvement initiatives that can be adopted. To accomplish that, the study used integrative review as one of the methods for critical content analysis.

METHODOLOGY

Integrative review was used as the methodology for assessing the effectiveness of the techniques, values, and limitations of measuring the ROI of predictive manufacturing equipment's maintenance. Integrative review is one of the critical content analysis methods that focuses on evaluating the existing theories and literature in the bid to find answers to the phenomenon being investigated (Gates, Vidueira, Komakhidze, Aldrich, & Shim, 2025). It believes that given the extensive studies conducted in a particular area, the answer to the research question of the concept being investigated can easily be obtained by evaluating and extracting insights from the existing studies. It is such insights that motivate the use of integrative review in this study.

Even if integrative review was not widely used in the past, the increasing adoption of internet use by multitudes of people and studies is driving the increasing use of critical content analysis methods like meta-analysis and systematic review (Knafl & Whittemore, 2017). However, this study will use the integrative review because unlike meta-analysis, systematic review gathers and evaluates views from all the studies irrespective of whether peer-reviewed or not peer-reviewed. While using such an approach, the process of integrative review was structured according to four stages encompassing formulation of the integrative research questions, search of literature, data extraction, and data analysis (Oermann & Knafl, 2021; Dhollande, Taylor, Meyer, & Scott, 2021).

Integrative Review Questions

Integrative review questions that guided the study examined questions exploring:

- What metrics are used for measuring ROI of predictive machine maintenance?
- What inhibitors often affect predictive machine maintenance's ROI measurement?

It is these integrative review questions that guided the process of literature analysis.

Literature Search

The literature search examined what are the techniques, values, and limitations of measuring the ROI of predictive manufacturing equipment's maintenance. To find answers to these questions, the process of literature search was guided by the keywords that included "ROI", "ROI of Predictive Maintenance", "Techniques for Measuring ROI of Predictive Maintenance", "Limitations of Measuring ROI of Predictive Maintenance", and "Values of Measuring the ROI of Predictive Maintenance". In the process of using these keywords, the process of literature search was accomplished using Google as the major search engine for the study.

Exclusion/Inclusion Criteria

While extracting relevant articles, initiatives were undertaken to ensure the articles accurately evaluated and reflected all the issues reflected in the keywords. Besides having full text and not just the abstract or a summary, the articles also had to have been published in English in the period between 2020 and 2025. As reflected in **Table 1** below, this led to the extraction of 26 articles.

Table 1. Extracted Articles

Author & Year	Article Title	Publisher/Journal
Aivaliotis, P., Xanthakis, E., & Sardelis, A. (2020).	Machines' behaviour prediction tool (BPT) for maintenance applications.	IFAC-PapersOnLine, 53(3), 325–329.
Alfionita, S., & Ikhwanul Alifin, F. (2023).	Preventive maintenance analysis based on mean time between failure (MTBF) and mean time to repair (MTTR).	Angkasa: Jurnal Ilmiah Bidang Teknologi.
Ameta. (2024).	Boosting ROI with predictive maintenance cost savings.	New Delhi: Ameta.
Baur, M., Albertelli, P., & Monno, M. (2020).	A review of prognostics and health management of machine tools.	International Journal of Advanced Manufacturing Technology, 107, 2843–2863.
Berrabah, F. Z., Belkacemi, C., & Zemmouchi-Ghomari, L. (2022).	Essential and new maintenance KPIs explained.	International Journal of Education and Management Engineering, 12(6), 11–20.
Booyse, W., Wilke, D. N., & Heyns, S. (2020).	Deep digital twins for detection, diagnostics and prognostics.	Mechanical Systems and Signal Processing, 140, 106612.
Duarte, A. L. C. M., & Santiago Scarpin, M. R. S. (2023).	Maintenance practices and overall equipment effectiveness: Testing the moderating effect of training.	Journal of Quality in Maintenance Engineering, 29(2), 442–459.
En-Nhaili, L., Muchiri, P., & Pintelon, L. (2021).	Resource overall equipment cost loss indicator to assess equipment performance and product cost.	International Journal of Productivity and Performance Management. Emerald.
Heim, S., Clemens, J., Steck, J. E., Basic, C., Timmons, D., & Zwiener, K. (2020).	Predictive maintenance on aircraft and applications with digital twin.	2020 IEEE International Conference on Big Data (Big Data), 4122–4127.
HexaState. (2025).	Investing in the future: How predictive maintenance can drive ROI.	New York: HexaState.
Keller, S., & Owen, A. (2025).	A comprehensive cost-benefit analysis of preventive maintenance versus corrective maintenance: Assessing the financial impact and operational benefits in engineering.	Berlin: IU International University of Applied Sciences.
Khan, S., Farnsworth, M., McWilliam, R., & Erkoyuncu, J. (2020).	On the requirements of digital twin-driven autonomous maintenance.	Annual Reviews in Control, 50, 13–28.
Limble. (2025).	Creating a predictive maintenance program that is right for you.	New York: Limble.
Moss, J. (2025).	The ROI of predictive maintenance: Why it's a game-changer.	Philadelphia: The Standard.
Oxmaint. (2025).	Predictive maintenance in manufacturing: ROI guide & implementation steps.	California: Oxmaint.
Rahman, F., Sugiono, S., Sonief, A. A., & Novareza, O. (2024).	Optimization maintenance performance level through collaboration of overall equipment effectiveness-machine effectiveness and machine reliability.	Journal of Applied Engineering Science, 20, 917–936.
Reliable Plant. (2025).	How to prove and maximize ROI in predictive maintenance.	Reliable Plant.
Sankar, S. (2025).	Predictive maintenance ROI for manufacturing executives.	Dubai: Hakunah Matata.
Sensemore. (2025).	The key factors impacting ROI in predictive maintenance.	London: Sensemore.
Siemens. (2025).	Maximising your ROI with scalable, predictive maintenance: A guide on optimizing your ROI potential by scaling predictive maintenance, utilizing data effectively, and tapping into the capabilities of the Senseye Predictive Maintenance ROI Calculator.	Chicago: Siemens.
Veerappan, G. (2025).	A guide to calculating maintenance and reliability initiative ROI.	New Delhi: Cryotos.
Villa, V., Naticchia, B., Bruno, G., Aliev, K., Piantanida, P., & Antonelli, D. (2021).	IoT open-source architecture for the maintenance of building facilities.	Applied Sciences, 11(11), 5374.
West, J., Siddhpura, M., Evangelista, A., & Haddad, A. (2024).	Improving equipment maintenance—Switching from corrective to preventative maintenance strategies.	Buildings, 14(11), 3581.
Yan, T., Lei, Y., Li, N., Si, X., Pintelon, L., & Dewil, R. (2022).	Online joint replacement-order optimization driven by a nonlinear ensemble remaining useful life prediction method.	Mechanical Systems and Signal Processing, 173, 109031.
Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023).	Overview of predictive maintenance based on digital twin technology.	Heliyon, 9(4), e14534.
Zonta, T., da Costa, C. A., Righi, R. D., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020).	Predictive maintenance in the Industry 4.0: A systematic literature review.	Computers & Industrial Engineering, 150, 106889.

Upon completion of the extraction of all the relevant articles, the process of analysis was accomplished using thematic analysis.

Data Analysis

After reading and re-reading each of the extracted articles, all the required themes and the accompanying chunks of text were extracted to elucidate the techniques, values, and limitations of measuring the ROI of predictive manufacturing equipment's maintenance. From such analysis, the details of the findings are analysed and presented below.

FINDINGS

In line with the research objectives and questions for the study, the findings from the systematic review are analysed and presented according to three sections encompassing:

- Measuring ROI of Predictive Maintenance
- Metrics for Measuring ROI of Predictive Machine Maintenance
- Inhibitors of Predictive Machine Maintenance's ROI Measurement

Details of these are evaluated as follows.

Measuring ROI of Predictive Maintenance

Theories indicate different approaches for measuring the ROI of predictive maintenance (Duarte & Santiago Scarpin, 2023). However, a general consensus exists that the process of measuring the ROI of equipment maintenance requires ensuring that all the systems for predictive maintenance are in place. It requires ensuring that all the equipment and machinery are functioning well. This improves the gathering, capturing, analysis and reliance on quality data. Better data quality improves the quality of the decisions made. It improves the accuracy of the analysis (Berrabah, Belkacemi & Zemmouchi-Ghomari, 2022).

ROI measurement is often not the exact returns obtained. Instead, it is often just the estimate. That implies if the used data is accurate, the analysis can also produce a more accurate estimate. This improves the decision of whether the manufacturing enterprise is doing all it requires to improve predictive equipment maintenance and influence achievement of the desired business decisions. In that process, theories imply the preparatory strategic process of ROI measurement requires the acquisition and establishment of the required equipment, technologies and tools (En-Nhaili, Muchiri & Pintelon, 2021). Most of the modern manufacturing machinery and equipment come with embedded sensors and remote control capabilities that improve predictive maintenance.

Once such compatible machinery and equipment are acquired and installed, the process must be accompanied by the acquisition and installation of the required software. It is through the software, sensors , and other network technologies that predictive maintenance works. Relevant technologies and adequate internet technologies and connections must be provided to ensure that all the manufacturing equipment, machines and the entire manufacturing system is connected and integrated with the internet (Rahman, Sugiono, Sonief & Novareza, 2024). Constant connectivity improves the seamless operation and functioning of the predictive equipment maintenance system.

Unfortunately, that is often the problem. Some manufacturing enterprises invest heavily in the acquisition and establishment of the equipment and machinery that support predictive analytics. But most of them, they are offline. This affects the utilization of all the sensors, robotics, artificial intelligence, and machine learning technologies that use the internet. It affects these technologies that require the internet to gather, analyse and provide accurate information on the state of different equipment's performance.

However, if the manufacturing enterprise ensures it is constantly connected to the internet and has proper network connections, the next initiative requires engagement in the actual data collection process (Alfionita & Ikhwanul Alifin, 2023). It requires ensuring that the required data and information on the state of each equipment's performance is systematically gathered, processed , and stored for retrieval at the time that such data will be required. This is a very important area that improves the overall value of predictive equipment maintenance. It is through gathering, analysis, and interpretation of the required data that the management is able to reach logical conclusions on whether or not a particular equipment requires repairs (Keller & Owen, 2025). It is from the gathering, analysis, and interpretation of the data that the operational managers can diagnose and respond to the actual root causes of the detected problem.

However, to accomplish that, the entire predictive maintenance system must be working well. It is difficult to ensure perfection, but all the systems must be working well to influence the attainment of the desired outcomes (Alfionita et al., 2023). If all systems are working well, even data quality is not compromised. This improves the quality of the decision undertaken to address the identified operational problems. For such outcomes to be achieved, it is not only the equipment, networks , and technology that must be working well, but also the employees. Even if artificial intelligence and robotics are used, it is still the ordinary employees who are the instructors and controllers of different machines and technologies. For that reason, the ordinary employees must be trained on how to use the available equipment and machinery (Rahman et al., 2024).

The ordinary employees must be trained to understand how to evaluate and make minor repairs, technology updates , and upgrades and maintenance like changing oil or putting oil if there is a shortage. Ordinary employees must be trained on how to give the required commands for the machines to perform the required evaluations. They must be taught how to read and interpret the information being relayed by the machines. Detailed understanding of the meaning of every piece of information improves the easy and timely detection and response to risks of machine failure before the machine breaks down.

To influence attainment of such outcomes, a range of ROI measurement techniques have been introduced by various manufacturing enterprises to aid the analysis of the ROI of predictive machine maintenance.

Metrics for Measuring ROI of Predictive Machine Maintenance

Thematic analysis of the existing literature and theories revealed the metrics for measuring ROI of predictive machine maintenance to be derived from:

- Financial Metrics
- Maintenance Management System
- Technology-Based Analytics

Details of these are evaluated as follows.

Financial Metrics

Financial metrics measure the financial gains obtained since the introduction of predictive machine maintenance. It evaluates the benefits and advantages attained so far as compared to the costs incurred in the application of predictive maintenance (Ameta, 2024). Apart from ROI, some of the used financial metrics encompass Cost-Benefit Analysis and Net Present Value (NPV). ROI analysis seeks to evaluate the benefits gained against the costs incurred in the use of predictive machine maintenance. It uses the formula:

(Maintenance' s Total Gains - Total Costs of Maintenance)/ (Total Costs of Maintenance) x 100%

For the purposes of ROI analysis, the gains from predictive machine maintenance encompass reduced downtime, improved productivity, improved quality, defect rate reduction, improved efficiency, reduced energy consumption , and improved throughput (Moss, 2025). In contrast, the costs of predictive maintenance encompass labour costs, spare parts, time of repairs, lost production time, lost sales. Some theories on the ROI of equipment maintenance classify costs according to direct and indirect costs. Direct costs include the straightforward costs of predictive equipment maintenance that include tools, technology, spare parts, labour , and contractor/consultant expenses. Indirect costs that must be factored during the ROI of predictive equipment maintenance encompass costs of reduced operational efficiency, downtime, quality issues , and reduced productivity.

In addition to direct and indirect costs, the other cost is the Total Cost of Ownership (TCO) (Sensemore, 2025). TCO includes costs like acquisition costs, operational costs , and the costs of disposing of the old equipment. Once all the costs are evaluated and factored in, the gains of predictive equipment maintenance are assessed by evaluating gains and savings like cost savings and revenues generated from reduced downtime, savings from reduced energy consumption, savings from the elimination of frequent costly repairs, sales generated from improved productivity , and savings from extended equipment lifespan (HexaState, 2025). From this analysis, the management can assess whether it is generating the desired returns from its predictive equipment maintenance approach.

However, apart from ROI, some theories suggest the importance of payback period analysis. Payback period analysis enables management to assess if the manufacturing enterprise is quickly generating the desired revenue from its predictive maintenance approach to recoup all the costs incurred in the predictive equipment maintenance (Keller & Owen, 2025). Longer periods imply there is a problem because maybe some of the equipment and machinery are not properly maintained. This causes frequent failures and delays that affect the faster recoup of the incurred costs.

Such analysis may be accompanied by Cost-Benefit Analysis as the other financial metrics that focus on evaluating and comparing the costs of predictive maintenance like usage of the required sensors and technology against the received benefits. The benefits of predictive equipment maintenance often arise from reduced downtime, improved productivity, improved quality, improved operational efficiency , and the extended asset lifespan (West, Siddhpura, Evangelista, & Haddad, 2024). In contrast, the Net Present Value (NPV) examines the overall returns that will be generated from the use of the predictive machine maintenance approach over a given period of time. If the NPV is positive, it is considered good as compared to if it is negative. Such initiatives are often accompanied by the use of a maintenance management system.

Maintenance Management System

Maintenance Management System enables operational managers assess and track all maintenance activities as well as the rate of equipment usage, costs , and performance. From such analysis, the management is able to make comparisons to assess if it is the predictive or the reactive equipment maintenance approach that must be used in certain areas of equipment maintenance processes (Keller & Owen, 2025). This is because reactive maintenance may not be good, but there are also situations where it tends to yield better results than the predictive equipment maintenance approach. While using such an approach, some managers often use the Operational Performance Measurement approach. This approach uses the indicators on the designated Dashboard that measure and track performance in areas like maintenance cost reduction, unplanned downtime reduction, asset utilization rate, and the spare-parts' inventory turnover period (Oxmaint, 2025).

Without even using more complex ROI analysis, the periodic analysis of these indicators can enable management discern whether or not the predictive equipment maintenance being used is a success. Even if the use of such technique may be proven effective, some high-performing business organisations often still use such metrics in conjunction with the use of the Computerized Maintenance Management System (CMMS). CMMS is an IT and internet-supported system that gathers, analyses, interprets and directs management to evaluate maintenance history, failure rates , and repair times in order to assess the overall avoided failure rates. Higher failure rates imply there is a problem with the predictive maintenance approach being used (Siemens, 2025). In a bid to improve the analysis of the financial implications of investing in a particular asset, Enterprise Asset Management System is often used to link financial indicators to certain asset lifecycle costs and performance. This enables management to discern the overall financial returns generated from the use of a particular manufacturing machine over a given period.

Such analysis is often integrated with the use of various sensors , artificial intelligence , and machine learning technologies to aid the assessment and tracking of failure rates (Zhong, Xia, Zhu, & Duan, 2023). It also profiles failure rates according to different areas of the manufacturing processes. This enables the manufacturing executives identify the areas to focus on and improve manufacturing efficiency going forward. Unfortunately, even if that is the case, the process of measuring the ROI of predictive machine maintenance is often still affected or undermined by a combination of management and organizational variables.

Technology-Based Analytics

To measure the ROI of predictive maintenance, a lot of various technologies and techniques have been introduced and adopted by various manufacturing businesses around the world. Such technologies or techniques include IoT Analytics Platforms and various forms of benchmarking platforms (Sensemore, 2025). IoT analytics platforms often use a range of various forms of sensors to evaluate if the use of predictive analytics has influenced the reduction of machine failures. Using FMEA (Failure Mode and Effects Analysis) tools, it accomplishes this by evaluating the risks avoided and costs incurred before and after predictive maintenance. This enables the manufacturing entity to assess the risks avoided and costs incurred to keep the manufacturing plant operating and running smoothly (HexaState, 2025). In that process, digital twins are also used to evaluate and model different scenarios when the manufacturing business is operating with or without predictive maintenance, to discern the avoided production losses. Such analysis enables the management assess the production losses that it would have avoided if it used predictive maintenance to keep the production planning running and operating smoothly.

In addition to IoT Analytics Platforms, various forms of benchmarking platforms enable the manufacturing enterprise assess the financial outcomes achieved after the use of predictive maintenance against the established industry standards like ISO 55000 (Aivaliotis, Xanthakis, & Sardelis, 2020). If the manufacturing entity is operating below the industry standards, it implies predictive maintenance is not being used in the right areas or the right way (Moss, 2025). This could prompt the need for change and modifications of various ways through which predictive maintenance is being used as well as the inclusion of other critical areas that must be subjected to predictive analysis. In that process, custom dashboards can also be introduced to gather, capture, process , and track data on the performance of the manufacturing enterprise in areas like financial and operational cost management (Baur, Albertelli, & Monno, 2020). It also aids the analysis and tracking of various risk-based metrics.

If the manufacturing enterprises are not using such techniques, they may opt to use the Industrial Internet of Things (IIoT) platforms that contain various forms of sensors for measuring and tracking the machines' performance in terms of temperature, vibration, pressure , or current that may affect quality or even slow performance of the machines (Ameta, 2024). Slower performance affects the productivity of the manufacturing enterprise in producing the desired quantities within the given time specification. Industrial IoT platforms are also integrated with the sensors for evaluating and tracking the state of the machine's performance as well as the recorded downtimes and savings arising from predictive maintenance. These suggest that as information technologies advance to include even the use of artificial intelligence, machine learning , and robotics, technology use in predictive analytics may emerge as the heart of the initiatives for improving manufacturing efficiency (Booyse, Wilke, & Heyns, 2020).

Using the other cloud IoT services, operational managers are able to calculate and evaluate the anomalies and downtimes avoided. The more avoided anomalies and downtimes, the more the business saves. Poor application of predictive maintenance causes the continuous use of faulty machines that subsequently break down beyond repair. As the business is forced to acquire new machines or to buy costly repairs to put the machine back into operation, it increases. It affects cost minimization in the way that leverages increased profit margins. Yet as the faulty machine is used without repairs, risks of periodic downtimes and slow production also become quite common. This affects production costs (Zonta, da Costa, Righi, de Lima, da Trindade, & Li, 2020).

But if the manufacturing enterprise is also using techniques like Edge and Real-Time Analytics, it can explore how poor predictive maintenance is causing frequent machine failures to affect the effective performance of the manufacturing enterprise. Capabilities of predictive maintenance to generate high returns on investment are reflected in the case of Tetra Pak, a Switzerland-based Multinational Corporation. Tetra Pak specializes in the manufacturing, sale , and distribution of food processing machinery as well as parts for such machines. Its manufacturing and sale of such machinery is also accompanied with the provision of the required maintenance services during a given period of warranty (Heim, Clemens, Steck, Basic, Timmons, & Zwiener, 2020). However, as Tetra Pak grew and expanded across the globe, the efficient provision of the required maintenance services also became difficult. To deal with such challenges and improve its operational efficiency, Tetra Pak invested in the acquisition and installation of various cloud computing technologies and remote monitoring tools. These enabled engineers from Tetra Pak to evaluate and monitor the conditions and performance of multitudes of their clients that are scattered in different parts of the world from their central location in Switzerland.

If there was a problem or the likelihood of the emergence of a breakdown, the engineers would alert the local technicians and guide them to address the problems before they became problematic (Yan, Lei, Li, Si, Pintelon, & Dewil, 2022). The return on investment for these initiatives was enormous as the use of these remote maintenance systems reduced direct site visits, thereby cutting off travel, food and accommodation costs. It also eliminated inconveniences and bolstered improved customer satisfaction. This spurred increased sales, revenue , and profitability to further boost the overall return of investment generated from the use of predictive maintenance.

Just like Tetra Pak, Mueller Industries was also a strong advocate of preventive maintenance because the business only spent money if the machines completely failed or collapsed. But as it briefly experimented with the use of predictive maintenance by adopting different technologies, Mueller Industries shifted to using the predictive maintenance approach. Mueller Industries is the manufacturer of various forms of aluminum, copper, plastic , and brass that it distributes and sells to various wholesalers and retailers around the world. However, to prevent the problems and costs of using preventive maintenance, it introduced microphone sensors, which are mobile handheld devices (Reliable Plant, 2025). The mobile device was remotely connected to all the machines and the entire manufacturing system.

The experiment focused on the evaluation, gathering and analyzing data on machine vibrations. The gathered data was uploaded to a cloud computing-supported database and subjected to analysis using some machine algorithms (Villa, Naticchia, Bruno, Aliev, Piantanida, & Antonelli, 2021). Results of the analysis indicated some bearing wear that Mueller Industries had not been able to detect for several past years. Following the integration of various predictive analytics technologies, Mueller Industries discovered the values and the overall ROI of predictive equipment maintenance to exceed the investment costs.

Predictive equipment maintenance does not just improve the proactive evaluation and response to the failing conditions of the existing equipment. Instead, it also improves the proactive evaluation and response to machine failures before the purchase and acquisition of the required machinery (Khan, Farnsworth, McWilliam, & Erkoyuncu, 2020). This applies in the Daimler Chrysler Case in which it had finished the plan for the acquisition of 600 machines for its new plant in Toledo, Ohio, and subjected all the 600 machines to analysis and evaluation. All the 600 machines were subjected to infrared and vibration analysis. Data was collected, processed , and evaluated from the analysis of the 600 machines using the advanced predictive maintenance software. The outcome of the analysis indicated that 100 of the 600 new machines had issues of bad or worn bearings, poor alignment, and poorly sized shims. These outcomes prevented Daimler Chrysler from incurring additional maintenance costs by purchasing the machines.

Inhibitors of Predictive Machine Maintenance's ROI Measurement

Thematic analysis of the existing studies indicated the inhibitors of predictive machine maintenance's ROI measurement often arise from:

- Cost
- Poor Data Utilization Culture
- Ignoring Predictive Maintenance

Details of these are evaluated as follows.

Cost

Cost is one of the inhibitors of effective analysis of the ROI of predictive equipment's maintenance. Before the manufacturing enterprise can take the option of using predictive equipment maintenance, the investment in the required technologies, sensors , and network connections is not easy (Sankar, 2025). Yet without the required technologies and sensors, the manufacturing enterprise cannot gather and analyse its data to reach logical conclusions about cost savings and the overall ROI of predictive equipment's maintenance.

Even if the costs of most remote technologies have dropped due to increased production, problems still arise from the fact that the best technologies are often more expensive and costly (Veerappan, 2025). Most of the best sensors and network technologies or the manufacturing machines with inbuilt or embedded technologies are often quite expensive and costly. Though with time the heavy expenditure on predictive equipment maintenance technologies pays off, in the initial stages, the manufacturing enterprise must have adequate financial resources. The manufacturing enterprise must have adequate financial resources for buying and installing the required machines (Duarte & Santiago Scarpin, 2023). Even the manufacturing facilities and layout must also be changed. As this increases costs, the manufacturing enterprise is also supposed to prepare and incur costs of training and developing the employees to use the new technologies. For that reason, during the initial years of acquiring and installing the required technologies, the manufacturing enterprise cannot gain much from its predictive equipment maintenance.

The manufacturing enterprise can calculate and get improved ROI during the initial periods of investment in the required technologies. Apart from the training and development costs, the manufacturing enterprise must also be able to put aside the funds for constant maintenance and repairs (Berrabah, Belkacemi, & Zemmouchi-Ghomari, 2022). Failure to incur and do the costs of repairs and maintenance can also affect the performance of the machines. This implies frequent breakdowns can affect the performance of the machine and delay the capability to quickly generate enough funds and recoup the cost of investment. If the machines break down a lot, it can also affect and delay the payback period. It means the manufacturing enterprise cannot quickly generate the funds to repay the loan within the shortest possible time. Besides that, poor data utilization culture can also affect the effective measurement of the ROI of predictive equipment maintenance (Rahman, Sugiono, Sonief, & Novareza, 2024).

Poor Data Utilization Culture

Poor data utilization culture is one of the major impediments of effective measurement of the ROI of predictive equipment maintenance. When new manufacturing technologies and machines that aid predictive equipment maintenance are installed, it requires new practices (Alfionita & Ikhwanul Alifin, 2023). Sometimes, the employees may just focus on using the machines for as long as they are working only for the machines to fail with time. Unless the management strongly emphasizes the need for change and the embracement of a new operational culture, the ordinary employees may fail to capture and gather some essential data.

For some machines to gather specific data, the machine must be activated in one way or another (En-Nhaili, Muchiri, & Pintelon, 2021). But this can become a problem in terms of the commitment of ordinary employees to ensure that all the required data on all aspects of the machine's state of performance are gathered, analysed , and responded to. For the machines to work well, the repairs, software upgrade , and maintenance must be done within the stipulated duration. But because of poor data utilization culture, sometimes the required data is collected , while in other cases, the data may not be gathered. This causes a problem of data quality (Veerappan, 2025). It also causes the problem of disconnected data , which cannot easily be assessed to discern the actual period which is required for the machines to be maintained. If there is not accurate data, it becomes difficult to assess and measure the ROI of predictive equipment's maintenance.

Effective assessment of the ROI of equipment's maintenance requires the evaluation of the number of days that the machines have worked, the units produced and sold, as well as the number of days that the machines broke down , and a lot of all other required data. If the manufacturing enterprise does not have accurate data on these areas, it means it cannot effectively evaluate and understand the ROI of predictive maintenance (Limble, 2025). During most periods that new machines are introduced, a misconception is created that it is only the managers or supervisors who are supposed to handle the issues of data collection.

If the supervisors or managers created such an impression, it means if the supervisor or manager moves a bit and a data gathering issue arises, the other employees will not intervene. It also signifies if the supervisor or managers are off, it can also become difficult for ordinary employees to discern how to operate the machines to gather and analyse the required data (Veerappan, 2025). Most of the manufacturing machines are often automated using the required robotics and artificial intelligence to gather the required data.

But still, the machines may require some form of human instructions and actions for them to accomplish the activities that they are required to do. This affects the consistent collection and utilization of quality data on the state of machine performance. Without quality data, management cannot calculate and process accurate information on the ROI achieved for different forms of predictive equipment maintenance (Limble, 2025). Dealing with such constraints requires management to invest in training and development of the ordinary employees to appropriately use the available data. Ordinary employees must be trained on the techniques for gathering, facilitating analysis, and interpretation of various machine data using the available technologies. Though such initiatives increase costs, problems may also arise from management's ignoring of predictive equipment maintenance (Duarte & Santiago-Scarpin, 2023).

Ignoring Predictive Maintenance

Ignoring predictive maintenance can be another problem affecting the measuring of the ROI of predictive equipment maintenance (Berrabah, Belkacemi, & Zemmouchi-Ghomari, 2022). In most cases, most of the modern manufacturing machines are embedded with inbuilt sensors and remote technologies for evaluating, controlling , and doing maintenance. In most cases, if they are programmed to alert and notify management when the maintenance days are approaching. But even if the machines alert, some managers often ignore the alert notices (Rahman, Sugiono, Sonief, & Novareza, 2024). Unless the compilation and provision of the required maintenance report is highly demanded by management, most of the employees may tend to be unwilling to respond to the machine's alert notices. Most of the time, the machines may alert and sound alarms, but the management may ignore them. The management may keep postponing the maintenance schedule until the machine completely breaks down. This is because machine maintenance, upgrade, or repairs require a lot of money, which sometimes the top management is not willing to release on time (Alfionita & Ikhwanul Alifin, 2023).

Top management may delay allocating and releasing funds for maintenance because they feel that since the machines are still running, doing maintenance is not necessary. They may postpone, and as they do so, the risks of frequent breakdowns also become quite eminent. Some other operational managers may also become unethical by trying to claim the machines are serviced and maintained, yet they are not. To meet the required financial targets, some of the managers may also try not to do the required machine upgrade, repairs , and maintenance even if the sensors are warning (En-Nhaili, Muchiri, & Pintelon, 2021). During the time of machine upgrade, repair , and maintenance, the machines often tend not to work.

The operation is temporarily closed, and that is what some managers don't want. When the machines are closed, the plant does not work to aid the achievement of the desired targets. To achieve the desired targets, some managers may try to postpone machine maintenance, upgrade , or repairs. Alternatively, they may also attempt to use the machines even if the sensors are indicating that the machines are faulty (Veerappan, 2025). This causes the production of poor-quality products that get rejected, affecting the ROI generated from predictive machine maintenance. Extending the period of maintenance also affects the accuracy of the gathered information. During ROI calculations, this also affects the accuracy of the data used on the days of machine breakdown, production, and the amount of money spent on machine maintenance.

CONCLUSION

In general, from this critical analysis of secondary data, it was evident that to improve the effectiveness of their predictive equipment maintenance, the manufacturing enterprises must consider investing in the establishment of predictive equipment maintenance system. This must be integrated with the investment in the use of supportive technologies like sensors, robotics, artificial intelligence & machine learning technologies. While predictive equipment maintenance is being undertaken, it is suggested that the manufacturing enterprises must measure the financial impact of predictive equipment maintenance using metrics like ROI, Cost-Benefit Analysis and Net Present Value (NPV). However, to ensure the effectiveness of predictive equipment maintenance, it is suggested that the manufacturing enterprises must consider the success factors for predictive equipment maintenance that include digitization, data utilization culture, proactive business management culture and adequate financial resources.

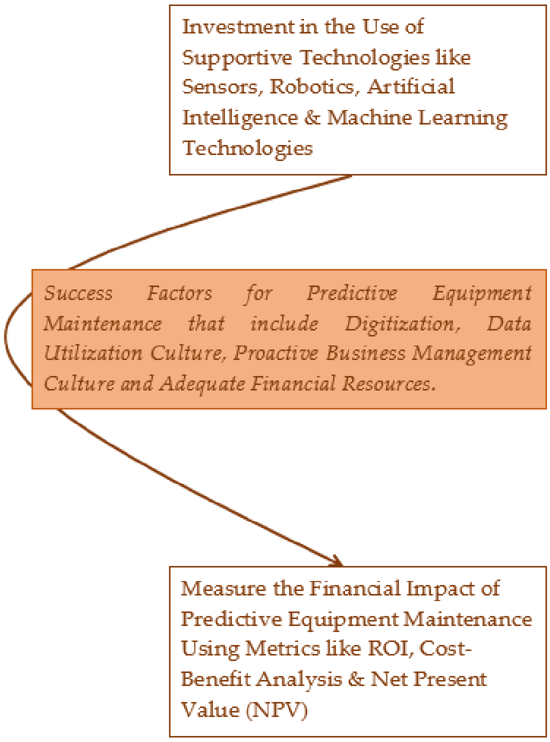

Figure 1. Framework for Measuring The Financial Impact Of Predictive Equipment Maintenance

It was evident that the manufacturing entities that underspend on equipment's maintenance use a dual equipment's maintenance system reflecting aspects of predictive and preventive equipment's maintenance. In contrast, overspending on equipment's maintenance causes risks of poor cost controls and wastes that affect operating profit margins and the overall profitability of the business. Yet as some manufacturing entities overspend on predictive equipment's maintenance, others tend to avoid it completely. Some manufacturing enterprises opt for the use of preventive equipment's maintenance. In such initiatives, predictive maintenance approaches are completely avoided in favour of the preventive maintenance approach.

Because of such business philosophy, most secondary studies also indicated preventive equipment's maintenance is perceived as more cost-effective. Because preventive equipment's maintenance waits for equipment to fail and then spend on repairs, maintenance, upgrade, or purchase of new equipment, it is often construed as more cost-effective. Preventive equipment's maintenance is construed to improve cost savings. No maintenance or repair expenditures are incurred unless the equipment breaks down or fails, signifying there is actually a need for the money to be spent.

To some or even most manufacturing executives, this often makes a lot of business sense. It releases pressure for money to be spent and used in the other areas as the management waits for the equipment to break down and respond. Unfortunately, even if that is so, frequent and sudden machine breakdowns must be some of the incidents that the manufacturing executives must be prepared to deal with. Frequently disrupted operational processes and manufacturing processes are some of the incidents that the operational managers must be prepared to deal with. This affects operational efficiency, productivity, throughput and effective cost management. Yet as most manufacturing executives adopt such business approaches, empirical facts imply the increasing competition in the global manufacturing business ecosystem is driving most manufacturing executives to adopt various predictive equipment's maintenance approaches. One of these approaches is to measure and understand the investments committed on equipment maintenance and the amount recouped within a specified period. This improves the management's decision to avoid waste and overspending on equipment's maintenance or the underspending that can cause operational inefficiencies. To understand such financial indicators, the study indicated the metrics for measuring ROI of predictive machine maintenance to be derived from financial metrics, maintenance management system , and certain technology-based analytics.

Limitations of the Study and Future Research

Limitations of the study arise from the fact that this study just used secondary data analysis without the conduct of primary research. That implies even if some findings are true, it may not necessarily reflect the actual real-world situations on the approaches, limitations and measures for improving predictive equipment maintenance in the modern manufacturing enterprises. Yet as the study only used Google as the major search engine, limitations also arose from the decision not to use only indexed databases like Scopus or Web of Science. But future research must still explore how artificial intelligence and machine learning technologies can be used for measuring the ROI of equipment's maintenance.

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