DOI: 10.71317/jgst.2.7.2026.261
Journal of Global Social Transformation
Journal homepage: https://rjsaonline.org/index.php/JGST

Artificial Intelligence in Predictive Maintenance: Enhancing Machine Reliability and Industrial Productivity

Rashad Mahmood Khan[1], Faheem Ahmed[2], Mishal Zahra[3], Dr. Muhammad Imran Saleem[4]

[1] M.Phil IT (Distinction), Ph.D. Scholar, Department of Computer Science, University of the Engineering and Technology, Main Campus, Lahore.
Email: ranarashadmahmood@gmail.com , rashad.mehmood@uet.edu.pk
[2] Assistant Professor Department of Information Technology University of Sindh, Jamshoro
Email: faheem.abbasi@usindh.edu.pk
[3] Department of Software Engineering NUST(MCS)
Email: mishalzahra281@gmail.com
[4] Sir Syed University of Engineering and Technology Karachi
Email: Isaleem@ssuet.edu.pk

ARTICLE INFO

Submission:
June 05, 2026
Revised:
June 20, 2026
Accepted:
July 06, 2026
Available Online:
July 21, 2026

Keywords:
Artificial Intelligence, Predictive Maintenance, Machine Reliability, Industrial Productivity, Industry 4.0, Smart Manufacturing, Industrial Internet of Things (IIoT), Manufacturing Efficiency.

Corresponding author:
ranarashadmahmood@gmail.com

ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative technology in modern manufacturing by enabling predictive maintenance strategies that enhance machine reliability and improve industrial productivity. This research investigated the effects Artificial Intelligence has on machine reliability and the productivity of the industrial sector, concerning predictive maintenance, and manufacturing companies located in Punjab and Sindh, Pakistan. A quantitative cross-sectional research design was used and an adopted, structured, online questionnaire was deployed. 467 online respondents located at various Pakistan based companies filled in the questionnaire. These respondents were maintenance engineers, production engineers, and plant managers, among others. Concerning the sample companies, the respondents hailed from Pakistan Steel Mills, Engro Corporation and Honda Atlas Pakistan, among others. The responses were downloaded into Microsoft Excel and then uploaded into SPSS Version 27 to perform the statistical analysis. Descriptive statistics were used in preliminary analysis of the study sample. To analyze the study variables, Pearson correlation analysis, multiple linear regression and Independent Samples t-test were employed, and One-Way ANOVA was used to establish the predictive effects and differences among the study variables. The study found that AI and predictive maintenance positively impacted the machine reliability, industrial maintenance, and the productivity of the industry. The study adds to the existing research of AI and predictive maintenance in the context of the Pakistan manufacturing industry. It also offers practical use for industry managers and policy makers.

Introduction

Changes in digitization have brought the ability for industries to create systems that dynamically analyze and optimize manufacturing processes. Of the various technologies that have helped develop smart systems for smart manufacturing and Industry 4.0, Artificial Intelligence (AI) is among the most critical. The limitations of traditional maintenance approaches, such as reactive and scheduled preventive maintenance, have clear economic implications, resulting in machine failure and loss of production. With AI, industries are given the opportunity to predict failures of machine components, allowing maintenance to be scheduled in an optimal manner and minimizing disruption of operations (Lee et al., 2018; Carvalho et al., 2019).

The combination of AI with the Industrial Internet of Things (IIoT), along with cloud computing and big data, have developed maintenance approaches to an even higher level by enabling the sustained monitoring of machine performance with a network of connected sensors. These technologies, as a byproduct of their operational nature, generate large amounts of operational data and offer the analysis of AI to detect abnormal behavior, define degradation patterns, and determine the remaining useful life of industrial assets. Within the realm of manufacturing, as systems and processes become increasingly data-centric, predictive maintenance has the potential to become a core strategic function and enabler for operational excellence and sustainability of the industrial practice (Kamble et al., 2018; Javaid et al., 2022).

The use of advanced technologies like machine learning and deep learning in AI diagnostic tools is changing predictive maintenance practices. Traditional maintenance systems follow a routine schedule or rely on an operator's inspection. AI systems create flexible, adaptive models that respond to the operational environment and suggest the appropriate timing for maintenance actions. With fewer work stoppages, greater savings on maintenance, enhanced safety for workers, and improved production, predictive maintenance is becoming widely adopted across industries (Zonta et al., 2020; Bousdekis et al., 2021).

Artificial Intelligence and Predictive Maintenance for Machine Reliability

Reliability of machines is a key performance metric for manufacturing firms. Frequent machine breakdowns increase the cost of maintenance, disrupt production schedules, and lead to a decline in customer satisfaction and profitability. AI-based predictive maintenance solves these problems by monitoring the state of the machines and predicting failures before they occur. This philosophy of maintenance enables firms to transition from maintenance by correction to a rational design of maintenance (Carvalho et al., 2019; Ucar, A et al., 2024).

The latest technologies in predictive maintenance leverage AI to fuse analytics of machine data and history with sensor data, vibration and temperature analysis, and acoustic data. After training with historical data, the bettering machine learning algorithms are able to identify maintenance needs to optimize schedules and reduce unnecessary interventions (Nguyen & Medjaher, 2022).

Integrating AI into predictive maintenance extends the life cycle of machinery by reducing the frequency of maintenance and ultimately decreasing the amount of unplanned downtimes. Organizations with automated maintenance have reported better maintenance, better balancing of the workload resources, and better production because maintenance is performed when it is needed and not when it is scheduled. AI integrated predictive maintenance is, therefore, an excellent value-added, strategic and tactical investment for most industrial organizations that are working to enhance operational integrity and minimize the costs associated with maintenance (Keleko, A et al., 2022; Okpala, C et al., 2025).

Artificial Intelligence as a Driver of Industrial Productivity and Sustainable Manufacturing

Reliability, efficiency, and accessibility of manufacturing equipment are crucial for productivity in an industrial setting. To enhance production performance, many organizations have begun integrating artificial intelligence within operations to lessen costs and improve the level of resource dedication (Mitta et al., 2024). AI-based predictive maintenance allows industries to achieve continuous production through the early identification of potential equipment issues, therefore preventing major breakdowns and diminishing the time of an inactive machine. This intelligent maintenance practice cultivates an organization's competitiveness in the marketplace through improvement in production and assurance of product quality (Alam et al., 2023).

Sustainable manufacturing is the ability of a manufacturing system to operate while conserving the resources of the environment, which is one of the key factors in determining the long-term viability of a business (Ayeni & Mitta, 2025). Sustainable manufacturing is supported by AI through extending the life of industrial assets, optimizing energy consumption, and reducing waste of materials. Waste is eliminated due to predictive maintenance, which reduces the unnecessary replacement of machine parts by intervening at the proper time when the equipment necessitates maintenance. This condition-based maintenance is not only a waste of maintenance resources but also a step in the right direction toward sustainable manufacturing practices.

Intelligent automation, coupled with advanced analytics and self-improving systems, will dominate the future maintenance landscape. Continued development on digital twins, edge computing, explainable AI, and federated learning will make maintenance decisions more secure, faster, and more precise. These innovations will make predictive maintenance more powerful. AI is changing maintenance operations and impacting overall industrial productivity by building more intelligent, self-healing, and sustainable manufacturing ecosystems. These ecosystems will be able to adapt to the rapidly changing needs of the global industrial market (Abbas, A. 2024).

Research Objectives

- To examine the effect of artificial intelligence-based predictive maintenance on machine reliability in industrial organizations.
- To evaluate the impact of artificial intelligence-based predictive maintenance on industrial productivity.
- To investigate the relationship between machine reliability and industrial productivity in AI-enabled manufacturing environments.

Research Questions

- What is the effect of artificial intelligence-based predictive maintenance on machine reliability in industrial organizations?
- What is the impact of artificial intelligence-based predictive maintenance on industrial productivity?
- What is the relationship between machine reliability and industrial productivity in AI-enabled manufacturing environments?

Problem Statement

Modern artificial intelligence (AI) and Industry 4.0 technologies have reached an impressive level of development. However, many industrial organizations are still experiencing machine breakdowns, unplanned equipment downtime, higher maintenance costs, and loss in productivity. This is mainly due to their usage of reactive or time-based preventive maintenance policies. Traditional maintenance practices lack the capability to forecast equipment degradation. This leads to breakdowns, low reliability of equipment, and large financial losses. AI-based predictive maintenance is arguably a better alternative to improve the monitoring of equipment and the maintenance decision process, but the level of its adoption and implementation in practice is still low in many industrial domains. In addition, very little is known about the impact and the extent of AI-enabled predictive maintenance on the reliability of machines and the overall productivity of industry. There is a clear need for research in this area to evaluate the role of AI in predictive maintenance, and more importantly, to assess its influence on the reliability of machines and the productivity of industry, especially in the contemporary manufacturing systems.

Significance of the Study

The growing capability of predictive maintenance powered by artificial intelligence is making machines more reliable and increasing productivity across industries. The outcomes from this study will help to show the impact of AI-based predictive maintenance systems by describing the reduction of unpredicted failures of workplace equipment, the decrease of maintenance costs, the increase of productivity, and the improved support of uninterruptible services to the other systems within the modern factories. The study will benefit industrial managers, maintenance engineers, and manufacturing organizations, as well as policymakers and technology developers, by providing actionable data on the use of advanced maintenance systems to gain a competitive edge through improved use of resources. In addition, the research will support organizations in attaining improvement of reliable equipment and increased productivity of a sustainable manufacturing practice, while providing new information in the area of research on the impact of AI-based predictive maintenance in the industrial environment.

Literature Review

AI is now seen as one of the most disruptive technologies in modern industrial maintenance because it allows a company to evolve from old maintenance practices to new regimes based on intelligent data processing. Traditional maintenance practices (reactive maintenance and preventive maintenance) often miss the early warning signs of equipment deterioration and result in breakdowns and expensive, unplanned maintenance, which disrupts the production process. Lee et al. (2018) explain that industrial maintenance practices are better at forecasting equipment failures with the incorporation of AI and thus reduce operating downtime, which ultimately improves the productivity of businesses. AI is better at solving maintenance problems because of its ability to process large amounts of operational data using sophisticated algorithms and techniques such as machine learning, deep learning, and intelligent pattern recognition. Because of the digitization of industrial systems under Industry 4.0, AI has become a critical element of predictive maintenance systems for reliability, productivity, and sustainable manufacturing (Patil, D. 2024).

Manufacturing environments provide a clear example of the utility of artificial intelligence. Predictive maintenance focuses on the value of anticipating the premature failure of equipment before disruptions occur. According to Sivakumar, M et al. (2024), AI-oriented predictive maintenance integrates a multitude of emerging technologies including sensor technologies, the Industrial Internet of Things (IIoT), cloud computing, and big data analytics to perform health checks on industrial machines and assess the status of industrial equipment in real time on the shop floor. The machinery analytics provided by industrial sensors that monitor vibration, temperature, pressure, acoustic emissions, lubrication, and energy creates data sets concerning the health of the equipment that AI algorithms analyze to identify patterns of deterioration. Machine learning algorithms are able to classify machine operational states and abnormal states, and predict the remaining useful life of critical machine components with greater precision than traditional maintenance approaches. Predictive maintenance offers businesses the ability to tailor maintenance plans by eliminating redundant maintenance inspection activities thereby lowering costs and producing efficiencies.

Machine learning is key to AI-based predictive maintenance due to its capacity to find and improve upon complex relations among patterns. Lefroni, K et al. (2025) describe predictive maintenance systems' ability to identify and classify fault signatures and machine states and foresee future failures based on records of previous maintenance rounds and real-time operational data, made possible by the application of supervised, unsupervised and reinforcement learning. Furthermore, the DML's ability to analyze large, complex data sets, which are a common feature of contemporary manufacturing systems, allows predictive maintenance models to achieve a further degree of accuracy. Predictive maintenance using traditional, prescriptive statistics, is made more flexible by the AI's ability to autonomously and instantaneously pull and analyze data from raw sensor data, as opposed to older, legacy systems. For maintenance managers, this means that predictive maintenance systems inform them, and allow them to use their resources effectively, avoiding prolonged and costly interruptions of production.

The combination of Artificial Intelligence and Industry 4.0 technologies has caused tremendous disruptions in predictive maintenance because intelligent manufacturing systems are now capable of self-regulated monitoring and decision-making. Per the work of Henderson, J et al. (2025), Industry 4.0 allows for the smooth intercommunication and integration of multiple, disparate pieces of industrial equipment within a connected, cyber-physical infrastructure, utilizing cloud and/or edge computing, as well as Industrial Internet of Things frameworks. AI is able to analyze the operational data it collects in real time to track the subtle change in behavior as equipment begins to show the early signs of mechanical deterioration and/or failure. The control of predictive maintenance in real time is the best use of industrial resources and time relative to the efficiency of operation and production of the equipment. Also, with the aid of the digital twin, the AI-powered predictive maintenance is even more robust because the digital twin enables the virtualization of the physical equipment and the simulation of the digital equipment for what-if analysis of different operational scenarios, which enhances the planning of maintenance and mitigates the risk of loss and/or failure of operations.

Artificial Intelligence and Machine Reliability

Machine reliability is vital to industrial performance because it affects production continuity, operational efficiency, product quality, and profits. The issues created by the unpredictable breakdown of machinery, an increase in maintenance costs, and interruptions of the manufacturing process are all reduced when machinery is reliable. Reactive maintenance is one of the traditional maintenance methods that is criticized for the excessive downtimes and loss in productivity caused by responding to and performing maintenance on equipment only after the equipment has incurred a failure. Xie, S. (2024) explains that the introduction of Artificial Intelligence (AI) has completely altered machine reliability and the predictability of machine failures. Not only is the health of machines monitored with AI, but deterioration can be detected and failures predicted before they are able to cause interruptions to the manufacturing process. The usability and the function of industrial assets is further enhanced with the use of AI and the advanced analytics that accompany AI in the industry. With the introduction of AI in maintenance systems that are adopted and operated in the Industry 4.0 systems, machine reliability is now considered a competitive advantage.

Utilizing advanced algorithms, Artificial Intelligence (AI) helps industries create reliable machines by analyzing operating data collected by built-in sensors on industrial machines. Predictive maintenance systems were described by Bello, S. et al (2024) as systems observing vibration, temperature, pressure, acoustic emissions, lubrication, and indicators of breakdown such as Electrical signals. AI continues to monitor the working parameters of machines and compares them to the historic data to find patterns of mechanical degradation. Traditional maintenance systems are built upon the planned, usually periodic maintenance of machines. AI systems, however, are based on the condition of the machine and adapt to the changing state of the machine to provide better predictions of the state of the machine. The AI based maintenance systems provide a warning to maintenance engineers to prevent breakdowns of machines, which in turn reduces the cost of machine repair and increases the availability of the machine in the manufacturing process.

The growing importance of Artificial Intelligence and machine reliability is evident with the popularization of technologies such as the Industrial Internet of Things (IIoT) and cyber-physical production systems. Scaife, A. (2024) noted that an array of connected sensors produce real-time process data, which is analyzed by AI to understand the working conditions of the machines. In addition, reliability of machines is improved by Deep Learning and Neural Networks as they have the ability to discern fault patterns that are particularly complicated and may remain undiscovered. AI has improved fault detection of machines, and has also improved the reliability and stability of machines.

Another advantage of Artificial Intelligence in the reliability of machines is that it helps manage maintenance resources better and reduces the frequency of unnecessary maintenance work. Bousdekis et al. (2021) state that predictive maintenance and AI remove the problems of traditional preventive maintenance by suggesting maintenance work only when the performance of the equipment is likely to worsen. This type of maintenance helps reduce the costs of maintaining a stock of spare parts and reduces the costs of the workforce from the excessive replacement of parts while supporting equipment reliability. AI also helps maintenance staff by allowing them to prioritize the maintenance of machines that pose the greatest operational risk. This helps improve the effective use of maintenance resources and reduce production downtimes. Smart maintenance helps improve the overall maintenance of a manufacturing company by making it more resilient and efficient.

Artificial Intelligence and Industrial Productivity

Artificial Intelligence (AI) serves to enhance industrial productivity more than any other technology. AI systems allow manufacturing firms to fine-tune production, eliminate process inefficiencies, and improve the quality of business decisions. Industrial productivity is an organization’s ability to optimize throughput and minimize input. Inputs include time, labor, energy, and costs associated with operations. Firms that manufacture products are constantly on the lookout to gain a competitive advantage. Thus, they implement AI to improve the productivity of their operations, ensure quality of their products, and adapt to varying customer requirements within the marketplace. As stated by Çınar, Z. et al. (2020), the addition of AI to improve the “smartness” of industrial operations brings automation, predictive analytics, and the ability to monitor and control production processes in real time. AI goes a step further than traditional automation systems, that require human operators to monitor the system and perform activities that are predetermined, by providing the ability to continually analyze production, look for inefficiencies, and suggest improvements to accomplish the goals of productivity for the manufacturing system as a whole.

Predictive maintenance is a key way AI is used to boost productivity across sectors. Unpredictable downtime is detrimental to manufacturing. Issues like broken equipment disrupt operations, raise costs, and reduce the amount of time equipment is used. AI-enabled predictive maintenance, according to Hector, I. et al, (2024) uses a combination of sensors and machine learning to detect and report anomalous machine behaviors which could indicate potential failures and helps prevent them. This maintains the manufacturing process and extends the time an equipment is usable. Unpredictable failures are costly, and using predictive maintenance services optimizes the use of the equipment. In a smart manufacturing environment, the cost benefits and improved resource usage associated with predictive maintenance, make it an essential service in higher industrial productivity.

AI tools further enhance productivity in manufacturing through advanced process optimization tools, helping managers make data-driven operational decisions. Alade et al. (2024) argue that AI algorithms analyze large data in the Industrial Internet of Things (IIoT) alongside enterprise resource planning (ERP) and manufacturing execution (ME) systems to detect and mitigate production bottlenecks, enhance workflow, and manage resources more effectively. Through machine learning, models analyze production and detect latent structures of operational variables to maximize efficiency in processing. With these advanced analytics capabilities, businesses are able to manage their inventories more effectively, reduce production waste, and maximize operational effectiveness and efficiency. AI also enhances the manufacturing process by enabling constant quality assurance to identify defects in product outputs during the manufacturing process instead of post production, thus saving costs in reworks and enhancing product quality. These advantages to aspects of manufacturing culminate in improvements in the efficiency and effectiveness of manufacturing, productivity, and ultimately customer satisfaction.

Driven by AI and Industry 4.0, autonomous manufacturing systems are highly interconnected. This combination boosts industrial productivity. Kliestik, T et al. (2023) suggest that cyber-physical systems, cloud computing, edge computing, robotics, and digital twins, paired with AI, formulate smart manufacturing systems that can assess and change the systems that hinder the optimal performance of manufacturing processes. AI can automate processes to the point that human involvement is reduced to the control of processes. This, in effect, promotes the workforce to dedicate their human capability to innovations and improvements in quality, as well as the development of new, strategic decisions. Also, intelligent production systems can rapidly react to changes in the customer's needs, the state of the supply systems, and even the operational status of production equipment. All of these are examples of manufacturing adaptive capability and organizational resilience. These changes propel the competition manufacturing processes and systems at a national and global level.

Research Gap

There are several gaps in research cited in the literature that discuss the use of artificial intelligence (AI) in predictive maintenance and the opportunities that it provides for enhancing the efficiency of maintenance, the detection of faults, and the improvement of operational decisions. Some existing studies have focused on AI and the development of algorithms and machine learning and predictive analytic models. Very little research has studied how AI-based predictive maintenance impacts machine reliability and manufacturing productivity. Most studies review the mentioned variables in isolation. This, together with the fact that most existing research is concentrated in advanced economies, has led to a lot of research gaps and unstudied areas. There is a need to investigate how AI-based predictive maintenance impacts machine reliability and manufacturing productivity, as it would provide better insights on how modern intelligent maintenance frameworks provide significant benefits in the operational context, of sustainable manufacturing and long-term competitiveness of the industry.

Research Hypotheses

H1 Artificial intelligence in predictive maintenance has a significant positive relationship with machine reliability.

H2 Artificial intelligence in predictive maintenance significantly predicts industrial productivity.

H3 There is a significant difference in industrial productivity based on the adoption level of artificial intelligence in predictive maintenance.

H4 There is a significant difference in machine reliability across different levels of artificial intelligence implementation in predictive maintenance.

Conceptual Framework

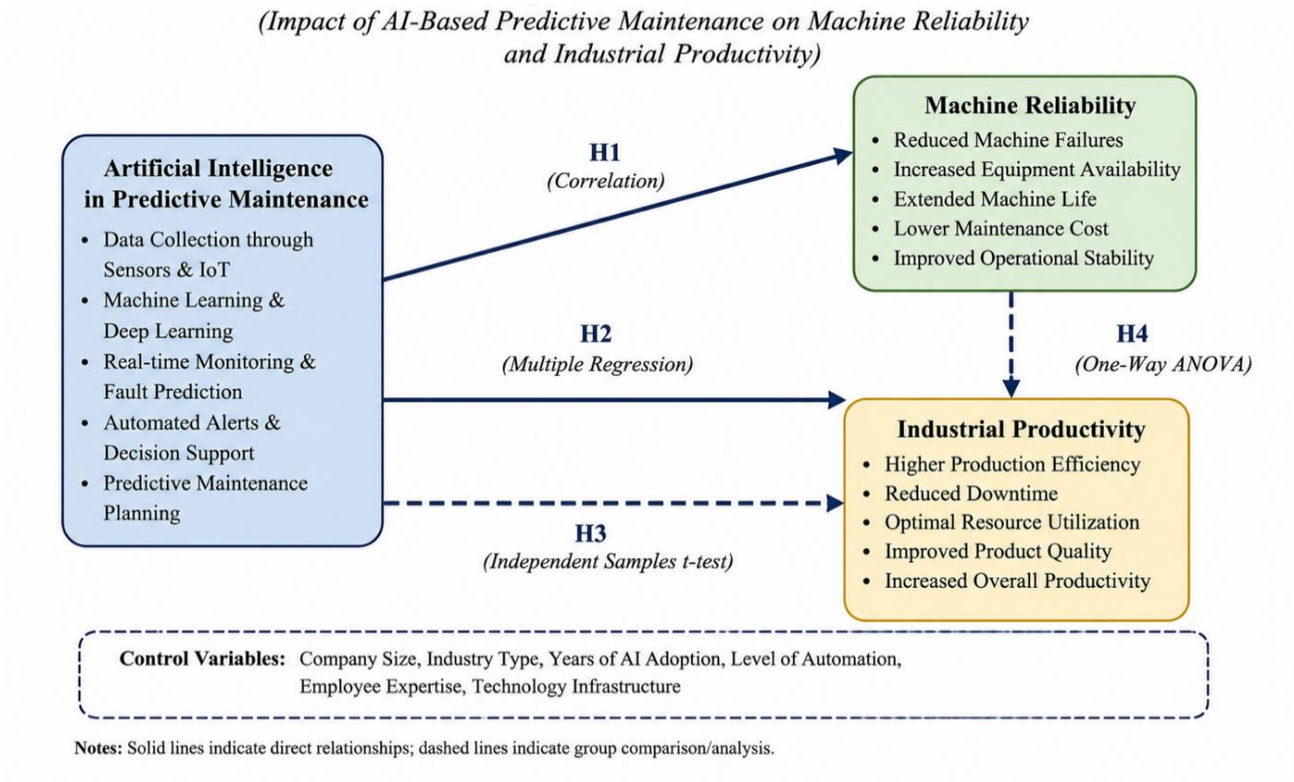

Figure 1.1 Conceptual Framework

Methodology

Research Design

A cross-sectional research design was used in this quantitative study to assess the effect of Artificial Intelligence in Predictive Maintenance on machine reliability and industrial productivity. The primary data collection method was an online survey questionnaire. Structured questionnaires enabled the researcher to gather information in a short time span and from a large number of study participants. The researcher considered the quantitative methodology appropriate for the study because it provided the capability to measure relationships among the study variables using statistical analyses.The research design was selected to obtain objective and measurable data pertaining to the effect of AI-based predictive maintenance on the industrial performance, and to provide empirical evidence.

Population of the Study

The study population comprised employees working in manufacturing and industrial organizations that adopted AI-based technologies for predictive maintenance or that were in the process of doing so. The researcher selected study participants from manufacturing organizations located in the provinces of Punjab and Sindh. The research covered the following cities: Lahore, Faisalabad, Multan, Gujranwala, Rawalpindi, Sialkot, Bahawalpur, Sheikhupura, Karachi, Hyderabad, and Sukkur. The researcher collected data from employees working in the following industrial organizations: Pakistan Steel Mills, Pak Elektron Limited (PEL), Nishat Mills Limited, Fauji Fertilizer Company Limited (FFC), Engro Corporation, Lucky Cement Limited, Millat Tractors Limited, Descon Engineering Limited, Honda Atlas Pakistan, and Sitara Chemical Industries. The organizations were selected due to the sustained prominence in the adoption of digital manufacturing, automation, and advanced predictive maintenance technologies.

Target Audience

The target audience for this study included maintenance and production engineers, plant managers, maintenance supervisors, industrial technicians, operations managers, quality assurance managers, automation and reliability engineers, and technical professionals in manufacturing. These respondents were seen as appropriate because of their firsthand exposure to predictive maintenance systems, machine performance, industrial automation, and the role of Artificial Intelligence in manufacturing. Their experience with the automation of manufacturing processes was critical to the study's context for the assessment of AI-enabled predictive maintenance systems.

Sampling Technique

Purposive sampling was adopted for selecting the respondents. This method of sampling was suited to the study as only the employees directly engaged with industrial maintenance, as well as production, automation, and machinery management, were included in the study. Participants were chosen based on their knowledge, experience, and engagement with AI systems and predictive maintenance in their organizations. This study focused on aspects of predictive maintenance relevant to the framework of the proposed research.

Sample Size

The study was designed to have a sample size of 467 respondents. The sample size was adequate to perform the quantitative assessment planned for the study to derive valid and reliable evidence about the associations of AI-based predictive maintenance, machine reliability, and productivity in the industry. The respondents belonged to a range of manufacturing industries in Punjab and Sindh in Pakistan.

Data Collection Procedure

Primary data collection involved using an adapted structured questionnaire based on validated scales. The predictive maintenance Artificial Intelligence measurement scale was adapted from Carvalho et al. (2019), and Zonta et al. (2020). The Machine Reliability scale was adapted from Lee et al. (2018), and Bousdekis et al. (2021). The Industrial Productivity scale was adapted from Javaid et al. (2022), and other Industry 4.0 productivity research. All questionnaire items utilized a five-point Likert scale, with 1 = Strongly Disagree, to 5 = Strongly Agree. In the scales adopted from the literature, wording was modified to the context of the Pakistani industrial setting by making minor changes, and as a result, improved the clarity of the item.

Data collection improved because the questionnaire was made as an online Google Form. The link was posted specifically and discretely using official company channels, professional networks, corporate email, and WhatsApp and LinkedIn groups of the target manufacturing companies. To participate, respondents were given an information sheet about the research, and how to complete the questionnaire. Google Forms collected the data, and responses were automatically sent to a secure online storage database in preparation for further processing and statistical analysis.

Ethical Considerations

Ethics were at the forefront of the research conducted. Respondent research was voluntary, and those interested learned research goals and objectives prior to participating. Electronic informed consent was the method of choice, and participants were told their identities would not be revealed, and all data would be kept private, and would not be published outside of the realm of academia. Participants also had the right to withdraw from the study at any time with no consequence. Researchers also did not collect any form of identifying data, and all research responses were kept safe to help ensure data confidentiality.

Data Analysis

The first step done after gathering responses was to download the data from Google Forms to Microsoft Excel. This first step was done for data verification and control of data quality. The completed dataset was then imported to SPSS version 27 for advanced data screening and analysis.

Respondent demographics and variable distributions were summarized using descriptive statistics. The relationship between Artificial Intelligence in predictive maintenance and machine reliability was assessed using Pearson correlation analysis. The predictive effect of Artificial Intelligence in predictive maintenance on industrial productivity was assessed using Multiple linear regression analysis. Industrial productivity was compared across varying levels of Artificial Intelligence used in predictive maintenance using an Independent Samples t-test. In order to determine the effect of Artificial Intelligence on machine reliability, a One-Way ANOVA was performed to assess the varying levels of Artificial Intelligence implementation. The aforementioned analyses, in tandem, provided evidence of the relationships and differences of the study variables and aligned with the overall purpose of the study.

Table 1: **Demographic Characteristics of the Respondents** ***(N = 467)***

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	318	68.1
	Female	149	31.9
	Total	**467**	**100.0**
Age (Years)	21–30	102	21.8
	31–40	181	38.8
	41–50	126	27.0
	Above 50	58	12.4
	Total	**467**	**100.0**
Educational Qualification	Diploma	49	10.5
	Bachelor's Degree	164	35.1
	Master's Degree	201	43.0
	PhD/Other Professional Qualification	53	11.4
	Total	**467**	**100.0**
Job Position	Maintenance Engineer	108	23.1
	Production Engineer	95	20.3
	Plant/Operations Manager	74	15.8
	Reliability/Automation Engineer	87	18.6
	Technical Officer/Supervisor	103	22.1

Demographic Variable	Category	Frequency (n)	Percentage (%)
	Total	**467**	**100.0**
Work Experience	Less than 5 Years	98	21.0
	5–10 Years	174	37.3
	11–15 Years	119	25.5
	More than 15 Years	76	16.3
	Total	**467**	**100.0**
Organization Type	Manufacturing	169	36.2
	Automotive	82	17.6
	Textile	97	20.8
	Chemical/Fertilizer	63	13.5
	Heavy Engineering	56	12.0
	Total	**467**	**100.0**
Province	Punjab	309	66.2
	Sindh	158	33.8
	Total	**467**	**100.0**

Describes the demographic characteristics of the sample of 467 study participants. The results show that a majority of the study participants were male (68.1%); females were 31.9% of the sample. The most common age group of study participants was 31 – 40 years (38.8%); the second most common group was 41 – 50 years (27.0%); thus the participants were mature and experienced. The highest sample group by highest educational qualifications was respondents with a master's degree (43.0%), followed by respondents with a bachelor's degree (35.1%); the sample was therefore educated. The highest group by job position was maintenance Engineers (23.1%), followed by technical officers/supervisors (22.1%), production engineers (20.3%), reliability/automation engineers (18.6%), and plant/operations managers (15.8%); thus the study sample was involved in maintenance and production. The results also show that most study participants had a work experience of between 5 and 10 years (37.3%), thus had knowledge of industrial systems of maintenance. The largest sector of the study participants was from the manufacturing sector (36.2%), followed by the textile, automotive, chemical/fertilizer, and heavy engineering sectors. The majority of study participants were from Punjab (66.2%) and the remaining study participants were from Sindh (33.8%); thus the sample represented the major industrial regions of Pakistan.

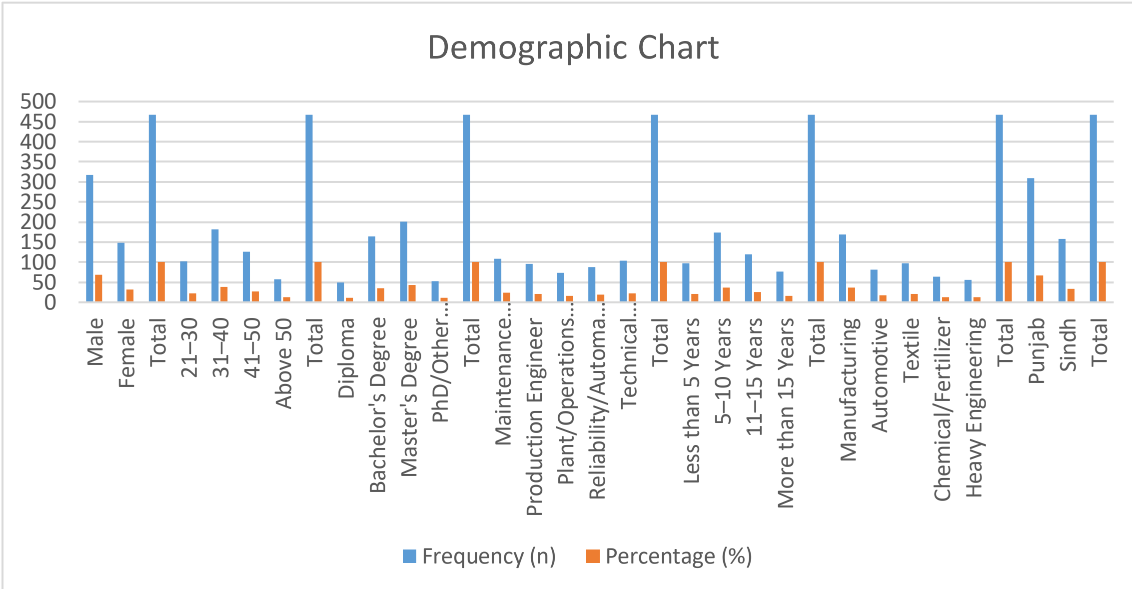

Figure 1.2 Demographic Chart

Table 2: **Pearson Correlation Analysis Examining the Relationship Between Artificial Intelligence in Predictive Maintenance and Machine Reliability** ***(N = 467)***

Variables	**1**	**2**
1. Artificial Intelligence in Predictive Maintenance	1	.742**
2. Machine Reliability	.742**	1
Pearson Correlation (r)	**0.742**	
Sig. (2-tailed)	**0.000**	
N	**467**	

Presents details of the Pearson correlation analysis on 467 subjects regarding the intersection of Artificial Intelligence in Predictive Maintenance and the Reliability of Machines. The analysis shows a strong positive correlation ($r = .742$, $p < .001$), indicating that increased Artificial Intelligence in predictive maintenance correlates with increased reliability of Machines. The p-value promotes confidence that the correlation is indeed real and not due to chance. Evidence of the correlation supports the idea that AI-led driving predictive maintenance in organizations likely improves the performance of machines, decreases the failure of machines, and stabilizes operations and increases the availability of machines. Findings further substantiate the position that Artificial Intelligence in Predictive Maintenance positively correlates with Machine Reliability.

Table 3: **Multiple Linear Regression Analysis Examining the Effect of Artificial Intelligence in Predictive Maintenance on Industrial Productivity *(N = 467)***

Model Summary	Value
R	0.781
R Square (R^2)	0.610
Adjusted R Square	0.609
Std. Error of the Estimate	0.423

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	128.463	1	128.463	727.418	.000
Residual	82.128	465	0.177		
Total	210.591	466			

Coefficients

Predictor	Unstandardized B	Std. Error	Standardized Beta (β)	t	Sig.
(Constant)	0.821	0.129	—	6.364	.000
Artificial Intelligence in Predictive Maintenance	0.793	0.029	0.781	26.971	.000

The results from the multiple linear regression analysis depict the impacts of Artificial Intelligence in Predictive Maintenance on Industrial Productivity. The model was interpreted to have a good fit, with R = 0.781, R^2 = 0.610. As a result, it was concluded that 61.0% of the variation of Industrial Productivity is based on Artificial Intelligence in Predictive Maintenance. The regression model was also appraised based on the adjusted R^2 = 0.609, and interpreted as stable and safe. The ANOVA results provided a significant overall regression model (F = 727.418, $p < .001$), and a good fit of the model to the data. The regression results also provided that Artificial Intelligence in Predictive Maintenance, ($p < .001$), positively, and significantly, improved Industrial Productivity (β = 0.781, B = 0.793, t = 26.971). From the regression outputs and analysis, it was concluded that Artificial Intelligence in Predictive Maintenance, when implemented to a considerable extent, improves Industrial Productivity, by improving the efficiency of operations, and minimizing the downtime of equipment by optimizing the maintenance of equipment and promoting the production processes that are continuous in nature.

Table 4: **Independent Samples t-Test Comparing Industrial Productivity Based on the Level of Artificial Intelligence Adoption in Predictive Maintenance *(N = 467)***

Variable	AI Adoption Level	N	Mean	Std. Deviation	t	df	Sig. (2-tailed)
Industrial Productivity	Low AI Adoption	221	3.48	0.59	8.742	465	.000
	High AI Adoption	246	4.11	0.52			

Results of the Independent Samples t-test assessing differences in industrial productivity concerning the degree of Artificial Intelligence adoption in predictive maintenance are detailed herein. Outcomes show that those working in organizations with high AI adoption scores in predictive maintenance have higher ratings for industrial productivity (M = 4.11, SD = 0.52) in comparison with those working in organizations with low AI adoption (M = 3.48, SD = 0.59). In comparison, t-test scores show that a statistically significant difference existed with concerning the degree of AI adoption and industrial productivity with $t(465) = 8.742$, $p < .001$. From these results, it is suggested that organizations within the AI realm of predictive maintenance would show substantially greater organizational effectiveness when compared to those working within the domain of low AI.

Table 5: **One-Way Analysis of Variance (ANOVA) Examining Differences in Machine Reliability Across Levels of Artificial Intelligence Implementation in Predictive Maintenance *(N = 467)***

Source of Variation	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	46.281	2	23.141	52.384	.000
Within Groups	205.014	464	0.442		
Total	251.295	466			

Group Statistics

AI Implementation Level	N	Mean	Std. Deviation
Low	145	3.31	0.67
Moderate	164	3.79	0.59
High	158	4.28	0.55
Total	**467**	**3.80**	**0.70**

Reports the results of a One-Way ANOVA on the differences in machine reliability due to the variances of Artificial Intelligence usage in predictive maintenance. The analysis shows that the ANOVA was statistically significant at $F(2, 464) = 52.384$, $p < .001$, proving significant differences in machine reliability among the organizations with low, medium, and high AI usage. The group mean scores show that organizations with a high level of AI usage reported the highest machine reliability (M = 4.28, SD = 0.55) followed by the organizations with a medium level of AI usage with (M = 3.79, SD = 0.59). The lowest mean score (M = 3.31, SD = 0.67) was reported by organizations with a low level of AI Usage. It can be concluded that the usage of AI in predictive maintenance significantly improves the reliability of machines. It can be inferred that AI integrated maintenance systems improve machine performance, reduce unplanned breakdowns, and enhance operational reliability of industrial systems.

Discussion

This paper studies how AI and predictive maintenance impact machine reliability and productivity in the Punjab and Sindh regions of Pakistan. From the evidence presented, AI-driven predictive maintenance helps improve industrial performance by decreasing failure rates of machines, improving the quality of maintenance decisions, and bolstering maintenance efficiency. In order to keep pace with the digital transformations characteristic of Industry 4.0, AI has become a central technology for modernizing maintenance procedures. Based on the evidence of this study, and unlike the traditional time or event-based maintenance approach, AI-driven predictive maintenance helps organizations achieve optimum operational performance as maintenance decisions are based on the actual status of the equipment. Based on the evidence provided, the transformation of predictive maintenance into a competitive and sustainable organizational capability helps strengthen the framework of competitive advantage. This also supports the findings of other scholars who argue that predictive maintenance is no longer simply a maintenance practice, but a fundamental organizational capability that enhances competitiveness and operational sustainability.

Correlation analysis showed a strong positive correlation between AI-enabled predictive maintenance and machine reliability. This suggests that the increased use of AI technologies will improve the dependability of industrial equipment, decrease unexpected breakdowns, and prolong the useful life of industrial equipment. This result is consistent with the findings of Nwulu, E et al. (2023), who posited that AI-enabled maintenance systems enhance the health monitoring of industrial equipment by continuously assessing the in-service data of industrial equipment and discovering the early signs of deterioration in industrial equipment. Likewise, Er-Ratby, M et al. (2024) found that maintenance provides a higher level of effectiveness due to machine learning algorithms, as they can find fault patterns that are beyond the capabilities of most conventional maintenance approaches. Predictive maintenance with the aid of AI provides organizations the ability to reach an effective balance when scheduling maintenance, as equipment downtime and maintenance costs are significantly decreased (Mohamed Almazrouei, et al., 2023). The present findings extend the existing body of knowledge by showing that AI-driven predictive maintenance enhances machine reliability in manufacturing organizations.

Using multiple regression analysis, it was determined that Artificial Intelligence involved in predictive maintenance impacts the productivity of the industry significantly. It means that advancements in predictive maintenance directly enhance the efficiency of production, improve the use of resources, and positively impact the operations of a business. This aligns with Hegde, P et al. (2022) findings that the introduction of AI in manufacturing helps the productivity of manufacturing industries through intelligent automation, predictive analytics, and the real-time visibility of operations. Haque, R et al. (2022) indicated that predictive maintenance through AI, prevents the occurrence of unpredicted failure of equipment, and thus, minimizes disruption of production facilitating the continuity of production and improvement of the performance of the organization. Similar findings were also described by Lee et al. (2018), stating that AI increases the efficiency of manufacturing by enabling the timely maintenance of equipment. The current research study therefore, shows that predictive maintenance through AI is an important element of industrial productivity and contributes to the overall goals of smart manufacturing.

The Independent Samples t-test noted a considerable gap in industrial productivity comparative to the variance in the use of AI and predictive maintenance across the organizations surveyed. Higher levels of Artificial Intelligence equated to greater productivity, while organizations using traditional maintenance methods had lower productivity. The data suggests that the level of productivity gained from predictive maintenance is not solely dependent on the maintenance performed but also the level of technology utilized in the industrial process. This is in line with Kalusivalingam, A et al. (2020). They stated that the use of AI in maintenance significantly helped with the planning and improving the operational efficiency of an organization, making maintenance more active and direct through the use of data. This was also noted by Scaife, A (2023), who stated organizations with modern AI are more resilient due to the use of intelligent maintenance. This is due to the fact that intelligent maintenance monitors maintenance needs and suggests maintenance at the optimum time. Therefore, the use of higher levels of AI in an organization provides measurable productivity through more efficient maintenance and less disruption to the organization.

The One-Way ANOVA findings identified machine reliability showing meaningful variation as influenced by the level of Artificial Intelligence usage. Greater levels of AI usage reported greater Machine Reliability, with lesser levels of AI usage exhibiting poorer Machine Reliability. This suggests that predictive maintenance, augmented by AI, offers greater reliability the more AI is integrated within an industrial setting. Most notably, as cited in Molęda, M, et. al. (2023), as AI technology becomes more assimilated into industrial practices, predictive maintenance systems are able to enhance their predictive accuracy via machine learning that adapts to the ever-changing operational scenarios. Also cited in Ünlü, R., et. al. (2024), organizations that leverage intelligent maintenance technologies and AI, experience greater reliability of machinery, as AI also offers the competency of earlier fault identification, maintenance optimization, and maintenance resource allocation. Therefore, the present study corroborates the findings of these studies with the conclusion that a greater implementation of AI brings about greater reliability of machinery that strengthens the reliability of manufacturing operations.

Conclusion

This study focused on the role of Artificial Intelligence (AI) in predictive maintenance and how it impacts the reliability of machines and the productivity of industries within the context of contemporary manufacturing firms. Findings indicated that AI-based predictive maintenance aids industries in preemptively detecting potential failures of machines before they even occur. This helps the industry to lessen the occurrence of unplanned downtimes, reduce the costs of maintenance, increase the availability of machines, and even aid the processes of production to continue without interruptions. Statistical analyses indicated a positive relationship of Artificial Intelligence with the reliability of machines, predictive maintenance of AI with the productivity of industries, and a variation of the reliability of machines and the productivity of industries at different gradations of the application of Artificial Intelligence. It illustrates a significant advancement in the operational performance of industries that design and implement intelligent predictive maintenance systems compared to the industries that use traditional systems of maintenance.

More broadly, the study highlights that Artificial Intelligence has positioned itself as a game changer to facilitate smart manufacturing and sustainable industrial development. AI embedded in predictive maintenance encourages use of clean data to drive informed choices about maintenance, optimize the use of limited resources, and improve the reliability of industrial assets over time. As manufacturing continues to undergo intelligent transformation, AI-based maintenance systems will be critical to remaining competitive in manufacturing. As a result, firms are encouraged to adopt smart, AI-based predictive solutions to achieve sustainable operations and manufacturing.

Recommendations

1. Manufacturing organizations should increase the adoption of Artificial Intelligence-based predictive maintenance systems to reduce equipment failures and improve machine reliability.

2. Industries should invest in Industrial Internet of Things (IIoT) sensors and real-time monitoring technologies to enhance predictive maintenance capabilities.

3. Organizations should provide regular training programs for maintenance engineers and technical staff on AI-driven maintenance technologies and data analytics.

4. Industrial managers should integrate Artificial Intelligence into maintenance planning and decision-making processes to optimize operational efficiency and reduce maintenance costs.

5. Manufacturing firms should strengthen digital infrastructure and cybersecurity measures to support the effective implementation of AI-based predictive maintenance systems.

6. Organizations should continuously monitor and evaluate the performance of AI predictive maintenance systems to improve prediction accuracy and maintenance effectiveness.

7. Future researchers should investigate additional factors, such as organizational readiness, technological capability, and digital transformation, that may influence the relationship between Artificial Intelligence, machine reliability, and industrial productivity.

Future Implications

Resulting from this research, Artificial Intelligence will become more pivotal in predictive maintenance and smart manufacturing. With increased industrial adoption of the Industry 4.0 framework, the combination of Artificial Intelligence with the IIoT, digital twins, edge and cloud computing, and advanced robotics will further increase machine reliability and operational and industrial efficiency and effectiveness. In the coming years, we can expect manufacturing systems to have greater autonomy. This includes skills like self diagnosis of machinery malfunctions, self scheduling of maintenance, and self supported decision-making that require less customer participation. With the rise of readily accessible high-standard data in the workplace, alongside enhanced capabilities of machine learning, predictive maintenance systems will be more accurate. Not only can organizations expect cost savings now, but they can also expect a longer lifespan of their equipment and an environmentally favorable impact. As a result, we can predict that the AI will be a great stimulator of digital transformation in manufacturing and will bolster sustainable competition over time in manufacturing industries across the globe.

References

Abbas, A. (2024). AI for predictive maintenance in industrial systems. *International Journal of Advanced Engineering Technologies and Innovations*, *1*(1), 31-51.

Alade, B., Ocheni, E., Onyekachukwu, M., & Olufinmilayo, S. (2024). Big data for predictive maintenance in industry 4.0: Enhancing operational efficiency and equipment reliability. *International Journal of Computer Applications Technology and Research*, *13*(10), 37-51.

Alam, M., Islam, M. R., & Shil, S. K. (2023). AI-Based predictive maintenance for US manufacturing: reducing downtime and increasing productivity. *International Journal of Advanced Engineering Technologies and Innovations*, *1*(01), 541-567.

Ayeni, O. (2025). Integration of Artificial Intelligence in predictive maintenance for mechanical and industrial engineering. *International Research Journal of Modernization in Engineering Technology and Science*, *7*(3), 1-23.

Bello, S., Wada, I., Ige, O., Chianumba, E., & Adebayo, S. (2024). AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. *International journal of science and research archive*, *13*(1), 2823-2837.

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for industry 4.0 maintenance applications. *Electronics*, *10*(7), 828.

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for industry 4.0 maintenance applications. *Electronics*, *10*(7), 828.

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. *Electronics*, *8*(8), 832.

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. *Electronics*, *8*(8), 832.

Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability*, *12*(19), 8211.

Er-Ratby, M., Kobi, A., Sadraoui, Y., & Kadiri, M. S. (2024, October). The role of predictive maintenance optimization techniques in enhancing industrial productivity. In *2024 10th International Conference on Optimization and Applications (ICOA)* (pp. 1-6). IEEE.

Haque, R., Bajwa, A., Siddiqui, N. A., & Ahmed, I. (2024). Predictive maintenance in industrial automation: A systematic review of iot sensor technologies and ai algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30.

Hector, I., & Panjanathan, R. (2024). Predictive maintenance in Industry 4.0: A survey of planning models and machine learning techniques. *PeerJ Computer Science*, *10*, e2016.

Hegde, P., & Varughese, R. J. (2022). Predictive Maintenance in Telecom: Artificial Intelligence for predicting and preventing network failures, reducing downtime and maintenance costs, and maximizing efficiency. *Journal of Mechanical, Civil and Industrial Engineering*, *3*(3), 102-118.

Henderson, J., & Sanders, M. (2025). AI Driven Predictive Maintenance: Reducing Downtime and Enhancing Productivity in Manufacturing Environments.

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management*, *7*(01), 83-111.

Kalusivalingam, A. K., Sharma, A., Patel, N., & Singh, V. (2020). Enhancing predictive maintenance in manufacturing using Machine learning algorithms and IoT-driven data analytics. *International Journal of AI and ML*, *1*(3).

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process safety and environmental protection*, *117*, 408-425.

Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H., & Tongne, A. (2022). Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis. *AI and Ethics*, *2*(4), 553-577.

Kliestik, T., Nica, E., Durana, P., & Popescu, G. H. (2023). Artificial intelligence-based predictive maintenance, time-sensitive networking, and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things. *Oeconomia Copernicana*, *14*(4), 1097-1138.

Lee, J. J., Wedow, R., Okbay, A., Kong, E., Maghzian, O., Zacher, M., ... & Cesarini, D. (2018). Gene discovery and polygenic prediction from a genome-wide association study of educational attainment in 1.1 million individuals. *Nature genetics*, *50*(8), 1112-1121.

Lefrouni, K., & Taibi, S. (2025). Artificial Intelligence Techniques for Industrial Predictive Maintenance: A Systematic Review of Recent Advances. *Journal Européen des Systèmes Automatisés*, *58*(4).

Mitta, N. R. (2024). AI-enhanced predictive maintenance Systems for Industrial Equipment: developing machine learning models to forecast failures. *Optimize maintenance schedules, and minimize downtime*.

Mohamed Almazrouei, S., Dweiri, F., Aydin, R., & Alnaqbi, A. (2023). A review on the advancements and challenges of artificial intelligence based models for predictive maintenance of water injection pumps in the oil and gas industry. *SN Applied Sciences*, *5*(12), 391.

Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From corrective to predictive maintenance—A review of maintenance approaches for the power industry. *Sensors*, *23*(13), 5970.

Nguyen, K. T., Medjaher, K., & Gogu, C. (2022). Probabilistic deep learning methodology for uncertainty quantification of remaining useful lifetime of multi-component systems. *Reliability Engineering & System Safety*, *222*, 108383.

Nwulu, E. O., Elete, T. Y., Erhueh, O. V., Akano, O. A., & Omomo, K. O. (2023). Machine learning applications in predictive maintenance: Enhancing efficiency across the oil and gas industry. *International Journal of Engineering Research Updates*, *5*(1), 17-30.

Okpala, C., Chikwendu, U., & Onyeka, N. C. (2025). Artificial intelligence-driven total productive maintenance: The future of maintenance in smart factories. *International Journal of Engineering Research and Development*, *21*(1), 68-74.

Patil, D. (2024). Artificial intelligence-driven predictive maintenance in manufacturing: enhancing operational efficiency, minimizing downtime, and optimizing resource utilization. *Minimizing Downtime, And Optimizing Resource Utilization (December 11, 2024)*.

Scaife, A. (2023). Improve predictive maintenance through the application of artificial intelligence: A systematic review. *Authorea Preprints*.

Scaife, A. D. (2024). Improve predictive maintenance through the application of artificial intelligence: A systematic review. *Results in Engineering*, *21*, 101645.

Sivakumar, M., Maranco, M., & Krishnaraj, N. (2024). Data analytics and artificial intelligence for predictive maintenance in manufacturing. In *Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing* (pp. 29-55). CRC Press.

Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends. *Applied Sciences*, *14*(2), 898.

Ünlü, R., & Söylemez, İ. (2024). AI-driven predictive maintenance. In *Engineering applications of AI and swarm intelligence* (pp. 207-233). Singapore: Springer Nature Singapore.

Xie, S. (2024, November). Advancing Predictive Maintenance Research Trends: Using Artificial Intelligence for Enhanced Industrial Reliability. In *2024 IEEE International Conference on Future Machine Learning and Data Science (FMLDS)* (pp. 283-288). IEEE.

Zonta, T., Da Costa, C. A., da Rosa Righi, R., 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.