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Review

Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends

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Abstract: Predictive maintenance (PdM) is a policy applying data and analytics to predict when one of the components in a real system has been destroyed, and some anomalies appear so that maintenance can be performed before a breakdown takes place. Using cutting-edge technologies like data analytics and artificial intelligence (AI) enhances the performance and accuracy of predictive maintenance systems and increases their autonomy and adaptability in complex and dynamic working environments. This paper reviews the recent developments in AI-based PdM, focusing on key components, trustworthiness, and future trends. The state-of-the-art (SOTA) techniques, challenges, and opportunities associated with AI-based PdM are first analyzed. The integration of AI technologies into PdM in real-world applications, the human–robot interaction, the ethical issues emerging from using AI, and the testing and validation abilities of the developed policies are later discussed. This study exhibits the potential working areas for future research, such as digital twin, metaverse, generative AI, collaborative robots (cobots), blockchain technology, trustworthy AI, and Industrial Internet of Things (IIoT), utilizing a comprehensive survey of the current SOTA techniques, opportunities, and challenges allied with AI-based PdM.

Keywords: predictive maintenance (PdM); artificial intelligence (AI); explainable artificial intelligence (XAI); explainability; interpretability; trustworthiness; generative AI

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1. Introduction

The maintenance of the systems has recently become increasingly important for enhancing product efficiency and continuity. Different varieties of system maintenance exist, such as reactive, planned, proactive, and predictive [1]. Figure 1 summarizes them. Reactive maintenance only solves the issue when the system breaks down or malfunctions. The malfunction becomes apparent, and then the repairing steps are applied. Planned maintenance is previously scheduled to perform regular inspections and maintenance tasks at predetermined intervals to prolong the system's life and reduce repair costs, regardless of whether the system has shown failure signs. Predictive maintenance (PdM) is an approach applying advanced analytics on the obtained data from multiple sensors to predict when the system tends to fail and organize the maintenance tasks accordingly to optimize maintenance intervals, reduce malfunction time, and enhance the system's reliability.

PdM has shown significant growth and advancements. Most recently, low-cost sensors have been developed, and new real-time condition monitoring systems have been successfully used to obtain big data. These developments, expert algorithms, and expert human experience brought considerable developments and progress in predictive maintenance. Current efforts are given to developing new multivariate statistical models and expert algorithms to improve predictions' accuracy and reduce labor costs [1–11].

Reaching next-step autonomy in a robotics system is possible thanks to sophisticated artificial intelligence (AI)-based algorithms, models, and expertise. Moreover, the potential AI-based PdM reduces costs and boosts efficiency and safety. Hence, the researchers pay special attention to AI models and techniques to improve the autonomy and adaptability of robotic systems in complex and dynamic industrial environments [12–22].

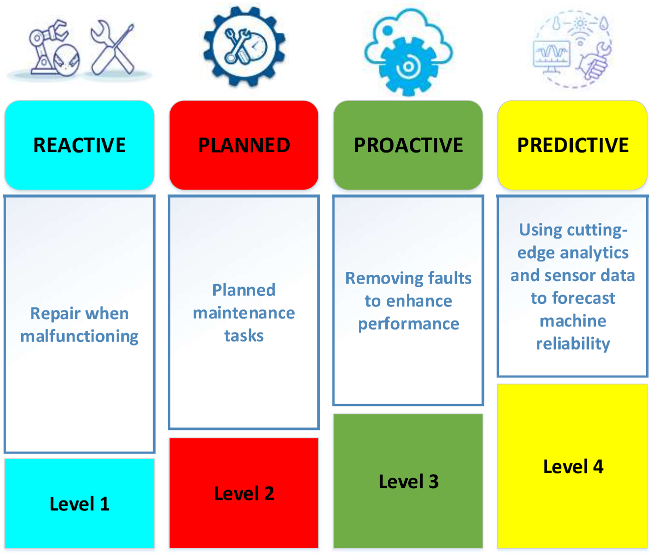

Figure 1. Diverse levels of system maintenance.

AI has been successfully employed in the automotive, manufacturing, energy, aerospace, and transportation industries by making real-time predictions and estimations of malfunctions and anomalies on big datasets [23]. It has been demonstrated that AI-based techniques, including machine learning and deep learning, exhibit improved performance and accuracy at PdM utilizing remaining useful life (RUL), fault diagnosis, and predictive maintenance scheduling [23–43]. Using AI brings some challenges, such as transparency, explainability, system integration, and ethical issues [44], leading to explainable artificial intelligence (XAI) [45]. Figure 2 shows the general AI cover. This paper aims to comprehensively survey the current state-of-the-art techniques, challenges, and opportunities exhibited by AI-based PdM, focusing on key components, trustworthiness, and future trends. The most recent outcomes and innovations in the field are discussed in this paper by suggesting directions for further investigation. Finally, it gives some insights into the most recent research and advancements in the subject and assists in suggesting prospective areas for future research by providing a thorough overview of the existing literature.

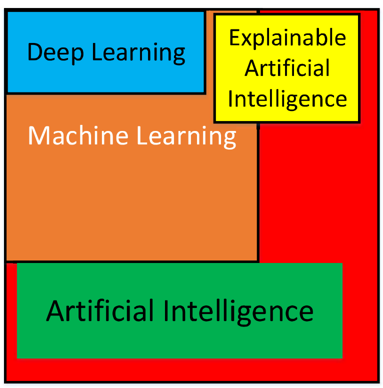

Figure 2. The connection between AI, ML, DL, and XAI.

Research Questions

This study examines current advances in AI-based PdM, particularly emphasizing next-generation autonomy. The following research inquiries are what this review is based on:

1. What are the main components of AI-based PdM systems?
2. What are the state-of-the-art (SOTA) PdM methods? Regarding accuracy, cost-effectiveness, and scale, what are their advantages?
3. What are the advantages of AI-based PdM techniques over traditional techniques regarding performance and cost-effectiveness?
4. What are the challenges and limitations of AI-based PdM?
5. How can AI-based PdM systems ensure high transparency and explanation?
6. How can AI be integrated into existing PdM systems and workflows?
7. What are the ethical issues in AI-based PdM?
8. How can an efficient human–machine interaction in AI-based PdM systems be obtained?
9. How can testing and validation of AI-based PdM systems be effectively conducted in real-world scenarios?
10. What are recent advances and future trends in AI-based PdM?

Taking in the research questions, the contributions of this review are (i) the description of the main components of AI-based PdM systems, (ii) the analysis of the SOTA methods in PdM, (iii) comparison of the AI-based PdM with traditional approaches, (iv) investigation of the challenges and limitations of AI-based PdM, (v) assessment of transparency and explainability in AI-based PdM, (vi) integration of AI into existing PdM systems and workflows, (vii) investigation of ethical issues related to AI-based PdM, (viii) enhancing human–machine interaction in the AI-based PdM systems, (ix) effective testing and validation of AI-based PdM systems, and (x) study of the AI-based PdM advances and emerging topics.

The rest of the paper is organized as follows: Section 2 comprehensively describes the key components of AI-based PdM. The SOTA for PdM and its enabling technologies are presented in Section 3. Then, Section 4 focuses on transparency and explainability in AI-based PdM. The challenges and limitations of using AI for PdM autonomy are highlighted in Section 5. Section 6 presents recent advances and future trends in AI-based PdM. Conclusions are given in Section 7.

2. Key Components in AI-Based Predictive Maintenance

AI-based PdM can be fundamentally broken down into six distinct components: data preprocessing, AI algorithms, decision-making modules, communication and integration, and user interface and reporting, as shown in Figure 3. This section briefly discusses each component to understand how they work together to enable AI-based PdM.

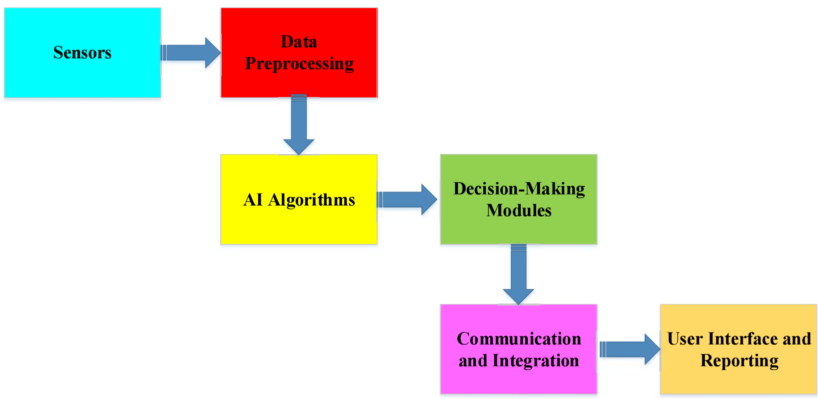

Figure 3. Key components of an AI-based PdM System.

1. Sensors: Sensors are the frontline data collectors in a PdM system. These specialized devices are strategically placed on equipment and machinery to continuously monitor various parameters, such as temperature, pressure, vibration, and more. Sensor data provides real-time insights into equipment health and forms the foundation for predictive maintenance analysis.
2. Data Preprocessing: Raw data obtained from sensors often contains noise and inconsistencies. Data preprocessing is the initial step in preparing the data for analysis. It includes data cleaning, normalization, and missing data handling. High-quality data are essential for accurate PdM modeling.
3. AI Algorithms: AI algorithms, including machine learning and deep learning techniques, are the brain of the PdM systems. The algorithms analyze the data to identify the most important features relating to possible failures. They learn from historical data to predict equipment failures, anomalies, and RUL.
4. Decision-Making Modules: The insights and predictions generated by the AI algorithms are processed by decision-making modules. These modules are responsible for determining when maintenance actions are needed. They can recommend preventive or corrective maintenance tasks, schedule maintenance, and trigger alerts to maintenance teams when necessary.
5. Communication and Integration: Communication and integration ensure that the insights generated by the system are effectively translated into action. This component involves interactions with various stakeholders, including maintenance personnel and management. Furthermore, integration with enterprise systems such as ERP and asset management software aligns predictive maintenance with broader organizational goals.
6. User Interface and Reporting: To make these insights accessible to maintenance staff and decision makers, user interfaces and reporting tools are essential. The tools make it easier for users to understand complex data patterns and make informed decisions by providing data visualization, dashboard, and reporting capabilities. Data visualization tools and dashboards communicate data insights and forecast information to maintenance teams and decision makers. Visual aids help understand complex data patterns and make informed decisions.

The following three data-related units are added to the advanced AI methods to obtain resilient, reliable, secure, and highly stable results using AI-based PdM in complex and dynamic environments.

Sensor data and the Internet of Things (IoT) integration: Integrating IoT and sensor technology is pivotal in next-step autonomy for PdM tasks. The IoT sensors are strategically placed in equipment and machines to monitor their condition in real-time continuously.

Data integration: Data integration combines data from various sources, including historical maintenance records, real-time sensor data, external factors (e.g., weather), and production schedules. This holistic view of equipment health enhances decision making.

Digital twins: Digital twins create virtual replicas of physical assets, facilitating real-time simulation and monitoring. AI systems monitor these digital twins, identifying performance irregularities and recommending optimal maintenance strategies before any physical equipment is adversely affected.

Edge and cloud computing: Edge computing proceeds closer to the data source through IoT sensors for real-time analysis rather than in a centralized data center, which reduces latency and enables real-time analysis. Cloud computing stores and manages enormous amounts of data to analyze historical events.

3. State-of-the-Art Techniques for Predictive Maintenance

SOTA consists of (i) the AI-based PdM approaches, including machine learning algorithms, deep learning, statistical control, and statistical modeling, (ii) data-driven approaches, including big data analytics, data mining, data visualization, and predictive data analysis, (iii) vibration and thermal analysis, (iv) augmented reality (AR), virtual reality (VR), mixed reality (MR), and their extended versions, and digital intelligent assistants, (v) methods based on prescriptive maintenance, (vi) edge and cloud computing, IoT, federated learning, and blockchain, (vii) energy-based methods, and (viii) methods based on prognostics and health management (PHM) [23–131]. This section reviews some PdM studies using these approaches. Each paper has been evaluated through the application and the proposed approach.

PdM applications employ all AI approaches, including the classification and/or regression problem type of the supervised learning approach, the clustering problem type of the unsupervised learning approach, or a problem type relating to the reinforcement learning (RL) approach to analyze the large volume of data obtained from real-time condition monitoring systems. The approaches have presented magnificent contributions to PdM tasks [23–52]. Deep neural networks (DNNs) covering CNNs, RNNs, and LSTMs have been used to generate the proposed predictive maintenance strategies and algorithms and improve their prediction accuracy [53–64]. In these works, the networks have been applied to extract the significant features from raw sensor data, including images or the data in the form of time series, and to detect, recognize, or predict sudden and expected changes in the system according to the features.

Machine learning algorithms have been successfully applied to many PdM applications [65–69]. Algorithms such as feedforward neural networks (FNNs), decision trees (DT), random forests (RF), and support vector machines (SVMs) have been used to classify sensor data.

Refs. [70–84] have shown various works applying statistical and probabilistic modeling approaches such as hidden Markov models (HMMs), Bayesian networks (BNs), Gaussian mixture models (GMMs), extreme gradient boosting (XGBoost), Density-based spatial clustering (DBSC), principal component analysis (PCA), and K-means to PdM tasks. Moreover, they introduced different DNN models, such as LSTM and autoencoders, for the tasks. They have identified the deterioration event by analyzing an interdependent relationship among the data collected from multi-sensors and predicted possible future failures.

In [85–92,129], data-driven approaches, including big data analytics relating to data from various sources, including sensor data, historical records, external factors, and data mining, have been used to improve the accuracy and comprehensiveness of PdM systems. Significantly, interactive and intuitive data visualization tools have contributed to quickly understanding the equipment's health and making informed decisions.

In [93–99], vibration analysis is a widely used method of PdM. The analytical method uses sensors to measure the vibrations of machinery and identify possible problem areas, such as bearing failure or misalignment on various machines, including motors, pumps, and gearboxes.

Thermal imaging is another widely known technique for PdM [100–104]. The technique uses infrared cameras to perceive potential problems, such as overheating, breakdown, friction, and energy inefficiencies, on a wide range of equipment, including electrical panels, transformers, and motors, by measuring the temperature of equipment.

In [105–108], the technologies of AR, VR, MR, digital intelligent assistant, digital twin, and IoT sensors have been leveraged. The IoT sensor has enabled real-time data collection from various sensors attached to equipment in PdM. The technologies of AR, VR, and MR increase the capabilities of maintenance technicians with visual guidance, remote assistance, real-time information, and a virtual view of equipment status to perform PdM, improving efficiency and accuracy. Ref. [109] showed an approach for maintenance experts and operators to interact with a PdM system by AI intelligent assistant through natural language processing (NLP) and user feedback about the success of maintenance interventions.

In [110–115], PdM is realized through prescriptive maintenance. It provides specific recommendations for maintenance actions going beyond prediction. It includes detailed instructions for technicians on what steps to take. This approach predicts when maintenance is needed and recommends the most effective and efficient maintenance actions.

Refs. [116–118,130,131] have used edge computing and cloud computing. Edge computing is used to proceed closer to the data source through IoT sensors for real-time analysis rather than in a centralized data center, which reduces latency and enables real-time analysis. To analyze historical events, cloud computing stores and manages enormous amounts of data.

In [119–121], federated learning, blockchain, and industrial IoT have been used. Federated learning allows multiple parties to train a machine learning model collaboratively without sharing their data. Blockchain ensures data integrity, while industrial IoT sensors provide real-time equipment condition data. It may be indicative of problems if unusual energy consumption is observed. In [122–125], PdM has been provided by analyzing their energy consumption patterns to gain information on the health of such devices.

In [126,127], PdM has been carried out by focusing on PHM. PHM techniques take a different approach to assessing equipment health from predicting failures. Advanced modeling and data analysis are generally included in these methods, enabling further RUL estimation of an asset and providing valuable insight into maintenance planning. Ref. [128] shows an example of a predictive analytics software platform for PdM. In order to make implementing PdM easier, numerous software platforms and tools have been developed. Premade models and features for data integration are frequently included in these platforms.

This article reviews real-world simulation and experimental applications in tables, while some utilize benchmark datasets. Table 1 describes the benchmark datasets such as the National Aeronautics and Space Administration (NASA) Turbofan [132,133], PHM 2008 [134], NASA Ames Milling [135], NASA Bearing Dataset [136], CWRU Bearing [137], FEMTO Ball Bearing [138], Roll Bearing [139], Backblaze [140], PAKDD2020 Alibaba AI OPS [141], NASA Ames Prognostics [142], Lithium-ion Battery of University of Maryland [143], MOSFET Thermal Overstress Aging [144], MAFAULDA [145], Microsoft Azure PdM [146], GEFCOM [147], and The UCI SECOM [148] in multivariate time-series forms commonly employed in PdM applications.

Table 1. Benchmark datasets for PdM tasks.

Ref.	Name	Description
[132,133]	NASA Turbofan Dataset-CMAPSSD and CMAPSSD-2	The turbofan engine degradation simulation dataset, generated with the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dynamical model.
[134]	PHM 2008 Dataset	The degradation collected from aircraft engines derived from CMAPSSD.
[135]	NASA Ames Milling Dataset	Acoustic emission, vibration, and motor current data collected under different experimental conditions for predicting the milling tool wear.
[136]	NASA Bearing Dataset	Run-to-failure vibration data from 4 accelerometers in a shaft.
[137]	Case Western Reserve University (CWRU) Bearing Dataset	Test rig operating with different load conditions.

[138]	FEMTO Ball Bearing Dataset from IEEE PHM Challenge	Run-to-failure temperature and vibration data from engine thermocouple and accelerometer sensors.
[139]	Roll Bearing Dataset from IEEE PHM Challenge	A training set of six rolling bearings operated in three different conditions, and a testing set of 11 more.
[140]	Backblaze Hard Disk Drive Dataset	The daily status of hard disk drives (HDDs), consisting of 433 failed drives and 22,962 good drives.
[141]	PAKDD2020 Alibaba AI OPS Competition Dataset	HDD daily health status data including both a raw and a normalized value as well as a label and the time of failure.
[142]	NASA Ames Prognostics Dataset	Li-ion battery degradation data during repeated charge and discharge cycles.
[143]	Lithium-ion Battery Dataset of the University of Maryland	The current and voltage data on different EV drive cycles at varying ambient temperatures (including 0 °C, 25 °C, and 45 °C).
[144]	MOSFET Thermal Overstress Aging Dataset	Run-to-failure experiments on power MOSFETs under thermal overstress.
[145]	MAFAULDA	Fault measurements from machinery simulators run under different load conditions.
[146]	Microsoft Azure PdM Dataset	Data modules of machines, telemetry, errors, maintenance, and failures collected by a Microsoft employee for PdM modeling collection.
[147]	Global Energy Forecasting Competition (GEFCOM) Dataset	Hourly solar power generation data and assigning numerical weather forecasts from 1 April 2012 to 1 July 2014.
[148]	The UCI SECOM Dataset	Measurements of features of semiconductor production within a semiconductor manufacturing process.

Table 2 shows a taxonomy for PdM applications in different problem types/approaches from various industries. The second column of Table 2 mainly indicates a class name relating to the repair and maintenance activities from [149]. Table 3 summarizes the study numbers in Table 2. As seen in Table 3, the electrical equipment class of the repair and maintenance field is the most popular in AI and maintenance, with 30 studies focused on this field. The machinery category is an essential topic with ten studies and attracts wide attention in this field. The classes of electronic and optical equipment and fabricated metal products attract attention with nine and eight studies, respectively.

Table 2. Summary of different AI techniques in PdM systems.

Ref.	Class of Repair and Maintenance	Industry	Application	Problem Type/Approach	Algorithm/Technology
[53]	Electrical equipment	Electrical and electronics	Aging monitoring for twisted pair specimens in low-voltage stator windings of electrical machines	Regression	2D-CNN
[54]	Computers and communication equipment	Information technology	RUL estimation on Microsoft Azure AI-based PdM dataset [146]	Regression	CNN, RNN, LSTM, CNN-LSTM, regression random forest (RRF), deep feed-forward (DFF) networks, and gated recurrent unit (GRU)
[55]	Electrical equipment Electronic and optical equipment	Electrical and electronics Metals and plastics	Failure prediction on PAKDD2020 Alibaba AI OPS competition [141] and NASA bearing dataset [136]	Classification	CNN and time-series encoding techniques
[56]	Electrical equipment	Metals and plastics	Health monitoring on NASA milling dataset [135]	Regression	1D CNN
[57]	Electrical equipment	Metals and plastics	RUL estimation on FEMTO bearing dataset [138]	Regression	LSTM and autoencoder
[58]	Electrical equipment		Diagnosis and classification of faults in rotating machinery using MAFAULDA dataset [145] and CWRU-bearing datasets [137]	Classification	CNN
[59]	Electrical equipment	Metals and plastics	Fault diagnosis on the experimental data collected from a rotor fault diagnosis experimental platform and the CWRU bearing dataset [137]	Regression Classification	ELM, CNN, and autoencoder
[60]	Electrical equipment	Electric vehicles battery technology	Charge estimation of lithium-ion battery state in electric vehicles	-	Bidirectional GRU circuit module, and attention circuit module
[61]	Electronic and optical equipment	Electrical and electronics	The condition of rotating machinery in university laboratory by using a single-axis piezoelectric accelerometer	Classification	CNN
[62]	Transport equipment	High-speed railway	Predictive and proactive maintenance for modeling physical degradation and failure in gas-insulated switchgear in high-speed railway	Regression	LSTM-RNN
[63]	Electrical equipment	Electrical and electronics	RUL estimation of lithium-ion batteries in NASA Ames prognostics data repository [142]	Regression	LSTM
[64]	Machinery	Aircraft manufacturing	Health condition in a horizontal machining center in an aircraft manufacturing cooperation	Regression	An attribute attentional LSTM

[65]	Electronic and optical equipment	Medical devices and healthcare services	Failure diagnosis for the Vitros immunoassay analyzer in a local hospital in the United Arab Emirates by using IoT sensors	Classification	SVM
[66]	Electronic and optical equipment	Nuclear power	Condition monitoring of nuclear infrastructure on NASA turbofan dataset [132,133]	Regression	SVM and logistic regression
[67]	Electronic and optical equipment	Electrical and electronics	RUL estimation on MOSFET thermal overstress aging dataset [144]	Regression	SVM
[68]	Buildings and other structures	Architecture, engineering, construction, and facility management	Data-driven condition monitoring based on building information modeling and IoT to predict the future condition of the mechanical, electrical, and plumbing components	Regression	FNN and SVM
[69]	Fabricated metal products	Large service management	Failure prediction on Backblaze dataset [140]	Classification	Decision tree-based machine learning method
[70]	Other machinery and equipment	Renewable energy, wind energy	Fault prediction in wind turbines	Classification	RF, decision tree algorithms, DBSC, and statistical process control
[71]	Electrical equipment	Electronics manufacturing	RUL estimation of the equipment in an industry manufacturer of memory modules (DRAM and SSD)	Regression	Combined statistical process control charts and RF, XGBoost, and LSTM
[72]	Electrical equipment	Electrical and electronics	PdM and health monitoring on appropriate quality data collected in the form of product measurements or readings from various machines	Classification	Statistical process control and naïve Bayes
[73]	Motor vehicles	Autonomous vehicles	Hierarchical component-based health monitoring system with fault detection, diagnosis, and prognosis on the CaRINA II autonomous vehicle platform and the CARLA simulator	Classification	Dynamic Bayesian network
[74]	Other machinery and equipment	Manufacturing	State and failure prediction of rim welding machine in the process of creating vehicle rims from the iron plate in the assembly line using IoT-based sensors	Classification	Naïve Bayes and Markov chain
[75]	Electrical equipment	Electrical and electronics	Failure prediction in an electrical motor	Classification	Bayesian network
[76]	Transport equipment, except motor vehicles	Transport Infrastructure	Failure prediction for rail bridges on the rail network in Great Britain	-	Bayesian network
[77]	Motor vehicles	Automotive	Anomaly detection for off-road vehicle maintenance	Classification	HMM, kNN and isolation forest, and

					autoencoders
[78]	Motor vehicles	Automotive	The ecological PdM through condition monitoring of a bus with diesel engines taking temperature, humidity, pollutant emissions (NOx, CO2, HC, and PM), emitted noise, etc.	-	HMM
[79]	Transport equipment	Energy and sustainability	RUL estimation of the machines on the PHM 2008 dataset [134]	Regression	Cluster-based HMM
[80]	Machinery	Semiconductor manufacturing	Condition monitoring in a semiconductor manufacturing station	Clustering	HMM
[81]	Transport equipment	Energy and sustainability	RUL estimation using degradation indicators in an airplane engine on NASA turbofan engine dataset [132,133]	Unsupervised Learning	HMM
[82]	Industrial machinery and equipment	Pumping systems	Fault detection and life cycle cost analysis of pumping systems	Statistics Regression Classification	SVM and HMM
[83]	Transport equipment	Marine	PdM for cost estimation during the design process of a ship engine room	-	Bayesian probabilistic inferential approach and HMM
[84]	Other machinery and equipment	Pharmaceutical manufacturing	Real-time health monitoring in an industrial freeze-dryer	Clustering, Classification	DBSC, K-means and GMMs, PCA, one-class SVM, and the local outlier factor
[85]	Fabricated metal products	Cloud services and data centers	The detection of imminent hard disk drive failures in Backblaze dataset [140]	Classification	Apache Spark, which is an in-memory distributed data analysis platform, and RF
[86]	Electronic and optical equipment	Smart manufacturing	A manufacturing big data ecosystem addressing the issues of big data ingestion, management, and analytics for fault/anomaly detection in IoT-based smart factories	Clustering	The distributed K-means clustering, MapReduce-based distributed PCA-based T-squared, and SPE algorithms A data lake, NoSQL database, and encryption protocol on the Apache Spark platform
[87]	Transport equipment	Transport	PdM approach for malfunction evaluation in relation to the kilometers of the train and the periodicity of faults in the Greek Railway Company	Regression Classification	Classification trees J48 and regression trees M5 form algorithms
[88]	Machinery and equipment	Electronics	Failure prediction of the monitored manufacturing industrial machinery by UCI SECOM dataset [148]	Classification	A fusion of data mining and semantics

[89]	Other machinery and equipment	Textile	Production quality prediction in the textile industry	Regression	Supervisory control and data acquisition (SCADA) architecture to develop a cloud-based analytics module
[90]	Transport equipment, except motor vehicles	Logistics and parcel delivery	A big data analytics framework for the data-driven prediction of courier package breaks in smart goods transportation systems	Classification	IoT networks Gradient boosting classifiers, SVM, logistic regression, and Apache Spark
[91]	-	Vinyl flooring	Quality management in the vinyl flooring industry	-	Big data analytics and optimization Edge computing
[92]	Electrical equipment	Industrial robots	Health status degradation assessment using real data of the ABB IRB 6400r industrial robot	Regression	Programmable logic controllers (PLC) One-class novelty detection using SVM and extreme learning machine (ELM) IIoT
[93]	Electrical equipment	Metal and metallurgy	Fault detection in the friction stir welding tool	Classification	Best first tree classifier
[94]	Electrical equipment	Electrical and electronics	Detection of the essence of the unbalanced conditions in the rotary machine in the constructed experimental setup	Classification	SVM
[95]	Electrical equipment	Building and construction	Failure prediction in HVAC installations at a sports facility in a building automation system in the Paris region using sensors such as vibration, temperature, and energy consumption meters	Regression	LSTM and autoencoders IoT
[96]	Electrical equipment	Manufacturing	Prediction of gradual degradation of an impeller using the sensors such as vibration, gyroscope/accelerometer, rotational speed, temperature, pressure, ambient pressure, temperature, and humidity on an industrial radial fan	Regression	Linear regression, RFR, and symbolic regression
[97]	Electrical equipment	Semiconductor	Vibration-related failure prediction on a dataset including machines, errors, maintenance, telemetry, and failures	Regression	Linear regression
[98]	Electrical equipment	Electrical and electronics	Fault detection in rotating machinery by monitoring and visualizing vibrations using transformed raw data into images through a short-time Fourier transform or Mel-frequency cepstral coefficients spectrogram	Classification	CNNs

[99]	Fabricated metal products	Nuclear energy	PdM in the research reactor by using core-cooling pump vibration signals	Classification	FNN
[100]	Electrical equipment	Railways	Fault detection using thermal imaging in rail systems in Turkiye	Classification	Fuzzy
[101]	Machinery	Railways	Locomotive maintenance in Sri Lanka Railways for the issues of premature axle bearing defects, suspension bearing conditions, diesel engine inspection, compressor inspection, weak thermal insulation detection, dynamic grid resister element inspection, water, air, fuel, and oil pipeline blocks, fuse contractors, resistors, relays, and loose electrical wires	-	Thermal imaging technology
[102]	Electrical equipment	Medical	PdM for progressive deterioration processes and failure mechanisms of different medical equipment	-	Infrared thermal imaging
[103]	Electrical equipment	Hydraulics	PdM for evaluating premature failures of hydraulic drive systems in a university laboratory using simulation software AMESim from SIEMENS LMS Imagine.Lab	-	Some numerical simulations using infrared thermography
[104]	Fabricated metal products, machinery, and equipment	Gearbox manufacturing	PdM through failure prediction and analysis in the gearbox high-speed shaft bearing using temperature and vibrational sensors	Classification	Decision trees
[105]	Electrical equipment	Automotive	Intelligent PdM control through the collected data from condition monitoring sensors of electrical monorail system	Classification	Rule-base intelligence system IIoT and AR
[106]	Fabricated metal products	Electrical and electronics	Fault detection and remote monitoring system to control the status of professional refrigeration systems	Regression	Planned SVM Digital twin, IoT, and MR
[107]	Electrical equipment Electronic and optical equipment	Machine tools manufacturing	Fault prediction in machine tools equipped with various sensors to acquire huge volumes of production data in a typical machining workshop in Wuxi, China	Regression Reinforcement Learning	CNN, LSTM, and deep reinforcement learning (DRL) AR and IoT
[108]	Fabricated metal products	Steel strip processing	Prediction of the real-time fatigue strength of the component under loading in steel strip processing lines	Regression	Finite element analysis, linear regression AR and IoT
[109]	-	-	PdM system by a digital intelligent assistant for industry	-	NLP and user feedback about the success of maintenance interventions

[110]	Electrical equipment	Automotive manufacturing	Prescriptive maintenance for evaluating failure and quality effects in an international manufacturer of gearboxes and engines for the automotive sector	-	Data management, predictive data analytic toolbox, recommender and decision support dashboard, and semantic-based learning and reasoning
[111]	Fabricated metal products	Chemical industry	The prediction of failure time and probability of a pump	Classification	Ensembles of SVMs
[112]	Electrical equipment	Manufacturing	The prediction of potential equipment failure, expected failure time, and expected repair time and providing the appropriate action for production planning and control in future factories	Reinforcement Learning	RL Digital twin
[113]	Machinery	Manufacturing	RUL estimation in a machine park consisting of 100 machines	Reinforcement Learning	DRL
[114]	Machinery	Rail transport	The optimal maintenance strategy jointly incorporates the effect of aging and degradation for locomotive wheelsets	-	Reliability analysis, sensitivity analysis, and a continuous stochastic process
[115]	Transport equipment	Aviation	Discrete-event simulation framework for post-prognostic decision for aircraft maintenance using tire pressure indication system for an Airbus A320	-	The technological maturity of an underlying PHM system
[116]	Electrical equipment	Manufacturing	Anomaly detection in all the equipment in a global manufacturing system	Unsupervised Learning	Autoencoder-based deep learning technique Edge computing and IoT
[117]	Machinery	Manufacturing	Failure prediction using different sensors such as temperature, rotation speed, vibration, and humidity in a ball-bearing automatic line	Regression	Autoregressive Integrated moving average model (ARIMA), ARIMA-LSTMs Traditional cloud-edge architecture
[118]	Machinery	Industrial robotics manufacturing	Failure prediction for monitoring the health status of all machines in COMAU industrial robots company	Regression Classification	NN, RF, logistic regression, SVM, and gradient-boosted tree A hybrid cloud-edge computing
[119]	Machinery	Air conditioning manufacturing	Failure prediction in air-conditioning systems	Classification	Centroid distance weighted federated averaging algorithm
[120]	Electronic and optical equipment	Industry 4.0	Blockchain framework for PdM in Industry 4.0	Classification	Fuzzy logic, blockchain, case-based reasoning, and KNN
[121]	Electrical equipment	Home energy	Failure prediction of the applications in a home energy	Classification	IoT sensors

		management	management system		SVM
[122]	Electrical equipment	Electric vehicles battery technology	Prediction of starter battery failure times from a fleet of vehicles	-	Maximum likelihood approach
[123]	Electrical equipment Machinery	Hydraulics	Energy-based maintenance for lubricant condition monitoring in a rubber-mixing hydraulic control system	Regression Classification	SVM and RF
[124]	Machinery	Steel manufacturing	RUL estimation in hot rolling milling machines regarding segment surface temperatures and hydraulic force measurements	-	Maximum likelihood approach
[125]	Fabricated metal products Machinery and equipment	Robotics manufacturing	Failure prediction in a discrete multi-robot mobile assembling line using sensors such as energy analyzer modules, temperature, vibration, corrosion, and humidity	Classification	FNN
[126]	Machinery and equipment	Electrical and electronics	PHM-based PdM for the degradation estimation of gear motor assembly in mechanical power transmission	-	Cloud computing and the multitenancy principle
[127]	Electrical equipment Electronic and optical equipment	Electrical and electronics	The detection of changes in the operating conditions and abrupt faults in the platform composed of an asynchronous motor and a gearbox made of two pulleys in the university laboratory	-	Edge and cloud analytics
[128]	-	Manufacturing	Product lifecycle management by connecting the industrial unit floor with design and manufacturing engineers	-	A predictive analytics software platform

Table 3. Summary of the studies in Table 2.

Class of Repair and Maintenance	Study Number	Industry	Study Number	PdM Task	Study Number	Problem Type/ Approach	Study Number
Electrical equipment	30	Electrical and electronics; electronics	13	Failure prediction	22	Classification	33
Machinery	10	Manufacturing; manufacturing of automotive manufacturing; aircraft semiconductor; machine tools; gearbox; smart; pharmaceutical; electronics; steel; robotics; industrial robotics; air conditioning; industrial robots; Industry 4.0	22	RUL estimation; Cost and charge estimation	11	Regression	26
Electronic and optical equipment	9	Transport; automotive; high-speed railway; autonomous vehicles; railways; rail transport	10	Fault detection	12	Clustering	3
Fabricated metal products	8	Metals and plastics; metal and metallurgy	5	Condition monitoring; Vibration monitoring	9	Reinforcement Learning	3
Transport equipment	6	Energy and sustainability; nuclear power; nuclear energy; renewable energy; wind energy	5	Anomaly detection	4	Unsupervised Learning	2
Other machinery and equipment	5	Information technology; cloud services and data centers	2	Production quality prediction	1	The others	16
Motor vehicles	3	Electric vehicle battery technology	2	Product lifecycle management	1		
Machinery and equipment	3	Medical; medical devices and healthcare services	2	Component fatigue strength prediction	1		
Transport equipment, except motor vehicles	2	Building and construction; architecture; engineering; construction; facility management	2	PdM system by a digital intelligent assistant	1		
Computers and communication equipment	1	Hydraulics	2	Blockchain framework for PdM	1		
Industrial machinery and equipment	1	Large service management	1	A big data analytics framework	1		
Buildings and other structures	1	Infrastructure; pumping systems; marine; textile; logistics and parcel delivery; steel strip processing; chemical industry; aviation; home energy management	9	Post-prognostic decision	1		

The transport equipment category in Table 3 is noted as an essential field with six studies. The other machinery and equipment category is also notable with five works. On the other hand, the categories computers and communication equipment, industrial machinery and equipment, and buildings and other structures have a lower level of interest, with one study each, respectively. As a result, industries such as electrical equipment, machinery, electronic and optical equipment, and fabricated metal products are popular areas for AI and maintenance. On the other hand, computers and communication equipment, industrial machinery and equipment, and buildings and other structures categories have received more limited attention. These results are essential guidance for directing future research and development efforts.

On the other hand, manufacturing industries, including automotive, aircraft, semiconductor, machine tools, gearbox, pharmaceutical, electronics, steel, robotics, industrial robotics, air conditioning, and industrial robots, are the industry sectors receiving the most attention in AI and maintenance, with 22 studies. This wide-ranging industry shows a significant research focus as it includes a variety of subsectors.

The industries of 'electrical and electronics' and 'electronics' also have attracted attention with 13 studies. Technological advances and maintenance practices have been reflecting significant interest in this industry. The transport, automotive, high-speed railway, autonomous vehicles, railways, and rail transport industries represent an important research area with ten studies. The combination of subsectors such as automotive, high-speed rail, and autonomous vehicles shows a wide range of topics covering various aspects of this industry. The industries of 'metals and plastics' and 'metal and metallurgy' have five studies. The energy and sustainability, nuclear power, nuclear energy, renewable energy, and wind energy industry is also a prominent field with five studies and covers a wide range of topics related to energy sustainability.

Information technology, cloud services and data centers, electric vehicle battery technology, medical, medical devices and healthcare services, large service management, building and construction, hydraulics, and architecture, engineering, construction, and facility management industries are important industries represented with two studies. A limited number of studies represent infrastructure, pumping systems, marine, textile, logistics and parcel delivery, steel strip processing, chemical industry, aviation, and home energy management.

In addition, Table 3 also shows different PdM tasks and study numbers. RUL, cost, and charge estimation tasks have attracted attention with 11 studies. These tasks cover strategically essential issues such as estimating the useful life of equipment and determining maintenance costs. Fault detection tasks are a vital topic, with 12 studies focusing on the early detection and prevention of malfunctions that may occur in systems. The condition and vibration monitoring task has attracted the attention of nine studies. The anomaly detection task is a distinct area with four studies focusing on detecting unexpected situations and abnormal behavior. Other tasks are represented by only one study each and seem to concentrate on more specific topics. These tasks include product lifecycle management, component fatigue strength prediction, PdM by a digital intelligent assistant, blockchain framework for PdM, and a big data analytics framework. As a result, basic tasks such as failure prediction, RUL estimation, fault detection, and anomaly detection are popular areas of AI and maintenance. In contrast, other tasks are more specialized and focus on specific topics.

Although PdM tasks often appear to be primarily classification and regression problems in Table 3, the presence of unknown events and the general nature of the data with ambiguous labels clearly shows the importance of unsupervised learning, reinforcement learning, and statistical and probabilistic applications in PdM applications.

In addition, Table 2 includes some PdM tasks without using AI. Ref. [89] includes production quality prediction in the textile industry. Ref. [101–103] use thermal imaging technology in railways, medical, and hydraulics industries. Ref. [110] applies data management, predictive data analytic toolbox, recommender and decision support dashboard, and semantic-based learning and reasoning for PdM in the automotive manufacturing industry. Ref. [114] introduces the optimal maintenance strategy applying reliability analysis, sensitivity analysis, and a continuous stochastic process in the rail transport industry. Ref. [115] applies a discrete-event simulation framework for post-prognostic decisions in the aviation industry. Ref. [128] introduces a predictive analytics software platform in the manufacturing industry. Moreover, Ref. [91] includes quality management in the vinyl flooring industry using big data analytics and optimization and edge computing without having a PdM task, but it is related indirectly.

Figures 4 and 5 show the number of studies carried out using different machine learning methods such as FNN, CNN, LSTM, autoencoder, SVM, RNN, fuzzy, RF, K-means, decision trees, rule-based intelligence system, DR, HMM, Bayes, ELM, and gradient boosting in Web of Science and Google Scholar for 2018 to 2023, respectively. Total study numbers in Web of Science and Google Scholar have been determined as (67, 104, 149, 213, 296, and 255) and (4406, 6506, 10,498, 16,638, 22,619, and 28,069) over 2018–2023, respectively. Both the results in Google Scholar and Web of Science clearly show that the fusion of PdM and AI will continue over the years. Since 2019, there has been a notable increase in the use of deep learning methods, specifically LSTM, CNN, and autoencoder, with a particularly pronounced surge in the utilization of DRL in the last two years. Additionally, SVM has maintained its relevance since 2018, and its usage has continued to grow. Another remarkable result has been observed in decision trees. The use of decision trees has shown a consistent upward trend since 2018. Notably, there has been a visible increase in the adoption of fuzzy and rule-based methods. Moreover, HMM, Bayes, gradient boosting, and FNN also exhibit a growing trend in usage since 2018. Even these escalating values in fundamental AI methods underscore the inevitability of AI becoming indispensable in future research endeavors. All the mentioned subjects show current relevance and an exponential increase has emerged, which signifies a robust and growing interest in these topics, indicating that AI will be indispensable in future studies. As a result, the figures exhibit an evolving landscape characterized by an increasing breadth of methods employed in PdM applications, suggesting a continuous effort by researchers to explore and integrate diverse machine learning methods, indicating the adaptability of the field and the ongoing quest for innovative approaches.

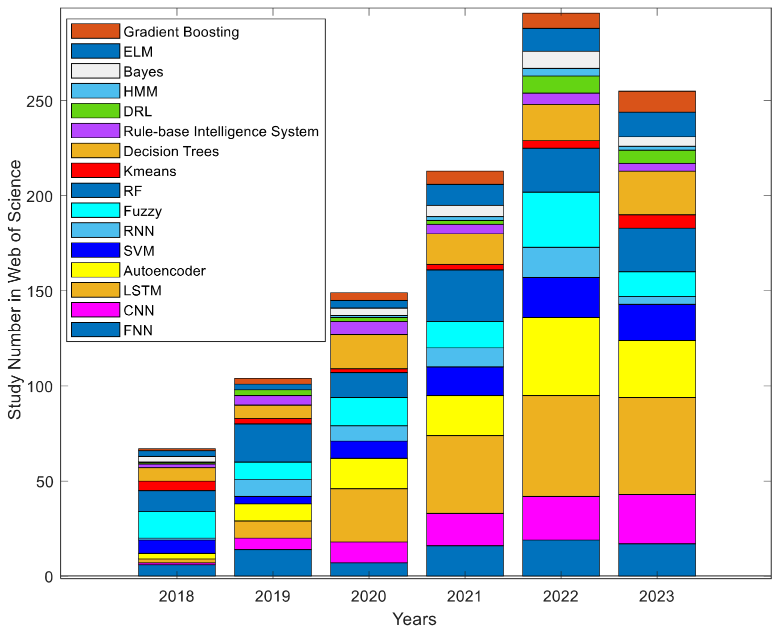

Figure 4. The number of different AI methods in Web of Science between 2018 and 2023.

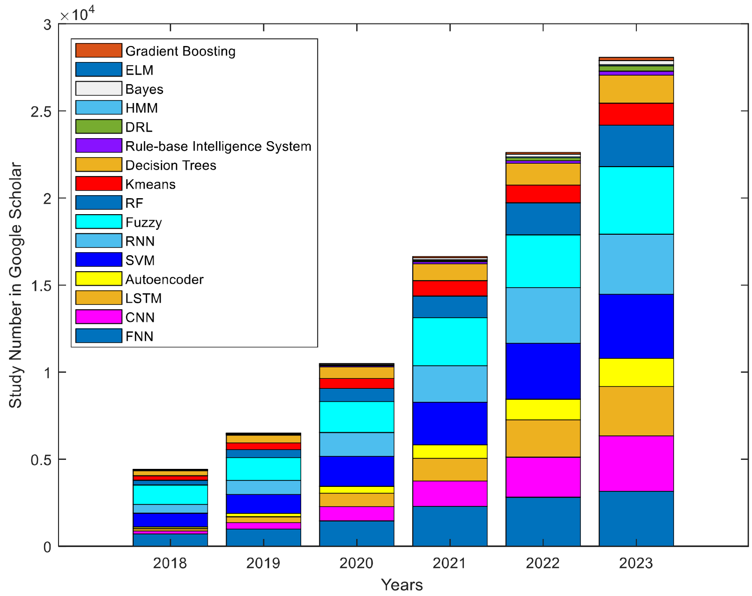

Figure 5. The number of different AI methods in Google Scholar between 2018 and 2023.

Figures 6 and 7 show the number of studies carried out relating to four recent advances in PdM, including (PdM, digital twin, and AI), (PdM, IoT, and AI), (PdM, edge and cloud computing, and AI), and (PdM, AR, VR, MR, and AI) in Google Scholar and Web of Science, respectively. The total number of studies relating to the four technological combinations in Web of Science and Google Scholar has been determined as (2, 15, 24, 42, 50, and 40) and (1184, 2102, 3542, 5554, 7684, and 9867) over 2018–2023, respectively. The number of studies has a consistent annual increase. The observed growth proves a rising interest in incorporating advanced technologies into PdM applications and the shifts in the focus of researchers, reflecting evolving priorities in the field. In addition, the numbers indicate that (PdM, digital twin, and AI) and (PdM, IoT, and AI) have been gaining momentum since 2018 and that the use of (PdM, Edge and cloud computing, and AI) and (PdM, AR, VR, MR, and AI) has increased in the past three years and will increase in the future. As a result, the upward direction of the study numbers points to a positive inclination to integrate innovative techniques in PdM. Researchers are encouraged to explore the potential of digital twin, IoT, edge and cloud computing, AR, VR, MR, and AI for PdM applications.

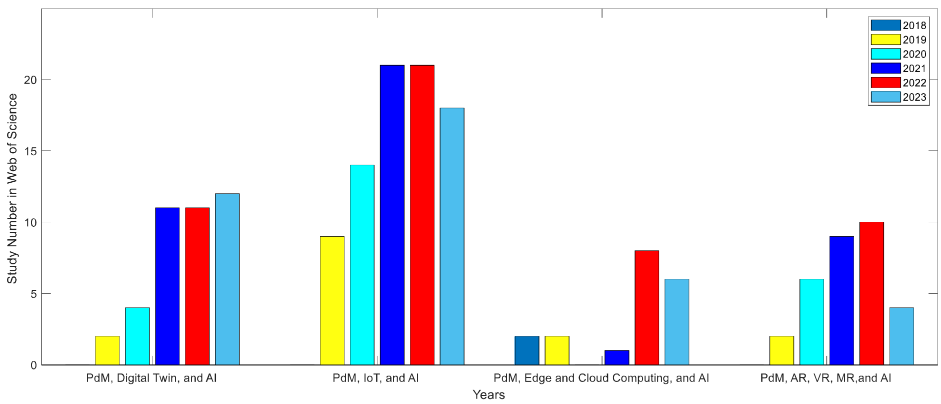

Figure 6. The number of studies relating to PdM, AI, IoT, edge and cloud computing, AR, VR, and MR in Web of Science between 2018 and 2023.

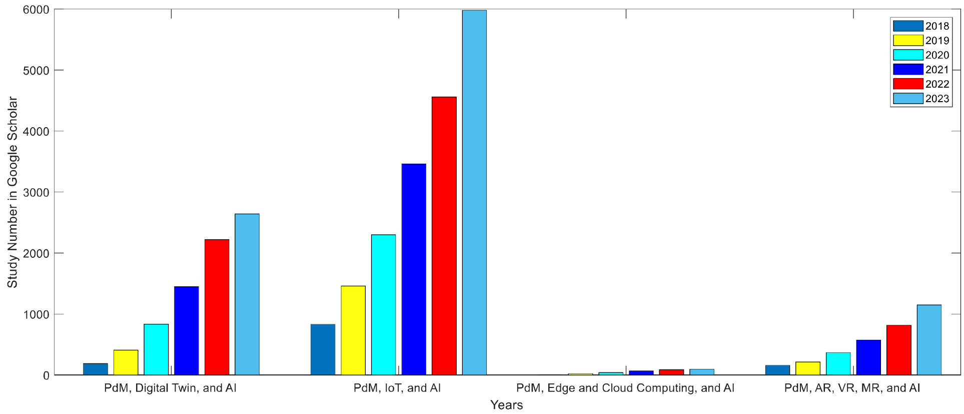

Figure 7. The number of studies relating to PdM, AI, IoT, edge and cloud computing, AR, VR, and MR in Google Scholar between 2018 and 2023.

Table 4 compares various AI methods. As observed, deep learning methods exhibit high accuracy and scalability. On the other hand, machine learning methods show higher cost-effectiveness in comparison. When comparing traditional methods with AI approaches, as in Table 5, AI methods outperform in stability and scalability. However, in terms of computational cost, traditional methods are more efficient.

Table 4. Comparison of AI methods in PdM systems.

Techniques	Accuracy	Cost-Effectiveness	Scalability
Deep Learning	High	Moderate	High
Machine Learning	Moderate	High	Moderate

Table 5. Comparison of AI-based PdM systems with traditional methods.

Methods	Accuracy	Cost-Effectiveness	Scalability
AI-based	High	Moderate	High
Traditional	Moderate	High	Low

4. Transparency and Explainability in AI-Based Predictive Maintenance

Model interpretability is critical to AI, as it allows us to gain insights into complex models' black-box nature and build trustworthy models. Various techniques have emerged to show how these models make predictions and decisions. Ref. [150] exhibited two concepts titled explainability and interpretability used in the XAI area. If the model's design is understandable to a human being, it is considered interpretable. On the contrary, explainability ties into the idea that explanation is a form of interaction between humans and decision makers. Explainability is regarded as a post hoc tool because this specification covers the techniques used to transform an uninterpretable model into an explainable one.

On the other hand, ref. [151] mentioned that if the models are inherently interpretable, they have their own explanations, which align with the model's calculation. This implies that interpretability inherently includes explainability. In the interpretable model, each step of the decision-making process can be traced. Still, there remains a gap in explaining why this specific sequence of steps was chosen during the decision-making process. Explainable models are interpretable by default, but the reverse is not always true [152], indicating that explainability is a subset of interpretability. In explainable AI systems, it can be challenging to understand how the model reached a decision, but it can grasp the underlying reasoning behind it. XAI takes a broader approach, striving to design inherently transparent and interpretable models for humans.

The interpretability techniques are classified in different ways. One way is to separate them into two branches, post hoc and ad hoc, concerning the training process [153]. Post hoc techniques use external tools to analyze the trained models. The techniques rely on input perturbations. That is why they can provide unreliable results in cases like adversarial attacks, as in [154].

Moreover, they are not concerned about the model's inner dynamics and the actions to generate different features. Ad hoc techniques modify the model's inner dynamics to facilitate understanding, and the model comes with some explanations during the training itself. The post hoc techniques require feature analysis, model inspection, saliency maps, proxy models, mathematical analysis, physical analysis, and explanation by using text and case to extract the explanations. They are divided into "model agnostic" and "model specific". Model-agnostic models also use any model covering neural networks.

On the other hand, model-specific techniques are developed as specific to the model. Some examples of post hoc techniques are local interpretable model-agnostic explanations (LIME) [155] and SHapley Additive exPlanations (SHAP) [156], class activation map (CAM) [157], layer-wise relevance propagation (LRP) [158], and gradient-weighted class activation mapping (Grad-CAM) [159]. Ad hoc methods include approaches to explaining the model in an explicitly understandable manner, using hand-crafted criteria for the selection of features or incorporating heuristics based on current physics [160,161].

Ref. [162] also classified the interpretation techniques as local and global. Local interpretability provides single predictions, whereas global predicting provides interpretation to make new predictions from model features. Local methods such as LIME and SHAP provide model-agnostic means to explain and interpret the predictions generated by a wide range of machine-learning models. Deep learning models, known for their complexity, benefit from techniques like Grad-CAM and attention mechanisms, which offer insights into the input regions that influence their decisions.

Some approaches to achieving model interpretability include techniques such as partial dependence plots (PDP) [163], decision tree visualization [163,164], attention module [165], and feature importance calculation by using methods such as wrapper, filter, embedded, and dimension reduction techniques [166]. PDPs represent a method of showing the relationship among one or several components and the expected outcomes of machine learning models. They give us an insight into how changes affect model predictions for a given feature. The structure of the decision tree, the observed features split, and the way the tree makes decisions based on the input features are displayed in the decision tree visualization.

On the other hand, the attention module contains a mechanism for generating feature weights consisting of parallel hidden layers. Each module part provides a value between 0 and 1, which shall be multiplied by the suitable feature to enter the rest of the network. The module can be visualized. Feature importance helps understand the features with the most weight in the model's predictions. Wrapper methods are trained with various input features to obtain the best results using heuristic and sequential search algorithms, which is time consuming [167]. Filter methods employ statistical metrics such as the Pearson correlation coefficient, mutual information, and X2 test prior to training to identify the importance of features. The techniques are unrelated to the model or its predictions after training, and they have no interest in interactions between features [168]. Embedded methods work on the subsets of the data along with techniques such as random forest, least absolute shrinkage and selection operator (LASSO) regression, ridge regression, regularization, decision tree, and XGBoost [169,170]. Dimension reduction techniques such as PCA, ICA (individual component analysis), linear discriminant analysis (LDA) reduce the dimensionality of the dataset to obtain a smaller set of principal components that explain most of the variance in the data [171].

In the literature, there are a lot of other methods, such as rule-based systems and sensitivity analysis. Rule-based systems utilize logical rules to describe the decision-making process of a model, making the decision logic explicit and understandable [172,173]. Lastly, sensitivity analysis helps identify the most influential input variables, contributing to a clearer understanding of a model's predictive behavior. In an era where AI plays an increasingly prominent role, these interpretability techniques and methods are indispensable tools for building trust, improving model performance, and ensuring ethical and accountable AI systems.

Table 6 summarizes interpretable and explainable studies between 2018 and 2023 and their application content. In [174–183], SHAP, LIME, ELI5, integrated gradients, SmoothGrad, and LRP have been used. Ref. [184–189] use the semantic web rule language, rule-based expert systems, fuzzy systems, quantitative association rule mining (QARM), and data-driven sensitivity analysis. In [190–204], some techniques and visualizations such as decision trees, graph-based approaches, the attention modules used together with LSTM, generative adversarial networks (GAN), PDPs, and feature importance calculation methods. Ref. [205–208] give some new algorithms, including interpretability and explainability, such as temporal fusion separable convolutional network, federated learning, HMM, and reinforcement learning.

An extensive application range of PdM consists of a coal crusher operating at the boiler of the real power plant and gantries in a steelworks converter, a transport line in a steelworks converter, the MW load range in a petrochemical plant, a real hybrid bus, hydraulic systems, a modular aero-propulsion system, an intelligent manufacturing system, the water pumping industry, a large gas distribution network, rolling bearings and a rotating machine, PdM for autonomous underwater vehicles (AUV), a water injection pump, wind turbine systems, the IoT-based manufacturing environment, hard disk drives, the turbofan engine, the drilling machine of an automotive manufacturer, solar photovoltaic energy systems, maintenance work orders, manufacturing, and structural health monitoring.

Table 6. Summary of different transparency and explainability approaches used in AI-based PdM.

Ref.	The Approach	Application
[174]	SHAP	PdM in a coal crusher operating at the boiler of the real power plant and gantries in a steelworks converter, a transport line in a steelworks converter
[175]	SHAP	PdM in a coal crusher operating presented in [174]
[176]	LIME, SHAP, and ELI5	Solar photovoltaic energy forecasting by GEFCOM dataset [147]
[177]	Integrated gradients, SHAP, and SmoothGrad	Anomaly detection in press machine data of a production line
[178]	SHAP and LIME.	RUL estimation of hard disk drive in the Backblaze dataset [140]
[179]	SHAP	RUL estimation of the engines on the NASA turbofan engine dataset [132,133]
[180]	Integrated gradients	PdM to reveal the most sensitive gearbox operations in the MW load range in a petrochemical plant to a specific abnormality
[181]	SHAP	RUL estimation of NASA turbofan engine dataset [132,133]
[182]	LIME and NLP	Maintenance work orders
[183]	LRP	Bearing health condition estimation on the NASA bearing dataset [136]
[184]	Knowledge-based system including domain ontologies and semantic web rule language rules	The detection of future machinery failures as well as the prediction of their time of occurrence in semiconductor manufacturing process by the UCI SECOM dataset [148]
[185]	Rule-based expert system	PdM of a real hybrid bus
[186]	Real type-2 fuzzy-based XAI	PdM within the water pumping industry
[187]	Rule-based model called logic language model	RUL estimation of the engines on the NASA turbofan engine dataset [132,133]
[188]	QARM algorithm	RUL prediction of a drilling machine of an automotive manufacturer
[189]	A data-driven sensitivity analysis	The prediction of the future reliability of components in a large gas distribution network
[190]	Bagged decision trees	A synthetic dataset that reflects real predictive maintenance data encountered in the industry
[191]	Gradient boosting decision tree	The prediction machine errors or tool failures on Microsoft Azure dataset [146]

[192]	A premier transparent, interpretable, and self-explainable automated machine learning software, including methods like random forest and gradient boosting	Manufacturing quality prediction in real-life environment
[193]	A virtual knowledge graph-based approach	PdM in the hydraulic systems
[194]	Attention and LSTM-GAN	PdM to reduce maintenance costs and downtime of machines in the intelligent manufacturing system
[195]	Attention and bidirectional LSTM	RUL estimation on the NASA turbofan engine dataset [132,133]
[196]	Bidirectional self-attention gated recurrent unit	The prediction of the health index on the NASA rolling bearing dataset from IEEE PHM challenge [138]
[197]	The attention mechanism	RUL estimation on the NASA turbofan engine dataset [132,133]
[198]	The attention mechanism	Structural Health Monitoring
[199]	The multi-layer, multi-source attention distribution	The fault detection and recognition on the general data hierarchy of AUV
[200]	Attention and LSTM	RUL estimation on the NASA turbofan engine dataset [132,133] IoT
[201]	Feature attribution and counterfactual generation	Fault diagnosis in water injection pump for production stimulation in offshore oil wells, offshore natural gas treatment plant
[202]	PCA/Kernel PCA/KNN-PCA, LIME, and integrated gradient	RUL estimation of the NASA turbofan engine dataset [132,133]
[203]	Pobability density function, Fourier transform, spectral kurtosis, autoencoder and variational autoencoder, and K-means clustering	Gearbox and bearing health assessment in wind turbine system
[204]	Unsupervised feature selection, adapting relevance metrics with the dynamic time-warping algorithm	Health indicators for a rotating machine
[205]	Temporal fusion separable convolutional network, a hierarchical latent space variational auto-encoder, and a regressor consisting of a linear layer and a sigmoid activation function	RUL estimation on the NASA turbofan engine dataset [132,133]
[206]	A blockchain-based architecture that achieves trustworthy federated learning	A service
[207]	Balanced K-star	PdM in an IoT-based manufacturing system
[208]	HMM and reinforcement learning	RUL estimation of the engines on the NASA turbofan engine dataset [132,133]

Figures 8 and 9 show numbers relating to PdM and explainable/interpretable AI in Web of Science and Google Scholar for 2018 to 2023, respectively. The total study numbers in Web of Science and Google Scholar are (6, 5, 9, 30, 34, and 18) and (2328, 3058, 4166, 5834, 7350, and 6540) over 2018–2023, respectively. All numbers show significant growth in using both PdM and explainable/interpretable AI over the specified time frame. The increasing number of studies presents a rising interest and emphasis on these subjects and methods. In addition, the numbers emphasize the importance of PdM and the need for AI systems that are transparent and interpretable. The numbers support that using PdM and explainable/interpretable AI will continue to expand and generate a broader shift in the research focus on these areas.

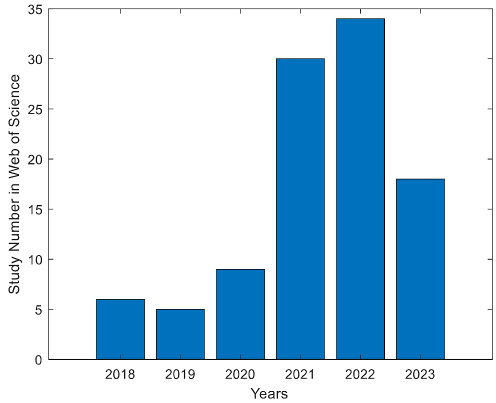

Figure 8. The number of studies relating to PdM and explainable/interpretable AI in Web of Science between 2018 and 2023.

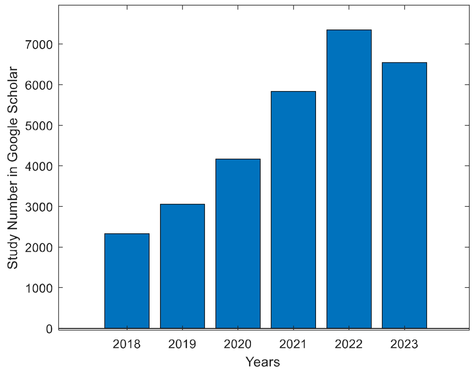

Figure 9. The number of studies relating to PdM and explainable/interpretable AI in Google Scholar between 2018 and 2023.

5. Challenges and Limitations of Using AI for PdM Autonomy

Several problems and limitations that need to be overcome to realize AI's potential benefits are posed by its use for PdM autonomy. Some key challenges and limitations are (i) transparency and explainability, (ii) integration with existing systems and workflows, (iii) data quality and quantity, (iv) the lack of real-world data, (v) the lack of standard evaluation metrics, (vi) ethical considerations, and vii) effective human–machine interaction.

Transparency and explainability could make understanding and believing the decisions adopted in this system difficult for human operators, leading to mistrust and lack of acceptance among users. All developments about transparency and explainability are given in Section 4. More development should be undertaken to gain the trust of human operators in PdM applications.

The seamless integration into existing systems and workflows requires specialized software and expertise. Moreover, the different types of data formats, communication methods, and protocols create difficulties in integrating AI systems into current systems. There are some approaches for the seamless integration of AI-based PdM systems into current systems and workflows [209–224]. In [209–221], a modular design has been applied. The design allows the AI-based system to be flexibly integrated with existing systems and workflows and adaptable using standard interfaces and protocols, such as Modbus, Snap7, and OPC-UA, to communicate with existing systems and develop APIs. Ref. [223,224] has leveraged a service-oriented architecture (SOA) for integration. Web services, such as RESTful APIs, to access the AI-based system and message-oriented middleware, such as MQTT, to communicate with existing systems have been applied. Additionally, some researchers have proposed using edge computing and fog computing to integrate AI-based PdM systems into existing systems [219–222].

Data quality and quantity are crucial for training and validating AI-based PdM models. High-quality data provides accurate predictions. In contrast, the time and costs of gathering and cleaning data may be considerable. In addition, it is essential to have large amounts of data for learning deep learning models, and in certain cases, they may be challenging to obtain [85,86,129,192,210]. AI-based PdM systems should be tested and validated under various conditions, such as different types of equipment, different operating conditions, and different levels of data quality for successful real-world applications. The lack of real-world data makes it difficult to test the system under realistic conditions and to evaluate its performance and accuracy. Researchers have proposed various methods for simulating real-world scenarios to overcome this challenge, such as using virtual environments and testbeds [26,35,37,42,96,109,210,225–231].

The lack of standard evaluation metrics is another challenge in testing and validating AI-based PdM systems. The shortcoming makes comparing different systems' performance and evaluating their accuracy and reliability difficult. Researchers have proposed various evaluation metrics to overcome this challenge, such as prediction accuracy, mean squared error, and precision and recall [24,232].

Ethical considerations are essential for AI-based PdM systems to ensure they are robust, reliable, and secure. Additionally, ethical considerations are associated with using AI-based PdM systems, such as transparency and explainability, trust and acceptance among users, integrating AI-based systems with existing systems and workflows, testing, validating, and data privacy and security [221,233,234].

Human–machine interaction is an essential aspect of AI-based PdM as it involves the interaction between human operators and autonomous systems. The goal of human–machine interaction in PdM is to enable human operators to monitor, control, and interact with autonomous systems safely, efficiently, and effectively. One of the critical challenges in HRI for AI-based PdM is the development of intuitive and user-friendly interfaces [235,236]. Researchers have proposed various methods for designing intuitive and user-friendly interfaces to overcome these challenges, such as virtual and augmented reality gestures and NLP [11,19,21,26,48,50,105,106,108,230]. Another challenge in HRI for AI-based PdM is the development of trust and acceptance among human operators. Generally, ML models, especially deep learning models, provide decisions that are too complicated for humans to understand, reducing people's trust in their predictions. That is why developing simplified and interpretable models is vital [182]. Recent works have proposed to use NLP and, its more powerful version, generative AI, including large language models (LLMs), such as ChatGPT, PaLM, and Llama [237–240], to predict component failure or service requirements and to analyze historical log data that include equipment performance, environmental conditions, and maintenance schedules [241–245]. Ref. [246] has used NLP, dimension reduction, and clustering techniques for the PdM of an aircraft by using previous reports. A human collaboration with ChatGPT has applied PdM for mobile firefighter turnout gear cleaning in [247]. Ref. [248] has applied GPT and RL to control an HVAC system. Ref. [249] has proposed to leverage ChatGPT in different areas of supply chain management, such as route optimization, predictive maintenance, and order shipment. Ref. [250] has proposed a new language model for network traffic, including PdM in telecommunication. Critical AI training, testing, and diligence methods for PdM in automotive projects have been introduced in [251]. In [252], LLMs have been investigated for the failure mode classification task, an essential maintenance step. The works in [241–252] have shown that NLP and LLMs have increased predictive maintenance efficiency and accuracy since they can be constantly updated with real-time equipment data, enabling them to learn the patterns associated with healthy operational functioning.

6. Recent Advances and Future Trends in AI-Based PdM

Recent advances in AI-based PdM have improved the performance and accuracy of predictive maintenance predictions and increased the autonomy and adaptability of machines in complex and dynamic working environments. Some recent advances in this field include the following:

1. Integration of advanced machine learning algorithms;
2. Edge and cloud computing for real-time analysis and data storing;
3. Predictive analytics with big data;
4. XAI for transparency;
5. IoT sensor integration;
6. Digital twin, AR, VR, MR, and extended versions.

The field of AI-based PdM has been developing and improving, as shown in Figure 10. The future research topics in the field are given below:

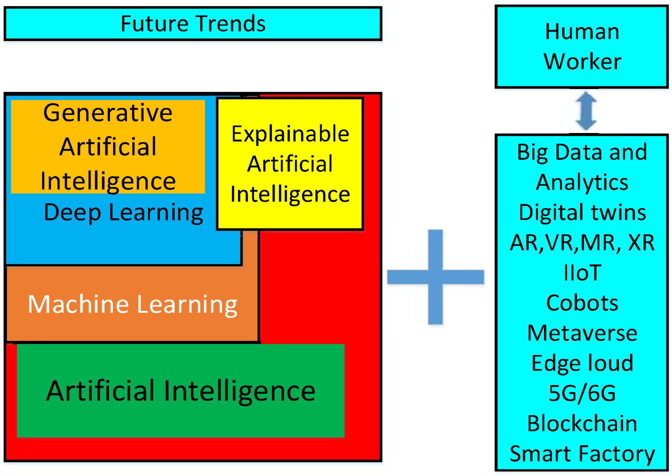

Figure 10. Future trends in AI-based PdM.

1. Big data and analytics are used to collect, analyze, and interpret large amounts of data.
2. The exponential growth of cyber–physical systems of digital twins, AR, VR, XR, metaverse, and human-driven industrial metaverse solutions to both physical and virtual work environments allows smooth collaboration and communication between employees, machines/ robots, and AI.
3. Development of autonomous maintenance systems that are capable of self-diagnosis, decision making, and proactive interventions without human intervention.
4. Evolving toward zero-touch maintenance operations where AI systems automate the maintenance process from detection to resolution.
5. Extraction of actionable insight advancements in AI algorithms to predict failures and provide actionable insights and recommendations for optimal maintenance strategies.
6. Integrating experiential learning and reinforcement learning techniques to improve AI models based on ongoing data and continuous feedback.
7. Implementation of blockchain technology for data security to enhance the security and integrity of PdM data, ensuring trust and transparency.
8. Development of trustworthy AI algorithms and human-centric AI interfaces for better collaboration between AI systems and human operators, facilitating seamless interaction and decision making.
9. Development of energy-efficient AI-based PdM to minimize resource consumption while maintaining high prediction accuracy.
10. Development of collaborative robots (cobots), IIoT, edge and cloud computing, and 5G/6G connectivity for next-step PdM autonomy and smart factory that can adjust to shifting circumstances and changing conditions and streamline manufacturing processes.
11. Development of generative AI models to contribute to the above items. For example, they can provide failure warnings, present encompassing instructions for repair and replacement methodologies, achieve suggestions to optimize energy consumption and cut down the carbon footprint to human operators by simulating the real system and/or analyzing maintenance logs and sensor data, and facilitate better collaboration between automated systems and human operators through natural language communication in automated maintenance planning.

7. Conclusions

This paper has reviewed the recent developments in AI-based PdM, focusing on next-step autonomy in robots. SOTA, challenges, and opportunities associated with AI-based PdM have been analyzed. The ethical considerations, integration, testing, and validation of AI-based PdM in real-world scenarios and human–machine interaction have also been discussed. The potential benefits of AI-based PdM, such as cost savings, increased efficiency, and improved safety, have been highlighted. It has been concluded that PdM is trustworthy thanks to explainable and interpretable AI for human operators. Therefore, AI is the main component of PdM for next-step autonomy in machines, which can improve the autonomy and adaptability of machines in complex and dynamic working environments. Finally, recent advances and future trends, including the use of generative AI models, have been addressed for further improvements and developments of the AI-based PdM.

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