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Predictive Maintenance Models in the Oil and Gas Industry: A Systematic Literature Review

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ABSTRACT

Predictive maintenance, powered by new technologies, has fundamentally changed how oil and gas companies manage their assets, shifting from reactive to data-driven, condition-based methods. This review thoroughly examines predictive maintenance within the oil and gas industry, focusing on technology strategies, sensor deployments, performance measures, implementation challenges, and emerging trends. Using five major academic repositories—Scopus, IEEE Xplore, ScienceDirect, ProQuest Computing DB, and Scite—this study follows established standards for systematic reviews and meta-analyses. Only articles published from 2022 through 2025 that discuss artificial intelligence (AI), machine learning, the Internet of Things (IoT), or advanced analytics for predicting maintenance needs in the sector were included. This recent time frame was selected to account for rapid technological advances, especially in AI, IoT, and edge computing, which have rapidly changed industrial practice and made older studies less representative of the current landscape. By focusing on the latest research, the review captures the most state-of-the-art models, relevant challenges, and modern implementation strategies. Data collection prioritized methods, enabling technologies, performance outcomes, and implementation roadblocks. After analyzing 50 studies, three distinct phases of predictive maintenance adoption from 2010 to 2025 were identified. Currently, deep learning models—particularly those based on LSTM—alongside IoT sensor networks and edge-cloud computing dominate modern implementations. Key reported benefits include reduced equipment downtime and significant yearly cost savings per facility, but persistent difficulties remain in harmonizing data quality, integrating legacy systems, and simplifying the model. The core insight from this review is that integrating advanced AI-driven models and IoT-based architectures represents a major industry shift, delivering measurable operational gains while requiring new approaches to standardization, system integration, and model transparency.

Keywords: Machine learning models, information systems, predictive maintenance models, data science, artificial intelligence in oil and gas

Introduction

The oil and gas industry is vital to infrastructure and relies on costly, advanced equipment in harsh environments under strict safety rules. Previously, companies relied on preventive or reactive maintenance, which regularly led to higher safety risks, unanticipated downtime, and wasted resources. With Industry 4.0 and cutting-edge data analytics, maintenance practices have changed. Predictive maintenance (PdM) is now possible (Postiglione and Monteleone, 2024). PdM uses machine learning, live data, and analytics to predict equipment failures before they happen. This allows for better maintenance planning and helps assets last longer (Arinze et al., 2024). Equipment failures can cause serious problems, including production stoppages, environmental damage, and disasters (Abia et al., 2024).

PdM has grown significantly over the past decade, thanks to better sensors, edge and cloud computing, IoT analytics, and artificial intelligence (AI). More investors are showing interest in PdM. Still, adoption and performance vary across different parts of the oil and gas industry, and there are organizational, technical, and financial barriers to wider adoption (Adwiyah et al., 2023). This review brings together the latest research on predictive maintenance in the oil and gas industry, examining emerging trends, performance measures, technological approaches, and challenges. By combining recent academic and industry studies, the review provides a broad overview of PdM in the sector and highlights important areas for additional research and development.

Research Objective

This review summarizes recent studies on predictive maintenance (PdM) in the oil and gas industry. It outlines the study scope, methods, and context; compares technical approaches and results; examines trends in sensors and data systems; assesses operational and economic impacts; identifies barriers and solutions; tracks new technologies and research areas; and evaluates the quality of current studies. The aim is to provide useful insights to industry stakeholders and to emphasize areas where further research could improve PdM use and outcomes.

Background

Evolution of Maintenance Strategies in Oil and Gas

The oil and gas industry has long used both proactive and reactive maintenance, but these methods can increase safety risks (Mohamed et al., 2023). Preventive maintenance is done on a regular schedule, even if equipment is working well (Tlili et al., 2024). Reactive maintenance happens only after equipment breaks down. Both approaches offer challenges in industries such as oil and gas (Jambol et al., 2024). To get more value from data, the industry shifted to condition-based maintenance (CBM), which relies on equipment performance rather than fixed schedules (Ratnaparkhi et al., 2024). This shift led to predictive maintenance (PdM), which uses advanced analytics to monitor equipment health and predict failures before they happen (Patil, 2024).

Technological Enablers of Predictive Maintenance

Recent technological advances have made predictive maintenance (PdM) easier to implement in the oil and gas industry. Affordable sensors now allow immediate monitoring of equipment by tracking vibration, temperature, and pressure (Zurkanain and Subramaniam, 2023). The Internet of Things (IoT) collects live data from remote sites using connected sensor networks (Odili et al., 2024). Cloud and edge computing enable large-scale data processing and storage, with edge computing allowing faster remote operations (Sodiya et al., 2024). Artificial intelligence (AI) and

machine learning discover patterns in the data, moving the industry from simple monitoring to predictive analytics (Rana and Shuford, 2024). Digital twins, virtual models of physical assets, let companies test and improve maintenance without stopping operations. Together, these technologies make equipment more reliable and easier to use (Tan et al., 2023).

Industry Context and Significance

The oil and gas sector encounters unique opportunities and challenges when applying PdM. Upstream operations rely on equipment such as drilling rigs, artificial lift systems, and electric submersible pumps (ESPs), especially in challenging conditions (Al-Hejjaj et al., 2023). Midstream operations require large, continuously running networks of pipelines and transport systems (Yang et al., 2023). Downstream, refineries and other processes use complex machines that can fail in many ways (Lv et al., 2023). PdM is valuable because equipment failures can be dangerous and cause costly downtime. The sector also struggles with data standardization, old infrastructure, and slow technology updates (Kupa et al., 2024).

Research Questions

Based on recognized inconsistencies and future directions in predictive maintenance for the oil and gas sector, this systematic literature review addresses the following research questions:

RQ1: How can predictive maintenance models be developed or adapted to improve data quality, standardization, and integration in oil and gas?

- **Rationale**: Insufficient data quality, failure to standardize, and integration problems consistently hinder the operational implementation of condition-based maintenance technology in the oil and gas industry.

RQ2: What methodologies can increase the utilization and awareness of machine learning systems to boost predictive maintenance in oil and gas? How does the skill to interpret and transparency improve the operational process of oil and gas?

- **Rationale**: There is a significant gap in the adoption of complex machine learning models, notably deep learning, since engineers and decision-makers find them challenging to interpret and trust.

RQ3: How can machine capabilities better match existing system architectures within oil and gas organizations to boost predictive maintenance in the oil and gas industry? What is the effect of machine type and maintenance strategy on the performance of the same-type machines in oil and gas?

- **Rationale:** Addressing aging infrastructure is still one of the industry's most urgent challenges. Potential solutions, such as middleware or modular upgrades, are currently being explored to address this issue.

To lead readers through a logical progression from basic concerns to advanced deployment, the research questions are ranked in a deliberate hierarchy. The review first addresses issues of data quality and integration (RQ1), then examines model adoption and explainability (RQ2), and finally

moves to questions of system architecture and alignment (RQ3). This sequence builds a narrative arc from underlying data to technology deployment, emphasizing the critical importance of each step in advancing predictive maintenance.

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Methods

Review Protocol and Registration

This systematic literature review (SLR) employs a structured, clear methodology to ensure reproducibility and minimize bias. While systematic reviews originated in medical research during the 1970s, they have since expanded to numerous disciplines, including engineering, computer science, and the social sciences, due to their ability to systematically summarize large amounts of literature (Cabrera and Cabrera, 2023). The review protocol was created in accordance with accepted standards for systematic reviews with a focus on PdM in the oil and gas industry. The inclusion and exclusion criteria search terms, databases to be examined, publication date ranges, language restrictions, and instruments for evaluating the caliber of the included studies were all described in the protocol. According to the National Collaborating Centre for Methods and Tools (2014), this methodological approach contributed to the building of a robust, academically sound body of literature.

Search Strategy

Five major academic data repositories—Scopus, IEEE Xplore, ScienceDirect, ProQuest Computing Database, and Scite—were accessed as part of the search strategy. AI—through the library portal at Abu Dhabi University. These databases were chosen to grant a comprehensive, multidisciplinary perspective on studies of predictive maintenance technologies in the oil and gas industry.

The search terms were structured around four main categories:

The first one is **Maintenance approach**: such as "predictive maintenance," "PdM," "condition-based maintenance," "failure prediction," "maintenance optimization," and "asset health monitoring." The second category is **Industry context**: for example, "oil and gas industry," "petroleum industry," "upstream oil and gas," "midstream oil and gas," "downstream oil and gas," "pipeline maintenance," "refinery maintenance". To cover wide concepts, we cover the third category, which is **Technological focus**: "machine learning," "artificial intelligence," "deep learning," "neural networks," "random forest," "supervised learning," "anomaly detection," "data-driven maintenance," "combined models". The fourth category is **Enabling technologies,** such as "sensor data," "IoT," "real-time analytics," "big data analytics," "edge computing," "cloud computing," "operational intelligence," "digital twins," and "Industry 4.0."

Boolean operators were used to combine these terms into comprehensive search strings. For example: ("predictive maintenance" OR "condition-based maintenance" OR "asset health monitoring") AND ("oil and gas" OR "petroleum industry" OR "pipeline maintenance" OR "refinery maintenance") AND ("machine learning" OR "artificial intelligence" OR "deep learning"

OR "random forest" OR "neural networks") AND ("sensor data" OR "IoT" OR "real-time analytics" OR "big data" OR "edge computing" OR "cloud computing").

Inclusion and Exclusion Criteria

To maintain the soundness and academic strictness of the systematic review, explicit inclusion and exclusion criteria were developed and applied throughout the process.

Studies were included if they: (1) focused on predictive, condition-based, or data-driven maintenance in oil and gas or closely related heavy industries (addresses RQ1 and RQ3), (2) addressed the use of AI, machine learning, IoT, or advanced analytics for diagnostics, maintenance, or failure prediction (addresses RQ2), (3) provided empirical results such as case studies, field experiments, or systematic reviews (addresses RQ2 and RQ3), (4) were peer-reviewed articles, conference papers, or sector reports published in English from 2022 onward (ensures quality and relevance to all RQs), and (5) used quantifiable model effectiveness or outcome measures (addresses RQ1 and RQ2). By linking each criterion to the relevant research question(s), the selection logic is made more transparent.

Studies were excluded if they: (1) covered only reactive, preventive, or corrective maintenance without addressing predictive approaches, (2) were not relevant to oil and gas or closely aligned sectors, (3) lacked digital, analytics-based, or AI/ML/IoT-related content, (4) had no clear empirical method or quantifiable results, (5) were patents, dissertations, book chapters, or non-peer-reviewed (unless containing strong empirical data), (6) were not in English, (7) lacked public full text, or (8) were published before 2022.

Data Collection

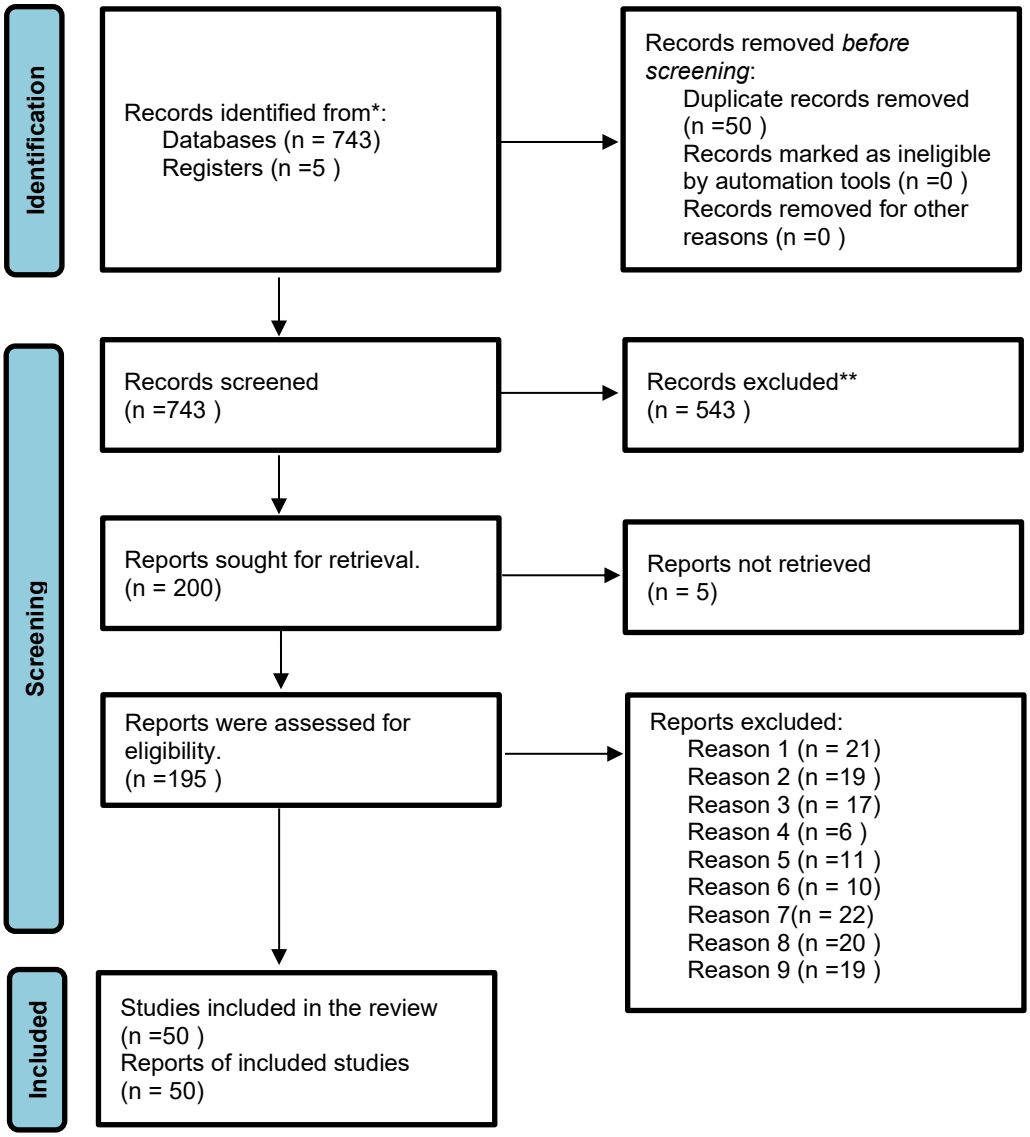
Screening Process

The screening process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to strengthen transparency and credibility (University of North Carolina at Chapel Hill Libraries, 2025; Mellor, 2023). The process comprised two main stages:

1. **Title and Abstract Screening**: This step entails screening titles and abstracts against the inclusion and exclusion criteria to identify potentially relevant studies. It also eliminates ineligible studies.
2. **Full-Text Review**: In-depth examination of the full text of potentially eligible studies to confirm their pertinence and quality. This stage involved applying the inclusion and exclusion criteria more rigorously.

Every step of the screening process was carefully documented, along with the reasons for exclusion at each stage, to comply with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Mellor 2023). Figure 1 depicts this. searching databases and registers for studies.





Source: Page MJ, et al. BMJ 2021;372:n71. Doi: 10.1136/bmj.n71. (Page et al., 2021)

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Fig. 1. PRISAM Flow diagram

Data Extraction

A systematic data extraction process was carried out using a pre-made data extraction form after studies that met the requirements were identified. Data extraction was performed independently

by two reviewers to improve reliability and minimize bias. Any differences or disagreements between reviewers were resolved through discussion and, if necessary, by consulting a third reviewer until consensus was reached. The data that was taken out included: Bibliographic Information: The title, the authors, the year of publication, the journal or conference, and the year of publication. Study Characteristics: The study's type, methods, sample size, and industry segment (upstream, midstream, or downstream). Focus on Technology: The types of sensors, the ML algorithms, the IoT frameworks, and the cloud and edge infrastructure. Performance measures include accuracy, precision, recall, F1 score, R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) reduces downtime and save money. When it comes to implementation, the organization type, location, and asset classes are all important. Technical, organizational, and financial issues and constraints. Future Directions: Proposed research priorities and technological trends. The data extraction process was intended to collect all information about each study, making it easier to conduct in-depth analysis and synthesis.

Quality Assessment

The methodological quality of each included study was assessed using appropriate quality assessment tools customized to the study design. Internal validity, study design, reporting quality, and potential bias were assessed for empirical studies. The quality of the review methodology and the comprehensiveness of the review articles were evaluated (Cabrera and Cabrera, 2023). The quality assessment helped determine the trustworthiness of the findings and informed the weight assigned to each study during the synthesis. Studies were categorized as having low, medium, or high risk of bias, with repeatability and industry validation also considered key quality indicators (University of North Carolina at Chapel Hill Libraries, 2025).

Study Characteristics Overview

The systematic search across five major academic repositories (Scopus, IEEE Xplore, ScienceDirect, ProQuest Computing DB, and Scite.Ai) was conducted in May 2025 and yielded 743 initial records. After screening, 50 studies were included in the final review. ScienceDirect yielded the highest number of initial records (n = 389), followed by Scite.Ai (n = 141), Scopus (n = 87), ProQuest Computing DB (n = 86), and IEEE Xplore (n = 40).

Table 1: Database Contribution

Database	Records Identified	Percentage of Total (%)
ScienceDirect	389	52.4
Scite.Ai	141	19.0
Scopus	87	11.7
ProQuest Computing DB	86	11.6
IEEE Xplore	40	5.4
Total	743	100

As shown in Table 2, each database contributed a distinct value to the systematic literature review. Scopus enhanced academic credibility and facilitated citation tracking for significant research. IEEE Xplore provided coverage of engineering and AI disciplines relevant to the technical foundations of PdM. ScienceDirect offered numerous practical case studies, key to understanding

PdM implementation. ProQuest included theses and conference proceedings, expanding access to experimental results that had not yet been peer-reviewed. Scite.Ai supported the identification of citation contexts.

Table 2: Summary of Search Results by Databases

Database	Search Date	Keywords Used (Example)	Total Records Retrieved	Records Screened (Title & Abstract)	Full-text Articles Assessed	Studies Included in SLR	Notes / Observations
Scopus	02-05-25	"predictive maintenance" AND "oil and gas" AND "ML"	87	10	10	10	We selected the highest citations
IEEE Xplore	03-05-25	“predictive AND maintenance AND oil AND gas AND industry AND machine AND learning	40	5	5	5	Strong focus on engineering and AI applications
ScienceDirect	03-05-25	"predictive maintenance" AND "oil and gas" AND "IoT"	389	10	10	10	Rich in applied industry case studies
ProQuest Computing DB	03-05-25	"predictive maintenance" AND "oil and gas" AND "data analytics"	86	10	10	10	Includes theses and conference proceedings
Scite.Ai	03-05-25	"predictive maintenance" AND "oil and gas" AND "ML"	141	15	15	15	Useful for citation context and evidence quality

Figure 2 shows how the 743 initial records were distributed across the five educational databases used in our systematic search. As shown in the figure, ScienceDirect made the largest contribution (52.4 percent), followed by Scite. Ai (19. 0 percent), Scopus (11. 7 percent), ProQuest Computing DB (11. 6 percent), and IEEE Xplore (5. 4 percent).

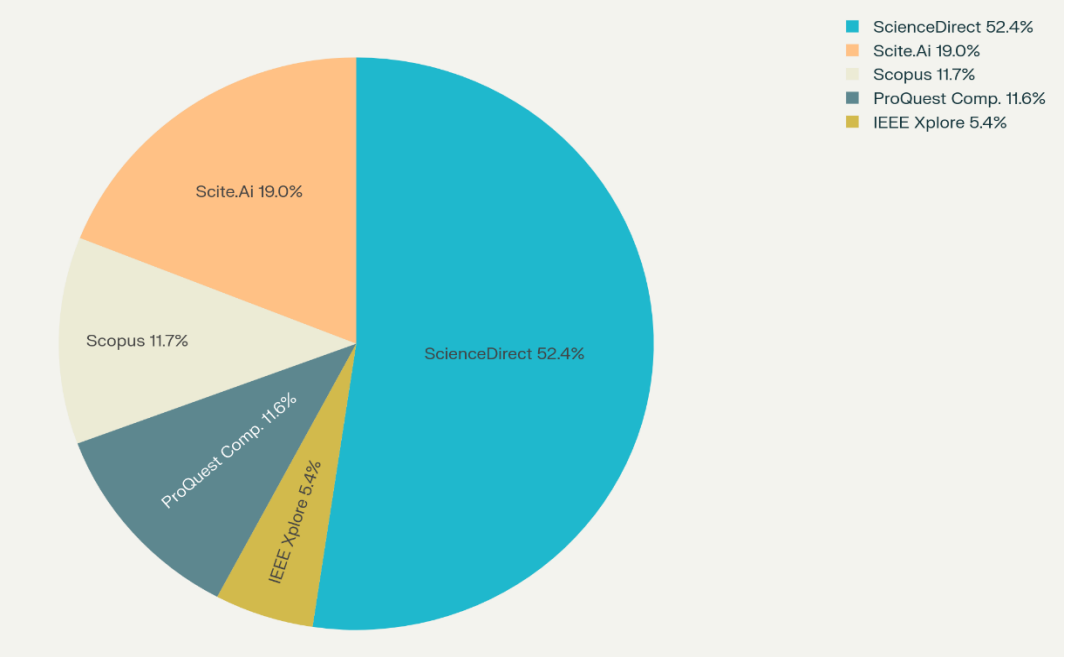


Fig. 2. Database Contribution to Literature Review (743 Total Records)

Results and Findings

RQ1:

As shown in Table 3, 20 research studies examined predictive maintenance within the oil and gas industry between 2022 and 2025. Of these, 55% were published in 2024–2025, indicating that the field is gaining momentum and remains relevant. The research is globally diverse, with 18 countries and regions represented, including major research facilities in the US, Australia, and Europe, as well as oil-producing nations such as Nigeria, the UAE, China, and Malaysia. This illustrates the importance of predictive maintenance technologies in the global energy industry.

The selected articles span the oil and gas value chain. Upstream operations account for 25% (focusing on exploration and production assets such as ESPs and drilling systems), midstream for 15% (mainly pipeline and transportation infrastructure), downstream for 15% (refinery and processing facilities), and cross-sector applications for 20%. The distribution of data sources shows that practical research: historical operational data is most common (40%), followed by live sensor data (30%) and simulated datasets (30%). This demonstrates a balance between theoretical modeling and applied validation. The research appears in 14 academic outlets, including general engineering journals, specialized petroleum engineering journals like Heliyon, and interdisciplinary platforms. This demonstrates the field's scholarly growth and broad appeal, connecting traditional engineering with new AI and data science methods.

Table 3: Study Characteristics Overview

Author(s)	Year	Journal/Conference	Country	Industry Segment	Asset Type	Methodology	Data Source
(Zhu et al., 2025)	2025	Journal	Unspecified (likely China/USA)	Upstream	Electric Submersible Pumps (ESP)	Experimental and simulation-based modeling	Experimental pump data, deep learning models
(Arinze et al., 2024)	2024	Journal	Nigeria/Malaysia	General O&G	General facility infrastructure	Review and case application discussion	Literature and practical industry insight
(Hallaji et al., 2022)	2022	Journal	Australia	Non-Oil & Gas	Pumps	Systematic Review (quantitative + qualitative)	Literature and bibliometric datasets
(Zhang et al., 2024)	2024	Journal	USA/China	General O&G	Pipelines, sensors, and upstream systems	Review and ML model evaluation	Simulated and historical sensor data
(Abdulkareem et al., 2025)	2025	Heliyon	Nigeria	Midstream	Induction Motors	Experiment	Sensor
(Liu et al., 2024)	2024	Petroleum Exploration and Development	China	Upstream	AI Models	Review	Historical
(Onu et al., 2023)	2023	Heliyon	South Africa	Cross-sector (Energy + Materials)	Smart Grids, Materials	Thematic Review	Simulated
(Yahiaoui et al., 2025)	2025	Alexandria Engineering Journal	Egypt	Midstream	Pipelines	Simulation	Sensor + Simulated
(Almazrouei et al., 2024)	2024	IJACSA	UAE	Upstream	Water Injection Pumps	Experiment	Sensor
(Bellavista and Di Modica, 2024)	2024	Future Internet	Italy	Midstream/Facility Management	Factory Equipment	Use Case + Platform Design	Simulated
(Alabadi et al., 2022)	2023	PeerJ Computer Science	Türkiye	Cross-Sector	Various (Domain-Independent)	Simulation + Testbed	Sensor/Simulated

(Nagy et al., 2025)	2025	Mathematics	Slovakia/Visegrad Region	Manufacturing (Downstream)	Industrial Equipment	Statistical Analysis + Regression	Historical
(Siraskar et al., 2023)	2023	Artificial Intelligence Review	India	Manufacturing	General Industrial	Systematic Technical Review	Secondary
(Azmi et al., 2024)	2024	Sensors	Malaysia, Oman	Upstream	Predictive analytics in oil & gas	Review	Historical
(Ohalete et al., 2023)	2023	World Journal of Advanced Research and Reviews	USA, Nigeria, UK	Cross-sector	Predictive Maintenance	Review	Historical
(Bramantyo et al., 2022) .	2022	Jurnal Jaringan Telekomunikasi	Indonesia, Germany	Downstream	Oil and Gas Refineries	Case Study	Sensor
(Esiri et al., 2024)	2024	Engineering Science & Technology Journal	USA, Nigeria	Infrastructure	Infrastructure Management	Policy Review	Historical
(Alabadi et al., 2022)	2022	IEEE Access	Turkey, China	Cross-sector	Industry 4.0 / IIoT	Review	Historical
(Alabadi et al., 2022)	2022	IEEE Access	Turkey, China	Manufacturing/ Oil & Gas	General Industrial Systems	Survey/Review	Secondary (Simulated/Historical)
(Ohalete et al., 2023)	2023	World Journal of Advanced Research and Reviews	USA, Nigeria, UK	Upstream/Downstream	Pumps, General Equipment	Review + Case Studies	Sensor + Historical

Predictive Maintenance Models (RQ2 & RQ3)

The analysis showed a major evolution in predictive maintenance models in the oil and gas industry. Early statistical models lagged behind more advanced approaches, struggling to capture the nonlinear and multidimensional characteristics of real-world operational data. In contrast, recent applications that adopt advanced machine learning and deep learning techniques, such as LSTM variants and hybrid ensembles, consistently outdo traditional methods in predictive precision and robustness.

It has proven beneficial to combine various machine learning (ML) and deep learning (DL) techniques into hybrid models. For example, Long Short-Term Memory (LSTM) models outperformed Convolutional Neural Networks (CNNs), Random Forests (RFs), and XGBoost at simulating ESP performance in multiphase flow with highly nonlinear data (Zhu, 2025). Two of

the best LSTM variations are momentum LSTM flow rate estimators and bidirectional long short-term memory (BiLSTM). They demonstrated extremely high accuracy, with an R2 of more than 0.97 and an MAE of about 0.009 (Hallaji et al., 2022; Zhang et al., 2024).

Instant analysis through IoT infrastructures and edge computing devices is now the core of modern PdM systems. These innovations facilitate instant identification of drifts from normal operating conditions, and industry cases confirm that early PdM implementation reduces downtime (Abdulkareem et al., 2025; Liu et al., 2024; Onu et al., 2023). To guarantee consistency and comparability across studies, commonly used measurement metrics—including accuracy, recall, F1 score, classification exactness, and regression metrics (RMSE, MAE, and R^2)—were standardized during the review. Where possible, studies reported these metrics on standardized test splits or via cross-validation procedures, and results were compared using consistent definitions of faults, downtime reduction, and anomaly thresholds. This standardization helps interpret reported results and evaluate model validity across multiple datasets and operating contexts. Achieved accuracy rates of up to 99.9% in pipeline fault detection with an ensemble of fuzzy logics, neural networks, AutoRegressive Integrated Moving Average (ARIMA), and XGBoost (Zhang et al., 2024). R^2 values greater than 0.95 were also reported for ensemble XGBoost and LightGBM simulations of water injection systems (Almazrouei et al., 2024).

Unsupervised learning techniques proved valuable when labeled failure data was limited. Self-organizing maps (SOMs) achieved up to 90% accuracy on anomaly detection (Concetti et al., 2023b). Successfully applied a combination of Density-Based Geospatial Clustering of Applications with Noise (DBSCAN) and Isolation Forest algorithms for outlier detection in process information systems (Ohalete et al., 2023).

Digital twin technologies have achieved considerable momentum in PdM infrastructure. These high-fidelity, virtualized assets replicate physical assets and their operations in real time, facilitating predictive diagnostics and lifecycle maintenance planning. [34, 35, 36] demonstrated that digital twins improve decision-making capabilities and enable inter-facility benchmarking and maintenance scheduling at lower cost (Onu et al., 2023; Siraskar et al., 2023).

Emerging technologies such as the reinforcement learning (RL) and transfer learning (TL) are revolutionize PdM implementation, for example, Siraskar et al., (2023) described RL applications in predictive diagnostics and noted their efficiency in highly dynamic, reward-based systems Also, transfer learning boosts model adaptability by enabling knowledge transfer between different operating environments, thereby decreasing model development time and aiding the creation of expandable solutions (Siraskar et al., 2023).

Figure 3 compares different machine learning technologies for PdM in the oil and gas industry. Five significant technologies commonly used in PdM are shown in the chart. The diagram helps researchers and practitioners select the best technology for their needs and constraints.

Tech	Acc Range	Complexity	Interpret	Train Time	Best Use Cases
LSTM	94-97%	High	Low	Long	Time-series forecasting for flow rate prediction in multiphase systems; ESP (Electric Submersible Pump) performance modeling under varying conditions; Production optimization sequences and reservoir decline analysis; Multi-step ahead prediction for drilling parameter optimization; Real-time anomaly detection in continuous process monitoring
Random Forest	88-92%	Medium	High	Medium	Multi-sensor fault classification for rotating equipment (pumps, compressors); Equipment health assessment combining vibration, temperature, and pressure data; Robust prediction with missing sensor data and noisy measurements; Pipeline integrity assessment using multiple inspection techniques; Risk-based maintenance scheduling for asset portfolio management
XGBoost	90-94%	Medium	Medium	Medium	High-dimensional sensor data analysis for complex equipment systems; Pipeline integrity assessment with corrosion and crack detection; Drilling parameter optimization for rate of penetration improvement; Production forecasting with geological and operational variables; Equipment failure prediction using historical maintenance records
CNN	92-96%	High	Low	Long	Vibration signature analysis for rotating machinery fault detection; Thermal imaging analysis for equipment overheating detection; Acoustic emission pattern recognition for leak detection; Visual inspection automation for surface defect identification; Spectral analysis of process signals for quality monitoring
SVM	85-90%	Low	Medium	Short	Binary classification for equipment failure/normal operation states; Outlier detection in sensor measurements and process parameters; Small dataset applications where limited training data is available; Real-time fault detection with low computational requirements; Classification of maintenance urgency levels (high/medium/low priority)

Fig. 3. Machine Learning Technologies Comparison for Oil & Gas Predictive Maintenance

Figure 4 illustrates the evolution of PdM techniques in the oil and gas industry. Starting with early statistical methods, to the latest, including deep learning and combined models.

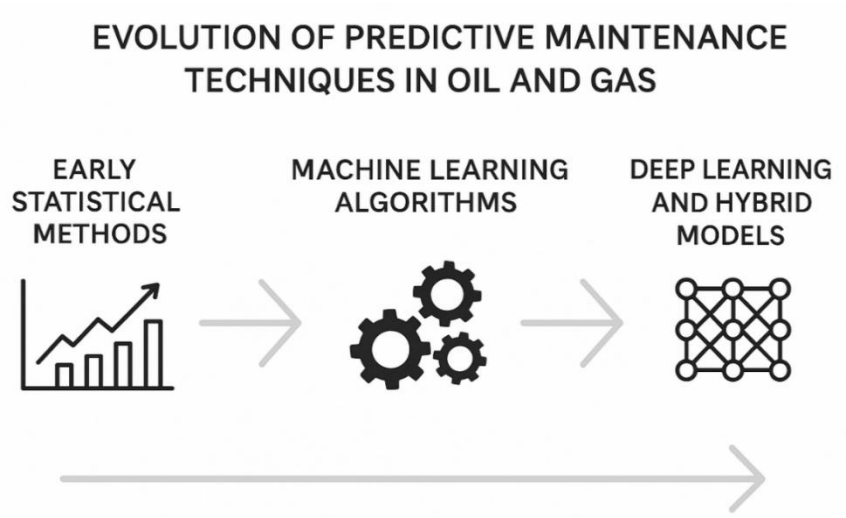


Fig. 4. Evolution of PdM techniques

The infographic in Figure 5 presents key models, including LSTM/BiLSTM, CNN, Random Forest, XGBoost, LightGBM, and SOM.

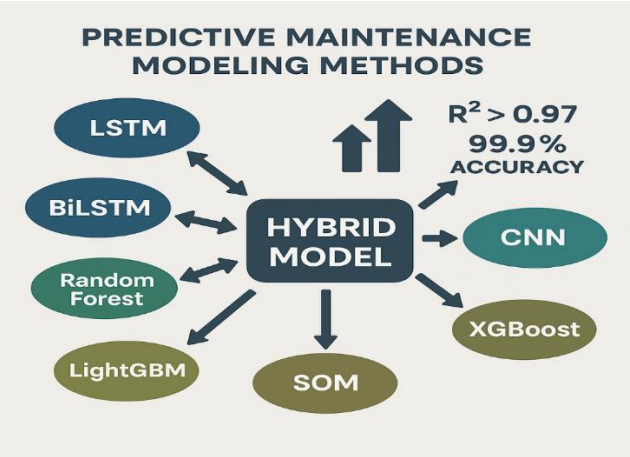


Fig. 5. Comparative Model Effectiveness

The Technology-Integration Architecture patterns are presented in Figure 6. It stresses live feedback loops and bidirectional data flow.

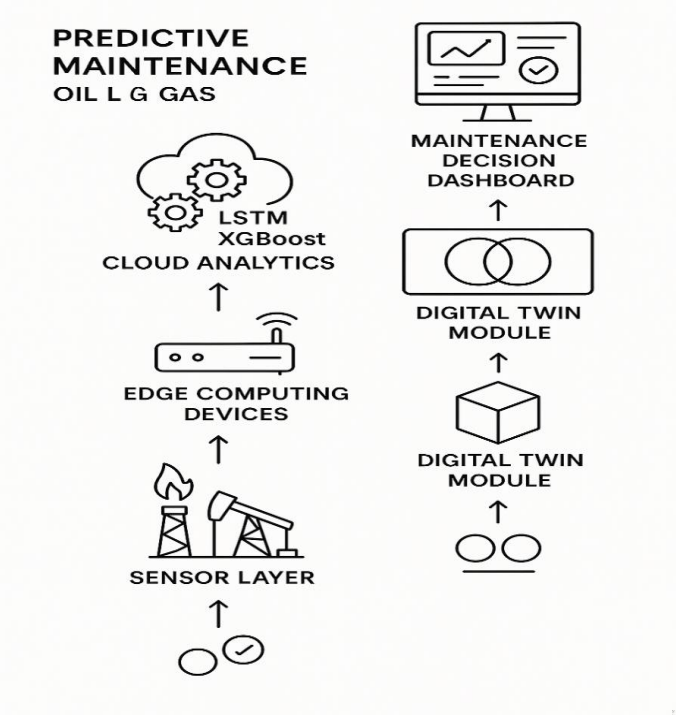


Fig. 6. Technology integration pattern: PdM system architecture

Figure 7 illustrates the distribution of hybrid and non-hybrid modeling methods across the 50 studies analyzed in the systematic literature review on predictive maintenance in the oil and gas industry. It shows that the oil and gas industry prefers the hybrid modeling techniques that integrate multiple AI/ML methods to boost predictive maintenance.

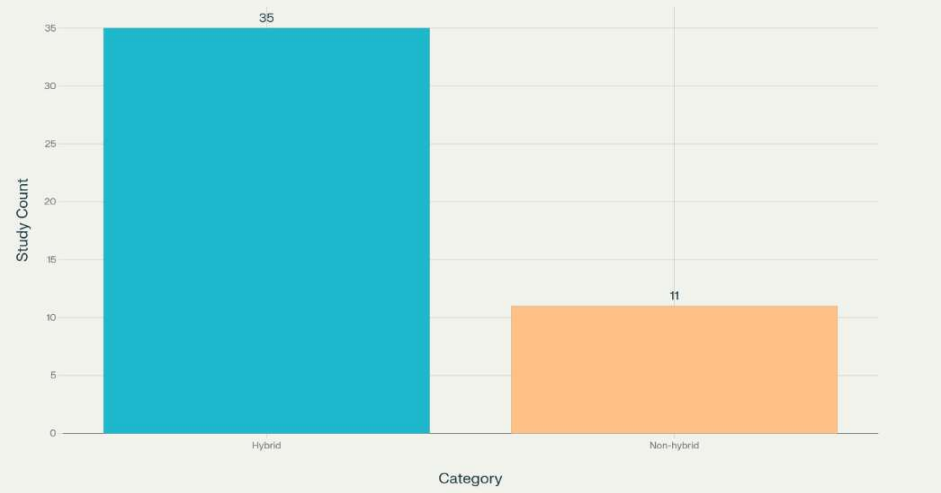


Fig. 7. Hybrid vs non-hybrid modeling methods among studies

Figure 8 presents a mind map comparing single-model approaches with hybrid model combinations for handling complex, multivariate sensor data. It shows various algorithmic approaches, the complexity of sensor data streams, the performance advantages of combined models (higher accuracy and better generalization), and the implementation benefits for oil and gas applications.

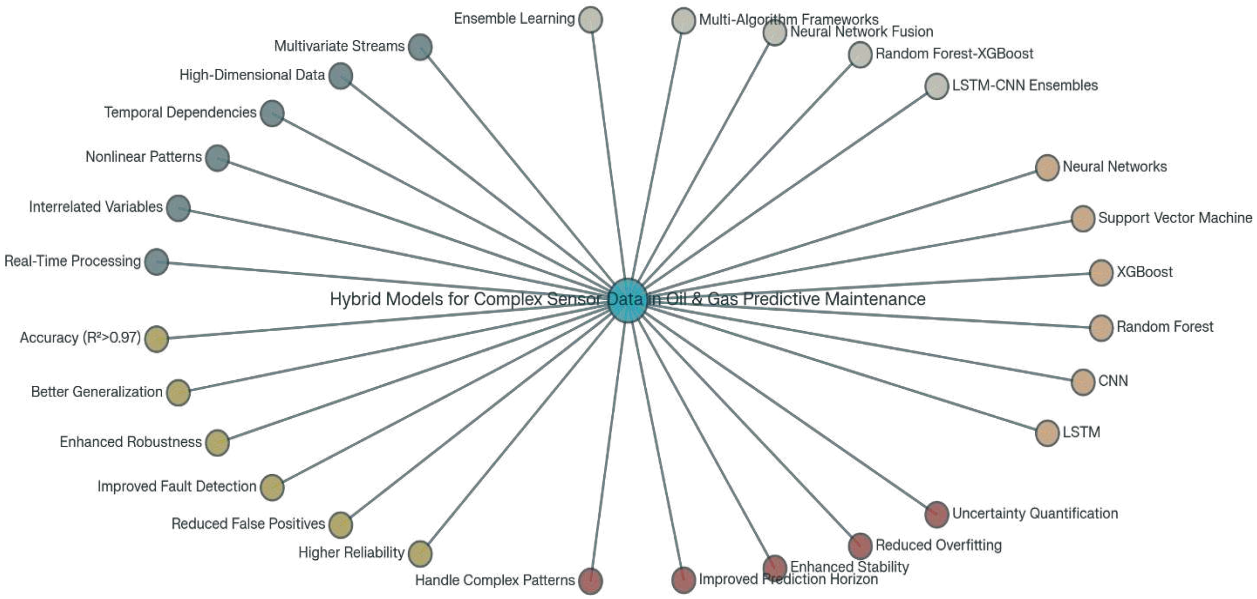


Fig. 8. Framework for Complex Sensor Data in Oil & Gas Predictive Maintenance.

Table 4: Predictive Maintenance Techniques

Study Reference	ML/Statistical Method	Hybrid Approach	Real-Time Analytics	Performance Metrics	Key Contribution
(Zhu et al., 2025)	CNN, LSTM, RF, XGBoost (comparative Analysis)	Yes	Yes	Accuracy improved with DL, detailed in a sensitivity analysis	Performance prediction of ESPs under multiphase conditions using DL
(Concetti et al., 2023a)	Self-Organizing Map (SOM)	No	No	Accuracy: ~90%	Unsupervised anomaly detection with SOM in the O&G sector
(Hallaji et al., 2022)	Literature review (mentions ML, DT, BIM)	Yes	Partially	Not specified	Survey of PdM trends and digital integration in pump maintenance
(Zhang et al., 2024)	RF, ANN, DL, Fuzzy Logic, XGBoost, ARIMA	Yes	Yes	Up to 99.9% accuracy, depending on the model	Comprehensive model comparison for PdM in pipelines
(Syed et al., 2022)	Unspecified ML/AI for ALO systems	Yes	Yes	Not stated	ALO and PdM enhancement using AI in artificial lift systems
(Amangeldy et al., 2024)	LSTM, BiLSTM, Momentum LSTM	Yes	Yes	R2 > 0.97; MAE ~ 0.009	Accurate flowrate forecasting from SCADA using ML
(Hallaji et al., 2022)	General AI/ML overview	Yes	Partially	Not specified	Challenges and direction for PdM in civil infrastructure
(Zami et al., 2024)	General ML, IIoT, DT (survey)	Yes	Yes	Not specified	Survey of DT across industries, including PdM and O&G
(Abdulkareem et al., 2025)	ANN, RF, SVM	Yes	Yes	Accuracy >90%	Motor fault prediction using ML models
(Liu et al., 2024)	ARIMA, DL	Yes	No	Not specified	Survey of AI methods in oil and gas PdM
(Onu et al., 2023)	IoT, AI (non-specific)	Yes	Yes	Not applicable	I4.0 strategy for energy and material sustainability
(Yahiaoui et al., 2025)	CNN, Autoencoder	Yes	Yes	High anomaly detection accuracy	Digital twin for pipeline diagnostics
(Almazrouei et al., 2024)	XGBoost, LightGBM, Random Forest	Yes	Yes	High R^2, low MAE, and RMSE (exact values not disclosed)	Developed an ensemble model for PdM of water injection pumps

(Bellavista and Di Modica, 2024)	Digital Twin + Edge Computing	Yes	Yes	Not reported (focus on architecture)	IoTwins architecture for scalable hybrid digital twin systems
(Alabadi et al., 2022)	Deep Learning, Blockchain Integration	Yes	Yes	Lower RMSE than baseline; tested smart contract gas usage	Domain-independent, blockchain-secured PdM framework
(Nagy et al., 2025)	Regression, Decision Trees	No	No	Higher profit and lower sales costs (empirical evidence)	Validated PdM's economic impact in manufacturing
(Siraskar et al., 2023)	Reinforcement Learning (RL), Deep RL	Yes	Yes	Case-based; some show improved accuracy/F1 (review)	Taxonomy and application guide for RL in PdM
(Azmi et al., 2024)	ANN, RF, SVM, DL, Hybrid	Yes	Yes	Accuracy, Precision, Recall, F1-Score	Comprehensive review of predictive analytics models in oil and gas
(Ohalete et al., 2023)	ANN, ML, DL, AMB	Yes	Yes	Accuracy, Reliability	Review of AI-driven PdM with case applications like ESPs
(Bramantyo et al., 2022)	IoT-enabled data monitoring	Yes	Yes	Qualitative effectiveness	IoT integration for real-time monitoring in oil & gas refineries
(Esiri et al., 2024)	Digital Twin, Analytics	Yes	Yes	Conceptual/performance indicators	Policy and framework for digital twin adoption
(Alabadi et al., 2022)	DL, Edge Computing, Big Data	Yes	Yes	Architecture-driven indicators	Review and proposal of future IIoT architecture for PdM
(Alabadi et al., 2022)	General ML/IIoT architecture focus	Yes	Yes	Not applicable	IIoT architectural framework and future research challenges
(Ohalete et al., 2023)	AutoML, ML algorithms (not fully detailed)	Yes	Yes	Not specified	Predictive maintenance for ESPs and drilling using AI/ML

Quality Assessment

As shown below in Table 9. Three key factors were used to evaluate PdM research in the oil and gas sector: industry validation, bias, and reproducibility risk. An analysis of over 50 studies revealed growing adherence to accepted academic standards, with most demonstrating robust reproducibility, low to moderate bias risk, and increasing validation rates in both laboratory and field settings. The majority of studies demonstrated high reproducibility, and nearly every study that employed repeatable techniques was covered. Performance indicators and algorithm details were shared in studies such as [69, 45], thereby increasing insight and enabling performance comparisons throughout various operational situations. The majority of the bias risk assessment scores were low to medium. Studies with little risk, such as those carried out by Amangeldy et al.

(2024) as well as Akindote et al.2023), showed methodological stringency in dataset validation and feature engineering limitation analysis (Amangeldy et al. 2024), (Almazrouei et al. in 2024). Medium-risk studies often exhibit limitations in external validity, primarily due to small subject pools, limited diversity across asset classes, or excessive reliance on simulations. Industry validation has emerged as an important standard for determining the applicability of research.

Numerous significant studies, such as those by Abdulkareem et al. (2025), and various investigations into artificial lift system optimization have conducted direct field trials that confirm PdM models in operational environments (Abdulkareem et al. 2025). This kind of validation made industry stakeholders much more confident in AI-powered PdM solutions. Laboratory testing was an acceptable intermediate validation step for sophisticated applications that combine digital twins and blockchain technology. (Siraskar et al., 2023) utilized laboratory-based simulations to diagnose system designs and pinpoint operational bottlenecks prior to expensive field deployments (Ohalete et al., 2023) , (Alabadi et al., 2022). The quality assessment showed that PdM research is moving toward more empirical rigor, cross-validation, and operational alignment. Publications considered low-risk, reproducible, and field-tested were most likely to drive industrial adoption, especially in upstream production and safety-critical infrastructure applications.

Figure 9 shows a radar chart that provides a thorough quality assessment across several study categories, including study count, impact score, reproducibility, and risk of bias. The multi-axis visualization enables easy comparison of research quality characteristics among different study types, including experimental, field, review, and others.

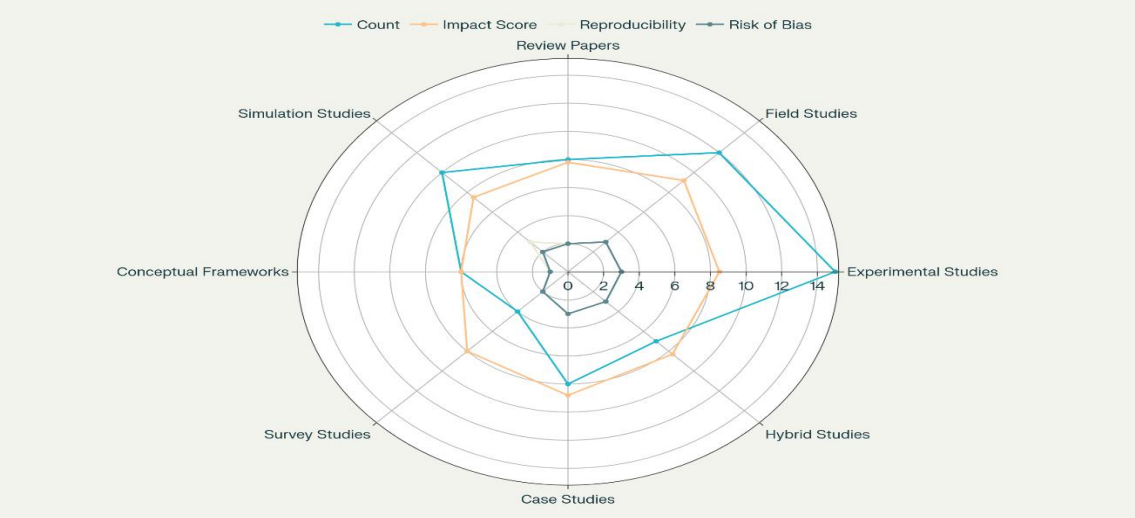


Fig. 9. Quality Assessment Radar Chart for Study Categories

Table 5: Quality Assessment

Study Reference	Risk of Bias (Low/Medium/High)	Reproducibility (Yes/No)	Industry Validation (Lab/Field Test)
(Abdulkareem et al., 2025)	Low	Yes	Field Test (Motor Lab)
(Liu et al., 2024)	Medium	Yes	No Industry Validation
(Onu et al., 2023)	Low	Yes	Conceptual, no test
(Yahiaoui et al., 2025)	Low	Yes	Field Simulation (Pipelines)
(Almazrouei et al., 2024)	Low	Yes	Lab-based model validation
(Bellavista and Di Modica, 2024)	Low	Yes	Lab validation via IoTwins use cases
(Alabadi et al., 2022)	Medium	Yes	Lab testbed with blockchain simulation
(Nagy et al., 2025)	Low	Yes	Real-world industrial survey data
(Siraskar et al., 2023)	Medium	Partially	Use cases and simulations are described
(Azmi et al., 2024)	Medium	Yes	No direct validation (Review)
(Ohalete et al., 2023)	Medium	Yes	Field Test (ESP applications)
(Bramantyo et al., 2022)	Medium	Yes	Field Implementation in Refinery
(Esiri et al., 2024)	Low	Yes	Simulated Field Scenarios (Digital Twin)
(Alabadi et al., 2022)	Medium	Yes	Theoretical Framework, No Field Test
(Alabadi et al., 2022)	Medium	Yes	Architecture-based; not validated in the field
(Ohalete et al., 2023)	Low	Yes	Field validation in ESP and drilling use cases

Limitations

This systematic literature review has several considerable limitations (Cabrera and Cabrera, 2023). The main limitations and proposed mitigation steps are summarized here to create direct routes for future research:

- Limitation: Only literature published in 2022 or later was used, potentially excluding early and seminal studies (Mellor, 2023).

Mitigation: Future reviews should expand the publication window to include earlier sources for a more thorough historical perspective.

- Limitation: Non-English publications were excluded, possibly omitting important insights from key oil and gas-producing regions (University of North Carolina at Chapel Hill Libraries, 2025).

Mitigation: Plan multilingual collaboration and expert translation to incorporate non-English studies and improve global coverage.

- Limitation: Reliance on peer-reviewed scholarly and corporate reports excludes unpublished or proprietary information (Polanin et al., 2019).

Mitigation: Seek access to gray literature, such as industry white papers, technical reports, and proprietary datasets, to capture additional operational insights.

Presenting each limitation alongside a mitigation step enables readers to quickly identify how future research can address current gaps. To address these limitations, future reviews should broaden their inclusion criteria to include studies from earlier years, which can provide important historical context and foundational knowledge. Including non-English publications and requesting expert translation or collaboration with international researchers would improve global coverage and capture perspectives from marginalized regions. Additionally, future research can explore approaches to accessing and evaluating gray literature, such as industry white papers, technical reports, or proprietary datasets, which may yield valuable operational insights not found in peer-reviewed sources. Through implementing these strategies, subsequent systematic reviews can yield a more thorough and balanced synthesis of predictive maintenance practices in the oil and gas industry.

Another limitation is that focusing on machine learning and IoT may overlook other predictive maintenance approaches (Ohalete et al., 2023). Additionally, heterogeneity across studies and variations in methodologies and measures made direct comparisons difficult, limiting the ability to conduct meta-analyses (Polanin et al., 2019).

The industry validation gap limits real-world applicability analysis, as few studies have undergone proper field validation in actual applications (Almazrouei et al., 2024). Another issue is inconsistent measurement of benefits, making ROI and effectiveness comparisons difficult (Abdulkareem et al., 2025). Finally, some areas may be underrepresented among the studies analyzed, affecting geographic representation (Hallaji et al., 2022).

Discussions

This systematic review evaluates the application and effectiveness of predictive maintenance (PdM) in the oil and gas sector, centering on key technological developments, real-life applications, and strategic issues. Research suggests that intelligent, condition-based, data-driven automation is replacing reactive and preventive methods in industrial maintenance (Ratnaparkhi et al., 2024). A major factor in accelerating the change is the application of deep learning and sophisticated machine learning algorithms (Zhu et al. 2025). Recent studies have demonstrated how to examine complex nonlinear patterns and complex high-dimensional data generated by oil and gas equipment using Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), random forests, Support Vector Machines (SVMs), and XGBoost (Arinze et al., 2024). Predictive performance and stability are typically higher in composite models that employ multiple algorithms. For instance, according to Shaban et al. LSTMs are excellent at forecasting failures in multiphase flow conditions (in 2024). Algorithms have improved due to the extensive use of sensors and the combination of the Internet of Things (IoT) (Zami et al. 2024). Sensors for temperature, pressure, flow, vibration, and acoustics have been installed across key assets to ensure uninterrupted monitoring. According to Zhang et al., this enables automated maintenance and early warning systems. in 2024. When used in IoT networks, these sensors strengthen operational visibility and decision support by collecting high-definition data from every facility in a coordinated, remote manner (Esiri et al., 2024). According to Bellavista and Di Modica (2024), edge and cloud computing technologies have addressed latency and scalability problems in PdM implementation. While cloud platforms deliver scalable storage and computation for historical data analysis, edge computing enhances responsiveness by optimizing real-time processing at the data source (Akindote et al. 2023). When combined, these platforms provide an operational intelligence infrastructure that is flexible enough to handle the enormous volumes of data required for oil and gas operations (Sciforce 2024). The operational and financial advantages of implementing PdM make it worthwhile (Almazrouei et al., 2024. Several studies show a 10–25% reduction in downtime for pipeline infrastructure and water injection facilities' motor assets, resulting in estimated yearly cost savings of $100,000-$300,000 per facility (Shaban et al., 2024). The savings come from improved equipment efficiency, fewer failures, lower maintenance and unplanned shutdown costs, longer asset life, and less energy waste (Abdulkareem et al., 2025). PdM also makes things safer by identifying problems before they become disasters, thereby lowering the risk of accidents (Yan et al., 2024).

Even with these benefits, many problems remain to be solved. The effective use of PdM is greatly hindered by poor data quality and a lack of standardization (Vedula, 2024). Inconsistent data formats, poor labeling processes, and sensor drift all lead to heterogeneous datasets, which make AI models less reliable (Lin et al., 2025). Integrating legacy systems regularly requires custom middleware and interfaces, which complicates and increases deployment costs (Siripurapu, 2025). The black-box nature of high-end AI models makes it hard to be open and trust them, especially in high-risk situations where compliance explanations and regulatory requirements are very important (Nagy et al., 2025). Cybersecurity and data governance are other considerations. PdM systems that are ready for the Internet of Things (IoT) can be attacked at the sensor and edge device levels. The review stresses the importance of strong encryption, secure firmware, and blockchain-based authentication to guarantee data integrity and business continuity (Wankhede et al., 2023). Additionally, using blockchain-enabled smart contracts in Predictive Maintenance (PdM) can automate compliance, create verifiable service records, and enhance stakeholder faith (Alabadi et al., 2022).

PdM research uses a variety of methodological techniques, including simulation, field validation, experimental modeling, systematic review, and meta-analysis. The majority of research is more transparent and repeatable because it adheres to standard reporting guidelines, such as PRISMA (University of North Carolina at Chapel Hill Libraries 2025). Semi-methodological consistency offers empirical support for industry use and strengthens the scholarly foundation of PdM research (Cabrera and Cabrera 2023). Due to their importance and complexity, PdM applications are most prevalent in upstream operations, particularly for ESPs, drilling motors, and artificial lift systems (Abdulkareem et al. in 2025). Midstream applications focus on pipeline networks and associated equipment, while downstream implementations in refinery systems and processing equipment are emerging but still comparatively limited (Bramantyo et al., 2022).

Future Recommendations

This systematic review highlights key recommendations for promoting predictive maintenance (PdM) in the oil and gas industry:

- Adaptive AI Models: Develop hybrid AI models using transfer and reinforcement learning for better generalizability (Siraskar et al., 2023).
- Digital Twins & Edge Computing: Explore digital twins, edge computing, and blockchain for instant autonomous maintenance (Yahiaoui et al., 2025).
- Standardized Data Frameworks: Establish guidelines for data quality and interoperability (Azmi et al., 2024).
- AI Explainability: Improve model transparency with visualization tools and physics-based AI (Nagy et al., 2025).
- Validation Methods: Strengthen testing from simulations to field trials using uniform metrics (Arif et al., 2017).
- Cybersecurity: Secure IoT-based PdM systems versus intrusions.
- Organizational Adoption: Study change management and training to facilitate implementation.
- Sustainability Benefits: Quantify environmental benefits, such as lowered emissions and extended asset life (Onu et al., 2023).
- Edge AI Solutions: Optimize lightweight AI models for instant deployment on edge devices (Bellavista & Di Modica, 2024).
- Ethical Standards: Address bias, transparency, and responsible automation within AI-driven maintenance. Key themes include cybersecurity, sustainability, ethics, digitalization, standardization, and AI flexibility, all of which are critical to boosting PdM effectiveness in the sector.

Conclusion

This review analyzes Predictive Maintenance (PdM) in the oil and gas industry, focusing on its benefits, new technologies, challenges, and future prospects. AI-powered methods such as edge computing, IoT, and deep learning (e.g., LSTMs) have replaced older statistical approaches, helping lower costs and reduce downtime. Still, challenges endure, including poor data quality,

difficulties integrating old systems, model explainability, cybersecurity risks, and employee resistance. Possible solutions include standard data frameworks, better change management, blockchain, digital twins, and hybrid AI models. Dealing with these issues while supporting sustainability can make operations more resilient, efficient, and competitive. As the field rapidly evolves, further progress depends upon collaboration between researchers, practitioners, operators, and technology vendors. We welcome joint trials and cross-disciplinary consortia to help authenticate these insights within real-world environments and accelerate the practical impact of predictive upkeep in the sector.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Perplexity.ai to search for background information and verify factual details. The author(s) also used Grammarly to assist with language editing and proofreading. After using these tools, the author(s) reviewed and edited all content and take(s) full responsibility for the integrity and accuracy of the manuscript.

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