State-of-the-art artificial intelligence approaches for anomaly detection and remaining useful life prediction: a review

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ABSTRACT

Background: Accurate prediction of the remaining useful life (RUL) of assets is fundamental to the development of effective maintenance strategies and overall asset management. Despite significant advancements, there remains a notable gap in integrating fault detection and diagnostics (FDD) with RUL prediction models to create more comprehensive and accurate maintenance systems. One of the key challenges in this field is the limited ability of current models to generalize effectively across different types of equipment and varying operating conditions. This gap emphasizes the need for further research and innovation in developing robust and adaptable RUL prediction methodologies that can be applied broadly across diverse industrial scenarios.

Methodology: This review systematically evaluates the machine learning (ML) and deep learning (DL) techniques used for anomaly detection and RUL prediction, focusing on their efficacy and practical application. By adhering to the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) criteria, the review identifies and addresses the deficiencies in existing models. It explores a range of machine learning and deep learning methods, including probabilistic approaches, hybrid models that combine multiple machine learning techniques, and neural networks designed to handle large-scale time-series data. The review also examines the potential for synergy between machine learning models and FDD, aiming to enhance the precision of equipment monitoring and the early detection of defects. The challenges of data variability, the irregularity in equipment deterioration, and the interpretability of complex models are highlighted.

Results: The analysis reveals that while current machine learning and deep learning models have made considerable strides in predicting the RUL of assets, significant challenges remain, particularly in their ability to generalize across various equipment types and operational contexts. Hybrid models and neural networks have shown promise in improving the accuracy of RUL predictions, especially when managing large, complex datasets. However, the irregular nature of equipment wears and tear, coupled with data variability, continues to pose significant challenges. The review highlights the need for more robust and adaptable models that can not only predict

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RUL more accurately but also integrate seamlessly with FDD systems to provide a more holistic approach to maintenance.
Conclusion: This comprehensive review focusses on the need for continued research in developing more integrated, generalizable, and efficient predictive maintenance systems. By exploring the application of AI in virtual assistants, the review suggests promising avenues for extending asset longevity and optimizing maintenance schedules. While current models offer valuable insights, they must evolve to address the identified gaps in generalizability and model interpretability.

Subjects Artificial Intelligence, Data Mining and Machine Learning, Data Science, Neural Networks
Keywords Remaining useful life, Fault detection, Anomaly detection, Health management, Predictive maintenance, Prognostic health management, Maintenance strategy, Health index, Machine learning, Deep learning

INTRODUCTION

Remaining useful life (RUL) is an estimate of the amount of time a machinery or system is likely to operate before it requires repair or replacement. It is a critical component in predictive maintenance strategies, allowing for timely decision-making to prevent failures and optimize operational efficiency (*Seman et al., 2023*; *Wang et al., 2022*). RUL predictions can be derived from various approaches, including physics-based, statistical-based, data-driven or hybrid which combine two or more method together to forecast the lifespan of equipment (*Wang et al., 2022*). When the RUL reaches zero, it signifies that the system or equipment has attained its failure point, indicating the end of its operational life. At this stage, it can no longer fulfill its intended function effectively or safely (*Arunthavanathan et al., 2023*; *Zhang et al., 2021*).

In machine learning (ML), supervised learning methods and neural networks are commonly employed because of their capacity to manage extensive time-series data and extract pertinent features automatically for precise RUL prediction (*Wu, Ding & Huang, 2020*). *Martins, Vale & Maitelli (2015)* use conventional neural network (CNN) with an adaptive shrinkage processing mechanism to predict the operational lifespan of machinery before it requires maintenance or to be replaced. Long short-term memory (LSTM) been used to detect early failures in rotating machinery by analyzing vibration data and learning to identify fault patterns (*Lee & Chang, 2020*). These deep learning models are very effective at identifying complicated patterns in time-series data. In addition, fault detection and diagnosis (FDD) were used in engineering to identify, localize and often diagnose faults or abnormalities in systems. The FDD bases can be categorized in four different types; Model, data-driven, knowledge and statistic and hybrid based approaches (*Ozkat et al., 2023*; *Zhao et al., 2019*). *Martins, Vale & Maitelli (2015)* use model-based together with ML-based approaches, developed for fault detection and isolation (FDI), with studies exploring the combination of both to enhance FDI performance. A hybrid-based method combining multivariate empirical mode decomposition, fuzzy entropy and an optimized support vector machine (SVM) for wind energy converter fault diagnosis, achieving high diagnostic accuracy under varying conditions (*Zhang et al., 2023c*). *Soualhi et al. (2022)* and *Fong et al. (2023)* use fault detection sensor in chiller plants, employing a hybrid algorithm that integrates ML with pattern recognition for effective fault diagnosis.

Despite notable progress in the estimation of RUL and FDD, there exist various research insufficiencies that hinder the optimal integration of these methodologies into holistic maintenance plans (*Liao & Tian, 2012*). While deep learning models generally produce very accurate findings, their complexity and lack of interpretability might make it difficult to acquire trust and approval from maintenance personnel. Similarly, classic machine learning approaches can have interpretability issues, making it more difficult to understand the reasoning behind forecasts (*Hu et al., 2023*). There remains an insufficiency of research to concentrate integration with all four main topics identified earlier to address the knowledge gap. Such interest like factor contributes the extending of RUL from anomaly detection with artificial intelligence was far from complete. The potential to considerably extend the lifespan of equipment through strategies that go beyond traditional maintenance, such as Artificial Intelligence (AI) and FDD, is still a subject of ongoing exploration and development. This discipline has not yet reached maturity, as there are still a multitude of challenges and uncertainties that must be resolved.

A foundation for future research and innovation in this critical domain is established by systematic reviews, which are instrumental in identifying these knowledge gaps and advancing our understanding. While existing review articles on anomaly detection and RUL prediction offer valuable insights, they present specific limitations that our article addresses. For example, the published review by *Zhang et al. (2023a)* concentrates exclusively on methodologies that are utilized in mechanical systems, without investigating broader industrial applications or integration with FDD. In the same aspect, *Kumar et al. (2024)* investigates rotating machinery techniques, but it does not provide any coverage of advanced AI-based methods or their generalizability beyond this field. In a different review, the practical integration of these techniques with FDD systems is not addressed, despite the fact that it emphasizes deep learning approaches (*Serradilla et al., 2022*). Moreover, *Ferreira & Gonçalves (2022)* emphasizes the practical applications of machine learning, but it fails to address the hybrid approaches and real-world obstacles associated with integrating these methods into FDD applications. Conversely, our article addresses these deficiencies by integrating RUL prediction with FDD, thereby encompassing a diverse array of industries and advocating for the practical application of hybrid and AI-driven strategies. Our research addresses real-world operational challenges and offers actionable insights for both academia and industry by emphasizing the synergy between physical and data-driven models. Our review is positioned as a substantial contribution that complements and expands the existing *corpus* of literature as a result of this comprehensive perspective.

In light of the challenges and opportunities discussed, this review explores the latest technologies revolutionizing predictive maintenance, with a focus on the critical concept of RUL. By exploring with these methodologies, the review seeks to bridges the gap between foundational principles of RUL estimation and the innovative, data-driven strategies that are transforming the field. This exploration not only highlights the technical advancements but also emphasizes their practical implications, aiming to provide actionable insights for industry professional, educators and policymakers. Finally, our effort aims to influence current maintenance practices, set new standards for industrial operations, and drive the creation of curricula that include the most recent advances in ML and predictive maintenance. In addition, it promotes a better knowledge of RUL and its critical role in improving efficiency, sustainability, and competitiveness across sectors.

MOTIVATION AND SIGNIFICANCE OF STUDY

This study is addressing several key gaps identified from the existing literature. Inadequate study on integration between anomaly detection and RUL estimation. However, as we looked through the current research, we noticed a few important things missing as summarized in Table 1. One of the biggest gaps is that most studies look at anomaly detection and RUL prediction as separate problems. The review conducted by *Zhang et al. (2023a)* offers a robust methodological framework for RUL estimation in mechanical systems, yet confines its analysis to particular sectors, such as rotating machinery. It neglects to consider broader industrial applicability or the practical integration with FDD systems, which are paramount for effective real-world implementation. Similarly, *Kumar et al. (2024)* stresses the value of signal centric and statistical techniques for rotating elements; however, it overlooks the integration of modern artificial intelligence frameworks, such as deep learning, transfer learning, or hybrid designs, that are progressively significant in current industrial applications. Very few try to bring them together into a single, connected approach yet doing so could lead to much more accurate and responsive maintenance strategies. Without addressing their synergistic potential when integrated. The absence of comparative evaluation across several industrial fields, there is limited literature evaluating cross industry for generalizability and adaptability of ML models for asset health monitoring. There is also a lot of potential in hybrid models that combine physical understanding of how machines fail with powerful data-driven AI methods. These can offer the best of both worlds: they are grounded in science, but flexible enough to handle real-world noise and complexity. But despite this promise, we found that these approaches haven't been explored as much as they should be.

The review conducted by *Rana (2025)* concentrates on the predictive maintenance and fault detection in electrical power systems that are driven by AI. Although it exhibits promising developments, its purview is limited to smart grids and does not account for the integration with RUL estimation or cross-sector adaptability, which are both critical for generalizable asset health monitoring. Similarly, *Han et al. (2024)* do not discuss unified frameworks that combine AD with RUL in dynamic industrial contexts, despite their comprehensive survey of fault diagnosis under varying operational conditions. *Neupane et al. (2025)* provide a thorough examination of machine learning for the detection of machinery faults. Nevertheless, they devote insufficient attention to hybrid modelling methods and the difficulties associated with the implementation of integrated systems across multiple domains.

Table 1 Overview of key review articles highlighting gaps in anomaly detection, fault diagnosis, and RUL estimation.

References	Focus area	Methodologies	Industrial domain	Key limitations/Gaps
Zhang et al. (2023a)	RUL estimation frameworks	Traditional ML methods	Rotating machinery	Lacks integration with FDD systems; sector-specific analysis
Kumar et al. (2024)	Signal-based and statistical techniques for diagnostics	Classical statistical methods	Rotating elements	Ignores modern AI (deep learning, transfer learning); lacks hybrid integration
Rana (2025)	Predictive maintenance and fault detection	AI for smart grid diagnostics	Electrical power systems	Limited to smart grids; does not integrate with RUL or generalize across sectors
Han et al. (2024)	Fault diagnosis under dynamic conditions	Fault diagnosis survey	General industrial systems	No discussion of unified AD-RUL frameworks
Neupane et al. (2025)	ML for machinery fault detection	Machine learning	Multiple sectors (generalized)	Limited coverage of hybrid modeling; lacks implementation strategies
Serradilla et al. (2022)	Deep learning for prognostics	Deep learning models	Manufacturing systems	Overlooks DL limitations (interpretability, data dependency); lacks FDD integration
Ferreira & Gonçalves (2022)	ML applications in various sectors	General ML approaches	Cross-sectoral	Superficial coverage of hybrid models; ignores imbalanced/scarce data challenges

Furthermore, there is a lack of comparative evaluations across various industries. There is still a lack of research on the adaptability and generalizability of machine learning models for asset health surveillance. Hybrid models that integrate the adaptability of data-driven AI methods with the physical principles of machine degradation demonstrate significant potential. These models maintain the adaptability necessary to manage chaotic, imbalanced, or limited failure data, while also providing the scientific rigour of traditional methods. However, these hybrid strategies are rarely investigated in a unified and cross-industry context, despite their potential.

In addition, the review by *Serradilla et al. (2022)* accentuates deep learning models, particularly in the realm of prognostics for manufacturing systems. Nevertheless, it does not critically evaluate the limitations associated with deep learning concerning data dependency, interpretability, or integration with fault detection frameworks. Concurrently, *Ferreira & Gonçalves (2022)* provide a practical overview of machine learning applications across diverse sectors; however, they lack a comprehensive analysis of hybrid models that amalgamate physical and data-driven methodologies, and they do not confront the challenges posed by imbalanced, noisy, or scarce failure data.

The exhaustive and integrative focus on the convergence of three critical components in predictive maintenance anomaly detection (AD), RUL estimation, and FDD distinguishes this study from previous reviews. In contrast to previous research, which has tended to investigate these components in isolation or with minimal overlap, this review systematically addresses their synergistic integration, which is crucial for the development of practicable and reliable predictive maintenance frameworks. This study not only categorizes advanced AI approaches including deep learning, ensemble methods, and hybrid models but also critically analyzes how these can be effectively integrated with FDD systems and applied in real-world industrial contexts, in contrast to earlier reviews that primarily concentrate on specific methodologies (*e.g.*, deep learning or signal-based analysis) or narrow industrial sectors (such as rotating machinery or smart grids). Additionally, this review broadens the scope by assessing the cross-sector adaptability of these integrated approaches across a variety of domains, such as aerospace, energy, manufacturing, and medical equipment. This comprehensive applicability directly addresses a critical limitation in the existing literature, which frequently lacks generalizability and overlooks the complexities inherent in diverse operational contexts. By offering a holistic perspective that bridges methodological advancements with authentic deployment scenarios, this research fills a significant gap and lays the groundwork for the next generation of intelligent, industry agnostic maintenance systems capable of adapting across heterogeneous implementation ecosystems.

METHODOLOGY

Search terms identification

The concept of asset life cycle encompasses a broad spectrum of keywords that are crucial for understanding its behavior throughout its expected lifespan. Selecting the right keyword is essential to find appropriate academic articles, as keywords serve as the primary tools for indexing and retrieving research articles in databases. To reflect the main objectives of this review, the keywords were chosen based on four main topics: Equipment Lifespan Prediction, FDD, Prognostics and Maintenance Management, and Machine Learning (Table 2). The selected keywords collectively embody the essence of a article, allowing for the targeted identification of relevant studies without the need to filter through irrelevant material. This includes a wide range of approaches and perspectives, allowing for a thorough examination of the junction of FDD, RUL prediction, maintenance management, and AI.

Research questions

In this study, we created a table of research questions to address significant topics and gaps discovered in the field of RUL, FDD and predictive maintenance (Table 3). By addressing these research questions, the study aims to contribute and improve understanding the concepts and applicable models for equipment reliability and maintenance.

Identification for reporting guideline

Selecting an appropriate research framework before screening research article is a first step in the systematic literature review process, thereby ensuring only the most relevant and high-quality studies are selected. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique was selected because of its suitability to the method applied in these studies and also widely adopted by high-impact journals and institutions (*Oumaima, Benabdellah & Zellou, 2023*). Thus, it facilitating the peer-review and publication processes (*Sewell, Schellinger & Bloss, 2023*). PRISMA employs a structured methodology that includes the following steps: first, the identification of pertinent studies through the use of predefined keywords, followed by the screening of

Table 2 **Research main category and its common keyword.**

Topic	Keywords
Equipment life span prediction	Remaining useful life, life cycle analysis, life span, survival analysis, weibull distribution, reliability engineering, circular economy, life data analysis and time-to-failure analysis
Fault detection and diagnosis (FDD)	Fault detection, anomaly detection, sensor data analysis, pattern recognition, performance degradation analysis, condition monitoring, root cause analysis and fault tolerance system
Prognostic and maintenance management	Health management, preventive maintenance, corrective maintenance, prognostic/predictive maintenance, work order management, asset management, maintenance strategy, health index, reliability-centered maintenance, total productive maintenance, prognostic health management,
Artificial intelligence (AI)	Machine learning, deep learning, neural networks, natural language processing, cognitive computing and artificial intelligence

Table 3 **Table of research questions.**

No.	Research questions
RQ1	What are the range of studies associated with predicting the RUL of equipment?
RQ2	How can hybrid models combining physical and data-driven methods improve RUL prediction for complex systems?
RQ3	What are the comparative accuracies between Artificial Intelligence approaches in RUL prediction?
RQ4	How effective are FDD approaches in detecting early indicators of equipment failure?
RQ5	What challenges are associated with the implementation of sensor technology for fault detection?
RQ6	What are the most effective methods use for monitoring condition in the predictive maintenance and how can root cause analysis be effectively determined in fault tolerance systems?
RQ7	How do life cycle analysis and survival analysis frameworks influence the selection of maintenance strategies and health indices in reliability driven maintenance?

articles to eliminate duplicates and irrelevant research, the assessment of the eligibility of studies based on specific criteria, the systematic collection and organization of data, and the final visualization of the findings through research maps and summaries (*Zamzam et al., 2021*). This process, which is facilitated by a 27-item checklist and 16 sub-items, ensures that only the most relevant and reliable studies are included, thereby facilitating reproducibility and peer review (*Page et al., 2021*) and. It also helps maintain high quality and transparency in the review.

Search strategy and data collection

The selection process prioritizes studies that employ machine learning techniques for prognostic anomaly detection and predictive maintenance. Using only the most relevant studies to enhances the quality data and focusing on each research findings (*PRISMA 2020 Checklist, 2020*). The inclusion and exclusion criteria as tabulated in studies were meticulously selected to ensure that the review concentrates on pertinent, high-quality studies that are consistent with its objectives (Table 4). In order to guarantee current, accessible, and original contributions, only research articles published in English between 2010 and 2024 were considered. Non-peer-reviewed sources, including conference articles, case studies, book chapters, and guidelines, were excluded due to their infrequent use of comprehensive data analysis, standardized peer-review processes, or detailed methodologies. To prevent the potential for language barriers that could influence the

Table 4 **Inclusion and exclusion studies.**

Inclusion and exclusion criterion

Criterion	Inclusion	Exclusion
Sources	Research article	Review article, conference article, proceedings article, case study, chapter in book, book section, encyclopedia, early access, guideline and other sources
Language	English	Non-English
Period	Between 2010 to 2024	Before 2010
Selection journal	(1) Focus on the using of method to find remaining useful life for all kind of equipment at various ages and condition or (2) Focus on the use of machine learning algorithm in prognosis either for faulty detection or predictive maintenance	Other than related equipment remaining useful life, prognosis, predictive maintenance and machine learning algorithm

interpretation of technical content, non-English studies were excluded. Additionally, publications prior to 2010 were omitted in order to emphasize more recent developments in the field. In order to maintain relevance and assure alignment with the review's scope, articles that were unrelated to predictive maintenance, FDD, machine learning in prognostics, or RUL were excluded. These criteria establish a precise framework for the identification of studies that contribute to the advancement of knowledge in this critical field while simultaneously preserving rigor and focus. The keywords were then strategically combined into a single search string using Boolean operators (*e.g.*, AND, OR) to ensure a comprehensive yet targeted search across multiple databases (Table 4). This approach enhances the search process by including all relevant studies while minimizing irrelevant results, providing a robust foundation for the systematic review. Data was subtracted from eight major databases; ScienceDirect, Scopus, IEEE Xplore, Web of Science, Emerald, MEDLINE Complete, Dimensions, and Springer Link from year 2010 until 2024. Google Scholar was excluded to avoid duplicate articles. Articles are initially selected based on relevance keywords and then screened for quality.

Quality assessment

A total 27 checklist item is divided into five main categories; preparation data, methods to cover RUL criteria for study selection, data collection, bias assessment, and results findings (*Oumaima, Benabdellah & Zellou, 2023*; *Page et al., 2021*). Figure 1 and Table 5 provide an overview of the search results at different stages of the screening process. A total of 27,507 journal articles were retrieved from eight major databases. After removing 652 duplicate records and 10,410 records under exclusion criteria, 16,445 records were screened. From these, 10,678 records were excluded, leaving 5,767 articles for further screening. Subsequently, 786 reports were sought for retrieval, with 522 reports not retrieved. This left 220 reports for eligibility assessment. During this assessment, 85 reports were excluded for not being related to engineering (50), asset management (23), or prediction of asset behavior (12). Ultimately, 22 studies were included in the review, emphasizing the importance of evaluating the quality of each study to mitigate the risk of bias.

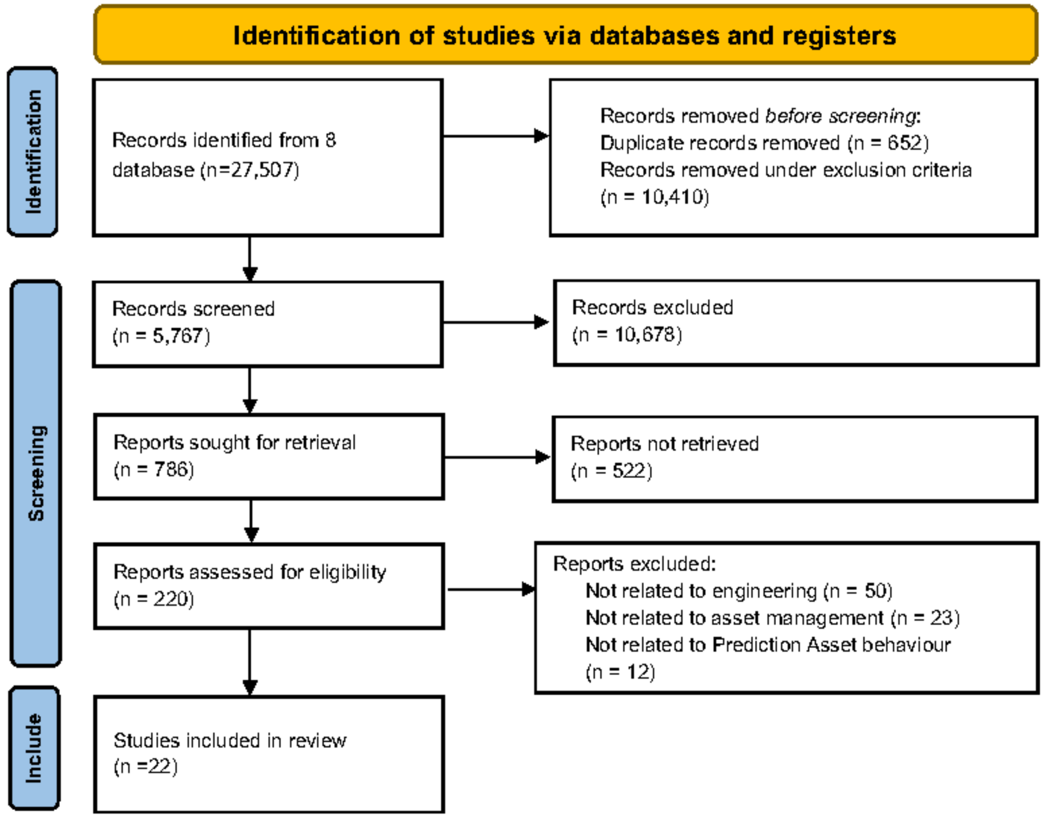

Figure 1 PRISMA reporting guideline identification, screening, and inclusion process from 27,507 to 22 selected articles. The diagram is a PRISMA flowchart. It describes the process from identification, screening, and final selection studies in a systematic review from an initial pool of records.

Full-size DOI: 10.7717/peerj-cs.3056/fig-1

Table 5 RUL Boolean keyword search result across eight major databases.

Search strings	Science Direct	Scopus	IEEE Explore	WoS	Emerald	Medline complete	Dimensions	Springer Link
(“Remaining useful life”) AND (“Fault detection” OR “Anomaly detection”) AND (“Machine Learning”)	731	31	44	31	25	327	6,344	268
(“Remaining Useful life”) AND (“prognostic health management” OR “Predictive Maintenance”) AND (“Machine learning”)	717	99	53	95	37	169	3,796	216
(“Machine Learning”) AND (“health management” OR “asset management” OR “maintenance strategy”) AND (“Remaining Useful Life”)	1,099	126	231	113	45	245	6,549	300
(“Machine Learning”) AND (“Health Index” OR “Predictive Maintenance”) AND (“Remaining useful life”)	814	101	69	100	39	192	4,253	247
Total including duplicate	3,361	357	397	340	146	933	20,942	1,031
Subtotal including duplicate	27,507							
Total selected area after quality assessment	22							

RESULT

Main findings

Table 6 presents a summary of 22 research articles on RUL, selected using the PRISMA framework. These studies span various industries and systematically categorized into condition based, asset specific, risk-based, and maintenance-based approaches. Among these, condition-based maintenance combined with predictive analytics emerged as the most prominent approach in the reviewed literature, with over 60% of the studies focusing on this topic. For example, *Aydemir & Acar (2020)* introduced anomaly-triggered RUL estimation method to improve detection during health operation anomalies in aerospace and manufacturing. However, the model's generalizability across a variety of operating environments is restricted by its dependence on a singular anomaly detection method, the Cumulative Sum Control Chart (CUSUM), which is a statistical tool used for monitoring changes in processes over time.

Wang et al. (2018) use nonlinear model with first-time hitting detection approach to predict degradation levels under imperfect maintenance in heavy industries. Although this method offers higher accuracy, it heavily depends on stochastic process assumptions, making it unsuitable for broader applications. Similarly *Zhang et al. (2020)* proposed a novel iterative standby system lifetime (SSL) estimation method that integrates both operational and storage degradation processes, offering comprehensive lifetime prediction for manufacturing and aerospace sectors. Although innovative, its iterative approach is not suitable for non-linear degradation models.

Another major topic involves deep learning applications for predictive maintenance. *Zheng, Liao & Zhu (2023)* developed a two-stage model using Robust-ResNet for fault detection and RUL prediction, providing improved classification accuracy across four degradation stages. However, accelerated life testing data used in their study may not fully represent natural degradation patterns. Similarly, *Cheng et al. (2021)* implemented a transferable convolutional neural network (TCNN) for RUL prediction in bearings, showcasing advancements in feature extraction and transfer learning across multiple failure behaviors In aerospace engineering. *Ture et al. (2024)* introduced a stacking ensemble learning method for deep learning-based anomaly detection, leveraging multiple regression algorithms to enhance predictive robustness.

In the context of data-driven approaches, several studies highlighted innovations in health monitoring and feature extraction. *de Pater & Mitici (2023)* expand health indicator functions with similarity based matching methods to predict unhealthy stages of aircraft engines with minimal failure data. *Rosero, Silva & Ribeiro (2022)* presented a novel classification methodology using HI to segregate health degradation into two stages, improving failure detection in aerospace systems. Similarly, *Duan et al. (2023)* applied principal component analysis (PCA) for dimensionality reduction while integrating similarity metrics to construct health indicators and monitor degradation trends effectively. However, the limited exploration of similarity metrics suggests room for further improvement. *Arunthavanathan et al. (2023)* established a self-learning fault detection framework using one-class support vector machines (OC-SVM) and neural network-based

Table 6 Existing literature on RUL from various field of industry.

Author (Region)	Dataset	Topic		Sector	Predictive method	Novelty	Gap and research opportunities
		Condition base	Asset specific				
Aydemir & Acar (2020) Turkey	Public data	✓		Aircraft engine	Anomaly triggered RUL estimation	Address ill define RUL during health operation	Applicability to varying operating conditions only focuses using the CUSUM control chart for anomaly detection.
Wang et al. (2018) China	Private data	✓		Draught fan	Nonlinear model and first hitting time to determine degradation level	RUL prediction systems under imperfect maintenance	Model Rely heavily on stochastic process assumption and not universally applicable to all types of industrial equipment
de Pater & Mitici (2023) Netherland	Public data		✓	Aircraft engine	Health indicator development and similarity base matching during unhealthy stages	Health state division equipment with few failure	Reliance on the limitation for failure data. Due to preventive maintenance, there are very few labeled samples available for training
Zheng, Liao & Zhu (2023) China	Private & public data	✓		Internal Gear Pump	Robust-ResNet, faulty detection and RUL in Four Stages Classifiers	Two-stage deep learning model for fault detection and RUL	Accelerated life testing to gather data, may not represent natural degradation patterns
Zhang et al. (2020) China	Private data	✓		Logistic and supply chain, storage parts	General iterative method for standby system lifetime (SSL) estimation,	Combine storage degradation and operational degradation processes spare parts in the lifetime estimation and standby systems	Extending iterative method to non-linear degradation model
Pei et al. (2019) China	Private data	✓		Gyroscope	Constructs a nonlinear degradation model	Degradation model considering bivariate time scales	Gap in research on adaptive estimation methods on multiple model and parameters
Liu et al. (2020) China	Private data		✓	Marine engineering (Subsea Valve actuator)	Dynamic Bayesian networks, physical models (Fatigue Crack Growth and Corrosion model)	Address structural degradation underwater structure and stress distribution.	Further refine fatigue crack growth models in extreme environmental conditions and material heterogeneity
Cheng et al. (2021) China	Private data	✓		Rolling bearings	Convolutional neural network on feature extraction, transfer learning, performance matrices	RUL prediction bearings under multiple failure behaviors	Present models struggle with inconsistent feature distributions caused by different bearing failure modes, impact the generalization ability of the models
Ture et al. (2024) Turkey	Public data	✓		Turbofan engine	Anomalies detection using deep learning method, data-driven approach	RUL prediction, Stacking Ensemble Learning and integrates the strengths of multiple regression algorithms	The model does not explicitly account for external factors like environmental conditions or variable operational scenarios that could impact RUL
Rosero, Silva & Ribeiro (2022) Portugal	Private data	✓		Aircraft cooling system	Health indicator for failure pattern identification	Novel classification methodology to segregate between two health degradation stages	Adaptive HI prediction by further extending study method evolving asset condition and operating environment. HI base fault detection and isolation classification matrix
Arunthavanathan et al. (2023) Canada	Private data	✓		Process industries, manufacturing	One-class support vector machine, neural network permutation algorithm	Self-learning fault detected capability	Fault to failure transition predominantly assume linear degradation model

(Continued)

Table 6 (continued)

Author (Region)	Dataset	Topic		Sector	Predictive method	Novelty	Gap and research opportunities
		Condition base	Asset specific				
Carroll et al. (2019) UK	Private data	✓		Wind turbine	Supervisory control and data acquisition (SCADA), high-frequency vibration data	Integration of SCADA and high-frequency vibration data for failure prediction. Focus on specific failure mode to achieve tailored prediction	Due to complexity of continuous prediction, The RUL is not estimated as a precise number of hours, days, or months. Instead, it is predicted within predefined time windows.
Biondi, Sand & Harjunkoski (2017) Germany	Private data		✓	Processing equipment	Mixed integer linear programming (MILP), state task network (STN) representation	Integrated maintenance and production scheduling problem using RUL as a singular indicator on health asset	Multiple feature extraction techniques need, particularly for complex and noisy data
Sayyad et al. (2021) India	Private data	✓		Milling machine	Multi sensor fusion, denoising, signal transformation and predictive model	Systematic integration of AI techniques with multi-sensor data fusion on real-time data	Develop frameworks for effective multi-sensor data integration, noise reduction for data processing
Wang & Mamo (2019) Taiwan	Public data	✓		Ball bearing of rotating machinery	ML model (Support Vector regression, Random Forest), Anomaly detection and optimization technique	Introduce novel element for confidence interval using Jackknife method	Dataset variability from a controlled environment with predefined operational conditions. This limits its applicability to real-world scenario
Lee, Kim & Lee (2023) South Korea	Private data	✓		Forklift	Multi-faceted methodology combining advanced sensor data analysis and ML Model	Comprehensive Feature Engineering for Forklift Failure Prediction, Data Augmentation Technique	Imbalanced datasets from left, center, and right weight conditions may lead to biased predictions
Duan et al. (2023) China, USA	Public data	✓		Aircraft engine	Principal Component Analysis (PCA) and Similarity method	Integrates PCA for dimensionality reduction and similarity-based methods (Manhattan distance) for health indicator	Limitation to exploration of distance metrics for similarity calculation, use PCA to construct health indicator to represent degradation trends
Ma, Xu & Yang (2023) Malaysia, China	Private data	✓		Medical equipment	Fault diagnosis, categorization and prediction, experimental validation, ABC optimization algorithm	Life cycle management framework of early, middle and late phases symptom	The model requires extensive data on historical failures and performance, which may not be readily available for all types of equipment
Solís-Martín, Galán-Páez & Borrego-Díaz (2023) Spain	Private data public data			Turbojet engine, fast charging battery, bearing	XAI method, matrix of evaluation, quantitative proxies	Introduced quantitative metric to measure time-dependence in explainable AI in evaluating explainability for time-series regression tasks	Limited research available in PHM highlights the need for tailored methods to improve model interpretability and applicability
Fan, Nowaczyk & Rögnvaldsson (2020) Sweden	Public data	✓		Turbojet engine	Transfer learning	Develop COSMO for RUL prediction in dynamic and variable conditions	To enhance transfer learning for unseen operating conditions with COSMO model to handle complex data
Wang & Zhao (2023) UK	Public data		✓	Turbojet engine	Prediction for multiple condition of complex machinery, three stage feature selection	Groups sensor data from various operating conditions using k-medoids clustering to uncover patterns related to a specific operational state that traditional methods might miss	Effective feature selection for reducing model complexity
Liao & Tian (2012) USA, Canada	Private data	✓		Ball beating of rotating machinery	Bayesian approach, accelerated degradation testing (ADT)	Handling time-varying conditions and adaptability to nonlinear model	Advanced degradation modeling, handling more complex operating conditions, incorporating with human factors

permutation algorithms, offering automated detection for fault progression. *Wang & Mamo (2019)* combined support vector regression and random forest models to introduce confidence intervals using the jackknife method, strengthening anomaly detection in machinery. While innovative, the reliance on controlled environment data limits real-world applicability. Similarly, *Wang & Zhao (2023)* presented a three-stage feature selection method with k-medoids clustering, uncovering operational patterns for complex machinery systems, yet their framework remains complex for large-scale applications. *Sayyad et al. (2021)* applied multi-sensor fusion techniques integrated with denoising and signal transformation to provide robust real-time predictive models for manufacturing applications. However, their framework requires further exploration for effective noise reduction and data integration.

Statistical and optimization models were also explored across multiple studies. *Liao & Tian (2012)* applied Bayesian approaches in combination with accelerated degradation testing (ADT) to handle time-varying conditions and improve adaptability in manufacturing and transportation sectors. Meanwhile, *Carroll et al. (2019)* integrate SCADA data with high-frequency vibration signals for predictive analysis of renewable energy systems, enhancing fault detection in wind turbines. *Biondi, Sand & Harjunkoski (2017)* introduced mixed-integer linear programming (MILP) and state task network (STN) models, offering a structured approach to handling noisy and complex datasets in renewable energy. *Ma, Xu & Yang (2023)* designed the Fine Life Cycle Prediction System for Failure of Medical Equipment to predict failures in medical devices in a structured way. The system comprises the Life Cycle Management Module, Status Detection, Fault Diagnosis and Fault Prediction Module. The module is distinguished by its integration with AI method to facilitate proactive maintenance approaches in healthcare.

Solís-Martín, Galán-Páez & Borrego-Díaz (2023) explores the predictive maintenance (PdM) application, predominantly on the Explanation AI (XAI) for prognostics and health management (PHM). The algorithm was applied to Grad-CAM for time-series regression by introducing time and feature dependencies addresses regression, which is inherently harder to explain than classification tasks. *Fan, Nowaczyk & Rögnvaldsson (2020)* and *Wang & Zhao (2023)* has enhanced PdM frameworks for complex machinery by introducing advanced methodologies, the former utilizes a feature representation-based transfer learning (TL) approach with consensus self-organizing models (COSMO) to address maintenance planning and operational issues in turbofan systems, while the latter proposes a three-stage feature selection framework combined with DL models to improve accuracy prediction under variable operating conditions. Meanwhile, *Liao & Tian (2012)* address prediction of single units under time-varying operating conditions using an advanced Bayesian updating methodology for RUL, which accommodates both linear and nonlinear degradation-stress dynamics, providing solutions for stochastic operational scenarios to facilitate real-time assessments while mitigate uncertainties in varying conditions.

The reviewed literature highlighted several challenges, with a major issue being the scarcity of failure data due to preventive maintenance practices, as noted by *de Pater & Mitici (2023)* and *Ma, Xu & Yang (2023)* has discover training models difficulty and requires better techniques to generate or augment data. *Liu et al. (2020)* and *Ture et al. (2024)* show that absence of environmental factors in models such as extreme conditions and operational variability are often ignored limits model accuracy in actual scenarios. Scaling models to new industries or unseen data remains difficult. *Fan, Nowaczyk & Rögnvaldsson (2020)* and *Cheng et al. (2021)* highlighted transfer learning methods struggle to adapt to different operating conditions or large datasets, reducing their effectiveness. Many models still rely on linear degradation assumptions, which oversimplify real-world trends. *Pei et al. (2019)*, *Zhang et al. (2020)* and *Arunthavanathan et al. (2023)* argue for adaptive approaches that can handle non-linear and multi-phase degradation more effectively. Imbalanced and noisy datasets impact model performance. Studies such as *Biondi, Sand & Harjunkoski (2017)*, *Wang & Mamo (2019)* and *Lee, Kim & Lee (2023)* show that biased predictions occur when data is incomplete or unbalanced.

Overview of frequently used datasets in RUL and fault diagnosis studies

In this review, the datasets analyzed are classified as publicly available, which are accessible for academic and research purposes, or private and proprietary datasets, which are typically collected in-house and often specific to industrial settings. The quality and characteristics of these datasets play a critical role in influencing model training, validation, and performance evaluation.

Table 7 presents an exhaustive summary of publicly accessible datasets that are frequently employed in research pertinent to condition-based RUL forecasting. These datasets serve as the cornerstone for the development, training, and benchmarking of data-driven prognostic models across a multitude of engineering domains. The table encompasses datasets from various sectors, including aerospace, battery systems, and rotating machinery. For example, the NASA C-MAPSS dataset, which simulates the degradation of turbofan engines, is often utilized in aerospace RUL investigations and comprises measurements such as pressure, temperature, fan speed, and fuel-air ratio across an array of fault scenarios. The N-CMAPSS dataset enhances this with more intricate degradation trajectories and multivariate conditions, rendering it particularly suitable for deep learning and transfer learning frameworks. Likewise, the NASA Battery Usage dataset and the MIT Battery Degradation dataset (*Severson et al., 2019*) are employed to examine battery cycle longevity by documenting charge/discharge patterns, voltage, current, temperature, and internal resistance. Within the domain of rotating machinery, datasets such as the IMS Bearing Dataset, FEMTO-ST, and PRONOSTIA provide high-resolution vibration data amassed under controlled experimental conditions and are extensively utilized for bearing fault detection and degradation analysis. Similarly with Gearbox Dataset provided from PHM on year 2009 provides vibration and temperature data for analyzing degradation on rotating gearbox.

Each dataset delineated in table is accompanied by its respective access link, thereby facilitating other researchers in replicating or extending previous experiments. Nonetheless, certain limitations are acknowledged. A considerable number of the datasets are generated through accelerated life testing or controlled laboratory conditions, which

Table 7 Publicly available physical dataset for condition base RUL.

Public data	Description	Category	Dataset	Measurement parameter	Accessible link
NASA jet engine simulated data	Commercial modular aero-propulsion system simulation (C-MAPSS)	Turbofan engine degradation simulation	Simulated data combination operation and fault mode	Temperature, pressure, fan speed, coolant bleed, fuel-air ratio	https://data.nasa.gov/dataset/c-mapss-aircraft-engine-simulator-data
NASA jet engine simulated data	Commercial modular aero-propulsion system simulation (C-MAPSS)	Turbofan engine degradation simulation	Run to failure trajectories	Fuel flow, fan speed, temperature, pressure, fan flow	https://www.nasa.gov/content/prognostics-center-of-excellence-data-set-repository
PHM gearbox dataset	Generic industrial gearbox (Year 2009)	Rotating machinery	Gearbox degradation under realistic operating conditions	Vibration, temperature, speed, torque	https://phmsociety.org/public-data-sets/
NASA randomized battery usage	Battery usage	Battery systems	State of health (SOH)	Voltage, current, temperature over charge/discharge cycles	https://www.nasa.gov/content/prognostics-center-of-excellence-data-set-repository
MIT battery degradation dataset	Fast-charging battery dataset (Severson et al.)	Batteries systems	Fast charge durability	SOC, internal resistance, temperature, charge profile	https://data.matr.io/1/projects/5c48dd2bc625d700019f3204
FEMTO bearing	PRONOSTIA	Rotating machine—bearings	Run to failure bearings	Vibration, accelerometer, bearing degradation	https://www.nasa.gov/intelligent-systems-division/discovery-and-systems-health/pcoe/pcoe-data-set-repository/

may not entirely capture the intricacies of real-world operational environments. Studies such as those by *Ma, Xu & Yang (2023)* and *de Pater & Mitici (2023)* acknowledge the limitations imposed by insufficient failure data particularly due to widespread preventive maintenance practices that prevent systems from running to failure. Additionally, they frequently lack contextual features such as ambient temperature variations, user variability, or unstructured anomalies. Furthermore, naturally degraded datasets those acquired from actual equipment over extended periods are notably scarce. This limitation undermines the external validity of models trained exclusively on synthetic or laboratory-derived data. Consequently, while these datasets are indispensable for methodological progress, there is a growing exigency for more comprehensive and diverse datasets that more accurately reflect operational uncertainties and realistic degradation behaviors.

Distribution of publication by component and years of study

This VOSviewer map illustrates the interconnected themes and concepts in the field RUL prediction, maintenance strategies, and related technologies (Fig. 2). An analysis using bibliometric mapping for review article enhances the quality of analysis by providing clear visual maps of keyword occurrences, temporal trend, cluster analysis and evolution in

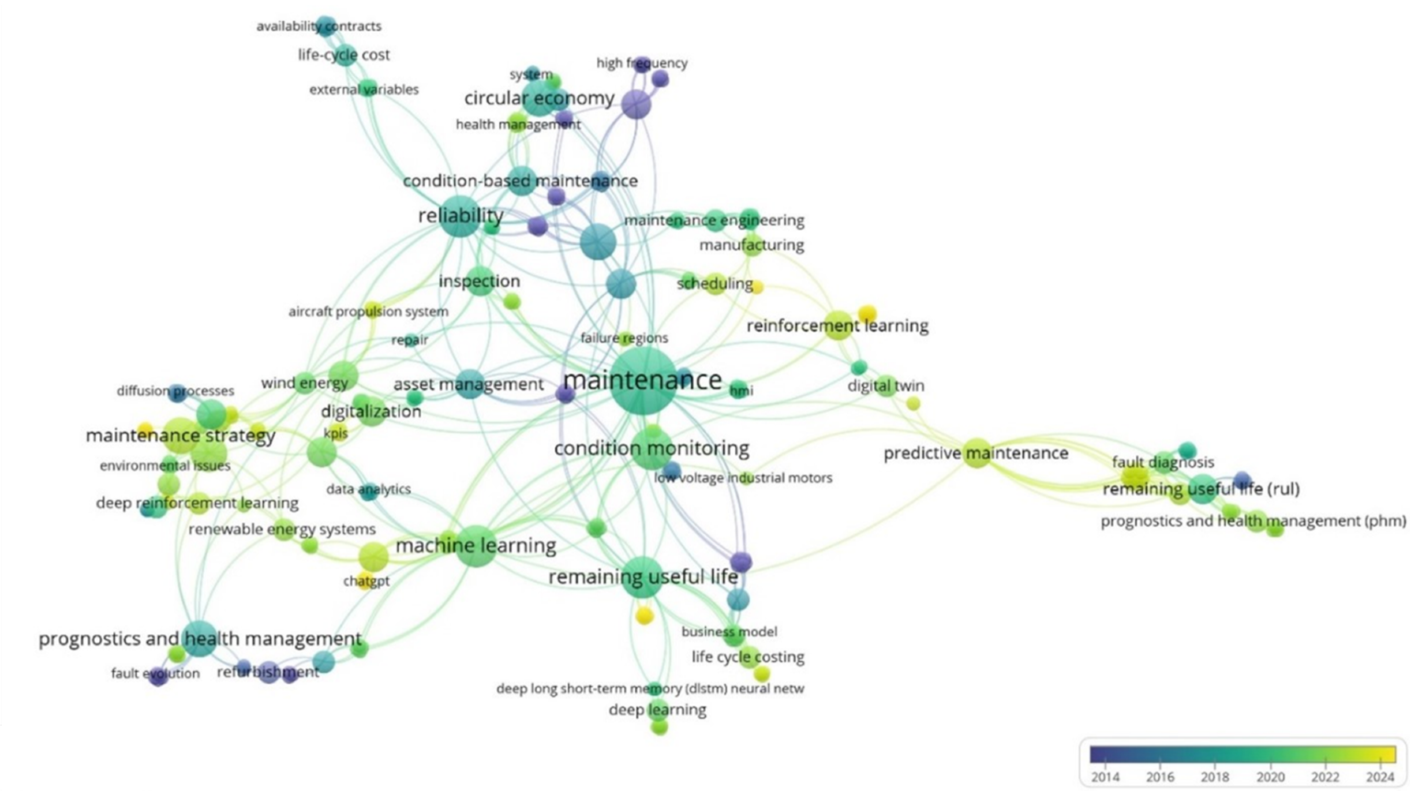

Figure 2 **Development of RUL key concepts since 2014.** Nodes: represent the key features of the map. Lines: lines between nodes represent the strength of relationships. Color: the development and prominence of concepts over time (2014–2024).

Full-size DOI: 10.7717/peerj-cs.3056/fig-2

research interest (*Nobanee et al., 2021*). This allows authors to identify knowledge gaps, emerging themes, and research trajectories effectively. The frequency and quantity of publications associated with each concept are indicated by the size of the nodes, which represent key terms (*van Eck & Waltman, 2010*). The larger the node, the more publications are available online. The intensity of the relationships between nodes is reflected in the links between them, with closer distances indicating stronger connections (*Nees Jan & Waltman, 2014*). To emphasize the publication year and the intensity of their association, the links' thickness and colors are used.

The map has revealed significant trends over the past decade. The frequency of publications on RUL experienced a significant increase between 2019 and 2022, which is indicative of the increasing interest in predictive maintenance applications. From 2021, there was a significant increase in the study of machine learning, with a particular emphasis on its application in maintenance optimization. In the same vein, defect diagnosis gained prominence in 2020. Nevertheless, the map suggests that there is limited connectivity between these critical areas, despite the growth in these individual domains. This suggests an opportunity to further investigate their integration, such as the use of machine learning for fault diagnosis in RUL prediction. This emphasizes the necessity of

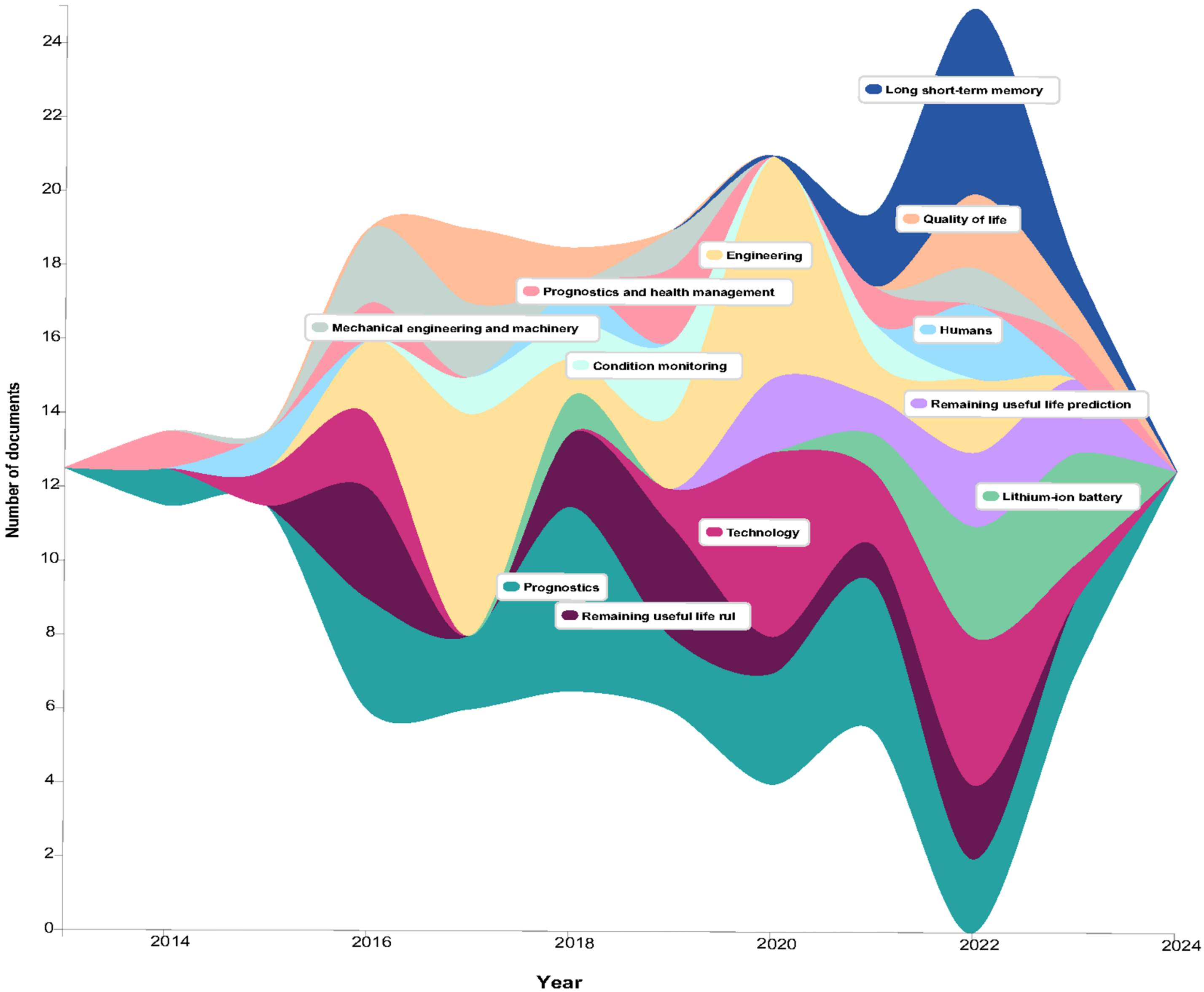

Figure 3 **Evolution numbers of RUL studies based on keywords over time.** X-axis: year of studies. Y-axis: number of documents.

Full-size DOI: 10.7717/peerj-cs.3056/fig-3

conducting research that connects these categories in order to improve the comprehensive solutions for predictive maintenance.

This Streamgraph depicts the progression of research interests in RUL prediction and related disciplines over the past 10 years. It indicates a consistent and moderate level of interest between 2014 and 2018, with research covering a wide range of subjects, including mechanical engineering, condition monitoring, and prognostics (Fig. 3). However, a substantial decline was observed after 2020, which is likely attributable to the COVID-19 pandemic, which disrupted research activities on a global scale. Research interest in this particular field resumed in 2022, concurrently with the increasing emphasis on AI architectures, particularly LSTM

Table 8 Distribution of RUL studies.

Life stage	Sub-stage	Failure rate	Failure	Article
Early stage Infant mortality	Design manufacturing, licensing, establishment	High	Decrease over time as defective units are identified and repaired or replaced	*Zhang et al. (2023b)*
Middle stage Normal life	Warranty period Normal use Heavy utilization Upgrade/ modification	Low and constant	Randomly due to external factors	*Arunthavanathan et al. (2023)*, *Aydemir & Acar (2020)* to *Zheng, Liao & Zhu (2023)*, *Pei et al. (2019)* to *Wang & Zhao (2023)*
Late stage Wear-out	Aging asset Approaching end of life	High	Predictable, often due to aging process	*Arunthavanathan et al. (2023)*, *de Pater & Mitici (2023)*, *Zheng, Liao & Zhu (2023)*, *Pei et al. (2019)*, *Rosero, Silva & Ribeiro (2022)*, *Biondi, Sand & Harjunkoski (2017)*, *Ma, Xu & Yang (2023)* to *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)*

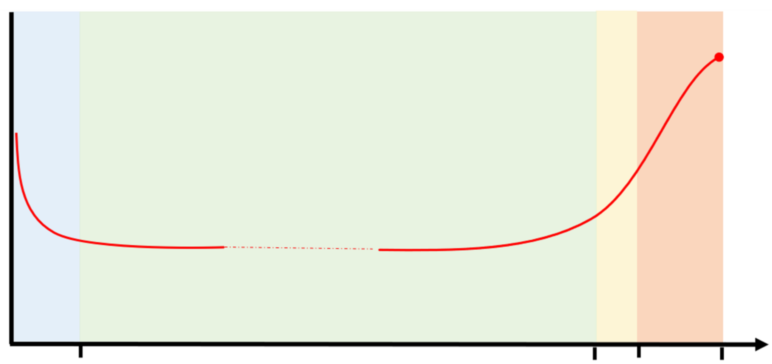

Figure 4 The bathtub curve for equipment life cycle and failure rate. X-axis: age of equipment; Y-axis: equipment failure rate over three phase of life; stage I, stage II and stage III.
Full-size DOI: 10.7717/peerj-cs.3056/fig-4

networks. This surge is indicative of the growing incorporation of AI into RUL prediction, which demonstrates its capacity to improve prediction accuracy and offer valuable insights for maintenance strategies. The emergence of LSTM and its applications emphasizes the transition to data-driven approaches in the field, indicating a resurgence in research activity following the pandemic (*Open Knowledge Maps, 2024*).

Synthesis and analysis based on research questions

RQ1 What are the range of studies associated with predicting the RUL of equipment?

Table 8 measures studies interest distributed based on stage in life span where the bathtub curve model was used to identify the range of study because it defines components failure rate over time (*Titu-Marius, 2021*). In Fig. 4, The bathtub curve typically comprises of three stages: an initial diminishing failure rate (infant mortality), a consistent failure rate (useful life), and a rising failure rate (wear-out) (*Ikonen, Corona & Harjunkoski, 2023*). Numerous models and methodologies have been devised to precisely elucidate and conform to this curve to empirical data. For example, the adjusted exponential-Weibull (MEW) model, which merges the exponential and Weibull distributions, presents a versatile approach to accommodating failure time data with a bathtub-shaped hazard rate, delivering superior outcomes in comparison to other models (*Al-Essa et al., 2023*).

The early stage is supported by one study *Zheng, Liao & Zhu (2023)*, indicating relatively less research focus on the high initial failure rates caused by manufacturing defects or early use issues. The absence of operational data is identified as a significant challenge, as RUL predictions heavily depend on this data, which is not available during the design and production stage since the equipment has not yet been put into use. In contrast, The operation stage has the most extensive research, with 19 studies. This extensive coverage indicates a well-established understanding of the low and normal constant failure rates during this phase, supporting effective maintenance strategies and reliability planning based on a broad consensus regarding random failures often due to external factors. The wear-out stage, which has been covered in eight studies, is mentioned divided into main two subphases: early wear out and late wear out stage. The transition phase marks the onset of increasing Major failure rates, accumulation of fatigue and outdated components. The late wear-out stage is defined by a sharp increase in failure frequency, signifies the approaching End of Life. Maintenance costs escalate, and decisions must be made regarding asset replacement, decommissioning, or life extension investments. This stage is particularly relevant for economic analysis comparing continued operation *vs*. replacement costs. Overall, the distribution of studies highlights well-researched middle and late stages, while the early stage presents an opportunity for further investigation to enhance early failure mitigation.

RQ2 How can hybrid models combining physical and data-driven methods improve RUL prediction for complex systems?

Accurately predicting the RUL is crucial for ensuring equipment achieves its expected life span. Hybrid models, which integrate two or more methods, offer a promising approach to enhance prediction accuracy by combining both physical principles with data-centric techniques particularly in a complex system. A common hybrid approaches, integrates physical-based with data-driven model. Physical-based models rely on mathematical representations of failure mechanisms, providing a fundamental understanding of system behavior (*Wang & Zhao, 2023*). Combining support vector regression (SVR) and random forest regression (RFR) alongside an exponential weighted moving average (EWMA) control chart for anomaly detection (*Arunthavanathan et al., 2023*; *Wang & Mamo, 2019*).

Meanwhile data-driven models, utilized historical data to identify patterns and predict future states, offering flexibility and adaptability to varying conditions (*Wang & Zhao, 2023*). In time frequency data transformations, Short-time Fourier Transform (STFT) and Wigner Ville Distribution (WVD), used to analyze non-stationary signals, which are common in complex systems (*Rosero, Silva & Ribeiro, 2022*). While in DL, CNN and RNN utilize in extracting multilevel features from data. PdM is a common example application of data-driven models. The integration with sensor and AI data processing technique enhanced the prediction and allow for faster decision making (*Sayyad et al., 2021*). Plus, a combine method will increase computational requirement and the accuracy of data-driven models hinges on the quality of their input data. Noisy data, often stemming from environmental influences, can significantly impact prediction accuracy (*Biondi, Sand & Harjunkoski, 2017*; *Fan, Nowaczyk & Rögnvaldsson, 2020*; *Ma, Xu & Yang, 2023*). Effective data pre-processing techniques are crucial to mitigate these issues and enhance model reliability. Furthermore, data-driven models must exhibit adaptability to varying operating conditions prevalent in industrial settings. Robust feature extraction methods and domain adaptation techniques are crucial to maintain prediction accuracy across diverse scenarios (*Wang & Zhao, 2023*).

RQ3 What are the comparative accuracies between Artificial Intelligence approaches in RUL prediction?

Among the most effective machine learning methods for predicting equipment's RUL, deep learning techniques such as LSTM networks have demonstrated remarkable results (Table 9). LSTM combine with Autoencoders (LSTM-AE) produce high accuracy, provides monotonicity (0.38), trend ability (0.95), and prognosability (0.94). This highlights its ability to provide consistent health indicators outperforming other autoencoders such as gated recurrent unit autoencoder (GRU-AE) and bidirectional long short-term memory autoencoder (BiLSTM-AE) (*de Pater & Mitici, 2023*; *Wu et al., 2022*). On fault detection, the use of Robust-ResNet combined with LSTM and CNN architectures, achieves up to 99.53% accuracy (*Zheng, Liao & Zhu, 2023*). LSTM with COSMO features reduce mean absolute percentage error (MAPE) between 13–15%, compared to 25% with traditional methods (*Duan et al., 2023*). This approach capable in managing large amounts of temporal data and detecting subtle changes indicative of degradation or failure (*de Pater & Mitici, 2023*; *Fan, Nowaczyk & Rögnvaldsson, 2020*; *Wang & Zhao, 2023*; *Zheng, Liao & Zhu, 2023*).

In a situation of understanding data patterns in sequence, recursive neural network (RNN) is used. These in combination with the extended Kalman filter (EKF) reduces mean absolute error (MAE) by 15–25% and MAPE by 10–20% compared to standalone RNNs or traditional models, improving prediction accuracy for nonlinear, noisy datasets. While differentiating abnormality, OC-SVM used to distinguish abnormalities by separating them from normal operating conditions. The fault margin was dynamically adjusted from data patterns by considering the highest anomaly count in a window and incorporating a noise margin for accurate anomaly detection (*Arunthavanathan et al., 2023*).

CNN architecture was developed that incorporates domain adaptation techniques to minimize distribution discrepancies across different failure modes. Notable studies, such as those by *Cheng et al. (2021)*, *Rosero, Silva & Ribeiro (2022)*, *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)* and *Ture et al. (2024)*, have highlighted the utility of CNNs in this domain. In TCNN, metrics assess higher accuracy and robustness RUL of bearings under

Table 9 AI application and performance for health monitoring.

Method	Advantages	Applications	Prediction	Article	Significant result	
					Performances	Error measurement
Long short-term memory networks	Handle time-series data, capture temporal dependencies	Health indicators	RUL prediction	*de Pater & Mitici (2023)*,	Accuracy: LSTM-AE 81–85%	RMSE 19%
				Fan, Nowaczyk & Rögnvaldsson (2020)	Accuracy: PHM Score 0.85–0.92	RMSE 15% to 25% MAPE <10%
				Aydemir & Acar (2020)	Accuracy: LSTM (One Fault): 392 LSTM (Two Fault): 424	RMSE (One Fault) 17.15 RMSE (Two Fault) 17.63
				Wang & Zhao (2023)	Accuracy: R-Square (R^2): 0.82	Attention-GRU RMSE 24.90 MAE 16.4 cycles Attention-LSTM RMSE 22.40 R^2 0.91 MAE 15.7 cycles
				Sayyad et al. (2021)	Accuracy: LSTM model 92.54%	MAE 2.75 cycles RMSE 3.20 cycles
Convolutional neural network	Effective for processing visual data, extracting degradation features	Enhanced feature extraction	RUL prediction	*Cheng et al. (2021)*,	Accuracy: R-square (R^2) 0.82	MAE: 0.10 RMSE: 0.12
				Ture et al. (2024),	Accuracy: 93.93%	RMSE: 33.93
				Solís-Martín, Galán-Páez & Borrego-Díaz (2023)	NASA scoring function 0.015 Nil NASA scoring functions 2.13	Bearing RMSE: 0.24 MAE: 0.17 Fast charging battery RMSE: 84.78 MAE: 51.98 Turbo engine RMSE: 10.46 MAE: 7.69
				Zheng, Liao & Zhu (2023)	Accuracy: Multi-channel: 81.74% Single-channel: 52.41%	–
				Sayyad et al. (2021)	Accuracy: 89.56%	RMSE: 4.50 MAE: 3.10
Stacking based ensemble learning	Enhances prediction accuracy by leveraging different base models	Improves prediction accuracy	RUL Prediction	*Ture et al. (2024)*	Accuracy: K-fold: 95.72% Leave one out: 95.69%	RMSE (K-fold): 33.25 RMSE (Leave one out): 31.30
Dynamic Bayesian networks	Models' temporal processes with time-dependent variables	Predicting RUL of underwater self-enhanced structures with probability crack growth (PCG)	Anomaly detection	*Liu et al. (2020)*	Accuracy: 1st year: PCG 45.2% Crack value 0.4418 7th year: PCG 37% Crack value 4.7072	1st four years <8.5% 5th to10th years 10–20.4% After 10 years <11.3%
Wiener process models	Models' random phenomena with independent, normally distributed increments	Characterizes degradation trajectories, includes negative jumps	RUL prediction	*Wang et al. (2018)*	Accuracy: 80.51%	Model with Weiner process MAPE: 19.49% RMSE: 49.03 days MAE: 41.62 days
				Zhang et al. (2020)	Accuracy: SSL estimation with spare part storage degradation: Final failure time: 170	–

(Continued)

Table 9 (continued)

Method	Advantages	Applications	Prediction	Article	Significant result	
					Performances	Error measurement
Maximum likelihood estimation	Provides robust parameter estimates in nonlinear, non-Gaussian noise scenarios	Measures model's explanation of observed predictive maintenance data	RUL prediction	*Pei et al. (2019)*	Accuracy: Monitoring time scale 96.43% reduction then on natural time scale	MSE (Natural time scale): 22.99 MSE (Monitoring time scale): 0.82
Least squares support vector machine	Constructs failure prediction models	Medical equipment failure prediction	Anomaly detection	*Ma, Xu & Yang (2023)*	–	AFS-ABC with SVM: error rate 2.5% in 0.85 s FMEA: error rate 5.3% in 1.23 s
Recursive neural network	Enhances prediction accuracy, reduces overfitting	Prediction tasks under complex conditions	RUL prediction	*Duan et al. (2023)*	–	MAE 11.83 MAPE 18.2% with Euclidean Distance: MAE 15.48 cycles MAPE 24.3%
Multi-layer Perceptron	Predicts failures based on historical data	Scheduling maintenance, reducing downtime+	RUL prediction	*Rosero, Silva & Ribeiro (2022)*	Accuracy: Elbow Point (with HI): 72 h: 18% 48 h: 38% 36 h: 31%	RMSE (Without HI): 14.01 RMSE (with HI): 8.62
Robust-ResNet	Fault detection, predicting RUL	Internal gear pumps analysis	RUL prediction	*Zheng, Liao & Zhu (2023)*	Accuracy: 99.53%	Error reduction: 17.79%
One-class support vector machine (OCSR)	Detects deviations from normal operating conditions	Identifying potential faults	Anomaly detection	*Arunthavanathan et al. (2023)*	Accuracy: Ordinary least squares: 98.55% Bayesian linear regression: 99.51%	Reactor cooling tower result: OLSR predicted RUL: 12,345 samples (compared to the actual 18,909 samples) Condenser cooling water valve stiction result: OLSR predicted RUL: 7,123 samples (compared to the actual 9,451 samples).

multiple failure behaviors with a low MAE of 0.10, root mean square error (RMSE) of 0.12, and a high R-squared (R^2) of 0.82 (*Cheng et al., 2021*). CNN has achieved an accuracy of 93.93% performed well among DL models but slightly lower than stacking based ensemble learning (95.72%) (*Ture et al., 2024*).

Dynamic Bayesian networks (DBN), and Wiener process models offer robust frameworks for modeling temporal and degradation processes in corrective maintenance. DBN incorporates time-dependent variables and their probabilistic dependencies, enabling effective representation of dynamic systems and their evolution over time. However, Wiener process models characterize degradation trajectories by accounting for both gradual wear and negative jumps caused by imperfect maintenance. These approaches as discussed in studies *Wang et al. (2018)*, *Liu et al. (2020)* and *Zhang et al. (2020)* provide robust tools for understanding and predicting equipment performance under varying operational conditions. Through a comparison with experimental data, DBN shows an error margin lower than 8.5% in the first 4 years, lower than 20.4% between 5–10 years and lower than 11.3% after 10 years (*Liu et al., 2020*).

Moreover, the use of Kalman filtering not only made an average improvement 18% in prediction results, but also reduce 10–15% compared to static methods like maximum likelihood estimation (MLE) (*Pei et al., 2019*). The least squares support vector machine (LS-SVM) algorithm with the artificial fish swarm—artificial bee colony algorithm (AFS-ABC) increase prediction in potential failures and assess equipment health. This model has accomplished lower error forecast compared to other methods (*Ma, Xu & Yang, 2023*). Bayesian methods, which involve developing exponential degradation models and updating parameters using real-time condition monitoring data, offer another effective approach (*Liao & Tian, 2012*).

Bar chart review methods in grouped categories based on functions (Fig. 5). For time-series analysis, methods like LSTM and RNN help track changes over time (four methods). Feature extraction, like CNN and ResNet, pulls useful patterns from data (two methods). Statistical modeling, such as Kalman filtering and Wiener process, uses mathematical approaches to predict outcomes (two methods). Anomaly detection, like OC-SVM and LS-SVM, identifies unusual patterns (two methods). Ensemble methods, like stacking, combine multiple models for better accuracy (one method) and general models, such as MLP and ResNet, are flexible tools for general predictions (two methods). These visualizations offer a well-rounded understanding of how different machine learning techniques, with components ranging from 1 to 4, utilize varying levels of complexity in their approaches to RUL prediction.

The high dependency on AI algorithms raises the risk of algorithmic biases, impact the fairness and reliability of these systems. Despite their prevalence, none of this research mentioned on the influence of these biases or proposed mitigation strategies. Algorithmic models may also reinforce historical inequalities by assuming that past trends predict future outcomes, as seen in recommender systems that limit diversity by continuously suggesting similar products.

RQ4 How effective are FDD approaches in detecting early indicators of equipment failure?

Figure 6 shows an overall schematic flow of FDD integration to anomaly detection. The integration of advanced technique such as FDD has significantly enhanced the ability to detect early indicators of equipment failure (*Rosero, Silva & Ribeiro, 2022*). Over the years, the technique has evolved and categorize into mathematical, analytical, data-driven, statistical, computational, and hybrid approaches (*Zhao et al., 2019*). To establish into one of these methods, variables associated with the fault need to be identified in advance. Abnormal values are detected by manually setting a threshold for these variables. These thresholds vary across different system components and must be adjusted for each specific application (*Arunthavanathan et al., 2023*; *Nelson & Culp, 2023*).

Table 10 encapsulates classification for fault detection studies in FDD strategy. In data-driven methods *Carroll et al. (2019)* and *Wang & Mamo (2019)* demonstrates the

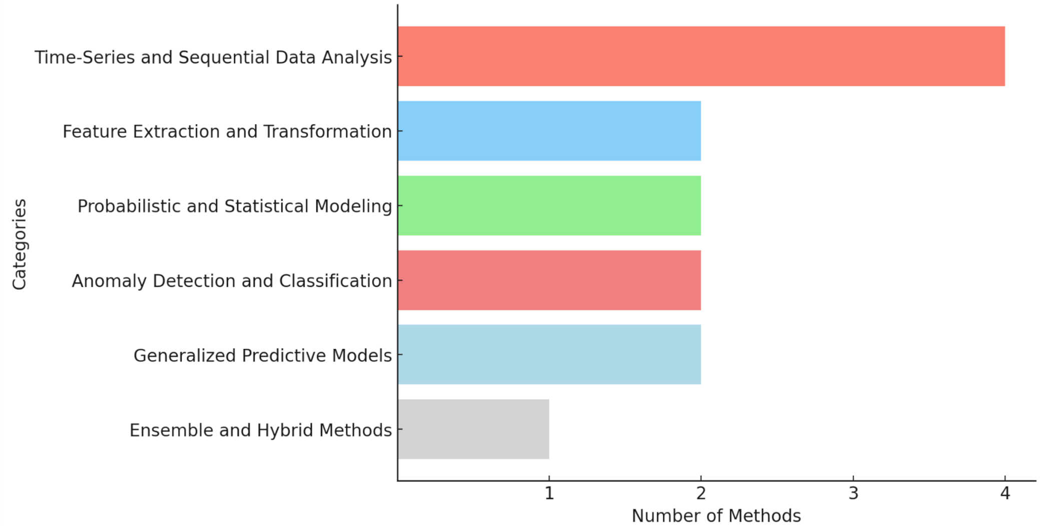

Figure 5 **Number of components involve in AI.** Grouping of methods by functional categories. X-axis: number of methods. Y-axis: categories. Full-size DOI: 10.7717/peerj-cs.3056/fig-5

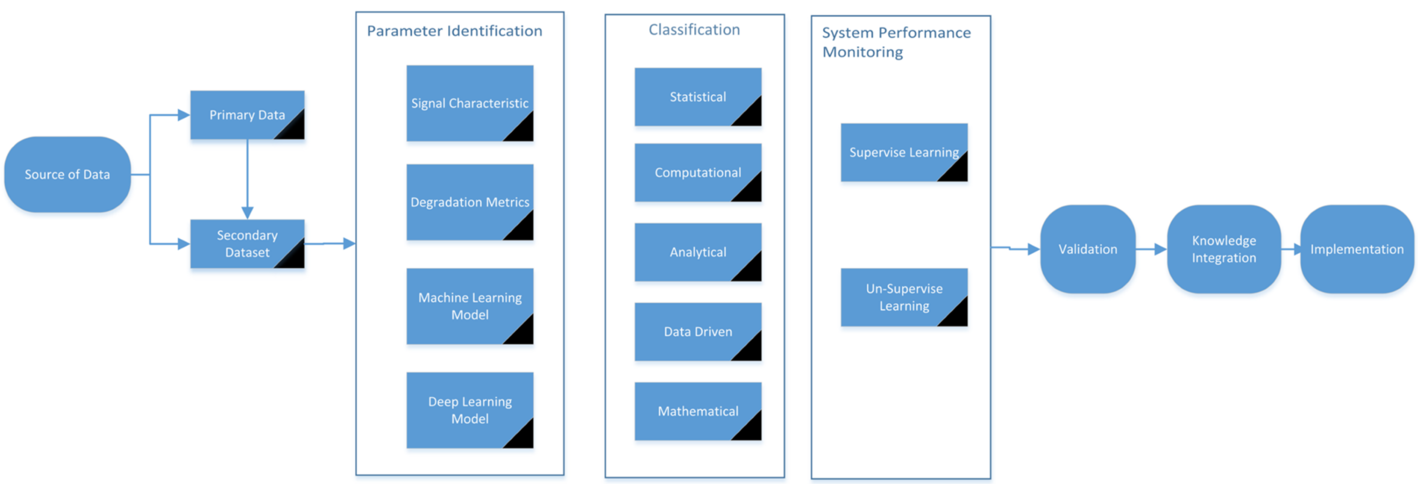

Figure 6 **FDD integration with anomaly detection flowchart.** Full-size DOI: 10.7717/peerj-cs.3056/fig-6

Table 10 **Method in FDD.**

Classification	Total	Article
Statistical and mathematical method	13	*Arunthavanathan et al. (2023)*, *Aydemir & Acar (2020)*, *Wang et al. (2018)*, *Zhang et al. (2020)*, *Pei et al. (2019)*, *Carroll et al. (2019)*, *Biondi, Sand & Harjunkoski (2017)*, *Wang & Mamo (2019)* to *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)* and *Liao & Tian (2012)*
Data-driven and analytical method	19	*Arunthavanathan et al. (2023)*, *Aydemir & Acar (2020)* to *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)* and *Liao & Tian (2012)*
Model based method	18	*Arunthavanathan et al. (2023)*, *Aydemir & Acar (2020)* to *Zheng, Liao & Zhu (2023)*, *Pei et al. (2019)* to *Ture et al. (2024)*, *Carroll et al. (2019)* to *Sayyad et al. (2021)*, *Lee, Kim & Lee (2023)* to *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)*, *Wang & Zhao (2023)* and *Liao & Tian (2012)*

real-time sensor to reflect the dynamic behavior of systems efficiency, combine with artificial neural networks (ANNs) in predicting gearbox failures using SCADA and vibration data to achieved higher accuracy particularly when using high-frequency vibration data (*Carroll et al., 2019*). *de Pater & Mitici (2023)* focus on LSTM autoencoders, showing that the reconstruction error, which increases with system degradation, can effectively identify early faults. Statistical methods are highlighted by *Aydemir & Acar (2020)* discuss the use of the CUSUM control chart for anomaly detection, which helps identify the degradation onset point and subsequently improves the performance of RUL estimators by focusing on active degradation periods. *Wang & Mamo (2019)* employ the EWMA control chart for anomaly detection, which is crucial in their hybrid approach, where detected anomalies trigger RUL prediction models, thereby enhancing early fault detection. Model-based methods such as those described by *Ma, Xu & Yang (2023)* utilize deterministic reasoning and fuzzy inference for precise and uncertain data respectively, achieving effective fault detection. Hybrid methods, including the approaches by *Arunthavanathan et al. (2023)*, *Lee, Kim & Lee (2023)*, combine techniques like OC-SVM for fault detection with neural network permutation algorithms for classification, and use alarm rules alongside contextual diagnosis to enhance fault detection accuracy.

System performance monitoring further model known faults (as supervised learning), while unsupervised learning detects to unknown anomalies or unusual patterns in the data. This real-time monitoring ensures that even early signs of failure are noticed. Finally, the models are tested during validation to ensure they work accurately, and the insights are stored in a knowledge base for future use. Once validated, the system is deployed in the implementation stage, where it operates as part of real-time monitoring to predict and prevent equipment failure effectively. Unlike existing reviews, this assesses the FDD efficiency, systematically evaluates their performance across various contexts, accentuating pragmatic applications. Whereas the most of the reviews concentrate on singular methodologies or particular domains, highlighting the integration of hybrid and data-driven techniques, which are often overlooked in similar studies, the review underscores the amalgamation of data-centric and hybrid strategies, offering an all-encompassing view of their real-world ramifications.

RQ5 What challenges are associated with the implementation of sensor technology for fault detection?

One of the methods in early detection equipment malfunction is implementing sensors as a primary data in FDD. This proactive approach minimizes downtime, reduces costs, and improves safety across various applications. Table 11 summarizes the integration of multiple sensors for continuous monitoring.

Deterioration measurement

At the stage period, the focus is essential on capturing wear and tear through deterioration measurements (*Sayyad et al., 2021*; *Solís-Martín, Galán-Páez & Borrego-Díaz, 2023*). Accelerated degradation testing (ADT) is often employed, subjecting equipment to harsher-than-normal operating conditions to model degradation behaviors

Table 11 Sensor integration of data driven method for data collection.

Sensor parameter	Article	Measurement	Benefits	Limitations
Deterioration	*Liao & Tian (2012)*, *Zhang et al. (2020)*, *Sayyad et al. (2021)*, *Solís-Martín, Galán-Páez & Borrego-Díaz (2023)*, *Fan, Nowaczyk & Rögnvaldsson (2020)*, *Wang & Zhao (2023)*	Wear and tear	Predictive maintenance, monitoring	Performance effect and increasing noise factor
Vibration	*Aydemir & Acar (2020)*, *Zheng, Liao & Zhu (2023)*, *Cheng et al. (2021)*, *Wang & Mamo (2019)*, *Lee, Kim & Lee (2023)*	Detect imbalance and alignment	Effective measures changes in mechanical condition, can detect wide range of faulty condition	Require proper mounting to ensure accurate reading and sensitive to environmental noise
Temperature	*Aydemir & Acar (2020)*, *Cheng et al. (2021)*, *Rosero, Silva & Ribeiro (2022)*, *Carroll et al. (2019)*	Overheating level and thermal stress	Cost effective, provide early warnings of thermal issue	Limited to surface temperature measurement, can't capture internal component temperature accurately
Corrosion	*Liu et al. (2020)*, *Ture et al. (2024)*	Integration physical models alongside stress mechanics to define rate of metal loss	Prevent catastrophic failure and reduce safety hazards	Environmental factor could lead to accelerated noise
Pressure	*Aydemir & Acar (2020)*, *Zheng, Liao & Zhu (2023)*, *Ture et al. (2024)*	Hydraulic pressure level Weight distribution	Essential for monitoring fluid system	Requires calibration, result effected by environmental condition
Abnormality trigger	*de Pater & Mitici (2023)*	Health indicator	Early detection of unhealthy stage	Generalization leads to unknown types of failure
Acoustic	*Solís-Martín, Galán-Páez & Borrego-Díaz (2023)*	Soundwave from abnormalities	Less sensitive to environmental, easy to deploy	Sensitive to environmental noise, need signal processing
Operating time	*Pei et al. (2019)*	Nonlinear degradation	Equipment schedule maintenance, asset utilization	Time consuming
Crack	*Liu et al. (2020)*	Stress distribution and fatigue growth	Prevent catastrophic failure and reduce safety hazards	Limited detection sensitivity and require combination with other measurement

(*Liao & Tian, 2012*). Additionally, emphasis is placed on linking degradation during operation, storage, and the recovery state after replacement (*Zhang et al., 2020*). Advanced techniques such LSTM networks and CNN are utilized to process from sensor data and identify patterns of degradation. This beneficial and performance can be significantly impacted accuracy of the predictive models (*Fan, Nowaczyk & Rögnvaldsson, 2020*; *Wang & Zhao, 2023*).

Vibration monitoring

Vibration sensors are highly effective in diagnosing health machine, by detecting vibrations caused by friction, tool wear, or fractured inserts between the tool and workpiece during operation (*Aydemir & Acar, 2020*; *Sayyad et al., 2021*). High-frequency accelerometers are used to measure vibration signals, capturing horizontal and vertical movements (*Cheng et al., 2021*). Metrics such as vibration amplitude, frequency components, and acceleration are extracted to create indicators (*Zheng, Liao & Zhu, 2023*). Vibration data serves to detect imbalance and misalignment in mechanical systems (*Lee, Kim & Lee, 2023*; *Wang & Mamo, 2019*). This method is highly effective in capturing changes in mechanical conditions and diagnosing a range of faulty conditions. However, proper sensor mounting is crucial to avoid errors, and the sensors are often susceptible to environmental noise, requiring additional filtering and processing for accurate readings.

Temperature sensors

Temperature sensors can detect overheating and thermal stress, providing cost-effective and early warnings of potential thermal issues. ML approaches, particularly deep learning algorithms like LSTM networks, been utilized for time-based inputs and predict RUL by learning from sensor data, including temperature measurements (*Aydemir & Acar, 2020*). As cited in articles (*Carroll et al., 2019*; *Cheng et al., 2021*; *Rosero, Silva & Ribeiro, 2022*) temperature monitoring is employed to assess overheating levels and thermal stress in equipment. This cost-effective method provides early warnings of thermal issues. However, it is limited to surface temperature measurements and may fail to capture internal temperature variations, leading to incomplete diagnostics.

Corrosion assessment

Corrosion data integrates physical models alongside stress mechanics to determine the rate of metal loss. Corrosion together with vibration sensor collect primary data, such as stress related degradation or material thickness reduction due to rust (*Ture et al., 2024*). This measurement helps prevent catastrophic failures and enhances safety by reducing hazards (*Liu et al., 2020*). However, external environmental factors can introduce noise, accelerating the degradation rate and complicating accurate assessments.

Pressure monitoring

Aydemir & Acar (2020), *Zheng, Liao & Zhu (2023)* and *Ture et al. (2024)* highlight the importance of pressure data for evaluating hydraulic pressure levels and weight distribution in fluid systems. Critical parameters such as outlet pressure, internal system pressure, and operational load in machinery are used to monitor. CUSUM is a statistical tool employed with pressure sensor data to detect significant deviations, marking the onset of degradation. It is highly effective in identifying gradual changes that might not be apparent in raw sensor data (*Aydemir & Acar, 2020*). Pressure sensors measure pulsation signals, directly reflect non-uniform fluctuations within the pump and are essential for early fault detection (*Zheng, Liao & Zhu, 2023*). This parameter is crucial for maintaining fluid system health but requires regular calibration. Furthermore, environmental conditions can significantly affect the accuracy of pressure readings.

Abnormality triggers

As discussed in *de Pater & Mitici (2023)* anomaly triggers (AT-AE) planted for detecting the early stages of equipment failure. They are effective in signaling unhealthy operational conditions but may generalize across fault types, leading to unidentified or unaccounted-for failures.

Acoustic sensors

Pressure and acoustic sensors can detect abnormal sound waves that indicate potential faults, offering a less environmentally sensitive option that is easy to deploy. For instance, feature extraction from hydraulic pressure signals using techniques like complementary ensemble empirical mode decomposition (CEEMD) and singular value decomposition (SVD) has been employed to construct feature vectors for fault diagnosis in hydraulic pumps (*Nelson & Culp, 2023*). Examines the role of soundwave detection in identifying abnormalities. Acoustic sensors are less affected by environmental conditions, but they are highly sensitive to external noise, requiring sophisticated signal processing for reliable interpretation.

Operating time

Operating time data monitors non-linear degradation trends. It is useful for scheduling maintenance and optimizing asset utilization (*Pei et al., 2019*). However, the process is time-intensive and requires significant computational resources.

Crack detection

Stress distribution and fatigue growth are monitored to prevent catastrophic failures. Crack detection enhances safety and reliability but has limited sensitivity and often requires integration with other measurement methods for comprehensive diagnostics (*Liu et al., 2020*).

Moreover, humidity sensors are critical for monitoring moisture levels, preventing corrosion, and maintaining the integrity of materials, though they require regular calibration and are sensitive to dust. Optical sensors, which measure light intensity, are effective for detecting changes in lighting conditions and are non-intrusive, though they require regular cleaning to maintain accuracy (*Solís-Martín, Galán-Páez & Borrego-Díaz, 2023*).

RQ6 What are the most effective methods use for monitoring condition in the predictive maintenance and how can root cause analysis be effectively determined in fault tolerance systems?

Table 12 highlight method currently practice in monitoring asset and system. One of the most common effective methods is predictive maintenance (PdM), which utilizes sensor data and advanced analytics to predict equipment failures before they occur. *Wang et al. (2018)* emphasized the importance of predictive maintenance of degrading systems, thereby improving overall reliability and maintenance scheduling. *Aydemir & Acar (2020)* demonstrated that anomaly monitoring significantly improves RUL predictions, ensuring timely and effective maintenance interventions. Condition-based monitoring (CBM) is another effective method that involves continuous or periodic monitoring of equipment condition using sensors to detect deviations from normal operation. *Zheng, Liao & Zhu (2023)* developed a fault detection model for internal gear pumps, which enhances the

Table 12 **Maintenance management and fault tolerance monitoring method.**

Method	Article	Focus area	Application in monitoring
Machine learning techniques	*Cheng et al. (2021)*	Integration with statistical degradation models	Predictive maintenance, risk management
Robust health indicators	*Rosero, Silva & Ribeiro (2022)*	Development of robust health indicators that can predict RUL accurately under varying conditions and limited failure data.	Maintenance planning and decision
Enhanced RUL predictions	*Aydemir & Acar (2020)*	Triggering estimation post-degradation detection	Maintenance planning, system reliability
Imperfect maintenance consideration	*Wang & Zhao (2023)*	Accounting for imperfect maintenance	Maintenance planning and decisions
Anomaly detection integration	*Aydemir & Acar (2020)*	Combining anomaly detection with machine learning	Preventing unexpected failures
Pressure self-enhancement effects	*Fan, Nowaczyk & Rögnvaldsson (2020)*	Study of pressure effects	Maintenance planning and decision, system reliability
Proactive maintenance strategies	*Aydemir & Acar (2020)*	Supported by accurate RUL predictions	System reliability
Feature selection process	*Duan et al. (2023)*	Improving feature selection for RUL prediction	Maintenance planning and decision
Transfer learning and domain adaptation	*Solís-Martín, Galán-Páez & Borrego-Díaz (2023)*	Adapting to varying conditions	Maintenance planning and decisions
Bayesian approach for real-time applications	*Ma, Xu & Yang (2023)*	Continuous prediction updates	Real-time applications

effectiveness of CBM by accurately detecting faults and predicting RUL. These advanced monitoring techniques, combined with the use of machine learning and AI, such as the work by Cheng et al. (2021) using transferable convolutional neural networks, provide robust solutions for fault detection and RUL predictions. Root cause analysis (RCA) is a systematic method that involves collecting data, analyzing failure modes, and identifying the underlying reasons for faults. This approach ensures that the real cause of the problem is addressed rather than just treating the symptoms. Arunthavanathan et al. (2023) highlighted the significance of RCA in estimating RUL and transforming fault-to-failure processes in process systems. Fault tree analysis (FTA) and failure mode and effects analysis (FMEA) are additional methods that support RCA by providing structured frameworks for identifying and prioritizing potential causes of failures.

RQ7 How do life cycle analysis and survival analysis frameworks influence the selection of maintenance strategies and health indices in reliability driven maintenance?

Life cycle analysis (LCA) and survival analysis frameworks significantly influence the selection in reliability-driven maintenance by providing a structured proactive and reactive approach to evaluate and optimize maintenance decisions. Preventive maintenance (PM) is characterized by its proactive approach, involving regular inspections, servicing, and timely interventions to prevent equipment failures. While corrective maintenance (CM) is reactive approach, initiated only after equipment has failed. This approach solves the issues in the short term but leads to higher overall costs and reduced equipment lifespan.

According to *Wang et al. (2018)*, continuous PM can substantially extend the lifespan of equipment, prolong RUL and predict failures before it occurs (*Pei et al., 2019*). Effective maintenance scheduling and consequently, a longer equipment lifespan (*Aydemir & Acar, 2020*). CM is reactive, initiated only after equipment has failed. While this strategy might seem cost-effective in the short term due to lower initial maintenance expenditures, leads to higher overall costs and reduced equipment lifespan. *de Pater & Mitici (2023)* assert that PM's focus on timely and planned interventions not only improves reliability but also optimizes maintenance resources. *Cheng et al. (2021)* illustrate how integrating AI with PM protocols enhances RUL predictions and fault detection accuracy.

CM results in extended downtimes and higher repair costs because failures are addressed only after they have occurred, often leading to significant damage (*Sayyad et al., 2021*). *Carroll et al. (2019)* mentioned the unpredictable nature of failures under CM necessitates expensive emergency repairs and replacements, further diminishing the equipment's operational life. *Ture et al. (2024)*, demonstrated that the implementation of predictive maintenance algorithms within PM frameworks significantly reduces unexpected failures and maintenance costs, thereby extending the operational life of assets.

In the context of equipment reliability, life cycle analysis helps identify potential failure points and maintenance needs at different stages of the equipment's life. *de Pater & Mitici (2023)* demonstrated by understanding the degradation effect of wear and tear item, the implementation of predictive maintenance strategies will help preventing unexpected failures and enhancing overall reliability. Integrating LCA with cost analysis allows for the identification of the most cost-effective maintenance interventions. *Aydemir & Acar (2020)* use CUSUM in anomaly detection techniques, an integration LCA with cost analysis to enhances the accuracy of RUL estimation.

In survival analysis, reliability measured in statistical approach, focusing on predicting the time until a system fails based on its current condition and operational history (*Arunthavanathan et al., 2023*). The analytical approach places emphasis on survival function analysis, time to failure analysis and hazard function analysis.

Time to failure analysis

According to *Wang et al. (2018)*, analysis models can incorporate various factors influencing equipment degradation. By utilizing historical failure data, survival analysis helps in forecasting future failures, enabling proactive maintenance actions. *Liu et al. (2020)* through the analysis of degradation patterns, it becomes feasible to accurately forecast the RUL. *Cheng et al. (2021)* indicate that the utilization of TCNN can adjust to diverse failure patterns, rendering the models highly efficient across various machinery types. *de Pater & Mitici (2023)* demonstrate that LSTM autoencoders, capable of learning from limited failure data and adjusting to diverse circumstances, offer dependable RUL predictions for systems with scarce failure records.

Survival function analysis

The process begins with collecting data from various sensors, including vibration and pressure pulsation signals, during the initial performance tests and throughout the pump's operational life (*Zheng, Liao & Zhu, 2023*). These advanced models help in identifying subtle signs of wear and tear that might be overlooked by traditional methods, thereby enhancing the reliability of equipment.

Hazard function analysis

Aydemir & Acar (2020) emphasizes the advantages of anomaly detection in enhancing RUL estimation. By identifying deviations from normal operations at an early stage, maintenance activities can be strategically scheduled, averting breakdowns and guaranteeing equipment dependability. However, in this analysis, identifying defect in time-varying conditions and nonlinear conditions is not sufficient due to its complexity. Therefore, the needs for secondary and tertiary analysis needed before any decision is made. Health indices can act as a critical bridge between life cycle analysis and survival analysis in maintenance decision-making processes.

Condition monitoring

These indices provide actionable insights for implementing condition-based maintenance strategies. The health indicators are evaluated using metrics such as monotonicity, trend-ability and prognostic-ability, measure the consistency, correlation with time and consistency across different units, respectively, providing clear signals of system degradation (*de Pater & Mitici, 2023*). One common approach is using root mean square (RMS) values of vibrations as health indicators, as demonstrated in the study where the RMS of horizontal vibration was selected for further analysis due to its significant correlation with the health state of bearings (*Wang & Mamo, 2019*). Another method involves PCA to simplify computations while retaining maximum original information. PCA standardizes sensor data, calculates covariance matrices, and projects data onto principal components to derive preliminary health indicators (*Duan et al., 2023*). LSTM autoencoders, employed to learn normal system behavior from unlabeled data and detect deviations indicative of degradation. Reconstruction errors from these models serve as health indicators, with variations including linear regression and Gaussian distribution models (*de Pater & Mitici, 2023*). Empirical mode decomposition (EMD) is another technique where the first intrinsic mode function (IMF) derived from time series data represents the HI, capturing the evolution of health conditions over time (*Rosero, Silva & Ribeiro, 2022*). Deep convolutional neural networks and recurrent neural networks, are used to map sensor inputs to HIs, which are then mapped to RUL. Techniques like stochastic modeling and distance-based approaches also contribute to HI calculation, with some methods simulating degradation paths using PCA space or employing exponential models for data-level fusion (*Fan, Nowaczyk & Rögnvaldsson, 2020*).

Real time reliability metrics

In maintenance management, particularly those incorporating PHM, continuous tracking and evaluate equipment status through data collection, real-time monitoring, and fault diagnosis, which allows for early detection of potential risks and effective maintenance planning (*Duan et al., 2023*). The system itself designed to collect and analyze data from various sensors and monitoring devices installed on equipment. Parts of its objectives to estimate equipment failure, reduce downtime thus allows for more effective maintenance planning and lower maintenance costs significantly. These systems utilize PHM to detect anomalies that trigger RUL estimation (*Aydemir & Acar, 2020*). By continuously monitoring, Systems can identify early signs of wear and tear, degradation effect and allow for maintenance teams to address issues early before major failures happen (*Ture et al., 2024*).

Failure threshold

Incorporating insights from both frameworks. PdM strategies, which are a subset of PHM, use RUL concepts to estimate the remaining time an equipment can function without failing, thus preventing unexpected downtimes and reducing maintenance costs (*Rosero, Silva & Ribeiro, 2022*; *Solís-Martín, Galán-Páez & Borrego-Díaz, 2023*). Integrating health indices into maintenance management systems enhances the safety and reliability of operations by providing continuous oversight and timely alerts for maintenance needs (*Ture et al., 2024*). Overall, maintenance management systems and health indices are integral to reliability-driven maintenance as they enable proactive maintenance strategies, extend the lifespan of components, and ensure the smooth operation of systems by providing timely and accurate predictions of equipment health and performance (*Duan et al., 2023*; *Ture et al., 2024*; *Wang & Zhao, 2023*).

DISCUSSION

RUL prediction is a crucial aspect in preventing equipment malfunctions and reducing maintenance costs, with AI algorithms being a popular choice due to their flexibility and convenience (*Heng et al., 2009*; *Lei, 2016*). However, these algorithms often require large datasets and feature selection of hyper-parameters for optimal performance. Classical machine learning is not adequate to learn from these data, a task that presents unique challenges (*Calabrese et al., 2022*; *He et al., 2023*). The prediction techniques for estimating the lifespan of equipment vary significantly depending on the stage and equipment's condition; methods use for newly developed equipment may differ from those applied to equipment in active use or aging equipment (*Zhang et al., 2023b*).

Research prospect

Predicting RUL multiple asset under different stage of life span

Predicting the life span in the early stages of a component's life is crucial for newly develop product, this to preventing unexpected failures in the early design stages (*Haobin, Zhang & Sinha, 2024*). Table 13 display predictable test used in different stages of the equipment's life (*Qian, Yan & Gao, 2017*; *Kim et al., 2004*). Accelerated life testing (ALT) is a critical methodology used in manufacturing with its primary goal to accelerate the aging process of components, thereby obtaining significant life span data in a shorter period (*Qiu & Li, 2024*). In the middle stage, multiple factors involve in life prediction from utilization of usage, corrective maintenance, replacement parts and upgrading is a multifaceted challenge that requires integrating various advanced methodologies (*Noot, Martin & Birmele, 2025*). A multi-stage maintenance-impact degradation model based on the

Table 13 Equipment prediction test under different stage of life span.

Objective	Stage of equipment	Prediction test	Dataset required
Life span prediction	Early stage	Accelerated life test Simulation test	Environment factor
			Component test data
			Quality test data
	Middle stage	Operational and utilization	Utilization data
		Maintenance	Corrective maintenance data
		Downtime action	Historical part replacement
		Upgrading	Hardware and software upgrade
	Late stage	End of life	Aging data
			Salvage value
			Disposal data
Remaining useful life	Equipment/Component	Degradation method	Wear and tear data
			Life span prediction (stage of equipment)

Wiener process can account for dynamic maintenance and failure thresholds, thereby improving the precision of RUL predictions (*Li et al., 2024*). Addressing uncertainties in RUL estimation is essential for improving the reliability and accuracy of predictive methods. These uncertainties fall into two main categories: epistemic and aleatory. Epistemic uncertainty comes from limited knowledge or incomplete information about the system, while aleatory uncertainty is due to the inherent randomness and variability in the system's behavior. Various strategies have been proposed to tackle these uncertainties (*Cao & Peng, 2023*). Model-based strategies frequently encounter difficulties with complicated connections and uncertainties, whereas data-driven approaches sometimes neglect previous knowledge and struggle with restricted data (*Liang, Liu & Xiao, 2024*).

Integration of FDD and RUL estimation for the early detection of system faults and the prediction of the system's future operational life, facilitating timely maintenance actions and reducing unexpected downtimes. A novel tree network framework can address fault classification and RUL prediction in parallel, improving model selection accuracy and prediction efficiency (*Chai et al., 2024*). Similarly, a joint learning model that simultaneously performs failure mode recognition and RUL prediction by leveraging multiple sensor signals has shown promising results (*Wang, Xian & Song, 2023*). Combining system modeling methods with regression-based approaches and genetic programming algorithms to predict fault occurrences and estimate RUL, even in the presence of measurement noise (*Bahareh & Jørn, 2023*). A range of studies have explored the use of probabilistic, highlight the importance of considering uncertainties in input variables. *Zamzam et al. (2021)* established a ranking assessment, prioritizing and predictive systems both for medical equipment maintenance, using machine learning algorithms for medical equipment. These studies collectively underscore the potential of probabilistic models in improving the accuracy and effectiveness of life cycle cost analysis in the medical equipment domain.

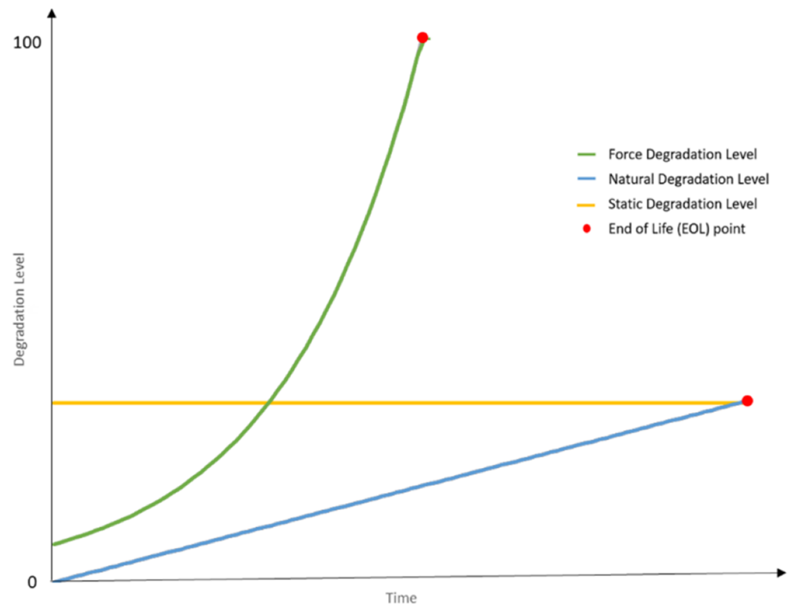

Figure 7 **State of degradation on equipment physical surface.** X-axis (Time): progression of time. Y-axis (Degradation level): the degree of degradation. Line chart: green line: force (accelerated) degradation level. Blue line: natural degradation level. Yellow line: static degradation level red dots (EOL point): mark the point where equipment can no longer maintain its intended function due to excessive degradation. Full-size DOI: 10.7717/peerj-cs.3056/fig-7

Uncertainty in equipment deterioration

There is often an incomplete information about all the factors influencing equipment deterioration. Models used to predict deterioration often rely on assumptions and historical data, which may not account for all possible future scenarios, leading to uncertainty in predictions (*Zhu et al., 2024*). State of degradation on equipment may consist of multiple types, including natural degradation, static degradation, and force-induced degradation, each contributing differently to the equipment's end-of-life (Fig. 7). Natural degradation refers to the gradual wear and tear that occurs over time due to regular usage and environmental factors (*Li et al., 2023*).

Performance degradation assessment (PDA) methods, which utilize statistical and intrinsic energy features, are crucial for evaluating such static degradation states by constructing high-dimensional feature sets and reducing them to sensitive health indices (*Lv, Hu & Wang, 2023*). *Zhang et al. (2020)* emphasize the role of health indicators in maintenance strategies by enabling more effective scheduling of maintenance activities. *Zheng, Liao & Zhu (2023)* develops health indicators based on the fault types classification and RUL stages, thus allowing for timely intervention. Further models and methods enhancement have been developed to enhance the predictions to support maintenance planning. For example, *Pei et al. (2019)* and *Duan et al. (2023)* highlight the importance of accurate RUL estimation for maintenance management, remarking that reliable predictions enable better scheduling of maintenance activities and improve the overall reliability of systems. The integration of ML and Internet of Things (IoT) has transformed maintenance management systems into a comprehensive solution, allowing for real-time data processing and more sophisticated analysis of health indices (*Cheng et al., 2021*; *Lee, Kim & Lee, 2023*).

Digital twin and virtual assistance

The integration of digital twin (DT) and virtual assistance (VA) technologies ML is revolutionizing fault identification, monitoring prediction in asset management. This is crucial in assisting decision making related to RUL identification. DT technology involves creating a digital replica of physical assets, capturing real-time data to mirror their operational behavior (*Abdullahi, Longo & Samie, 2024*). This process includes data acquisition from sensors and IoT devices, data integration to form a cohesive dataset, model development using simulation tools and ML algorithms, continuous monitoring, and fault identification and prediction through ML analysis (*Alam & El Saddik, 2017*; *Solari, Lysova & Montanari, 2023*).

While, virtual assistants provide interactive support and decision-making capabilities, aiding maintenance teams in managing RUL and detecting anomalies. VA technology uses AI to process data, interact with users through conversational interfaces and implement automated actions based on predictive analytics thus to predict RUL estimation. VA tools are categorized into chatbots, virtual advisors, and autonomous agents, each providing varying degrees of interaction and decision-making capabilities. Research indicates significant benefits of integrating DT and VA with ML for predictive maintenance. *Lu & Li (2023)* show that for rolling element bearings, a hybrid DT and LSTM model significantly improved RUL prediction accuracy by integrating simulation data with experimental data, achieving over 97.5% accuracy.

Challenges

Determining the RUL of equipment is a complex issue, without a standardized approach, numerous published works from various perspectives, each offering new insights and findings on maintenance strategies and performance monitoring, highlighting different strengths and weaknesses (*Mehta, Prabhu Bam & Prabu Gaonkar, 2024*). While integration with ML to model a prediction task requires comprehensive historical machine defect, sequences of reactive action and different kind of failure data to build a robust dataset. This often results in generation of a huge amount of processing data which requires a special infrastructure and expert knowledge (*Rozhkovskaya & Sychev, 2020*).

In addition, most institution are reluctant to share their data publicly due to concerns over privacy and competition issue. Despite various methods implemented in predicting RUL, there remains significant potential for improvement and optimization, particularly in healthcare and emerging markets (*Arunan et al., 2023*). The application of these advanced algorithms to predict RUL in upgraded equipment could significantly enhance the reliability and performance of such systems, yet this remains underexplored.

The concept of midlife upgrades, which extending the life of equipment through component upgrades, has not been explored extensively. Existing studies primarily from a theoretical perspective, with limited empirical evidence on its effectiveness (*Khan, West & Wuest, 2020*; *Wang & Zhao, 2022*).

The significance of accurate RUL prediction in healthcare is heightened by the essential role of medical devices in healthcare. Equipment malfunctions can have severe repercussions, affecting patient outcomes and operational efficacy. However, maintenance procedures for medical equipment have not completely utilized the capabilities of RUL prediction models. Most existing methods depend on reactive or preventative maintenance, which are less effective than predictive approaches driven by RUL predictions. Integrating RUL prediction models into healthcare systems enables hospitals and clinics to adopt a proactive maintenance strategy, thereby decreasing downtime, lowering expenses, and maintaining continuous patient care. Medical devices, including imaging machines, ventilators, and surgical instruments, frequently function in complex environments characterized by extremely varied usage patterns. This unpredictability adds complications to the development of precise RUL models. The substantial expense of medical equipment and its essential function in diagnosis and treatment highlight the necessity for accurate and dependable RUL projections. *Khan, West & Wuest (2020)*, empirical research regarding the efficacy of midlife enhancements in healthcare is limited, highlighting an essential want for studies that integrate RUL prediction models with upgrade plans to maximize the usage of medical equipment (*Wang & Zhao, 2022*). The hesitance of healthcare organizations to disclose operational data, stemming from privacy and competitive apprehensions, exacerbates the implementation of RUL prediction models. Collaborative initiatives and anonymised data-sharing frameworks may facilitate the resolution of these obstacles, allowing researchers to create more robust and generalizable models. Moreover, integrating IoT devices and sensor data may yield real-time insights into equipment performance, hence improving the precision of RUL projections.

CONCLUSIONS

This review establishes a critical foundation for future research aimed at improving the integration of RUL, FDD, and anomaly detection within predictive maintenance frameworks. While significant progress has been made, continuous challenges such as limited model generalizability, low interpretability, and lack of integration across heterogeneous datasets in industrial environments continue to hinder practical deployment. The analysis underscores that most current approaches treat RUL prediction and anomaly detection in isolation, missing the synergistic potential of a unified framework. Furthermore, despite the promise shown by hybrid and ensemble AI models, these methods remain underutilized in operational environments where real-time accuracy, reliability, and explainability are crucial. To address these gaps, this review advocates for a new research direction centered on the development of integrated, explainable, and adaptive AI frameworks capable of handling noisy, incomplete, or imbalanced sensor data while maintaining predictive accuracy across diverse use cases. Thus, by leveraging the strengths of deep learning, hybrid modeling, and transfer learning, and embedding them within a fault-aware decision-support system, future research can significantly enhance the accuracy of actual lifespan predictions for equipment in complex settings. This study identifies the current limitations in AI approaches and proposes a roadmap for advancing predictive maintenance through intelligent systems that are more aligned with operational realities. The findings are expected to contribute to smarter, data driven maintenance strategies, reduced downtimes and extended asset life span.

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Author Contributions

- Mohd Khidir Gazali conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Khairunnisa Hasikin conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, authored or reviewed drafts of the article, and approved the final draft.
- Khin Wee Lai conceived and designed the experiments, authored or reviewed drafts of the article, and approved the final draft.
- Aizat Hilmi Zamzam conceived and designed the experiments, performed the experiments, analyzed the data, authored or reviewed drafts of the article, and approved the final draft.
- Rafat Damseh conceived and designed the experiments, authored or reviewed drafts of the article, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

This is a literature review.

REFERENCES

Abdullahi I, Longo S, Samie M. 2024. Towards a distributed digital twin framework for predictive maintenance in industrial internet of things (IIoT). *Sensors* **24(8)**:2663 DOI 10.3390/s24082663.

Alam KM, El Saddik A. 2017. C2PS: a digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE Access* **5**:2050–2062 DOI 10.1109/access.2017.2657006.

Al-Essa LA, Muhammad M, Tahir MH, Abba B, Xiao J, Jamal F. 2023. A new flexible four parameter bathtub curve failure rate model, and its application to right-censored data. *IEEE Access* **11**:50130–50144 DOI 10.1109/access.2023.3276904.

Arunan A, Qin Y, Li X, Yuen C. 2023. A federated learning-based industrial health prognostics for heterogeneous edge devices using matched feature extraction. *IEEE Transactions on Automation Science and Engineering* **21(3)** DOI 10.1109/TASE.2023.3274648.

Arunthavanathan R, Khan F, Ahmed S, Imtiaz S. 2023. Remaining useful life estimation using fault to failure transformation in process systems. *IEEE Systems Journal* **17(2)**:2512–2522 DOI 10.1109/JSYST.2022.3205179.

Aydemir G, Acar B. 2020. Anomaly monitoring improves remaining useful life estimation of industrial machinery. *Journal of Manufacturing Systems* **56**:463–469 DOI 10.1016/j.jmsy.2020.06.014.

Bahareh T, Jørn V. 2023. Adaptive remaining useful life prediction framework with stochastic failure threshold for experimental bearings with different lifetimes under contaminated condition. *International Journal of System Assurance Engineering and Management* **14(5)**:1756–1777 DOI 10.1007/s13198-023-01979-0.

Biondi M, Sand G, Harjunkoski I. 2017. Optimization of multipurpose process plant operations: a multi-time-scale maintenance and production scheduling approach. *Computers & Chemical Engineering* **103(20)**:293–294 DOI 10.1016/j.compchemeng.2017.01.007.

Calabrese F, Regattieri A, Bortolini M, Galizia FG. 2022. Data-driven fault detection and diagnosis: challenges and opportunities in real-world scenarios. *Applied Sciences* **12(18)**:9212 DOI 10.3390/app12189212.

Cao X, Peng K. 2023. Stochastic uncertain degradation modeling and remaining useful life prediction considering aleatory and epistemic uncertainty. *IEEE Transactions on Instrumentation and Measurement* **72(5)** DOI 10.1109/tim.2023.3236323.

Carroll J, Koukoura S, McDonald A, Charalambous A, Weiss S, McArthur S. 2019. Wind turbine gearbox failure and remaining useful life prediction using machine learning techniques. *Wind Energy* **22(3)**:341–446 DOI 10.1002/we.2290.

Chai S, Dong L, Ren W, Li Y, Chen Z, Wang Z. 2024. A treelike framework combining fault diagnosis and RUL prediction. *Measurement Science and Technology* **35(6)**:066108 DOI 10.1088/1361-6501/ad2d50.

Cheng H, Kong X, Chen G, Wang Q, Wang R. 2021. Transferable convolutional neural network based remaining useful life prediction of bearing under multiple failure behaviors. *Measurement* **168(3)**:108286 DOI 10.1016/j.measurement.2020.108286.

de Pater I, Mitici M. 2023. Developing health indicators and RUL prognostics for systems with few failure instances and varying operating conditions using a LSTM autoencoder. *Engineering Applications of Artificial Intelligence* **117(Part A)**:105582 DOI 10.1016/j.engappai.2022.105582.

Duan C, Shen Y, Guo K, Sheng B, Wang Y. 2023. Remaining useful life prediction based on a PCA and similarity methods. *Measurement Science and Technology* **35(3)**:35020 DOI 10.1088/1361-6501/ad0685.

Fan Y, Nowaczyk S, Rögnvaldsson T. 2020. Transfer learning for remaining useful life prediction based on consensus self-organizing models. *Reliability Engineering and System Safety* **23**:107098 DOI 10.1016/j.ress.2020.107098.

Ferreira C, Gonçalves G. 2022. Remaining useful life prediction and challenges: a literature review on the use of machine learning methods. *Journal of Manufacturing Systems* **63**:550–562 DOI 10.1016/j.jmsy.2022.05.010.

Fong KF, Lee CK, Leung MKH, Sun Y, Zhu G, Baek SH, Luo XJ, Lo TKK, Leung HSY. 2023. A hybrid multiple sensor fault detection, diagnosis and reconstruction algorithm for chiller plants. *Journal of Building Performance Simulation* **16(5)**:588–608 DOI 10.1080/19401493.2023.2189303.

Han P, Liu Z, He X, Ding SX, Zhou D. 2024. Multi-condition fault diagnosis of dynamic systems: a survey, insights, and prospects. *Systems and Control* **22**:15728–15744 DOI 10.1109/TASE.2025.3571516.

Haobin W, Zhang L, Sinha JK. 2024. Early prediction of remaining useful life for rolling bearings based on envelope spectral indicator and Bayesian filter. *Applied Sciences* **14(1)**:436 DOI 10.3390/app14010436.

He Y, Kang Y, Tsung F, Xiang D. 2023. Directional fault classification for correlated high-dimensional data streams using hidden Markov models. *Journal of Quality Technology* **55(5)**:535–549 DOI 10.1080/00224065.2023.2210320.

Heng A, Zhang S, Tan ACC, Mathew J. 2009. Rotating machinery prognostics: state of the art, challenges and opportunities. *Mechanical Systems and Signal Processing* **23(3)**:724–739 DOI 10.1016/j.ymssp.2008.06.009.

Hu Q, Zhao Y, Wang Y, Peng P, Ren L. 2023. Remaining useful life estimation in prognostics using deep reinforcement learning. *IEEE Access* **11**:32919–32934 DOI 10.1109/ACCESS.2023.3263196.

Ikonen TJ, Corona F, Harjunkoski I. 2023. Likelihood maximization of lifetime distributions with bathtub-shaped failure rate. *IEEE Transactions on Reliability* **72(2)**:759–773 DOI 10.1109/TR.2022.3190542.

Khan MA, West S, Wuest T. 2020. Midlife upgrade of capital equipment: a servitization-enabled, value-adding alternative to traditional equipment replacement strategies. *CIRP Journal of Manufacturing Science and Technology* **29(4)**:232–244 DOI 10.1016/j.cirpj.2019.09.001.

Kim WD, Lee HJ, Kim JY, Koh SK. 2004. Fatique life estimation of an engine rubber mount. *International Journal of Fatigue* **26(5)**:553–560 DOI 10.1016/j.ijfatigue.2003.08.025.

Kumar S, Raj KK, Cirrincione M, Cirrincione G, Franzitta V, Kumar RR. 2024. A comprehensive review of remaining useful life estimation approaches for rotating machinery. *Energies* **17(22)**:5538 DOI 10.3390/en17225538.

Lee C-K, Chang SJ. 2020. Fault detection in multi-core C&I cable via machine learning based time-frequency domain reflectometry. *Applied Science* **10(1)**:158 DOI 10.3390/app10010158.

Lee J-G, Kim Y-S, Lee JH. 2023. Preventing forklift front-end failures—predicting the weight centers of heavy objects, remaining useful life prediction under abnormal conditions, and failure diagnosis based on alarm rules. *Sensor* **23(18)**:7706 DOI 10.3390/s23187706.

Lei Y. 2016. 6—Remaining useful life prediction. In: *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Oxford: Butterworth-Heinemann, 281–358.

Li N, Lei Y, Liu X, Yan T, Xu P. 2023. Machinery health prognostics with multimodel fusion degradation modeling. *IEEE Transactions on Industrial Electronics* **70(11)**:11764–11773 DOI 10.1109/TIE.2022.3231273.

Li K, Ren L, Li X, Wang Z. 2024. Remaining useful life prediction of equipment considering dynamic thresholds under the influence of maintenance. *Eksploatacja i Niezawodność—Maintenance and Reliability* **26(1)**:174903 DOI 10.17531/ein/174903.

Liang J, Liu H, Xiao N-C. 2024. A hybrid approach based on deep neural network and double exponential model for remaining useful life prediction. *Expert Systems with Applications* **249(Part A)**:123563 DOI 10.1016/j.eswa.2024.123563.

Liao H, Tian Z. 2012. A framework for predicting the remaining useful life of a single unit under time-varying operating conditions. *IIE Transactions* **45(9)**:964–980 DOI 10.1080/0740817x.2012.705451.

Liu P, Dai C, Zhao S, Li S, Liu B, Liu G. 2020. Prediction method for RUL of underwater self-enhancement structure: subsea Christmas tree high-pressure valve actuator as a case study. *Journal of Marine Science and Technology* **25(4)**:1177–1185 DOI 10.3390/jmse11051065.

Lu Q, Li M. 2023. Digital twin-driven remaining useful life prediction for rolling element bearing. *Machines* **11(7)**:678 DOI 10.3390/machines11070678.

Lv S, Hu X, Wang B. 2023. Mechanical equipment performance degradation assessment method based on improved degradation feature extraction and sample completeness. *International Journal of Acoustics and Vibration* **28(1)**:21–33 DOI 10.20855/ijav.2023.28.11891.

Ma H, Xu C, Yang J. 2023. Design of fine life cycle prediction system for failure of medical equipment. *Journal of Artificial Intelligence and Technology* **3(2)**:39–45 DOI 10.37965/jait.2023.0161.

Martins RS, Vale MRBG, Maitelli AL. 2015. Hybrid methods for detection and identification of faults in dynamic systems. *Asian Journal of Control* **17(5)**:1831–1847 DOI 10.1002/asjc.1039.

Mehta S, Prabhu Bam RV, Prabu Gaonkar RS. 2024. Machine learning based remaining useful life estimation—concept and case study. In: *Reliability Engineering for Industrial Processes*. Cham: Springer Link, 155–180.

Nees Jan VE, Waltman L. 2014. Visualizing bibliometric networks. In: *Measuring Scholarly Impact*. Cham: Springer, 285–320.

Nelson W, Culp C. 2023. FDD in building systems based on generalized machine learning approaches. *Energies* **16(4)**:1637 DOI 10.3390/en16041637.

Neupane D, Bouadjenek MR, Dazeley R, Aryal S. 2025. Data-driven machinery fault detection: a comprehensive review. *Neurocomputing* **627**:129588 DOI 10.2139/ssrn.4856168.

Nobanee H, Youssef Al Hamidi F, Ali Abdulaziz F, Abukarsh LS, Falah Alqahtani A, Khalifa AlSubaey S, Mohamed Alqahtani S, Abdulla Almansoori H. 2021. A bibliometric analysis of sustainability and risk management. *Sustainability* **13(6)**:3277 DOI 10.3390/su13063277.

Noot J-P, Martin M, Birmele E. 2025. LSTM and transformers based methods for remaining useful life prediction considering censored data. *International Journal of Prognostics and Health Management* **16(2)** DOI 10.36001/ijphm.2025.v16i2.4260.

Open Knowledge Maps. 2024. Streamgraph for research on remaining useful life. *Available at https://openknowledgemaps.org/streamgraph/6762e3f7ffdcdb629f534fa7e9df7d22*.

Oumaima R, Benabdellah NC, Zellou A. 2023. A systematic literature review on data quality assessment. *Bulletin of Electrical Engineering and Informatics* **12(6)**:3736–3757 DOI 10.11591/eei.v12i6.5667.

Ozkat EC, Bektas O, Nielsen MJ, la Cour-Harbo A. 2023. A data-driven predictive maintenance model to estimate RUL in a multi-rotor UAS. *International Journal of Micro Air Vehicles* **15**:1–14 DOI 10.1177/17568293221150171.

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P, Moher D. 2021. The PRISMA, 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* **372**:71 DOI 10.1136/bmj.n71.

Pei H, Hu C, Si X, Zheng J, Zhang Q, Zhang Z, Pang Z. 2019. Remaining useful life prediction for nonlinear degraded equipment with bivariate time scales. *IEEE Access* **7**:165166–165180 DOI 10.1109/access.2019.2951804.

PRISMA 2020 Checklist. 2020. PRISMA. *Available at https://www.prisma-statement.org/prisma-2020-checklist*.

Qian Y, Yan R, Gao RX. 2017. A multi-time scale approach to remaining useful life prediction in rolling bearing. *Mechanical Systems and Signal Processing* **83**:549–567 DOI 10.1016/j.ymssp.2016.06.031.

Qiu Y, Li Z. 2024. Neural network-based approach for failure and life prediction of electronic components under accelerated life stress. *Electronics* **13(8)**:1512 DOI 10.3390/electronics13081512.

Rana S. 2025. AI-driven fault detection and predictive maintenance in electrical power systems: a systematic review of data-driven approaches, digital twins, and self-healing grids. *American Journal of Advanced Technology and Engineering Solutions* **1(1)**:258–289 DOI 10.63125/4p25x993.

Rosero RL, Silva C, Ribeiro B. 2022. Remaining useful life estimation of cooling units via time-frequency health indicators with machine learning. *Aerospace* **9(6)**:309 DOI 10.3390/aerospace9060309.

Rozhkovskaya AA, Sychev IO. 2020. Problems of predicting the remaining useful life. In: *2020 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus),* St. Petersburg and Moscow.

Sayyad S, Kumar S, Bongale A, Kamat P, Patil S, Kotecha K. 2021. Data-driven remaining useful life estimation for milling process: sensors, algorithms, datasets, and future directions. *IEEE Access* **9**:110255–110286 DOI 10.1109/access.2021.3101284.

Seman LO, Camponogara E, Stefenon SF, Mariani VC, Coelho LDS. 2023. Machine fault detection using a hybrid CNN-LSTM attention-based model. *Sensors* **23(9)**:4512 DOI 10.3390/s23094512.

Serradilla O, Zugasti E, Rodriguez J, Zurutuza U. 2022. Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects. *Applied Intelligence* **52(10)**:10934–10964 DOI 10.1007/s10489-021-03004-y.

Severson KA, Attia PM, Jin N, Perkins N, Jiang B, Yang Z, Chen MH, Aykol M, Herring PK, Fraggedakis D, Bazant MZ, Harris SJ, Chueh WC, Braatz RD. 2019. Data-driven prediction of battery cycle life before capacity degradation. *Nature Energy* **4**:383391 DOI 10.1038/s41560-019-0356-8.

Sewell KA, Schellinger J, Bloss JE. 2023. Effect of PRISMA 2009 on reporting quality in systematic reviews and meta-analyses in high-impact dental medicine journals between 1993–2018. *PLOS ONE* **18(12)**:e0295864 DOI 10.1371/journal.pone.0295864.

Solari F, Lysova N, Montanari R. 2023. Digital twin based on historical data and simulation results: fault detection and estimation of the remaining useful life of a cyclone bag filter. *Applied Sciences* **13(14)**:8297 DOI 10.3390/app13148297.

Solís-Martín D, Galán-Páez J, Borrego-Díaz J. 2023. On the soundness of XAI in prognostics and health management (PHM). *Information* **14(5)**:256 DOI 10.3390/info14050256.

Soualhi A, Lamraoui M, Elyousfi B, Razik H. 2022. PHM SURVEY: implementation of prognostic methods for monitoring industrial systems. *Energies* **15(19)**:6909 DOI 10.3390/en15196909.

Titu-Marius BI. 2021. Reliability and failures of electronic components/systems. *Electrotehnica, Electronica, Automatica (EEA)* **69(2)**:76–82 DOI 10.46904/eea.21.69.2.1108009.

Ture BA, Akbulut A, Zaim AH, Catal C. 2024. Stacking-based ensemble learning for remaining useful life estimation. *Soft Computing* **28**:1337–1349 DOI 10.1007/s00500-023-08322-6.

van Eck NJ, Waltman L. 2010. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **84**:523–538 DOI 10.1007/s11192-009-0146-3.

Wang Z-Q, Hu C-H, Si X, Zio E. 2018. Remaining useful life prediction of degrading systems subjected to imperfect maintenance: application to draught fans. *Mechanical Systems and Signal Processing* **100(7)**:802–813 DOI 10.1016/j.ymssp.2017.08.016.

Wang F-K, Mamo T. 2019. Hybrid approach for remaining useful life prediction of ball bearings. *Quality and Reliability Engineering International* **35(7)**:2494–2505 DOI 10.1002/qre.2538.

Wang X, Wang C, Zhu K, Zhao X. 2022. A mechanical equipment fault diagnosis model based on TSK fuzzy broad learning system. *Symmetry* **15(1)**:83 DOI 10.3390/sym15010083.

Wang D, Xian X, Song C. 2023. Joint learning of failure mode recognition and prognostics for degradation processes. *IEEE Transactions on Automation Science* **21(2)**:1421–1433 DOI 10.1109/TASE.2023.3239004.

Wang Y, Zhao Y. 2022. Multi-scale remaining useful life prediction using long short-term memory. *Sustainability* **14(23)**:15667 DOI 10.3390/su142315667.

Wang Y, Zhao Y. 2023. Three-stage feature selection approach for deep learning-based RUL prediction methods. *Quality and Reliability Engineering International* **39(4)**:1223–1247 DOI 10.1002/qre.3288.

Wu Q, Ding K, Huang B. 2020. Approach for fault prognosis using recurrent neural network. *Journal of Intelligent Manufacturing* **31(7)**:1621–1633 DOI 10.1007/s10845-018-1428-5.

Wu Z, Wang Z, Wei H, Ren J, Yuan Y, Wang T, Duan W, Wei H, Wang S. 2022. Remaining useful life prediction for equipment based on RF-BiLSTM. *AIP Advances* **12(11)**:209 DOI 10.1063/5.0125885.

Zamzam AH, Ibrahim Al-Ani AK, Abdul Wahab AK, Lai KW, Satapathy SC, Khalil A, Azizan MM, Hasikin K. 2021. Prioritisation assessment and robust predictive system for medical equipment: a comprehensive strategic maintenance management. *Frontiers in Public Health* **9**:782203 DOI 10.3389/fpubh.2021.782203.

Zhang Y, Fang L, Qi Z, Deng H. 2023a. A review of remaining useful life prediction approaches for mechanical equipment. *IEEE Sensors Journal* **23(24)**:29991–30006 DOI 10.1109/jsen.2023.3326487.

Zhang Z, Li T, Zhang J, Du D, Si X. 2023b. An age-dependent prognostic model for nonlinear degrading devices based on diffusion process. *IEEE Sensors Journal* **23(9)**:9500–9511 DOI 10.1109/JSEN.2023.3257160.

Zhang J-X, Si X, Du D-B, Hu C-H, Hu C. 2020. A novel iterative approach of lifetime estimation for standby systems with deteriorating spare parts. *Reliability Engineering & System Safety* **201**:106960 DOI 10.1016/j.ress.2020.106960.

Zhang Y, Yang Y, Xiu X, Li H, Liu R. 2021. A remaining useful life prediction method in the early stage of stochastic degradation process. *IEEE Transactions on Circuits* **68(6)**:2027–2031 DOI 10.1109/TCSII.2020.3034393.

Zhang Y, Yu K, Lei Z, Ge J, Xu Y, Li Z, Ren Z, Feng K. 2023c. Integrated intelligent fault diagnosis approach of offshore wind turbine bearing based on information stream fusion and semi-supervised learning. *Expert Systems with Applications* **232(7)**:120854 DOI 10.1016/j.eswa.2023.120854.

Zhao Y, Li T, Zhang X, Zhang C. 2019. Artificial intelligence-based fault detection and diagnosis methods for building energy systems: advantages, challenges and the future. *Renewable and Sustainable Energy Reviews* **109**:85–101 DOI 10.1016/j.rser.2019.04.021.

Zheng J, Liao J, Zhu Y. 2023. Two-stage multi-channel fault detection and remaining useful life prediction model of internal gear pumps based on robust-ResNet. *Sensors* **23(5)**:2395 DOI 10.3390/s23052395.

Zhu D, Lyu J, Gao Q, Lu Y, Zhao D. 2024. Remaining useful life estimation of bearing using spatio-temporal convolutional transformer. *Measurement Science and Technology* **35(4)**:108308 DOI 10.1016/j.engappai.2024.108308.