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Applications of Machine Learning Techniques in Asset Management of Engineering Systems: A Bibliometric Analysis

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Abstract. This bibliometric analysis systematically maps the scientific landscape of machine learning (ML) applications in asset management for engineering systems. It uses a corpus of 1,158 publications from 2005 to 2025. The study's methodology is based on a comprehensive asset lifecycle perspective (ALC), aligning findings with the strategic clauses of the ISO 55001standard. The analysis reveals exponential growth in publications since 2018, confirming the field's rapid maturity and relevance. Keyword co-occurrence analysis identified seven thematic clusters, with the intellectual core overwhelmingly concentrated on the operational phase (ISO 55001, Clause 8) and specifically on predictive maintenance (PdM), fault detection, and diagnostics (Clusters 2 and 3). Citation burst analysis reinforces this focus, highlighting systematic reviews on PdM as the most influential literature defining the current research frontier. The study also identifies significant research gaps in the holistic application of ML across the entire ALC. strategic phases such as planning, acquisition, operation and disposal (including value recovery and end-of-life management) are underrepresented in the core literature. These findings suggest that, although ML provides a highly developed set of tools for technical operations, future research must shift its focus strategically to support the strategic objectives of the ISO 55001 framework. This will facilitate a complete, value-driven ALC management system.

Keywords: Machine Learning, Asset Management, ISO 55001, Engineering Systems, Bibliometric Analysis

1 Introduction

In modern industrial and infrastructural environments, asset management is crucial for ensuring operational efficiency, reducing costs, extending asset lifecycles, and creating value for organizations [1, 2]. Recently, there has been considerable interest in asset management research in both academia and industry. Similarly, organizations with intensive asset utilization have contributed significantly to advancing knowledge in asset management [3]. Standards help organizations align their practices with common principles, terminology, and requirements, ensuring that asset management encompasses more than the technical maintenance of individual components. According to ISO 55000, asset management is the alignment of organizational objectives with the value derived from assets throughout their lifecycle. This frames asset management as a strategic, value-driven discipline rather than a purely operational activity [4].

In asset management-related fields, a variety of Industry 4.0 (I4.0) technologies are emerging that support highly efficient organizations [5]. The integration of digital technologies across organizational functions is transforming business operations and the delivery of value to customers and stakeholders [6]. Although the term "digital transformation" is widely used, it varies significantly in practice. Essentially, it refers to strategic organizational change and internal restructuring driven by the adoption and use of new digital technologies to transform existing business models, processes, and relationships with external actors [7]. This transformation has important implications for asset management, requiring companies to reassess their approaches across different lifecycle phases. Adopting digital technologies can optimize asset performance, enhance maintenance management, improve decision-making processes, and increase value for the organization and its stakeholders [8].

Despite significant progress in standardization and process-oriented approaches, one of the remaining key challenges is integrating advanced analytical methods, particularly machine learning (ML) and artificial intelligence (AI), into asset management systems operating in real-world environments [9]. This is especially relevant for data-rich systems that rely on sensors, the Internet of Things (IoT), and condition monitoring technologies. These systems can generate large amounts of operational data, but they often lack systematic frameworks for predictive and decision-support applications [10].

The application of ML in asset management is rapidly gaining attention as organizations seek to improve performance, optimize maintenance, and enhance decision-making across engineering systems [11, 12]. Despite the growing body of research in this field, it remains highly interdisciplinary, encompassing areas such as predictive maintenance (PdM), reliability engineering, and digital technologies. This can lead to a fragmented understanding of its developments [13, 14]. Bibliometric analysis is a valuable method for systematically mapping literature, identifying influential works and authors, and uncovering emerging trends and research gaps [15, 16]. While prior studies have examined bibliometric patterns in asset management and digital technologies more broadly, there is still a lack of comprehensive analysis specifically addressing ML applications in engineering asset management. This study aims to address this gap by providing a structured overview of the scientific landscape and highlighting important research directions and opportunities for future exploration.

1.1 Study Focus: ML Applications in Engineering Asset Lifecycle

Effective asset management is essential for the competitiveness, reliability, and sustainability of engineering systems [17, 18], as well as other sectors such as critical infrastructure [19]. As industrial data has proliferated, ML algorithms have become the primary enabler for transitioning from reactive or time-based maintenance to comprehensive, data-driven management optimized across the entire asset lifecycle [11, 20].

This bibliometric analysis primarily focuses on the utilization of ML within manufacturing systems. However, the study's methodology is based on the comprehensive asset lifecycle perspective, as structured by the ISO 55001 [21] standard. Asset management is a universal discipline, and the principles underlying the application of ML for strategic decision-making (e.g., risk reduction, maintenance optimization, and demand forecasting) can be transferred across various engineering systems. Therefore, the following table includes key examples from related fields (e.g., power systems, logistics, and critical rotating equipment) to demonstrate the breadth and maturity of ML techniques available for adoption in the manufacturing sector. This selection provides a holistic view, avoiding an overly narrow or isolated interpretation.

This holistic approach emphasizes that ML serves not only technical operational goals, such as PdM (Clause 8), but also the core strategic objectives of the ISO 55001 standard. These objectives include planning (Clause 6) and actions to address risks and opportunities (Clause 6.1) and maximizing residual value through the principles of sustainable development.

Table 1 presents representative examples of critical ML applications and positions them within this framework, serving as a conceptual model for interpreting the bibliometric analysis's findings. The table illustrates how ML enables the transformation from isolated decisions to comprehensive, data-driven asset management, where optimization is achieved across every phase, from identifying a need to disposal.

Table 1. Machine learning in asset management: A full lifecycle perspective

Asset lifecycle stage	ML application / key function	ISO 55001 alignment	Supporting literature (key reference and focus)
1. Identify need	Demand and capacity forecasting	6.2.1 Asset management objectives: Aligning creation with organizational goals.	Muñoz-Villamizar A, Rafavy CY, Casey J (2022) [22]; Rajora, G. L., et al. (2024) [23]: Power systems
2. Create or acquire	Risk assessment & portfolio optimization	6.1 (Balancing C-R-P & opportunities)	Ni, J., Hu, Y., & Zhong, R. Y. (2021) [24]: Price uncertainty; Husna, A. ul, Ghasempoor, A., & Amin, S. H. (2024) [25]: Clustering/Optimization
3. Operate and maintain	PdM optimization & system reliability (ML/DL)	8.1 Operational planning and control: Maximizing performance and reducing operational risk.	Zhu, T., Ran, Y., Zhou, X., & Wen, Y. (2024) [26]: Deep Learning for PdM; Shahin, M., Chen, F.F., Hosseinzadeh, A. et al. (2023) [27]: Comparative ML study; Yang, C., Liu, J., Zeng, Y., & Xie, G. (2019) [28]: Real-time monitoring.
4. Dispose and/or replace	Value recovery, remanufacturing & recycling optimization	6.2.2 (Sustainability & Life-cycle planning)	Koulinas, G., Paraschos, P., & Koulouriotis, D. (2021) [29]: RL for recycling policies; Cherrington, M., Lu, Z., Xu, Q. et al. (2020) [30]: DL for sustainable DSS.

2 Research Methodology

A systematic search was conducted. It was done following the PRISMA 2020 guidelines [31]. The goal was to identify publications related to maintenance and asset management.

2.1 Analytical Tools

Two specialized tools were applied to process the collected data for the subsequent bibliometric analysis.

- Burst Detection: Analysis of sudden increases in the frequency of keyword usage over time (burst detection) was performed using the CiteSpace software tool (https://citespace.podia.com).
- Co-occurrence and Clustering Analysis: Keyword co-occurrence, country collaboration, and clustering analyses were performed using VOSviewer (https://www.vosviewer.com/).

2.2 Search Strategy and Keyword Selection

A comprehensive search was conducted in relevant databases using a broad set of keywords to explore the application of ML techniques in asset management. The search strategy incorporated terms associated with different ML techniques, including "ML," "DL," and "artificial neural networks," to encompass the diverse ML methodologies employed in the field. Additionally, terms such as "asset management," "asset lifecycle," and "life-cycle management" were included to focus on studies related to the entire asset lifecycle, from initial acquisition to decommissioning and replacement. Keywords such as "PdM," "condition monitoring," and "reliability engineering" were also incorporated to ensure the inclusion of research on predictive techniques. The search was also extended to the manufacturing sector, where many asset management strategies are implemented, by including terms such as "manufacturing systems" and "manufacturing assets."

This search strategy was designed to identify foundational research on ML applications in asset management, as well as more specialized studies related to specific phases of the asset lifecycle. There was a particular emphasis on PdM, emerging strategies for risk assessment, portfolio optimization, and asset replacement.

2.3 Scopus Search Query

The comprehensive search strategy outlined above produced the following Scopus search string. It was executed across the title, abstract, and keywords (TITLE-ABS-KEY) fields:

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TITLE-ABS-KEY ( ("machine learning" OR "deep learning" OR "artificial intelligence" OR "artificial neural network*") AND ("asset management" OR "asset life* cycle" OR "life-cycle management" OR "engineering assets" OR "maintenance management" OR "reliability engineering" OR "predictive maintenance" OR "condition monitoring" OR "risk assessment" OR "portfolio optimization" OR "asset replacement strategy") AND ("manufacturing" OR "manufacturing system*" OR "manufacturing asset*") )
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The comprehensive filtering process involved several exclusion criteria related to publication date, language, subject area, document type, and source type. Table 2 summarizes the screening and analysis process used in this study. It details the records identified and the number of exclusions applied at each stage.

Table 2. Overview of the document selection process

Step	Stage	Details	Records (n)
Identification of new studies	Identification	Records identified from: Scopus Databases	2,549
		Records removed before screening:	
		Limited to 2005 - 2025	2,469
		Limited to English	2,434
	Screening	Limited to Engineering area	1,659
		Limited to conference paper, article, book chapter	1,466
		Excluded trade journals	1,460
		Records screened	1,460
		Records excluded	302
	Included	Total studies included in review	**1,158**

The bibliographic data were extracted on November 17, 2025. After the selection process, the final corpus of 1,158 publications was categorized into three types of documents: Articles (545; 47.06%), conference proceedings (482; 41.62%), and book chapters (131; 11.31%).

To ensure the dataset's relevance and consistency, this study focuses on publications classified under engineering, even though some of these articles may also be assigned to other subject areas in Scopus. This choice is justified because the research aims to explore asset management and maintenance practices within industrial and technical systems, topics that are primarily addressed in engineering literature. While other disciplines, such as computer science, mathematics, and decision sciences, may discuss related methods or models, they often lack direct application to practical engineering contexts. Restricting the analysis to engineering enables a more coherent comparison of trends, authorship, and citation patterns and aligns with the methods employed in previous bibliometric studies in this field [9, 14].

3 Results and Discussion

Figure 1 illustrates the chronological analysis of the selected document corpus and reveals a clear and sustained trend of accelerating research interest in the convergence of ML and asset management. The annual publication count remained relatively low and stable until around 2017, confirming the topic's initial status as a niche or emerging area. A significant inflection point occurred around 2018, marking the beginning of an exponential growth phase. This surge reflects the simultaneous industrial adoption of digital transformation, the proliferation of large-scale industrial data, and the increasing maturity of advanced ML techniques. Consequently, the cumulative number of publications demonstrates a steep, almost vertical trajectory in the final years of the analyzed period (2021–2025). This confirms that ML in asset management is now a highly relevant and rapidly maturing field of scholarly inquiry.

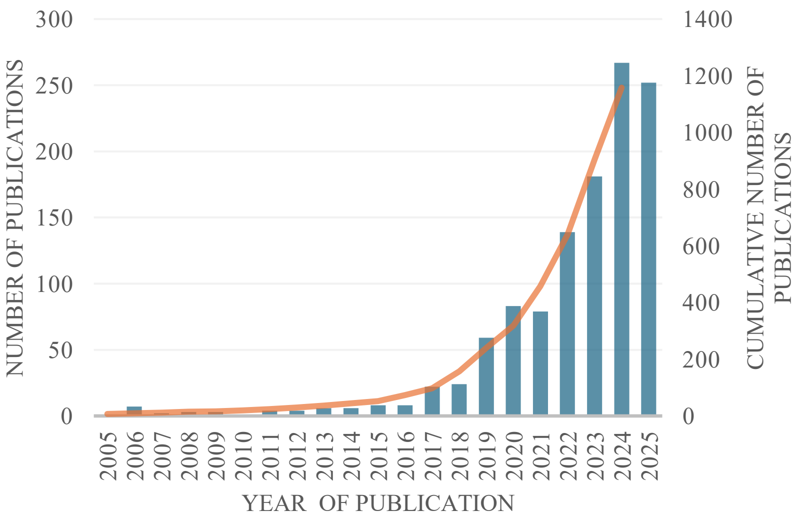

Fig. 1. Annual and cumulative number of publications on machine learning in asset management (2005–2025).

A geographical analysis of the research output reveals a high concentration of scholarly contributions, indicating that a few key nations dominate the field of ML in asset management. As shown in Table 3, the top ten contributing countries account for 938 of the 1,158 documents in the corpus. India emerged as the most prolific country in terms of document volume (n = 266), while the United States exhibited the highest research impact, leading significantly in total citations (n = 6,894). Other major contributors include China (156 documents, 4,368 citations) and the United Kingdom (81 documents, 2,981 citations). Data from the Total Link Strength column suggests that India is a primary driver of production while the United States remains a central, highly influential hub within the global collaborative network.

Tabel 3. Geographical distribution of research contribution (top 10 countries)

Country	Documents	Citations	Total Link Strength
India	266	2,286	111
United States	170	6,894	85
United Kingdom	81	2,981	69
China	156	4,368	65
Germany	99	1,562	38
France	38	572	28
Australia	23	623	25
Italy	62	1,780	25
Spain	34	680	25
Canada	29	700	20
Total (Top 10)	**938**	**22,446**	

Figure 2 provides an additional visualization of the collaborative landscape derived from the bibliometric analysis. This visualization confirms the centrality of the top contributors identified in Table 1, and it reveals distinct co-authorship clusters. The largest cluster, colored red and centered around India, primarily includes other Asian countries, such as China, Saudi Arabia, and Turkey. This suggests a strong regional research alliance in terms of output volume. In contrast, the green cluster (centered around the United States and Germany) and the blue cluster (centered around the United Kingdom) showcase established research partnerships involving European and Anglosphere countries. These partnerships have a high research impact, as evidenced by citation data. These clusters highlight the fragmented yet rapidly forming nature of the global research network on ML in asset management.

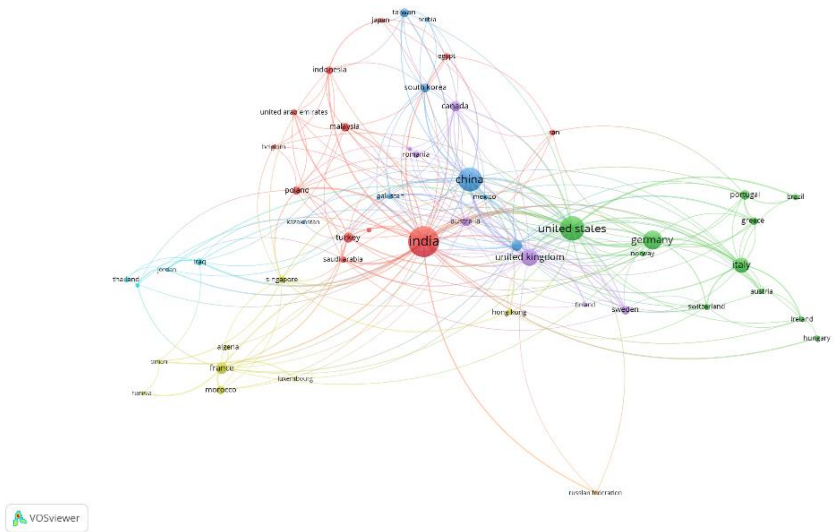

Fig 2. Country co-authorship network for machine learning in asset management. The size of the nodes (circles) reflects the volume of publications (Documents), and the lines represent co-authorship links. The clusters (colors) indicate groups of countries with strong collaboration ties.

An analysis of the ten most-cited publications (presented in Table 3) reveals the intellectual backbone of ML in the asset management domain. The core research focuses on systematic literature reviews [20] and fundamental PdM methodologies [11, 32]. Although the 2019 article by Carvalho et al. has the highest overall citation count, the calculated Citations Per Year (CPY) metric indicates that the 2020 article by Zonta et al. [11] leads in citation velocity with 152.33 Citations Per Year (CPY), demonstrating its immediate impact. This emphasis on data-driven methods confirms the field's shift toward ML-driven fault detection [33, 34] over traditional methods.

Tabel 4. Top 10 most cited publications

Rank	Authors	Year	Title (as truncated)	Abbreviated title (source)	Cited by (Total)	Citations per year (CPY)
1	Carvalho, T. et al. [20]	2019	A systematic literature review	Computers Ind. Eng.	1044	149.14
2	Zonta, T. et al. [11]	2020	Predictive maintenance	Computers Ind. Eng.	914	152.33
3	Susto, G.A. et al. [32]	2015	Machine learning for predictive maintenance	IEEE Trans. Ind. Electron.	698	63.45
4	Wu, D. et al. [35]	2017	A comparative study	J. Manuf. Sci. Eng.	585	65.00
5	Zhang, W. et al. [33]	2019	Data-driven methods	IEEE Syst. J.	513	73.29
6	Ayvaz, S. et al. [36]	2021	Predictive maintenance	Expert Syst. Appl.	403	80.60
7	Luo, B. et al. [34]	2018	Early fault detection	IEEE Trans. Ind. Electron.	275	34.38
8	Essien, A. et al. [37]	2020	A deep learning model	IEEE Trans. Ind. Inform.	258	43.00
9	Al-Dulaimi, A. et al. [38]	2019	A multimodal and fusion	Computers Ind.	255	36.43
10	Amrutha, M. et al. [39]	2018	A research agenda	5th Int Conf Ind Eng & App (ICIEA)	228	28.50

Note: The publication years used for CPY calculations and temporal analysis adhere to the year provided in the Scopus CSV database export to ensure dataset consistency. Therefore, the year 2018 for Luo et al. is retained, despite the official journal volume print year being 2019.

The scholarly publishing landscape further solidifies the field's focus on applied engineering and technology. The International Journal of Advanced Manufacturing Technology is the most prolific publication venue with 53 documents. A significant portion of the corpus is distributed across high-ranking conference proceedings and book series, such as Lecture Notes in Networks and Systems (46 documents) and Procedia CIRP (45 documents), which highlights the rapid dissemination of knowledge through conferences. The prominence of journals such as Computers and Industrial Engineering (20 articles) indicates that the primary area of research is industrial and manufacturing applications.

Citation burst analysis identifies references that received an intense surge in citations over a specific period. This pinpoints the most influential papers currently driving the field’s intellectual momentum. Analysis of the top eight references confirms two key aspects of the corpus. First, the research front is focused almost exclusively on ML and DL applications for PdM. Second, the most influential papers are systematic literature reviews (SLRs) and surveys, suggesting that the field is currently in a phase of methodological consolidation and synthesis.

The strongest citation bursts are associated with recent reviews that define the state of the art. The highest burst strength (5.18) was observed for the systematic literature review on ML for PdM by Carvalho (2019) [20], with a burst period from 2022 to 2023. Similarly, Susto's [32] influential paper on ML for PdM (published in 2015) registered a strength of 4.79, indicating a long period of influence from 2015 to 2020.

Crucially, references with burst periods extending into the present and near future (2023–2025) define the current research trajectory. The SLR on PdM in Industry 4.0 by Zonta (2020) [11] exhibits a strong recent burst (3.38) from 2023 to 2025, while the paper on ML in PdM towards Smart Manufacturing by Çınar (2020) [40] also shows a highly active burst (3.22) from 2022 to 2025. This finding reinforces the thematic centrality of Cluster 1 (AI-driven data analytics) and the core concept of PdM as the most active areas of scholarly pursuit.

The structural analysis of the corpus keywords uses a co-occurrence map to delineate the field's intellectual landscape (Figure 3). A quantitative review confirms that "PdM" (515 occurrences, total link strength 5,096) and "ML" (449 occurrences, total link strength 4,635) are the central concepts for the domain. Frequent terms such as "condition monitoring" (295 occurrences) and "learning systems" (258 occurrences) support this foundation.

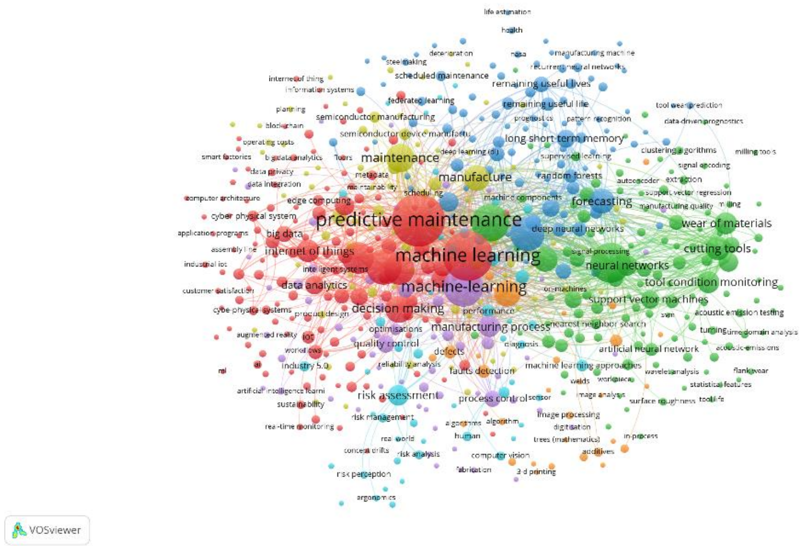

Fig. 3. Keyword co-occurrence network visualization of ML in asset management

The VOSviewer analysis identified seven distinct, interconnected thematic clusters, which are labeled in Table 5. The research focus is organized around four primary domains (Clusters 1–4), which collectively account for the largest share of the literature and form the field's core intellectual structure. The remaining three clusters (Clusters 5–7) represent nascent or peripheral research domains.

Table 5: Identification and labeling of thematic clusters (Keyword co-occurrence analysis)

Cluster	Items	Cluster color	Core concept label	Defining keywords
Cluster 1	146	Red	AI-Driven Data Analytics & Cyber-Physical Systems	AI, Big Data, Cyber-Physical Systems
Cluster 2	125	Blue	Signal Processing and Data-Driven Diagnostics	Acoustic Emission, FFT, Data Fusion, ANN
Cluster 3	101	Green	Advanced DL for Prognostics (PHM)	DL, Federated Learning,

				Explainability, Forecasting
Cluster 4	82	Yellow	Economic and Decision Support Systems	Cost Reduction, Decision Support System, Fuzzy Logic
Cluster 5	63	Purple	Advanced AI Architectures and Intelligent Manufacturing (DRL/GAN)	Deep Reinforcement Learning (DRL), Adversarial Networks, Digital Manufacturing
Cluster 6	47	Orange	Human Factors, Safety, and Industry 5.0	Industry 5.0, Occupational Risks, Human Resource Manag
Cluster 7	30	Brown	Additive Manufacturing and Image-Based Diagnostics	3D Printing, Image Processing, Faults Detection

The visualization further details the internal thematic links (Figure 3). Cluster 1 (red), the methodological core, centers on the frequent terms "ML" and "PdM" This domain is closely linked to foundational infrastructure technologies, such as the Internet of Things and cyber-physical systems.

Clusters 2 and 3 together define the Prognostics and Health Management (PHM) domain. Cluster 2 (Blue) focuses on traditional ML methods, sensor inputs, and signal processing techniques (e.g., "acoustic emission," "fast Fourier transforms"). Cluster 3 (Advanced DL for Prognostics) introduces more complex models (e.g., "federated learning," "CNN"), focusing on PHM outcomes such as "fault prediction" and the critical aspect of "explainability."

Cluster 4 (yellow) addresses the strategic and financial viability of PdM, covering topics such as cost reduction, investments, and decision support systems.

Clusters 5–7 represent nascent or highly specific research domains. Cluster 5 focuses on advanced AI architectures and intelligent manufacturing. Cluster 6 focuses on human factors, safety, and Industry 5.0. Cluster 7 focuses on niche applications such as additive manufacturing and image-based diagnostics. The strong link between the methodological core (Cluster 1) and the applied clusters (Clusters 2 and 3) highlights the practical, application-oriented nature of the entire research field.

3.1 Core Findings: Validation and Concentration of Research Focus

Integrating the bibliometric findings (Tables 4 and 5) with the asset lifecycle perspective (Table 1) provides a robust framework for evaluating the current intellectual landscape and pinpointing significant research gaps in using ML for engineering asset management.

The results of the keyword co-occurrence analysis clearly show that the field focuses heavily on the operational phase of the asset life cycle (ISO 55001: Clause 8, "Operation"), while the strategic phases ("Planning," "Acquisition," and "Disposal") are significantly underrepresented.

Overwhelming Operational Focus (Stage 3): The largest thematic domains are dedicated to the technical execution of maintenance. Clusters 2 and 3 (Signal Processing and Diagnostics and Advanced DL for

Prognostics, respectively) directly support the core functions of PdM, fault detection, and condition monitoring, as detailed in Table 1 (Stage 3).

Technical Foundation: The dominance of Cluster 1 (AI-driven data analytics and cyber-physical systems) confirms that foundational research focuses on establishing the necessary infrastructure (IoT and big data) and methodology (AI and ML) required to enable data-driven operational decisions across the entire system.

Support for Strategic Clauses: The bibliometric results demonstrate that ML research extends beyond simple technical operations and supports strategic management clauses, albeit often indirectly.

Risk and Economic Alignment (Clause 6.1): Cluster 4 (Economic and Decision Support Systems) supports the ISO 55001 requirement to manage risks and opportunities, facilitating the balance between cost, risk, and performance.

Human Factors Integration: Including Cluster 6 (Human Factors, Safety, and Industry 5.0) broadens the strategic scope by addressing the socio-technical aspects of future industrial environments.

Advanced Applications: The presence of Cluster 5, which focuses on advanced AI architectures and intelligent manufacturing, indicates a forward-looking trend of integrating sophisticated AI models, such as deep reinforcement learning (DRL), into highly optimized, self-regulating manufacturing processes.

3.2 Major Research Gaps in the Asset Lifecycle

The analysis reveals clear gaps in holistic support for the full ALC framework in the literature:

- Underrepresented planning and acquisition (stages 1 and 2): The research focus on demand and capacity forecasting or market trend analysis (Table 1, Stage 1) is not defined by a dedicated cluster.
- Underrepresented disposal phase and value recovery (stage 4): The most significant gap is found in the final stage of the ALC concerning disposal decision-making and value recovery. Research on utilizing ML for disposal strategies, such as remanufacturing, recycling policy optimization, and maximizing asset residual value (Table 1, Stage 4) is minimal. This crucial strategic stage is only peripherally addressed by niche topics, such as Cluster 7 (additive manufacturing and image-based diagnostics). This gap is particularly notable as it aligns with the ISO 55001 emphasis on sustainability and climate change, which requires assets to be managed as part of a circular economy. This suggests a lack of focus on sustainable, long-term asset management goals beyond operational longevity.

4 Conclusion

The bibliometric analysis confirms that the field is driven primarily by the technical imperatives of PdM, which provides a robust and highly developed set of methodologies and applications for the operation and maintenance phase of the asset lifecycle. However, to transition to a comprehensive, strategic approach to asset management aligned with ISO 55001, future research must shift its focus to the underrepresented areas of initial planning and acquisition, as well as the final phases of an asset's disposal. The strong link between methodological and application clusters underscores the actionable nature of existing research and positions the field for strategic expansion. This study provides the first evidence-based roadmap demonstrating that future ML value lies in solving complex strategic challenges of asset planning and disposal. Closing these gaps is crucial to realizing the full potential of digital transformation and achieving holistic, value-driven asset management that aligns with global sustainability goals.

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