Production & Manufacturing Research
An Open Access Journal

ISSN: 2169-3277 (Online) Journal homepage: www.tandfonline.com/journals/tpmr20

A review on three decades of manufacturing maintenance research: past, present and future directions

Roberto Sala, Emmanuel Francalanza & Simone Arena

To cite this article: Roberto Sala, Emmanuel Francalanza & Simone Arena (2025) A review on three decades of manufacturing maintenance research: past, present and future directions, Production & Manufacturing Research, 13:1, 2469037, DOI: 10.1080/21693277.2025.2469037

To link to this article: https://doi.org/10.1080/21693277.2025.2469037

Published online: 20 Feb 2025.

PRODUCTION & MANUFACTURING RESEARCH
2025, VOL. 13, NO. 1, 2469037
https://doi.org/10.1080/21693277.2025.2469037

A review on three decades of manufacturing maintenance research: past, present and future directions

Roberto Sala[a], Emmanuel Francalanza[b] and Simone Arena[c]

[a]Department of Management, Information and Production Engineering, University of Bergamo, Dalmine (BG), Italy; [b]Department of Industrial and Manufacturing Engineering, University of Malta Msida, Malta Msida, Malta; [c]Department of Mechanical, Chemical, and Material Engineering, University of Cagliari, Cagliari, Italy

ABSTRACT

Maintenance engineering has taken up more and more a strategic function in recent decades due to technological advancements and its role in asset productivity. Over time, a plethora of methods have been proposed, shifting from reactive approaches to complex, data-driven strategies focused on failure prediction (e.g. through Machine learning) and knowledge management (e.g. based on ontologies and large language models). The advancements achieved by maintenance have also beneficially impacted production quality, sustainability, and safety. This work presents the results of a systematic literature review of papers published on the topic of maintenance in the past 30 years. In particular, natural language processing has been used to analyze abstract, extract topics and, through further analysis delineate past, current, and future trends in the field of maintenance engineering in manufacturing. This work contributes to define a vision on how maintenance in manufacturing will evolve in the next future.

ARTICLE HISTORY
Received 23 December 2024
Accepted 14 February 2025

KEYWORDS
Maintenance; bibliometric analysis; manufacturing; bertopic; natural language processing

1. Introduction

Maintenance engineering is a cornerstone of manufacturing engineering and operations, playing a vital role in ensuring the efficiency, reliability, and sustainability of production systems (Garg & Deshmukh, 2006). Over the past 30 years, research in this field has grown extensively, encompassing a wide range of topics and concepts, especially considering the advancements in digital technology and data analytics, which have transformed maintenance strategies from reactive methods to proactive, data-driven, approaches.

Before the 1990s, maintenance practices were predominantly reactive, focusing on addressing failures post-occurrence. However, the 1990s marked a shift toward preventive maintenance, driven by methodologies like lean engineering and Six Sigma (Shah & Ward, 2003). This period also saw the emergence of condition-based maintenance

CONTACT Roberto Sala roberto.sala@unibg.it Department of Management, Information and Production Engineering, University of Bergamo, Dalmine (BG), Italy

(CBM) approaches, supported by the introduction of software tools tailored for maintenance management.

The 2010s brought transformative changes with the rise of Industry 4.0 (I4.0) technologies. These advancements facilitated the development of predictive maintenance, powered by the integration of advanced analysis approaches such as Machine Learning (ML) algorithms (Roda & Macchi, 2021). Simultaneously, concepts like life cycle engineering and sustainability began gaining traction, reflecting a broader focus on resource efficiency and environmental stewardship (Franciosi et al., 2018; Vrignat et al., 2022).

Despite a growing body of literature and several bibliometric analyses addressing maintenance engineering (Section 2), there remains a gap in comprehensive scoping reviews that analyze the field's evolution over the past three decades while forecasting future trends. This paper addresses that gap by systematically reviewing 30 years of research in maintenance engineering within manufacturing, aiming to uncover key trends and predict future developments in the field.

To achieve this, the authors conducted a systematic literature review, leveraging Natural Language Processing (NLP) techniques and the BERTopic algorithm to analyze paper abstracts. This approach enabled a detailed exploration of thematic trends and research directions over time of a large body of work, as discussed in Section 3.

Our findings (Section 4) reveal a notable increase in interest and diversification in maintenance engineering research, particularly in the past decade. Emerging themes include the integration of data-driven and intelligent approaches alongside a growing emphasis on sustainability and life cycle engineering. By providing a snapshot of the field's evolution, this paper not only captures the progress made but also offers insights into the future trajectory of maintenance engineering in manufacturing (Sections 5 and 6).

2. Literature background

Published literature reviews in maintenance management for manufacturing are not something new. For instance, Adaramola et al. (2024) provided a review, spanning from 2017 to 2023, of advantages and disadvantages of industrial maintenance strategies, focusing on reactive, preventive, and predictive maintenance emphasizing the importance of selecting a strategy aligned with the organization's needs and challenges. Despite, this study does not highlight future research directions or evaluate the evolution of maintenance over a long period.

Recently, several reviews focused on I4.0 impact on maintenance were published. Zonta et al. (2020) conduct a systematic review of predictive maintenance initiatives in the context of I4.0, focusing on methods, standards, and applications identifying challenges and limitations, while proposing a novel taxonomy to classify research in this field. The review highlights how predictive maintenance can enhance machine downtime, cost control, and production quality, yet is often overlooked in favour of data analytics and ML in manufacturing processes. Similar to Roda and Macchi (2021), the authors of this work emphasize the increasing involvement of computer science, AI, and distributed computing in a traditionally engineering-dominated field, underscoring the importance of a multidisciplinary approach to effectively address I4.0 needs. Dafflon et al. (2021)

conduct a similar study on CPS for manufacturing in I4.0 paradigms through 2010 to 2019. Through this review, the authors highlight how the challenges to CPS for manufacturing can be observed from four viewpoints: improve production, dynamic reconfiguration, standardization, and information technology.

As the more recent term and paradigm of Industry 5.0 (I5.0) has emerged, review articles started including this term. Psarommatis et al. (2023), provide direction and advice for future research on I4.0 maintenance. To do so, the authors conducted an analysis of 344 eligible journal papers published between 2013 and 2022. The results highlight the importance of sustainability, human aspects, and the implementation of environmental KPIs in future research. Following, the authors propose a Maintenance 5.0 framework, which emphasizes the integration of human-centered and AI-driven strategies for achieving efficient and sustainable maintenance in Zero-Defect Manufacturing systems. Similarly, Ahmed Murtaza et al. (2024) provided a comprehensive analysis of the roles of ML, Digital Twins (DT), the Internet of Things (IoT), and Big Data (BD) in transforming predictive maintenance and condition monitoring. Interestingly, due to the increased connectivity and data exchange in I4.0 which can potentially expose systems to various cyber threats, the authors highlight the importance of raising questions about the integrity of the data being processed and exchanged, especially with relation to human biometric data in the context of I5.0.

Another field which recently gained relevance is the impact of maintenance on sustainability from the economic, environmental, and social perspectives. Franciosi et al. (2018), and more recently Vrignat et al. (2022), provide interesting reviews which relate the various concepts of industrial maintenance and sustainability in manufacturing. While the work by Franciosi et al. (2018) highlighted the increasing interest at the time on these topics, they envisaged the big potentiality of enabling technologies 4.0 in this frame. Vrignat et al. (2022) reviewed publications in the period between 1987 and 2021 to provide a full update on the KPIs and methods that may respond to sustainable manufacturing, maintenance policies, prognostics, and health management. The authors conclude that maintenance policies must be adapted to the paradigms of sustainable and green manufacturing. The authors also highlight the challenges brought on by the abundance of data, including more noise and uncertainty associated with the operating environment, and the data transmission which need to be processed to extract useful maintenance knowledge.

Recent literature reviews have also concentrated on domains and applications, specifically within the field of digital manufacturing. Leukel et al. (2021), have reviewed the use of ML approaches for failure prediction. Previously, Carvalho et al. (2019) pointed out the importance of choosing the appropriate ML method for predictive maintenance applications. Çinar et al. (2020), provide a wider ranging review as they consider the importance of ML in predictive maintenance for sustainable smart manufacturing in I4.0. To do so, the authors carry out a comprehensive review of the recent advancements of ML techniques applied to predictive maintenance and classify their findings by various categories. Other technologies which are reviewed for application in maintenance include the use of augmented reality, as presented by Palmarini et al. (2018), and the use of DT technologies, as presented by Errandonea et al. (2020).

It is also typical for such literature reviews to envisage the future directions within the research field. Such reviews where of primary importance for defining the scope of this publication. Garg and Deshmukh (2006) reviewed literature on maintenance management with the aim of suggesting possible gaps from the point of view of researchers and practitioners. At the time, the paper identified that the important issues in maintenance management ranged from optimization models, maintenance techniques, scheduling, and information systems. While highlighting aspects relating to the integration of maintenance within other tools such as ERP, it was already hypothesised that aspects of human behavior such as the knowledge and expert judgment of maintenance engineers may be useful in the design of customized maintenance concepts. Sharma et al. (2011) carried out a review which outlines the important techniques used at the time in various maintenance optimization models including the analytical hierarchy process, the Bayesian approach, the Galbraith information processing model, and genetic algorithms. The authors identified the emerging trend toward use of data and simulation for maintenance optimization. As previously highlighted, this would then be exacerbated with the advent of the I4.0 paradigm.

Recently, Roda and Macchi (2021) have provided an overview of the evolution of maintenance concepts. This research aimed at defined the concept of advanced maintenance, based on the state of the art of research and empirical evidence of practices. That said, this work primarily focuses on the effect of digital transformation, e-maintenance, smart and intelligent maintenance, and the impact of digitalization on maintenance approaches. In view of this, this work concludes that future research in advanced maintenance will focus on DT, AI-driven predictive capabilities, and BD analytics. The researchers conclude that key areas of future research will include improving interoperability, human-machine interfaces, and cognitive decision-making within maintenance operations.

Current literature reviews in the field of manufacturing maintenance provide a comprehensive review of industrial maintenance strategies, particularly focusing on the influence of I4.0 and the emerging I5.0 paradigms. Key emerging topics include reactive, preventive, and predictive maintenance, with a shift toward AI-driven strategies, DT, and human-machine collaboration. That said while these reviews highlight the maintenance trends up to 2023, few works evaluate the evolution of maintenance practices over a longer period. There is a gap in understanding how maintenance strategies have evolved over multiple decades, particularly with technological disruptions and changing industrial needs. This research paper therefore aims at addressing this gap by analysing literature published in this field between 1994 and 2024 and contributing a future outlook and research agenda answering these research questions:

R1. How has the manufacturing maintenance research field evolved over the past 30 years?

R2. What are the latest trends and future directions in the field of manufacturing maintenance?

3. Methodology

This section describes the methodological approach used for the research. The Scopus database was chosen due to the presence of multidisciplinary and peer-reviewed articles.

Table 1. Filters available in Scopus adopted for the literature review.

Filter	Sample dimension (after filter)
Initial sample	64,612
Allowed dates (1994–2024)	57,875
Subject area (included)	44,602
Subject area (excluded)	40,471
Document type (Article)	18,941
Source type (Journal)	15,619
Language (English)	13,305

3.1. Query definition and dataset filtering

The query *'maintenance' AND ('manufacturing' OR 'industr*')*, was launched on 24 July 2024 returning 64,612 results. To narrow the sample, Scopus' filters were applied (Table 1).

It is useful to clarify that, for the subject areas, we used the following inclusion and exclusion criteria:

- Inclusion: Engineering, Computer Science, Mathematics, Environmental Science, Business Management and Accounting, Decision science, Economics, Econometrics and Finance
- Exclusion: Biochemistry, Genetics and Molecular Biology, Medicine, Health Professions, Psychology, Immunology and Microbiology, Pharmacology, Toxicology and Pharmaceutics, Arts and Humanities. Veterinary, Neuroscience, Nursing, Multidisciplinary, Social Sciences.

Subsequently, the authors used the ScimagoJR classification to filter the results, keeping only papers published in Q1 and Q2 ranked Journals and with SJR ≥ 0.5, as in (Sgarbossa et al., 2023). This led the analysis sample to halve, from 13,305 to 6841 articles. A final check on the content of the database made it possible to remove papers lacking information considered mandatory for analysis (i.e. authors, abstract, and keywords), reducing the final sample to 6280 papers.

The data processing phase focused mainly on the analysis of abstracts through NLP and the use of the BERTopic (Grootendorst, 2022) in python 3.11. The goal was to extract the topics covered in the papers, as described in the abstracts, to understand how the interest of researchers, and their research, changed over time. BERTopic was selected because of the flexibility and customization it provides in terms of the analysis pipeline, which consists of six blocks. Table 2 shows the modeling choices and/or the configuration of the parameters and hyperparameters (if different from default). Other configurations were tested but discarded due to the results.

Abstracts were split into sentences using the *sent_tokenizer* of *nltk* (Bird et al., 2009). This step was executed because, on the one hand, it made it possible to reduce the length of the individual model inputs, thus remaining below the limit of 512 tokens. On the other hand, this allowed highlighting the multiplicity of topics characterizing each abstract. When splitting abstracts into sentences, the authors kept track of the related paper ID and, therefore, all the information related to the paper. The decision to set the values of *n_neighbours = 5* in UMAP and *min_cluster_size = 25* in HDBSCAN was made

Table 2. Bertopic customization.

Step		Configuration
Embeddings	Sentence Transformer	all-mpnet-base-v2
Dimensionality reduction	UMAP	N_neighbors = 5, random_state = 42
Clustering	HDBSCAN	Min_cluster_size = 25, metric='euclidean', cluster_selection_method='eom' prediction_data=True, gen_min_span_tree=True
Tokenizer	CountVectorizer	Stop_words='english', ngram_range = (1,4), lowercase=True
Weighting Scheme	ClassTfidfTransformer	Reduce_frequent_words=True
Fine-tune representation (optional)	KeyBERTInspired	Top_n_words = 25, random_state = 42

with the intention of maintaining a good balance between the level of detail and the number of topics resulting from the analysis. Similarly, in the tokenization phase, the decision to set *ngram_range=(1,4)* was dictated by the intention to favour clustering of similar topics based on recurring expressions.

Once set the parameters, the BERTopic model was applied to the 6280 abstracts, now split into 62,697 sentences. The model returned 383 topics as output including the topic numbered as '−1', which identifies the outliers. BERTopic's *reduce_outliers* method was applied to reanalyze outliers and automatically assign each one to the most similar topic. To ensure consistency, the same *embeddings*, *vectorizer_model*, *ctfidf_model* and representation models have been used.

The list of 382 topics was manually analyzed by the authors to identify similar and overlapping topics, thus manually reducing their number. This operation was preferred to alternative topic reduction methods because it allowed manual control over their content, thus guaranteeing satisfactory results. In particular, 33 topics have been identified and named, as detailed in Section 4. Following, each sentence was assigned the new topic and abstracts were reconstructed by keeping track of each associated topic. This step made it possible to reconstruct the initial database with the additional information on the topics.

Following, several qualitative and quantitative analyses were performed. The choice of the analyses was based both on the research interests and on a literature review of the most frequent analyses performed in bibliometric reviews.

4. Analytical analysis

This section aims to describe the results that emerged from the quantitative and qualitative analysis of the dataset.

Looking at Figure 1, an increasing trend in terms of article publication can be noticed. Considering the time of execution of the query, it is very likely that, in terms of publications, 2024 will surpass 2023. The profiling analysis of 6280 articles reveals the rising significance of the manufacturing maintenance research field, showing how the number of publications has consistently increased since 1994. Particularly, by focusing on the article publication trend, the first decade (1994–2003) accounts for 6% of the

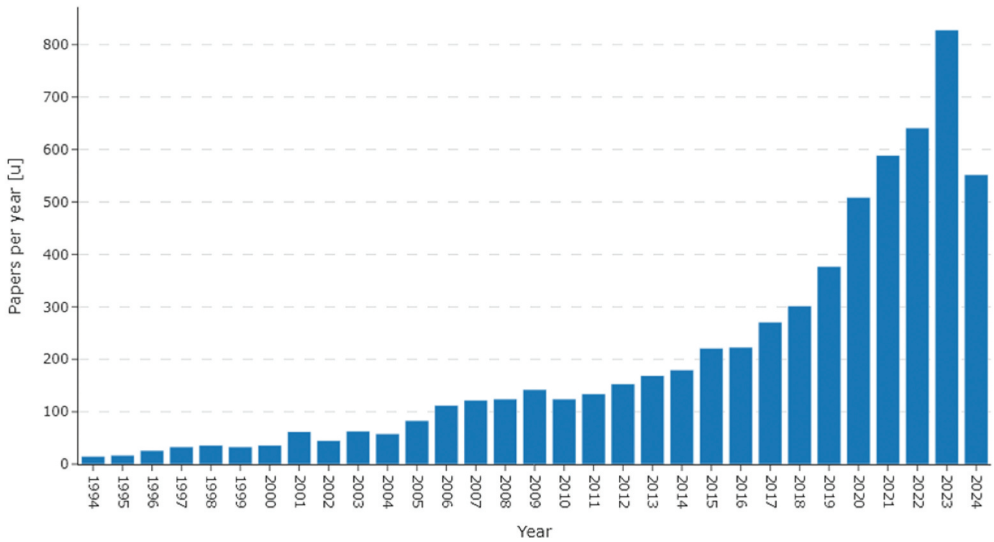

Figure 1. Number of publications by year.

Table 3. Authors' publications.

Author_Name	Current/Last affiliation	Papers
Xia, Tangbin	Shanghai Jiao Tong University, Shanghai, China	35
Pan, E.	Shanghai Jiao Tong University, Shanghai, China	32
Xi, Li-Feng	Shanghai Jiao Tong University, Shanghai, China	25
Gharbi, A.	École de Technologie Supérieure, Montreal, Canada	20
Ni, Jun	Shanghai Jiao Tong University, Shanghai, China	19
Rezg, N.	Université de Lorraine, Nancy, France	19
Zied, Hajej	Université de Lorraine, Nancy, France	17
Skoogh, Anders	Chalmers University of Technology, Gothenburg, Sweden	17
Xi, Li-Feng	Shanghai Jiao Tong University, Shanghai, China	14
Lee, Jay	University of Maryland, College Park, United States	14
Zhou, Xiaojun	Shanghai Jiao Tong University, Shanghai, China	14
Zio, Enrico	Politecnico di Milano, Milan, Italy	13
He, Yihai	Beihang University, Beijing, China	13
Kenne, J.P.	École de Technologie Supérieure, Montreal, Canada	13
Iung, Benoit	Université de Lorraine, Nancy, France	13

collected papers, the second decade (2004–2013) for 19%, and the third decade (2014–-2023) for 75% of the total, with a compound annual growth rate of around 10%.

Table 3 shows the authors with the highest number of publications in the sample of analysis. It is interesting to notice the presence, in this shortlist, of many authors from the same institution. This may be due to their collaboration, which resulted in a high number of joint publications and, consequently, a high publication count. For instance, out of the 35 papers published by Prof Xia Tangbin, 23 were published with Prof. Pan E. and Prof. Xi Li-Feng. The same can be said for Prof. Rezg N., who shares 13 papers with Prof. Zied Hajej.

Table 4 shows the most active authors by decade. In particular, the First decade covers the period 1994–2003, the Second decade the period 2004–2013 and the Third decade the period 2014–2024. The same breakdown will also be used in the rest of the paper when the analysis compares these three periods.

Table 4. Most active authors by decade.

First decade		Second decade		Third decade	
Authors	*Papers*	*Authors*	*Papers*	*Authors*	*Papers*
Boukas, E.K.	5	Ni, Jun	14	Xia, T.	32
Zhang, Q.	4	Xi, Li-Feng	12	Pan, E.	27
Wang, W.	3	Kumar, D.	9	Xi, Li-Feng	25
Tor, S.B.	3	Lee, Jay	9	Skoogh, A.	17
Yam, R.	3	Probert, S.D.	8	Zied, H.	16
Deshpande, V.S.	3	Ogaji, S.O.T.	8	Rezg, N.	15
Chan, W.L.	3	Djurdjanovic, D.	8	Gharbi, A.	14
Lin, C.	3	Eti, M.C.	7	He, Yihai	13
Modak, J.P.	3	Chan, F.T.S.	6	Si, Guojin	12
Pheng, L.S.	2	Gharbi, A.	6	Kaewunruen, S.	11
Yang, J.	2	Biller, S.	6	Chen, Zhen	11
Khoo, L.P.	2	Kenne, J.P.	6	Bokrantz, J.	11
Asama, H.	2	Kumar, P.	6	Zhou, Xiaojun	10
Thomas, L.	2	Pan, E.	5	Zio, E.	10
Li, J.R.	2	Li, N.	5	Garza-Reyes, J. A.	9

Table 5. Top 10 most cited authors (at least five papers).

Author	Number of papers	Total citations	Average citations
Lee, Jay	14	2764	197
Ni, Jun	19	1325	69
Tiwari, M.K.	7	1109	158
Iung, B.	13	1098	84
Hodkiewicz, M.	7	1090	155
Nee, A.Y.C.	7	1049	149
Ong, S.K.	6	1018	169
Horvath, A.	6	986	164
Mourtzis, D.	8	930	116
Zio, E.	13	921	70

Table 6. Top 10 authors with higher average number of citations per paper (at least five papers).

Author	Number of papers	Total citations	Average citations
Lee, Jay	14	2764	197
Wang, Jinjiang	5	889	177
Ong, S.K.	6	1018	169
Horvath, A.	6	986	164
Tiwari, M.K.	7	1109	158
Hodkiewicz, M.	7	1090	155
Nee, A.Y.C.	7	1049	149
Yan, Ruqiang	7	862	123
Gao, R.	5	615	123
Feng Zhang, Ying	6	731	121

Publishing many papers is not a synonym of major impact on the sector. To understand this aspect, the average number of citations per author in the sample was analyzed (Tables 5 and 6). With the aim of removing possible outliers, only authors with at least 5 papers were considered. Noticeably, Prof. Jay Lee is the author with the most total citations and with the most average citations. Other authors such as Prof. Tiwari, Prof. Hodkiewicz, Prof. Nee, Prof. Ong, Prof. Hovart, Prof. Mourtzis, Prof. Wang, Prof. Yan are present in both tables. It is also interesting to see that authors who deal with maintenance from different points of view,

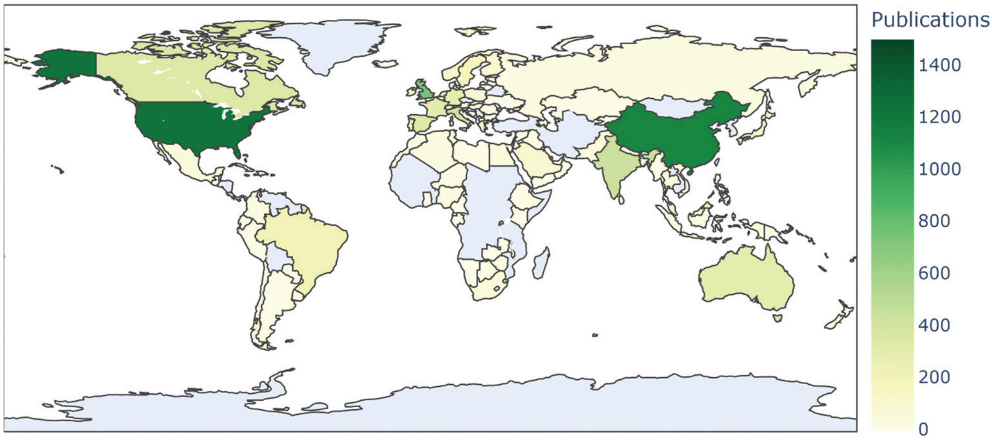

Figure 2. Publications per country.

whether they are technological, ontological, process, data analysis, and other aspects, are widely cited. As far as Table 6 is concerned, it is also possible to note the high impact that these authors have had and are having despite the relatively low number of articles in the dataset.

The United States is the most productive nation along with China (Figure 2). It must be specified that the reported values refer to the unique values per publication. This means that if an article has multiple authors from the same country, the country has been counted only once.

Table 7 shows the publications with the most citations. The titles show that the publications touch maintenance from different points of view, whether it is as an approach within a managerial philosophy, or as part of a business offer. More frequent publications are related to technological or methodological aspects. It is interesting to note that half of the papers in Table 7 have been published in the last 10 years and deal with technological aspects for data collection or calculation methods, underlining the importance that these aspects have assumed recently.

Papers published in the engineering area are predominant, this is not surprising (Table 8). The presence of a substantial number of papers published in the 'Environmental Science' area is interesting, demonstrating the growing importance that the sustainability aspect is acquiring.

Table 9 shows the list of journals with the most publications for each decade. The table shows five journals (*Computers in Industry*, *International Journal of Advanced Manufacturing Technology*, *International Journal of Quality & Reliability Management*, *Computers & Industrial Engineering*, *Reliability Engineering & System Safety*) always present, signalling their prestige. Other journals are present in two decades, always consecutively. Finally, it is interesting to notice that the top three journals of the third decade are not present in the previous ones and that two of them have been founded after 2010. Although journals focused on advanced and intelligent manufacturing technologies, energy, information systems, and reliability are the main publication outlets for papers on the maintenance field, a wide range of contributions have also appeared in journals focused on environmental and social

Table 7. Top 10 cited publications.

Authors	Title	Source	Year	Citations	Ref.
Shah, Rachna; Ward, Peter T.	Lean manufacturing: Context, practice bundles, and performance	*J Oper Manage*	2003	2024	(Shah & Ward, 2003)
Lee, Jay; Wu, Fangji; Zhao, Wenyu; Ghaffari, M.; Liao, Linxia; Siegel, David	Prognostics and health management design for rotary machinery systems – Reviews, methodology and applications	*Mech Syst Signal Process*	2014	1254	(Lee et al., 2014)
Qi, Qinglin; Tao, Fei	Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison	*IEEE Access*	2018	1023	(Qi & Tao, 2018)
Kaushal, Hemani; Kaddoum, Georges	Underwater Optical Wireless Communication	*IEEE Access*	2016	969	(Kaushal & Kaddoum, 2016)
Cua, Kristy O.; Mckone, Kathleen E.; Schroeder, Roger G.	Relationships between implementation of TQM, JIT, and TPM and manufacturing performance	*J Oper Manage*	2001	808	(Cua et al., 2001)
Sikorska, J.Z.; Hodkiewicz, M.; Ma, L.	Prognostic modelling options for remaining useful life estimation by industry	*Mech Syst Signal Process*	2011	760	(Sikorska et al., 2011)
Webb, Douglas C.; Simonetti, Paul J.; Jones, Clayton P.	SLOCUM: An underwater glider propelled by environmental energy	*IEEE J Oceanic Eng*	2001	753	(Webb et al., 2001)
Koka, Balaji R.; Prescott, John E.	Strategic alliances as social capital: A multidimensional view	*Strategic Manage J*	2002	730	(Koka & Prescott, 2002)
Carvalho, Thyago P.; Soares, Fabrízzio A. A. M. N.; Vita, Roberto; Francisco, Roberto Da P.; Basto, João P.; Alcalá, Symone G. S.	A systematic literature review of machine learning methods applied to predictive maintenance	*Comput Ind Eng*	2019	698	(Carvalho et al., 2019)
Zhao, Rui; Wang, Jinjiang; Wang, Dongzhe; Yan, Ruqiang; Mao, Kezhi; Shen, Fei	Machine health monitoring using local feature-based gated recurrent unit networks	*IEEE Trans Ind Electron*	2017	641	(Zhao et al., 2018)

Table 8. Subject area.

Area_Name	Count
Engineering	4831
Computer Science	2648
Business, Management and Accounting	1132
Materials Science	981
Mathematics	874
Environmental Science	772
Decision Sciences	747
Energy	745
Physics and Astronomy	514
Chemical Engineering	474
Agricultural and Biological Sciences	193
Earth and Planetary Sciences	132
Chemistry	75

science, with a significant increase over the analyzed decades of computer science-based journals.

Figure 3 provides an overview of the sample content in terms of keywords through the means of a word-cloud. Noticeably, predictive and preventive maintenance are among

Table 9. Top 15 journals per decade.

First decade		Second decade		Third decade	
Journal	*Papers*	*Journal*	*Papers*	*Journal*	*Papers*
Construction Management and Economics	16	*The International Journal of Advanced Manufacturing Technology*	61	*Applied Sciences*	231
Computers in Industry	13	*International Journal of Production Research*	58	*IEEE Access*	209
The International Journal of Advanced Manufacturing Technology	11	*Reliability Engineering & System Safety*	37	*Journal of Cleaner Production*	140
European Journal of Operational Research	10	*Expert Systems with Applications*	27	*The International Journal of Advanced Manufacturing Technology*	140
IEEE Transactions on Industry Applications	10	*Computers in Industry*	24	Energies	132
Computers & Chemical Engineering	9	*Construction Management and Economics*	21	*Reliability Engineering & System Safety*	115
Production Planning & Control	9	*Production Planning & Control*	20	*Computers & Chemical Engineering*	98
International Journal of Quality & Reliability Management	9	*European Journal of Operational Research*	20	*International Journal of Production Research*	86
International Journal of Operations & Production Management	8	*Journal of Manufacturing Technology Management*	20	*Journal of Manufacturing Systems*	80
Quality and Reliability Engineering International	8	*Journal of Loss Prevention in the Process Industries*	19	*Expert Systems with Applications*	61
Computers & Industrial Engineering	7	*Energy Policy*	19	*Engineering Failure Analysis*	59
Reliability Engineering & System Safety	7	*International Journal of Computer Integrated Manufacturing*	17	*International Journal of Quality & Reliability Management*	54
Journal of the Operational Research Society	6	*Journal of Intelligent Manufacturing*	17	*Journal of Intelligent Manufacturing*	52
CIRP Annals – Manufacturing Technology	6	*International Journal of Quality & Reliability Management*	17	*Electronics (Switzerland)*	50
Fusion Engineering and Design	6	*Computers & Chemical Engineering*	15	*Computers in Industry*	49

the most used keywords along with the general 'maintenance' keyword. It is worth noting that keywords related to analysis techniques such as ML, simulation, deep learning, and others are present as well as an important part of the sample. It should be noted that in some cases, different keywords might be used to refer to the same concept, thus falling under the same umbrella in terms of topic.

The maintenance keyword is obviously among the most present in every decade (Table 10) with reliability and preventive maintenance. Optimization is also among the most discussed topics in the papers, consistent with the presence of preventive maintenance. In general, what clearly emerges (especially for the last decade) is the shift from preventive to condition-based and predictive maintenance, thanks to the technological advances. In this sense, the presence of keywords related to ML, deep learning, DT, and AI is not surprising. Once again, sustainability emerges in relation to the last decade of papers. It is useful to highlight those new keywords that appeared in the last years, specifically referring to themes such as I5.0 and Human Factors. Due to the size of the sample analyzed, these new keywords cannot appear in Table 10, but it is interesting to

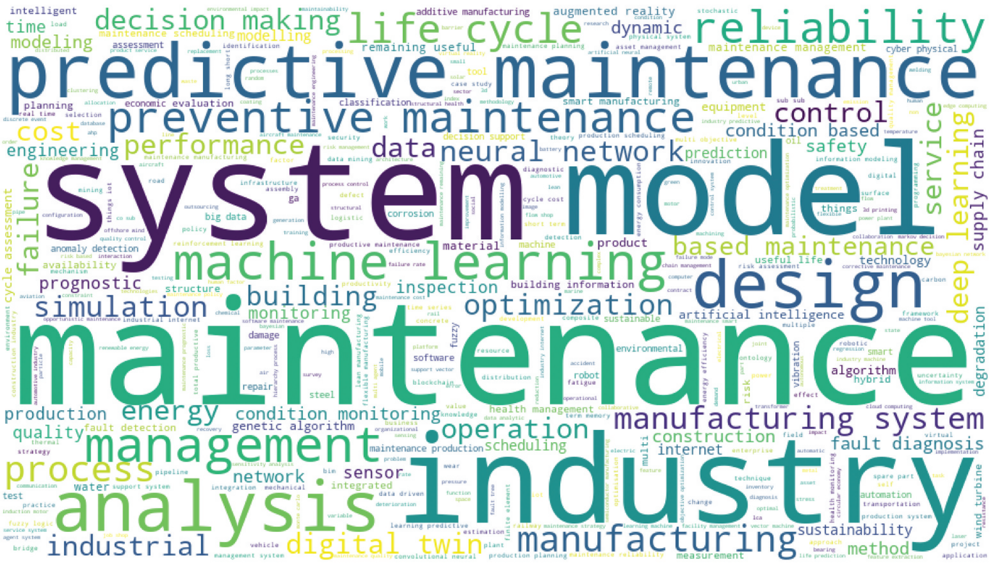

Figure 3. Word-cloud keywords.

Table 10. Keywords importance by decade.

First decade		Second decade		Third decade	
Keyword	*Count*	*Keyword*	*Count*	*Keyword*	*Count*
maintenance	48	maintenance	122	predictive maintenance	313
reliability	14	preventive maintenance	42	maintenance	311
preventive maintenance	13	reliability	39	industry 4.0	301
flexible manufacturing system	10	genetic algorithm	32	machine learning	227
manufacturing	9	schedule	26	deep learning	151
manufacturing system	8	manufacturing system	23	digital twin	139
simulation	7	condition based maintenance	19	preventive maintenance	121
life cycle assessment	7	construction industry	18	reliability	108
schedule	7	optimization	18	internet of things	108
optimization	6	life cycle assessment	18	condition based maintenance	91
neural network	6	predictive maintenance	17	life cycle assessment	88
safety	6	manufacturing	17	fault diagnosis	83
production planning	5	simulation	16	condition monitor	78
condition monitor	5	availability	16	manufacturing	73
management	5	maintenance management	16	sustainability	71
total productive maintenance	5	supply chain management	14	artificial intelligence	68
expert system	4	fault diagnosis	14	optimization	68
concurrent engineering	4	condition monitor	13	smart manufacturing	67
quality	4	modelling	13	augmented reality	63
steel industry	4	case study	13	prognostic health management	62

notice this trend, which is strongly connected to the Triple Bottom Line view of sustainability. Thus, the inclusion of I5.0, Human Factor, and Resilience are critical to be considered in the analysis, also considering maintenance management and delivery.

Table 11 shows the most frequent keyword combinations per decade. While the first two decades rely mainly on scheduling and optimization of preventive maintenance or

Table 11. Keywords co-occurrence.

First decade		Second decade		Third decade	
Keywords pairs	*Count*	*Keywords pairs*	*Count*	*Keywords pairs*	*Count*
maintenance–reliability	5	maintenance–reliability	11	industry 4.0 - predictive maintenance	88
maintenance–optimization	3	availability–reliability	8	machine learning–predictive maintenance	65
maintenance–management	3	India–manufacturing industry	6	industry 4.0 - machine learning	31
optimization–reliability	3	inventory–maintenance	6	deep learning–predictive maintenance	27
maintenance–repair	3	preventive maintenance–reliability	6	deep learning–machine learning	25
maintenance–stock control	2	maintenance–manufacturing	6	artificial intelligence–machine learning	23
optimization–system effectiveness	2	maintenance–simulation	5	maintenance–reliability	22
bpr (business process reeingineering)–implementation	2	corrective maintenance–preventive maintenance	5	industry 4.0 - maintenance	20
assembly–maintenance	2	preventive maintenance–production scheduling	5	industry 4.0 - smart manufacturing	19
flexible manufacturing system–maintenance	2	manufacturing system–preventive maintenance	4	artificial intelligence–predictive maintenance	18
maintenance scheduling–production planning	2	India–productive maintenance	4	deep learning–industry 4.0	17
construction–maintenance	2	optimization–preventive maintenance	4	anomaly detection–predictive maintenance	17
integration–iso 9000	2	construction industry–United Kingdom	4	maintenance–schedule	17
human error–risk management	2	life cycle assessment–recycle	3	digital twin–industry 4.0	16
maintenance–manufacturing	2	data mining–knowledge discovery	3	maintenance–manufacturing	16

the study of reliability, the third has a strong orientation toward data mining, with the use of I4.0 technologies and AI for data analysis and prediction purposes. Also, the presence of sustainability-related keywords is interesting. Of course, the availability of fewer articles in the first two decades might also limit the number of keywords combinations available.

Figure 4 provides an overview of the content of the abstracts analyzed. The presence of words related to equipment, system, component, machine, and process clarifies the different level of details that the analysis might cover. Other interesting aspects are related to the presence of words linked to approach, tool, model, technique, framework, analysis, which might suggest the proposal of discussion of various analysis methods. Additionally, different factors to be used as index for the analysis are listed such as reliability, cost, use, and others, clarifying that the maintenance analysis can be based on different aspects.

Table 12 presents the topics identified from the analysis of the abstracts. The topics are related both to purely methodological (e.g. failure analysis) and strategic (e.g. preventive maintenance, predictive maintenance, condition-based maintenance) aspects concerning maintenance, and technological aspects (data mining, AI, smart manufacturing, and I4.0) supporting its management. The content of the topics was defined based on the keywords

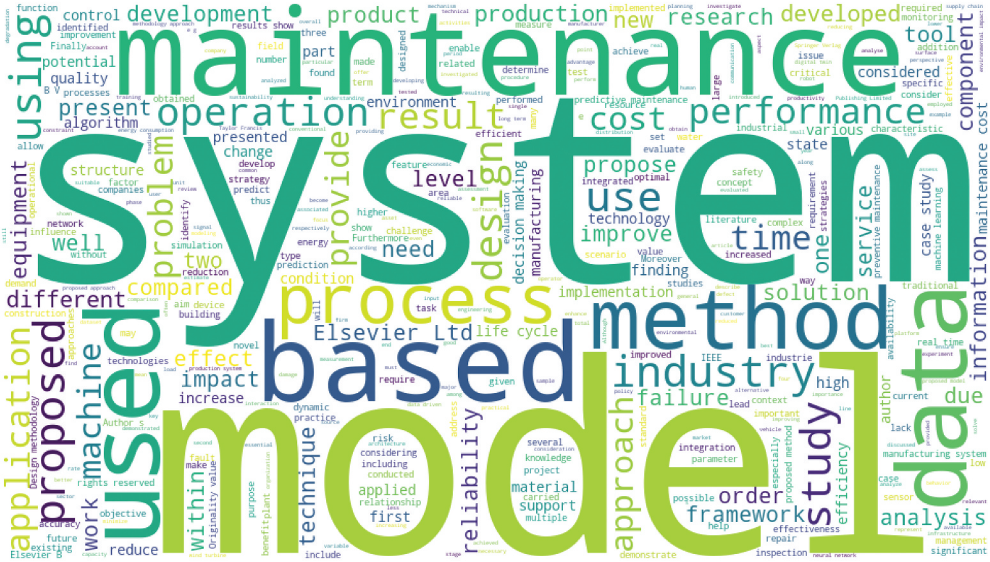

Figure 4. Word-cloud of the abstracts' content.

returned by BERTopic. As clarified earlier, it is interesting to notice the presence of a human resource and human factor category that, according to the results, is still rarely addressed but has recently showed an increase in interest. Additionally, it must be noted that the topic naming and grouping has been carried out manually by the authors and that, due to the presence 10 keywords to interpret the topics, some might have been misclassified (i.e. some keywords might have led the authors to highlight one aspect like digital or sustainability over some more recent ones like I5.0 and/or human factor). Also, due to the decision of focusing only on journal papers, some trend related to these topics currently more present into conference papers might have been lost.

Table 13 deepens the analysis of the topics evolution. In particular, the first aspect worth emphasizing concerns the growing importance of data mining. In the last decade, this topic has very often been associated with the topic of AI, as evidenced by their rank in the third decade. Precisely because of the availability of advanced tools and technologies, interest in predictive maintenance has grown, which proves to be one of the most discussed maintenance aspects in the literature together with preventive maintenance. In the same way, we can see the increasing interest in sustainability. Despite the growing diffusion of business models related to the sale of maintenance as a service or the sale of the performance of machinery guaranteed through the execution of maintenance, the issue of the business model seems to be giving way compared to the recent past. This could also be due to a greater interest, in the sample analyzed, in technical or managerial aspects, rather than in business.

Table 14 shows the evolution over time of the topic pairs considering the top 10 topics for each decade, showing which aspects were analyzed together. The first and second decades focus on preventive maintenance optimization in terms of scheduling and management, also in connection with reliability analysis techniques. The third decade, on the other hand, has a much more marked focus on the data analysis, predictive and

Table 12. Topics content.

Topic	Description
Additive manufacturing	Concerns additive manufacturing and 3D printing process and technology as well as its impact on the spare parts management
Artificial intelligence	Concerns the AI applications in maintenance and the related technologies (e.g. chatbot, deep learning, svm, cnn)
Asset management	Concerns the management of the asset and the decision made to generate and maximize value
Augmented and virtual reality	Concerns augmented, virtual and mixed reality technology and applications in maintenance
Business model	Concerns the business model aspects of maintenance (e.g. maintenance as a service)
Condition-based maintenance	Concerns condition-based maintenance management and applications
Cost	Concerns the economic impact of maintenance on production and maintenance management
Data mining	Concerns data mining techniques (not AI based) in support of maintenance.
Decision-making	Concerns the maintenance decision-making process
Digital twin	Concerns DT and their applications in maintenance
Failure analysis	Concerns algorithms and techniques for failure analysis
Human resources and human factor	Concerns human resource management and the human factor theme in the maintenance context
ICT and IoT	Concerns the technological aspects of data collection, storage and transmission
Knowledge management	Concerns the management and use of knowledge in the context of maintenance as well as the use of ontologies in support of this task
Lifecycle management	Concerns the study of the impact of maintenance at lifecycle level in terms of life extension and cost as well as product design
Maintenance management	Concerns the maintenance management and strategy selection
Maintenance repair overhaul	Concerns the maintenance repair and overhaul activities and the related management
Maintenance software	Concerns the software used to manage maintenance
Performance	Concerns the aspects of maintenance and production performance, also in terms of KPIs
Physical and chemical properties	Concerns the physical and chemical properties of the materials and components studies for maintenance optimization
Predictive maintenance	Concerns predictive maintenance management, techniques, and technologies
Preventive maintenance	Concerns preventive maintenance management, techniques, and technologies
Production	Concerns the production processes and their connection to maintenance
Prognostic health management	Concerns Prognostics Health Management (PHM) approaches and management
Reliability-centered maintenance	Concerns reliability-centered maintenance management, techniques and metrics
Safety	Concerns the safety aspects related to maintenance and the benefits connected to maintenance execution
Scheduling and optimization	Concerns the techniques and methods used to schedule or optimize maintenance and production
Simulation	Concerns the simulation of components behavior or the simulation of the maintenance delivery process
Smart manufacturing and Industry 40	Concerns the technologies connected to the machines and I4.0 and their relation to maintenance
Spare parts management	Concerns the management and optimization of the spare parts used during maintenance activities
Supply chain management	Concerns the management of the maintenance supply chain (e.g. service suppliers, spare parts suppliers and related aspects)
Sustainability	Concerns the sustainability aspects of maintenance (e.g. reduced CO_2 emissions, energy consumption and others)
Total productive maintenance	Concerns the application of Total Productive Maintenance logic in a lean context to improve maintenance management and execution

condition-based maintenance parts, thanks to the spread of AI-related approaches. Of course, preventive maintenance still covers an important role. Despite the absence in the table, it must be underlined once again the importance of sustainability, which is among the top 10 topics in all the decades.

Table 13. Topic relevance over time.

First decade		Second decade		Third decade	
Topic	*Count*	*Topic*	*Count*	*Topic*	*Count*
Preventive maintenance	72	Preventive maintenance	247	Data mining	986
Scheduling and optimization	67	Maintenance management	246	Artificial intelligence	795
Maintenance management	67	Scheduling and optimization	232	Scheduling and optimization	777
Maintenance software	66	Reliability-centered maintenance	211	Sustainability	774
Reliability-centered maintenance	53	Maintenance software	188	Predictive maintenance	754
Data mining	51	Data mining	172	Preventive maintenance	740
Cost	47	Sustainability	169	Maintenance management	740
Sustainability	46	Business model	159	Physical and chemical properties	697
Physical and chemical properties	44	Simulation	154	Condition-based maintenance	654
Performance	42	Physical and chemical properties	153	Reliability-centered maintenance	623
Safety	37	Decision-making	149	Smart manufacturing and Industry 40	579
Business model	37	Cost	145	Decision-making	563
Simulation	36	Condition-based maintenance	116	Failure analysis	541
Decision-making	33	Performance	108	ICT and IoT	496
Condition-based maintenance	31	Safety	106	Maintenance software	488
Production	25	Failure analysis	95	Cost	467
Failure analysis	23	Supply chain management	93	Simulation	463
Smart manufacturing and Industry 40	21	Production	77	Performance	371
Lifecycle management	18	Lifecycle management	73	Business model	343
Supply chain management	18	Predictive maintenance	70	Safety	327
Artificial intelligence	17	Smart manufacturing and Industry 40	62	Asset management	262
ICT and IoT	15	ICT and IoT	61	Prognostic health management	218
Total productive maintenance	15	Asset management	55	Supply chain management	192
Asset management	14	Knowledge management	51	Production	186
Predictive maintenance	13	Total productive maintenance	46	Knowledge management	185

5. Discussion of results

The maturity and multidisciplinary nature of maintenance in manufacturing and industry emphasize the need for a systematic and comprehensive understanding of this research field. Indeed, as expected, the findings achieved by reviewing the extant literature on maintenance-oriented topics reveal a large and highly heterogeneous literature in terms of sources, labels, contents, and application areas. This discussion section aims at providing a more detailed view of all aspects examined throughout the performed bibliometric analysis. This work does not aim to provide an exhaustive review or classification of the articles related to maintenance and reliability (interested readers may refer to existing reviews, such as (Psarommatis et al., 2023; Vrignat et al., 2022) but rather to outline some general perspectives and the core features aiming at mapping the evolution of maintenance in manufacturing and industrial fields over the last 30 years. Although the literature, in fact, offers a variety of concepts that have been developed through a combination of theoretical insights and practical experiences with a plethora of case studies, it is also true that it is possible to observe how research streams have changed as the complexity of industrial systems and processes has increased, as more

Table 14. Top 10 topic co-occurrence over time.

First decade		Second decade		Third decade	
Topics	*Count*	*Topics*	*Count*	*Topics*	*Count*
Maintenance management – preventive maintenance	27	Preventive maintenance – scheduling and optimization	110	Preventive maintenance – scheduling and optimization	328
Preventive maintenance – scheduling and optimization	26	Maintenance management – preventive maintenance	104	Artificial intelligence – data mining	297
Preventive maintenance – reliability centered maintenance	24	Preventive maintenance – reliability centered maintenance	96	Artificial intelligence – predictive maintenance	290
Cost- preventive maintenance	17	Maintenance management – reliability centered maintenance	75	Data mining – predictive maintenance	252
Maintenance management – reliability centered maintenance	16	Maintenance management – scheduling and optimization	66	Preventive maintenance – reliability-centered maintenance	240
Reliability-centered maintenance – scheduling and optimization	16	Reliability-centered maintenance – scheduling and optimization	54	Maintenance management – preventive maintenance	227
Cost – scheduling and optimization	15	Preventive maintenance – simulation	45	Condition-based maintenance – data mining	225
Maintenance management – maintenance software	13	Scheduling and optimization – simulation	41	Artificial intelligence – condition-based maintenance	205
Cost – reliability-centered maintenance	12	Maintenance management – maintenance software	41	Maintenance management – reliability-centered maintenance	195
Performance – preventive maintenance	12	Data mining – maintenance management	39	Condition-based maintenance – predictive maintenance	195

and more ambitious objectives (in terms of productivity, safety, and reducing costs and failures), have been set and, finally, new technologies and tools have been introduced. Therefore, the goal is to answer the two research questions formulated in Section 2 to direct the literature review and target the main topics to be investigated.

5.1. How has the manufacturing maintenance research field evolved over the past 30 years?

As shown in Figure 1, the article publication trend identifies a significant and consistent research interest in maintenance-oriented topics. This interest not only progressively grows but also exhibits an intriguing evolution concerning the different strategies and approaches that have been adopted to address the challenges that new industrial revolutions have posed over time. Consequent to the transformation in contemporary industry and development in the approach to manufacturing processes, the evolution of maintenance strategies can be depicted in the order: (i) reactive-based maintenance, i.e. maintenance usually performed on an as-needed basis which involves repairing equipment after failure; (ii) time-based maintenance, planned maintenance or cyclic maintenance of production machinery and tools; (iii) condition-based maintenance where sensors generating data and measurements are adopted to control machines aiming at observing abnormal conditions and avoiding failures; (iv) predictive maintenance that utilizes data analytics to forecast failures; and (v) prescriptive maintenance that employs data to both predict the system future health condition and make suggestions to address the failure mode also recommending specific maintenance tasks or action plans. From a strategic point of view, the literature reveals certain commonalities over the three decades examined. Although the most recent trends undoubtedly show a move toward predictive approaches, reactive and preventive ones have not been dismissed; rather, they continued to be a focus due to the adoption of I4.0's enabling technologies (see, e.g. Dursun et al., 2024; Levitin et al., 2024; Zhang & Chen, 2022) which have certainly enhanced their efficacy and efficiency (e.g. the integration of AI and robotics that has revolutionized inspection processes, particularly in hazardous environments (see, e.g. Campari et al., 2023; Castro et al., 2018; Cox et al., 2024). Nevertheless, to date, it is evident that advances in data collection and algorithmic capabilities have drawn attention to prognostic, condition monitoring, predictive and prescriptive maintenance, offering the potential to leverage the ensuing valuable knowledge into the maintenance decision-making process. These drivers have a relevant impact on thematic maintenance evolution. Accordingly, the ongoing research streams characterizing the activity of researchers and professionals are mainly focused on data-driven approaches based on AI (see, e.g. (Jasiulewicz-kaczmarek, Piechowski, & Mikołajewski, 2023; Ding et al., 2024)) and ML models (see, e.g. Lin & Chen, 2024; Meddaoui et al., 2024), as well as DT (see, e.g. Toothman et al., 2023; Urso et al., 2024), Internet of Things (see, e.g. Christou et al., 2022; Nguyen et al., 2024)), Cyber-Physical Systems (see, e.g. Lee & Kundu, 2022; Ulhe et al., 2024), and simulation (Darmawan & Sheu, 2021; Subramaniyan et al., 2018). The adoption of these technologies not only provides insights essential for condition monitoring and early fault detection aiming at supporting the decision-making processes for maintenance strategies but also shows its potential to increase the self-awareness and adaptability of industrial systems (Ahmed Murtaza et al., 2024).

5.2. What are the latest trends and future directions in the field of manufacturing maintenance?

The previous paragraph highlighted the current research streams and their connections to the technological development driven by the I4.0 paradigm advent. Specifically, by examining the extant literature, advanced maintenance methods including condition monitoring, predictive and prescriptive maintenance, and prognosis appear to be the most popular topics. It is worth mentioning that contemporary and upcoming technological advancements already present new challenges calling for actual and future research works.

It is expected that literature will keep focusing on these topics by proposing new and innovative theoretical approaches, frameworks, and an increasing number of real-world cases that allow to consolidate and improve the knowledge on industrial and manufacturing maintenance. In this scenario, DT, Augmented Reality (AR) tools, Edge Computing, and Data analytics, including BD for ML at scale, will play a vital role as they may ensure better fault diagnosis/prognosis outcomes as well as more precise and robust tailor-made solutions. Blockchain is one of the technologies that may be essential in securing the integrity of maintenance records and sensor data (see, e.g. Alazab & Alhyari, 2024; Feng et al., 2023) even though not many publications at this stage cover this topic. Another topic that is gaining popularity is the prescriptive maintenance aided by AI. Indeed, as previously said, the ability to use AI allows the analysis of a vast amount of operational data, which not only enables the identification of potential failures before they occur but also the development of more precise and informed maintenance interventions. In this scenario, by integrating ML with IoT, AI-supported prescriptive maintenance has the capability to incorporate contextual data to suggest actions based on the assets' requirements, resulting in more effective and targeted interventions that reduce downtime and increase productivity (see, e.g. Sala et al., 2023; Yigin & Celik, 2024).

A relevant future research stream will focus on the I5.0 paradigm. This concept enhances I4.0 by shifting the focus from automation to human-machine collaboration and, particularly, emphasizing the development of more inclusive, human-centric, resilient, and sustainable industrial processes. While the use of collaborative human-AI systems will enhance maintenance procedures, it will also present new challenges, such as the demand for highly skilled personnel or the integration of human factors (stress, safety, etc.) into maintenance processes.

Also, studies related to ontologies and knowledge management approaches are rising in the scope of improving maintenance management and favour the development of digital approaches in its support (see, e.g. Louadah et al., 2024; Polenghi et al., 2022). Ontologies enable to formalize knowledge and achieve high semantic interoperability of complex maintenance knowledge in industrial practice. The goal is to attain rigorous logical reasoning and carefully designed semantic language by providing fundamental concepts, taxonomies, relationships, and domain axioms. The emergence of the I5.0 paradigm may be beneficial for the development of ontologies and knowledge management in general. Indeed, while they support system interoperability and, as a result, collaborate in the integration of company information, they also need skilled workers who are capable of working in knowledge-intensive smart factories. These two features are considered focal points within I5.0 because they will enable the proper balancing of automated and human maintenance decision-making processes (Guo et al., 2024). To be seen is also the impact which the development of large language models (LLMs) will have on future research in the field, specifically when it comes to the analysis and characterization of historical data collected from the shopfloor.

Another theme that maintenance researchers are addressing is related to the sustainability impact of maintenance, both as an approach to manage the machines' (or assets) lifecycle (e.g. maximizing the assets and components lifecycle, minimizing failures), and as a process (e.g. economic, environmental, and social impact of maintenance activities) (Franciosi et al., 2020). In this context, current literature proposes several research streams seeking to cope with the essential objective of integrating sustainability principles throughout the entire life cycle of assets that open novel challenges and opportunities for future research agendas. By exploiting the capabilities of I4.0 and AI, maintenance management may enhance data flow (acquisition and processing) enabling a successful decision-making process and consequently improving overall productivity and sustainability (Djamel et al., 2024). Also, exploring how maintenance practices can support a circular economy by focusing on reuse, recycling, remanufacturing, and extending the life of assets is currently considered a viable alternative for promoting sustainability (Ghaleb & Taghipour, 2022).

6. Conclusions

This study has provided a comprehensive analysis of the evolution of maintenance engineering in manufacturing over the past 30 years. This analysis has highlighted the significant shifts in practices, technologies, and research trends that have been ongoing within this research field. The transition from reactive to proactive maintenance strategies is illustrative of the impact of advancements in parallel fields such as digital technologies and data analytics. I4.0 has played a transformative role, enabling real-time monitoring, intelligent decision-making, and seamless integration of maintenance within manufacturing systems.

The findings of this research highlight the steady increase in scholarly interest in maintenance engineering, particularly over the last decade. Key themes such as sustainability, life cycle engineering, and the integration of ML with IoT are shaping the future of the field. These advancements reflect a growing recognition of maintenance not merely as a support function but as a strategic enabler of operational efficiency, reliability, and environmental stewardship.

The use of NLP tools, specifically the BERTopic algorithm, used for this analysis has enabled a unique perspective on the thematic evolution of maintenance engineering research. By identifying emerging trends, this study contributes to a deeper understanding of the field's trajectory.

Looking ahead, the research points to several critical areas for further investigation. Primarily it is of note how various authors are looking toward integrating various elements of sustainability, specifically exploring how maintenance strategies can more effectively support sustainable manufacturing practices. Advanced analytics and AI will continue to drive further development in the field of predictive maintenance and will leverage next-generation AI algorithms, such as LLMs, and DT. In this context, knowledge management will increase in importance. With the introduction of I5.0, human factors and workforce development will take on a larger role, and will drive the development of both the skills requirements, as well as the integration of maintenance personnel in increasingly automated environments.

By synthesizing three decades of progress and projecting future directions, this study serves as a valuable resource for researchers to enhance maintenance engineering's role in the ever-evolving world of manufacturing and production systems. Continued innovation and interdisciplinary collaboration will be pivotal in addressing emerging challenges and harnessing new opportunities in this dynamic and critical field.

Acknowledgments

Roberto Sala has been supported by the project funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3—Call for tender No. 341 of 15/03/2022 of Italian Ministry of University and Research funded by the European Union—NextGenerationEU. Award Number: PE00000004, Concession Decree No. 1551 of 11/10/2022 adopted by the Italian Ministry of University and Research, CUP F13C22001230001, MICS (Made in Italy - Circular and Sustainable).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The work was supported by the Ministero dell'Università e della Ricerca [PE00000004]; MICS (Made in Italy – Circular and Sustainable) [F13C22001230001].

ORCID

Roberto Sala http://orcid.org/0000-0001-7671-6927
Emmanuel Francalanza http://orcid.org/0000-0003-0317-5909
Simone Arena http://orcid.org/0000-0002-9932-6080

References

Adaramola, B. A., Kayode, J. F., Monye, S. I., & Afolalu, S. A. (2024). Overview of maintenance management strategies in the industry. *2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG)* (pp. 1–11). https://doi.org/10.1109/SEB4SDG60871.2024.10629938

Ahmed Murtaza, A., Saher, A., Hamza Zafar, M., Kumayl, S., Faisal Aftab, M., & Sanfilippo, F. (2024). Paradigm shift for predictive maintenance and condition monitoring from Industry 4.0 to Industry 5.0: A systematic review, challenges and case study. *Results in Engineering*, *24*, 102935. https://doi.org/10.1016/j.rineng.2024.102935

Alazab, M., & Alhyari, S. (2024). Industry 4.0 innovation: A systematic literature review on the role of blockchain technology in creating smart and sustainable manufacturing facilities. *Information*, *15*(2), 1–33. https://doi.org/10.3390/info15020078

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with python: Analyzing text with the natural language toolkit*. O'Reilly Media Inc.

Campari, A., Nakhal Akel, A. J., Ustolin, F., Alvaro, A., Ledda, A., Agnello, P., Moretto, P., Patriarca, R., & Paltrinieri, N. (2023). Lessons learned from HIAD 2.0: Inspection and maintenance to avoid hydrogen-induced material failures. *Computers & Chemical Engineering*, *173* (November 2022), 108199. https://doi.org/10.1016/j.compchemeng.2023.108199

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

Castro, M. D., Ferre, M., & Masi, A. (2018). CERNTAURO: A modular architecture for robotic inspection and telemanipulation in harsh and semi-structured environments. *Institute of Electrical and Electronics Engineers Access*, *6*, 37506–37522. https://doi.org/10.1109/ACCESS.2018.2849572

Christou, I. T., Kefalakis, N., Soldatos, J. K., & Despotopoulou, A. (2022). End-to-end industrial IoT platform for quality 4.0 applications. *Computers in Industry*, *137*, 103591. https://doi.org/10.1016/j.compind.2021.103591

Çinar, Z. M., Nuhu, A. A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability (Switzerland)*, *12*(19), 8211. https://doi.org/10.3390/su12198211

Cox, A., Colaw, C., Richer, E., Galla, M., & Hurmuzlu, Y. (2024). Design and static equilibrium analysis of a modular pipe inspection robot. *IEEE/ASME Transactions on Mechatronics*, *29*(3), 2196–2207. https://doi.org/10.1109/TMECH.2023.3328947

Cua, K. O., Mckone, K. E., & Schroeder, R. G. (2001). Relationships between implementation of TQM, JIT, and TPM and manufacturing performance. *Journal of Operations Management*, *19*(6), 675–694. https://doi.org/10.1016/S0272-6963(01)00066-3

Dafflon, B., Moalla, N., & Ouzrout, Y. (2021). The challenges, approaches, and used techniques of CPS for manufacturing in industry 4.0: A literature review. *International Journal of Advanced Manufacturing Technology*, *113*(7–8), 2395–2412. https://doi.org/10.1007/s00170-020-06572-4

Darmawan, A., & Sheu, D. D. (2021). Preventive maintenance scheduling: A simulation-optimization approach. *Production and Manufacturing Research*, *9*(1), 281–298.

Ding, X., Gong, Y., Wang, C., & Zheng, Z. (2024). Artificial intelligence based abnormal detection system and method for wind power equipment. *International Journal of Thermofluids*, *21*, 100569. https://doi.org/10.1016/j.ijft.2024.100569

Djamel, A. B., Hadef, H., & Innal, F. (2024). Maintenance as a sustainability tool in high-risk process industries: A review and future directions. *Journal of Loss Prevention in the Process Industries*, *89*, 105318. https://doi.org/10.1016/j.jlp.2024.105318

Dursun, İ., Grishina, A., Akcay, A., & van Houtum, G. (2024). Spare parts recommendation for corrective maintenance of capital goods considering demand dependency. *European Journal of Operational Research*, *318*(1), 71–86. https://doi.org/10.1016/j.ejor.2024.04.024

Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital twin for maintenance: A literature review. *Computers in Industry*, *123*, 103316. https://doi.org/10.1016/j.compind.2020.103316

Feng, X., Wu, J., Wu, Y., Li, J., & Yang, W. (2023). Blockchain and digital twin empowered trustworthy self-healing for edge-ai enabled industrial internet of things. *Information Sciences*, *642*, 119169. https://doi.org/10.1016/j.ins.2023.119169

Franciosi, C., Iung, B., Miranda, S., & Riemma, S. (2018). Maintenance for sustainability in the industry 4.0 context: A scoping literature review. *IFAC-Papersonline*, *51*(11), 903–908. https://doi.org/10.1016/j.ifacol.2018.08.459

Franciosi, C., Voisin, A., Miranda, S., Riemma, S., & Iung, B. (2020). Measuring maintenance impacts on sustainability of manufacturing industries: From a systematic literature review to a framework proposal. *Journal of Cleaner Production*, *260*, 121065. https://doi.org/10.1016/j.jclepro.2020.121065

Garg, A., & Deshmukh, S. G. (2006). Maintenance management: Literature review and directions. *Journal of Quality in Maintenance Engineering*, *12*(3), 205–238. https://doi.org/10.1108/13552510610685075

Ghaleb, M., & Taghipour, S. (2022). Assessing the impact of maintenance practices on asset's sustainability. *Reliability Engineering and System Safety*, *228*, 108810. https://doi.org/10.1016/j.ress.2022.108810

Grootendorst, M. (2022). Bertopic: Neural topic modeling with a class-based TF-IDF procedure. arXiv Preprint arXiv220305794. https://doi.org/10.48550/arXiv.2203.05794

Guo, Z., Zhou, D., Yu, D., Zhou, Q., Wu, H., & Hao, A. (2024). An ontology-based method for knowledge reuse in the design for maintenance of complex products. *Computers in Industry*, *161*, 104124. https://doi.org/10.1016/j.compind.2024.104124

Kaushal, H., & Kaddoum, G. (2016). Underwater optical wireless communication. *Institute of Electrical and Electronics Engineers Access*, *4*, 1518–1547. https://doi.org/10.1109/ACCESS.2016.2552538

Koka, B. R., & Prescott, J. E. (2002). Strategic alliances as social capital: A multidimensional view. *Strategic Management Journal*, *23*(9), 795–816. https://doi.org/10.1002/smj.252

Lee, J., & Kundu, P. (2022). Integrated cyber-physical systems and industrial metaverse for remote manufacturing. *Manufacturing Letters*, *34*, 12–15. https://doi.org/10.1016/j.mfglet.2022.08.012

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—reviews, methodology and applications. *Mechanical Systems and Signal Processing*, *42*(1–2), 314–334. https://doi.org/10.1016/j.ymssp.2013.06.004

Leukel, J., González, J., & Riekert, M. (2021). Adoption of machine learning technology for failure prediction in industrial maintenance: A systematic review. *Journal of Manufacturing Systems*, *61*(September), 87–96. https://doi.org/10.1016/j.jmsy.2021.08.012

Levitin, G., Xing, L., & Dai, Y. (2024). Optimizing corrective maintenance for multistate systems with storage. *Reliability Engineering and System Safety*, *244*, 109951. https://doi.org/10.1016/j.ress.2024.109951

Lin, J., & Chen, K. (2024). A novel decision support system based on computational intelligence and machine learning: Towards zero-defect manufacturing in injection molding. *Journal of Industrial Information Integration*, *40*, 100621. https://doi.org/10.1016/j.jii.2024.100621

Louadah, H., Papadakis, E., Mccluskey, T. L., & Tucker, G. (2024). Supporting the management of rolling stock maintenance with an ontology-based virtual depot. *Applied Sciences*, *14*(3), 1220–1226. https://doi.org/10.3390/app14031220

Meddaoui, A., Hachmoud, A., & Hain, M. (2024). Advanced ML for predictive maintenance: A case study on remaining useful life prediction and reliability enhancement. *International Journal of Advanced Manufacturing Technology*, *132*(1–2), 323–335. https://doi.org/10.1007/s00170-024-13351-y

Nguyen, T., Nguyen, P., & Cho, M. (2024). Internet of things novel cloud-AIoT fault diagnosis for industrial diesel generators based hybrid deep learning CNN-BGRU algorithm. *Internet of Things*, *26*, 101164. https://doi.org/10.1016/j.iot.2024.101164

Palmarini, R., Erkoyuncu, J. A., Roy, R., & Torabmostaedi, H. (2018). A systematic review of augmented reality applications in maintenance. *Robotics and Computer-Integrated Manufacturing*, *49*, 215–228. https://doi.org/10.1016/j.rcim.2017.06.002

Polenghi, A., Roda, I., Macchi, M., & Pozzetti, A. (2022). Ontology-augmented prognostics and health management for shopfloor-synchronised joint maintenance and production management decisions. *Journal of Industrial Information Integration*, *27*, 100286. https://doi.org/10.1016/j.jii.2021.100286

Psarommatis, F., May, G., & Azamfirei, V. (2023). Envisioning maintenance 5.0: Insights from a systematic literature review of industry 4.0 and a proposed framework. *Journal of Manufacturing Systems*, *68*(May), 376–399. https://doi.org/10.1016/j.jmsy.2023.04.009

Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *Institute of Electrical and Electronics Engineers Access*, *6*, 3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265

Roda, I., & Macchi, M. (2021). Maintenance concepts evolution: A comparative review towards advanced maintenance conceptualization. *Computers in Industry*, *133*, 103531. https://doi.org/10.1016/j.compind.2021.103531

Rojek, I., Jasiulewicz-Kaczmarek, M., Piechowski, M., & Mikołajewski, D. (2023). An artificial intelligence approach for improving maintenance to supervise machine failures and support their repair. *Applied Sciences*, *13*(8), 4971.

Sala, R., Pirola, F., Pezzotta, G., & Cavalieri, S. (2023). Improvement of maintenance-based product-service system offering through field data: A case study. *Production and Manufacturing Research*, *11*(1), 2278313. https://doi.org/10.1080/21693277.2023.2278313

Sgarbossa, F., Arena, S., Tang, O., & Peron, M. (2023). Renewable hydrogen supply chains: A planning matrix and an agenda for future research. *International Journal of Production Economics*, *255*(April 2022), 108674. https://doi.org/10.1016/j.ijpe.2022.108674

Shah, R., & Ward, P. T. (2003). Lean manufacturing: Context, practice bundles, and performance. *Journal of Operations Management*, *21*(2), 129–149. https://doi.org/10.1016/S0272-6963(02)00108-0

Sharma, A., Yadava, G. S., & Deshmukh, S. G. (2011). A literature review and future perspectives on maintenance optimization. *Journal of Quality in Maintenance Engineering*, *17*(1), 5–25. https://doi.org/10.1108/13552511111116222

Sikorska, J. Z., Hodkiewicz, M., & Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, *25*(5), 1803–1836. https://doi.org/10.1016/j.ymssp.2010.11.018

Subramaniyan, M., Skoogh, A., Salomonsson, H., Bangalore, P., Gopalakrishnan, M., & Sheikh Muhammad, A. (2018). Data-driven algorithm for throughput bottleneck analysis of production systems. *Production and Manufacturing Research*, *6*(1), 225–246. https://doi.org/10.1080/21693277.2018.1496491

Toothman, M., Braun, B., Bury, S. J., Moyne, J., Tilbury, D. M., Ye, Y., & Barton, K. (2023). A digital twin framework for prognostics and health management. *Computers in Industry*, *150*, 103948. https://doi.org/10.1016/j.compind.2023.103948

Ulhe, P. P., Dhepe, A. D., Shevale, V. D., Warghane, Y. S., Jadhav, P. S., & Babhare, S. L. (2024). Flexibility management and decision making in cyber-physical systems utilizing digital lean principles with brain-inspired computing pattern recognition in Industry 4.0. *International Journal of Computer Integrated Manufacturing*, *37*(6), 708–725. https://doi.org/10.1080/0951192X.2023.2257633

Urso, D. D., Chiacchio, F., Cavalieri, S., Gambadoro, S., & Khodayee, S. M. (2024). Predictive maintenance of standalone steel industrial components powered by a dynamic reliability digital twin model with artificial intelligence. *Reliability Engineering and System Safety*, *243*, 109859. https://doi.org/10.1016/j.ress.2023.109859

Vrignat, P., Kratz, F., & Avila, M. (2022). Sustainable manufacturing, maintenance policies, prognostics and health management: A literature review. *Reliability Engineering and System Safety*, *218*, 108140. https://doi.org/10.1016/j.ress.2021.108140

Webb, D. C., Simonetti, P. J., & Jones, C. P. (2001). SLOCUM: An underwater glider propelled by environmental energy. *IEEE Journal of Oceanic Engineering*, *26*(4), 447–452. https://doi.org/10.1109/48.972077

Yigin, B., & Celik, M. (2024). A prescriptive model for failure analysis in ship machinery monitoring using generative adversarial networks. *Journal of Marine Science and Engineering*, *12*(3), 1–22. https://doi.org/10.3390/jmse12030493

Zhang, X., & Chen, L. (2022). A general variable neighborhood search algorithm for a parallel-machine scheduling problem considering machine health conditions and preventive maintenance. *Computers & Operations Research*, *143*, 105738. https://doi.org/10.1016/j.cor.2022.105738

Zhao, R., Wang, D., Yan, R., Mao, K., Shen, F., & Wang, J. (2018). Machine health monitoring using local feature-based gated recurrent unit networks. *IEEE Transactions on Industrial Electronics*, *65*(2), 1539–1548. https://doi.org/10.1109/TIE.2017.2733438

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, *150*(April 2019), 106889. https://doi.org/10.1016/j.cie.2020.106889