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Review

Envisioning maintenance 5.0: Insights from a systematic literature review of Industry 4.0 and a proposed framework

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ABSTRACT

To provide direction and advice for future research on Industry 4.0 maintenance, we conducted a comprehensive analysis of 344 eligible journal papers published between 2013 and 2022. Our systematic literature review identifies key trends in advanced maintenance techniques and the consolidation of traditional maintenance concepts, which are driven by the increasing adoption of Industry 4.0 technologies and the need to optimize manufacturing systems' performance and reliability. In light of our findings, we highlight the importance of addressing sustainability factors, human aspects, and the implementation of environmental KPIs in future research. Building upon these insights, we introduce the 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 (ZDM) systems. We propose a novel framework that links traditional and advanced maintenance policies for small and medium-sized enterprises (SMEs) to facilitate the adoption of Industry 4.0 technologies in the maintenance field. This work underscores the need for future research to bridge the gap between these policies, enabling a seamless transition for SMEs towards Industry 4.0 maintenance practices, while fostering sustainable and socially responsible operations.

1. Introduction

The fourth Industrial Revolution, also known as Industry 4.0, has been driven by modern technologies such as AI, the IoT, and big data [1]. These technologies are rapidly influencing the industrial landscape, and Industry 4.0 reflects the current shift in business and industry towards increased intelligence. This paradigm shift is driven by both the increasing demand for these technologies in industrial applications and the rapid advancement of the technologies themselves [2]. Cyber-physical systems are a key part of this process, providing a means of closely monitoring and synchronizing information between the factory floor and the online computational space [3,4]. This integration enables improved maintenance practices as it allows the tracking and diagnosis of system and product health. The use of modern monitoring technologies, coupled with the vast amount of data generated by Industry 4.0 innovations, has also led to the development of sophisticated AI algorithms for big data analytics. These algorithms can extract important information from big data, including the features and mechanisms of failure, as well as the degradation processes, enabling the more effective control and management of assets [3–5]. The main idea behind advanced maintenance policies in Industry 4.0 environments is to perform maintenance tasks in a timely and resource-efficient manner based on the monitoring and diagnosis of the target system [6]. This approach, known as predictive maintenance (PdM), has several advantages over traditional maintenance strategies. Table 1 illustrates the evolution of maintenance strategies with each industrial paradigm, evolving in the order (i) reactive-based maintenance, in other words, inspecting during the downtime of each machine, (ii) planned maintenance of production machines and tools, (iii) adding machine sensors, and (iv) predictive analysis. PdM allows higher system reliability at a lower cost [7] and can provide industrial benefits such as increased return on investment, reduced maintenance costs, and fewer breakdowns and less downtime. PdM can also minimize inventory, spare parts, and overtime costs, leading to increased production and efficiency [6–8].

In 2021, Industry 5.0 was presented as a complement to the existing

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Table 1
History of evolution of industry and maintenance.

Industry X	Maintenance X
2021 – Industry 5.0	Maintenance 5.0
Human centricity – resilient manufacturing	Advanced Predictive maintenance
2011 – Industry 4.0	Maintenance 4.0
Smart/intelligent manufacturing	Predictive maintenance
1969 – Industry 3.0	Maintenance 3.0
Electronics/automation/IT systems	Productive maintenance
1870 – Industry 2.0	Maintenance 2.0
Division of labor/electrical energy	Planned maintenance
1784 – Industry 1.0	Maintenance 1.0
Mechanical production/steam power	Reactive maintenance

Industry 4.0 paradigm by having research and innovation drive the transition to a sustainable, human-centric and resilient industry [9]. Industry 4.0 remains primarily focused on achieving economic goals through digital transformation and automating repetitive job processes, but Industry 5.0 will also include social and ecological goals [10]. More specifically, Industry 5.0 aspires to put the welfare of people at the center of manufacturing systems, attaining social goals beyond employment and growth to solidly offer wealth for the long-term advancement of all of humanity [11]. Human-centricity, sustainability, and resiliency are three of Industry 5.0's key features of Industry 5.0, which does not included in the Industry 4.0 concept[9,11,12]. PdM was envisioned for Industry 5.0 in [13] as the center of the workplace. They identified *control, trust, demands* and *resources,* and *organizational allocation of decision-making* as the over-arching factors that enhance PdM adoption. Finally, Maintenance 5.0 was for first time envisioned in [14] as "a maintenance system that increases resilience of physical assets by increasing human-physical asset interaction". For them, Maintenance 5.0 uses advanced analytics and retrofit with the human-in-the-loop.

Modern manufacturing companies are building advanced maintenance platforms to manage their assets, procedures, and resources as part of Industry 4.0. However, the integration of new technologies in these platforms can be challenging, and many companies lack the knowledge and expertise to effectively design and utilize these platforms for big data analytics in the maintenance space. As a result, many companies are not yet fully leveraging the benefits of big data in their maintenance operations. Manufacturing companies are increasingly focused on achieving high product quality in a sustainable manner [15]. As a result, effective and high-quality maintenance is crucial for maintaining production equipment at a level that can realize the desired product quality and meet key performance indicators (KPIs) related to competitiveness and sustainability. Therefore, many companies are moving from traditional quality improvement methods to the latest quality assurance approach, known as zero-defect manufacturing (ZDM) [16,17]. According to the literature, the adoption of ZDM has grown significantly in recent years, surpassing more traditional quality assurance methods such as the Six Sigma and lean methods [17,18]. Product quality is closely related to the health status of machines and therefore to maintenance. According to Psarommatis et al. (2020, 2021, and 2022), ZDM can be implemented with two different approaches: the product-oriented approach, where the focus is on the product quality, and the process-oriented approach, where the focus is on the process quality and, by extension, the health of the machines [16,17,19]. Therefore, maintenance and ZDM are interrelated topics and, more specifically, maintenance is part of the ZDM framework. Even more specifically, it is impossible to achieve sustainable high-quality parts without sustainable high-quality maintenance [20]. The generic framework of ZDM as defined by Psarommatis et al. (2020) is composed of four strategies: defect, repair, predict, and prevent [16]. To demonstrate the usage of the four ZDM strategies, we utilize the product-oriented approach in this review for ease of reader understanding. In the product-oriented ZDM approach, if a defect is detected, then it can be repaired if possible. Moreover, the data collected during defect detection can be used to create models for predicting defects, enabling preventive action can take place to ensure that the defects never occur. In Section 5, we present the initial ZDM model adapted to the maintenance concept [15,17,18,20]. Businesses are struggling to manage and analyze the large volumes of data generated by Industry 4.0 technologies. The need for an architecture for Industry 4.0 maintenance originates from the increasing complexity and interconnectivity of modern manufacturing systems. A comprehensive and integrated architecture can provide a framework for designing and implementing effective and efficient maintenance strategies that can adapt to changing conditions and requirements. Although recent advancements in Industry 4.0 maintenance have been significant, there is a lack of a comprehensive architecture that links traditional and advanced maintenance policies, particularly for small and medium-sized enterprises (SMEs). SMEs often face challenges in adopting Industry 4.0 technologies due to resource constraints and a lack of expertise. This research aims to address this gap by proposing a novel framework that bridges the gap between traditional and advanced maintenance policies for SMEs, facilitating the adoption of Industry 4.0 technologies and approaches in the maintenance field.

This paper presents a thorough analysis of the state of the art for maintenance in the context of Industry 4.0/5.0, which is based on a survey of 344 publications on the topic, with the following objectives:

- Investigate key factors of current research on Industry 4.0 maintenance.
- Provide a comprehensive and systematic literature review method for state-of-the-art analysis.
- Offer an overview and classification of the literature on Industry 4.0 maintenance.
- Design a novel framework taking into consideration Industry 5.0 concept, to map the important constructs in Industry 4.0/5.0 maintenance, focusing on bridging the gap between traditional and advanced maintenance policies for SMEs and moving towards Maintenance 5.0.
- Set the research agenda for future work, emphasizing the need for further research to address the challenges faced by SMEs in adopting Industry 4.0 technologies in the maintenance field.

The paper is structured as follows. In Section 2, we review the existing literature reviews on Industry 4.0 maintenance as well as identify the challenges and research gaps in this field. Section 3 explains the systematic review methodology used in this study. Section 4 presents the results of our analysis, and Section 5 discusses their implications. In Section 6, we introduce a conceptual framework for maintenance in Industry 4.0. Finally, in Section 7, we summarize our main findings and conclude the paper.

2. Previous literature reviews on Industry 4.0 maintenance

This section summarizes the accomplishments of earlier review articles on the combined topic of maintenance and Industry 4.0. We outline the findings from relevant literature reviews and identify areas of concern that require more research. To this end, we searched for and found 20review articles on maintenance and Industry 4.0. These articles were then examined and mapped in Table 1 according to their content, their contribution regarding the target maintenance policy, technical procedure, and challenges, and whether they provide a new framework.

3. Research methodology

This section describes the research methodology of this paper, which employs the systematic method of content analysis. The four main steps of this study are material collection, descriptive analysis, category selection, and material evaluation. According to Higgins and Green (2011), the primary characteristics of a systematic review include a clear set of objectives with predefined eligibility criteria, a reproducible methodology, a systematic search for studies that meet eligibility criteria, an evaluation of the validity of findings, and a presentation and synthesis of the characteristics and findings of the included studies [15,16,40–45]. The review approach is highlighted in Tables 2 and 3 and includes the databases used, article type, the search query, the time frame, the article type, the screening and paper selection process, and the removal criteria.

In this study, we conducted a systematic literature review of the existing research in the field of maintenance using the Scopus and Web of Science databases. We chose these databases for several reasons. First, Scopus includes ScienceDirect as one of its sources, enabling us to access publications from ScienceDirect through Scopus. Additionally, Scopus is widely recognized as one of the largest and most comprehensive databases of scholarly literature, covering over 22,000 titles from more than 5000 publishers. Its use allowed us to conduct a thorough and comprehensive search of the literature in the field of maintenance. We also considered using Google Scholar for our literature search, but we ultimately decided against it because it is not primarily a scientific database and does not have the same level of quality control and curation as Scopus and Web of Science. Therefore, we concluded that using Scopus and Web of Science would provide more reliable and consistent results for our study. Overall, this decision was based on the comprehensiveness and reliability of these databases, as well as their relevance to the field of maintenance. This approach allowed us to conduct a robust and thorough systematic literature review of the existing research in this area.

We created our search query as ("Maintenance") AND ("Manufacturing" OR "Industry 4.0″), because this research focuses on envisioning the future of maintenance; thereby, current practices in the current paradigm, in other words, Industry 4.0, must be mapped. The search with TITLE yielded 376 results on Scopus and 287 articles on Web of Science; after deleting duplicates, 412 papers remained. We then examined each manuscript to decide whether to include it in the final sample by following the screening and paper selection procedure shown in Fig. 1. As a result, a total of 34 publications were used in our research.

We used two different filtering techniques. First, because the final report of the Industry 4.0 working group was issued in 2013 [44], we focused on papers published after January 1st, 2013. All articles were also filtered by domain, document type (only journal papers), and language (English only). Finally, each abstract was evaluated for inclusion using the following criteria, which generated the final sample of 344 papers [45–389]:

- The primary subject should be maintenance.
- The primary subject matter should be manufacturing.
- An article from a peer-reviewed journal should be used.
- Access to the complete text is required.

4. Results

In this section, we present the findings from our evaluation of the 344 selected articles on maintenance in the manufacturing sector. Our analysis covers research articles published over the last 10 years, providing a broad overview of the current state of research on maintenance in the age of Industry 4.0. We begin by examining the distribution of publications by year, as shown in Fig. 2. This allows us to identify trends in the research on maintenance in the manufacturing sector over the past decade.

Our analysis reveals that only 20 papers—less than 6% of the total number of publications analyzed—were published in the first two years of our study period. This is consistent with the timing of the introduction of the Industry 4.0 concept, and it also suggests that our strategy of only considering publications published after 2013 is valid. There was a significant increase in the number of publications on maintenance in 2017, and this trend has continued without any sign of slowing. This trend reflects the rapid development of Industry 4.0 and indicates that research on maintenance in the manufacturing sector is gaining increasing attention and interest. Given the tremendous potential of this research field, we expect to see continued growth in future.

4.1. Maintenance policies, focus, problem formulation, and ZDM

The types of maintenance policies examined in research on Industry 4.0 maintenance were next examined. The result of the analysis of the relevant publications regarding maintenance policies is given in Fig. 3. From our analysis, we found that advanced maintenance practices such as preventive maintenance (around 28% of papers), predictive maintenance (18%), condition-based maintenance (9%), and hybrid maintenance (6%) predominated in research on Industry 4.0 maintenance. In contrast, research on more sophisticated maintenance practices such as prescriptive, proactive, and sustainable maintenance methods was lacking. Traditional maintenance strategies such as reactive maintenance (4%) and total productive maintenance (3%) are still being studied, mainly to determine the best combination of traditional maintenance strategies with cutting-edge maintenance strategies or to optimize maintenance schedules by adopting cutting-edge enabling technologies. Finally, about 7% of the articles did not explicitly mention the target maintenance policy.

Next, we investigated the main focus of these selected articles. Fig. 4 highlights the results of this analysis.

The three major aspects covered were related to maintenance scheduling (21%), prediction (11.5%), and diagnosis (9%) since they are considered as fundamentals for advanced maintenance. Following these predominant subjects were other important aspects of advanced maintenance such as quality considerations (4%), feature extraction (4%), root cause analysis (3%), and data collection (2.5%). Among the topics covered in the literature were performance metrics, cost factors, optimization, visualization, human factors, sustainability, and planning, all of which are relevant for the upcoming Industry 5.0 paradigm. Other themes included a variety of subjects and accounted for 17% of our entire sample. Another aspect considered in our analysis was to examine how these research studies formulated their maintenance problems. Fig. 4 presents the findings.

Optimization problems (30%) and decision support (22%) are the most common types of maintenance challenges highlighted in these studies, followed by sustainability problems (12%) and process modeling (9%). The remaining publications framed their maintenance problems as cost optimization (2%), anomaly detection (6%), classification problems (5%), or a mixture of these issues Fig. 5.

Another essential point concerns the types of technologies listed in the selected papers as potential instruments for solving maintenance-related problems. Fig. 6 presents the results. Augmented reality was found to be the most widely mentioned technology in these articles (20.83%). Other relatively dominant technologies were multi-objective decision support (9.17%), heuristics (5.28%), simulation (4.44%), genetic algorithms (4.17%), artificial neural networks (3.89%), and questionnaire (3.33%). The remaining articles covered a range of topics, as illustrated in Fig. 6.

Four essential ZDM strategies are provided by Psarommatis et al. (2020): predict, prevent, detect, and repair [16]. These strategies are also utilized in pairs during the implementation stage. Therefore, we investigated the documentation of these crucial ZDM procedures in the chosen maintenance publications. Fig. 7 presents the findings of our analysis. The most prevalent strategy in the publications was prevent (36.67%), followed by predict (14.44%), predict–prevent (8.89%), detect–prevent (8.06%), repair (7.22%), detect–repair (3.89%), and detect (3.33%).

4.2. Sustainability factor in maintenance

Since maintenance improves operations and extends asset life, it is

Table 2
Previous literature reviews.

Pertinent Literature	Target Maintenance Policy	Technical Procedure				Challenges							New Framework
		Data acquisition	Diagnosis/ Monitoring	Prognosis/ Forecasting	Maintenance Decision Making	Limited Data Availability	Big Data Analytics	Improvement of Diagnosis and Prognosis Techniques	Integration Solution for Multiple Sensors and Assets	Design of Maintenance Solution for System Level	Decentralized Decision-making Solution	Governance, Standard	
[14]	Maintenance 5.0 (Worker-in-the-loop)	-	x	-	x	-	-	-	-	x	x	-	x
[21]	PdM (CBM & PHM)	x	x	x	x	-	-	x	-	x	-	-	x
[22]	Prognostics and Health Management (PHM)	x	x	x	x	-	-	x	’	’	’	-	-
[23]	AR-Based Maintenance	-	x	-	x	-	-	x	x	-	-	-	-
[24]	PHM	x	x	x	x	’	’	x	’	’	’	’	x
[25]	PdM (CBM & PHM)	x	’	x	x	’	x	x	’	x	’	’	x
[26]	PdM	’	’	x	x	’	x	’	’	’	’	’	’
[27]	Total Productive Maintenance (TPM)	’	’	’	x	’	’	x	’	’	’	’	’
[28]	PdM	x	x	x	x	’	x	x	’	x	’	’	’
[29]	PdM & CBM	x	’	x	x	’	x	x	’	x	’	’	’
[30]	Self-maintenance	’	’	’	x	x	x	’	’	’	x	’	’
[31]	Mixed	’	’	’	x	’	’	’	’	’	’	x	x
[32]	PdM	’	’	x	x	’	x	’	’	’	’	’	’
[33]	PdM	x	x	x	x	’	x	’	’	’	’	’	’
[34]	Replacement and Maintenance				x				x				
[35]	Condition-Based Maintenance (CBM)	x	x	x	’	x	x	’	x	x	’	’	’
[36]	Mixed (Including PdM)	x	x	x	’	’	’	’	’	x	x	’	’
[37]	PHM	x	x	x	x	’	’	’	’	x	’	’	x
[38]	Intelligent Maintenance (CBM)	’	x	x	’	’	’	x	x	’	’	’	’
[39]	PdM (CBM & PHM)	x	’	x	x	’	x	x	’	x	’	’	’

Table 3
Method used for screening papers.

Database	Scopus, Web of Science
Article type	Scientific articles published in peer-reviewed journals
Search query (TITLE)	(“Maintenance”) AND (“Manufacturing” OR “Industry 4.0″)
Time frame	From 1st January 2013–1 st January 2023
Screening & paper selection procedure	Full paper available; article in English; article in the manufacturing domain; article related to maintenance
Removal criteria	Review articles (and generic articles) are removed

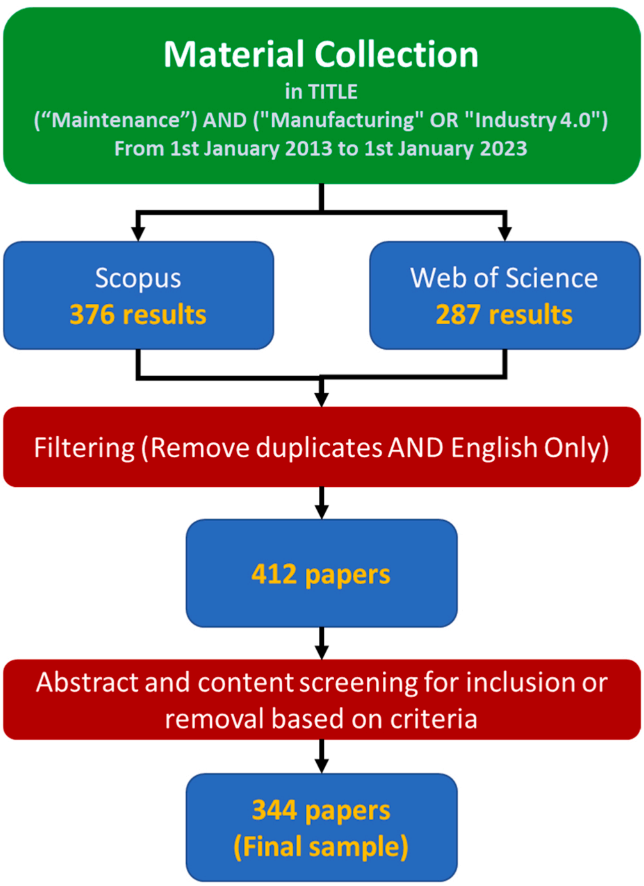

Fig. 1. Research method and steps.

frequently the focus of environmental legislation. Maintenance is therefore a crucial component of sustainability. For this reason, we examined whether sustainability was considered during the different types of maintenance and implementations described in the publications. Proper maintenance operations are essential for the sustainable operation of manufacturing plants. However, as shown in Fig. 8, more than 68% of the articles did not consider sustainability, and this is a key area to be improved for future studies on industrial maintenance.

Environmental impact is a key dimension of sustainability. We thus investigated whether the use of any environmental KPIs was mentioned in these articles, and, if so, which specific KPIs were used. Fig. 9 shows that most of the articles (79.23%) did not mention the use of any environmental KPIs. Among the 20.77% of sample publications that mentioned the use of environmental KPIs, the specific indicators used are illustrated in Fig. 10. Energy consumption (34.38%), pollution (21.88%), waste (18.75%), carbon emissions (14.06%), water consumption (7.81%), and noise levels (3.13%) are among these KPIs.

4.3. Human factors in maintenance

Another essential point for investigation is related to the decision makers of these maintenance activities. The largest proportion of the maintenance systems mentioned in these publications were triggered by a decision support system (20.56%), highlighting the efforts in research on the automation of maintenance activities and decisions in the next generation of smart manufacturing systems. Maintenance managers (12.39%) and operators (13.80%) were the other two important decision makers regarding taking action for maintenance. Fig. 11 provides a snapshot of these results.

A key issue for consideration in maintenance operations is human factors, and this problem should be approached as follows. Consideration of human aspects is a key cornerstone for the future smart manufacturing landscape and operations. In this regard, we examined whether the selected maintenance publications considered social aspects. As illustrated in Fig. 12, there is still a lack of consideration of these aspects within the maintenance research community. Only 16% of the articles discussed social aspects. To study this social aspect and human dimension in greater depth, we investigated whether the stress levels and satisfaction of operators in the workplace were considered. Only 3.42% of the papers in our sample included a consideration of this dimension (Fig. 13) [133,164,182,218,223,243,263].

Next, we examined the the consideration of maintenance safety in the papers. As illustrated in Figs. 14, 16.47% of the publications considered this important aspect, which is also relevant to the human aspects in manufacturing.

Finally, upskilling is essentially a type of specialized training with clear objectives and should be aligned with maintenance management goals to increase performance. Fig. 15 illustrates the results of our analysis, revealing that 18.84% of publications considered the issue of upskilling for maintenance.

4.4. Keyword co-occurrence analysis

In this section, we present our keyword co-occurrence analysis to determine the keywords and their links for the sample of 344 papers analyzed. The keyword co-occurrence analysis was performed using VOSviewer software. We inputted the software with the RIS file exported from Mendeley, with all the references used in the literature analysis added. In total, the RIS file comprised 344 papers, and the unit of analysis was the keywords of the papers. The counting method selected was full counting (i.e., each co-author or co-occurrence link has the same weight). A thesaurus document was used to ensure the correct counting of keywords. In addition, a filter was set to limit the extracted words to those with at least five occurrences. In total, 838 keywords were extracted, but only 35 occurred at least five times, and the keywords were classified into five clusters (scale of image: 1.30) (Figs. 16 and 17). The results had 140 links and a total link strength of 313. We used the association strength to normalize the strength of the links between items.

The following five clusters were formed on the basis of the association strength between keywords.

Cluster 1 (RED, 10 items): corrective maintenance, failures, human factors, numerical methods, opportunistic maintenance, overall equipment effectiveness, preventive maintenance, quality control, simulation, total productive maintenance. “Preventive maintenance” is the third most commonly occurring keyword (34 mentions). Its strongest links are with “quality control” (6), “corrective maintenance” (6) “manufacturing system” (5), and “failures” (5). According to our analysis there is no clear strong correlation with other terms.

Cluster 2 (GREEN, 8 items): condition-based maintenance, degradation, energy efficiency, flexible manufacturing, inventory control, maintenance management, optimization, reliability. This cluster includes the hybrid strategies for maintenance. “Condition-based maintenance” is the most commonly occurring keyword (8 mentions). In the

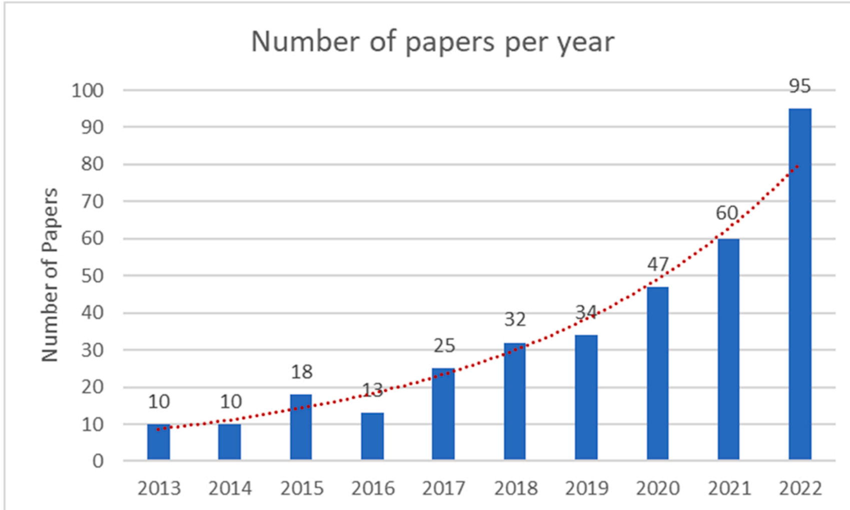

Fig. 2. Number of papers per year.

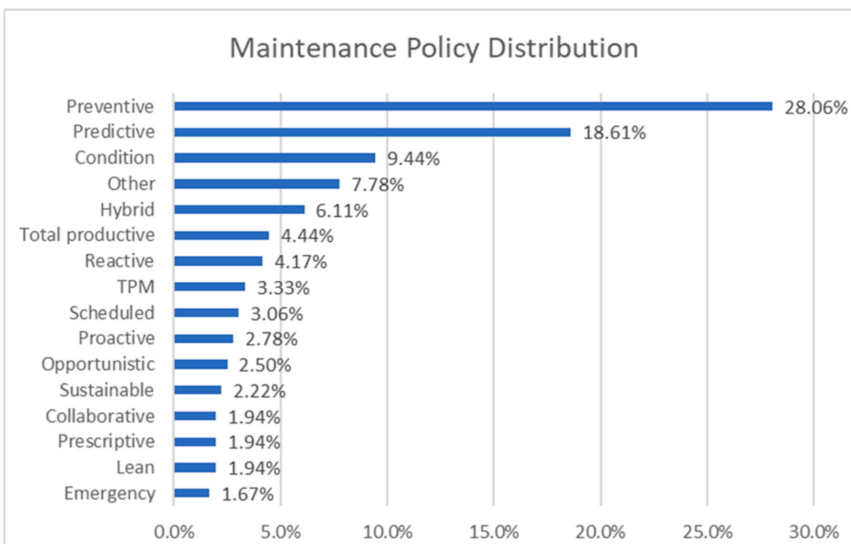

Fig. 3. Distribution of articles according to the maintenance policy covered.

graph distribution, the cluster does not have a specific location or dominant term.

Cluster 3 (BLUE, 7 items): big data, Industry 4.0, IoT, machine learning, maintenance scheduling, predictive maintenance, smart factory. The dominant keyword of this cluster, "Predictive maintenance", is the second most commonly occurring keyword on our list (37 mentions) and it is mentioned 18 times together with "Industry 4.0″, six times with "manufacturing", six times with "machine learning", six times with "internet of things", and four times with big data.

Cluster 4 (YELLOW, 5 items): computer-aided engineering, industrial and production engineering, mechanical engineering, media management, production system.

Cluster 4 represents the most common disciplines in the field of mechanical, computer-aided, media, industrial, and production engineering.

Cluster 5 (PURPLE, 4 items): augmented reality, maintenance, manufacturing system, sustainability. "Maintenance" is the most commonly occurring keyword on our list (43 mentions). "Manufacturing system" has an occurrence of 38. Interestingly, among the maintenance policies, in our analysis "maintenance" is only linked with "predictive maintenance". Predictive maintenance is also the only maintenance linked to "sustainability".

4.5. Co-authorship analysis

Co-authorship analysis allows the identification of authorship patterns and the degree of collaboration among the most productive researchers in the field. For the co-authorship analysis, we followed the same procedure as that in Section 4.4. Here, we set the filter to a minimum of 10 papers per author. Again, a thesaurus document was used. In total, 762 authors were identified, but only seven met the requirement of more than four papers (scale of image: 1.48).

Cluster 1 (RED, 2 items): Han Xiao and He Yihai.

This cluster focuses on multistage manufacturing systems, predictive maintenance, and the reliability of advanced systems without considering environmental impact or any type of sustainability. Among the five papers in this cluster, only one paper considered environmental sustainability, but no KPI was used [247]. Furthermore, this figure also presents the most active researcher in the domain of maintenance and worth mentioning.

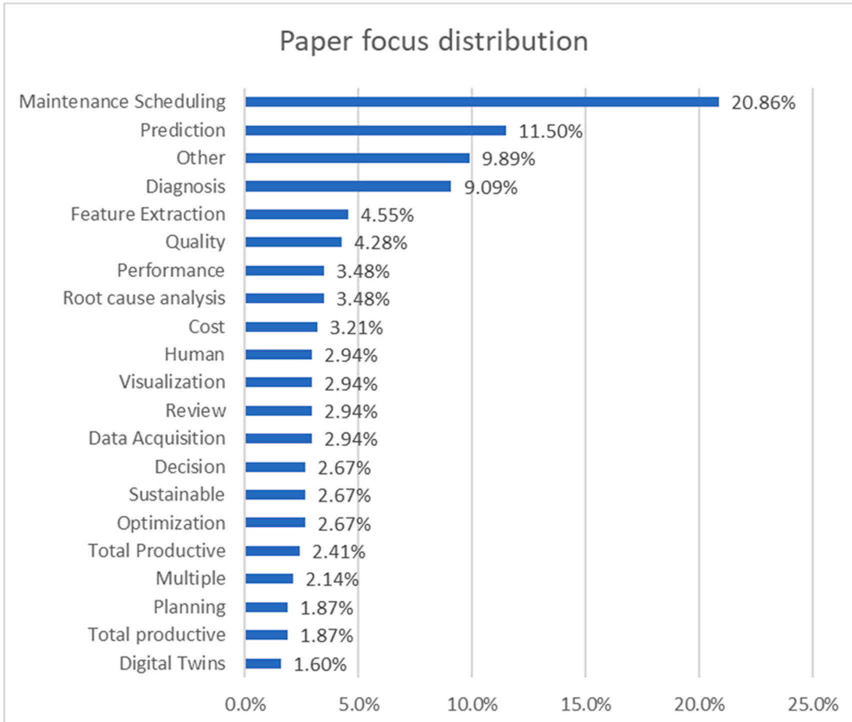

Fig. 4. Distribution of articles according to the focus of the papers.

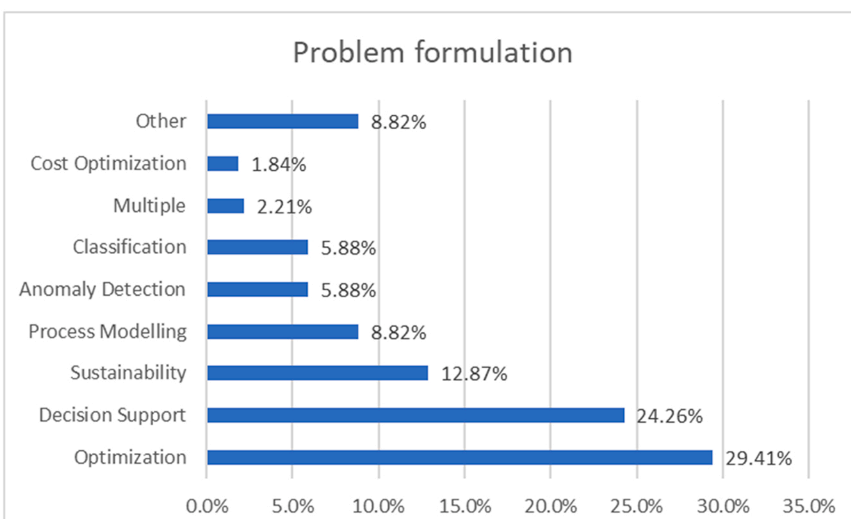

Fig. 5. Problem formulation.

Cluster 2 (GREEN, 2 items): Gharbi Ali and Kenné Jean Pierre.

This is the largest cluster. Gharbi is the author of 10 papers, with Kenné Jean Pierre a co-author of four of them. These papers mostly focused on preventive maintenance for unreliable and imperfect manufacturing systems. Gharbi has analyzed the degradation of manufacturing systems from both the product and production sides, namely preventive maintenance and quality inspection solutions.

Gharbi and co-authors considered sustainability in four of the 10 papers, and Gharbi considered environmental sustainability in three of the 10 papers, using carbon emission as the KPI [84,121,203]. Additionally, in Polotski, Jean Pierre, and Gharbi (2019), social sustainability was considered through the measurement of operator stress [164].

Cluster 3 (BLUE, 2 items): Lu Biao and Zhou Xiaojun.

The papers considered sustainability in terms of carbon emission. They focused on data-driven dynamic predictive maintenance, quality deterioration, online sensors, and scheduling of multistage manufacturing, and they also considered opportunistic preventive maintenance. None of the six papers in this analysis considered any type of sustainability. These authors used computers as decision makers in two of the six papers.

Cluster 4 (YELLOW): Ni Jun.

Ni Jun is sole author in this cluster. This cluster is mostly focused on predictive and preventive maintenance for reconfigurable manufacturing systems, with some work on opportunistic maintenance. To our knowledge, sustainability has not been considered by this author. Sustainability is mentioned twice, once as environmental sustainability [253] and once as social sustainability [176]. In both cases, no KPI for

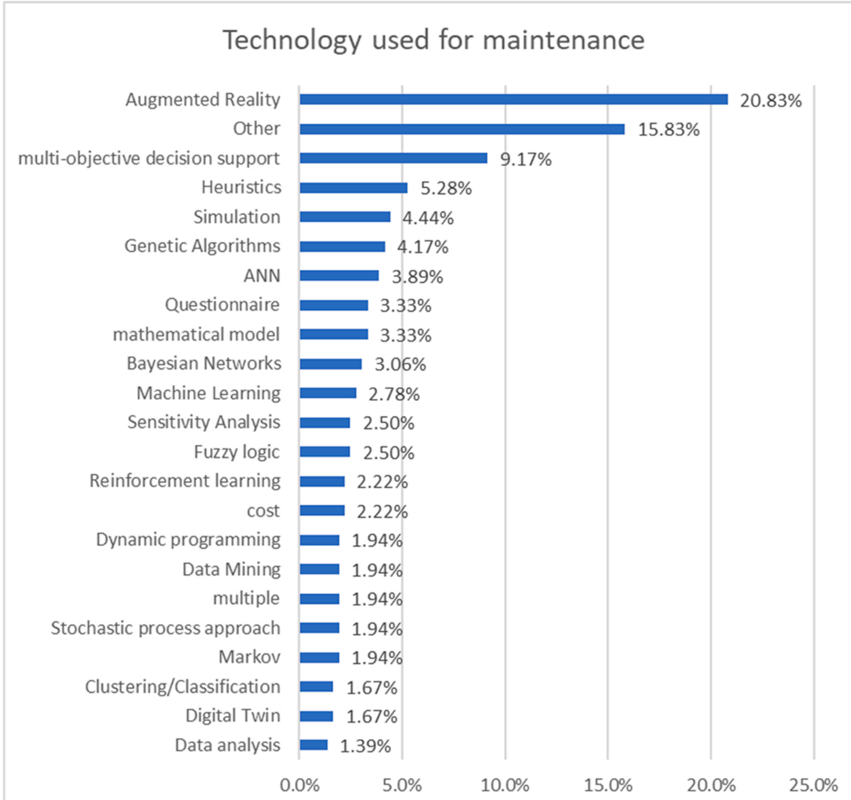

Fig. 6. Technology used for maintenance.

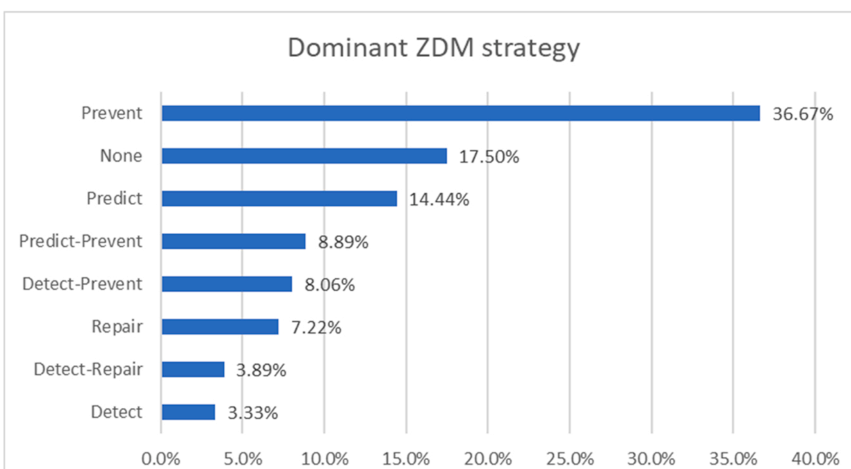

Fig. 7. Dominant ZDM strategies.

sustainability was used or mentioned.

5. Framework of maintenance 5.0 in the era of ZDM

Previous research in the field of maintenance has mainly focused on methods for diagnosis and prognosis. While many studies have proposed system architectures, they have often lacked a comprehensive perspective on Industry 4.0 and the incorporation of Industry 5.0 concepts. Most of the architectures in the literature were designed to address a specific aspect of maintenance, rather than provide a comprehensive framework that incorporates all types of maintenance. This lack of a conceptual framework makes it difficult for modern firms to design and implement effective and efficient maintenance strategies.

To address this gap, in this section we propose a framework for the implementation of Maintenance 5.0 in the era of ZDM. The proposed framework is an adapted version of the ZDM concept presented by Psarommatis et al. (2020)[16], and it encompasses all types of maintenance. Maintenance is triggered by two events: the monitoring of production and the prediction of maintenance needs based on monitoring data. The prediction of maintenance needs is a key aspect of Industry 4.0. Once maintenance is triggered, the next step is to identify the cause of the abnormality and plan the maintenance. If there is a fault in a machine, corrective maintenance is required. In all other cases, the applied maintenance is preventive. Furthermore, it is essential to pay careful attention to the human aspect in manufacturing systems, not only from the business and economic viewpoints but also from the

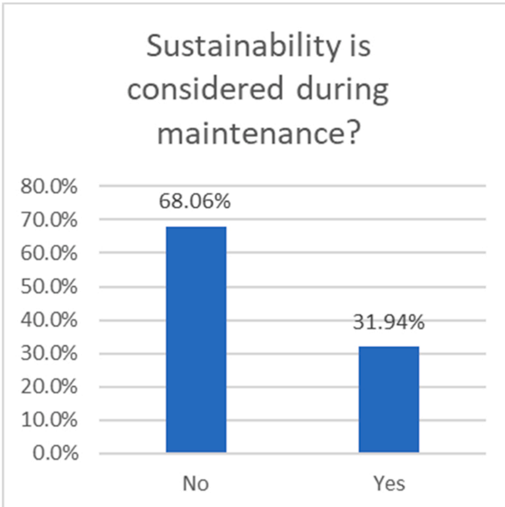

Fig. 8. Sustainability consideration during maintenance.

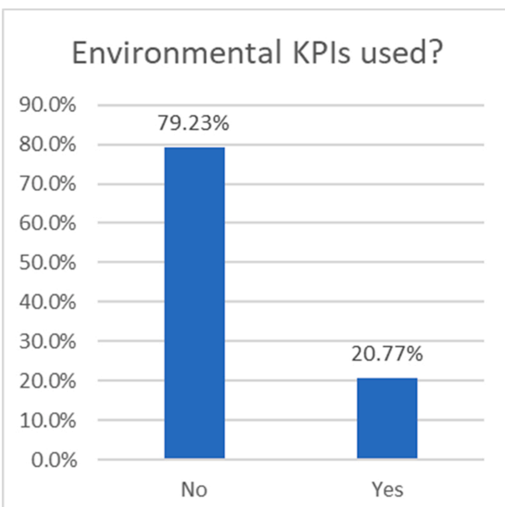

Fig. 9. Consideration of environmental KPIs.

viewpoints of efficiency and the social aspect of manufacturing. The currently adapted framework suggests that providing bidirectional relationships between operators and machines will increase the performance of both while simultaneously increasing the performance of the overall system. Training models with 100% accuracy and reliability cannot be realized due to the uncertainty and stochasticity that characterize manufacturing systems, necessitating the implementation of continuous learning methods, not only for the digital models but also for the operators, to achieve high efficiency, resilience, and flexibility. Digital models can be trained using data from the operators, whereas operators can be taught from the decisions that digital models provide, leading to a virtuous circle of improvement [15].

Based on the time that maintenance is applied, two types exist: maintenance is applied before or after an equipment fault. Therefore, Maintenance 5.0 includes two types of maintenance: corrective and preventive. These categories encompass other well-known types of maintenance, such as predictive maintenance, which uses predictive tools to forecast when a component will fail or fall below desired performance levels to implement preventive action and avoid potential failures.

"Maintenance 5.0 is a concept that focuses on a more human-centric approach to maintenance, where software, hardware, and people work together to improve maintenance processes [5]". This approach involves the use of collaborative human–AI systems, which can enhance learning and increase the quality and confidence of maintenance operations [390]. Maintenance 5.0 incorporates many of the technologies associated with Industry 4.0, but also places a strong emphasis on the social aspect of maintenance, recognizing its importance in achieving sustainable maintenance practices [391].

The key to achieving Maintenance 5.0 is to integrate maintenance tools directly with the scheduling tool [20]. More specifically, a dynamic scheduling tool is essential to realize the maintenance tasks in the schedule in the most efficient manner [392–395]. Figs. 18 and 19 illustrates the cycle of the Maintenance 5.0 concept, including all the key elements that must be implemented for successful and efficient maintenance.

The analysis of maintenance tasks often requires advanced decision-making tools. In some cases, these tools can be decentralized to reduce information technology costs and improve decision making. For example, in the context of Industry 4.0 and big data analytics, decentralized decision making can reduce networking costs and improve efficiency. This approach involves the use of a centralized decision-making tool to create rules and models, which can then be applied in real-time by decentralized decision-making tools for individual decision making [396–398]. Overall, this hybrid approach can provide cost

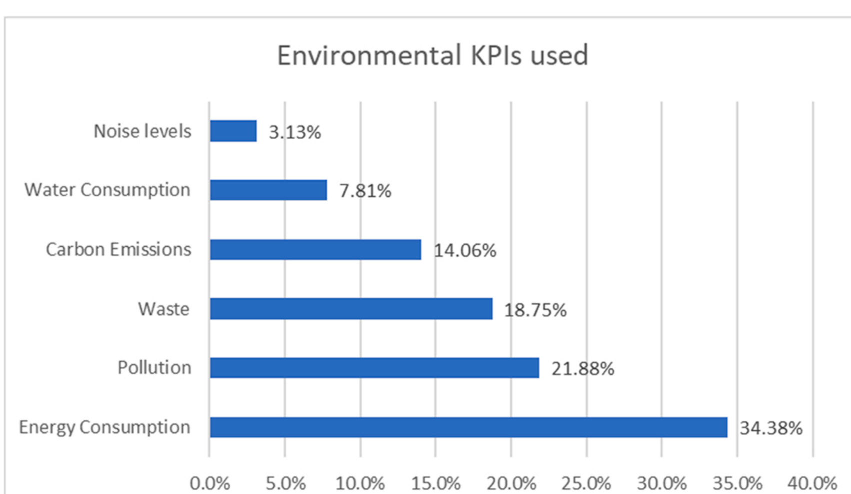

Fig. 10. Environmental KPIs used.

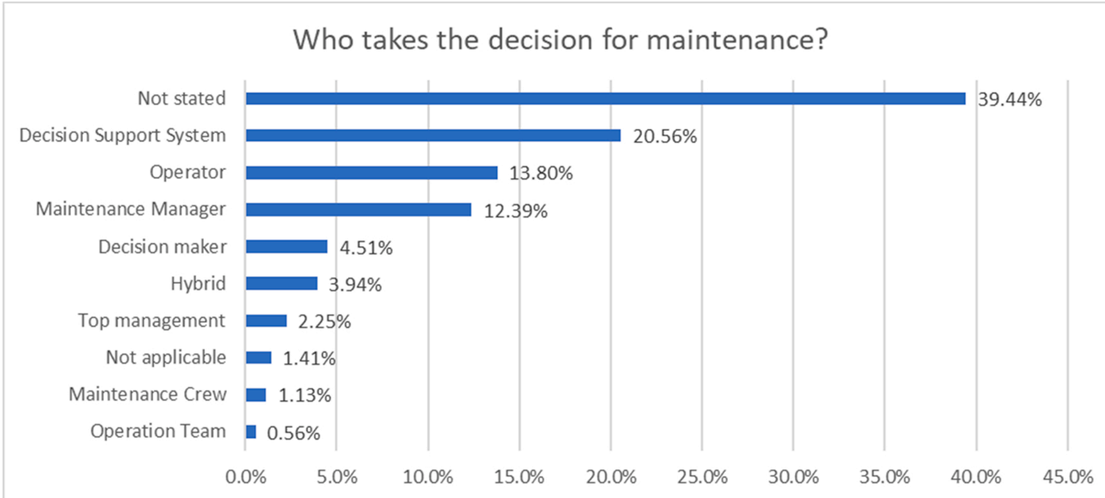

Fig. 11. Decision makers for maintenance activities.

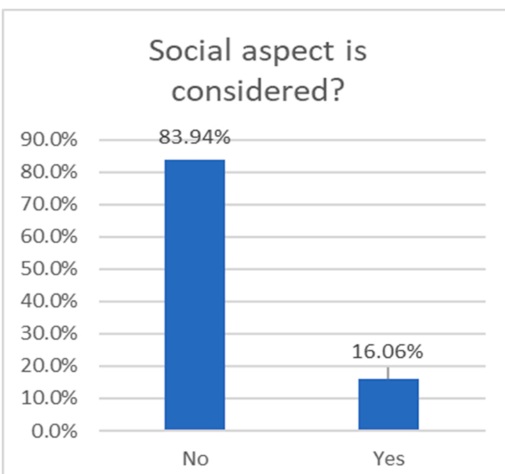

Fig. 12. Consideration of social aspects.

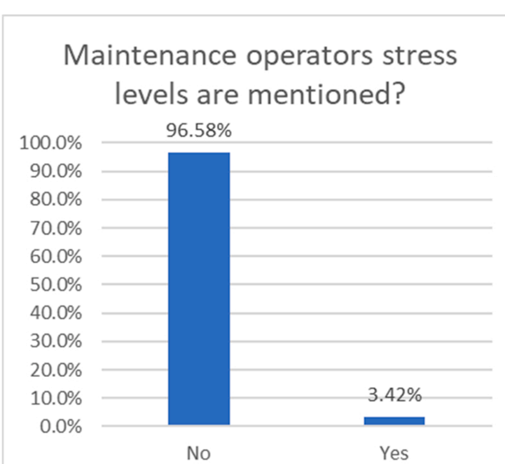

Fig. 13. Consideration of stress level of maintenance operators.

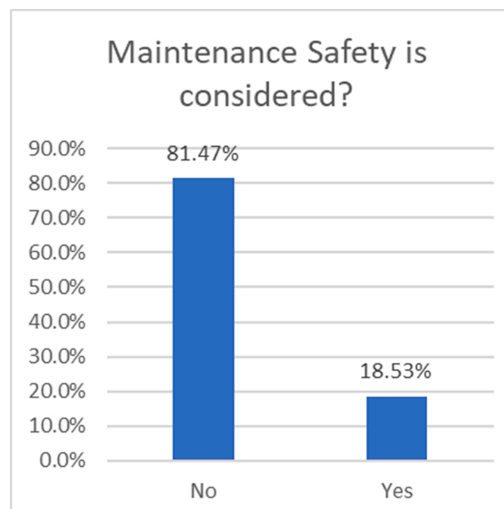

Fig. 14. Consideration of maintenance safety.

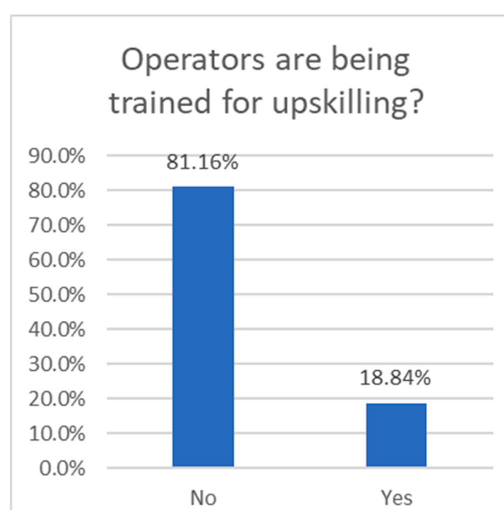

Fig. 15. Upskilling of maintenance operators.

benefits and improve the effectiveness of maintenance operations in Industry 4.0 environments. In the practical implementation of maintenance using IoT devices, interoperability is crucial. Semantic

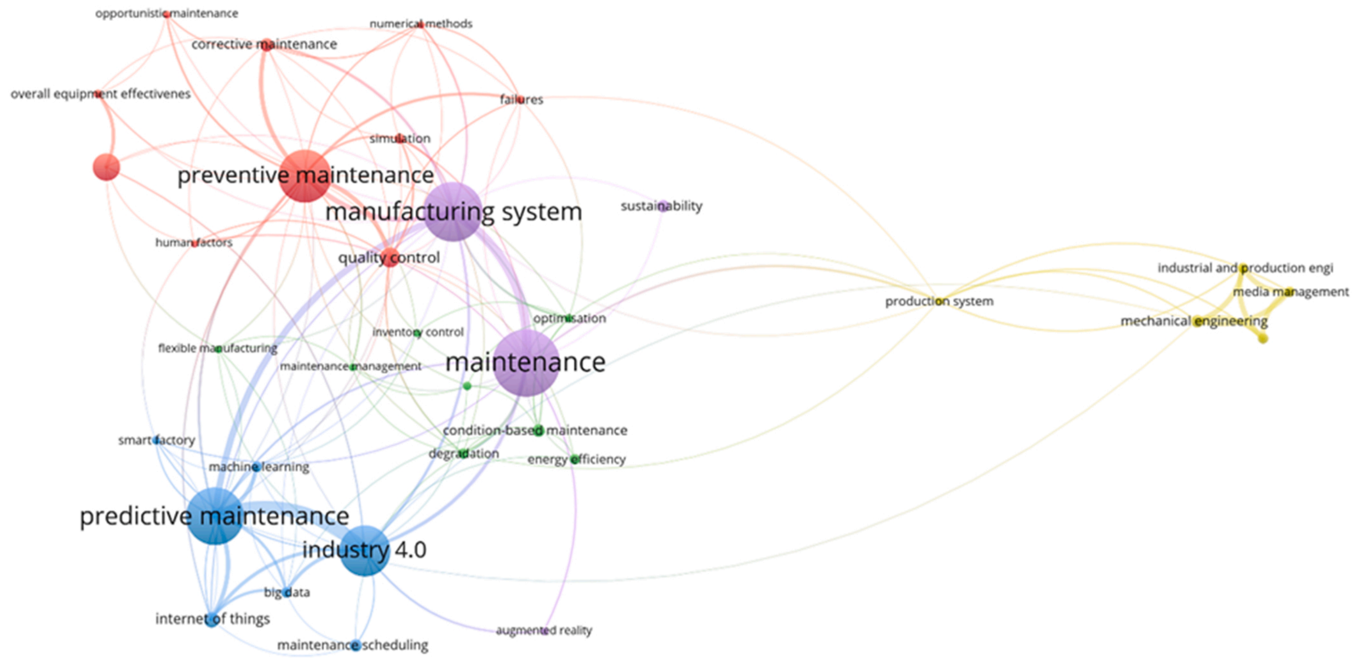

Fig. 16. Co-occurrence network visualization.

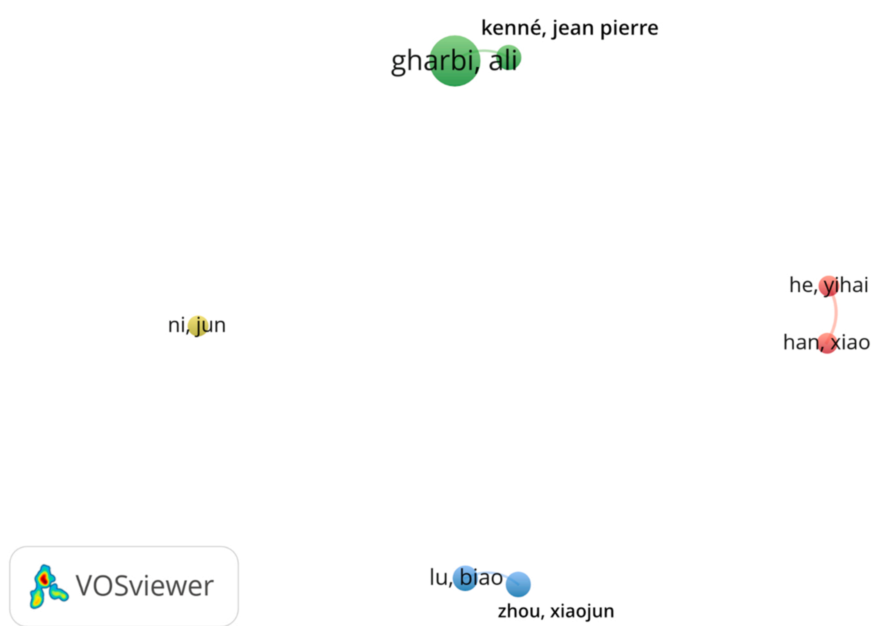

Fig. 17. Co-author network.

interoperability, in particular, allows computer systems to manage and exchange data with a common understanding using shared vocabulary and logic [399,400]. In the context of Industry 4.0, manufacturing companies must often integrate data from multiple sources with different formats. Semantic interoperability is a key requirement for a successful Industry 4.0 maintenance solution because it enables data federation and allows machines to interpret data using an ontology. By linking each data element to an ontology, semantic interoperability enables effective data management and sharing in Industry 4.0 environments. Currently, with the development of the IoT, manufacturing lines produce vast amounts of data. By exploiting sensors, it is now possible to capture valuable industrial information in an Industry 4.0 environment. Big data is currently underexploited [401], but data analytics exploiting this data could be a valuable asset for maintenance. Indeed, through the use of machine learning algorithms, it is possible to find patterns that predict a future defect or machine breakdown. As discussed in Section 5.2, both decentralized and centralized decision-making tools are useful for cost efficiency. Therefore, the information transparency part can take into account big data analysis, strategic decision making, and so forth. In addition, it can be a training module for individual decision making that provides trained parameters of the machine learning model.

Due to the increasing complexity of production, the main role of humans is shifting from machine operator to strategic decision maker and flexible problem solver [402]. However, humans need technical support to enable them to understand the operation of very complicated systems instinctively. Such technical assistance includes the acquisition, aggregation, visualization, and reuse of data and information [399,400,

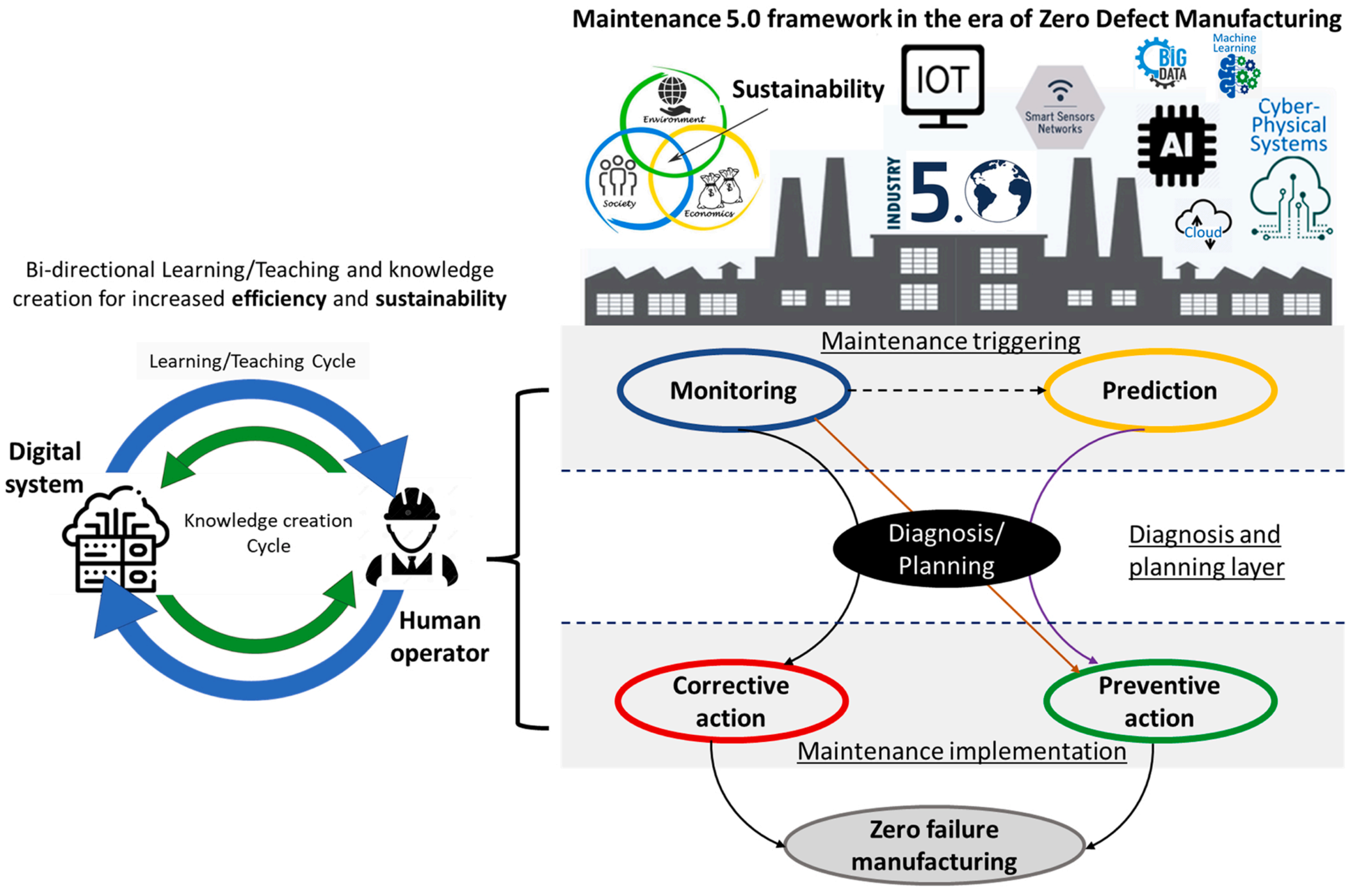

Fig. 18. Maintenance 5.0 framework.
Adapted from [16].

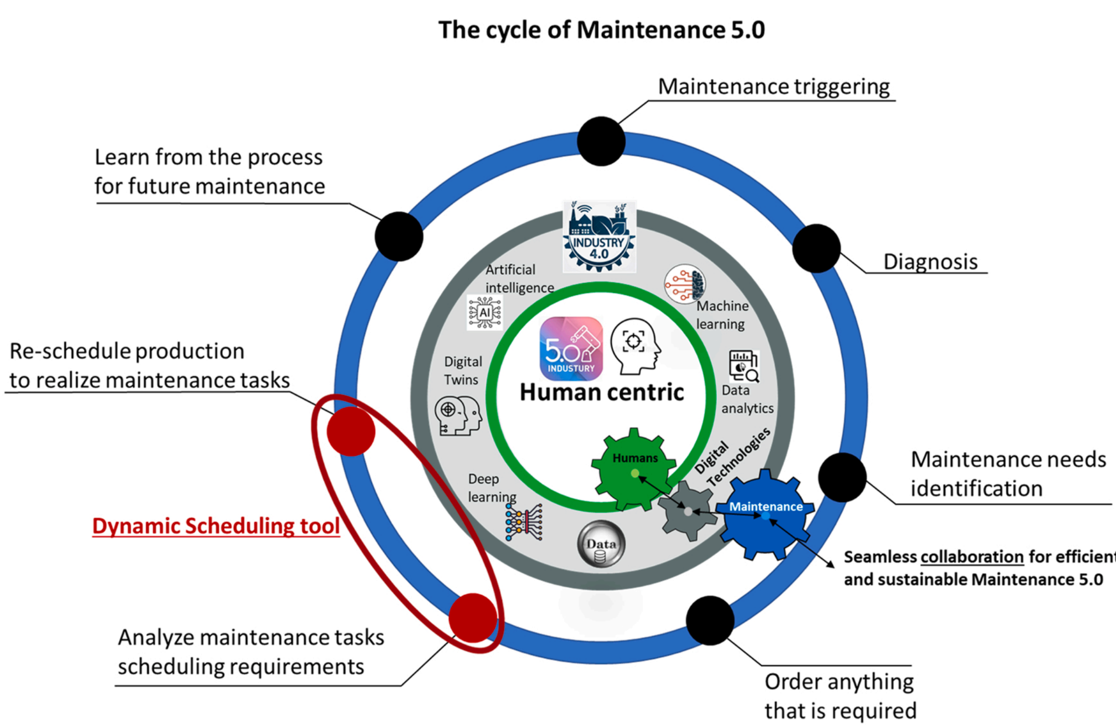

Fig. 19. Cycle of Maintenance 5.0.

403].

Information transparency should include context-aware information for sustainable manufacturing. However, one obstacle still makes the exploitation of data sets difficult. Since manufacturing data originates from various sources, it is also in various formats, including SQL databases, timestamp series, XML sheets, Excel sheets, and JSON streams. This creates several problems. First, when writing an algorithm, one must consider the source of data to adapt the program to the data schema and the data format. This implies that the programmer needs to understand the data schema. However, data schemas are sometimes difficult to interpret without sufficient context. For example, fields may have meaningless names or names that are understandable only in a certain domain. Two fields from two different data sets may also hold the same information or hold information about an entity from another dataset. However, it is difficult to address such problems without clear explanations from the entities maintaining the different data sets.

A solution to this issue is the combined use of ontologies and graph data. Through graph data, it is possible to identify different entities along an assembly line, for example, a specific machine or process. Graph data helps link entities to each other (i.e., identify that a machine belongs to a process), and also helps link entities to their data (i.e., identify that a machine has a sensor that captures the temperature at different points in time). Ontologies provide a common vocabulary that allows this data to be understood the same way across different systems. They help graph data to be marked up with meaningful metadata (i.e., they help identify that a specific entity is a sensor, spindle, and so forth).

The benefits of this approach are twofold: graph data helps link data together, making it easier to retrieve all information about one entity or a specific type of information about one entity, whereas ontologies offer a common vocabulary, making it easier for both the user and the machine to understand the data. Ontologies also make it easier to develop algorithms that interact with data sets. Indeed, since the vocabulary used to describe the data is the same across all data sets, to write an algorithm that can process data regardless of its source, a developer or data scientist need learn and understand only one ontology rather than several data schemas.

6. Discussion

Through a comparison with the current literature review in the field [14,21,23,404–407] in this work we study the maintenance in the context of true sustainability. Guidelines towards Maintenance 5.0 have only been given by Cortés-Leal et al. (2022) [14]. Their review focused on wearable devices and their usage in maintenance. This study differs from previous literature reviews in that it focuses on how Industry 4.0 technologies, together with maintenance policies, can be used to achieve human-centric ZDM.

It can be seen in Fig. 2 in Section 4 that the field of maintenance has grown exponentially over the last 10 years, attracting increasing interest with the rapid development of Industry 4.0. This is especially true for advanced maintenance practices such as preventive maintenance, predictive maintenance, condition-based maintenance, and hybrid maintenance (Fig. 3).

6.1. Discussion of analysis

We found that, despite the search for sustainable organizations, in this case maintenance teams, sustainability is not a priority, with only 29.34% of the papers focusing on sustainability. More information regarding the important topic of sustainability will be given in the following discussion points. Economic growth is a major priority represented over the years without connections to sustainable growth. When analyzing problem formulation (see Fig. 5) we found that optimization and decision support are the largest areas by far. However, few papers attempted to address economic growth in combination with social (18.53%) and environmental (15.89%) aspects [203,247,253]. This is reflected in the reduced amount of research on more sophisticated maintenance practices, such as prescriptive, proactive, and sustainable maintenance methods. Therefore, the predominant subjects were maintenance scheduling (25%), prediction (12.5%), and diagnosis (10%), since they are considered as fundamentals for advanced maintenance. Among the topics covered, human factors, sustainability, and planning were considered (Fig. 4). For companies to truly become sustainable, economic, social, and environmental factors must be balanced and studied together rather than individually.

As can be seen in Fig. 11, many papers (44.37%) did not specify who is responsible for taking maintenance decisions. Most of the decisions have to be taken by humans under different forms of execution (operator, operation team, maintenance crew, maintenance manager, top management, and decision maker). This fact further increases the need for sustainable maintenance and to take into account the social aspect of manufacturing and the humanity of workers, as well as the consequences of poor maintenance [408].

Research efforts towards the automation of maintenance activities and decisions will be manifested in the next generation of smart manufacturing systems, where 18.77% of decisions are made automatically and 4.78% of decisions are hybrid decisions.

Contrary to the rise of automation in decision-making and AR technologies (23.75%), in our analysis only 16.67% of operators are being trained to upskill maintenance skills. Despite the dominance of human decision makers, our analysis revealed that safety is only 18.53%, social aspects are barely considered at 17.05%, of which stress levels are only 3.11%.

ZDM was mentioned in 81.48% of the articles, with “prevent” as the most researched strategy (38.52% of articles), which is in line with the most common research maintenance policy of preventive maintenance (33%). The detection strategy received less interest. Although the detection strategy is a subject more associated with quality inspection, both strategies should be used interchangeably in more sophisticated strategies [394,409]. Additionally, repair was only considered in 11% of studies. The results indicate that academics and practitioners are pursuing prevention and predictive strategies. Nevertheless, deviations from standards are inevitable, and thus repair is critical for zero waste.

6.1.1. Research groups should collaborate with each other

Our bibliometric analysis of co-authorship occurrence reveals that the majority of authors with extensive interest and knowledge in the area (i.e., preventive, scheduled, reactive, condition, hybrid, and other types of maintenance policies) do not collaborate. Encouraging collaboration among research groups could lead to a more comprehensive and multifaceted understanding of the challenges and opportunities in the field of maintenance and ultimately drive the development of more effective and sustainable maintenance strategies. Collaboration among research groups can also facilitate the sharing of data, resources, and expertise, which can accelerate progress and help ensure that the findings and insights of one group are more readily applied and integrated into the work of other groups.

6.1.2. Consideration of true sustainability

Our bibliometric analysis on keyword occurrence revealed that “sustainability” is not connected with a particular maintenance policy but with “maintenance” as a whole. This lack of attention to true sustainability in the field of maintenance suggests a continued need for greater awareness and understanding of the full range of economic, social, and environmental impacts of different maintenance policies and practices. According to our analysis, 29.34% of the reviewed papers discussed sustainability without considering all its aspects (economy, environment and society). Sustainability has economic, environmental, and social aspects, and true sustainability addresses all these areas at the same time. The results of our analysis revealed that the majority of papers in which sustainability was considered referred to environmental and economic aspects and disregarded the social aspect.

Additionally the literature review articles can be criticized for their narrow vision of maintenance and sustainability. The main maintenance policy in these articles was predictive maintenance, and sustainability, when mentioned, was either economic or environmental sustainability. To increase economic sustainability, instead of addressing the problem of scarce human resources, the majority of papers focused on removing humans from decision making. Stefanini et al. (2022) considered environmental sustainability. They unexpectedly found that out of the 70 interviewed Italian companies, 2.6% stated increased emissions and waste, while 34.2% achieved lower water, air, and soil pollution and reduced water use [404]. The researchers could not conclude whether Industry 4.0 technologies are sustainable. In this study, true sustainability was considered, namely social, economic, and environmental sustainability, thus providing a more realistic view of the current state of research in the field.

6.1.3. Maintenance policy

Our keyword co-occurrence analysis using VOSviewer software shows that the keyword "preventive maintenance" is more commonly used than "predictive maintenance" in the manufacturing industry. This may be due to various factors, such as the cost-effectiveness of preventive maintenance and the availability of appropriate tools and technologies for implementing such a policy.

6.1.4. Knowledge and education

Our bibliometric analysis on keyword occurrence also suggests a lack of integration between engineering disciplines, education, and maintenance policy when considering sustainability in modern production systems. This could indicate a gap in the knowledge and understanding of the interrelated nature of these paradigms and the potential benefit of considering them together in the design and operation of production systems.

6.1.5. Human factors

From our literature analysis, we found that human factors such as "social" (17.05% of papers), "stress" (3.11%), "safety" (18.53%), and "upgrade of skills" (16.67%) were considered. In the papers of the most productive authors in the field, social sustainability was barely mentioned. The bibliometric analysis also revealed that "human" factors are connected to the word "defect" in the preventive maintenance cluster. This indicates that although human factors such as social sustainability, stress, safety, and the upgrading of skills are important considerations in the maintenance of production systems, they may not be adequately addressed in current practices and policies. The connection between human factors and defects in the preventive maintenance cluster suggests that addressing these factors could potentially improve the effectiveness of preventive maintenance and reduce the occurrence of defects in production systems.

In addition, we identified the following research gaps between academia and industry in the area of Industry 4.0 maintenance from our comprehensive literature review:

Diverse viewpoints across papers: Each study may take a different approach to the problem of Industry 4.0 maintenance; thus, it is essential that each one performs independent research to establish its uniqueness. However, many issues now act as a "roadblock" for the industry in finding a reference for Industry 4.0, making it necessary to summarize all the viewpoints.

Diagnosis and prognosis are the primary focus of most papers: Because numerous components (such as inventory management, scheduling, cost-effectiveness, and energy effectiveness) have emerged from maintenance research, the challenges in maintenance are complex. Most of the research, however, focuses on failure prediction and health monitoring. All facets of Industry 4.0 maintenance research should be categorized.

Shift in the maintenance paradigm: As previously indicated, IoT devices make it easier to monitor physical assets effectively, and cutting-edge data analytic techniques help to identify significant phenomena or mechanisms from big data. Due to these developments, traditional maintenance practices are being replaced by advanced maintenance practices including PHM, PdM, and CBM. These terms might have several meanings depending on the context. Even though numerous studies have explicitly addressed this paradigm shift, none of them have discussed how it has evolved over time.

6.2. Discussion based on the literature

We next list the six major issues in the Industry 4.0 domain based on a relevant literature analysis:

Limited data availability: Event data for newly commissioned equipment is mostly scarce or nonexistent [35]. Since model-driven approaches are led by problems in the domain in the relevant sector and rely on the intuition and firsthand knowledge of specialists in the field of physical principles or business, they may perform better in addressing this challenge. Nevertheless, understanding physical principles and creating a model for diagnosis and prognosis are challenging tasks.

Big data analysis: Industry 4.0 makes it easier to gather big data, which increases the prospects for diagnosis and prognosis [35]. The analysis of big data poses difficulties because it requires considerable time and specific methods that require a large amount of computing power and storage space. Even though this topic has been covered in a few papers, additional research is required.

Improvement of diagnosis and prognosis techniques: Manufacturing companies must improve their operation and maintenance intelligence through predictive and preventive control and management to handle and analyze industrial big data. There is a significant gap between benchmark problems and real-world production applications when testing the performance of intelligent systems [38]. The integration of intelligent procedures with various industrial systems, such as maintenance, scheduling, and control, should also be the subject of greater research [410].

Integration solution for multiple sensors and assets: To get toward Industry 4.0, contemporary manufacturing companies must manage and oversee numerous sensors and resources. They cannot be integrated through data federation because their technology is not sufficiently mature. Since most manufacturing sectors employ integrated systems, these systems must be able to communicate with one another without any interruptions [38]. Through the addition of sensors and assets, Industry 4.0 systems continue to grow and become more complex. For a large-scale mechanical system, data from multiple sensors or locations may show various sensitivities [35]. Data federation requires interoperability from the integration solution. To reduce subjectivity in decision making in fleet and portfolio asset management, the manufacturing environment requires additional study regarding the incorporation of components with various values and the deployment of data-driven methodologies [34].

Design of maintenance solution for a system level: A critical task is to analyze the interactions of faults among various components for system-level machinery prognosis [35]. However, compared with the machine-level and component-level studies, there has been a limited amount of technical work on improved maintenance for factory applications [39]. The maintenance framework should be created with the following factors in mind for the adoption of advanced maintenance solutions: 1) machine-to-machine communication, 2) wireless and sensor networks (IoT), 3) machine collaboration, 4) real-time diagnosis, and 5) big data [36]. The use of advanced maintenance in manufacturing systems has certain difficulties, particularly for small and medium-sized enterprises (SMEs), which face a lack of internal knowledge, time, and resources [37]. As a result, it is essential to create a reference model and guidelines for the creation of a maintenance solution.

Decentralized decision-making solution: Manufacturing execution systems have been used to manage traditional manufacturing processes, but such surveillance systems are unable to identify undetectable abnormalities and alert the responsible work manager [36]. Although real-time monitoring and big data techniques that enable autonomous data mining from massive industrial data have advanced quickly, research on a comprehensive approach to integrate both techniques is now required.

6.3. Future research directions

We identified the following future research directions to address the gaps and challenges we determined in the field of Industry 4.0/5.0 maintenance and sustainability based on our comprehensive and critical review of the literature.

6.3.1. Integration of human factors in maintenance strategies

Human factors like safety, stress, and skill development should be considered when developing maintenance plans and decision-making procedures, according to our comprehensive analysis. This may entail the creation of human-centric models and tools that consider the health and job satisfaction of employees as well as the effects of human factors on the effectiveness of maintenance operations and the dependability of systems.

6.3.2. Improvement of data availability, big data analysis, and decentralized decision-making solutions

The challenges associated with limited data availability and big data analysis in Industry 4.0 maintenance should be addressed. This may entail creating innovative thoughts for gathering, storing, and processing data as well as improving methods for using data-driven modeling to make diagnoses, prognoses, and decisions. For Industry 4.0 maintenance to advance, decentralized decision-making solutions that can successfully integrate big data and real-time monitoring are essential. The development and application of autonomous and adaptive decision-making systems that can recognize abnormalities, react to them, and enhance maintenance procedures should be the main focus of future research.

6.3.3. Development of advanced maintenance practices

It is important to investigate the transition to more advanced maintenance techniques like prescriptive, proactive, and sustainable maintenance techniques. To improve the effectiveness and efficiency of maintenance practices while reducing waste and resource consumption, research should concentrate on the development and application of advanced analytics, machine learning, and AI techniques.

6.3.4. Holistic approach to three pillars of sustainability

Future studies should work to create a more comprehensive theory of sustainability in maintenance that simultaneously considers the factors related to the three pillars of sustainability: economic, environmental, and social. This would necessitate the creation of brand-new frameworks, methodologies, and performance indicators that consider these interdependencies and their effects on the overall sustainability of maintenance processes and systems.

6.3.5. Interdisciplinary collaboration and knowledge integration

A more thorough understanding of the difficulties and opportunities in sustainable maintenance can result from encouraging interdisciplinary collaboration between researchers and practitioners in a variety of fields, including engineering, education, and maintenance policy. Future studies should concentrate on combining knowledge from various fields to create maintenance strategies and systems that are more efficient and long-lasting.

6.3.6. System-level maintenance solutions

Future studies should focus on creating maintenance solutions for applications at the system level, considering how different components interact with faults and the complexity of large-scale mechanical systems. This may entail creating frameworks for maintenance that take machine-to-machine communication, the Internet of Things, machine collaboration, real-time diagnosis, and big data analysis into account.

By addressing these potential directions for future research, the field of Industry 4.0 maintenance can advance toward more human-centered, efficient, and sustainable manufacturing system maintenance solutions.

7. Concluding remarks

This review paper provides a comprehensive analysis of the state of the art for Industry 4.0 maintenance. We addressed the lack of an architecture giving an overarching perspective on Industry 4.0 maintenance and provided such a framework. The following is an overview of our findings to pave the way for future studies. This research followed the four main steps in the systematic method of content analysis, and 344 journal articles were selected for this purpose. Then, the analysis results were provided for different categories. Subsequently, we solved the problem of the lack of an architecture designed with an overall viewpoint toward Industry 4.0 by providing a reference architecture for Industry 4.0 maintenance that follows design principles.

Despite the dominance of PdM in papers on Industry 4.0 maintenance, traditional maintenance strategies including reactive and preventive maintenance have been actively investigated. The deployment of advanced maintenance as well as the consolidation of old concepts may be a future trend. Traditional maintenance remains helpful for developing manufacturing enterprises, most of which are SMEs. Additionally, we suggest that future research on enabling SMEs to achieve advanced maintenance should focus on creating a bridge between traditional and advanced maintenance policies.

A research gap in the relevant literature, which mostly focuses on diagnosis and prognosis, was confirmed as a result of our thorough analysis, with only a small percentage of studies extending diagnosis and prognosis to incorporate cost-effectiveness or optimization of the maintenance schedule. Such extension and consideration of new factors, such as cost-effectiveness, maintenance scheduling optimization, and environmental implications, are required in future studies.

Similarly, there has been little in-depth research on data federation in the literature. Advanced maintenance for IoT devices requires data federation, which is also one of the crucial elements contributing to the launch of Industry 4.0. The majority of research, however, began with the premise that data federation has already been accomplished. Future work must focus on data federation and interoperability in the context of Industry 4.0 maintenance environments.

Additionally, most of the foundational concepts in machine learning date back a few decades. Most of the related research was on developing technical solutions for Industry 4.0 maintenance or resolving more challenging mathematical problems. Both big data analysis and rapid decisions are necessary in the current production environment, necessitating the consideration of how to use big data to utilize near-real-time insights.

Finally, the results obtained from the detailed analysis of the literature were used to develop the specific maintenance framework presented in Section 5. The proposed framework aims to align researchers and industries in a common understanding of maintenance with the ultimate goal of increasing the sustainability of manufacturing systems. Despite the highly critical nature of this goal, our literature analysis suggests that it has been considered in relatively few studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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