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Review Article

Artificial Intelligence and Big Data Strategies for Predictive Maintenance in Industry 4.0: A Systematic Review from 2019 to 2024

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Abstract - *In recent years, predictive maintenance within Industry 4.0 has acquired considerable relevance, mainly due to its ability to improve operational efficiency and reduce costs. This study aims to systematically analyze the use of Artificial Intelligence and Big Data in predictive maintenance using the STAR methodology. To do so, scientific databases such as Scopus were reviewed, initially obtaining 399 documents, which were filtered until 166 relevant studies. The results show that countries such as India, France, and Germany lead research in this field, while Latin America has a much more limited presence. Regarding thematic areas, Engineering and Computer Science have the highest scientific production, demonstrating the dominant focus on developing these technologies. In summary, incorporating Artificial Intelligence and Big Data in predictive maintenance has established itself as an essential tool for optimizing industrial processes, highlighting the need for multidisciplinary approaches and data-driven strategies to enhance efficiency and sustainability within Industry 4.0.*

Keywords - *Predictive maintenance, Artificial Intelligence, Big data, Industry 4.0, Review.*

1. Introduction

Currently, we define Industry 4.0 as the emergence of a new technological revolution, where a deeper integration of digital technologies occurs, including the Internet of Things (IoT), automation, and connectivity, among others. Therefore, the creation of a new structured system, the way to carry out the new process management and the impact it would have on each of them leads us to examine the relevance and connection that the implementation of predictive maintenance practices has, which have become an integral part of improving efficiency and reducing operating expenses [1]. In this way, it is found that Machine Learning facilitated the improvement in decision-making and the optimization of resources, reducing costs and increasing efficiency in maintenance [2]. At the international level, large companies have spearheaded the implementation of predictive maintenance strategies in manufacturing, aviation, and energy sectors. In some cases, tools such as Artificial Intelligence (AI) and big data have been implemented to reduce maintenance costs, which indicates that these applications have allowed companies to minimize downtime and improve the safety and sustainability of their operations [3]. While global leaders such as Germany, India, and the United States are advancing rapidly in the implementation of predictive maintenance technologies, emerging economies-particularly in Latin America-are beginning to explore and adopt these innovations within specific industrial sectors. For instance, in Latin America, predictive maintenance has gained relevance in the energy and manufacturing industries, reflecting a growing recognition of the benefits of data-driven strategies. Specifically in Peru, early-stage adoption is evident through cases like Cementos Pacasmayo, which has implemented online monitoring systems powered by machine learning to anticipate equipment failures and reduce downtime [3]. The first stage of industrial adoption of predictive maintenance technologies is underway in Peru. In particular, manufacturing companies have already begun implementing AI-based solutions, especially in producing cement and consumer goods. For example, Cementos Pacasmayo has implemented online monitoring systems that predict potential failures in production plants using machine learning algorithms. As a result, the company has faced less downtime and greater operational efficiency [3, 4]. This study analyses AI and big data strategies for predictive maintenance in Industry 4.0. A systematic review of studies published between 2019 and 2024 seeks to identify trends, benefits, and challenges in implementing these technologies in different industrial sectors, focusing on operational efficiency and resource optimization. Systematic reviews consolidate knowledge on a specific topic by analyzing academic sources and business cases. In the context of predictive maintenance, these reviews facilitate the identification of technological trends, practical

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methodologies, and areas for improvement, which is essential for informed decision-making in the industry. Furthermore, they generate new lines of research and strengthen the knowledge base for future applications. This study addresses the application of AI and big data in predictive maintenance within the framework of Industry 4.0. It begins with introducing the concept of predictive maintenance and its importance in various sectors. It then presents a state of the literature to analyze its applications in different contexts. The methodology used and its phases are then presented. The analysis results are then presented, along with a bibliometric analysis using VOSviewer. Finally, the discussions and conclusions on the topic are presented, and future lines of research are proposed based on the identified trends.

2. Literature Review

Predictive Maintenance (PdM) in Industry 4.0 has emerged as a key solution for reducing downtime and operating costs through the use of advanced technologies such as Machine Learning (ML) and the Internet of Things (IoT). This review analyzes recent AI and big data advances, highlighting their impact on industrial efficiency. According to [5], Predictive Maintenance (PdM) optimization in Industry 4.0 through AI, ML, and big data has proven to be key to reducing downtime and operating costs in industrial environments. In an analysis of advanced ML techniques applied to PdM, it was highlighted that automatic fault detection extends the useful life of equipment and minimizes production interruptions. Complementarily, [6] evaluated the effectiveness of different AI models, such as deep, recurrent, and convolutional neural networks, showing that the implementation of these technologies in sectors such as manufacturing, automotive, and energy can improve the accuracy of predictions and reduce operating costs by up to 30%. However, challenges such as the opacity of the algorithms and the lack of validation standards continue to limit their large-scale adoption.

On the other hand, [7] highlighted the importance of IoT and data analytics in PdM, emphasizing that cleaning, normalization, and feature extraction are essential to ensure the accuracy of predictive models. Furthermore, the need to integrate AI and deep learning to optimize decision-making and improve the competitiveness of companies was emphasized. These studies reinforce the relevance of AI and big data-based PdM as a key strategy for operational efficiency in Industry 4.0. However, its adoption requires continuous research and improvements in model interpretation. Advances in AI and ML have revolutionized Industry 4.0, enabling the detection, prediction, and prevention of faults in industrial systems with high levels of accuracy [8]. A study on cloud / fod / edge architectures showed that ML-based diagnostic systems can repair defective products in 98.7% of cases. In comparison, real-time monitoring with IoT sensors and neural networks achieves an accuracy of 93.1% to 100% in fault detection. On the other hand, [9] highlighted the importance of PdM as an efficient alternative to traditional methods, developing an AI-based model with Recurrent Neural Networks (RNNs) and Support Vector Machines (SVMs) optimized with hybrid J- SLnO algorithms. Likewise, [10] analyzed how the Industrial Internet of Things (IIoT) and cloud computing have enhanced PdM by enabling real-time analysis of large volumes of data improving the detection of patterns and anomalies in industrial equipment. These studies highlight the key role of AI and big data in optimizing predictive maintenance driving operational efficiency and sustainability in Industry 4.0.

On the other hand, the need to improve safety and reduce maintenance costs has driven the development of new strategies based on machine learning. In a study on PdM in the automotive industry, [11] analyzed the most used approaches, highlighting that SVMs achieve accuracies of 100%. In comparison, the ANFIS system achieved fault classification with 98.8% accuracy under different engine speeds. Likewise, in manufacturing, [12] addressed the challenge of transforming large volumes of data into actionable intelligence in real-time through digital twin infrastructure and IoT sensor integration. Together, these studies highlight how machine learning and big data have revolutionized predictive maintenance, enabling greater accuracy in fault detection and comprehensive process optimization in Industry 4.0. The reviewed literature confirms that integrating AI, ML, and big data into predictive maintenance optimizes industrial asset management, improves operational efficiency, and reduces costs. Despite these advances, challenges persist in the implementation and scalability of these technologies, which creates new research opportunities to refine their applications in different industrial sectors.

3. Methodology

This study uses the STAR methodology in its four phases (Situation, Task, Action, and Results). This approach allows for context assessment, objective definition, description of actions, and measurement of the results obtained. This method facilitates data collection and analysis, ensuring transparency, reproducibility, and accuracy in machine-learning reports applied to the scientific literature [13]. This study will complement the STAR methodology with bibliometric tools such as VOSviewer to analyze trends in predictive maintenance research in Industry 4.0. In addition, the selection criteria for the reviewed studies are explained, as well as the specific steps to ensure the validity and reliability of the results. Additionally, machine learning based on the STAR methodology has demonstrated its viability in knowledge acquisition in various fields, such as construction accident prevention, reinforcing its applicability in industrial maintenance [14]. Likewise, this method will identify advantages, limitations, and opportunities for improvement in operational efficiency, cost reduction, and extension of the useful life of industrial equipment. Figure 1 shows the phases of the STAR methodology.

Fig. 1 Star methodology flowchart

3.1. Phases of the STAR Methodology

For the development of this study, the four phases of the STAR methodology were used, each according to its usefulness in this topic.

- Situation: In this phase, the impact of Industry 4.0 on predictive maintenance process management is contextualized. To this end, a search was conducted for research on the implementation of AI and ML-based methods, demonstrating the transition from inefficient and cost-intensive practices to optimized strategies.

- Task: This section defines the activities for analyzing and evaluating the most effective methods based on AI and big data for predictive maintenance optimization. This stage includes relevant and substantiated documents for the study.

- Action: This phase describes specific procedures for excluding information based on academic sources and subject areas related to predictive maintenance strategies. Prioritizing information that reflects significant efficiency and cost reduction improvements is also prioritized.

- Results: The findings derived from the analysis are presented, providing quantitative data that allow evaluation of the impact of the assessment of AI and big data adoption in the optimization of predictive maintenance in Industry 4.0.

3.2. Tools to Apply the STAR Methodology

- Scopus: Scopus is a high-quality abstract and citation database used for large-scale analysis in research assessments [15]. Its data are powerful and objective for literature searching, indicating a journal's impact, prestige or influence [16]. It is a valuable tool for exploring the scientific literature and understanding the impact of research [17]. Bibliometric methods, such as citation and co-citation analysis, can increase the rigour and mitigate researcher bias in scientific literature reviews [18].

- VOSviewer: VOSviewer is a software tool for creating and visualizing bibliometric maps based on network data [19]. It analyzes and graphically represents networks of relationships between elements such as authors, keywords, citations or institutions in large bibliographic datasets [20]. VOSviewer helps to explore co-authorship, co-citation and keyword networks in research by analyzing citation structures and co-occurrence patterns [21]. This facilitates an in-depth understanding of the development of knowledge in a discipline, where the opportunities for new research are and the most relevant new trends in the area of interest.

- Python: It is a high-level programming language with a simple and intuitive syntax, making it easy for beginners to get started and for advanced tasks [22]. Python's dynamic language has less support for code-time error detection than tools like Eclipse, especially for machine-learning code [23]. Furthermore, it handles large volumes of data, performs complex analysis, and automates repetitive tasks due to its extensive set of standard libraries and ease of use [24]. It also can create attractive visualizations and compatibility with other technologies in data science, AI, and scientific research [25].

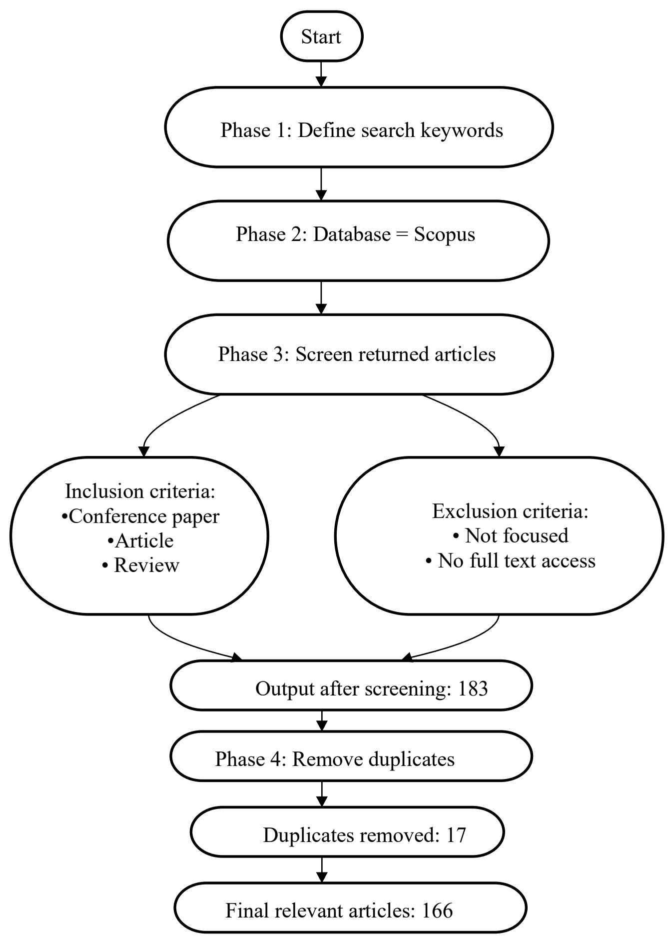

Fig. 2 PRISMA

To expand on the STAR methodology previously introduced in Figure 2, the Situation phase began with a targeted search using Boolean keywords across the Scopus database, yielding an initial output of 399 documents related to predictive maintenance, artificial intelligence, and Industry 4.0. In the Task phase, inclusion criteria were applied, limiting the selection strictly to conference papers, journal articles, and systematic reviews. This filtering process narrowed the pool to 183 documents. Lastly, a duplicate screening was conducted in the Result phase, removing 17 redundant entries and arriving at a final set of 166 relevant publications. This filtering process is clearly outlined in a PRISMA-style flow diagram (Figure 1) to visually represent the review protocol and support transparency in selecting sources.

4. Results

This section illustrates the most important research results, which are supported by a rigorous analysis of the data collected on AI strategies for predictive maintenance in Industry 4.0.

4.1. Analysis of the Situation Phase

In this step, a Boolean search algorithm was designed and applied to databases such as Scopus. The AND and OR operators were used to combine terms, facilitating the search for documents relevant to the research. The algorithm also includes a time restriction, selecting documents from 2019 to 2024, ensuring the studies are presented in a current context. The selection criteria for the documents were based on the following algorithm: (TITLE -ABS-KEY (predictive AND maintenance) AND TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (optimization AND methods) AND TITLE-ABS-KEY (industry 4.0)) AND PUBYEAR > 2018 AND PUBYEAR < 2025.

This method facilitates the detection of research related to the topic, as specific filters are placed with key terms that align with the research developed in this study. In the initial search, the total number of documents found was 399.

4.2. Analysis of the Task Phase

Regarding the inclusion of sources, a specific criterion was established to consider journal articles, indexed conference papers, and systematic reviews. This approach ensures the quality and relevance of the selected documents, as they are supported by scientific journals and high-value sources in the field of research. This filter is detailed in Table 1.

Table 1. Filters by document type

Inclusion of Sources by Document Type	
Document Type	Number of documents
Conference paper	157
Article	136
Review	38

4.3. Analysis of the Action Phase

In this process phase, the selected documents were filtered by subject area to exclude documents from areas unrelated to AI and big data for predictive maintenance in Industry 4.0. This filter is illustrated in Table 2.

Finally, a general exclusion of the selected articles was performed, analyzing in detail the 399 documents obtained in the initial search. The total number of documents was reduced to 166 through inclusion and exclusion screening, which will be used in subsequent analysis phases.

Table 2. Filters by subject area

Exclusion of Sources by Subject Area	
Areas Excluded	**Number of Documents**
Math	59
Physics and Astronomy	48
Energy	32
Engineering Chemistry	18
Science environmental	14
Medicine	12
Chemistry	11
Biochemistry, Genetics and Molecular Biology	11
Earth and Planetary Sciences	6
Arts and Humanities	4
Health Professions	2
Sciences Agricultural and Biological	2
Dentistry	1

4.4. Analysis of the Results Phase

This section presents the key findings of the systematic review of AI and big data in predictive maintenance in Industry 4.0. The objective of this study is to identify current trends, benefits, and challenges in the application of these emerging tools. The STAR methodology was used to organize data collection and analysis, allowing for an orderly and systematic structuring of the information in each phase. The findings are described below and organized into categories relevant to the study.

Figure 3 shows the evolution of research in predictive maintenance in Industry 4.0 between 2019 and 2024. In 2019, research was limited, with only 12 studies reported. However, since 2020, there has been an increase in interest in this topic, with 23 publications that year and steady growth in subsequent years. In 2021, a considerable increase was recorded with 31 studies. This trend continued to rise in 2023 and 2024, reaching its peak with 42 and 41 publications, respectively.

The increase in scientific production highlights the growing importance of AI and big data in optimizing predictive maintenance, establishing itself as an essential area of study in the digital transformation of the industry.

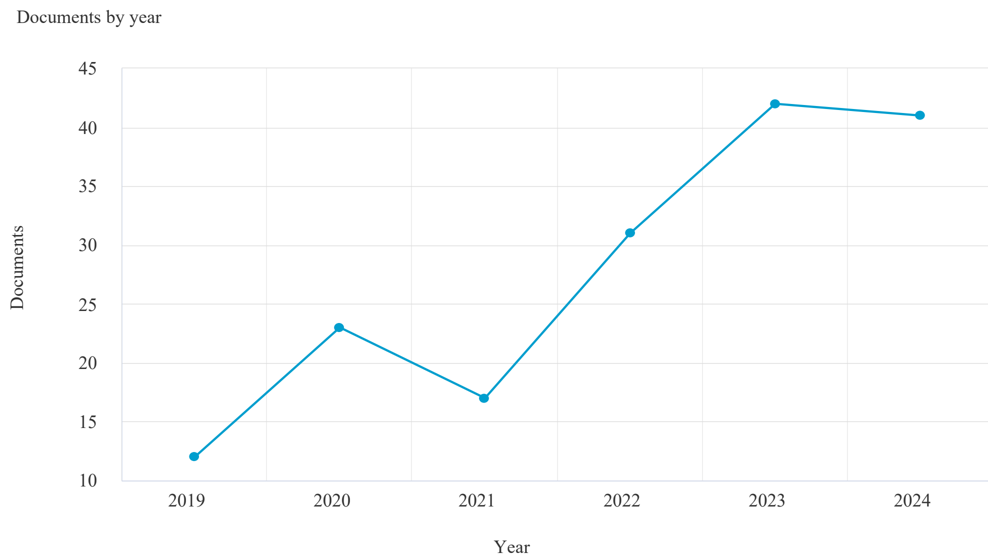

Fig. 3 Analysis by year

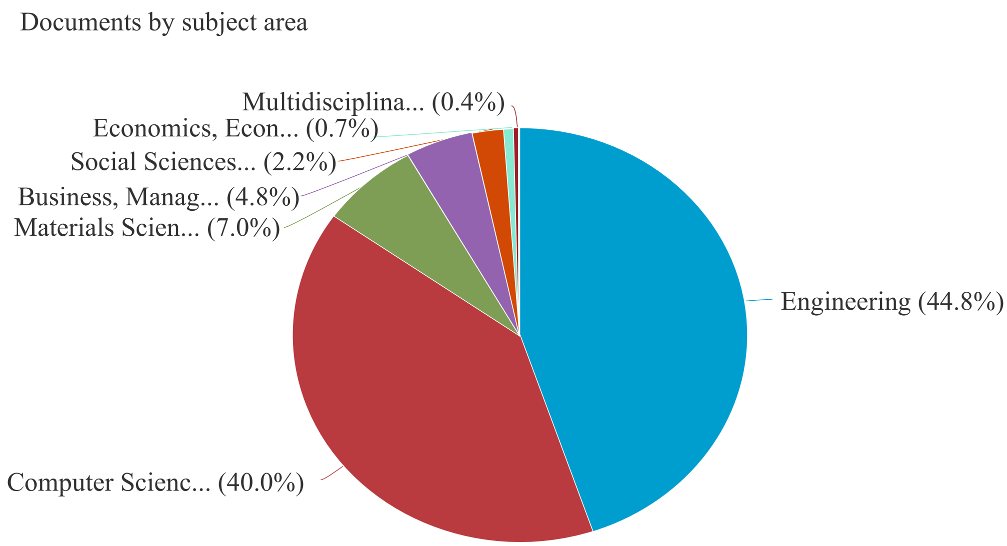

Fig. 4 Analysis by thematic area

Figure 4 shows the distribution of research on predictive maintenance in Industry 4.0 by subject area. Engineering, with 121 studies, and Computer Science, with 108, stand out as the main contributors to the development of this technology, demonstrating its relevance in the design of algorithms, AI models, and big data-based solutions. Likewise, Materials Science records 19 studies on optimizing and performance in industrial environments. On the other hand, disciplines such as Business, Management, and Accounting contribute 13 studies, while Social Sciences contributes 6, demonstrating a lesser focus on organizational and human aspects. Finally, Economics, Econometrics, Finance, and Multidisciplinary studies represent a small share of the analyzed literature, demonstrating a predominance of technical approaches in this field. Figure 5 shows the number of documents published in various academic sources on predictive maintenance in Industry 4.0. IEEE Access has the most significant number of publications, with 11 studies highlighting its relevance in disseminating advanced technological research. Lecture Notes in Networks and Systems follows with 9 publications, consolidating its position as a reference in network and systems analysis applied to industrial optimization. IFAC PapersOnline, with 8 studies, reflects the interest in automatic control and efficient management of industrial processes. On the other hand, CEUR Workshop Proceedings and Advances in Intelligent Processes (CEUR) Systems and Computing contribute 6 and 4 publications, respectively, highlighting the contribution of conferences and studies on intelligent systems in this field. The variability in the number of publications per journal suggests the importance of considering continuously updated sources in the development of AI and big data-based solutions for predictive maintenance.

Figure 6 shows the distribution of scientific papers on predictive maintenance in Industry 4.0 by publication type. Articles constitute the largest proportion, with 79 documents indicating solid theoretical and applied development in this field. Conference publications also have a strong presence, with 71 documents demonstrating the importance of disseminating advances and fostering academic discussion at specialized events. On the other hand, systematic reviews contribute 16 documents, demonstrating the interest in synthesizing existing knowledge and evaluating trends using AI and big data to optimize industrial maintenance. This distribution suggests that, although scientific production in articles predominates, conferences play an important role in the evolution of research in this area. Figure 7 shows the distribution of publications on predictive maintenance in Industry 4.0 by country between 2019 and 2024. India leads the scientific production with 22 studies, followed by France with 18 and Germany with 17, demonstrating strong research activity in AI and big data applied to industrial maintenance in these nations. Furthermore, Italy, with 15 studies, and the United States, with 14 studies, also stand out as key contributors, reflecting their commitment to industrial process optimization. On the other hand, in Latin America, Brazil with 4 studies, Colombia with 2, Ecuador with 1, and Peru with 1 have lower representation, suggesting opportunities for expansion in predictive research in these locations.

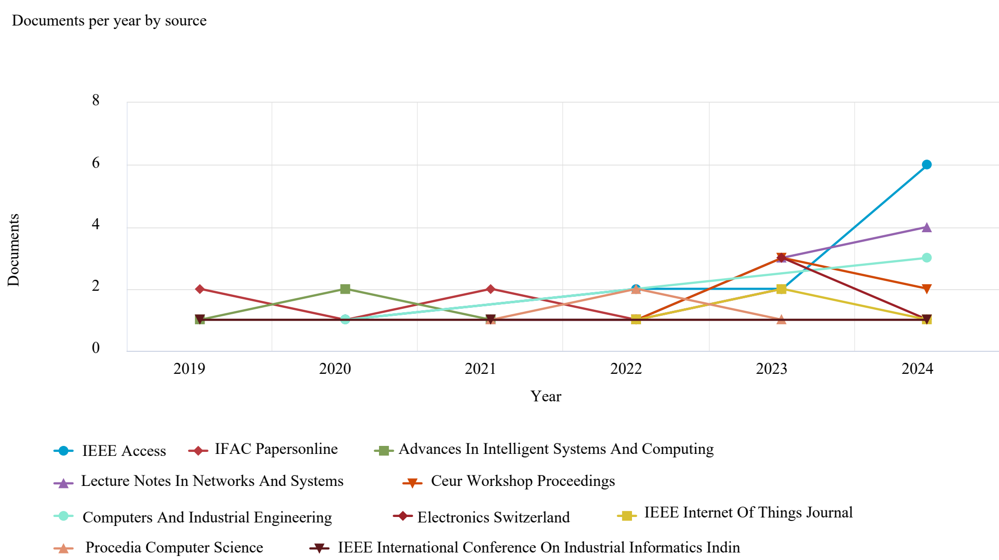

Fig. 5 Analysis by journal

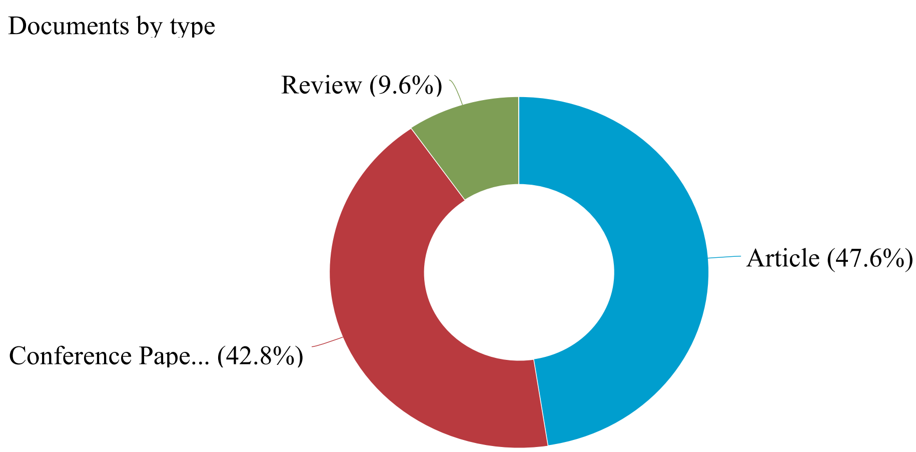

Fig. 6 Analysis by document type

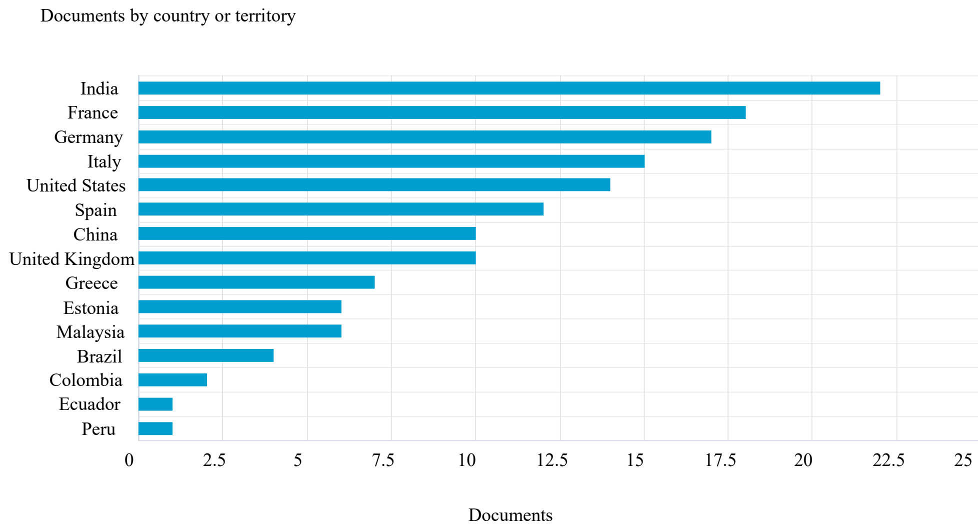

Fig. 7 Analysis by country

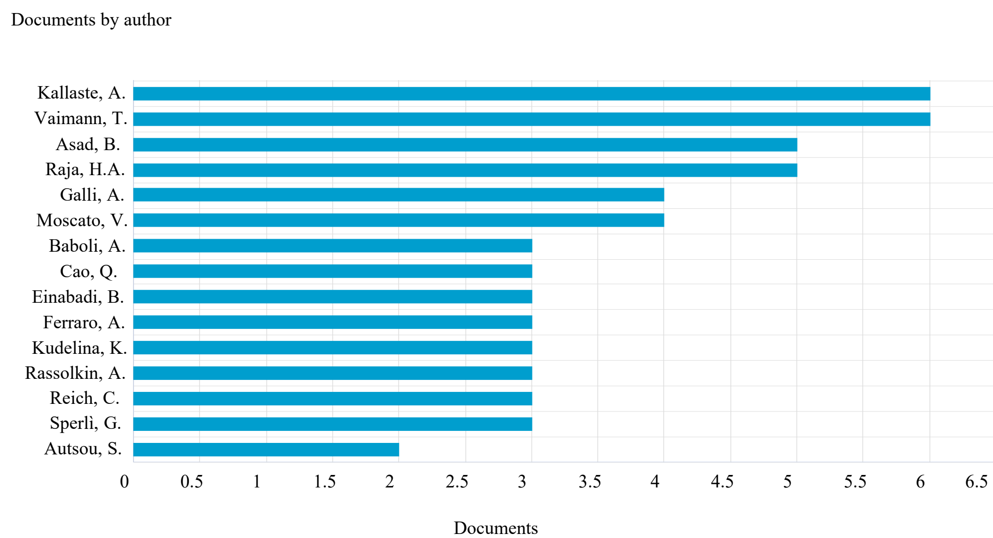

Fig. 8 Analysis by author

Figure 8 shows the scientific output of the most relevant authors in the field of predictive maintenance in Industry 4.0. Kallaste, A. and Vaimann, T. lead with six publications each, consolidating their position as the main contributors in this field. They are followed by Asad, B. and Raja, H.A., with five publications each, reflecting a significant impact on developing AI and big data methodologies. For his part, Galli, A. has four publications, also standing out in research on predictive maintenance. These authors have contributed significantly to the evolution of the discipline, promoting new strategies and approaches to optimizing industrial processes. Figure 9 shows the co-occurrence of keywords for 1471 indexed key terms in the analyzed publications. Notably, the highlighted term is 'industry 4.0' with 116 occurrences, followed by 'predictive maintenance' with 116 occurrences and 'artificial intelligence' with 67 occurrences. In this context, 77 occurrences were recorded distributed in five clusters: cluster 1 (21 occurrences), cluster 2 (17 occurrences), cluster 3 (16 occurrences), cluster 4 (13 occurrences) and cluster 5 (10 occurrences). Each group of keywords was represented with different colors using the visualization program VOSviewer, which simplified the detection of thematic patterns. In this study, cluster 1 (red) stands out for its central node," Industry 4.0", which includes key terms such as "deep learning and manufacturing process ". Cluster 2 (green) stands out for its main node of "big data", which includes key terms such as "data analytics" and "automation". Similarly, Cluster 4 stands out for key terms such as 'artificial intelligence' and 'machine learning '. These results allow us to differentiate the main themes of each cluster and understand the dynamics of research on predictive maintenance in Industry 4.0.

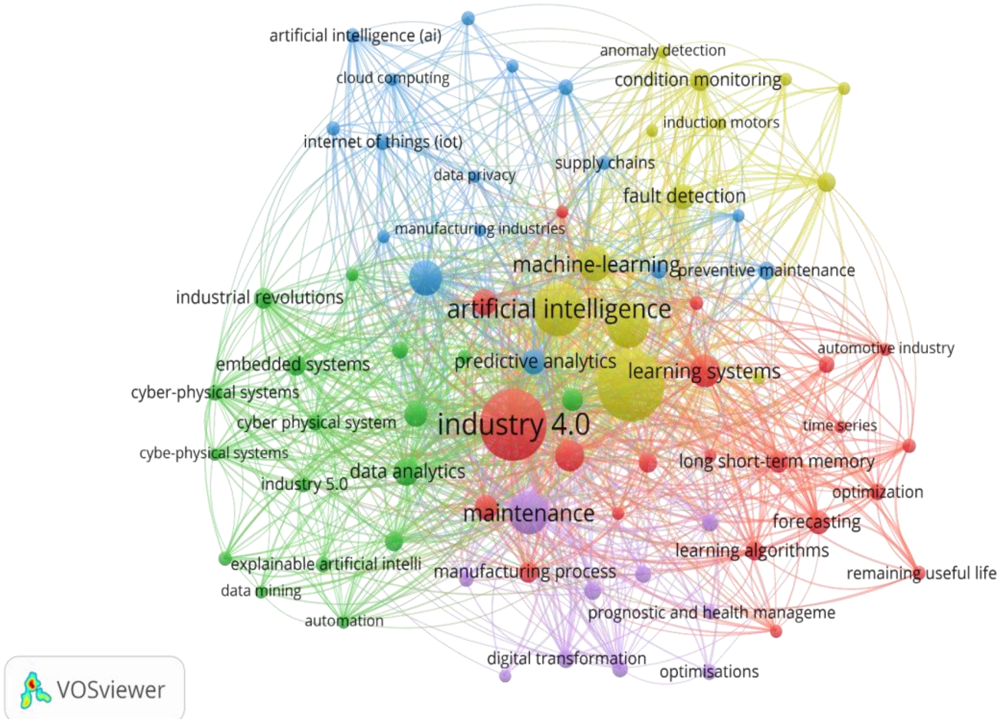

Fig. 9 Co-occurrence of keywords

5. Discussion and Conclusion

The first and most significant discovery is the sustained increase in scientific production around predictive maintenance based on AI and big data. The annual analysis reveals a notable increase in publications since 2020, peaking in 2023 with 42 studies and remaining high in 2024 with 41 studies. This increase demonstrates a growing interest in optimizing operational efficiency through advanced techniques, aligning with the transition to automated practices in Industry 4.0.

Another key finding is the diversity of sources and interdisciplinary collaborations. Analysis by thematic area reveals that Engineering (121 studies) and Computer Science (108 studies) lead the scientific production in this field, followed by Materials Science with 108 studies. The combination of these disciplines demonstrates a joint effort between academic institutions and technology companies to develop more efficient predictive maintenance methods. In contrast, Social Sciences (6 studies) and Economics (2 studies) are underrepresented, suggesting less exploration of these technologies' organizational, regulatory, and economic impacts. In terms of impact, implementing machine learning algorithms has improved failure prediction accuracy, reducing downtime and operating costs. While previous research has highlighted the effectiveness of AI in this area, this analysis reinforces the importance of its integration with robust methodologies and hybrid approaches that combine different machine-learning techniques to improve the interpretation and reliability of results.

The geographical study shows the active involvement of nations such as India (22 investigations), France (18), Germany (17) and Italy (15), which indicates a worldwide adoption of these techniques. In contrast to the high scientific output observed in countries like India, France, and Germany, Latin American nations remain underrepresented, with countries such as Brazil, Colombia, Ecuador, and Peru contributing only a handful of publications. This disparity suggests a need for strategic investment and regional research collaboration, particularly given the growing interest in digital transformation across industries in Latin America. Moreover, aligning regional efforts with global trends in AI and predictive maintenance could enable technology transfer, capacity building, and the development of context-specific solutions for manufacturing and energy sectors in the region. The support of organizations such as the European Commission and other technological innovation investment funds suggests increasing financial support for this research, which could influence its development and application in the industrial field.

Despite this progress, significant challenges remain, such as the lack of clarity in specific AI models, which limits their acceptance in certain industrial contexts. Furthermore, adapting predictive models to different environments remains a significant challenge for future research. These limitations underscore the importance of developing hybrid approaches that merge various machine-learning techniques and provide greater interpretability and confidence for end users. The results support the hypothesis that AI-based predictive maintenance substantially improves operational efficiency and industrial sustainability. However, continued research is required to address remaining methodological challenges and expand the reach of these technologies to less developed sectors and countries in this field. Based on the findings, future research should explore the integration of AI-driven predictive maintenance with emerging technologies such as digital twins and edge computing, particularly in resource-constrained industrial environments. Additionally, regional studies in underrepresented areas like Latin America could provide valuable insights into localized implementation challenges and opportunities, helping to close the global research gap in Industry 4.0 applications. Future studies recommend exploring integrating these tools with emerging technologies such as the Internet of Things (IoT) and digital twins, in addition to promoting international partnerships to diversify scientific production and enhance the usefulness of these solutions in diverse industrial settings.

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