# A bibliometric analysis and systematic literature review of Predictive Maintenance in the Industry 4.0 era

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**Abstract**: These This study aims to provide a bibliometric analysis and systematic literature review of Predictive maintenance research in the industry 4.0 area and to understand related contemporary research technologies, challenges, and trends. A bibliometric analysis was conducted to empirically analyse the literature related to predictive maintenance in the industry 4.0 era. This study retrieved papers from the Scopus database, reviewing 723 articles from the period 2014 to 2024 (July) for bibliometric analysis. Bibliometrix, using R software, was used for the bibliometric analysis, and VOSviewer was used for network analysis. The growth of publications, research productivity and citation analysis were presented. Most of the articles were published in journals and conferences, this research benefits researchers by identifying potential research areas for predictive maintenance technologies and challenges in industry 4.0 era and providing directions for future research.

*Keywords*: Predictive maintenance, industry 4.0, bibliometric analysis, literature review, VOSviewer.

## 1. INTRODUCTION

In the Industry 4.0 era, predictive maintenance has evolved significantly with the use of technologies like Big Data, Blockchain, Artificial Intelligence (AI), Internet of Things (IoT), and Machine Learning (ML) (Rachad et al., 2023). During this stage, data from Internet of Things devices is gathered, preprocessed, and machine learning models are trained to anticipate equipment issues (Madasamy et al.,2023). Predictive maintenance uses various sensor devices to monitor machinery and equipment, it is becoming more and more important in the field of maintenance (Aksa et al., 2021). The use of digital technologies and Industry 4.0 ideas allows businesses to collect real-time information about equipment health for preventive maintenance via predictive maintenance (PdM) (Ciancio et al., 2024). Challenges such as developing sensory systems and evaluating real-world data have been handled using novel methodologies such as anomaly detection and system adaptation to Industry 4.0 connection needs (Costa et al., 2023). In general, the combination of modern technology and processes has transformed predictive maintenance, allowing enterprises to optimize operations, reduce downtime, and improve equipment efficacy in the Industry 4.0 era.

This paper aims to address the following five important research questions:

RQ1: What are the most influential challenges in implementing predictive maintenance in industry 4.0 era that have been identified from the literature?

RQ2: What are the most searched countries for predictive maintenance in industry 4.0 era?

RQ3: What are the most impactful technologies on predictive maintenance in industry 4.0 era?

RQ4: What are the future research directions and perspectives in Predictive maintenance in the context of the defined technology?

The organization of this study is as follows: Section 2 provides a more comprehensive exploration of the methodological framework; Section 3 delves into the qualitative and quantitative discussion of the results and finally we summarize the main conclusion.

## 2. METHODOLOGICAL FRAMEWORK

Document type of articles used in this study were retrieved from Scopus data. Quotation marks (“ ”) and Boolean operator “AND”,”OR” were used which ensured the appearance of at least one search keyword in the terms of TOPIC (title, abstract, author keywords,). The search in Scopus is accomplished with a query that finding articles, witch their titles contained the expression ("Predictive maintenance" AND [ "trends" OR "opportunities" OR " solution " OR " technologies " OR " application " OR " challenges " ] AND industry 4.0). The search terms were restricted to all the Scopus subject areas in order to check their belonging to the scope of the research and to avoid any misleading attribution to it. We found 723 papers in the first research, Table 1 summarize the inclusion and exclusion criteria for this study, to ensure the utmost relevance, a qualitative and manual analysis of their contents was performed to verify their alignment with the subject matter of this paper and to prevent any misattribution caused by overlapping keywords. After conducting the final search, a total of 702 documents were identified. The screening process was completed using RStudio and the Bibliometrix package, facilitated by the Biblioshiny app. Descriptive data on the resulting dataset can be found in Table 2.

**Table 1. Inclusion and exclusion criteria**

| | Inclusion | Exclusion |
|---|---|---|

| | | |
|---|---|---|
| Literature type | Indexed journals, book chapters, conference proceeding, industry reports | Non-indexed journals. |
| Language | English | Non-English |
| Timeline | Between years 2014 and 2024 | Before year 2014 |

**Table 2. Main information about data**

| Description | Results |
|---|---|
| MAIN INFORMATION ABOUT DATA | |
| Timespan | 2014:2024 |
| Sources (Journals, Books, etc) | 396 |
| Documents | 702 |
| Annual Growth Rate % | 53,79 |
| Document Average Age | 2,54 |
| Average citations per doc | 18,88 |
| References | 25410 |
| DOCUMENT CONTENTS | |
| Keywords Plus (ID) | 3408 |
| Author's Keywords (DE) | 1617 |
| AUTHORS | |
| Authors | 2411 |
| Authors of single-authored docs | 17 |
| AUTHORS COLLABORATION | |
| Single-authored docs | 18 |
| Co-Authors per Doc | 4,06 |
| International co-authorships % | 19,94 |
| DOCUMENT TYPES | |
| article | 241 |
| book | 7 |
| book chapter | 45 |
| conference paper | 342 |
| conference review | 19 |
| editorial | 3 |
| note | 1 |
| review | 41 |

## 3. RESULTS AND DISCUSSION

In this section, various facets of the bibliometric analysis are presented and discussed separately in individual title. Each facet contributes to the overall bibliometric study, enhancing our understanding of the research landscape.

### *3.1 Country of Publication Analysis*

The references to" the most productive country," and similar phrases pertain specifically to predictive maintenance in industry 4.0 era' research with managerial implications, as elucidated in both the Introduction and Methods sections. Figure 1 provides a visualization of the world's most productive countries generated through "Biblioshiny", with darker shades of blue indicating higher scientific production. The analysis reveals that Germany, Italy, India, Spain, China, Usa, Portugal, as the top scientific contributors based on publication volume.

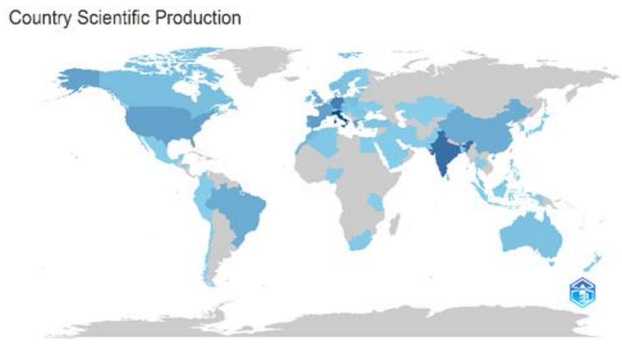


Figure 1. The most productive country

### *3.2 Documents by country or territory*

To provide a reference indication of the nations that make scientific contributions to this field, we determined the place of origin of every document utilised in this study. This indicator can provide us with a quick understanding of the direct correlation between predictive maintenance research in science and each nation's industrial progress. Thus, our RQ2 question is answered.

**Table 3. Document by country**

| Countries/territoires | Documents |
|---|---|
| ITALY | 401 |
| INDIA | 290 |
| GERMANY | 245 |
| SPAIN | 144 |
| GREECE | 141 |
| FRANCE | 133 |
| USA | 131 |
| PORTUGAL | 106 |
| UK | 103 |
| CHINA | 98 |

### *3.3 Most Relevant Sources:*

Figure 2 depict the Source production over time that represents the developments of the top five sources over the last 10 years [2014-2024] that relate to a topic" predictive maintenance in industry 4.0 era" The Five sources mentioned in figure 2 are: Procedia Computer Science, Applied science (Switzerland), Ifac parersonline, IEEE Access and Lecture notes in networks and systems. It may be concluded, then, that the issue has been explored besides of a core of interdisciplinary articles, mostly in papers pertaining to technology.

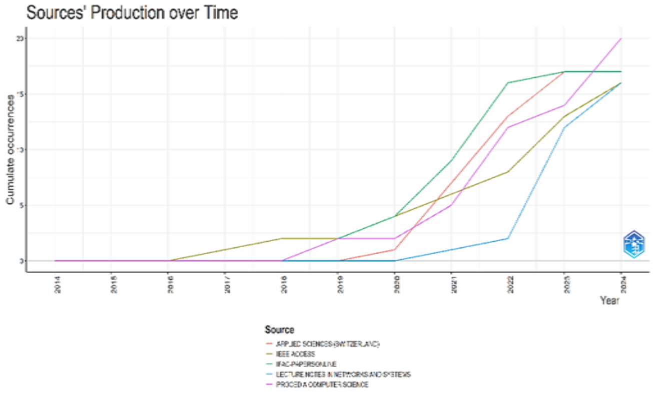


Figure 2. Most relevant sources

### *3.4 Most global cited documents*

Table 4 shows the 10 most cited articles in the publishing research, ordered according to the number of citations. It also includes information on authors, year of publication, total citations. This figure showing that the most cited document is by LEE J with 1368 citation.

**Table 4. The most globel cited documents**

| Paper | Total Citations | TC per Year |
|---|---|---|
| LEE J, 2014, PROCEDIA CIRP | 1368 | 124,36 |
| QI Q, 2018, IEEE ACCESS | 1048 | 149,71 |
| ZONTA T, 2020, COMPUT IND ENG | 476 | 95,20 |
| SINGH M, 2021, APPL SYST INNOV | 365 | 91,25 |
| YAN J, 2017, IEEE ACCESS | 331 | 41,38 |
| ÇINAR ZM, 2020, SUSTAINABILITY | 321 | 64,20 |
| DALZOCHIO J, 2020, COMPUT IND | 265 | 53,00 |
| EGGER J, 2020, COMPUT IND ENG | 247 | 49,40 |
| SAHAL R, 2020, J MANUF SYST | 233 | 46,60 |
| AHELEROFF S, 2020, ADV ENG INF | 214 | 42,80 |

### *3.5 Most cited country*

We choose top 10 countries in citations. From the data shows in "Table 5", USA is the most impact country in the platform area (1845 citations per publication). CHINA and ITALY are ranked two and three with 1477 and 1150 citations per publication, respectively.

**Table 5. Most cited country**

| **Country** | **TC** | **Average Article Citations** |
|---|---|---|
| USA | 1845 | 92,20 |
| CHINA | 1477 | 86,90 |
| ITALY | 1150 | 22,10 |
| BRAZIL | 840 | 70,00 |
| IRELAND | 792 | 99,00 |
| UNITED KINGDOM | 654 | 27,20 |
| GREECE | 591 | 24,60 |
| INDIA | 476 | 9,30 |
| SPAIN | 436 | 20,80 |
| CYPRUS | 327 | 163,50 |

### *3.6 Average Citations Per Year*

The publications exponentially increased after 2014 If we do not enter into the account the year 2024 (because it has not been completed yet). Research growth noted moderate between the period of (2014) and (2024) figure 3. The highest number of publications (161) was recorded in 2023, while the lowest number of publications (1) was reported in 2014. The year 2014 had the greatest mean total citations per article, 1368, while the year 2023 had the lowest mean total citations per item. 2014 had the highest mean of citations per year (124.36), while 2016 had the lowest mean of citations per year (1.30).

**Table 6. Average citations per year**

| Year | MeanTCperArt | N | MeanTCperYear | CitableYears |
|---|---|---|---|---|
| 2014 | 1 368,00 | 1 | 124,36 | 11 |
| 2016 | 11,67 | 3 | 1,30 | 9 |
| 2017 | 62,67 | 12 | 7,83 | 8 |
| 2018 | 56,55 | 33 | 8,08 | 7 |
| 2019 | 17,11 | 56 | 2,85 | 6 |
| 2020 | 42,77 | 87 | 8,55 | 5 |
| 2021 | 17,23 | 127 | 4,31 | 4 |
| 2022 | 10,36 | 148 | 3,45 | 3 |
| 2023 | 5,02 | 161 | 2,51 | 2 |
| 2024 | 0,32 | 74 | 0,32 | 1 |

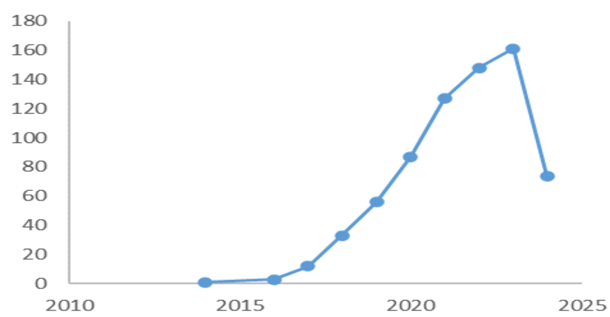


Figure 3. Annual total citation per year

### *3.7 Documents by author*

One of the determining aspects is to identify the authors with the highest scientific production for the subject "predictive maintenance in industry 4.0 era ". Table 7 shows the most productive authors who have published at least five articles about the subject of study during the last 10 years. The most productive authors are Kumar s , Mentzas g And ` Patil s , the first is a Professor at Symbiosis Institute of Technology in India and the second is a Professor at National Technical University of Athens in Greece and the third one is Professor (Associate) at Symbiosis Institute of Technology in India.

**Table 7. Document by author**

| **Authors** | **Articles** | **Articles Fractionalized** |
|---|---|---|
| KUMAR S | 7 | 1,32 |
| MENTZAS G | 6 | 1,66 |
| PATIL S | 6 | 1,15 |
| BOUSDEKIS A | 5 | 1,46 |
| CERQUITELLI T | 5 | 1,15 |
| IOANNIDIS D | 5 | 0,69 |
| KAMAT P | 5 | 1,17 |
| KIRITSIS D | 5 | 1,05 |
| KOTECHA K | 5 | 0,95 |

### *3.8 Countries' scientific collaboration :*

As this study takes into account, scientific cooperation between countries in the field of geosynthetic materials research is deeply rooted in administrative implications. Bluer countries are those that cooperate the most, less blue are those that cooperate the least, and gray represents uncooperative countries. Country collaboration: as for global scientific collaborations, the main cross-country relationships and knowledge exchange flows involve the following couples: Germany–Italy, Greece -France, India– United Kingdom. China-France However, Figure 4 show that the global collaboration map is highly fragmented.

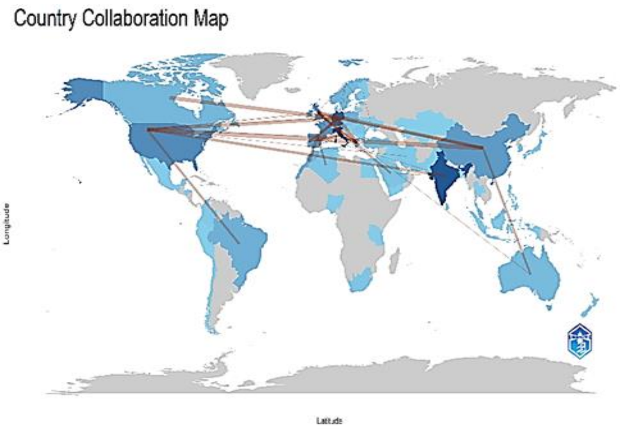


Figure 4. Countries' scientific collaboration

### *3.9 Wordcloud*

The underlying conceptual structure at hand was accurately recognized by the topic dendrogram, according to the Factorial analysis employing a multi-correspondence analysis report. Indeed, the same conclusions are supported by a straightforward comparison of Figure 5's word clouds with Figure 6's word occurrence analysis.


Figure 5. Wordcloud

### *3.10 Keyword Co-Occurrence Analysis*

A key component of bibliometric study is topic mapping. Figure 6 shows every issue area pertaining to the predictive maintenance keywords in the industry 4.0 era as a whole. VOSviewer is capable of displaying three distinct mapping visualizations in the bibliometric analysis: network, density, and overlay visualizations. We employed network visualization in our investigation. Following the analysis of all subjects by the VOSviewer software, seven clusters were identified in the mapping. The clusters demonstrated the connections between the various topics. The strength of topic area or keyword pairings was indicated by the thickness of the connecting line. The size of the nodes, in addition to clusters and lines, showed how frequently the term or topic appeared. Table 8 lists the most common keywords along with how often they occur. in this analysis the first question RQ1 are addressed, and therefore, we present the outcomes from the qualitative analysis.

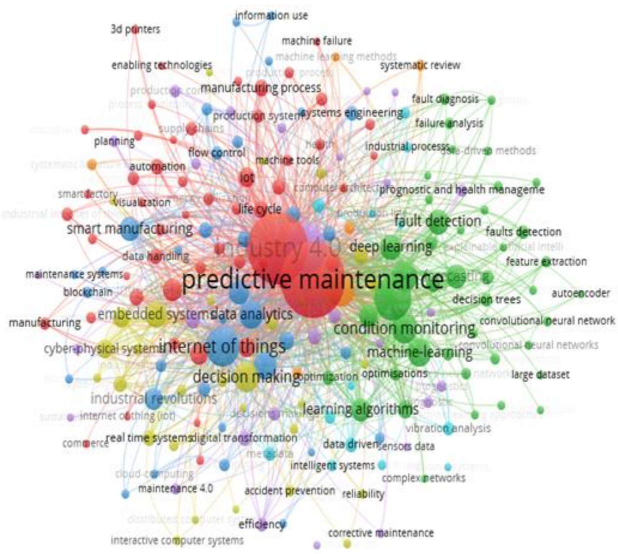


Figure 6. Keyword Co-Occurrence using VOSviewer

Top 15 keywords used in our research are shown in Table 8

**Table 8. The most frequent keyword**

| Words | Occurrences |
|---|---|
| predictive maintenance | 495 |
| industry 4 0 | 443 |
| maintenance | 196 |
| machine learning | 163 |
| internet of things | 134 |
| Artificial intelligence | 97 |
| condition monitoring | 79 |
| learning systems | 78 |
| decision making | 71 |
| machine-learning | 68 |
| data analytics | 66 |
| Predictive analytics | 62 |
| embedded systems | 59 |

RQ1: What are the most influential challenges in implementing predictive maintenance in industry 4.0 era that have been identified from the literature?

In this analysis, our question RQ1 is addressed, and therefore, we extracted from 202 Keyword Co-Occurrence presented by VOS the challenges in implementing predictive maintenance in industry 4.0 era, Table 9 resumes these challenges with its apparencies.

**Table 9. Challenges in implimenting predictive maintenance**

| Words | Occurrences | Total link strength |
|---|---|---|
| Condition monitoring | 79 | 626 |
| Data acquisition | 35 | 313 |
| costs | 25 | 237 |
| Information management | 23 | 235 |
| Data driven | 20 | 181 |
| Flow control | 16 | 176 |
| Data handling | 22 | 174 |
| Engineering education | 14 | 166 |
| Quality control | 15 | 141 |
| performance | 14 | 118 |
| Production control | 14 | 114 |
| Cost effectiveness | 12 | 101 |
| Process control | 12 | 94 |
| Maintenance management | 11 | 89 |
| Maintenance cost | 9 | 77 |
| Interoperability | 10 | 73 |
| Network security | 8 | 67 |

Some keywords have different text forms but have the same meaning and significance for example keywords: Data acquisition, Information management, Data driven and Data handling, refers to challenge “Data management”.
Change Management is one of the primary hurdles in implementing predictive maintenance, the keywords “Condition monitoring, Flow control, Production control and Maintenance management, refers to this challenge.
The keywords costs, Cost effectiveness, Maintenance cost refers to “budgeting and cost” challenge. Keyword: Engineering education or we can say workforce training is one of the challenges facing the implementation of predictive maintenance in the era of Industry 4.0.
Keyword Interoperability is one of the challenges refers to the implementation of predictive maintenance, the two keywords quality control and performance refers to quality control challenge, and finally network security refers to privacy and security challenges.

The challenges of implementing predictive maintenance in industry 4.0 from our study:

*1) Cost*

The cost challenge in predictive maintenance is a major concern because of the high costs involved with overestimating and underestimating maintenance requirements. Predictive maintenance demands significant time and financial commitments for successful implementation; hence it is critical to ensure that the projected results significantly minimize maintenance costs (Znaidi et al., 2023). Machinery maintenance expenditures can range between 20% and 60% of total expenses, stressing the necessity of reducing these costs through better predictive maintenance procedures (Maktoubian et al., 2021). Predictive maintenance solutions, such as those based on machine learning algorithms, seek to assess machinery health and predict remaining usable life in order to optimize maintenance planning and reduce costs (Ince et al., 2020).

*2) Quality control*

Quality control is a critical difficulty in predictive maintenance, affecting industrial systems' efficiency and dependability (Del Moral et al., 2022). Quality control should be integrated into predictive maintenance decision-making to ensure stable equipment operation, eliminate probable failures, and improve product quality (Gu et al., 2017). A more efficient predictive maintenance approach can be built by identifying important process variables related to equipment wear and product quality levels, allowing maintenance decisions to be optimized for quality costs, maintenance costs, and disruption costs all at the same time (Gu et al., 2017).

*3) Data management*

Predictive maintenance (PdM) has considerable data management challenges in its implementation, as highlighted in numerous research studies. PdM project success is strongly dependent on data dependability and machine learning model performance (Znaidi et al., 2023). Implementing an intelligent maintenance system that properly maintains data can be difficult for industrial practitioners, emphasising the importance of scalable data management capabilities and open standards in the automotive industry (Ciancio et al., 2024). While PdM has advantages such as lower operational costs and more efficiency, problems such as data quality concerns, initial investment requirements, and the need for specialized labor persist (Patel et al., 2023).

*4) Change Management*

Because of the difficulty in anticipating and managing changes in maintenance procedures, predictive maintenance faces change management challenges. To reduce delays and cost overruns, predictive maintenance solutions must be utilized in conjunction with proper change management practices (Zhao et al. 2010). Unexpected and costly changes can hinder design development in predictive maintenance, stressing the necessity of accurately projecting change propagation and discovering hidden linkages between components (Keller et al., 2006). Furthermore, in order to achieve successful implementation and adaption of management accounting change in predictive maintenance systems, it is necessary to address behavioral and cultural concerns in addition to selecting ideal methodologies (Ezzamel et al., 2003). By combining these insights, predictive maintenance may more successfully traverse the problems of change management.

*5) workforce training*

The difficulty in providing predictive maintenance workforce training stems from the requirement for ongoing skill development and adaptation to stay up to date with new technology and procedures. Deep learning and data analytics are the driving forces behind predictive maintenance techniques (Hurtado et al., 2023). To interpret sensor data, put maintenance plans into action, and maximize efficiency, competent professionals are needed (Patel et al., 2023). Workforce training in predictive maintenance must take into account the dynamic nature of maintenance requirements and the crucial role that human factors play in guaranteeing safety and operational excellence as technologies and industries progress.

*6) Interoperability challenge:*

The requirement to successfully integrate multiple systems and components is what drives the interoperability challenge in predictive maintenance. Traditional techniques frequently lack a systematic integration process, resulting in poor code quality and longer development times and expenses (Margaria et al., 2021). The choice of proper standards for system integration is critical, as component interoperability is determined by the interfaces used in their implementation (DelaHostria, 2002). Finally, attaining interoperability in predictive maintenance necessitates a comprehensive methodology that takes into account standards, system integration, and interdependence modeling among components.

*7) Privacy and security challenges:*

Privacy and security challenges in predictive maintenance are major considerations in the Industry 4.0 era, where industrial equipment complexity and the requirement for predictive maintenance collide (Ao & Jiang, 2022). The use of smart sensors and IoT technologies for data collecting in predictive maintenance creates privacy concerns, since sensitive data may possibly violate vehicle owners' location and identity privacy (Konget et al., 2020). To address these issues, novel techniques like as federated learning and split-learning-based frameworks have been developed to enable privacy-preserving collaborative predictive maintenance while maximising available resources and assuring efficient model training (Bharti et al., 2023).

From the same keywords co-occurrence analysis by Vos-viewer our question RQ3 is addressed:

RQ3: What are the most impactful technologies on predictive maintenance in industry 4.0 era?

So, we aim to identify the most impactful technologies on predictive maintenance in industry 4.0 era. Analyzing the 202-keyword obtained by VOS, Table 10 summarize the result.

**Table 10. Most impactful technologies on predictive maintenance**

| Words | Occurrences | Total link strength |
|---|---|---|
| Machine learning | 163 | 1327 |
| Internet of things | 134 | 1220 |
| Artificial intelligence | 97 | 763 |
| Data analytics | 66 | 678 |
| Machine-learning | 68 | 657 |
| Deep learning | 56 | 497 |
| Big data | 51 | 482 |
| forecasting | 50 | 478 |
| Cyber–physical systems | 31 | 331 |
| iot | 36 | 282 |
| Digital twin | 38 | 241 |
| Machine learning technique | 18 | 171 |
| Augmented reality | 16 | 122 |
| Cloud computing | 15 | 122 |
| iiot | 14 | 118 |
| Industrial internet of things | 16 | 116 |
| blockchain | 12 | 113 |
| Deep neural network | 11 | 108 |
| Big data analytics | 9 | 100 |
| Cyber-physical systems (cps) | 8 | 86 |
| Cloud computing | 8 | 84 |
| ai | 8 | 76 |
| Digital twins | 10 | 5 |
| 3d-printers | 10 | 73 |

Some keywords have different textual forms, for example Artificial intelligence and AI necessitating their consolidation into a single keyword. Keywords (Machine learning, deep learning, forecasting, Machine learning technique, deep neural network) can be considered a part or technique of artificial intelligence technology. We can consolidate the keywords (Internet of things, iot, iiot, Industrial internet of things) into a single keyword Internet of things.

Figure 7 shown that 9 different technologies have been identified from this analysis.

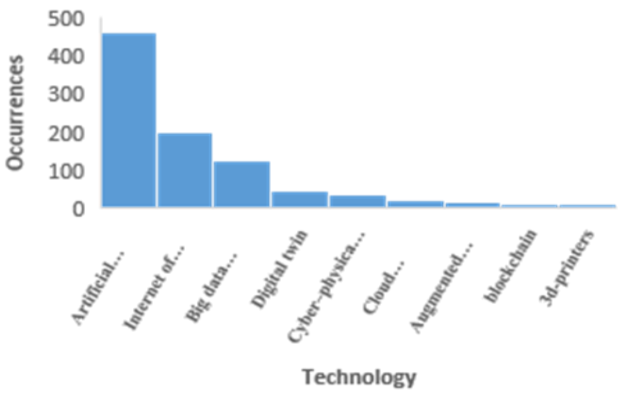


Figure 7. Most influential technology on predictive maintenance

The definitions of these technologies as follows:

**1.** *Artificial intelligence (AI):*

Artificial intelligence (AI) can be defined as the scientific applied direction for developing technological and software cognitive complexes that mimic human intelligence, capable of learning, retraining, self-realization, and development based on preference criteria (Evgeniy et al., 2020).

**2.** *Internet of things IoT:*

The mainstream definition of the Internet of Things (IoT) is the networked interconnection of physical items or objects via the Internet, allowing them to share data and communicate with one another and with humans (Gowda et al., 2022).

**3.** *Big data*

Big data is typically defined as datasets that are too huge or complicated for traditional processing tools to handle successfully, as evidenced by characteristics such as volume, diversity, and velocity (Dedeepya & Yarlagadda, 2022).

4. *Cyber-physical systems (CPS)*

Cyber-physical systems (CPS) are interconnected devices and networks that integrate computational and communication technologies deeply into physical systems, enhancing their capabilities and characteristics (Möller, 2023).

***5. digital twin***

A digital twin, according to the literature, is a virtual representation of real items or systems that allows for predictive tactics and high-fidelity modeling via continuous updates and self-learning (Sun et al., 2022).

***6. Cloud computing***

Through the usage of the internet, cloud computing is a revolutionary new paradigm in computing that allows users to have shared, configurable access to resources such as servers, storage, apps, and services whenever they need them (Aparna et al., 2022).

*7. Augmented Reality (AR)*

is a technology that overlays digital information, such as 3D models, images, or videos, onto the real-world environment in real time, enhancing the user's perception of reality (Figueiredo et al., 2023).

*8. Blockchain:*

According to Laura (2023), blockchain is a distributed digital ledger system that tracks assets in a network and securely saves transactions. According to Amarpreet et al. (2020), it is essentially a continuously expanding list of records or a public distributed ledger system called blocks that are connected and safeguarded using cryptography.

*9. 3D printers*

A standard definition of 3D printers refers to machines that create three-dimensional objects from digital models through an additive process, where materials are deposited layer by layer to form the final object. These printers are distinct from traditional machining methods that rely on subtractive processes like cutting or drilling (Singhet al.,2024).

RQ4: What are the future research directions and perspectives in Predictive maintenance in the context of the defined technology?

To answer this question and after analyzing and studying the articles on predective maintenece in the industry 4.0 era , we propose the following points:

- enhancing the precision and dependability of prediction models by using more complicated machine learning and artificial intelligence algorithms. So, we can apply reinforcement learning to dynamically optimize scheduled maintenance based on real-time data and leverage deep learning techniques to handle complicated patterns and vast datasets.
- The integration of edge computing and the Internet of Things (IoT) has greatly expanded the capabilities of predictive maintenance systems. Real-time data collection and analysis made possible by these technologies will result in more accurate predictions about the equipment's future health and more efficient maintenance decisions with less downtime.
- In the future, digital twins will be a radical solution to improve decision-making by simulating different scenarios and predicting the outcomes of different maintenance strategies.
- Technologies like as big data and advanced analytics can be used to manage the enormous volumes of data produced by PDM systems. This may be achieved by developing an infrastructure for data processing and storage that is scalable and capable of managing and analyzing vast volumes of varied data.
- constructing strong cybersecurity defenses to safeguard PdM systems and the private information they manage. We can do it by ensuring secure communication protocols for data transfer between edge nodes and IoT devices.

## 4. CONCLUSIONS

In the context of Industry 4.0, predictive maintenance offers several benefits, including reduced downtime, improved equipment reliability, and cost savings. Nevertheless, in order to fully realize these benefits, a number of challenges need to be addressed. Overcoming issues related to quality control, high initial costs, workforce training, data management, complexity integration, Interoperability, change management, and security is essential. In order to overcome these challenges, strategic planning, a dedication to innovation and constant improvement and technological investment are needed, among the most influential technologies in predictive maintenance in industry 4.0 era we mention: artificial intelligent, internet of things and big data analysis. By doing this, companies may attain operational excellence in the rapidly changing field of smart manufacturing and successfully use predictive maintenance.

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