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Digital transformation in industrial maintenance: an overview of Industry 4.0 technologies, their advantages and challenges

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Abstract

Purpose – The Fourth Industrial Revolution (Industry 4.0) is transforming industrial maintenance into a strategic, technology-driven function. Maintenance 4.0, particularly predictive maintenance (PdM), leverages IoT, AI and Big Data to enhance asset reliability, reduce downtime, lower costs and improve overall operational efficiency. While these innovations promise substantial competitiveness gains, challenges such as high investment costs and specialized expertise persist. This study conducts a systematic literature review to map current Industry 4.0 maintenance technologies, identify their benefits, and explore implementation barriers. By systematizing existing knowledge, it fills a critical gap, providing insights into Maintenance 4.0's potential to drive industrial modernization and sustainable performance.

Design/methodology/approach – This study employed a structured methodological framework combining exploratory research, a systematic literature review (SLR), and descriptive and content analyses. The exploratory stage identified key terms and concepts, guiding search strings applied to Scopus and Web of Science databases. Following the PRISMA protocol, 949 documents were screened, duplicates removed and relevance assessed, resulting in a final sample of 29 studies. Descriptive analysis mapped publication trends, countries, and maintenance types, while content analysis examined Industry 4.0 technologies, applications, benefits and challenges. A summary table synthesized findings, providing a comprehensive, accessible overview of Maintenance 4.0 practices and insights into digital transformation in industrial maintenance.

Findings – Analysis of 29 studies highlights predictive maintenance as the dominant focus within Industry 4.0-driven industrial maintenance. Key technologies identified include IoT, AI, Machine Learning, Big Data, Digital Twins and Cyber-Physical Systems, enabling real-time monitoring, data-driven decision-making and predictive interventions. Benefits include reduced costs, minimized downtime, enhanced reliability, extended equipment lifespan, improved sustainability, and optimized resource utilization. However, adoption is constrained by high initial investment, data quality issues, integration challenges with legacy systems, personnel shortages and cybersecurity concerns. This study provides a comprehensive synthesis of Maintenance 4.0 practices, demonstrating how digital technologies transform maintenance strategies, improve operational efficiency and foster industrial competitiveness.

Research limitations/implications – This study advances research on Industry 4.0 and industrial maintenance by offering an integrated framework that synthesizes technologies, benefits, and implementation challenges of Maintenance 4.0. It strengthens theoretical understanding by positioning predictive maintenance as a central value-generation mechanism and by clarifying how digital technologies – such as IoT, AI, ML and big data – translate into performance outcomes. Furthermore, the study highlights the interaction between technological adoption and organizational constraints, supporting the development of more realistic, context-sensitive models. By moving beyond fragmented and technology-centric approaches, the research contributes to theory building and provides a foundation for future empirical and conceptual investigations in digital maintenance transformation.

Practical implications – This study provides actionable insights for organizations implementing Industry 4.0 in maintenance. It highlights the need to prioritize investments in data infrastructure and data quality as key enablers of predictive maintenance and advanced analytics. The findings emphasize adopting an integrated and

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strategic approach, combining technologies such as IoT, AI and cloud computing to maximize efficiency and reliability. Additionally, the study underscores the importance of workforce development, training, and fostering a data-driven culture. By identifying barriers – including high costs, integration complexity, and cybersecurity risks – it helps managers anticipate challenges and design more effective implementation strategies, supporting better decision-making and improved operational performance in maintenance environments.

Social implications – This study offers relevant social implications by highlighting how the adoption of Industry 4.0 technologies in maintenance can reshape workforce dynamics and organizational practices. The emphasis on workforce development and new skill requirements underscores the need for continuous learning and professional reskilling. By promoting data-driven cultures, the study supports more transparent and informed decision-making processes. Additionally, improved maintenance efficiency and reliability can enhance operational safety and reduce environmental impacts through optimized resource use and reduced downtime. However, challenges such as technological complexity and skill gaps may create inequalities, reinforcing the importance of inclusive strategies to ensure that digital transformation benefits employees and society more broadly.

Originality/value – This study provides a novel, comprehensive synthesis of Maintenance 4.0, addressing a critical gap by systematically mapping the adoption, applications and impacts of Industry 4.0 technologies in industrial maintenance. It establishes predictive maintenance as the central framework and underscores the transformative potential of IoT, AI, Machine Learning, Big Data, Digital Twins and Cyber-Physical Systems in optimizing operational efficiency, reducing costs and extending asset lifespan. By integrating measurable benefits with implementation challenges, the research offers actionable insights and a strategic roadmap for practitioners and policymakers, advancing theory and practice in digital maintenance. It positions Maintenance 4.0 as a key driver of competitiveness, sustainability and industrial modernization.

Keywords Industry 4.0, Industrial maintenance, Systematic literature review

Paper type Literature review

1. Introduction

The global industry is undergoing a profound transformation driven by the Fourth Industrial Revolution, or Industry 4.0. This paradigm merges the physical and digital worlds to create smarter, connected, autonomous, and more efficient systems that dynamically respond to demands and optimize operations. Industrial maintenance plays a crucial role in achieving these goals. According to Jasiulewicz-Kaczmarek *et al.* (2021), maintenance enhances sustainability, equipment availability, product quality, and a company's ability to meet demand, thereby boosting competitiveness.

In this digital era, maintenance management has become increasingly strategic. Traditionally, maintenance evolved from reactive (corrective) approaches—addressing failures after they occur—to preventive models based on fixed schedules. This progression parallels industrial revolutions: reactive maintenance dominated the First Industrial Revolution; preventive methods emerged in the Second; the Third emphasized automation and reliability; and Industry 4.0 advances predictive maintenance focused on anticipating failures (Saraswat and Agrawal, 2023).

Industry 4.0 has catalyzed Maintenance 4.0, emphasizing Predictive Maintenance (PdM). This data-driven approach improves asset reliability and lifespan while reducing maintenance costs and downtime, thereby enhancing operational efficiency and competitiveness. The Fourth Industrial Revolution has accelerated adoption of technology-based maintenance aimed at cost reduction, waste elimination, and prevention of critical failures (Peter *et al.*, 2023; Saraswat and Agrawal, 2023). These advancements have extended asset lifespan, decreased downtime, and lowered expenditures on spare parts and labor (Arena *et al.*, 2022).

Interest in applying Industry 4.0 technologies to maintenance has grown across academia and industry due to the benefits for operational efficiency and process optimization. However, challenges remain, including high investment costs and the need for specialized knowledge of these technologies, their capabilities, and limitations. The literature highlights trends in industrial maintenance policies focused on continuous process improvement and enhanced competitiveness (Putnik *et al.*, 2024).

An exploratory review identified a gap in comprehensive studies offering broad insights into Industry 4.0 technologies applied to maintenance. Thus, this research aims to conduct a systematic literature review to map employed technologies, identify key advantages, and explore implementation challenges.

Industry 4.0 drives significant changes in maintenance through technologies such as the internet of Things, Artificial Intelligence, and Big Data, enabling predictive models that optimize efficiency, reduce costs, and improve asset reliability. Understanding which technologies are used, their applications, benefits, and challenges is essential. This study addresses the need to systematize current knowledge by mapping key technologies, tangible benefits, and critical challenges, filling a literature gap and providing an initial understanding of Maintenance 4.0's potential to support industrial modernization and competitiveness.

While prior systematic reviews have examined predictive maintenance or specific Industry 4.0 technologies in isolation (e.g. focusing on machine learning applications or sector-specific implementations), they often lack a comprehensive perspective that connects technologies to both their realized benefits and the practical challenges of implementation. Moreover, existing studies rarely provide a structured synthesis that simultaneously supports strategic decision-making and theoretical consolidation.

In this context, this study advances the literature by offering an integrated perspective that bridges this gap, enabling a more holistic understanding of how Industry 4.0 technologies collectively shape maintenance strategies and outcome.

This article is organized into five sections: the introduction, which outlines the study's context and relevance; the theoretical framework, covering key concepts and definitions; the methodology, detailing research procedures and data analysis; followed by results and discussion; and concluding with a summary of findings.

2. Theoretical framework

According to EN 13306, maintenance encompasses a set of technical, administrative, and managerial actions performed throughout an item's life cycle to preserve or restore it to a condition capable of fulfilling its essential functions, ensuring service continuity (Rojek *et al.*, 2023). Maintenance is classified into three primary types: corrective, preventive, and predictive. Corrective maintenance, or reactive maintenance, occurs after failures. Preventive maintenance is scheduled periodically to mitigate risks. Predictive maintenance anticipates interventions by detecting early warning signs such as abnormal noises or corrosion (Duarte and Scarpin, 2023).

The rising complexity of industrial processes has driven innovation in maintenance management, targeting cost reduction and improved efficiency. Industry 4.0 plays a pivotal role in this context, characterized by the integration of advanced information and manufacturing technologies, marking a digital revolution in the industrial sector. This paradigm includes innovations such as Artificial Intelligence (AI), cybersecurity, the internet of Things (IoT), cloud computing, and Machine Learning (ML). A key objective is enabling decentralized, autonomous system operations, particularly during exceptional events, disruptions, or conflicting objectives requiring external feedback (Javaid *et al.*, 2022).

To grasp the Fourth Industrial Revolution's impact, it is crucial to examine emerging technologies facilitating continuous monitoring and more efficient industrial asset management. IoT enables real-time data acquisition; AI supports pattern recognition and failure prediction; and Big Data facilitates decision-making through historical failure analysis and optimization of predictive maintenance strategies (Fasuludeen Kunju *et al.*, 2022).

Industry 4.0 aims to transform conventional machines into autonomous, learning-capable devices that enhance performance and optimize maintenance by interacting with their environment (Fasuludeen Kunju *et al.*, 2022). This shift relies on sensors, Big Data analytics, cloud computing, mobile devices, and real-time location systems, which collectively improve production processes and strengthen organizational competitiveness (Fasuludeen Kunju *et al.*, 2022).

Therefore, Industry 4.0 has driven a significant advancement in industrial maintenance management, enhancing asset availability and reliability.

3. Methodology

The methodological framework began with an exploratory study aimed at identifying the most relevant terms and concepts. Subsequently, to conduct the Systematic Literature Review (SLR), the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) methodology was applied, which provides a set of criteria and a flowchart to help organize and report how studies were identified, selected, assessed, and included in the review. Following this, descriptive and content analyses were performed. Figure 1 illustrates the general steps followed in this study's procedure.

3.1 Exploratory research

An exploratory study was conducted to gain a general understanding of the topic, identifying key terms and concepts. This initial step provided insight into the current state of the art and informed the development of search strings for the Systematic Literature Review (SLR).

The exploratory search was performed on Scopus using the following query: ("Industry 4.0" OR "Fourth Industrial Revolution") AND ("Industrial Maintenance" OR "Predictive maintenance" OR "Preventive maintenance" OR "Corrective maintenance"). Without applying filters, this search retrieved 1,602 documents.

To analyze this dataset, VOSviewer software was employed. VOSviewer is a scientific visualization tool that constructs and explores bibliometric maps, facilitating the analysis of large volumes of academic publication data. Figure 2 presents the keyword network generated from this search, which guided the refinement of the final search strings.

After acquiring knowledge about the main concepts and terms related to the topic, the search strings were defined. These were selected because they directly encompass the subject matter and aim not to exclude any potentially relevant information. Table 1 presents the search terms used to proceed with the Systematic Literature Review (SLR).

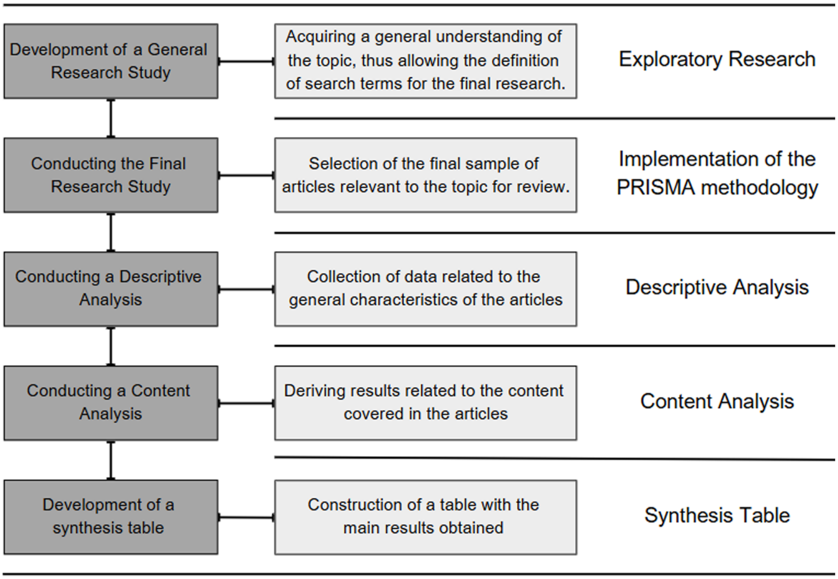


Figure 1. Methodological steps for conducting the research. Source: Authors' own elaboration (2025)

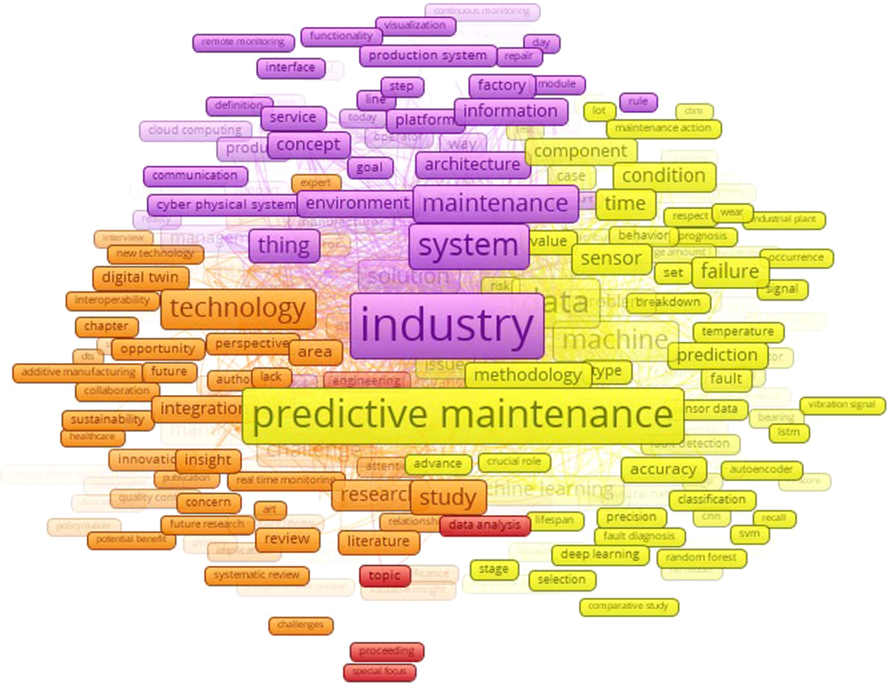


Figure 2. Initial network generated from Scopus data. Source: Authors' own elaboration (2025)

Table 1. Search strings selected for conducting the SLR

Group 1: Industry 4.0		Group 2: Industrial maintenance
("Industry 4.0" OR "Industrial Digital Transformation" OR "Fourth Industrial Revolution")	AND	("Industrial Maintenance" OR "Plant Maintenance" OR "Equipment Maintenance" OR "Predictive maintenance" OR "Data-Driven Maintenance" OR "Condition-Based Maintenance" OR "Preventive maintenance" OR "Scheduled Maintenance" OR "Time-Based Maintenance" OR "Planned Maintenance" OR "Corrective maintenance" OR "Breakdown Maintenance" OR "Reactive Maintenance" OR "Unscheduled Maintenance")

Source(s): Authors' own elaboration (2025)

3.2 Systematic literature review

After defining the search terms, the Systematic Literature Review (SLR) was conducted following the PRISMA protocol, which comprises four stages: Identification, Screening, Eligibility, and Inclusion.

The SLR was guided by three research questions: (1) What is the impact of Industry 4.0 technologies on industrial maintenance? (2) Which Industry 4.0 tools have been most prominent? (3) How have maintenance types been affected by these transformations? Subsequently, database searches were performed.

Two searches, based on the defined terms, were carried out on February 14, 2025: one in Scopus (1,668 documents) and another in Web of Science (1,114 documents).

Inclusion criteria were applied to refine the results: (1) journal articles only; (2) publications from the last five years (2020–2025); and (3) English language documents. This reduced the sample to 480 documents in Scopus and 469 in Web of Science. The datasets were merged, totaling 949 documents.

Duplicates were removed using Mendeley, which identified 340 overlapping records. After deduplication, 606 documents remained. Titles and abstracts were screened for relevance to the research questions, excluding 540 articles. A second screening of the remaining 66 articles excluded 30 more.

Of the 36 remaining documents, full access was obtained for 33. These were fully read and analyzed, resulting in the exclusion of 4 articles. The final sample comprised 29 studies. Figure 3 summarizes these steps.

3.3 Descriptive and content analysis and development of the summary table

The final sample was analyzed in three stages: descriptive analysis, content analysis, and the creation of a summary table synthesizing the study's findings. This approach provides a structured overview of the literature, allowing identification of patterns, trends, and gaps that support the development of a theoretical model aligned with the research objectives.

The descriptive analysis examined publication years, countries, and maintenance types addressed by the articles. Additionally, keyword networks were generated using VOSviewer, including terms appearing at least five times in titles and abstracts. These data contextualized the study's development and indicated the topic's maturity and distribution within the academic community.

Next, content analysis involved an interpretative, categorized reading of the selected texts. This phase aimed to identify key concepts, tools, applications, and impacts related to digital

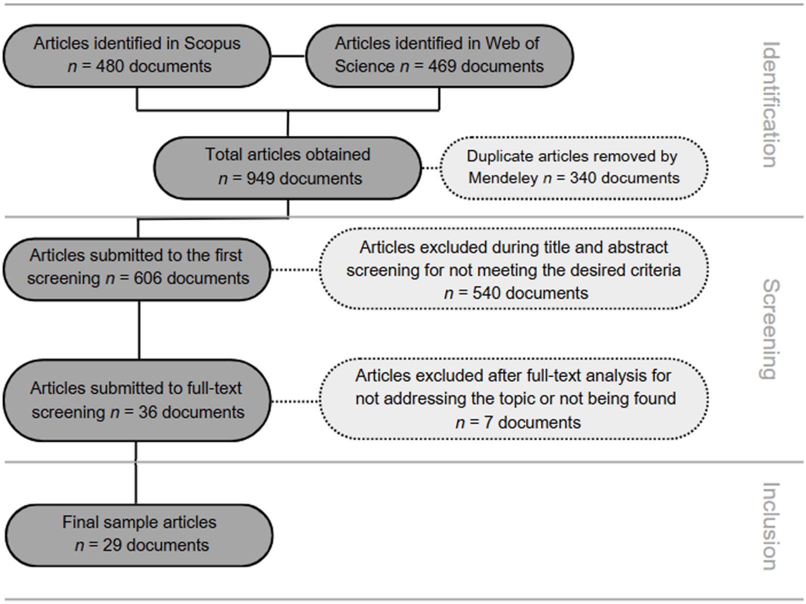


Figure 3. Flowchart of the methodological steps based on the PRISMA Methodology. Source: Authors' own elaboration (2025)

transformation and industrial maintenance. Specifically, it investigated which Industry 4.0 technologies were applied, the benefits and challenges of their implementation, and the maintenance types emphasized, whether as main topics, secondary themes, or brief mentions.

Based on these findings, a summary table was developed to synthesize the analyzed content. This table organizes key elements logically and visually, highlighting the relationships between Industry 4.0 technologies and their impacts on industrial maintenance.

4. Results and discussion

Analysis of the final sample ($n = 29$) revealed a strong emphasis on predictive maintenance within the context of Industry 4.0 technologies. Figure 4 shows that predictive maintenance was the primary focus in over 79% of the selected studies. Saraswat and Agrawal (2023) highlight that Industry 4.0 bridges production and maintenance planning, enabling more efficient and cost-effective production systems. To realize technical and financial benefits, industries have adopted Industry 4.0 principles as a foundation for modernizing maintenance strategies, shifting from traditional practices to predictive maintenance approaches.

Traditional maintenance classifications tend to be more costly, which can impede efforts to achieve a cost-effective production system. However, these maintenance types have not been disregarded. Analysis of the dataset revealed that, although not the primary focus, corrective and preventive maintenance were also discussed in the selected studies, indicating their continued relevance and use across industries of various sizes. These proportions are illustrated in Figure 5.

Analysis of the keyword networks reveals a strong association between Industry 4.0 and Artificial Intelligence (AI), particularly tools such as machine learning (Figure 6). As highlighted by Cinar *et al.* (2020), predictive maintenance presents significant market opportunities, with machine learning emerging as a key innovation for its implementation. This network underscores the close relationship among Industry 4.0, AI, and predictive maintenance.

4.1 Main technologies identified

Figure 7 presents a chart showing the most frequently cited technologies and the number of articles in which they appeared. Having this overview is essential to understand the impacts brought by the Fourth Industrial Revolution and to identify which technologies are most implementable and prevalent across various companies operating in the market.

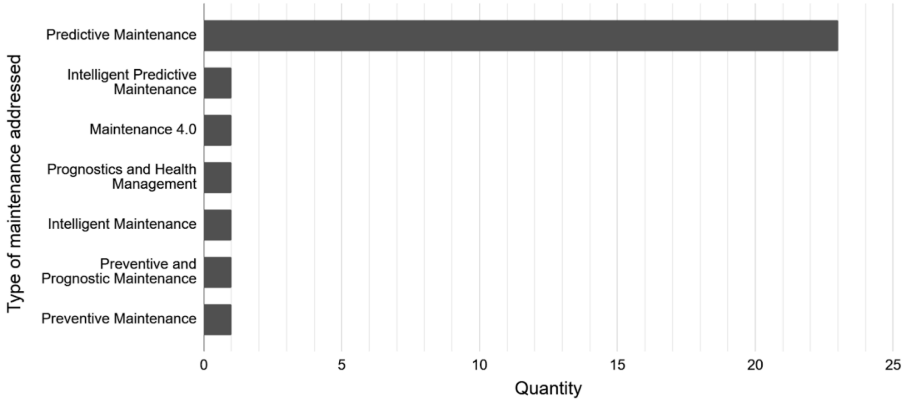


Figure 4. Number of articles by type of maintenance that was the main research focus of the analyzed article
Source: Authors’ own elaboration (2025)

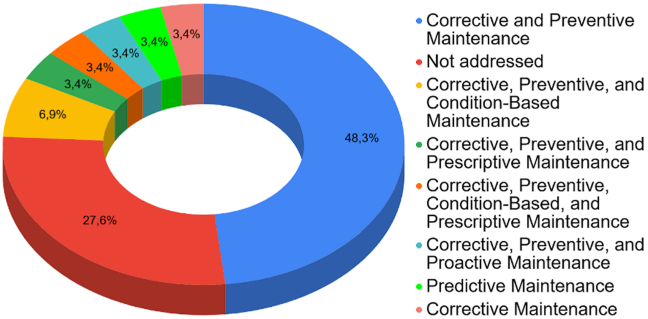


Figure 5. Types of maintenance mentioned concurrently in the subset of articles. Source: Authors' own elaboration (2025)

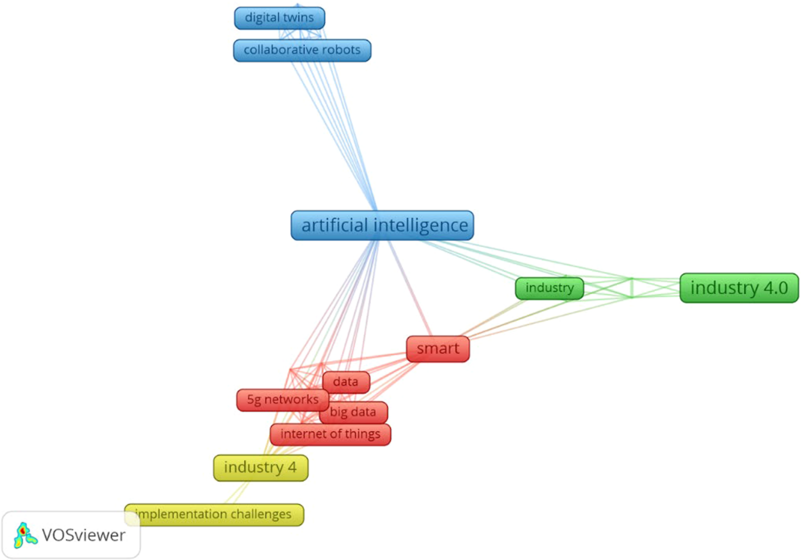


Figure 6. Keywords identified at least once by VOSviewer. Source: Authors' own elaboration (2025)

The graph clearly shows that the internet of Things (IoT) was the most prominent technology, appearing in at least 18 studies. According to Khan *et al.* (2020) and Fasuludeen Kunju *et al.* (2022), the Industrial Internet of Things (IIoT) is a network of intelligent, highly connected industrial components designed to achieve high production rates and reduce operational costs.

IIoT enables real-time monitoring, efficient management, and control of industrial processes, assets, and operational time. Furthermore, IoT facilitates real-time condition monitoring by linking machines and sensors. When combined with predictive maintenance, it allows automatic fault detection, reducing downtime and improving operational efficiency (Fasuludeen Kunju *et al.*, 2022).

Artificial Intelligence (AI) was another prominent technology. Muthuswamy and Sanithi (2023) define AI as algorithms that enable machines to develop problem-solving skills,

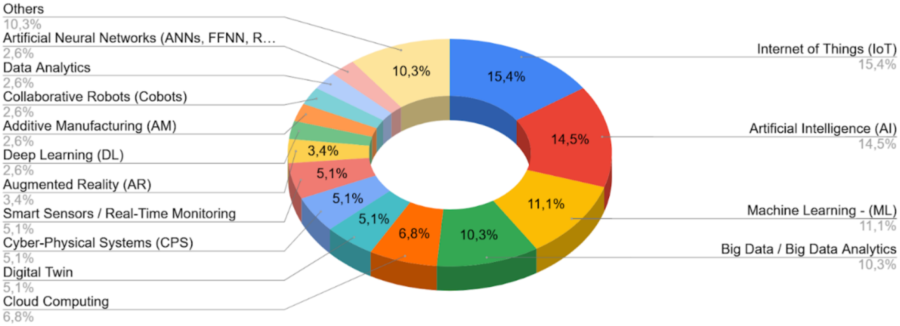


Figure 7. Main technologies/tools identified in the sample. Source: Authors' own elaboration (2025)

decision-making abilities, and task execution similar to humans. Javaid *et al.* (2022) emphasize AI's critical role in recent Industry 4.0 advancements.

AI holds vast potential to transform society, including the industrial sector. Maintenance is an area where AI offers broad and long-term benefits. Saraswat and Agrawal (2023) highlight AI's ability to extract relevant insights from large datasets, leading to increased equipment availability, improved operational performance, reduced maintenance costs, and enhanced decision-making support.

Machine Learning (ML), a subset of AI, also stood out in the analysis, indicating its significant impact. Arena *et al.* (2022) describe ML as systems that learn and improve performance based on data. Four main types of ML algorithms exist—supervised, semi-supervised, unsupervised, and reinforcement learning—each differing in how they process data to generate predictions.

Big Data ranked fourth among highlighted terms. It refers to large datasets collected through various sources such as sensors and IoT devices. Big Data's primary purpose is to manage and process extensive information to enhance operational efficiency, support decision-making, and minimize workplace risks (Fasuludeen Kunju *et al.*, 2022; Lucas *et al.*, 2024).

Several other technologies were also identified, often used in combination. Fasuludeen Kunju *et al.* (2022) observe that many companies deploy multiple resources—including sensors, Big Data analytics, real-time location systems, and cloud technologies—to optimize production and strengthen competitiveness.

4.2 Advantages or benefits obtained

The adoption of various technologies in maintenance—particularly predictive maintenance—offers numerous advantages. However, these benefits come with challenges and implementation barriers. Understanding both is essential to grasp the complexities and prerequisites for successful technology integration. Figure 8 presents a graph highlighting the primary benefits of applying Industry 4.0 technologies in the maintenance sector.

The graph shows that the primary benefits are cost reduction, decreased downtime, and increased operational efficiency. These factors, along with others such as sustainability, improved reliability and equipment lifespan, and resource optimization, directly influence a company's profitability and competitiveness.

Most technologies highlighted in Figure 9 are closely linked to predictive maintenance, as many benefits stem from this approach. According to Rojek *et al.* (2023), reactive maintenance involves corrective actions taken only after failures or when wear limits are reached, often resulting in prolonged downtime and unplanned interventions. Preventive maintenance, on the

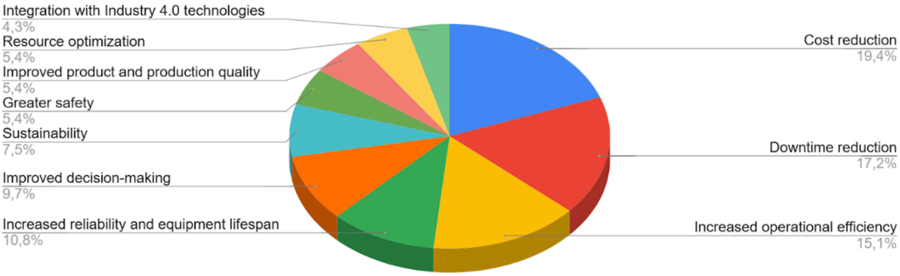
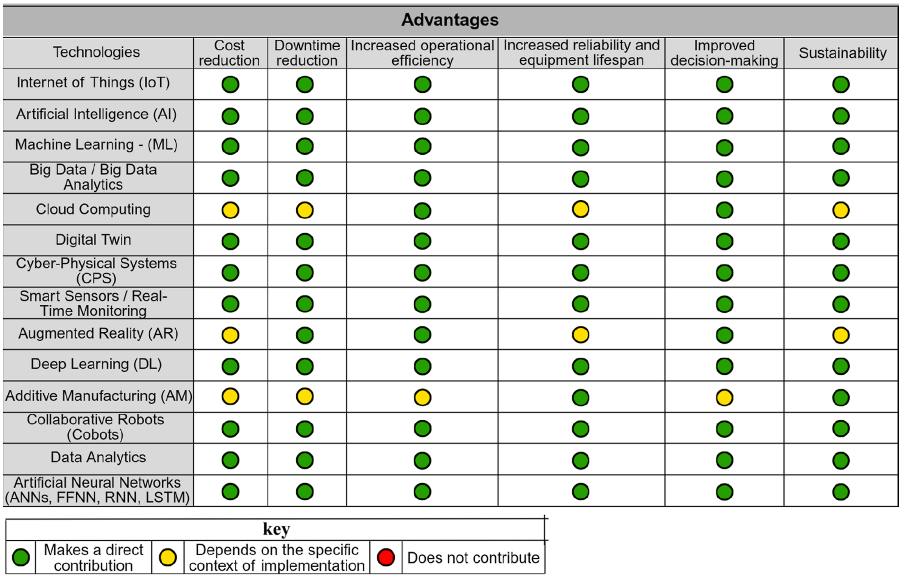


Figure 8. Main positive outcomes achieved through the implementation of Industry 4.0 technologies. Source: Authors' own elaboration (2025)



Technologies	Advantages					
	Cost reduction	Downtime reduction	Increased operational efficiency	Increased reliability and equipment lifespan	Improved decision-making	Sustainability
Internet of Things (IoT)	🟢	🟢	🟢	🟢	🟢	🟢
Artificial Intelligence (AI)	🟢	🟢	🟢	🟢	🟢	🟢
Machine Learning - (ML)	🟢	🟢	🟢	🟢	🟢	🟢
Big Data / Big Data Analytics	🟢	🟢	🟢	🟢	🟢	🟢
Cloud Computing	🟡	🟡	🟢	🟡	🟢	🟡
Digital Twin	🟢	🟢	🟢	🟢	🟢	🟢
Cyber-Physical Systems (CPS)	🟢	🟢	🟢	🟢	🟢	🟢
Smart Sensors / Real-Time Monitoring	🟢	🟢	🟢	🟢	🟢	🟢
Augmented Reality (AR)	🟡	🟢	🟢	🟡	🟢	🟡
Deep Learning (DL)	🟢	🟢	🟢	🟢	🟢	🟢
Additive Manufacturing (AM)	🟡	🟡	🟡	🟢	🟡	🟢
Collaborative Robots (Cobots)	🟢	🟢	🟢	🟢	🟢	🟢
Data Analytics	🟢	🟢	🟢	🟢	🟢	🟢
Artificial Neural Networks (ANNs, FFNN, RNN, LSTM)	🟢	🟢	🟢	🟢	🟢	🟢

key					
🟢	Makes a direct contribution	🟡	Depends on the specific context of implementation	🔴	Does not contribute

Figure 9. Summary table relating the identified technologies to the main advantages. Source: Authors' own elaboration (2025)

other hand, aims to avoid failures through scheduled actions, but typically relies on estimates rather than real-time data, which can cause premature component replacements and higher material and labor costs.

The predictive maintenance (PdM) balances reactive and planned maintenance by combining their advantages while minimizing downtime caused by failures. Literature reports several benefits from the correct implementation of PdM, including increased equipment lifespan (33–60%), reduced maintenance costs (10–15%), enhanced sustainable capacity (15–40%), shortened maintenance planning time (20–50%), increased equipment uptime (10–20%), and overall maintenance cost reduction (5–10%) (Peter *et al.*, 2023).

Thus, adopting these technologies enables industries to become more competitive, fostering sustainable growth, improving customer retention, strengthening market position, and ultimately achieving higher profit margins.

To better illustrate these benefits, a summary table was created linking the main technologies identified in this study with their key advantages. This table is presented in Figure 9, followed by an analysis of some of these relationships.

Cost reduction stands out as one of the most significant and sought-after benefits resulting from the implementation of Industry 4.0 technologies in the maintenance sector, representing a substantial portion of the advantages perceived by industries, as shown in the synthesis table in Figure 9. This saving is achieved through a multifaceted approach, where core technologies such as IoT, sensors, Big Data, and AI/ML enable Predictive Maintenance (PdM) by optimizing interventions, avoiding unnecessary maintenance or catastrophic failures, and reducing costs related to parts and labor. Predictive maintenance has great optimization potential, capable of increasing machine availability by up to 15% and reducing costs by up to 25% (Becherer *et al.*, 2020). Additionally, Digital Twins and Cyber-Physical Systems contribute directly by enabling simulations and efficient system management. Other technologies like Cloud Computing, Augmented Reality, Additive Manufacturing, and Collaborative Robots also offer cost-saving potential in specific contexts, such as reducing IT expenses, enabling remote assistance, and optimizing inventory.

Increased reliability and extended equipment lifespan are also key impacts of Industry 4.0 on maintenance. Continuous monitoring through the internet of Things (IoT) and smart sensors generates data that feed Artificial Intelligence (AI) algorithms such as Machine Learning (ML), often complemented by Digital Twins. These tools analyze degradation patterns, predict Remaining Useful Life (RUL) of components, and optimize intervention strategies before physical failures occur. Such predictive capabilities enable more proactive and precise maintenance, thereby improving system reliability and extending asset operability. Technologies like Additive Manufacturing and Augmented Reality further support this by expediting repairs and parts supply.

Beyond cost reduction and increased reliability and lifespan, the application of Industry 4.0 technologies in maintenance delivers several other essential benefits. Downtime reduction is a direct outcome of predictive maintenance empowered by IoT and AI, naturally leading to higher operational efficiency in industrial plants. This is further enhanced by improved decision-making, as Big Data Analytics and AI provide predictive insights and accurate diagnostics for managers.

Sustainability is also positively impacted, with smart maintenance minimizing material and energy waste and optimizing resource use—such as extending the lifespan of wear parts. Consequently, improvements in product and production quality often follow, reflecting greater equipment availability and optimized performance. Enhanced operational safety is another important benefit, as the ability to anticipate potentially hazardous failures enables safer, better-planned interventions.

Ultimately, the synergistic integration of diverse Industry 4.0 technologies—such as IoT, AI, Big Data, Cloud Computing, and Digital Twins—creates a more robust, adaptable, and inherently efficient maintenance ecosystem, transforming asset management and driving competitive advantage.

4.3 Challenges in implementing industry 4.0 technologies

Figure 10 presents a chart illustrating the main obstacles and difficulties faced both during the implementation of these technologies and in the post-implementation phase.

The most significant challenge in implementing Industry 4.0 technologies is the high initial investment cost. This financial barrier also contributes to concerns about risk and uncertainty regarding return on investment. Consequently, adoption tends to be concentrated in well-established companies with strong capital reserves, for whom the upfront costs are more manageable and the benefits discussed earlier are more readily achievable. Stefanini *et al.* (2023) corroborate the link between company size and maintenance strategy, noting that 36.8% of adopters are large firms, followed by small firms at 34%, medium-sized firms at 21%, and microenterprises at 7.9%.

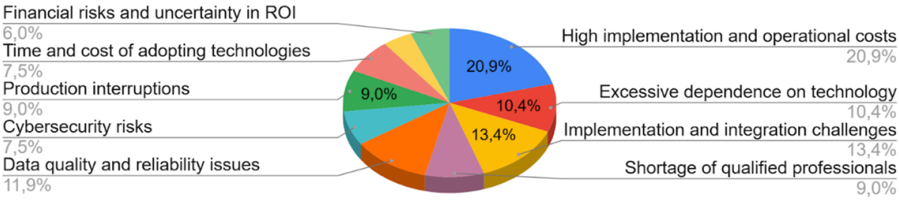


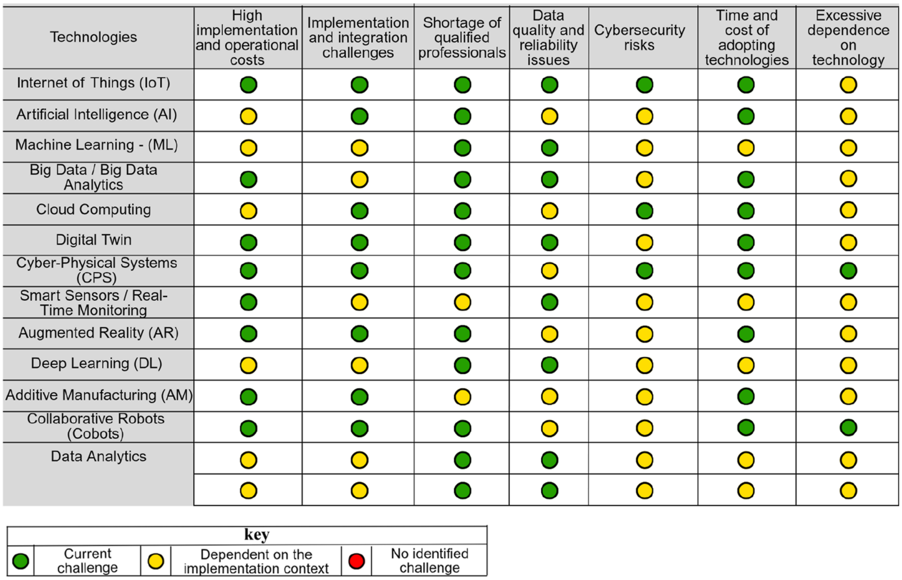
Figure 10. Main issues arising from the implementation of Industry 4.0 technologies. Source: Authors' own elaboration (2025)

This trend is supported by other studies as well. Duarte and Scarpin (2023) report that predictive maintenance has a greater impact in high-performance companies, whereas low-performance firms rely more heavily on preventive maintenance. Nonetheless, sound corrective maintenance remains critical even in top-performing organizations.

Another key challenge is the shortage of qualified personnel capable of managing these complex technologies on a daily basis. Duarte and Scarpin (2023) emphasize the importance of training, particularly for predictive maintenance, and suggest that investments in education significantly enhance the effectiveness of these practices.

Data security is also a major concern, as Industry 4.0 technologies generate and store vast amounts of data, increasing vulnerability to cyber threats. Duarte and Scarpin (2023) further highlight that while these technologies contribute to economic sustainability by reducing waste, improving quality, optimizing processes, and extending asset lifespan, they often overlook the environmental costs associated with data generation and processing. The high computational power and energy required for managing large datasets pose additional sustainability challenges.

To provide a comprehensive overview, Figure 11 synthesizes the main implementation challenges associated with the technologies identified in this study.



Technologies	High implementation and operational costs	Implementation and integration challenges	Shortage of qualified professionals	Data quality and reliability issues	Cybersecurity risks	Time and cost of adopting technologies	Excessive dependence on technology
Internet of Things (IoT)	🟢	🟢	🟢	🟢	🟢	🟢	🟡
Artificial Intelligence (AI)	🟡	🟢	🟢	🟡	🟡	🟢	🟡
Machine Learning - (ML)	🟡	🟡	🟢	🟢	🟡	🟡	🟡
Big Data / Big Data Analytics	🟢	🟡	🟢	🟢	🟡	🟢	🟡
Cloud Computing	🟡	🟢	🟢	🟡	🟢	🟢	🟡
Digital Twin	🟢	🟢	🟢	🟢	🟡	🟢	🟡
Cyber-Physical Systems (CPS)	🟢	🟢	🟢	🟡	🟢	🟢	🟢
Smart Sensors / Real-Time Monitoring	🟢	🟡	🟡	🟢	🟡	🟡	🟡
Augmented Reality (AR)	🟢	🟢	🟢	🟡	🟡	🟢	🟡
Deep Learning (DL)	🟡	🟡	🟢	🟢	🟡	🟡	🟡
Additive Manufacturing (AM)	🟢	🟢	🟡	🟡	🟡	🟢	🟡
Collaborative Robots (Cobots)	🟢	🟢	🟢	🟡	🟡	🟢	🟢
Data Analytics	🟡	🟡	🟢	🟢	🟡	🟡	🟡
	🟡	🟡	🟢	🟢	🟡	🟡	🟡

key					
🟢	Current challenge	🟡	Dependent on the implementation context	🔴	No identified challenge

Figure 11. Summary table relating the technologies to the main implementation challenges. Source: Authors' own elaboration (2025)

One of the major challenges hindering widespread adoption of Industry 4.0 technologies in industrial maintenance is the high cost of both initial implementation and ongoing operation. Transitioning to Maintenance 4.0 often requires substantial investment in infrastructure, including intelligent sensors, IoT connectivity, and especially the modernization of legacy plants, which can be prohibitively expensive or economically unfeasible in some cases (Hoffmann and Lasch, 2025). High upfront costs are frequently cited as a primary barrier to adoption by companies pursuing innovation (Stefanini *et al.*, 2023). Beyond physical infrastructure, significant financial resources are also required for advanced platforms and software related to Big Data Analytics, Artificial Intelligence (AI), Machine Learning (ML), and Digital Twins, with uncertain return on investment timelines (Hoffmann and Lasch, 2025).

Data quality issues—including missing data, outliers, noise, lack of annotation, and concerns about data availability and integrity—seriously undermine system capabilities. AI models require large volumes of clean, representative, and often labeled data to train algorithms that accurately diagnose faults and predict equipment Remaining Useful Life (RUL). Poor data quality leads to faulty analyses and ineffective or premature maintenance decisions. Consequently, even sophisticated tools like Digital Twins, which integrate IoT and AI data to simulate and monitor assets (Muthuswamy and Sanithi, 2023), and Cyber-Physical Systems have limited transformative potential when operating on low-quality data, impeding real optimization and expected asset management benefits.

Beyond costs and data quality, other significant obstacles impede the Maintenance 4.0 transition. Integration of new technologies with legacy systems is often complex and time-consuming, requiring major adaptations to existing IT infrastructure (Hoffmann and Lasch, 2025; Stefanini *et al.*, 2023). The shortage of qualified professionals to operate, analyze, and manage these advanced tools is a critical barrier (James *et al.*, 2023; Stefanini *et al.*, 2023), potentially resulting in overreliance on technology without adequate human oversight (Jasiulewicz-Kaczmarek *et al.*, 2020). Additional challenges include cybersecurity risks inherent to increased connectivity and large volumes of sensitive data (James *et al.*, 2023), financial risks and uncertain ROI (Hoffmann and Lasch, 2025), concerns about AI explainability which may reduce user trust (Cummins *et al.*, 2024; Jagatheesaperumal *et al.*, 2022), and potential production disruptions if transitions are not carefully managed (Jasiulewicz-Kaczmarek *et al.*, 2020).

4.4 Theoretical and managerial implications

This study offers several important theoretical contributions to the literature on Industry 4.0 and industrial maintenance. First, it advances existing knowledge by providing an integrated and structured synthesis of the main technologies, benefits, and implementation challenges associated with Maintenance 4.0. Whereas prior studies have often examined these dimensions in isolation, this research consolidates them into a comprehensive analytical framework, thereby contributing to a more holistic understanding of how digital transformation reshapes maintenance strategies.

Second, the study reinforces the central role of predictive maintenance as a key mechanism through which Industry 4.0 technologies generate value. By systematically linking technologies such as the internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and big data to specific operational and strategic outcomes, this research clarifies the pathways through which digital capabilities translate into performance improvements.

Third, the study highlights the interplay between technological adoption and organizational constraints, including data quality, workforce capabilities, and system integration. This perspective supports the development of more realistic and context-sensitive models of digital transformation in maintenance, moving beyond purely technological determinism.

From a managerial perspective, the findings provide practical insights for organizations seeking to implement Industry 4.0 technologies in maintenance processes. First, the results suggest that managers should prioritize investments in data infrastructure and data quality, as these are critical enablers of advanced analytics and predictive maintenance systems.

Second, the study underscores the importance of adopting a strategic and integrated approach to technology implementation. Rather than focusing on isolated tools, organizations should consider the combined use of technologies—such as IoT, AI, and cloud computing—to maximize operational benefits and achieve higher levels of efficiency and reliability.

Third, the findings emphasize the need for workforce development and organizational readiness. The successful adoption of Maintenance 4.0 requires not only technological investment but also the development of skills, training programs, and a culture that supports data-driven decision-making.

Finally, the study provides guidance for decision-makers by identifying key barriers—such as high initial costs, integration complexity, and cybersecurity risks—thereby enabling organizations to anticipate challenges and develop more effective implementation strategies. In doing so, the research supports more informed and strategic decision-making in the context of digital transformation in industrial maintenance.

5. Conclusion

This literature review demonstrates that Industry 4.0 significantly and positively impacts industrial maintenance practices. Emerging technologies—such as intelligent sensors, communication networks, predictive analytics, and integrated platforms—not only enable failure anticipation and downtime reduction but also support the shift from reactive to proactive and predictive maintenance models. These innovations yield substantial improvements in operational efficiency and strategic decision-making.

Despite its contributions, this study presents limitations. As a systematic literature review, it does not include primary empirical data, and its findings are therefore contingent upon the scope, rigor, and quality of the existing body of research. To reduce potential bias, the analysis was deliberately restricted to articles published in well-established, peer-reviewed journals, as detailed in the methodology.

The study primarily emphasizes current research trends and dominant themes within the literature, rather than providing an assessment of the actual industrial maturity or operational effectiveness of the technologies discussed. In addition, the integrated treatment of Industry 4.0 technologies reflects prevailing implementation approaches but limits the isolation of individual technological effects. Finally, as several of the technologies reviewed are at varying stages of industrial development, their practical applicability and the extent of the benefits reported may differ across industrial contexts.

Future research should focus on strategies to overcome key implementation challenges, particularly in data security, technical training, and systems integration. Investigating cost-effective approaches to broaden Industry 4.0 adoption across diverse companies is also recommended, contributing to wider, more accessible modernization of the industrial maintenance sector.

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Further reading

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