



Integration of CMMS in Industry 4.0: Towards an AI-Driven Maintenance Management System

Master's thesis in MIMI

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Abstract: The emergence of Industry 4.0 has significantly reshaped industrial maintenance by promoting the integration of intelligent technologies that enhance efficiency, reliability, and data-driven decision-making.

Traditional Computerized Maintenance Management Systems (CMMS), once focused solely on planning and documentation, are now evolving into smart platforms capable of supporting real-time monitoring, predictive analytics, and automated maintenance workflows. This paper explores the integration of Industry 4.0 technologies such as IoT, Artificial Intelligence, and Augmented Reality within CMMS environments. It highlights commonly adopted solutions, identifies key limitations and discusses futures opportunities such as integrating emerging technologies like digital twins and advanced AI tools, including Natural Language Processing (NLP) and Large Language Models (LLM). This work aims to provide insights into building next-generation CMMS aligned with the principles of Industry 4.0.

Key-Words: Industry 4.0, Next generation CMMS, Maintenance Process Optimization, AI-Powered Decision-Making, Smart Maintenance.

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1. Introduction

Industry 4.0 represents a transformative process that involves integrating its nine key pillars into manufacturing process. These pillars include the Industrial Internet of Things (IIoT), Big Data and Analytics, Cloud Computing, Simulation, and Cyber Security, which form the foundation of this transformation [1].

In recent years, Industry 4.0 has revolutionized industrial operations by introducing smart and connected technologies. One of the most significantly impacted areas is maintenance management, which plays a crucial role in nearly every industrial production process [2]. Many companies consider maintenance management as the first step in adopting Industry 4.0, enabling the shift from reactive and scheduled maintenance to predictive maintenance [1]. This transition enhances efficiency, flexibility, and decision-making. However, it also requires substantial changes in manufacturing process, human resource management, and the development of technical expertise to handle system failures and repairs [1, 3].

Since the first Industrial Revolution, maintenance strategies have evolved alongside technological advancements to meet changing market demands, such as higher product quality, lower costs, and shorter delivery times. As industries grow more complex, traditional maintenance methods alone are no longer sufficient. To address this, Computerized Maintenance Management Systems (CMMSs) have become essential tools, enabling industries to effectively manage maintenance programs [3]. CMMS solutions help plan maintenance tasks, improve equipment availability, and optimize resource allocation [4]. Acting as a centralized platform, CMMS stores and organizes all maintenance data, allowing maintenance managers to schedule tasks, monitor equipment performance, and make informed decisions to enhance overall efficiency [4].

With the emergence of Industry 4.0, advancements such as smart sensors and automation have further enhanced CMMS capabilities, making them more data-driven and intelligent [5]. By integrating Industry 4.0 technologies, modern CMMS solutions now support predictive maintenance, real-time monitoring, and data-driven decision-making. These innovations help companies minimize downtime, increase equipment reliability, and optimize maintenance operations.

The objective of this paper is to explore the intersection of Computerized Maintenance Management Systems (CMMSs) and Industry 4.0, focusing on the technologies being integrated, the processes involved in their implementation, and their impact on modern maintenance management. This study examines how Industry 4.0 innovations, such as IoT, AI, and Big Data Analytics, enhance CMMS functionalities,

enabling predictive maintenance, real-time monitoring, and data driven decision making. Furthermore, it discusses the challenges and opportunities associated with this technological transformation and highlights future research directions to optimize the adoption and effectiveness of CMMS in Industry 4.0 .

The structure of this paper is as follows: Section 2 outlines the research methodology. Section 3 provides a review of the evolution of Maintenance Management, the roles and benefits of CMMS, and the key principles and advantages of Industry 4.0. Section 4 examines studies that integrate CMMS within the framework of Industry 4.0 pillars. In Section 5, these studies were analyzed to identify the most frequently adopted technologies, the reasons behind their adoption, the limitations observed, and the technologies that remain underutilized, along with explanations for their limited use. Section 6 presents our future outlook based on the findings and Section 7 concludes the paper.

2. Research methodology

2.1. Research method

The research approach adopted in this study is a Systematic Literature Review (SLR). This method was selected for its ability to offer a structured, transparent, and reproducible overview of the current state of knowledge. Unlike traditional or descriptive literature reviews, the SLR provides a more comprehensive and methodical synthesis of relevant academic work. It is recognized as a scientific and informative method for systematically collecting, analyzing, and synthesizing research findings on a specific topic. As noted by [6], a systematic literature review is an efficient technique for hypothesis testing, summarizing the results of existing studies, and evaluating the consistency among them. Furthermore, SLRs enable readers to gain a deep understanding of the literature and help identify gaps in the research area [7].

The objective of this SLR is to explore the evolution of maintenance systems, understand the roles and benefits of Computerized Maintenance Management Systems (CMMS), and analyze their integration with Industry 4.0 technologies.

To guide this review, the following research questions (RQs) were formulated:

- RQ1: How have maintenance management systems evolved across different industrial revolutions? What are their key functions, types of maintenance used, and challenges encountered?
- RQ2: What is a CMMS? What are its core functions, benefits, and limitations in its traditional form?
- RQ3: What is Industry 4.0? What are its core technologies, principles, and strategic advantages?

- RQ4: How can CMMS be integrated with Industry 4.0 technologies? What technologies are most relevant?

2.2. Search strategy

Given the structured nature of an SLR, the search strategy followed four main steps:

2.2.1 Selection of databases

To ensure a comprehensive and reliable collection of relevant literature, searches were conducted across multiple academic databases and platforms. The primary sources included Scopus, ScienceDirect, IEEE Xplore, ResearchGate, MDPI, and Taylor & Francis, which are widely recognized for their rigorous peer-reviewed content in the fields of engineering, information systems, and management sciences. These databases were selected to ensure access to a wide range of peer-reviewed and high-impact journal articles relevant to the research topic. The focus was strictly on academic publications, to maintain a consistent level of scientific rigor and reliability across the selected literature. In some cases where institutional access was limited, Sci-Hub was cautiously utilized as an access tool, solely for retrieving full-text versions of articles identified through legitimate searches. Keywords and Boolean operators were carefully tailored for each database to refine results and ensure relevance to the research objectives.

2.2.2 Inclusion Criteria and Search Terms

To ensure the relevance and quality of the literature included in this study, specific inclusion criteria were applied during the selection process:

Only peer-reviewed journal articles were considered, ensuring a high level of scientific reliability. The review was limited to publications written in English and published between 2019 and 2025, in order to focus on the most recent and relevant developments.

The search strategy involved the use of specific keywords such as “CMMS”, “Industry 4.0”, “Integration”. These terms were combined using the Boolean operator AND to refine the results, while OR was used to explore the integration of individual Industry 4.0 technologies with CMMS. A screening process was carried out by reviewing the titles, abstracts, introductions, and conclusions of the articles to assess their relevance to the research objectives.

Furthermore, the search strategy was iteratively refined by incorporating additional keywords and synonyms discovered during the initial review, including terms like “smart manufacturing”, “digital maintenance”, “maintenance 4.0”, and “e-maintenance”.

2.2.3 Article Selection and Analysis

An initial pool of 250 articles was identified based on the predefined search criteria. The titles and abstracts of these articles were independently evaluated by the two authors (acting as reviewers), who categorized each article as either: Adequate, partially adequate or inadequate.

Articles deemed inadequate by at least one reviewer were excluded from the study. Those considered partially adequate were subjected to a second round of evaluation to determine their final eligibility. The remaining articles underwent a full-text review, during which relevant information was systematically extracted and organized into a structured database for further analysis.

The overall methodology adhered to a standard SLR structure, which included the following steps:

1. Duplicate removal ;
2. Title and abstract screening ;
3. Application of inclusion/exclusion criteria ;
4. Full-text analysis and data extraction.

The results of this selection process are summarized in Table 1:

Selection Stages	Identified	Deduped	Post Abstract	Post Fulltext
Total number	250	150	100	48

Table 1: Article selection summary.

2.2.4 Classification and Storing

The articles were categorized according to the research questions (RQs), which helped in organizing the literature review:

- MMS Evolution: From Industry 1.0 to 3.0;
- CMMS: Concepts, benefits, and challenges;
- Industry 4.0: Technologies and principles ;
- Integration of Industry 4.0 with CMMS.

For Research Question 4 (RQ4), the selected papers were further divided into the following categories:

- Use Cases ;
- Theoretical Studies.

The results of this classification are illustrated in Figure 1 , which shows the distribution of selected articles across the four main research questions. This visualization highlights that a significant number of articles focused on Industry 4.0 technologies, reflecting the current interest and relevance of this topic in academic research.

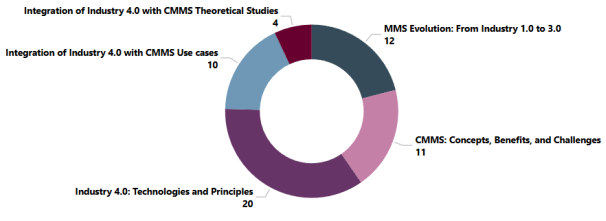


Figure 1: Number of articles according to the research questions

Additionally, Figure 2 presents a more detailed view, mapping individual articles to their corresponding categories. This classification allows for a clearer understanding of the focus areas of each paper and supports a thematic synthesis of the literature.

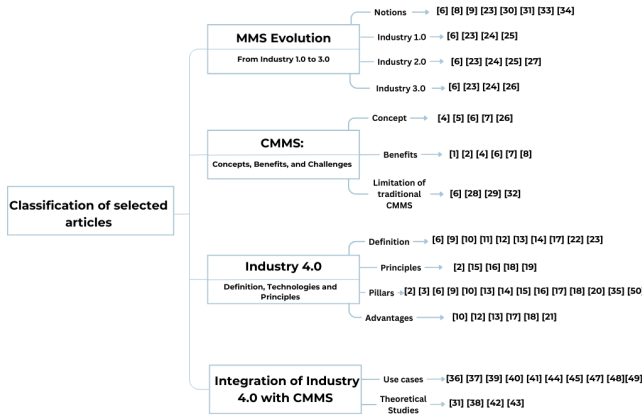


Figure 2: Classification of articles according to the research questions

In summary, the methodology adopted in this study was carefully designed to ensure both depth and reliability in exploring the intersection between CMMS and Industry 4.0. By following the principles of a Systematic Literature Review, we ensured a transparent and replicable process, grounded in academic rigor. Each step from database selection to the classification of articles was carried out with the aim was to gather the most relevant, recent, and useful information available on the topic. The categorization of the selected literature not only helped structure the review around key research questions, but also laid the groundwork for a focused and meaningful analysis in the following sections.

By following this structured methodology, we aim to provide a well-rounded understanding of how maintenance systems have evolved over time, present a clear overview of CMMS and Industry 4.0 technologies, and highlight and analyze the current integration strategies of these technologies with CMMS that are shaping the future of maintenance systems.

3. Literature review on CMMS and industry 4.0

3.1. Maintenance Management Systems (MMS): Evolution, Key Functions, and Challenges

Maintenance refers to all technical, managerial, and administrative actions taken throughout an item's life-cycle, to retain or restore it to a state where it can perform its required function [4, 8]. Its main objectives are to ensure system safety, extend equipment lifespan, maintain operational efficiency, and protect human well-being [9].

In industrial installations where productivity, reliability, and safety are essential, the importance of effective maintenance has led to the emergence of maintenance management [9, 10], which is defined as the systematic organization of maintenance activities aimed at optimizing asset performance and maximizing return on investment (ROI) through the selection of suitable maintenance strategies and efficient asset handling [9, 10].

As maintenance activities became more complex, the need to standardize and optimize them gave rise to maintenance management systems (MMS) [9]. While maintenance management defines "what" must be done and "why," MMS addresses "how" to execute these tasks, acting as a practical tool to implement and monitor maintenance strategies in a structured way. These systems facilitate the organization of maintenance activities, including equipment tracking, spare parts inventory, task scheduling, time management, and workforce coordination [10, 11].

Driven by advances in computing, MMS evolved from early Failure Modes and Effects Analysis (FMEA) into more sophisticated Computerized Maintenance Management Systems (CMMS), offering expanded capabilities for planning, tracking, and optimizing maintenance activities [1, 9].

This section will discuss the evolution of maintenance management systems from Industry 1.0 to Industry 3.0, highlighting how maintenance practices evolved across each industrial era. It will also examine the emergence of Computerized Maintenance Management Systems (CMMS), their impact on maintenance operations, and the limitations of traditional CMMS that have created the need for advanced automation solutions in the context of Industry 4.0.

3.1.1 Evolution of MMS through industrial revolutions: From its origin to industry 3.0

The term Industrial Revolution was initially popularized by English economic historian Arnold Toynbee to describe Britain's economic development from 1760 to 1840 [8]. It is defined as the rapid and dramatic change that creates an industrialized society, transforming it in ways that earlier purported industrial revolutions never achieved [8].

Industry 1.0: the era of reactive maintenance

The first industrial revolution, often referred to as Industry 1.0, began in England and was marked by innovative changes. A key development of this period was the invention of steam engines by James Watt in 1765, which became a symbol of this transformative era [4, 8].

During this period maintenance practices were primarily reactive, known as "breakdown maintenance", or "corrective maintenance", later termed Maintenance 1.0. This approach involved taking actions only after a failure occurred, which reduced maintenance costs and extended intervals, but led to frequent breakdowns, safety issues, and high repair costs [8, 12].

According to [13], Maintenance decisions were based on operator's experience, with data gathered manually and stored in memory. There were no structured tools or formal data management; knowledge transfer relied on verbal communication, making it prone to errors and inconsistencies. Maintenance practices were subjective and lacked reliability due to the absence of analytical approaches and documentation.

Industry 2.0: The shift to preventive maintenance

The second industrial revolution, which began in late 1870s, was marked by significant advancements in electrification and the introduction of assembly lines. This period saw the widespread adoption of mass production based on electrically powered lines, replacing steam and water power in many industries [4, 8].

As machines became more complex and production volumes increased, frequent unplanned breakdowns caused higher costs and operational disruptions [8]. This led to the rise of "Preventive Maintenance", also known as "Maintenance 2.0" [8]. Which involves performing scheduled maintenance tasks to prevent unplanned downtime such as lubrication, adjustments, oil change, and advanced diagnosis to avoid unexpected failures [12, 14]. While this approach increased system availability, reduced failure rates, and extended system lifespan, it also has drawbacks, including higher costs due to routine part replacements, the need for more spare parts, and the possibility of unnecessary maintenance [8, 12, 14].

In this era, data sources expanded to include both operators and machines. Although data collection was still manual, it began to be documented in writing, allowing for better tracking and analysis. Reliability theory, particularly the bathtub curve, was introduced to predict failure rates more effectively [13]. Data transfer became more reliable through written records, and maintenance activities were more structured, marking a transition toward formalized data management [13].

Industry 3.0: The rise of proactive maintenance and early CMMS

The third industrial revolution, began in 1969 with the development of the first programmable logic controller (PLC) and lasted until the early 1990s [8]. Marked by advances in automation, electronics, and information technology, which revolutionized manufacturing and industrial processes [4, 8]. Maintenance practices evolved by combining both Corrective and Preventive actions with data-driven analysis [8], leading to the emergence of proactive maintenance, which focused on addressing potential issues early in a product's lifecycle to prevent future failures [8, 15].

Operators played a key role in early fault detection through sensory observations, helping reduce breakdowns and enabling timely intervention [15]. This proactive approach extended equipment lifespan, reduced spare parts inventory, and improved cost-efficiency, though it required major cultural and organizational changes [8].

This period marked a significant shift in maintenance practices. Data collection became semi-automated through the use of basic sensors and digital tools, with information stored in databases, enabling better retrieval and analysis. Conventional algorithms enhanced failure prediction, while digital file sharing enhanced communication and reliability. Additionally, information systems increasingly supported maintenance management, reducing errors and improving efficiency [13, 15].

The Emergence of CMMS

The evolution of maintenance during the third industrial revolution paralleled with the emergence of the first and second generations of Computerized Maintenance Management Systems (CMMS), a maintenance software designed to simplify maintenance tasks, and improve monitoring in manufacturing [16, 17]. The earliest CMMS, introduced in the 1960s, using punch-card technology to record and manage routine maintenance tasks, marked the beginning of maintenance digitalization [4, 18].

The first generation of CMMS, introduced in the 1970s, focused primarily on data registration and administration, providing basic support for maintenance data

management, offering limited functionality, but represented the initial steps toward automating maintenance tasks, laying the foundation for more advanced systems [15].

In the 1980s and 1990s, the second generation of CMMS expanded to include cost control, work order management, and Maintenance, Repair, and Operating supplies (MRO) management, while also integrating with financial modules, reflecting the increasing complexity and digitalization of maintenance [15].

3.1.2 Core functions and benefits of CMMS

A CMMS has become an essential tool due to its crucial role in optimizing maintenance operations and improving asset management across various industries [4, 18]. It acts as a centralized database that stores detailed information related to assets, spare parts, personnel, and maintenance strategies. By handling large volumes of data, a CMMS supports trend analysis, helping organizations refine their maintenance strategies, and make more informed, data-driven decisions [4]. It also provides real-time feedback, making maintenance processes more responsive and efficient [4].

Many CMMS platforms also support user interaction, planning, and collaboration through access control and shared documentation [19]. They also improve efficiency through preventive maintenance scheduling, inventory tracking, and integration with other systems, helping to reduce breakdowns, extend equipment life, control costs, and ensure regulatory compliance [18]. Furthermore, they enhance collaboration and accountability by allowing user interaction, task tracking, and real-time notifications. Moreover, they build a knowledge base of past issues and solutions, speeds up spare parts procurement, and supports better supplier negotiations [20].

Lastly, CMMS supports informed decision-making by offering powerful analytics and reporting features. Managers can evaluate data on energy use, equipment downtime, maintenance costs, and performance trends to improve strategic planning, operational efficiency, and resource allocation [10, 16].

3.1.3 Limitations of traditional CMMS and the need for automation

The shift from traditional maintenance methods to Information and Communication Technologies (ICT)-based systems, such as CMMS, has become essential, especially as the systems must evolve alongside technological advancements [4]. With the increasing digitization and automation in recent years, the demands on maintenance management have changed significantly. Traditional CMMS still play a key role by centralizing maintenance data [4]. However, their limitations prevent the full realization of Industry 4.0's potential.

One major drawback is their reliance on manual data entry [4, 5], which is both time-consuming and prone to errors. Moreover, without direct integration with machines, CMMS cannot effectively support predictive maintenance or real-time data-driven decision-making [5]. As noted by [21], these systems also lack advanced decision analysis capabilities, which is crucial for modern maintenance strategies.

To address these limitations, [22] suggests integrating diagnostic, prognostic, machine learning, and decision-support algorithms into existing CMMS platforms. These tools can analyze equipment data, forecast failures, and recommend optimized maintenance actions. When integrated, the CMMS could automatically plan and schedule maintenance tasks based on real time insights.

Additionally, incorporating the latest technologies enables information to be transmitted to the systems immediately, eliminating the need for manual data entry. By collecting and analyzing data in real time, the system can process insights and transfer them to humans for final decision-making [4]. This capability enables maintenance managers to oversee and monitor multiple operations or facilities simultaneously [4].

3.2. Industry 4.0: The era of predictive maintenance and the transformation of CMMS

As we move into the era of Industry 4.0, advanced technologies are reshaping the field of maintenance management, driving smarter and more efficient operations. This section of the literature review will examine the fundamental principles, key concepts, and pillars underlying Industry 4.0, including the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, cloud computing, and advanced robotics. These technologies are fundamentally changing the way industries approach maintenance.

Moreover, they are unlocking new possibilities for predictive maintenance strategies. Understanding these technologies is essential, as they will serve as the foundation for future discussions on their integration into modern maintenance management systems.

3.2.1 Industry 4.0 : An Introduction

Industry 4.0, often called the fourth Industrial Revolution, signifies a profound shift in industrial production, driven by the rise of internet technologies since the late 1990s and accelerated by global interconnectedness [8]. It introduces an advanced phase of digital transformation where technologies such as cyber-physical systems (CPS), the Internet of Things (IoT), Artificial intelligence (AI), big data analytics and cloud computing converge to create smarter, more connected, and auto-

mated industrial systems [1, 4, 23, 24].

Unlike earlier industrial revolutions, Industry 4.0 enables real-time interaction between machines, systems, and humans, allowing for intelligent production processes with greater flexibility and efficiency [24, 25].

Originating in Germany as a strategic initiative to modernize manufacturing Industry 4.0 promotes the concept of “smart factory”, where machines communicate, analyze large data sets, and make autonomous decisions to optimize performance and reduce waste [25, 26]. It supports predictive maintenance, reduces downtime, and allows for more personalized production to meet evolving market demands [24, 27, 28].

Importantly, industry 4.0 is not solely technology driven; it also emphasizes human integration. While automation and AI enhance productivity, human expertise remains essential for supervision, strategic decisions, and continuous improvement. The goal is to augment human roles by shifting them toward creative, value-added tasks, fostering a collaborative environment between people and technology [24, 25, 27].

3.2.2 Predictive maintenance and the third generation of CMMS

Predictive Maintenance, referred as “PdM 4.0” or “Maintenance 4.0”, is a concept developed under the influence of Industry 4.0, aims at preventing asset failure by performing servicing shortly before a failure is expected [12]. By using big data, AI, and continuous real-time asset monitoring, it identifies patterns and anomalies to predict and prevent failures, thus reducing both planned and unplanned downtimes while increasing equipment availability and cost efficiency [8, 12, 13].

In the Maintenance 4.0 era, the integration of these advanced technologies has led to fully automated data collection from a wide range of sources, including sensors, operators, from Original Equipment Manufacturers (OEMs), and IT systems. Advanced analytical methods such as fuzzy logic, neural networks, and machine learning enable predictive and prescriptive maintenance strategies, while cloud services ensure scalable, accessible, and efficient data management [13].

The evolution of CMMS into its third generation in the 1990s laid the groundwork for these advancements. These systems introduced features like EHS modules (Environmental, Health, and Safety), e-MRO capabilities (e-Maintenance, Repair and Operations), multimedia support, and ERP integration, reflecting the early shift toward connected, analytical, and web-based maintenance tools [15]. This evolution enabled today’s fully digital and intelligent maintenance practices characteristic of Maintenance 4.0.

3.2.3 Core principles and key concepts of I4.0

Industry 4.0 is centered around automation, digitalization, and the integration of advanced technologies to enhance industrial and manufacturing processes [29]. A foundational step in implementing Industry 4.0 is establishing reliable data collection and storage systems, which enable more advanced capabilities like pattern recognition, predictive analytics, automated decision-making, and self-optimization [29]. While individual technologies offer value on their own, their full potential is unlocked when integrated into a smart and connected system [30].

The core principals of Industry 4.0 include **Interoperability**, which ensures seamless interaction and information exchange between cyber-physical systems and humans, **Virtualization**, which relies on digital twins to monitor physical processes in real time through sensor data, **Real-time Capability** for instant analysis and decision-making based on latest knowledge and predictions, **Service Orientation** through the integration of IoT and Internet of Services creating a more connected and efficient system, **Modularity** for flexibility and adaptability using modular equipment and production lines, and **Decentralized Control**, allowing autonomous decision-making at different levels [19]. Additional principles like **Technical Assistance**, which supports human operators through digital tools and intelligent systems that enhance their performance, **Information Transparency** that provides businesses with valuable data insights to improve decision-making and **Interconnection** that allows machines, software systems, and human workers to communicate easily, ensuring a fully integrated industrial ecosystem [31].

Building on these principles, Industry 4.0 introduces key concepts that translate these ideas into practical applications, [30] identifies 24 critical concepts including **Mass Customization** allowing companies to produce personalized products using smart technologies **Servitization** shifts the focus from selling physical products to offering service-based solutions, **Logistics 4.0** uses smart technologies to improve supply chains, **New Product and Service Development**, encouraging innovation through connected and intelligent products, **Adaptation to Human Needs** improves human-machine interactions using IoT and Big Data, and **Products** allow intelligent communication and interaction with systems. While Sustainability is promoted through **Circular Economy (CE)** which focuses on reducing waste by reusing and recycling materials, **Recycling 4.0** that uses smart technologies to improve recycling processes, and **Remanufacturing**, which restores used products to like-new conditions using Industry 4.0 innovations.

In addition, concepts like **Lean Manufacturing**, and **Knowledge Management** supports efficiency and informed decision-making, **Systems Science** explores interactions between various Industry 4.0 components.

Innovation Management ensures the integration of new ideas and technologies into industrial processes, while **Business Process Reengineering (BPR)** focuses on redesigning operations to improve efficiency. **Self-Organization** allows businesses to enable decentralized and autonomous decision-making. To strengthen collaboration and connectivity, **Collaborative Networks (CN)** enhance internal and external communication, while **Vertical and Horizontal Integration** optimize inter-organizational processes [30]. Advanced manufacturing techniques such as **Flexible Manufacturing (FM)** and **Agile Manufacturing (AM)** enable industries to quickly adapt to new market demand. One of the most significant developments in Industry 4.0 is the rise of **Smart Factories**, where automation and interconnected systems drive efficiency, supported by **Product Life-cycle Management (PLM)** that provides smooth management from design to disposal [30]. **Digital Transformation** underpins all these changes, reshaping operations and business models. Finally, these innovations extend beyond industry into **Smart City**, enhancing infrastructure and sustainability in urban environments [30].

Moreover, A recent emerging development within Industry 4.0 is the concept of **Biologicalization** in manufacturing, which involves integrating biological and bio-inspired principles into intelligent and sustainable manufacturing systems. While the idea itself is not entirely new, the rapid progress in digitalization and Industry 4.0 technologies has accelerated its implementation. This approach aims to create more sustainable, efficient, and adaptive production processes by incorporating biological principles into industrial applications. The underlying concept of biologicalization is built on existing capabilities and is expected to be further enhanced by future developments within Industry 4.0. [32].

By embracing these principals alongside advanced digital technologies, businesses can fully leverage Industry 4.0 to boost productivity, foster innovation, and adapt to dynamic industrial landscape.

3.2.4 Pillars of Industry 4.0

While these concepts define the strategic and operational advancements of Industry 4.0, their realization depends on a set of enabling technologies. These technologies, often referred to as the ‘pillars’ of Industry 4.0, provide the necessary digital infrastructure, automation capabilities, and intelligent systems that make these concepts actionable. These nine pillars (Figure 3) include the Industrial Internet of Things (IIoT), big data and analytics, horizontal and vertical system integration, simulation, cloud computing, augmented reality (AR), autonomous robots, additive manufacturing, and cybersecurity with cyber-physical systems [1, 4, 19, 26, 27, 30].



Figure 3: Pillars of the fourth industrial revolution [33]

These interconnected technologies enable industries to optimize processes, improve decision-making, and address challenges in modern manufacturing.

– Big Data and Analytics:

Big data and analytics are essential in modern industries, enabling the collection and analysis of large, diverse, and fast-moving data from various sources like production systems and customer platforms [27]. This supports advanced analytics that improve production quality, reduce energy use, and enhance equipment performance [26]. Built on the three key characteristics of big data; Volume, Variety, and Velocity; that enable real-time monitoring, process automation, and efficient production management [29]. It also aids in predictive maintenance by identifying patterns and anticipating equipment failures, helping to minimize downtime and costs. Moreover, big data enhances business intelligence, improves customer relationships, and promotes sustainable manufacturing through optimized resource usage and process improvements [26, 29].

– Autonomous Robots:

Autonomous robots have evolved significantly since Industry 3.0, where they were primarily used to handle complex tasks [26]. Today, they are becoming smarter, more flexible, and capable of working safely alongside humans. These robots can learn from human interactions, collaborate with other robots, and communicate effectively for better efficiency [27]. Their autonomy allows them to perform precise tasks, operate in hazardous environments, and improve overall workplace safety and productivity. As they continue to advance, autonomous robots are becoming more adaptable, collaborative, and essential in modern industries [26].

– Simulation:

Simulation technology has become an essential tool in modern industries, allowing virtual models to represent real-world systems and reduce the need for physical testing [27]. In factories, simulations help

optimize machine setup, improve product quality, and strengthen decision-making by reflecting real-time data from machines, workers, and processes. Simulation has significantly reduced failures and saved industries substantial costs [26]. Additionally, 2D and 3D simulations enable virtual commissioning, cycle time analysis, energy efficiency assessment, and workplace ergonomics evaluation, contributing to more reliable and efficient industrial operations [27].

– **System Integration:**

System Integration is a key aspect of Industry 4.0, enabling factories and production systems to become more connected and automated [27]. This integration occurs in three main ways: horizontal integration, where different companies collaborate to optimize the supply chain; vertical integration, where machines, systems, and processes within a factory are interconnected to enhance performance integration [27] involving a company managing its value chain internally, covering everything from product design and manufacturing to sales and marketing [26], and end-to-end integration, which digitally links the entire product life cycle, from design to production and customer use [27]. By integrating systems at all levels, industries achieve better automation, communication, and coordination, leading to more efficient and optimized production processes [27].

– **The Internet of Things:**

The Internet of Things (IoT), also known as the Internet of Everything (IoE), is a global network of connected devices that communicate using standard protocols, enabling real-time data collection and sharing [26]. It improves interaction between people, machines, and sensors across industries [29]. Key components include the Internet of Services (IoS), Internet of Manufacturing Services (IoMs), and Internet of People (IoP), supported by embedded systems and ICT integration for efficient operation [27]. IoT is driven by three core features: context-awareness, omnipresence, and process optimization. These features enable devices to interact with their environment, share data, and automate improvements [27]. Ultimately, IoT plays a vital role in advancing manufacturing excellence and supporting the digital transformation of industries [25].

– **Cybersecurity and Cyber-Physical Systems (CPS):**

Cybersecurity and Cyber-Physical Systems (CPS) are vital in Industry 4.0 due to increased connectivity and the resulting cyber risks [27]. Cybersecurity ensures the protection of data, systems, and networks from cyber threats through secure communication and access control [26].

Cyber-Physical Systems (CPS) integrate physical components with digital networks, using sensors and smart technologies to monitor, automate, and make real-time

decisions [27, 32]. Commonly used in manufacturing and traffic control, CPS enhance efficiency and responsiveness [27]. They also leverage cloud systems to create digital representations of physical assets, enabling performance tracking, failure prediction, and process improvement [27].

– **Cloud Computing:**

Cloud technology is essential in Industry 4.0, enabling real-time communication and data sharing across systems, sites, and stakeholders [27]. In smart factories, cloud platforms allow efficient data storage, analysis, and access, enhancing decision-making, collaboration, and operational efficiency [26]. Cloud manufacturing builds on this by providing decentralized, on-demand access to computing resources, software, and services; boosting flexibility and resource optimization [32]. Supported by cloud computing, IoT, and service-oriented architecture, this model is backed by major tech companies like Microsoft, Google, and Autodesk [26]. Additionally, cloud manufacturing promotes sustainability by reducing waste and improving resource use, contributing to a more resilient, automated, and scalable industrial future [25].

– **Additive manufacturing:**

Additive manufacturing, or 3D printing, is a key Industry 4.0 technology that builds products layer by layer, enabling complex, lightweight, and customized designs with minimal waste [25, 32]. It is widely used for prototyping and producing small parts, especially in industries like aerospace where weight reduction lowers fuel consumption [26]. Decentralized 3D printing cuts shipping and storage costs by producing parts closer to demand locations [27]. This technology supports sustainability by reducing waste and enabling closed-loop recycling, making it both environmentally and economically beneficial [25]. Consequently, additive manufacturing is considered essential for product personalization and adaptation in modern industry [29].

– **Augmented Reality:**

Augmented Reality (AR) is a key Industry 4.0 technology that enhances user interaction with the real world by overlaying digital content such as images, videos, and data [34]. It is used in sectors like healthcare and automotive for training, diagnostics, and design [26]. In manufacturing, AR supports quality control, maintenance, assembly, and safety by providing real-time guidance and improving human-machine interaction [32, 35]. It also enables virtual training and remote expert assistance [29].

– **Blockchain:**

Beyond core technologies, Blockchain is emerging as another vital Industry 4.0 component. It offers secure, transparent, and tamper-proof data sharing, especially

useful in supply chain management, smart contracts, and data integrity [25, 36].

– Artificial Intelligence (AI) and Machine Learning (ML):

Artificial Intelligence (AI) and Machine Learning (ML) are also crucial, enabling data-driven decision-making, automation, and process optimization. These technologies enhance efficiency, reduce errors and costs, and support sustainable and high-precision manufacturing [25]. Building upon the capabilities of AI and ML as illustrated in Figure 4, Natural Language Processing (NLP) and Large Language Models (LLM) further improve the potential of Industry 4.0 technologies. NLP allows machines to understand, interpret, and generate human language, facilitating more intuitive human-machine interactions. LLM, a subset of NLP, leverages vast amounts of text data to generate coherent and contextually relevant responses, enhancing the capabilities of AI-driven systems. The integration of NLP and LLM in industrial applications can automate and optimize various processes, such as report generation, data analysis, and decision-making, thereby enhancing operational efficiency and effectiveness[37].

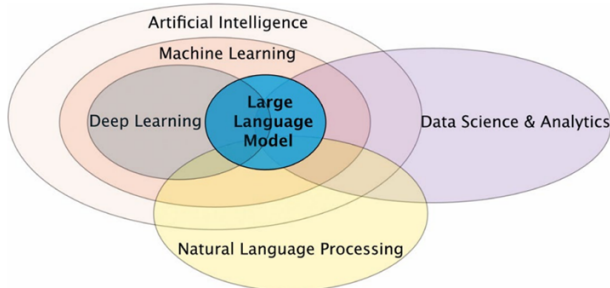


Figure 4: Intersection of Key Technologies in Industry 4.0 [37]

3.2.5 Advantages of Industry 4.0

Industry 4.0 marks a major transformation in manufacturing by integrating advanced technologies such as automation, artificial intelligence (AI), cloud computing, and the Internet of Things (IoT). It enables smart, efficient, and cost-effective production, including individualized and customized manufacturing, while maintaining reasonable costs [24, 27].

A key goal of Industry 4.0 is to create a structured and autonomous production system, where products can manage their own production processes using smart technologies [26].

According to [26], Industry 4.0 significantly impacts four main areas:

- **Productivity:** Many companies report productivity increases of 25-30% and the automotive in-

dustry expects a 10-20% boost in production efficiency.

- **Revenue Growth:** As productivity improves, industries experience higher revenues.
- **Employment:** While automation raises concerns about job losses, studies predict a 5-10% increase in employment over the next decade, particularly in fields such as mechatronics, software engineering, and communication engineering.
- **Investment:** The adoption of AI and cloud computing has led to increased investment in industrial innovation.

Industry 4.0 also improves competitiveness by integrating sustainability into production and enhancing system efficiency [25]. The horizontal and vertical integration of technologies helps companies become more flexible, resilient, and profitable [38].

Another major benefit is the connectivity between all stakeholders; including machines, raw materials, and products, supporting sustainability and long-term growth. Smart factory technologies, such as improved robotics and machine-to-machine communication, enable better decision-making and higher-quality, more efficient production [38]. As highlighted in [30], Industry 4.0 introduces several essential characteristics:

- **Cost Savings:** Automation reduces production costs.
- **Data Reliability & Transparency:** Real-time data improves decision-making.
- **Autonomous Decision-Making:** AI and machine learning optimize processes.
- **Time Savings:** Automated workflows reduce production and delivery times.
- **Improved Quality:** Smart technologies enhance product reliability and minimize defects.
- **Higher Productivity:** Automated systems handle repetitive tasks, freeing workers for complex activities.
- **Sustainability & Resource Efficiency:** Energy use is optimized and waste reduced.
- **Agility & Flexibility:** Businesses can quickly adapt to market changes.
- **Real-Time Inventory Tracking:** IoT and RFID prevent overstocking or shortages.

In summary, Industry 4.0 is revolutionizing manufacturing by making it more intelligent, sustainable, and profitable. It drives economic growth, encourages innovation and investment, and creates new job opportunities in technology-driven sectors.

4. Exploring the Integration of CMMS within the Pillars of Industry 4.0: Related Work and Advances

To gain a deeper understanding of which Industry 4.0 pillars have been explored in previous research and how they can be integrated with Computerized Main-

tenance Management Systems (CMMS), this section presents a selection of case studies and conceptual frameworks drawn from the existing literature on the topic. The reviewed articles reveal a frequent use of certain Industry 4.0 pillars, including Augmented Reality (AR), Simulation, the Industrial Internet of Things (IIoT), Artificial Intelligence (AI) and Machine Learning (ML) algorithms, as well as Big Data & Cloud computing, each applied through various methods and perspectives proposed by different authors. These pillars are sometimes implemented individually and, in other cases, combined to create more advanced and integrated maintenance solutions.

The integration of these pillars into CMMS has served multiple objectives aimed at enabling advanced maintenance strategies, the most prominent objectives identified in the literature are Maintenance Process Optimization, Improving Intervention and Decision-Making, and the Implementation of predictive maintenance (PdM) strategies.

In the following sections, the case studies and frameworks associated with each of these objectives will be detailed and analyzed to illustrate the practical applications and benefits of combining Industry 4.0 technologies with CMMS.

4.1. Maintenance Process Optimization

Maintenance process optimization involves automating and enhancing maintenance activities through the adoption of advanced Industry 4.0 technologies. According to the literature, this objective is typically achieved by combining multiple pillars of Industry 4.0, which provide a cohesive framework for improving system connectivity, data flow, decision-making capabilities, and automated maintenance processes.

The article by [39], presents a method to transform conventional maintenance workflows into intelligent, automated processes within CMMS/EAM environments. The authors propose integrating Machine Learning (ML) and Multi-Criteria Decision Making (MCDM) methods to reduce the reliance on manual operations, more specifically, the goal is to automate the filling out of maintenance order forms and the allocation of maintenance technicians, with the overall aim of improving efficiency, reducing delays, and minimizing human error in maintenance operations.

Specifically, the article links CMMS to the broader context of Industry 4.0 by introducing a smart workflow architecture as illustrated in Figure 5. This integration begins at the physical level with industrial assets equipped with sensors that monitor various parameters such as temperature, vibration, and pressure. These sensors transmit data in real time to industrial controllers using standardized communication protocols like OPC UA, MQTT, and RESTful HTTP. The collected data is then routed into CMMS/EAM systems, creating a continuous data pipeline that supports real-

time monitoring and decision-making.

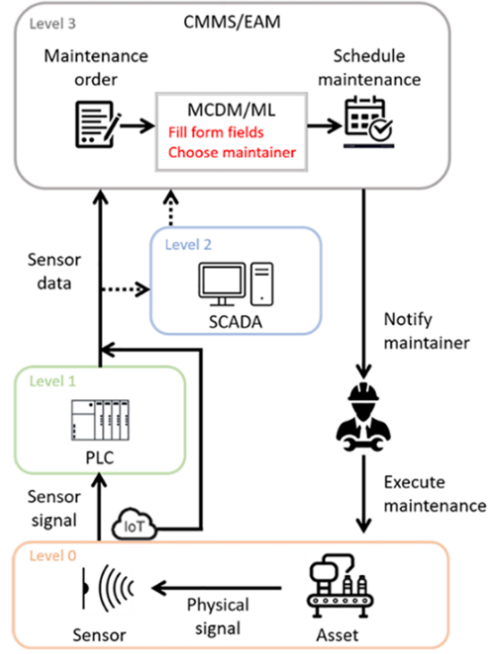


Figure 5: CMMS smart workflow [39]

To automate the workflow, the authors introduce two complementary frameworks: a serial approach and a parallel approach.

In the serial approach (Figure 6), MCDM is used to select the most relevant features from the maintenance database. These features are then passed to ML algorithms such as Decision Trees, Naive Bayes, and Support Vector Machines (SVM) to classify and auto-fill fields in maintenance order forms. This reduces the need for manual data entry and ensures standardized, accurate documentation.

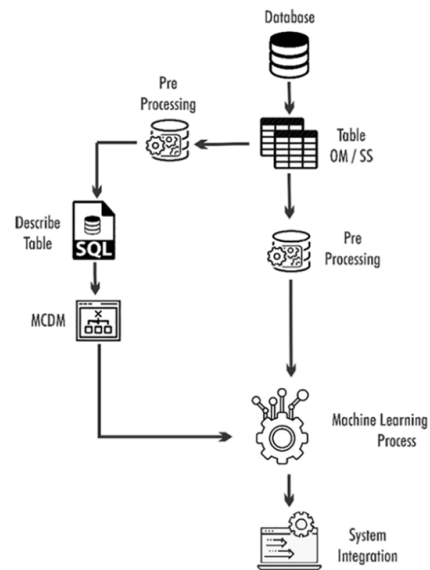


Figure 6: Serial approach framework [39]

In the parallel approach (Figure 7), MCDM first evaluates and ranks maintenance personnel based on criteria

such as skill level, availability, seniority, and absence records. If the TOPSIS-based ranking yields alternatives with very close scores, ML is then used as a secondary classifier to make a more precise assignment.

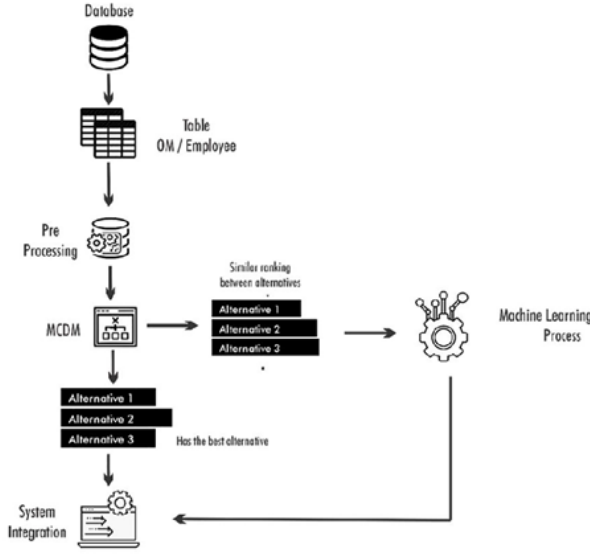


Figure 7: Parallel approach framework [39]

A case study conducted in a Brazilian multinational company that develops and distributes CMMS/EAM systems worldwide to support theoretical proposal. The study involved the analysis of over 400,000 maintenance orders recorded between 2017 and 2019, comprising 113 data fields per record. The implementation of the proposed smart workflows in this real-world setting demonstrated a measurable improvement in the efficiency and accuracy of maintenance operations. Notably, the auto-filling of forms and automated technician assignment led to faster execution of maintenance tasks and reduced delays caused by human intervention.

Moreover, the system was positively evaluated by the internal development team, composed of five experts with over four years of experience in maintenance software. Their feedback, collected through a structured survey, confirmed that the integration of ML and MCDM not only streamlined operations but also enhanced the overall reliability and usability of the CMMS.

Another study, [40], emphasizes the integration of the Industrial Internet of Things (IIoT), Augmented Reality (AR), Artificial Intelligence (AI), and Cloud Computing into a centralized, cloud-based Computerized Maintenance Management System (CMMS). The main objective of this integration is to digitalize and automate maintenance processes, enhance real-time decision-making, and improve data accessibility across the maintenance chain.

To illustrate this integration, the study presents a conceptual framework supported by a smart maintenance testbed. This testbed combines several Industry 4.0 components :

- An IIoT platform for real-time data acquisition from machines and sensors,
- A cloud-based CMMS for centralized maintenance management and work order generation,
- AR technology for providing interactive maintenance instructions on-site,
- Autonomous Robots to deliver tools and spare parts to maintenance personnel,
- Standard communication protocols (OPC UA, Modbus, WebSockets) to ensure interoperability among all components,
- AI and data analytics tools to interpret maintenance data and trigger appropriate actions.

Within this testbed, an IIoT Gateway connects multiple components to the IIoT platform via WebSockets. The system comprises two main stations, and the architecture of the testbed is shown in Figure 8.

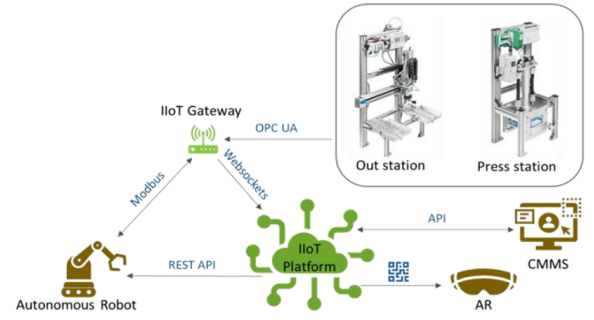


Figure 8: Architecture for the testbed [40]

- Press-station: When 70 parts have been pressed, the IIoT platform automatically generates a work order in the cloud-based CMMS. This order is displayed on the platform's dashboard, detailing the required maintenance tasks. Simultaneously, the Autonomous Robot delivers the necessary tools and spare parts, and a QR code is displayed, providing digitalized maintenance instructions via AR.
- Out-station: A gripper moves along a linear guide between two points (A and B), with sensors measuring the travel time. If the measured time exceeds a predefined threshold, the IIoT platform generates a work order in the cloud-based CMMS, signaling the need for cleaning, lubrication, or component replacement. This triggers the Autonomous Robot to deliver the required tools and spare parts while displaying a QR code for AR-based maintenance instructions.

The article shows that cloud-based CMMS enhances smart maintenance by integrating real-time data, analytics, and AR to support autonomous strategies.

The research by [41] also contributes by developing a next-generation platform that incorporates industry 4.0 technologies to overcome the limitations of traditional CMMS solutions.

The proposed CMMS is cloud-based that can be accessed by internet and integrates seamlessly with real-time sensory data collection, leveraging two key Industry 4.0 pillars: the Industrial Internet of Things (IIoT) and Big Data & Cloud computing. These technologies are applied to support Condition Based Maintenance (CBM), real-time monitoring, and remote interaction. To this end, a suite of wireless sensors was developed to monitor critical machine parameters, including vibration, temperature, gas levels, and power consumption, ensuring compatibility across various equipment types. Additionally, a wireless maintenance call button was introduced to address downtime caused by communication delays; identified as a major source of inefficiency. When triggered, the button sends an instant alert to the responsible personnel, significantly reducing response time and increasing equipment availability.

The platform further automates maintenance by linking sensor thresholds directly to maintenance planning. When a predefined threshold is exceeded, the system autonomously generates and assigns a maintenance task to the appropriate staff, eliminating the need for manual input.

According to the authors, the developed platform incorporates key Industry 4.0 technologies by enabling IIoT based connectivity, real time data monitoring, and automated maintenance task generation. Sensor data is continuously collected and visualized, allowing for timely interventions and improved decision-making. The system automatically assigns recurring maintenance tasks, tracks user performance, and facilitates digital work order management. It also enhances traceability through QR-coded spare parts and provides cost monitoring tools to assess operational efficiency. These features collectively contribute to a smart, data-driven maintenance environment aligned with the goals of Industry 4.0.

To complete this overview, a Real Time Equipment Monitoring (RTEM) system was developed for industrial oil and gas company, as described in [42], to improve asset management and effectively track asset locations while gathering data on their operation and maintenance status. The system utilized GPS, barcodes, and RFID tags which are integrated with the CMMS. RFID, in particular, is wireless, and contactless technology that enables automated identification and data exchange between devices within the system. It functions through three primary components: the tag, the reader, and the antenna, allowing the system to capture and process specific information about a targeted object using radio frequency signals [42].

The data collected from the RFID tags is stored in the CMMS which is connected to the intranet to ensure efficient information flow. The primary purpose of the data stored in the CMMS is to enable management and personnel to easily monitor the condition of the asset. The system aims to significantly reduce the time spent locating assets and increase their utilization by capturing data related to:

- Identification of equipment, parts and products;

- Tracking their time and position throughout the value chain;
- Record their manufacturing and maintenance history.

The implementation of the system follows several key steps. First, all available asset data including location, types, serial number and maintenance history, is gathered from the existing CMMS. Next, the mapping and installation phase involves the setup of GPS devices and the attachment of barcode labels to the assets. The third step include updating the CMMS to reflect the newly tagged information. Finally, a BETA test; an acceptance test performed by the end-user of a product to validate its functionality, reliability, and compatibility [33]; is conducted to ensure that the system meets the user expectations in terms of functionality, reliability, and alignment with the asset management strategy.

According to [42], the RTEM model brought substantial automation to the company's process, covering everything from maintenance planning to spare parts management and asset monitoring. Asset related activity data is now stored digitally and can be accessed with ease. Using this system, maintenance staff simply scan the barcode on an asset's tag during its maintenance, and fill out a checkbox on a digital form using a portable device. This information is sent to the cloud and recorded in a centralized database, automatically updating the asset's maintenance history. When the database is queried, it provides details such as the asset's current location, completed tasks, and any outstanding work. Additionally, technicians can upload photos to document the asset's condition. If the system detects an asset in an unauthorized area, it can alert to the asset manager for immediate investigation.

The reviewed studies under the objective of maintenance process optimization demonstrate how the integration of CMMS with Industry 4.0 technologies enables the transformation of traditional maintenance systems into intelligent, efficient workflows [39]. By combining sensor data, communication protocols, AI-based decision-making, and automation, these systems improve responsiveness, accuracy, and overall operational performance. In particular, cloud-based CMMS platforms serve as central hubs, integrating real-time IIoT data, advanced analytics, and AR tools [40]. Moreover, the RTEM model discussed in [42] reinforces these findings by showcasing a fully digitized and automated maintenance environment, where real-time data acquisition, centralized tracking, and smart alerts contribute to significant streamlined process and improved asset management efficiency.

4.2. Improving Intervention and Decision-Making

The second objective of integrating Industry 4.0 pillars with a CMMS is to increase the efficiency of maintenance interventions through real-time support for on-

site operations, aiming to minimize downtime, reduce delays, and ensure equipment availability, and enhance decision-making while leveraging unstructured historical maintenance data stored in databases. To achieve this, the most frequently cited technologies in the literature include Augmented Reality (AR), often combined with Cyber-Physical Systems (CPS) and Machine Learning algorithms to provide effective, context aware maintenance assistance, as well as Natural Language Processing (NLP) techniques to extract valuable insights from unstructured data.

A first example is found in [43] where the authors proposed an architecture for integrating a CMMS with Augmented Reality (AR), to reduce equipment breakdowns and unexpected delays. The system consists of three main components: a CMMS, a wearable AR device (Microsoft HoloLens), and an information controller, as illustrated in Figure 9.

To demonstrate the concept, a desktop 3D printer was used as an example; an emerging technology expected to revolutionize future manufacturing processes.

The development of the system followed several key steps. First, the relationship between different data components were structured to ensure efficient storage and retrieval, this includes linking each machine to its failure history, potential causes, and corresponding maintenance instructions based on manuals and expert knowledge. Next, a Graphical User Interface (GUI) was designed for the AR-CMMS system to present asset information in formats such as text, verbal messages, labels, 3D animations, or videos to guide maintenance tasks. AR targets were attached to the equipment to define where digital content should appear in the user's view. And multiple image targets allowed for the placement of various virtual elements. Finally, web-based services were created to enable data exchange between the AR system and the CMMS web server.

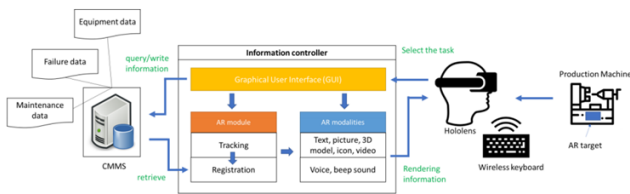


Figure 9: System architecture [43]

The AR-CMMS system allows users to interact with maintenance tasks via a graphical interface on the HoloLens. Users can access the AR application's features via the GUI to perform tasks or create work orders using a wireless keyboard. When the user looks directly at a marker on the machine, the system detects its ID and retrieves data from the CMMS. In the event of a breakdown, operators can report the issue through voice or text. The system then suggests possible causes, guiding the operator through step-by-step diagnostics with text and video instructions.

Confirmed non issues are marked green, and once the problem is resolved, the operator must close the work order (WO) to update the machine's history. If the issue is unknown or unresolved, a Skype call with a technician can be initiated. If the root cause is found but cannot be fixed immediately, or if the problem remains undefined, a WO is created and forward for further action by maintenance staff.

This system offers several advantages, including the potential to reduce downtime caused by unexpected breakdowns. It enables untrained operators to carry out basic diagnostics and minor repairs, allowing skilled technicians to focus on more complex issues. The integration of augmented reality in maintenance can significantly enhance productivity and reduce overall production costs [43].

Similarly, the authors of [44] assert that combining Augmented Reality (AR) with a Computerized Maintenance Management System (CMMS) can serve as a strategic information system for manufacturing decision-making. This integration aligns with the concept of intelligent factories in the industry 4.0 ecosystem.

The main contribution of [44] lies in the development of a methodology for creating a next generation information system that merges AR-based data visualization with CMMS functionalities. According to the authors, CMMS solutions are essential for storing and managing maintenance data from machine registration to preventive maintenance planning. While many companies rely on these systems to support their decisions, [44] point out that the way information is presented lacks clarity.

To address this limitation, the authors propose integrating AR with CMMS to improve the clarity, usability and accessibility of maintenance data. The study describes a three-phase methodology for developing and implementing the proposed approach aimed at improving decision-making in maintenance management.

– Phase 1: CMMS Development

The first step is to develop a CMMS for a León-based company specializing in dyes and paints, aiming to optimize maintenance operations and failure tracking. The CMMS included key features such as:

- Catalog management (equipment, tools, technicians, users, etc.).
- Service management (work orders, scheduling).
- Corrective and preventive maintenance tracking.
- Automated reports and data visualization with export options (Excel, PDF, etc.).
- User permissions and session management.

The system was iteratively tested and refined at each development stage, with feedback from the company to ensure alignment with operational needs.

– Phase 2: Augmented Reality (AR) Integration

After establishing the CMMS, an AR-based visualization system was developed to improve maintenance reporting. The AR component was built using Unity and connected to the CMMS database via a web server where MySQL data was accessed through PHP scripts. The AR visualization process evolved:

- Developing Unity scripts using UnityEngine;
- Fetching CMMS data via a PHP script that retrieved maintenance reports;
- Displaying key metrics in AR using Vuforia, enabling users to scan CMMS-related tags and visualize maintenance trends dynamically.

– Phase 3: System Evaluation

The final phase focused on validating the CMMS-AR integration through usability, functionality, and performance testing. Both user feedback and technical performance metrics were analyzed to assess the system’s effectiveness.

According to [44], integrating a CMMS with Augmented Reality (AR) enhances decision-making, user experience, and maintenance efficiency by providing interactive, real-time data visualization. AR simplifies access to maintenance records, accelerates fault diagnosis, and improves report accessibility, enabling technicians to quickly identify issues and implement corrective actions. The system facilitates dynamic, interactive reporting, reducing reliance on static reports and manual data entry. Additionally, AR supports knowledge transfer, training, and standardization of maintenance procedures, ensuring best practices are consistently followed.

Another notable study [45] explores the integration of NLP with multidimensional classifiers to improve CMMS metadata prediction. CMMS platforms often contain unstructured text such as maintenance issue descriptions written by technicians that is difficult to analyze due to abbreviations, technical jargon, and incomplete sentences. The goal of the study is to use NLP techniques to automatically interpret and categorize these descriptions, helping to identify the failure type, its cause, and the necessary corrective action. The study uses maintenance data from a large pharmaceutical company, comprising thousands of records over ten years. Each record includes both structured and unstructured text. Researchers cleaned and standardized the text, grouped similar terms, and tested various machine learning models including Random Forests, SVMs, GRUs, CNNs, and RobBERT (a Dutch language model). They also accounted for relationships between metadata components, such as failure types and corresponding corrective actions. Performance was evaluated using metrics like accuracy, precision, and recall. Neural network models performed best, especially with longer text inputs. Challenges included ambiguous text, unclear labels, and overly short descriptions. Key findings show that NLP can:

- Automate Metadata Prediction: Reducing manual effort and human error by automatically generating structured data from text.
- Correct Mislabeled Entries: Enhancing data quality by identifying and fixing incorrect labels.
- Model Metadata Dependencies: Improving prediction accuracy by understanding how metadata elements relate to each other.

In summary, The studies reviewed demonstrate that the integration of Augmented Reality with CMMS significantly enhances maintenance efficiency by improving decision-making, streamlining interventions, and enabling real-time data access, while also facilitating faster diagnostics and procedural standardization aligning perfectly with Industry 4.0 objectives [44]. Complementing these benefits, Natural Language Processing demonstrates transformative potential for CMMS by automating classification, improving data accuracy and advanced analysis of unstructured maintenance records.

4.3. Driven Predictive Maintenance via CMMS

The third objective aims to improve maintenance operations by integrating predictive maintenance strategies within CMMS through the adoption of Industry 4.0 technologies. This transition from reactive and preventive approaches to a data-driven predictive model improves equipment reliability and minimizes downtime. Several studies have proposed reference architectures, conceptual frameworks, and practical implementation approaches to position CMMS as the central component of an intelligent maintenance ecosystem.

A notable contribution is provided by [46], which proposes a reference software architecture for an integrated predictive platform aimed at efficiently utilizing data from existing industrial systems, particularly CMMS. This architecture, illustrated in Figure 10, enables seamless integration with CMMS and related systems, reducing the time and effort required to extract critical data for process optimization.

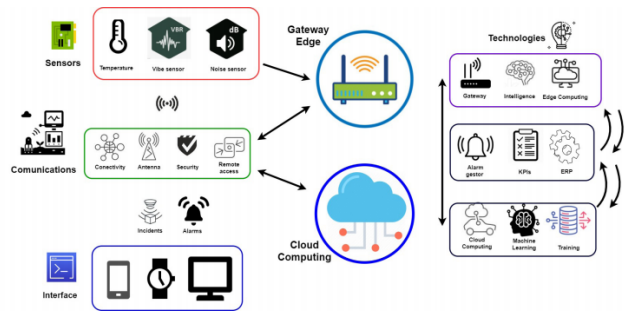


Figure 10: System architecture diagram [46]

The solution incorporates a Smart Data platform op-

erating within a Fog/Edge Computing environment, enabling real-time processing and integration of data from various sources including CMMS, ERP, SCADA, and IIoT systems. It collects and analyzes key factory parameters such as vibration, noise, temperature, and more. By combining this capability with artificial intelligence and machine learning algorithms, the system can manage and interpret a vast range of operational data.

In the context of predictive maintenance, the system continuously monitors critical system components by analyzing maintenance records from CMMS, machine performance, and sensors data. The aim is to reduce both corrective and preventive interventions, moving toward a fully predictive maintenance model. This involves breaking down incidents, using Failure Tree Analysis (FTA) to understand root causes, and applying Failure Mode and Effects Analysis (FMEA) to anticipate the impact of abnormal patterns. Additionally, the system integrates a learning module based on Deep Reinforcement Learning, supported by expert input via Natural Language Processing (NLP), recommend preventive actions and avert potential failures.

Successful integration with existing industrial information systems requires a clear methodology and a degree of customization tailored to the specific needs of each industry. As illustrated in Figure 11, the proposed system consists of:

- A horizontal platform for information processing, security policy generation, and integration of vertical solutions;
- A suite of vertical solutions designed for automated monitoring and enhancement of various industrial aspects;
- A sensor network to monitor environmental and operational parameters, linked through communication gateways;
- User interfaces deployed on mobile devices for seamless interaction with the platform.

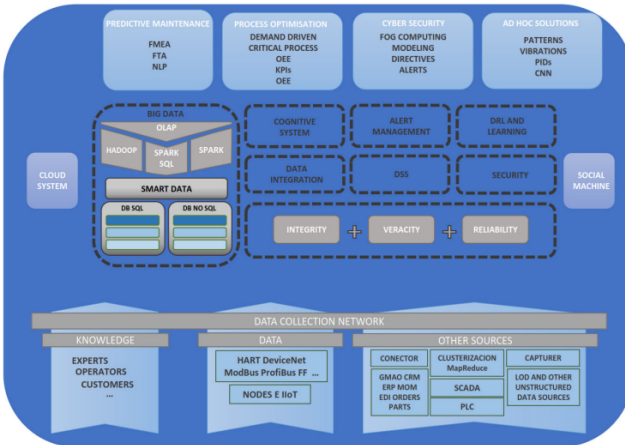


Figure 11: Software technologies and system components [46]

This integrated predictive platform offers a smart and scalable solution for improving maintenance efficiency and process optimization, enabling real-time insights

and seamless integration with existing industrial systems like CMMS.

In addition, [47] proposes a conceptual architecture designed to enhance predictive maintenance (PdM) by integrating Industry 4.0 technologies with existing Computerized Maintenance Management Systems (CMMS). Rather than offering a turn key solution, the study outlines how a Cyber-Physical System (CPS) can work in synergy with a CMMS to create a smarter, more autonomous maintenance environment.

The architecture is built on two interconnected layers: a physical layer, where machines are equipped with IoT sensors that collect real-time data (e.g., temperature, vibration, pressure), and a cyber layer, which stores and analyzes this data using machine learning and data mining techniques. These analyses help assess equipment health, predict failures such as the remaining useful life (RUL) of components, and optimize maintenance planning.

A maintenance process within the CPS framework is illustrated in Figure 12. In this process, when the cyber layer detects an anomaly or predicts a failure, it automatically generates a maintenance work order in the CMMS. This work order triggers the scheduling process, taking into account technician availability, spare parts, and tool readiness. During the repair, the CPS supports technicians with guidance and collects real-time data, which updates the CMMS and refines future predictions and inventory management.

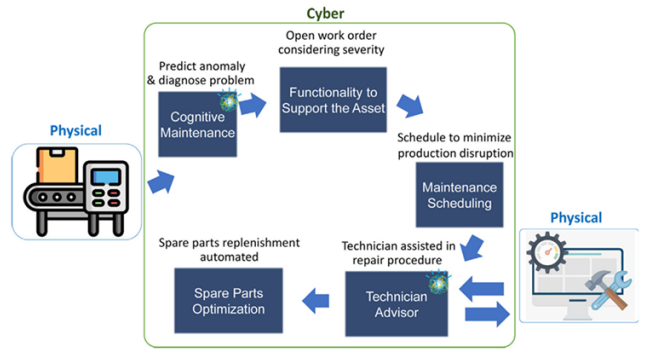


Figure 12: Cyber-physical process to perform maintenance [47]

The authors of the article show that a CMMS integrated within a CPS can become a proactive maintenance platform. Although they highlight challenges such as data heterogeneity, latency, and model adaptability, this integration marks a shift from traditional, reactive practices to intelligent, predictive maintenance workflows aligned with the goals of Industry 4.0.

Furthermore, another architecture is presented in [22], aiming to enhance maintenance operations by interconnecting the CMMS with advanced diagnostic, prognostic, and decision-making algorithms. This is achieved through the integration of Industry 4.0 technologies namely the Internet of Things (IoT), Big Data, Ma-

chine Learning (ML), and Artificial Intelligence (AI) within the Norwegian Petroleum Directorate (NPD) maintenance loop for the Oil & Gas sector.

This integration facilitates real-time data exchange, enables automated decision-making, and improves maintenance planning and scheduling by allowing the CMMS to process and analyze large volumes of data efficiently. The authors identify three main areas of improvement in this approach [22]:

- Perception: IoT-enabled smart sensors collect real-time data and detect early signs of equipment failure;
- Computation: Advanced algorithms analyze data and predict fault evolution;
- Cognition: Analytics are used to identify abnormalities and assess equipment health.

Moreover, the study stresses the necessity of transitioning from traditional maintenance models to a more flexible, data-driven system capable of managing the complexities of Big Data and IoT. Big Data technologies enhance the CMMS by enabling it to store, process, and analyze diverse datasets, thus improving fault detection speed and performance analysis accuracy. ML and AI also play a crucial role in predictive maintenance, allowing the system to learn from historical data, identify patterns, and forecast potential failures.

In addition to improve predictive capabilities, the proposed architecture facilitates seamless communication between the CMMS and external systems, ensuring accurate and automated decision-making. The article also underscores the importance of a user-friendly and adaptable system that supports easy reconfiguration and integration with various services.

By incorporating Industry 4.0 capabilities into existing maintenance architecture, the proposed system aims to increase efficiency, enhance decision-making accuracy, and better align with the evolving demands of modern industrial environments.

Lastly, [48] outlined a structured, seven-step process for implementing predictive maintenance algorithms within the Computerized Maintenance Managements systems (CMMS) for electrical equipment.

The first step involves conducting an asset inventory and identifying the critical equipment to be included in the predictive maintenance strategy. These assets are prioritized according to their operational significance, safety implications, and the potential impact on production or service delivery in case of failure.

The second step focuses on determining the key parameters to be monitored for the selected assets and deploying appropriate sensors, meters, and monitoring devices to gather these data. Additionally, this step requires the calibration, synchronization, and integration of data collection systems into the organization's data infrastructure. It also includes preprocessing, cleaning, and transforming the raw data to ensure quality and consistency.

The third step consist of developing predictive models to be integrated withing the CMMS. This includes

selecting suitable machine learning algorithms, statistical methods, and predictive tools based on the nature of the available data and the specific needs of the predictive maintenance application. The models are then trained using historical data, maintenance records, and failure events. Once the training phase is complete, the models are validated and evaluated using holdout datasets, cross-validation methods, or simulated scenarios to ensure performance accuracy, reliability, and generalizability.

The next step concerns the integration of the developed algorithms into the existing CMMS to streamline maintenance workflows and enable effective data exchange. To ensure seamless interaction between predictive models and the CMMS, interfaces, APIs, or connectors may be implemented. This integration ensures that maintenance tasks are prioritized, scheduled, and tracked effectively, while also enabling the system to anticipate equipment failures, estimate Remaining Useful Life (RUL), and support data-driven maintenance decision making.

The final steps consist of the Deployment and implementation of predictive maintenance solutions, which involve configuring the necessary infrastructure, training personal, and integrating insights into daily operations. This is followed by continuous monitoring and optimization, where performance is evaluated using KPIs and predictive models are refined based on feedback and operational data. Lastly, stakeholder engagement and communication ensure collaboration across teams, promote awareness at all levels, and foster a culture of continuous improvement and innovation.

The authors presented five case studies that successfully implemented the predictive maintenance process previously defined. These real-world examples span various industries and demonstrate how the integration of predictive maintenance models within Maintenance Management Systems such as CMMS can yield tangible benefits. General Electric (GE) Aviation applied its Prognostic Health Management system to aircraft engines, enabling real-time monitoring and proactive maintenance that reduced delays by 35% and maintenance costs by 10%. Schneider Electric leveraged sensor data in its electrical distribution equipment to detect anomalies early, improving reliability and achieving a fast return on investment (ROI). In mining, Rio Tinto used predictive analytics to monitor autonomous haul tracks, resulting in increased equipment availability by 10% and lower maintenance expenses by 15%. Siemens Gamesa implemented predictive maintenance on its wind turbines, enhancing energy output and operational efficiency. Lastly, Pacific Gas and Electric Company (PG&E) integrated predictive strategies into its electrical grid, using smart data to reduce outage frequency by 15% and duration by 20% while improving service quality. These case studies illustrate the effectiveness of a structured predictive maintenance approach integrated with CMMS for electrical equipment across diverse operational contexts.

The integration of predictive maintenance within CMMS systems, supported by Industry 4.0 technologies, offers a significant leap forward in the optimization of maintenance strategies. The reviewed studies illustrate a variety of scalable and intelligent architectures that enable real time monitoring, failure prediction, and automated decision-making. Whether through cyber-physical systems, edge computing platforms, or structured implementation frameworks, these solutions enhance the ability of CMMS to manage complex datasets, generate accurate forecasts, and trigger timely maintenance actions. This not only improves asset reliability and operational efficiency but also ensures that maintenance planning aligns with the broader objectives of digital transformation and smart manufacturing.

5. Discussion

In this section, we will analyze the contributions of the articles already presented earlier regarding the integration of CMMS within the Industry 4.0 pillars. To provide a concise overview, we will present a table summarizing the key contributions and limitations of each article. In addition, we will delve into the most commonly used technologies across the studies, exploring the reasons behind their popularity and their relevance in modern maintenance management. We will also highlight the common challenges faced in the implementation of these technologies, as well as discuss Industry 4.0 technologies that have been underutilized in the studies and speculate on the reasons for their limited use. This comprehensive analysis will provide insights into the current state of CMMS-Industry 4.0 integration and lay the groundwork for proposing more effective and secure maintenance management practices.

Based on the studies summarized in the discussion table 2, several important patterns emerge regarding the integration of technologies Computerized Maintenance Management Systems (CMMS) within Industry 4.0 pillars.

5.1. Technology Combinations Most Frequently Used and Their Justification

The most commonly integrated technologies are the Internet of Things (IoT), Artificial Intelligence and Machine Learning (AI/ML), Big Data analytics, Cloud Computing, and Augmented Reality (AR). Most of technologies complement each other to enable real-time asset monitoring, centralized data management, and intelligent decision-making support within CMMS platforms. Specifically, IoT infrastructure collects critical asset health indicators (e.g., vibration, temperature), cloud services handle data integration and remote access, and Big Data tools facilitate anomaly de-

tection and predictive analytics. In parallel, integrating AR technologies with CMMS significantly improves technician productivity by delivering real-time, contextual maintenance information directly onto equipment through wearable devices. This hands-free access to work orders, maintenance histories, and procedural guidance accelerates interventions and reduces operational errors. Collectively, these integrations enhance situational awareness, support condition-based maintenance, and minimize manual effort and human error. Several specific technology combinations are particularly prominent :

- **IoT + Big Data + Cloud:** This trio automates asset monitoring and data processing, improving decision-making, and streamlining spare parts management. The immediate access to real-time data enables faster response times and more accurate maintenance planning.
- **AI/ML + IoT:** The coupling of AI/ML models with IoT-generated data supports predictive diagnostics and optimized maintenance scheduling. Machine learning techniques such as decision trees, SVMs, and neural networks analyze sensor data and historical records to forecast failures, moving CMMS towards autonomous, cognitive maintenance frameworks.

Each of these technology combinations addresses critical shortcomings of traditional CMMS platforms, particularly regarding the latency, fragmentation, and passivity of maintenance data. They transform CMMS from static record-keeping systems into proactive, smart maintenance platforms capable of supporting Industry 4.0-driven operational excellence.

Table 2: Discussion Table

Article	Year	Used Technologies	Contributions	Limitations
[44]	2019	AR	-Proposes the development of a new strategic information system that combines CMMS and AR to enhance decision-making in smart factories. -Displays real-time maintenance data (failures, work orders, preventive tasks) through augmented reality (AR). -Improves technician interaction with machines by facilitating fault diagnosis, enabling preventive detection, enhancing quality control, and simplifying operator training through the overlay of instructions and procedures directly on equipment. -The case study validates the usefulness of CMMS in a real company (Grupo Solder).	-System under development: AR visualization part was incomplete at the time of study, requires advanced skills in Unity, Vuforia, server communication (PHP/MySQL), and software development (MVC architecture). -Integration process is complex and still under development. - High dependency on the quality, completeness, and structure of maintenance data in the CMMS, which is still new and lacks a large volume of historical data. -Scalability not validated: solution implemented in a single company; its adaptation to larger or different industrial contexts is not demonstrated.
[42]	2020	IoT Big data & Cloud computing	-The author developed a RTEM system integrating RFID tags, GPS and barcodes with a cloud-based CMMS to track location and maintenance history in dynamic environments like oil and gas industries. -It proposes a clear and structured implementation methodology, detailing each phase, specific actions, equipment types, and selection criteria. -The system was successfully deployed and validated through a BETA test, demonstrating practical feasibility. -The outcomes of the system are easier access to maintenance activity data and the automation of maintenance processes, from maintenance planning to spare parts management, leading to improved operational efficiency.	-The study lacks detailed quantitative analysis to measure the improvements of the mentioned benefits of the system's implementation. -Cybersecurity concerns related to cloud-based CMMS and real-time tracking are not addressed. -Potential integration challenges with existing CMMS platforms are not considered. -Cost and resource requirements for implementation are not evaluated. -The study focuses only on the oil and gas industries which can limit the generalization of the proposed system.

[43]	2020	AR	-The study proposed a system architecture integrating AR with a CMMS, composed of a wearable AR device, a CMMS database, and an information controller. -Provides a practical implementation example, including the system setup, materials used, and the process followed. -Shows how the AR integration enables rapid access to maintenance data stored in the CMMS by detecting the equipment tag and automatically displaying equipment related information. -Improves technician assistance during maintenance by guiding tasks step-by-step and suggesting root causes, improving operator autonomy and productivity.	-The solution was demonstrated via an example, but broader industrial validation or large testing is missing. -The results of the article remain qualitative, with no detailed performance evaluation or measurable KPIs. -The study does not explore cybersecurity, which is critical when exposing CMMS data through networked wearable devices. -Although the implementation is described, the methodological framework lacks structure, making it difficult to replicate the system for other use cases. -Cost implication and the potential complexity of deploying AR technology in industrial environments are not evaluated.
[46]	2020	IIoT System Integration Big Data & Cloud Computing	-The authors propose a reference software architecture that can be integrated with existing industrial systems like CMMS to facilitate critical data extraction for process optimization. -They demonstrate how I4.0 technologies enable predictive maintenance by analyzing CMMS data through structured techniques such as FTA and FMEA, combined with AI and machine learning algorithms. -The proposed system introduces a horizontal and vertical integration model to cover data management, cybersecurity policies, and industrial process optimization.	-Lack of practical implementation or industrial validation, the proposal remains conceptual without a detailed real-world case study. -Adapting the proposed architecture to specific CMMS and industrial environments might require significant customization, which is not discussed. -Potential challenges when scaling across industries or integrating with CMMS are not addressed. -Cybersecurity focus is outlined but not deeply explored regarding concrete measures or protocols.
[47]	2020	ML IoT CPS	-Conducted a Systematic Literature Review (SLR) analyzing 562 papers and selecting 38 relevant studies. -The article outlines how a Cyber-Physical System (CPS) can work in synergy with a CMMS to create a smarter, more autonomous maintenance environment. -Linked IoT and CPS to predictive maintenance processes and discussed integration with CMMS. -Highlighted the concept of cognitive maintenance where predictive models autonomously create maintenance requests in CMMS.	-The integration of CMMS with AI/ML is discussed only at a conceptual level, with no practical implementation case studies. The article is purely a systematic review and does not propose any new framework or model. -The absence of practical implementation leads to a lack of empirical results, validation, and detailed operationalization of the proposed cognitive maintenance concept.

[22]	2020	AI ML Big data and analytics IoT	-Developed and modeled a complete intelligent maintenance management architecture aligned with Industry 4.0 requirements. -Proposed a new architecture integrating maintenance program, reporting, and analyses modules. -Designed automated diagnosis, prognosis, and decision support based on big data and cloud analytics. -Modeled the integration between PdM systems and CMMS/ERP systems to automatically generate maintenance work orders. -Applied systems engineering methodology to extract stakeholder needs, derive system requirements, and allocate functional modules. -Addressed how intelligent maintenance would support opportunistic maintenance and full lifecycle management in the oil and gas sector.	-Architecture is fully modeled but not practically implemented or tested, no field validation yet. -No real-world performance results or stress testing of the proposed system. -Algorithms for diagnosis and prognosis are conceptually included but specific AI/ML models are not detailed. -Security, data privacy, and interoperability challenges acknowledged but no concrete solutions provided. -Focused on a single case (compression system in O and G), so generalization across industries is limited. -CMMS integration is discussed, but full technical details for integration is not demonstrated.
[39]	2021	ML MCDM IIoT	-Introduces a Smart Workflow to automate two main maintenance steps: filling in maintenance orders and allocating maintainers. Proposes two structured frameworks : • Serial approach: uses MCDM to select features, ML to classify form fields. • Parallel approach: uses MCDM to pre-classify maintainers and ML as a confirmation if needed. -Development of a pre-processing description to clean and select relevant features before ML/MCDM application. Provides a real case study in a multinational company to validate the framework. -The specialists' survey confirms that automation reduces human errors, improves workflow, enhances response times, and enables faster maintenance planning.	-Expert bias in MCDM weights: subjective judgments can affect decisions. -No strategy for protecting sensitive maintenance data (confidentiality, authentication, access control). -Limited generalization: solution validated in a single case study; no proof of effectiveness across different industries or CMMS platforms. -No stress tests (e.g., what happens with bad data, incomplete data, cyber-attacks, system overload?). -The survey suffers from a small and homogeneous sample size (only 5 programmers from the same department), leading to a risk of internal bias, lack of diverse user perspectives (no technicians or maintenance planners included). -Although the article describes a pre-processing strategy to clean and filter maintenance order data, the actual implementation details of the script are not provided. Consequently, it is unclear whether the resulting dataset ensures sufficient quality, which is critical given the system's high dependency on data quality; poor data leads to poor classification and allocation.

[41]	2022	IIoT Big Data Cloud computing	-In this article a CMMS integrated with industry 4.0 technologies was developed to enable CBM, remote interaction, and real-time asset monitoring. -The authors provide a comprehensive description of the materials, technologies, and the data flow architecture used in the system. -The system improves data-driven decision-making and spare parts management through real-time data visualization. -It automated maintenance task generation, reduces manual errors, and eliminates communication delays, improving overall maintenance efficiency.	-The article lacks a detailed implementation methodology, making it difficult to replicate or adapt the system in different contexts. -Validation and testing results of the platform are not extensively discussed, limiting the assessment of its real-world effectiveness. -Potential challenges in integration with existing CMMS are not addressed.
[40]	2023	AI IoT AR SI Cloud	-Develop and demonstrate a real-world experimental testbed that combines IIoT sensors, data analytics, and CMMS systems to implement smart maintenance strategies practically. -Provided a safe environment for companies to test smart maintenance technologies without risking operations. -Identified integration challenges and best practices for future smart maintenance adoption.	-Testbed limited to lab environment — no full industrial factory validation yet. -Focus only on simple sensor types (vibration, temperature); complex data types not tested.
[45]	2023	ML NLP	-The article effectively combines NLP with multidimensional classifiers to predict and correct CMMS metadata, improving maintenance operations. -It deals with technical and short text in maintenance logs by using a special process to clean and prepare the text for analysis.	-The approach is tailored to the pharmaceutical industry and may not be directly applicable to other sectors. -Some types of failures are rare, which makes it harder for the models to predict them correctly.
[48]	2024	AI ML	-The article proposes a structured seven-steps process for integrating predictive maintenance algorithms into CMMS and provides clear justification for each step, ensuring a logical and applicable methodology from asset prioritization to algorithm deployment. -The authors demonstrate the practical application of the methodology through five real-world case studies across different industries. -In addition, quantitative results (maintenance cost reduction, delay reduction, and increased equipment availability) were presented to validate the effectiveness of the proposed approach.	-The article focuses only on electrical equipment, which may limit its generalization to other types of assets or industries. -The development details of the predictive algorithms (model selection, training, validation method) are not explained. -Integration challenges with existing CMMS infrastructures are not discussed.

5.2. Common challenges and limitations

Despite these promising integrations, the literature reviewed highlights several recurring challenges and limitations.

First, a major issue is the limited full-scale implementation and validation of proposed systems. Many studies present architectural models or software frameworks without deploying them in real-world operational settings. When systems are developed, they are often only tested in laboratory conditions or small-scale experiments, with few examples of real-world testbeds that allow for experimentation in full-scale factories. Similarly, AR prototypes and algorithm integrations are rarely implemented in industrial environment, making it difficult to prove the generalizability of the approaches across different industries or CMMS platforms. Additionally, common gap is the insufficient quantitative evaluation of the systems. While many articles report qualitative benefits such as improved response time or reduced downtime, they provide few rigorous metrics such as actual maintenance cost savings or system reliability improvements. Furthermore, expert's surveys are rarely used to evaluate system efficiency.

Another challenge is the assumption that CMMS integration with new models can occur seamlessly without addressing the real-world difficulties of interfacing with legacy software and systems. Security and privacy considerations are also largely overlooked, with few concrete cybersecurity measures or protocols in place, despite the risks associated with opening CMMS systems to external networks and wearable devices.

Finally, cost and resource requirements are rarely evaluated, with the effort and expense needed to deploy Industry 4.0 technologies typically acknowledged but not quantified.

Overall, while the integration of advanced technologies with CMMS holds great potential, significant gaps remain in terms of full-scale implementation, rigorous evaluation, and real-world validation. Future studies should focus on addressing these challenges, providing more quantitative data, considering security protocols, and quantifying the costs and resources required for successful deployment in industrial environments.

A related concern is that the focus of current research is often concentrated on a narrow subset of technologies mainly IoT, AI/ML, and cloud computing while other equally promising innovations remain underexplored. This selective attention not only limits the scope of current advancements but also delays the adoption of more transformative solutions. Understanding why these technologies are less present in the literature can help uncover new opportunities for enhancing CMMS capabilities.

5.3. Less Explored Technologies and Potential Reasons

Certain Industry 4.0 technologies, such as Digital Twins and Cybersecurity, appear only infrequently or are notably absent in the CMMS literature, despite their significant potential for improving maintenance management. Digital Twin concepts which are a virtual, real-time dynamic replicas of physical assets are not represented in the reviewed studies. This absence may be attributed to several factors: developing accurate digital twins requires high-fidelity asset modeling, continuous synchronization between the physical and virtual systems, and substantial computational resources. Moreover, integrating Digital Twins with traditional CMMS platforms presents considerable challenges, as many existing systems were not designed to handle real-time, bi-directional data flows or complex simulation environments. The significant investment in terms of both infrastructure and expertise further explains the limited adoption of Digital Twin technology in maintenance management contexts.

Similarly, Among the listed studies, Cybersecurity concerns are rarely addressed in implementation. Only one work explicitly includes a cybersecurity dimension in its reference architecture, yet no concrete security solutions are provided. This suggests that authors are more focused on enabling functionality than on securing it, or that security is considered out of scope, alternatively, it might be perceived as a separate domain outside the immediate research objectives of CMMS enhancement.

Technologies such as Natural Language Processing (NLP) and Large Language Models (LLM) remain relatively unexplored in the field of maintenance management. Although some studies have begun to address these technologies, their application has been limited. For instance, the study by [49] utilized NLP and Machine Learning (ML) to analyze breakdown reports using a Computerized Maintenance Management System (CMMS) as a database, while another [50] employed NLP models to automate the classification of maintenance requests. However, these studies have primarily treated CMMS as a mere database and have only scratched the surface of NLP's capabilities, focusing mainly on basic text classification and keyword extraction. Challenges such as unstructured text, spelling and grammar mistakes, and the use of slang have hindered the achievement of high-performance accuracy. Despite their contributions, these studies have not fully explored the potential of NLP and LLM in maintenance management, leaving significant room for further integration and advancement.

Addressing these underexplored areas is critical to advancing toward a fully integrated, secure, and intelligent maintenance management system.

6. Future perspective

Based on the gaps identified in the discussion, future developments should aim to strengthen CMMS integration with Industry 4.0 technologies by addressing current limitations and exploring new technological and practical opportunities. This section highlights the main directions for research and industrial application.

One of the key technologies to be incorporated within connected CMMS systems is cybersecurity. As CMMS platforms become increasingly interconnected, integrating security-by-design principles, adhering to international cybersecurity standards, and implementing real-time threat detection mechanisms will be essential. Moreover, raising cybersecurity awareness among maintenance personnel will play a crucial role in enhancing overall system resilience and mitigating cyber risks.

Another major opportunity lies in the integration of Digital Twins with CMMS. When combined with deployed technologies such as AI, these virtual replicas of physical assets continuously updated with real-time sensor data, enable simulation of equipment behavior, optimization of repair schedules, and virtual testing of maintenance strategies. AI algorithms can analyze operational data to predict failures and optimize maintenance process, ultimately reducing downtime, lowering maintenance costs, and improving safety, compliance, and resource allocation, thus maximizing the overall effectiveness of maintenance strategies.

Moreover, additive manufacturing or 3D printing integrated with CMMS offers new opportunities for maintenance operations, either as a standalone solution or combined with other Industry 4.0 technologies. It enables on-demand fabrication of spare parts, significantly reducing downtime and costs linked to traditional supply chain. A CMMS could automatically trigger the 3D printing of a needed component when predictive models forecast wear or failure. Overall, this combination improves efficiency, cost-effectiveness, and operational flexibility, providing a more agile and responsive maintenance strategy.

Another transformative opportunity is the integration of Natural Language Processing (NLP) and Large Language Models (LLM) within CMMS. These technologies can revolutionize how maintenance data is processed and utilized. By leveraging NLP, maintenance reports and logs can be automatically analyzed and categorized, enabling more efficient data retrieval and decision-making. LLM can further enhance these capabilities by understanding and generating human-like text, facilitating more intuitive interactions between maintenance personnel and CMMS. This integration can lead to advanced predictive maintenance strategies, where the system not only predicts potential

failures but also suggests optimal maintenance actions in natural language, making it easier for technicians to understand and act upon.

In summary, the future of CMMS lies in the deeper integration of cybersecurity measures, Digital Twin technology, and Additive Manufacturing. By pursuing these developments, industries can build smarter, safer, and more efficient maintenance systems that are fully aligned with the principles of Industry 4.0.

7. Conclusion

This research explored the intersection between Computerized Maintenance Management Systems (CMMS) and Industry 4.0, aiming to understand how the integration of emerging technologies is transforming modern maintenance strategies. Through a systematic literature review, we traced the historical evolution of maintenance practices across the four industrial revolutions; from reactive and preventive methods to proactive and predictive maintenance. We examined how CMMS evolved as a digital tool to manage maintenance activities efficiently, and how its traditional limitations such as reliance on manual data entry and lack of intelligent decision support have prompted the need for integration with Industry 4.0 technologies.

The study highlighted the key technologies associated with Industry 4.0 namely the Internet of Things (IoT), Big Data analytics, Artificial Intelligence (AI), Cloud Computing, Augmented Reality (AR), and Cyber-Physical Systems and demonstrated how they drive transformation in both manufacturing and maintenance management. These technologies enable real-time data collection, remote monitoring, predictive analytics, and more informed decision-making, ultimately improving equipment availability, reducing downtime, and optimizing resource allocation.

Through the analysis of various research papers and case studies, we identified three main objectives driving this integration: optimizing maintenance processes, improving on-site interventions and decision-making, and enabling predictive maintenance strategies. The reviewed literature showed that smart CMMS platforms, when enhanced with Industry 4.0 capabilities, can automatically detect potential failures, generate work orders, assign tasks based on technician availability, and guide interventions using AR and machine learning. These advancements not only improve operational efficiency but also support a shift from reactive maintenance to more strategic and autonomous systems.

However, the research also identified several challenges. Data security, integration complexity, the need for standardization, and limited access to technical expertise continue to hinder widespread adoption. Moreover, while some technologies like IoT and AI are frequently

implemented, others such as Cybersecurity or Digital twin remain underexplored, indicating areas for future research and development.

In summary, this study provides a comprehensive overview of how CMMS is evolving within the framework of Industry 4.0. It underscores the importance of embracing digital transformation in maintenance management to meet the demands of modern industry. For organizations aiming to stay competitive, the integration of intelligent CMMS platforms with advanced technologies offers not only operational advantages but also long-term sustainability and resilience in an increasingly data-driven industrial landscape.

Furthermore, the insights gained from this research will serve as a foundational reference for a capstone project focused on the practical implementation of a CMMS, coupled with the integration of a chosen Industry 4.0 technology. This future work aims to apply the concepts discussed in this study to a real-world context, thereby bridging theory and practice. Specifically, the project will incorporate Natural Language Processing (NLP) and Large Language Models (LLM) as the selected Industry 4.0 technology within the CMMS framework. Unlike previous studies that have treated CMMS merely as a database, our approach harnesses the advanced capabilities of NLP and LLM to transform maintenance management.

This exploration leads us to the practical implementation of a conversational agent (chatbot) within a CMMS, an original idea that has not been extensively explored in existing literature. Fully integrated into the CMMS, the chatbot will enable advanced functionalities such as report analysis and generation, providing real-time insights and automating maintenance reports. This novel approach enhances the efficiency and effectiveness of maintenance operations, streamlining processes and offering a more intuitive and responsive system. It allows maintenance personnel to interact with the CMMS database more naturally, reducing the time and effort required for data search and analysis. This integration represents a significant step forward in the evolution of CMMS, aligning with Industry 4.0 principles and paving the way for smarter, safer, and more efficient maintenance systems.

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