

A Comprehensive Review of Computerized Maintenance Management Systems (CMMS)

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Abstract: *Computerized Maintenance Management Systems (CMMS) are essential for manufacturing industries to transform their maintenance operations into a more digital and automated format. Using basic work order capabilities, inventory, assets, and scheduled preventative maintenance, a CMMS improves operational efficiency, maximizes resource utilization, and minimizes equipment downtime. Various incidents across companies that advance beyond Industry 4.0 have increased CMMS capabilities with new advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and predictive analytics being added as a means for real-time data capture, better decision making, and predictive-based maintenance schedules for improving equipment reliability and productivity of the plant. Unfortunately, there are ongoing issues, such as interfaceability between systems, lack of formalized standards for data exchange, cybersecurity reliability, and especially predictive output for real-time applicability. This survey examines the literature on CMMS utilization in the manufacturing sector and reviews different technology trends, research approaches, and applications in several key maintenance areas. This study reviews critical research gaps and discusses avenues for establishing intelligent, autonomous, and integrated maintenance management systems aligned with Industry 5.0. Ultimately, this analysis concludes that future CMMS frameworks must develop into adaptive, data-driven, and self-learning maintenance ecosystems capable of supporting proactive decision-making, seamless connections, and sustainability via advanced manufacturing operations*

Keywords: Computerized Maintenance Management System (CMMS), Predictive Maintenance, Internet of Things (IoT), Asset Management, Industry 4.0

I. INTRODUCTION

In the era of digital transformation and Industry 4.0, manufacturing industries are experiencing increasing demands for efficiency, reliability, and sustainability. Unplanned equipment failures, subpar maintenance planning, and ineffective data-driven decision-making are major contributors to production losses in industrial cases. Conventional maintenance processes are typically manual and reactive and cannot fulfill the complexity and pace of operations in modern manufacturing settings [1, 2]. Maintenance teams would start using paper-based logs and manual scheduling; however, isolated databases made managing their assets difficult and forecasting when things might fail effectively difficult. As manufacturing systems have become more automated and interconnected, the need for a holistic technology-enabled maintenance management approach has become unavoidable. This need has given rise to Computerized Maintenance Management Systems (CMMS), which have changed how organizations manage, monitor, and implement maintenance activities [3, 4].

A Computerized Maintenance Management System is a software-based platform created to enhance and streamline maintenance activities, consolidate asset-related information, and develop predictive maintenance approaches. The CMMS provides an accessible and systematic framework for managing work orders, planning preventive maintenance, managing spare part inventories, and evaluating asset performance. CMMS brings digitization to maintenance workflows, which increases transparency and consistency, as well as opportunities for data accessibility across an entire organization. In manufacturing environments, machine uptime is directly related to productivity and profit, and CMMS



assists organizations in improving equipment uptime, increasing reliability, and extending the life of their assets. Over the past ten years, CMMS has transitioned from a basic data-recording tool to an intelligent, interconnected system capable of performing predictive analytics and providing real-time decision support. This is driven by the convergence of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and data analytics, which allow maintenance teams to transition from reactive to predictive and prescriptive maintenance paradigms [5, 6]. The advancement in maintenance management techniques mirrors this change. Maintenance activities were largely reactive, meaning that activities requiring fixing occurred only after the equipment broke down. The simplicity of this approach, which reacts only after failure, typically results in downtimes that can be costly, as well as safety concerns that are prevalent in these approaches. The next step introduced preventive maintenance, where the focus of maintenance tasks reduced the need for service on equipment/parts by performing regular scheduled service and replacement of parts at predefined intervals. Although this approach is a notable improvement over the purely reactive maintenance approach, it leads to as many, if not more, instances of over-maintenance or serviced parts that do not require servicing or otherwise limit the frequency of maintenance on an asset. Assisted databases and sensors have advanced condition-based and predictive maintenance strategies for wind turbines. CMMS has embedded predictive models to analyze the sensor data, with the guidance of chips or devices that can determine any deviations from the expected performance, calculate the remaining useful life (RUL), and manage to maintain assets at intervals that approach or are below the RUL thresholds. The impact of these changes leads to a more optimized use of resources in manufacturing firms, with significant potential limitations in maintenance efforts when comprehensive, maximizing overall equipment effectiveness (OEE) endeavors.

In today's manufacturing settings, computerized maintenance management systems (CMMS) are vital for addressing the demands of complicated maintenance processes. A CMMS is widely considered a centralized database that digitally connects maintenance teams, assets, and operational data. This allows maintenance engineers to use digital dashboards and reporting tools to visualize the health of equipment, plan intervention requirements, and track the completion of work in real time. A core feature of CMMS is work order management, which automates the process of generating, assigning, and monitoring requested work for maintenance and is specialized for documentation. The inventory management modules provide organizations with visibility to safely stock sufficient spare parts and consumable items as needed, eliminating either outages or excessive storage. The asset management feature allows organizations to track all of their asset information, such as the entire lifecycle of machinery from when the asset was purchased until the time the asset is disposed of, and provides the organization with the asset performance, depreciation, and maintenance history. Preventive maintenance scheduling allows organizations to schedule machinery maintenance before breakdowns at optimal intervals. These functionalities enable manufacturers to establish and support a data-driven maintenance culture that focuses on efficient, accountable, and continuous improvement [9-11].

The amalgamation of Computerized Maintenance Management Systems (CMMS) with Industry 4.0 technologies has led to further advancements in their function. In novel manufacturing environments, Internet of Things (IoT) sensors continuously collect real-time data related to the condition of machines, such as temperature, vibration, and pressure. These data then become available to the CMMS, which uses artificial intelligence algorithms to process the collected data and recognize faulty conditions or conditions outside the normal operating parameters. Predictive analytics in a CMMS can estimate failures and autonomously generate maintenance requests before they occur. Cloud computing delivers scalability and remote access, allowing maintenance departments to access asset data and work orders from anywhere [12]. This accessibility can be beneficial for large-scale manufacturing and multiple locations. Additionally, digital twins, or virtual models of physical assets, will increasingly be integrated with CMMS to model equipment, create maintenance schedules, and simulate the potential for maintenance decisions before their application. This type of integration will drive CMMS to become the backbone of intelligent maintenance systems, enabling autonomous monitoring and reasoning in an adaptive framework [13].

When a manufacturing organization adopts a CMMS, it obtains several advantages. First, unplanned downtimes are significantly reduced because CMMS allows scheduling work orders based on predictive maintenance instead of reactive maintenance. Automated labor scheduling and job task allocation reduce idle time (when a machine is capable of running but not doing anything) as CMMS manages resource allocation and minimizes machine failure without prior



warning. Additionally, CMMS makes it easier for organizations to spend less on maintenance costs by reducing reliance on emergency repairs, minimizing redundant maintenance, and reducing spare parts inventories. Similarly, CMMS helps organizations make data-driven decisions regarding maintenance operations by producing analytical reports from maintenance histories and trends in performance and reliability. These data allow organizations to identify and rectify operational failures, improve equipment reliability, and adjust maintenance plans to optimize reliability within a framework of continuous improvement. From a compliance perspective, CMMS provides a digital trail without the usual paperwork for regulatory audits and provides organizations with traceability of safety inspections and maintenance records. As the sustainability of operations is being increasingly recognized, CMMS enhances the environmentally sustainable practices of a manufacturing organization by monitoring energy consumption, reducing waste, and extending the usable life of the equipment. The long-term practical advantages of CMMS lead to higher productivity, reduced operational costs, and improved competitiveness. [14, 15].

Although CMMS has many advantages, various challenges in its implementation must be addressed to realize its full potential. The most significant challenge is the high initial investment required for CMMS software, infrastructure, and training. Many small- and medium-sized enterprises (SMEs) experience financing and technical limitations that may prevent them from adopting these technologies. Data management is also a challenge because the performance of CMMS relies on the input data being of good quality, consistency, and completeness. Integrating CMMS with other enterprise systems, such as Enterprise Resource Planning (ERP) and Supervisory Control and Data Acquisition (SCADA), is complicated because mismatches can occur in formats and communication protocols that provide alternatives to supplying the command. Cybersecurity threats have increased as CMMS systems are made available in the cloud and embedded within IoT devices, requiring strong protections to ensure data security, including encryption, multi-factor authentication, and access management. The implementation of CMMS is further reliant on user buy-in and training. Resistance to change toward digital measures, user awareness, and poor adoption of new preservation programs within the maintenance crew will impact system utilization and overall return on investment. Addressing these challenges requires technical solutions, managerial authority, and change management [16]. As the manufacturing sector progressively shifts toward Industry 5.0, focusing on human-machine collaborations and sustainability, CMMS will become a significant component of valuable and adaptable maintenance systems. The next generation of CMMS platforms will leverage artificial intelligence for real-time fault prediction, natural language processing for voice-based work order generation, and augmented reality for interactive maintenance. For example, maintenance technicians may wear AR headsets that allow them to visualize information on an asset, receive instructions for step-by-step repair, or consult experts remotely through integrated communication systems. Machine learning algorithms continuously evaluate historical data to optimize maintenance planning, resources, and spare part inventories. These developments will transform CMMS from a simple maintenance tool to a fully self-learning, completely autonomous maintenance ecosystem that will build continuous improvement and operational resilience [17]. Furthermore, the increasing focus on sustainability and energy efficiency in manufacturing is broadening the scope of CMMS from operational performance to environmental impact. Intelligent CMMS platforms can capture energy consumption behaviors, identify areas of inefficiency, and issue recommendations for correcting each issue to reduce waste. The introduction of digital twins and blockchain will further enhance the assurance of traceability, accountability, and transparency throughout the maintenance supply chain. Such a system can authenticate the legitimacy of components, effectively record maintenance transactions, and help implement circular economy principles by tracking asset reuse and recycling processes.

Given the critical role of CMMS in modern manufacturing, there is a pressing need to consolidate the existing body of research to understand its capabilities, limitations, and future directions. Although numerous studies have explored individual aspects of CMMS, such as predictive maintenance, IoT integration, and asset management, comprehensive reviews focusing on CMMS as a unified system remain limited. This survey aims to fill this gap by providing an in-depth analysis of CMMS research and applications in the manufacturing context. This study examined four key functional domains: work order management, inventory management, asset management, and preventive maintenance, each representing a vital CMMS ecosystem component. Through a systematic literature review, this study identifies technological advancements, implementation challenges, and open research issues that require further exploration.



Special emphasis is placed on understanding how CMMS contribute to smart manufacturing, the role of data analytics in predictive maintenance, and the challenges related to system interoperability, cybersecurity, and user adoption.

The introduction of Computerized Maintenance Management Systems has fundamentally transformed maintenance operations in manufacturing, shifting them from reactive to proactive and predictive paradigms. A CMMS enhances operational efficiency and equipment reliability and aligns with digital transformation and sustainability objectives. As industries embrace intelligent manufacturing technologies, CMMS will remain central to achieving data-driven, autonomous, and sustainable maintenance. Therefore, this survey serves as a timely and comprehensive overview of CMMS evolution, current research trends, and the future trajectory of maintenance management in the era of Industry 4.0 and beyond.

II. RELATED WORK ON COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM

This section surveys recent and influential literature on Computerized Maintenance Management Systems (CMMS) as applied to manufacturing, organized into four functional domains commonly handled by CMMS: work order management, inventory (spare parts) management, asset management, and preventive (including predictive) maintenance. For each domain, we summarize the key approaches, representative findings, and practical/technical trends reported in the literature, highlighting where CMMS research has concentrated and where gaps remain.

Work order management

Work order management is the workflow backbone of a CMMS; it covers fault reporting, ticket generation, prioritization, routing, technician assignment, execution, and closure with documentation. Recent research has focused on automating and optimizing these sub-processes using text mining of unstructured work order descriptions, prioritization heuristics, and decision support systems that use asset criticality and production impact to triage work. Studies have shown that natural language processing (NLP) and machine learning classifiers can dramatically reduce sorting and improve assignment accuracy. Simultaneously, fuzzy logic and multi-criteria decision-making models have been proposed to prioritize work when multiple constraints (safety, spare availability, and production schedules) compete. There is also growing interest in mobile-enabled CMMS features (technician apps, barcode/RFID scanning) that reduce the latency between fault detection and work order closure.

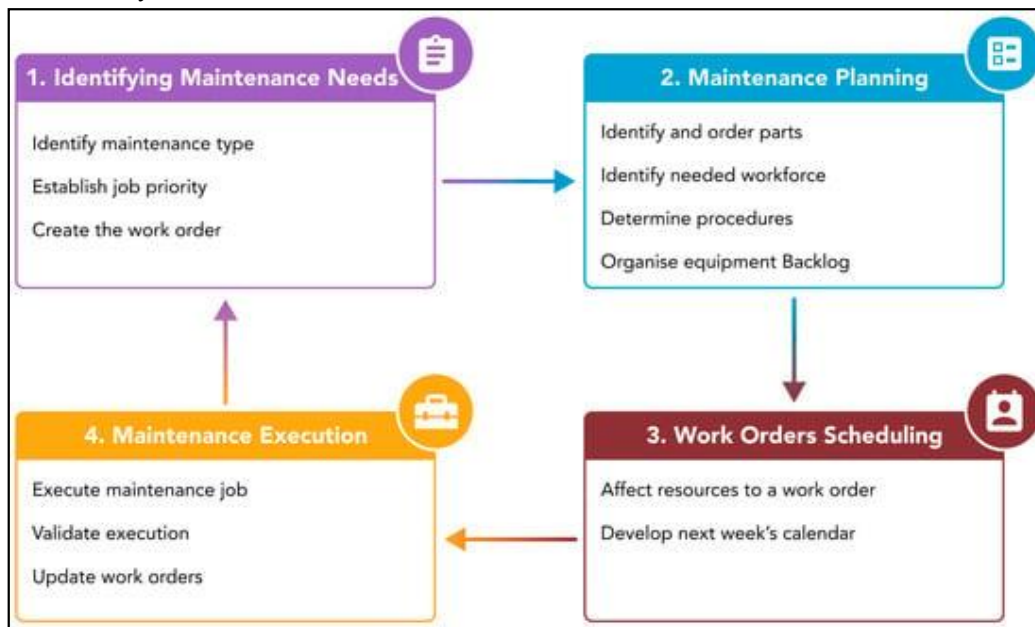


Fig. 1. Key steps of the work order management



Despite these advances, persistent issues remain unresolved. Many industrial work orders remain noisy/unstructured, automated detection (IoT alerts) integration with human-reported tickets often causes duplicate or inconsistent records, and adaptive scheduling under dynamic production constraints remains an open optimization problem.

Shankar et al. [19] conducted a comprehensive study on the impact of implementing Computerized Maintenance Management Systems (CMMS) in manufacturing industries, emphasizing its role in improving productivity, cost efficiency, and safety performance. In a structured survey of Indian sectors, we identified 11 key performance indicators (KPIs) for evaluating a computerized maintenance management system (CMMS). The findings indicate that CMMS enhances productivity, maintenance planning, and resource utilization with less downtime. This study suggests that a well-implemented CMMS enables data-driven decision-making but requires further customization for various industrial environments.

Abdalaal and Shukri [20] investigated the deployment of a CMMS to replace existing traditional paper systems in industrial maintenance workshops. A CMMS is essential for facilitating preventive and predictive maintenance, scheduling, and resource allocation. This study acknowledges that attendant issues with implementation or lack of user training will result in an inability to harness the system's full implications and loss of worker engagement with the process. Abdalaal and Shukri posit that CMMS can be leveraged successfully under proper conditions, including providing training, phased implementation, and sustained engagement to facilitate long-term working reliability.

Shankar et al. [21] addressed the obstacles and solutions for integrating CMMS in the manufacturing environment. This study identified nine significant barriers: employee reluctance to change, legacy data integration, insufficient training, and technological issues. The authors provided solutions such as clear communication, engaging staff, training, and data governance frameworks. Their study indicates the need to align technology implementation with organizational change management to achieve successful digital transformation in maintenance functions.

Ogbeifun et al. [22] reviewed how organizations can take advantage of the different benefits of CMMS to manage maintenance through three case studies, two at academic institutions and one at a manufacturing organization. The study demonstrated that the benefits received rely significantly on user competence and analytical use of the data. While educational institutions primarily use CMMS for planning and reporting, manufacturing organizations are achieving advanced performance benchmarking. The authors concluded that the nature of human capacity is key to fully capitalizing on the CMMS promise of reliability and continuous improvement. Simard et al. [23] developed VulcanH, a modern prototype CMMS for preventive and predictive maintenance of underground mining equipment. In this study, we employed human-centered design and explainable artificial intelligence (XAI) to mitigate end-user distrust of automation. They used predictive maintenance experts to conduct usability tests with the VulcanH. They found that VulcanH performed efficiently and was easy to use to support the transition from preventive to predictive maintenance. Participants preferred graphical explanations of AI outputs, reinforcing the importance of transparency in predictive maintenance. The study emphasizes that explainable CMMS platforms can enhance user confidence and decision accuracy in industrial maintenance.

Benhanifia et al. [24] systematically reviewed predictive maintenance (PdM) practices in the manufacturing sector following the PRISMA 2020 framework. This review analyzes academic research and patient data to identify the technological trends and industrial applications. It highlights the role of AI, IoT, and big data analytics in enabling real-time monitoring and predictive fault diagnosis, significantly improving equipment uptime, and reducing maintenance costs. However, the study noted a lack of standardized ROI assessment models for PdM implementation, calling for future research on unified performance metrics and cost-benefit evaluation methodologies to address this gap.

Table 1: Summary of the Computerized maintenance management system for work order management

Ref.	Author(s) & Year	Title	Study Focus / Objectives	Major Findings	Limitations / Future Scope
[19]	L. Shankar, C. D. Singh, and R. Singh	Impact of Implementation of CMMS for Enhancing the	To evaluate CMMS's benefits and key performance	Identified 11 KPIs for CMMS selection. CMMS improved productivity,	The study is limited to survey-based data and suggests developing



	(2021)	Performance of Manufacturing Industries	indicators (KPIs) in Indian manufacturing industries.	reliability, safety, and cost efficiency.	customized CMMS models for different industry types.
[20]	O. A. A. Abdalaal and M. I. Shukri (2020)	Implementation of the Computerized Maintenance Management System in the Maintenance Workshop	To compare traditional paper-based systems with CMMS-based preventive maintenance.	Demonstrated CMMS enhances scheduling, data recording, and preventive maintenance; user training is crucial.	Limited field testing emphasized the need for stepwise training and phased deployment for successful implementation.
[21]	L. Shankar, C. D. Singh, and R. Singh (2024)	Challenges and Solutions for Implementing CMMS in Manufacturing Industries	To identify significant challenges and propose solutions for CMMS implementation.	Highlighted nine significant barriers (resistance to change, data integration, training)—proposed communication, training, and phased rollout strategies.	It lacked quantitative analysis; validation was suggested through industrial case studies.
[22]	E. Ogbeifun, P. Pasipatorwa, and J. H. C. Pretorius (2021)	Harnessing the Multiple Benefits of a Computerised Maintenance Management System	To assess CMMS utilization in academic and industrial organizations through case studies.	The benefits found depend on human analytical capacity. Manufacturing firms achieved advanced benchmarking and reliability analysis.	Focused on limited case studies; recommended broader cross-sector studies for generalization.
[23]	S. R. Simard, M., Gamache, P. Doyon-Poulin (2024)	Development and Usability Evaluation of VulcanH, a CMMS Prototype for Preventive and Predictive Maintenance of Mobile Mining Equipment	To design and evaluate a human-centered CMMS integrating preventive and predictive maintenance (PdM).	VulcanH showed high usability and promoted transition from PM to PdM; users preferred explainable AI with visual data.	Prototype stage only; recommended inclusion of full-scale planning and real-world deployment testing.
[24]	A. Benhanifia, Z. B. Cheikh, P. M. Oliveira, A. Valente, and J. Lima (2025)	Systematic Review of Predictive Maintenance Practices in the Manufacturing Sector	To systematically review AI- and IoT-driven predictive maintenance approaches in manufacturing.	I found that PdM improves reliability and cost efficiency using AI and IoT. Identified global industrial trends and technology gaps.	Noted lack of standardized ROI models and unified evaluation metrics; urged interdisciplinary and empirical research.



Inventory management

Spare parts and consumables management within a CMMS has been extensively studied because stock-outs or excess inventories directly affect maintenance costs and downtime. Classic inventory approaches (safety stock, min-max policies, and EOQ variants) remain widely used, but contemporary research increasingly combines inventory control with conditions or predictive signals from assets. Data-driven joint models that link predicted failure times to spare-part demand lead to lower holding costs and require fewer emergency procedures than conventional models. RFID and barcode-enabled tracking, plus ERP-CMMS integration, are recurring practical recommendations to improve the accuracy of part counts and lead-time management. Literature surveys covering decades of spare-part research highlight heterogeneity in part criticality, demand intermittency, and lead-time variability as the primary modeling challenges motivating stochastic and classification-based stocking policies (critical vs. non-critical spares). Open issues include modeling multi-echelon spare networks for large manufacturers, better real-time demand forecasting when predictive maintenance is used, and automatic requisitioning that respects budget constraints and production priorities.

Fig. 2 shows that the cost-benefit analysis in maintenance includes fixed order costs, spare part purchasing costs, and inventory holding costs, emphasizing the intricate link between inventory and overall maintenance profitability.

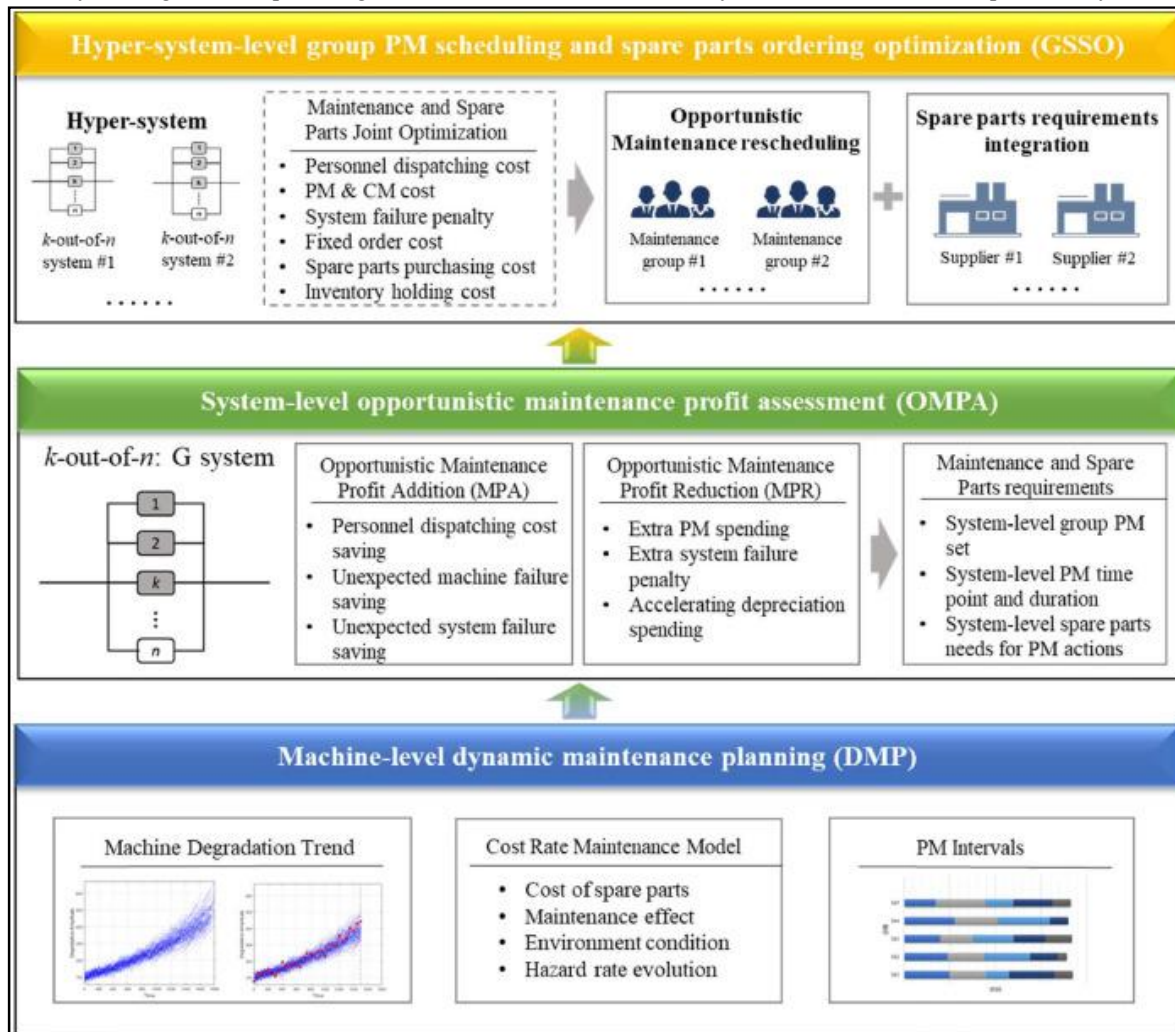


Fig. 2. Cost-benefit analysis in inventory management



Shankar Lakshmi et al. [21] present a comprehensive overview of challenges and solutions for implementing Computerized Maintenance Management Systems (CMMS) in manufacturing industries. Their 2024 study emphasized that a CMMS is crucial for manufacturing sectors that aim to increase productivity, reduce downtime, minimize maintenance and operation costs, and achieve profitability, competitiveness, and sustainability goals. This study highlights the automation of maintenance activities through CMMS as a key enabler for these objectives, stressing the importance of proper implementation to harness its full benefits.

Farid Sukmana et al. [25] in their 2024 study, scrutinize the efficiency of CMMS project stages using the K-Means clustering method. They demonstrated how this methodology can identify areas that require improvement by evaluating four CMMS development projects (Tim, Lix, Akb, and Mnk). Their findings indicate that the "Tim" project exhibited more efficient CMMS development stages, whereas "Lix" and "Akb" projects were less efficient, particularly during the implementation phases. The "Mnk" project showed mixed efficiencies across its stages. This study contributes to the understanding of optimizing CMMS deployment by identifying the bottlenecks.

Md Mahamudur Rahaman Shamim [26] contributes a systematic literature review 2025 focusing on maintenance optimization within smart manufacturing facilities. Guided by the PRISMA 2020 framework, this review synthesizes the advancements, applications, and challenges of integrating Lean, Total Productive Maintenance (TPM), and digitally driven reliability models. This study analyzed 112 peer-reviewed articles published between 2010 and 2024 to comprehensively understand the evolution of CMMS-supported maintenance strategies in the context of Industry 4.0.

Ogbeifun et al. [22] highlighted the multiple benefits of computerized maintenance management systems in their 2021 study. They explained that CMMS leverages information and communication technology to enhance the planning and management of maintenance activities, resource allocation, and production scheduling. The authors emphasize that CMMS facilitates improved communication among stakeholders, streamlines planning processes, provides easy access to historical data, and enhances reporting and performance measurements, allowing maintenance operations to thrive in the digital era.

Simon Robatto Simard et al. [23] detail the design, development, and usability evaluation of "VulcanH," a CMMS prototype specifically designed for preventive and predictive maintenance of mobile mining equipment. Published in 2024, this study aims to expand the knowledge of trust in automation (TiA) for predictive maintenance (PdM) and contribute to the literature on explainability considerations for AI-driven PdM. Their qualitative research focused on helping empirical realities in operational environments, showing the possibilities of targeted solutions for CMMS in less demanding industrial contexts.

Piyush Sehgal et al. [27] discussed CMMS as a means to harness the performance of Indian manufacturing industries in their 2021 publication. The authors argued that CMMS creates a simple method for predicting an asset that requires preventive maintenance, thus leading to better business by reducing costs and enhancing profits. The authors also found that CMMS organizes work orders, which helps minimize paperwork and eventually gives management the power to manage tasks for better organizational management and subsequently improve maintenance practices.

Abdeldjalil Benhanifia et al. [24] conducted an in-depth literature review regarding predictive maintenance (PdM) practices for the manufacturing sector in 2025, which was aligned with the PRISMA 2020 method. The study asserted that PdM could transform Industry 4.0 and significantly enhance sustainable management in manufacturing process efficiency. The authors also discussed the use of PdM in various manufacturing methods with a relevant intention focused on integrating advanced technological applications, such as AI and IoT, which commonly produce advanced CMMS.

Lakshmi Shankar et al. [19] studied the use of the CMMS implementation to enhance the performance of the manufacturing industry in 2021. They define CMMS as maintenance-based software or Enterprise Asset Management (EAM) used for planning, scheduling, managing, and monitoring maintenance activities related to equipment, machinery, automobiles, or other facilities. The authors concluded that industry CMMS applications increase productivity, organizational growth and operational efficiency.

Tangbin Xia et al. [28] published research in 2023 on multi-level maintenance and inventory joint optimization for a k-out-of-n hyper-system, considering supplier selection with incentive discount policies. With a high impact factor of 11.000000, this study proposes a multilevel opportunistic maintenance and inventory control joint optimization (M-



OMICJO) policy to maximize maintenance outsourcing profits. It considers complex factors such as personnel dispatching costs, PM and CM costs, system failure penalties, fixed order costs, spare part purchasing costs, and inventory holding costs. It provides an advanced model for integrated maintenance and inventory management.

Table 2: Summary of the Computerized maintenance management system for Inventory management

Ref.	Author(s) & Year	Title / Focus	Study Objective / Methodology	Major Findings	Limitations / Future Scope
[19]	L. Shankar, C. D. Singh, and R. Singh (2021)	Impact of CMMS Implementation on Enhancing Manufacturing Performance	Investigated CMMS as Enterprise Asset Management (EAM) software for optimizing maintenance processes.	Found that CMMS enhances productivity, organizational growth, and overall operational efficiency.	Suggested further expansion to other industrial sectors for validation.
[21]	L. Shankar, C. D. Singh, and R. Singh (2024)	Challenges and Solutions for Implementing CMMS in Manufacturing Industries	Identified key barriers to CMMS adoption and proposed strategies for effective implementation.	Highlighted that CMMS increases productivity, reduces downtime, and lowers costs when properly implemented.	Recommended empirical validation of proposed solutions through industrial case studies.
[22]	E. Ogbeifun, P. Pasipatorwa, and J. H. C. Pretorius (2021)	Harnessing the Multiple Benefits of a Computerised Maintenance Management System	Explored CMMS advantages through three case studies from academia and industry.	Demonstrated that CMMS improves communication, resource planning, data access, and performance reporting.	Case studies are limited to specific institutions; broader industrial validation is needed.
[23]	S. R. Simard, M., Gamache, P. Doyon-Poulin (2024)	Development and Usability Evaluation of VulcanH, a CMMS Prototype for Preventive and Predictive Maintenance	Developed and tested "VulcanH," a CMMS prototype integrating AI-driven predictive maintenance.	Found that VulcanH improves trust in automation and usability for predictive maintenance in mining equipment.	In the prototype stage, future work should include full-scale deployment and comparative analysis.
[24]	A. Benhanifia, Z. B. Cheikh, P. M. Oliveira, A. Valente, and J. Lima (2025)	Systematic Review of Predictive Maintenance Practices in the Manufacturing Sector	Conducted a systematic review (PRISMA 2020) on PdM integration using AI and IoT.	Showed PdM enhances reliability and cost-efficiency while improving manufacturing sustainability.	Identified gaps in ROI measurement and standardization of PdM evaluation metrics.
[25]	F. Sukmana, M. S. R. F. Arif, and D. A. D. P. Susanto (2024)	Efficiency Evaluation of CMMS Project Stages Using K-Means Clustering	Analyzed four CMMS development projects (Tim, Lix, Akb, Mnk) using K-Means clustering.	Found "Tim" most efficient; "Lix" and "Akb" less efficient, especially during implementation phases.	Recommends optimization



Asset management

Asset management research related to CMMS addresses lifecycle tracking, reliability assessment, and decision support for repair versus replacement choices. Contemporary works emphasize condition-monitoring integration (vibration, thermal, and acoustic sensors) and the rise of “digital twin” approaches that pair a virtual asset model with CMMS records to enable simulations of maintenance strategies and what-if analyses. Machine learning models, ranging from classical survival analysis to deep learning-based remaining useful life (RUL) estimators, are increasingly embedded into asset-management modules to produce health scores and prognostics. Reviews on predictive maintenance and digital twins report improved fault detection rates and more informed lifecycle decisions when CMMS stores high-quality historical maintenance logs linked to the sensor streams. However, integration challenges persist: heterogeneous data formats, varying sampling rates, and sparse failure labels complicate model training, and ensuring that prognostic outputs are explainable and actionable for maintenance planners remains a research/implementation need.

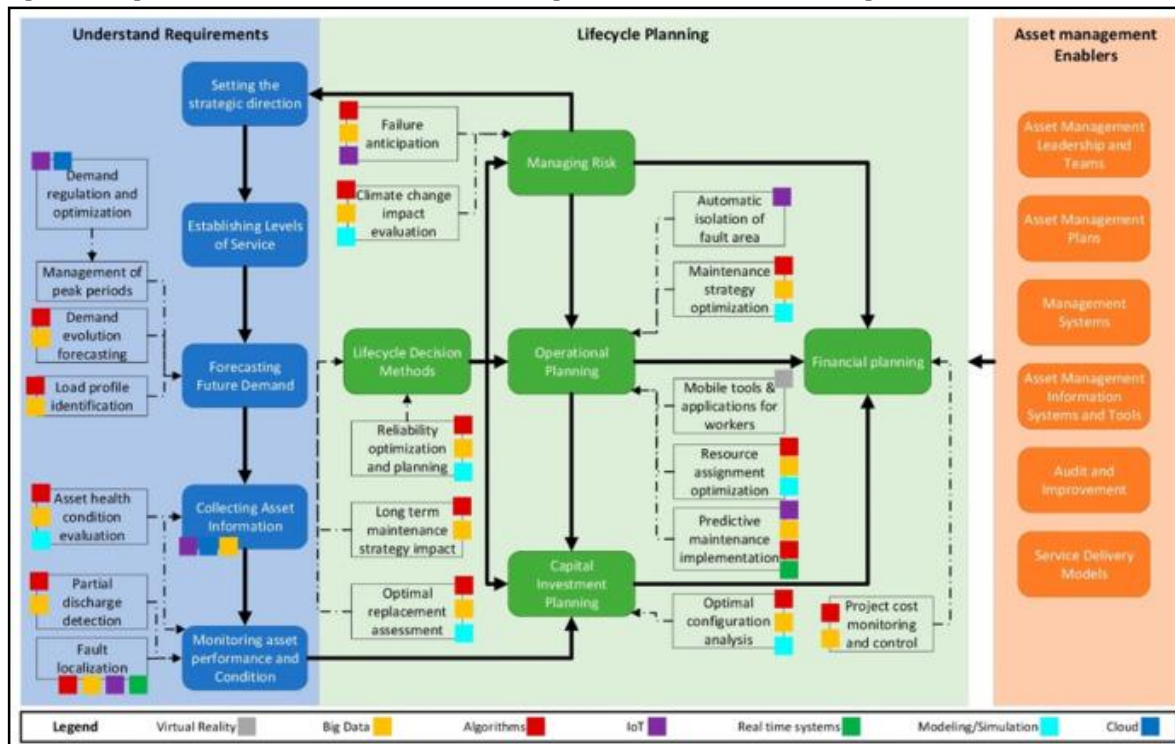


Fig. 3. Asset management flowchart

Mhlaba and Masinde [26] designed a hardware-based asset-monitoring prototype to automate laptop tracking in academic environments. The system reduces manual supervision and prevents equipment loss by integrating the real-time data. Their research highlighted how low-cost microcontrollers and wireless modules can be integrated into a CMMS to provide continuous asset condition updates. This type of automation significantly improves the accuracy of maintenance schedules, allows for reduced asset downtime, and provides timely services. The following study exemplifies how systems can be scaled in an industrial setting, where CMMS integration can add value to asset utilization and lifecycle efficiency management.

Wang et al. [27] provided the design of an IoT-enabled enterprise asset management framework that focused on the real-time monitoring of industrial assets. Their design connected sensor data collection to cloud-connected CMMS modules, automating the CMMS's fault detection process and maintenance scheduling. Using wireless sensors located within operational machines will create the system's ability to provide uninterrupted performance telemetry and automatically generate a work order. The results prove that enhanced asset management with IoT increases operational visibility and precision in preventative maintenance. This model connects the physical equipment and digital



management system and identifies the critical rollout of interoperability between the design of both ideal states of the IoT and CMMS architectural models in an intelligent manufacturing system.

Li et al. [28] examined the role of RFID technology in gaining real-time tracking and monitoring of assets. This proposed system uses RFID tags and readers to monitor the movement and location of the tagged equipment and place them into the CMMS database. RFID technology enables improved inventory records, decreases human error, and supports proactive decisions regarding preventive maintenance. This study illustrates how RFID can enhance the abilities of CMMS by automating the identification and monitoring of assets. In addition, this group strongly suggested using hybrid RFID and sensor data to overcome read range and physical interference issues in industrial environments.

Thaduri, Galar, and Kumar [29] investigated big data analytics concerning railway asset management and highlighted a shift to predictive maintenance. This study integrates sensor-based data collection with CMMS analytics to forecast equipment degradation and optimize maintenance intervals. Using advanced analytics, asset performance data is transformed into actionable insights for decision-making. This study demonstrates that real-time data integration into CMMS can drastically improve reliability, safety, and cost efficiency. The authors concluded that data-driven CMMS solutions are critical for developing intelligent asset management systems for large-scale industrial operations.

Adame et al. [30] developed CUIDATS, an RFID–Wireless Sensor Network hybrid monitoring platform for medical equipment tracking. This system enhances asset visibility, reduces losses, and supports proactive maintenance. Data from distributed sensors is transmitted to a centralized CMMS to ensure real-time condition awareness. This study highlights the potential of hybrid architectures to merge environmental and positional data for comprehensive asset management. Such systems can be utilized directly in manufacturing through IoT-based CMMS frameworks that provide enhanced operational reliability, less downtime, and strategic planning based on real-time asset data.

Al Mamun et al. [31] have proposed an intelligent model for bin-status monitoring that uses rule-based algorithms for real-time asset monitoring. Although this model applies to waste management, it illustrates a pathway for IoT data streams to trigger actions for automated maintenance in a CMMS. For example, their architecture can detect real-time anomalies, issue alerts, and prioritize service activities based on usage intensity. This application demonstrates how condition-based maintenance (CBM) principles can be applied to asset domains beyond the industrial machinery domain. Suppose the CMMS framework in manufacturing uses rules-based logic, similar to the CMMS references above, which assists industries that rely heavily on machinery and equipment. In this case, the net impact is increased efficiency, thoughtful (or optimized and balanced) resource allocation, and maintenance will evolve (hopefully) into a predictive maintenance culture across asset networks.

Manbachi et al. [32] explicitly proposed a co-simulation monitoring framework to enhance asset operational efficiency in smart infrastructure. This system employs virtual simulation models integrated synchronously with real-time sensor data to determine asset health, eliminate bottlenecks, predict failures, and optimize service windows. The framework enables proactive decision-making and reduces unscheduled downtime when integrated with a CMMS. The authors emphasize that simulation-enhanced CMMS architectures can test multiple maintenance scenarios and minimize production disruption. This study underscores the relevance of digital twin technology in asset management and provides a foundation for intelligent CMMS integration in Industry 4.0 environments.

Roe, O'Banion, and Olsen [33] discussed mobile LiDAR-based methodologies for large-scale asset inspection in utility management. This study emphasizes data acquisition accuracy and standardized condition assessment for CMMS input. LiDAR-derived measurements enable the precise detection of surface wear, alignment issues, and structural deformations. When combined with CMMS databases, these insights facilitate data-driven maintenance prioritization. The study's methodology demonstrates how geospatial data integration enhances the CMMS's capability for predictive analysis and asset lifecycle management, particularly for distributed infrastructures like pipelines, highways, and power transmission networks.

Rahimi, Gøtze, and Møller [34] proposed an enterprise architecture framework that aligns asset management systems with corporate data strategies. Their taxonomy improves the interoperability between CMMS, ERP, and SCADA platforms by defining standardized data models and integration workflows. The research demonstrates that a structured enterprise architecture enhances CMMS reliability and supports more accurate asset lifecycle analysis. This alignment



ensures that asset data collected through IoT and monitoring devices is processed coherently across departments, improving decision-making efficiency and reducing data redundancy in the maintenance ecosystem.

Campbell, Jardine, and McGlynn [35] established holistic asset management strategies based on the financial, operational, and maintenance approach. Their model allows for systematically optimizing lifecycle costs via data-driven computer maintenance management system (CMMS) modules. Campbell et al. also demonstrated that if performance metrics, such as the Mean Time Between Failures (MTBF) and Return on Assets (ROA), are coupled with maintenance analysis, CMMS is a strategic decision-support system. This study identifies how the role of a CMMS is evolving from a simple operational tool to that of an enterprise-level intelligence solution that can help organizations align maintenance strategies with broader business and sustainability goals. Fang et al. [36] also combined Building Information Modeling (BIM) and RFID to locate indoor assets in construction contexts. Their hybrid system provides real-time asset management and condition monitoring, which is directly integrated into CMMS for automatic maintenance scheduling. Their methodology also spans 3D visualization and maintenance analytics, improving situational awareness and resource efficiency. This approach demonstrates a hybrid space-time data stream that showcases how a CMMS can evolve as a complete visualization-driven asset management solution in both the construction and manufacturing industries. Ferdinandus and Setiawan [37] created a web-based road asset management system that utilizes GeoJSON and mobile GPS-based technology to provide real-time data updates, asset mapping, and condition assessments. Using a CMMS, the system can generate automatic work orders to maintain infrastructure at an appropriate standard. The authors state that incorporating mobile sensing and geospatial analytics enhances asset transparency and responds rapidly to the deterioration of assets. Their work demonstrated the importance of interoperability between mobile sensing systems and CMMS frameworks to manage geographically dispersed assets efficiently and ensure optimal maintenance scheduling.

Congress, Puppala, and Lundberg [38] explored using uncrewed aerial vehicles (UAVs) for remote asset inspection in transportation systems. When processed and integrated with CMMS, UAV-generated imagery enhances defect detection and maintenance planning capabilities. This study reports substantial time savings and safety improvements by reducing manual inspections in hazardous environments. The authors propose that UAV-assisted CMMS modules can improve condition monitoring accuracy, create digital inspection logs, and support predictive maintenance models. Their findings demonstrate the growing role of aerial sensing in intelligent asset management systems in industrial applications.

Shah, Zhong, and Ly [39] examined smartphone-based road asset monitoring using crowdsourced data to update CMMS records dynamically. Their system allows real-time fault reporting and geo-tagged image submission by field technicians. Integrating mobile technologies improves the responsiveness and data accuracy of CMMS asset databases. The authors emphasize the importance of quality assurance protocols for validating the collected data before maintenance execution. This model demonstrates how distributed mobile systems empower decentralized asset management and enhance collaborative maintenance workflows within industrial organizations.

Yu, Yuan, and Zheng [40] implemented a university fixed asset information management system using IoT devices. The system automates the tracking of movable assets and connects directly to CMMS for condition monitoring and maintenance alerts. The results show a significant improvement in preventive maintenance compliance, asset accountability, and lifecycle tracking. This study highlights that IoT-driven CMMS can effectively manage diverse equipment portfolios while reducing human effort. Such integration is highly relevant to industrial manufacturing, where similar frameworks enhance asset utilization and sustainability.

Zhao [41] investigated GPS tracking data processing to support spatiotemporal analytics for mobile asset management. The study's data-cleaning and pattern-extraction algorithms improve the accuracy of the asset movement history within CMMS databases. The model allows predictive routing and scheduling of maintenance based on the actual equipment usage. This study emphasizes the integration of advanced data-processing pipelines with CMMS platforms to enhance operational foresight. This approach provides a foundation for intelligent decision-making regarding mobile industrial assets, logistics planning, and field maintenance operations.

Robert [42] provided foundational principles for effective asset management, emphasizing the establishment of standardized asset hierarchies and performance indicators. His framework aligns with the ISO 55000 guidelines and



highlights the necessity of structured CMMS configurations. This study recommends defining data ownership, accountability, and continuous improvement metrics to enhance CMMS adoption success. By institutionalizing these governance mechanisms, organizations can ensure physical assets' long-term reliability and cost control. This study is a guiding reference for industries implementing comprehensive CMMS-driven asset management programs.

Kusuma wardhani, Gundersen, and Markeset [43] systematically mapped asset management research in the petroleum sector, identifying emerging trends in digitalization and reliability-centered maintenance. Their study revealed that CMMS adoption improves traceability and facilitates adaptive maintenance strategies under uncertain operational conditions. They argued for integrating knowledge management and AI analytics into CMMS to support decision-making in complex asset environments. These findings provide a roadmap for advancing from traditional to intelligent asset management paradigms across critical infrastructure sectors.

Elehinafe et al. [44] presented a real-time process simulation model for industrial systems and linked it with CMMS to enable proactive maintenance and performance benchmarking. Their approach enhances equipment reliability through continuous feedback on the condition of the equipment and predictive analytics. Integrating process modeling with CMMS data offers a unified view of asset health and operational efficiency. The authors concluded that such hybrid architectures significantly improve maintenance scheduling and reduce resource wastage, paving the way for next-generation self-optimizing maintenance systems in smart manufacturing plants.

Thaduri et al. [45] further explored large-scale distributed asset management systems for transportation and utilities. Their research underscores the need for scalable CMMS architectures to process high-volume sensor data. The proposed framework utilizes data aggregation and pattern recognition to generate meaningful asset-health indicators. The study demonstrates that when integrated with CMMS, robust data pipelines enable proactive maintenance planning, reduce downtime, and improve the operational resilience of CMMS. Their findings contribute to the foundation of data-intensive asset management strategies applicable across industrial domains.

Table 3: Summary of the Computerized maintenance management system for asset management

Ref.	Author(s) & Year	Title / Focus	Study Objective / Methodology	Major Findings	Limitations / Future Scope
[26]	T. Mhlaba & M. Masinde (2015)	Hardware prototype for laptop asset monitoring	Developed a low-cost microcontroller-based asset tracking system integrated with CMMS.	Automated asset condition updates, reduced manual errors, improved maintenance scheduling.	Focused on an academic setting; industrial-scale validation required.
[27]	C. Wang, Y. Tan & Z. Li (2015)	IoT-based enterprise asset management system	Designed an IoT-enabled CMMS framework for real-time fault detection.	Improved operational visibility and automated preventive scheduling.	Limited to small-scale experimental validation.
[28]	W. Li et al. (2016)	Real-time locating systems in construction management	Reviewed RTLS applications for asset movement and lifecycle monitoring.	Enhanced CMMS asset traceability and utilization accuracy.	Implementation complexity in large sites.
[29]	A. Thaduri, D. Galar & U. Kumar (2015)	Big data analytics for railway assets	Integrated sensor analytics with CMMS for predictive maintenance.	Improved asset reliability, safety, and cost efficiency.	Focused on transportation; requires industrial cross-validation.
[30]	T. Adame et al. (2018)	CUIDATS: RFID–WSN hybrid	Developed a hybrid IoT system for healthcare asset	Enhanced asset visibility and proactive	Need for scalability testing in manufacturing



		monitoring system	tracking.	maintenance scheduling.	contexts.
[31]	M. A. Al Mamun et al. (2016)	Intelligent bin-status monitoring	Applied IoT and rule-based logic to trigger CMMS maintenance actions.	Automated servicing and improved condition-based scheduling.	Domain-specific; industrial adaptation required.
[32]	A. Manbachi et al. (2016)	Real-time co-simulation monitoring framework	Combined simulation models with sensor data for predictive analysis.	Enabled proactive maintenance and reduced downtime via CMMS.	Needs validation on full-scale industrial plants.
[33]	J. Roe, T. O'Banion & E. Olsen (2016)	Mobile LiDAR-based utility inspection	Introduced LiDAR-guided asset assessment for CMMS data input.	Improved inspection accuracy and lifecycle monitoring.	Costly data acquisition and processing.
[34]	A. Rahimi, J. Götze & C. Möller (2017)	Enterprise architecture for asset management	Proposed data governance model for CMMS-ERP-SCADA integration.	Enhanced interoperability and data consistency.	Lacked a quantitative assessment of integration efficiency.
[35]	J. D. Campbell et al. (2016)	Asset Management Excellence	Established lifecycle-based decision framework for CMMS.	Integrated financial and operational KPIs with maintenance analytics.	Theoretical; implementation studies suggested.
[36]	Y. Fang et al. (2016)	BIM + RFID for indoor asset localization	Designed a hybrid model linking BIM visualization with CMMS.	Improved spatial awareness and automatic maintenance scheduling.	Applicable primarily to construction; needs manufacturing adaptation.
[37]	R. Ferdinandus & E. Setiawan (2016)	GeoJSON web-based road asset system	Created a mobile-GPS and web-integrated CMMS platform.	Enabled real-time asset mapping and work order automation.	Limited field testing on infrastructure assets.
[38]	E. Congress, A. Puppala & B. Lundberg (2018)	UAV-based asset inspection	Integrated drone-collected imagery into CMMS databases.	Enhanced defect detection, reduced manual inspection risks.	Dependent on weather and terrain, it requires automation of image analysis.
[39]	R. Shah, R. Zhong & T. Ly (2017)	Smartphone-based road-asset monitoring	Used mobile crowd-sensing for CMMS record updating.	Improved responsiveness and data accuracy in maintenance reporting.	Requires strict quality control of field data.
[40]	M. Yu, J. Yuan & H. Zheng (2018)	IoT-based fixed asset information management	Implemented IoT-driven CMMS for asset tracking in institutions.	Improved PM compliance and asset accountability.	Focused on academic institutions, industrial trials are recommended.



[41]	J. Zhao (2015)	GPS data processing for mobile assets	Developed data-cleaning algorithms for spatiotemporal tracking.	Enhanced CMMS accuracy and predictive maintenance planning.	Limited dataset; scalability analysis required.
[42]	J. Robert (2016)	Introduction to Asset Management Principles	Established ISO 55000-aligned CMMS framework.	Defined hierarchical asset modeling and governance practices.	Conceptual work; needs empirical implementation studies.
[43]	R. Kusumawardhani, O. Gundersen & O. Markeset (2017)	Mapping petroleum asset management research	Conducted systematic mapping of digital asset management trends.	Highlighted CMMS integration benefits for adaptive maintenance.	Petroleum-centric; cross-sector applicability needed.
[44]	B. A. Elehinafe et al. (2019)	Real-time process simulation and CMMS integration	Linked process simulation outputs with CMMS modules.	Enabled proactive maintenance and process optimization.	Simulation is limited to a specific industry; it needs a generalized model.
[45]	A. Thaduri et al. (2015)	Distributed asset data analytics for CMMS	Proposed large-scale data aggregation for CMMS integration.	Improved scalability and predictive maintenance accuracy.	Focused on transport assets; manufacturing adaptation required.

Preventive maintenance

Preventive maintenance (PM) scheduling is a classical CMMS function, a time- or usage-based trigger that reduces the likelihood of sudden breakdowns. The literature indicates a clear trend from calendar-based PM to condition-based and predictive maintenance (PdM) enabled by IoT sensors, edge/cloud analytics, and machine learning. Systematic reviews have summarized that PdM can substantially reduce maintenance costs and downtime when implemented correctly; however, success depends on sensor placement, data quality, and the maturity of analytic pipelines. Key research directions include feature engineering for anomaly detection, hybrid physics–data models for RUL estimation, and prescriptive modules that convert predictions into optimized work orders and spare-part actions. Recent studies have also stressed the need to co-design predictive models and inventory policies (joint PdM–spare optimization) to avoid situations where accurate failure forecasts cannot be acted upon because parts or personnel are unavailable. Finally, there is growing attention on practical deployment challenges, model drift, analytics lifecycle, explainability, and cybersecurity for cloud/edge-connected CMMS.

Shaheen and Németh [49] presented a comprehensive overview of preventive maintenance (PM) evolution, tracing its roots to post–World War II Japanese practices that reduced downtime but increased inspection costs. They explained how PM transitioned into reliability-centered and risk-based maintenance, aligning objectives with cost, reliability, and safety requirements. Their work emphasizes the shift from rigid, time-based scheduling toward knowledge-driven decision models, positioning PM as a proactive, data-oriented component of modern maintenance management systems integrated within Industry 4.0 ecosystems.

Duffuaa and Raouf [50] developed a framework for managing maintenance, which includes PM under planning and control. Their framework helped ensure that equipment was operated within specified performance limits by utilizing PM as part of computerized systems that balanced workloads, scheduling, and capacity. The authors indicated that a well-developed PM system would lead to improved machine productivity and reliability, as well as improved maintenance function predictability. The study also illustrates how computerized maintenance management systems



(CMMS) can support the PM philosophy in practice by managing schedules and coordinating resources systematically, thus providing a systematic approach to preventive care in an industrial context.

Hardt et al. [51] present a digitized model of Total Productive Maintenance (TPM) combining new forms of data environments. Their approach utilizes preventive inspection-type processes coupled with real-time data analytics to improve maintenance intervals and resource utilization. Their digital TPM approach allows for real-time predictive rescheduling based on sensor input, significantly decreasing manual effort and downtime. The findings suggest that further PM actions can advance system reliability, prevent premature canning, and improve availability. This study also indicates the critical intersections between TPM and Industry 4.0 analytics for continuous advances in preventive maintenance. Fusko et al. [52] outlined guidelines for implementing digital PM in Industry 4.0. Their model outlines three essential layers: real-time data acquisition, preprocessing, and predictive models, which convert static PM schedules into dynamic, condition-based maintenance schedules. Their system links sensors with computerized maintenance management systems (CMMS) platforms, supporting ongoing equipment performance monitoring and appropriate intervention timing. The authors demonstrated digital PM strategies to minimize the costs associated with maintenance, reduce downtime, minimize reliance on people, and improve the responsiveness of the overall system. This study focused on the importance of data architecture and model accuracy for managing adaptive preventive maintenance.

Alves and Ravetti [53] proposed a hybrid scheduling model of predictive-preventive maintenance for concurrent manufacturing systems. Their work included a combination of robust and semi-heuristic algorithms to incorporate PM activities into the production flow design. The simulation results showed considerably reduced downtime and increased machine throughput. This study bridges the preventive and predictive domains with the ability of PM schedules to adapt to the moment based on operational demand. This shows that integrated PM schemes make significant contributions to multi-objective optimization in the manufacturing process, aligning resource use, reliability, and performance, all consistent with Industry 4.0 manufacturing systems. Kiangala and Wang [54] provide an experimental framework integrating preventive maintenance with SCADA systems with respect to conveyor motors. The framework uses vibration sensors to gather data on machine conditions and graphical dashboards to forecast potential maintenance needs. This study demonstrates that integrating sensor networks with CMMS disciplines improves the flexibility and accuracy of PM practices and decreases downtime by allowing for timely corrective actions. Additionally, the SCADA integration of the PM framework can be set up as a closed-loop feedback system based on the condition of the operating machines. This development shows how the connections of Industry 4.0 support dynamic maintenance scheduling.

Li et al. [55] presented a preventive maintenance framework integrating an artificial neural network (ANN) algorithm to identify faults and schedule maintenance activities within machining centers. Li et al. used sensor data acquisition, signal preprocessing, and ANN-based fault classification to create the framework to determine the probability of failure and subsequently adjust the PM interval. Their results demonstrated reduced unplanned downtime and the ability to schedule maintenance work optimally. In addition, encouraging intelligent PM scheduling using neural networks can decrease over-maintenance. It aligns maintenance activities with the actual degradation conditions of the machine, thus optimizing the use of people and resources in automated production environments.

Chiu et al. [56] have defined a cyber-physical PM management system that marries multi-agent control with a cloud-of-things architecture. The system integrates real-time maintenance activities across multiple machines to ensure that PM activities are performed simultaneously on all connected assets. Prior work has indicated that the cloud-based shareability of maintenance scheduling and monitoring roles improves PM accuracy in large-scale smart factories. Their work highlighted the benefits of applying CPS, IoT, and cloud intelligence to design scalable preventive maintenance solutions that can be used across various sectors.

Spendla et al. [57] presented an ANN-driven preventive maintenance model to enhance production quality using predictive analytics. Their Industry 4.0-based system uses IoT sensors and machine learning to monitor process deviations and initiate PM actions before the occurrence of failures. A closed feedback loop between maintenance and manufacturing outcomes is established by linking product quality metrics with PM triggers. The results confirm that integrating PM with data-driven quality control reduces defect rates, increases uptime, and supports continuous process improvement in digital manufacturing systems.



Alarcón et al. [58] present an integrated Energy and Maintenance Management System (EMMS) that fuses energy analytics with preventive maintenance scheduling. Their system employs energy consumption as an indirect measure of equipment condition, enabling proactive PM actions. Integrating maintenance data and energy parameters ensures that performance and efficiency are optimized simultaneously. Their results demonstrated that energy-informed PM strategies reduce unnecessary interventions while extending equipment lifespan. This study highlights sustainability as an emerging dimension of preventive maintenance in innovative manufacturing.

Toeh et al. [59] present a hybrid preventive–predictive framework using machine learning and fog computing to optimize maintenance timing. The system applies genetic algorithms and logistic regression to predict the likelihood of machine failure, allowing for decentralized, real-time PM scheduling. Processing data closer to the equipment reduces the latency and dependence on the network. It improves the speed and dependability of decision-making and demonstrates the value of distributed computing for PM decision-making, specifically with geographically distributed industrial assets in Industry 4.0 situations.

Nordal and El-Thalji [60] described an intelligent maintenance management framework that ties PM functions to an enterprise-level digital strategy. Their system connects machine-level monitoring to the ERP module to align PM actions with the organization's operational and financial priorities. The model automates the scheduling of maintenance tasks and resource planning using AI-based optimization. They positioned PM as a bridge between shop-floor reliability management and strategic business objectives, advancing self-learning and data-driven maintenance ecosystems in smart manufacturing.

Bourezza and Mousrij [61] presented an intelligent PM strategy that integrated condition monitoring and remaining useful life (RUL) estimation. Their architecture processes real-time sensor data to predict degradation trends and issue maintenance recommendations for the equipment. The study shows that RUL-based PM significantly improves decision accuracy by reducing both under- and over-maintenance. Technicians benefit from real-time insights that prioritize preventive tasks based on equipment condition. This system exemplifies the evolution of scheduled PM to quantitative, data-supported maintenance strategies in Industry 4.0.

Caterino et al. [62] present a decision-support framework that determines optimal preventive or opportunistic maintenance strategies using CPS and IoT integration. Their algorithm selects actions that minimize the total cost and maximize reliability under dynamic operational conditions. Simulation tests showed that adaptive PM decisions outperformed static maintenance scheduling by balancing performance and cost efficiency. This study advances the prescriptive maintenance paradigms by optimizing preventive decisions using real-time analytics and intelligent control.

Masoni et al. [63] present a remote preventive maintenance model utilizing augmented reality (AR) interfaces for guided servicing. The system enables remote expert supervision and visual assistance for field technicians performing PM tasks. Studies have shown reduced human error, better procedural adherence, and usefulness in training and workforce development. This AR-based approach can support maintenance teams distributed across vast geographies while expanding PM capabilities to remote or hazardous work environments. The authors note that AR-enabled PM operations will enhance and flatten the technical skills in the field.

Konstantinidis et al. [64] describe their implementation of the MARMA (Maintenance Augmented Reality Maintenance Assistant) system in AR with computer vision, which is used to support technicians in performing planned maintenance (PM) activities. MARMA provides visual aids in a contextual step-by-step format to provide a degree of task validation (as operators have camera-based recognition). Their user-centered designs aim to improve procedural accuracy and reduce equipment downtime. Their results suggest that integrating AR with AI and computer recognition will elevate PM activities from a "documentation-tied process" to an overall interactive and intuitive maintenance experience to support human–machine collaboration principles in Industry 4.0.

Ceruti et al. introduced a powerful combination of augmented reality (AR) and additive manufacturing (AM) for the preventive maintenance (PM) of aerospace parts. The hybrid system features real-time PM visualization to manufacture parts using on-demand 3D printing. This Wi-Fi system reduces spare part stock and decreases repair time. This article depicts the fusion of digital visualization and fabrication, as well as observation and service for maintenance practice, which is shifting PM ecosystems in high-value aerospace manufacturing to be more sustainable and flexible.



Kumar and Galar introduce the term "Maintenance 4.0," and characterize PM as transitioning from reactivity in maintenance to predictive and prescriptive paradigms. They noted that PM data ensure the foundation for developing AI and IoT initiatives to develop self-learning and adaptive maintenance systems. Their framework encourages sustainability, reduces waste, and enhances resource efficiency in modern factories. Maintenance methods, analytics, and enterprise digitalization would redefine PM processes as a strategic enabler of intelligent manufacturing systems.

Giacotto and colleagues majored in the Smart Prescriptive Maintenance Framework (SPDF), which is designed for aerospace assembly lines. The framework integrates RAMS indicators with real-time CMMS feedback to synchronize PM activities with production operations. This model ensures higher reliability and safety by automatically optimizing preventive measures. Their findings confirm that integrating PM into digital twins and feedback loops significantly improves asset performance and operational continuity, contributing to data-driven prescriptive maintenance solutions in critical manufacturing sectors.

Shaheen and Németh [68] concluded that PM under Industry 4.0 has evolved from time-based inspection to intelligent, interconnected maintenance ecosystems. They assert that integrating PM with AI, IoT, CPS, and cloud computing enhances sustainability, machine uptime, and cost-effectiveness. Nonetheless, they identified persistent challenges—cybersecurity, interoperability, and workforce adaptation—that must be resolved for complete digital transformation. Their review positioned preventive maintenance as the cornerstone of intelligent autonomous maintenance management systems.

Table 4: Summary of the Computerized maintenance management system for Preventive maintenance

Ref. No.	Author(s) & Year	Focus / Title	Study Objective / Methodology	Major Findings	Limitations / Future Scope
[49]	Shaheen & Németh (2022)	Integration of maintenance functions with Industry 4.0	Reviewed PM evolution from time-based to knowledge-driven strategies.	Shifted PM to a data-oriented approach linking reliability and cost.	Requires further industrial validation and cybersecurity integration.
[50]	Duffuaa & Raouf (2015)	Planning and Control of Maintenance Systems	Modeled PM as a core planning and control function within CMMS.	Enhanced reliability and predictability through standardized scheduling.	It focuses on the conceptual framework and needs proof of digital implementation.
[51]	Hardt et al. (2020)	Digital Total Productive Maintenance	Embedded PM within data-driven TPM environments.	Improved efficiency and equipment availability via sensor-based rescheduling.	Lacked real-time industrial case validation.
[52]	Fusko et al. (2021)	Digitalizing Preventive Maintenance	Outlined a three-layer model (data collection, pre-processing, prediction).	Enabled condition-based PM, reducing cost and human dependency.	Relies on data quality and modeling accuracy.
[53]	Alves & Ravetti (2021)	Hybrid Preventive–Predictive Scheduling	Optimized PM and production planning for parallel systems.	Reduced downtime and improved throughput via robust scheduling.	Limited to simulation; needs industrial validation.
[54]	Kiangala & Wang (2020)	SCADA-Integrated PM for Motors	Merged sensor feedback with CMMS dashboards.	Enabled real-time PM adjustments and downtime reduction.	Confined to specific equipment; scalability issues remain.
[55]	Li et al. (2020)	ANN-Based PM for Machining	Used neural networks for fault diagnosis and dynamic PM	Reduced unscheduled shutdowns and optimized resource	A data-intensive model requires domain-specific training.



		Centers	scheduling.	use.	
[56]	Chiu et al. (2021)	Cyber-Physical PM System	Developed a multi-agent cloud-based PM architecture.	Improved coordination of maintenance across smart factories.	Dependent on cloud reliability and network latency.
[57]	Spendla et al. (2022)	ANN-Driven PM for Quality Improvement	Applied IoT and ML for quality-linked PM triggering.	Reduced defects and enhanced production continuity.	Limited scope of test environment.
[58]	Alarcón et al. (2021)	Energy & Maintenance Management Integration	Linked energy analytics to preventive scheduling.	Optimized maintenance and energy efficiency simultaneously.	Needs further validation in energy-intensive plants.
[59]	Toeh et al. (2021)	Fog-Computing Preventive–Predictive Model	Used ML and genetic algorithms for PM timing.	Enabled low-latency real-time PM decisions.	Computational load limits deployment in small firms.
[60]	Nordal & El-Thalji (2021)	Intelligent Maintenance Management	Aligned PM with enterprise digital strategies.	Automated scheduling and resource allocation via AI.	Integration with ERP requires data standardization.
[61]	Bourezza & Mousrij (2022)	RUL-Based PM Strategy	Applied condition monitoring and remaining-life prediction.	Reduced under- and over-maintenance; prioritized tasks accurately.	Sensor accuracy and data fusion remain challenges.
[62]	Caterino et al. (2022)	CPS-Based Decision Support for PM	Optimized preventive vs. opportunistic maintenance selection.	Lowered total cost and increased asset reliability.	Requires real-time integration with shop-floor systems.
[63]	Masoni et al. (2021)	AR-Enabled Remote Preventive Maintenance	Used AR interfaces for guided servicing and expert support.	Reduced human error and improved maintenance efficiency.	Dependent on AR hardware availability and training.
[64]	Konstantinidis et al. (2021)	MARMA: AR Maintenance Assistant	Combined AR and AI for real-time PM guidance.	Improved procedural accuracy and technician interaction.	High setup cost and camera calibration issues.
[65]	Ceruti et al. (2021)	AR + Additive Manufacturing for PM	Enabled on-demand part fabrication with AR instruction.	Reduced spare inventory and accelerated repairs.	Limited to aerospace; broader validation needed.
[66]	Kumar & Galar (2019)	Maintenance 4.0 Framework	Defined PM as a foundation for predictive and prescriptive maintenance.	Enhanced sustainability and resource optimization.	Implementation barriers in legacy systems.
[67]	Giacotto et al. (2021)	Smart Prescriptive Maintenance Framework	Integrated RAMS and digital twins for PM synchronization.	Improved asset performance and safety in assembly lines.	It focuses on aerospace and needs a cross-industry application.
[68]	Shaheen &	Future	Summarized the	Highlighted AI-, IoT-,	Emphasized



	Németh (2022)	Directions of PM in Industry 4.0	evolution of PM into intelligent ecosystems.	and CPS-driven PM benefits.	cybersecurity and workforce adaptation challenges.
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Research gap

Despite significant advancements in Computerized Maintenance Management Systems (CMMS), several gaps hinder their full potential in industrial environments. First, most studies focus on isolated CMMS functionalities, such as work order management, inventory control, or preventive maintenance, rather than developing an integrated, interoperable framework that supports end-to-end lifecycle management. Second, although IoT, AI, and cloud computing have enhanced real-time monitoring and predictive capabilities, their industrial adoption remains limited by data interoperability, cybersecurity, and system scalability challenges. Third, many CMMS implementations still rely on static rule-based decision models, and adaptive self-learning algorithms that evolve with operational data remain unexplored. Moreover, there is limited empirical validation of CMMS-driven predictive maintenance systems across heterogeneous manufacturing environments, particularly in small- and medium-sized enterprises (SMEs), where resource constraints inhibit digital transformation. The literature also reveals a lack of standardized metrics for evaluating CMMS performance, sustainability impact, and return on investment (ROI). Additionally, human-machine collaboration aspects, such as user training, change management, and XAI integration, have received insufficient attention. Therefore, future research should emphasize the development of intelligent, interoperable, and human-centric CMMS architectures aligned with Industry 5.0 principles, incorporating cyber-secure data frameworks, digital twins, and adaptive analytics for sustainable and autonomous maintenance management.

III. DISCUSSION

The evolution of Computerized Maintenance Management Systems (CMMS) reflects the broader digital transformation within modern manufacturing ecosystems. The reviewed literature demonstrates that CMMS has transitioned from a purely record-keeping tool to an intelligent, data-driven asset and maintenance optimization platform. However, this evolution is not uniform across all industrial sectors or technological dimensions. A key discussion point of this review is the disparity between theoretical advancements and practical adoption. Although numerous studies propose sophisticated models integrating artificial intelligence (AI), the Internet of Things (IoT), and cloud-based data architectures, industrial implementation often remains fragmented because of high costs, data heterogeneity, and limited interoperability among legacy systems.

Work order management has benefited substantially from digitalization, with CMMS modules enabling automatic job scheduling, resource tracking, and feedback logging. Studies have shown that integrating real-time sensor inputs with enterprise resource planning (ERP) systems enhances the accuracy of maintenance prioritization. Nonetheless, many organizations still rely on reactive workflows or manual approvals, suggesting that further integration with predictive analytics is essential for fully autonomous maintenance planning in the future. In addition, user-centered interface design remains a challenge; technicians often face complexity in navigating CMMS dashboards, which limits the effectiveness of data capture and feedback loops.

In inventory management, CMMS-enabled predictive replenishment and spare part optimization have shown measurable benefits in reducing downtime and maintenance costs. Integrating IoT-based tracking and RFID systems allows real-time monitoring of spare-part usage and inventory levels. However, gaps persist in synchronizing inventory systems with predictive maintenance schedules. A truly efficient CMMS should dynamically forecast spare-part requirements based on asset health trends rather than static reorder thresholds. This lack of predictive inventory intelligence impedes the seamless flow between maintenance planning and logistics management.

Asset management research within the CMMS framework has made significant strides toward real-time asset health monitoring using embedded sensors, wireless communication, and analytics platforms. The literature indicates that coupling condition monitoring with CMMS databases enhances equipment reliability and extends the lifecycle performance. However, implementing digital twins and automated decision support remains in its infancy. Few organizations possess the infrastructure to deploy such cyber-physical asset ecosystems on a large scale. Moreover,



concerns regarding data ownership, cybersecurity, and interoperability across vendor platforms continue to constrain widespread adoption.

Preventive maintenance management is one of the most dynamic areas influenced by Industry 4.0. The reviewed studies highlight a paradigm shift from calendar-to condition-based and predictive maintenance models. Machine learning, neural networks, and augmented reality (AR) tools have enabled the proactive identification of potential faults, thereby improving uptime and operational efficiency. Nevertheless, while predictive techniques outperform conventional PM approaches, algorithm deployment and data interpretation complexity often require specialized expertise that is not readily available in all industries. Furthermore, most case studies focus on large enterprises, and the scalability and cost-effectiveness of such advanced PM frameworks for small and medium-sized enterprises (SMEs) remain underexplored.

Another critical issue is the human factor in CMMS adoption. Although automation reduces the reliance on manual decision-making, it simultaneously demands higher levels of digital literacy among maintenance staff. The literature reveals a consistent lack of attention to user training, change management, and human-machine collaboration strategies. Therefore, successful CMMS implementation must focus on technological sophistication and address organizational readiness, user trust, and system usability.

From a strategic perspective, the discussion highlights the growing significance of sustainability and circular economy principles in CMMS design. Preventive maintenance supported by energy analytics, such as the EMMS model, shows how CMMS can contribute to resource conservation and reduce carbon emissions. However, only a limited number of studies have quantified the environmental and economic impacts of CMMS interventions, leaving a gap in sustainability-oriented maintenance assessments.

The synthesis of findings indicates that CMMS is evolving into an intelligent, interconnected ecosystem, but is still constrained by fragmented architectures, inadequate data governance, and inconsistent performance evaluation metrics. Future CMMS research and implementation must emphasize interoperability standards, secure cloud integration, and self-adaptive decision-making algorithms. The convergence of AI, digital twins, and IoT under the umbrella of Industry 4.0 and 5.0 promises to transform CMMS into the cornerstone of autonomous and sustainable manufacturing.

IV. CONCLUSION AND FUTURE SCOPE

The review shows that Computerized Maintenance Management Systems (CMMS) have changed from simple maintenance record-keeping tools into innovative, data-based platforms that are central to modern manufacturing operations. CMMS solutions have enhanced maintenance efficiency, equipment reliability, and decision accuracy across all industries through their core work order, inventory, asset, and preventive maintenance management modules. Industry 4.0 technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and cyber-physical systems (CPS), have significantly influenced maintenance management, moving from reactive to predictive and preventive maintenance paradigms. Further advances have allowed real-time monitoring of equipment health and condition-based scheduling of maintenance interventions. Automated fault detection and measurement of productivity and cost benefits of using data in maintenance management in the manufacturing sector.

However, despite technological advances, barriers continue to limit the universal adoption of CMMS and their full impact. Many industrial systems are still segmented and lack the interoperability of maintenance, production, and enterprise resource planning systems. Data heterogeneity, cybersecurity considerations, and cost barriers to large IOT setups restrict the scalability of large technologies in many sectors, especially small and medium-sized enterprises (SMEs). Moreover, the full potential of AI-driven maintenance prediction and decision automation remains underutilized because domain-specific datasets, integration frameworks, and standardized evaluation metrics are lacking. Human factors, such as workforce resistance to digital tools, insufficient training, and usability issues, pose practical barriers to CMMS efficiency improvement. Additionally, sustainability and circular economy considerations are only beginning to be incorporated into maintenance analytics, despite their growing relevance in global manufacturing policy.

The future scope of CMMS research and development lies in creating intelligent, interoperable, and adaptive maintenance ecosystems. Future systems must emphasize seamless integration across the production, logistics, and



enterprise layers through open communication standards and cloud-based architectures. Incorporating digital twin technology can enable virtual asset modeling for predictive and prescriptive maintenance, thereby enhancing decision accuracy and system resilience. Machine learning and deep reinforcement learning further support adaptive maintenance planning by allowing CMMS to learn from operational data continuously. Moreover, embedding augmented reality (AR) and virtual reality (VR) interfaces improves technician interaction, remote support, and safety in maintenance operations.

Future CMMS platforms should also focus on sustainability-driven design by incorporating energy analytics, carbon footprint tracking, and eco-efficiency metrics to align with Industry 5.0 objectives. Integrating blockchain technology can improve data security, traceability, and transparency in maintenance transactions. Furthermore, developing low-cost, scalable CMMS solutions tailored to SMEs will democratize access to digital maintenance management, fostering broader industrial adoption. Human-centered design and XAI mechanisms ensure user trust, transparency, and interpretability in AI-based decision-making systems.

The CMMS is steadily transitioning to a new generation of innovative, sustainable, and autonomous maintenance systems. The convergence of AI, IoT, digital twins, and human-machine collaboration will redefine maintenance as a strategic function that ensures equipment uptime and contributes to organizational intelligence, energy efficiency, and long-term sustainability. Continued interdisciplinary research and industry collaboration will be vital for overcoming existing challenges and realizing the full transformative potential of CMMS within the framework of Industry 4.0.

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