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From Predictive to Prescriptive Maintenance in Power Generation: An Integrated Five-Layer Framework Validated through Systematic Comparative Analysis

Abstract
Prescriptive maintenance (RxM) has emerged as a strategic evolution in power generation, advancing beyond reactive and predictive approaches by leveraging technologies associated with Industry 4.0. The potential of RxM lies in its ability to support proactive and data driven decision processes. However, existing frameworks remain fragmented and lacking the modularity in complex and variable power plant environments. This study conducts a systematic literature review guided by five research questions to explore the conceptual foundations of RxM, the enabling technologies that support its application including the Internet of Things, machine learning, digital twins, and deep reinforcement learning, the structural components that define its architecture, the primary challenges to its implementation, and the strategies used for validation. Based on these findings, a modular and adaptive RxM framework is developed and conceptually validated using a systematic comparative analysis against seven benchmark studies. The proposed framework integrates cloud-edge computing infrastructures, advanced analytical layers, multi criteria evaluation mechanisms, and iterative feedback processes. The comparative results emphasize the framework's ability to support integrated and responsive maintenance strategies while remaining compatible with industrial platforms. Its design supports both new and existing operational environments, allowing gradual integration without requiring complete system replacement. This study offers a generalizable reference model that can guide organizations seeking to transition from predictive to prescriptive maintenance in power generation. Future research should prioritize field implementation, real time validation, and alignment with broader industry goals including environmental sustainability, transparent artificial intelligence, and improved protection of digital infrastructure.

Keywords:
Prescriptive maintenance, Systematic literature review, Systematic Comparative Analysis, Prescriptive Maintenance Framework

Introduction
Over the past few decades, industrial maintenance practices have undergone a paradigm shift, transitioning from reactive and time-based approaches to increasingly intelligent and data-driven strategies, culminating in the adoption of prescriptive maintenance as a forward-looking solution in asset management. Prescriptive maintenance (RxM) represents a proactive and data-driven approach that not only forecasts potential failures but also recommends optimal actions based on real-time operational data, system constraints, and evolving conditions. In high-stakes industries such as power generation, where reliability, efficiency, and asset longevity are critical, RxM holds the potential to significantly transform maintenance planning and execution. The acceleration of Industry 4.0 has further enhanced the feasibility of RxM by enabling the **integration of** advanced technologies including the Internet of Things (IoT), digital twins, machine learning, and cloud-edge hybrid infrastructures into asset management systems. These technologies allow for seamless data acquisition, complex analytics, and autonomous decision support, thereby facilitating dynamic and context-aware maintenance strategies. Despite the proliferation of such technologies, existing RxM frameworks often remain fragmented and constrained to limited industrial contexts. Many current models emphasize only certain enabling components, lacking a comprehensive architecture that incorporates key functionalities such as execution mechanisms and continuous feedback-based learning (Gutierrez-Franco et al., 2021; Walton et al., 2024; Zhao et al., 2024). Additionally, **integration** with legacy systems such **as SCADA (Supervisory Control and Data Acquisition) and** CMMS (Computerized Maintenance Management Systems) is inconsistent, further complicating implementation efforts in real-world settings (Goby et al., 2023; R. Kumar et al., 2024).
Several scientific studies have attempted to develop prescriptive maintenance models across a range of industrial domains. Studies such as those by (Bousdekis et al., 2020; Goby et al., 2023; Gutierrez-Franco et al., 2021; Walton et al., 2024), demonstrate notable advancements in the use of AI-driven analytics, digital twins, and decision support systems. For instance, (Goby et al., 2023) explore deep reinforcement learning in adaptive maintenance contexts, while (Walton et al., 2024) highlight predictive insights via real-time simulation models. These studies contribute to the ongoing development of prescriptive maintenance. However, some limitations can still be observed. Certain frameworks seem to place less emphasis on architectural components such as execution mechanisms and feedback processes, which are important for building responsive and adaptive systems. Additionally, many validation efforts rely primarily on simulations or controlled environments, offering limited insights into their performance under real-world conditions. This gap is further supported by a systematic extraction of 118 journal articles, where trends reveal the partial implementation of RxM capabilities. Such patterns point to a structural imbalance that hampers the realization of fully integrated and responsive RxM systems. While analytics and decision-making are commonly addressed, execution mechanisms and feedback loops are either weakly developed or entirely absent. Implementation challenges such as poor data quality, integration complexity, lack of interoperability, and insufficient workforce skills frequently emerge as barriers. These findings emphasize the need for a generalizable and modular framework that accommodates real-world complexities and allows progressive integration within existing infrastructures. Addressing this need, the present study develops a scalable framework tailored for power generation environments, grounded in a Systematic Literature Review (SLR) guided by PRISMA protocols (Haddaway et al., 2022). The framework synthesizes insights from the literature into a five-layer architecture: data collection, analytics, decision making, execution, and feedback, that promoting adaptability, interoperability, and continuous learning. To evaluate its robustness and relevance, a Systematic Comparative Analysis (SCA) is conducted against seven benchmark RxM models, enabling structured assessment of its architectural completeness and integration potential.
This paper aims to provide a structured and objective synthesis of how prescriptive maintenance is conceptualized, implemented, and validated within the context of power generation. The primary goal is to investigate how organizations can leverage advanced technologies to not only anticipate failures but also support real-time decision making and continuous system adaptation. By clarifying the architectural components and operational conditions required for scalable RxM implementation, this study encourages further exploration of frameworks that balance technological innovation with practical readiness. To support this aim, we summarize our investigation through the following guiding research questions:
1. RQ1 - What distinguishes prescriptive maintenance from predictive approaches in terms of concept and value?
2. RQ2 - What enabling technologies support the implementation of prescriptive maintenance in power generation?
3. RQ3 - What architectural components define a modular and generalizable RxM framework?
4. RQ4 - What are the key challenges and contextual considerations in implementing RxM?
5. RQ5 - How have existing frameworks been validated, and how can validation enhance the credibility of the proposed model?
As an effort to address the research questions, we conduct a systematic literature review (SLR) to explore how prescriptive maintenance has been studied and applied across various industrial contexts, with a focus on applicability to power generation systems. The contribution of this study is twofold.

First, it synthesizes insights into how, where, and why RxM can be applied by reviewing literature related to the collection, processing, and application of operational data through enabling technologies. Second, by performing a structured comparison of seven benchmark frameworks using a Systematic Comparative Analysis (SCA), we assess the architectural coherence and practical readiness of the proposed model. The SLR is based on the systematic review methodology described by (Haddaway et al., 2022), while the comparative analysis follows guidance from (Rihoux & Lobe, 2009) and (Yin, 2011). Accordingly, the structure of this paper is organized as follows. Section 2 elaborates on the conceptual foundations and background knowledge essential for understanding RxM. Section 3 outlines the research methodology, including search strategies, selection criteria, and data extraction procedures. Section 4 presents the results of the SLR and the formulation of the proposed framework. Section 5 introduces the proposed RxM framework, followed by a detailed comparative analysis and practical implications. Section 6 presents a detailed discussion of the findings and their implications, and Section 7 concludes the paper by summarizing the key conclusions and outlines directions for future research and practical application.

Theoretical Background

- Prescriptive Maintenance: Concepts and Characteristics

Prescriptive maintenance represents a more advanced stage in the development of maintenance strategies by combining optimization methods, continuous feedback, and adaptive decision making. Unlike predictive maintenance, which focuses on estimating the likelihood and timing of failures, prescriptive maintenance goes further by using post-prognostic data along with optimization techniques such as chance constrained models to develop targeted strategies that improve system performance (Cho et al., 2022). Its key advantages include the use of advanced analytics to generate actionable insights, the ability to respond to changing operational conditions, and improved scheduling that reduces downtime and costs. These capabilities make prescriptive maintenance especially valuable in complex environments, where the interaction between multiple components requires a coordinated and flexible maintenance approach.

- Technological Enablers for RxM Implementation

The effective application of prescriptive maintenance in power generation has been made possible through the advancement and integration of several digital technologies. The growing use of Internet of Things sensors has significantly improved the way equipment is monitored, offering detailed and real-time data that supports better maintenance decisions. At the same time, artificial intelligence and machine learning play a crucial role in identifying patterns and detecting irregularities within large datasets, which strengthens both predictive insights and prescriptive actions (Elfarri et al., 2023; Zhao et al., 2024). The introduction of digital twin technology adds another dimension by creating virtual models of physical assets that reflect their real-time behavior. This makes it possible to simulate operations, detect anomalies, and evaluate maintenance plans more effectively (De Benedictis et al., 2023; Elfarri et al., 2023). In addition, cyber physical systems along with cloud-edge based infrastructures provide the computing power and responsiveness needed to process data quickly and support real-time decision making.

Methodology

This research adopts a qualitative exploratory approach based on a Systematic Literature Review (SLR) aligned with the PRISMA 2020 protocol (Haddaway et al., 2022). The SLR method enables the structured identification, selection, and analysis of relevant studies on prescriptive maintenance (RxM), allowing for the formulation of a generalizable framework applicable to power generation systems.

- Literature Search Strategy

The literature review was carried out using Watase Uake, a web-based platform developed in Indonesia to facilitate systematic reviews. This tool, which is openly accessible, is directly connected to the Scopus database and provides essential functions for filtering, organizing, and analyzing scholarly articles. By leveraging Scopus, the review ensures access to a broad collection of peer-reviewed and high-impact journals. The search covered publications from 2014 to 2024, aiming to capture key developments over the past ten years in the area of intelligent maintenance systems. Keywords included combinations such as: "prescriptive maintenance framework", “prescriptive digital twin”, “prescriptive internet of things”, “prescriptive maintenance analytics”, “prescriptive maintenance energy”, “prescriptive machine learning artificial intelligence”, “prescriptive and predictive maintenance”, “prescriptive in power plants". The inclusion and exclusion criteria applied to refine the article selection **are summarized in Table 1** and for further details and visualization **of the selection process are presented in** Section 4.

Table 1. **The inclusion and exclusion criteria**

Inclusion Criteria	Exclusion Criteria
Published in English	Articles focusing exclusively on predictive maintenance
Indexed in Scopus Q1 journals (published between 2014 and 2024)	Studies not addressing prescriptive maintenance concepts, frameworks, or implementation
Addressed at least one RxM component (e.g., data analytics, decision making, feedback)	
Relevant to prescriptive maintenance applications, including but not limited to the industrial and energy sectors	

- Data Extraction and Classification Technique

Each article included in the review was carefully examined, and key information was extracted and sorted according to relevant thematic categories. This involved capturing general details such as the author’s name, publication year, country, and the type of industry being studied. The extraction also focused on conceptual insights, particularly how each study defined prescriptive maintenance and differentiated it from predictive approaches. Special attention was given to how the frameworks were structured, especially regarding components like data acquisition, analytical methods, decision processes, execution strategies, and feedback mechanisms. The review also explored practical challenges encountered during implementation, along with the methods used to assess the effectiveness of each framework. All the extracted data were compiled in a structured matrix using Microsoft Excel, allowing for organized classification into conceptual, technological, structural, and evaluative themes. This matrix provided the basis for a thematic synthesis that helped uncover common patterns and significant insights across the reviewed studies. The resulting themes were then aligned with five core research questions, ensuring that the analysis was clearly connected to the overarching aims of the study.

- Proposed Framework Development Process

The development of the proposed RxM framework followed a multi-stage and structured methodology (See Figure 1). The process commenced with a systematic literature search using the PRISMA 2020 protocol (Haddaway et al., 2022), which enabled the identification of high-quality peer-reviewed studies relevant to RxM in the power generation sector. This comprehensive search laid the groundwork for further analytical steps by ensuring that only relevant and impactful studies were included. Following this, key information was extracted and classified into thematic matrices. This classification stage organized the literature according to conceptual, technological, structural, and evaluative criteria, facilitating alignment with five predefined research questions. These questions explored the foundational concepts and advantages of RxM, the enabling technologies supporting its implementation, the structural components required for an effective framework, the practical challenges and contextual considerations, and the validation strategies adopted in existing models.

The next phase involved thematic synthesis, where recurring patterns and insights from the classified literature were identified and organized in accordance with the research questions. This synthesis informed the design of the RxM framework, which is composed of five interrelated functional layers: data collection, analytics, decision making, execution, and feedback. Each layer represents a critical component of the maintenance process, with mechanisms for integrating real-time sensor data, conducting intelligent analysis through machine learning, optimizing decision logic via multi-criteria methods and reinforcement learning, executing maintenance tasks using digital twin simulations and mobile workflows, and adapting continuously through feedback loops. The framework's modular and scalable architecture was designed specifically to support implementation within the complex and dynamic environments of power plants, while ensuring compatibility with existing systems such as SCADA, CMMS, and DCS. The validation step, depicted in the final phase (see Figure 1), involved comparing the framework against seven benchmark models selected from the literature based on their relevance, clarity of structure, and empirical grounding. Each benchmark was evaluated across the five core layers of RxM to identify areas of convergence, divergence, and innovation.

Figure 1. Flowchart to develop the proposed RxM framework.

- Framework Validation via Systematic Comparative Analysis

To confirm that the proposed prescriptive maintenance framework is both conceptually strong and practically applicable, a validation process was conducted using systematic comparative analysis. This method, which is qualitative in nature, is well suited for examining conceptual models, particularly when the goal is to identify structural similarities and thematic differences across multiple frameworks (Rihoux & Lobe, 2009; Yin, 2011). In the context of this study, it allowed the proposed model to be evaluated against established references while also drawing attention to its distinct features. The benchmark studies used in the comparison include works by (Bousdekis et al., 2020; Goby et al., 2023; Gutierrez-Franco et al., 2021; R. Kumar et al., 2024; Leahy et al., 2018; Walton et al., 2024) and (Zhao et al., 2024). These were not selected randomly but were chosen based on three key criteria. First, each of these frameworks presents a clear architectural structure that addresses several of the core functional layers of prescriptive maintenance, even though not all of them cover every layer. Second, they were developed in the context of power generation or other industrial settings with similar complexity. Third, they show clarity in methodology and offer replicable approaches, which are essential for meaningful comparison.

The comparative analysis was organized using a coding system derived from five core functional layers found in the literature: data collection, analytics, decision making, execution, and feedback. For each framework, its use of these layers was assessed and categorized as comprehensive, partial, or not present. This classification follows the evaluation approach outlined by (Bousdekis et al., 2020), and the layer definitions are based on the work of (Diez-Olivan et al., 2019). The results of this analysis, showing where the proposed model aligns with or differs from the reference studies (see Table 3). Most of the existing frameworks rely on SCADA and Internet of Things systems for data collection but show a wide range of approaches when it comes to analytics and decision support. Some focus on rule-based methods or traditional predictive tools, while the proposed model includes advanced techniques such as deep reinforcement learning, multi criteria decision making, and hybrid optimization. Notably, the proposed framework also provides a clearer structure for execution and feedback functions than the models it was compared with. While systematic comparative analysis is effective in identifying conceptual alignment, its limitation lies in the fact that it does not assess performance using empirical evidence. Therefore, even though the findings support the robustness and originality of the proposed model within the existing body of literature, further testing in real operational settings will be necessary to evaluate its practical performance (Gutierrez-Franco et al., 2021; Walton et al., 2024).

Results

- Overview of Selected Literature

This section presents the results of the systematic literature review (SLR) conducted to address five predefined research questions (RQ1-RQ5) RxM. A total of 118 articles published in Scopus Q1 journals between 2014 and 2024 were selected through a structured screening procedure guided by the PRISMA 2020 protocol (Haddaway et al., 2022). The article **selection process involved four stages: identification, screening, eligibility assessment, and** final inclusion (see Figure 2). From an initial pool of 378 records retrieved using targeted keywords, 149 articles remained after removing duplicates, non-Q1 sources, and ineligible entries. Following a retrieval step and full-text eligibility check, 118 articles were deemed suitable for inclusion in the review. The selected studies span a variety of industrial and academic domains, including power generation, manufacturing, transportation, and infrastructure systems. Collectively, they provide the conceptual and empirical basis for the development of a generalizable and modular RxM framework presented in the next sections.

Figure 2. A PRISMA flow diagram of selection process

- Bibliometric Characteristics

- Publication Trends Over

The volume of RxM related publications has grown significantly over the past decade, with a marked acceleration beginning in 2018 (see Figure 3). The number of relevant articles rose from fewer than 5 publications annually prior to 2017 to double-digit figures starting in 2018, reaching a peak of 24 articles in 2023 and 23 in 2024. This sharp increase, particularly from 2020 onward, coincides with the widespread adoption of digital transformation, Industry 4.0 practices, and the integration of artificial intelligence in asset management and maintenance planning. The upward trajectory reflected in the figure highlights the growing academic and industrial recognition of prescriptive maintenance as a critical enabler for intelligent and data-driven operational strategies. It also signals that the field is moving from conceptual exploration toward more mature, structured, and application-focused research.

Figure 3. The distribution of publications by year (2014-2024).

- Keyword Analysis

An analysis of the word cloud generated from the selected articles reveals a rich and diverse set of terms that reflect the technological foundations and strategic priorities of prescriptive maintenance (see Figure 4). Dominant keywords such as "machine learning", "prescriptive maintenance", "Internet of Things", "digital twin", and "predictive maintenance" appear prominently at the center of the visualization, indicating their central role in shaping current methodologies. Closely associated terms such as "artificial intelligence", "anomaly detection", "health monitoring", and "optimization" further emphasize the analytical and diagnostic depth involved in prescriptive systems. The distribution and frequency of terms, also suggest that prescriptive maintenance is inherently interdisciplinary, combining elements of data science, automation, and industrial control. Technical keywords like "deep learning", "decision trees", and "mathematical programming" coexist with broader operational goals such as "sustainability", "asset reliability", and "condition-based monitoring". This interplay demonstrates how technological capabilities are being leveraged to meet evolving maintenance objectives across sectors.

Figure 4. Word cloud visualization.

- Distribution by Industrial Domain

The reviewed literature covers a wide range of sectors, with the largest share of studies concentrating on manufacturing, accounting for 38 articles, followed by energy systems with 25. This suggests a strong focus on industries that rely heavily on physical assets. Other fields represented include transportation with 15 studies, 17 articles from either mixed or unspecified domains, and several emerging areas such as microgrids with 10 publications, healthcare with 8, and aerospace with 6 (see Figure 5). This distribution indicates both the established role of prescriptive maintenance in conventional industrial settings and its growing relevance in newer and more specialized domains. Pie chart illustrates the spread of articles across different sectors, emphasizing the broad applicability of prescriptive maintenance in industries with varying operational demands.

Figure 5. Distribution of publications by industrial domain (2014-2024).

- Distribution by Journal Outlet

The articles reviewed in this study were published across a wide array of Scopus Q1 indexed journals, reflecting the multidisciplinary scope and broad academic engagement with prescriptive maintenance research. The twenty most active journals contributing to this topic include IEEE Access, Sustainability, and Energies, each contributing between six and seven relevant publications (see Figure 6). Other frequently cited sources include Sensors, Computers and Industrial Engineering, Expert Systems with Applications, and Reliability Engineering and System Safety, indicating the strong presence of technical and data-driven perspectives in the field. This distribution demonstrates that discussions on prescriptive maintenance extend beyond conventional maintenance-focused publications. The topic is also widely addressed in journals that emphasize engineering systems, artificial intelligence, smart manufacturing, and decision support. The range of journals suggests that prescriptive maintenance is increasingly viewed as a critical subject in both academic and industrial communities. Its visibility across these diverse outlets affirms its relevance for solving complex problems in modern operational environments.

Figure 6. Top 20 journal classifications of RxM publications (2014-2024).

- Result of Article Extraction

This section summarizes the main findings of the systematic literature review by detailing how each of the 118 selected articles addresses the five research questions that guide this study. A structured approach was used to extract key information from each article, ensuring consistency in the analysis and sufficient depth for thematic interpretation. The extracted data covered a range of aspects, including conceptual definitions, enabling technologies, framework structures, practical implementation issues, and validation methods.

The thematic analysis reveals several important trends. For the first research question, 70 articles focused on the fundamental concepts and advantages of prescriptive maintenance, often emphasizing its development beyond predictive methods and its ability to produce targeted and optimized recommendations (Gibey et al., 2024; Matyas et al., 2017). Regarding the second question, 115 articles examined enabling technologies such as the Internet of Things, machine learning, cloud-based systems, and digital twins, showing broad agreement on the technological foundation required for prescriptive maintenance (Fox et al., 2022; Zhao et al., 2024). In response to the third question, 116 articles discussed the architectural design of prescriptive maintenance frameworks, consistently emphasizing the importance of modular structures organized into five key layers: data collection, analytics, decision making, execution, and feedback. These studies also stressed the need for compatibility with industrial systems such as SCADA and CMMS (Stadtmann et al., 2023). The fourth question was addressed by 117 studies, which identified recurring challenges like integration with existing systems, readiness of human resources, and the limited interpretability of artificial intelligence, while also noting opportunities in areas such as asset reliability and sustainability (Bousdekis et al., 2020; Leahy et al., 2018). The fifth research question, which deals with validation, was explored in 105 articles. While many studies used simulations or data driven evaluation methods (Ahmed et al., 2021; Karakaya et al., 2024), only a small number applied multiple case comparisons or structured framework assessments. This highlights a continuing gap in empirical validation, reinforcing the relevance of the Systematic Comparative Analysis approach used in this study. To ensure clarity and consistency, we provide a summary of article distribution across the five research questions (see Table 2). It includes bibliometric details such as years of publication, citation counts, and journal groupings, as well as the number of studies linked to each research question. A complete breakdown of the articles and their thematic contributions is available in Appendix A.

Table 2. Summary of Article Characteristics and RQ Coverage

Criteria	Summary
Total Articles	118
Publication Years	2017-2024
Average Citations	61 citations
Main Publishers	Elsevier, IEEE, MDPI, Springer, Taylor & Francis
RQ1 Coverage	70 articles
RQ2 Coverage	115 articles
RQ3 Coverage	116 articles
RQ4 Coverage	117 articles
RQ5 Coverage	105 articles

Proposed Framework for Prescriptive Maintenance in Power Plants

- Overview of Proposed Framework

This section presents a prescriptive maintenance framework that was developed through a systematic review of the literature, following the guidelines of the PRISMA 2020 protocol (Haddaway et al., 2022). The framework is organized into five interconnected functional layers: data collection, analytics, decision making, execution, and feedback. These layers are the result of thematic synthesis drawn from a range of empirical studies that consistently highlight the value of modular design and flexibility in industrial maintenance systems. Each layer represents a key operational aspect of prescriptive maintenance. The data collection layer brings together both real-time and historical data sourced from devices such as Internet of Things sensors, SCADA systems, and MES platforms. The analytics layer processes this data using various machine learning techniques, including support vector machines, random forests, artificial neural networks, and deep reinforcement learning, as well as methods for detecting anomalies and managing uncertainty. The decision-making layer includes tools such as multi criteria decision analysis, rule-based systems, and optimization techniques like mixed integer nonlinear programming and genetic algorithms. In the execution layer, the framework enables mobile workflows, simulates actions using digital twins, and triggers operational responses through system integration. The feedback layer completes the cycle by supporting continuous model learning and real-time system adjustment. This layered structure was intentionally designed to address limitations found in previous models, particularly in terms of scalability, system compatibility, and real-time functionality. It is well suited for condition-based maintenance strategies in power generation and can integrate with existing systems such as distributed control systems, computerized maintenance management systems, and SCADA platforms. The framework draws on insights from several empirical studies, including those by (Bousdekis et al., 2020; Goby et al., 2023; Gutierrez-Franco et al., 2021; R. Kumar et al., 2024; Leahy et al., 2018; Walton et al., 2024; Zhao et al., 2024). Each of these studies contributes to the framework's architectural integrity. As a result, the proposed model offers a flexible and broadly applicable solution for use in complex, asset dependent industries, especially within the energy sector.

- Comparative Validation of the Framework

Prior to conducting the comparative validation, a careful selection process was undertaken to identify suitable benchmark studies. The aim was to find prescriptive maintenance frameworks that had been tested or applied in real industrial settings and could serve as reliable references for structured comparison. This selection was informed by a systematic review of 118 relevant articles and was based on three main criteria: first, the presence of empirical implementation through simulations, field trials, or deployment in actual operations; second, the inclusion of functional layers that are central to prescriptive maintenance frameworks; and third, the relevance of the industrial domain, with preference given to sectors closely related to power generation. Following these criteria, seven studies were chosen to support the comparative validation. These include works by (Bousdekis et al., 2020; Goby et al., 2023; Gutierrez-Franco et al., 2021; R. Kumar et al., 2024; Leahy et al., 2018; Walton et al., 2024; Zhao et al., 2024). Each of these studies has been applied or evaluated within real or simulated environments in sectors such as cyber physical systems, aerospace, power distribution, and industrial automation. The comparative analysis is structured around five core layers derived from the proposed framework: data collection, analytics, decision making, execution, and feedback (see Table 3). These layers are used to examine each benchmark study in terms of shared strengths, areas that remain underdeveloped, and the unique contributions found within the proposed model.

Table 3. Systematic Comparative Analysis (SCA) of RxM frameworks

Layer	Proposed Framework	(Gutierrez-Franco et al., 2021)	(R. Kumar et al., 2024)	(Zhao et al., 2024)	(Goby et al., 2023)	(Walton et al., 2024)	(Leahy et al., 2018)	(Bousdekis et al., 2020)
Data Collection	IoT, SCADA, MES, real-time + historical, cloud-edge hybrid.	Relies on IoT sensors for monitoring key variables.	Relies on sensor networks within a cyber physical system.	Relies on data from IoT sensors.	Relies on SCADA and IoT integration.	Relies on data from IoT sensors.	Relies on SCADA and sensor-based data from wind turbines.	Relies on IoT-based sensor readings.
Analytics	ML (SVM, RF, ANN, DRL), anomaly detection, uncertainty quantification.	Uses machine learning for fault detection and prognostics.	Combines Random Forest and Gaussian Mixture Models for anomaly detection.	Uses DRL and transformer models to extract optimal policies.	Uses deep reinforcement learning (TranDRL) for decision-making.	Applies virtual reality and simulation-based analytics via digital twins.	Uses rule-based logic and statistical trend analysis.	Uses a learning-based model calibrated through sensor data.
Decision Making	Optimization (MINLP, GA), rule-based systems, MCDM (AHP, TOPSIS), dynamic DRL.	Rule-Based System and Decision Support System.	Decision Support System using a machine learning model.	Uses an optimization engine to recommend maintenance policies.	Uses DRL optimization for combinatorial action spaces.	Applies OODA loop integrated with simulation and ranking logic.	No structured decision layer defined.	Uses desirability functions to optimize prescriptive outputs.
Execution	Digital twin validation, mobile workflow integration.	No structured execution layer defined.	No structured execution layer defined.	No structured execution layer defined.	No structured execution layer defined.	The framework allows digital twin-driven simulation triggering.	No structured execution layer defined.	No structured execution layer defined.
Feedback	Continuous learning, model recalibration, real-time update.	No structured feedback layer defined.	No structured feedback layer defined.	Feedback-driven policy updates through DRL.	Feedback loop via reinforcement learning model.	Feedback enabled through simulation discrepancies.	Partial feedback based on alarms.	Continuous feedback loop through sensor recalibration.

The existing models shows strong performance in gathering data, most of them rely only on sources like IoT devices or SCADA systems. The proposed framework builds upon this by combining both real-time and historical data within a cloud and edge computing environment, which enhances its ability to respond effectively to changing operational conditions. In the analytics component, most benchmark studies apply either conventional machine learning techniques or focus specifically on deep reinforcement learning. The framework introduced in this study expands on these methods by incorporating statistical learning, deep learning, and approaches that account for uncertainty, allowing the system to adapt and provide reliable insights even under fluctuating and noisy conditions. For decision making, some models adopt rule-based logic or optimization methods, as illustrated in studies by (Bousdekis et al., 2020; Goby et al., 2023; R. Kumar et al., 2024). Unlike these previous efforts, the proposed framework combines multiple decision-making tools, such as multi criteria evaluation, metaheuristic algorithms, and reinforcement learning into a single integrated layer that supports more flexible and informed decisions. The most noticeable gaps among the benchmark models are found in the execution and feedback components. Studies such as those by (Goby et al., 2023; R. Kumar et al., 2024; Leahy et al., 2018) do not explicitly address these layers. In contrast, the proposed framework incorporates simulation through digital twins, mobile enabled task execution, and continuous feedback for model recalibration, resulting in a system that closes the loop and supports real time learning. Although each reference model offers valuable contributions, none provides a fully integrated structure that spans all layers of prescriptive maintenance with modular flexibility and continuous feedback. The proposed framework fills this gap by introducing a complete and adaptable architecture that supports advanced maintenance strategies, particularly in the complex setting of power generation.

- Functional Layer Description and Visual Integration

This section describes the five fundamental layers of the proposed prescriptive maintenance (RxM) framework, aligning each with the structured flow (see Figure 7). The figure illustrates how inputs, analytical techniques, and outputs are organized across interconnected layers, forming a continuous operational loop that transforms raw data into executable insights and adaptive learning. The first layer (1.1-1.3 in Figure 7) initiates the process by aggregating data from IoT sensors, SCADA systems, MES platforms, and historical maintenance logs. This combination is designed to integrate real-time and historical information into a single, unified input stream (1.3), supported by a hybrid cloud and edge computing infrastructure. Unlike models from (Bousdekis et al., 2020; Leahy et al., 2018), which focus predominantly on SCADA, or those from (R. Kumar et al., 2024) and (Gutierrez-Franco et al., 2021), which emphasize sensor networks, this framework consolidates both dimensions at the input level. As visualized in second layer (2.1-2.3 in Figure 7), the collected data is processed through cleansing, feature extraction, and anomaly detection (2.1), followed by predictive modeling using various machine learning algorithms (2.2), including support vector machines, random forests, artificial neural networks, and deep reinforcement learning. The output of this stage is predictive insight, such as failure forecasting and remaining useful life estimation (2.3). Although studies like (Goby et al., 2023) and (Zhao et al., 2024) highlight advanced reinforcement learning, and (Walton et al., 2024) focuses on digital twin modeling, few integrate these components into a cohesive analytics engine that supports both static and adaptive learning as this framework does. The third layer (3.1-3.3 in Figure 7) translates predictive insights into concrete maintenance recommendations. This is achieved through a combination of optimization methods (such as mixed integer nonlinear programming and genetic algorithms), multi-criteria decision-making tools (such as AHP and TOPSIS), and reinforcement learning-based policy adaptation (3.2). The resulting recommendations (3.3) are context-aware and operationally targeted. In contrast (R. Kumar et al., 2024) and (Gutierrez-Franco et al., 2021) use fixed rule-based logic, and (Goby et al., 2023) focuses exclusively on DRL. (Walton et al., 2024) incorporates simulation but lacks multi-method reasoning integration. The Fourth layer (4.1-4.3 in Figure 7) focuses on implementing the prescribed actions. Maintenance recommendations (4.1) are validated via digital twin simulation and deployed using mobile platforms or integrated into maintenance systems such as CMMS (4.2). The outcome is traceable, real-time executed maintenance activities (4.3). This layer addresses a gap in many prior models, including those by (Goby et al., 2023; R. Kumar et al., 2024), and (Leahy et al., 2018), which do not describe execution mechanisms in detail. While (Walton et al., 2024) incorporates simulation feedback, it is not directly tied to mobile or enterprise-level execution workflows. The final layer (5.1-5.3 in Figure 7) enables continuous improvement by feeding the results of executed actions back into the analytics model. This is done through real-time performance monitoring, recalibration, and retraining (5.2), enabling the framework to adapt to evolving conditions. The feedback loop (5.3) ensures that learning is reintegrated into the analytical engine (specifically Layer 2.2), closing the cycle. While structured feedback is rare in earlier models, only a few studies like (Bousdekis et al., 2020; Goby et al., 2023), and (Zhao et al., 2024) address it comprehensively. Others, such as (R. Kumar et al., 2024; Leahy et al., 2018), do not feature this capability. Each layer contributes to a closed-loop process of data acquisition, analysis, decision generation, execution, and feedback-driven refinement. Grounded in empirical evidence and enhanced by digital twin and learning technologies, the framework offers an integrated pathway to achieving effective prescriptive maintenance in complex industrial environments.

Figure 7. Proposed prescriptive maintenance (RxM) framework.

- Practical Implementation in Power Generation Contexts

The prescriptive maintenance framework introduced in this study was designed with adaptability in mind, making it suitable for various power generation systems, including thermal, hydroelectric, wind, and solar plants. Its modular structure integrates live monitoring, advanced analytics, and a continuous feedback loop, allowing it to function effectively in both centralized and distributed environments. In thermal power stations, combining SCADA outputs with historical records from MES platforms and asset logs supports early detection of irregularities and enables more accurate scheduling for critical components like boilers, turbines, and feedwater systems. The approach proposed by (R. Kumar et al., 2024) shows how cyber physical systems that rely on sensor-based monitoring and optimized decision logic can be implemented in large-scale energy operations. Within this framework, the use of rule-based reasoning and multi-criteria analysis helps plant operators prioritize interventions based on equipment condition and operational urgency. In the context of hydropower, simulation tools play a vital role in observing component wear, pressure variations, and flow behavior. (Walton et al., 2024) highlights the usefulness of digital twin platforms for conducting real-time simulations and validating maintenance strategies in fluid dynamic environments. The execution mechanism of the framework, which accommodates mobile access and CMMS integration, is particularly useful in remote or hard-to-reach hydropower sites. For wind and solar applications, where components are spread out geographically and manual intervention is often limited, the ability to process data at the edge and conduct remote diagnostics becomes essential. As demonstrated in studies by (Bousdekis et al., 2020) and (Leahy et al., 2018), even in locations with limited sensor infrastructure or intermittent connectivity, systems powered by IoT and SCADA can generate valuable operational insights. The feedback component of the framework, which supports ongoing learning and dynamic recalibration, enhances the system's reliability by enabling real-time adaptation to shifting conditions. Further evidence from (Gutierrez-Franco et al., 2021) suggests that prescriptive maintenance models can be integrated with logistics and inventory planning, which is crucial for managing spare parts and coordinating maintenance windows. Additionally, the studies by (Goby et al., 2023) and (Zhao et al., 2024) confirm the effectiveness of deep reinforcement learning in adapting decision policies under uncertain circumstances, an approach that this framework extends across various asset types. From a deployment standpoint, the execution layer has been structured for compatibility with widely adopted enterprise asset management platforms, including IBM Maximo and other CMMS solutions, using protocols such as OPC UA. This ensures the framework is not only operationally feasible but also measurable. As pointed out by (Bousdekis et al., 2020) and (Tektaş et al., 2022), the lack of standardized performance indicators for prescriptive maintenance remains a significant challenge. Therefore, building in integration points also helps in evaluating how the system performs in real settings through pilot-scale trials. The propose framework combines architectural insights from diverse studies into a structure that is ready to be applied in practice. Its flexibility across different energy technologies, coupled with its emphasis on real-time intelligence and continuous adaptation, offers a forward-looking foundation for improving maintenance management in the power sector.

Discussion

This section presents a comprehensive discussion that brings together the key insights gained from the systematic literature review and the validation process of the proposed prescriptive maintenance framework, as they relate to the five research questions. The discussion provides context for each question while also exploring their wider significance, especially within the context of power generation. Each part of the section corresponds to a specific research question and expands on the theoretical contributions, practical relevance, and existing gaps identified in the reviewed literature.

- Core Concept of RxM (RQ1)

RQ1 focused on understanding the core concept of prescriptive maintenance and how it differs from predictive maintenance (PdM), including the strategic benefits that arise from its implementation. The evolution of maintenance strategies reflects a gradual shift from reactive to proactive decision-making. RxM represents the most advanced phase in this progression, following corrective, preventive, and predictive paradigms. While PdM focuses on anticipating equipment failures using historical and real-time data, it typically stops at forecasting. RxM extends this capability by recommending what specific actions should be taken to mitigate or prevent those failures, taking into account operational constraints and strategic objectives. Conceptually, RxM emphasizes the role of decision support in maintenance. PdM answers the question "what might fail, and when?", while RxM asks "what should be done, how, and under what conditions?". This difference is not merely functional but structural RxM systems combine real-time sensing, analytics, and optimization models to generate context-sensitive prescriptions. Benchmark studies such as (R. Kumar et al., 2024) and (Goby et al., 2023) illustrate implementations where intelligent algorithms produce prescriptive outputs that guide or automate maintenance interventions. The benefits of RxM observed in the literature include improved asset reliability, reduced unplanned downtime, more effective task prioritization, optimized inventory use, and closer alignment between maintenance operations and production goals. (Bousdekis et al., 2020) and (Walton et al., 2024) emphasize how prescriptive approaches can enhance situational decision-making under uncertainty, while studies such as (Goby et al., 2023) show that systems with integrated feedback loops support incremental learning and system adaptability capabilities generally absent from predictive-only strategies.

- Enabling Technologies for RxM Implementation (RQ2)

RQ2 focused on identifying the key technologies that support the implementation of RxM. The literature and benchmark studies consistently highlight the importance of several enabling technologies, each contributing to a specific phase in the RxM process. The Internet of Things (IoT) enables real-time monitoring by connecting sensors and actuators across assets, allowing continuous data capture on variables such as vibration, temperature, and load. Studies such as (Bousdekis et al., 2020) and (Gutierrez-Franco et al., 2021) demonstrate how IoT platforms form the foundation of responsive maintenance systems. Machine Learning (ML) techniques particularly supervised models like Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) are widely used for detecting anomalies and forecasting failures. In more advanced settings, Deep Reinforcement Learning (DRL) is applied to learn optimal maintenance policies through iterative interaction with changing system states, as shown by (Goby et al., 2023) and (Zhao et al., 2024). Digital twins complement these technologies by simulating asset behavior and validating prescriptive actions in a virtual environment. (Walton et al., 2024), for example, illustrates how digital twin simulations can support model-based diagnostics and scenario testing prior to implementation. Collectively, these technologies enable intelligent and adaptive maintenance systems. Their respective roles are further contextualized in the next section, which discusses the architectural structure required to integrate them effectively.

- Structural Components of a Generalizable RxM Framework (RQ3)

RQ3 addressed the structural elements required to build a generalizable framework for RxM, particularly in power generation contexts. The systematic literature review and comparative analysis revealed a recurring architectural pattern built around five interrelated functional layers: data collection, analytics, decision making, execution, and feedback. These layers reflect the typical flow of information and control within RxM systems, beginning with the acquisition of real-time and contextual data from IoT and SCADA platforms, followed by data processing through machine learning models. Decision making builds on these insights using optimization techniques or rule-based reasoning, which are then operationalized through execution systems such as CMMS and validated via feedback loops that support continuous learning. Benchmark studies such as (Goby et al., 2023; R. Kumar et al., 2024; Walton et al., 2024) vary in their coverage of these layers, with most focusing on data and analytics while underemphasizing execution and feedback. This gap underscores the importance of a complete structural model that not only processes data but also links decisions to actions and learning mechanisms. The five-layer structure formalized in this study offers a modular foundation for adapting RxM across different asset types and system complexities. Its separation of concerns allows organizations to implement the framework incrementally, enhancing interoperability with existing systems such as SCADA, DCS, and CMMS. As such, the framework is positioned not as a rigid model, but as a flexible guide that supports both standardization and local adaptation in power plant environments.

- Implementation Challenges and Emerging Opportunities (RQ4)

RQ4 focused on identifying the key challenges and opportunities associated with implementing RxM in operational environments. The review and benchmarking studies highlight that while RxM offers promising capabilities, its adoption is shaped by both technical and organizational constraints. Among the technical challenges, data interoperability remains a central issue. Integrating data from heterogeneous sources such as legacy SCADA systems, IoT sensors, and CMMS platforms often requires middleware or custom APIs. Additionally, infrastructure limitations, particularly in aging facilities, can constrain the deployment of newer technologies like digital twins or cloud-edge computing. Another concern is the limited explainability of AI models, which can reduce operator trust in automated recommendations. On the organizational side, skill gaps, cross-functional misalignment, and lack of structured change management are frequently cited as barriers. Successful RxM adoption requires coordination between maintenance teams, IT departments, and plant management. Studies such as (Gutierrez-Franco et al., 2021) and (Walton et al., 2024) stress the importance of phased implementation and user-oriented system design. Despite these challenges, several opportunities are emerging. Modular architectures, like the one proposed in this study, offer backward compatibility and allow incremental deployment without overhauling entire systems. The rise of explainable AI (XAI) improves the transparency of model-based decisions, while advances in low-cost sensors and edge computing make RxM more accessible to resource-constrained facilities. These developments suggest that while implementation requires careful planning, the conditions for broader RxM adoption especially in power generation are increasingly being met. As pilot projects and industry trials expand, shared learning and practical standards are likely to follow.

- Validation and Practical Credibility of RxM Frameworks (RQ5)

RQ5 examined how earlier studies have validated RxM frameworks and how this process contributes to the credibility of the model proposed in this research. The review indicates that most existing RxM studies are still conceptual in nature, with validation efforts often restricted to simulations, prototype trials, or comparisons with current technological solutions. Field-based validations are still relatively rare, often due to operational constraints in industrial environments. In this study, the proposed framework was evaluated using SCA, which examined structural and functional alignment with seven empirically grounded RxM models. The comparison focused on the presence of five core layers “data collection, analytics, decision making, execution, and feedback” as well as enabling technologies such as IoT, ML, DRL, and digital twins. While not a substitute for field trials, this method allows structured reflection on conceptual completeness and functional readiness. The SCA revealed that although many models addressed data and analytics, they often lacked formalized mechanisms for execution and feedback. By contrast, the proposed framework integrates these components explicitly, positioning it as a more complete and adaptive system. This analytical depth enhances the internal consistency of the framework and provides a reference point for future implementation efforts. Nonetheless, further validation is needed. Future work should include pilot testing in operational power plant settings, accompanied by performance evaluation, cost-benefit analysis, and feedback from practitioners. Such efforts are essential to demonstrate not only conceptual soundness but also practical viability under real-world conditions. While the framework demonstrates alignment with existing architectural patterns and addresses gaps identified in comparative studies, its validation remains conceptual. The insights derived from this analysis provide a basis for further exploration but do not substitute for empirical field testing. The broader implications, limitations, and future directions of this study are outlined in the concluding section that follows.

Conclusions and Future Research

This study aimed to advance the understanding and practical application of RxM in the power generation sector by conducting a systematic literature review of 118 high quality articles published between 2014 and 2024. Through five well defined research questions, the study examined the conceptual basis of RxM, enabling technologies, architectural structures, implementation challenges, and validation strategies. These insights were synthesized into a modular, five-layer framework consisting of data collection, analytics, decision making, execution, and feedback components. The framework is designed to address the complexity of operational environments in power plants, offering a scalable and adaptable solution for transitioning from predictive to prescriptive maintenance strategies. The results show that RxM represents a significant evolution beyond predictive maintenance by enabling systems not only to anticipate equipment failures but also to recommend specific and context aware actions. This capability relies on the integration of technologies such as IoT sensors, machine learning algorithms, digital twins, and deep reinforcement learning. Each of these technologies plays a distinct role across the maintenance lifecycle, from sensing and data acquisition to simulation, real time analysis, and adaptive feedback. When systematically combined, they offer a robust platform for continuous improvement, increased operational efficiency, and enhanced asset reliability. The proposed framework draws from benchmark studies, aligning with existing models while addressing frequently overlooked aspects such as execution mechanisms and feedback-based learning, thus improving both theoretical depth and practical readiness.

However, implementing RxM in industrial settings presents several challenges. The study identifies key barriers, including technical limitations related to system interoperability, uncertainties regarding the reliability of artificial intelligence generated recommendations, gaps in organizational preparedness, and skill mismatches among maintenance personnel. These challenges underline the need for flexible architectures and phased implementation strategies. Modularity, transparency in decision logic, and compatibility with existing platforms such as SCADA and CMMS are essential for practical deployment. Although the literature reviewed includes various conceptual frameworks and simulation-based validations, there remains a lack of evidence from actual field applications, emphasizing the gap between academic development and operational implementation. To address this gap, future research should focus on applying the proposed RxM framework in operating power plant environments to evaluate its performance under authentic conditions. This includes assessing its consistency, accuracy of recommendations, user acceptance, and responsiveness to changing operational variables. In addition, it is necessary to establish standardized metrics for evaluating prescriptive maintenance systems. These metrics should go beyond predictive accuracy and measure the quality, impact, and timing of recommended interventions. Such indicators would not only enable effective evaluation but also provide a basis for ongoing improvement. Moreover, incorporating explainable artificial intelligence methods is vital for enhancing trust among users, especially as advanced models such as deep reinforcement learning become increasingly complex. The ability to interpret and trace system suggestions is essential to ensure effective collaboration between humans and intelligent systems in maintenance planning.

Furthermore, future studies should investigate the social and organizational aspects of RxM adoption, including workforce training, coordination across departments, and structured change management. As the industry progresses toward the principles of Industry 5.0, which emphasize human centered and sustainable technological development, prescriptive maintenance systems must evolve to support a balanced integration of analytical technologies with human expertise. This shift requires research that encompasses not only technological and economic factors but also ethical, regulatory, and workforce related considerations. Taken together, these insights reinforce the broader significance of this study, which offers a comprehensive and integrative outlook on prescriptive maintenance within the power generation context.

Appendix A. Detailed Mapping of Extracted Articles

1. This appendix provides a comprehensive mapping of the 118 articles analyzed in this study. Each entry includes the author(s), publisher, citation count, and their thematic contributions to the five research questions (RQ1-RQ5). The mapping was conducted using a structured extraction framework, ensuring consistency and traceability across the SLR process. This appendix serves as the empirical foundation for the bibliometric and thematic synthesis discussed in Section 4.

2. Table A.1. synthesized distribution of articles contributing to each RQ

Author	Publisher	Citation	RQ1	RQ2	RQ3	RQ4	RQ5
(Leahy et al., 2018)	MDPI	47	✓	✓	✓	✓	✓
(Mazon-Olivo et al., 2018)	Elsevier	46		✓	✓	✓	✓
(Matyas et al., 2017)	Elsevier	104	✓	✓	✓	✓	✓
(Gibey et al., 2024)	Elsevier	7	✓	✓	✓	✓	✓
(Pinciroli et al., 2023)	Elsevier	9	✓	✓	✓	✓	✓
(Gordon & Pistikopoulos, 2022)	AIChE	17	✓	✓	✓	✓	✓
(Elele et al., 2024)	IEEE	11	✓	✓	✓	✓	✓
(A. Kumar et al., 2019)	Elsevier	102	✓	✓	✓	✓	✓
(Spyrou et al., 2024)	Taylor & Francis	4	✓	✓	✓	✓	✓
(Koot et al., 2021)	Elsevier	144	✓	✓	✓	✓	✓
(Esnaola-Gonzalez et al., 2018)	IOS Pres	15		✓	✓	✓	✓
(Fox et al., 2022)	MDPI	37	✓	✓	✓	✓	✓
(Dutta et al., 2022)	Elsevier	13	✓	✓	✓	✓	✓
(Adamczyk et al., 2024)	Elsevier	1	✓	✓	✓	✓	✓
(W. Wang et al., 2019)	WILEY	19		✓	✓	✓	✓
(Kothona et al., 2024)	Elsevier	4	✓	✓	✓	✓	✓
(Bousdekis et al., 2020)	IEEE	11	✓	✓	✓	✓	✓
(Makarov et al., 2021)	Elsevier	9	✓	✓	✓	✓	✓
(Arias et al., 2023)	Elsevier	18		✓	✓	✓	
(Bulut & Özcan, 2024)	Elsevier	11	✓	✓	✓	✓	✓
(Lombardi et al., 2017)	Elsevier	78		✓	✓	✓	✓
(Y. Wang et al., 2022)	IEEE	5	✓	✓	✓	✓	✓
(Kaur et al., 2019)	Springer	261		✓	✓	✓	✓
(Diez-Olivan et al., 2019)	Elsevier	464	✓	✓	✓	✓	✓
(Zhao et al., 2024)	IEEE	4	✓	✓	✓	✓	✓
(Kibria et al., 2018)	IEEE	400	✓	✓	✓	✓	✓
(Mat Esa & Muhammad, 2023)	Elsevier	12	✓	✓	✓	✓	✓
(Ighravwe, 2022)	MDPI	9	✓	✓	✓	✓	✓
(Gordon et al., 2020)	ACS	21	✓	✓	✓	✓	✓
(B. Liu et al., 2019)	IEEE	25	✓	✓	✓	✓	✓
(Subramaniyan et al., 2019)	Elsevier	21	✓	✓	✓	✓	✓
(Martínez-Llop et al., 2021)	MDPI	6	✓	✓	✓	✓	✓
(Sedighi Maman et al., 2020)	Elsevier	85	✓	✓	✓	✓	✓
(Papaioannou, Dimara, Kouzinopoulos, et al., 2024)	MDPI	5	✓	✓	✓	✓	✓
(Elele et al., 2022)	MDPI	27	✓	✓	✓	✓	✓
(Rodríguez et al., 2024)	MDPI	1	✓	✓	✓	✓	✓
(Hoffmann & Lasch, 2024)	ACM	5	✓	✓	✓	✓	✓
(Jeon et al., 2024)	Elsevier	28	✓	✓	✓	✓	✓

(Walton et al., 2024)	Elsevier	2		✓	✓	✓	✓
(Rabkin et al., 2024)	Elsevier	3		✓	✓	✓	✓
(Goby et al., 2023)	Elsevier	20	✓	✓	✓	✓	✓
(Stein et al., 2018)	Springer	25	✓	✓	✓	✓	✓
(Stadtmann et al., 2023)	IEEE	28	✓	✓	✓	✓	✓
(Meissner et al., 2021)	Elsevier	51	✓	✓	✓	✓	✓
(C.-Y. Lee & Chien, 2022)	Springer	33	✓	✓	✓	✓	✓
(Ansari et al., 2019)	Taylor & Francis	152	✓	✓	✓	✓	✓
(Cho et al., 2022)	IEEE	9	✓	✓	✓	✓	✓
(Zhang et al., 2021)	MDPI	54		✓	✓	✓	
(Ariesen-Verschuur et al., 2022)	Elsevier	77		✓	✓	✓	
(Roma et al., 2024)	Elsevier	5		✓	✓	✓	✓
(Elfarri et al., 2023)	IEEE	15		✓	✓	✓	✓
(Longo et al., 2023)	Elsevier	15	✓	✓	✓	✓	✓
(Sainati et al., 2019)	Elsevier	34				✓	✓
(Raptodimos & Lazakis, 2020)	Taylor & Francis	45	✓	✓	✓	✓	✓
(Ilizástigui Pérez, 2021)	Elsevier	11		✓	✓	✓	
(Sexton et al., 2024)	Elsevier	0	✓	✓	✓	✓	✓
(Siddiqui et al., 2020)	Elsevier	23		✓	✓	✓	✓
(Zvoncek et al., 2017)	Elsevier	9		✓	✓	✓	✓
(Li et al., 2024)	Elsevier	3		✓	✓	✓	✓
(Kamble et al., 2020)	Elsevier	703		✓	✓	✓	
(Armstrong & Banks, 2015)	Elsevier	57	✓	✓		✓	✓
(Gutierrez-Franco et al., 2021)	MDPI	59		✓	✓	✓	✓
(Ahmed et al., 2021)	Elsevier	100		✓	✓	✓	✓
(Habibzadeh et al., 2020)	ACM	68		✓	✓	✓	
(Pessach et al., 2020)	Elsevier	175		✓	✓	✓	✓
(Sjödin et al., 2023)	Elsevier	94	✓	✓	✓	✓	✓
(Brzezińska et al., 2019)	MDPI	13		✓	✓	✓	✓
(Baldin et al., 2021)	MDPI	19			✓	✓	
(Y. Liu et al., 2023)	IEEE	15	✓	✓	✓	✓	✓
(Lepenioti et al., 2021)	IEEE	11		✓	✓	✓	✓
(Tektaş et al., 2022)	MDPI	3		✓	✓	✓	✓
(Quinn et al., 2020)	Elsevier	65		✓	✓	✓	✓
(Sharma et al., 2022)	MDPI	27	✓	✓	✓	✓	✓
(Santiago et al., 2024)	MDPI	11	✓	✓	✓	✓	✓
(Bonifazi et al., 2022)	Springer	11		✓	✓	✓	✓
(De Benedictis et al., 2023)	IEEE	24		✓	✓	✓	✓
(Tinoco et al., 2021)	Elsevier	17	✓	✓	✓	✓	✓
(Musacchio et al., 2020)	JMIR	28	✓	✓	✓	✓	✓
(G. Wang et al., 2016)	Elsevier	1103			✓	✓	✓
(Riedl, 2022)	Springer	41		✓	✓	✓	✓
(Carvalho et al., 2024)	MDPI	0	✓	✓	✓	✓	✓
(Mateo-Fornés et al., 2021)	MDPI	12		✓	✓	✓	✓
(Susnjak, 2024)	Springer	24		✓	✓	✓	✓
(Consilvio et al., 2024)	Springer	4	✓	✓	✓	✓	✓
(Brennecke et al., 2024)	Springer	0		✓	✓	✓	
(Y. Liu, Shen, Fan, et al., 2022)	MDPI	22	✓	✓	✓	✓	✓
(R. Kumar et al., 2024)	Springer	6	✓	✓	✓	✓	✓
(T. Denton, 2023)	Taylor & Francis	6		✓	✓	✓	
(Nadiri et al., 2018)	Springer	41		✓	✓	✓	✓
(Kim et al., 2023)	Sage	0		✓	✓	✓	
(Lavy et al., 2014)	Taylor & Francis	41	✓	✓	✓	✓	✓
(Yildiz et al., 2022)	Springer	8		✓	✓	✓	✓
(Gupta et al., 2023)	POMS	16		✓	✓	✓	✓
(Pearlstein, 2017)	Taylor & Francis	1	✓	✓	✓	✓	✓
(Karakaya et al., 2024)	Taylor & Francis	0	✓	✓	✓		✓
(Mammadov et al., 2023)	Springer	8		✓	✓	✓	✓
(Ardito et al., 2022)	Emerald	47		✓	✓	✓	
(Wu et al., 2023)	Elsevier	42	✓	✓	✓	✓	✓
(X. Wang et al., 2024)	Elsevier	16	✓	✓	✓	✓	✓
(Tian et al., 2023)	Elsevier	36	✓	✓	✓	✓	✓
(Gnekpe et al., 2024)	Elsevier	2		✓	✓	✓	✓
(Chaves Franz et al., 2024)	Elsevier	3	✓	✓	✓	✓	✓
(Marzouk & Seleem, 2018)	Elsevier	20	✓	✓	✓	✓	✓
(Leturiondo et al., 2017)	Elsevier	42	✓	✓	✓	✓	✓
(Al Hanbali et al., 2022)	Elsevier	11	✓	✓	✓	✓	✓

(Nakousi et al., 2018)	Elsevier	15	✓	✓	✓	✓	✓			
(J. Lee et al., 2016)	Elsevier	169	✓	✓	✓	✓	✓			
(Notz et al., 2023)	Elsevier	3	✓	✓	✓	✓				
(Panayiotou et al., 2023)	IEEE	43	✓	✓	✓	✓	✓			
(Hoyos et al., 2023)	Elsevier	4	✓	✓	✓	✓				
(Y. Wang et al., 2019)	IEEE	967	✓	✓	✓					
(Srinivas & Ravindran, 2018)	Elsevier	112	✓	✓	✓	✓	✓			
(Papaioannou, Dimara, Krinidis, et al., 2024)	Elsevier	1	✓	✓	✓	✓	✓			
(Cromie & Bott, 2016)	Elsevier	0	✓	✓	✓					
(Singh et al., 2023)	IEEE	7	✓	✓	✓	✓	✓			
(Y. Liu, Shen, Guo, et al., 2022)	IEEE	14	✓	✓	✓	✓				
(J. Wang et al., 2023)	IEEE	11	✓	✓	✓	✓				
(Zhu et al., 2018)	Elsevier	155	✓	✓	✓	✓	✓			

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1. The authors conceptualized the study, conducted the literature review, performed the analysis, and wrote the manuscript.

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