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Research Article

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

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ABSTRACT
Prescriptive Maintenance (RxM) has emerged as an important development in power generation maintenance by extending data-driven maintenance beyond failure prediction toward action-oriented decision support. Its potential lies in helping organizations move from anticipating equipment failures to considering what maintenance actions should be taken, under which operational conditions, and with what constraints. However, existing RxM frameworks remain fragmented, particularly in relation to modular design, execution mechanisms, feedback processes, and integration with complex power plant environments. This study conducts a systematic literature review guided by five research questions to examine the conceptual foundations of RxM, its enabling technologies, architectural components, implementation challenges, and validation approaches. Based on the synthesis, a modular five-layer RxM framework is proposed, consisting of data collection, analytics, decision-making, execution, and feedback. The framework was conceptually assessed through Systematic Comparative Analysis against seven benchmark studies. The comparison suggests that the proposed framework provides broader architectural coverage by linking cloud-edge infrastructure, analytical models, multi-criteria decision logic, execution support, and feedback-based learning. Rather than demonstrating empirical effectiveness, the study offers a structured pathway for future practical implementation in power generation, subject to simulation, expert validation, pilot testing, and field-based assessment. The findings may inform researchers and practitioners seeking to advance from predictive to prescriptive maintenance while maintaining attention to transparency, system integration, cybersecurity, and empirical validation.

Keywords: Prescriptive Maintenance Framework, Prescriptive Maintenance, Systematic Comparative Analysis, Systematic Literature Review.

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INTRODUCTION

Maintenance practices in industrial systems have moved beyond reactive repair and fixed-schedule servicing toward more data-driven and decision-oriented strategies. As industrial operations become increasingly interconnected, maintenance is expected not only to prevent failures, but also to support reliability, cost control, operational continuity, and strategic asset management. Within this transition, Prescriptive Maintenance (RxM) has gained attention because it extends maintenance analytics from predicting what may happen to recommending what should be done. While predictive maintenance focuses on failure estimation, degradation patterns, and remaining useful life, RxM seeks to transform these insights into executable maintenance decisions by considering operational constraints, asset conditions, risk priorities, and system-level consequences (Bulut and Özcan, 2024; Fox *et al*., 2022). Power plants operate under strict reliability requirements, high asset criticality, and continuous production pressure. Maintenance scheduling in this context directly affects generator availability, system reliability, operational cost, and the coordination between asset condition and production schedules (Froger *et al*., 2016; Okumuşoğlu *et al*., 2024). A maintenance decision is therefore rarely a purely technical choice. It is closely related to outage planning, safety requirements, spare-part availability, production schedules, and the need to avoid forced outages or unnecessary downtime (Mehairjan, 2016; Okumuşoğlu *et al*., 2024). Consequently, the value of RxM in power generation depends not only on prediction accuracy, but also on whether predictive insights can be converted into feasible recommendations, integrated with operational systems, executed under real constraints, and improved through feedback from actual maintenance outcomes.

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Industry 4.0 technologies have strengthened the technical foundation for RxM by enabling advanced data acquisition, analytics, simulation, optimization, and adaptive decision support. IoT sensors, SCADA, DCS, machine learning, digital twins, cloud-edge computing, and reinforcement learning can support anomaly detection, degradation estimation, scenario evaluation, and maintenance decision-making. However, the availability of these technologies does not automatically result in a complete RxM architecture. Existing frameworks often emphasize selected components, such as data collection, predictive analytics, optimization, or simulation, without sufficiently explaining how recommendations are executed and how execution outcomes are reintegrated into future learning processes (Gutierrez-Franco *et al*., 2021; Walton *et al*., 2024; Zhao *et al*., 2024). Moreover, integration with legacy systems such as SCADA, DCS, CMMS, sensor networks, and historical maintenance databases remains inconsistent, making practical deployment in power generation environments more difficult (Gnekpe *et al*., 2024; Goby *et al*., 2023).

Previous studies have made important contributions to the development of Prescriptive Maintenance (RxM) across various industrial domains. The previous studies have advanced the use of AI-driven analytics, digital twins, reinforcement learning, simulation models, and decision support systems for maintenance planning (Bousdekis *et al*., 2020; Goby *et al*., 2023; Gutierrez-Franco *et al*., 2021; Walton *et al*., 2024). The previous studies demonstrate the relevance of deep reinforcement learning for adaptive maintenance decisions (Goby *et al*., 2023), while the other highlight the potential of real-time simulation models to generate predictive insights (Walton *et al*., 2024). These studies indicate that RxM is no longer a purely conceptual idea, but an emerging maintenance approach supported by increasingly sophisticated analytical capabilities. Nevertheless, the literature still shows an uneven development of RxM capabilities. Most existing studies have paid considerable attention to the analytical layer of RxM, particularly data processing, failure prediction, degradation estimation, simulation, and optimization. However, the operational layer remains less consistently developed. Key components such as execution mechanisms, feedback structures, interoperability, and integration with enterprise maintenance systems are often not fully specified. This limitation is important because RxM should not stop at generating predictions or optimal recommendations; it should also explain how recommendations are executed, monitored, evaluated, and reintegrated into future decision-making processes. In addition, many validation efforts still rely primarily on simulations or controlled environments, which limits understanding of how RxM frameworks perform under real-world industrial conditions. Therefore, a more complete architectural perspective is needed to connect prediction, recommendation, execution, feedback-based learning, and system integration within a coherent RxM framework.

The systematic extraction of 118 journal articles shows that Prescriptive Maintenance (RxM) has gained increasing attention, but its development remains uneven across the reviewed literature. Many studies have advanced the use of predictive analytics, anomaly detection, simulation, optimization, and decision-support models, yet fewer explain how maintenance recommendations are validated, implemented, monitored, and used to improve future decisions. This imbalance creates a clear gap between prediction and prescription, because the ability to forecast failures does not automatically ensure that recommendations can be translated into real maintenance workflows. The issue becomes more critical in power generation, where maintenance decisions must fit with control systems, asset management routines, outage planning, safety requirements, operational risk, and workforce capability. Responding to this gap, the present study proposes a five-layer RxM framework consisting of data collection, analytics, decision-making, execution, and feedback. The framework does not simply combine IoT, SCADA, DCS, CMMS, digital twins, machine learning, and reinforcement learning into one model; rather, it arranges these elements into a connected architecture that links predictive insight with context-aware recommendation, operational execution, and continuous learning. The data collection layer integrates information from IoT sensors, SCADA systems, MES platforms, and historical maintenance records, while the analytics layer processes these inputs through data cleansing, feature extraction, anomaly detection, and predictive modeling. The decision-making layer then converts analytical outputs into maintenance recommendations by combining optimization, multi-criteria decision-making, and adaptive learning logic. The execution layer gives the framework a practical orientation by linking prescribed actions with digital twin simulation, CMMS integration, and maintenance deployment mechanisms. The feedback layer closes the loop by allowing completed maintenance actions, asset responses, and operational outcomes to support recalibration, retraining, and future improvement. Methodologically, this study is grounded in a Systematic Literature Review guided by PRISMA protocols, which supports a transparent process for identifying RxM concepts, enabling technologies, architectural components, and implementation barriers (Haddaway *et al*., 2022). The proposed framework is then examined through a Systematic Comparative Analysis against seven benchmark RxM models to assess its architectural coverage, integration potential, and conceptual completeness. This assessment shows how the framework addresses recurring weaknesses in earlier approaches, particularly the limited attention given to execution and feedback mechanisms. However, the framework should be interpreted as a conceptual and architectural contribution rather than as an empirically tested industrial solution. Further validation through simulation, expert evaluation, case studies, or implementation in operating power plants is still needed to examine its feasibility, user acceptance, integration requirements, cybersecurity resilience, cost implications, and practical value.

This study aims to provide a structured synthesis of how prescriptive maintenance is conceptualized, implemented, and validated in power generation environments. It contributes theoretically by clarifying the transition from predictive to prescriptive maintenance and by emphasizing that RxM requires not only prediction and optimization, but also execution, feedback-based learning, and continuous system adaptation. The study further integrates fragmented RxM components into a five-layer architecture that can be used to assess the completeness and maturity of existing and future RxM models. Practically, the proposed framework provides a reference for researchers, engineers, and asset managers seeking to develop RxM capabilities while still operating within existing infrastructures, including SCADA, DCS, CMMS, sensor networks, and historical maintenance databases. Therefore, the framework supports gradual and scalable implementation rather than assuming immediate full-scale deployment. The study is guided by the following research questions:

- RQ1-What distinguishes prescriptive maintenance from predictive approaches in terms of concept and value?
- RQ2-What enabling technologies support the implementation of prescriptive maintenance in power generation?
- RQ3-What architectural components define a modular and generalizable RxM framework?
- RQ4-What challenges and contextual considerations influence the implementation of RxM in industrial and power generation environments?
- RQ5-What assessment approaches have been used in existing RxM frameworks, and how can systematic comparative analysis be used to examine the conceptual and architectural coverage of the proposed framework?

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 and Lobe, 2009; Robert, 2012). Accordingly, the structure of this paper is organized as follows. Section 2 discusses the conceptual foundations of prescriptive maintenance and the enabling technologies that support its implementation. 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 five-layer RxM framework and explains the interaction among its layers. Section 6 presents the systematic comparative analysis, practical implications, and limitations of the proposed framework. Section 7 concludes the paper by summarizing the main contributions and outlining future research directions for empirical validation and industrial deployment.

LITERATURE REVIEW

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 (Fox *et al.*, 2022; Jeon *et al.*, 2024; Meissner *et al.*, 2021). 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 (Bulut and Özcan, 2024; Cho *et al.*, 2022).

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 (Santiago *et al.*, 2024; Zhao *et al.*, 2024). 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 (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.

Trustworthy and Human-Centered Foundations of Prescriptive Maintenance

The implementation of prescriptive maintenance requires more than sensor data, machine learning models, and optimization techniques. In power generation, where maintenance decisions affect safety, reliability, outage planning, and operational continuity, system-generated recommendations must be transparent, interpretable, and trusted by human decision-makers. Explainable Artificial Intelligence (XAI) provides an important foundation for this requirement by helping engineers understand why a model identifies a failure pattern, risk level, or maintenance action. This perspective is consistent with responsible AI literature, which emphasizes interpretability, accountability, and user-oriented transparency in decision-support systems (Rocha-Meneses *et al*., 2023). Recent studies on explainable predictive maintenance further show that model explanations, feature importance, and decision traces can make predictive outputs more accessible to maintenance engineers. For RxM, this interpretability is even more critical because the system moves beyond prediction toward recommending actions; therefore, explainability should connect the analytics layer with the decision-making layer and keep recommendations auditable and open to human review (Bugarski *et al*., 2026). Digital twin and human-centered decision-support literature also strengthen the theoretical foundation of the proposed RxM framework. Digital twins provide a digital representation of physical assets, enabling monitoring, simulation, and scenario-based reasoning before maintenance actions are executed. This function is especially relevant in power generation because interventions must be assessed against operational constraints, safety requirements, and system availability. Prior studies show that digital twin architectures can support fault diagnosis, simulation, data management, and decision-support services, although stakeholder involvement and security remain underdeveloped issues (Bugarski *et al*., 2026). At the same time, prescriptive recommendations in critical industrial environments should not be treated as fully autonomous decisions. They should remain human-supervised, allowing engineers to review, approve, or adjust recommendations before execution. This human-centered approach maintains organizational accountability while allowing analytical models, digital twins, and optimization methods to support more informed maintenance decisions (Bugarski *et al*., 2026; Passalacqua *et al*., 2024).

METHODOLOGY

Research Design and Review Protocol

This study adopts a qualitative exploratory design based on a Systematic Literature Review (SLR). The review was conducted to identify, organize, and synthesize existing knowledge on Prescriptive Maintenance (RxM), with particular attention to its conceptual foundation, enabling technologies, architectural components, implementation challenges, and relevance to power generation systems. The SLR procedure was aligned with the PRISMA 2020 protocol to improve transparency in article identification, screening, eligibility assessment, and final inclusion (Haddaway *et al*., 2022). Rather than treating the literature review as a narrative summary, this study used a structured review process to support the development of a five-layer RxM framework consisting of data collection, analytics, decision-making, execution, and feedback.

Literature Search Strategy and Eligibility Criteria

The literature search was conducted using Watase Uake, a web-based platform developed in Indonesia to support systematic literature review activities. The platform was used because it is connected to the Scopus database and provides functions for searching, filtering, organizing, and exporting bibliographic data. Scopus was selected as the primary database because it indexes a wide range of peer-reviewed journals and provides broad coverage of engineering, energy, computer science, industrial systems, and maintenance-related research. The search covered publications from 2014 to 2024 to capture the development of intelligent maintenance systems over the last decade. The search terms were developed to capture studies related to prescriptive maintenance, digital twins, machine learning, artificial intelligence, IoT, predictive-prescriptive maintenance transition, energy systems, and power plant applications.

If several search strings were used separately, each string should be reported individually to allow replication of the search process. The keywords used in the search included combinations of the following terms: “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”, and “prescriptive in power plants”. The article selection process was guided by predefined inclusion and exclusion criteria. These criteria were established to ensure that the selected studies were relevant to prescriptive maintenance and contributed to the development of a conceptual framework for power generation systems. Studies were included when they addressed at least one important component of RxM, such as data acquisition, analytics, decision-making, execution mechanisms, feedback loops, or implementation challenges. Articles were excluded when they focused exclusively on predictive maintenance without discussing prescriptive decision-making, maintenance recommendations, framework development, or implementation logic (Table 1).

PRISMA- Based Screening and Article Selection

The screening process followed the main stages of PRISMA 2020: identification, screening, eligibility assessment, and inclusion. In the identification stage, records were retrieved from Scopus through Watase Uake using the predefined search strategy. The initial search produced 378 records. After applying database filters related to publication year, language, document type, and source quality, 149 records remained. The next stage involved title and abstract screening. At this stage, studies that were clearly unrelated to prescriptive maintenance, industrial maintenance, energy systems, or power generation were excluded. Articles that focused only on predictive maintenance without prescriptive decision support were also removed. After this screening stage, 149 articles were retained for full-text assessment. The full-text assessment examined whether each article addressed RxM concepts, enabling technologies, framework structures, implementation challenges, or validation strategies. Articles were excluded at this stage when they did not provide sufficient discussion of prescriptive maintenance, did not contain relevant architectural or conceptual insights, or were not applicable to industrial or power generation contexts. The final set consisted of 118 articles included in the synthesis. The screening process was conducted independently by two reviewers. Inter-reviewer agreement was assessed using Cohen's kappa to evaluate consistency in study selection. Any disagreement between reviewers was resolved through discussion and consensus.

Data Extraction and Quality Appraisal

All articles included in the final synthesis were reviewed using a structured data extraction matrix developed in Microsoft Excel. The matrix was designed to ensure that comparable information could be collected from each article in a consistent way. The extracted information covered bibliographic details, research context, conceptual definitions, enabling technologies, architectural elements, implementation issues, and validation approaches. The data extraction process focused not only on what technologies were used, but also on how each study conceptualized prescriptive maintenance and how the proposed or discussed model moved from prediction to action (Table 2). Particular attention was given to whether each article addressed data acquisition, analytical techniques, decision-making logic, execution mechanisms, and feedback processes. These categories were used because they represent the core functional layers required for developing a closed-loop RxM framework.

Thematic Synthesis and Framework Development

The extracted data were analyzed through thematic synthesis to identify recurring concepts, technological patterns, architectural components, implementation challenges, and validation approaches in the reviewed literature. This process was guided by the five research questions and organized into four main themes: conceptual, technological, structural, and evaluative themes. The conceptual theme examined how prescriptive maintenance was defined and how it differs from predictive maintenance. The technological theme focused on enabling technologies, including IoT, SCADA, machine learning, digital twins, reinforcement learning, and optimization methods. The structural theme analyzed the architectural components commonly found in existing RxM models, particularly data collection, analytics, decision-making, execution, and feedback functions. The evaluative theme examined how previous studies assessed their proposed models, including conceptual assessment, simulation, case studies, expert evaluation, and field implementation.

The synthesis provided the basis for developing the proposed five-layer RxM framework. The data collection layer represents the integration of real-time sensor data, SCADA inputs, MES platforms, and historical maintenance records. The analytics layer covers data preprocessing, anomaly detection, predictive modeling, and remaining useful life estimation. The decision-making layer translates predictive outputs into maintenance recommendations using optimization, multi-criteria decision-making, and reinforcement learning. The execution layer connects these recommendations to maintenance activities through digital twin simulation, mobile workflows, and integration with systems such as CMMS. Finally, the feedback layer supports continuous refinement through performance monitoring, model recalibration, and retraining. After the framework was developed, it was assessed using Systematic Comparative Analysis against selected benchmark frameworks. This step was intended to examine the conceptual and architectural coverage of the proposed framework, particularly in relation to the five functional layers. Therefore, the assessment should be understood as a structured conceptual comparison rather than empirical validation. The process begins with a systematic literature search based on the PRISMA 2020 protocol, followed by data extraction and classification into thematic matrices. The extracted data are then analyzed through thematic synthesis to identify recurring concepts, enabling technologies, architectural components, and validation approaches. The synthesis results are used to construct the proposed five-layer framework, which is subsequently assessed through Systematic Comparative Analysis against selected benchmark frameworks.

Quality Appraisal Procedure

To strengthen the transparency and reliability of the review process, a quality appraisal procedure was conducted after the full-text screening stage. The purpose of this appraisal was not only to determine whether a study was relevant to prescriptive maintenance, but also to assess the extent to which each article provided sufficient conceptual, methodological, technological, and practical value for developing the proposed RxM framework. This step was particularly important because the reviewed literature covered different types of studies, including conceptual frameworks, simulation-based models, case studies, and technology-oriented maintenance studies. The quality appraisal was guided by a checklist developed specifically for studies on prescriptive maintenance frameworks in power generation and industrial maintenance contexts. The checklist consisted of nine criteria: clarity of research objective, methodological rigor, relevance to prescriptive maintenance, relevance to power generation or industrial maintenance, architectural contribution, discussion of enabling technologies, treatment of execution and feedback mechanisms, validation or evaluation approach, and practical implementation relevance. These criteria were selected because they reflect the main dimensions required to assess whether a study could meaningfully contribute to the development of a modular and closed-loop RxM framework. Each criterion was assessed using a three-point scoring system. A score of 2 indicated that the criterion was fully addressed, a score of 1 indicated that the criterion was partially addressed, and a score of 0 indicated that the criterion was not addressed. The maximum possible score for each article was 18. The appraisal results were used to support the interpretation of the reviewed literature and to identify which studies provided stronger conceptual or methodological foundations for framework development. If the appraisal was conducted by more than one reviewer, differences in scoring were resolved through discussion and consensus. The appraisal did not automatically exclude articles solely on the basis of score unless the study also failed to meet the inclusion criteria. Instead, the scoring process was used to indicate the relative strength of each article and to support a more transparent synthesis. Studies with higher scores were prioritized when defining the framework layers, identifying benchmark models, and interpreting architectural gaps. Studies with moderate scores were used when they offered relevant insights into specific technologies, implementation challenges, or validation approaches. This approach helped ensure that the proposed framework was built not only from thematically relevant literature but also from studies with sufficient conceptual and methodological value.

Framework Assessment through Systematic Comparative Analysis

After the literature synthesis and quality appraisal, the proposed prescriptive maintenance framework was assessed through Systematic Comparative Analysis (SCA). The purpose of this stage was to examine the conceptual completeness and architectural positioning of the proposed framework in relation to existing RxM models. SCA was selected because it is suitable for comparing conceptual frameworks, identifying structural similarities, and clarifying differences across models developed in related research contexts (Rihoux and Lobe, 2009; Robert, 2012). In this study, the method was used as a comparative and conceptual assessment rather than as an empirical validation of operational performance. Seven benchmark studies were selected for comparison: (Bousdekis *et al*., 2020; Goby *et al*., 2023; Gutierrez-Franco *et al*., 2021; Leahy *et al*., 2018; Walton *et al*., 2024; Kumar *et al*., 2024; Zhao *et al*., 2024). These studies were selected because they met three main criteria. First, they presented clear architectural or methodological structures relevant to prescriptive maintenance. Second, they addressed power generation, energy systems, or industrial maintenance contexts with comparable operational complexity. Third, they provided sufficient conceptual, technological, or methodological detail to support meaningful comparison with the proposed five-layer framework. The comparison was organized around five functional layers derived from the literature: data collection, analytics, decision-making, execution, and feedback. Each benchmark framework was examined to determine whether these layers were comprehensively addressed, partially addressed, or not addressed. This coding approach made it possible to identify which elements of RxM have been well developed in prior models and which remain underrepresented. The layer definitions were informed by prior work on maintenance analytics and industrial maintenance architectures, including (Bousdekis *et al*., 2020; Diez-Olivan *et al*., 2019).

RESULTS

Descriptive Quantitative Summary of the Reviewed 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

Table 1: Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Published between 2014 and 2024	Published outside the selected time range
Written in English	Not written in English
Indexed in Scopus and classified as Q1 based on the Scopus CiteScore percentile.	Not indexed in Scopus or not meeting the selected journal quality criteria
Addresses prescriptive maintenance concepts, frameworks, technologies, or implementation	Focuses only on predictive maintenance without prescriptive components
Discusses at least one RxM component, such as data analytics, decision-making, execution, or feedback	Does not discuss RxM concepts, frameworks, implementation, or decision support
Relevant to industrial maintenance, energy systems, or power generation contexts	Not relevant to industrial, energy, or maintenance contexts
Provides conceptual, methodological, empirical, or framework-related contribution to RxM	Lacks sufficient methodological or conceptual relevance to the review objectives.

Table 2: Data extraction matrix.

Extraction Category	Information Extracted
Bibliographic information	Author, year, title, journal, country, and research domain
Study context	Industry sector, power generation relevance, type of asset or system studied
RxM concept	Definition of prescriptive maintenance and distinction from predictive maintenance
Enabling technologies	IoT, SCADA, digital twin, machine learning, artificial intelligence, optimization, reinforcement learning
Data layer	Data sources, sensors, operational data, historical maintenance data
Analytics layer	Diagnostic, prognostic, anomaly detection, failure prediction, remaining useful life estimation
Decision-making layer	Optimization method, multi-criteria decision-making, recommendation logic, policy adaptation
Execution layer	Maintenance scheduling, CMMS integration, work order generation, mobile workflow, digital twin simulation
Feedback layer	Model retraining, recalibration, performance monitoring, continuous learning
Implementation challenges	Interoperability, data quality, workforce readiness, system integration, cybersecurity, organizational barriers
Validation approach	Conceptual validation, simulation, case study, expert assessment, industrial implementation
Contribution to framework development	Relevance to the proposed five-layer RxM framework

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. Figure 1 illustrates the article selection process used in this systematic literature review. The review identified 378 records from the Scopus database using keywords related to prescriptive maintenance, maintenance frameworks, digital twins, machine learning, artificial intelligence, and energy systems. Before screening, the selection process removed 105 duplicate records, 53 records marked as ineligible by automation tools, and 71 records from non-Q1 sources. After this filtering stage, the review retained 149 records for screening. The screening process did not exclude additional records at this stage, so all 149 reports were sought for retrieval. However, 31 reports could not be retrieved, leaving 118 reports for eligibility assessment. The eligibility assessment confirmed that all 118 retrieved reports met the inclusion criteria and were included in the final review. These 118 articles formed the basis for the descriptive quantitative analysis and thematic synthesis. The extraction matrix organized information from each article, including publication year, application domain, research method, dominant technology, validation approach, maintenance strategy, and recurring research gaps. This structure allowed the review to examine not only the conceptual development of RxM, but also the distribution of research patterns across the selected literature. Therefore, the PRISMA flow diagram provides a transparent basis for explaining how the final dataset was obtained and how it supported the subsequent quantitative and thematic analysis.

Bibliometric Characteristics

The publication profile indicates that RxM research developed gradually before entering a stronger growth phase. During the early publication period from 2014 to 2017, the number of studies remained relatively limited, suggesting that RxM was still emerging as a research topic. Publication activity became more visible between 2018 and 2022, alongside the broader adoption of Industry 4.0, artificial intelligence, and digital maintenance technologies. The strongest increase appeared in the most recent period, with 24 articles published in 2023 and 23 articles in 2024. Together, these two years accounted for 47 articles, or nearly 40% of the reviewed sample. This pattern shows that scholarly interest in RxM has accelerated sharply in recent years. It also indicates that researchers increasingly view maintenance not only as a predictive task, but also as a decision-oriented process. The growth pattern supports the relevance of reviewing RxM as a developing field that is moving toward more structured and application-focused research.

Publication Trends

The volume of RxM related publications has grown significantly over the past decade, with a marked acceleration beginning in 2018. 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 2).

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 (Figure 3). 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.

Distribution by Application Domain

The application profile in Table 3 shows that manufacturing remains the dominant domain, with 38 articles representing 32.20% of the reviewed literature. Energy systems also form a substantial portion of the sample, with 25 articles or 21.19% of the total articles. Microgrid-related studies add another 10 articles, indicating growing attention to distributed and energy-related maintenance applications. Other domains, including transportation, mixed or unspecified industrial settings, healthcare, and aerospace, show that RxM has been applied across different asset-intensive and high-reliability sectors. This distribution suggests that RxM is not confined to one industrial context, but power generation-specific applications remain less dominant than broader manufacturing studies. The journal outlet profile further reinforces the multidisciplinary character of the field. Studies appear in outlets related to engineering, artificial intelligence, sustainability, reliability, sensors, and decision support, including IEEE Access, Sustainability, Energies, Sensors, Computers and Industrial Engineering, Expert Systems with Applications, and Reliability Engineering and System Safety.

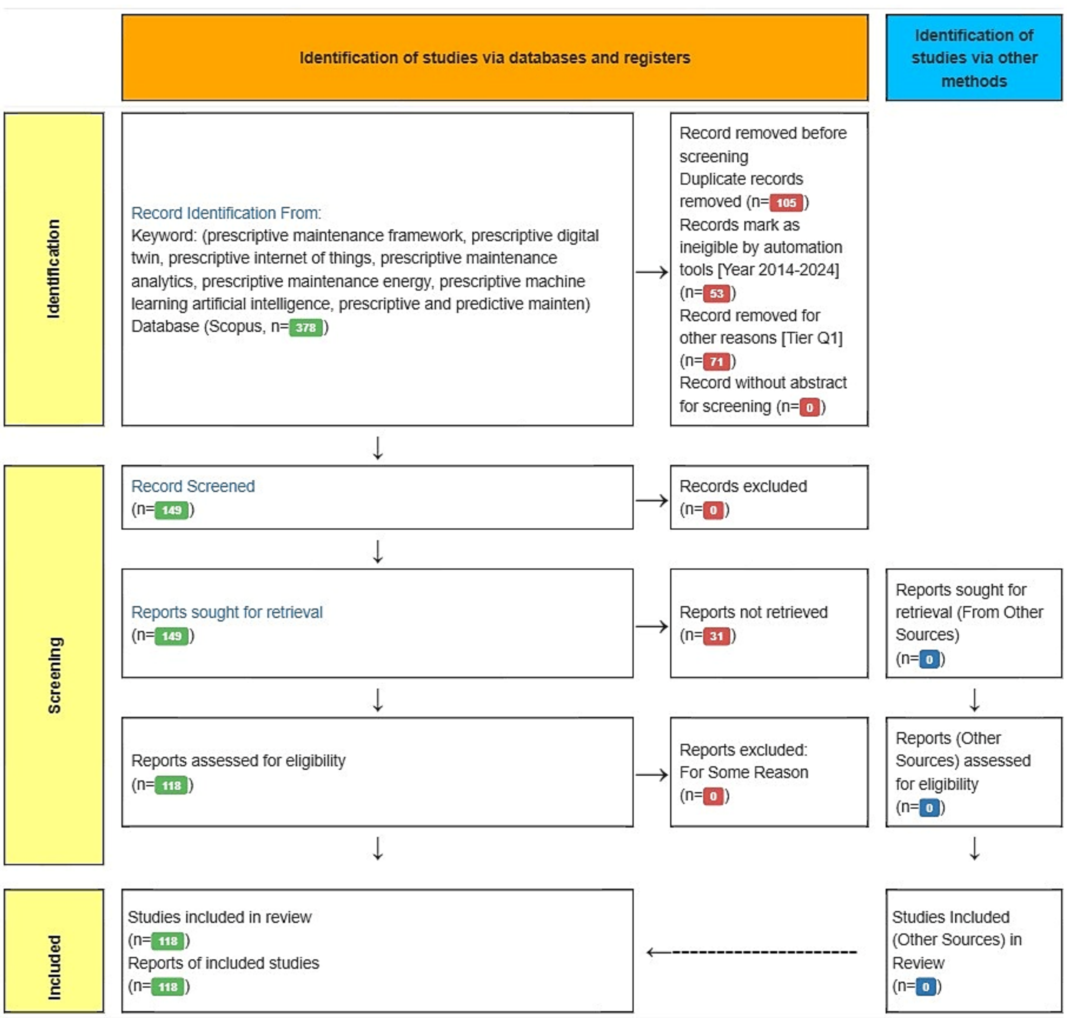

Figure 1: PRISMA flow diagram of selection process.

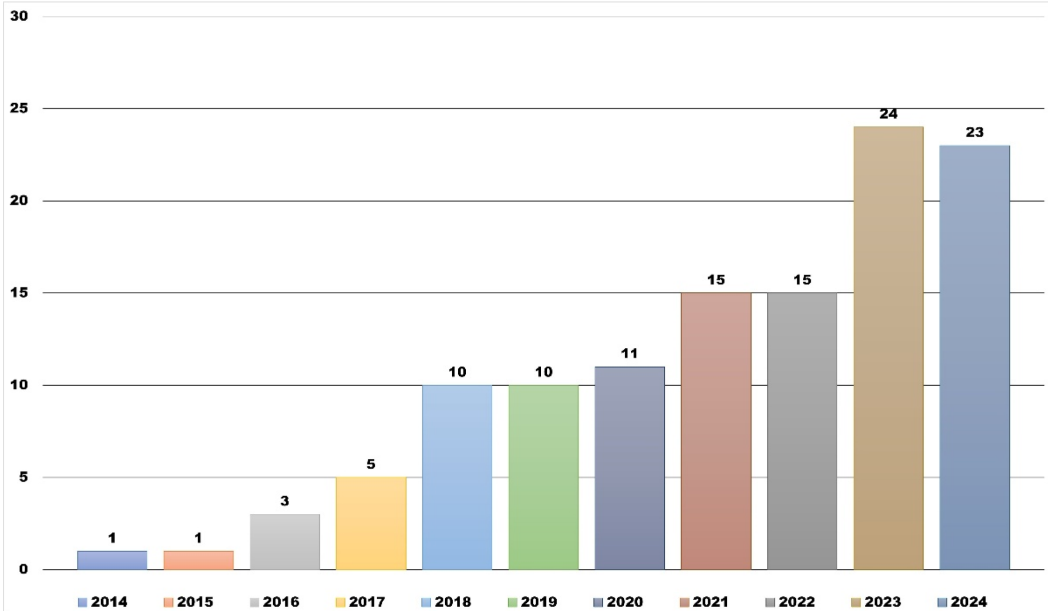

Figure 2: The distribution of publications by year (2014-2024).

This publication spread indicates that RxM research sits at the intersection of industrial maintenance, digital transformation, intelligent systems, and reliability engineering.

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. 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.

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 in Table 4. 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. 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.

The pattern shown in the table suggests that RxM research has become technologically rich but not yet fully mature in practical implementation. A large proportion of studies discusses IoT, machine learning, digital twins, optimization, reinforcement learning, and cloud-edge computing as the main technical foundations of RxM. These technologies support the movement from failure prediction toward maintenance recommendation, but the literature still shows uneven progress in translating recommendations into executable maintenance workflows. The high coverage of architectural components also indicates that many studies propose system structures, yet not all of them explain how execution and feedback should operate in real industrial environments. Validation remains another important issue because many studies rely on conceptual assessment, simulation, or data-driven evaluation rather than field implementation. The recurring gaps in execution mechanisms, feedback loops, explainability, cybersecurity, data interoperability, and SCADA/CMMS/DCS integration show why a more complete framework is still needed. These gaps become more critical in power generation, where maintenance decisions influence safety, reliability, outage planning, and operational continuity. Therefore, the thematic profile provides a direct basis for developing an RxM framework that links data collection, analytics, decision-making, execution, and feedback into a more coherent architecture.

FRAMEWORK FOR PRESCRIPTIVE MAINTENANCE IN POWER PLANTS

Overview of the Proposed Framework

The proposed prescriptive maintenance framework was developed from the thematic synthesis of the reviewed literature, with the PRISMA 2020 protocol used to guide the identification, screening, and organization of relevant studies (Haddaway *et al*., 2022). Rather than presenting RxM as a stand-alone technology, the framework places maintenance decision-making within five connected layers: data collection, analytics, decision-making, execution, and feedback. The data collection layer integrates real-time and historical information from IoT sensors, SCADA systems, MES platforms, and maintenance records, reflecting the need for reliable operational data in complex industrial environments (Bousdekis *et al*., 2020; Leahy *et al*., 2018). These data provide the starting point for understanding asset condition, operating behavior, and early signs of degradation. The analytics layer then processes this information through anomaly detection, diagnostic analysis, prognostic modeling, uncertainty handling, and remaining useful life estimation. Previous studies have shown that machine learning and sensor-based systems can support fault identification and failure prediction, especially when operational data are continuously updated and interpreted within an industrial context (Gutierrez-Franco *et al*., 2021; Kumar *et al*., 2024). However, in prescriptive maintenance, analytical outputs should not be treated as final decisions because prediction alone does not explain what action should be taken. For this reason, the decision-making layer uses optimization, rule-based reasoning, multi-criteria assessment, and adaptive learning approaches to translate predictive insights into possible maintenance recommendations (Goby *et al*., 2023; Zhao *et al*., 2024).

Table 3: Distribution of reviewed articles by application domain.

Application Domain	Number of Articles	Percentage of Total Articles	Brief Interpretation
Manufacturing	38	32.20%	Dominant application domain in the reviewed literature.
Energy systems	25	21.19%	Strong relevance to asset-intensive energy operations.
Transportation	15	12.71%	Indicates RxM relevance for mobility and infrastructure systems.
Mixed or unspecified industrial domains	17	14.41%	Shows cross-sectoral use of RxM concepts.
Microgrids	10	8.47%	Reflects emerging interest in distributed energy systems.
Healthcare	8	6.79%	Indicates broader use of predictive-prescriptive logic.
Aerospace	5	4.23%	Reflects relevance for high-reliability systems.
Total	118	100%	The current total exceeds 118 and should be checked against the extraction matrix.

Table 4: Thematic, Methodological, and Gap Profile of the Reviewed Literature.

Dimension	Quantitative / Thematic Summary	Interpretation
RQ1: Core concept and advantages of RxM	70 articles (59.32%)	A substantial portion of the literature discusses how RxM extends predictive maintenance toward action-oriented decision support.
RQ2: Enabling technologies	115 articles (97.46%)	Technologies such as IoT, machine learning, digital twins, cloud-edge computing, and optimization dominate the RxM literature.
RQ3: Architectural components	116 articles (98.31%)	Most studies discuss system architecture or framework components, although not all provide complete closed-loop structures.
RQ4: Implementation challenges and opportunities	117 articles (99.15%)	Deployment barriers such as interoperability, human readiness, and system integration are widely recognized.
RQ5: Validation approaches	105 articles (88.98%)	Validation is frequently discussed, but many studies rely on conceptual assessment, simulation, or data-driven evaluation rather than field implementation.
Dominant technologies	IoT, machine learning, digital twins, reinforcement learning, optimization, cloud-edge computing.	These technologies form the main technical foundation of RxM, but their integration into executable maintenance workflows remains uneven.
Research methods	Conceptual frameworks, simulation studies, data-driven modeling, case studies, comparative assessment, and limited field implementation.	The field remains methodologically diverse, but empirical implementation in real industrial settings is still limited.
Maintenance strategies	Predictive maintenance, prescriptive maintenance, condition-based maintenance, reliability-centered maintenance, risk-based maintenance, and hybrid strategies.	RxM is positioned as an extension of existing maintenance strategies rather than a replacement for all prior approaches.
Major research gaps	Limited execution mechanisms, weak feedback loops, lack of empirical validation, limited explainability, cybersecurity concerns, data interoperability, and limited SCADA/CMMS/DCS integration.	These gaps justify the need for a five-layer framework that explicitly includes execution and feedback components.
Relevance to power generation	Strong relevance to safety-critical and asset-intensive systems, but still requiring further empirical testing.	Power generation provides a relevant domain for RxM because maintenance decisions affect safety, reliability, outage planning, and operational continuity.

The execution and feedback layers give the framework a stronger operational orientation by connecting recommendations with maintenance action and subsequent learning. In the execution layer, recommendations can be examined through digital twin-supported scenario testing before being converted into maintenance activities, mobile workflows, or CMMS-based work orders (Walton *et al*., 2024). This step is important because maintenance decisions in power generation cannot rely only on model outputs; they must also consider asset criticality, outage planning, safety requirements, resource availability, and compatibility with existing systems. The feedback layer then returns execution results, work order outcomes, asset responses, and updated condition data to the analytical process. This feedback mechanism allows the system to learn from previous interventions and refine future recommendations over time. Such a closed-loop structure responds to a recurring limitation in earlier RxM models, where data acquisition, analytics, and decision logic often receive greater attention than execution and feedback mechanisms (Bousdekis *et al*., 2020; Goby *et al*., 2023; Kumar *et al*., 2024; Leahy *et al*., 2018). RxM recommendations will be useful only when they can work together in power generation with the systems already used by engineers, such as SCADA, DCS, historian databases, and CMMS. They should not remain as separate analytical outputs that are difficult to translate into daily maintenance practice. The proposed framework is best viewed as a conceptual and architectural guide rather than as a solution that has already been proven in real plant operations. Further testing in operating power plants is still needed to understand how well the framework can be applied, integrated, accepted by users, and translated into practical maintenance value.

Systematic Comparative Analysis of RxM Frameworks

The structured comparison (Table 5) shows that previous RxM frameworks have contributed valuable elements to the development of advanced maintenance systems, but their coverage is not evenly distributed across the full maintenance cycle. Most benchmark studies give strong attention to data acquisition, diagnostics, prognostics, and decision logic, which confirms the central role of IoT, SCADA, machine learning, optimization, and reinforcement learning in RxM research. At the same time, the comparison reveals that execution, feedback, explainability, human review, cybersecurity, and integration with existing systems remain less consistently developed. This pattern matters in power generation because maintenance recommendations must eventually enter real workflows, interact with SCADA, DCS, historian databases, and CMMS, and remain understandable to engineers before execution. The proposed framework responds to this gap by arranging RxM into a connected architecture that links data collection, analytics, decision-making, execution, and feedback rather than treating these elements as separate technical modules. Its contribution lies in clarifying how predictive insights may be translated into prescriptive recommendations, how those recommendations may be connected to maintenance action, and how execution outcomes may inform later model refinement. The comparison should be read carefully, as it reflects a conceptual and architectural assessment rather than evidence that the proposed framework performs better in practice. Although the analysis shows that the framework covers several important RxM elements, its real value still needs to be examined in operational settings. Future studies should therefore test the framework through simulation, expert assessment, pilot implementation, and real power plant data. Such validation would help clarify how feasible the framework is in practice, how users respond to it, how cybersecurity risks can be managed, what costs may be involved, and how much practical value it can offer to maintenance operations.

Functional Layer Description and Visual Integration

This section describes the five functional layers of the proposed Prescriptive Maintenance (RxM) framework and explains how they are connected in the structured flow presented in Figure 4. The figure shows a continuous process in which operational data are collected, analyzed, converted into maintenance recommendations, executed through maintenance workflows, and refined through feedback. The first layer begins by integrating data from IoT sensors, SCADA systems, MES platforms, and historical maintenance records into a unified input stream. This design allows the framework to combine real-time operating signals with historical information, rather than relying only on

Figure 3: Word cloud visualization.

Table 5: Structured Comparative Assessment of RxM Frameworks.

Evaluation Dimension	Assessment Focus	Pattern Observed in Benchmark Frameworks	Position of the Proposed Framework
Data acquisition	Use of IoT, SCADA, MES, sensors, historical logs, or operational data sources.	Most benchmark models address data acquisition clearly through IoT, sensors, or SCADA-based monitoring.	Integrates real-time and historical data from IoT, SCADA, MES, and maintenance records.
Diagnostics and prognostics	Fault detection, anomaly detection, degradation monitoring, failure prediction, or remaining useful life estimation.	Analytics is widely represented, although prognostics is not always developed consistently.	Combines anomaly detection, diagnostics, prognostics, uncertainty handling, and RUL estimation.
Decision-making and optimization	Use of optimization, rule-based logic, reinforcement learning, or multi-criteria decision-making.	Several models include decision logic, but the approaches vary across rule-based systems, optimization, DRL, and simulation.	Links predictive outputs to maintenance recommendations through optimization, MCDM, rule-based logic, and adaptive learning.
Explainability and human involvement	Transparency of recommendations and role of engineers or operators in decision review.	Explainability and human-in-the-loop mechanisms are often partial or not clearly stated.	Positions recommendations as human-supervised outputs that require review before execution.
Digital twin readiness	Use of simulation, virtual representation, or scenario testing.	Digital twin support appears strongly in only a limited number of models, particularly simulation-oriented frameworks.	Uses digital twin-supported scenario testing to examine maintenance alternatives before execution.
Industrial system integration	Compatibility with SCADA, DCS, CMMS, historian databases, or enterprise maintenance systems.	Integration with industrial systems is uneven and often not explained in operational detail.	Connects recommendations to existing maintenance workflows and systems such as SCADA, DCS, historian databases, and CMMS.
Cybersecurity consideration	Attention to OT/IT security, cyber risk, or secure integration.	Cybersecurity is generally not visible in the reviewed framework descriptions.	Recognizes cybersecurity as an important deployment issue, although further empirical assessment is still required.
Execution and feedback	Translation of recommendations into actions and use of outcomes for model refinement.	Execution and feedback are less consistently developed than data and analytics layers.	Explicitly includes execution and feedback as core layers to support work order linkage, recalibration, and continuous learning.
Scalability and feasibility	Potential extension across assets, plants, or industrial contexts.	Most models show partial scalability, but practical feasibility is often described at a general level.	Provides a modular architecture that may support phased implementation, subject to further testing.

one source of maintenance data. Earlier frameworks tend to emphasize either SCADA-based monitoring or sensor-driven data collection, whereas the proposed framework brings both types of information together at the input level (Bousdekis *et al*., 2020; Gutierrez-Franco *et al*., 2021; Kumar *et al*., 2024; Leahy *et al*., 2018). The second layer processes the collected data through cleansing, feature extraction, anomaly detection, and predictive modeling. This stage generates predictive insights such as failure forecasting and remaining useful life estimation, which are needed before maintenance recommendations can be formulated. Prior studies have shown the value of reinforcement learning and digital twin modeling, but these approaches are often developed as separate analytical components rather than as part of a connected maintenance cycle (Goby *et al*., 2023; Walton *et al*., 2024; Zhao *et al*., 2024).

The third layer translates predictive insights into maintenance recommendations by combining optimization, multi-criteria decision-making, and adaptive learning approaches. This layer is important because prescriptive maintenance should not stop at identifying potential failures, but should also help determine what maintenance action is more suitable under specific operational conditions. Some previous models rely more strongly on fixed rule-based logic, while others focus mainly on deep reinforcement learning or simulation-based reasoning (Goby *et al*., 2023; Gutierrez-Franco *et al*., 2021; Kumar *et al*., 2024; Walton *et al*., 2024). The fourth layer focuses on execution by linking recommended actions with digital twin-supported scenario testing, mobile workflows, and maintenance systems such as CMMS. This layer responds to a limitation in several earlier models, where the movement from recommendation to actual maintenance work is not explained in sufficient detail (Goby *et al*., 2023; Kumar *et al*., 2024; Leahy *et al*., 2018). The fifth layer closes the process by returning the results of executed maintenance actions to the analytics layer. Through monitoring, recalibration, and retraining, the framework allows new operational evidence to improve future recommendations. Structured feedback has been discussed in some prior studies, although it is not consistently developed across existing RxM models (Figure 5) (Bousdekis *et al*., 2020; Goby *et al*., 2023; Kumar *et al*., 2024; Leahy *et al*., 2018; Zhao *et al*., 2024).

DISCUSSION

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 illustrate implementations where intelligent algorithms produce prescriptive outputs that guide or automate maintenance interventions (Goby *et al*., 2023; Kumar *et al*., 2024). 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. The previous studies emphasize how prescriptive approaches can enhance situational decision-making under uncertainty (Bousdekis *et al*., 2020; Walton *et al*., 2024), while studies show that systems with integrated feedback loops support incremental learning and system adaptability capabilities generally absent from predictive-only strategies (Goby *et al*., 2023).

Enabling Technologies for RxM Implementation (RQ2)

RQ2 examines the main technologies that enable the implementation of Prescriptive Maintenance (RxM). The reviewed literature shows that RxM depends on a combination of digital, analytical, and simulation-based technologies, with each technology supporting a different stage of the maintenance process. The Internet of Things (IoT) plays an important role in

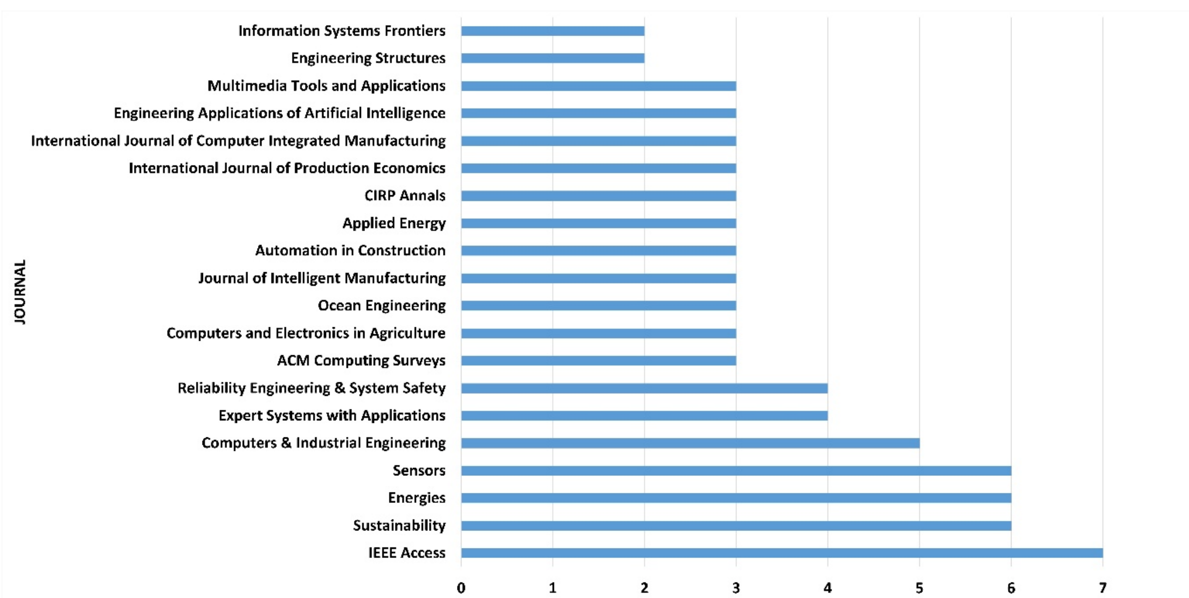

Figure 4: Top 20 journal classifications of RxM publications (2014-2024).

Figure 5: Proposed Prescriptive Maintenance (RxM) framework.

real-time monitoring because it connects sensors and actuators across industrial assets and allows continuous observation of operating variables such as vibration, temperature, pressure, and load. In maintenance systems, IoT-based platforms provide the initial data foundation needed to detect equipment condition changes and support timely decision-making (Gutierrez-Franco *et al*., 2021; Lepenioti *et al*., 2021; Gutierrez-Franco *et al*., 2021; Lepenioti *et al*., 2021). Machine learning techniques are also widely used in RxM, particularly for anomaly detection, fault diagnosis, and failure prediction. Supervised learning models such as Support Vector Machines, Random Forest, and Artificial Neural Networks help convert operational data into predictive insights that can inform maintenance planning. More advanced approaches, such as Deep Reinforcement Learning, extend this capability by learning adaptive maintenance policies through repeated interaction with changing system conditions (Goby *et al*., 2023; Zhao *et al*., 2024). Digital twins further strengthen RxM by providing a virtual representation of physical assets, allowing maintenance scenarios to be tested before actions are implemented in real systems. This simulation capability is useful for evaluating possible interventions, reducing operational uncertainty, and supporting more informed maintenance decisions (Walton *et al*., 2024). Taken together, IoT, machine learning, reinforcement learning, and digital twins provide the technological foundation for intelligent and adaptive maintenance systems. However, these technologies can only support RxM effectively when they are organized within an architecture that connects monitoring, analytics, decision-making, execution, and feedback.

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; 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; 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.

Conceptual and Architectural Assessment of RxM Frameworks (RQ5)

RQ5 examines the assessment approaches used in existing RxM frameworks and explains how Systematic Comparative Analysis can support the conceptual and architectural evaluation of the proposed framework. The review indicates that earlier RxM studies have commonly relied on conceptual evaluation, simulation, prototype testing, data-driven experiments, case-based analysis, and comparison with existing technological solutions (Basciftci *et al*., 2019; Consilvio *et al*., 2024; Gordon *et al*., 2020). These approaches provide useful evidence for examining model logic, technical feasibility, and architectural relevance, but they do not always demonstrate how an RxM framework performs in long-term industrial operation. Field-based assessment remains limited because maintenance systems in asset-intensive industries are difficult to test without affecting safety, production continuity, and asset reliability (Froger *et al*., 2016; Kumar *et al*., 2024). As a result, many existing frameworks are still evaluated at the conceptual, computational, or laboratory level rather than through direct operational deployment. In this study, SCA was used to compare the proposed framework with seven benchmark RxM-related models. The comparison examined whether each model addressed five core functional layers: data collection, analytics, decision-making, execution, and feedback. It also considered how enabling technologies such as IoT, machine learning, deep reinforcement learning, and digital twins support these layers.

The SCA results show that existing frameworks tend to provide stronger coverage of data acquisition, analytics, and decision-making than execution and feedback (Ahmed *et al*., 2021; Rabkin *et al*., 2024). This pattern suggests that RxM research has made important progress in prediction, optimization, and recommendation logic, but still gives less attention to how recommendations are translated into action and how execution outcomes are used for future learning. The proposed framework responds to this gap by placing execution and feedback as explicit parts of the RxM architecture (Leturiondo *et al*., 2017; Spyrou *et al*., 2023). This arrangement helps clarify the connection between predictive insight, maintenance recommendation, operational action, and continuous refinement. However, the comparison should be read carefully because SCA offers a structured conceptual and architectural assessment, not empirical evidence that the proposed framework performs better in practice. The framework therefore serves as a reference for future implementation and testing rather than as a proven industrial solution. Further studies are still needed to examine its feasibility through simulation, expert assessment, case studies, pilot testing, and operational data-based evaluation. These future assessments would help determine whether the framework can be applied reliably in real maintenance environments.

Industrial Integration and Deployment Considerations in Power Generation

In power generation, the proposed prescriptive maintenance framework functions as an integration pathway that connects plant-level data, analytical decision support, maintenance execution, and human supervision. The process begins with real-time operating signals from SCADA and DCS platforms, supported by IoT sensors installed on critical assets such as turbines, boilers, generators, pumps, transformers, and auxiliary systems. These signals become more meaningful when they are combined with MES records, CMMS maintenance histories, and historian databases that store operating loads, alarms, process variables, previous failures, maintenance actions, and asset behavior over time (Kaur *et al*., 2019). This combination allows the framework to read current asset conditions while also learning from historical degradation patterns and past interventions. Before the data are used for diagnostics or recommendations, they need to be cleaned, synchronized, transformed into relevant features, and screened for abnormal patterns. This preparation reduces the risk of producing maintenance recommendations from incomplete, noisy, or inconsistent information. Machine learning models can then support fault detection, degradation analysis, and remaining useful life estimation, while digital twin simulation, optimization, reinforcement learning, or multi-criteria decision-making can help compare possible maintenance actions under operational constraints (Panayiotou *et al*., 2023; Pessach *et al*., 2020). This integration logic is consistent with prior RxM studies that emphasize sensor-based monitoring, SCADA-enabled maintenance, learning-based analytics, and simulation-supported decision-making (Bousdekis *et al*., 2020; Goby *et al*., 2023; Gutierrez-Franco *et al*., 2021; Leahy *et al*., 2018; Kumar *et al*., 2024; Walton *et al*., 2024; Zhao *et al*., 2024).

The framework becomes useful in practice only when recommendations can enter the maintenance systems that engineers already use. A selected recommendation should therefore be routed into the CMMS or work order system, where it can support scheduling, resource planning, spare-part preparation, task assignment, approval, and execution tracking (Kaur *et al*., 2019; Marzouk and Seleem, 2018). This step is important because prescriptive maintenance will have limited operational value if its recommendations remain separate from daily maintenance routines. The framework also keeps human review at the center of execution, especially because power generation is a safety-critical environment. Engineers and operators should be able to approve, adjust, delay, or reject recommendations by considering asset criticality, outage windows, regulatory requirements, resource availability, and local operating knowledge (Rabkin *et al*., 2024; Tinoco *et al*., 2021). After the approved work is completed, the system should record feedback such as work order status, maintenance duration, replaced components, asset response, post-maintenance condition, and deviations from the original recommendation. These feedback data can return to the CMMS, historian database, and analytics layer to support model recalibration and improve later recommendations. In this way, RxM is not treated as an isolated analytical tool, but as a decision-support process that remains connected to existing plant systems, maintenance workflows, and professional judgment.

Deployment readiness is equally important because power plants differ in infrastructure maturity, data availability, cybersecurity posture, workforce capability, and openness to technological change. Newer plants may already have stronger data acquisition and control systems, while older plants may need upgrades in sensors, communication networks, middleware, data standards, and maintenance platforms before RxM can operate reliably. Investment cost should be assessed early because RxM may require digital twin development, software integration, cloud-edge resources, cybersecurity protection, and workforce training. Data governance also needs attention because missing values, inconsistent timestamps, sensor faults, and incomplete maintenance histories can weaken diagnostics, prognostics, and maintenance recommendations. Cybersecurity should be considered from the beginning because RxM connects field devices, control systems, analytics platforms, enterprise applications, and remote access points (Kumar *et al*., 2023; Wang *et al*., 2024). Secure implementation requires clear access control, network segmentation, monitoring, incident response procedures, and compliance with relevant industrial cybersecurity requirements. A phased deployment strategy is more realistic than immediate full-scale adoption, beginning with selected critical assets, pilot subsystems, or simulation-based testing before expanding to wider plant operations (Ilizástigui Pérez, 2021; Siddiqui *et al*., 2020). This approach allows organizations to examine technical feasibility, workflow compatibility, operator acceptance, cybersecurity resilience, and operational impact while reducing unnecessary disruption to plant performance.

CONCLUSION

This study contributes to the literature on prescriptive maintenance in power generation by synthesizing 118 Scopus Q1 articles published between 2014 and 2024. Guided by five research questions, the review examined the conceptual foundations of RxM, enabling technologies, framework architectures, implementation challenges, and validation practices. The synthesis resulted in a modular five-layer framework consisting of data collection, analytics, decision-making, execution, and feedback. This structure clarifies how predictive insights can be organized into a more action-oriented maintenance decision process, in which failure anticipation is extended toward context-aware recommendations. The findings indicate that RxM research has increasingly emphasized digital technologies such as IoT sensors, machine learning, digital twins, optimization methods, and feedback mechanisms. However, the review also shows that many existing models focus more strongly on data collection, analytics, and decision-making, while execution and feedback mechanisms are less consistently developed. The proposed framework responds to this gap by positioning execution and feedback as core architectural components of RxM. This should not be interpreted as evidence of superiority over previous models, but rather as an indication that the framework offers broader conceptual coverage across the five functional layers.

The framework provides a conceptual and architectural reference for organizations seeking to explore the transition from predictive to prescriptive maintenance in power generation. It may help practitioners identify the functional capabilities required for RxM implementation, including real-time data acquisition, predictive analytics, decision logic, execution support, feedback-based learning, and integration with existing systems such as SCADA, DCS, historian databases, and CMMS. Nevertheless, this study does not claim that the framework has been empirically validated or proven effective in operating power plants. Its practical application remains subject to further validation through simulation, expert review, pilot testing, integration assessment, and evaluation under real operating conditions. Future research should move beyond conceptual assessment by testing the framework through simulation-based validation, expert panel or Delphi assessment, pilot implementation in power plant settings, and integration testing using real operational and maintenance data. Further studies should also examine cost-benefit implications, cybersecurity risks, operator trust, explainability, and organizational readiness. These future efforts are necessary to determine how the proposed architecture can be adapted, validated, and refined across different types of power generation systems.

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ABBREVIATIONS

AI: Artificial Intelligence; **CMMS:** Computerized Maintenance Management System; **DCS:** Distributed Control and Data Acquisition; **IEEE:** Institute of Electrical and Electronics Engineers; **IISE:** Institute of Industrial and Systems Engineers; **IT:** Information Technology; **IoT:** Internet of Things; **MES:** Manufacturing Execution System; **PdM:** Predictive Maintenance; **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses; **Q1:** First Quartile; **RQ:** Research Question; **RxM:** Prescriptive Maintenance; **SCA:** Systematic Comparative Analysis; **SCADA:** Supervisory Control and Data Acquisition; **SLR:** Systematic Literature Review; **UMSIDA:** Universitas Muhammadiyah Sidoarjo; **XAI:** Explainable Artificial Intelligence.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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