Predictive Maintenance Integration with CMMS: Advancing Preventive Maintenance Approaches in Facilities Management

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Abstract: Integrating Predictive Maintenance (PdM) with Computerized Maintenance Management Systems (CMMS) marks a significant shift from traditional time-based preventive maintenance (PM) to data-driven, condition-based methods. This study reviews existing preventive maintenance practices, identifies challenges and opportunities in PdM-CMMS integration, and assesses its effects on efficiency, cost savings, and equipment reliability. Results show that PdM, using real-time condition monitoring, can greatly reduce unplanned downtime, improve resource use, and prolong equipment service life. Key obstacles include compatibility issues, data handling, and workforce skill gaps. The proposed framework focuses on automation, real-time analytics, and targeted training to overcome these barriers. The findings confirm that PdM-CMMS integration delivers tangible operational and financial gains, supporting both sustainability objectives and digital transformation efforts, while offering practical guidance for organisations aiming to improve maintenance performance.

Keywords: *Predictive Maintenance, Computerized Maintenance Management System, Preventive Maintenance, Maintenance Efficiency*

1.0 INTRODUCTION

Facilities management (FM) plays a crucial role in ensuring operational continuity, asset longevity, and occupant safety across various sectors, including healthcare, aviation, and commercial buildings. In recent years, the integration of advanced technologies such as Building Information Modelling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI) has transformed traditional maintenance strategies, enabling more proactive and data-driven approaches (Asare et al., 2023; Casini, 2022; Cheng et al., 2020). Conventional preventive maintenance, often based on fixed schedules, can lead to unnecessary interventions or overlooked failures. Predictive maintenance (PdM), by contrast, uses real-time monitoring, historical data analysis, and machine learning algorithms to anticipate equipment failures before they occur, improving reliability and resource efficiency (Bouabdallaoui et al., 2021; ElJazzar et al., 2022).

The adoption of PdM is increasingly supported by Computerised Maintenance Management Systems (CMMS), which serve as centralised platforms for scheduling, tracking, and optimising maintenance activities (Bakar & Kamaruzzaman, 2023). Integration of PdM capabilities into CMMS leverages condition-based monitoring and predictive analytics to refine decision-making, reduce downtime, and extend asset lifecycles (Ablhuail, 2025; D'Orazio et al., 2023). For instance, studies have demonstrated that AI-driven models, such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM), can effectively prioritise maintenance requests and allocate resources with greater accuracy (D'Orazio et al., 2023). Similarly, in critical environments such as hospitals, predictive models enhance the maintenance of life-support systems, where downtime could compromise patient safety (Al-Tal & Al-Aomar, 2021).

Recent advancements have also explored the integration of BIM and GIS for spatially enriched FM, offering comprehensive visibility of assets and their maintenance requirements (Carrasco et al., 2024). This integration supports PdM by providing a visual and data-rich environment for identifying potential failures and streamlining intervention planning. Moreover, IoT-enabled CMMS platforms allow for continuous monitoring of Mechanical, Electrical, and Plumbing (MEP) components, facilitating automated alerts and performance tracking (Cheng et al., 2020; ElJazzar et al., 2022). Despite these technological opportunities, challenges persist, including interoperability issues, high implementation costs, data governance concerns, and skill gaps among FM professionals (Bakar & Kamaruzzaman, 2023; Casini, 2022).

This research investigates the integration of PdM with CMMS in the context of facilities management, aiming to assess its potential for advancing preventive maintenance strategies. By synthesising insights from AI applications, BIM-IoT convergence, and predictive modelling frameworks, the study seeks to outline a pathway for improving operational efficiency, cost-effectiveness, and asset reliability in FM.

1.1 Problem Statement

Despite substantial progress in maintenance technologies, the pursuit of optimal maintenance strategies in facilities management remains unresolved. Preventive maintenance (PM), which is still the most widely adopted approach, is inherently limited by its reliance on fixed schedules. This often results in premature interventions that increase operational costs, or in some cases, delayed responses that fail to prevent unexpected failures. Such inefficiencies are particularly problematic in critical facilities, where downtime can directly impact safety, productivity, and service quality.

Predictive maintenance (PdM), supported by real-time data analytics, machine learning, and IoT-enabled monitoring, offers the ability to assess equipment health accurately and intervene only when necessary. However, the integration of PdM capabilities into Computerised Maintenance Management Systems (CMMS) remains a complex undertaking. Many organisations continue to depend on traditional time-based strategies that do not account for variations in equipment conditions, largely due to technical, organisational, and procedural constraints.

Key barriers include the lack of standardised integration protocols between PdM and CMMS platforms, inconsistent or incomplete data capture, and resistance to organisational change among maintenance personnel. These challenges limit the scalability and effectiveness of PdM-CMMS integration, leaving many facilities unable to fully capitalise on its potential benefits. Without addressing these integration and adoption barriers, organisations risk continued reliance on inefficient maintenance practices, missing opportunities to improve asset reliability, reduce lifecycle costs, and enhance decision-making in facilities management.

2.0 LITERATURE REVIEW

2.1 Overview of Predictive Maintenance in Facilities Management

Predictive maintenance (PdM) represents a significant shift from traditional time-based preventive maintenance towards a more proactive, condition-based strategy. It leverages advanced analytics, machine learning, and IoT-enabled monitoring to detect patterns and predict failures before they occur. Bouabdallaoui et al. (2021) demonstrated that machine learning models can accurately analyse building system data to identify early signs of performance degradation, allowing for timely interventions. Similarly, Onuegbu et al. (2024) showed how AI-based PdM frameworks in the oil and gas sector improved asset integrity management by predicting component failures with high accuracy. By focusing on real-time monitoring, PdM reduces unnecessary interventions, optimises resource allocation, and extends the service life of assets (Kim & Choi, 2023; Panov et al., 2021).

Applications of PdM in critical infrastructure settings underscore its value in high-risk environments. For example, Al-Tal and Al-Aomar (2021) developed a predictive model for hospital critical systems, reducing downtime and improving patient safety. Sabah et al. (2022) also confirmed PdM's effectiveness in healthcare by preventing equipment failures that could disrupt essential services. By combining continuous monitoring with data-driven analytics, PdM provides more accurate and actionable maintenance planning compared to traditional preventive strategies, which rely heavily on static schedules and often overlook asset condition variability. Despite these benefits, effective PdM implementation requires integration with robust management platforms, such as CMMS, to fully realise operational gains (Martins et al., 2022; Zuppolini & Di Nardo, 2024).

2.2 Role of CMMS in Maintenance Optimisation

Computerised Maintenance Management Systems (CMMS) play a central role in modern facilities management by providing a unified platform for recording, scheduling, and tracking maintenance activities. Bakar and Kamaruzzaman (2023) highlighted that CMMS adoption among Malaysian facility managers improves workflow efficiency, asset documentation, and compliance with planned schedules. Salonen et al. (2020) emphasised that analysing CMMS-generated data can reveal performance patterns, enabling data-driven decision-making for asset care. Advanced CMMS platforms also integrate cloud computing and mobile access, making it easier for maintenance teams to receive and update work orders in real time (Pramudito et al., 2020; Widyotriatmo et al., 2020).

However, CMMS performance often depends on the quality and completeness of the data entered. Jain et al. (2021) noted that without accurate and timely updates, CMMS cannot provide the actionable insights required for optimal maintenance scheduling. Elkholy and Ibrahim (2021) explored the use of machine learning to improve CMMS data quality, showing that AI-enhanced analytics can address common data inconsistencies. Villa et al. (2021) further proposed an open-source IoT architecture to feed CMMS with real-time asset condition data, creating a more responsive maintenance ecosystem. While CMMS offers strong

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organisational control over maintenance tasks, its integration with predictive analytics tools is essential for moving from reactive or scheduled maintenance toward truly predictive operations.

2.3 Integration of Predictive Maintenance and CMMS

The integration of PdM capabilities into CMMS platforms can transform maintenance management by directly linking real-time asset monitoring to work order generation and resource allocation. ElJazzar et al. (2022) demonstrated that combining IoT analytics with CMMS reduced downtime and enhanced preventive maintenance efficiency in building facilities. Zuppolini and Di Nardo (2024) presented a CMMS-integrated smart monitoring model that issued predictive alerts based on live equipment data, enabling facilities managers to address potential failures before they escalated. D'Orazio et al. (2023) further showed that AI-based models, including Long Short-Term Memory (LSTM) and Bi-LSTM networks, can be embedded in CMMS to prioritise maintenance requests based on urgency and resource availability.

Despite promising outcomes, integration remains challenging due to technical and organisational barriers. Khudhair et al. (2021) identified interoperability issues between predictive analytics platforms and CMMS as a major obstacle, while Sivanuja and Sandanayake (2022a, 2022b) highlighted the need for Industry 4.0 readiness in FM organisations to support PdM adoption. IoT-enabled CMMS solutions, such as those described by Cheng et al. (2020) and Habib et al. (2021), facilitate condition-based maintenance by connecting sensor networks directly to maintenance workflows. Yet, without standardised protocols, many organisations implement PdM-CMMS integration on an ad hoc basis, leading to inconsistent results. This underscores the importance of developing structured integration frameworks to ensure scalability and reliability.

2.4 Advanced Technologies Supporting PdM-CMMS Integration

Emerging technologies such as Building Information Modelling (BIM), Geographic Information Systems (GIS), and digital twins provide valuable enhancements to PdM-CMMS integration. Asare et al. (2023) demonstrated how BIM supports facility management by consolidating spatial and asset data into a single platform, while Carrasco et al. (2024) combined GIS and BIM for 3D facilities management, improving maintenance planning accuracy. Fargnoli and Kimura (2023) proposed integrating CMMS with digital twins to create virtual replicas of building systems for real-time performance tracking and predictive analysis. Such tools offer a holistic view of asset conditions, facilitating more informed maintenance decisions.

IoT and AI applications further extend PdM-CMMS capabilities. Cheng et al. (2020) and Habib et al. (2021) showcased how BIM-IoT integration enhances predictive maintenance for mechanical, electrical, and plumbing (MEP) components, while Lee and Ha (2023) applied deep learning within CMMS for real-time HVAC fault detection. Ablhuail (2025) and Hong and Kim (2022) illustrated how AI-driven analytics and text mining of maintenance records can improve predictive accuracy when linked to CMMS data. Open-source IoT architectures (Villa et al., 2021) offer cost-effective integration pathways, particularly for organisations with budget constraints, making advanced PdM-CMMS frameworks more accessible.

2.5 Challenges and Barriers to Adoption

While the technological capabilities for PdM-CMMS integration are advancing, several barriers hinder widespread adoption. Elkholy and Ibrahim (2021) and Moat and Coleman (2021) pointed to inconsistent data quality and the lack of sensor infrastructure for certain assets as limitations that reduce predictive accuracy. High implementation costs, cybersecurity concerns, and the need for specialised technical skills further constrain adoption, especially in organisations with limited resources (Bakar & Kamaruzzaman, 2023). Organisational resistance and cultural barriers also slow integration efforts, with Kim and Choi (2023) noting that staff buy-in is essential for successful deployment.

A broader challenge is the absence of standardised integration methodologies across industries. Panov et al. (2021) observed that predictive maintenance standards are still evolving, making it difficult for organisations to benchmark and replicate successful implementations. Sivanuja and Sandanayake (2022a) stressed the importance of aligning PdM adoption with Industry 4.0 transformation strategies to overcome these issues. Without addressing these technological, organisational, and procedural gaps, many facilities will continue to operate with suboptimal maintenance strategies, missing the opportunity to achieve higher asset reliability, cost efficiency, and operational resilience.

2.6 Conceptual Framework

The conceptual framework illustrates how predictive maintenance (PdM) technologies integrate with Computerised Maintenance Management Systems (CMMS) to enhance preventive maintenance in facilities management (FM). On the left, PdM technologies include AI, IoT sensors, machine learning models, Building Information Modelling (BIM), and digital twins (Bouabdallaoui et al., 2021; Cheng et al., 2020; Fargnoli & Kimura, 2023). These tools collect real-time asset condition data, predict potential failures, and generate actionable maintenance insights.

On the right, CMMS platforms function as the centralised repository for asset records, maintenance history, and work order management (Bakar & Kamaruzzaman, 2023; Salonen et al., 2020). They handle scheduling, resource allocation, and reporting functions essential to organised maintenance operations.

At the core, an integration layer facilitates interoperability between PdM systems and CMMS. This layer encompasses data interoperability protocols, API connections, and real-time monitoring interfaces that ensure seamless data exchange (ElJazzar et al., 2022; Zuppolini & Di Nardo, 2024). By linking predictive analytics with operational workflows, this integration allows maintenance triggers from PdM to automatically generate work orders, prioritise tasks, and allocate resources through CMMS.

The lower section of the framework represents the FM outcomes achieved through this integration. These include optimised preventive maintenance schedules, reduced downtime, cost efficiency, and improved asset reliability (Martins et al., 2022; Kim & Choi, 2023). Additionally, this approach supports long-term asset lifecycle planning and aligns with Industry 4.0 strategies for smart facility operations (Sivanuja & Sandanayake, 2022a)

3.0 METHOD

3.1 Research Design

The research design outlines the structured plan used to collect, measure, and analyse numerical data to address the study objectives. For this study, a quantitative research design is employed to objectively assess the operational and financial impacts of integrating Predictive Maintenance (PdM) into a Computerised Maintenance Management System (CMMS) within a real industrial setting. The choice of a quantitative approach allows for measurable, statistically supported conclusions regarding the effectiveness of the integration in improving maintenance outcomes.

The conceptual framework guiding this research positions PdM technologies—including AI algorithms, IoT-based sensor monitoring, machine learning models, Building Information Modelling (BIM), and digital twins—as the data generation layer. This is integrated with the CMMS platform, which manages asset records, work orders, maintenance scheduling, and reporting. Between these components lies an integration layer responsible for data interoperability, API connections, and real-time condition monitoring. The integrated system is expected to generate tangible facilities management outcomes, namely:

- Reduced unplanned downtime
- Optimised preventive maintenance scheduling

- Increased equipment availability rates
- Lower overall maintenance costs
- Improved asset reliability over time

The research is conducted at a steel manufacturer in Malaysia, a large-scale production facility specialising in the fabrication of steel pipes and structural steel products. The facility operates with a fully implemented InnoMaint CMMS for digital work order management, spare parts tracking, and asset performance reporting. The study focuses on 14 critical production machines that have both PdM capabilities and CMMS tracking enabled. Facility utilities such as compressors and cooling towers are excluded to concentrate on production-impacting assets.

The design adopts a before-and-after comparative framework, assessing operational data from two equal six-month periods:

- Pre-integration period: January 1, 2024 – June 30, 2024 (CMMS in use, PdM not integrated)
- Post-integration period: July 1, 2024 – December 31, 2024 (PdM fully integrated with CMMS)

This enables direct comparison of performance metrics to determine whether PdM integration yields measurable improvements in operational efficiency, cost reduction, and asset reliability.

3.2 Quantitative Method

The quantitative method is applied to evaluate performance changes using measurable indicators derived from CMMS-maintained maintenance logs. The analysis focuses on three core metrics:

- Downtime Hours – Total hours each machine is unavailable due to maintenance or breakdown.
- Maintenance Costs – Includes labour costs, spare parts expenses, and associated energy consumption during downtime.
- Equipment Availability Rates – The percentage of time equipment is available for production relative to total scheduled operational hours.

Following Mertens (2014), descriptive statistical methods will summarise data trends, allowing comparison across machines and timeframes. Metrics such as means, medians, ranges, and standard deviations will be computed to capture central tendencies and variability. In line with Gravetter and Wallnau (2016), correlational analysis may be conducted to explore relationships between PdM adoption and changes in maintenance costs or downtime reduction.

The study applies a quasi-experimental, non-randomised before-and-after design, as recommended by Field (2018), using naturally occurring operational conditions without artificially altering workflows. This approach is well suited to industrial research where experimental manipulation is not practical. Bryman (2016) notes that such designs, when supported by robust statistical analysis, can yield generalisable findings applicable to similar industrial environments.

The InnoMaint CMMS platform's built-in reporting tools serve as the primary data source, ensuring that all records are systematically logged, timestamped, and verifiable. These include:

- Work Order Records – Detailing maintenance tasks, assigned technicians, and completion times.
- Spare Parts Usage Logs – Tracking quantities, costs, and replacement frequencies.
- Asset Performance Reports – Summarising utilisation, availability, and performance trends.

The focus on machine-level analysis enables the detection of asset-specific patterns, such as whether certain machine types benefit more significantly from PdM integration. This granularity also supports more precise maintenance planning and resource allocation recommendations.

4.0 RESULTS AND DISCUSSION

This section presents and interprets the findings derived from descriptive statistical analysis of three key performance indicators—downtime hours, spare parts cost, and machine availability—across the 12-month study period. The analysis compares operational data from the pre-integration period (January–June 2024) with the post-integration period (July–December 2024) following the implementation of Predictive Maintenance (PdM) integrated with a Computerised Maintenance Management System (CMMS). Additional percentage change and cumulative measures are examined to highlight the magnitude of improvement and the stability of performance metric

4.1 Trends of Downtime Hours

The analysis of downtime hours reveals a marked improvement in the latter half of the year following PdM-CMMS integration. In January, downtime hours stood at 184.7, reflecting the inefficiencies associated with reactive or time-based preventive maintenance strategies. The first quarter showed some reduction, declining to March, before increasing again in April and May, indicating instability in downtime control under pre-integration practices.

From July onwards, the data depicts a consistent downward trend, with downtime hours steadily decreasing month by month and reaching 102.2 hours in November. This sustained reduction demonstrates the effectiveness of predictive analytics in anticipating failures and scheduling maintenance before breakdowns occur. The stabilisation of downtime hours post-integration also indicates that PdM allowed for maintenance scheduling based on asset condition rather than arbitrary intervals, significantly reducing unnecessary stoppages.

4.2 Trends of Spare Parts Cost

Spare parts expenditure also exhibits substantial improvement after PdM-CMMS integration. At the beginning of the year, costs were RM91,978.57 in January, with frequent fluctuations in subsequent months. A pronounced spike occurred in April, peaking at RM76,286.07, which can be attributed to emergency repairs requiring urgent procurement of parts.

Following July, spare parts costs became more stable, settling at approximately RM60,000 per month. This indicates a shift towards planned maintenance interventions where parts replacement was forecasted and budgeted rather than driven by sudden equipment failure. The post-integration trend confirms that PdM reduced the frequency of unplanned breakdowns, resulting in fewer urgent part replacements and enabling more cost-effective inventory management.

4.3 Trends of Machine Availability

Machine availability showed a steady and continuous improvement over the study period, rising from 97.67% in January to 98.70% in December. Prior to PdM implementation, availability improvements were modest and reactive, with operational efficiency vulnerable to unexpected failures.

From July onwards, availability improved more consistently, with July recording 98.34% and November peaking at 98.71%. This positive trend is directly related to the reduction in downtime hours, as improved maintenance predictability ensured higher operational readiness. The results suggest that PdM-CMMS integration enhanced asset utilisation by minimising interruptions and ensuring that maintenance activities were strategically aligned with production schedules.

4.4 Percentage Change in Downtime Hours

The percentage change in downtime hours further validates the shift in maintenance performance. The first six months show inconsistent variations, including a -14.2% drop in February followed by several erratic fluctuations. Such instability reflects the limitations of non-predictive maintenance strategies, where reductions were often temporary and dependent on short-term corrective actions.

From July onwards, the trend became more stable, with July recording a significant -15.5% decrease in downtime hours compared to June. This sustained and more uniform reduction across the second half of the year illustrates the role of PdM in enabling consistent downtime control. Predictive insights allowed maintenance teams to pre-empt issues, plan interventions during non-critical periods, and avoid the reactive patterns seen in the first half of the year.

4.5 Cumulative Spare Parts Cost

The cumulative analysis of spare parts expenditure reveals that in the first half of the year, costs rose sharply, particularly in April, which saw an 85% increase from March due to reactive repairs. Monthly changes during this period were large and unpredictable, suggesting an absence of structured inventory planning.

In contrast, after PdM integration, month-to-month variations in cumulative costs remained below 20%, indicating more predictable and controlled spending. This shift demonstrates that PdM, coupled with CMMS, improved forecasting accuracy for spare parts demand, enabling better procurement planning and reducing instances of excess or emergency stock orders. The integration also minimised waste by ensuring parts were replaced only when condition-based triggers were met.

4.6 Percentage Change in Machine Availability

The percentage change in machine availability underscores the operational gains achieved post-integration. Pre-integration data show an initial peak in March followed by a sharp decline in April, reflecting instability in maintaining high availability levels.

After PdM-CMMS integration, there was an immediate improvement in July, with availability increasing sharply and maintaining an upward trajectory for the remainder of the year. Although minor fluctuations persisted, the post-integration trend was significantly more stable, signalling a sustained improvement in operational reliability. This suggests that CMMS-supported predictive scheduling directly contributed to fewer breakdowns, higher uptime, and more dependable production performance.

4.7 Summary of Descriptive Analysis

The combined analysis of downtime hours, spare parts costs, and machine availability clearly indicates that PdM-CMMS integration had a positive and measurable effect on maintenance performance. In the pre-integration period, downtime was high and erratic, costs fluctuated sharply due to unplanned repairs, and machine availability was inconsistent. These issues reflect the inherent limitations of reactive and purely preventive maintenance strategies.

Following integration, all three metrics improved markedly. Downtime hours declined steadily, spare parts costs stabilised at lower levels, and machine availability increased to near-optimal levels. The results validate the research hypothesis that predictive strategies integrated with CMMS can deliver significant operational benefits in manufacturing environments.

5.0 CONCLUSION

The integration of Predictive Maintenance (PdM) with Computerised Maintenance Management Systems (CMMS) represents a significant advancement in modern maintenance management, enabling a transition from reactive and rigid time-based strategies to proactive, data-driven approaches. This research set out to examine existing preventive maintenance practices, develop a structured framework for PdM-CMMS integration, and evaluate the operational, financial, and reliability impacts of such integration in an industrial manufacturing context. The results provide strong evidence that PdM-CMMS integration can substantially improve maintenance efficiency, optimise costs, and enhance asset reliability.

The initial analysis of preventive maintenance practices revealed that, while time-based approaches offer structured scheduling, they often result in over-maintenance, higher costs, and limited capacity to prevent unplanned failures. Reactive maintenance methods exacerbate these issues, leading to sudden downtime and costly emergency repairs. Although emerging PdM tools such as vibration analysis and infrared thermography are being introduced in certain sectors, their adoption remains inconsistent, hindered by budgetary constraints, technical infrastructure limitations, and uneven prioritisation across asset categories. This highlighted the need for a more standardised, organisation-wide approach to predictive maintenance adoption.

To address this, a comprehensive integration framework was developed, prioritising automation, real-time analytics, mobile accessibility, and user-friendly interfaces. The proposed framework aligns PdM-generated insights directly with CMMS workflows, automating work order creation and enabling timely, condition-based interventions. By resolving integration challenges—such as system incompatibility, manual data entry, and inconsistent data flows—the framework provides a practical pathway for organisations to fully realise the benefits of predictive strategies.

Quantitative analysis following PdM-CMMS integration demonstrated clear performance improvements. Downtime hours declined steadily, spare parts costs stabilised with more predictable expenditure patterns, and machine availability rates rose consistently, reaching 98.70% by the end of the study period. These results confirm that PdM-CMMS integration enables proactive scheduling aligned with actual equipment condition, thereby reducing unplanned interruptions, improving resource allocation, and increasing operational readiness.

Despite these positive outcomes, the research also identified challenges, including the high initial investment required for advanced PdM technologies, increased workloads during early implementation, and the need for specialised skills to interpret and act on predictive data. These issues underscore the importance of targeted training programs, role-specific support, and cross-functional collaboration to ensure sustainable integration and maximise return on investment.

In summary, this study affirms that PdM-CMMS integration offers a transformative pathway for industrial maintenance, delivering tangible benefits in efficiency, cost management, and reliability. The proposed framework and evidence-based findings provide both a strategic and operational blueprint for organisations aiming to modernise their maintenance strategies in line with digital transformation and sustainability goals. Moving forward, continued industry collaboration, technological innovation, and policy support will be essential to overcoming adoption barriers. Future research should investigate how emerging technologies such as artificial intelligence, IoT, and advanced analytics can further strengthen predictive maintenance capabilities, enabling organisations to achieve even greater operational excellence and long-term asset sustainability

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