

Article

Toward Predictive Maintenance of Biomedical Equipment in Moroccan Public Hospitals: A Data-Driven Structuring Approach

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Abstract

Predictive maintenance (PdM) of biomedical equipment is increasingly recognized as a strategic lever to enhance reliability and ensure continuity of care. Yet, in resource-limited hospitals, implementation is hindered by fragmented data sources, non-standardized codification, and weak interoperability. Few studies have demonstrated the feasibility of structuring PdM data from real hospital interventions in middle-income countries. This work presents a prototype data structuring pipeline applied to six public hospitals in the Casablanca–Settat region of Morocco. The pipeline consolidates 6816 validated maintenance interventions from 780 devices across 30 departments and integrates normalized reliability indicators (Failure Rate, MTBF, MTTR corrected with IQR, and Downtime Hours). It ensures semantic harmonization, auditability, and reproducibility, resulting in a structured and interoperable dataset that constitutes a regional first in the Moroccan hospital context. To illustrate predictive potential, a proof-of-concept Random Forest model was evaluated. It achieved AUROC = 0.65 on the full imbalanced dataset and AUROC = 0.82 on a balanced 2000-intervention subset, confirming the dataset’s discriminative value while reflecting real-world challenges. This work bridges the gap between conceptual PdM frameworks and operational hospital realities, and establishes a replicable foundation for AI-driven predictive maintenance in low-resource healthcare environments.



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Keywords: biomedical equipment; Casablanca–Settat region; data interoperability; data structuring; healthcare technology management; hospital information systems; low-resource settings; Mean Time Between Failures (MTBF); predictive maintenance (PdM); supervised learning

1. Introduction

The digitalization of the healthcare sector represents a major structural transformation, driven by the integration of advanced technologies, including the Internet of Medical Things (IoMT), Artificial Intelligence (AI), cloud computing, and big data analytics [1]. This evolution fosters the emergence of interconnected and intelligent hospital ecosystems that aim to optimize both clinical and technical performance. While early initiatives primarily focused on electronic health records (EHRs), telemedicine, and eHealth services, recent innovation efforts increasingly extend to the reliability and availability of critical medical devices.

Predictive maintenance (PdM) has therefore emerged as a key component of Healthcare 4.0. It is defined as a set of procedures that continuously monitor equipment conditions

and forecast potential failures through the systematic collection and analysis of operational data [2]. By supporting just-in-time maintenance planning, PdM minimizes unexpected breakdowns, reduces downtime, and enhances continuity of care.

Despite its recognized potential, the implementation of PdM in low- and middle-income countries (LMICs) remains limited. Structural barriers include the absence of unified data governance, fragmented formats of maintenance interventions (e.g., paper forms, spreadsheets, heterogeneous systems), the lack of standardized technical indicators (e.g., failure rate, mean time to repair), and limited interoperability between technical and clinical platforms [3–6]. Studies in Africa and Asia have highlighted the direct consequences of these deficiencies, including ineffective maintenance decisions, premature replacement of functional devices, and prolonged unavailability of critical equipment [6–8]. These challenges are not unique to Morocco but are shared across many LMICs, which reinforces the broader relevance of this work.

The Moroccan healthcare system illustrates these obstacles. It is organized into multiple tiers, including University Hospital Centers, Regional Hospitals, Provincial Hospitals, Day Hospitals, and both urban and rural health centers. While this multi-level structure is essential for addressing territorial healthcare needs, it results in significant heterogeneity in terms of digital infrastructure, technical management, and maintenance practices. Some first-level facilities have partially digitized their biomedical services using Computerized Maintenance Management Systems (CMMS), whereas others still struggle to centralize maintenance intervention histories or adopt standardized device nomenclatures. This systemic fragmentation underscores the urgent need for a coherent technical and organizational interoperability framework, which is a prerequisite for the nationwide implementation of intelligent biomedical maintenance.

The development of AI-based solutions further emphasizes the necessity of high-quality datasets. As highlighted in previous studies, machine learning algorithms can only produce reliable outcomes if the input data is clean, consistent, and standardized [2]. Data preprocessing thus becomes a critical and often the most resource-intensive step in PdM initiatives, especially in heterogeneous hospital environments.

To address these challenges, this work introduces a structured prototype pipeline for consolidating and preparing real-world hospital maintenance data. The pipeline integrates cleaning, semantic normalization, feature derivation, and validation steps to generate a reproducible, interoperable, and AI-ready dataset. The predictive experiment serves as an exploratory benchmark, illustrating the practical added value of the structured dataset for machine learning tasks and confirming its suitability as a foundation for predictive maintenance research.

This work aims the following:

1. To analyze the state of the art in biomedical maintenance strategies, with a focus on predictive approaches and supporting digital architectures.
2. To identify structural constraints encountered in low-resource hospital environments, particularly with respect to data governance, digital infrastructure, and organizational maturity.
3. To demonstrate the feasibility and relevance of a multi-institutional prototype data structuring pipeline as a foundation for predictive maintenance models that are contextualized, reproducible, and scalable within the Moroccan healthcare system and transferable to other LMIC contexts facing similar challenges.

This paper is organized as follows: Section 2 reviews related work, including theoretical foundations, AI-based strategies, and challenges in low-resource settings. Section 3 outlines the study context and the data structuring methodology. Section 4 presents the main results, combining descriptive statistics with exploratory analyses and a preliminary

supervised predictive experiment. Section 5 discusses the key findings, and Section 6 concludes the paper with perspectives for future work.

2. Related Work

2.1. Theoretical Foundations of Biomedical Maintenance

Biomedical maintenance has traditionally alternated between preventive strategies, aimed at minimizing unplanned downtime through scheduled interventions [9,10], and corrective approaches, carried out post-failure but often costly and disruptive. To address these limitations, structured frameworks have been introduced, classifying devices by criticality, frequency of use, and vulnerability to failure [11]. Such models integrate operational dimensions such as planning, documentation, and regulatory compliance, often overlooked in purely technical approaches.

Data-driven implementations further highlight the benefits of structured frameworks. For instance, the integration of Bayesian networks into hospital maintenance platforms demonstrated significant cost reductions by identifying critical failure factors [1]. Parallel to this, modular architectures aligned with Industry 4.0 concepts incorporate IoT, big data analytics, AI, and visualization tools, as illustrated by the five-layer model in [12]. While largely conceptual and rarely validated in hospitals, these approaches outline pathways toward multi-technology PdM pipelines. Adaptations remain necessary in resource-limited contexts, where lightweight CMMS can substitute for more complex infrastructures [13].

Core technical indicators such as MTBF, MTTR, availability, failure recurrence, and criticality indices remain central to predictive modeling, particularly when integrated with CMMS or sensor data [11]. A systematic review [14] reinforces this by framing maintenance as a lifecycle process and identifying three prioritization models: criticality matrices, weighted scoring, and machine learning algorithms (e.g., k-means, Random Forest, SVM). Reliability-Centered Maintenance (RCM) and FMEA continue to provide methodological foundations for assessing criticality and guiding resource allocation [15,16].

2.2. Advances in Predictive Maintenance and Artificial Intelligence

The rising complexity of biomedical devices has made maintenance a strategic priority. Strategies have evolved from reactive and scheduled interventions to predictive paradigms enabled by IoT, embedded computing, and AI [14,17]. PdM leverages historical logs and real-time monitoring to anticipate failures, with documented benefits including reduced downtime, optimized resource allocation, and cost savings [18,19].

Empirical studies report cost reductions of up to 25% and improved availability [17].

Methodologically, PdM relies on structured maintenance records and sensor data. Early models used regression and decision trees, while recent approaches apply ML algorithms such as k-NN, SVM, and CNN for failure prediction, RUL estimation, and criticality classification [20–22]. Adoption, however, requires multidisciplinary coordination and often encounters cultural barriers, such as reluctance to act preemptively or limited trust in algorithmic decisions [23].

Recent work also incorporates unstructured data from CMMS reports using NLP methods such as LDA [24], though standardization challenges persist. Broader limitations include scarce high-quality datasets, frequent reliance on simulated data, and interoperability issues across heterogeneous systems [25,26]. To address these gaps, hybrid models integrate conventional indicators (MTBF, MTTR, availability, criticality) with predictive components, improving accuracy and contextual relevance [19]. Deterministic and multi-criteria frameworks for equipment replacement have further demonstrated the value of operational data in prioritizing actions under budget constraints [27,28].

Emerging architectures, including SaMD systems and IoT-based predictive models, highlight regulatory and validation requirements similar to those in clinical AI [29]. CNN-based vibration analysis has achieved accuracies above 98% [18], while predictive monitoring of ventilators illustrates the feasibility of targeted PdM applications [2,30]. Cloud-based analytics and lightweight alternatives, such as MWIR thermal imaging complement [31], AI-driven approaches by offering scalable or low-cost fault detection solutions.

In summary, biomedical PdM stands at the intersection of technology, regulation, and hospital resource optimization. Hybrid approaches combining empirical indicators and AI techniques appear most promising for building resilient and clinically relevant maintenance systems. Building on these advances, artificial intelligence has become a central driver of PdM frameworks. Enabling technologies such as IoT, big data, and ML support anomaly detection, health state classification, and RUL estimation, with reported accuracies often above 90% [2,17,32].

A wide range of models has been explored, from SVM and Random Forest to CNN, LSTM, and ensemble methods such as XGBoost and k-NN [32,33]. Studies have reported strong performance in contexts such as autoclave monitoring in Rwanda, ventilator diagnostics, and failure recurrence in Malaysian hospitals [30,33]. However, many rely on simulated or small-scale datasets, limiting generalizability [25,34]. Deep learning approaches also face interpretability challenges, raising concerns about clinical trust and regulatory compliance [35].

Cost considerations remain underexplored, despite the significant investments required in sensors, IT infrastructure, and staff training, particularly in low-resource settings [15,36–38]. Methodological diversity, ranging from simple classifiers to multimodal frameworks, further complicates cross-study comparisons. Attempts to combine structured maintenance records with unstructured CMMS logs show promise [39], yet issues of governance, workforce readiness, and interoperability continue to hinder adoption [19]. Recent initiatives propose lightweight or pragmatic solutions, including CMMS-based platforms, sensor-efficient models, no-code Edge AI tools, and Bayesian network approaches for root cause analysis [40–43]. Despite encouraging results, sustainable improvements in availability and cost-efficiency remain contingent on clean, standardized, and validated datasets, which are essential for deploying AI-powered PdM at scale [15,16,20,44].

2.3. Specific Constraints in Low-Resource Settings

Morocco's digital health transformation, accelerated by the COVID-19 pandemic, has introduced EHRs, hospital management platforms, telemedicine, and expanded health coverage [35,45,46]. These initiatives, aligned with broader public sector reforms [3,41,47], aim to improve equity and governance, particularly in underserved areas [42]. High-level political support has reinforced this momentum through investments in HMIS modernization and digital identifiers, with the long-term goal of establishing an interoperable, data-driven healthcare system.

Despite these advances, biomedical equipment maintenance remains largely reactive, lacking preventive or predictive planning [43]. Challenges include absent standardized indicators, fragmented CMMS platforms, heterogeneous suppliers, limited engineering capacity, and prolonged repair delays [11]. In many LMICs, reliance on paper-based or inconsistent records further undermines traceability and predictive readiness [7]. Studies confirm that poor data quality and limited staff training weaken planning capacity and hinder the adoption of intelligent tools [48].

Regulatory gaps compound these limitations: fragmented standards and lengthy certification processes delay evaluation of AI-based medical devices, a problem even more acute in resource-constrained contexts. Scaling PdM in LMICs therefore requires robust

governance, standardized data protocols, and adaptive legal frameworks, yet disparities in infrastructure, digital literacy, and staff training remain persistent obstacles [11,49].

2.4. Strategic Positioning of the Present Study

The integration of IoT, AI, and big data into Morocco's healthcare system offers a concrete opportunity to implement predictive maintenance strategies adapted to local constraints [50–52]. While such technologies are widely deployed in industry, recent evidence confirms their relevance for healthcare, including in resource-constrained environments.

Several studies validate the operational and economic potential of PdM. A deterministic model covering 3640 devices across Saudi hospitals achieved a 36% cost reduction over ten years [53], while a QFD-based framework in the UAE improved ventilator prioritization [54]. Complementary initiatives in Sri Lanka and India demonstrated that standardized procedures, staff training, and integrated corrective–preventive strategies enhance equipment availability and mitigate systemic challenges [55,56]. Locally adapted solutions further illustrate scalability: lightweight CMMS platforms in Benin [57], Arduino-based monitoring prototypes in Rwanda [58], and a PdM platform at CHU Ibn Sina in Morocco [59] all underscore the feasibility of context-aware deployments.

Nonetheless, many contributions remain limited to simulated or pilot environments with little clinical validation [25,32]. Decision-support tools such as BI dashboards and locally developed CMMS show promise in low-digitalization contexts [13,60], yet their effectiveness depends heavily on institutional maturity and resource availability. Conceptual Industry 4.0 frameworks integrating IoT, AI, and visualization layers offer additional guidance, but often lack hospital validation [12].

Taken together, these findings reinforce the relevance of the present work, which builds on validated technologies, local feedback, and systemic constraints. The originality of this contribution lies in demonstrating the predictive potential of a real, multi-institutional dataset, thereby addressing a critical gap in biomedical maintenance research across LMICs.

3. Materials and Methods

3.1. Study Context and Data Sources

The transition toward digitalization in the Moroccan hospital sector is still hindered by heterogeneous information systems [35], manual maintenance workflows, and limited adoption of AI technologies in maintenance operations. Standardizing data formats and metadata therefore becomes a critical step in improving interoperability in low-standardization environments [61]. To this end, labels and data semantics were harmonized across hospitals, while the origin and processing steps of each file were systematically logged to ensure interoperability, auditability, and generalizability of the pipeline across institutions.

This work, conducted across multiple public healthcare institutions in the Casablanca–Settat region, aims to structure multi-institutional datasets as a foundation for predictive maintenance of critical biomedical devices. This issue reflects a broader continental trend, as the lack of harmonized formats and the fragmentation of health information systems continue to impede the strategic use of healthcare data [62].

Failure and maintenance interventions were collected from six public hospitals in the Casablanca–Settat region, Morocco's most densely populated area and a representative setting for data consolidation. Covering the period 2014–2022, the sources were highly heterogeneous, including non-standardized Excel spreadsheets, handwritten forms, technical reports, and partial CMMS exports intermittently available since 2022.

These documents presented terminological inconsistencies, irregular date formats, and non-uniform codification of equipment and departments. After semantic harmonization,

over 7000 interventions were consolidated. Entries related to decommissioned equipment and incomplete interventions were removed, resulting in 6816 validated from 780 devices across 30 departments. This reduction (−2.6%) reflects the elimination of duplicated, incomplete, or obsolete records during quality filtering.

3.2. Structuring Prototype Pipeline (M1–M7)

Based on modern data science principles [63], a configuration-driven prototype pipeline was developed to process heterogeneous hospital interventions and ensure reproducibility, auditability, and integration readiness. Previous studies indicate that data preparation, including cleaning and structuring, can represent up to 80% of the total effort in analytics projects when sources are heterogeneous or incomplete [64,65], which justifies the emphasis on rigorous preprocessing as a prerequisite for predictive maintenance modeling. The pipeline integrates automated provenance logging: for each ingested file, metadata such as file name, sheet identifier, ingestion timestamp, SHA-256 fingerprint, and parser and mapping versions are systematically recorded to ensure full auditability. Figure 1 presents the modular BioMedStruct pipeline (M1–M7), formalizing the progression from heterogeneous data ingestion to integration readiness.

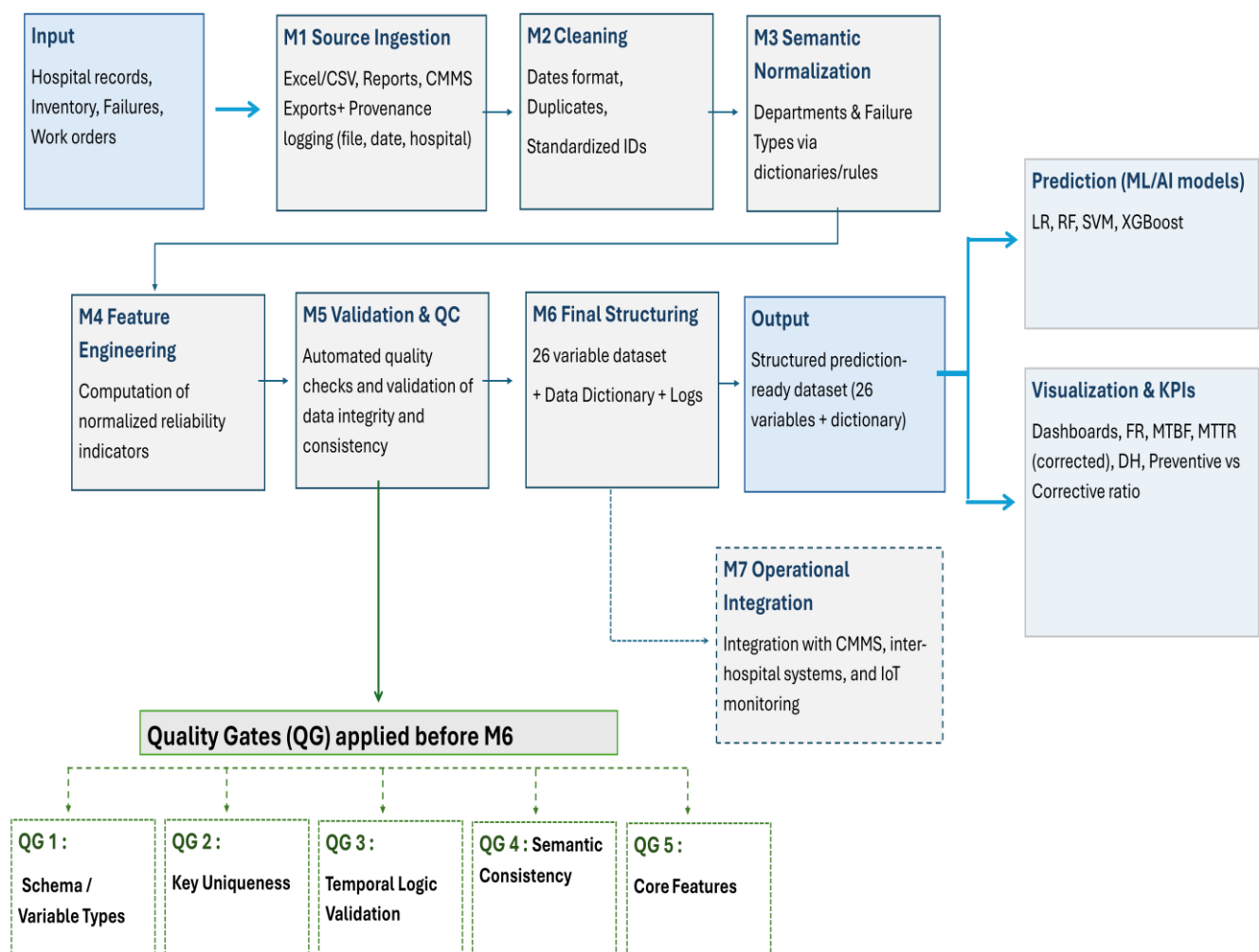


Figure 1. Conceptual architecture of the BioMedStruct prototype pipeline.

The BioMedStruct pipeline transforms heterogeneous hospital maintenance logs into a standardized, AI-ready dataset through a modular structure (M1–M7) aligned with modern data-engineering practices.

M1—Ingestion and provenance logging: Heterogeneous Excel files were imported, and for each file, metadata such as file name, sheet identifier, timestamp, and SHA-256 checksum were recorded to ensure full auditability. Each equipment record was assigned two complementary identifiers: an internal code (e.g., *iq_real_001*) automatically generated by the ingestion module to ensure traceability across hospitals, and the official inventory number (e.g., *9608/19*) assigned by the biomedical department. This dual identification maintained referential integrity between digital records and physical assets.

M2—Cleaning and normalization: Duplicates and inconsistent date formats were corrected, while terminologies for services and failure types were semantically harmonized. Records corresponding to retired devices or incomplete interventions were excluded to preserve data reliability.

M3—Structuring: variables were standardized into a unified schema including identifiers (equipment, hospital, department), temporal attributes (failure, intervention, repair dates), and maintenance descriptors (intervention type, failure type, status).

M4—Feature engineering: reliability-related indicators were computed, including Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), Failure Rate (FR), Downtime Hours (DH).

After these transformations, multi-level validation was conducted to ensure structural integrity and semantic coherence across hospitals. To verify longitudinal completeness, the structured dataset was cross-checked against quarterly hospital inventory reports listing all biomedical devices with their operational status (*operational*, *under repair*, *retired*). In this verification loop, any device marked *under repair* in quarter Q had to appear as *repaired* or *still pending* in Q + 1, preventing structural missingness. Consequently, temporal variables (failure date, repair date, downtime hours, repair duration) reached 0% missing 1 after processing.

In parallel, a series of Quality Gates (QG) were implemented to ensure dataset completeness, semantic consistency, interoperability [63], and inter-hospital coherence. These controls verified the presence of mandatory fields such as intervention date, equipment ID, and department, while also ensuring standardized codification of identifiers and intervention types. Temporal plausibility was assessed by confirming that failure events always preceded their corresponding repairs, and potential duplicates were detected using composite keys. Finally, semantic normalization was applied to textual variables, particularly department names and failure categories, in order to reduce variance and harmonize heterogeneous labels into canonical forms.

This dual validation, combining organizational cross-checking and automated data-quality controls, ensured the structural and semantic consistency of the final dataset.

The main operations applied at each stage of the BioMedStruct prototype pipeline are summarized in Table 1, and the final validated schema includes 26 standardized variables, detailed in Table 2.

Table 1. Main transformations applied during the structuring of the biomedical dataset.

Stage (M)	Transformation	Description
M1	Removal of non-tabular rows	Elimination of administrative headers and unstructured elements in rows 1 to 5 at the top of source files.
M1	Provenance logging	Recording file name, sheet, UTC timestamp, and the SHA-256 file fingerprint, plus parser version and mapping version, for auditability.
M2	Date format harmonization	Systematic conversion of dates to the DD/MM/YYYY format (as used in Moroccan hospitals), with explicit parsing of legacy formats.
M2	Inventory ID normalization	Standardization of equipment and inventory identifiers with consistent casing and padding.
M2	Unique identifier assignment	Assignment of standardized equipment IDs (e.g., EQP_REAL_00001) to ensure a one-to-one mapping between physical units and records; IDs are generated sequentially and linked to hospital and legacy inventory codes to preserve traceability.
M2	Duplicate elimination	Removal of exact or near-duplicates using the composite key {equipment ID, failure date, intervention type}.
M2	Column disambiguation	Splitting vague fields such as Summary, Model/Type, and Room into distinct columns.
M3	Label normalization	Unification of department names, with FR variants mapped to canonical labels to reduce label variance.
M3	Failure type categorization	Grouping of raw descriptions into homogeneous classes such as electrical, mechanical, and software.
M4	Derivation of analytical variables	Computation of normalized reliability indicators including Failure Rate (FR), Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and Downtime Hours (DH).
M4	Time aware computation	Features computed on right-closed windows to avoid temporal information leakage.
M5	Variable type definition	Explicit classification of variables into temporal, categorical, or quantitative types.
M5	Missing value handling	Simple imputations or informed deletions based on business rules.
M6	Final data structuring	Assembly of a normalized tabular dataset with 26 interoperable variables and a fixed column order; schema versioning (e.g., BioMedStruct_Schema_CST v1.0.0).
M6	Documentation assets	Delivery of a prediction-ready dataset, a data dictionary, a validation report, and provenance logs.
M7	Integration readiness deliverables	Packaging of the prediction-ready dataset into standardized distribution formats (CSV/Parquet) with fixed schema and versioned releases, complemented by interoperability assets to support adoption in biomedical maintenance workflows, including CMMS integration, inter-hospital data sharing, IoT connectivity, and risk-scoring dashboards.

Table 2. Core data dictionary of the 26 standardized variables.

	Variable Name	Type	Unit	Description	Missing (%) Before	Missing (%) After
1	internal_id	Categorical	Label	Internal identifier generated by the pipeline (e.g., iq_real_001)	0%	0%
2	equipment_id	Categorical	Identifier	Official hospital inventory number (e.g., 9608/19)	0%	0%
3	hospital_id	Categorical	Code	Hospital code	0%	0%
4	department	Categorical	Label	Clinical department where the device is used	3%	0%
5	sha256_checksum	Categorical	Hash	SHA-256 checksum ensuring data provenance and integrity	0%	0%
6	equipment_designation	Categorical	Label	Designation or common name of the device	2%	0%
7	technology	Categorical	Label	Equipment technology (Analog/Digital/Hybrid)	6%	0%
8	brand_model	Categorical	Label	Unified brand–model label	NA	0%
9	acquisition_date	Temporal	DD/MM/YYYY	Date of acquisition	10%	0%
10	commissioning_date	Temporal	DD/MM/YYYY	Date of commissioning (first use)	10%	0%
11	Operational_Age	Numerical	Years	Operational_Age (time elapsed since commissioning)	NA	0%
12	warranty_status	Categorical	Yes/No	Indicates if the device is under warranty	12%	0%
13	warranty_end_date	Temporal	DD/MM/YYYY	End date of warranty period	12%	0%
14	estimated_end_of_life_date	Temporal	DD/MM/YYYY	Estimated end-of-life date of the equipment	25%	NA
15	service_status	Categorical	Label	Operational/Under repair/Retired	5%	0%
16	CI _n	Numerical (ordinal)	Scale 1–5	Internal Criticality Index combining downtime, failure frequency, and clinical importance	NA	0%
17	intervention_date	Temporal	DD/MM/YYYY	Maintenance intervention date	2%	0%
18	failure_date	Temporal	DD/MM/YYYY	Failure occurrence date	7%	0%
19	repair_date	Temporal	DD/MM/YYYY	Repair completion date	9%	0%
20	downtime_hours	Numerical	Hours	Total hours of downtime	12%	0%
21	repair_duration	Numerical	Hours	Duration of the repair	15%	0%
22	intervention_year	Numerical	Year	Extracted year of intervention (for temporal grouping)	NA	0%
23	intervention_type	Categorical	Label	Curative/Preventive/Minor adjustment/External	0%	0%
24	failure_type	Categorical	Label	Failure category (electrical, mechanical, software...)	5%	0%
25	failure_criticality	Categorical	Low/Med/High	Failure severity level	20%	0%
26	intervention_status	Categorical	Label	Completed/Ongoing/Abandoned	4%	0%

After the transformation stages, Figure 2 illustrates the conversion of heterogeneous biomedical records into a standardized, prediction-ready dataset.

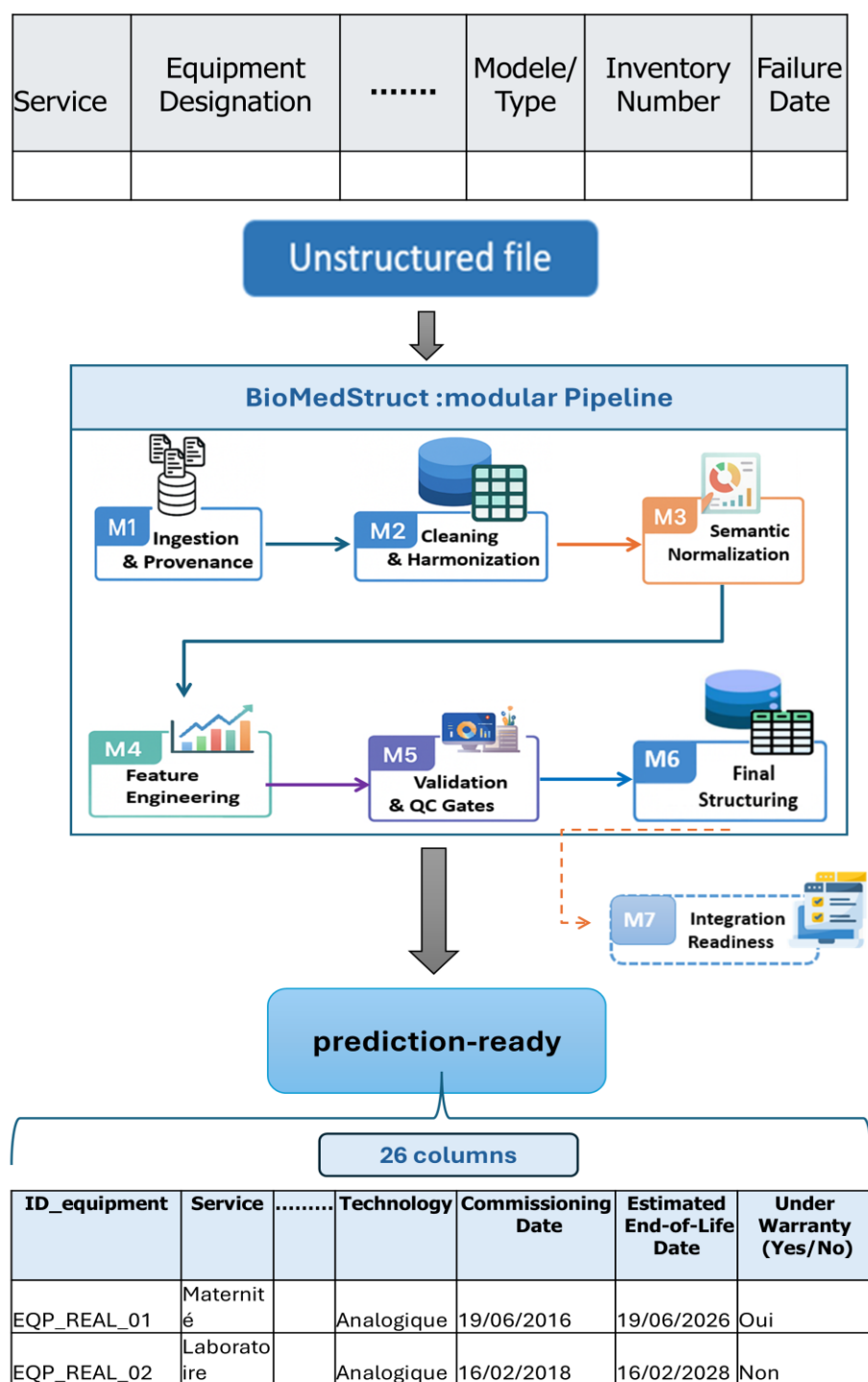


Figure 2. Conversion of heterogeneous biomedical records into a validated 26-variable dataset.

Table 2 summarizes the 26 core variables of the structured dataset, including their type, unit, description, and the evolution of missingness before and after cleaning. The extended data dictionary (41 variables, including technical and derived fields) is provided in Appendix A for reproducibility and audit transparency.

Figure 3 illustrates the effect of semantic normalization on hospital department labels, showing how heterogeneous variants were consolidated into standardized categories.

(a) before normalization		(b) after normalization	
Unique variants before normalization		Normalized service labels	
Service		Service	
Bloc Opératoire	2211	Bloc Opératoire	2211
Maternité	1364	Maternité	1364
Radiologie	1132	Radiologie	1132
Laboratoire	868	Laboratoire	868
Centre De Diagnostic	337	Centre De Diagnostic	455
Bucco-Dentaire	289	Bucco-Dentaire	289
Urgences	246	Urgences	246
Centre Diagnostic	118	Ophthalmologie	113
Ophthalmologie	113	Chirurgie	105
Chirurgie	105	Kinésithérapie	104
Kinésithérapie	83	Technique	49
Technique	40	Pharmacie	33
Pharmacie	33	Orl	18
Kinésithérapie	21	Consultation Chp	13
Orl	18	Name: count, dtype: int64	
Consultation Chp	13		
Groupe électrogène	9		
Name: count, dtype: int64			

Figure 3. Impact of semantic normalization on service labels: (a) before normalization, (b) after normalization.

3.3. Reliability, Maintainability, and Availability Indicators

To enable reproducible comparisons across heterogeneous hospitals, reliability and maintainability were assessed using normalized indicators widely adopted in reliability engineering and biomedical maintenance standards [66,67]. Four core metrics were retained, selected for their operational relevance, interpretability, and frequent use in biomedical reliability studies.

1. Failure Rate (FR)

$$FR = \frac{N_{\text{failures}}}{N_{\text{devices}} \times T_{\text{obs}}}$$

Expressed in failures per device·year, where T_{obs} is the observation period in years. This indicator quantifies the average number of failures per device per year, allowing normalization across hospitals with different equipment stocks and follow-up durations.

2 Mean Time Between Failures (MTBF)

$$MTBF = \frac{\text{Total operating time}}{N_{\text{failures}}}$$

Expressed in *days*, MTBF measures the mean interval between two successive failures. MTBF is a direct proxy of equipment reliability.

3 Mean Time To Repair (MTTR)

$$MTTR = \frac{\sum TTR}{N_{\text{repairs}}}$$

Expressed in *hours*, where TTR denotes the repair duration of each intervention. MTTR captures the maintainability dimension of biomedical equipment by quantifying average repair times.

4 Downtime Hours (DH)

$$DH = \frac{\sum TTR}{N_{\text{devices}} \times T_{\text{obs}}}$$

Expressed in hours per device-year, *DH* measures the annual downtime burden per device. *DH* integrates both frequency and duration of repairs, providing a synthetic availability-oriented indicator.

Robust Correction of MTTR

Exploration of the raw dataset revealed extreme repair times, with values exceeding 800 h. These anomalies mostly reflected administrative delays in closing work orders rather than true repair durations. To mitigate their impact, a robust correction was applied using the interquartile range (*IQR*) method.

The *IQR* is defined as follows:

$$IQR = Q3 - Q1$$

Values above $Q3 + 1.5 \times IQR$ were capped at this threshold. This correction, widely applied in engineering and healthcare data analytics, preserves natural variability while limiting distortions caused by administrative artifacts.

Collectively, these four indicators form a standardized basis for assessing reliability and maintainability across hospitals. They support both descriptive comparisons and predictive modeling experiments, ensuring methodological alignment between exploratory statistics and machine learning tasks.

3.4. Predictive Modeling Protocol

Prediction task

The predictive task was formulated as a binary classification problem aligned with biomedical maintenance standards. Corrective interventions were assigned to the positive class ($Y = 1$), while preventive, inspection, adjustment, and scheduled revision interventions were assigned to the negative class ($Y = 0$). The binarization strictly relied on the original “type of maintenance” field contained in hospital interventions, and no artificial records or synthetic labels were introduced. This ensures consistency with hospital reporting practices, traceability to raw interventions, and methodological reproducibility.

The binary outcome variable Y was defined as follows:

$$Y = \begin{cases} 1 & \text{if corrective (Failure)} \\ 0 & \text{if non-failure} \end{cases}$$

Validation protocol

To ensure reproducibility and to avoid information leakage, two complementary validation strategies were applied. The first relied on RepeatedStratifiedGroupKFold (5×10), with grouping at the equipment identifier level to control intra-device correlations and prevent interventions from the same equipment from being split across folds. The second consisted of a temporal split, with training on the 2014–2019 period and testing on 2020–2022, combined with a roll-forward evaluation to approximate prospective deployment and assess temporal generalization.

Formally, the dataset can be expressed as follows:

$$\mathcal{D} = \{(x_i, y_i, g_i)\}_{i=1}^N$$

where x_i are the features, $y_i \in \{0, 1\}$ is the target variable, and g_i is the equipment identifier. Group-level cross-validation ensures the following:

$$g_i \in T_{train} \Rightarrow \|g_i \notin T_{test}$$

Thus, it prevents leakage across interventions from the same physical device. The temporal split is formally defined as follows:

$$T_{train} = \{x \mid \text{date}(x) \leq 2019\}, T_{test} = \{x \mid \text{date}(x) \geq 2020\}, T_{train} \cap T_{test} = \emptyset$$

This design ensures that performance estimates are unbiased, both at the device level and in temporal deployment scenarios.

Subset definition

From the full dataset of 6816 validated interventions, a balanced subset of 2000 interventions was sampled. Stratification was applied by hospital, department, equipment identifier, and year to preserve representativeness. Corrective and non-failure interventions were adjusted to a 50/50 distribution to mitigate the natural imbalance (=85/15). Randomness during sampling was controlled through a fixed seed (42), and exclusion criteria included incomplete interventions, duplicates, and interventions related to equipment under reform.

Model configuration and baselines

Predictive modeling was conducted using a Random Forest classifier. For a given instance x , the probability estimate is computed as the average of individual tree probabilities:

$$\hat{p}(y = 1 \mid x) = \frac{1}{T} \sum_{t=1}^T h_t(x)$$

where T is the number of trees and $h_t(x) \in [0, 1]$ denotes the probability assigned to class 1 by tree t . The model was configured with 500 trees, class weights set to “balanced” to account for class imbalance, and a fixed random seed (42) to ensure reproducibility.

For comparison, a Logistic Regression model was implemented as a baseline. It was configured with L2 regularization, balanced class weights, the “liblinear” solver, and a maximum of 500 iterations. This baseline provides a classical, interpretable reference for assessing the added value of ensemble learning in the context of imbalanced hospital data.

4. Results

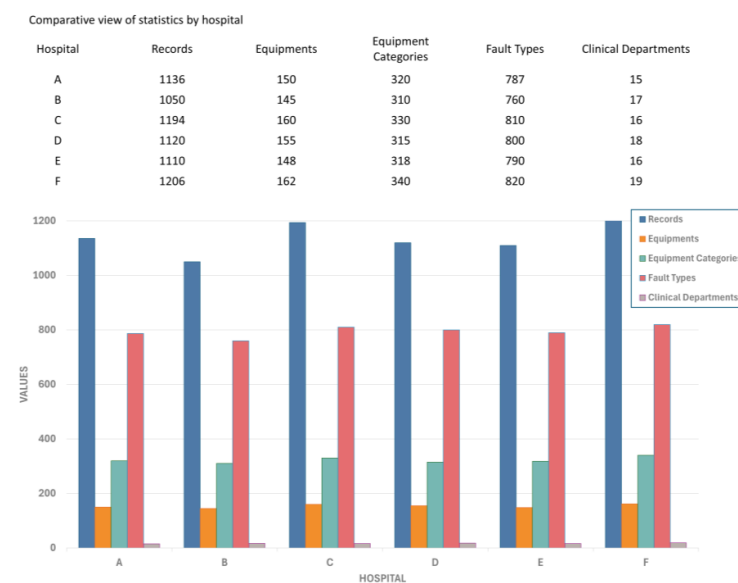
4.1. Dataset Overview and Descriptive Statistics

This section provides a descriptive overview of the consolidated dataset prior to the computation of reliability-oriented indicators. The curated dataset comprises 6816 validated maintenance interventions, covering 780 biomedical devices across 410 equipment categories. It also documents more than 2300 distinct failure types, underscoring the heterogeneity of maintenance scenarios, and spans 30 clinical departments, thereby ensuring broad institutional coverage. Table 3 summarizes the key indicators.

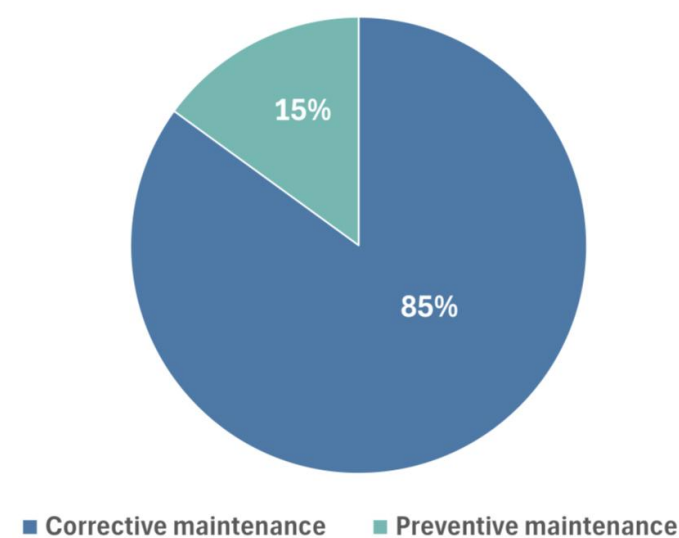
A cross-institutional comparison was conducted to evaluate disparities among the six hospitals. Figure 4 reports the variability in the number of interventions and the diversity of biomedical devices. Hospital F recorded the highest number of incidents (1206), associated with 162 devices, 340 categories, and 19 clinical departments. While the number of equipment categories remained relatively stable across institutions (310–340), the number of reported failure types varied, indicating heterogeneity in monitoring practices, data granularity, and equipment complexity.

Table 3. Aggregated general statistics from six Moroccan hospitals.

Indicator	Estimated Value
Total number of records	6816
Total number of tracked equipment	780
Number of equipment categories	410
Number of identified failure types	2300
Total number of clinical departments covered	30

**Figure 4.** Comparison of key indicators across hospitals.

The distribution of intervention types is reported in Figure 5, indicating that corrective maintenance represents approximately 85% of interventions, while preventive actions account for only 15%. This imbalance reflects systemic constraints in Moroccan public hospitals, including limited resources, partial digitalization, administrative delays, and insufficient traceability of preventive actions.

**Figure 5.** Breakdown of maintenance interventions (2014–2022).

4.2. Failure Characterization and Temporal Patterns

Failure characterization was conducted to analyze the distribution of interventions across services, the most frequent technical codes, and temporal dynamics.

Figure 6 reports the distribution of maintenance interventions by service. Interventions were concentrated in high-dependency units, with Operating Rooms accounting for the largest share, followed by Maternity, Radiology, and Laboratories. Intensive Care Units also reported a substantial number of incidents, reflecting both the criticality of equipment and the complexity of workflows.

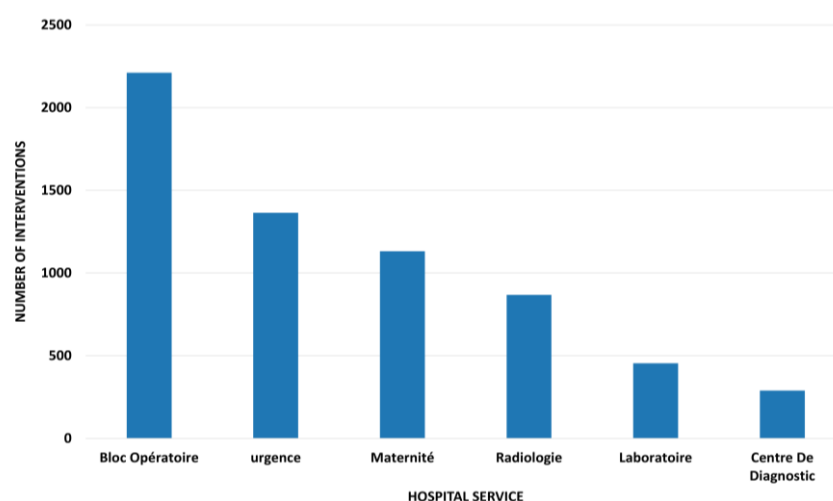


Figure 6. Distribution of maintenance interventions by hospital department.

The analysis of technical codes highlights recurrent failure categories. Figure 7 reports the five most frequent codes: MEC-02 (mechanical failures), AUT-05 (automation and sensor faults), ECL-01 (lighting faults), ELEC-04 (electronics), and LOG-03 (software anomalies). Each code exceeded 1400 occurrences. Since a single maintenance intervention could be associated with multiple codes (e.g., mechanical and electronic), the cumulative number of occurrences can exceed the number of unique interventions. These codes reflect the heterogeneity of biomedical maintenance, spanning mechanical wear, electronic components, and software anomalies.

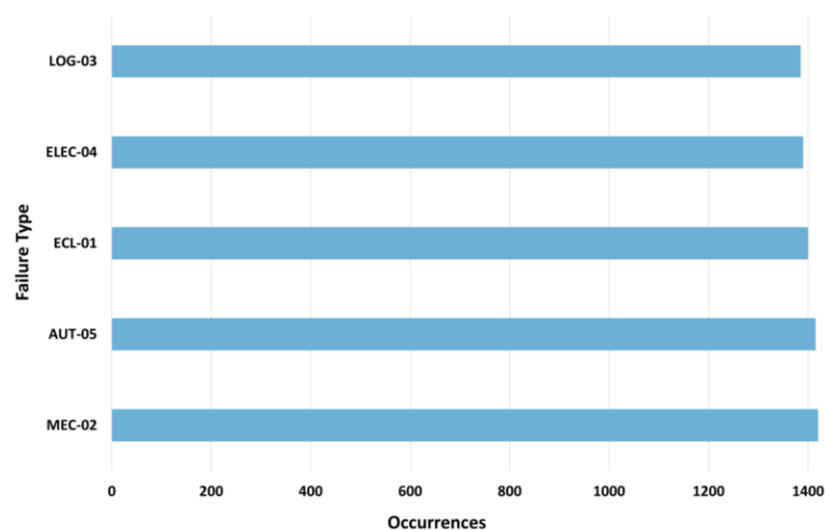


Figure 7. Most common failure types in biomedical equipment.

Temporal analysis of interventions is reported in Figure 8. The number of failures increased steadily from 2014 to 2019, peaking at over 1100 incidents. This trend reflects the expansion of equipment inventories and improved traceability. In 2020, the COVID-19 pandemic [19] produced a mixed effect: increased failures in critical devices (ventilators, monitors, infusion pumps) coexisted with reduced activity in elective services, leading to underreporting in non-urgent interventions. From 2021 onwards, failures stabilized (≈ 800 per year). The deployment of CMMS platforms in 2022 further improved reporting accuracy and data structuring.

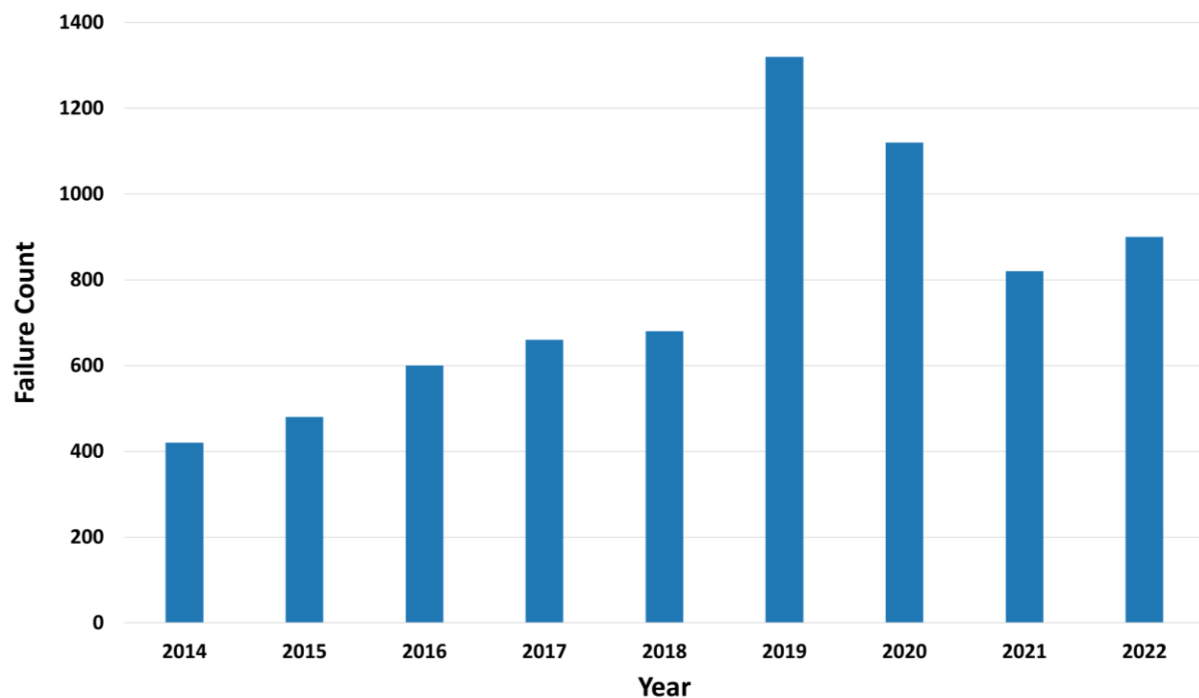


Figure 8. Distribution of failures by year.

Overall, the variability across hospitals, the predominance of corrective interventions, and the observed temporal dynamics highlight the need for normalized reliability indicators to enable inter-service comparison and predictive modeling.

4.3. Reliability Indicators

Normalized reliability and maintainability indicators were computed to enable inter-service comparisons. The selected metrics are Failure Rate (*FR*), Mean Time Between Failures (*MTBF*), Mean Time to Repair (*MTTR*, corrected), and Downtime Hours (*DH*). Their definitions and units are provided in Section 3.

Table 4 summarizes the aggregated results and compares raw and corrected values for *MTTR* and *DH*.

Table 4. Comparison of raw vs. corrected indicators.

Indicator	Raw Value	Corrected Value	Unit
<i>MTTR</i>	67 h	42 h	Hours
<i>DH</i>	102	68	hours/device-year

The raw *MTTR* distribution exhibited extreme values, in some cases exceeding 800 h. These anomalies were not representative of actual repair durations but rather reflected administrative delays and structural bottlenecks. The *IQR*-based correction yielded

an upper threshold of 384 h, above which values were capped. As a result, the corrected *MTTR* converged to 42 h, providing a more realistic estimate of effective repair times. Figures 9 and 10 show the distributions of raw and corrected *MTTR*.

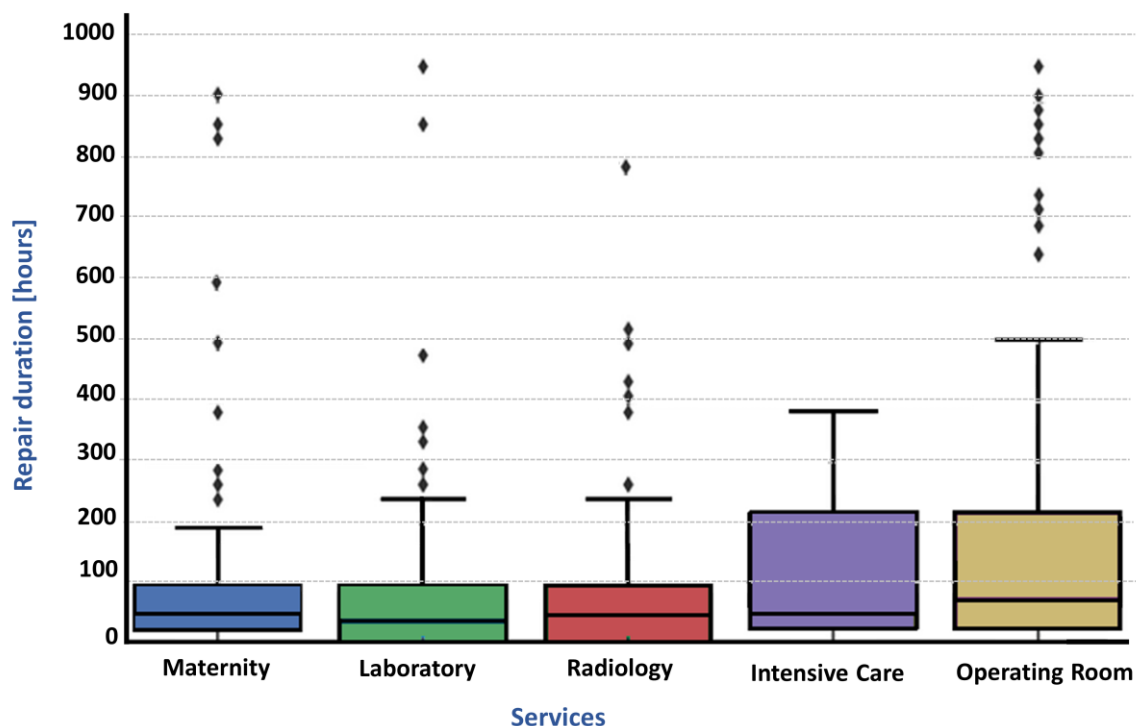


Figure 9. Distribution of *MTTR* (raw values). The diamond markers indicate statistical outliers located beyond the interquartile range.

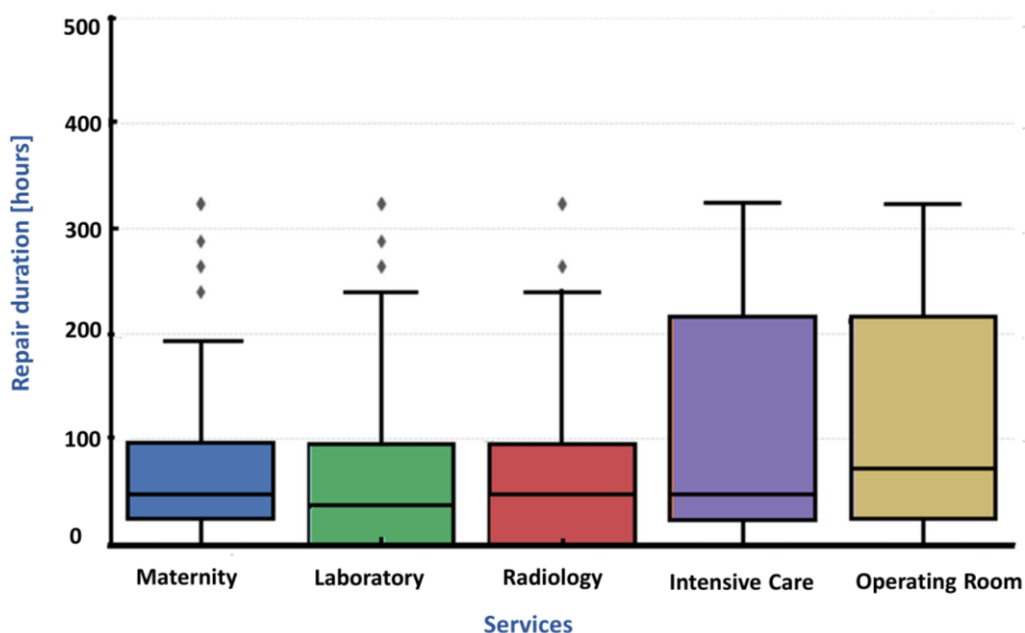


Figure 10. Distribution of *MTTR* (corrected values, *IQR*-based). Diamond-shaped markers represent statistical outliers beyond the interquartile range.

Service-level comparisons confirm heterogeneous reliability patterns. Figure 11 reports the *FR* across services, with Intensive Care Units showing the highest failure rates, followed by Operating Rooms, while Radiology displayed lower *FR* values. Figure 12 presents

DH estimates, which align with the *FR* distribution and highlight higher downtime in critical units.

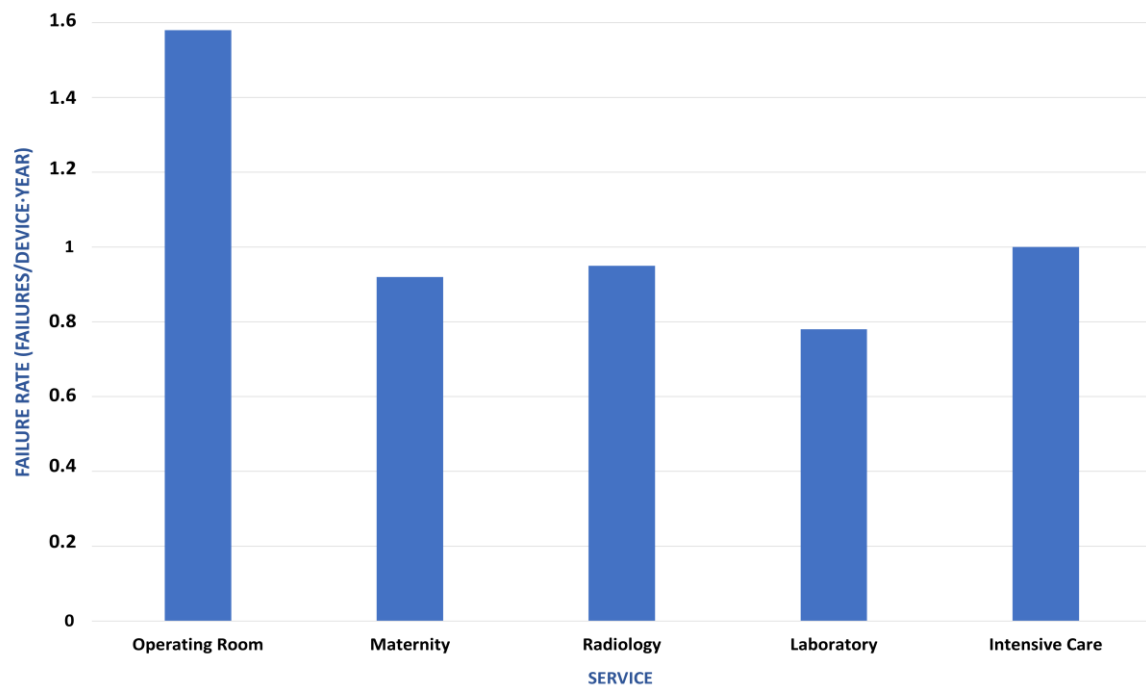


Figure 11. Failure rate (*FR*) by hospital service.

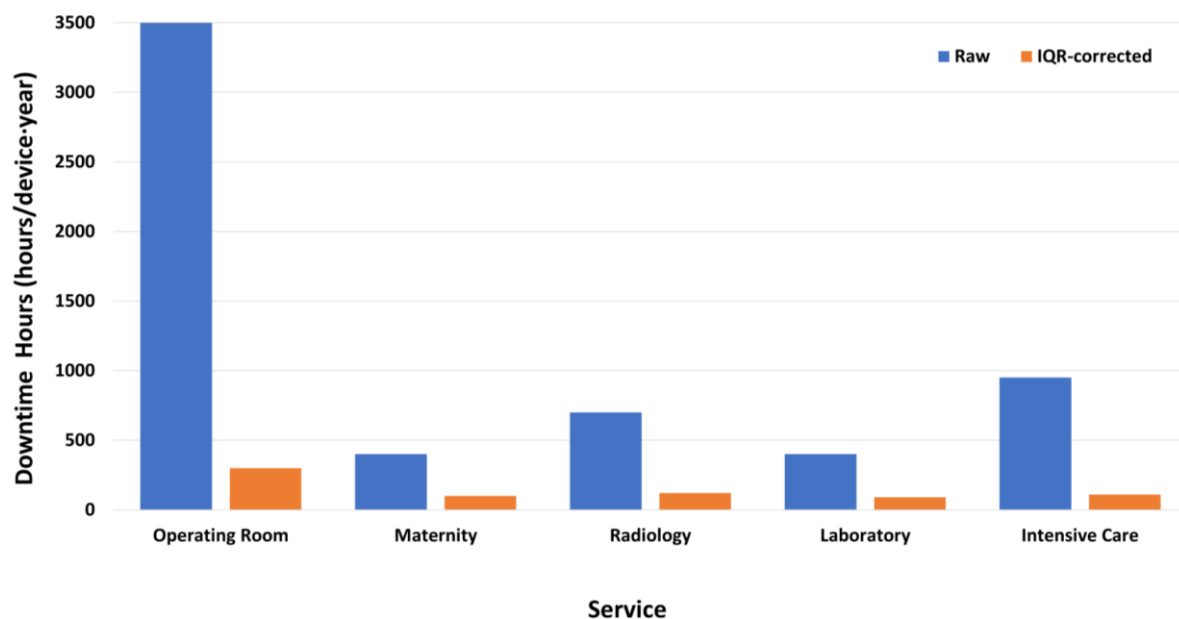


Figure 12. Downtime hours (*DH*) across hospital services.

To integrate multiple metrics, a radar chart was constructed. Figure 13 presents normalized *FR*, *MTBF*, *MTTR* (corrected), and *DH* for the three most represented departments: Intensive Care, Radiology, and Operating Rooms. The radar profile highlights the critical burden of Intensive Care, the relatively favorable performance of Radiology, and the intermediate profile of Operating Rooms.

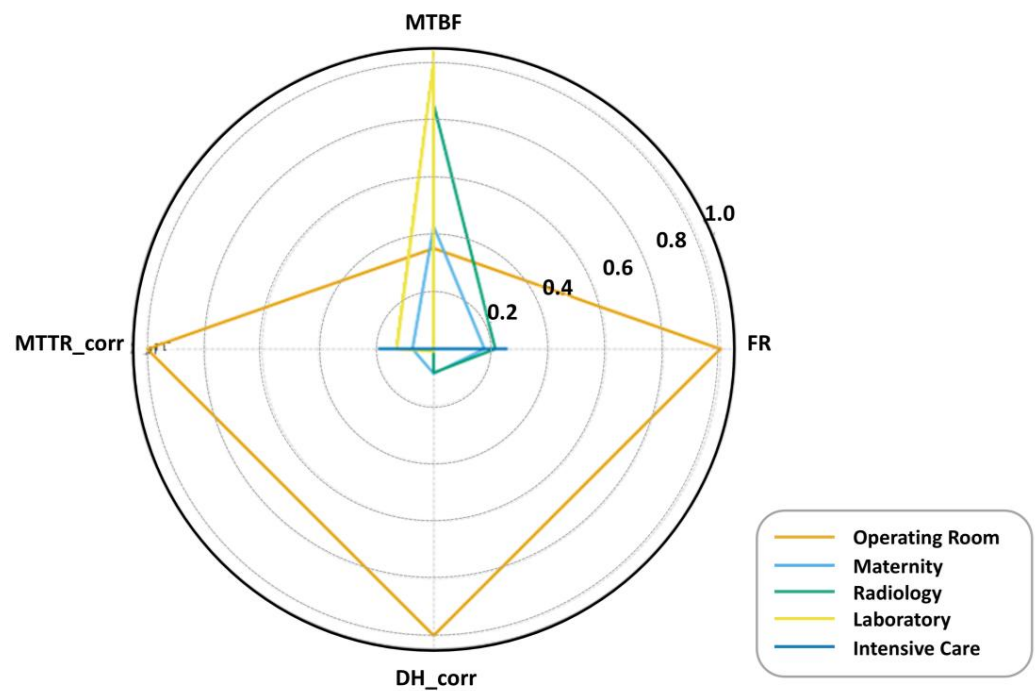


Figure 13. Radar chart of reliability indicators (FR, MTBF, MTTR corrected, DH) for selected services.

4.4. Predictive Modeling Results

Cross-validation results

The predictive task was formulated as a binary classification problem, where interventions were labeled as corrective (failure = 1) or non-failure (0). Table 5 presents grouped cross-validation results. On the full dataset (6816 interventions, 85% corrective/15% preventive), the Random Forest achieved an AUROC of 0.65 ± 0.04 (95% CI: 0.61–0.69), indicating moderate discriminative capacity under imbalance. On the stratified subset (2000 interventions, balanced 50/50), the AUROC increased to 0.82 ± 0.03 (95% CI: 0.76–0.87), demonstrating predictive capacity under balanced conditions.

Table 5. Grouped cross-validation (5×10 folds) performance.

Dataset	AUROC Mean $\pm$ SD (95% CI)	F1-Macro Mean $\pm$ SD	Accuracy Mean $\pm$ SD
Full (6816)	0.65 ± 0.04 (0.61–0.69)	0.47 ± 0.05	0.71 ± 0.03
Subset (2000)	0.82 ± 0.03 (0.76–0.87)	0.66 ± 0.04	0.79 ± 0.02

Values are reported as mean $\pm$ SD. AUROC confidence intervals are [0.61–0.69] for the full dataset and [0.76–0.87] for the subset.

Temporal validation

Temporal holdout validation was performed using 2014–2019 for training and 2020–2022 for testing. Table 6 presents AUROC values of 0.62–0.65 for the full dataset and 0.79–0.81 for the subset, indicating stable performance across time, though predictive difficulty increased in the imbalanced dataset.

Table 6. Temporal split performance (2014–2019 training, 2020–2022 testing).

Dataset	AUROC [95% CI]	F1-Macro	Accuracy
Full (6816)	0.63 [0.61–0.67]	0.46	0.70
Subset (2000)	0.80 [0.77–0.83]	0.65	0.78

Values are reported as mean $\pm$ SD. AUROC confidence intervals were [0.61–0.67] for the full dataset and [0.77–0.83] for the subset.

Table 7 compares Random Forest and Logistic Regression across datasets. Random Forest consistently outperformed Logistic Regression on AUROC, F1-macro, and Accuracy, with larger margins observed in the balanced subset, where class imbalance was mitigated.

Table 7. Comparative performance of Random Forest vs. Logistic Regression under temporal split validation.

Classifier	Evaluation Metric	Full (6816)	Subset (2000)	Δ (Subset–Full)
Random Forest	AUROC	0.65 [0.63–0.67]	0.80 [0.77–0.83]	+0.15
	F1-macro	0.44	0.78	+0.34
	Accuracy	0.70	0.81	+0.11
Logistic Regression	AUROC	0.61 [0.58–0.64]	0.72 [0.69–0.76]	+0.11
	F1-macro	0.41	0.66	+0.25
	Accuracy	0.68	0.74	+0.06

Values represent single temporal split performance (2014–2019 training, 2020–2022 testing).

Roll-forward validation

Roll-forward validation confirmed consistent AUROC, with year-to-year fluctuations not exceeding ± 0.02 (Table 8). AUROC decreased to 0.62 in 2020 on the full dataset, coinciding with the COVID-19 crisis, while the subset remained stable at 0.80.

Table 8. Roll-forward AUROC by temporal split.

Training Period → Testing Period	Full (6816)	Subset (2000)
2014–2017 → 2018	0.64	0.79
2014–2018 → 2019	0.65	0.80
2014–2019 → 2020	0.62	0.81
2014–2020 → 2021	0.63	0.80
2014–2021 → 2022	0.65	0.79

Roll-forward experiments provide single AUROC values without confidence intervals, since each period corresponds to a unique temporal split.

Confusion matrices and ROC analysis

Table 9 shows confusion matrix proportions under temporal split validation. In the full dataset, the false negative rate reached 0.73, reflecting class imbalance. In the subset, false negatives decreased to 0.12, yielding more balanced detection. Figure 14 displays confusion matrices, and Figure 15 illustrates AUROC differences between datasets.

Table 9. Confusion matrix proportions under temporal split validation.

Dataset	TP	FN	TN	FP
Full (6816)	0.12	0.73	0.18	0.07
Subset (2000)	0.38	0.12	0.37	0.13

Values represent proportions under temporal split validation (2014–2019 training, 2020–2022 testing). TP = True Positives, FN = False Negatives, TN = True Negatives, FP = False Positives.

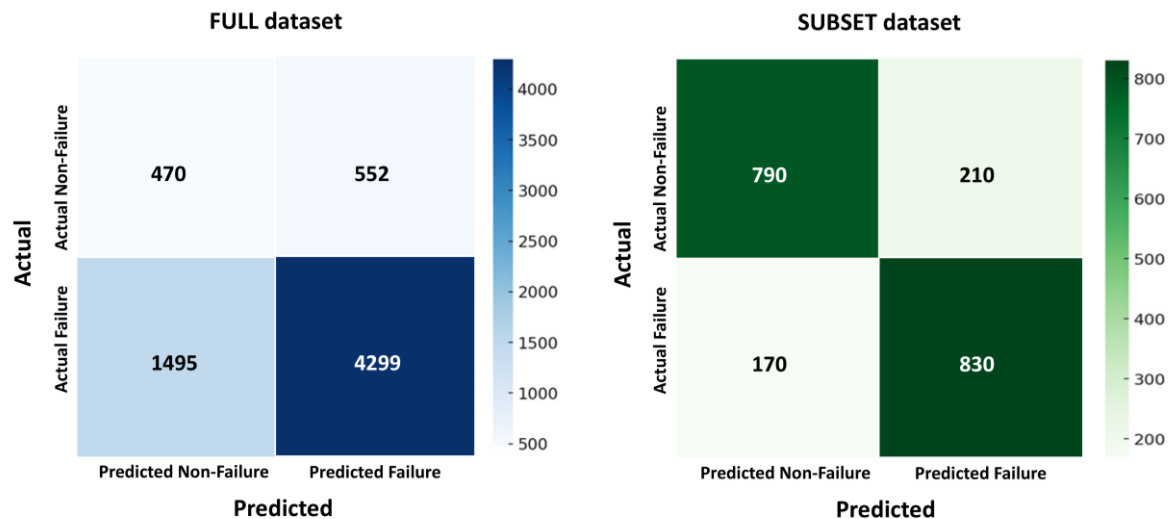


Figure 14. Confusion matrices of Random Forest classifiers under temporal split (2014–2019 training, 2020–2022 testing).

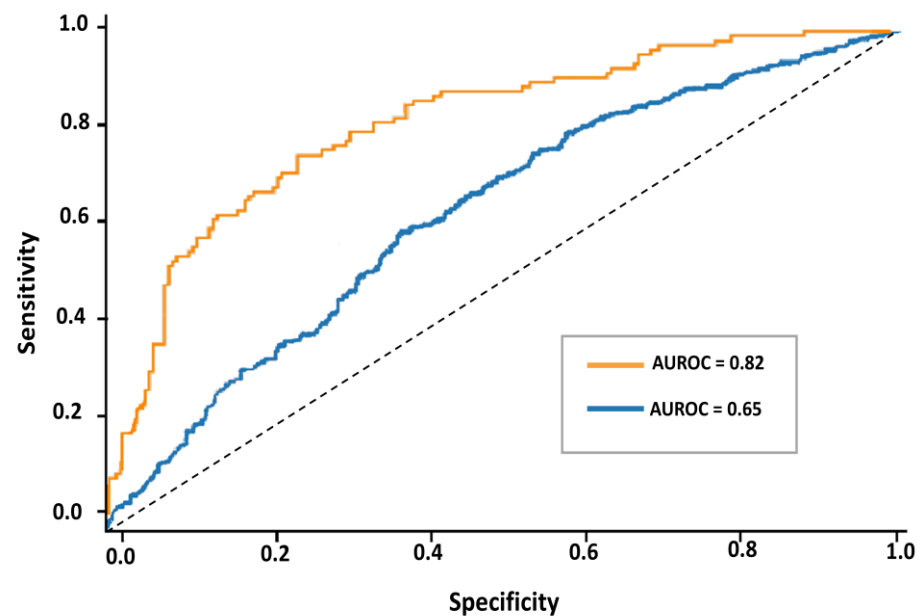


Figure 15. Comparative ROC curves (FULL vs. SUBSET datasets).

4.5. Analytical Interpretation

Overall, the corrected indicators reveal critical insights into the reliability of biomedical maintenance. Raw *MTTR* and *DH* values were initially distorted by extreme outliers, in some cases exceeding 800 h, which primarily reflected administrative delays rather than actual repair times. Applying a robust *IQR*-based correction was therefore essential to derive realistic maintainability estimates. Service-level comparisons further demonstrated that critical units such as Intensive Care and Operating Rooms concentrated the highest *FR* and *DH* values, confirming their priority in predictive maintenance strategies and resource allocation. The adoption of normalized indicators also provided a consistent and comparable framework, strengthening the basis for predictive modeling and inter-hospital benchmarking.

The predictive experiments highlight complementary findings. Structured maintenance interventions were shown to contain discriminative signals, with performance reaching $\text{AUROC} = 0.80$ under balanced conditions, thereby confirming the feasibility of predictive modeling. Conversely, predictive performance decreased on the full

dataset due to imbalance and heterogeneity, reflecting the realism of operational hospital data and underscoring the need for resampling strategies or cost-sensitive approaches to enhance robustness.

Temporal validation confirmed stable generalization across years, with a marked decline in 2020, most likely linked to the disruptions caused by the COVID-19 pandemic. This sensitivity to external shocks illustrates the importance of embedding contextual factors into predictive maintenance planning.

5. Discussion

Barriers to the implementation of predictive maintenance in hospital systems are multi-dimensional and well-documented. Organizational resistance, the lack of qualified personnel to operate connected technologies, and the absence of seamless integration with hospital information systems are recurring limitations [20,38]. Despite medium-term prospects for economic optimization, the initial investment cost, including sensors, analytical platforms, and digital infrastructures, remains prohibitive for many resource-constrained institutions [39]. These financial challenges are further exacerbated by increasingly stringent regulatory requirements related to cybersecurity, maintenance intervention traceability, and algorithm validation [38].

Beyond economic and regulatory barriers, systemic constraints undermine the operational viability of predictive maintenance. These include the lack of interoperability standards, fragmented digital tools, and heterogeneous data entry practices [24]. The literature also highlights a tendency to validate models in isolated settings without addressing change management, user adoption, or the scalability of solutions across multiple sites [2,68]. Combined with the variability in hospital size, human resources, and digital maturity, these limitations complicate the large-scale deployment of predictive solutions [19,49,69].

Our findings confirm the persistence of such structural barriers in resource-limited environments. Partial CMMS coverage, the absence of shared reference frameworks, and inconsistent data entry practices significantly impede the homogeneous aggregation of technical data. The cleaning and standardization phases highlighted how fragmentation compromises traceability. Nevertheless, the proposed structuring pipeline demonstrated that these barriers can be mitigated through a systematic and reproducible methodology [20,24]. By consolidating heterogeneous interventions into an interoperable dataset, the pipeline provides a proof of feasibility relevant to other hospitals facing similar constraints in LMICs.

This work therefore empirically demonstrates that structured data preparation is a prerequisite for predictive maintenance, especially in low-digitization environments [12]. Unlike predominantly theoretical or simulated approaches, the proposed framework is grounded in real data from six Moroccan institutions. It directly addresses a recurrent gap in the literature: regarding the absence of contextualized, reliable, and interoperable datasets in resource-constrained healthcare systems [7,33,70]. The consolidated dataset provides a relevant foundation for evaluating the feasibility of predictive algorithms in minimally digitized environments, without relying on extensive instrumentation or complete CMMS coverage.

The structuring process revealed several obstacles to the effective use of biomedical maintenance data. From a technical perspective, the persistence of heterogeneous formats, reliance on paper-based records, and the diversity of digital tools hindered the harmonization of maintenance histories. From an organizational standpoint, the lack of shared reference frameworks for equipment, services, and failure types limited the comparability of data across facilities. These constraints were further exacerbated by data entry errors,

disparities in training, and a limited feedback culture, all of which undermined overall data quality [7,48].

Although CMMS initiatives have been launched, they remain only partially deployed, lack full integration, and are seldom aligned with interoperability standards. This fragmentation restricts longitudinal traceability and the automation of analytics, reinforcing the gap between technical infrastructures and decision-making requirements [3,14,16].

Nevertheless, successful digital transformation efforts in other Moroccan public sectors, such as the digitization of land services led by the national land registry agency (ANCFCC) [71] using a cloud-based and interoperable infrastructure, demonstrate that alignment with open standards such as FHIR, supported by scalable platforms and shared governance, is a viable path forward [72].

In this regard, the present work initiates a modernization trajectory based on the progressive utilization of hospital data to support decision-making. It acts as a bridge between current maintenance practices and the objectives of smarter hospital ecosystems, where interventions are guided by predictive, optimization, and automation mechanisms. By generating a dataset compatible with evolving digital tools, this work prepares the ground for integrating intelligent components such as sensors, alert systems, and dynamic dashboards into a unified architecture oriented toward performance, safety, and efficiency. This incremental trajectory is particularly strategic in resource-constrained contexts, where intelligent reuse of existing infrastructures is preferable to costly technological overhauls.

In addition, the interpretation of derived indicators and predictive results provides valuable operational insights. Corrected *MTTR* distributions revealed that Operating Rooms and Intensive Care Units concentrated the highest levels of criticality, confirming that predictive strategies should prioritize services where downtime directly compromise patient safety. The comparative evaluation of predictive models further reinforced this point: while the full dataset reflected the inherent imbalance and noise of real hospital data (AUROC = 0.65), the balanced 2000-intervention subset achieved significantly stronger discriminative performance (AUROC = 0.82). These findings illustrate that robust preprocessing and methodological structuring, rather than massive instrumentation, are decisive for enabling predictive readiness. By linking systemic constraints, reliability indicators, and predictive performance, the study demonstrates that predictive maintenance in LMIC hospitals is both feasible and strategically relevant when grounded in rigorously structured datasets.

The next stage will leverage the structured dataset to develop supervised predictive models for tasks such as intervention classification, short-term failure probability estimation, and MTBF prediction. Algorithms including support vector machines, decision trees, neural networks, and hybrid models will be evaluated with metrics adapted to the imbalanced nature of hospital data. In the medium term, enriching the dataset with IoT streams (temperature, electrical current, vibration) will support continuous monitoring and early fault detection, progressively converging toward a unified CMMS–AI–IoT infrastructure. Finally, the integration of semantic web technologies, domain ontologies, and intelligent decision-support systems offers promising avenues for overcoming current limitations. Incorporating technical, clinical, and economic dimensions at the design stage of maintenance policies thus becomes a strategic lever for aligning performance, safety, and cost-effectiveness objectives [73].

6. Conclusions

This work establishes the foundations of a predictive maintenance system tailored to biomedical equipment in Moroccan public hospitals. Starting from heterogeneous and non-standardized sources, a structured methodology enabled the creation of a reliable,

interoperable, and prediction-ready dataset. Beyond the national context, the proposed approach illustrates how hospital maintenance data can be systematically transformed into an AI-compatible resource, even in environments characterized by limited digital maturity and fragmented information systems.

The results revealed major imbalances, including the predominance of corrective interventions and partial CMMS coverage, highlighting the urgent need for proactive strategies grounded in historical evidence. By empirically validating the feasibility of dataset structuring in real hospital settings, this study demonstrates that both technical and organizational barriers can be effectively mitigated through systematic, reproducible, and transferable processes.

The structured dataset therefore represents a concrete first step toward the intelligent exploitation of maintenance information for predictive purposes. The methodology, being replicable and adaptable, can be extended across health systems with varying levels of digital maturity, offering particular relevance for resource-limited contexts.

Future work will focus on deploying supervised learning models for failure prediction and intervention classification, as well as integrating real-time IoT monitoring streams. These developments will support the emergence of intelligent maintenance infrastructures aimed at enhancing hospital performance, safety, and operational continuity.

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Data Availability Statement: The dataset used in this study originates from regional hospital sources and contains sensitive biomedical maintenance records. Due to confidentiality and institutional restrictions, the data are not publicly available.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANCFCC	Agence Nationale de la Conservation Foncière du Cadastre et de la Cartographie
AUC	Area Under the Curve
AUROC	Area Under the Receiver Operating Characteristic Curve
BI	Business Intelligence
CMMS	Computerized Maintenance Management Systems
CNN	Convolutional Neural Networks
EHRs	Electronic Health Records
FDA	Food and Drug Administration
FHIR	Fast Healthcare Interoperability Resources

FMEA	Failure Mode and Effects Analysis
IoMT	Internet of Medical Things
IoT	Internet of Things
k-NN	k-Nearest Neighbors
LDA	Latent Dirichlet Allocation
LMICs	Low- and Middle-Income Countries
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
NLP	Natural Language Processing
PdM	Predictive Maintenance
RCM	Reliability-Centered Maintenance
RUL	Remaining Useful Life
SaMD	Software as a Medical Device
SVM	Support Vector Machines

Appendix A

Table A1. Extended Data Dictionary.

	N°	Variable Name	Type	Unit	Description	Missing (%) Before	Missing (%) After	Included in Core Dataset
Identifiers & Provenance	1	internal_id	Categorical	Label	Internal identifier generated by the pipeline (e.g., iq_real_001)	0%	0%	Yes
	2	equipment_id	Categorical	Identifier	Official hospital inventory number (e.g., 9608/19)	0%	0%	Yes
	3	hospital_id	Categorical	Code	Hospital code	0%	0%	Yes
	4	department	Categorical	Label	Clinical department where the device is used	3%	0%	Yes
	5	file_source	Categorical	Label	Excel file name used as data source	0%	0%	No (merged)
	6	sha256_checksum	Categorical	Hash	SHA-256 checksum ensuring data provenance and integrity	0%	0%	Yes
	7	file_uid	Categorical	Hash	Unique identifier automatically assigned to each imported Excel source file	0%	0%	No (technical)
	8	ingestion_timestamp	Temporal	ISO-Datetime	Exact time of ingestion (YYYY-MM-DD HH:MM:SS) logged for auditability	0%	0%	No (technical)
	9	last_update_timestamp	Temporal	ISO-Datetime	Last modification or validation timestamp of each record	NA	0%	No (technical)
	10	checksum_verified	Categorical	Boolean	Indicates whether checksum integrity was verified (True/False)	NA	0%	No (technical)
	11	data_source	Categorical	Label	Source of data (manual entry, GMAO export, external file, etc.)	0%	0%	No (technical)
Contextual/Technical	12	equipment_designation	Categorical	Label	Designation or common name of the device	2%	0%	Yes
	13	technology	Categorical	Label	Equipment technology (Analog/Digital/Hybrid)	6%	0%	Yes
	14	brand	Categorical	Label	Manufacturer brand	7%	0%	No (merged)
	15	model	Categorical	Label	Model or type	9%	0%	No (merged)
	16	brand_model	Categorical	Label	Unified brand–model label	NA	0%	Yes
	17	acquisition_date	Temporal	DD/MM/YYYY	Date of acquisition	10%	0%	Yes
	18	commissioning_date	Temporal	DD/MM/YYYY	Date of commissioning (first use)	10%	0%	Yes
	19	Operational_Age	Numerical	Years	Operational_Age (time elapsed since commissioning)	NA	0%	Yes
	20	warranty_status	Categorical	Yes/No	Indicates if the device is under warranty	12%	0%	Yes

Table A1. Cont.

	N°	Variable Name	Type	Unit	Description	Missing (%) Before	Missing (%) After	Included in Core Dataset
Contextual/Technical	21	warranty_end_date	Temporal	DD/MM/YYYY	End date of warranty period	12%	0%	Yes
	22	estimated_end_of_life_date	Temporal	DD/MM/YYYY	Estimated end-of-life date of the equipment	25%	NA	Yes
	23	service_status	Categorical	Label	Operational/Under repair/Retired	5%	0%	Yes
	24	spare_parts_used	Categorical	Label	Spare parts replaced	18%	5%	No
	25	CI _n	Numerical (ordinal)	Scale 1–5	Internal Criticality Index combining downtime, failure frequency, and clinical importance	NA	0%	Yes
	26	location	Categorical	Label	Room or unit location	20%	8%	No
	27	supplier_name	Categorical	Label	Supplier or vendor name	18%	NA	No
Temporal Variables	28	intervention_date	Temporal	DD/MM/YYYY	Maintenance intervention date	2%	0%	Yes
	29	failure_date	Temporal	DD/MM/YYYY	Failure occurrence date	7%	0%	Yes
	30	repair_date	Temporal	DD/MM/YYYY	Repair completion date	9%	0%	Yes
	31	downtime_hours	Numerical	Hours	Total hours of downtime	12%	0%	Yes
	32	repair_duration	Numerical	Hours	Duration of the repair	15%	0%	Yes
	33	intervention_year	Numerical	Year	Extracted year of intervention (for temporal grouping)	NA	0%	Yes
Maintenance/Failure	34	intervention_type	Categorical	Label	Curative/Preventive/Minor adjustment/External	0%	0%	Yes
	35	failure_type	Categorical	Label	Failure category (electrical, mechanical, software...)	5%	0%	Yes
	36	failure_criticality	Categorical	Low/Med/High	Failure severity level	20%	0%	Yes
	37	intervention_status	Categorical	Label	Completed/Ongoing/Abandoned	4%	0%	Yes
Derived Indicators	38	MTBF	Numerical	Days	Mean Time Between Failures	NA	0%	Derived
	39	MTTR	Numerical	Hours	Mean Time to Repair	NA	0%	Derived
	40	FR	Numerical	%/year	Annualized Failure Rate normalized by equipment and time	NA	0%	Derived
	41	DH	Numerical	Hours	Downtime Hours per intervention cycle	NA	0%	Derived

References

- Li, J.; Mao, Y.; Zhang, J. Construction of Medical Equipment Maintenance Network Management Platform Based on Big Data. *Front. Phys.* **2023**, *11*, 1105906. [\[CrossRef\]](#)
- Manchadi, O.; Ben-Bouazza, F.-E.; Jioudi, B. Predictive Maintenance in Healthcare System: A Survey. *IEEE Access* **2023**, *11*, 61313–61330. [\[CrossRef\]](#)
- Fakhkhari, H.; Bounabat, B.; Bennani, M.; Bekkali, R. Moroccan Patient-Centered Hospital Information System: Global Architecture. In Proceedings of the ArabWIC 6th Annual International Conference Research Track, Rabat, Morocco, 7–9 March 2019.
- Oufkir, L.; Oufkir, A.A. Understanding EHR Current Status and Challenges to a Nationwide Electronic Health Records Implementation in Morocco. *Inform. Med. Unlocked* **2023**, *42*, 10134. [\[CrossRef\]](#)
- Arab-Zozani, M.; Imani, A.; Doshmangir, L.; Dalal, K.; Bahreini, R. Assessment of Medical Equipment Maintenance Management: Proposed Checklist Using Iranian Experience. *Biomed. Eng. OnLine* **2021**, *20*, 49. [\[CrossRef\]](#)
- Woldeyohanins, A.E.; Molla, N.M.; Mekonen, A.W.; Wondimu, A. The Availability and Functionality of Medical Equipment and the Barriers to Their Use at Comprehensive Specialized Hospitals in the Amhara Region, Ethiopia. *Front. Health Serv.* **2025**, *4*, 1470234. [\[CrossRef\]](#)
- Abdul-Rahman, T.; Ghosh, S.; Lukman, L.; Bamigbade, G.B.; Oladipo, O.V.; Amarachi, O.R.; Olanrewaju, O.F.; Toluwalashe, S.; Awuah, W.A.; Aborode, A.T.; et al. Inaccessibility and Low Maintenance of Medical Data Archive in Low-Middle Income Countries: Mystery behind Public Health Statistics and Measures. *J. Infect. Public Health* **2023**, *16*, 1556–1561. [\[CrossRef\]](#)
- Hillebrecht, M.; Schmidt, C.; Saptoka, B.P.; Riha, J.; Nachtnebel, M.; Bärnighausen, T. Maintenance versus Replacement of Medical Equipment: A Cost-Minimization Analysis among District Hospitals in Nepal. *BMC Health Serv. Res.* **2022**, *22*, 1023. [\[CrossRef\]](#)

9. Basri, E.I.; Abdul Razak, I.H.; Ab-Samat, H.; Kamaruddin, S. Preventive Maintenance (PM) Planning: A Review. *J. Qual. Maint. Eng.* **2017**, *23*, 114–143. [\[CrossRef\]](#)
10. Wu, S. Preventive Maintenance Models: A Review. In *Replacement Models with Minimal Repair*; Tadj, L., Ouali, M.-S., Yacout, S., Ait-Kadi, D., Eds.; Springer: London, UK, 2011; pp. 129–140. ISBN 978-0-85729-215-5.
11. Benisch, J.; Helm, B.; Bertrand-Krajewski, J.-L.; Bloem, S.; Cherqui, F.; Eichelmann, U.; Kroll, S.; Poelsma, P. *Operation and Maintenance*; IWA Publishing: London, UK, 2021. [\[CrossRef\]](#)
12. Zhou, J.; Xu, B.; Fang, Z.; Zheng, X.; Tang, R.; Haroglu, H. Operations and Maintenance. In *Digital Built Asset Management*; Edward Elgar Publishing: Cheltenham, UK, 2024; pp. 161–189. ISBN 978-1-0353-2144-5.
13. Fajrin, H.R.; Pramudya, T.; Supriyadi, K. The Development of a Medical Equipment Inventory Information System. In Proceedings of the 2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS), Virtual Conference, 22–23 February 2024; pp. 1–6.
14. Lin, Z.; Kang, J.; Wei, Y.; Zou, B. Maintenance Management Strategies for Medical Equipment in Healthcare Institutions: A Review. *BME Horiz.* **2024**, *2*, 135. [\[CrossRef\]](#)
15. Gandhare, S.; Narad, S.; Kumar, P.; Madankar, T. Integrating Quantitative Parameters for Automating Medical Equipment Maintenance Using Industry 4.0 and FMEA. In Proceedings of the 2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), Wardha, India, 29–30 November 2024; pp. 1–6.
16. Tripathi, R.; Mishra, V.K.; Maheshwari, H.; Tiwari, R.G.; Agarwal, A.K.; Gupta, A. Extrapolative Preservation Management of Medical Equipment through IoT. In Proceedings of the 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI), Raipur, India, 29–30 December 2023; Volume 1, pp. 1–5.
17. Shamayleh, A.; Awad, M.; Farhat, J. IoT Based Predictive Maintenance Management of Medical Equipment. *J. Med. Syst.* **2020**, *44*, 72. [\[CrossRef\]](#)
18. Guissi, M.; Alaoui, M.H.E.Y.; Belarbi, L.; Chaik, A. IoT for Predictive Maintenance of Critical Medical Equipment in a Hospital Structure. *Inform. Autom. Pomiarowy Gospod. Ochr. Śr.* **2024**, *14*, 71–76. [\[CrossRef\]](#)
19. Rahman, N.H.A.; Zaki, M.H.M.; Hasikin, K.; Razak, N.A.A.; Ibrahim, A.K.; Lai, K.W. Predicting Medical Device Failure: A Promise to Reduce Healthcare Facilities Cost through Smart Healthcare Management. *PeerJ Comput. Sci.* **2023**, *9*, e1279. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Ahmed Qaid, M.S.; Mohd Noor, A.; Norali, A.N.; Zakaria, Z.; Ahmad Firdaus, A.Z.; Abu Bakar, A.H.; Fook, C.Y. Remote Monitoring and Predictive Maintenance of Medical Devices. In *Proceedings of the International e-Conference on Intelligent Systems and Signal Processing*; Thakkar, F., Saha, G., Shahnaz, C., Hu, Y.-C., Eds.; Springer: Singapore, 2022; pp. 727–737.
21. Shah Ershad Bin Mohd Azrul Shazril, M.H.; Mashohor, S.; Amran, M.E.; Fatinah Hafiz, N.; Rahman, A.A.; Ali, A.; Rasid, M.F.A.; Safwan, A.; Kamil, A.; Azilah, N.F. Predictive Maintenance Method Using Machine Learning for IoT Connected Computed Tomography Scan Machine. In Proceedings of the 2023 IEEE 2nd National Biomedical Engineering Conference (NBEC), Melaka, Malaysia, 5–7 September 2023; pp. 42–47.
22. Li, X.; Williams, J.; Swanson, C.; Berg, T. A Machine Learning Approach to Predictive Maintenance: Remaining Useful Life and Motor Fault Analysis. *Comput. Ind. Eng.* **2025**, *206*, 111222. [\[CrossRef\]](#)
23. Sabah, S.; Moussa, M.; Shamayleh, A. Predictive Maintenance Application in Healthcare. In Proceedings of the 2022 Annual Reliability and Maintainability Symposium (RAMS), Tucson, AZ, USA, 24–27 January 2022; pp. 1–9.
24. Titah, M.; Bouchaala, M.A. An Ontology-Driven Model for Hospital Equipment Maintenance Management: A Case Study. *J. Qual. Maint. Eng.* **2024**, *30*, 409–433. [\[CrossRef\]](#)
25. Habib Shah Ershad Mohd Azrul Shazril, M.; Mashohor, S.; Effendi Amran, M.; Fatinah Hafiz, N.; Mohd Ali, A.; Saiful Bin Naseri, M.; Rasid, M.F.A. Assessment of IoT-Driven Predictive Maintenance Strategies for Computed Tomography Equipment: A Machine Learning Approach. *IEEE Access* **2024**, *12*, 195505–195515. [\[CrossRef\]](#)
26. Manchadi, O.; Ben-BOUAZZA, F.-E.; Dehbi, Z.E.O.; Said, Z.; Jioudi, B. Towards Industry 4.0: An IoT-Enabled Data-Driven Architecture for Predictive Maintenance in Pharmaceutical Manufacturing. In Proceedings of the International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD’2023), Marrakech, Morocco, 15–17 October 2023; Ezziyyani, M., Kacprzyk, J., Balas, V.E., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 28–45.
27. Wang, B.; Rui, T.; Skinner, S.; Ayers-Comegys, M.; Gibson, J.; Williams, S. Medical Equipment Aging: Part I—Impact on Maintenance. *J. Clin. Eng.* **2024**, *49*, 52. [\[CrossRef\]](#)
28. Amran, M.E.; Aziz, S.A.; Muhtazaruddin, M.N.; Masrom, M.; Haron, H.N.; Bani, N.A.; Mohd Izhar, M.A.; Usman, S.; Sarip, S.; Najamudin, S.S.; et al. Critical Assessment of Medical Devices on Reliability, Replacement Prioritization and Maintenance Strategy Criterion: Case Study of Malaysian Hospitals. *Qual. Reliab. Eng. Int.* **2024**, *40*, 970–1001. [\[CrossRef\]](#)
29. Tettey, F.; Parupelli, S.K.; Desai, S. A Review of Biomedical Devices: Classification, Regulatory Guidelines, Human Factors, Software as a Medical Device, and Cybersecurity. *Biomed. Mater. Devices* **2024**, *2*, 316–341. [\[CrossRef\]](#)

30. Peruničić, Ž.; Lalatović, I.; Spahić, L.; Ašić, A.; Pokvić, L.G.; Badnjević, A. Enhancing Mechanical Ventilator Reliability through Machine Learning Based Predictive Maintenance. *Technol. Health Care* **2025**, *33*, 1288–1297. [\[CrossRef\]](#)
31. Zheng, F.; Sun, G.; Suo, Y.; Ma, H.; Feng, T. Research on Through-Flame Imaging Using Mid-Wave Infrared Camera Based on Flame Filter. *Sensors* **2024**, *24*, 6696. [\[CrossRef\]](#)
32. Montes-Sánchez, J.M.; Uwate, Y.; Nishio, Y.; Vicente-Díaz, S.; Jiménez-Fernández, Á. Predictive Maintenance Edge Artificial Intelligence Application Study Using Recurrent Neural Networks for Early Aging Detection in Peristaltic Pumps. *IEEE Trans. Reliab.* **2024**, *74*, 3730–3744. [\[CrossRef\]](#)
33. Zamzam, A.H.; Hasikin, K.; Wahab, A.K.A. Integrated Failure Analysis Using Machine Learning Predictive System for Smart Management of Medical Equipment Maintenance. *Eng. Appl. Artif. Intell.* **2023**, *125*, 106715. [\[CrossRef\]](#)
34. Singgih, M.L.; Zakiyyah, F.F. Andrew Machine Learning for Predictive Maintenance: A Literature Review. In Proceedings of the 2024 Seventh International Conference on Vocational Education and Electrical Engineering (ICVEE), Malang, Indonesia, 30–31 October 2024; pp. 250–256.
35. Ouardi, A.; Sekkaki, A.; Mammass, D. Towards an Inter-Cloud Architecture in Healthcare System. In Proceedings of the 2017 International Symposium on Networks, Computers and Communications (ISNCC), Marrakech, Morocco, 16–18 May 2017; pp. 1–6.
36. Rezende, M.C.C.; Santos, R.P.; Coelli, F.C.; Almeida, R.M.V.R. Reliability Analysis Techniques Applied to Highly Complex Medical Equipment Maintenance. In Proceedings of the IX Latin American Congress on Biomedical Engineering and XXVIII Brazilian Congress on Biomedical Engineering, Florianópolis, Brazil, 24–28 October 2022; Marques, J.L.B., Rodrigues, C.R., Suzuki, D.O.H., Marino Neto, J., García Ojeda, R., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 184–192.
37. Boppana, V.R. *Data Analytics for Predictive Maintenance in Healthcare Equipment*; EPH-International Journal of Business & Management Science: Perth, Australia, 2023.
38. Daniel, C. Medical Device Maintenance Regimes in Healthcare Institutions. In *Inspection of Medical Devices: For Regulatory Purposes*; Badnjević, A., Cifrek, M., Magjarević, R., Džemić, Z., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 59–91. ISBN 978-3-031-43444-0.
39. Haninie Abd Wahab, N.; Hasikin, K.; Wee Lai, K.; Xia, K.; Ying Taing, A.; Zhang, R. Predicting Medical Device Life Expectancy and Estimating Remaining Useful Life Using a Data-Driven Multimodal Framework. *IEEE Access* **2025**, *13*, 117300–117327. [\[CrossRef\]](#)
40. Ahmed, R.; Nasiri, F.; Zayed, T. A Novel Neutrosophic-Based Machine Learning Approach for Maintenance Prioritization in Healthcare Facilities. *J. Build. Eng.* **2021**, *42*, 102480. [\[CrossRef\]](#)
41. Jallal, M.; Serhier, Z.; Berrami, H.; Othmani, M.B. Telemedicine: The Situation in Morocco. In *Studies in Health Technology and Informatics*; IOS Press: Amsterdam, The Netherlands, 2023.
42. Jallal, M.; Serhier, Z.; Berrami, H.; Othmani, M.B. Current State and Prospects of Telemedicine in Morocco: Analysis of Challenges, Initiatives, and Regulatory Framework. *Cureus* **2023**, *15*, e50963. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Mohssine, N.; Raji, I.; Lanteigne, G.; Amalik, A.; Chaouch, A. Impact organisationnel de la préparation à l'accréditation en établissement de santé au Maroc. *Santé Publique* **2015**, *27*, 503–513. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Ramadan, E.A.; Abu-Ghaleb, A.A.; El-Brawany, M.A. Medical Equipment Maintenance Management and Optimization in Healthcare Facilities: Literature Review. In Proceedings of the 2023 3rd International Conference on Electronic Engineering (ICEEM), Menouf, Egypt, 7–8 October 2023; pp. 1–11.
45. Zinaoui, T.; El Khettab, M.K. La digitalisation des administrations publiques à l'ère de la pandémie. *Commun. Organ. Rev. Sci. Francoph. Commun. Organ.* **2022**, *62*, 143–161. [\[CrossRef\]](#)
46. Mansoury, O.; Sebbani, M. Réflexion Sur le Système de Santé du Maroc Dans la Perspective de la Promotion de la Santé. *Maghreb Rev.* **2023**, *48*, 317–321. [\[CrossRef\]](#)
47. Mahdaoui, M.; Kissani, N. Morocco's Healthcare System: Achievements, Challenges, and Perspectives. *Cureus* **2023**, *15*, e41143. [\[CrossRef\]](#)
48. Hoxha, K.; Hung, Y.W.; Irwin, B.R.; Grépin, K.A. Understanding the Challenges Associated with the Use of Data from Routine Health Information Systems in Low- and Middle-Income Countries: A Systematic Review. *Health Inf. Manag. J.* **2022**, *51*, 135–148. [\[CrossRef\]](#)
49. Jidane, S.; Zidouh, S.; Belyamani, L. The Impact of Telemedicine in Morocco: A Transformative Shift in Healthcare Delivery. *Int. J. Biomed. Eng. Clin. Sci.* **2025**, *11*, 6–10. [\[CrossRef\]](#)
50. Ahmad, A. Enhancing Hospital Efficiency through IoT and AI: A Smart Healthcare System. *J. Comput. Sci. Appl. Eng.* **2024**, *2*, 34–38. [\[CrossRef\]](#)
51. Janjua, J.I.; Ghazal, T.M.; Abushiba, W.; Abbas, S. Optimizing Patient Outcomes with AI and Predictive Analytics in Healthcare. In Proceedings of the 2024 IEEE 65th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCon), Riga, Latvia, 10–12 October 2024; pp. 1–6.

52. Patnaik, S.K.; Kushagra, D.P.; Sahran, D.; Kalita, B.J.; Kumar, B.; Prusty, H.; Pandit, P. Optimising Medical Equipment Utilisation and Serviceability: A Data-Driven Approach through Insights from Five Healthcare Institutions. *Med. J. Armed Forces India* 2025, *in press*. [\[CrossRef\]](#)
53. Alahmadi, K.M.; Mahmoud, E.R.I.; Imaduddin, F. Model Development to Improve the Predictive Maintenance Reliability of Medical Devices. *Inform. Autom. Pomiary Gospod. Ochr. Śr.* 2025, *15*, 117–124. [\[CrossRef\]](#)
54. Aljasmī, M.; Piya, S. Identification of Suitable Maintenance Strategy for Medical Devices in UAE Healthcare Facilities. In Proceedings of the 2024 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD), Sharjah, United Arab Emirates, 4–6 November 2024; pp. 1–8.
55. Amitabh, K.; Mathur, A. Impact of Repair and Maintenance of Hospital Equipment on Health Services in Government Hospitals in North—Eastern Region of India. In Proceedings of the NIELIT's International Conference on Communication, Electronics and Digital Technology, Guwahati, India, 16–17 February 2024; Shivakumara, P., Mahanta, S., Singh, Y.J., Eds.; Springer Nature: Singapore, 2024; pp. 411–422.
56. Chaminda, J.L.P.; Dharmagunawardene, D.; Rohde, A.; Kularatna, S.; Hinchcliff, R. Implementation of a Multicomponent Program to Improve Effective Use and Maintenance of Medical Equipment in Sri Lankan Hospitals. *WHO South-East Asia J. Public Health* 2023, *12*, 85. [\[CrossRef\]](#)
57. Medenou, D.; Fagbemi, L.A.; Houessouvo, R.C.; Jossou, T.R.; Ahouandjinou, M.H.; Piaggio, D.; Kinnouezan, C.-D.A.; Monteiro, G.A.; Idrissou, M.A.Y.; Iadanza, E.; et al. Medical Devices in Sub-Saharan Africa: Optimal Assistance via Acomputerized Maintenance Management System (CMMS) in Benin. *Health Technol.* 2019, *9*, 219–232. [\[CrossRef\]](#)
58. Niyonambaza, I.; Zennaro, M.; Uwitonze, A. Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda. *Future Internet* 2020, *12*, 224. [\[CrossRef\]](#)
59. Gallab, M.; Ahidar, I.; Zrira, N.; Ngote, N. Towards a Digital Predictive Maintenance (DPM): Healthcare Case Study. *Procedia Comput. Sci.* 2024, *232*, 3183–3194. [\[CrossRef\]](#)
60. Castañeira, M.; Rubio, D.; Salguero, M.G.; Ponce, S.; Madrid, F. Optimizing Biomedical Equipment Management Through a Business Intelligence Platform. In Proceedings of the Advances in Bioengineering and Clinical Engineering, Buenos Aires, Argentina, 3–6 October 2023; Ballina, F.E., Armentano, R., Acevedo, R.C., Meschino, G.J., Eds.; Springer Nature Switzerland: Cham, Switzerland, 2024; pp. 114–121.
61. Fan, C.; Chen, M.; Wang, X.; Wang, J.; Huang, B. A Review on Data Preprocessing Techniques Toward Efficient and Reliable Knowledge Discovery from Building Operational Data. *Front. Energy Res.* 2021, *9*, 652801. [\[CrossRef\]](#)
62. Brand, D.; Singh, J.A.; McKay, A.G.N.; Cengiz, N.; Moodley, K. Data Sharing Governance in Sub-Saharan Africa during Public Health Emergencies: Gaps and Guidance. *S. Afr. J. Sci.* 2023, *118*, 11–12. [\[CrossRef\]](#)
63. Sarker, I.H. Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. *SN Comput. Sci.* 2021, *2*, 377. [\[CrossRef\]](#)
64. Kandel, S.; Paepcke, A.; Hellerstein, J.; Heer, J. Wrangler: Interactive Visual Specification of Data Transformation Scripts. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; Association for Computing Machinery: New York, NY, USA, 2011; pp. 3363–3372.
65. Barapatre, D.; Vijayalakshmi, A. Data Preparation on Large Datasets for Data Science. *Asian J. Pharm. Clin. Res.* 2017, *10*, 485–488. [\[CrossRef\]](#)
66. Dhillon, B.S. *Maintainability, Maintenance, and Reliability for Engineers*; CRC Press: Boca Raton, FL, USA, 2006; ISBN 978-0-429-12821-9.
67. Iadanza, E.; Gonnelli, V.; Satta, F.; Gherardelli, M. Evidence-Based Medical Equipment Management: A Convenient Implementation. *Med. Biol. Eng. Comput.* 2019, *57*, 2215–2230. [\[CrossRef\]](#) [\[PubMed\]](#)
68. Cinar, E.; Kalay, S.; Saricicek, I. A Predictive Maintenance System Design and Implementation for Intelligent Manufacturing. *Machines* 2022, *10*, 1006. [\[CrossRef\]](#)
69. Zamzam, A.H.; Al-Ani, A.K.I.; Wahab, A.K.A.; Lai, K.W.; Satapathy, S.C.; Khalil, A.; Azizan, M.M.; Hasikin, K. Prioritisation Assessment and Robust Predictive System for Medical Equipment: A Comprehensive Strategic Maintenance Management. *Front. Public Health* 2021, *9*, 782203. [\[CrossRef\]](#)
70. Pakala, A.; Shah, D.; Jha, S. Advancing Predictive Maintenance: A Data-Driven Approach for Accurate Equipment Failure Prediction. In *Proceedings of the Industry 4.0 and Advanced Manufacturing, Volume 1*; Chakrabarti, A., Suwas, S., Arora, M., Eds.; Springer Nature: Singapore, 2025; pp. 219–228.
71. Taouabit, O.; Touhami, F.; Elmoukhtar, M. Transformation digitale de l'administration publique au Maroc et son impact sur l'expérience utilisateur: Cas des services rendus aux notaires par l'Agence Nationale de la Conservation Foncière du Cadastre et de la Cartographie. *Int. J. Account. Finance Audit. Manag. Econ.* 2023, *4*, 384–401. [\[CrossRef\]](#)

72. Mandel, J.C.; Kreda, D.A.; Mandl, K.D.; Kohane, I.S.; Ramoni, R.B. SMART on FHIR: A Standards-Based, Interoperable Apps Platform for Electronic Health Records. *J. Am. Med. Inform. Assoc.* **2016**, *23*, 899–908. [[CrossRef](#)]
73. Zhou, H.; Liu, Q.; Liu, H.; Chen, Z.; Li, Z.; Zhuo, Y.; Li, K.; Wang, C.; Huang, J. Healthcare Facilities Management: A Novel Data-Driven Model for Predictive Maintenance of Computed Tomography Equipment. *Artif. Intell. Med.* **2024**, *149*, 102807. [[CrossRef](#)]

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