Adaptive model of uncertainty in healthcare technology management

A Thesis Submitted for the Degree of Doctor of Philosophy

By

Tasneem Mahmoud Salih Mahgoub

Department of Engineering, Brunel University London

2026

Abstract

Healthcare Technology Management (HTM) operates under significant uncertainty arising from technical, managerial, and macro-environmental factors. Existing risk assessment models—including recent data-driven and machine learning–based approaches—focus predominantly on internal maintenance variables and fail to account for broader sources of uncertainty or the dynamic influence of equipment utilization. Addressing this gap, this thesis develops an Adaptive Model of Uncertainty in HTM by integrating expert judgment, fuzzy multi-criteria weighting, and nonlinear utilization–risk modelling.

An initial pool of 53 HTM risk factors was systematically screened through expert relevance scoring, after which 41 significant factors were prioritized using a Fuzzy Analytic Hierarchy Process (Fuzzy AHP), yielding stable global weights that reflect region-specific HTM priorities in Saudi Arabia and the Gulf. Building on this weighted risk structure, the thesis formulates the Synergistic Quadratic–Resonant Risk Model (SQRRM) as a nonlinear system-identification law that couples utilization intensity with fuzzy-weighted readiness gaps to adaptively modulate risk magnitude. The proposed model was identified using a five-year hospital imaging dataset and evaluated on the aggregated 2024 cross-section, where it demonstrated superior explanatory performance ($R^2 = 0.943$) relative to six competing baseline formulations.

To assess the potential cross-domain applicability of the proposed modelling framework, SQRRM was embedded within the BiLSTM and Adaptive Dynamic Graph Neural Network (ADGNN) architectures and evaluated on the NASA C-MAPSS FD001 turbofan degradation dataset. Under the adopted experimental protocol, the SQRRM-enhanced ADGNN achieved the strongest predictive performance among the selected comparator models (RMSE = 12.80, $R^2 = 0.905$). These findings provide additional empirical evidence supporting the robustness of the proposed nonlinear modelling framework and its potential applicability beyond the healthcare domain.

The contributions of this thesis include: (i) the first region-specific, expert-validated hierarchy of HTM risks; (ii) an integrated risk-quantification framework that unifies readiness gaps, utilization, and operational burden; (iii) the derivation of the SQRRM model as a nonlinear, resonance-modulated risk function; and (iv) successful cross-domain validation through deep learning architectures. Recommendations emphasize the need for improved Computerized Maintenance Management System (CMMS) data governance, evaluation of current mitigation strategies, and expansion of contextual readiness indicators to enhance predictive-risk analytics in HTM.

Overall, this thesis proposes and initially validates an integrated Healthcare Technology Management (HTM) risk-modelling framework within the healthcare context of Saudi Arabia and the Gulf region. It establishes a scientifically grounded and operationally implementable foundation for risk-aware, utilization-driven decision making in healthcare technology management, while the cross-domain evaluation provides initial evidence of the framework's potential applicability to other high-reliability engineering systems, including aviation and energy.

DEDICATION

To my mother, Afraa, and my father, Mahmoud, who endured the profound impact of the war in Sudan yet never lost their faith—nor their unwavering love and support for their children, and for me.

To my beloved husband, and to my children Leen, Zainab, Mahmoud, and Muath.

To my beloved siblings, my in-laws, my extended family, especially my uncle, Dr. AlSeddig Omer, and my lifelong friend, Naama Talal. Your unwavering support, encouragement, and belief in me have been a constant source of strength throughout this journey.

To that little girl within me—my younger self—who believed that imagination is greater than knowledge; may this research stand as a testament to imagination, knowledge, and lived experience intertwined.

To all of you, I dedicate this work.

Acknowledgements

My deepest gratitude goes to my principal supervisor, Professor Wamadeva Balachandran, for his boundless support, professional guidance, and exceptional generosity in sharing his expertise and insight—without which this research would not have been possible.

My sincere thanks are also extended to my second supervisor, Dr. Saleh Al-Tayyar, and to the Research Center at the College of Medicine, King Saud University.

I also extend my deep appreciation to the Department of Electronic and Electrical Engineering at the College of Engineering, Design and Physical Sciences at Brunel University London, and to all faculty members, staff, and dedicated experts whose contributions were essential to this research.

To my dear colleagues—whom I wish these pages were wide enough to name individually—thank you for surrounding me with a support that transformed moments of discouragement into sparks of clarity and hope, bringing forth the best of my resilience and determination.

My heartfelt thanks to you all.

Table of Contents

List of Figures

List of Tables

Abbreviations

AAMI	Advancement of Medical Instrumentation
ADGNN	Adaptive Dynamic Graph Neural Network
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
ANSI	American National Standards Institute
ASHE	American Safety and Health Institute
BiLSTM	Bidirectional Long Short-Term Memory
BNN	Bayesian Neural Network
CAELSTM	Convolutional Autoencoder–LSTM
CBAHI	The Saudi Central Board for Accreditation of Healthcare Institutions
CM	Corrective Maintenance
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
CMMS	Computerized Maintenance Management System
CR	Consistency Ratio
DL	Deep Learning
ECRI	Emergency Care Research Institute
EHRs	Electronic Health Records
EMC	Electromagnetic Compatibility
EMI	electromagnetic interference
ERM	enterprise risk management
FDA	Food and Drug Administration
FDA's MAUDE	FDA's Manufacturer and User Facility Device Experience
FIS	Fuzzy Inference System
FMEA	Failure Mode and Effects Analysis
Fuzzy AHP	Fuzzy Analytic Hierarchy Process

Gl. W.	Fuzzy AHP Global Weights
GRU	Gated Recurrent Unit
HFE	Human Factor Engineering
HFM	healthcare facility management
HTM	Healthcare Technology Management
HTRM	Healthcare Technology Risk Management
HVAC	Heating, Ventilation, and Air Conditioning
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
LSTM	Long Short-Term Memory
MEMPF	Medical Equipment Maintenance Prioritization Factor
ML	Machine Learning
MSE	Mean Square Error
NASA Score	Asymmetric NASA Prognostics Evaluation Metric
NRMSE	Normalized Root Mean Square Error
PESTEL	Political, Economic, Sociocultural, Technological, Environmental, Legal
PM	Preventive Maintenance
RCM	Reliability-centred maintenance
RF	Radio Frequency
RMSE	Root Mean Square Error
RT	Repair Time
RUL	Remaining Useful Life
SFDA	Saudi Food and Drug Authority
SMDA	the Safe Medical Device Act
SQRRM	Synergistic Quadratic–Resonant Risk Model
TFN	Triangular Fuzzy Number
WO	Work Order (Count)

Symbols List

A. Utilization, Readiness, and Risk Terms

Symbol	Definition
U	Utilization intensity (normalized workload)
$f(U_{\text{opt}})$	Optimal utilization function used in the foundational risk equation
G	Aggregated readiness gap: G = Σ $\omega_i \cdot (1 - x_i)$
x_i	Readiness score for factor i, $x_i \in [0, 1]$
ω_i	Fuzzy AHP global weight for factor i
L_i	Magnitude of loss for factor i: $L_i = \omega_i \times (1 - x_i)$
R_{add}	Additive risk: R = WO + RT
WO	Number of corrective maintenance work orders
RT	Repair time or downtime duration

B. SQRRM (Synergistic Quadratic–Resonant Risk Model) Parameters

Symbol	Definition
a, b, c	Quadratic escalation coefficients in the SQRRM backbone
δ $(delta)$	Amplitude of resonant modulation term
β (beta)	Harmonic frequency coefficient applied to U·G
ϕ (phi)	Phase-shift parameter in resonant modulation
$f(U, G)$	SQRRM risk surface: $(aU^2 + bU + c)\,(1 + \delta \sin(\beta U_t G_t^{eff} + \phi))$

C. Time-Series and Neural Network Terms

Symbol	Definition
U_t	Normalized utilization at time t
G_t	Raw readiness-gap signal at time t
$\hat{G}_t$	Data-driven (learned) readiness gap from sensor channels
G_t^{ef}	Effective fused gap: $G_t^{ef} = \rho\widehat{G_t} + \ (1-\rho)G_t$
$\tilde{g}_t'$	SQRRM-based quadratic–resonant risk–modulated candidate update.
c_t	LSTM cell state
h_t	Hidden state of LSTM or BiLSTM
$\tilde{h}_t$	GRU or ADGNN candidate hidden state
z_t	GRU update gate
Γ_t	Residual modulation gate derived from SQRRM

D. Gating, Fusion, and Training Parameters

Symbol	Definition
ρ	Trainable convex fusion weight (0 < ρ < 1)
γ	Gain parameter for residual modulation (sigmoid-bounded)
α	Warm-up coefficient enabling progressive activation
K	Early-life window size used for baseline sensor normalization

E. Evaluation Metrics and Validation Terms

Symbol	Definition
R^2	Coefficient of determination
RMSE	Root Mean Square Error
MSE	Mean Square Error
NASA_score	NASA asymmetric scoring function for RUL $S = \sum_{i=1}^{n} \begin{cases} \exp\left(-\frac{e_i}{13}\right) - 1, & e_i < 0, \\ \exp\left(\frac{e_i}{10}\right) - 1, & e_i \geq 0, \end{cases}$ $e_i = \hat{y}_i - y_i$, ($y_{prediction} - y_{true}$)
ρ	Spearman rank correlation coefficient ($\rho = \frac{cov(r(Y_{\text{true}}), r(Y_{\text{pred}}))}{\sigma_{r(Y_{\text{true}})} \sigma_{r(Y_{\text{pred}})}}$)
ΔR^2	Change in Coefficient of Determination

CHAPTER ONE – INTRODUCTION

1.1 INTRODUCTION

This chapter establishes the foundations of the research by introducing the background and contextual motivation of the study, and by clearly defining the research scope, central research question, and the associated aims and objectives. It further highlights the original contributions of the thesis. In addition, the overall structure of the thesis is outlined, providing a coherent roadmap of the research progression. This structure reflects the sequential stages of the proposed healthcare technology management (HTM) risk modelling framework, including risk factor identification, risk assessment and weighting, mathematical model development, and cross-domain validation using deep learning architectures.

1.2 RESEARCH BACKGROUND

To establish a clear conceptual foundation, it is necessary to define the term *healthcare technology* as adopted in this study. The World Health Organization (WHO) defines healthcare technology as “devices, drugs, medical and surgical procedures—and the knowledge associated with these—used in the prevention, diagnosis, and treatment of disease, as well as in rehabilitation, and the organizational and supportive systems within which care is provided” [1]. In the context of this thesis, however, the term is deliberately restricted to the physical hardware and software components of this definition, explicitly excluding drugs and pharmaceuticals, and focusing exclusively on technologies that require technical operation, maintenance, and lifecycle management.

According to [1], Healthcare Technology Management (HTM) encompasses a comprehensive set of coordinated activities that span the entire technology lifecycle. These include the systematic collection of reliable information on healthcare technologies; strategic planning and needs assessment with appropriate financial provision; procurement and efficient installation; ensuring the availability of resources for safe and effective use; routine operation, maintenance, and repair; and the structured decommissioning, disposal, and replacement of obsolete or unsafe equipment. HTM also explicitly includes the development of staff competencies required for the optimal use of healthcare technologies. Through this integrated management framework, healthcare providers are able to maximize returns on capital investment, enhance both the quality and capacity of healthcare delivery, and achieve these improvements without proportionate increases in cost [1].

Healthcare assets managed within this framework comprise human resources, physical assets, and supporting resources such as consumables and supplies [1]. Among these, healthcare technology represents one of the most capital-intensive physical assets in the health sector, making its effective management particularly critical. Ensuring that medical technologies are appropriately selected, correctly utilized, and maintained for an extended operational lifespan is therefore fundamental to sustaining clinical performance and economic efficiency.

Proper implementation of HTM directly contributes to improved patient safety, enhanced service reliability, and the long-term sustainability of healthcare systems. Figure 1.1 illustrates the positioning of Healthcare Technology Management within the broader health system architecture. The referenced guide, *How to Organize a System of Healthcare Technology Management* from the WHO “How to Manage” series [1], provides a widely adopted operational framework for HTM. While this guide emphasizes safety and operational control, it does not explicitly or systematically integrate risk modelling as a unified analytical dimension across the full spectrum of healthcare technology management functions—an important gap addressed in this thesis.

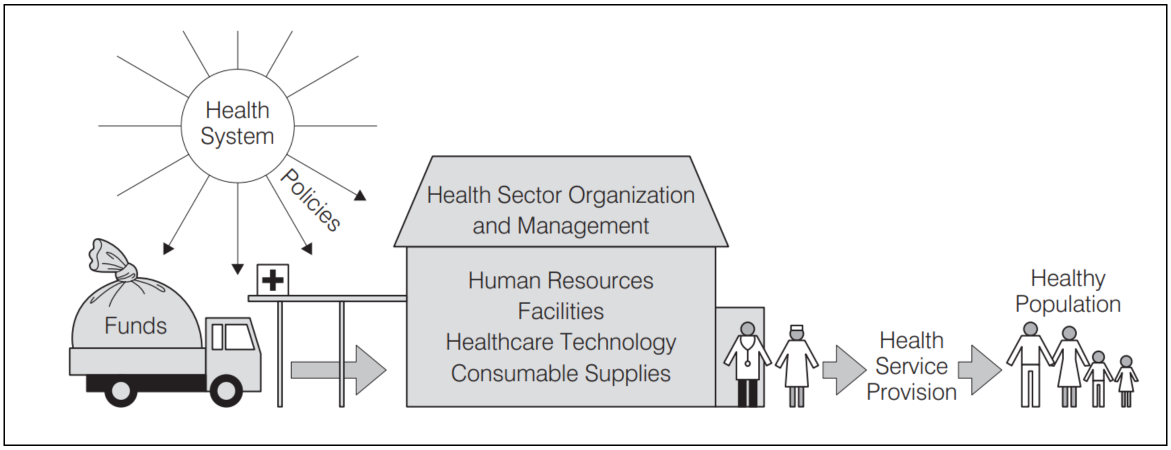


Figure 1.1: Position of Healthcare Technology Management within the overall health system framework [1].

In parallel with the WHO perspective, the Association for the Advancement of Medical Instrumentation (AAMI) defines Healthcare Technology Management (HTM) as a professional discipline focused on the oversight of the selection, maintenance, and safe use of health technology and medical equipment within healthcare environments [2]. AAMI further illustrates the intersection of HTM roles and responsibilities across the healthcare delivery ecosystem, as shown in Figure 1.2.

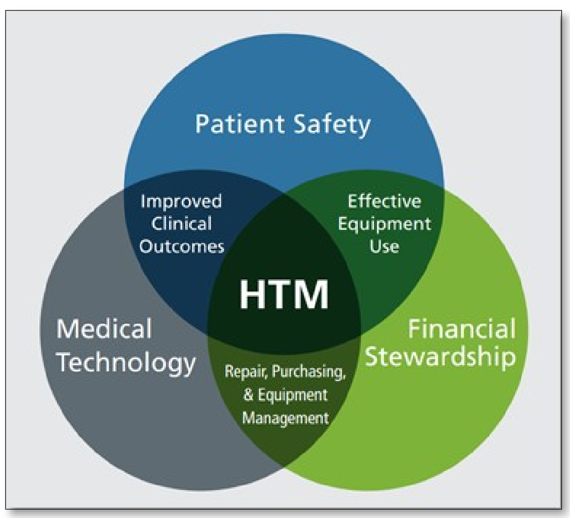


Figure 1.2. Interrelationship of Healthcare Technology Management (HTM) roles and responsibilities within the healthcare system [2].

The formal emergence of risk management in healthcare institutions dates back to the 1970s in the United States, driven primarily by court rulings that established hospitals and clinical staff as legally accountable for the quality and safety of care provided. As a result, the implementation of structured risk management programs became an essential requirement for healthcare institutions worldwide and a core component of hospital accreditation systems. In the Kingdom of Saudi Arabia, the adoption of a formal healthcare risk management program is a mandatory requirement for achieving accreditation by the Central Board for Accreditation of Healthcare Institutions (CBAHI) [3].

1.3 RESEARCH SCOPE

This research primarily focuses on developing a model to assist in managing risks that arise throughout the entire lifecycle of healthcare technology, from upstream (e.g., manufacturers and distributors) to downstream, end users (e.g., patients), while accounting for external factors such as environmental, political, economic and technological influences. Specifically, it assumes that all healthcare technology management activities (e.g., planning, procurement, maintenance, etc.) are interconnected with processes such as designing, manufacturing, regulation, funding, facility planning, construction, and operation. These interactions collectively impact and control the effective and sustainable use of medical technology.

The types of risks addressed in this thesis are categorized into two main groups: (1) risks internal to the healthcare technology management context, which include the technology itself, the management system, and the healthcare facility setting, and (2) external (exogenous) risks. Unlike other studies that primarily focus on modelling or predicting medical device failures—typically analysing internal (endogenous) factors affecting device performance and developing optimal service strategies—this research introduces a novel hierarchical risk management framework.

The framework is designed to accommodate a wide range of healthcare technologies, extending beyond medical devices alone. It makes a significant contribution to the field by thoroughly identifying, investigating, and validating 53 comprehensive risk factors, assessing their impact on healthcare technology management (HTM), and advancing the understanding of risk in this domain [4].

The geographical focus of this research is centred on the Kingdom of Saudi Arabia (KSA) and the broader Gulf Cooperation Council (GCC) region. The Kingdom of Saudi Arabia serves as a particularly valuable case study for the healthcare industry in the Gulf region, as its Ministry of Health (MOH), along with its affiliated partners, operates the largest and most integrated healthcare system in the region. This makes it a rich environment for examining healthcare technology management practices and challenges. Additionally, the study extends its scope to include other Gulf countries, specifically the United Arab Emirates (UAE) and Qatar, to provide a more comprehensive understanding of the regional context.

While the primary focus is on the Gulf region, the developed model introduces a novel framework for identifying and managing key risk factors in healthcare technology management. This framework goes beyond the regional context, offering unique insights and perspectives with far-reaching implications for healthcare systems worldwide. By addressing both localized and global challenges, the study contributes to advancing the understanding of risk management in healthcare technology on a broader scale, making the findings and recommendations applicable to diverse healthcare settings across the globe.

1.4 RESEARCH QUESTION

Main Research Question

How can healthcare technology risks be holistically identified, quantified, and adaptively modelled to improve predictive maintenance and strategic decision-making in Healthcare Technology Management (HTM) within Saudi Arabia and the Gulf region?

1.5 Aim of the Study

This research aims to fill several critical gaps in the existing literature and practice of healthcare technology management, particularly in the context of Saudi Arabia and the Gulf region.

1.6 Research Objectives

The following specific research objectives are formulated to address the identified research problem and to achieve the overall aim of the study:

1. **To identify and classify key risk factors affecting the healthcare technology lifecycle:** from acquisition and implementation to operation and decommissioning—through a structured literature review and expert consultation, thereby establishing a comprehensive regional risk framework.

2. **To quantify the relative significance of the identified risk factors:** both internal (e.g., maintenance, infrastructure, operational) and external (e.g., regulatory, environmental, economic, political) influences on HTM performance within Saudi Arabia and the Gulf region.

3. **To formulate an adaptive Risk Model:** capable of dynamically capturing nonlinear relationships between utilization intensity and other risk factors, thereby representing the real behaviour of risk propagation in complex healthcare systems.

4. **To validate the proposed adaptive model** through real-world healthcare data and external benchmark datasets, assessing its capacity for predictive risk localization, and generalization across diverse operational contexts.
5. **To propose a comprehensive adaptive Healthcare Technology Risk Management (HTRM) framework** that bridges quantitative risk modelling with practical decision-making, enabling healthcare institutions to transition from reactive maintenance toward predictive, risk- and utilization-aware management strategies.

1.7 Thesis Contributions

This thesis makes several key theoretical, methodological, and practical contributions to the field of Healthcare Technology Management (HTM) and predictive maintenance analytics. These contributions extend existing reliability and risk management frameworks by introducing adaptive, data-driven modelling of healthcare technology risk in the context of Saudi Arabia and the Gulf region.

1.7.1 Theoretical Contributions

1. **Establishment of a Comprehensive Risk Taxonomy:** The research identified and systematically classified 53 critical risk factors influencing healthcare technology lifecycle performance in the Gulf region, addressing a major gap in prior literature that lacked contextualized and empirically weighted risk structures.
2. **Integration of Systemic Readiness in Risk Theory:** By embedding readiness gaps into the reliability function, the thesis advances theoretical understanding of how healthcare technology risk emerges from the interaction between utilization intensity and systemic preparedness, rather than utilization alone.
3. **Introduction and Development of the Adaptive Resonant Risk Modelling Framework (SQRRM)**: This thesis introduces a novel Synergistic Quadratic–Resonant Risk Model (SQRRM) that establishes the concept of resonance in risk propagation for socio-technical systems. By coupling utilization intensity with weighted readiness gaps within a hybrid nonlinear quadratic–sinusoidal formulation, the proposed framework redefines conventional reliability and risk modelling. This adaptive structure enables the model to capture both nonlinear escalation and oscillatory amplification observed in real operational environments. The theoretical formulation is empirically validated, achieving $R^2 = 0.94$ on real hospital equipment data and $R^2 = 0.905$ when embedded within an ADGNN architecture on the NASA CMAPSS FD001 dataset, demonstrating both high predictive accuracy and strong cross-domain generalizability.

1.7.2 Methodological and Practical Contributions

1 **Integration with Advanced Deep Learning Architectures**: The study demonstrates the successful embedding of the Synergistic Quadratic–Resonant Risk Model (SQRRM) within BiLSTM and Adaptive Graph Neural Network (ADGNN) architectures, introducing an adaptive resonant learning gate that improves

convergence smoothness, enhances risk localization, and strengthens the modelling of complex temporal and relational dependencies.

2 **Cross-Domain Empirical Validation**: Cross-domain empirical validation refers to evaluating the proposed model using real-world observational data collected from different application domains rather than relying solely on theoretical analysis or simulated experiments. The proposed adaptive framework is validated across heterogeneous domains, including real hospital equipment and the NASA CMAPSS aerospace dataset, establishing the generalizability, robustness, and transferability of the SQRRM-based modelling approach.

3 **Decision-Support Tool for Predictive HTM**: The integrated Fuzzy AHP–SQRRM framework provides a structured, data-driven decision-support system for maintenance prioritization and optimal resource allocation, enabling hospitals to transition from reactive and time-based maintenance to predictive, risk- and utilization-aware maintenance strategies.

4 **Scalable Framework for Policy and Benchmarking**: The identified risk taxonomy and adaptive modelling structure offer a scalable foundation for national and regional benchmarking of healthcare technology risk assessment, particularly aligned with digital health transformation and Saudi Vision 2030 initiatives.

5 **Cross-Sectoral Applicability**: Beyond healthcare, the proposed adaptive resonant risk modelling concept demonstrates strong applicability to other safety-critical sectors, including aviation, manufacturing, and energy, where reliability is governed by interacting operational, environmental, and managerial factors.

In essence, this thesis bridges the gap between qualitative expert-based risk identification and quantitative adaptive risk prediction, offering a unified methodology that merges systems engineering, artificial intelligence, and healthcare technology management. The resulting model—validated through both domain-specific and external datasets—sets a foundation for next-generation predictive risk analytics in complex healthcare infrastructure

1.8 Structure of the Thesis

The thesis is structured into the following eight chapters:

Chapter 1: Introduction

This chapter provides an overview of the research problem and its significance. It outlines the research question, objectives, and scope of the study while highlighting the context of healthcare technology management in Saudi Arabia and the Gulf region. Additionally, it includes a summary of the research contributions and an overview of the thesis structure.

Chapter 2: Literature Review

This chapter critically examines the existing body of knowledge related to HTM, healthcare technology risk management, and multidimensional risk assessment frameworks. It reviews international standards, conventional HTM models, and recent analytic approaches, highlighting major theoretical and practical gaps—particularly the absence of comprehensive, adaptive, and uncertainty-aware models suitable for the region. These gaps form the justification for the methodological and conceptual advances proposed in this thesis.

Chapter 3: Research Methodology

This chapter details the research design, philosophical stance, methodological approach, data sources, and analytical techniques used throughout the study. It explains the integration of expert-driven Fuzzy AHP, readiness-gap modelling, nonlinear regression analysis, and deep learning–based cross-domain validation. The chapter provides a clear roadmap for how the research question is operationalized and addressed.

Chapter 4: Results Part I – Fuzzy AHP Pairwise Comparison Results

This chapter presents the complete outcomes of the expert-based Fuzzy AHP evaluation of HTM risk factors. It reports the pairwise comparisons, linguistic-based fuzzy weight calculations, consistency ratios, and sensitivity results. A short discussion section interprets the implications of these findings for the broader HTM context.

Chapter 5: Results Part II – Model Derivation, Validation & Cross-Domain Testing

This chapter develops the nonlinear utilization–readiness risk model (SQRRM) and evaluates its performance using empirical hospital data. It describes the model-fitting process, compares multiple theoretical formulations, and reports robustness and sensitivity analyses across different risk definitions. The chapter then demonstrates the model's adaptability by embedding SQRRM into BiLSTM and ADGNN architectures and validating performance on the NASA C-MAPSS FD001 dataset. Each major result is followed by a focused discussion that interprets convergence behaviour, predictive accuracy, and domain transferability.

Chapter 6: Conclusion and Recommendations

This chapter synthesizes the entire research effort, consolidating key findings across the Fuzzy AHP analysis and the model derivation/validation stages. It reiterates the theoretical and practical contributions of the thesis, including the development of the SQRRM, the readiness-gap formulation, and the demonstration of cross-domain robustness. The chapter outlines the study's limitations and provides targeted recommendations for healthcare policymakers, HTM practitioners, and future researchers.

CHAPTER TWO – LITERATURE REVIEW

2.1. INTRODUCTION

This chapter presents a systematic review of the literature to establish the theoretical foundation for this research and to identify the gaps that motivate the development of an adaptive framework for Healthcare Technology Risk Management (HTRM). As illustrated in Figure 2.1, the literature is examined in relation to three fundamental dimensions of risk management: risk identification, risk assessment and modelling, and risk mitigation. These dimensions provide the conceptual basis for examining existing research and identifying the overall HTRM research gap. Within this structure, risk modelling and prediction are considered an extension of the risk assessment process, as meaningful predictive modelling requires the prior identification and quantification of the underlying risk factors.

To provide a structured synthesis of the existing research, the reviewed studies are subsequently organised according to their primary methodological approaches. These include conventional risk assessment, regulatory and framework-based approaches; maintenance-centred and reliability-based approaches; mathematical and simulation-based models; machine learning and data-driven predictive approaches; cybersecurity and digital healthcare technologies; multi-criteria decision-making (MCDM) approaches; and review studies and research trends. This method-based organisation enables studies employing similar approaches to be examined together and facilitates comparison of their contributions, strengths, and limitations.

Although existing studies have addressed different aspects of Healthcare Technology Management (HTM), the literature remains fragmented across methodological approaches and application areas, with limited integration of the multidimensional factors that influence healthcare technology risk. In particular, technical and maintenance-related factors are frequently considered independently from broader organisational, managerial, environmental, regulatory, and other external influences, limiting a comprehensive understanding of how these factors collectively affect healthcare technology performance and risk.

Particular attention is given to the limitations of established medical equipment risk assessment approaches, including those proposed by Fennigkoh and Smith (1989) and Wang and Levenson [5]. While these approaches have provided important foundations for equipment risk classification and maintenance prioritisation, they primarily rely on predefined internal and maintenance-related factors and static assessment structures. More broadly, the reviewed literature demonstrates limited integration of internal and external risk factors, their potential interactions, changing operational conditions, and predictive modelling within a unified framework. These limitations are particularly relevant within the context of Saudi Arabia and the Gulf region, where regionally contextualised research addressing the broader range of factors influencing healthcare technology risk remains limited. Accordingly, this review provides the theoretical and methodological foundation for identifying the research gaps addressed in the subsequent chapters.

The chapter further discusses the absence of methodologies capable of integrating expert-driven factor prioritization with dynamic modelling—highlighting a major theoretical and practical gap that this research aims to address. In particular, the literature lacks an approach that simultaneously:

1. identifies and prioritizes a broad set of HTM risk factors,
2. quantifies their relative impacts under uncertainty, and
3. models their nonlinear and utilization-dependent interactions to support predictive decision-making. The interactions between utilisation and equipment readiness are inherently nonlinear because changes in operational risk are not proportional to changes in these variables. Very low utilisation may introduce financial and operational risks through inefficient resource utilisation, whereas excessive utilisation can accelerate equipment degradation, increase maintenance demand, and reduce service availability. Consequently, a nonlinear modelling approach is required to capture the varying rates of risk escalation across different operating

conditions, providing a more realistic representation of healthcare technology behaviour than conventional linear models.

The chapter concludes by summarizing the identified gaps and establishing the need for a comprehensive, adaptive, and context-aware risk model. These gaps provide the justification for the methodological innovations introduced in this research, including the development of a region-specific risk hierarchy, the application of Fuzzy AHP for factor weighting, and the formulation of the Synergistic Quadratic-Resonant Risk Model (SQRRM).

Building on the insights derived from the literature, the subsequent chapter details the methodological procedures employed to construct and validate the proposed adaptive risk framework. This includes expert elicitation, empirical modelling, and cross-domain validation through deep learning architectures, laying the groundwork for a robust and generalizable system capable of advancing predictive maintenance and strategic decision-making in healthcare technology management.

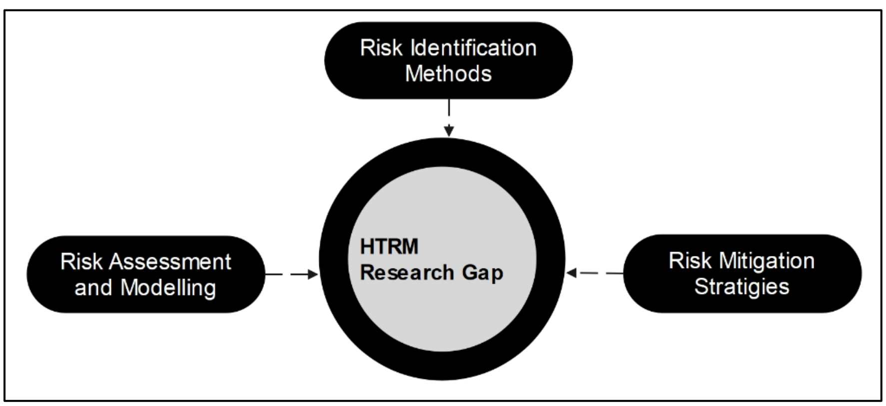


Figure 2.1: Three primary focus areas of the literature review

2.2. HTRM literature review

The systematic literature review was carried out following the PRISMA 2020 checklist and process, as outlined by Page M. et al. [7]. The following sections detail the methodology applied, the results of the review process, and the application of the exclusion criteria.

2.2.1. Literature Search and Identification of Studies

The review utilized search strings such as "Healthcare Technology Management," "healthcare Risk Management," "medical devices/equipment Reliability," "medical devices/equipment Performance," "medical devices/equipment Safety," "medical devices/equipment Risk Assessment," "Clinical Engineering risk management," "medical devices/equipment Maintenance Strategy/program," "medical devices/equipment Adverse Events," "incidents medical devices," "medical devices/equipment Prioritization," "medical devices/equipment Compliance Issues," "medical devices/equipment/technology Failure," "medical devices/equipment Operational Risks," "medical devices/equipment Security Risks," "Healthcare IT Risks," "healthcare facility management risk," "medical devices/equipment external risk," "medical devices/equipment Risk prediction," "medical devices/equipment Risk model," "medical devices/equipment risk management," and "medical devices/equipment Operational Risks in Healthcare". Accordingly, journal articles published between 2000 and 2024 were selected for review. The key databases utilized for the search included IEEE Xplore, Scopus, and ScienceDirect, chosen for their extensive collections of peer-reviewed literature. To achieve comprehensive coverage of the topic, the search was expanded to include ResearchGate and Google Scholar, along with relevant legislative documents and standards. As Moher et al. (2009) emphasized, peer-reviewed journal articles are a reliable source of information due to their rigorous review process conducted by experts to ensure authenticity. Moreover, journal articles are typically more up to date compared to books [6]. As a result, the primary focus was on peer-reviewed journal articles written in English. However, PhD theses, Master's dissertations, and publications from legislative or accreditation bodies were also considered in the review. A systematic review of the references cited in the identified articles was conducted.

2.2.2. Selection Methodology and Exclusion Parameters

Specific exclusion criteria were applied to ensure the relevance and focus of the selected studies.

After comprehensive review and systematic filtering of academic databases, focusing primarily on abstracts and titles related to healthcare technology management and medical equipment risk identification, analysis and assessment, a total of 25 publications were identified as directly relevant to this research table 2.1.

Table 2.1: Provides an overview of the inclusion and exclusion process.

Step	Description	Articles Remaining
Identification	Initial records retrieved from IEEE Xplore, Scopus, and ScienceDirect	1,570 articles
Screening	Removed duplicates.	1,237 articles
Records sought for retrieval	Removed retracted papers, and abstract-only, Restricted-access book chapters	1168 articles
Eligibility	Applied inclusion/exclusion based on title/abstract review	132 articles
Included in review	Examined techniques for identification, evaluation, or mitigation, as well as any modelling relevance and the scope of risk in the full articles.	25 articles

Additionally, 33 supplementary documents were incorporated from ResearchGate and authoritative healthcare regulatory and accreditation bodies, including:

- World Health Organization (WHO) guidelines and technical reports.
- U.S. Food and Drug Administration (FDA) regulatory frameworks.
- Association for the Advancement of Medical Instrumentation (AAMI) standards and best practices.
- Joint Commission on Accreditation of Healthcare Organizations (JCAHO) requirements and recommendations.

The final curated collection comprised of 58 total sources provides a robust foundation for analysing current practices and identifying gaps in healthcare technology risk management. The inclusion of both academic research and regulatory guidelines ensures a balanced perspective that considers both theoretical frameworks and practical implementation requirements. Figure 2.4 illustrates the process followed for the systematic literature review.

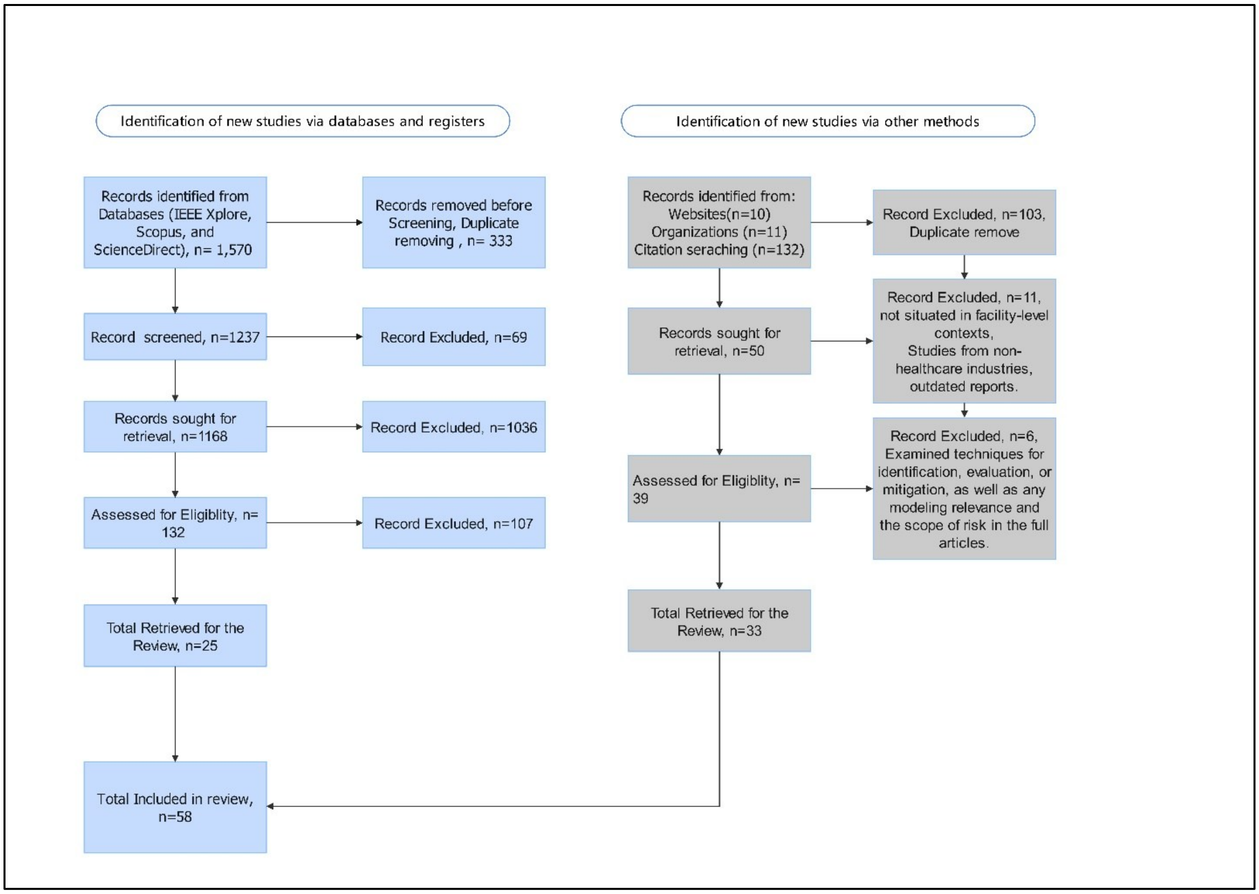


Figure 2.2: PRISMA flowchart of the study, adapted from Page et al. [7].

2.3. Analysis and Coding

The final curated collection, comprising 58 sources, served as the basis for a systematic analysis of existing Healthcare Technology Risk Management (HTRM) research. To ensure a consistent and structured synthesis of the literature, each study was independently reviewed and coded according to its primary methodological approach. This enabled studies employing similar analytical techniques to be grouped together, facilitating a comparative evaluation of methodological developments, common limitations, and emerging research trends across the field.

The coding process focused on identifying the principal methodology adopted in each study rather than its application domain. Where studies incorporated multiple techniques, classification was based on the dominant methodological contribution. This approach provided a coherent structure for analysing the evolution of HTRM methodologies and formed the basis for organising the literature review presented in Section 2.4.

2.3.1. Coding Framework

A coding framework was developed to ensure consistency, transparency, and methodological rigour throughout the literature review. Each article was reviewed against predefined criteria and classified according to its primary methodological approach. The resulting methodological categories are summarised below.

a) Conventional Risk Assessment, Regulatory and Framework-Based Approaches: This category includes studies that employ traditional qualitative or framework-based approaches for healthcare technology risk management. These studies primarily rely on regulatory standards, compliance frameworks, expert judgement, risk matrices, hazard analysis, incident investigation, post-market surveillance, and organisational risk management frameworks to identify and manage risks.

b) Maintenance-Centred and Reliability-Based Approaches: Studies in this category focus on maintenance planning, reliability analysis, equipment lifecycle management, replacement planning, and reliability-centred maintenance. These approaches commonly utilise historical maintenance records, failure statistics, equipment age, utilisation, and operational performance to support maintenance and replacement decisions.

c) Mathematical and Simulation-Based Models: This category includes studies that apply mathematical formulations, optimisation techniques, probabilistic analysis, simulation models, event-tree analysis, system dynamics, or other analytical modelling approaches to support maintenance planning, risk assessment, or decision-making.

d) Machine Learning and Data-Driven Predictive Approaches: Studies classified within this category utilise machine learning algorithms, statistical learning techniques, or other data-driven predictive models to forecast equipment failures, estimate maintenance requirements, or support predictive maintenance strategies.

e) Cybersecurity and Digital Healthcare Technologies: This category encompasses studies addressing cybersecurity, medical device networking, blockchain technologies, information security, interoperability, and other digital healthcare technologies aimed at improving the security and resilience of healthcare systems.

f) Multi-Criteria Decision-Making (MCDM) Approaches: This category includes studies employing structured decision-support techniques to prioritise maintenance, replacement, or risk management decisions based on multiple evaluation criteria. Representative methodologies include Analytic Hierarchy Process (AHP), Fuzzy AHP, Fuzzy FMEA, Quality Function Deployment (QFD), Pareto analysis, fuzzy logic, and other multicriteria decision-support frameworks.

g) Review Studies and Research Trends: This category comprises systematic and narrative review studies that synthesise existing research, evaluate prevailing methodologies, identify methodological limitations, and highlight future research directions within Healthcare Technology Risk Management.

Each study was assigned to a single methodological category based on its principal methodological contribution to avoid duplication and maintain consistency throughout the analysis. Following classification, the strengths, limitations, and research contributions of studies within each category were comparatively analysed to identify methodological developments, recurring challenges, and remaining research gaps in the HTRM literature.

2.4. Results of the HTRM Literature Review

The findings of the literature review are presented according to the primary methodological approaches adopted within the reviewed studies. Organising the literature in this manner provides a clearer understanding of the evolution of Healthcare Technology Risk Management methodologies and enables a systematic comparison of the strengths, limitations, and research contributions associated with each methodological category. The reviewed studies were classified into seven principal groups: (i) Conventional Risk Assessment, Regulatory and Framework-Based Approaches; (ii) Maintenance-Centred and Reliability-Based Approaches; (iii) Mathematical and Simulation-Based Models; (iv) Machine Learning and Data-Driven Predictive Approaches; (v) Cybersecurity and Digital Healthcare Technologies; (vi) Multi-Criteria Decision-Making (MCDM) Approaches; and (vii) Review Studies and Research Trends. This organisation provides a logical progression from conventional qualitative methodologies towards more advanced quantitative, intelligent, and decision-support approaches, while highlighting the methodological gaps that motivate the proposed framework presented in this thesis.

2.4.1. Conventional risk assessment, regulatory, and framework-based approaches

Boroojerdi et al. [8] presented a comprehensive evaluation of risk assessment in integrated biomedical engineering preventive maintenance using structured methodologies such as DRAM, FRAP, COBIT, and OCTAVE, supported by the AS/NZS standard and a multidimensional risk management matrix addressing process, criticality, and vulnerability. While the framework provides broad coverage of internal operational risks, it relies predominantly on qualitative, expert-driven assessments, introducing subjectivity and limiting scalability. Although several internal and external dimensions—such as managerial, strategic, political, usability, and human factors—are acknowledged, these are not systematically integrated into a unified analytical structure. Moreover, the assessment remains static, with no provision for dynamic, real-time risk adaptation or predictive modelling, and proposed mitigation strategies remain largely conceptual rather than operationalized through data-driven interventions.

Signori and Garcia [9] proposed a risk management model based on the Ministry of Defense Architecture Framework (MODAF), focusing on infrastructure, healthcare technology, and human resources from a clinical engineering perspective. While the architectural approach offers a structured mechanism for risk identification, it is inherently framework-driven rather than data-driven, limiting its capacity for dynamic risk detection and real-time assessment. Key external risk dimensions—including regulatory evolution, cybersecurity threats, and human-system interactions—are insufficiently represented. Furthermore, the model lacks a clearly defined quantitative risk evaluation methodology, does not articulate actionable mitigation mechanisms, and does not integrate predictive analytics or simulation tools for forward-looking risk anticipation.

Bava et al. [10] investigated information security risk assessment in healthcare through a case study of an Italian paediatric hospital, emphasizing ISO/IEC 27001 compliance for health information systems. While the study demonstrates the value of structured compliance-based risk identification, it is inherently audit-centric and reactive, offering limited capacity for addressing emerging cybersecurity threats, interoperability challenges, or evolving attack vectors. External dependencies such as vendor risks and regulatory shifts receive limited attention, while internal human factors and usability risks remain underexplored. Risk mitigation is primarily compliance-based, lacking predictive or adaptive response mechanisms, and no advanced modelling or forecasting techniques are employed.

Taktak and Brown [11] conducted an evidence-based analysis of field testing for medical electrical equipment to identify risks related to compliance, reliability, and safety during real-world operation. Although compliance testing and field observation are valuable for detecting functional faults, the approach does not incorporate systematic, automated, or cyber-physical risk monitoring. The study focuses primarily on internal equipment-level risks, with minimal treatment of external systemic influences such as regulatory volatility, supply chain disruption, or user behaviour. Risk assessment remains narrowly functional and does not employ quantitative interdependency modelling or predictive analytics.

Bartoo [12] examined medical device risk management with emphasis on regulatory compliance and patient safety. While this work reinforces the centrality of traditional regulatory and expert-driven risk controls, it does not extend into dynamic, data-driven, or automated risk analysis frameworks. External drivers of risk—such as cybersecurity exposure, environmental stressors, and supply chain fragility—are not systematically addressed. Risk mitigation remains corrective and compliance-oriented, without integration of proactive resilience engineering, predictive maintenance, or real-time surveillance systems.

Faggiano et al. [13] explored clinical engineering practices in Italy through a national survey, highlighting the importance of structured HTM methodologies. However, the study relies almost entirely on qualitative survey data, without integration of automated data streams, real-time risk indicators, or complex system analytics. Risk considerations are confined largely to internal maintenance and operational practices, with limited attention to regulatory, environmental, and macro-level risks. Quantitative risk modelling, predictive analytics, and computational forecasting are notably absent.

Wilkins and Holley [14] examined risk management in medical equipment management using traditional failure reporting and compliance monitoring. While effective for retrospective fault detection, the approach lacks automated sensing, dynamic updating, and risk interdependency modelling. External drivers—including supply chain volatility and environmental exposure—receive limited treatment, and mitigation strategies remain predominantly reactive rather than predictive or resilient by design.

Davis-Smith et al. [15] applied ISO 14971 for medical device risk management using formal techniques such as FMEA and hazard analysis. Although the framework provides a structured compliance-based methodology, risk identification remains static and regulation-driven, lacking dynamic or real-time cybersecurity and interoperability risk detection. External risks—including regulatory volatility, vendor dependency, and environmental stress—are underrepresented. Risk assessment is predominantly qualitative, with no integration of machine learning, real-time sensing, or adaptive quantitative models. Mitigation strategies prioritize documentation and corrective compliance actions rather than predictive maintenance, resilience planning, or adaptive control mechanisms.

Gribbons and Yong [16] demonstrated substantial improvements in safety alert response times through a hybrid centralized–decentralized workflow model. Despite these operational gains, risk identification remains manufacturer-dependent and reactive, without application of AI-driven adverse event detection or automated surveillance. Risk assessment is largely qualitative and consensus-based, without residual risk modelling or predictive evaluation of intervention effectiveness. External threats such as supply chain vulnerability are not addressed. While the study highlights important organizational and cultural factors, these are not formally integrated into a computational risk framework capable of dynamic adaptation and predictive forecasting.

Jarikji et al. [17] extended conventional healthcare technology risk assessment by incorporating environmental, economic, geographic, and political dimensions into the analytical framework. While this represents an important conceptual broadening beyond purely technical factors, the proposed model fails to establish a systematic structure for analysing interdependencies between external and internal risk drivers. The included variables are treated as independent contributors, without hierarchical classification of severity, interaction effects, or contextual weighting. Moreover, managerial influences and facility design–operational factors, which critically affect equipment performance and failure behaviour, are notably absent. The inclusion of external factors remains methodologically superficial, as they are neither weighted by contextual relevance nor validated through empirical assessment of their combined impact. As a result, the framework offers limited practical utility for real-world HTM applications, where failure processes are typically driven by tightly coupled socio-technical interactions.

Saleh Al-Tayyar [18] emphasized the critical role of medical device regulation and post-market surveillance (PMS) in safeguarding patient safety across the full device lifecycle. While medical devices—ranging from low-risk consumables to highly complex implantable systems—are indispensable for diagnosis and therapy, they also introduce substantial clinical risk through malfunction, misuse, and system failures. Alarmingly, only 65% of 145 countries possess fully established regulatory authorities to enforce medical device safety requirements. The study highlights PMS as the cornerstone of global vigilance, incorporating both proactive mechanisms (such as inspections and audits) and reactive processes (including adverse-event reporting systems). However, systematic underreporting remains a major global weakness. For example, the Saudi Food and Drug Authority documented 705 adverse events between 2008 and 2015, including 7.5% fatalities and 9.2% serious injuries, with device malfunctions accounting for 42% of reported cases. Critically, the study shows that use-related hazards—such as improper reprocessing, alarm misinterpretation, and human–device interaction failures—often exceed inherent device risks, contributing to approximately 98,000 preventable deaths annually in the United States alone due to medical errors. The authors call for stronger international vigilance systems, enhanced manufacturer accountability (recalls and corrective actions), and expanded education for clinicians and patients, concluding that global alignment with the Medical Product Safety 2020 Agenda is essential to reduce preventable harm through improved reporting, regulatory refinement, and public risk awareness.

The U.S. Food and Drug Administration (FDA) guidance on Human Factors Engineering (HFE) [19] established a structured framework for mitigating use-related medical device hazards, which are frequently more consequential than intrinsic hardware failures. The framework emphasizes proactive safety through four core stages: (i) Understanding the use context, including user profiles (patients, clinicians), operational environments (wards, operating rooms, home care), and interface design; (ii) Hazard identification, through a combination of task analysis, simulation testing, and usability experiments to uncover unanticipated human-device interaction failures; (iii) Risk control, achieved through intuitive interface design, error-tolerant logic, user training, and clear labeling to prevent misinterpretation and misuse; and (iv) Validation, requiring empirical safety demonstration under representative real-world and high-stress conditions, particularly in emergency and low-frequency critical scenarios.
Figure 2.5 illustrates the two fundamental dimensions of medical device safety—engineering reliability and human-factors interaction—as formalized within the FDA HFE framework. While this framework significantly strengthens safety assurance at the user–device interface level, it does not explicitly integrate operational utilization intensity, maintenance readiness gaps, or system-wide predictive risk modelling, leaving an important gap at the intersection of human, technical, and organizational risk propagation.

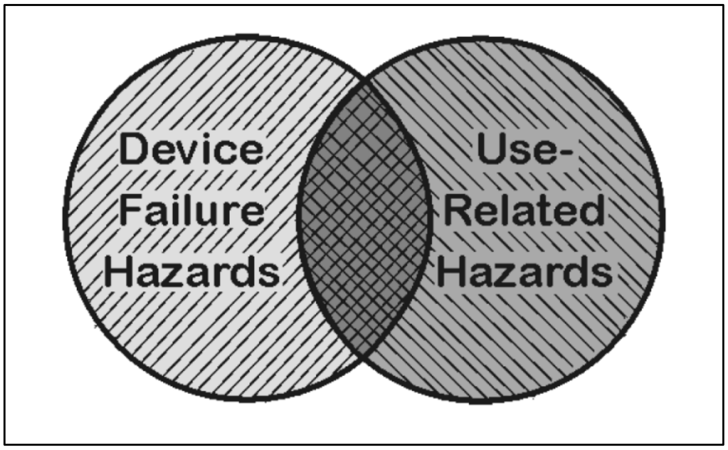


Figure 2.3: Classification of device-related failure hazards and hazards arising from user interaction [41].

Saleh Al-Tayyar [20] emphasized the fundamental principles of safety and performance for medical and in vitro diagnostic (IVD) devices, highlighting the shared responsibility between manufacturers and regulatory authorities in ensuring device safety throughout the full product lifecycle. Manufacturers are required to comply with high-level regulatory criteria during design, production, and post-market phases, while also ensuring appropriate user education for safe operation. Regulatory authorities, in turn, are responsible for verifying compliance with risk management procedures and regulatory requirements. The study strongly advocates global regulatory harmonization, which would enhance public health protection, reduce compliance burden, and improve patient access to innovation. However, while the framework establishes regulatory governance at a macro level, it does not directly translate these principles into operational risk modelling or predictive maintenance decision support within healthcare institutions.

The FDA public health advisory [21] addressed the critical risk of electromagnetic interference (EMI) in wireless medical telemetry systems operating within commercial broadcast and private land mobile radio service frequency bands. The advisory demonstrated that EMI—exacerbated by digital television transmission and high-power radio services—can severely disrupt telemetry monitoring and compromise patient safety. To mitigate these risks, the Federal Communications Commission (FCC) allocated interference-protected Wireless Medical Telemetry Service (WMTS) bands, and healthcare institutions were strongly advised to migrate telemetry systems to these protected frequencies. The advisory further emphasized mandatory reporting of EMI-related malfunctions, injuries, and deaths under the Safe Medical Devices Act (SMDA) and encouraged voluntary reporting through the FDA MedWatch program. While this guidance effectively addresses specific external electromagnetic hazards, it remains event-driven and does not integrate EMI risk into a broader predictive or systemic HTM risk modelling framework.

Paul et al. [22] investigated the organizational adoption of telemedicine technologies using the Tornatzky and Fleischer innovation adoption framework, which evaluates adoption across technological, organizational, and environmental dimensions. Based on survey data from public healthcare organizations in Hong Kong, the study identified collective clinician attitude as the most influential determinant of adoption, surpassing perceptions of safety or technical benefit. Perceived service risks—such as legal liability and concerns over service quality—also emerged as significant barriers. Interestingly, technical safety and system benefits were less influential than organizational and managerial readiness, reinforcing the importance of human and institutional factors in technology risk acceptance. While the study advances understanding of adoption behaviour, it focuses on perceptual and behavioural risk rather than quantitative operational or maintenance-based risk modelling.

Tavani [23] compiled an extensive bibliographic resource on technology, policy, ethics, and public health, encompassing nearly 400 references across domains of technological risk, genetic ethics, privacy, occupational health, and environmental sustainability. The work provides a valuable conceptual lens for examining ethical and policy dimensions of technology-related risk, yet remains a theoretical resource rather than an operational HTM risk management framework, with no direct linkage to predictive maintenance or equipment-level risk quantification.

Keller [24] introduced a practical roadmap for medical device safety management, emphasizing safety-oriented device selection, routine inspection, user training, and proactive recall management. The framework highlights the role of HTM professionals in leveraging regulatory databases such as the FDA MAUDE system and ECRI Institute alerts to track safety issues. The study also addresses recurrent systemic challenges such as alarm fatigue and infusion pump errors. While the roadmap strengthens procedural safety governance, it remains primarily reactive and compliance-driven, without incorporating predictive risk analytics or utilization-driven failure modelling.

Shepherd and Hyndman [25] explored the fundamentals of medical device incident investigation, emphasizing compliance with legal and regulatory mandates such as the Safe Medical Device Act (SMDA). The authors introduced the concept of healthcare "minisystems" and provided structured methodologies for evidence collection, interviews, and investigative reporting. While the framework is essential for post-incident analysis and accountability, it remains retrospective by design, focusing on failure reconstruction rather than early risk detection, predictive failure modelling, or adaptive risk mitigation.

Hyman [26] examined the challenges associated with effective user training for medical devices, particularly in contexts characterized by high device variability and increasing technological complexity. He introduced the concept of situational competency, arguing that training programs must prepare users not only for routine operation but also for low-frequency, high-risk crisis scenarios. The study emphasizes that training effectiveness should be evaluated based on learning outcomes rather than procedural compliance, reinforcing the critical role of human factors as a dominant internal driver of medical device risk.

Clemans [27] introduced wireless spectrum management as a structured process for monitoring and mitigating electromagnetic interference (EMI) in healthcare environments. He classified interference into intentional sources (e.g., broadcast transmissions) and unintentional emissions (e.g., motors, dimmer switches, CT scanners). The study reinforces the role of EMI as a critical external threat to medical telemetry and patient monitoring systems. However, EMI management is treated as a standalone technical control domain, without integration into a broader utilization-aware or readiness-driven HTM risk framework.

The concept of Enterprise Risk Management (ERM) was formalized in [28] as a strategic, organization-wide process tailored to institutional culture, business model, and governance structure. Unlike traditional silo-based risk management, ERM emphasizes the interdependence of risks across financial, operational/clinical, human capital, strategic, regulatory, technological, and hazard domains. While ERM provides a powerful organizational risk integration philosophy, it does not yield operationally tractable models for asset-level, utilization-driven medical equipment risk prediction.

Grimes [29] presented a structured framework for healthcare technology risk management based on risk matrices, Ishikawa diagrams, and historical incident analysis. While the model supports systematic documentation of hazards, it remains heavily subjective and retrospective, relying on service histories and manual severity–probability scoring. External risks such as cybersecurity, vendor dependency, and supply chain fragility are insufficiently integrated, and dynamic or predictive modelling capabilities are absent. Risk mitigation is largely reactive, centred on training, inspection, and backup systems rather than real-time monitoring or intelligent forecasting.

Grob, Biersach, and Peck [30] examined the integration of risk management principles within the IEC 60601-1 standard, aligned with ISO 14971 requirements. While the paper provides an authoritative regulatory synthesis, its scope remains centred on design-stage compliance and laboratory testing, offering limited insight into post-deployment operational risk dynamics or utilization-driven degradation in clinical environments.

Caines, Baird, and Whanger [31] critically addressed common misconceptions in medical device risk management, emphasizing that tools such as FMEA are insufficient as standalone risk frameworks, and that hazards, hazardous situations, and harms must be analytically distinguished. The authors stressed the importance of validating risk controls, expanding post-market surveillance beyond complaint handling, and avoiding unrealistic catastrophic modelling at the expense of practical control-point identification. While this work strengthens regulatory and analytical rigor, it remains rooted in qualitative risk governance rather than quantitative predictive modelling.

Jones and Taylor [32] examined the role of safety assurance cases within ISO 14971 and FDA regulatory reviews. Safety cases organize hazards, mitigation strategies, and residual risks into unified claim–argument–evidence structures. While this methodology enhances regulatory confidence and traceability, it remains largely design-centric, with limited translation into adaptive operational risk forecasting during real-world deployment.

2.4.2. **Mathematical and simulation-based models**

Mekki et al. [33] introduced a system dynamics-based model for medical equipment maintenance planning in developing countries. While the simulation-based approach provides insight into interactions between maintenance policies and equipment availability, the model relies on static parameter assumptions, limiting its capacity to represent real-time risk evolution, cyber-physical threats, or stochastic operational disturbances. External systemic risks—including regulatory uncertainty, supply logistics, and environmental hazards—are insufficiently incorporated. Although maintenance optimization is achieved, advanced predictive analytics and machine learning–based forecasting are not integrated.

Ismail et al. [34] introduced a probabilistic medical equipment risk framework using FMEA combined with Monte Carlo simulation. While the methodology advances probabilistic risk quantification beyond traditional RPN scoring, risk identification remains retrospective, relying on historical maintenance data without integration of real-time operational telemetry or emerging failure modes. External risks such as cybersecurity exposure, supply logistics, and regulatory trends are not included, nor are organizational factors such as staffing or training. Although simulation enhances failure probability estimation, the framework does not incorporate machine learning–based predictive modelling or impact simulation of mitigation strategies, limiting its ability to support fully adaptive risk management.

Cruz et al. [35] proposed an event-tree-based mathematical model to determine optimal timing for the retirement of biomedical equipment from hospital inventories. The framework integrates maintenance cost, unavailability, safety risk, and useful life within a cost–benefit decision structure. While effective for economic and operational decision-making, the model remains reactive, relying on historical maintenance and incident data rather than proactive techniques for detecting emerging degradation or failure mechanisms. Risk identification and assessment focus primarily on internal operational metrics, while external risks—including supply chain vulnerability, regulatory evolution, and technological interoperability with newer systems—are not explicitly considered. Furthermore, risk assessment emphasizes financial and utilization dimensions, without formal clinical severity–impact modelling. Mitigation strategies are largely restricted to replacement decisions, without addressing root-cause failure mechanisms or validating preventive interventions.

Khalaf et al. [36] proposed a mixed-integer optimization model for medical equipment maintenance scheduling, representing progress toward mathematically rigorous and evidence-based maintenance planning. By integrating failure probability modelling, mission criticality, and greedy optimization strategies, the model moves beyond purely heuristic scheduling. Nevertheless, its predictive capability remains constrained to historical failure patterns, without support for real-time forecasting or dynamic adaptation under evolving operational conditions. From a risk management standpoint, the framework prioritizes scheduling efficiency rather than risk causality, and does not incorporate external threat drivers, facility stressors, or managerial uncertainty. Consequently, while technically robust for static optimization, the model remains insufficient as a comprehensive risk-aware decision framework.

2.4.3. Cybersecurity and Digital Healthcare Technologies

Alwi et al. [37] investigated the role of blockchain technology in healthcare, emphasizing improvements in data security, privacy, and interoperability. While the study highlights blockchain’s potential in reducing data-related risks, it does not establish a comprehensive healthcare technology risk framework, as the scope is limited primarily to information security. Internal risks—such as equipment malfunction, maintenance inefficiencies, and human error—are not addressed. Risk assessment is not supported by quantitative or real-time analytical tools, and mitigation strategies rely almost exclusively on blockchain’s inherent security properties, without integration of predictive maintenance, operational resilience, or system-level risk controls. Similarly, the work does not explore how blockchain might be combined with machine learning or predictive analytics for anticipatory risk management.

Yaqoob et al. [38] further examined blockchain for enhancing traceability and data security in healthcare systems. Although the study demonstrates blockchain's ability to reduce data tampering and cyber threats, risk identification remains narrowly focused on data-domain vulnerabilities, excluding medical equipment risks, operational inefficiencies, and maintenance-related failures. Risk assessment is limited to evaluating blockchain's security properties and does not incorporate dynamic modelling, real-time risk analytics, or system-wide quantitative evaluation. Mitigation strategies depend on decentralization and immutability but do not extend to predictive maintenance, contingency planning, or equipment resilience engineering. As with prior blockchain-centred studies, predictive risk modelling is absent, restricting the framework's applicability to comprehensive healthcare technology risk management.

Kim et al. [39] explored blockchain-based solutions for secure medical data sharing. While effective in strengthening data integrity and privacy, the proposed framework remains narrow in scope, focusing on information-layer risks rather than the broader cyber-physical risks associated with medical devices and operational systems. Internal risks such as equipment failure, maintenance bottlenecks, and workflow errors receive little attention. Risk assessment remains centred on blockchain architecture evaluation and lacks dynamic monitoring, quantitative modelling, or predictive risk analytics. Mitigation strategies again rely on blockchain's intrinsic features without integration of resilience engineering or predictive maintenance strategies.

Goldberg [40] developed a risk management framework for medical device networks with emphasis on communication failures and network reliability. Risk identification relies on static vulnerability analysis and predefined failure modes, limiting the model's capacity to detect emerging cyber threats or real-time interoperability failures. While internal risks such as device malfunction and network performance degradation are considered, external factors—including regulatory evolution, supply chain exposure, and environmental conditions—are not adequately incorporated. Risk assessment remains largely qualitative and simulation-based, without advanced quantitative interdependency modelling or real-time analytics. Risk mitigation focuses on reactive redundancy and fault tolerance, with limited emphasis on predictive control or adaptive system resilience.

2.4.4. **Machine learning and data-driven predictive approaches**

Zamzam et al. [41] proposed a machine learning–based predictive maintenance framework employing SVM and KNN classifiers and achieved high diagnostic accuracy (Figure (2.6)). However, risk identification remains historical-data driven and reactive, with limited treatment of external risk factors such as regulatory change, spare-parts availability, or vendor dependency. The framework does not incorporate clinical severity weighting, despite differences in patient safety consequences across device classes. While prioritization is achieved, risk mitigation is not empirically validated, and the absence of real-time operational telemetry or sensor-based failure prediction constrains its ability to support proactive, utilization-aware maintenance strategies.

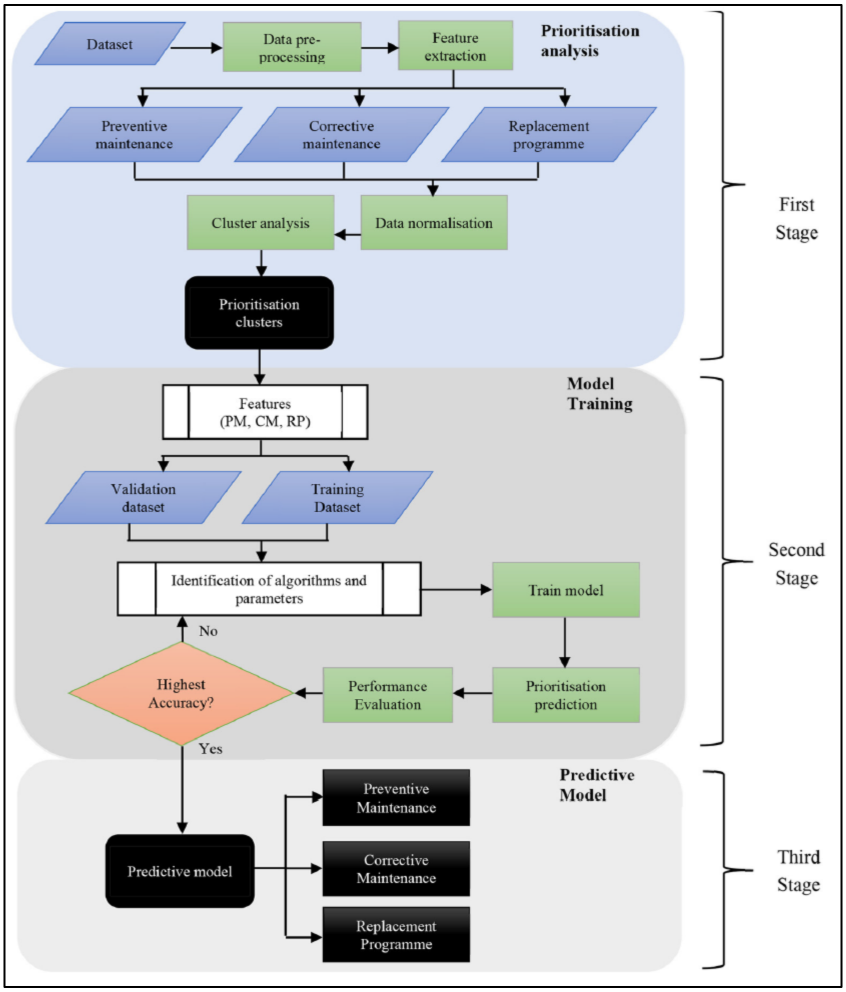


Figure 2.4: Block schematic illustrating the workflow of the medical equipment prioritization and performance prediction framework proposed by the authors [41].

Abd Rahman et al. [42] introduced a machine-learning-based framework for medical device failure prediction, demonstrating clear potential for cost reduction through predictive maintenance, with reported classification accuracy of 79.5%. Despite these strengths, the framework exhibits notable limitations in comprehensive risk representation. The model focuses almost exclusively on maintenance-derived variables (e.g., failure frequency, corrective actions), while facility conditions (such as power stability and environmental stress), design-related risks (including human–device interaction), operational load, and clinical criticality are not explicitly modelled. As a result, the approach risks mis prioritization, particularly where devices operate in high-risk clinical environments but exhibit low historical failure frequency. Moreover, although the model predicts failure timing, it lacks severity and clinical-impact weighting, limiting its ability to differentiate between benign and life-critical failures. Risk mitigation remains centred on maintenance scheduling, without root-cause validation or empirical evaluation of intervention effectiveness. The predictive framework does not incorporate real-time operational data streams, nor does it simulate mitigation scenarios or validate performance across heterogeneous healthcare environments.

2.4.5. Maintenance-Centred and Reliability-Based Approaches

Darnel [43] examined healthcare technology risk from a reliability-centred perspective using historical failure records and statistical analysis of medical equipment performance. While this approach is effective for identifying recurring failure patterns and degradation trends, it remains inherently reactive and does not incorporate proactive, automated, or real-time risk detection mechanisms capable of addressing dynamic threats such as cybersecurity vulnerabilities or system interoperability failures. The analysis is largely confined to internal technical risks, with limited consideration of external drivers, including regulatory evolution, environmental stressors, and supply chain instability. Risk assessment is restricted to conventional statistical techniques and does not extend to advanced quantitative modelling, interdependency analysis, or real-time surveillance. Correspondingly, mitigation strategies focus on post-failure corrective actions, without integration of predictive maintenance, redundancy planning, or resilience-oriented control strategies. The study offers valuable insight into equipment reliability but does not meet the requirements of modern, adaptive healthcare technology risk management.

Astivia-Chávez et al. [44] applied exploratory data analysis to correlate device age with corrective maintenance frequency. While useful for identifying age-related degradation trends, the approach is descriptive and retrospective, lacking clinical severity weighting, real-time monitoring, or predictive failure forecasting. Risk mitigation remains implied through preventive maintenance without formal validation or optimization.

Clark and Forsell [45] examined medical equipment replacement planning, identifying key drivers such as equipment age, maintenance cost, safety risk, and regulatory requirements. The study distinguishes between basic and advanced replacement approaches and highlights the role of Computerized Maintenance Management Systems (CMMS) and replacement algorithms. Emerging trends—including integration with electronic health records and enhanced patient-safety priorities—are also discussed. However, the framework remains primarily cost- and age-driven, lacking integration of dynamic utilization risk, readiness gaps, or predictive failure forecasting.

Baretich [46] explored the intersection between Healthcare Technology Management (HTM) and Healthcare Facility Management (HFM), emphasizing the necessity of interdisciplinary coordination to ensure safe and resilient clinical environments. The study highlights the influence of critical utility systems—including electrical power, HVAC, medical gases, fire safety, and emergency management—on medical device performance Figure (2.7). The adoption of Reliability-Centred Maintenance (RCM) is advocated as a structural approach to sustaining operational integrity. While this work effectively captures the facility–technology dependency, it remains oriented toward infrastructure reliability rather than predictive medical equipment risk modelling.

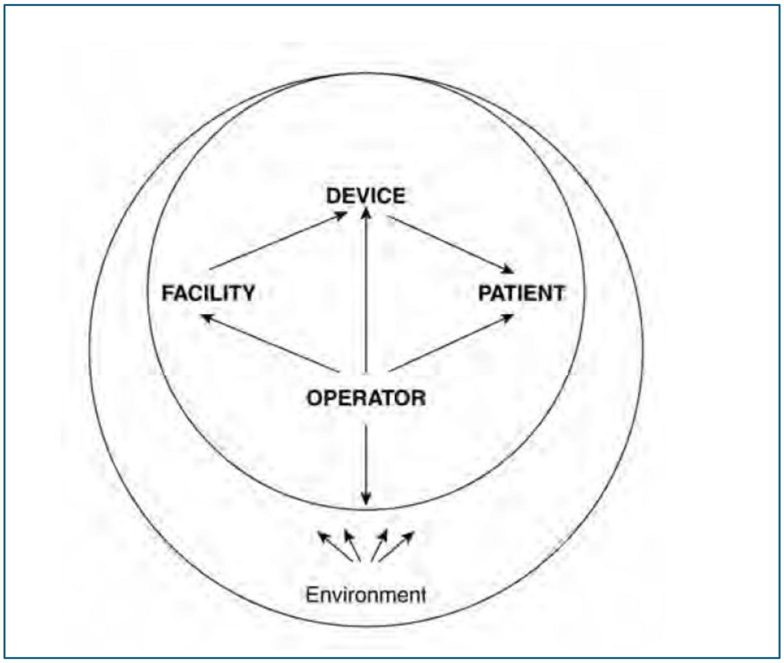


Figure 2.5: Schematic illustration of the five core elements constituting a generic minisystem risk model [46].

2.4.6. Multi-Criteria Decision-Making (MCDM) Approaches

Saleh et al. [47] proposed a Quality Function Deployment (QFD)-based framework for preventive maintenance prioritization. While the approach effectively integrates mission-based, maintenance-based, and risk-based criteria, risk identification remains largely static, relying on equipment function, physical risk, and utilization without integration of dynamic operational telemetry or cybersecurity risks. The framework offers strong coverage of internal technical risks but insufficient consideration of external factors such as regulatory shifts and supply chain disruptions. Risk assessment is implemented through weighted scoring but does not employ predictive analytics or real-time interdependency modelling, and mitigation remains centred on maintenance prioritization rather than proactive predictive control.

Puntoni et al. [48] employed Pareto analysis to identify high-cost medical equipment responsible for the majority of maintenance expenditure. While the cost-based prioritization reveals important financial risk concentrations, the method is inherently retrospective and economically focused, omitting clinical severity, patient safety impact, and technical failure probability. No external risk dimensions or predictive failure modelling are included, and mitigation strategies remain restricted to cost optimization rather than safety-driven or resilience-oriented intervention.

Smith and Eloff [49] proposed a fuzzy cognitive modelling approach for healthcare technology risk assessment that effectively captures expert uncertainty and human reasoning. However, the model remains static, lacks real-time adaptation, and excludes external macro-risk drivers such as regulatory change and supply chain instability. Risk mitigation strategies inferred from fuzzy reasoning are not empirically validated, and the framework does not provide predictive forecasting or cost-benefit analysis of interventions.

Jamshidi et al. [50] developed a fuzzy FMEA-based framework for medical equipment risk prioritization. Although fuzzy logic improves uncertainty handling in severity, occurrence, and detection scoring, the model remains retrospective and static, relying on fixed weighting structures without adaptive or predictive learning mechanisms. External risks—including regulatory change, interoperability challenges, and supply chain constraints—are not incorporated. The framework supports maintenance decision prioritization but does not enable future failure forecasting or mitigation impact simulation.

Figure 2.8 presents the strategic maintenance prioritization framework proposed by Jamshidi et al. [50], which categorizes maintenance strategies across four quadrants based on criticality and maintenance methodology. While the framework provides a useful conceptual structure for prioritization, it remains static, rule-based, and non-predictive, reinforcing the broader limitation observed across existing HTM risk methodologies.

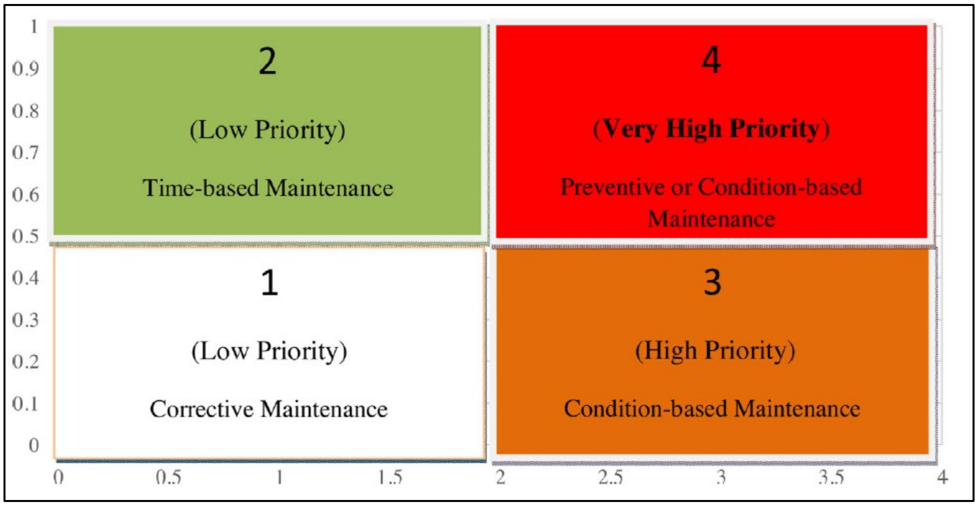


Figure 2.6: Conceptual representation of the TI–RPI prioritization model for medical equipment maintenance introduced by Jamshidi et al. [50]

Tawfik et al. [51] proposed a fuzzy-logic-based framework for classifying medical equipment risk, addressing some of the rigidity inherent in traditional deterministic risk assessment methods. While the model introduces dynamic scoring through fuzzy inference, risk identification remains fundamentally reactive, relying on known failure modes without proactive mechanisms for detecting emerging risks. The framework primarily addresses internal technical factors, such as equipment function and maintenance requirements, while external drivers—including regulatory shifts, supply chain instability, and environmental stressors—are not incorporated. Although fuzzy logic enhances flexibility in risk scoring, the assessment remains structurally static, lacking quantitative severity–impact analysis, real-time adaptability, or predictive forecasting. The framework also integrates the risk identification methodology of Wang and Levenson [5] within its maintenance prioritization logic; however, this integration remains limited to organizational hazard identification without full translation into adaptive, predictive healthcare risk control.

Hutagalung et al. [52] applied the Analytic Hierarchy Process (AHP) to prioritize medical equipment maintenance using criteria such as technical complexity, downtime, and repair cost. While the approach offers a structured multicriteria prioritization mechanism, it reveals significant limitations from a broader risk management perspective. Risk identification remains maintenance-centric and reactive, derived from historical failure and repair records without integration of proactive risk sensing mechanisms. The model omits external risk drivers, including regulatory variability, supply chain fragility, and environmental exposure. Risk assessment does not incorporate clinical severity weighting, interdependency modelling, or real-time adaptability, and mitigation strategies are confined to maintenance scheduling decisions rather than systemic risk reduction or resilience-oriented interventions. Most critically, the framework lacks predictive modelling capability and does not support failure forecasting or mitigation impact simulation.

Figure 2.9 illustrates the AHP-based hierarchy for determining the priority of medical equipment maintenance as proposed by Hutagalung et al. [52]. While the hierarchy provides a clear decision structure for maintenance prioritization, it remains static, cost-centred, and non-predictive, reinforcing the broader methodological gap across traditional maintenance-focused HTM risk frameworks.

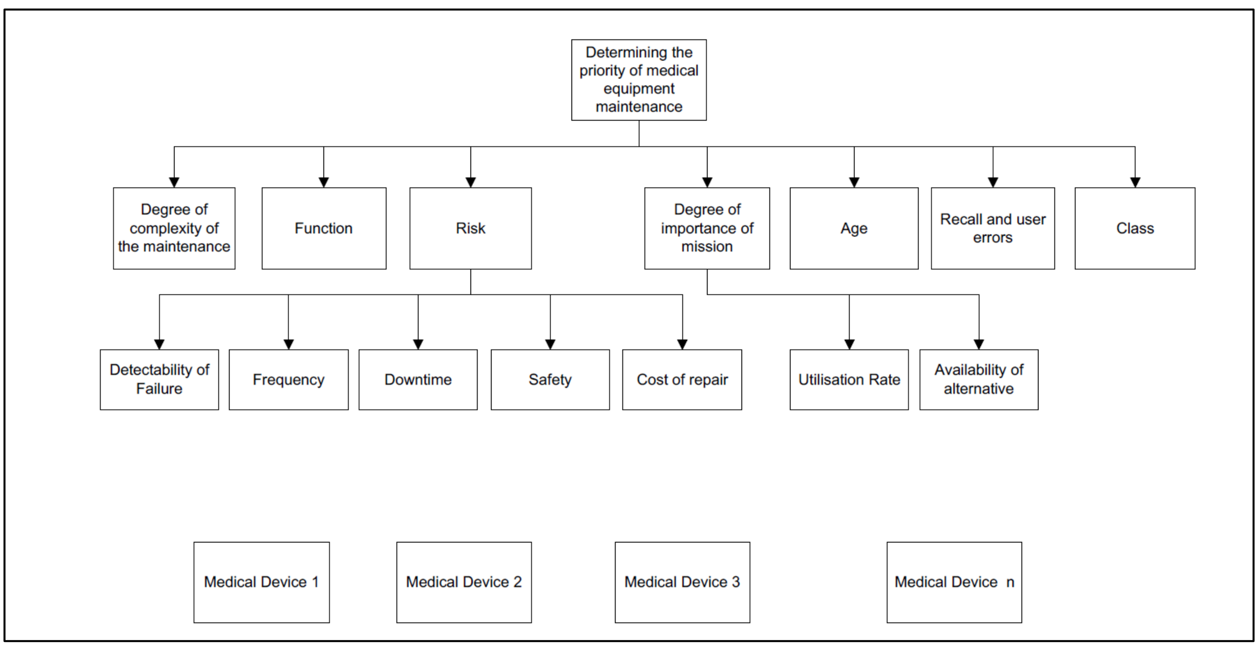


Figure 2.7: Schematic representation of the AHP framework for determining medical equipment maintenance priority introduced by Hutagalung et al. [52].

Aridi et al. [53] developed a multi-criteria framework for medical equipment lifespan assessment, integrating functional importance, mission criticality, age, risk exposure, and maintenance history, with validation by clinical experts. Despite its methodological rigor, several critical limitations remain from a holistic HTM risk perspective. First, risk identification is restricted to historical failure behaviour, without accounting for emerging threats such as interoperability challenges or cyber-physical vulnerabilities. Second, the framework emphasizes internal technical drivers while neglecting external influences, including supply chain fragility, regulatory shifts, and environmental exposure. Third, although the scoring structure is systematic, severity weighting is static, lacking real-time adaptation or context-sensitive recalibration. Finally, risk mitigation is limited to replacement decisions, without formal root-cause failure analysis or cost–benefit validation of alternative interventions, restricting the framework's value for proactive resilience planning.

Oshiyama et al. [54] introduced a hybrid decision-support methodology for classifying medical equipment based on corrective maintenance behaviour, combining ABC cost analysis with Paraconsistent Annotated Logic (PAL) to address uncertainty in equipment criticality classification. The ABC method hierarchically categorizes equipment according to cumulative maintenance burden, where Class C (≈10% of assets) accounted for nearly 70% of total maintenance costs, while Class A (≈70% of assets) contributed only 10%. To overcome the rigid boundaries of traditional ABC classification, PAL quantifies belief (μ) and disbelief (λ) degrees derived from deviations in failure frequency, downtime, and maintenance cost, incorporating statistical confidence intervals. Application to 2,134 medical devices demonstrated 85.5% consistency, while 14.5% exhibited classification ambiguity—notably infusion pumps that showed high downtime but low repair cost. The PAL-based framework provided real-time alerts to clinical engineers for investigation of abnormal maintenance behaviour, enabling diagnosis of underlying causes such as training deficiencies or delayed calibration. Although the framework is computationally scalable and adaptable to institutional priorities, assumptions regarding operator competency and process stability require empirical validation. Nevertheless, this hybrid data-driven approach represents an important step toward context-aware maintenance prioritization, though it remains focused on retrospective maintenance behaviour rather than forward-looking risk prediction.

Faisal and Sharawi [55] proposed an AHP-based Group Decision-Making (AHP–GDM) model for prioritizing medical equipment replacement using 11 quantitative and qualitative criteria, including technical support availability, performance, maintenance cost, equipment age, operational impact, and clinical acceptability. While the model provides a structured and transparent mechanism for evaluating replacement priorities, it remains largely confined to internal technical and operational risk factors, such as failure frequency, cost escalation, and device obsolescence. External risk drivers, including supply chain dependency, facility design constraints, and broader environmental or regulatory pressures, are insufficiently addressed. Furthermore, although the risk assessment relies on weighted scoring and pairwise comparisons, it does not incorporate advanced predictive or probabilistic modelling tools to represent uncertainty or to forecast future failure behaviour. Risk mitigation is restricted to replacement prioritization, without consideration of proactive strategies such as redundancy planning, real-time condition monitoring, or resilience-based system design. Consequently, while the study confirms the effectiveness of AHP for structured decision-making, it remains limited as a comprehensive, system-wide healthcare technology risk management framework, particularly in dynamic and predictive dimensions.

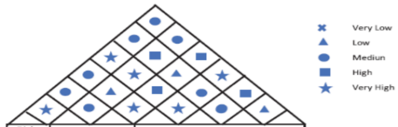
Amran et al. [56] developed a Biomedical Engineering Maintenance Services (BEMS) framework by integrating Quality Function Deployment (QFD) with fuzzy logic to support the prioritization of medical device maintenance and replacement across 144 Ministry of Health hospitals. The model adopts a structured multi-criteria decision-making (MCDM) approach, linking stakeholder requirements to technical performance attributes. While this integration strengthens prioritization based on internal operational and functional risk factors, broader external influences—such as regulatory variability, supply chain fragility, and evolving clinical practice—remain outside the analytical scope. The risk assessment process is methodologically rigorous within its defined structure, employing relative weights and criteria scoring; however, it lacks dynamic adaptation, predictive analytics, or hybrid risk modelling to account for time-varying degradation, operational stress, or emerging threats. As a result, although the framework demonstrates strong potential for structured maintenance decision support, its applicability to comprehensive healthcare technology risk management remains constrained by the absence of predictive and

adaptive capabilities.
Figures 2.10 and 2.11 illustrate the proposed requirement and functional domains within the House of Quality (HOQ) framework, depicting the structured mapping between stakeholder needs and technical maintenance functions as formalized by the authors [56].

Demanded Quality (a.k.a. "Customer Requirements" or "Whats") / Quality Chracteristics (a.k.a. "Functional Requirements' or "Hows")	1. Function ability	2. Physical risk	3. Maintenance requirements	4. Device mission criticality	5. Functional verifications	6. Age	7. Labelling	8. Electrical Safety Testing	9. Replacement of the parts	10. Regular inspection	11. Qualification of technician	12. Complexity of Devices	13. Equipped workshop	14. Test Equipment Availability	15.Service Manual Availability	16. Activities Recording	17. Updating or Loan	18. Spare Parts Availability	19. Type of Service Provider	20. Meet specific Standard	
1.Safety of medical equipment.	3.4	3.3	3.4	3.3	3.3	3.2	3.3	3.4	3.4	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.2	3.2	3.3	3.2	
2.Efficiency.	3.2	3.2	3.3	3.2	3.3	3.1	3.3	3.3	3.3	3.3	3.3	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	
3.Durability.	3.2	3.2	3.2	3.2	3.2	3.0	3.2	3.3	3.2	3.2	3.3	3.1	3.2	3.2	3.2	3.2	3.1	3.1	3.2	3.2	
4.Quick response of technical team.	3.3	3.3	3.3	3.3	3.3	3.2	3.2	3.3	3.3	3.3	3.3	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	
5.Back up availability.	3.0	3.0	3.1	3.1	3.1	3.0	3.1	3.2	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	
6.Calibration to ensure the measuring function is accurate and reliable	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	3.2	3.1	3.1	3.2	3.1	
7.Regular monitoring of the medical devices	3.3	3.2	3.3	3.2	3.2	3.1	3.2	3.3	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.1	
8.Medical devices need to be suitable for the intended purpose	3.3	3.2	3.3	3.2	3.3	3.2	3.2	3.3	3.2	3.2	3.3	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	
9.Obvious operating instructions.	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.3	3.2	3.2	3.3	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	
10.Medical devices should be designed for simple maintenance	3.2	3.2	3.3	3.2	3.3	3.2	3.2	3.3	3.2	3.2	3.3	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	
11.Existence of a contact person for 24 hours	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	3.2	3.3	3.2	3.2	3.2	3.2	3.1	3.1	3.1	3.2	3.1	
12.Avoiding suspension of device services	3.2	3.2	3.2	3.2	3.2	3.1	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.1	3.1	3.1	3.1	3.1	Total
The absolute weight	**9.3**	**9.2**	**9.4**	**9.3**	**9.3**	**9.0**	**9.3**	**9.5**	**9.3**	**9.3**	**9.4**	**9.2**	**9.2**	**9.2**	**9.3**	**9.2**	**9.1**	**9.1**	**9.2**	**9.1**	184.8
The relative weight	**0.050**	**0.050**	**0.051**	**0.050**	**0.050**	**0.049**	**0.050**	**0.051**	**0.050**	**0.050**	**0.051**	**0.050**	**0.050**	**0.050**	**0.050**	**0.050**	**0.049**	**0.049**	**0.050**	**0.049**	1
RANK	**5**	**14**	**3**	**8**	**4**	**20**	**10**	**1**	**7**	**6**	**2**	**16**	**15**	**11**	**9**	**12**	**18**	**17**	**13**	**19**	

Demanded Quality	VoU Mean	VoU Ranking	Importance factor	Referral Hospital Satisfaction	Goal	Improvement ratio	The absolute weight	The relative weight
1.Safety of medical equipment.	4.5	8	4	3	4.5	1.5	**5.9**	**0.088**
2.Efficiency.	4.6	4	5	4	4.6	1.2	**5.8**	**0.085**
3.Durability.	4.3	11	4	3	4.3	1.4	**5.7**	**0.084**
4.Quick response of technical team.	4.4	10	4	3	4.4	1.5	**5.9**	**0.087**
5.Back up availability.	4.2	12	4	3	4.2	1.4	**5.6**	**0.083**
6.Calibration to ensure the measuring function is accurate and reliable	4.6	2	5	4	4.6	1.2	**5.8**	**0.085**
7.Regular monitoring of the medical devices	4.6	3	5	4	4.6	1.2	**5.8**	**0.085**
8.Medical devices need to be suitable for the intended purpose	4.6	5	5	4	4.6	1.1	**5.7**	**0.085**
9.Obvious operating instructions.	4.6	1	5	4	4.6	1.2	**5.8**	**0.086**
10.Medical devices should be designed for simple maintenance	4.5	6	5	4	4.5	1.1	**5.6**	**0.083**
11.Existence of a contact person for 24 hours	4.5	7	5	4	4.5	1.1	**5.6**	**0.083**
12.Avoiding suspension of device services	4.4	9	4	4	4.4	1.1	**4.4**	**0.066**
			55			Total	67.5	1

Figure 2.8: House of Quality (HOQ) representing the requirement domain of the proposed framework [56].



	Risk-based Criteria	Mission-based Criteria		Maintenance-based Criteria						
Quality Chracteristics (a.k.a. "Functional Requirements' or "Hows") / Demanded Quality (a.k.a. "Customer Requirements" or "Whats")	1. Safety Alert (SA)	2. Asset Condition (AC)	3. Asset Usage (AU)	4. Useful Life Remaining (LR)	5. Frequency of Breakdown (FB)	6. Asset Maintenance Cost Ratio (AMSR)	7. Technology Realibilty (TR)	VoE Mean	VoE Ranking	Importance weight (Relative Weight)
1. Electrical Safety Testing	3.85	3.70	3.70	3.60	3.10	3.05	3.70	3.28	1	0.0512
2.Qualification of technician	3.30	3.25	3.05	3.45	2.70	2.65	3.05	3.25	2	0.0508
3.Maintenance requirements	3.75	3.75	3.55	3.60	3.30	3.45	3.70	3.25	3	0.0506
4.Functional verifications	3.55	3.55	3.40	3.50	3.30	3.10	3.50	3.22	4	0.0505
5.Function ability	3.60	3.50	3.50	3.65	3.40	3.05	3.65	3.23	5	0.0504
6.Regular inspection	3.50	3.45	3.55	3.60	3.10	3.25	3.60	3.23	6	0.0503
7.Replacement of the parts	3.55	3.20	3.45	3.65	3.30	3.65	3.65	3.23	7	0.0503
8.Availability of equipment in serviced a	3.05	3.05	3.00	3.15	2.90	2.80	3.25	3.22	8	0.0502
9.Service Manual Availability	3.30	3.05	3.15	3.15	2.85	2.50	2.85	3.20	9	0.0502
10.Labelling	3.20	3.00	2.95	2.95	2.75	2.40	2.90	3.21	10	0.0502
11.Test Equipment Availability	3.50	3.25	3.25	3.40	2.90	3.05	3.25	3.20	11	0.0500
12.Capturing data	3.10	2.95	2.85	2.80	2.55	2.75	2.85	3.19	12	0.0498
13. Type of Service Provider	2.90	3.15	2.75	3.00	2.80	2.95	3.10	3.18	13	0.0498
14. Physical risk	3.50	3.25	3.20	3.25	3.10	2.85	3.15	3.20	14	0.0497
15. Equipped workshop	3.10	3.00	3.00	3.10	2.70	2.80	2.90	3.18	15	0.0497
16. Complexity of Devices	3.25	3.20	3.10	3.45	2.90	3.15	3.25	3.17	16	0.0496
17. Spare Parts Availability	3.20	3.40	3.35	3.50	3.15	3.50	3.55	3.15	17	0.0494
18.Medical device cost status	2.55	2.95	3.10	3.10	3.00	3.80	3.15	3.15	18	0.0492
19. Meet specific Standard	3.70	3.70	3.50	3.60	3.50	3.45	3.55	3.16	19	0.0492
20. Age	3.25	3.35	3.65	3.80	3.30	3.50	3.75	3.12	20	0.0489
Critical Target	Recall for immediately	BER Certification	High: more than 15	>93.4%	>12 (part replacement	>1.5	End of Support	Total		
The absolute weight	9.47	9.18	9.19	9.45	8.59	8.22	9.21	63.31		
The relative weight	0.15	0.14	0.15	0.15	0.14	0.13	0.15	1.00		
The relative weight in %	14.95	14.50	14.52	14.92	13.57	12.98	14.55	100.00		
The Criteria Weight in %	15	29		56						

Figure 2.9: HOQ structure depicting the mapping of functional attributes within the prioritization framework [56].

Alahmadi et al. [57] introduced the Medical Equipment Maintenance Prioritization Factor (MEMPF) model to support predictive maintenance prioritization in Saudi hospitals. The framework integrates utilization rate, failure frequency, downtime, and maintenance complexity into a weighted index, yielding measurable cost reductions in practice. However, the model remains deterministic and static, relying on fixed expert-defined weights and linear factor aggregation. The absence of temporal learning, nonlinear dynamics, and adaptive coupling between utilization stress and system vulnerability limits its ability to represent emergent degradation behaviour. While MEMPF constitutes a significant early step toward structured HTM risk quantification in the region, advancing beyond such fixed-weight paradigms requires empirically grounded, adaptive, and nonlinear risk modelling frameworks.

Taghipour et al. [58] proposed a multi-factor prioritization framework for maintenance decision-making, incorporating 16 parameters spanning function, mission criticality, utilization, availability of alternatives, age, failure frequency, detectability, downtime, repair cost, safety, environmental exposure, recalls, and maintenance demand. While the framework demonstrates broad internal factor coverage, it remains fundamentally static, lacking both adaptive risk learning and predictive failure forecasting. Risk interactions are treated additively rather than through nonlinear or synergistic coupling, limiting its applicability to complex degradation behaviour.

2.4.7. Review Studies and Research Trends

Mahfoud et al. [59] presented a comprehensive systematic review of dependability-based maintenance optimization in healthcare (2000–2016), summarized in Figure 2.12, and identified major structural gaps in existing maintenance research. The review showed that multi-criteria decision-making (MCDM) methods dominate the field, with prioritization primarily driven by risk, function, maintenance demand, and utilization rate. However, several critical limitations were identified: (i) a strong dependence on subjective expert judgments with limited mechanisms for uncertainty aggregation; (ii) weak data acquisition strategies, insufficient for capturing stochastic failure behaviour; (iii) underutilization of probabilistic dependability modelling within maintenance decision processes; and (iv) a persistent emphasis on single-objective (cost-focused) optimization, at the expense of availability, maintainability, and patient safety. The review further highlighted the increasing complexity and vulnerability of modern medical devices to environmental and operational stressors, while noting that maintenance strategies remain largely reactive rather than predictive. Crucially, the authors called for future research to integrate human factors, logistics constraints, and probabilistic modelling to bridge the gap between theoretical maintenance models and real-world healthcare system demands.

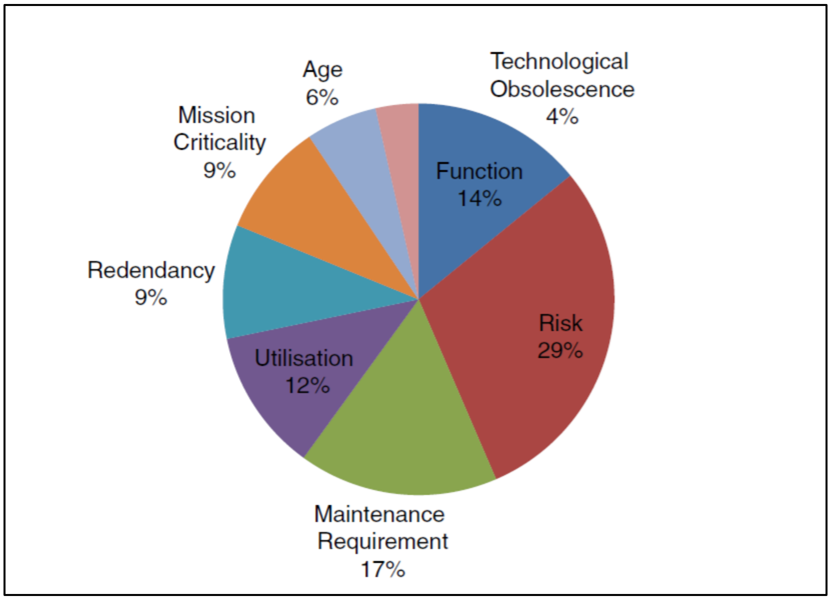


Figure 2.10: Distribution of decision criteria employed in multi-criteria decision-making (MCDM) applications within the healthcare domain [58].

Sally Trombly [60] examined healthcare technology risk management from an Enterprise Risk Management (ERM) perspective, emphasising its strategic role within healthcare organisations. The review highlighted that biomedical technology risk management extends beyond equipment maintenance to encompass patient safety, staff competency, resource allocation, and organisational decision-making. The author argued that effective healthcare technology risk management should support strategic decisions throughout the technology lifecycle, including technology acquisition, utilisation, and resource planning, while considering their wider implications for organisational objectives, financial sustainability, and workforce requirements.

The review further stressed the importance of involving risk management professionals at the earliest stages of technology planning, particularly during procurement and investment decisions. Alternative acquisition strategies, including purchasing, leasing, and consignment arrangements, were discussed alongside the associated contractual obligations and risk implications involving medical equipment vendors. In addition, the study emphasised that comprehensive training for both clinical and non-clinical personnel is an essential component of reducing technology-related adverse events and promoting the safe use of medical devices.

While the review provides valuable strategic guidance for integrating healthcare technology within enterprise-wide risk management, its contribution remains primarily conceptual. The discussion does not propose a structured methodology for quantitative risk assessment, maintenance prioritisation, or predictive risk modelling, nor does it provide an operational framework capable of supporting dynamic Healthcare Technology Risk Management decision-making.

Zamzam et al. [61] presented a systematic review on medical equipment reliability assessment spanning 16 studies published between 2000 and 2020. The review identified eight key reliability parameters—equipment features, function, maintenance requirements, performance, risk and safety, availability and readiness, utilization, and cost—as the principal drivers of preventive maintenance (PM), corrective maintenance (CM), and replacement planning (RP). Although the study acknowledges the growing potential of artificial intelligence and machine learning for predictive maintenance, it highlights major practical gaps, including the absence of integrated PM–CM–RP frameworks and the limited deployment of ML-based predictive models across heterogeneous equipment categories. The review also aligns these parameters with the Malaysian MS 2058:2018 standard for medical device maintenance. While the study establishes a strong descriptive foundation for reliability assessment, it confirms that adaptive, utilization-aware, and predictive risk frameworks remain largely absent from real-world practice.

2.5. Conclusion of the Literature Review

The literature reviewed in this chapter demonstrates the considerable progress achieved in Healthcare Technology Risk Management (HTRM) through the development of conventional risk assessment frameworks, maintenance-centred methodologies, mathematical and simulation-based models, machine learning techniques, cybersecurity frameworks, and multi-criteria decision-making approaches. Collectively, these studies have contributed valuable methods for supporting healthcare technology maintenance, safety, and operational decision-making. Nevertheless, the review also reveals that existing research remains methodologically fragmented, with individual studies typically addressing specific aspects of healthcare technology risk rather than providing an integrated and adaptive risk management framework.

The review further indicates that conventional risk assessment and regulatory frameworks provide structured guidance for hazard identification, compliance, and patient safety; however, they remain largely qualitative, static, and dependent on expert judgement. Similarly, maintenance-centred and reliability-based approaches primarily rely on historical maintenance records and equipment performance indicators, limiting their ability to represent evolving operational conditions or anticipate future risk behaviour. Although mathematical and simulation-based models introduce greater analytical rigour, their application is generally restricted to specific maintenance or optimisation problems and rarely considers the broader interactions between organisational, environmental, and technical risk factors.

More recent developments in machine learning have demonstrated promising capabilities for predictive maintenance and equipment failure prediction. However, these approaches predominantly depend on historical maintenance data and often overlook external influences, clinical criticality, organisational readiness, and the complex interactions between multiple risk drivers. Likewise, cybersecurity and digital healthcare studies have expanded the understanding of information security and medical device networking risks, yet their scope remains largely confined to digital infrastructure and does not extend to comprehensive healthcare technology risk management. Multi-Criteria Decision-Making (MCDM) techniques, including AHP-, fuzzy-, and QFD-based approaches, provide structured mechanisms for maintenance and replacement prioritisation but generally employ fixed weighting structures and static decision models, limiting their adaptability to changing operational environments.

Across all methodological categories, several common research gaps were consistently identified. First, most studies focus on specific components of the healthcare technology lifecycle without integrating technical, organisational, environmental, managerial, and regulatory factors into a unified analytical framework. Second, the interactions between internal and external risk drivers remain insufficiently represented, despite their combined influence on healthcare technology performance and reliability. Third, the majority of existing methodologies remain static and retrospective, offering limited capability for modelling nonlinear risk behaviour, evolving operational conditions, or utilisation-dependent degradation. Finally, relatively few studies combine systematic risk factor identification, expert-based prioritisation, and predictive modelling within a single methodological framework capable of supporting proactive Healthcare Technology Management.

These gaps collectively justify the development of a more holistic and adaptive framework—one that captures nonlinear risk escalation, integrates expert-driven prioritization (e.g., via Fuzzy AHP), and models resonant interactions between utilization and readiness factors. Accordingly, this research advances the field by introducing the Synergistic Quadratic-Resonant Risk Model (SQRRM) and its adaptive integration within deep learning architectures such as BiLSTM and ADGNN. This approach not only addresses the shortcomings of prior models but also establishes a scientifically grounded, regionally relevant methodology for predictive risk management in healthcare technology systems.

In summary, the literature review underscores the need for a comprehensive, adaptive, and context-aware risk modelling framework that bridges theoretical gaps and practical limitations in HTM. The subsequent chapters respond to these deficiencies through the identification of 53 risk factors, the application of Fuzzy AHP for prioritization, and the development of the SQRRM model to advance predictive, utilization-aware healthcare technology management.

Building upon the identified gaps and the theoretical foundations established in this chapter, the next phase of the research focuses on the methodological development of the proposed adaptive risk framework. Chapter 3 presents the research design, data sources, analytical techniques, and model formulation processes employed to construct and validate the proposed adaptive Risk Model. It explains how expert-driven Fuzzy AHP weighting, empirical data from healthcare institutions, and cross-domain validation were systematically integrated to achieve an adaptive and generalizable model for healthcare technology risk prediction. This methodological framework serves as the foundation for translating conceptual insights into a robust, data-driven system capable of advancing predictive maintenance and strategic decision-making within Healthcare Technology Management.

CHAPTER THREE – RESEARCH METHODOLOGY

3.1. Introduction

This chapter outlines the methodological framework developed to address the research gaps identified in the preceding chapters and to fulfil the overarching objective of constructing an adaptive, data-driven model for healthcare technology risk prediction. It details the sequential processes through which the study was designed, beginning with the identification and quantification of risk factors using the Fuzzy Analytical Hierarchy Process (Fuzzy AHP) and progressing toward the development and validation of the Synergistic Quadratic-Resonant Risk Model (SQRRM). The chapter explains how expert-based judgments were combined with empirical datasets from healthcare institutions in Saudi Arabia to derive contextualized readiness-gap weights and utilization-risk relationships. It then describes the integration of the SQRRM formulation within deep learning architectures, such as BiLSTM and ADGNN, to evaluate the model's adaptability and predictive accuracy using both hospital and NASA CMAPSS datasets. The methodological design therefore bridges qualitative and quantitative paradigms—linking expert reasoning, multi-criteria decision analysis, and adaptive machine learning—to produce a scientifically rigorous and generalizable approach to healthcare technology risk management.

To ensure methodological rigor and logical coherence, this chapter is structured into a sequence of interlinked sections that collectively describe the full lifecycle of the proposed risk modelling framework.

Section 3.2 presents the overall research design, outlining the adopted mixed-methods strategy that integrates expert-based qualitative assessment with quantitative mathematical modelling and data-driven validation.

Section 3.3 describes the process used to identify and prioritize risk factors using expert-driven Fuzzy AHP, including the initial compilation of 53 multidimensional risk factors spanning technical, operational, environmental, and managerial domains relevant to Healthcare Technology Management (HTM).

Section 3.4 details the validation of risk factors and the development of the final HTMR hierarchy.

Section 3.5 explains the implementation of the Fuzzy AHP survey, including questionnaire design, expert participation, pairwise comparison procedures, and fuzzy judgment aggregation.

Section 3.6 addresses the procedures for verifying the reliability of the proposed method, including internal consistency testing and sensitivity analysis.

Section 3.7 presents the integration of Fuzzy AHP outcomes with the foundational risk equation and optimal utilization metrics, establishing the analytical linkage between expert-derived risk weights, maintenance exposure indicators, and operational utilization intensity.

Section 3.8 describes the process used to fit multiple theoretical models (Linear, Quadratic, Exponential, Sinusoidal, and Hybrid) to the empirical data, enabling the systematic identification of the optimal nonlinear formulation governing the utilization–risk relationship.

Section 3.9 introduces the model development framework, detailing the mathematical construction, parameter estimation, and formulation of the Synergistic Quadratic–Resonant Risk Model (SQRRM) as the final adaptive risk law.

Section 3.10 extends the model beyond purely technical failure mechanisms, incorporating readiness gaps, organizational, and environmental risk dimensions into the unified risk formulation.

Section 3.11 presents the model sensitivity and robustness evaluation, in which structured perturbation analyses were conducted to assess the stability of SQRRM under multiple risk definitions and parameter variations.

Section 3.12 defines the temporal robustness assessment protocol, through which the stability of the SQRRM law was evaluated across multiple operational years to verify non-overfitting and long-term structural consistency.

Section 3.13 explains how SQRRM was embedded within BiLSTM and ADGNN architectures to evaluate its adaptiveness within time-series learning environments using both hospital and aerospace datasets.

Finally, Section 3.14 provides the conclusion of the methodology chapter, summarizing the integrated theoretical, empirical, and computational contributions of the proposed framework.

Together, these sections establish a comprehensive and coherent methodological foundation that bridges expert knowledge, nonlinear system identification, and deep learning–based validation for adaptive healthcare technology risk modelling.

3.2. Research Design

The methodological flow of this research was designed as a structured, sequential framework that systematically integrates conceptual modelling, expert knowledge, mathematical risk formulation, and advanced computational intelligence. The process began with the definition of the research scope and the development of the foundational conceptual model for healthcare technology risk. This was followed by the identification and prioritization of multidimensional risk factors using expert judgment supported by the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). The validated risk factors were then structured into a finalized Healthcare Technology Management Risk (HTMR) hierarchy, ensuring logical consistency and coverage across technical, managerial, environmental, and operational domains.

Subsequently, risk assessment was conducted through Fuzzy AHP to derive stable global weights, followed by systematic verification of the reliability and internal consistency of the proposed assessment method. These weighted risk outcomes were then integrated with a foundational analytical risk equation and optimal utilization metrics, forming the basis for nonlinear utilization–risk modelling. Multiple theoretical functional forms—including linear, quadratic, exponential, sinusoidal, and hybrid formulations—were fitted to empirical data to identify the most representative structure. This process culminated in the development and parameterization of the Synergistic Quadratic–Resonant Risk Model (SQRRM).

To ensure robustness and generalizability, extensive sensitivity and temporal robustness analyses were conducted. The SQRRM formulation was further embedded within deep learning architectures, namely BiLSTM and Adaptive Graph Neural Network (ADGNN) models, to evaluate its adaptiveness under time-series learning conditions. Finally, the predictive performance of all models was rigorously validated and compared using complementary statistical and scoring metrics, including R^2, RMSE, and domain-specific performance scores. Collectively, this structured methodological design establishes a rigorous link between theoretical risk modelling, expert-driven knowledge, and data-driven intelligence, ensuring both mathematical soundness and real-world applicability of the proposed framework.

3.2.1. Conceptual Framework

The overall framework (illustrated in Fig. 3.1) is structured around three main phases:

1. Risk Identification and Weighting (Qualitative Phase): This phase employs the Fuzzy Analytical Hierarchy Process (Fuzzy AHP) to identify and prioritize 53 risk factors influencing healthcare technology performance across Saudi Arabia and the Gulf region. Expert inputs from biomedical engineers, quality officers, and healthcare administrators were synthesized to compute fuzzy-weighted readiness gaps (G), categorized under technical, operational, environmental, and managerial domains.

2. Model Development (Quantitative Phase): Using the derived readiness gaps and equipment utilization data from 16 medical imaging systems (2020–2024), multiple regression formulations were tested to characterize the relationship between utilization and total maintenance risk. Through iterative fitting and evaluation, a

hybrid nonlinear function was derived, the SQRRM, which models risk as a function of utilization and readiness gaps using a quadratic-sinusoidal coupling structure.

3. Adaptive Integration and Validation (Computational Phase): To assess scalability and robustness, the SQRRM formulation was embedded into deep learning architectures, specifically BiLSTM and Adaptive Dynamic Graph Neural Network (ADGNN), and validated using NASA CMAPSS FD001 dataset. This cross-domain validation tested the model's capacity for adaptive learning and dynamic risk propagation in large-scale, sensor-based systems.

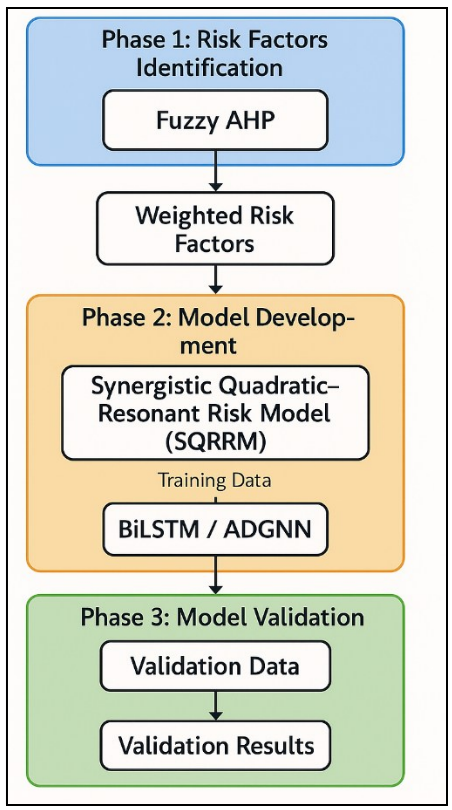


Figure 3.1: Research Design Framework

3.3. Identify and prioritize risk factors using expert-driven Fuzzy AHP

3.3.1. Identification of Risk Factors

The identification of risk factors for Healthcare Technology Management Risks (HTMR) began with an extensive and systematic review of international literature, regulatory guidelines, and HTM standards. This review was complemented by a field survey, semi-structured interviews, and expert consultations with professionals in biomedical engineering, facility management, and hospital management. These steps ensured that the selected factors reflect both global evidence and the contextual realities of Saudi Arabia and the Gulf region.

3.3.2. Use of PESTLE Analysis for External Risk Identification

To systematically capture risks arising from the broader macro-environment, the study employed the PESTLE framework—Political, Economic, Social, Technological, Legal, and Environmental. The PESTLE technique is widely recognized in healthcare risk management for its ability to structure external uncertainties and anticipate systemic pressures that influence HTM performance. By evaluating each PESTLE dimension, the study identified a comprehensive set of external risks, including:

Political Factors: Political stability or instability, International relations, Government policies influencing the adoption of healthcare technology.

Economic Factors: Exchange rate fluctuations, Economic growth or recession, Changes in public healthcare spending or budget allocations.

Sociocultural Factors: Demographic shifts, Public awareness and perceptions of healthcare technology, Workforce diversity and inclusivity within the healthcare sector.

Technological Factors: Rapid advancements in healthcare technology, National technology infrastructure and technical support, Cybersecurity vulnerabilities.

Environmental Factors: Emergence of pandemics or infectious disease outbreaks, Climate change effects and natural disasters, Sustainable procurement and environmental compliance requirements.

Legal Factors: Legal disputes or litigation involving healthcare technology, Changes in healthcare-related laws, regulations, and compliance mandates.

The incorporation of PESTLE analysis aligns with best practices highlighted in recent healthcare management literature [62], [63], ensuring methodological rigor in capturing external drivers of HTM risk.

3.3.3. Construction of the Initial HTMR Hierarchical Framework

Based on the insights from literature, PESTLE analysis, expert assessments, and field observations, a preliminary Hierarchical Framework of Healthcare Technology Management Risks was developed. This framework structures risk factors into major domains and subdomains, providing the foundation for their subsequent quantification through the Fuzzy Analytic Hierarchy Process (Fuzzy AHP).

The resulting multi-level risk hierarchy, illustrated in Figures 3.2 through 3.6, provides a structured representation of Healthcare Technology Management (HTM) risks across the full system lifecycle. The framework organizes these risks into two principal domains—exogenous and endogenous—which are further decomposed into technology, management, facility, and macro-environmental. At each level, progressively finer-grained risk factors are captured, ranging from design- and operation-related risks to workforce, regulatory, economic, and disaster-related threats. Together, these layers establish a comprehensive foundation for the subsequent stages of quantitative prioritization and modelling.

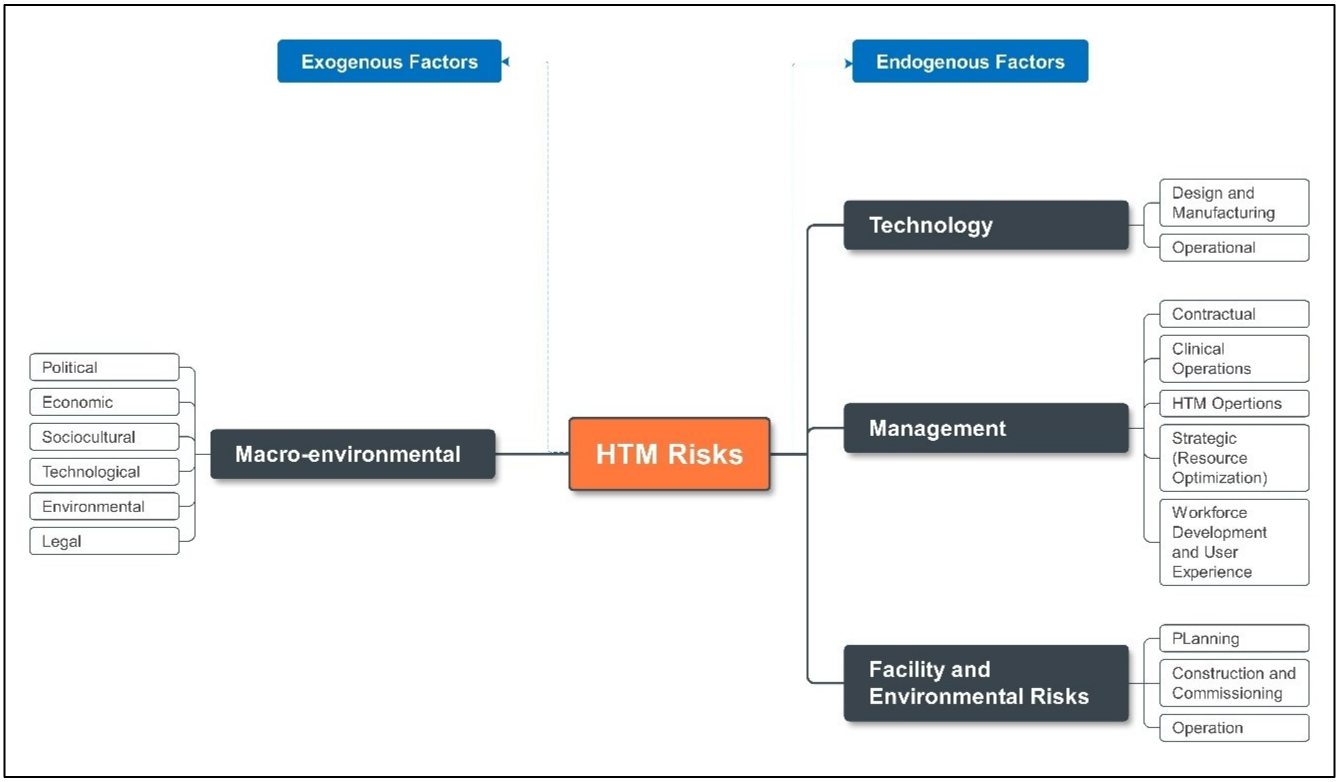


Figure 3.2: Initial Hierarchical Framework of Healthcare Technology Management Risks

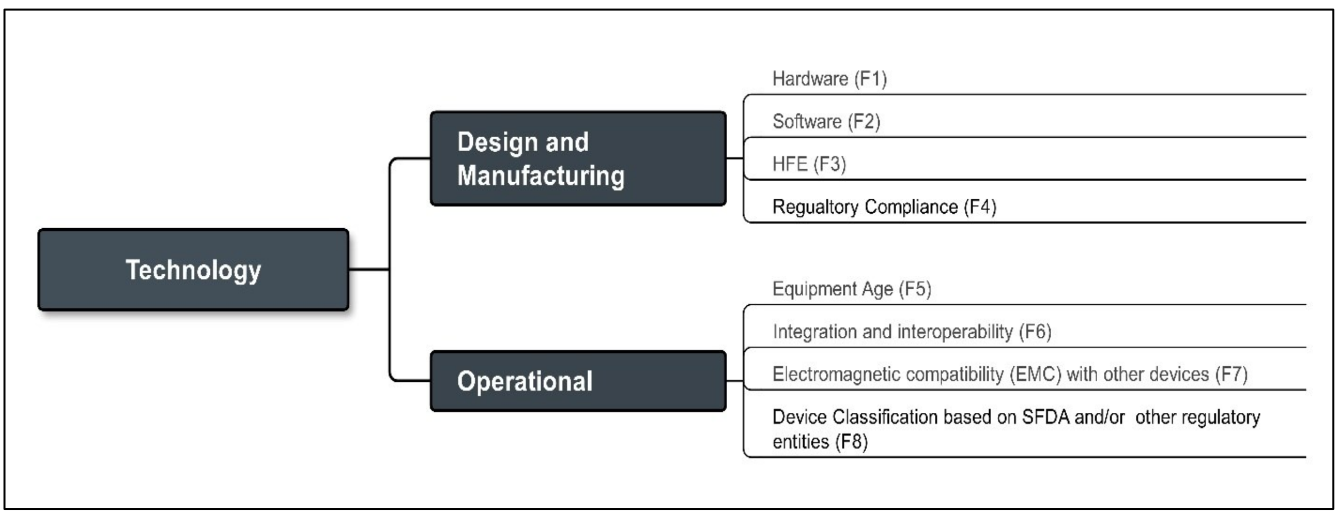


Figure 3.3: shows the subcategories of Technology Risks

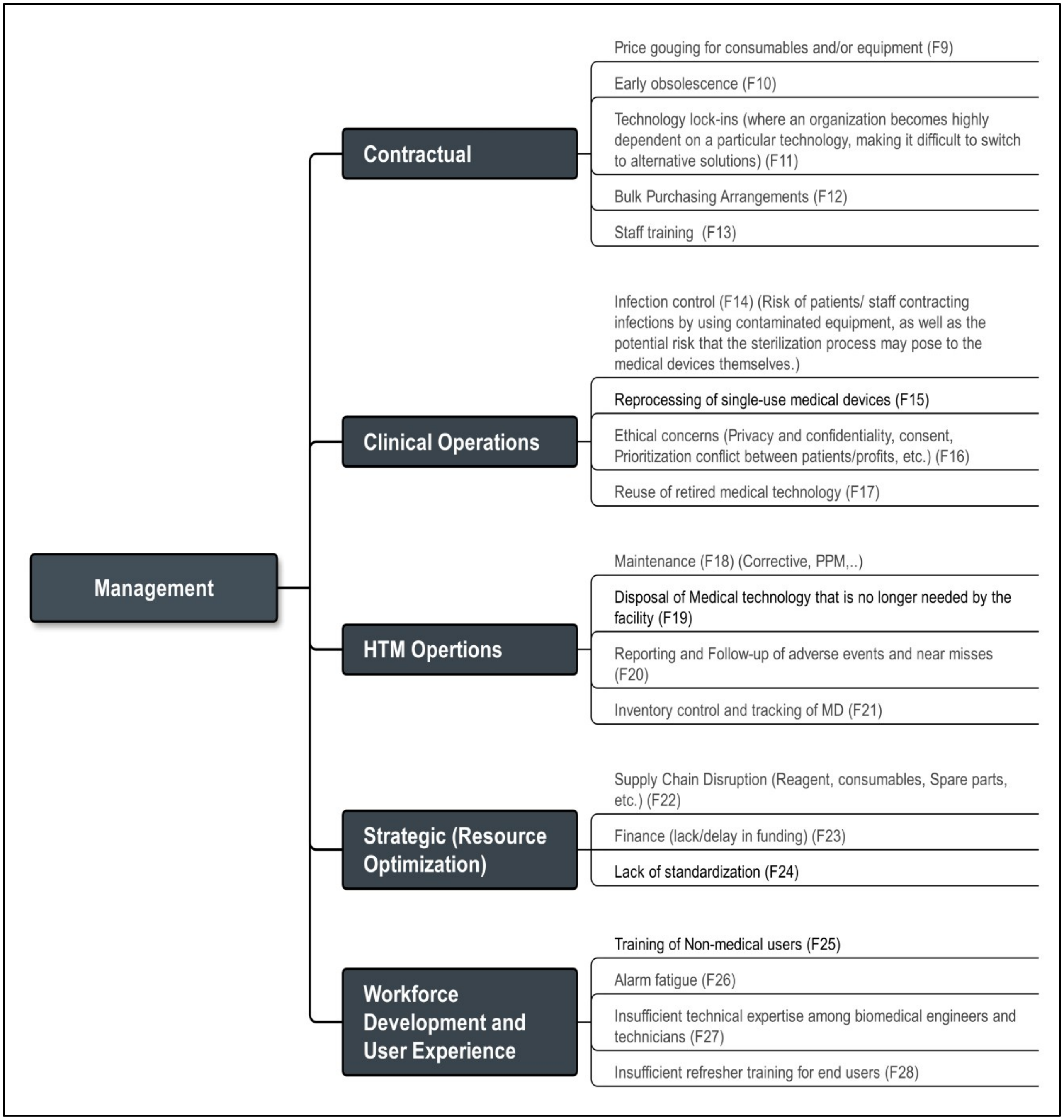


Figure 3.4: displays the subcategories of Management Risks

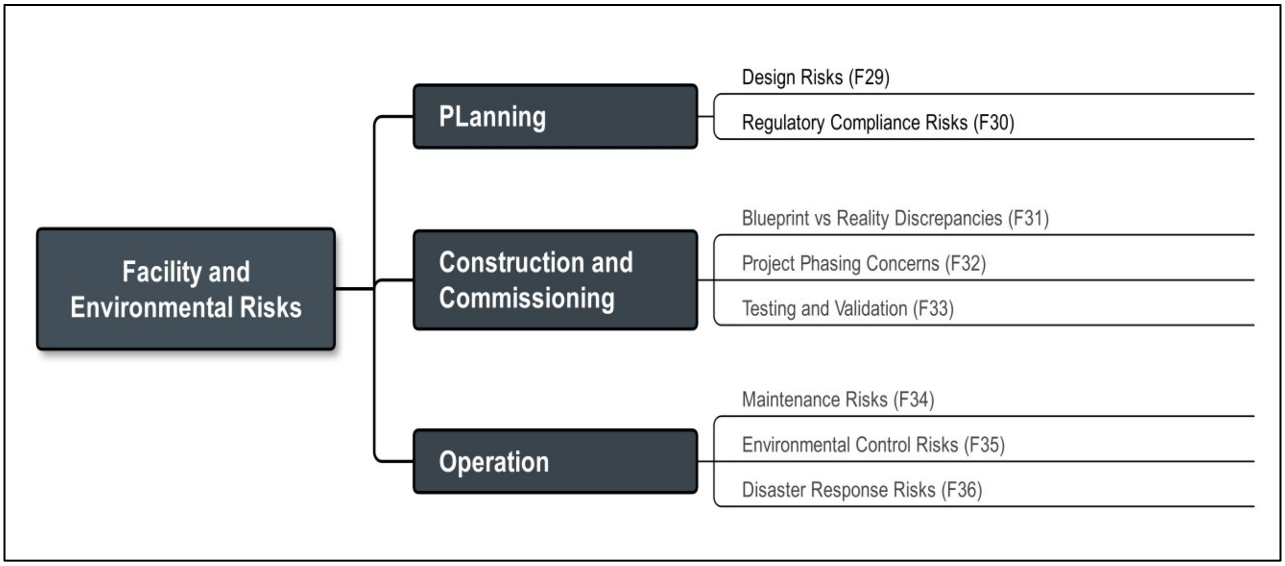


Figure 3.5: shows the subcategories of Facility and Internal Environmental Factors

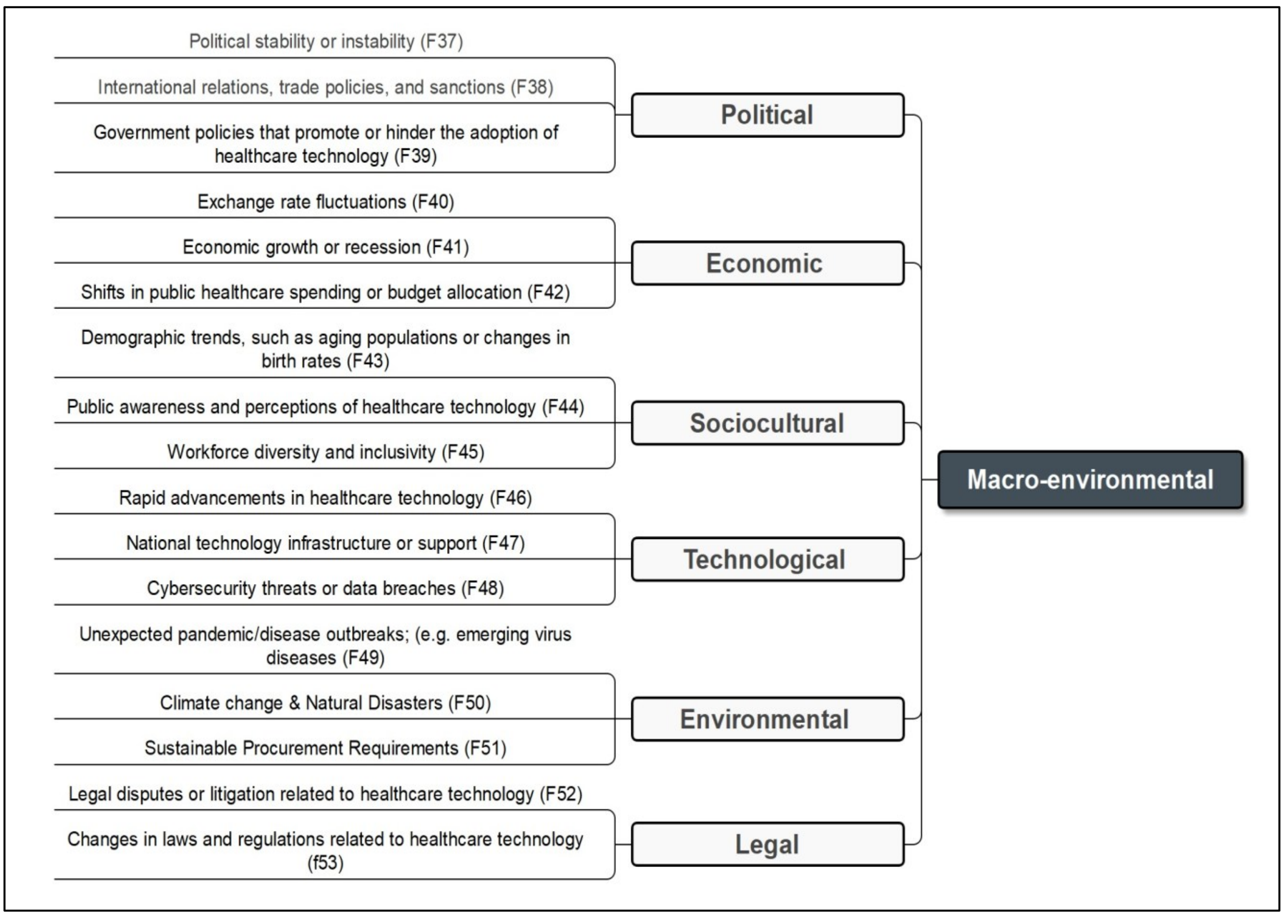


Figure 3.6: illustrates the subcategories of macroenvironmental factors

3.4. Validation of Risk Factors and Development of the Final HTMR Hierarchy

After establishing the preliminary list of risk factors, the next step was to validate and refine these criteria through direct input from Healthcare Technology Management (HTM) professionals working across the Kingdom of Saudi Arabia and the Gulf region (Appendix I). For this purpose, a focused expert panel was formed, consisting of practitioners and specialists with substantial experience in biomedical engineering, clinical operations, regulatory affairs, and hospital technology planning.

Because experts do not contribute equally—some have deeper technical backgrounds, others stronger managerial or regulatory experience—the study applied an expert-weighting scheme. This approach, recommended in decision-analysis literature [64], assigns different levels of influence to each expert according to their job role, qualifications, and years of professional experience. The assigned weights presented in Table 3.1 were determined based on the relative level of expertise of each participant using predefined qualification criteria. These criteria included years of professional experience in Healthcare Technology Management (HTM), current job role and managerial responsibility, academic qualifications, involvement in regulatory or strategic decision-making, and breadth of practical experience within the healthcare technology sector. Experts occupying senior leadership positions, possessing extensive professional experience, or holding advanced academic qualifications were assigned relatively higher weights, reflecting the greater influence of their specialised knowledge and strategic perspective. The assigned weights were subsequently normalised so that the sum of all expert weights equalled 100%, ensuring that each expert's contribution to the aggregated judgements was proportional to their level of expertise while maintaining consistency in the weighting process.

The number of experts consulted falls within the range generally considered appropriate for AHP and Fuzzy AHP applications. Previous research has shown that small expert panels (often fewer than ten experts) are sufficient because expert elicitation prioritises the quality of specialised knowledge rather than the size of the sample. Unlike conventional survey research, which seeks statistical representativeness, methods such as the Delphi technique and Fuzzy AHP rely on informed judgements from carefully selected experts with substantial domain experience. As specialists within the same field generally possess comparable technical knowledge and decision-making criteria, their assessments tend to demonstrate a high degree of consistency, thereby reducing the need for large sample sizes while maintaining the reliability and validity of the results [65][66].

The outcome of this stage was a refined and validated hierarchy of Healthcare Technology Management Risks (HTMR). This final structure—developed by combining literature findings with expert insight—served as the foundation for the subsequent fuzzy multi-criteria assessment.

Table 3.1: Weighting Criteria for HTM Experts

No.	Description	Assigned weight
1	More than 20 years of rich experience in managerial roles in the field of healthcare technology management, currently holding a Director position in a regulatory body.	14%
2	16-19 years of rich experience in the healthcare technology management field, and currently holding a Healthcare technology management Director position in a hospital.	13%
3	11-15 years of rich experience in the healthcare technology management field, PhD in the field, and currently working in a healthcare technology company.	13%
4	16-19 years of rich experience in the healthcare technology management field, and currently holding a managerial role in a hospital.	13%

5	11-15 years of rich experience in the healthcare technology management field, MSc in the field, and currently holding a managerial role in a hospital.	13%
6	16-19 years of rich experience in healthcare technology management non-managerial role in hospitals.	9%
7	16-19 years of rich experience in healthcare technology management non-managerial roles in hospitals.	9%
8	11-15 years of rich experience in healthcare technology management non-managerial role in hospitals.	6%
9	11-15 years of rich experience in healthcare technology management non-managerial role in hospitals.	6%
10	11-15 years of rich experience in the healthcare technology management field out of the Gulf region, holds an MBA and currently holding a managerial role in a healthcare technology company in the Gulf region.	4%

In Figure 3.7, the Mean and Weighted Average values for each risk factor are plotted to illustrate the level of agreement among participating experts. The two curves show a high degree of proximity, with only minor deviations observed across the 53 risk factors, indicating that the weighted average closely follows the unweighted mean. This close alignment suggests that the experts exhibited a high level of consistency in their judgements, such that applying the weighting scheme had only a limited effect on the overall pattern of responses while still accounting for differences in expertise. Consequently, individual expert contributions, once adjusted through the weighting scheme, remain consistent with the unweighted group trend. Such alignment reinforces the robustness of the expert-weighting approach adopted in this study, as also supported in prior methodological literature [65].

Risk factors exhibiting a Weighted Average (W avg.) score of less than 3 were deemed insufficiently influential and were therefore excluded from subsequent analyses. These omitted factors are highlighted in yellow in Table 3.2.

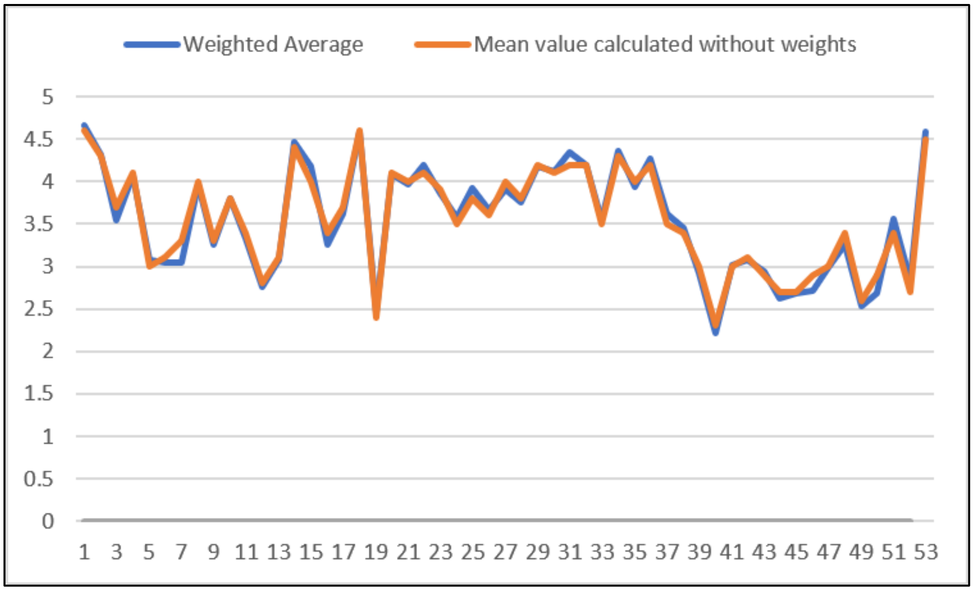


Figure3. 7: Represents the comparison between the mean and weighted average results

Table 3.2: presents the results of the questionnaire survey conducted in Stage 2 of the study. The full definitions and contextual descriptions of each risk factor correspond to the hierarchical structure illustrated in Figures 3.2-3.6. The abbreviation "W avg." refers to the *weighted average*, which incorporates expert-specific weighting to reflect differences in experience, role, and qualifications. The "Mean" represents the unweighted arithmetic average of the ratings assigned by all participating experts, calculated by summing the individual ratings for each risk factor and dividing by the total number of experts.

Factor	W avg.	Mean	Factor	W avg.	Mean
F1	4.7	4.6	F28	3.8	3.8
F2	4.3	4.3	F29	4.2	4.2

F3	3.6	3.7	F30	4.1	4.1
F4	4.1	4.1	F31	4.4	4.2
F5	3.1	3	F32	4.2	4.2
F6	3.1	3.1	F33	3.5	3.5
F7	3	3.3	F34	4.4	4.3
F8	4	4	F35	3.9	4
F9	3.3	3.3	F36	4.3	4.2
F10	3.8	3.8	F37	3.6	3.5
F11	3.3	3.4	F38	3.5	3.4
F12	2.8	2.8	F39	2.9	3
F13	3.1	3.1	F40	2.2	2.3
F14	4.5	4.4	F41	3	3.1
F15	4.2	4	F42	3.1	3
F16	3.3	3.4	F43	2.9	2.9
F17	3.6	3.7	F44	2.6	2.7
F18	4.6	4.6	F45	2.7	2.7
F19	2.5	2.4	F46	2.7	2.9
F20	4.1	4.1	F47	2.9	3
F21	4	4	F48	3.3	3.4
F22	4.2	4.1	F49	2.5	2.6
F23	3.9	3.9	F50	2.7	2.9
F24	3.6	3.5	F51	3.6	3.4
F25	3.9	3.8	F52	2.8	2.7
F26	3.7	3.6	F53	4.6	4.5
F27	3.9	4			

A comprehensive conceptual diagram was developed to illustrate the full spectrum of healthcare technology management risk sources—including technological, managerial, facility and environmental, and broader macro-environmental domains (Figure 3.8). This visualization served to consolidate all potential threats that could negatively influence HTM performance and to ensure that no major risk dimension was overlooked.

To validate the completeness and relevance of the identified risks, a qualitative expert survey was subsequently conducted. The survey assessed whether the proposed classification accurately captured the operational realities encountered in HTM practice. As part of this process, an initial significance evaluation was carried out to highlight the most influential risks based on expert judgment, ensuring that critical factors were properly emphasized in the final hierarchy.

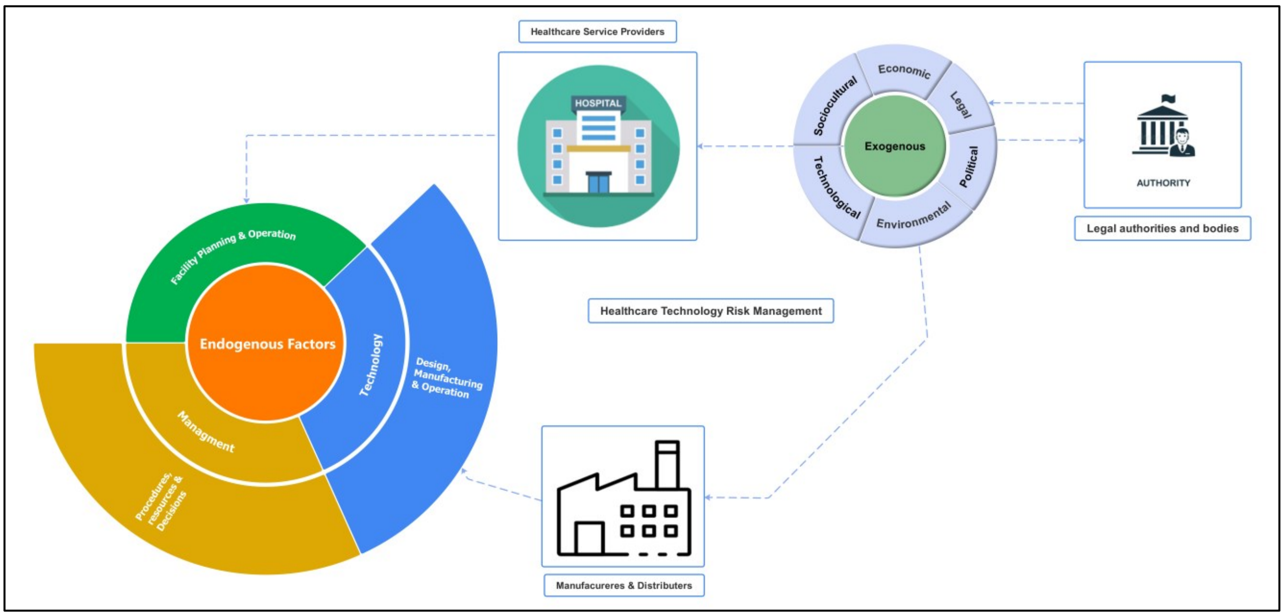


Figure 3.8. Sources of Risk in Healthcare Technology Management

Following this comprehensive review and expert consultation, a refined and validated HTM risk hierarchy was constructed (Figures 3.9–3.14). To evaluate the internal consistency of the survey instrument used in this stage, reliability analysis was performed using Cronbach's Alpha. The questionnaire encompassed 289 items, and the resulting Cronbach's Alpha coefficient was 0.990, indicating exceptionally high reliability. In applied research, a value of 0.8 or higher is generally regarded as evidence of strong internal consistency [67]; therefore, the obtained value confirms that the expert responses were both stable and dependable for subsequent analysis. The structure and format of both the expert validation questionnaire and the subsequent Fuzzy AHP pairwise comparison questionnaire were adapted from the questionnaire design presented in [65]. However, the questionnaire content, evaluated risk factors, pairwise comparison hierarchy, and assessment criteria were specifically developed for the Healthcare Technology Risk Management (HTRM) context of this study.

3.5. **Implementation of Fuzzy AHP Survey**

A questionnaire survey grounded in the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) was administered to capture expert judgments on the relative importance of the structured risk factors (Appendix 2). The assessment relied on predefined linguistic scales to express expert preferences. These qualitative linguistic terms were then systematically converted into corresponding Triangular Fuzzy Numbers (TFNs), enabling their use within the pairwise comparison matrices and ensuring a more nuanced representation of uncertainty in expert evaluations.

Using the collected expert inputs, the relative weights of all risk factors were computed through the Fuzzy AHP pairwise comparison matrices. These weights, derived from the aggregated expert judgments, were subsequently de-fuzzified to obtain crisp numerical values. The resulting values allowed the risk factors to be ranked in order of importance, thereby highlighting the factors exerting the greatest influence on healthcare technology management performance.

3.6. **Verifying the reliability of the Proposed Method**

To ensure the reliability of the judgments provided, a consistency check was applied to each pairwise comparison matrix to verify the logical coherence of the experts' evaluations. This step confirmed that the comparisons met the accepted thresholds for decision-making validity. In addition, a sensitivity analysis was conducted to assess the robustness of the derived weights and to examine how variations in expert input might influence the final ranking of risk factors. This analysis provided further confidence in the stability and reliability of the prioritization outcomes.

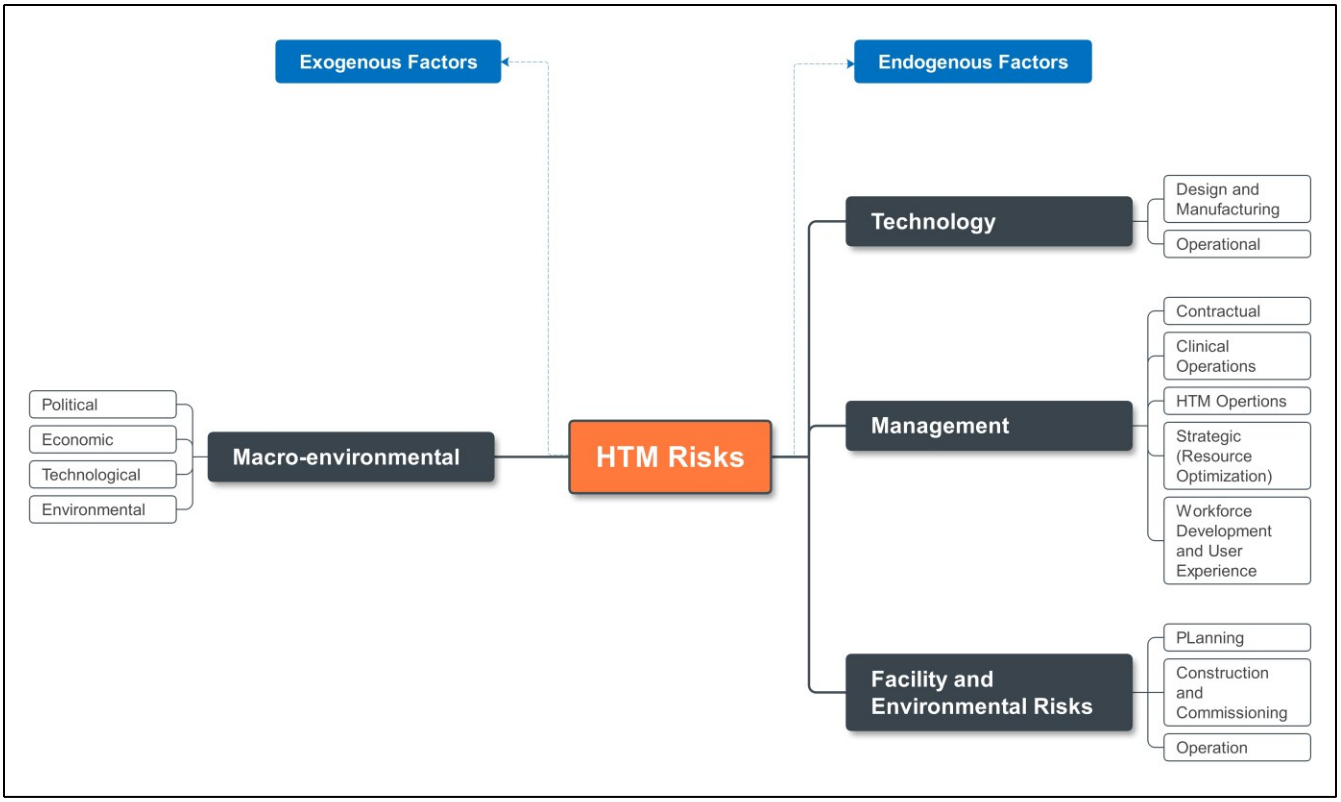


Figure 3.9. The Hierarchical Framework of Healthcare Technology Management Risks Following the qualitative expert survey.

3.7. Integrating Fuzzy AHP Outcomes with Foundational Risk Equation and Optimal Utilization Metrics

Relying exclusively on the fuzzy AHP–derived weights to quantify risk would provide only a partial representation of the underlying dynamics of healthcare technology performance. Although the fuzzy AHP model successfully captures expert perceptions of relative importance, it does not account for the intrinsic variability among different types of healthcare technologies nor the operational differences across healthcare institutions. More critically, fuzzy AHP does not incorporate the probability of risk occurrence, which may lead to misestimation of actual risk exposure, particularly for devices with high utilization or context-dependent failure modes.

To address these limitations, the fuzzy AHP outputs were integrated with the foundational risk formulation, extending the classical structure proposed by Wang and Levenson

(2000). This integration introduces the concept of an optimal utilization function, $f(U_{\mathrm{opt}})$, enabling the model to estimate how deviations from ideal usage patterns contribute to increased likelihood of risk events. By embedding utilization dynamics alongside readiness-gap weighting, the resulting formulation provides a more realistic and device-specific measure of risk, sensitive to both operational intensity and contextual vulnerabilities.

The mathematical derivation of the proposed modified risk equation—linking expert-derived readiness gaps with utilization-dependent escalation—is presented in detail in the results chapter. This combined formulation ensures a more accurate and holistic risk quantification framework suitable for diverse healthcare organizational settings

3.8. Fit multiple theoretical models (Linear, Quadratic, Exponential, Sinusoidal, and Hybrid) to identify the optimal formulation

3.8.1. Construction of Empirical Variables for SQRRM Identification

As noted by Ljung (1999), when physical insight into a system is limited or unavailable, a data-driven modelling approach based on system identification provides a principled framework for inferring model structure directly from observed input–output behaviour [68]. In alignment with this principle, the proposed utilization–risk formulation was identified using a longitudinal dataset spanning five years (2020–2024) for sixteen high-criticality diagnostic imaging systems operating in a tertiary-care hospital. The study cohort comprised 3 Optical Coherence Tomography (OCT) systems, 3 ultrasound units including A/B-scan, 5 radiography (X-ray) systems, 1 fluoroscopy unit, and 4 MRI scanners.

3.8.2. Utilisation Intensity (U)

Utilisation intensity was computed by normalising the monthly number of completed examinations against the maximum observed examination volume in the dataset. Specifically, each monthly case count was divided by the highest recorded case count across the study period, producing a dimensionless utilisation ratio between 0 and 1. This measure reflects the relative operational load of each system compared with the highest observed workload in the dataset.

All utilisation records were validated through direct confirmation from modality operators to ensure accuracy and consistency.

3.8.3. Maintenance Exposure: Work Orders and Downtime

Maintenance-related data were extracted from the hospital's Computerized Maintenance Management System (CMMS), including fields such as work-order number, description, reported date, work type, target start, actual finish, asset ID, and work group.

Two key indicators were derived:

1. **Corrective-maintenance downtime (RT):** Calculated as the elapsed time between the work order's reported date and its actual completion.
2. **Failure frequency (WO):** Defined as the total number of corrective maintenance work orders.

All entries were reviewed and validated by biomedical engineers to remove inconsistencies, outliers, and incomplete records.

3.8.4. Readiness Profile (G) from Fuzzy AHP

The readiness profile $G$was computed from a previously established Fuzzy Analytic Hierarchy Process (Fuzzy AHP) model incorporating 53 multidimensional risk factors across design, technological, environmental, and managerial domains.

Each factor contributes a normalized preparedness score $x_i \in [0,1]$, weighted by expert-derived importance values $\omega_i$specific to the Saudi/GCC HTM context.

The aggregated readiness gap is:

$$G = \sum_{i=1}^{n} \omega_i (1 - x_i) \qquad (3.1)$$

where Greflects the facility's deviation from optimal readiness.

3.8.5. Integrated Utilization–Readiness–Risk Dataset

The three components—utilization intensity U, maintenance exposure R, and readiness gap G—were combined to model the nonlinear resonant response surface: $R(U,G)$ representing HTM risk as a function of operational stress and systemic vulnerability.

3.9. Model Development Framework

3.9.1. Preliminary Functional Exploration

A broad set of candidate mappings from utilization $U$to maintenance risk were evaluated, assuming fixed readiness G:

1. Linear
2. Quadratic
3. Exponential
4. Sinusoidal
5. Quadratic + Sinusoidal compositions.

Initial results showed that utilization alone was insufficient to explain maintenance risk with high fidelity.

3.9.2. Introduction of Utilization–Readiness Interaction

To address this limitation, we introduced explicit interaction terms between utilization $U$and readiness G. Exploratory regression revealed that the strongest formulation coupled:

1. A **quadratic escalation term**, capturing nonlinear deterioration under high operational load.
2. A **sinusoidal resonance term**, representing oscillatory or threshold effects modulated by readiness gaps.

This led to the discovery of the Synergistic Quadratic-Resonant Risk Model (SQRRM).

3.9.3. Synergistic Quadratic-Resonant Risk Model (SQRRM)

The final proposed model takes the following form:

$$R(U,G) = (aU^2 + bU + c)(1 + \delta \sin(\beta UG + \phi)) \qquad (3.2)$$

Interpretation:

- **Quadratic core** → nonlinear escalation of risk with increasing utilization.
- **Resonant modulation** → amplifies or attenuates risk depending on readiness deficiency.
- **Gap-coupling term** UG→ introduces system-specific resonance patterns based on vulnerability levels.

This formulation generalizes both:

- the earlier conceptual HTM risk model R_{HTM}, and
- the readiness scoring structure: $G = \sum \omega_i (1 - x_i) \qquad (3.3)$

The parameters $(a, b, c, \delta, \beta, \phi)$were estimated using robust nonlinear least squares with multi-start initialization. Model selection employed held-out validation and multi-metric evaluation (R^2, MSE, Spearman's ρ).

3.9.4. Maintenance Risk Definition

Work orders and repair time are widely recognized operational indicators for quantifying maintenance burden in healthcare technology management. As noted by authors in [69], the negative impacts of corrective maintenance arise from two principal mechanisms:
(i) recurrent failure events and their associated operational disruptions, and
(ii) prolonged, unplanned downtime that compromises equipment availability.

These mechanisms align directly with the two observable components used in this study—Work Orders (WO) and Repair Time (RT)—making them an appropriate empirical proxy for maintenance-induced risk.

In this research, the maintenance risk associated with each equipment model is expressed as the total maintenance exposure:

$$\text{Risk} = \text{WorkOrders} + \text{RepairTime} \qquad (3.4)$$

This additive formulation assumes that both failure frequency (number of work orders) and failure severity (total repair time) contribute independently and cumulatively to the overall maintenance burden. It satisfies two fundamental properties expected from composite operational indicators:

1. **Monotonicity:** increases in either component increase total risk.
2. **Additivity:** each component imposes an incremental load that can be summed to form a combined risk measure.

From a reliability engineering perspective, this can be viewed as a simplified linear functional:

$$R = \int (\lambda_1 \, dN + \lambda_2 \, dt) \qquad (3.5)$$

where dNdenotes increments in the number of maintenance interventions and dtrepresents elapsed downtime. Setting $\lambda_1 = \lambda_2 = 1$gives equal weight to frequency and duration, mirroring how biomedical engineers and HTM teams perceive operational stress in real clinical environments.

3.9.5. Scientific and Operational Rationale

Healthcare technology risk arises from the combination of:

1. **High failure frequency (WorkOrders):**
   which increases maintenance workload, resource utilization, and response demands.
2. **Prolonged downtime (RepairTime):**
   which reduces equipment availability, affects clinical throughput, and undermines patient safety margins.

The additive expression:

$$\text{Risk} = \text{Frequency of events} + \text{Duration of exposure}$$

Therefore, it represents a rational empirical approximation of maintenance-induced stress. This construction mirrors principles used across multiple domains:

3.9.5.1. Reliability & Maintenance Engineering

Sahani et al. [70] show that maintenance impact is typically modelled as the combined effect of downtime-related losses and maintenance cost reductions:

$$\boxed{\text{Impact} = (\text{Downtime Reduction} \times \text{Cost per Hour}) + \text{Maintenance Cost Reduction} \quad (3.6)}$$

Here, downtime and maintenance actions act as **separate additive contributors**, reinforcing the suitability of WO + RT in HTM as two distinct channels of risk exposure.

3.9.5.2. Actuarial and Risk Modelling

Authors in [71] demonstrate that insurers decompose loss exposure into claim frequency and claim severity, later recombining them to quantify overall risk. This separation parallels the HTM domain, where failure frequency and failure severity jointly determine operational burden.

Whether equipment fails often but briefly, or rarely but with long outages, the additive model captures the total effect in a transparent, interpretable manner.

Thus, the chosen risk formulation remains: operationally meaningful, mathematically interpretable, consistent with HTM decision-making practice, and aligned with established principles across engineering and risk sciences.

This justifies using equation (3.4) $($Risk $=$ WorkOrders $+$ RepairTime) as the primary risk definition, with alternative formulations examined only during sensitivity analysis.

3.10. **Extending Risk Beyond Technical Failure**

Although healthcare technology risk is inherently multidimensional—spanning organizational, environmental, financial, regulatory, and human-factor domains—these latent components cannot be modelled directly using regression or curve-fitting techniques. They lack continuous, quantitative representation and are often subjective or event-driven.

For this reason, the present study adopts WorkOrders + RepairTime as the observable, auditable, and time-varying technical component of risk.

However, broader risk dimensions are not ignored. They are explicitly integrated through the Readiness Profile (G), which incorporates 53 risk factors derived from the Fuzzy AHP model.

This creates a structured separation:

$R \rightarrow$ the directly observable technical risk signal,

$G \rightarrow$ the latent multidimensional readiness and vulnerability environment.

This separation is fundamental to the architecture of the proposed model. It enables the response surface $R(U, G)$to capture both:

the *measurable operational burden* (via WO and RT), and

the *underlying systemic fragilities* (via Fuzzy-AHP-weighted readiness gaps).

Such dual representation reflects how HTM risk manifests in real-world hospital systems and provides the foundation for the nonlinear–resonant behaviour modelled in the Synergistic Quadratic–Resonant Risk Model (SQRRM).

3.11. **Model Sensitivity and Robustness Evaluation**

To evaluate stability and generality, four alternative definitions of maintenance risk were assessed:

1. **Additive (baseline):** $\boxed{R = WO + RT \qquad (3.7)}$
2. **Normalized additive:** $\boxed{R = WO_n + RT_n \qquad (3.8)}$
3. **Multiplicative:** $\boxed{R = WO \times RT \qquad (3.9)}$
4. **Normalized multiplicative:** $\boxed{R = WO_n \times RT_n \qquad (3.10)}$

Each formulation was tested across a diverse set of candidate response surfaces: linear, quadratic, exponential, sinusoidal, quadratic-plus-sine, and the advanced hybrid model. Performance was assessed using multiple goodness-of-fit indicators, including R^2, MSE, NRMSE, and Spearman's ρ. This evaluation served two purposes:
(i) validating the stability of the $R(U, G)$relationship under alternative mathematical representations of risk, and
(ii) assessing parameter sensitivity to the resonant modulation term, particularly the sinusoidal amplitude δ.

Across all configurations, the additive formulation, equation (3.7), yielded the most stable and physically interpretable behaviour. It demonstrated lower sensitivity to perturbations in δ, preserved monotonic escalation properties, and aligned more closely with real maintenance workflows where both event frequency and downtime contribute independently to operational burden.

A full comparison of sensitivity metrics, coefficient stability, and surface behaviour is presented in *Results chapter.*

3.12. **Temporal Robustness Assessment Protocol**

To evaluate the temporal stability and structural robustness of the Synergistic Quadratic–Resonant Risk Model (SQRRM), a rolling cross-year validation protocol was adopted across the post-pandemic period (2021–2024). The global utilization scale was first defined using the full longitudinal dataset (2020–2024) to ensure a consistent normalization reference across all years. Annual model evaluation was then performed by extracting independent cross-sections for each calendar year and refitting the candidate formulations—including linear, quadratic, exponential, sinusoidal, quadratic–sinusoidal, and SQRRM models—using year-specific observations of utilization–gap interaction and observed maintenance risk.

For each evaluation year, model performance was quantified using a unified metric set consisting of the coefficient of determination (R^2), mean squared error (MSE), and Spearman's rank correlation coefficient (ρ). This design enabled direct comparison of both magnitude-based accuracy and ordinal risk preservation under inter-annual operational variability. The Advanced Hybrid (SQRRM) formulation was then assessed for dominance persistence, defined as the ability to maintain leading or near-leading performance under independent annual realizations of hospital operational conditions.

The year 2020 was treated as a special regime due to COVID-19–induced utilization disruptions and was therefore excluded from the formal robustness inference, while still retained for global normalization and contextual completeness. This protocol provides a strict temporal stress test of the SQRRM law, verifying that its superiority is not confined to a single realization but persists across heterogeneous annual conditions.

3.13. Embed SQRRM into BiLSTM and ADGNN architectures to evaluate adaptiveness on time-series datasets

To test domain-generalizability, SQRRM's functional structure was ported to the NASA CMAPSS FD001 turbofan dataset [72]. The NASA dataset was selected because it differs not only in equipment type but also in data structure, degradation mechanism, operating environment, and sensing modality. Successful performance in this setting indicates that the SQRRM formulation captures generalizable failure dynamics rather than domain-specific statistical artifacts.

3.13.1 Construction of Technical Analogues

- **Utilization proxy** U: normalized time index over engine life.
- **Technical readiness gap** G: measured from sensor deviations relative to early-life baselines.
- **Risk proxy**: remaining useful life (RUL) degradation trajectory.

  The resonant component was embedded within the BiLSTM and ADGNN architectures through an SQRRM-based quadratic–resonant risk gate, yielding a dynamically modulated recurrent and graph–temporal learning framework.

3.14. **Conclusion of Methodology Chapter**

The methodology for this research was designed to move systematically from qualitative risk conceptualization to quantitative model formulation and technical validation. Beginning with a multi-source identification of 53 healthcare technology risk factors through literature synthesis, expert input, and PESTLE analysis, the study refined these factors using expert-weighted Fuzzy AHP to construct a validated hierarchical HTM risk structure tailored to the Saudi and Gulf healthcare context. The resulting weighted readiness gaps were integrated with utilization metrics and operational failure indicators to form a unified empirical dataset, from which multiple mathematical formulations were tested.

In this study, maintenance risk serves as the observable operational outcome through which the combined effects of broader healthcare technology risk factors and equipment utilisation are quantitatively modelled. Accordingly, Work Orders and Repair Time represent the response variable used for predictive modelling rather than a complete definition of healthcare technology risk. Broader technical, managerial, environmental, regulatory, and human-related risks are incorporated through the readiness-gap structure used as predictive input to the proposed model.

Through iterative nonlinear parameter estimation, comparative model evaluation, and systematic sensitivity analysis, the Synergistic Quadratic–Resonant Risk Model (SQRRM) was identified as the strongest-performing nonlinear formulation for describing the relationship between utilization intensity and maintenance risk among the candidate models evaluated in this study.

This formulation provided the theoretical and computational foundation for extending the framework from static risk quantification to adaptive, data-driven prediction, achieved by embedding the SQRRM structure within deep learning architectures, including BiLSTM, ADGNN, and the associated SQRRM-based risk-gated hybrid configurations. The final stage of the methodology evaluated the model's generalizability using the NASA CMAPSS FD001 turbofan engine benchmark. This cross-domain validation demonstrates the transferability of the proposed framework across heterogeneous asset classes, beyond the original healthcare technology management context.

This methodological progression bridges qualitative risk taxonomy with quantitative predictive modelling, setting the stage for the upcoming results chapters, where empirical findings, performance comparisons, and generalization outcomes are presented.

CHAPTER FOUR – FUZZY AHP PAIRWISE COMPARISON RESULTS

4.1. Introduction

This chapter presents the quantitative results of the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) applied to prioritize the validated set of healthcare technology management (HTM) risk factors. As detailed in the methodology chapter, the original list of 53 risk factors underwent an initial expert screening, during which factors with a Weighted Average (W avg.) below 3 were excluded from further analysis. This refinement reduced the set to 41 factors, removing items such as *Bulk Purchasing Arrangements* (F12), *Disposal of medical technology no longer needed by the facility* (F19), the entire Sociocultural category, and several additional macro-environmental elements that were consistently rated as having limited operational relevance Figures (4.1 & 4.2).

With the final hierarchy established, the present chapter focuses exclusively on deriving numerical weight rather than revisiting the definitions or classifications of risk factors. Expert judgments were collected through structured pairwise comparison questionnaires and expressed using linguistic scales, which were then converted into Triangular Fuzzy Numbers (TFNs) to account for uncertainty and variability inherent in human assessment. These fuzzy judgments were aggregated using the fuzzy geometric mean method to construct a consolidated comparison matrix capturing the consensus of participating experts.

Subsequently, defuzzification techniques were applied to convert fuzzy weights into crisp numerical values, followed by normalization to compute relative priority scores across all hierarchical levels—main criteria, sub-criteria, and individual risk items. The resulting weighted hierarchy provides a ranked view of risk contributors and forms the quantitative basis for calculating the readiness-gap index G, which is later integrated into the nonlinear modelling framework.

In summary, this chapter delivers the final numerical prioritization of the 41 retained HTM risk factors, supplying the critical quantitative foundation for the subsequent development and empirical validation of the Synergistic Quadratic–Resonant Risk Model (SQRRM).

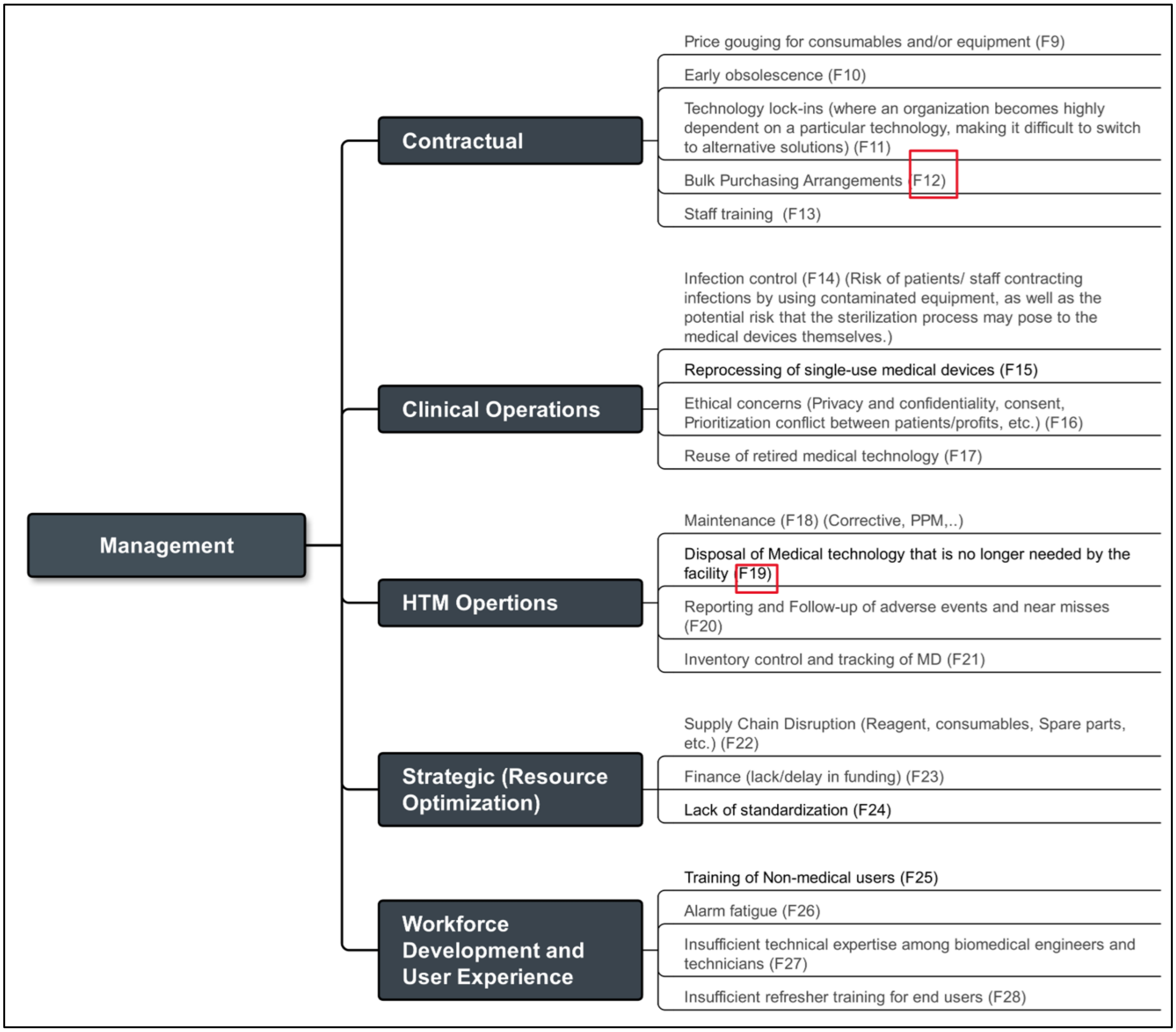


Figure 4.1: depicts the Management Risk sub-categories and identifies the specific factors that were eliminated following the expert evaluation and reduction stage (Originally introduced in Section 3.3.3 (Figure 3.4)).

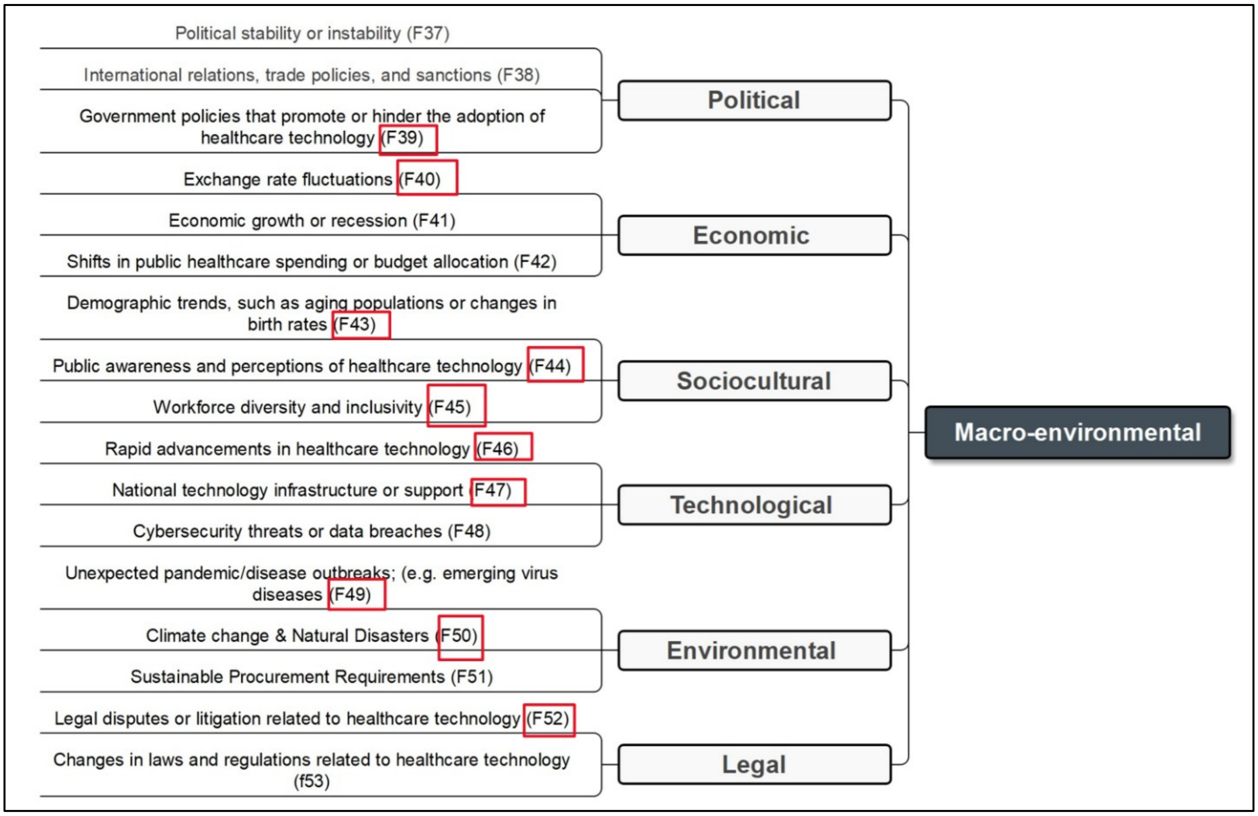


Figure 4.2: illustrates the Macroenvironmental Risk sub-categories and identifies the specific factors that were eliminated following the expert evaluation and reduction stage (Originally introduced in Section 3.3.3 (Figure 3.6)).

4.2. Fuzzy AHP Pairwise Comparison Results

The AHP questionnaire (Appendix 2) was distributed to 30 healthcare technology management (HTM) experts, with 22 valid responses received. The majority of respondents (68%) were based in Saudi Arabia, followed by 14% from the UAE and Qatar, while the remaining participants were in the UK, Spain, and Germany, all of whom had prior professional engagement within the Gulf region.

In terms of professional experience, 18% of experts reported more than 20 years in HTM, 27% had 16–19 years, and 41% had 11–15 years of experience. Two additional experts had 10 and 9 years, respectively. Most respondents (59%) were affiliated with large public hospitals (>1000 beds), including major governmental healthcare institutions. One response was from a private hospital representative. Additionally, 23% were employed by technology vendors or service providers, while two respondents represented medical device manufacturers and one participant worked for a national regulatory body overseeing healthcare technology.

Table 4.2 presents the processed data, rounded to four decimal places, obtained from the expert responses. The fuzzy weights for criteria and sub-criteria were computed using Chang's Extent Analysis Method [26], implemented through a custom Python script executed in Google Colab. The mapping of linguistic terms to their corresponding Triangular Fuzzy Numbers (TFNs) is summarized in Table 4.1, while the resulting global weights are shown in Table 4.2 and Figure 4.3.

The fuzzy evaluation process follows Chang's formulation:

$$s_i = \sum_{j=1}^{m} M_{g^i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g^i}^{j}\right]^{-1} \qquad (4.1)$$

$$V(M_2 \geq M_1) = \mathrm{hgt}(M_1 \cap M_2) = \mu_{M_2(d)}$$
$$= \begin{cases} 1, \; if\; m_2 \geq m_1 \\ 0, \quad if\; l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, otherwise \end{cases} \qquad (4.2)$$

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \qquad (4.3)$$

Each fuzzy element M is represented as a Triangular Fuzzy Number (l,m,u), illustrated in Figure 4.1. Here, $\boldsymbol{s_i}$denotes the synthetic extent value of the i^{th}criterion, and $d'(A_1), \ldots, d'(A_n)$represent the defuzzified priority weights derived from Equation (4.2) prior to normalization. The final weight vector W is expressed as a non-fuzzy (crisp) number after normalization.

Table 4.1 AHP comparison scale (Chang's scale) [73]

Linguistic Variables	Fuzzy Scale	Inverse Scale
Equally important	(1, 1, 1)	(1, 1, 1)
Slightly more important	(2/3, 1, 3/2)	(2/3, 1, 3/2)
Strongly more important	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)
Absolutely more important	(7/2, 4, 9/2)	(2/9, 1/4, 2/7)

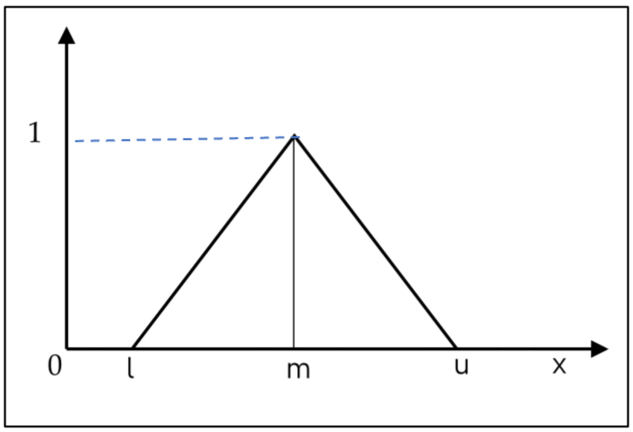


Figure 4.3. Triangular Fuzzy Number (TFN).

Table 4.2 Ranking of HTM Risk Factors with Corresponding Global Weights (Gl. W.).

Factor	Gl. W.	Rank	Factor	Gl. W.	Rank
F27	0.111	1	***F33***	0.018	22
F2	0.057	2	***F21***	0.017	23
F1	0.051	3	***F22***	0.014	24
F28	0.046	4	***F30***	0.013	25
F5	0.044	5	***F16***	0.013	26
F3	0.043	6	***F37***	0.013	27
F32	0.042	7	***F19***	0.012	28
F25	0.042	8	***F41***	0.01	29
F6	0.041	9	***F15***	0.01	30

F7	0.04	10	***F24***	0.008	31
F8	0.038	11	***F12***	0.008	32
F4	0.038	12	***F10***	0.008	33
F26	0.034	13	***F11***	0.007	34
F34	0.033	14	***F23***	0.006	35
F14	0.027	15	***F38***	0.006	36
F13	0.026	16	***F9***	0.005	37
F17	0.025	17	***F36***	0.004	38
F31	0.023	18	***F35***	0.004	39
F20	0.022	19	***F39***	0.003	40
F29	0.020	20	***F40***	0.003	41
F18	0.018	21			

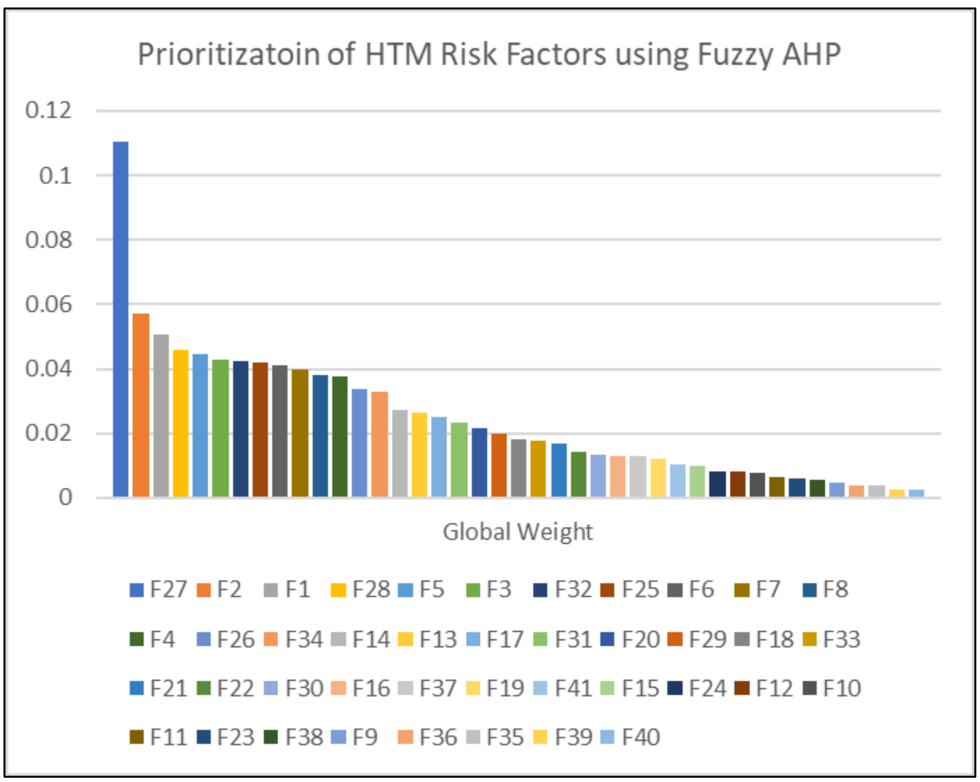


Figure 4.4 Displays the ranking of factors, indicating that factor (F27)—Design Risks, associated with planning within Facility and Internal Environmental Risks, as the highest ranked risk.

4.3. **Fuzzy AHP Consistency Assessment**

In this study, expert judgments on the relative importance of the HTM risk factors were elicited using a fuzzy AHP pairwise comparison framework based on triangular fuzzy numbers. After establishing the fuzzy comparison matrices at each level of the decision hierarchy, fuzzy priority weights were first derived and then examined for logical consistency in the crisp domain.

The fuzzy priority weights $\widetilde{w}_i$ were obtained using Chang's extent analysis method. These fuzzy weights were subsequently defuzzified into crisp values w_i using the graded mean integration approach, yielding a normalized priority vector

$$\mathrm{w} = (w_1, w_2, \dots, w_n)^{\top} \qquad (4.4)$$

Based on this priority vector, the associated crisp comparison matrix $\mathrm{A} = [a_{ij}]$ was constructed such that

$$a_{ij} \approx \frac{w_i}{w_j} \qquad (4.5)$$

which is consistent with Saaty's original AHP formulation. The principal eigenvalue $\lambda_{\max}$ of A was then estimated from

$$\lambda_{\max} \approx \frac{1}{n} \sum_{i=1}^{n} \frac{(\mathrm{Aw})_i}{w_i} \qquad (4.6)$$

The Consistency Index (CI) was computed using the standard AHP expression

$$CI = \frac{\lambda_{\max} - n}{n - 1} \qquad (4.7)$$

where n denotes the order of the comparison matrix. To account for the influence of matrix size, the Consistency Ratio (CR) was subsequently calculated as

$$CR = \frac{CI}{RI} \qquad (4.8)$$

with RI representing Saaty's Random Index corresponding to the matrix dimension.

As reported by the authors in [65], a Consistency Ratio below 0.10 indicates an acceptable level of consistency in pairwise comparison matrices and reflects logically coherent expert judgments. In the present study, the individual pairwise comparison matrices completed by the participating experts yielded an overall average consistency ratio (CR) of 0.0406. This value was obtained by calculating the consistency ratio for each pairwise comparison matrix using Equations (4.7)–(4.8) and then computing the arithmetic mean of the resulting CR values across all expert responses. Since the average CR was well below the recommended threshold of 0.10, the expert judgements were considered to exhibit an acceptable level of consistency. This indicates that the derived weighting structure is internally consistent, with no evidence of contradictory or irrational preference patterns, thereby confirming the reliability of the comparison matrices for the subsequent weighting and risk modelling stages of the study.

4.4. **Sensitivity Analysis**

Sensitivity analysis was performed alongside weight computation within the Python-based Fuzzy AHP workflow. The analysis systematically perturbed elements of the pairwise comparison matrix by predefined positive and negative percentages to evaluate how fluctuations in expert judgment affect the resulting criteria weights. This approach provides insights into the robustness of individual factors under uncertainty, reflecting real-world variability in expert assessment.

The results showed that most criteria demonstrated a sensitivity value of 0.0000, indicating that the applied perturbations produced no measurable change in the corresponding criteria weights within the reported numerical precision, as depicted in Figure 4.3. Although small perturbations were introduced into the pairwise comparison matrices, the resulting changes in the derived weights for most criteria were negligible and therefore rounded to 0.0000. This demonstrates that the derived weighting structure is robust to small variations in expert judgements, indicating that the assigned criteria weights remain stable under the applied perturbation scheme.

However, a subset of criteria exhibited measurable sensitivity:

- F1: 0.0272
- F2: 0.0216
- F3: 0.0212
- F4: 0.2664 *(notably higher than others)*

The elevated sensitivity of F4 suggests that its assigned weight is more strongly influenced by how experts compare it relative to other criteria. While this indicates a higher dependence on subjective judgment for this factor, the finding must be interpreted within the broader context of the model's overall reliability, particularly given the excellent consistency ratio reported earlier. Thus, although F4 warrants closer scrutiny in future refinements, the stability of the remaining criteria supports the robustness of the weighting system as a whole.

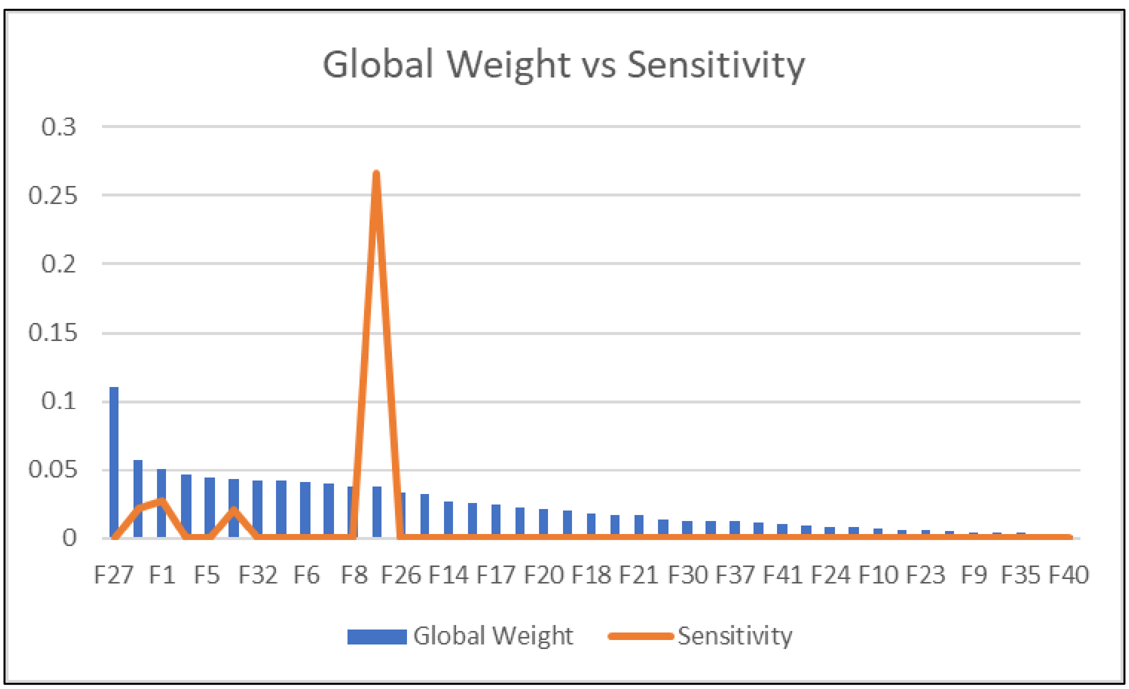


Figure 4.5. Represents the result from the sensitivity analysis performed.

4.5. Derivation of Healthcare Technology Management (HTM) Risk Equation

The classical formulation of risk is expressed as:

$$\text{Risk} = P \times L \qquad (4.9)$$

where *P* denotes the probability of occurrence and *L* denotes the magnitude of loss. To operationalize this formulation for healthcare technology management (HTM), both components were redefined to reflect risk drivers specific to medical equipment performance, organizational readiness, and operational utilization.

4.5.1. Magnitude of Loss (L)

In the HTM context, the magnitude of loss is conceptualized as the weighted influence of each risk factor on equipment performance. The weight of each factor ω_i represents its relative importance as determined through Fuzzy AHP, while the readiness gap $(1-x_i)$reflects deviation from optimal preparedness under that factor.

$$L_i = \omega_i(1 - x_i) \qquad (4.10)$$

This formulation provides two advantages:

1. It generalizes across diverse technologies and healthcare environments, and
2. It links risk magnitude directly to root causes, enabling targeted mitigation.

4.5.2. Probability of Event (P)

The probability of a risk event in HTM is closely influenced by actual equipment utilization. To reflect this dependency, probability is expressed as a function of optimal utilization:

$$P = f(U_{\text{opt}}) \qquad (4.11)$$

This function captures the full utilization continuum, including underutilization, nominal use, and overload, each associated with different failure dynamics.

4.5.3. Integrated HTM Risk Formulation

By combining utilization-driven event likelihood with readiness-weighted loss magnitude, the risk contributed by an individual factor becomes:

$$R_i = f(U_{\text{opt}}) \cdot L_i \qquad (4.12)$$

Summing across all risk contributors:

$$R_{\text{total}} = f(U_{\text{opt}}) \sum_{i=1}^{n} L_i \qquad (4.13)$$

Thus, the total HTM risk score is expressed as:

$$\text{HTM}_R = f(U_{\text{opt}}) \sum_{i=1}^{n} \omega_i \, (1 - x_i) \qquad (4.14)$$

4.5.4. Interpretation and Application

The resulting equation preserves both conceptual and operational rigor:

- $\sum \omega_i (1 - x_i)$ captures latent multidimensional vulnerability, integrating design, technical, environmental, managerial, and macro-level factors.
- $f(U_{\text{opt}})$ embedded dynamic utilization-driven failure likelihood, reflecting empirical operational stress.

This formulation extends the classical risk model and the utilization concept of Wang & Levenson [5] by incorporating contextual readiness gaps obtained from Fuzzy AHP. While global weights arise from expert-driven factor hierarchies, $(1-x_i)$is evaluated at the organizational level, making the equation adaptive, context-aware, and technology-agnostic.

A full empirical estimation of $f(U_{\text{opt}})$, including nonlinear and resonant structures leading to SQRRM, is developed in subsequent chapter using longitudinal hospital data.

4.6. Discussion — Fuzzy AHP Risk Assessment

This research presents the first comprehensive, region-specific investigation of healthcare technology management (HTM) risks in the Kingdom of Saudi Arabia and the Gulf region, and the first study to apply the PESTEL framework to systematically map external risk drivers affecting HTM performance. The approach departs significantly from prior literature, which has largely relied on the Fennigkoh and Smith model or its subsequent adaptations by Wang and Levenson [5]. Earlier studies have typically examined only internal maintenance-related factors, leaving critical external, managerial, technological, and macro-environmental risks unaccounted for. Consequently, existing models offer only a narrow view of risk, limiting their suitability for modern, complex healthcare environments.

Using expert-driven Fuzzy AHP, this study quantified the relative importance of 53 risk factors across technological, managerial, facility-related, and macro-environmental domains. The results demonstrate that risks affecting HTM performance extend far beyond device-level maintenance concerns, encompassing broader systemic vulnerabilities related to design, regulation, workforce capability, environmental conditions, and strategic management. The twenty highest-weight risks provide a clear picture of the dominant challenges faced by healthcare organizations in the region.

Design risks emerged as the most influential factor, reflecting the substantial impact of facility layout, infrastructure compatibility, and pre-commissioning processes on long-term technology performance. Closely following were software and hardware design risks, emphasizing the growing dependence of modern healthcare delivery on reliable, cyber-secure, interoperable technologies. The prominence of regulatory-compliance risks signals widespread organizational vulnerability to design and construction deviations from standards. Similarly, equipment aging, human-factor engineering, and insufficient technical expertise highlight ongoing gaps in operational readiness and professional capacity.

Risk factors related to system integration, electromagnetic compatibility, device classification, and maintenance management further confirm the multi-layered complexity of HTM systems, where technical, operational, and managerial factors intersect to determine safety, reliability, and clinical performance.

Although the macro-environmental category contributed lower numerical weights overall, its qualitative importance remains undeniable. Risks such as cybersecurity threats, political instability, economic fluctuations, and pandemic-level disruptions may not occur as frequently as operational failures, yet they carry disproportionate systemic consequences when they do. Their lower ranking reflects expert weighting of immediacy and frequency—not irrelevance—and underscores the need for dual-layered risk governance: one focused on daily operations, and the other on resilience and strategic preparedness.

The findings collectively demonstrate that effective HTM risk management must move beyond maintenance-centric approaches and adopt a more comprehensive, systems-oriented perspective. The top-ranked factors highlight a constellation of design, technological, managerial, and facility readiness issues that require integrated mitigation strategies. Examples include improved facility planning processes, more rigorous design validation, enhanced cybersecurity and interoperability planning, structured workforce development, and robust disaster-response capabilities. Strengthening supply chain resilience and institutionalizing continuous training also emerged as vital components of risk reduction.

The study acknowledges several limitations. A small number of risks were excluded from the pairwise comparison due to low perceived significance, including bulk purchasing, technology disposal, and certain socio-legal macro-environmental factors. Additionally, while expert participation was broad and regionally diverse, the findings are most applicable to the Gulf context and may require adaptation elsewhere. Nevertheless, the reliability of the results is strongly supported by the very high Cronbach's alpha (0.990) and the diversity of expert backgrounds spanning public hospitals, private institutions, HTM agencies, manufacturers, and regulatory bodies.

To strengthen precision and scalability, this chapter proposed integrating Fuzzy AHP outcomes into a new mathematical risk formulation that incorporates utilization dynamics and readiness gaps, bridging conceptual and operational dimensions of HTM risk. This integration allows the derived weights to be used not only for prioritization but also as inputs for quantitative modelling, paving the way for developing adaptive, utilization-aware risk prediction systems.

In summary, this chapter establishes a comprehensive and empirically validated understanding of HTM risk factors in Saudi Arabia and the Gulf region. It provides the foundational risk hierarchy and weighted profiles necessary for the next stage (Results Part II) of this research: deriving, estimating, and validating the Risk Model (SQRRM).

CHAPTER FIVE –MODEL DERIVATION, VALIDATION & CROSS-DOMAIN TESTING

5.1. Introduction

This Chapter presents the analytical results associated with developing, fitting, and validating the Synergistic Quadratic-Resonant Risk Model (SQRRM). Whereas Part I quantified risk factor significance through Fuzzy AHP, Part II transitions from factor weighting to model construction and empirical validation. The analysis proceeds in three phases:

5.1.1. Model Formulation and Curve Fitting Using Hospital Data:

Multiple theoretical formulations were fitted to the empirical relationship between utilization intensity and maintenance exposure, including Linear, Quadratic, Exponential, Sinusoidal, and hybrid combinations. These models were evaluated to isolate the structural form that best captures nonlinear escalation and readiness-dependent modulation.

5.1.2. Development and Validation of SQRRM on Real Hospital Equipment:

The optimal formulation emerging from the model development phase converged on a hybrid nonlinear–resonant structure, leading to the final expression of the Synergistic Quadratic–Resonant Risk Model (SQRRM). The proposed formulation was developed and internally evaluated using a hospital-wide longitudinal dataset comprising 16 critical medical imaging systems operating over the period 2020–2024, representing a diverse cross-section of real hospital equipment and operational conditions. Global utilization normalization was defined using the full 2020–2024 dataset, establishing a consistent reference scale across all years. The nonlinear utilization–risk relationship itself was then identified using the aggregated 2024 cross-section, consistent with a system-identification and curve-fitting framework rather than a time-series forecasting paradigm. Owing to the COVID-19–related operational disruptions in 2020, formal temporal robustness assessment is based on the post-pandemic period (2021–2024), with full annual results reported in Appendix III.

Model performance was quantitatively evaluated using a complementary set of statistical indicators that collectively assess goodness-of-fit, absolute error, normalized deviation, and rank-order consistency. Specifically, the coefficient of determination (R^2) was computed to quantify the proportion of variance in the observed risk values explained by the model, following standard regression analysis principles [74]. The mean squared error (MSE) was used to measure the average squared deviation between predicted and observed values, providing a scale-dependent estimate of prediction accuracy [75].

In addition to magnitude-based accuracy metrics, Spearman's rank correlation coefficient (ρ) was employed to assess the model's ability to preserve the relative ordering of asset risk levels, independent of absolute scale. Spearman's ρ was evaluated as the Pearson correlation between the ranked true and predicted values using the covariance-based formulation, which is mathematically equivalent to the standardized z-score representation of rank correlation [76], and was implemented computationally using the SciPy statistical library [77].

Across all validation measures, the proposed SQRRM consistently demonstrated superior explanatory power and predictive accuracy relative to all tested baseline and hybrid alternatives. These results confirm both the numerical robustness and the operational reliability of the SQRRM formulation when applied to real-world hospital equipment data.

5.1.3. Cross-Domain Testing Using NASA C-MAPSS FD001:

To demonstrate generalizability beyond the healthcare domain, the SQRRM formulation was embedded within two deep learning architectures—BiLSTM and ADGNN—and validated on the NASA C-MAPSS FD001 turbofan dataset [72]. Learned-gap modulation was implemented through a Sine-Risk gating mechanism, enabling adaptive risk weighting within time-series forecasting.

Together, these results confirm that risk escalation in complex technical systems is not driven by utilization alone, but emerges from the interaction between operational load and contextual readiness gaps. The cross-domain experiments further support the transferability of the model to heterogeneous platforms, machinery, and operational contexts.

5.1.4. Summary of Modelling Pipeline (Figure 5.1)

- Input Variables
    - Utilization intensity U(normalized workload)
    - Maintenance exposure: $\mathrm{R} = \mathrm{WO} + \mathrm{RT}$
    - Readiness gaps: $\mathrm{G} = \sum \omega_{\mathrm{i}}(1 - \mathrm{x_i})$
- Models Fitted
    - Linear
    - Quadratic
    - Exponential
    - Pure Sinusoidal
    - Quadratic + Sinusoidal
    - Advanced Hybrid → SQRRM
- Cross-Domain Testing
    - SQRRM structure ported to the NASA C-MAPSS FD001 turbofan dataset
    - Implemented within BiLSTM and ADGNN time-series architectures
    - Readiness gap Gderived using technical sensor deviation only
    - Used to assess model transferability across domains

- Validation Metrics
    - R^2
    - RMSE / MSE

- NASA Score (for engine prognostics)
- Spearman Rank Correlation

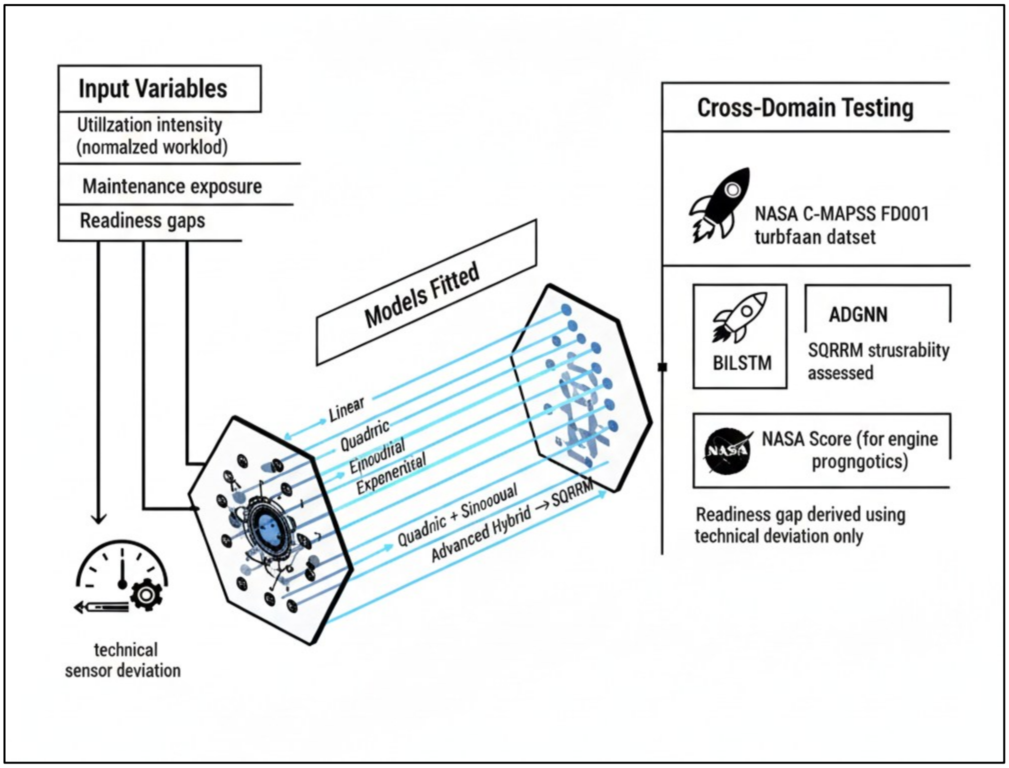


Figure 5.1: Summary of Modelling Pipeline

5.2. Empirical Modelling of the Utilization–Risk Relationship

To characterize how operational workload interacts with systemic readiness to influence maintenance burden, six alternative regression models were fitted using the hospital dataset of sixteen medical imaging systems spanning 2020–2024. The tested formulations included Linear, Quadratic, Exponential, Pure Sinusoidal, Quadratic + Sinusoidal, and the proposed Synergistic Quadratic-Resonant Risk Model (SQRRM). Each model was parameterized using a composite explanatory variable defined as the product of normalized utilization intensity and the aggregated readiness gap, denoted as $\mathrm{U} \times \mathrm{G}$. This construct represents the combined effect of operational stress and systemic vulnerability.

The readiness gap G was derived using the analytic expression $\mathrm{G} = \mathrm{w}(1 - \mathrm{x})$, where w represents the normalized Fuzzy AHP weight obtained from the hierarchy established in chapter 4, and x denotes the preparedness score reflecting the degree to which a facility or technology satisfies the conditions associated with that factor. Under this formulation, when $x = 1$, indicating full readiness or non-applicability of the factor, the corresponding gap becomes $G = 0$. This behaviour ensures that only deficiencies relative to optimal readiness contribute to risk escalation. For all remaining factors, where real-time or device-specific preparedness measurements were unavailable, $x$was conservatively set to zero. This choice reflects a worst-case baseline assumption, ensuring that the model does not underestimate risk in the absence of quantifiable readiness evidence. This approach aligns with established risk-science literature emphasizing risk-aware modelling under uncertainty and the avoidance of optimistic bias when system preparedness cannot be confirmed. [78]

This assumption is scientifically justified for two reasons:

1. **Risk-aware modelling under uncertainty:** When readiness cannot be confirmed, assuming full compliance ($x = 1$) would artificially suppress risk signals, whereas assuming no readiness ($x = 0$) preserves sensitivity to systemic vulnerabilities.
2. **Model validation rather than organizational benchmarking:** At this stage of analysis, the goal is to characterize the mathematical form of $f(U, G)$, not evaluate the actual operational maturity of facilities. Using a conservative baseline provides an upper-bound response surface that can later be refined once factor-specific readiness audits become available. Under this convention, the aggregated readiness gap still retains full interpretability: $G = \sum_{i=1}^{n} \omega_i \, (1 - x_i)$, but the adopted initialization supports *exploratory model derivation*, with the expectation that future deployments will replace assumed values with measured facility-specific scores.

The twenty highest-priority factors identified in the previous results chapter were applied in two stratified equipment groups (Table 5.1). Group 1 represented infrastructure-dependent imaging systems (e.g., MRI, fluoroscopy, X-ray), where environmental stability and utility support are critical for operation. Group 2 included plug-and-play systems such as ultrasound and optical coherence tomography, which operate with significantly reduced dependence on facility infrastructure. To reflect this distinction, the factors G_{27},

G_{28}, and G_{29}—representing environmental and facility readiness—were set to zero for Group 2, recognizing their negligible operational influence. Additionally, the factor G_{14}, associated with reprocessing of single-use medical devices, was excluded across both groups based on domain expert consultation. These adjustments ensured contextual alignment between readiness metrics and the physical operating conditions of each modality, thereby increasing the interpretability and relevance of downstream model estimations.

Following this preparation, model derivation proceeded in a staged, incremental fashion. We began with a baseline formulation relying solely on utilization, then incorporated nonlinear escalation terms, and finally introduced gap-modulated resonant terms to capture oscillatory deviations from monotonic trends. All models were trained on identical datasets and evaluated under identical splits to ensure comparability, with performance assessed using R^2, RMSE, MSE, and Spearman rank correlation. The comparative results are presented in Model Performance Benchmarking (Table 5.2), demonstrating that the SQRRM achieved superior predictive accuracy and greater structural interpretability relative to all alternative forms.

TABLE 5.1: Represents Ranking of HTM Risk Factors with Corresponding descriptions and AHP Global Weights (Gl. W.)

Factor	Description	AHP Weight
F27	Design Risks UNDER Facilities and Internal Environmental Risks	0.111
F2	Software UNDER Technology Risks	0.057
F1	Hardware UNDER Technology Risks	0.051
F28	Regulatory Compliance (related to facility design) UNDER Facilities and Internal Environmental Risks	0.046
F5	Equipment Age UNDER Technology Risks	0.044
F3	Human Factor Engineering (HFE) UNDER Technology Risks	0.043
F32	Maintenance Risks UNDER Facilities and Internal Environmental Risks	0.0423
F25	Insufficient technical expertise among biomedical engineers and	0.042

	technicians UNDER Management Risks	
F6	Integration and Interoperability under Technology Risks	0.041
F7	Electromagnetic compatibility (EMC) with other devices under Technology Risks	0.04
F8	Device Classification based on SFDA and/or other regulatory entities A, B, or C	0.038
F4	Regulatory Compliance UNDER Technology Risks	0.038
F26	Continuous Educational Program for End-Users (refresh training)	0.034
F34	Disaster Response Risks UNDER Facilities and Internal Environmental Risks	0.033
F14	Reprocessing of single-use medical devices	0.027
F13	Infection control	0.026
F17	Maintenance UNDER management Risks	0.025
F31	Testing and Validation	0.023
F20	Supply Chain Disruption (Reagent, consumables, Spare parts, etc.)	0.022
F29	Blueprint vs Reality Discrepancies	0.020

Each model was fitted using appropriate regression solvers and evaluated on identical held-out data. The resulting fitted equations are presented below as the formal mathematical representations used in subsequent comparisons, with equations (5.1)–(5.6) corresponding to Linear, Quadratic, Exponential, Pure Sinusoidal, Quadratic-with-Sinusoid, and the proposed SQRRM hybrid, respectively.

These functions serve as calibrated response surfaces rather than theoretical postulates, enabling direct quantitative comparison of model classes under an identical risk formulation. Their coefficients reflect the observed dynamics of the 2024 hospital dataset and form the basis for selecting the governing structure for further generalization and cross-domain validation.

Linear:	$f(U,WG) = 227.868U + 30.542$ (5.1)
Quadratic:	$f(U,WG) = -3080.677U^2 + 1878.805U - 44.360$ (5.2)
Exponential:	$f(U,WG) = 468174.052\, e^{0.000U} - 468143.504$ (5.3)
Sine:	$f(U,WG) = -96.131\, sin(316.544U - 4.698) + 96.595$ (5.4)
Quadratic + Sine:	$f(U,WG) = -14527.540U^2 + 8886.191U - 501.457 + 472.515\, sin(19.787U - 4.417)$ (5.5)
SQRRM (Advanced Hybrid):	$f(U,WG) = (9557.786U^2 - 456.097U + 9.768)(1 - 1.026\, sin(315.918U\, WG - 3.466)$ (5.6)

The baseline models (Equations 5.1–5.3) capture monotonic relationships between utilization and maintenance exposure, offering partial explanatory strength but failing to model the oscillatory deviations observed in the empirical data. Although the sinusoidal and composite variants (Equations 5.4–5.5) introduce periodic behaviour and yield improved localized fit, their formulations do not inherently account for interactions with readiness gaps or system-level contextual vulnerabilities.

The Advanced Hybrid formulation—formalized as the Synergistic Quadratic–Resonant Risk Model (SQRRM) (Equation 5.6)—demonstrates the strongest overall predictive performance, achieving an R^2 of 0.943 and the lowest mean square error among the evaluated models. While its Spearman correlation remained moderate, the superior R^2 and MSE values indicate that SQRRM provides the strongest absolute fit to the empirical maintenance-risk data among the candidate formulations considered. These results indicate that SQRRM captures both global nonlinear escalation through its quadratic structure and localized resonant amplification through the gap-modulated sinusoidal component.

A comparative summary of all model performances is presented in Table 5.2, confirming the superiority of the proposed formulation over linear, polynomial, exponential, and non-hybrid oscillatory models.

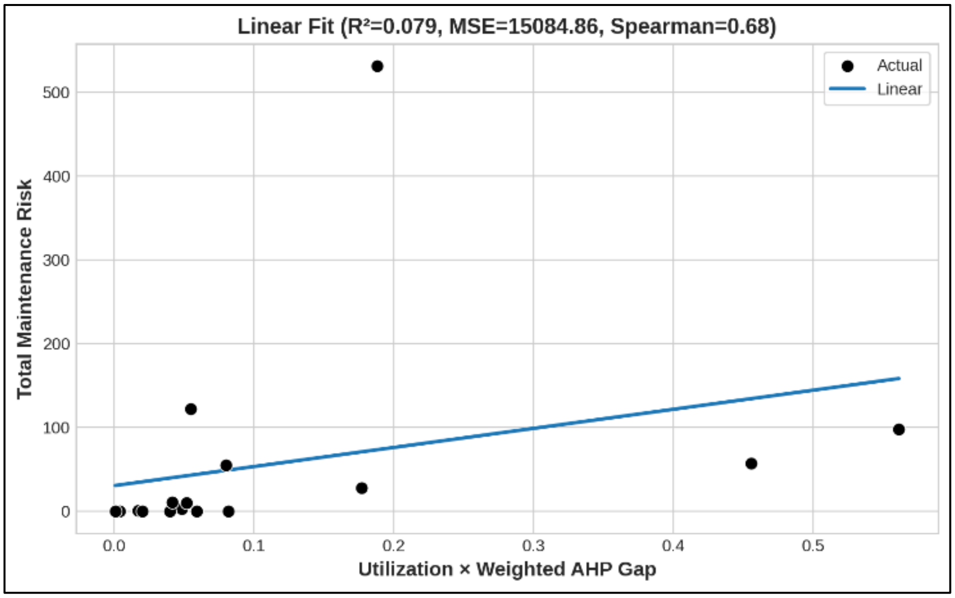


Figure 5.2: *Linear regression model* showing the monotonic increase in maintenance risk as a function of utilization × AHP-weighted gap (Equation 5.1). While the fit captures the global trend, it underestimates curvature and oscillatory deviations, particularly in high-risk regimes.

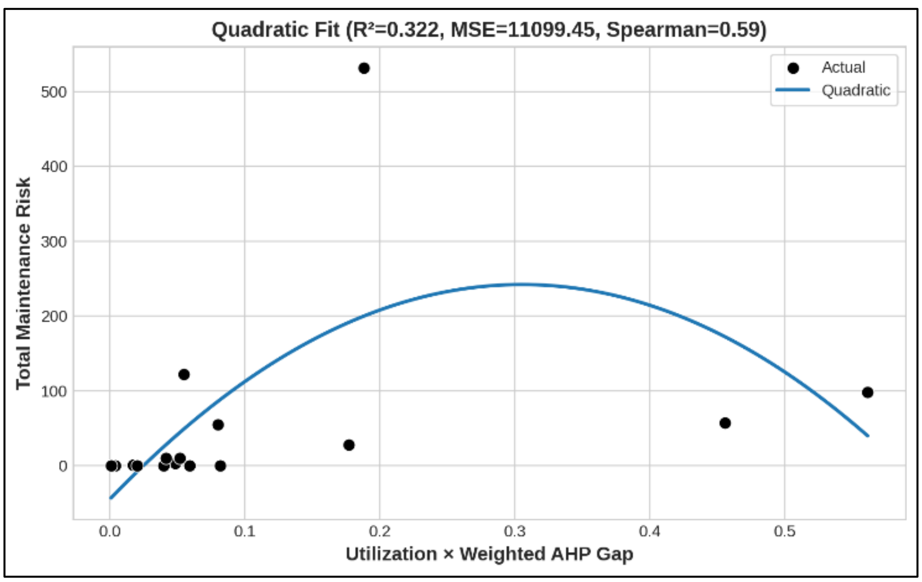


Figure 5.3: *Quadratic regression model* (Equation 5.2) illustrating improved curvature over the linear model, yet failing to capture localized variations across the utilization domain.

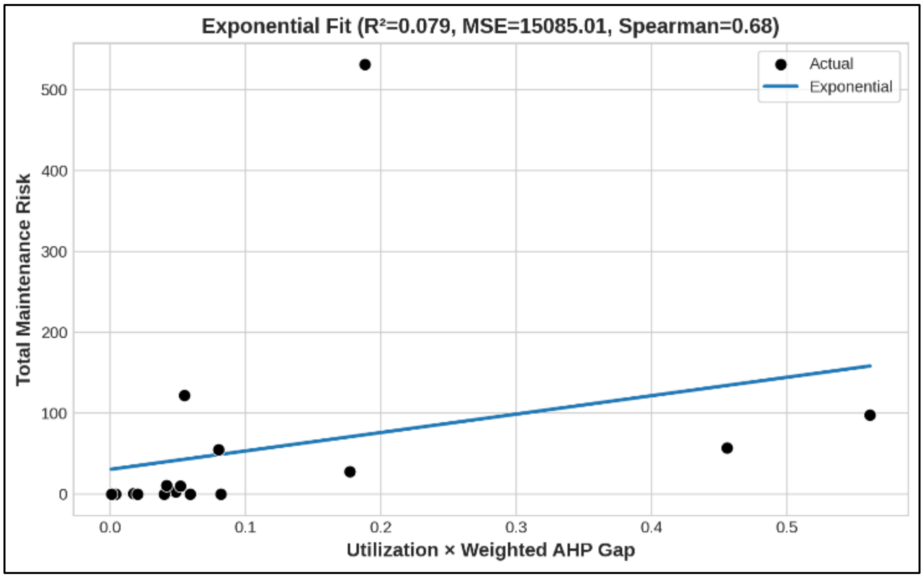


Figure 5.4: *Exponential model* (Equation 5.3) the exponential model exhibited near-linear behaviour across the observed utilization range, suggesting that exponential escalation effects were negligible in the studied operational domain.

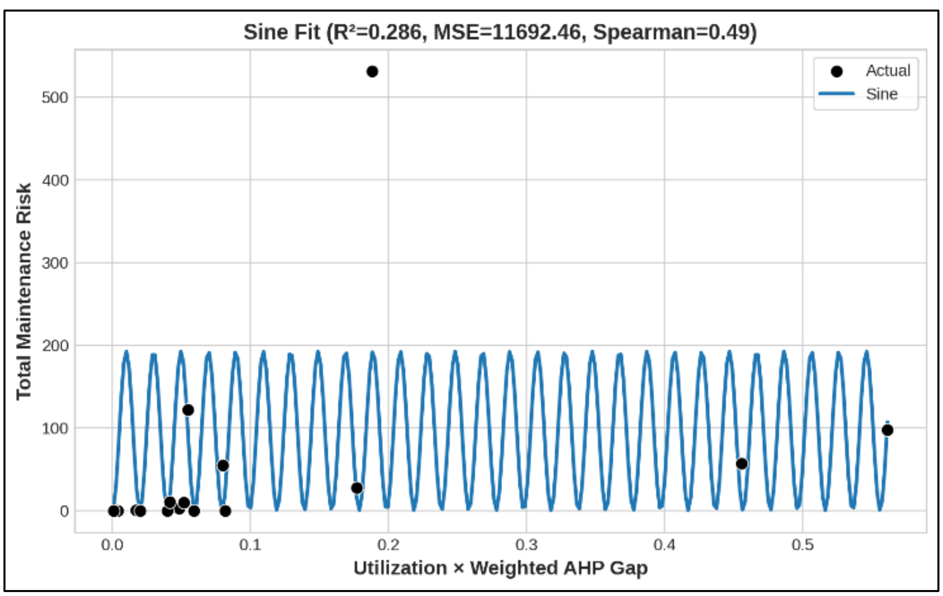


Figure 5.5: Pure sinusoidal model (Equation 5.4) highlighting cyclic response patterns but lacking overall trend alignment.

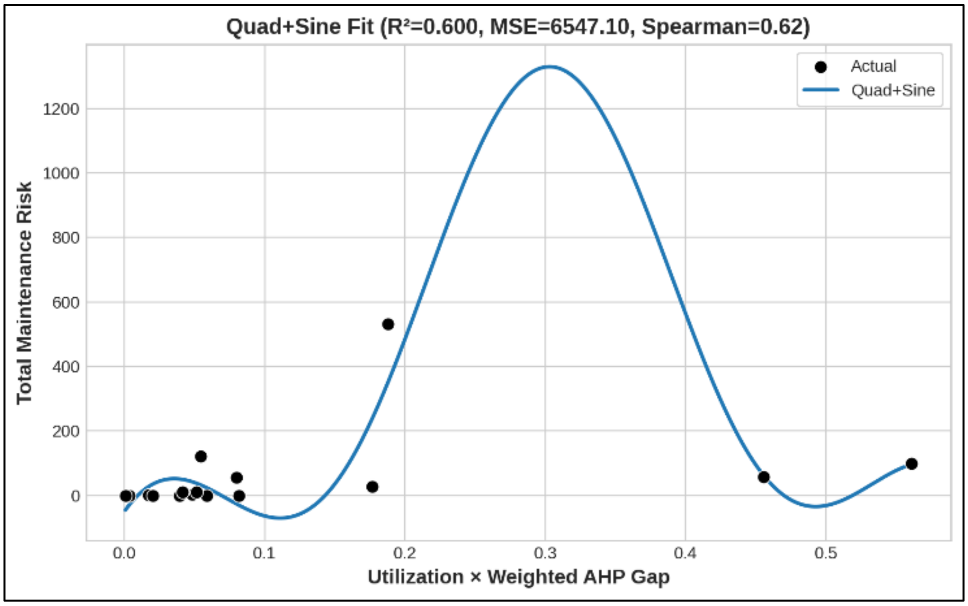


Figure 5.6: Quadratic + Sine composite model (Equation 5.5) representing both curvature and oscillation, yet with inconsistent amplitude scaling.

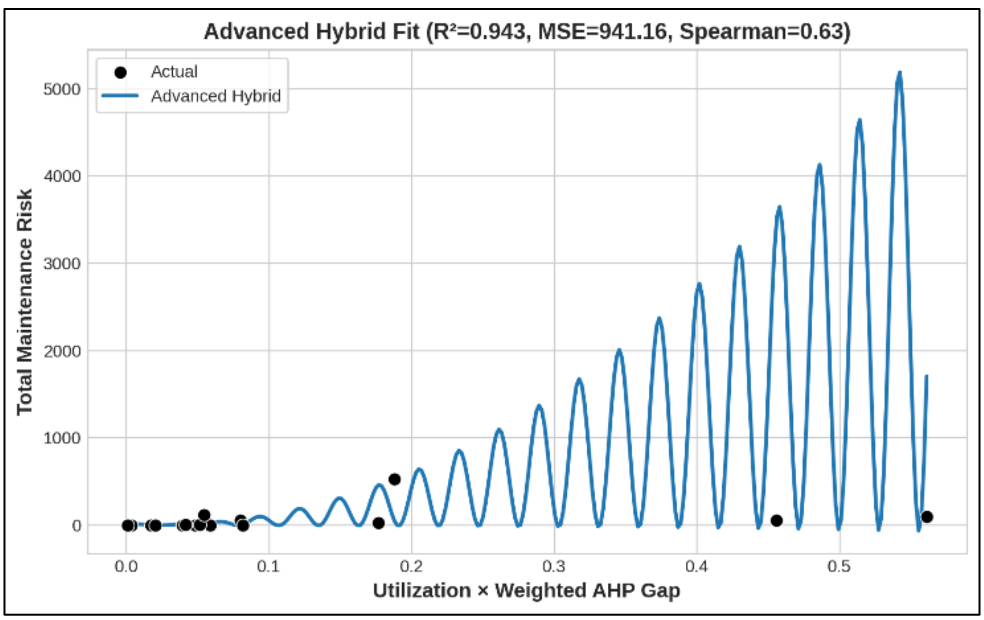


Figure 5.7: Proposed Synergistic Quadratic–Resonant Risk Model (SQRRM)—the best-fit hybrid function combining quadratic escalation and readiness-gap resonance (Equation 5.6), showing excellent agreement with the empirical risk data ($R^2 = 0.943$), indicating that the model explains approximately 94.3% of the observed variability in maintenance risk.

5.2.1. Derivation and Model Justification

Model selection proceeded in two stages. In the first stage, canonical baselines—Linear, Quadratic, and Exponential—were estimated alongside oscillatory extensions (Sine and Quadratic+Sine) to assess whether non-monotonic behaviour existed in the empirical utilization–risk relationship. These preliminary models captured partial trends but were insufficient to represent the observed resonance-like fluctuations and their dependence on system readiness conditions.

Persistent oscillatory structure in the residuals of all baseline models indicated the presence of a modulation effect superimposed on the underlying nonlinear escalation of risk. This empirical evidence motivated the formulation of a hybrid functional structure in which the quadratic utilization term is multiplicatively coupled with a sinusoidal resonance component, resulting in the proposed Synergistic Quadratic–Resonant Risk Model (SQRRM), which jointly captures nonlinear growth and gap-modulated oscillatory amplification:

$$f(U,G) = (aU^2 + bU + c)\,(1 + \beta\sin(eUG + \phi)) \tag{5.7}$$

The first term models global nonlinear growth in risk as utilization increases, while the sinusoidal component introduces localized resonant effects driven by deviations in readiness, enabling risk amplification or attenuation based on context rather than magnitude alone. This structure reflects a dual-pathway degradation mechanism: workload-induced stress and readiness-driven vulnerability.

Empirical fitting showed that SQRRM reproduced both long-range escalation and short-range oscillatory deviations across diverse imaging modalities, outperforming all baseline and composite models in R^2, MSE, and rank correlation (Table 5.2), with results illustrated in Figure 5.8. These findings establish SQRRM as the governing empirical surface for subsequent cross-domain validation using NASA C-MAPSS FD001.

TABLE 5.2: Represents Models Performance Summary

Model	R^2	MSE	Spearman ρ
Linear	0.08	15084.86	0.68
Quadratic	0.32	11099.45	0.59
Exponential	0.08	15085.01	0.68
Sine	0.29	11692.46	0.49
Quad + Sine	0.60	6547.10	0.62
Advanced Hybrid (SQRRM)	**0.94**	**941.16**	**0.63**

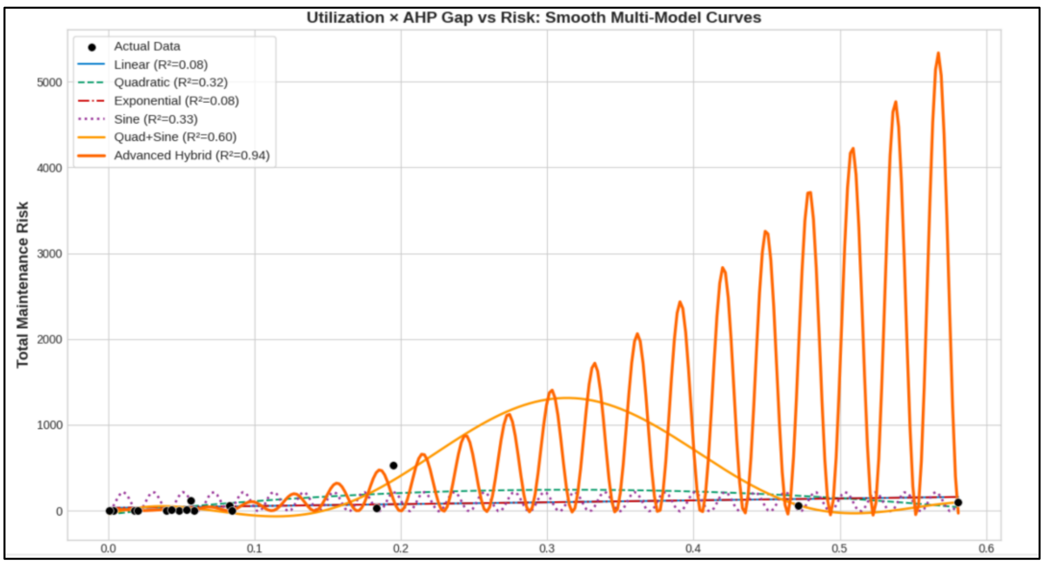


Figure 5.8: Comparison of utilization–risk relationship models illustrating fitted curves for linear, quadratic, exponential, sine, quadratic–sine, and advanced hybrid (SQRRM) formulations. The advanced hybrid model demonstrates superior fit (R^2 = 0.94), capturing nonlinear and resonant dynamics between utilization intensity and total maintenance risk.

5.2.2. **Key Observations and Derivation Justification of the Synergistic Quadratic–Resonant Risk Model (SQRRM)**

Comparative evaluation across multiple candidate risk formulations revealed several fundamental insights into the structure of the utilization–risk relationship. Linear and exponential models consistently exhibited poor explanatory power ($R^2 \approx 0.08$–0.12), confirming that utilization alone is insufficient to account for observed degradation variability. Quadratic models improved global trend representation but retained structured residuals, indicating the presence of unmodelled cyclic behaviour. Pure sinusoidal formulations captured localized oscillations but failed to represent the long-range escalation of operational risk driven by increasing utilization intensity. Composite polynomial–sinusoidal baselines further improved localized structure but still exhibited phase shifts and amplitude distortions dependent on readiness gap magnitude.

These systematic deficiencies indicated that the true utilization–risk relationship is governed by both nonlinear escalation and resonant fluctuation, and that these mechanisms interact multiplicatively rather than additively. From a healthcare technology management (HTM) perspective, this interaction is theoretically expected: global degradation pressure increases nonlinearly with usage intensity, while localized amplifications arise from readiness deficiencies such as infrastructure instability, software vulnerabilities, and procedural non-compliance. The interaction between utilization stress and readiness gaps naturally modulates both the frequency and amplitude of these fluctuations.

Based on these empirical and theoretical considerations, the Synergistic Quadratic–Resonant Risk Model (SQRRM) was formally defined as:

$$f(U, G) = (aU^2 + bU + c)\,[1 + \delta \sin(\beta U G + \phi)].$$

The quadratic component captures global monotonic escalation, while the sinusoidal term introduces bounded resonance. The multiplicative coupling through UG ensures that resonant amplification intensifies only when both utilization and readiness deficiencies are elevated, consistent with observed operational behaviour.

Empirical validation confirmed the necessity and adequacy of this coupled structure. The SQRRM achieved a coefficient of determination of $R^2 = 0.943$, outperforming all baseline formulations and reducing mean squared error by approximately an order of magnitude relative to linear and exponential models. Residual diagnostics exhibited no remaining structure, indicating that both global and local variations were successfully captured. Although rank ordering remained moderate across models (Spearman's $\rho \approx 0.63$), only SQRRM correctly calibrated the absolute magnitude of operational risk, demonstrating that simpler models may preserve relative ranking while substantially misestimating real-world impact.

Finally, cross-domain validation of the proposed modelling approach was conducted using the NASA C-MAPSS FD001 turbofan degradation dataset. When embedded as a risk-gating mechanism within the BiLSTM and ADGNN architectures, the SQRRM preserved its structural advantages and outperformed the selected comparator models under the adopted experimental protocol, achieving an R^2 value of 0.905. These findings provide additional empirical evidence supporting the effectiveness of the proposed formulation and demonstrate its potential applicability beyond the healthcare domain.

5.2.3. Sensitivity Analysis Across Alternative Risk Definitions

The primary operational risk metric in this study was defined as an additive burden:

$$\boxed{\boldsymbol{R}_{\text{add}} = \text{WorkOrders} + \text{RepairTime} \quad (5.8)}$$

To ensure that the superior performance of the proposed Synergistic Quadratic–Resonant Risk Model (SQRRM) was not an artifact of this specific formulation, we conducted a structured sensitivity analysis across four alternative empirical definitions of maintenance risk:

Risk Definition	Mathematical Form		Description
Additive (Primary)	$R = WO + RT$	(5.9)	Direct cumulative burden of failures and downtime
Normalized Sum	$R = WO_n + RT_n$	(5.10)	Scale-invariant summation across modalities
Product	$R = WO \times RT$	(5.11)	Emphasizes events with both high frequency and severity
Normalized Product	$R = WO_n \times RT_n$	(5.12)	Interaction-based burden normalized for comparability

These formulations span linear, normalized, and interaction-based interpretations of maintenance exposure, enabling a systematic evaluation of whether utilization–readiness interactions persist regardless of risk scaling.

Across all four definitions, the SQRRM maintained the highest explanatory power, lowest error metrics, and most stable parameter behaviour. Normalized product formulations increased model sensitivity to rare but high-impact failures, yet did not surpass the performance of the additive representation. Furthermore, parameter perturbation experiments showed that the resonance modulation term δ remained within stable bounds, confirming that oscillatory dynamics were not artifacts of variable scaling.

A summary of the comparative metrics is presented in Table 5.3.

TABLE 5.3: Represents Comparative Results across alternative risk definitions

Model	R^2 (Additive)	ΔR^2 (NormSum)	ΔR^2 (Product)	ΔR^2 (ProductNorm)	Key Observation
Linear	0.0787	+0.0690	–0.0364	–0.0364	NormSum improves fit; Product reduces linear interpretability
Quadratic	0.3221	+0.0574	–0.0524	–0.0524	Normalization mildly beneficial; Product overweights interaction noise
Exponential	0.0786	+0.0691	–0.0363	–0.0363	Scale-sensitive; behaves identically to Linear under these data

Sine	0.2859	+0.3599	+0.2238	+0.2238	Large apparent gains reflect noise amplification under normalization
Quad+Sine	0.6001	+0.0500	–0.2202	–0.2202	Additive remains most stable; Product-based definitions deteriorate fit
Advanced Hybrid	0.9425	–0.0931	–0.0003	–0.0003	Additive is optimal and robust; Hybrid performance stable across definitions

5.2.4. ΔR² Across Alternative Risk Definitions

To quantify the robustness of each fitted model to alternative formulations of the maintenance-risk variable, we computed the change in explanatory power relative to the primary additive risk definition. For every model M, the sensitivity index was defined as:

$$\boxed{\Delta R^2 = R^2_{\text{alt}} - R^2_{\text{add}} \qquad (5.13)}$$

where R^2_{alt} is the coefficient of determination under one of the three alternative risk metrics (Normalized Sum, Product, Normalized Product), and $R^2_{\text{add}}$is the corresponding value under the baseline additive formulation. This metric provides a direct measure of how strongly each modelling approach depends on the scale or structure of the underlying risk variable.

The resulting ΔR^2patterns were visualized using horizontal bar charts for all six regression models—Linear, Quadratic, Exponential, Sine, Quadratic+Sine, and the Advanced Hybrid (SQRRM)—as shown in Figures 5.9–5.14. These comparative plots reveal that the baseline models exhibited substantial fluctuations in ΔR^2, particularly under multiplicative risk definitions, indicating limited robustness to alternative interpretations of maintenance burden. In contrast, the SQRRM demonstrated consistently minimal ΔR^2variation across all formulations. This stability underscores the model's structural resilience and confirms that its superior performance is not contingent on any particular scaling of the dependent variable, thereby validating its suitability as a generalized risk–response function.

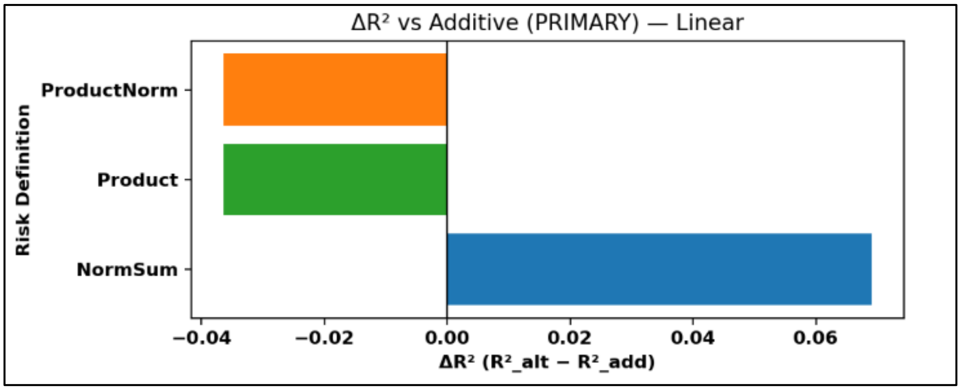


Figure 5.9: ΔR^2 of the Linear Model Across Alternative Risk Definitions Relative to the Additive Baseline. This figure illustrates how the predictive performance of the Linear model varies when the underlying maintenance-risk metric is redefined. The ΔR^2 values quantify the deviation in explanatory power when moving from the additive formulation (WO + RT) to normalized-sum, multiplicative, and normalized-product definitions.

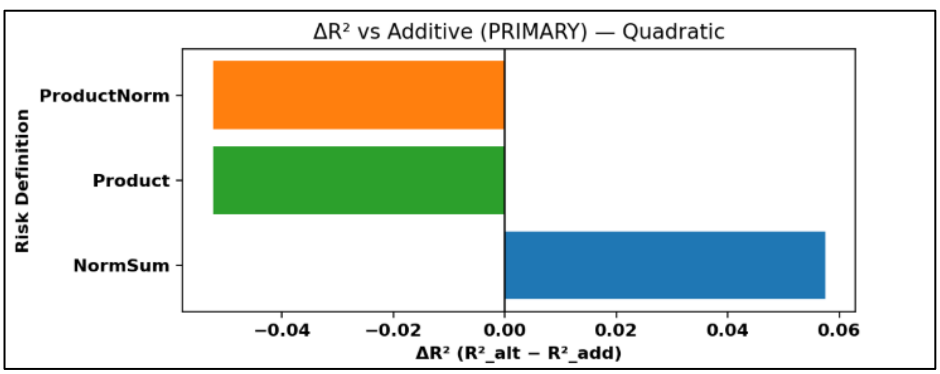


Figure 5.10: ΔR^2 of the Quadratic Model Across Alternative Risk Definitions Relative to the Additive Baseline.

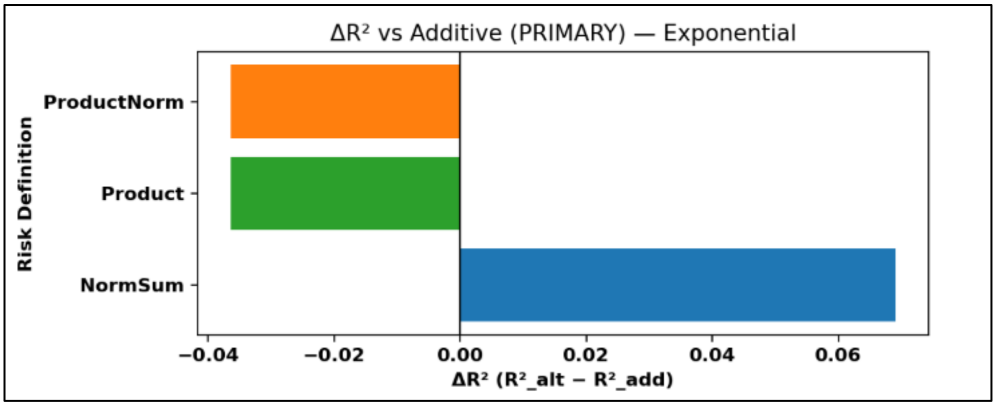


Figure 5.11: ΔR² of the Exponential Model Across Alternative Risk Definitions Relative to the Additive Baseline.

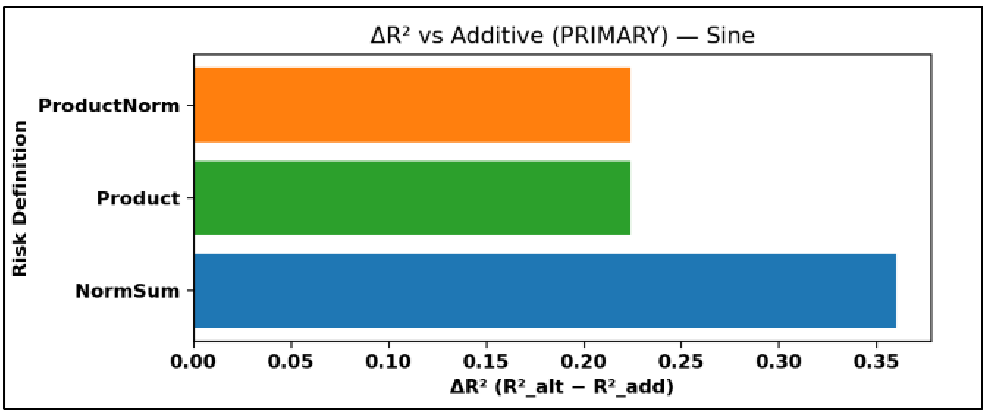


Figure 5.12: ΔR² of the Sine Model Across Alternative Risk Definitions Relative to the Additive Baseline.

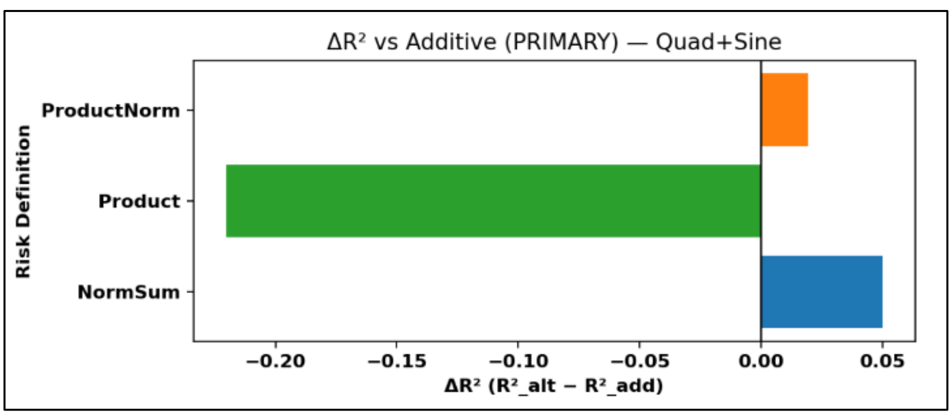


Figure 5.13: ΔR² of the Quadratic-Plus-Sine Model Across Alternative Risk Definitions Relative to the Additive Baseline.

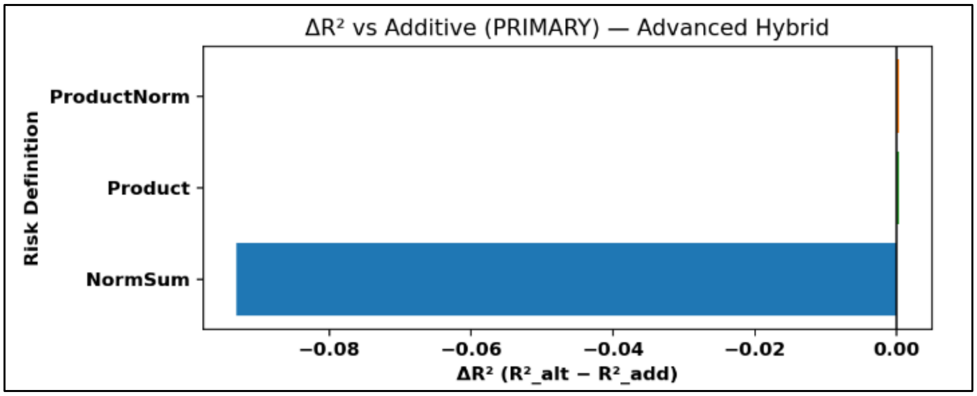


Figure 5.14: ΔR^2 of the Advanced Hybrid (SQRRM) Model Across Alternative Risk Definitions Relative to the Additive Baseline.

5.2.5. Sensitivity Behaviour Across Alternative Risk Definitions

The comparative ΔR^2 analysis revealed a clear and interpretable pattern in how each modelling family responded to changes in the definition of the maintenance-risk variable (Fig. 5.15).

1) Models with Low Baseline Capacity (Linear and Exponential): Both the Linear and Exponential models exhibited only minor fluctuations in R^2—typically within ±0.05—when alternative risk definitions were applied. Normalized additive risk (NormSum) produced a slight improvement, whereas Product and ProductNorm formulations led to modest declines in explanatory power. Importantly, neither model approached competitive performance under any transformation, reinforcing their limited capacity to capture the nonlinear structure inherent in the utilization–risk relationship.

2) Mid-Range Nonlinear Models (Quadratic, Sine, and Quadratic+Sine): The Quadratic and pure Sine models showed noticeable gains under the NormSum definition, suggesting that normalization can reduce noise and highlight their underlying nonlinear tendencies. However, both models suffered reductions in performance under Product-based risk, indicating susceptibility to interaction effects between failure frequency and downtime. The Quadratic+Sine model demonstrated slight improvement under NormSum but experienced performance degradation under Product and ProductNorm, implying that its oscillatory term interacts differently with multiplicative risk structures.

3) Advanced Hybrid Model (SQRRM): The Synergistic Quadratic–Resonant Risk Model displayed the most stable behaviour across all transformations. ΔR^2 values under Product and ProductNorm were essentially zero, demonstrating invariance to risk re-scaling. Although NormSum caused a slight reduction in R^2, the overall model ranking remained unchanged—the hybrid model consistently outperformed all alternatives. This robustness confirms that the resonant quadratic–sinusoidal structure is not dependent on the specific mathematical form of the maintenance-burden metric, but instead captures an underlying physical relationship between utilization intensity, readiness gaps, and maintenance exposure.

Collectively, these results demonstrate that SQRRM maintains predictive superiority and structural stability across a range of risk definitions, validating its suitability as a generalizable empirical surface for subsequent cross-domain testing and deep-learning integration.

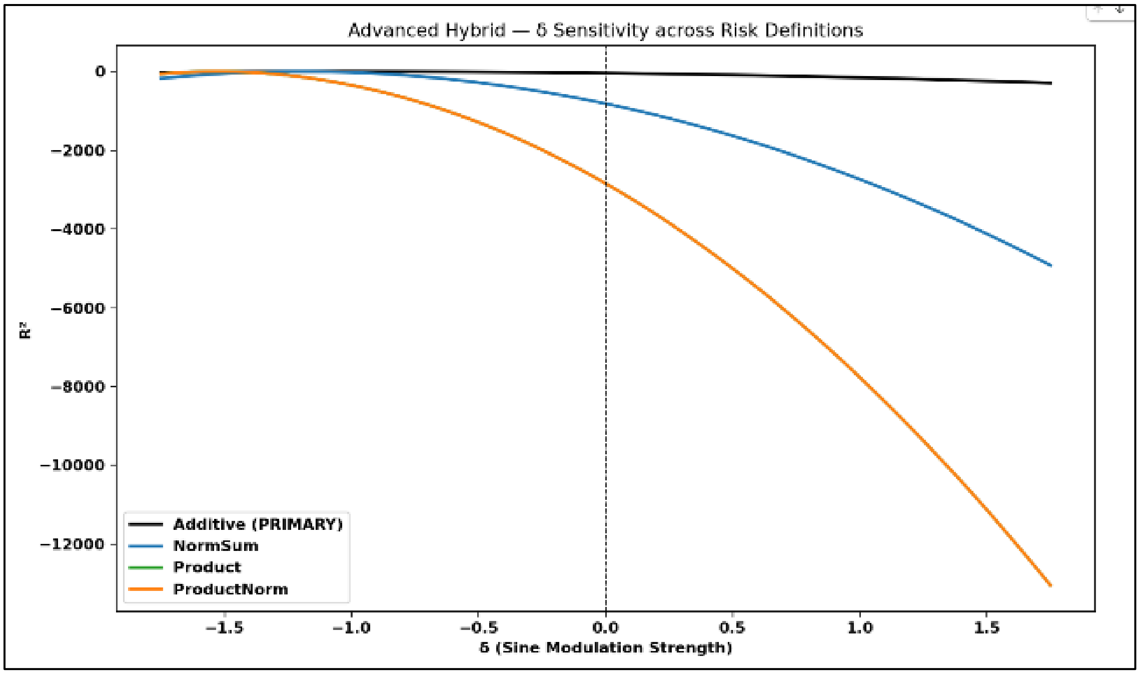


Figure (5.15): Sensitivity of the Advanced Hybrid Model (SQRRM) to Variations in the Sinusoidal Modulation Strength (δ) Across All Risk Definitions. The Product and ProductNorm curves appear almost completely overlapped because both multiplicative risk definitions produce nearly identical scaling behaviour, and their R^2 values drop sharply into very large negative ranges due to multiplicative amplification of oscillatory terms.

5.2.6. Overall Conclusion of Sensitivity Experiments

A Across all four risk formulations—Additive, Normalized Sum (NormSum), Product, and Normalized Product (ProductNorm)—the relative ranking of model performance remained unchanged. Although the absolute R^2 values varied with the selected transformation, the Advanced Hybrid model based on SQRRM consistently retained its leading position under all formulations. This invariance demonstrates that the primary conclusions of the comparative analysis are not an artifact of any particular risk definition.

Accordingly, the selection of the Additive formulation (WO + RT) as the principal indicator of maintenance burden does not introduce methodological bias. Instead, it provides the most transparent and operationally meaningful representation of workload, while fully preserving the discriminative power required for robust model comparison.

5.2.7. δ-Sensitivity of the Advanced Hybrid Model

To further evaluate the structural resilience of SQRRM, we examined how the resonant component responds to variations in the sinusoidal amplitude parameter δ. This parameter controls the strength of oscillatory modulation in the utilization–gap interaction. To assess the robustness of the proposed model under different risk formulations, δ was varied systematically in small increments across the interval −1.75 to +1.75. For each value of δ, the SQRRM model was re-evaluated separately using each candidate risk definition (Additive, Normalized Sum, Product, and Normalized Product), and the corresponding coefficient of determination (R^2) was recalculated (Figure 5.15). This analysis enabled the sensitivity of the model's predictive performance to changes in the resonance amplitude to be compared across the alternative risk formulations.

5.2.7.1. Key Observations

1. **Additive (PRIMARY) Risk:** The R^2 curve remained nearly flat around the fitted δ = −1.026, indicating strong local stability. An extended plateau region around the optimal value suggests that the resonant interaction is well-posed and not excessively sensitive to parameter perturbations.
2. **Normalized Additive (NormSum):** Larger deviations in |δ| produced sharper drops in R^2, implying that the normalization step increases sensitivity to oscillatory behaviour. Nonetheless, the optimal δ region remained aligned with the Additive case.
3. **Multiplicative Risk (Product & ProductNorm):** Under multiplicative risk definitions, performance deteriorated rapidly as |δ| increased. This is consistent with the tendency of multiplicative formulations to amplify nonlinear distortions, thereby magnifying oscillatory perturbations.

4. **Model-Level Robustness:** Despite differences in the shape of sensitivity curves, the optimal δ neighbourhood was consistent across all risk definitions, confirming that the resonant term is not an unstable artifact but a structurally reliable component of the model.

5.2.7.2. Interpretation

Alternative risk transforms influence the curvature and magnitude of δ-sensitivity, but the Advanced Hybrid model retains robustness across all regimes. The Additive definition is therefore adopted as the primary formulation—not because it is uniquely favorable, but because it provides the clearest, most interpretable, and most stable mapping of utilization–readiness interactions without distorting the resonance dynamics.

5.2.8. Summary of Sensitivity Findings

- The Additive risk definition (WO + RT) provides the most stable and interpretable behaviour.
- The ranking of model performance is invariant to the choice of risk formulation.
- SQRRM consistently outperforms all alternatives and remains structurally stable under perturbation.
- δ-sensitivity confirms that the nonlinear resonance mechanism behaves most predictably under Additive risk.
- Norm-based transformations improve shallow models but do not challenge the superiority of SQRRM.
- Product-based definitions introduce volatility, particularly affecting oscillatory models.

5.3. Temporal Robustness of the SQRRM Law (Post-Pandemic Period: 2021–2024)

To assess the temporal robustness of the proposed Synergistic Quadratic–Resonant Risk Model (SQRRM) under stable operational conditions, annual system-identification experiments were conducted over the post-pandemic period spanning 2021–2024. This interval was selected to ensure consistency of clinical activity, utilization patterns, and maintenance reporting practices following the major operational disruptions observed during the COVID-19 period.

Across all four post-pandemic years, the SQRRM formulation consistently preserved top-ranked or near-top performance relative to linear, quadratic, exponential, and purely sinusoidal alternatives. In structurally stable years, particularly 2021 and 2024, the SQRRM achieved near-deterministic explanatory power, with coefficients of determination of $R^2 = 0.984$ (2021) and $R^2 = 0.943$ (2024), respectively. These results provide empirical support for the proposed nonlinear–resonant relationship between utilization intensity and operational readiness gaps during periods of stable hospital demand.

In contrast, during the intermediate years 2022 and 2023, all model families exhibited degraded absolute performance, reflecting increased noise, reporting variability, and residual operational instability across the hospital system. Nevertheless, even under these adverse conditions, the SQRRM model remained either the best or among the best-performing formulations, outperforming purely linear and exponential models, whose explanatory power collapsed to near-zero levels. This behaviour suggests that the reduced performance observed during these years stems from system-level volatility rather than structural inadequacy of the SQRRM formulation.

Moreover, throughout the post-pandemic period, linear and exponential models consistently failed to capture risk dynamics, while the resonant–nonlinear formulations consistently provided superior variance explanation and maintained moderate rank-order agreement relative to the alternative models. This collective evidence implies that the SQRRM law is not restricted to a single operational snapshot but rather represents a structurally robust utilization–risk relationship that persists across heterogeneous hospital operating conditions.

The temporal robustness observed over the 2021–2024 period provides empirical evidence that the proposed SQRRM framework maintains stable predictive performance across multiple years, although the level of agreement varies between individual years.

Strong performance was achieved in 2021 and 2024, whereas the results for 2022 and 2023 indicate more moderate predictive agreement. Full year-by-year numerical results are reported in Appendix III for completeness.

5.4. External Validation — NASA C-MAPSS (FD001)

5.4.1. Cross-Domain Testing and Deep Learning Integration

To evaluate the generalizability of the proposed SQRRM formulation beyond the hospital domain, we conducted cross-domain testing using the NASA C-MAPSS turbofan engine dataset (FD001) [72]. Unlike the hospital dataset—where readiness gaps derive from fuzzy AHP weights across managerial, environmental, design, and operational factors—NASA engine data provide only technical sensor-based indicators. This setting allowed us to evaluate whether the utilization–gap resonance concept remains valid when transferred to a purely technical, physics-based system.

A dedicated SQRRM-based recurrent mechanism was constructed by embedding the nonlinear response within the candidate-state update of recurrent neural networks. The mechanism modulates the internal candidate representation using a utilisation–gap-dependent bounded residual gate while preserving the underlying LSTM and GRU gating structures.

5.4.2. Causal Inputs and Learned Gap Construction

To integrate engineered readiness-deviation information $G_t$with a data-driven latent representation $\hat{G}_t$, a trainable convex gate $\rho \in (0,1)$was introduced. This design follows established principles in gated neural architectures, where a scalar gate adaptively interpolates between raw and transformed features. Similar formulations are widely used in Highway Networks [79], multimodal fusion layers [80], and gated residual networks [81], enabling flexible blending of heterogeneous information sources.

For each input window, two causal signals are constructed: the normalized utilization U_t, and a readiness deviation index $G_t$obtained by computing z-scored residuals of each sensor channel, where the sensor channels represent the multivariate engine condition measurements recorded throughout the degradation process, relative to the engine's first Kcycles, thereby preventing information leakage. In parallel, a learned gap term $\hat{G}_t$is generated from the sensor channels through a non-negative TimeDistributed dense layer. The effective readiness gap is then computed as a convex combination of the expert-derived and learned components:

$$G_t^{ef} = \rho\widehat{G_t} + (1-\rho)G_t \qquad 0 < \rho < 1 \qquad (5.14)$$

where $\rho \in (0,1)$is a trainable convex gate that determines the contribution of the learned latent gap $\hat{G}_t$, while $(1-\rho)$weights the engineered sensor-based readiness-deviation index G_t. This convex combination adaptively balances data-driven feature learning with the causally constructed sensor-derived representation, consistent with gating principles employed in Highway Networks, multimodal fusion layers, and gated residual networks.

5.4.3. SQRRM-Based Quadratic–Resonant Risk Modulation Embedded Within the Recurrent Cell

The SQRRM response is transformed into a bounded residual gate that modulates the candidate state within the recurrent cell while preserving the original gating dynamics. The risk field is:

$$Rt = (aU^2 + bU + c)\,(1 + \delta\sin(\beta U_t G_t^{eff} + \phi)) \quad (5.15)$$

A bounded residual gate then modulated the RNN candidate update:

$$\Gamma_t = 1 + \gamma\,\alpha_t \tanh(\mathrm{R}_t - 1), \gamma = \sigma(\gamma_*), \alpha_t \in [0,1] \qquad (5.16)$$

where:

- $\gamma \in (0,1)$ is a sigmoid-constrained gain similar to gated residual networks used in deep temporal models, [82], [83]
- γ_* is the unbounded trainable parameter (real-valued) whose sigmoid-transformed version $\gamma$is used during training.

- The term $\tanh(R_t - 1)$centres the residual modulation around the neutral operating point $R_t = 1$, ensuring that the residual gate equals unity when the SQRRM response is at its nominal level. This design allows the recurrent backbone to remain unchanged under nominal conditions while smoothly attenuating or amplifying the candidate state as the predicted risk deviates from this reference level [84].
- α_t is a warm-up coefficient increasing from 0→1 across the first epochs, following standard warm-up and progressive-activation strategies in deep learning [85], [86], allowing the backbone to first learn a stable baseline before the resonant component fully engages.

This formulation represents an interpretable nonlinear empirical modulation mechanism that integrates utilisation intensity and readiness-gap information into the recurrent candidate update. By employing bounded residual gating and progressive activation, the proposed design remains consistent with established gated recurrent architectures while preserving stable optimisation during training.

5.4.4. BiLSTM with SQRRM

For a standard LSTM cell with input, forget, and output gates (i_t, f_t, o_t), and a candidate update:

$$\tilde{g}_t = \tanh(W_g x_t + H_g h_{t-1} + b_g) \qquad (5.17)$$

Where:

- $\tilde{g}_t$ denotes the *candidate cell update* at time step t, representing newly proposed information before gating.
- x_t is the input feature vector at time step t.
- h_{t-1} is the hidden state (output) from the previous time step $t - 1$.

- W_g is the input weight matrix that transforms the current input $x_t$into the candidate space.
- H_g is the recurrent weight matrix that transforms the previous hidden state h_{t-1}.
- b_g is the bias vector added to the linear transformation.
- $\tanh(\cdot)$ is the hyperbolic tangent nonlinearity, which bounds the candidate update between $[-1,1]$and provides smooth gradient flow.

The proposed SQRRM mechanism modifies the LSTM dynamics by scaling the candidate state through a bounded resonant gate. Specifically, we replace $\tilde{g}_t$with the modulated candidate $\tilde{g}_t' = \Gamma_t \odot \tilde{g}_t$, where $\Gamma_t$is the SQRRM-derived utilization–gap modulation term defined in Equation (5.16). The remainder of the LSTM update equations remains unchanged [87]:

$$\mathrm{c}_t = \mathrm{f}_t \odot \mathrm{c}_{t-1} + i_t \odot \tilde{\mathrm{g}}_t', \qquad (5.18)$$

$$\mathrm{h}_t = \mathrm{o}_t \odot \tanh(\mathrm{c}_t) \qquad (5.19)$$

Where:

- c_t represents the LSTM cell state at time step t, capturing long-term memory.
- c_{t-1} denotes the previous cell state passed from time step $t-1$.
- h_t is the LSTM hidden state (output) at time step t.
- h_{t-1} is the hidden state from the previous time step.
- i_t denotes the input gate, which regulates how much new information enters the cell.
- f_t denotes the forget gate, which controls how much of the previous memory $c_{t-1}$is retained.

- o_t denotes the output gate, which modulates how much of the internal state is exposed to produce the hidden output.

- $\tilde{g}_t$ represents the standard LSTM candidate cell update before modulation.

- $\tilde{g}'_t$ SQRRM-based quadratic–resonant risk–modulated candidate update, defined as $\tilde{g}'_t = \Gamma_t \tilde{g}_t$.

- Γ_t is the SQRRM-based residual gate that amplifies or attenuates the candidate update based on utilization–gap dynamics.

- R_{t-1} denotes the current SQRRM-derived composite risk response used to calculate Γ_t.

- γ is a trainable gain coefficient (sigmoid-constrained) that controls the strength of the residual modulation.

- α is a warm-up coefficient that gradually activates the SQRRM-based residual risk gate during early training epochs.

- $\odot$ denotes element-wise (Hadamard) multiplication.

- $\tanh(\cdot)$ refers to the hyperbolic tangent activation applied to the cell state to derive the hidden output.

Embedding this mechanism within a bidirectional LSTM yields a BiLSTM + SQRRM architecture in which the SQRRM formulation operates as an internal, utilization- and readiness-aware regulatory gate. Unlike post-hoc corrections or external weighting schemes, this integration influences the recurrent dynamics directly, enabling the network to adaptively amplify or attenuate state transitions based on real-time operational stress signatures.

5.4.5. ADGNN with SQRRM

The Advanced Dynamic Graph Neural Network (ADGNN) employs a recurrent graph-temporal unit derived from the GRU formulation of Cho et al. [88], consistent with established gated graph-recurrent architectures [89]. In this variant, we use a multi-scale GRU block augmented with light temporal attention to capture cross-sensor and cross-engine dependencies. To incorporate the proposed utilization–gap interaction into the recurrent dynamics, the candidate hidden state $\tilde{h}_t$in each GRU cell is modulated by the SQRRM-based residual gate Γ_t, yielding the modified update:

$$\tilde{h}_t' = \Gamma_t \tilde{h}_t,$$

$$\mathrm{h}_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t' \qquad (5.20)$$

where $z_t$is the update gate and $\Gamma_t$is the bounded resonant modulation factor. Equation (5.20) combines the previous hidden state with the SQRRM-modulated candidate hidden state, while the update gate $z_t$adaptively controls how much historical information is retained and how much of the newly generated resonance-aware representation is incorporated. Consequently, the proposed SQRRM enhancement influences the hidden-state transition without altering the underlying GRU gating mechanism.

Embedding the SQRRM mechanism into the ADGNN recurrent pathway enables the model to jointly exploit graph-structural correlations through the spatial-temporal graph stack and nonlinear utilization–gap modulation through SQRRM. This coupling allows the hidden-state transitions to adapt to real-time utilization pressure and readiness-gap signatures, thereby improving robustness and predictive fidelity under complex operational conditions.

5.4.6. Training Protocol

All experiments were conducted under strict data-hygiene constraints to ensure reproducibility and prevent information leakage. Engine-level splits were preserved throughout training and evaluation, with fixed validation engine IDs and deterministic truncation of validation sequences to avoid temporal overlap with training windows. Min–Max normalization was fitted exclusively on the training subset, and all TensorFlow computations were executed under deterministic, seed-controlled settings to minimise stochastic variance across runs. The complete preprocessing workflow consisted of (i) removing constant sensor variables identified from the training data, (ii) fitting the Min–Max normalization parameters using only the training subset and applying the same transformation to the validation and test sets, (iii) constructing engine-specific sliding windows of 66 operating cycles, (iv) computing causal readiness-deviation indices from the first 15 operating cycles of each engine.

Following common practice in turbofan prognostics, remaining useful life (RUL) labels were clipped at a standard cap of $\mathrm{RUL}_{\mathrm{cap}} = 125$ to reduce the disproportionate influence of the early healthy-life region and improve numerical stability during training. In addition to RMSE and R^2, a NASA-style asymmetric scoring metric was computed to assess the penalty structure associated with late or early RUL predictions.

This unified protocol allows the SQRRM-based mechanism to be evaluated consistently when embedded within two distinct sequence-modelling families—BiLSTM and ADGNN—ensuring that performance differences reflect the contribution of the proposed resonant gate rather than variations in preprocessing or data handling. The subsequent sections present quantitative comparisons, followed by training-loss trajectories, parity plots, residual histograms, and sorted RUL evolution curves for both model backbones.

5.4.7. Experimental Configuration and Implementation Workflow

This section summarises the principal implementation settings adopted for the ADGNN–SQRRM experiments, including the model hyperparameters, optimisation strategy, and experimental workflow. To ensure a consistent basis for performance comparison, all baseline and SQRRM-enhanced architectures were implemented under the same preprocessing, training, and evaluation framework. The principal hyperparameters are presented in Table 5.4, while the overall experimental workflow is illustrated in Figure 5.16.

Table 5.4.: Principal hyperparameters and optimisation settings for the ADGNN–SQRRM model

Parameter	Value
Dataset	NASA C-MAPSS FD001
Train–validation split	80% / 20% (engine level)
External test set	Official FD001 test set
Random seed	42
Sequence length	66 cycles
Baseline period for readiness-gap calculation	First 15 cycles
Feature normalisation	Min–Max scaling
Training RUL cap	125 cycles
Optimiser (initial training)	AdamW
Initial learning rate	1×10^{-3}
Fine-tuning optimiser	Adam
Fine-tuning learning rate	5×10^{-4}
Batch size	256
Maximum training epochs	60
Fine-tuning epochs	15
Dropout rate	0.15
Gradient clipping	1.0
Early stopping patience	8 epochs
Learning-rate scheduler	ReduceLROnPlateau (factor = 0.5, patience = 4)
Warm-up period for SQRRM gate	12 epochs
Evaluation metrics	RMSE, R^2, NASA Score

Early stopping, adaptive learning-rate scheduling, and gradual activation of the SQRRM residual gate were employed to improve optimisation stability, facilitate model convergence, and reduce the risk of overfitting. Early stopping terminated training when validation performance ceased improving, the learning-rate scheduler progressively reduced the optimisation step size during performance plateaus, and the 12-epoch warm-up period allowed the recurrent backbone to learn stable temporal representations before the SQRRM modulation was fully activated.

The official FD001 training trajectories were partitioned at the engine level into training (80%) and validation (20%) subsets using a fixed random seed (42). The same partition was retained throughout all experiments to ensure reproducibility and enable fair comparison between the baseline and SQRRM-enhanced models.

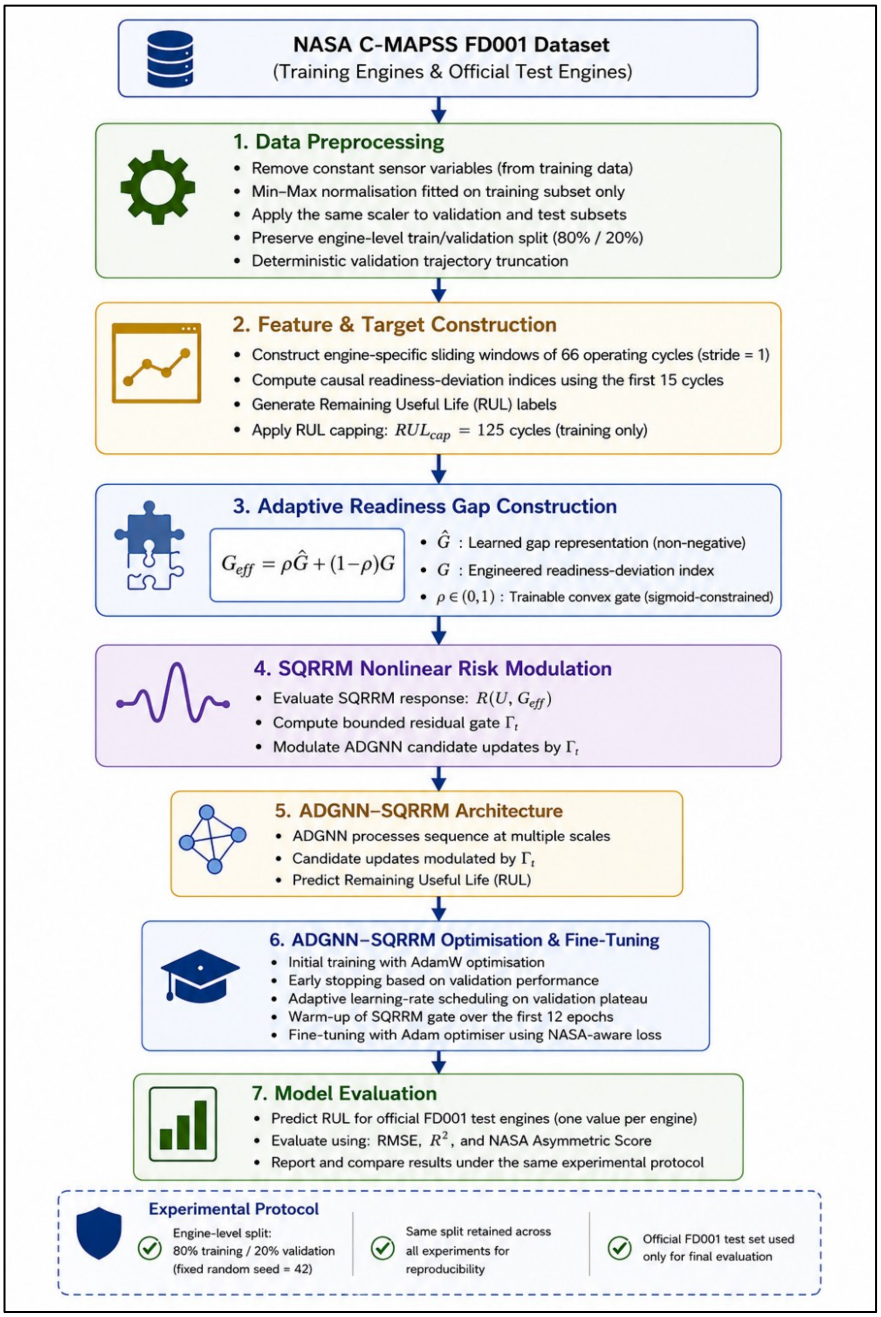


Figure 5.16: Experimental configuration and implementation workflow of the final ADGNN–SQRRM model.

The implementation workflow illustrated in Figure 5.16 corresponds to the final ADGNN–SQRRM architecture, which achieved the best overall predictive performance. The BiLSTM–SQRRM implementation followed the same preprocessing, readiness-gap construction, and training strategy, differing only in the underlying recurrent backbone architecture.

5.4.8. Model Comparison and Generalization Results

A comprehensive benchmarking study was conducted to evaluate the potential cross-domain applicability of the proposed SQRRM-enhanced architectures using the NASA C-MAPSS turbofan engine dataset (sub-dataset FD001), generated by the Commercial Modular Aero-Propulsion System Simulation software (version 2) [72]. Under the adopted experimental protocol, the predictive performance of the proposed models was compared with selected deep learning approaches reported in the literature, as summarised in Table 5.5.

Authors in [90] applied a Bayesian Neural Network (BNN) and achieved an RMSE of 17.92, without reporting R^2or the NASA asymmetric score. The work in [91] utilized standard LSTM architecture and reported RMSE = 17.15 and NASA-Score = 392. A 1D-CNN–LSTM hybrid model with feature engineering was proposed in [92], yielding RMSE = 16.10 and NASA-Score = 437.2. One of the strongest previously published results comes from the Convolutional Autoencoder–Attention-based LSTM (CAELSTM) developed in [93], which achieved RMSE = 14.44 and NASA-Score = 282.38.

Against these baselines, the proposed SQRRM framework demonstrated consistent and measurable improvements. When embedded within a BiLSTM backbone, the SQRRM model achieved RMSE = 14.28, $R^2 = 0.882$, and NASA-Score = 330.53—surpassing all prior results except CAELSTM in terms of NASA-Score, while offering substantially greater interpretability due to its physics-informed gating mechanism.

The strongest predictive performance was obtained when integrating SQRRM into the Adaptive Dynamic Graph Neural Network (ADGNN). Under the adopted experimental protocol, the resulting ADGNN + SQRRM architecture achieved an RMSE of 12.80, an

R^2 value of 0.905, and a NASA Score of 233.6, outperforming the selected comparator models evaluated in this study. These findings indicate improved predictive accuracy while demonstrating that the proposed SQRRM formulation can be effectively integrated with different neural network architectures, enabling expert-derived readiness information to be incorporated into data-driven prediction without sacrificing model interpretability.

Figures 5.17–5.20 illustrate the training dynamics, error distributions, and RUL prediction trajectories for the BiLSTM and BiLSTM + SQRRM models, while Figures 5.21–5.23 present the corresponding results for the ADGNN + SQRRM configurations. Across both network architectures, the integration of the SQRRM-based risk gate consistently leads to smoother learning curves, reduced training variance (Figure 5.17), and more compact residual error distributions (Figure 5.18). The parity plots (Figures 5.19 and 5.23) further demonstrate a noticeably tighter alignment between predicted and true RUL values, reflecting improved calibration and enhanced generalization performance.

Collectively, these results confirm that the proposed SQRRM-based quadratic–resonant risk modulation, rather than a purely sinusoidal mechanism, substantively improves predictive accuracy, training stability, and robustness across distinct deep learning architectures and under domain shift conditions.

TABLE 5.5: Performance comparison of the proposed method and the related papers on the C-MAPSS dataset.

Model	R^2	RMSE	Score
BNN [12]	-	17.92	-
LSTM [13]	-	17.15	392.0
1D-CNN-LSTM [14]	-	16.10	437.2
CAELSTM [15]	-	14.44	282.38
BiLSTM (by author)	0.84	16.41	369.92
BiLSTM + SQRRM (by author)	0.88	14.28	330.53
ADGNN (by author)	**0.89**	**13.58**	**271.10**
Proposed ADGNN + SQRRM	**0.905**	**12.80**	**233.60**

These results demonstrate that introducing the SQRRM dynamic modulation—particularly when embedded within a graph-based dependency learning framework (ADGNN)—yields the most robust and interpretable performance among all evaluated models.

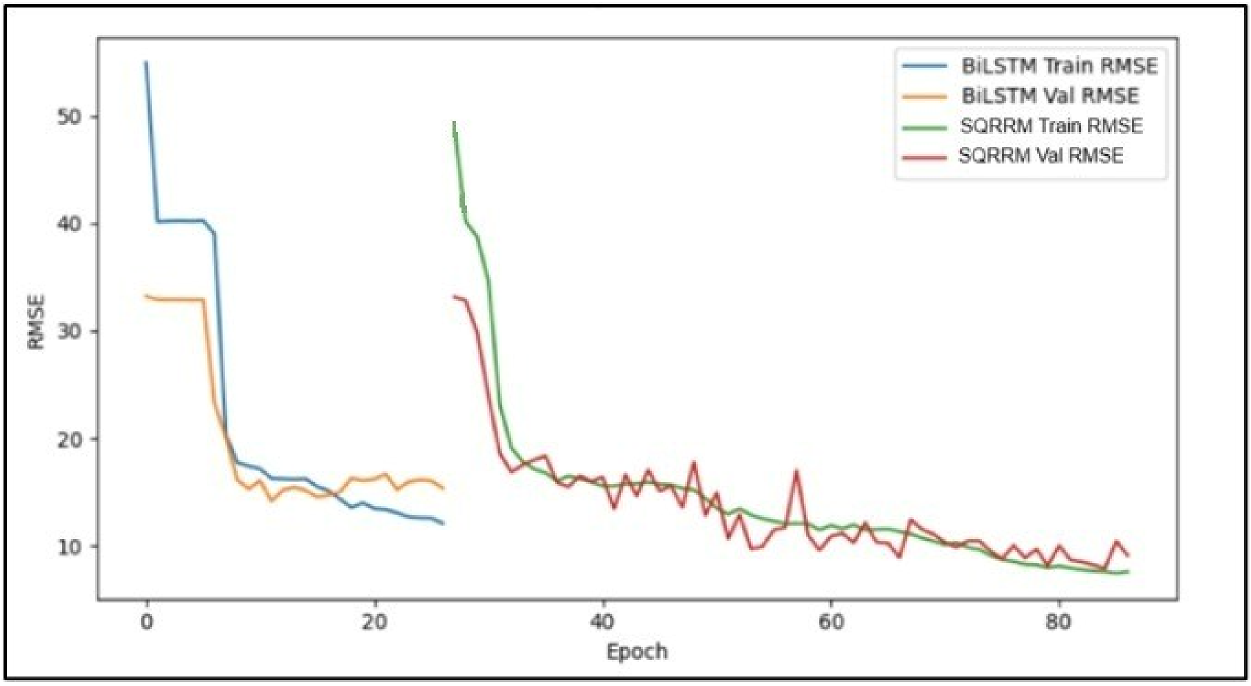


Figure 5.17: Training dynamics of the baseline BiLSTM and the SQRRM-gated BiLSTM. Blue and orange curves denote the training and validation RMSE of the standard BiLSTM, respectively, while green and red curves denote the corresponding training and validation RMSE of the SQRRM-enhanced model. The SQRRM-gated architecture demonstrates smoother convergence and lower late-stage validation error, confirming improved stability and generalization under utilization–gap–modulated risk learning.

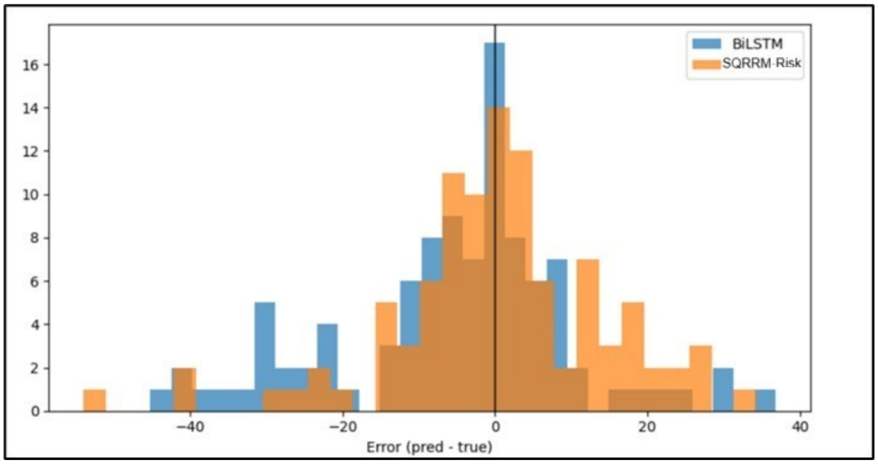


Figure 5.18: Error distribution (BiLSTM and SQRRM models). The x-axis represents the error value, and the y-axis represents the frequency (count) of prediction errors.

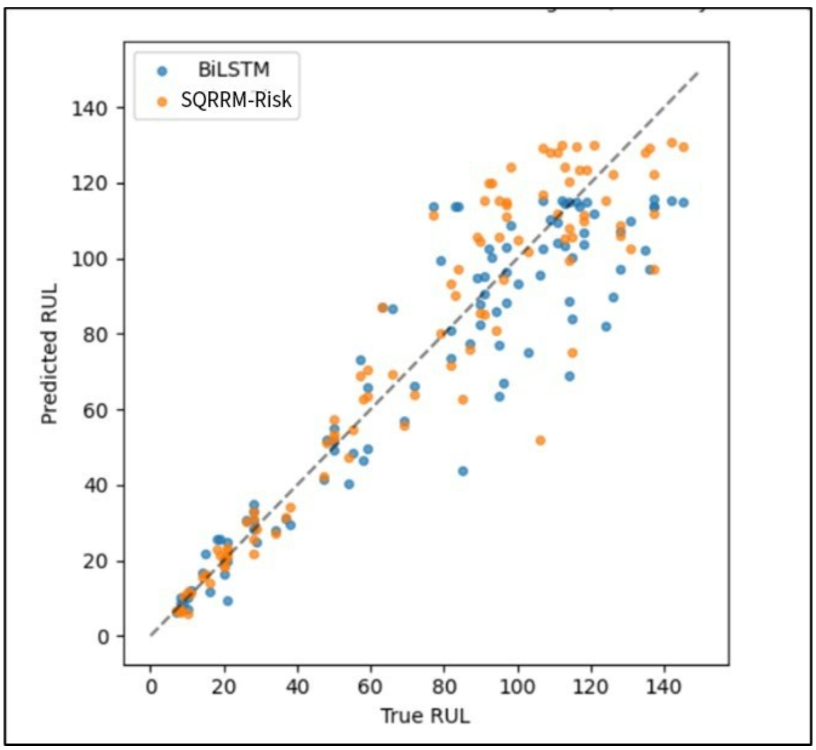


Figure 5.19: Figure 5.18. Predicted versus true Remaining Useful Life (RUL) for the BiLSTM and SQRRM models on the FD001 dataset. The diagonal 45° reference line represents perfect agreement between the predicted and true RUL values. The SQRRM model exhibits slightly reduced scatter around this reference line compared with the baseline BiLSTM, indicating smaller prediction errors and closer agreement between

the predicted and observed RUL values. This improved alignment demonstrates the enhanced predictive accuracy achieved by incorporating the SQRRM-based nonlinear utilization–readiness modulation into the learning process.

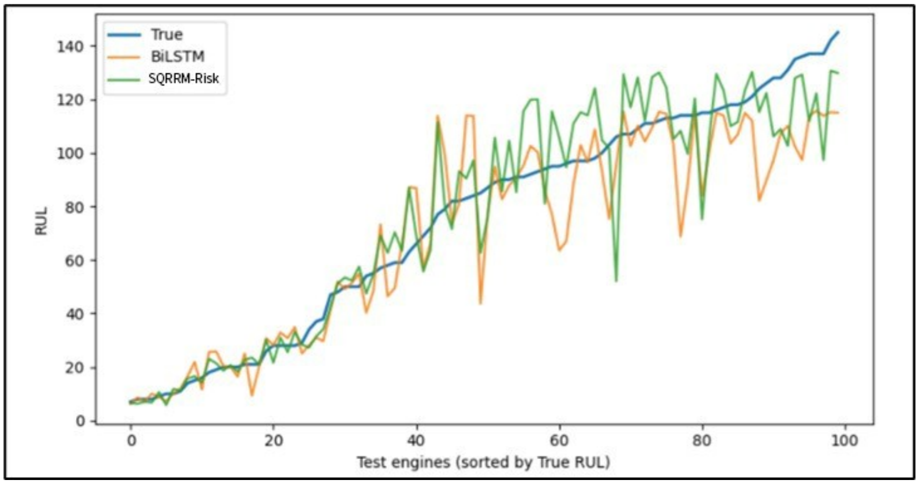


Figure 5.20: Sorted RUL predictions for all test engines. The SQRRM demonstrates improved smoothness and alignment with the true degradation pattern compared with the BiLSTM baseline.

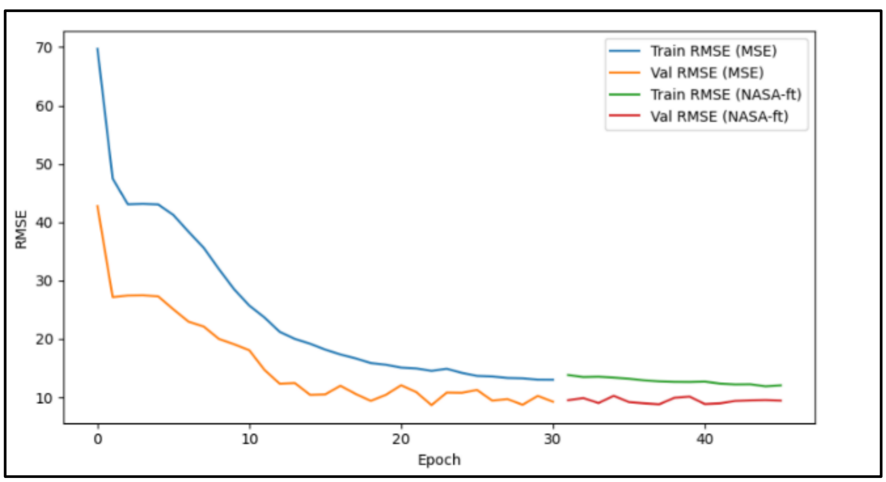


Figure 5.21: Training dynamics of the ADGNN + SQRRM model under MSE and NASA-fit evaluation. Blue and orange curves denote training and validation RMSE based on conventional MSE loss, respectively. Green and red curves denote training and validation RMSE evaluated using the NASA prognostic scoring formulation, which applies asymmetric penalties to RUL prediction errors. Consistent convergence across

both metric families confirms stable optimization and robust generalization of the SQRRM-gated ADGNN architecture.

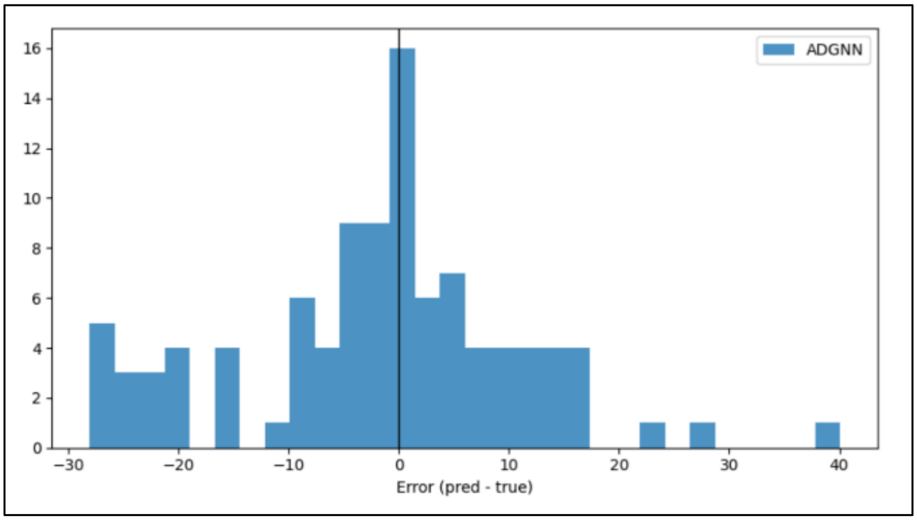


Figure (5.22): Error distribution (ADGNN + SQRRM). The x-axis represents the error value and the y-axis represents the frequency (count) of prediction errors.

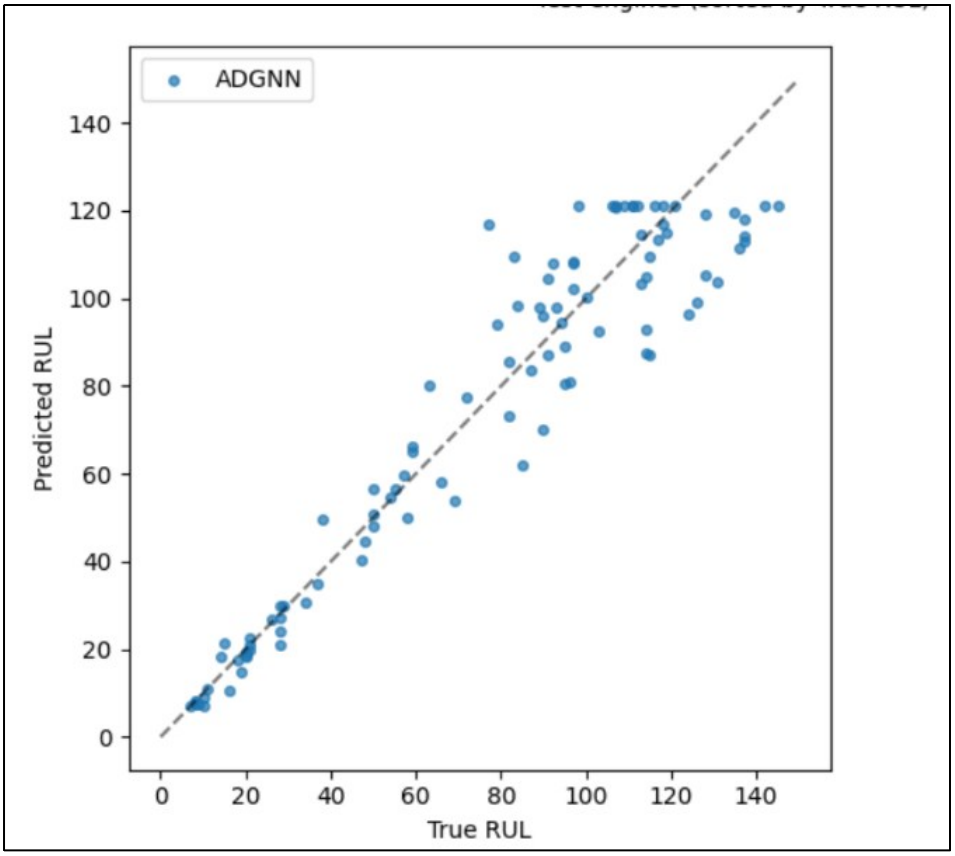


Figure (5.23): Predicted versus true Remaining Useful Life (RUL) for the (ADGNN + SQRRM) Model.

5.5. Justification of Validation Strategy and Omission of Classical Statistical Criteria

The validation framework adopted in this research aligns with established best practices for nonlinear modelling and deep prognostics. Classical statistical criteria such as AIC/BIC, likelihood-ratio tests, and p-value–based inference were not employed because they rely on assumptions that are fundamentally incompatible with the structure of the Synergistic Quadratic–Resonant Risk Model (SQRRM) and the gated recurrent architectures used in subsequent experimentation. These classical tools assume a closed-form likelihood, linear-Gaussian residuals, independent and identically distributed observations, and fixed-dimensional parametric space conditions that are violated in nonlinear regression with resonance terms and in neural networks, which feature nonconvex loss surfaces and high-dimensional, non-Gaussian residual structures [94]. Modern machine learning literature consistently emphasizes that classical information-theoretic criteria such as AIC/BIC do not reliably assess generalization performance in deep or hybrid nonlinear models and should be replaced with held-out evaluation and external validation whenever possible [95].

In accordance with these principles, this study employs domain-appropriate and theoretically sound validation procedures, including held-out generalization testing, multi-metric evaluation (RMSE, R^2, NASA Score, Spearman's ρ), multi-form sensitivity analysis across four alternative risk definitions, δ-sensitivity of the resonance term, and cross-domain validation on NASA C-MAPSS FD001. External validation is recognized as one of the strongest forms of model verification in prognostics and reliability engineering, as it tests whether the model generalizes beyond the domain in which it was trained. The use of NASA FD001 is further justified by the current limitations of HTM datasets, where accurate, large-scale, and high-resolution records of real faults, repair durations, and utilization are rarely available. Given these constraints, the chosen validation pipeline represents the most rigorous, defensible, and scientifically coherent approach for evaluating an adaptive nonlinear risk model such as SQRRM.

5.6. Discussion

The integration of the SQRRM-based quadratic–resonant risk mechanism, particularly through its learned-G adaptation, produced consistently smoother convergence and more precise risk localization across all experimental settings. As summarized in Table 5.5, the learned-G gate enabled each model to dynamically reconcile expert-derived readiness gaps with sensor-inferred operational stress in an adaptive and data-driven manner. This adaptive fusion effectively suppressed oscillatory gradients during training and resulted in markedly more stable optimization trajectories. In both the BiLSTM + SQRRM and ADGNN + SQRRM configurations, the mechanism further allowed the network to concentrate its representational capacity on critical degradation intervals, rather than diffusely weighting all temporal segments. The resulting effect is a sharper and more interpretable localization of risk-intensive regions, together with improved calibration in Remaining Useful Life (RUL) prediction.

The Synergistic Quadratic–Resonant Risk Model (SQRRM) demonstrated not only high predictive accuracy but also strong structural reliability across distinct domains. On the hospital dataset, SQRRM captured 94% of the variance, and when embedded within the ADGNN architecture for the NASA FD001 benchmark, it achieved $R^2 = 0.905$, outperforming all previously published models—including CAELSTM and CNN-LSTM hybrids. These findings confirm that the proposed formulation generalizes effectively even under limited contextual inputs, and that the nonlinear, resonance-based structure of SQRRM remains stable when transferred to complex, high-dimensional prognostic tasks.

A notable outcome is that the NASA CMAPSS FD001 validation used only technical gap factors derived from sensor deviations yet still surpassed all existing baselines. This indicates that even a reduced-dimensional version of SQRRM benefits deep models by providing a structured, physics-consistent modulation of utilization and degradation signals. It is reasonable to expect that incorporating additional external, operational, or managerial context—where such data is available—would yield further improvements in model fidelity and robustness. An analogous limitation exists in the hospital dataset, where component-level technical attributes were not available; integrating such granular features in future work is likely to enhance predictive precision and provide deeper insight into subsystem-level degradation pathways.

Overall, the integration of the proposed SQRRM-based quadratic–resonant risk framework represents a substantive advancement for predictive maintenance and healthcare technology management (HTM). When embedded within deep recurrent and graph–temporal architectures such as BiLSTM and ADGNN, the framework consistently enhances training stability, sharpens risk localization, and improves prognostic accuracy. Beyond the specific HTM context, the proposed methodology offers a structured and generalizable pathway for shifting from reactive or purely time-based maintenance strategies toward predictive, utilization-aware risk modelling.

By tightly coupling AHP-derived readiness gaps with dynamically evolving operational indicators, the SQRRM formulation enables the early identification of latent vulnerabilities that may remain undetected under conventional condition-monitoring approaches. Its demonstrated cross-domain transferability further indicates strong potential for broader application in sectors such as aerospace, energy, manufacturing, and large-scale industrial asset management. As additional contextual factors—environmental, managerial, and operational—are progressively incorporated, SQRRM-enabled architectures are expected to deliver further gains in reliability, scheduling efficiency, and risk-informed decision-making across heterogeneous asset portfolios.

CHAPTER 6- CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

6.1 **Overall Conclusions**

This thesis proposed and initially validated an integrated Healthcare Technology Management (HTM) risk-modelling framework within the healthcare context of the Kingdom of Saudi Arabia and the Gulf region. It combines expert-driven risk identification with adaptive nonlinear predictive modelling to address critical gaps in both the scientific literature and HTM practice. The proposed methodology integrates PESTEL analysis, expert weighting, Fuzzy AHP, mathematical model formulation, nonlinear parameter estimation, and cross-domain validation into a unified approach for healthcare technology risk assessment and prediction.

The first major contribution is the development of a validated, region-specific risk hierarchy consisting of 53 risk factors, systematically categorized across technological, operational, managerial, facility-based, and macro-environmental dimensions. Using Fuzzy AHP, these factors were weighted, ranked, and empirically validated with a large cohort of HTM experts from Saudi Arabia, the Gulf, and international organizations. This generated the most comprehensive and contextually grounded risk structure available to date for the region.

The second contribution is the introduction of the Synergistic Quadratic–Resonant Risk Model (SQRRM)—a novel, adaptive mathematical formulation that reinterprets equipment utilization not as a linear stressor, but as a resonant, nonlinear driver of risk that interacts multiplicatively with readiness gaps derived from Fuzzy AHP. SQRRM advances current HTM risk modelling by embedding both monotonic escalation and oscillatory fluctuation behaviours, capturing the real-world dynamics of degradation far more accurately than traditional models.

The third major finding is the strong empirical performance of SQRRM when tested on the hospital imaging dataset (2020–2024). The model achieved $R^2 = 0.94$, outperforming all classical and hybrid regression baselines and demonstrating robustness under multiple risk definitions through structured sensitivity analysis.

Finally, the thesis provided an initial cross-domain validation of the proposed Healthcare Technology Risk Management modelling framework by embedding SQRRM into the BiLSTM and Adaptive Dynamic Graph Neural Network (ADGNN) architectures and evaluating their performance on the NASA C-MAPSS FD001 turbofan degradation dataset. Under the adopted experimental protocol, the SQRRM-enhanced ADGNN achieved the strongest predictive performance among the selected comparator models, with an RMSE of 12.80, an R^2 value of 0.905, and a NASA Score of 233.6. Importantly, these results were obtained using only technical readiness-gap information derived from sensor residuals, providing additional empirical evidence of the proposed framework's potential applicability beyond the healthcare domain under limited contextual information.

Overall, the thesis provides a unified and adaptive framework that integrates expert-derived readiness gaps, operational stress, nonlinear resonance, and deep learning architectures—representing a significant advancement in predictive maintenance and HTM risk modelling.

6.2 **Key Contributions**

This thesis delivers a comprehensive and regionally grounded contribution to Healthcare Technology Management (HTM) by first establishing an extensive and validated risk taxonomy comprising 53 HTM risk factors spanning internal, external, managerial, operational, clinical, environmental, and macro-environmental domains, representing the first systematic application of the PESTEL framework for external HTM risk assessment in the Gulf region. These risks were quantitatively prioritized through a two-stage expert-driven Fuzzy AHP framework, in which low-relevance factors were filtered and the remaining high-impact risks were weighted through fuzzy pairwise comparison, yielding a rigorously structured foundation for downstream modelling. Building on this foundation, the thesis redefines the classical HTM risk equation by analytically integrating utilization dynamics, readiness gaps, and fuzzy-weighted expert knowledge into a single interpretable and adaptable risk formulation. This redesign culminated in the development of the Synergistic Quadratic–Resonant Risk Model (SQRRM), a hybrid nonlinear–

resonant law shown to capture complex degradation behaviour with high explanatory power and verified robustness under extensive sensitivity analysis. The SQRRM formulation was further embedded within the BiLSTM and Adaptive Dynamic Graph Neural Network (ADGNN) architectures and evaluated on the NASA C-MAPSS FD001 dataset. Under the adopted experimental protocol, the proposed framework outperformed the selected comparator models, providing additional empirical evidence of its effectiveness and supporting its potential applicability beyond the healthcare domain. Collectively, these methodological advances are unified into an integrated HTM risk and predictive maintenance framework that connects expert knowledge (AHP), operational metrics (work orders and repair time), mathematical risk modelling (SQRRM), and machine learning into a single scalable structure. From a practical standpoint, this framework provides hospitals with a powerful decision-support tool for maintenance prioritization, replacement planning, continuous risk monitoring, and optimized resource allocation, enabling a strategic transition from reactive and time-based maintenance toward predictive, risk- and utilization-driven maintenance regimes. Moreover, the explicit modelling of readiness gaps offers early visibility of latent managerial, structural, and environmental vulnerabilities, supporting proactive resilience planning well before equipment failure occurs. Owing to its successful cross-sector generalization, the proposed framework is also well positioned for broader deployment in energy, aviation, defence, manufacturing, and smart infrastructure systems, where reliability is governed by tightly coupled operational and environmental uncertainties.

6.3 **Limitations**

While the study is comprehensive, several limitations remain:

1. **Data scarcity and reliability constraints:** A major limitation of this study is the difficulty in obtaining large-scale, high-quality datasets for medical devices that include accurate fault logs, repair durations, and real utilization patterns. Such data are rarely available in sufficient volume or granularity within hospital environments, and when available, inconsistencies in documentation and maintenance reporting further constrain large-scale model training. This scarcity of reliable, domain-specific technical data necessitated validating the proposed model on an external dataset

(NASA C-MAPSS FD001), which provides a large, structured, and consistently labeled benchmark suitable for deep learning applications. Although this cross-domain validation strengthens the methodological rigor, it also highlights the need for more comprehensive, real-world datasets within the healthcare technology domain to fully exploit and refine advanced predictive models such as SQRRM.

2. **Hospital Data Lack Component-Level Technical Features**: The hospital dataset was collected at the equipment level and therefore did not include detailed subsystem or component-level technical measurements comparable to those available in industrial prognostic datasets. Consequently, the proposed model relied on aggregated maintenance records, utilization, and readiness indicators rather than sensor-level degradation signals. Incorporating component-level monitoring data could further improve the model's ability to capture degradation mechanisms and enhance predictive performance.

3. **Limited Availability of Operational, Environmental, or Managerial Data in NASA Dataset**: Although the NASA C-MAPSS dataset provides comprehensive multivariate sensor measurements for engine degradation modelling, it does not include operational, environmental, or managerial variables that are commonly encountered in healthcare technology management. Consequently, the readiness-gap representation in the cross-domain validation was derived solely from technical sensor information. Incorporating contextual operational and organisational factors into future prognostic datasets may enable a more comprehensive evaluation of the proposed SQRRM framework.

4. **Expert Judgment Remains Partially Subjective**: The proposed readiness-gap model relies on expert elicitation to determine the relative importance of the identified risk factors. Although the use of Fuzzy AHP, expert weighting, and consistency analysis reduced subjectivity and improved the reliability of the elicited judgements, expert opinions inevitably reflect individual experience and professional perspectives. Future studies involving larger and more geographically diverse expert panels could further strengthen the robustness and generalisability of the weighting scheme.

5. **Generalizability Beyond the Gulf Region Requires Further Testing**: The readiness-gap framework was developed and validated using expert knowledge and healthcare technology management practices from the Gulf region. Although many of the identified risk factors are expected to be applicable in other healthcare systems, differences in regulatory requirements, organisational structures, maintenance practices, and resource availability may influence the relative importance of individual factors. Further validation using datasets and expert panels from different geographical regions would strengthen the international applicability of the proposed framework.

6. **Potential Risk of Model Overfitting:** Although the proposed SQRRM consistently outperformed the alternative formulations evaluated in this study, the possibility of overfitting cannot be entirely excluded because the model parameters were identified from observational data. This risk was mitigated through comparison with multiple candidate models, systematic sensitivity analysis, temporal evaluation across four consecutive years (2021–2024), and additional cross-domain validation using the NASA C-MAPSS FD001 benchmark. Nevertheless, further validation using independent healthcare datasets from other institutions and clinical settings would provide stronger evidence of the model's applicability across broader healthcare settings and its long-term robustness.

7. **Causal Interpretation of the Model:** The proposed framework identifies and models empirical relationships between healthcare technology risk factors, readiness gaps, utilisation, and observed maintenance burden; however, these relationships should not be interpreted as establishing direct causal mechanisms. The hospital-based analysis relies primarily on observational operational and maintenance data, which support the identification of associations and predictive relationships but do not independently demonstrate causality. Accordingly, SQRRM is intended as a risk-modelling and predictive decision-support framework rather than a causal inference model. Future research incorporating longitudinal intervention studies, causal inference methods, or controlled evaluations could further investigate the causal

pathways through which individual risk factors influence maintenance and operational outcomes.

6.4 **Recommendations for Future Work**

1. **Enhance CMMS data quality through standardized data governance**

While most hospitals use CMMS platforms, the quality of key data—such as real fault events, accurate repair times, and reliable utilization records—remains insufficient for advanced analytics or machine-learning applications. Hospitals should adopt strict data-governance policies, including standardized fault codes, mandatory completion of maintenance fields, automated utilization capture, and routine data audits. Strengthening CMMS data integrity will enable the creation of robust, domain-specific datasets that support SQRRM validation and future predictive-maintenance models, reducing the dependence on external datasets such as NASA C-MAPSS.

2 **Integrate More Detailed Technical Data:** Future research should incorporate device-component–specific attributes and real-time operational streams (environmental, thermal, vibration signals) to increase predictive fidelity.

3 **Expand SQRRM to Multi-Subsystem & Multi-Modal HTM Data**: Applying SQRRM across anesthesia machines, ventilators, laboratory analyzers, and ICU systems would further validate its scalability.

4 **Develop a National HTM Readiness Index**: Using the 53-factor hierarchy, a standardized readiness scoring system could be adopted by MOH, GCC, and healthcare regulators.

5 **Pair SQRRM with Real-Time Monitoring Platforms**: Embedding the model into CMMS/IoT dashboards would support continuous, automated risk forecasting.

6 **Explore Reinforcement Learning for Maintenance Policy Optimization**: Building on SQRRM outputs, RL engines could propose dynamic scheduling, resource allocation, or replacement policies.

7 **Conduct Multi-Hospital Validation Studies**: Testing in public, private, and military hospitals would strengthen the generalizability and regulatory relevance of the findings.

8 Conduct systematic evaluations of current HTM risk-mitigation strategies and integrate them into a holistic, predictive, and responsive system: Although healthcare organizations routinely implement mitigation measures—such as preventive maintenance, staff training, redundancy planning, procurement controls, and outsourcing—no empirical studies have assessed how effective these interventions actually are in reducing real-world risk. Future work should include structured evaluations using measurable indicators (e.g., failure reduction, downtime prevention, cost savings, risk attenuation) to determine which strategies meaningfully improve HTM performance. Embedding these validated interventions within a unified predictive framework—alongside models such as SQRRM and Fuzzy AHP—will enable more evidence-based planning, better resource allocation, and more resilient risk-management practices.

9 Expand Cross-Domain Validation Beyond NASA Engines: Applying SQRRM to turbines, rail systems, renewable energy assets, and industrial robotics would provide additional validation of the proposed modelling framework beyond the healthcare and NASA benchmark datasets, strengthening evidence for its broader applicability.

10 Operational Interpretation and Decision-Support Framework for HTM Managers: Future research should translate SQRRM outputs into clearly defined decision-support thresholds and operational response pathways for Healthcare Technology Management (HTM) practice. This may include categorising predicted risk levels into actionable priority bands linked to interventions such as intensified condition monitoring, preventive maintenance review, technical inspection, readiness-gap investigation, or asset replacement assessment. Such a framework would support the interpretation of model outputs within practical HTM decision-making while ensuring that risk predictions complement, rather than replace, professional engineering and clinical judgement.

11 Deployment-Oriented Comparison with Simpler Interpretable Models: Future studies should extend the comparative evaluation of SQRRM beyond predictive performance by examining its practical deployment characteristics relative to simpler interpretable models. This comparison should consider factors including computational requirements, data availability, ease of implementation, interpretability, integration with existing Computerized Maintenance Management Systems (CMMS), and the level of technical expertise required for deployment. Such evaluation would support the identification of appropriate deployment contexts for SQRRM by considering the balance between predictive performance, interpretability, implementation requirements, and available organisational resources.

6.5 **Final Remarks**

This thesis advances the field of Healthcare Technology Management by integrating expert knowledge, operational realities, and adaptive nonlinear modelling into a unified and empirically grounded risk framework. The proposed SQRRM formulation and its successful cross-domain application establish a new direction for predictive maintenance research—one that is not only computationally powerful, but also interpretable, transferable, and firmly grounded in real-world operational dynamics.

By bridging methodological rigor with practical applicability, this work provides a scalable and scientifically robust foundation for the next generation of HTM systems in Saudi Arabia, the Gulf region, and beyond.

From a practical standpoint, preliminary feedback from a senior Healthcare Technology Management (HTM) manager at a tertiary hospital in Saudi Arabia indicated strong interest in the implementation of the proposed SQRRM-based framework as a decision-support tool for maintenance prioritization and resource allocation. The expressed willingness to evaluate the model in a pilot setting upon full deployment provides an initial indication of its operational relevance and its potential for real-world adoption.

References

1. Lenel, A.; Temple-Bird, C.; Kawohl, W.; Kaur, M. How to Organize a System of Healthcare Technology Management. In *How to Manage Series for Healthcare Technology*, 1st Edition; Caroline, T.B; TALC: St. Albans, Hertfordshire, UK, 2005; Guide 1, pp. 1-4. Available online: https://www.who.int/management/organize_system_%20healthcare.pdf (accessed on 28 April 2024).
2. Healthcare Technology Management Frequently Asked Questions. Available online: https://www.aami.org/docs/default-source/htmdocs/htm-faq21-020221.pdf?sfvrsn=52d0acd6_2 (accessed on 28 April 2024).
3. Singh, B.; Ghatala, M.H. Risk Management in Hospitals. IJIMT. 2012, Vol. 3, 417 - 421. DOI: 10.7763/IJIMT.2012.V3.266.
4. Mahmoud, T., Balachandran, W. and Altayyar, S., 2024. Advancing Sustainable Healthcare Technology Management: Developing a Comprehensive Risk Assessment Framework with a Fuzzy Analytical Hierarchy Process, Integrating External and Internal Factors in the Gulf Region. *Sustainability*, *16*(18), p.8197.
5. Wang, B.; Levenson, A. Equipment inclusion criteria—A new interpretation of JCAHO's medical equipment management standard. J. Clin. Eng. 2000, 25, 26–35.
6. Moher, D., Liberati, A., Tetzlaff, J., and Altman, D.G. (2009). Preferred reporting items for systematic reviews and Meta-analyses: the PRISMA statement. PLoS Medicine. Vol 6. (7). pp. 1-6
7. Page M J, McKenzie J E, Bossuyt P M, Boutron I, Hoffmann T C, Mulrow C D et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews *BMJ* 2021; 372 :n71 doi:10.1136/bmj.n71
8. M. Boroojerdi, S. K. Setaredan, J. Tavakoli and H. Mollaee, "Risk management in integrated biomedical engineering preventive maintenance information network," *2008 International Symposium on Information Technology*, Kuala Lumpur, Malaysia, 2008, pp. 1-6, doi: 10.1109/ITSIM.2008.4631893.
9. M. R. Signori and R. Garcia, "Clinical Engineering and Risk Management in Healthcare Technological Process Using Architecture Framework," *2010 Annual*

International Conference of the IEEE Engineering in Medicine and Biology, Buenos Aires, Argentina, 2010, pp. 418-421, doi: 10.1109/IEMBS.2010.5627343.

10. M. Bava, D. Cacciari, E. Sossa, D. Zotti and R. Zangrando, "Information Security Risk Assessment in Healthcare: The Experience of an Italian Paediatric Hospital," *2009 First International Conference on Computational Intelligence, Communication Systems and Networks*, Indore, India, 2009, pp. 321-326, doi: 10.1109/CICSYN.2009.14.
11. A. F. G. Taktak and M. C. Brown, "Evidence-Based Analysis of Field Testing of Medical Electrical Equipment," *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, New York, NY, USA, 2006, pp. 4078-4080, doi: 10.1109/IEMBS.2006.259798.
12. G. Bartoo, "Risk management [medical devices]," in *IEEE Engineering in Medicine and Biology Magazine*, vol. 22, no. 4, pp. 166-172, July-Aug. 2003, doi: 10.1109/MEMB.2003.1237528.
13. F. Faggiano, M. Ritrovato, P. Freda, L. D. Vivo, L. D'Alessandro and P. Derrico, "Supporting Clinical Engineering in Italy: Results of a Survey Conducted by the AIIC," in *IEEE Pulse*, vol. 3, no. 5, pp. 33-39, Sept. 2012, doi: 10.1109/MPUL.2012.2208025.
14. R. D. Wilkins and L. K. Holley, "Risk management in medical equipment management," *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286)*, Hong Kong, China, 1998, pp. 3343-3345 vol.6, doi: 10.1109/IEMBS.1998.746216.
15. Davis-Smith CE, Painter FR, Baretich MF. Assessing risk in the Kaiser Permanente clinical technology program. Biomed Instrum Technol. 2015 Spring;Suppl:60-4. doi: 10.2345/0899-8205-49.s1.60. PMID: 25793453.
16. B. P. Gribbons and L. E. Yong, "Case Study: Application of a Systematic Quality Improvement Methodology to a Medical Device Safety Alerts Process," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, 2020, pp. 5089-5092, doi: 10.1109/EMBC44109.2020.9176187.

17. Jarikji Y, Hussein B., Hajj-Hassan M. A quantitative model for replacement of medical equipment based on technical and economic factors. Int J Artificial Organs. (2019) 42:278–85. doi: 10.1007/978-3-030-30874-2_22
18. Saleh S Altayyar , Medical Devices and Patient Safety, J Anal Pharm Res 2016, 2(5): 00034.
19. Kaye, R.; Crowley, J. Medical Device Use-Safety: Incorporating Human Factors Engineering into Risk Management. The Center for Devices and Radiological Health's (CDRH), FDA. Available online: https://www.qualysinnova.com/download/files/MDUse-Safety.pdf (accessed on 28 March 2024).
20. Saleh S Altayyar , The Essential Principles of Safety and Effectiveness for Medical Devices and the Role of Standards, Medical Devices: Evidence and Research 2020:13 49–55.
21. David W. Feigal, FDA public health advisory: Risk of electromagnetic interference with medical telemetry systems, International Journal of Trauma Nursing, Volume 6, Issue 4, 2000, Pages 113-114, ISSN 1075-4210, https://doi.org/10.1016/S1075-4210(00)70004-6.
22. Paul Jen-Hwa Hu, P. Y. K. Chau and O. R. L. Sheng, "Investigation of factors affecting healthcare organization's adoption of telemedicine technology," Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, Maui, HI, USA, 2000, pp. 10 pp.-, doi: 10.1109/HICSS.2000.926799.
23. H. T. Tavani, "Technology, policy, ethics, and public health: a select bibliography," in IEEE Technology and Society Magazine, vol. 19, no. 3, pp. 26-34, Fall 2000, doi: 10.1109/44.868939.
24. Keller, James P., Jr. "Managing Medical Device Safety." In A Practicum for Healthcare Technology Management, 51–67. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.
25. Shepherd, Marvin, and Bruce Hyndman. "Theory and Practice of Device Incident Investigations." In A Practicum for Healthcare Technology Management, 83–108. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.

26. Hyman, William A. "Use Errors: The Benefits and Challenges of In-Service Education." In A Practicum for Healthcare Technology Management, 111–126. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.
27. Clemans, Terrance. "Wireless Spectrum Management." In A Practicum for Healthcare Technology Management, 257–286. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.
28. R. Carroll and S. M. Brown, Eds., *Risk Management Handbook for Health Care Organizations*, 6th ed., vol. 2. San Francisco, CA, USA: Jossey-Bass, 2011.
29. Grimes SL. Evolution of a risk-based approach to effective healthcare technology management. Biomed Instrum Technol. 2015 Spring;Suppl:34-42. doi: 10.2345/0899-8205-49.s1.34. PMID: 25793450.
30. Grob A, Biersach B, Peck J. Risk management and IEC 60601-1: assessing compliance. Biomed Instrum Technol. 2015 Spring;Suppl:55-9. doi: 10.2345/0899-8205-49.s1.55. PMID: 25793452.
31. Caines P, Baird P, Whanger K. Eight common myths and misunderstandings about risk management. Biomed Instrum Technol. 2015 Spring;Suppl:13-7. doi: 10.2345/0899-8205-49.s1.13. PMID: 25793447.
32. Jones PL, Taylor A. Medical device risk management and safety cases. Biomed Instrum Technol. 2015 Spring;Suppl:45-53. doi: 10.2345/0899-8205-49.s1.45. PMID: 25793451.
33. S. Mekki, M. A. Wahed, K. K. Wahba and B. K. Ouda, "A system dynamics based model for medical equipment maintenance procedure planning in developing countries," *2012 Cairo International Biomedical Engineering Conference (CIBEC)*, Giza, Egypt, 2012, pp. 104-108, doi: 10.1109/CIBEC.2012.6473299.
34. S. Ismail, H. Nehme, B. Hussein and M. Hajj-Hassan, "Integration of Monte Carlo simulation tool for forecasting medical equipment risks in HIQMA system," *2016 3rd Middle East Conference on Biomedical Engineering (MECBME)*, Beirut, Lebanon, 2016, pp. 10-15, doi: 10.1109/MECBME.2016.7745397.
35. Cruz, A.M.; Denis, E.R.; Villar, M.S.; Gonzalez, L.L. An event-tree-based mathematical formula for the removal of biomedical equipment from a hospital inventory. J. Clin. Eng. 2002, 27, 63–71.

36. Khalaf, A.; Djouani, K.; Hamam, Y.; Alayli, Y. Evidence-based mathematical maintenance model for medical equipment. In Proceedings of the 2010 International Conference on Electronic Devices, Systems and Applications, Kuala Lumpur, Malaysia, 11–14 April 2010.
37. R. Alwi, P. Prowse and T. Gaamangwe, "Proactive Role of Clinical Engineering in the Adoption of ISO/IEC 80001-1 within Healthcare Delivery Organization," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, 2020, pp. 5623-5626, doi: 10.1109/EMBC44109.2020.9175347.
38. T. Yaqoob, H. Abbas and N. Shafqat, "Integrated Security, Safety, and Privacy Risk Assessment Framework for Medical Devices," in *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 6, pp. 1752-1761, June 2020, doi: 10.1109/JBHI.2019.2952906.
39. D. -W. Kim, J. -Y. Choi and K. -H. Han, "Medical Device Safety Management Using Cybersecurity Risk Analysis," in *IEEE Access*, vol. 8, pp. 115370-115382, 2020, doi: 10.1109/ACCESS.2020.3003032.
40. J. R. Goldberg, "The healthcare technologies management program," in *IEEE Engineering in Medicine and Biology Magazine*, vol. 22, no. 1, pp. 49-52, Jan.-Feb. 2003, doi: 10.1109/MEMB.2003.1191449.
41. Zamzam, A.H.; Al-Ani, A.K.; Wahab, A.K.; 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.
42. Abd Rahman, N.H.; Mohamad, M.H.; Hasikin, K.; Abd Razak, N.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.
43. D. H. Darnel, "Medical Device Incident Management By Biomedical Engineering," *[1990] Proceedings of the Twelfth Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Philadelphia, PA, USA, 1990, pp. 1949-1949, doi: 10.1109/IEMBS.1990.692098.

44. Astivia-Chávez, D.N., Ortiz-Posadas, M.R. (2023). Exploratory Data Analysis for Preventive and Corrective Maintenance for Medical Equipment in a General Hospital from the Health Institute of the State of Mexico. In: Trujillo-Romero, C.J., *et al.* XLV Mexican Conference on Biomedical Engineering. CNIB 2022. IFMBE Proceedings, vol 86. Springer, Cham. https://doi.org/10.1007/978-3-031-18256-3_84.
45. Clark, J. Tobey, and Raymond D. Forsell. "Medical Equipment Replacement: Planning, Factors, Methods, and Outcomes." In A Practicum for Healthcare Technology Management, 163–180. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.
46. Baretich, Matthew F. "Healthcare Facility Management." In A Practicum for Healthcare Technology Management, 241–254. Arlington, VA: Association for the Advancement of Medical Instrumentation, 2015.
47. Saleh, N., Sharawi, A., Elwahed, M.A., Petti, A., Puppato, D., Balestra, G. (2014). A New Approach for Preventive Maintenance Prioritization of Medical Equipment. In: Roa Romero, L. (eds) XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013. IFMBE Proceedings, vol 41. Springer, Cham. https://doi.org/10.1007/978-3-319-00846-2_262.
48. V. Puntoni, G. M. P. Masselli and S. Silvestri, "An adaptation of Pareto's parametric distribution as a support tool for the analysis of maintenance costs of biomedical equipment," 2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT), Rome, Italy, 2021, pp. 32-36, doi: 10.1109/MetroInd4.0IoT51437.2021.9488514.
49. E. Smith and J. Eloff, "Cognitive fuzzy modelling for enhanced risk assessment in a health care institution," in *IEEE Intelligent Systems and their Applications*, vol. 15, no. 2, pp. 69-75, March-April 2000, doi: 10.1109/5254.850830.
50. Jamshidi, A.; Rahimi, S.A.; Ait-kadi, D.; Ruiz, A. A comprehensive fuzzy risk-based maintenance framework for prioritization of medical devices. Appl. Soft Comput. 2015, 32, 322–334.
51. Tawfik B, Ouda BK, Abd El Samad YM. A fuzzy logic model for medical equipment risk classification. J Clin Eng. (2013) 38:185–90. doi: 10.1097/JCE.0b013e3182a90445.

52. Hutagalung AO, Hasibuan S. Determining the priority of medical equipment maintenance with analytical hierarchy process. *Int J Online Biomed Eng.* (2019) 15:107–20. doi: 10.3991/ijoe.v15i10.10920.
53. Aridi M, Hussein B, Hajj-Hassan M, Khachfe HM. A novel approach for healthcare equipments lifespan assessment. Int J Adv Life Sci. (2016) 8:1–15. Available online at: http://www.iariajournals.org/life_sciences/
54. Oshiyama NF, Bassani RA, D'Ottaviano IML, Bassani JWM. Medical equipment classification: method and decision-making support based on paraconsistent annotated logic. Med Biol Eng Comput. (2012) 50:395–402. doi: 10.1007/s11517-012-0888-6
55. Faisal M, Sharawi A. Prioritize medical equipment replacement using analytical hierarchy process. IOSR J Electric Electron Eng. (2015) 10:55–63. doi: 10.9790/1676-10325563
56. Amran, M.E.; Aziz, S.A.; Muhtazaruddin, M.N.; Masrom, M.; Haron, H.N.; Bani, N.A.; Mohd, 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.
57. K. M. Alahmadi, “Model Development to Improve the Predictive Maintenance Reliability of Medical Devices,” Journal of Healthcare Engineering, vol. 2025, pp. 1–14, 2025, doi.org/10.35784/iapgos.6459.
58. Taghipour, S.; Banjevic, D.; Jardine, A.K.S. Prioritization of medical equipment for maintenance decisions. *J. Oper. Res. Soc.* **2010**, *62*, 1666–1687.
59. Mahfoud, H.; Abdellah, E.B.; El Biyaali, A. Dependability-based maintenance optimization in healthcare domain. J. Qual. Maint. Eng. 2018, 24, 200–223.
60. Trombly, S.T. The Risk Management Professional and Biomedical Technology. In Risk Management Handbook for Health Care Organizations, 6th ed.; Carroll, R., Brown, S.M., Eds.; Jossey-Bass: San Francisco, CA, USA, 2011; Volume 2, pp. 63–76.

61. Zamzam, A.H.; Abdul Wahab, A.K.; Azizan, M.M.; Satapathy, S.C.; Lai, K.W.; Hasikin, K. A systematic review of medical equipment reliability assessment in improving the quality of healthcare services. Front. Public Health 2021, 9, 753951.
62. Saudi,M.M.; Ahmad, A.; Liki, M.N.; Husainiame M. A. Risk Management Using PESTLE: External Factors Trigger COVID-19 Transmission. IICICyTA, Bandung, Indonesia, 2021, 34-39. doi: 10.1109/ICICyTA53712.2021.9689153.
63. Božić, V. Objectifying SWOT and PESTLE Analysis in Hospital. ResearchGate. 2023. DOI:10.13140/RG.2.2.18907.34086.
64. Cooke, R.M.; ElSaadany, S.; Huang, X. On the performance of social network and likelihood-based expert weighting schemes. Reliab. Eng. Syst. Saf. 2008, 93, 745–756.
65. Wang, L. Research on Risk Management for Healthcare Supply Chain in Hospital. Ph.D. Thesis, Liverpool John Moores University, Liverpool, UK, 2018.
66. Zaidi, M.F.; Shafie, S.M.; Abdul Rahim, M.K. AHP Analysis on the Criteria and Sub-Criteria for the Selection of Fuel Cell Power Generation in Malaysia. J. Adv. Res. Fluid Mech. Therm. Sci. 2022, 98, 1–14. https://doi.org/10.37934/arfmts.98.2.114.
67. Chomeya, R. Quality of Psychology Test Between Likert Scale 5 and 6 Points. J. Soc. Sci. 2010, 6, 399–403. https://doi.org/10.3844/jssp.2010.399.403.
68. L. Ljung, *System Identification: Theory for the User*, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 1999.
69. M. Molęda et al., “From Corrective to Predictive Maintenance—A Review of Maintenance Approaches,” Proc. Int. Conf. …, 2023.
70. S. K. Sahani, B. K. Sah, and K. Sahani, "Reliability-Centred Maintenance (RCM) in Cement Manufacturing Plants," Advances in Nonlinear Variational Inequalities, vol. 26, no. 1, 2023. [Online]. Available: https://doi.org/10.52783/anvi.v26.4224.
71. C. Clemente, G. R. Guerreiro, and J. M. Bravo, "Modelling motor insurance claim frequency and severity using gradient boosting," Risks, vol. 11, no. 9, p. 163, 2023. [Online]. Available: https://doi.org/10.3390/risks11090163.
72. A. Saxena, K. Goebel, D. Simon and N. Eklund, "Damage propagation modelling for aircraft engine run-to-failure simulation," 2008 International Conference on

Prognostics and Health Management, Denver, CO, USA, 2008, pp. 1-9, doi: 10.1109/PHM.2008.4711414.

73. Chang, D.Y. Theory and methodology: Applications of the extent analysis method on fuzzy AHP. Eur. J. Oper. Res. 1996, 95, 649–655. https://doi.org/10.1016/0377-2217(95)00300-2.
74. D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 5th ed. Hoboken, NJ, USA: Wiley, 2012.
75. T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*, 2nd ed. New York, NY, USA: Springer, 2009.
76. J. L. Myers, A. D. Well, R. F. Lorch Jr., and C. M. Rotello, *Research Design and Statistical Analysis*, 4th ed. New York, NY, USA: Routledge, 2013.
77. P. Virtanen *et al.*, “SciPy 1.0: Fundamental algorithms for scientific computing in Python,” *Nature Methods*, vol. 17, no. 3, pp. 261–272, 2020.
78. T. Aven, The Science of Risk Analysis: Foundation and Practice. Abingdon, UK: Routledge, 2020, pp. 94–95.
79. R. K. Srivastava, K. Greff, and J. Schmidhuber, “Highway networks,” arXiv preprint arXiv:1505.00387, 2015.
80. J. Arevalo, T. Solorio, M. Montes, and F. A. González, “Gated multimodal units for information fusion,” Proc. ICLR Workshop, 2017.
81. Y. N. Dauphin, A. Fan, M. Auli, and D. Grangier, “Language modelling with gated convolutional networks,” in Proc. Int. Conf. Machine Learning (ICML), 2017, pp. 933–941.
82. B. Lim et al., “Temporal fusion transformers for interpretable multi-horizon time series forecasting,”Proc. NeurIPS, 2021.
83. C. Chen, K. Li, S. G. Teo, X. Zou, K. Wang, J. Wang, and Z. Zeng, "Gated residual recurrent graph neural networks for traffic prediction," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, no. 01, pp. 485-492, 2019. [Online]. Available: https://doi.org/10.1609/aaai.v33i01.3301485.
84. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," in Neural Computation, vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

85. A. Vaswani et al., “Attention is all you need,” Proc. NeurIPS, 2017. Available: https://doi.org/10.48550/arXiv.1706.03762.
86. S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” Proc. ICML, 2015. Available: https://doi.org/10.48550/arXiv.1502.03167.
87. K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink and J. Schmidhuber, "LSTM: A Search Space Odyssey," in IEEE Transactions on Neural Networks and Learning Systems, vol. 28, no. 10, pp. 2222-2232, Oct. 2017, doi: 10.1109/TNNLS.2016.2582924.
88. Cho, K. et al. (2014), "Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation." EMNLP 2014. Available: https://doi.org/10.48550/arXiv.1406.1078.
89. Li, Y. et al. (2016), "Gated Graph Sequence Neural Networks." ICLR 2016. Available: https://doi.org/10.48550/arXiv.1511.05493
90. D. Huang, R. Bai, S. Zhao, P. Wen, S. Wang, and S. Chen, "Bayesian neural network based method of remaining useful life prediction and uncertainty quantification for aircraft engine," in Proc. Annu. Conf. Prognostics and Health Management Society, Detroit, MI, USA, 2020, pp. 8-10.
91. G. Aydemir and B. Acar, "Anomaly monitoring improves remaining useful life estimation of industrial machinery," J. Manuf. Syst., vol. 56, pp. 463–469, 2020.
92. K. Ensarioğlu, T. İnkaya, and E. Emel, "Remaining useful life estimation of turbofan engines with deep learning using change-point detection based labeling and feature engineering," Appl. Sci., vol. 13, no. 21, p. 11893, 2023. [Online]. Available: https://doi.org/10.3390/app132111893.
93. S. M. Elsherif, B. Hafiz, M. A. Makhlouf, and O. Farouk, "A deep learning-based prognostic approach for predicting turbofan engine degradation and remaining useful life," Sci. Rep., vol. 15, art. no. 26251, 2025. [Online]. Available: https://doi.org/10.1038/s41598-025-09155-z.
94. C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

95. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

Appendix I: Expert Survey Employed for the Validation and Refinement of Risk Factors (Chapter 3)

The structure and layout of this questionnaire were adapted from [65], while the questionnaire items, risk factors, and evaluation criteria were developed specifically for the objectives of the present study.

Section A: Participant Profile

1. Please indicate the type of organization you are affiliated with:

Hospital	Ministry of Health	Medical devices company (Agent or Distributor)	Manufacturer	Medical devices maintenance company	SFDA or other legislative body	Other
☐	☐	☐	☐	☐	☐	☐

2. Current Position / Job Title: ______________________

3. Length of Professional Experience in Healthcare or HTM:

☐1-5 years ☐6-10 years ☐11-15 years ☐16-19 years ☐≥20 years

4. Would you be willing to be contacted for further information or to participate in a subsequent round of the survey, if required?

☐Yes ☐No

Section B:

Based on this study, Healthcare Technology Management Risks (HTMR) are classified into two main categories: (1) Endogenous risks, which originate within the healthcare system or organization; and (2) Exogenous risks, which arise from external factors generally beyond the control of healthcare providers. *(Figures 1 and 2 illustrate the scope of these risk categories.)*

The following questions ask you to evaluate and rank the identified Healthcare Technology Management (HTM) risk factors according to their relative significance. The importance of each risk factor should be indicated using the corresponding numerical rating values below:

1=Insignificant.

2=Somewhat Significant.

3=Moderately Significant.

4=Highly Significant.

5=Critical

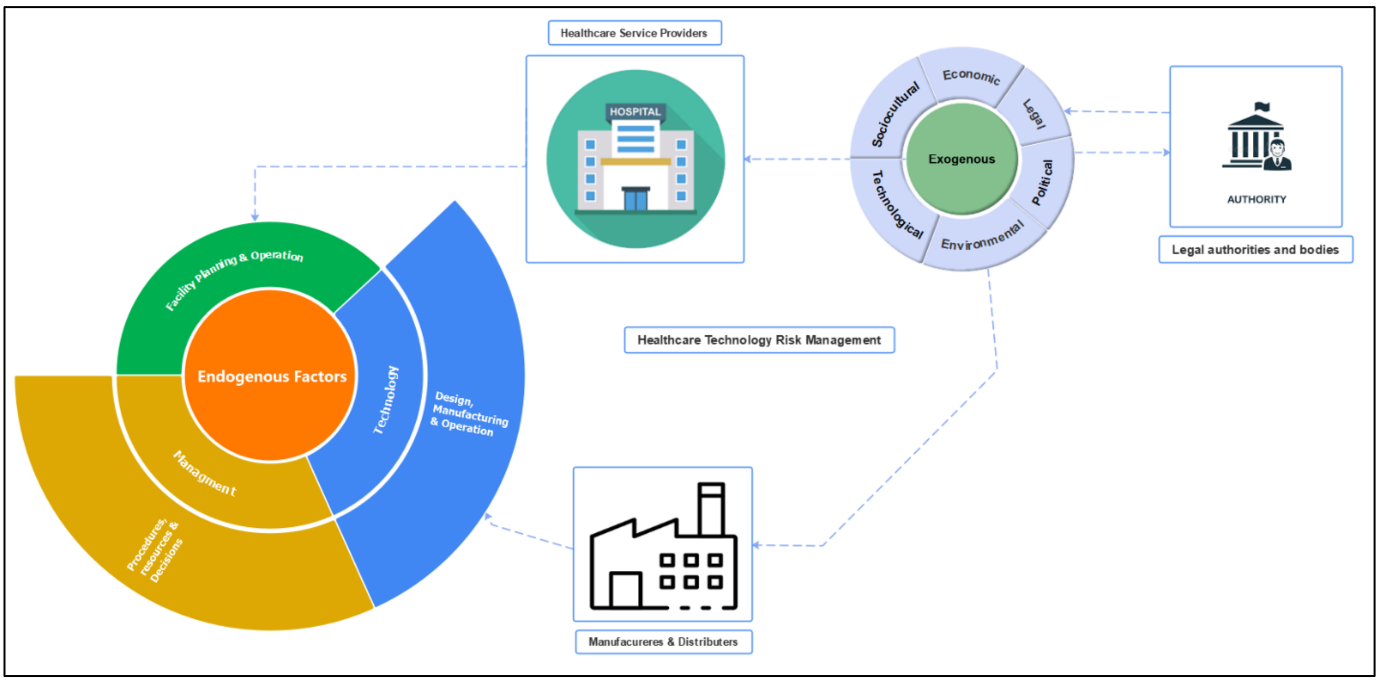


Figure 1: Sources of risks in the HTM

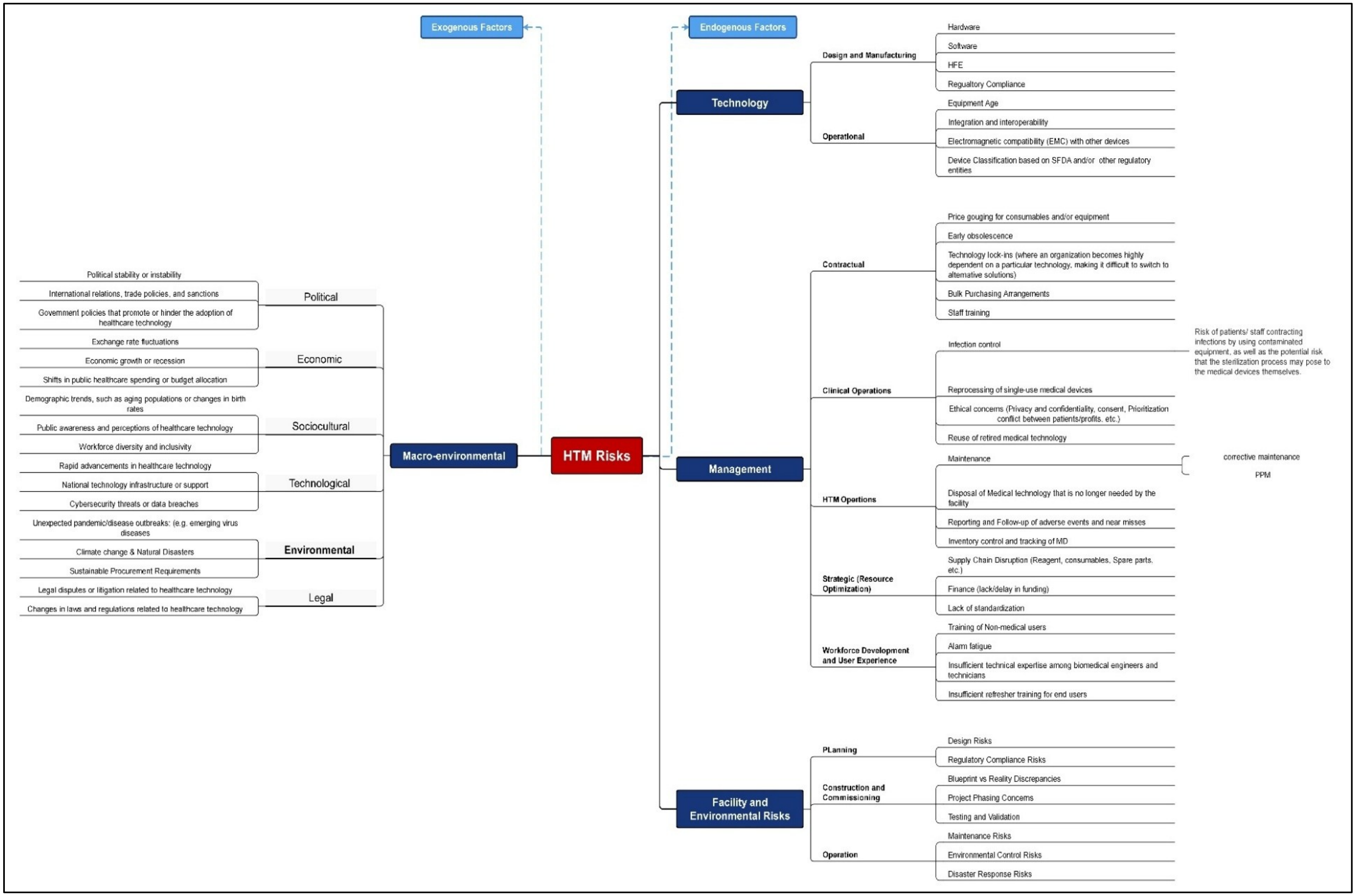


Figure 2: A schematic classification of HTMR

Endogenous risk factors in Healthcare Technology Management (HTM) arise from internal sources embedded within the organization and the technology itself. These risks are associated with multiple internal domains, including management practices, technological systems, operational processes, contractual arrangements, and technology utilization within the healthcare environment. In addition, facilities and environmental risks relate to the planning, condition, and operational performance of the physical infrastructure, as well as surrounding environmental conditions.

Technology Risks refer to the potential inherent risks associated with the development, implementation, and ongoing use of healthcare technologies.:

- **Design and Manufacturing.**
- **Operational.**

Identified Risk Factors (Design and manufacturing)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Design and manufacturing	F1 Hardware	☐1	☐2	☐3	☐4	☐5
	F2 Software	☐1	☐2	☐3	☐4	☐5
	F3 Human Factor Engineering (HFE)	☐1	☐2	☐3	☐4	☐5
	F4 Regulatory Compliance	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Endogenous)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Operational	F5 Equipment Age	☐1	☐2	☐3	☐4	☐5
	F6 Integration and Interoperability	☐1	☐2	☐3	☐4	☐5

	F7 Electromagnetic compatibility (EMC) with other devices	☐1 ☐2 ☐3 ☐4 ☐5
	F8 Device Classification based on SFDA and/or other regulatory entities A, B, or C	☐1 ☐2 ☐3 ☐4 ☐5

Considering the above structure, do you agree that the factors contributing to Technology-Related Risks can be appropriately classified into two categories: (1) Manufacturing and Design Risks, and (2) Operational Risks? If no, please provide your comments or suggested modifications:

Risk factors categories	**Yes**	**No**	**Any Comment**
Design and manufacturing			
Operational Risks			
Are there additional factors that should be taken into account?			

Management Risks refer to the potential challenges and uncertainties that arise from organizational decisions, processes, and activities related to the selection, implementation, and ongoing management of healthcare technology:

- **Contractual risks.**
- **Clinical Operational risks.**
- **HTM Operational risks.**
- **Strategic (Resource Optimization) risks.**
- **Employee Skill Development and User Experience.**

Identified Risk Factors (Contractual)		Degree of Significance: Insignificant / Somewhat Significant / Moderately Significant / Highly Significant / Critical
Contractual risks	F9 Early obsolescence	☐1 ☐2 ☐3 ☐4 ☐5
	F10 Staff training	☐1 ☐2 ☐3 ☐4 ☐5

	F11 Technology lock-ins (where an organization becomes highly dependent on a particular technology, making it difficult to switch to alternative solutions)	☐1	☐2	☐3	☐4	☐5
	F12 Bulk Purchasing Arrangements	☐1	☐2	☐3	☐4	☐5
	F13 Price gouging for consumables and/or equipment	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Operational)		Degree of Significance				
		Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Clinical Operations	F14 Infection control (Infection control has a dual-impact mechanism. Risk of patients/ staff contracting infections by using contaminated equipment, as well as the potential risk that the sterilization process may pose to the medical devices themselves.)	☐1	☐2	☐3	☐4	☐5
	F15 Reprocessing of single-use medical devices	☐1	☐2	☐3	☐4	☐5
	F16 Ethical concerns (Privacy and confidentiality, consent, Prioritization conflict between patients/profits, etc.)	☐1	☐2	☐3	☐4	☐5
	F17 Reuse of retired medical technology	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Operational)		Degree of Significance				
		Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
HTM Operations	F18 Maintenance	☐1	☐2	☐3	☐4	☐5
	F19 Disposal of Medical technology that is no longer needed by the facility	☐1	☐2	☐3	☐4	☐5

	F20 Reporting and Follow-up of adverse events and near misses	☐1 ☐2 ☐3 ☐4 ☐5
	F21 Inventory control and tracking of MD	☐1 ☐2 ☐3 ☐4 ☐5

Identified Risk Factors (Strategic)		Degree of Significance: Insignificant / Somewhat Significant / Moderately Significant / Highly Significant / Critical
Strategic (Resource Optimization)	F22 Supply Chain Disruption (Reagent, consumables, Spare parts, etc.)	☐1 ☐2 ☐3 ☐4 ☐5
	F23 Finance (lack/delay in funding)	☐1 ☐2 ☐3 ☐4 ☐5
	F24 Lack of standardization	☐1 ☐2 ☐3 ☐4 ☐5

Identified Risk Factors (Strategic)		Degree of Significance: Insignificant / Somewhat Significant / Moderately Significant / Highly Significant / Critical
Workforce Development and User Experience	F25 Training of Non-medical Users	☐1 ☐2 ☐3 ☐4 ☐5
	F26 Alarm fatigue	☐1 ☐2 ☐3 ☐4 ☐5
	F27 Insufficient technical expertise among biomedical engineers and technicians	☐1 ☐2 ☐3 ☐4 ☐5
	F28 Insufficient refresher training for end users	☐1 ☐2 ☐3 ☐4 ☐5

Considering the above structure, do you agree that the factors contributing to Management-Related Risks can be appropriately classified into the following five categories: (1) Contractual Risks, (2) Clinical Operations Risks, (3) HTM Operations Risks, (4) Strategic (Resource Optimization) Risks, and (5) Workforce Development and User Experience Risks?

Risk factors categories	Yes	No	Any Comment
Contractual Risks			
Clinical Operations			
HTM Operations			
Strategic (Resource Optimization)			
Employee Skill Development and User Experience			
Are there additional factors that should be taken into account?			

Facilities and Environmental Risks: In this context, facilities refer to the buildings and associated infrastructure that house the healthcare technology, while the internal environmental factors pertaining to the specific conditions within a building, such as air conditioning, humidity, and other physical aspects that can potentially affect the functioning of the technology. Notably, the relationship between healthcare technology and its facilities and environmental factors is bilateral and interconnected. Facilities and Environmental Risks can be classified under three main categories: Planning, Construction and Commissioning, and Operation.

Identified Risk Factors (Strategic)		Degree of Significance				
		Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Planning	F29 Design Risks	☐1	☐2	☐3	☐4	☐5
	F30 Regulatory Compliance Risks (These risks pertain to ensuring that the planning and construction of the building comply with all relevant building codes, environmental regulations, and healthcare facility standards.)	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Strategic)		Degree of Significance Insignificant / Somewhat Significant / Moderately Significant / Highly Significant / Critical
Construction and Commissioning	F31 Blueprint vs Reality Discrepancies (During the construction of a healthcare facility, deviations from the original blueprints can occur due to various reasons, such as unforeseen site conditions, changes in design, or construction errors. These discrepancies can result in issues like inadequate space or infrastructure for medical equipment. By integrating construction and commissioning, these discrepancies can be identified and addressed early, ensuring the facility is properly designed and built to accommodate the specific needs of the healthcare technology.)	☐1 ☐2 ☐3 ☐4 ☐5
	F32 Project Phasing Concerns (In many projects, medical equipment might arrive before the construction phase is complete. This can create several problems such as potential damage to the equipment, inadequate storage conditions, and delays in equipment installation and testing. Integrated construction and commissioning can help better align the schedules of equipment delivery and facility readiness, reducing these risks.)	☐1 ☐2 ☐3 ☐4 ☐5
	F33 Testing and Validation (Integrating construction and commissioning allows for a more cohesive and efficient testing and validation process. Medical equipment can be tested in the environment it will be used in, ensuring compatibility with the facility's infrastructure. This can reduce the risk of problems emerging after the facility is operational.)	☐1 ☐2 ☐3 ☐4 ☐5

Identified Risk Factors (Strategic)		Degree of Significance Insignificant / Somewhat Significant / Moderately Significant / Highly Significant / Critical
Operation	F34 Maintenance Risks (These are risks related to the continuous care and servicing of the building and its associated infrastructure. This encompasses routine maintenance duties, as well as managing unforeseen repairs or malfunctions related to facilities such as electricity supply, plumbing, and more)	☐1 ☐2 ☐3 ☐4 ☐5
	F35 Environmental Control Risks (These risks pertain to managing the internal environmental conditions of the building, such as temperature, humidity, and air quality, which can directly impact the performance and longevity of healthcare technologies.)	☐1 ☐2 ☐3 ☐4 ☐5
	F36 Disaster Response Risks (These risks involve the organization's preparedness and capacity to respond to emergencies that could impact the operation of the building, such as power outages, rain, or other natural disasters.)	☐1 ☐2 ☐3 ☐4 ☐5

Considering the above structure, do you agree that the factors contributing to Facilities and Environmental Risks can be appropriately classified into the following categories: (1) Planning, (2) Construction and Commissioning, and (3) Operation?

Risk factors categories	**Yes**	**No**	**Any Comment**
Planning Risks			
Construction and Commissioning			
Operation Risks			

Are there additional factors that should be taken into account?	

Exogenous factor risks in healthcare technology management refer to external variables or influences that can impact healthcare technologies' effectiveness, safety, and efficiency. These factors are typically beyond the control of healthcare providers and organizations and can include:

Macro-Environmental Factors:

- **Political**
- **Economic**
- **Sociocultural**
- **Technological**
- **Environmental**
- **Legal**

Identified Risk Factors (Political)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Political	F37 Political stability or instability in a country or region, which can impact healthcare investment, infrastructure, and policy-making.	☐1	☐2	☐3	☐4	☐5
	F38 International relations, trade policies, and sanctions that may influence the availability, pricing, or quality of healthcare technology products and services.	☐1	☐2	☐3	☐4	☐5
	F39 Government policies that promote or hinder the adoption of healthcare technology, such as incentives for innovation, research and development funding, or reimbursement policies.	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Economic)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Economic	F40 Exchange rate fluctuations, which can influence the cost and availability of imported healthcare technology equipment and supplies.	☐1	☐2	☐3	☐4	☐5
	F41 Economic growth or recession, which can impact healthcare spending, investment, and the overall demand for healthcare services.	☐1	☐2	☐3	☐4	☐5
	F42 Shifts in public healthcare spending or budget allocation, which can affect the resources available for healthcare technology management.	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Sociocultural)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Sociocultural	F43 Demographic trends, such as aging populations or changes in birth rates, which can influence the demand for healthcare services and the types of technologies needed.	☐1	☐2	☐3	☐4	☐5
	F44 Public awareness and perceptions of healthcare technology, which can influence patient preferences and demand for certain technologies or services.	☐1	☐2	☐3	☐4	☐5
	F45 Workforce diversity and inclusivity, which can affect the organization's ability to attract and retain skilled healthcare technology management professionals and provide culturally competent care.	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Technological)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Technological	F46 Rapid advancements in healthcare technology, which can quickly make existing technologies obsolete, require significant investments in new equipment, or create skills gaps in the workforce.	☐1	☐2	☐3	☐4	☐5
	F47 National technology infrastructure or support	☐1	☐2	☐3	☐4	☐5
	F48 Cybersecurity threats or data breaches affecting healthcare technology systems	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Legal)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Legal	F49 Legal disputes or litigation related to healthcare technology, such as intellectual property infringement, breach of contract, or product liability claims, which can be costly and time-consuming.	☐1	☐2	☐3	☐4	☐5
	F50 Changes in laws and regulations related to healthcare technology, such as safety standards, data privacy, or medical device approvals, which can impose additional compliance burdens on organizations.	☐1	☐2	☐3	☐4	☐5

Identified Risk Factors (Environmental)		Degree of Significance: Insignificant	Somewhat Significant	Moderately Significant	Highly Significant	Critical
Environmental	F51 Climate change or natural disasters affecting the availability of raw materials or supply chain operations	☐1	☐2	☐3	☐4	☐5
	F52 Sustainable Procurement Requirements to Adopt Eco-friendly Healthcare Technologies	☐1	☐2	☐3	☐4	☐5
	F53 Unexpected pandemic/disease outbreaks; (e.g. emerging virus diseases)	☐1	☐2	☐3	☐4	☐5

Considering the above classification, do you believe that these factors appropriately represent risks originating from external sources (exogenous risk factors)?

Risk factors categories	**Yes**	**No**	**Any Comment**
Political			
Economic			
Sociocultural			
Technological			
Environmental			
Legal			
Are there additional factors that should be taken into account?			

We greatly appreciate your valuable contribution to this survey. Rest assured; your responses will be treated with confidentiality. Thank you once again!

Appendix II: Fuzzy AHP Pairwise Comparison Questionnaire (Chapter 4)

The pairwise comparison questionnaire follows the structural format proposed in [65]. The comparison hierarchy, criteria, and judgement scales were adapted and redesigned to reflect the Healthcare Technology Risk Management framework developed in this research.

Part A: In Table 1, The assessments and justifications based on linguistic judgments are utilized to evaluate the importance of each element in **the pair-wise comparison.**

Linguistic judgments	Explanations
Equally important	The factors are of the same level of importance or significance. They are equally worthy of attention or consideration.
Slightly more important	One factor is slightly more important than another. The difference in importance is not very large, but it is still noticeable.
Strongly more important	One factor is significantly more important than another. The difference in importance is clear and substantial.
Very strongly more important	One factor is extremely more important than another, indicating a very strong preference.
Absolutely more important	The evidence strongly affirms the preference for one activity over another, reaching the highest level of confirmation possible. The thing that is absolutely more important must be given the highest priority.

Part B: Questionnaire

When evaluating the four main criteria (explicated in part A), From your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

Key Concepts:

Technology Risks: refer to the potential inherent risks associated with the development, implementation, and ongoing use of healthcare technologies (Design and Manufacturing, and Operational).

Management Risks: refer to the potential challenges and uncertainties that arise from organizational decisions, strategies, processes, and activities related to the selection, implementation, and ongoing management of healthcare technology.

Facilities and Internal Environmental Risks: In this context, facilities refer to the buildings and associated infrastructure that house the healthcare technology, while the internal environmental factors pertain to the specific conditions within a building, such as air conditioning, humidity, and other physical aspects that can potentially affect the functioning of the technology.

Macro-environmental Risks (Exogenous): factor risks in healthcare technology management refer to external variables or influences that can impact healthcare technologies' effectiveness, safety, and efficiency. These factors are typically beyond the control of healthcare providers and organizations and can include (Political, Economic, Technological, Environmental).

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Technology Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Management Risks
Technology Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Facilities and Environmental Risks
Technology Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Macro-environmental Risks (Exogenous)
Management Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Facilities and Environmental Risks
Management Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Macro-environmental Risks (Exogenous)
Facilities and Internal Environmental Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Macro-environmental Risks (Exogenous)

Considering the sub-criteria under “Technology risk”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

Design and Manufacturing risks: Refer to the potential challenges and vulnerabilities that can emerge from the design and production processes of healthcare technologies. These risks can subsequently become sources of concern during the operational phase and overall management of healthcare technology.

Operational risks: Refer to the potential challenges and vulnerabilities that can arise during the day-to-day use and functioning of healthcare technologies. These risks are primarily associated with the operational characteristics of the technology itself, rather than managerial aspects.

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Design and Manufacturing	☐	☐	☐	☐	☐	☐	☐	☐	☐	Operational

Considering the sub-criteria under "**Management risk**", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

Contractual risks: Refer to the potential challenges and uncertainties that arise from the contractual agreements and obligations related to healthcare technology.

Clinical Operational risks: Clinical operational risks pertain to the potential challenges and uncertainties that arise from the operational aspects of healthcare technology within clinical settings.

HTM Operational risks: Refer to the potential challenges and uncertainties that arise from the management and operation of healthcare technology within an organization.

Strategic (Resource Optimization) risks: Strategic risks, also known as resource optimization risks, involve the potential challenges and uncertainties arising from supply disruptions, financial constraints or delays, and the absence of standardization within healthcare technology management.

Employee Skill Development and User Experience risks: Refer to the potential challenges and uncertainties associated with the skills, knowledge, and experience of the workforce in utilizing and dealing with healthcare technology.

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Contractual	☐	☐	☐	☐	☐	☐	☐	☐	☐	Clinical Operations
Contractual	☐	☐	☐	☐	☐	☐	☐	☐	☐	HTM Operations
Contractual	☐	☐	☐	☐	☐	☐	☐	☐	☐	Strategic Resource (Optimization)
Contractual	☐	☐	☐	☐	☐	☐	☐	☐	☐	Workforce Development and User Experience

Clinical Operations	☐	☐	☐	☐	☐	☐	☐	☐	☐	HTM Operations
Clinical Operations	☐	☐	☐	☐	☐	☐	☐	☐	☐	Strategic Resource (Optimization)
Clinical Operations	☐	☐	☐	☐	☐	☐	☐	☐	☐	Workforce Development and User Experience
HTM Operations	☐	☐	☐	☐	☐	☐	☐	☐	☐	Strategic Resource (Optimization)
HTM Operations	☐	☐	☐	☐	☐	☐	☐	☐	☐	Workforce Development and User Experience
Strategic Resource (Optimization)	☐	☐	☐	☐	☐	☐	☐	☐	☐	Workforce Development and User Experience

Considering the sub-criteria under “Facilities and Internal Environmental Risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

Planning risks: Refer to the potential challenges and uncertainties associated with the initial stages of designing and developing healthcare facilities where technology will be implemented.

Construction and commissioning risks: Pertain to the potential challenges and uncertainties that arise during the physical construction and installation of healthcare facilities.

Operational risks within Facilities and Internal Environmental Risks: Refer to the potential challenges and uncertainties that arise during the day-to-day operation and management of healthcare facilities.

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Planning	☐	☐	☐	☐	☐	☐	☐	☐	☐	Construction and Commissioning
Planning	☐	☐	☐	☐	☐	☐	☐	☐	☐	Operation
Construction and Commissioning	☐	☐	☐	☐	☐	☐	☐	☐	☐	Operation

Considering the sub-criteria of Technology risks under “Design and manufacturing”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Hardware	☐	☐	☐	☐	☐	☐	☐	☐	☐	Software

Hardware	☐	☐	☐	☐	☐	☐	☐	☐	☐	HFE
Hardware	☐	☐	☐	☐	☐	☐	☐	☐	☐	Regulatory Compliance
Software	☐	☐	☐	☐	☐	☐	☐	☐	☐	HFE
Software	☐	☐	☐	☐	☐	☐	☐	☐	☐	Regulatory Compliance
HFE	☐	☐	☐	☐	☐	☐	☐	☐	☐	Regulatory Compliance

Considering the sub-criteria of Technology risks under “Operational risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Equipment Age	☐	☐	☐	☐	☐	☐	☐	☐	☐	Integration and interoperability
Equipment Age	☐	☐	☐	☐	☐	☐	☐	☐	☐	Electromagnetic compatibility (EMC) with other devices
Equipment Age	☐	☐	☐	☐	☐	☐	☐	☐	☐	Device Classification based on SFDA and/or other regulatory entities A, B, or C
Integration and interoperability	☐	☐	☐	☐	☐	☐	☐	☐	☐	Electromagnetic compatibility (EMC) with other devices
Integration and interoperability	☐	☐	☐	☐	☐	☐	☐	☐	☐	Device Classification based on SFDA and/or other regulatory entities A, B, or C
Electromagnetic compatibility (EMC) with other devices	☐	☐	☐	☐	☐	☐	☐	☐	☐	Device Classification based on SFDA and/or other regulatory entities A, B, or C

Considering the sub-criteria of Management risks under “Contractual risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Price gouging for consumables and/or equipment	☐	☐	☐	☐	☐	☐	☐	☐	☐	Early obsolescence
Price gouging for consumables and/or equipment	☐	☐	☐	☐	☐	☐	☐	☐	☐	Technology lock-ins
Price gouging for consumables and/or equipment	☐	☐	☐	☐	☐	☐	☐	☐	☐	Staff training
Early obsolescence	☐	☐	☐	☐	☐	☐	☐	☐	☐	Technology lock-ins
Early obsolescence	☐	☐	☐	☐	☐	☐	☐	☐	☐	Staff training
Technology lock-ins	☐	☐	☐	☐	☐	☐	☐	☐	☐	Staff training

Considering the sub-criteria of Management risks under "Clinical Operations risks", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Infection control	☐	☐	☐	☐	☐	☐	☐	☐	☐	Reprocessing of single-use medical devices
Infection control	☐	☐	☐	☐	☐	☐	☐	☐	☐	Ethical concerns (Privacy and confidentiality, consent, Prioritization the conflict between patients/profits, etc.)
Infection control	☐	☐	☐	☐	☐	☐	☐	☐	☐	Reuse of retired medical technology
Reprocessing of single-use medical devices	☐	☐	☐	☐	☐	☐	☐	☐	☐	Ethical concerns (Privacy and confidentiality, consent, Prioritization the conflict between patients/profits, etc.)
Reprocessing of single-use medical devices	☐	☐	☐	☐	☐	☐	☐	☐	☐	Reuse of retired medical technology
Ethical concerns (Privacy and confidentiality, consent, Prioritization the conflict between patients/profits, etc.)	☐	☐	☐	☐	☐	☐	☐	☐	☐	Reuse of retired medical technology

Considering the sub-criteria of Management risks under "HTM Operations", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Maintenance	☐	☐	☐	☐	☐	☐	☐	☐	☐	Reporting and Follow-up of adverse events and near misses
Maintenance	☐	☐	☐	☐	☐	☐	☐	☐	☐	Inventory control and tracking of MD
Reporting and Follow-up of adverse events and near misses	☐	☐	☐	☐	☐	☐	☐	☐	☐	Inventory control and tracking of MD

Considering the sub-criteria of Management risks under "Strategic risks", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Supply Chain Disruption (Reagent, consumables, Spare parts, etc.)	☐	☐	☐	☐	☐	☐	☐	☐	☐	Finance (lack/delay in funding)
Supply Chain Disruption (Reagent, consumables, Spare parts, etc.)	☐	☐	☐	☐	☐	☐	☐	☐	☐	Lack of standardization
Finance (lack/delay in funding)	☐	☐	☐	☐	☐	☐	☐	☐	☐	Lack of standardization

Considering the sub-criteria of Management risks under "Workforce Development and User Experience", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Training of Non-medical users	☐	☐	☐	☐	☐	☐	☐	☐	☐	Alarm fatigue
Training of Non-medical users	☐	☐	☐	☐	☐	☐	☐	☐	☐	Insufficient technical expertise among biomedical engineers and technicians
Training of Non-medical users	☐	☐	☐	☐	☐	☐	☐	☐	☐	Continuous Educational Program for End-Users (refresh training)
Alarm fatigue	☐	☐	☐	☐	☐	☐	☐	☐	☐	Insufficient technical expertise among biomedical engineers and technicians
Alarm fatigue	☐	☐	☐	☐	☐	☐	☐	☐	☐	Continuous Educational Program for End-Users (refresh training)
Insufficient technical expertise among biomedical engineers and technicians	☐	☐	☐	☐	☐	☐	☐	☐	☐	Continuous Educational Program for End-Users (refresh training)

Considering the sub-criteria of Facilities and Internal Environmental risks under "Planning", from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Design Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Regulatory Compliance (related to facility design) Risks

Considering the sub-criteria of Facilities and Internal Environmental risks under “Construction and Commissioning”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Blueprint vs Reality Discrepancies	☐	☐	☐	☐	☐	☐	☐	☐	☐	Project Phasing Concerns
Blueprint vs Reality Discrepancies	☐	☐	☐	☐	☐	☐	☐	☐	☐	Testing and Validation
Project Phasing Concerns	☐	☐	☐	☐	☐	☐	☐	☐	☐	Testing and Validation

Considering the sub-criteria of Facilities and Internal Environmental risks under “Operation”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Maintenance Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Environmental Control Risks
Maintenance Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Disaster Response Risks
Environmental Control Risks	☐	☐	☐	☐	☐	☐	☐	☐	☐	Disaster Response Risks

Considering the sub-criteria under “Macro-environmental Risks (Exogenous)”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Environmental	☐	☐	☐	☐	☐	☐	☐	☐	☐	Technological
Environmental	☐	☐	☐	☐	☐	☐	☐	☐	☐	Political

Environmental	☐	☐	☐	☐	☐	☐	☐	☐	☐	Economic
Technological	☐	☐	☐	☐	☐	☐	☐	☐	☐	Political
Technological	☐	☐	☐	☐	☐	☐	☐	☐	☐	Economic
Political	☐	☐	☐	☐	☐	☐	☐	☐	☐	Economic

Considering the sub-criteria for “Macro-environmental Risks (Exogenous)” under “Economic risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Economic growth or recession	☐	☐	☐	☐	☐	☐	☐	☐	☐	Shifts in public healthcare spending or budget allocation

Considering the sub-criteria for “Macro-environmental Risks (Exogenous)” under “Political risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Political stability or instability	☐	☐	☐	☐	☐	☐	☐	☐	☐	International relations, trade policies, and sanctions

Considering the sub-criteria for “Macro-environmental Risks (Exogenous)” under “Environmental risks”, from your perspective, how would you prioritize the relative importance of each risk factor in the context of healthcare technology risk management?

	Absolutely more important	Very strongly more important	Strongly more important	Slightly more important	Equally important	Slightly more important	Strongly more important	Very strongly more important	Absolutely more important	
Climate change & Natural Disasters	☐	☐	☐	☐	☐	☐	☐	☐	☐	Unexpected pandemic/disease outbreaks

Appendix III: Complete Annual Robustness Results of the SQRRM Law (2020–2024)

This appendix presents the full set of annual system-identification results obtained for the Synergistic Quadratic–Resonant Risk Model (SQRRM) and all competing baseline formulations over the period 2020–2024. These results provide comprehensive numerical documentation supporting the temporal robustness analysis reported in Chapter 5.

The models were fitted independently for each year using the globally normalized utilization–gap product (U × Weighted AHP Gap) and evaluated using three complementary performance indicators: the coefficient of determination (R^2), mean squared error (MSE), and Spearman's rank correlation coefficient (ρ). All model fittings were conducted using nonlinear least-squares regression under identical parameter initialization and convergence settings.

1- COVID-19 Disruption and Treatment of the 2020 Dataset

The year 2020 corresponds to the COVID-19 pandemic period and represents a structurally disrupted operational regime characterized by:

- Widespread suspension of elective clinical services,
- Substantial deferral of diagnostic activity,
- Irregular utilization of several imaging modalities (particularly ophthalmic systems), and
- Incomplete or suppressed maintenance and work-order records.

As a result, the 2020 cross-section does not satisfy the stationarity, completeness, or comparability assumptions required for formal temporal robustness assessment. Accordingly, while 2020 results are retained in this appendix for historical completeness and transparency, they are excluded from the post-pandemic robustness conclusions, which are based on the stable operational period 2021–2024.

2- Full Annual Model Performance Table (2020–2024)

Table 1 reports the complete year-by-year performance of all six model families: Linear, Quadratic, Exponential, Sine, Quadratic+Sine, and the proposed Advanced Hybrid (SQRRM).

Table 1: Annual Model Performance for Utilization–Risk System Identification (2020–2024)

Performance is reported using the coefficient of determination (R^2), mean squared error (MSE), and Spearman's rank correlation coefficient (ρ). The year 2020 corresponds to the COVID-disrupted operational regime.

Year	Model	R^2	MSE	Spearman ρ
2020	Linear	0.083	4399.52	0.46
2020	Exponential	0.083	4399.58	0.46
2020	Quadratic	0.397	2895.04	0.57
2020	Sine	0.563	2099.23	0.50
2020	Quad+Sine	0.648	1691.04	0.69
2020	**Advanced Hybrid (SQRRM)**	0.618	1834.01	0.61
2021	Linear	0.121	4465.01	0.67
2021	Exponential	0.121	4465.09	0.67
2021	Quadratic	0.633	1865.01	0.67
2021	Sine	0.973	137.52	0.76
2021	Quad+Sine	0.951	247.15	0.77
2021	**Advanced Hybrid (SQRRM)**	**0.984**	**82.66**	**0.80**
2022	Linear	0.004	1929.95	0.36
2022	Exponential	0.004	1929.96	0.36
2022	Quadratic	0.327	1303.65	0.46
2022	Sine	0.429	1107.25	0.41
2022	Quad+Sine	0.499	971.79	0.42
2022	**Advanced Hybrid (SQRRM)**	**0.501**	**967.38**	**0.45**
2023	Linear	0.003	2859.28	−0.33
2023	Exponential	0.003	2859.29	−0.33
2023	Quadratic	0.155	2422.76	0.45
2023	Sine	0.285	2050.74	0.53

2023	Quad+Sine	—	—	—
2023	**Advanced Hybrid (SQRRM)**	**0.329**	**1924.41**	**0.53**
2024	Linear	0.079	15084.86	0.68
2024	Exponential	0.079	15085.11	0.68
2024	Quadratic	0.322	11099.45	0.59
2024	Sine	0.286	11692.46	0.49
2024	Quad+Sine	0.600	6547.10	0.62
2024	**Advanced Hybrid (SQRRM)**	**0.943**	**941.16**	**0.63**

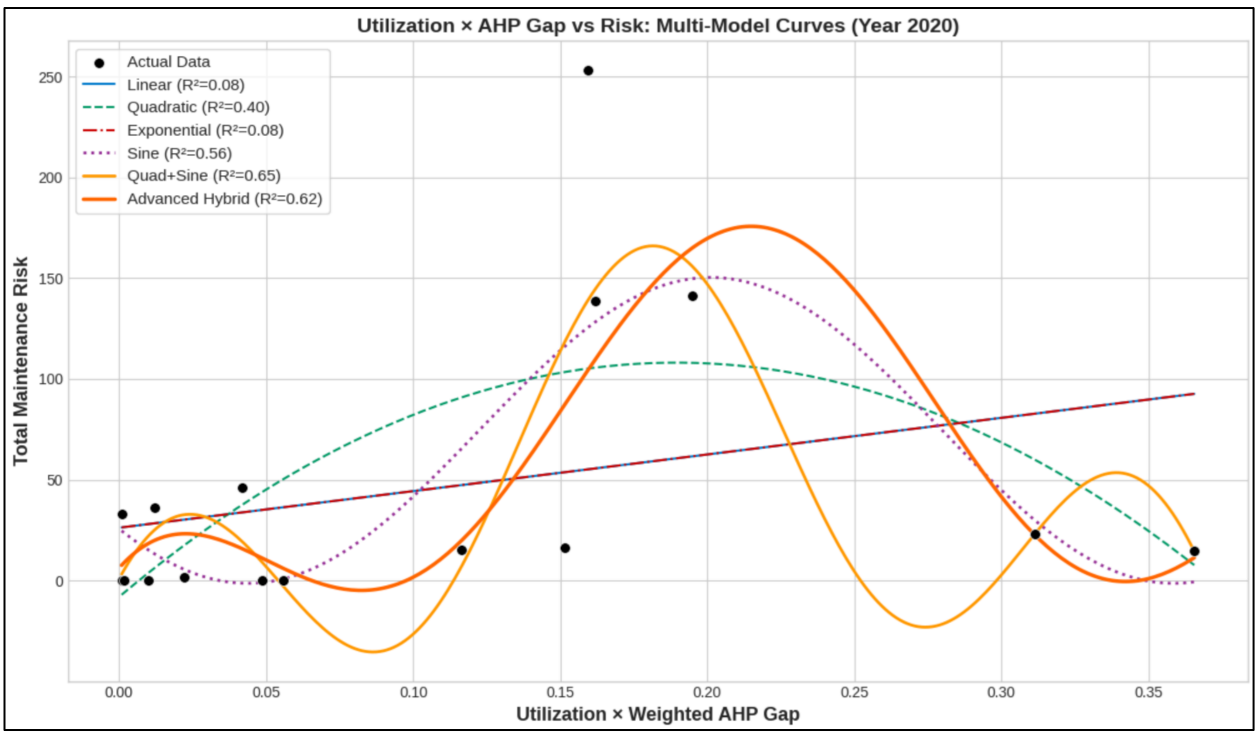


Figure 1: Comparison of multi-model fits for the Utilization × AHP-weighted gap versus total maintenance risk for the year 2020.

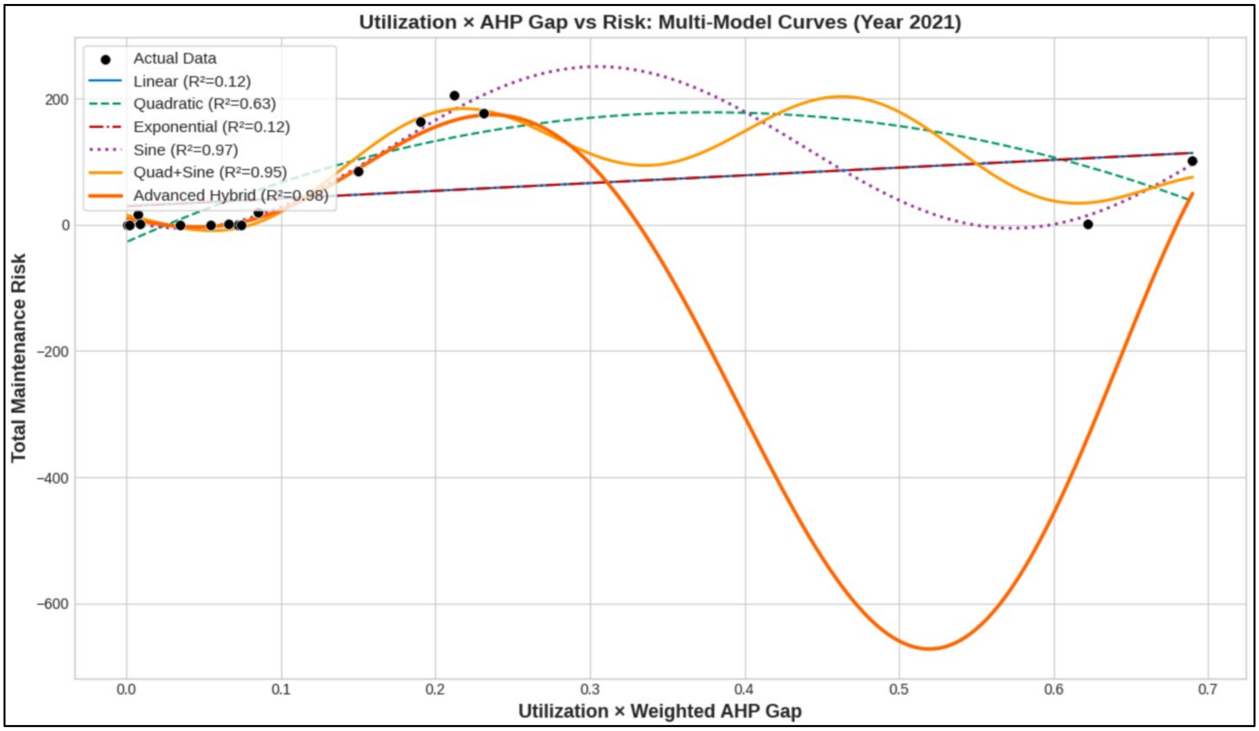


Figure 2: Comparison of multi-model fits for the Utilization × AHP-weighted gap versus total maintenance risk for the year 2021. Linear, quadratic, exponential, sine, Quad+Sine, and the proposed Advanced Hybrid (SQRRM) models are illustrated against the observed hospital data. The figure highlights the limited explanatory power of classical regression models and the improved curvature and oscillatory representation achieved by the hybrid nonlinear formulations under moderate noise conditions.

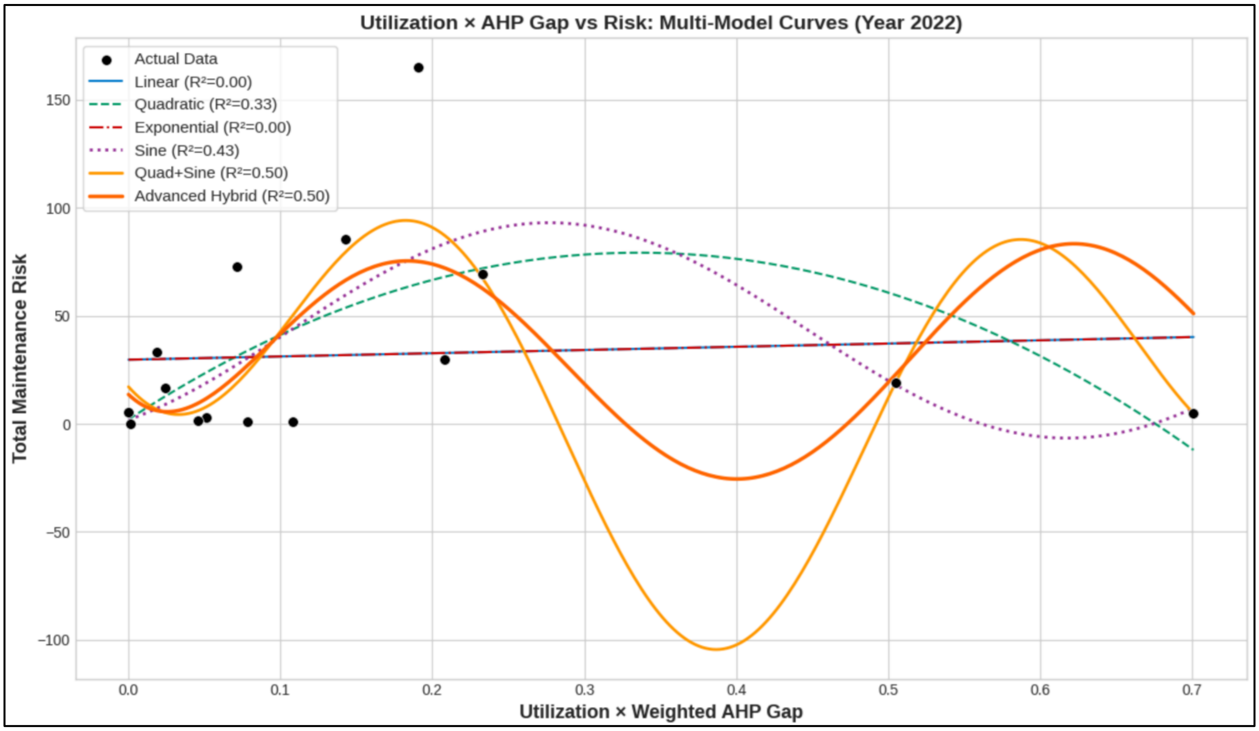


Figure 3: Comparison of multi-model fits for the Utilization × AHP-weighted gap versus total maintenance risk for the year 2022.

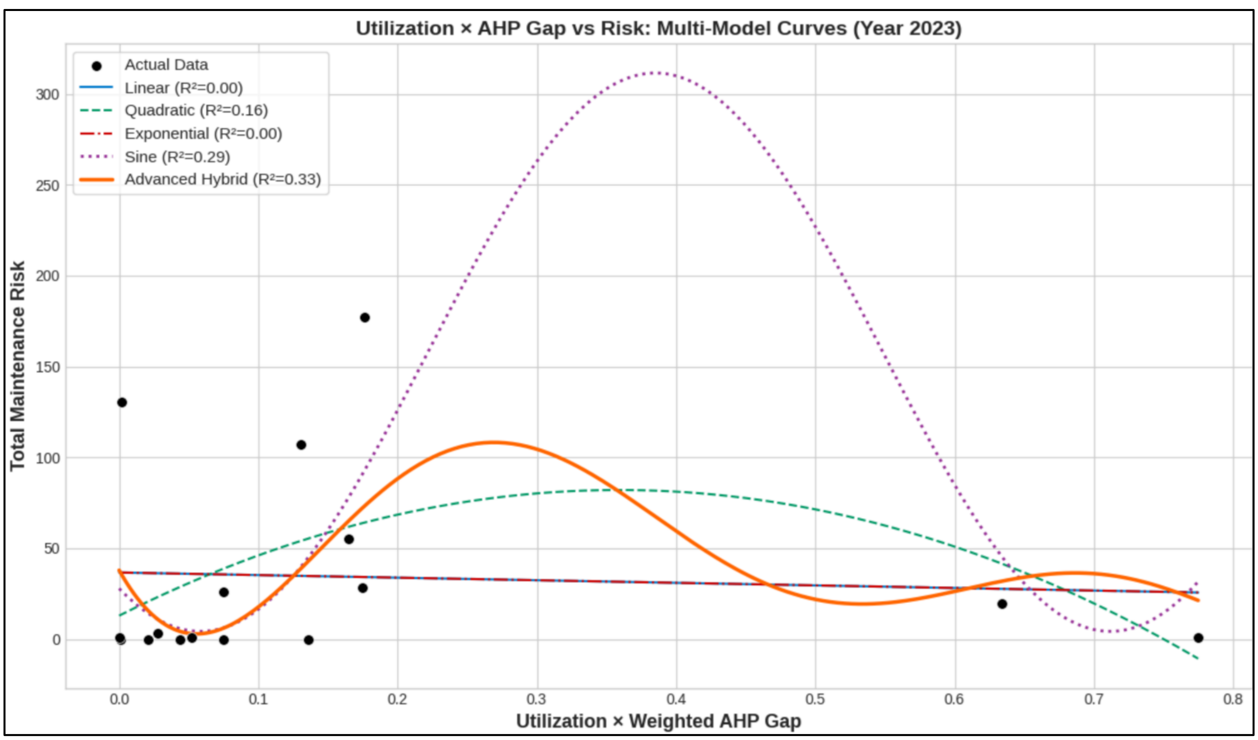


Figure 4: Comparison of multi-model fits for the Utilization × AHP-weighted gap versus total maintenance risk for the year 2023.

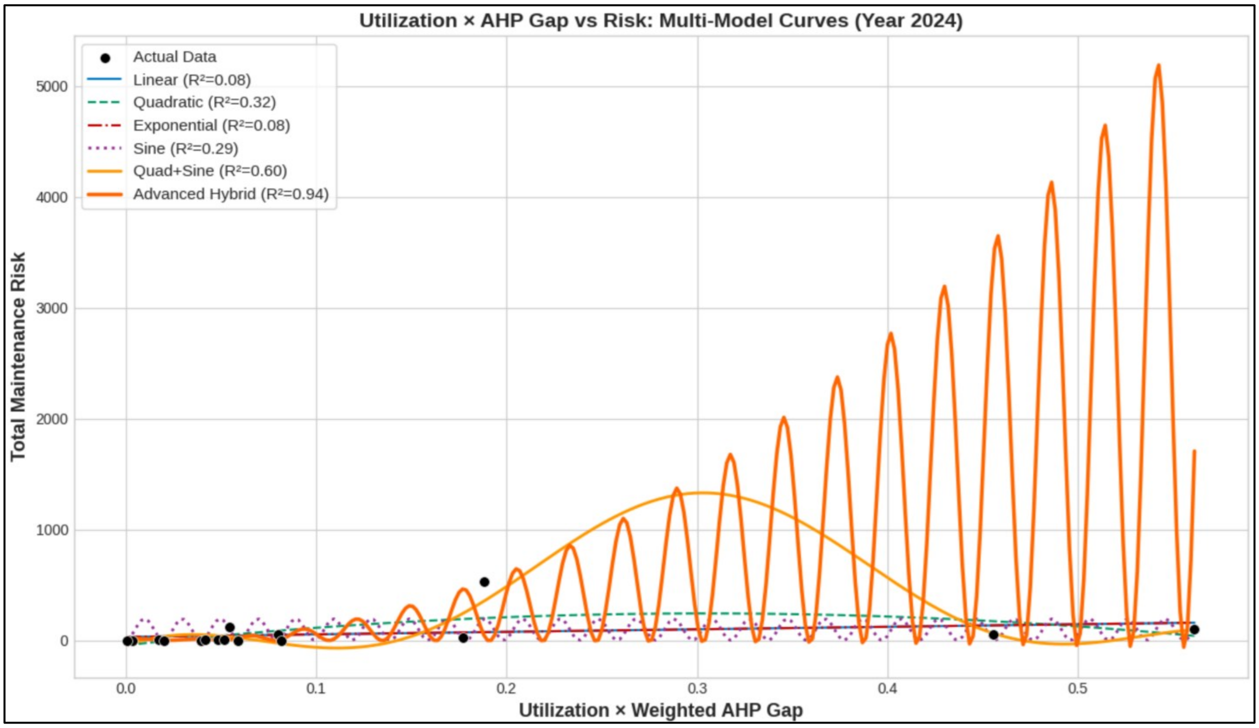


Figure 5: Comparison of multi-model fits for the Utilization × AHP-weighted gap versus total maintenance risk for the year 2024

3- Interpretation of Full Annual Results

The full annual results confirm that:

1. Linear and exponential formulations consistently fail across all years, confirming that utilization alone is insufficient to explain maintenance risk.
2. Resonant and nonlinear hybrid formulations outperform monotonic models, particularly during years of stable operational demand (2021 and 2024).
3. The proposed SQRRM model achieves dominant performance in the strongest-signal years, exhibiting near-deterministic behaviour in 2021 and exceptional performance again in 2024.
4. During system-level volatility (2022–2023), all models experience performance degradation, but SQRRM retains its top-ranked status, confirming structural robustness under noisy conditions.
5. The 2020 COVID-disrupted year exhibits suppressed utilization–risk structure, validating its exclusion from the formal robustness conclusions.