

## Article

# 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

Tasneem Mahmoud <sup>1,\*</sup> , Wamadeva Balachandran <sup>1,\*</sup>  and Saleh Altayyar <sup>2</sup>

<sup>1</sup> Department of Electronic and Electrical Engineering Research, Brunel University London, Uxbridge UB8 3PH, UK

<sup>2</sup> Department of Biomedical Technology, College of Applied Medical Sciences, King Saud University, Riyadh 11451, Saudi Arabia; saltayyar@cureprint.sa

\* Correspondence: tasneemmahmoudsalih.mahgoub@brunel.ac.uk or bme.tasneem@hotmail.com (T.M.); wamadeva.balachandran@brunel.ac.uk (W.B.)

**Abstract:** In the context of healthcare technology management (HTM) in Saudi Arabia and the Gulf region, this study addresses a significant gap by exploring both external and internal risk factors affecting HTM performance. Previous studies have primarily focused on modeling or predicting failures in medical devices, mostly examining internal (endogenous) factors that impact device performance and the development of optimal service strategies. However, a comprehensive investigation of external (exogenous) factors has been notably absent. This research introduced a novel hierarchical risk management framework designed to accommodate a broad array of healthcare technologies, not limited to just medical devices. It significantly advanced the field by thoroughly investigating and validating a comprehensive set of 53 risk factors and assessed their influence on HTM. Additionally, this study embraced the perspective of enterprise risk management (ERM) and expanded it to identify and incorporate a wider range of risk factors, offering a more holistic and strategic approach to risk assessment in healthcare technology management. The findings revealed that several previously underexplored external and internal factors significantly impacted HTM performance. Notably, the Fuzzy AHP survey identified “design risk” under facility and environmental risks as the highest risk for HTM in this region. Furthermore, this study revealed that three out of the top ten risks were related to “facility and internal environmental” factors, six were related to technological endogenous factors, and only one was related to managerial factors. This distribution underscores the critical areas for intervention and the need for robust facility and technology management strategies. In conclusion, this research not only fills a critical void by providing a robust framework for healthcare technology risk assessment but also broadens the scope of risk analysis to include a wider array of technologies, thereby enhancing the efficacy and safety of healthcare interventions in the region. Additionally, the proposed hierarchy provides insights into the underlying risk factors for healthcare technology management, with potential applications extending beyond the regional context to a global scale. Moreover, the equation we proposed offers a novel perspective on the key risk factors involved in healthcare technology management, presenting insights with far-reaching implications applicable not only regionally but also on a global level. This framework also supports sustainability goals by encouraging the efficient and responsible utilization and management of healthcare technologies, essential for ensuring the long-term economic and environmental sustainability of medical technology use. This research is of an exploratory nature, with the findings from the Fuzzy AHP analysis being most applicable to the specific geographic regions examined. Additional research is required to validate these results and to confirm the trends observed in various other regions and contexts.

**Keywords:** healthcare technology management (HTM); healthcare risk management (HRM); healthcare technology risk management (HTRM); analytic hierarchy process (AHP); endogenous risk factor;



**Citation:** Mahmoud, T.; Balachandran, W.; Altayyar, S. 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* **2024**, *16*, 8197. <https://doi.org/10.3390/su16188197>

Academic Editors: Lotfi Aleya, Francisco Ródenas Rigla, Jordi Garcés Ferrer and Ascensión Doñate-Martínez

Received: 22 June 2024

Revised: 14 September 2024

Accepted: 18 September 2024

Published: 20 September 2024



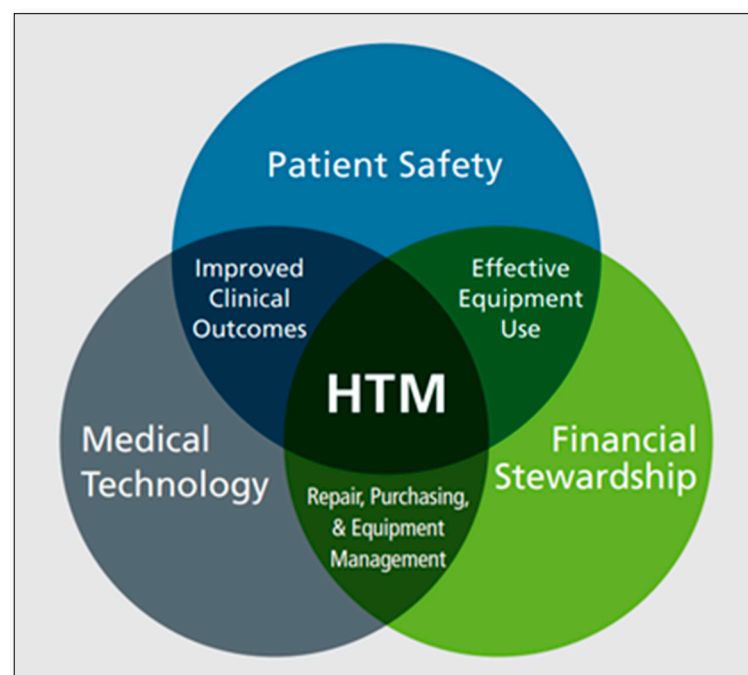
**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

exogenous risk factors; facility management; regulatory compliance; blue print; enterprise risk management; PESTLE; comparison matrix; sustainability; healthcare system

## 1. Introduction

To commence, it is crucial to define what is meant by “healthcare technology.” The World Health Organization (WHO) offers a comprehensive definition: “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 this paper, however, the term ‘healthcare technology’ specifically refers to the physical hardware and software components from the WHO definition that require maintenance, explicitly excluding drugs and pharmaceuticals.

The Association for the Advancement of Medical Instrumentation (AAMI) defines Healthcare Technology Management (HTM) as the discipline dedicated to overseeing the selection, maintenance, and safe utilization of all health technology and medical equipment in healthcare settings [2]. AAMI has also provided a diagram (Figure 1) that illustrates how HTM roles and responsibilities intersect within the healthcare environment [2].



**Figure 1.** The diagram shows the intersection of HTM roles and responsibilities within healthcare [2].

Risk management in healthcare institutions began to take shape in the 1970s in the USA, following court rulings that held hospitals and clinical staff accountable for the quality of care provided. As a result, a formal risk management program became a critical requirement in healthcare facilities around the world and a prerequisite for hospital accreditation. In the Kingdom of Saudi Arabia, implementing a healthcare risk management program is a necessary condition for CBAHI and JCI accreditation [3].

In their work cited as [4], the authors pose the question, “What is enterprise risk management (ERM)?” They suggest that the definition of ERM should align with an organization’s business model, strategy, culture, and climate, which means it can vary significantly across different organizations. Unlike traditional risk management, which typically focuses on specific risk categories and assesses the impact of isolated risks on a single aspect of

organizational health, enterprise risk management provides a comprehensive overview of all risks an organization faces and their interrelationships. This comprehensive approach allows for more strategic planning.

Furthermore, traditional risk management often overlooks the interconnections between risks, which can lead to more efficient resource utilization—including people, money, time, and ideas—reduce redundant efforts, foster innovative thinking, and enhance the early identification and evaluation of risks.

The most appropriate definition of enterprise risk, found in [4] titled “Enterprise Risk Management—An Analytic Approach” describes it as “the possibility that something, directly or indirectly, will obstruct the achievement of business objectives.” Based on [4], the categories of Enterprise Risk Management (ERM) include:

- Financial
- Operational/Clinical
- Human Capital
- Strategic
- Legal/Regulatory
- Technological
- Natural Disaster/Hazard [4]

S Taghipour et al. examined 16 factors in their study titled “Prioritization of medical equipment for maintenance decisions,” which included: function, mission criticality, utilization, availability of alternative devices, age, total risk, failure frequency, detectability, failure consequence, operational downtime, non-operational, downtime, cost of repair, safety and environment, recalls and hazard alerts, and maintenance requirements [5]. Conversely, Malek Masmoudi et al. examined 13 criteria in their research “Quantitative techniques for medical equipment maintenance management,” which included degree of complexity of the maintenance, detectability, frequency, safety, downtime, degree of importance of the mission, utilization rate, availability of alternative devices, age, recalls and user errors, classes of equipment, function, and risk [6]. Both studies derived their selection of criteria from the risk assessment method proposed by Fennigkoh and Smith in 1989, which introduced Equipment Management (EM) numbers [7]. They also considered the subsequent adaptations found in Wang and Levenson’s algorithms, which include the Equipment Management Rating (EMR) and the adjusted EMR [8].

Ron Kaye and Jay Crowley [9] emphasize that addressing medical device hazards during the development phase can improve the risk management process. They advocate for the inclusion of human factors engineering (HFE) to identify potential hazards effectively. The authors outline the key elements of HFE as follows:

- End users (such as patients, family members, physicians, nurses, and professional caregivers);
- Typical and atypical uses of the device;
- Device specifications;
- Characteristics of the environments where the device will be used;
- The interactions among users, devices, and their environments [9].

John Collins suggests that a more precise assessment of potential physical risks to patients can be achieved by analyzing data from the Food and Drug Administration (FDA) [10]. By reviewing adverse event reports for each medical device, according to Collins, a risk score can be assigned. The author presented a data-driven method that aims to lower the total risk score and preventive maintenance costs of devices that pose physical risks to patients. Collins also recommends an annual reevaluation of maintenance data along with FDA records for individual hospitals, although he does not specify the analysis tools to be used. His method assigns risk scores annually using historical data from these two sources, but it does not predict future trends. Additionally, Collins’ approach includes a modification of the Fennigkoh and Smith scoring protocol based on insights from the FDA data analysis [10].

Amran et al. introduced a multi-criteria decision-making (MCDM) model that employs quality function deployment (QFD) and fuzzy logic to rank medical devices according to their criticality [11]. This model was applied to assess customer requirements and the technical characteristics within the House of Quality (HOQ). However, it did not consider factors related to the facility, internal environmental conditions, or external influences.

Abd Rahman et al. developed a predictive model to categorize critical medical devices in healthcare facilities across Malaysia [12]. The model, utilizing both machine learning and deep learning techniques, divides devices into three classes based on their projected failure times: (i) class 1 for devices unlikely to fail within the first three years after purchase, (ii) class 2 for devices likely to fail within three years of purchase, and (iii) class 3 for devices expected to fail more than three years post-purchase [12]. The analysis incorporated 17 input parameters, including service support, asset condition, service intention of function, frequency of maintenance requirements, maintenance complexity, total downtime, alternatives and backups, operations, maintenance costs, and details specific to the device's manufacturing country, model, manufacturer, and brand. Notably, the study focused solely on factors inherent to the medical devices or their maintenance operations, excluding external or facility-related factors.

Khalaf et al. [13] proposed a preliminary model, which posits that the operational probability of equipment can be modeled as an exponential function of its age and the time since last maintenance and presented a simplified view that may not hold up under the complex realities of equipment management in practical settings. This model's primary limitation is its reductionist approach, assuming that all factors influencing equipment reliability can be adequately captured merely through age and maintenance intervals. This hypothesis fails to consider the inherent differences between types of equipment, the other critical factors such as the quality of maintenance, the environment in which the equipment is used, operator errors, and manufacturing defects. These factors can significantly impact the actual operational lifetime and reliability of the equipment. Furthermore, the model does not account for the strategic and economic implications of maintenance decisions. In many cases, maintenance strategies are influenced by cost considerations, availability of parts, and technological obsolescence, factors that an exponential model based solely on age and maintenance history cannot predict or accommodate.

In their 2021 study, Zamzam et al. examined smart prioritization strategies, focusing on preventive, corrective, and replacement programs [14]. They developed three robust models that categorize healthcare facilities into low, medium, and high priority groups for better management. The importance of such prioritization is further emphasized in references [15,16], which discuss the complexity and the numerous interconnected components of most medical equipment. These complexities have direct implications on patient care, underscoring the need for strategically planned maintenance to prevent equipment failures, as detailed in [16].

In their 2015 study, Jamshidi et al. employed a fuzzy multi-criteria decision-making approach to prioritize medical devices, incorporating a variety of expert opinions and addressing uncertainties by proposing a risk-based framework for device replacement [17]. This approach utilized a risk-based methodology that assessed both the probability and severity of failures. The framework considered four main factors and seven additional dimensions, including use-related hazards, age, and utilization, to cover all relevant aspects of hazards and risks. These factors were primarily technology-related, in addition to considering the economic impact of monetary losses and safety concerns for patients and workers. However, the study did not encompass strategic, managerial, and facility-related aspects, nor did it consider internal or external environmental factors, as its primary aim was to improve decisions related to device replacement.

In the study by Cruz et al. [18], the authors introduced a mathematical model that can be integrated into a hospital informatics system to provide alerts when medical equipment requires maintenance or replacement. This model employed an event tree approach to systematically assess several critical factors, including patient and operator safety risks,

equipment surpassing its useful life, high maintenance costs, suboptimal maintenance practices, catastrophic downtime, and malfunctions due to user or technical errors.

The study by Pinho [19] involved an analysis of 15 criteria aimed at supporting the maintenance management of medical equipment. Despite its broad scope, this analysis omitted several essential aspects, such as facility-specific conditions, internal and external environmental factors, user training, and contractual considerations. Moreover, the study did not cover the management of equipment alerts and recalls.

The studies cited in references [18,19] primarily focused on prioritizing risks to enhance maintenance management or to make informed decisions about replacements. This study expanded on that approach by considering risk as an integral part of the entire lifecycle of healthcare technology. This broader perspective aimed to enhance management decisions across all stages of healthcare technology management. These stages include building the appropriate infrastructure, ensuring the proper maintenance of the healthcare technology infrastructure, collecting reliable information, planning and assessing technology needs, allocating adequate funding, procuring technology, providing necessary resources for usage, operating technology effectively and safely, maintaining and repairing technology, and finally, decommissioning, disposing of, and replacing unsafe or obsolete items. Furthermore, this study also explores additional factors such as contractual aspects, staff training, workforce development, and user experience.

Using only the Fuzzy AHP model to assess risk might not capture the unique attributes of each healthcare technology or the differences among healthcare organizations. Additionally, this method could overlook the probability of risk events occurring, which may result in less accurate risk assessments. Thus, there is a vital need to amalgamate the findings from the Fuzzy AHP model with the foundational risk equation to enhance the accuracy and comprehensiveness of the risk assessment process.

In this paper, we proposed a novel risk equation specifically designed for healthcare technology management (HTM), advancing the classic risk calculation by integrating a more comprehensive view of equipment utilization, as initially suggested by Wang and Levenson [8]. We redefined this utilization concept to include both extremes of equipment use, from overuse to underuse, terming it 'optimal utilization'. The equation leverages global weights derived from the fuzzy analytic hierarchy process (AHP) and readiness assessments from healthcare organizations to establish a refined risk metric. The quantification of the effect of optimal utilization on risk, represented by  $f(U_{opt})$ , will be the focus of a subsequent paper, which will aim to empirically validate the model using data from specific healthcare technologies. This advancement holds significant implications for the precision and applicability of risk assessment in HTM. This approach also enhances healthcare technology management effectiveness, reducing resource depletion and contributing to more sustainable healthcare practices.

This study is exploratory, and the insights derived from the Fuzzy AHP analysis primarily pertain to the geographic regions specifically examined. Further investigative efforts are essential to validate these findings across different territories and under varied conditions.

## 2. Materials and Methods

This study adopted a mixed-methods approach, initiating with a comprehensive literature review to identify risk factors in healthcare technology management within Saudi Arabia and the Gulf Region. The review employed specific search terms including "Healthcare Technology", "Medical Devices", "Risk Management", "HTM", "Reliability", "Device Performance", "Safety", "Risk Assessment", "Clinical Engineering", "Maintenance Strategy", "Technology in Healthcare", "Adverse Events", "incidents medical devices", "Medical Equipment Prioritization", "Compliance Issues", "Technology Failure", "Operational Risks", "Security Risks", "Healthcare IT Risks", "Medical Device Safety", "Technology Failures", "Operational Risks in Healthcare", and "Security Risks in Healthcare Technology".

The scope of the literature search encompassed various types of publications, including peer-reviewed journals, conference proceedings, book chapters, and early access articles, specifically focusing on works published from 2000 to 2024. Key databases accessed included IEEE Xplore, Scopus, ScienceDirect, Web of Science, and ResearchGate, selected for their extensive repositories of peer-reviewed literature. This search was further enhanced by Google Scholar and pertinent legislative documents and standards to guarantee comprehensive coverage of the subject.

The search initially yielded 337 papers, and after a meticulous analysis of all abstracts to confirm coverage of critical topics in healthcare technology risk management—including medical devices, biomedical engineering, clinical engineering, and maintenance strategies—67 articles were retained for detailed study. This careful selection and review process, which also included a review of references cited in the articles, was strategically designed to validate the relevance and thoroughness of the literature selected, thereby establishing a robust foundation for identifying and understanding the risk factors impacting healthcare technology management. The reliability and validity of the identified risk factors were further tested through a questionnaire survey, which also explored additional risks not previously documented in the literature. To gain deeper insights, face-to-face interviews were conducted, evaluating the practical applicability of the proposed hierarchical model. Following this, a fuzzy analytic hierarchy process (Fuzzy AHP) survey was undertaken, and subsequently, a Fuzzy AHP model was developed to prioritize the identified risk factors, thereby enhancing the effectiveness of the risk assessment process. A novel risk equation for healthcare technology management was introduced, to be optimized and empirically validated in our subsequent paper using data from specific healthcare technologies.

### *2.1. Risk Evaluation Using Fuzzy Analytic Hierarchy Process (Fuzzy AHP)*

The structure of this process is divided into five main stages:

#### Stage 1: Identification of Risk Factors

The process of establishing criteria and sub-criteria for healthcare technology management risks (HTMR) commenced with an extensive review of existing literature. This was complemented by a field survey and interviews with professionals to identify the most pertinent risk factors.

The PESTLE (Political, Economic, Social, Technological, Legal, and Environmental) analysis technique was employed to identify external risk factors affecting healthcare technology management. This approach ensures a comprehensive understanding of the broader macro-environmental influences that can impact HTM performance. By examining each element of the PESTLE framework, this study captured a wide array of external risks, ranging from regulatory changes and economic fluctuations to technological advancements and societal trends. The use of PESTLE analysis in identifying external risks is a well-established practice in the healthcare industry, providing a structured method to anticipate challenges and adapt strategies accordingly. This methodological inclusion enriches the depth of the risk assessment and aligns with industry best practices as referenced in the recent healthcare management literature [20,21].

From these insights, an Initial Hierarchical Framework of Healthcare Technology Management Risks was constructed, as illustrated in Figures 2–6.

#### Stage 2: Validation of Risk Factors and Development of the Final HTMR Hierarchy

The initially proposed criteria were refined and validated through a survey conducted with HTM professionals from the Kingdom of Saudi Arabia and the Gulf region. An expert panel specializing in HTM was formed to oversee this phase. The impact of different experts on ultimate decisions and results differs, leading to the development of evaluation weighting criteria assigned to each expert based on their job role, qualifications, and professional experience. According to the authors in [22], expert weighting criteria denotes a method for assessing data relevance, which is defined by the organizational position and years of professional experience of the expert. The specific details and descriptions of the

weighting assigned to each expert evaluation criterion used in identifying the respondents are presented in Table 1. The sample size selected for this phase was deemed suitable based on recommendations from prior studies, which indicated that fewer than ten expert responses are typically adequate for analytic hierarchy process (AHP) studies. This is due to the expected uniformity in expert opinions, which diminishes the necessity for a larger sample [23,24].

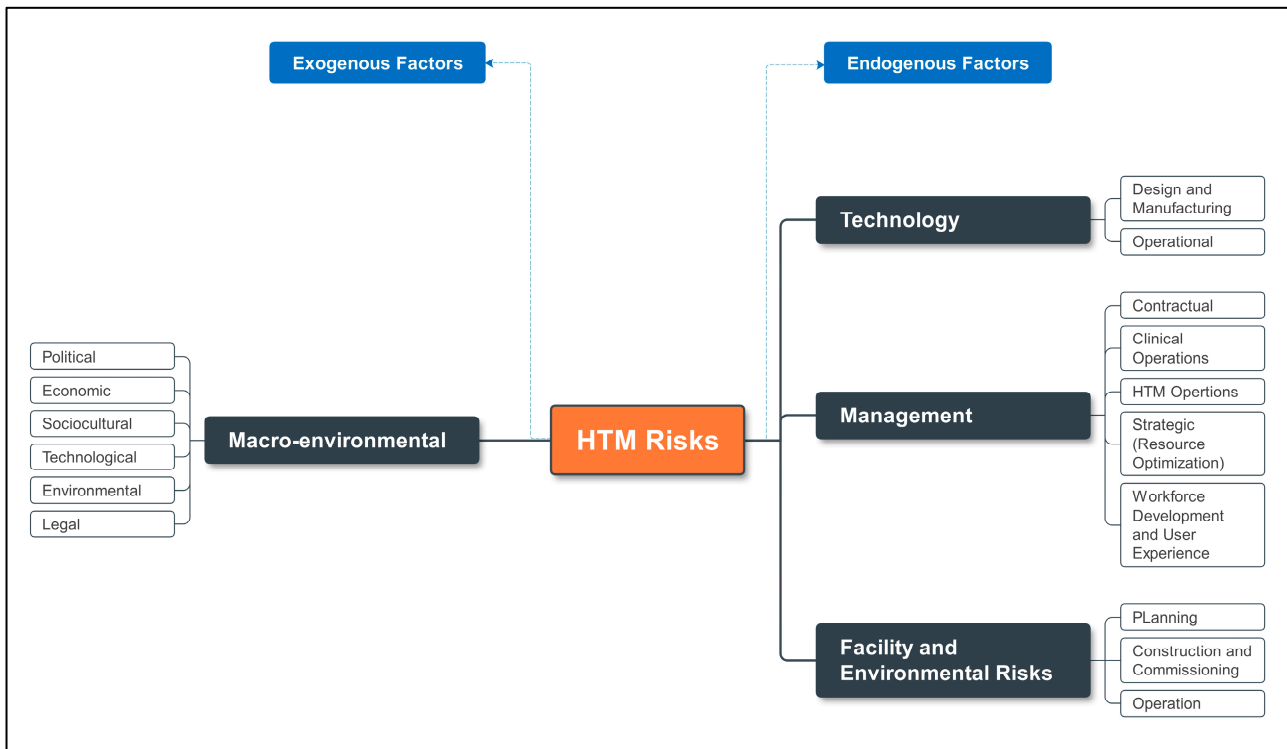


Figure 2. Initial Hierarchical Framework of Healthcare Technology Management Risks.

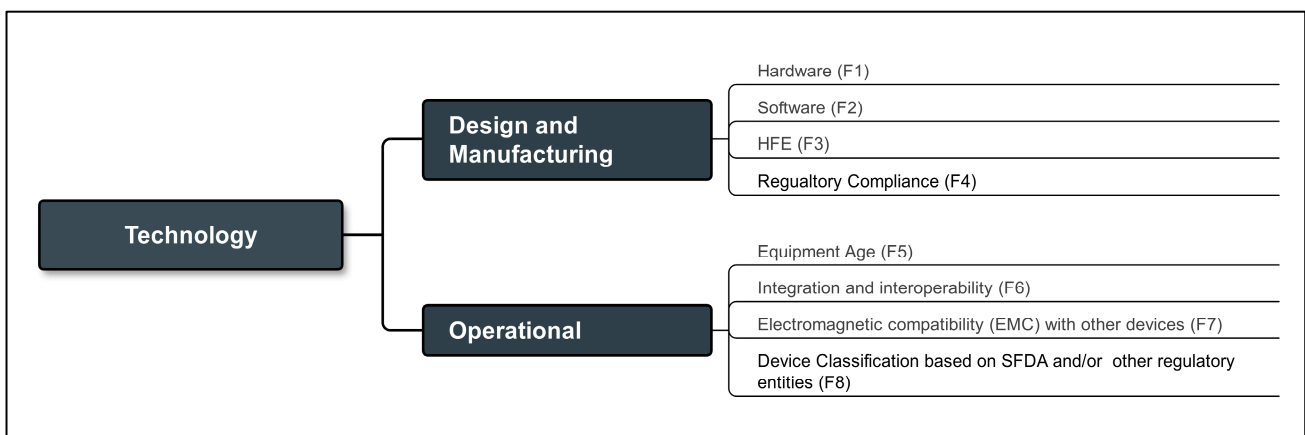


Figure 3. The subcategories of Technology Risks.

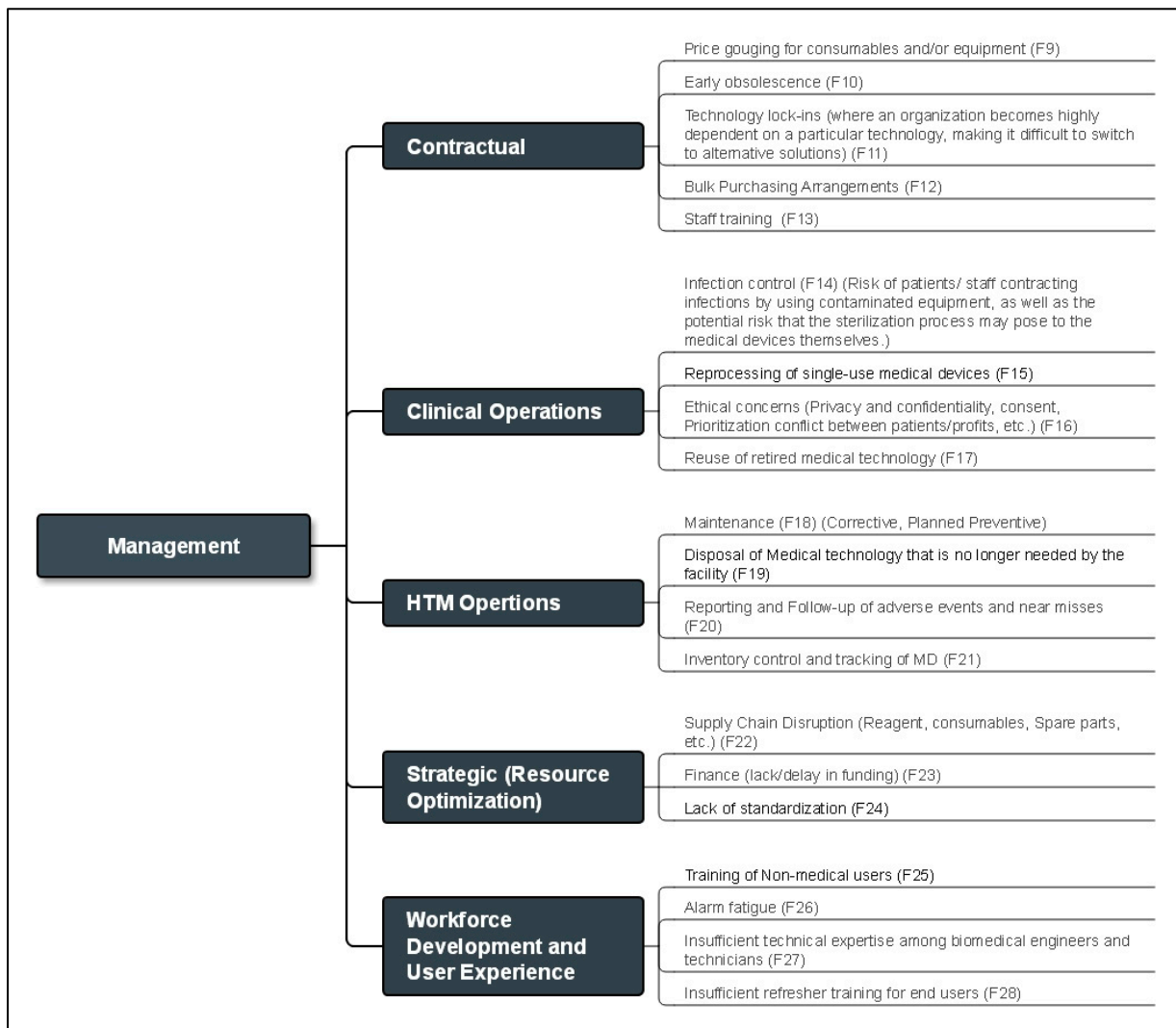


Figure 4. The subcategories of Management Risks.

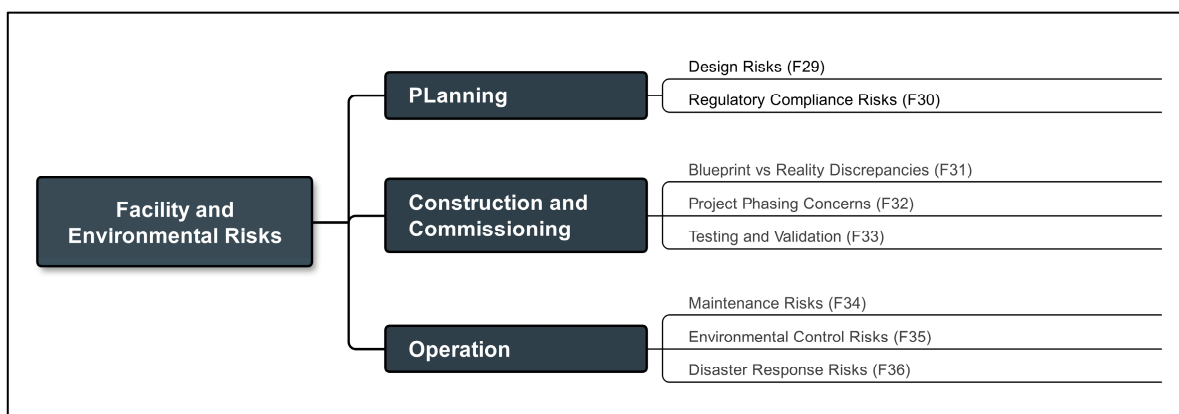


Figure 5. The subcategories of Facility and Internal Environmental Factors.



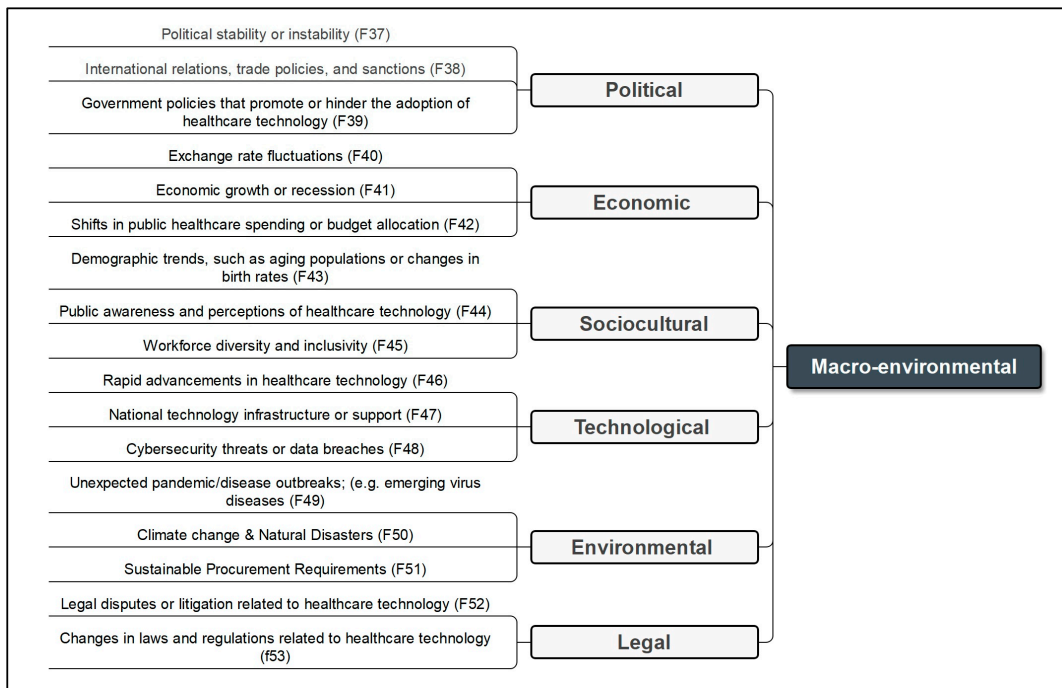


Figure 6. The subcategories of macroenvironmental factors.

Table 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 in non-managerial role in hospitals.	9%
7	16–19 years of rich experience in healthcare technology management in non-managerial roles in hospitals.	9%
8	11–15 years of rich experience in healthcare technology management in non-managerial roles in hospitals.	6%
9	11–15 years of rich experience in healthcare technology management in non-managerial roles 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 7, the two lines represent the mean and the weighted average for each risk factor, demonstrating a close alignment between the two metrics. This proximity corroborates the reliability of the expert weighting criteria utilized [24]. Risk factors with

weighted average (W avg.) values below 3 were excluded from further analysis due to their lesser significance, and these excluded factors are denoted in yellow in Table 2.

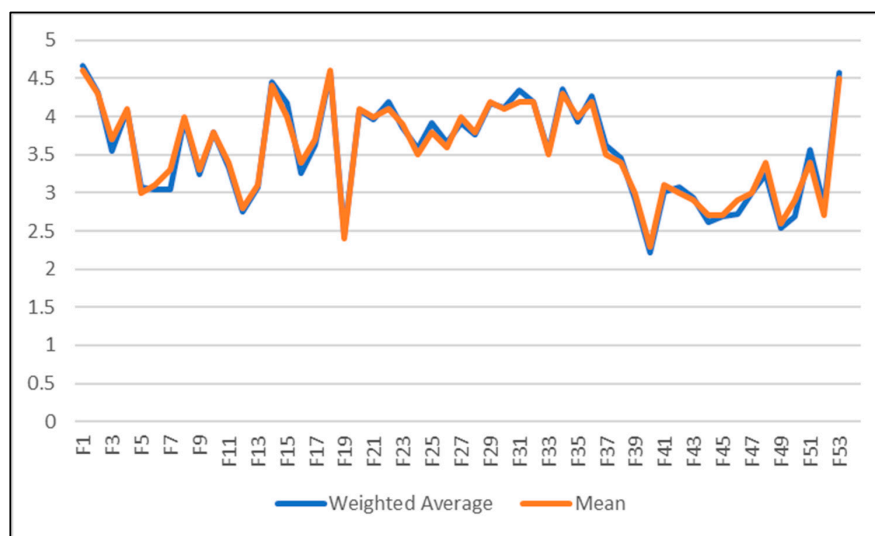
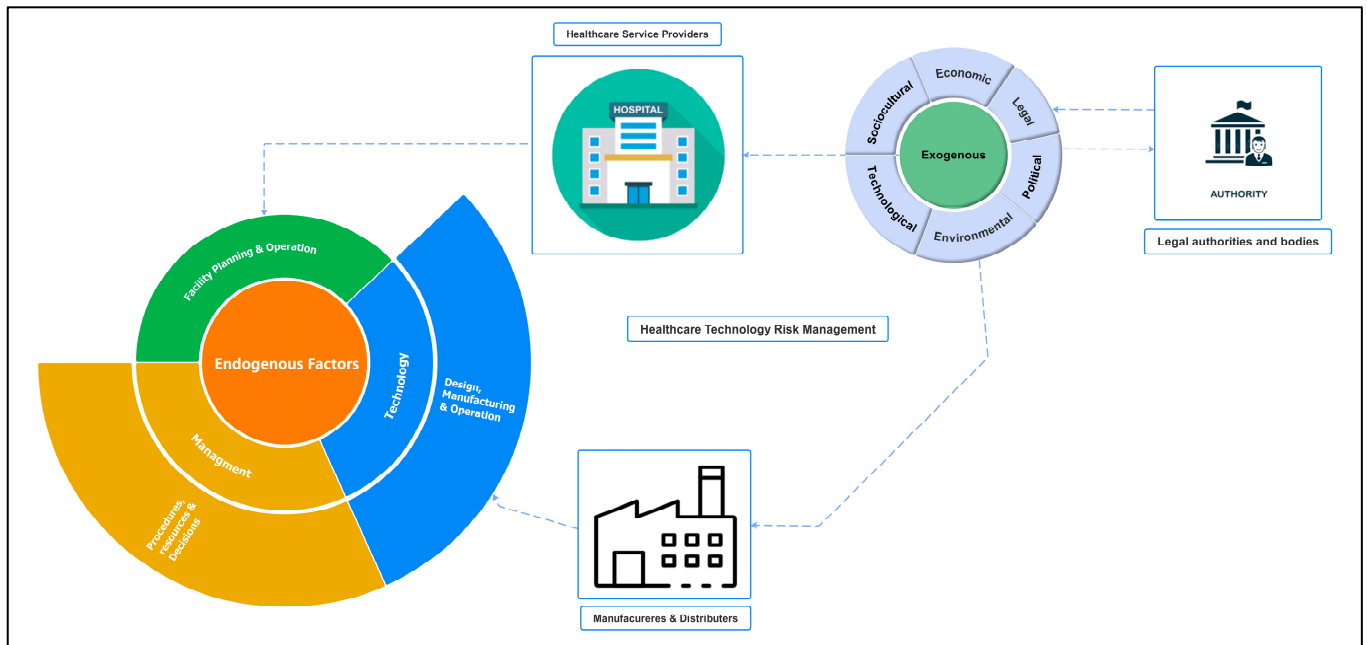


Figure 7. The comparison between the mean and weighted average results.

Table 2. The outcomes from the questionnaire survey conducted in stage 2. The detailed descriptions for each factor are provided in the hierarchy shown in Figure 2. “W avg.” stands for weighted average.

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 also created to offer a detailed view of the various risk sources, including technology, management, facility and environmental, and macroenvironmental factors (Figure 8). This diagram aimed to pinpoint all potential threats that might adversely affect the HTM's performance.



**Figure 8.** Sources of Risk in Healthcare Technology Management.

To ensure the thoroughness and accuracy of the identified risks, a qualitative survey was conducted. This survey analyzed the risks to confirm the comprehensiveness and appropriateness of the risk classification method. An initial assessment was also performed to determine the significance of the identified risks, focusing on those the experts identified as the most critical.

Following this comprehensive review and consultation with experts, a refined HTM risk hierarchy was established (Figure 9).

The reliability of the conducted survey was assessed using Cronbach's Alpha method. The questionnaire evaluated 289 questions in total, yielding a Cronbach's Alpha value of 0.990. In practical terms, a Cronbach's Alpha value of 0.8 or above is considered indicative of reliable data [25].

### Stage 3: Implementation of Fuzzy AHP Survey

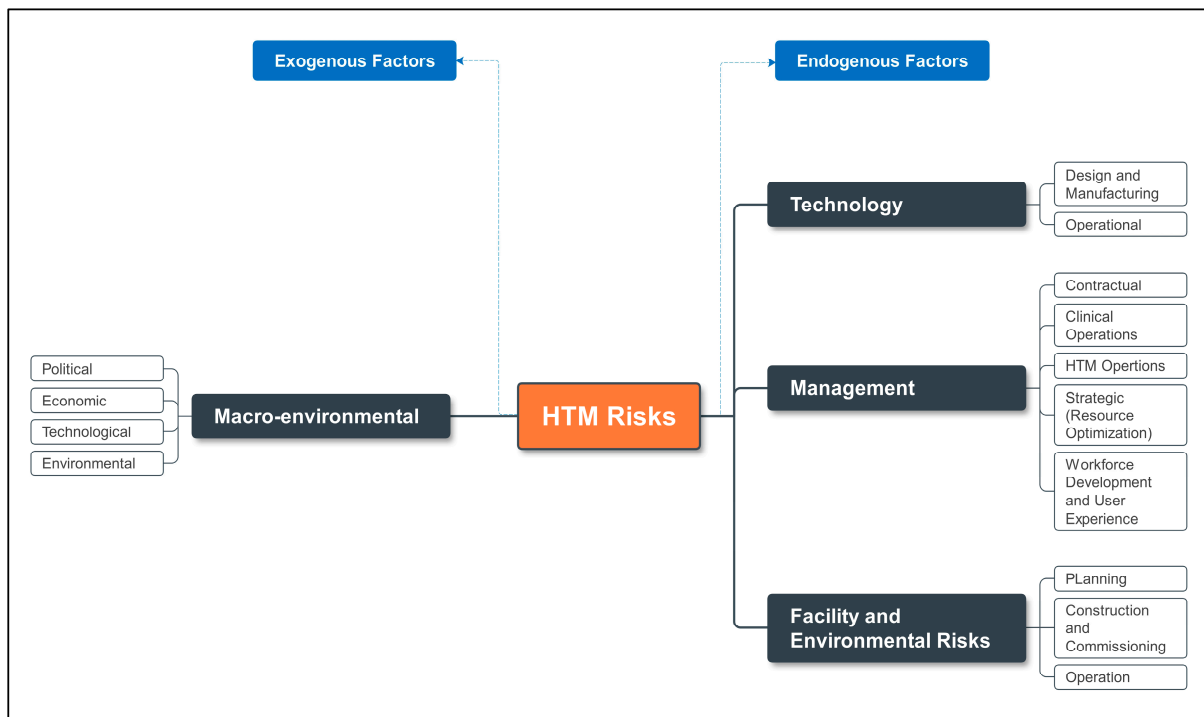
A questionnaire survey utilizing the fuzzy analytic hierarchy process (AHP) was carried out to capture the expert judgments on the importance of structured risk factors. This assessment was based on predefined linguistic variables. These linguistic variables were subsequently transformed into triangular fuzzy numbers (TFNs) to support the pairwise comparisons.

### Stage 4: Evaluation and Prioritization of Risk Factors

Using the data gathered, the weights of the risk factors were determined through the experts' judgments and pairwise comparison matrices. The risk factors were then ranked based on their numerical values to underscore their relative importance.

### Stage 5: Verifying the reliability of the proposed method

To ensure the reliability of the data, a consistency check was conducted on the comparison matrix to confirm the rationality of the experts' judgments and pairwise comparisons. Additionally, a sensitivity analysis was performed.



**Figure 9.** The Hierarchical Framework of Healthcare Technology Management Risks Following Stage 2, by the Author.

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

Relying solely on the outcomes of the Fuzzy AHP model to measure risk may overlook the unique characteristics of each healthcare technology and the variations among healthcare organizations. Additionally, this approach might omit the crucial aspect of the probability of a risk event occurring, which could result in inaccuracies in risk assessment. Therefore, there is a critical need to integrate the results from the Fuzzy AHP model with the foundational risk equation. This integration should include the concept of utilization as outlined by Wang and Levenson [8]. By incorporating a function  $f(U_{opt})$  that reflects optimal utilization, we can more accurately assess the likelihood that current levels of equipment usage might lead to risk events. This approach ensures a more comprehensive and precise quantification of risk, tailored to the specific conditions and usage patterns of healthcare technology within different organizational contexts.

The derivation of the proposed equation, which modifies the foundational risk equation for specific applications, is outlined in the results section of this paper.

## 3. Results

The AHP questionnaire was distributed to 30 HTM experts, with responses received from 22, the majority of whom (68%) were based in Saudi Arabia, followed by 14% from the UAE and Qatar, and the remainder from the UK, Spain, and Germany, all with substantial prior experience in the Gulf region. Among the experts, 18% had over 20 years of experience, 27% had between 16 and 19 years, 41% had between 11 and 15 years, and two experts had 10 and 9 years of experience in HTM, respectively. The majority (59%) of respondents were employed in large public hospitals with more than 1000 beds, while one participant worked in a private hospital. Additionally, 23% were employed by healthcare technology companies, either as agencies or service providers. Two participants worked for a manufacturer, and one was employed by a healthcare technology legislative body.

The data in Table 3 rounded to four decimal places, were derived from an AHP questionnaire that a group of HTM experts answered. The fuzzy weights for the criteria

and sub-criteria were determined using Chang’s extent analysis method [26], as outlined in Equations (1)–(3). These equations were solved using a Python code (<https://www.python.org/>), within the Colab environment, developed specifically to implement Chang’s method. Table 4 displays the linguistic terms alongside their corresponding weights. The calculated global weight values are displayed in both Table 4 and Figure 10.

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

$$V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_2) = \mu_{M_2(d)} = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{2}$$

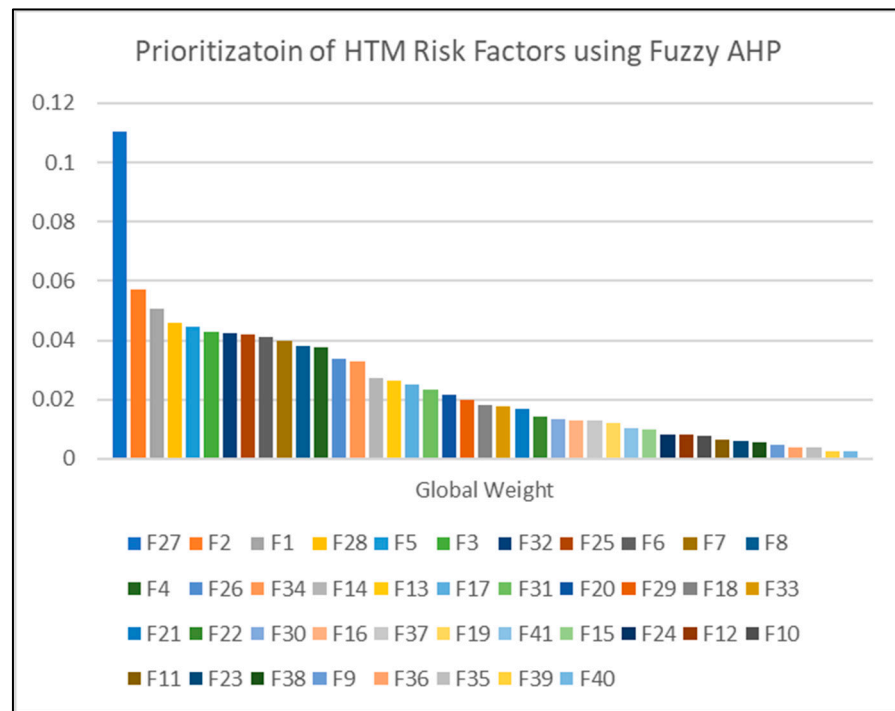
$$W = (d(A1), d(A2), \dots, d(An))T \tag{3}$$

**Table 3.** Ranking of HTM Risk Factors with Corresponding Global Weights (Gl. W.).

Fact.	Gl. W.	Rank	Fact.	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			

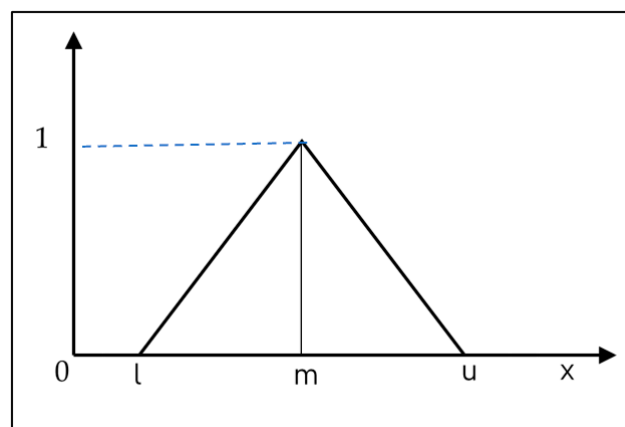
**Table 4.** AHP comparison scale (Chang’s scale).

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 10.** The ranking of factors, indicating that factor (F27)—Design Risks, associated with planning within the Facility and Internal Environmental Risks, is the highest-ranked risk.

M is characterized as a triangular fuzzy number (TFN) with three parameters (l, m, and u), as shown in Figure 11.  $S_i$  represents the synthetic extent value derived from pairwise comparisons. In this context,  $A_i$  is the  $i$ th element and  $d'(A_1), \dots, d'(A_n)$  are the priority weights computed using Equation (2) prior to their normalization.  $W$  is considered a non-fuzzy number.



**Figure 11.** Triangular Fuzzy Number (TFN).

### 3.1. Validation

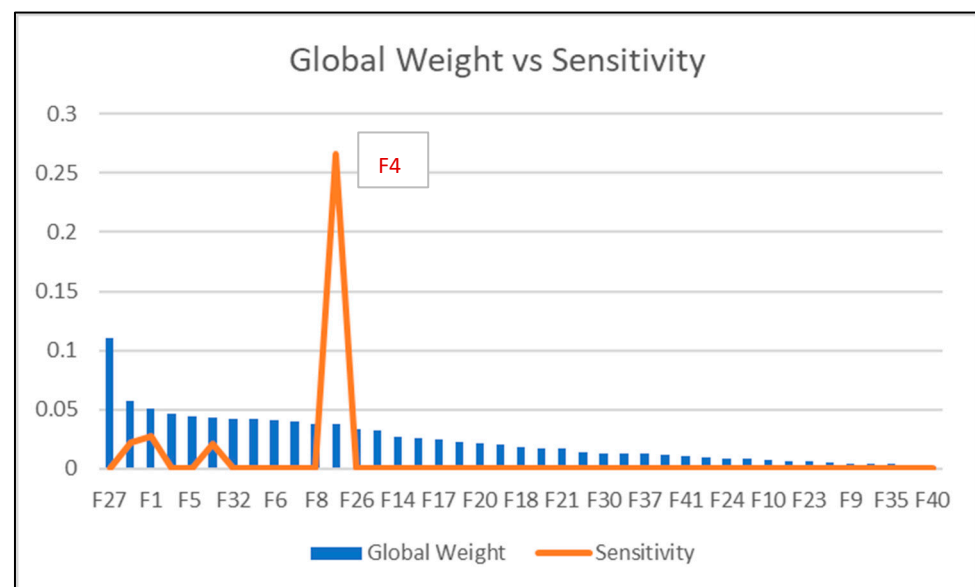
#### 3.1.1. Consistency Ratio

According to the author of [15], if the consistency ratio (CR) is less than 0.1, the results are deemed acceptable, demonstrating a satisfactory level of consistency in the comparative judgments. The pairwise comparison matrices resulted in an average consistency ratio of 0.04, leading us to conclude that the derived weights for the criteria are consistent.

### 3.1.2. Sensitivity Analysis

In the Python-based Fuzzy AHP model, sensitivity analysis was performed concurrently with the computation of global weights for each factor, employing a structured and methodical approach to perturbing input parameters—specifically, the elements of the pairwise comparison matrix. This process involved precise adjustments of each element by a predetermined percentage in both the positive and negative directions to evaluate the effects of slight modifications on the resulting criteria weights. This thorough examination of the model's sensitivity to input changes provided detailed insight into the stability of each criterion, ensuring a deep understanding of how these factors might behave under real-world conditions that involve fluctuations.

The results indicated that the majority of the criteria exhibited a sensitivity of 0.0000, demonstrating that their associated weights are highly stable with respect to variations in the input comparison matrix, as shown in Figure 12. Such stability is a favorable attribute in decision-making models, as it implies that the outcomes are resilient to minor disturbances and can therefore be deemed reliable.



**Figure 12.** The sensitivity analysis results.

However, there are a few exceptions:

- Criterion F2 has a sensitivity of 0.0216.
- Criterion F1 has a sensitivity of 0.0272.
- Criterion F3 has a sensitivity of 0.0212.
- Criterion F4 has a sensitivity of 0.2664.

These criteria display a range of sensitivities, with Criterion F4 showing particularly high sensitivity. This high sensitivity suggests that the weight assigned to this criterion is significantly influenced by its comparison to other criteria. Nonetheless, this observation should not be isolated from the overall context of the model, especially given the high consistency observed in the comparison matrix.

### 3.1.3. Derivation of the Healthcare Technology Management (HTM) Risk Equation

The foundational risk equation in the broader context is given by the following equation:

$$\text{Risk} = \text{Probability of Event (P)} \times \text{Magnitude of Loss (L)} \quad (4)$$

To adapt this equation for use in HTM, we redefined its components as follows:

1. Magnitude of Loss (L)

The magnitude of loss was redefined to incorporate the impact of each risk factor within the HTM domain. It is represented by the global weight ( $\omega_i$ ) of the risk factor, which indicates its relative importance, modulated by the readiness gap ( $1 - x_i$ ), which measures the deviation of a specific healthcare technology's performance from the standard, based on this particular criterion. Incorporating the gap analysis in this manner offers two key advantages: First, it makes the equation adaptable and applicable to any type of technology or healthcare organization. Second, the resulting value not only indicates the intensity of risk but also provides insights into the source of the deficiency (the root cause). This detailed understanding aids decision-makers in identifying potential corrective actions.

The modified expression for the magnitude of loss for each risk factor is as follows:

$$L_i = \omega_i \times (1 - x_i) \quad (5)$$

## 2. Probability of Event (P)

The probability of event in the context of HTM is influenced by the utilization of medical equipment. We introduce a function of optimal utilization ( $f(U_{opt})$ ), which captures the likelihood that utilization levels will lead to risk events. This function accounts for the entire spectrum of equipment utilization, from overuse to underuse.

The probability of event is, therefore, expressed as a function of utilization:

$$P = f(U_{opt}) \quad (6)$$

## 3. Integrating Utilization into the Risk Equation

Given the interdependence of utilization on the occurrence of risk events in HTM, we combined the probability of event as a function of utilization with the magnitude of loss across all risk factors.

The risk for each individual risk factor is now represented as follows:

$$R_i = f(U_{opt}) \times L_i \quad (7)$$

To derive the total risk score for the healthcare technology, we sum the risks across all risk factors:

$$R_{total} = \sum_{i=1}^n R_i = f(U_{opt}) \times \sum_{i=1}^n L_i \quad (8)$$

## 4. Total Risk Score Calculation

The final step is to calculate the total risk score for the healthcare technology ( $htmR$ ), which is the sum of the individual risks associated with each factor, all influenced by the equipment utilization:

$$htmR = f(U_{opt}) \cdot \sum_{i=1}^n \omega_i \cdot (1 - x_i) \quad (9)$$

This re-derived risk equation,  $htmR$ , is both specific to the HTM context and allows for the integration of utilization as a variable influencing the probability of risk events. It provides a framework for quantifying risk that considers the organization's preparedness and the actual usage of the technology. It incorporates a measure that captures how much a specific healthcare technology's performance deviates from the standard, assessed according to a particular criterion.

This paper introduced a revised equation for evaluating risk within the realm of healthcare technology management (HTM). It builds upon the fundamental risk formula, integrating the concept of utilization as delineated by Wang and Levenson [8], reinterpreted here as 'optimal utilization' to encompass the entire range from overuse to underutilization. The global weights are derived from the outcomes of the Fuzzy AHP (Analytic Hierarchy Process) model, while the readiness gap is determined by the healthcare organization. The estimation of  $f(U_{opt})$ , which will quantify the influence of optimal utilization on risk, is



arranged for exploration in our forthcoming paper, utilizing empirical data from specific healthcare technologies.

#### 4. Discussion and Conclusions

This research represents the first comprehensive study of HTM risk factors in the Kingdom of Saudi Arabia and the Gulf region, and it is the inaugural research to employ the PESTEL framework for a thorough examination of all external risk factors and their influence on HTM performance. The approach taken in this study is entirely innovative, as previous research primarily relied on the Fennigkoh and Smith [7] mathematical model or its modified version by Wang and Levenson [8]. Some variations of the same classifications have been explored in [5,6,11]. Previously, studies focused on assessing medical device risk have predominantly concentrated on internal maintenance factors, overlooking the importance of incorporating broader external elements into risk analysis. Furthermore, the scope of these studies was often restricted to improving medical device maintenance strategies, which is seen as a limitation since it does not cover the wider spectrum of healthcare technology management.

In this study, the evaluation of risk factors in healthcare technology management (HTM) revealed a broad spectrum of concerns that span from highly technical issues to macro-environmental influences.

Using the Fuzzy AHP model, the top 20 risk factors identified based on their global weights are:

- Design Risks (Global Weight: 0.110548984)—Under Facility and Internal Environmental Risks in planning.
- Software Risks (Global Weight: 0.057322275)—Under Technology Risks in design and manufacturing.
- Hardware Risks (Global Weight: 0.050745647)—Under Technology Risks in design and manufacturing.
- Regulatory Compliance related to Facility Design (Global Weight: 0.045956915)—Under Facilities and Internal Environmental Risks in planning.
- Equipment Age (Global Weight: 0.044375066)—Under Technology Risks in the operational category.
- Human Factor Engineering (Global Weight: 0.042752409)—Under Technology Risks in design and manufacturing.
- Maintenance Risks (Global Weight: 0.042342317)—Under Facility and Internal Environmental Risks.
- Insufficient Technical Expertise (Global Weight: 0.041855872)—Among biomedical engineers and technicians under Management in workforce development.
- Integration and Interoperability (Global Weight: 0.040933724)—Under Technology Risks in the operational category.
- Electromagnetic Compatibility (Global Weight: 0.039631732)—With other devices under Technology Risks in the operational category.
- Device Classification (Global Weight: 0.038091717)—Based on regulatory entities Under Technology Risks in the operational category.
- Regulatory Compliance (Global Weight: 0.03760016)—Under Technology Risks in design and manufacturing.
- Insufficient Refresher Training (Global Weight: 0.03359518)—For end users under Management in workforce development.
- Disaster Response Risks (Global Weight: 0.032762298)—Under Facility and Internal Environmental Risks in the operation category.
- Reprocessing of Single-Use Devices (Global Weight: 0.027418526)—Under Management risks in Clinical operations.
- Infection Control (Global Weight: 0.026351732)—Under Management risks in Clinical operations.
- Maintenance (Global Weight: 0.025177756)—Under management Risks in HTM Operations.

- Testing and Validation (Global Weight: 0.023179116)—Under Facility and Internal Environmental Risks in construction and commissioning.
- Supply Chain Disruption (Global Weight: 0.021573761)—Under Management risks in strategic risks category.
- Blueprint vs Reality Discrepancies (Global Weight: 0.020009202)—Under Facility and Internal Environmental Risks in construction and commissioning.

These top 20 risks reflect a mix of technological, operational, managerial, and facility and internal environmental challenges that require comprehensive and proactive management strategies to mitigate their impact.

The most critical risk identified is Design Risks under the Facilities and Internal Environmental Risks sub-criteria of planning, holding the highest global weight of 0.110548984. This suggests that design flaws or inadequacies in facility planning can significantly jeopardize healthcare operations, emphasizing the need for meticulous design processes that consider both current needs and future adaptability.

Software risks and hardware risks under Technology Risks in the design and manufacturing category follow, highlighting the pivotal role of technological reliability and integration in modern healthcare. These elements are crucial for ensuring that medical devices and software systems function seamlessly and support rather than hinder healthcare delivery.

Interestingly, Regulatory Compliance related to facility design also ranked highly, underscoring the importance of adhering to established standards and regulations to mitigate legal and operational risks. The focus on regulatory compliance reflects an acute awareness of the potential repercussions of non-compliance, including penalties and compromised patient safety.

Another significant area of concern is the aging of equipment under Technology Risks in the operational category. As medical equipment ages, it often requires more frequent maintenance, may become incompatible with newer technologies, or fail to meet the latest clinical standards, thus posing risks to patient safety and healthcare efficiency. Human Factor Engineering (HFE) also emerges as a critical consideration, indicating a growing recognition of the need to design medical technology and environments that are intuitive and minimize the potential for human error. This factor is essential in enhancing overall safety and effectiveness in healthcare settings.

Among the various categories evaluated for risk in healthcare technology management, macro-environmental risks capture external factors that can significantly influence healthcare operations. These are often beyond the direct control of healthcare facilities but are crucial for strategic planning. Macro-environmental factors such as cybersecurity threats, shifts in public healthcare spending, political stability, and unexpected pandemics have broader implications that transcend individual healthcare facilities. For example, cybersecurity threats, while ranked 27th in terms of global weight, pose significant risks to the integrity of healthcare data and the privacy of patient information. Similarly, shifts in public healthcare spending or budget allocations directly influence the financial resources available for upgrading technology, conducting training, and maintaining equipment.

Political instability can lead to changes in healthcare policy and funding, which may disrupt service provision and delay the implementation of crucial healthcare projects. The recent global experience with the COVID-19 pandemic underscores the dramatic impact that sudden health crises can have on the demand for medical services, supply chains, and the overall capacity of healthcare systems.

The relatively lower ranking of these macro-environmental factors in our study does not diminish their importance. Instead, it highlights the need for healthcare administrators to maintain a dual focus: managing immediate and direct risks associated with healthcare operations and technology, while also developing strategies to mitigate the effects of broader environmental and systemic challenges. Effective risk management in healthcare must include preparedness and resilience planning to address these macro-environmental risks, which, although they may seem less immediate, can cause significant disruptions.

To effectively mitigate the top risk factors identified in healthcare technology management (HTM), a focused approach is necessary, one that prioritizes both immediate risk reduction and the long-term sustainability of healthcare systems. It starts with robust design and planning to mitigate design risks and ensure compliance from the outset. A crucial aspect is updating and upgrading technology, especially software and hardware, to handle risks associated with aging equipment, which can often be resolved through a well-considered replacement strategy.

Equally important is a well-structured preventive maintenance strategy that includes regular checks and proactive measures to maintain operational efficiency and ensure system integration. Continuous training and professional development are essential to improve the use of healthcare technology and address gaps in technical expertise.

Moreover, developing comprehensive disaster response plans and strengthening supply chain resilience are key for managing unforeseen disruptions and sustaining operations. By embedding these strategies into a dynamic risk management framework that evolves with new challenges, healthcare facilities can greatly improve the safety and efficiency of their HTM systems.

Given the complex and varied nature of the risks identified, we recognize the critical need for succeeding research dedicated to exploring effective mitigation strategies. Therefore, we recommend that future researchers build upon the groundwork laid by this study to develop and evaluate targeted mitigation strategies for each of the risk factors identified. Such research will be instrumental in moving from a theoretical understanding of risks to practical, actionable strategies that can significantly enhance the efficacy and sustainability of healthcare technology risk management.

In the early stages of this study, some risks were assessed as less significant and therefore removed from the pairwise comparison matrix. These excluded risks encompassed Bulk Purchasing Arrangements, the Disposal of Medical Technology no longer needed by the facility, and certain macro-environmental factors, particularly those related to sociocultural and legal dimensions as shown in Figure 2.

Despite recognizing inherent study limitations such as potential survey biases and the challenge of generalizing findings across diverse healthcare settings, this study's reliability and consistency were rigorously maintained. Expert involvement from various sectors of the healthcare industry, including hospitals, legislative body, agencies, and manufacturers, all with specialized experience in healthcare technology management, significantly reinforced the robustness of our methodology and the relevance of our findings.

To enhance the precision of the risk assessment methodology, we proposed integrating Fuzzy AHP outcomes with foundational risk equations and optimal utilization metrics. This integration ensures a comprehensive and precise quantification of risk, tailored to the specific conditions and usage patterns of healthcare technology across different organizational contexts. Additionally, we have added gap analysis to the risk equation, achieving two main objectives: firstly, to adapt the equation for application across various technologies and healthcare organizations, and secondly, to provide a risk intensity value that also offers insights into the root cause of deficiencies.

This study is exploratory, with conclusions from the Fuzzy AHP analysis applicable mainly to the geographic areas specifically investigated. To confirm these findings and ensure their applicability across diverse regions and contexts, additional research is necessary.

**Author Contributions:** Originality of dataset, T.M.; conceptualization, T.M., W.B. and S.A.; Methodology, T.M.; software, T.M.; validation, T.M.; data curation, T.M.; visualization, T.M.; supervision, W.B. and S.A.; Writing—review and editing T.M. and W.B.; original draft preparation, T.M. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** This research received approval from the Institutional Review Board of King Saud University in Saudi Arabia (IRB Approval of Research Project No. E-24-9004, Ref. No. 24/1515/IRB).

**Informed Consent Statement:** Informed consent was obtained from the participants involved in this study.

**Data Availability Statement:** The data can be made available upon reasonable request by contacting the corresponding authors.

**Acknowledgments:** The authors sincerely appreciate the participation of all HTM experts in our questionnaire. Your significant contributions have been instrumental in progressing our research. We thank you for your commitment to the field of Healthcare Technology Management.

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

## 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 ed.; Caroline, T.B., Ed.; TALC: St. Albans, UK, 2005; Guide 1; pp. 1–4. Available online: <https://f.hubspotusercontent30.net/hubfs/8702981/HCT%20Guide%201%20-%20How%20to%20Organize%20a%20System%20of%20Healthcare%20Technology%20Management.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](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. *Int. J. Innov. Manag. Technol.* **2012**, *3*, 417–421. [CrossRef]
4. 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.
5. Taghipour, S.; Banjevic, D.; Jardine, A.K.S. Prioritization of medical equipment for maintenance decisions. *J. Oper. Res. Soc.* **2010**, *62*, 1666–1687. [CrossRef]
6. Houria, Z.B.; Masmoudi, M.; Al Hanbali, A.; Ikram, K. Quantitative techniques for medical equipment maintenance management. *Eur. J. Ind. Eng.* **2017**, *10*, 703–723. [CrossRef]
7. Fennigkoh, A.L.; Smith, B. Clinical equipment management. *JCAHO PTSM Series* **1989**, *2*, 5–14. Available online: [https://www.researchgate.net/publication/284687775\\_Clinical\\_Equipment\\_Management](https://www.researchgate.net/publication/284687775_Clinical_Equipment_Management) (accessed on 17 September 2024).
8. Wang, B.; Levenson, A. Equipment inclusion criteria—A new interpretation of JCAHO's medical equipment management standard. *J. Clin. Eng.* **2000**, *25*, 26–35. [CrossRef]
9. 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/MD-Use-Safety.pdf> (accessed on 28 March 2024).
10. Collins, J. Risk Assessment of Medical Equipment. *ASHE* **2015**, 1–37. Available online: <https://www.ashe.org/medrisk> (accessed on 17 September 2024).
11. 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. [CrossRef]
12. 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. [CrossRef] [PubMed]
13. 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.
14. 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. [CrossRef] [PubMed]
15. 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. [CrossRef] [PubMed]
16. Mahfoud, H.; Abdellah, E.B.; El Biyaali, A. Dependability-based maintenance optimization in healthcare domain. *J. Qual. Maint. Eng.* **2018**, *24*, 200–223. [CrossRef]
17. 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. [CrossRef]
18. 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. [CrossRef]

19. Pinho, M. Multicriteria Sorting Methodology to Support the Maintenance Management of Medical Equipment: The Case of Hospital da Luz Lisboa. Master's Thesis, Biomedical Engineering, Universidade de Lisboa, Lisboa, Portugal, 2020.
20. 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; pp. 34–39. [[CrossRef](#)]
21. Božić, V. Objectifying SWOT and PESTLE Analysis in Hospital. *ResearchGate* **2023**. [[CrossRef](#)]
22. 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. [[CrossRef](#)]
23. Wang, L. Research on Risk Management for Healthcare Supply Chain in Hospital. Ph.D. Thesis, Liverpool John Moores University, Liverpool, UK, 2018.
24. 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. [[CrossRef](#)]
25. Chomeya, R. Quality of Psychology Test Between Likert Scale 5 and 6 Points. *J. Soc. Sci.* **2010**, *6*, 399–403. [[CrossRef](#)]
26. Chang, D.Y. Theory and methodology: Applications of the extent analysis method on fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [[CrossRef](#)]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.