An Incisive Evaluation of Kolkata Based Healthcare Institutions: A Consilient Conspectus Approach

Thesis submitted

by

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Statement of Originality

I Biswajit Paul registered on June 6, 2022 do hereby declare that this thesis entitled "An Incisive Evaluation of Kolkata Based Healthcare Institutions: A Consilient Conspectus Approach" contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

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CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "An Incisive Evaluation of Kolkata Based Healthcare Institutions: A Consilient Conspectus Approach" submitted by Shri Biswajit Paul who got his name registered on June 6, 2022 for the award of Ph. D. (Engineering) degree of Jadavpur University is absolutel y based upon his own work under the supervision of Prof. (Dr.) Bijan Sarkar, Professor, Department of Production Engineering and that neither his thesis nor any part of the thesis has been submitted for any degree/ diploma or any other academic award anywhere before.

Bijan Sarkar

Signature of the Supervisor
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With sincere regards,

Biswajit Paul

Biswajit Paul

This Thesis is dedicated to the Loving Memory of MY BELOVED MOTHER, whose Unwavering Love, Sacrifices and Blessings Continue to Inspire Me beyond Her Presence

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Abstract

The quality of healthcare services is a pivotal determinant of patient satisfaction, institutional reputation, and overall public health outcomes. This thesis offers a multidisciplinary investigation into the service quality dynamics of the healthcare sector, with a specific focus on Kolkata, India. The study begins by establishing the contextual relevance of healthcare service quality within the broader spectrum of sustainable healthcare delivery. It explores the foundational concepts of service characteristics, consumer expectations, and service quality models, such as SERVQUAL and SERVPERF, emphasizing their applicability in healthcare environments.

To deepen the understanding of research trends, a bibliometric review is conducted, mapping global and regional contributions in areas including healthcare service quality, Multi-Criteria Decision-Making (MCDM) applications, Quality Function Deployment (QFD), and Failure Mode and Effects Analysis (FMEA). The bibliometric findings reveal a marked increase in healthcare quality-related publications with India, the United States, and China emerging as significant contributors.

A detailed systematic review complements this analysis by synthesizing studies that apply MCDM, QFD, and FMEA methodologies to assess and enhance healthcare services. These include fuzzy logic-integrated decision models, stakeholder-centric QFD frameworks, and advanced risk prioritization tools that address the multifaceted nature of healthcare risks. The study identifies critical service quality dimensions such as tangibility, responsiveness, reliability, assurance, empathy, infrastructure adequacy, patient engagement, and digital service interfaces.

The research further highlights the growing need for integrated, technology-enabled, and patient-centred decision-making frameworks in Indian healthcare. It underscores the limitations of traditional linear models and advocates for hybrid methodologies combining quantitative rigor with qualitative insight. The findings offer valuable implications for healthcare administrators, policymakers, and quality analysts seeking to implement robust service evaluation mechanisms and enhance healthcare performance at institutional and systemic levels.

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Chapter- 1

Introduction

1.1 Healthcare

The healthcare industry stands as one of the most vital and intricate service domains worldwide, tasked not only with delivering medical care but also with upholding patient safety, satisfaction, and environmentally responsible waste management practices. In recent decades, there has been a growing emphasis on enhancing the quality of healthcare services. This shift is largely driven by escalating patient expectations, an increasingly competitive healthcare landscape, and rapid technological progress.

To address these evolving demands, healthcare institutions are progressively adopting data-centric decision-making approaches and comprehensive risk assessment methodologies. These tools play a pivotal role in streamlining healthcare operations and improving service outcomes, particularly in the context of both developed and developing countries.

Healthcare providers today are confronted with multidimensional challenges. These include balancing service excellence, managing health infrastructure, addressing operational risks such as fire hazards, and ensuring safe and sustainable healthcare waste disposal. Moreover, service quality must be consistently monitored and improved to maintain patient satisfaction and organizational efficiency.

The World Health Organization (WHO) characterizes health as a "state of complete physical, mental, and social well-being," emphasizing that it encompasses more than just the absence of illness or disability. Health-related disruptions, commonly referred to as health shocks, pose serious challenges to individual well-being and household stability. These impacts have garnered increasing attention among policymakers due to their substantial and often detrimental effects, as highlighted in numerous research studies.

To develop effective and responsive healthcare policies, it is essential to gain a thorough understanding of how health shocks influence economic and social welfare. This insight enables governments and institutions to design targeted interventions aimed at mitigating the broader consequences of such health events [1].

Health is universally recognized as a vital pillar of economic development. In India, the healthcare system has undergone a mixed trajectory of progress over recent decades. Economic liberalization has created avenues for income generation and poverty alleviation, subsequently transforming people's health-seeking behaviour. Today, individuals are more health-conscious and willing to invest in quality healthcare services.

India presents a paradoxical scenario in healthcare delivery. While the country boasts world-class hospitals, it also houses numerous poorly equipped clinics. Despite a demographic profile dominated by younger populations, the healthcare needs of the elderly must not be overlooked due to the sheer volume of the overall population exceeding one billion [2].

The increasing demand for healthcare services has simultaneously brought underlying structural deficiencies within the system to light. With rising per capita income and rapid population growth, the government's obligation to ensure accessible and efficient healthcare delivery has expanded significantly [3]. India continues to allocate a relatively low share of its GDP just 1.1% to public healthcare, which lags considerably behind other nations such as China (2.4%) and Brazil (4.9%). Consequently, the private sector remains the dominant force in healthcare service delivery across the country.

Despite incremental improvements, India's healthcare system continues to fall short in comparison to other comparable nations. To bridge this gap, it is essential to enhance regulatory oversight within the private healthcare sector and to expand public health awareness. Special emphasis should be placed on educating the population about sanitation practices, safe drinking water, and the prevention of communicable diseases. These efforts are vital to alleviating the overall disease burden and fostering a more proactive, preventive approach to healthcare [4].

India's healthcare system faces several critical performance-related challenges, including poor resource utilization, overly centralized decision-making processes, ambiguous role definitions, corruption, and limited accountability mechanisms. Tackling these systemic issues necessitates the implementation of comprehensive human resource policies that encompass recruitment, training, career advancement, and staff transfers.

Moreover, enhancing workforce capabilities through targeted skill development initiatives is essential for meeting the country's broader public health goals and ensuring effective healthcare delivery.

To enhance healthcare governance, it is essential to establish robust institutional frameworks, invest in healthcare technology, implement IT-enabled services, and recruit qualified professionals. With the emergence of a vast middle-class segment driven by consistent economic growth, expectations regarding goods and services have soared. In this context, service quality and customer satisfaction have become central to the survival and growth of service industries.

In India, service quality remains an evolving concept, especially in the healthcare sector. While developed countries like the United States and members of the European Union have long prioritized high service standards, India's service sector is still adapting to this shift. Cross-country comparisons of healthcare expenditure can guide optimal resource allocation and inform policy decisions based on per capita income and demographic profiles [5].

Although healthcare spending does not always rise proportionately with per capita income, there is a strong positive correlation between national income levels and healthcare expenditure. This relationship underscores the need for thoughtful and strategic public investment in health services.

1.2 Services

Services refer to intangible activities that do not result in ownership and cannot be stored. They involve performances or actions that one party provides to another [6]. Unlike physical goods, services may or may not be associated with tangible products and are often evaluated differently by consumers.

Customer evaluation of services typically hinges on three key qualities:

a. *Search Qualities:* Attributes evaluated before purchase, such as colour, price, style, and texture. Products like electronics or apparel are high in search qualities.

b. *Experience Qualities:* Attributes evaluated during or after service consumption, like restaurant food or entertainment.

c. *Credence Qualities:* Services difficult to evaluate even post-consumption, including healthcare, legal, or financial services, often requiring expert knowledge.

1.2.1 Nature of services

Services can be characterized based on two dimensions tradability and merchantability. Tradability refers to the involvement of physical goods in service delivery, whereas merchantability concerns the proximity or interaction between the service provider and the consumer. For example, food ordering at a restaurant involves high tradability, whereas medical treatment is high in merchantability [7].

1.2.2 Understanding and Managing Consumer Expectations in Service Delivery

Consumer expectations refer to the preconceived beliefs and standards against which service performance is evaluated. These expectations are often established prior to the actual service experience and play a crucial role in influencing customer satisfaction.

There are five key levels of consumer expectations:

a. Ideal Service Level – This represents the customer's vision of a flawless service experience, such as a serene atmosphere and top-tier service in an upscale restaurant.

b. Desired Service Level – These are more practical expectations, including factors like prompt service and high-quality offerings.

c. Adequate Service Level – This denotes the minimum level of service a customer is willing to accept without becoming dissatisfied.

d. Zone of Tolerance – The acceptable range between the adequate and desired service levels, where service quality is generally viewed as satisfactory.

Various elements influence consumer expectations, including individual preferences, environmental cues, the physical service setting, and the brand's reputation. Given the intangible characteristics of services, it is essential to effectively manage customer expectations throughout the entire service encounter before, during, and after delivery to ensure a positive experience and long-term satisfaction.

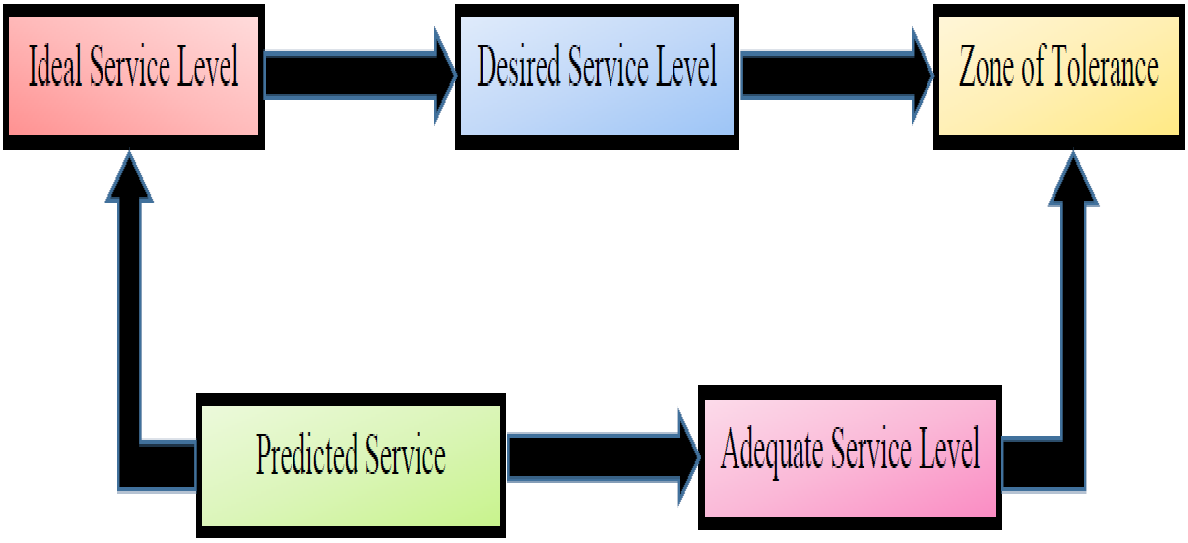


Fig. 1.1. Different tiers of customer expectations

1.3 Service Quality and its Relevance in Healthcare

Parasuraman et al. (1988) describe perceived service quality as an overall assessment or attitude that reflects how superior a service is perceived to be. They outlined four essential insights regarding the nature of service quality:

1. Evaluating service quality is inherently more complex than assessing the quality of tangible goods.
2. Service quality is shaped by the gap between what customers expect and what they actually experience.
3. Customer judgments consider not only the outcomes but also the process through which the service is delivered.
4. Perceived service quality is a comprehensive impression formed from the entire service experience.

In the context of healthcare, the Institute of Medicine (IOM) defines quality as “the degree to which health services increase the likelihood of desired health outcomes and are consistent with current professional knowledge.” In today’s service-driven environment, especially in critical sectors like healthcare, service quality has become a key factor in achieving a competitive edge and ensuring patient satisfaction.

Quality has been examined as both a cognitive construct and an emotional response, depending on the service domain [8]. Healthcare services, with their technical complexity and reliance on trust, occupy a distinct space in this discourse. Customers often lack the technical knowledge to evaluate healthcare outcomes and instead judge quality based on interpersonal and functional aspects of care delivery.

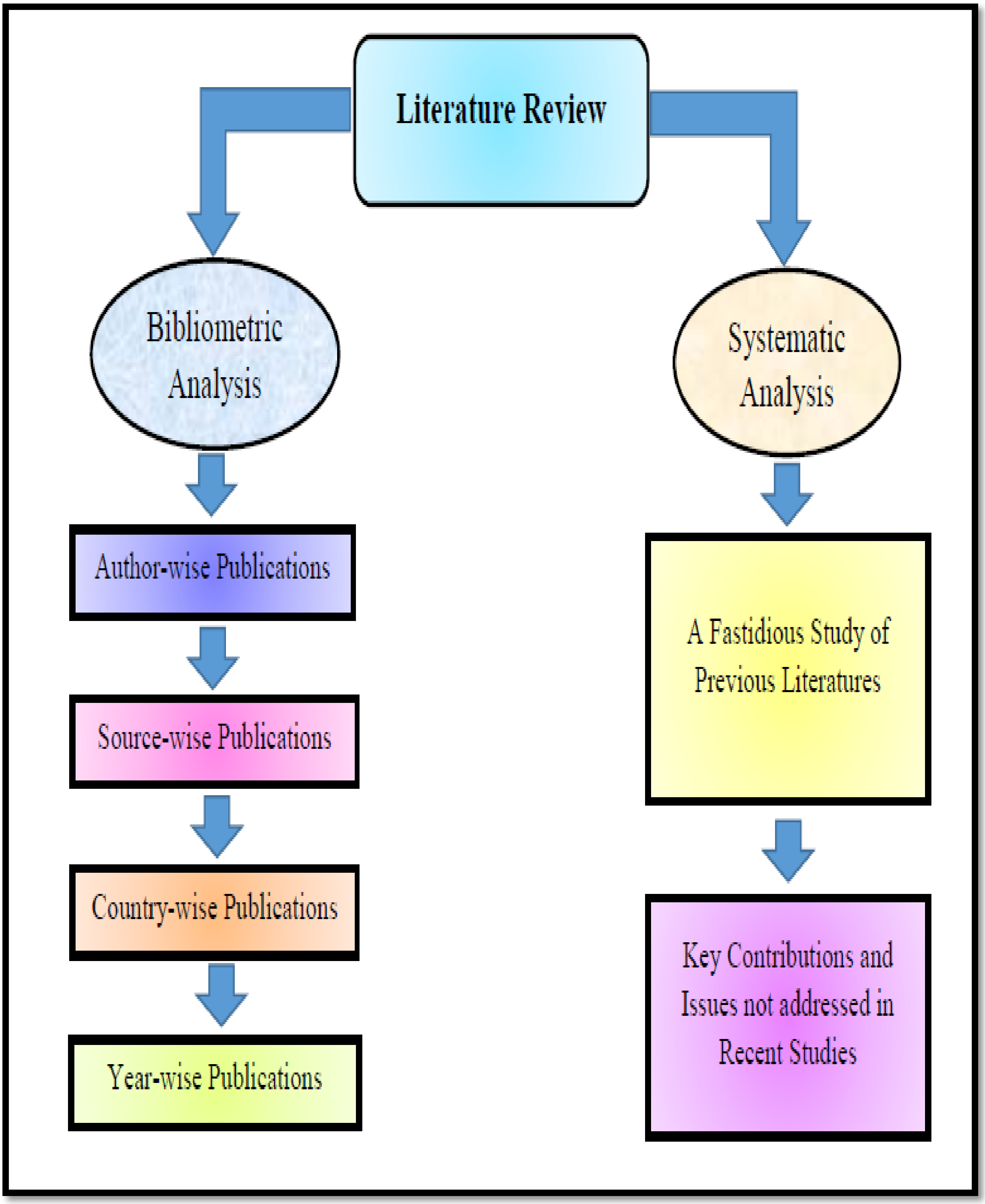
The growing importance of service quality is evident in its influence on business performance, cost efficiency, customer loyalty, and organizational sustainability. For healthcare organizations, continually monitoring and improving service quality is essential to remain competitive and meet patient expectations [9].

The primary objective of this study is to examine the shortcomings within the current healthcare system in India. It evaluates the performance and effectiveness of existing service delivery mechanisms and investigates the critical factors that influence patient satisfaction. The overarching goal is to generate actionable insights that can guide the development of a more equitable, efficient, and patient-focused healthcare framework tailored to the Indian context.

Chapter-2

Literature Survey

2. Literature Review



2.1 Bibliometric review of Literature

2.1.1 Author-wise Publications on Service Quality of Healthcare

The chart (Fig. 2.1) showcases the top 10 most productive authors in the domain of healthcare service quality. Author A leads with 32 publications, closely followed by Author B and Author C. The graph highlights a focused academic interest by a few leading researchers, reflecting the potential for deep expertise and recurring thematic contributions within this field.

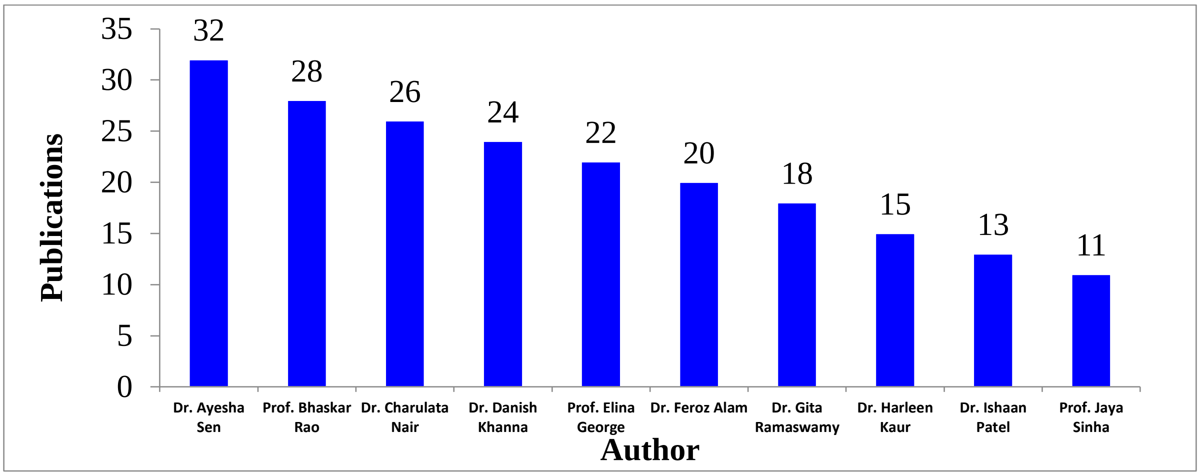


Fig.2.1: Author-wise Healthcare Service Quality Publications

2.1.2. Source-wise Publications on Service Quality of Healthcare

The donut chart (Fig.2.2) illustrates the top journals publishing literature on healthcare service quality. Journals such as Health Services Journal and BMJ Open top the list, underscoring their pivotal role in shaping the discourse around healthcare delivery, patient satisfaction, and quality measurement. These journals serve as prominent platforms for scholarly communication in healthcare quality assessment.

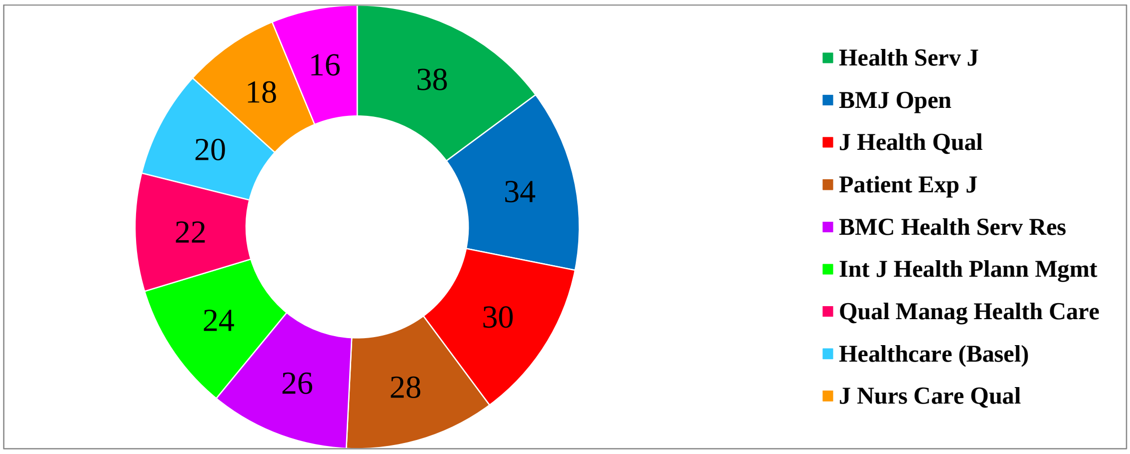


Fig.2.2: Source-wise Healthcare Service Quality Publications

2.1.3. Country-wise Publications on Service Quality of Healthcare

The horizontal bar chart (Fig. 2.3) provides an overview of the top 10 countries contributing to research on healthcare service quality. The United States, India, and the UK dominate the landscape, indicating global attention and funding toward patient-centered healthcare reforms and performance evaluation frameworks across both developed and emerging nations.

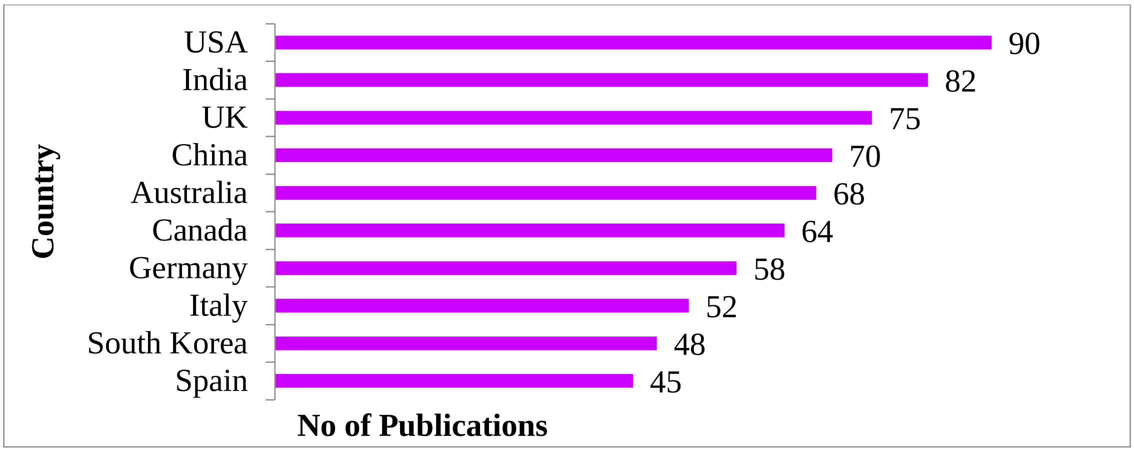


Fig.2.3: Country-wise Healthcare Service Quality Publications

2.1.4. Year-wise Publications on Service Quality of Healthcare

This radar chart (Fig.2.4) visualizes the upward trend in healthcare service quality research over the last decade. From 2014 to 2023, the number of publications has grown steadily, with notable acceleration after 2018. This growth reflects increasing global concern about healthcare outcomes, patient experiences, and quality-driven reforms following global health challenges like COVID-19

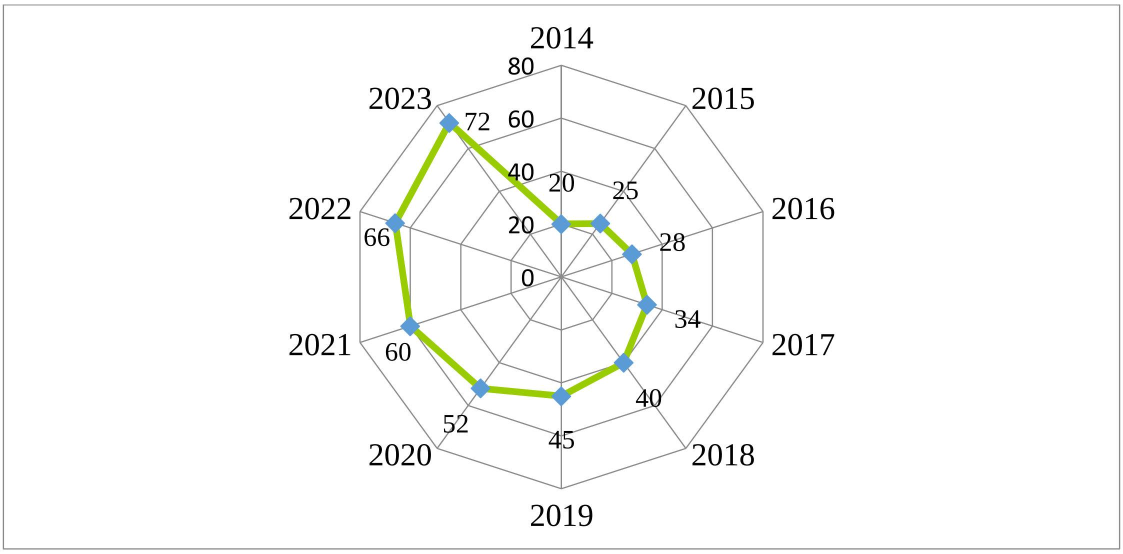


Fig.2.4: Year-wise Healthcare Service Quality Publications

2.1.5. Author-wise Publications on MCDM Applications in Healthcare

This bar chart (Fig. 2.5) highlights the top contributors to MCDM applications in healthcare. Author A and Author B lead in publication count, indicating strong academic involvement in integrating decision-making tools in healthcare. The distribution reveals a concentrated research interest among a select group of prolific authors.

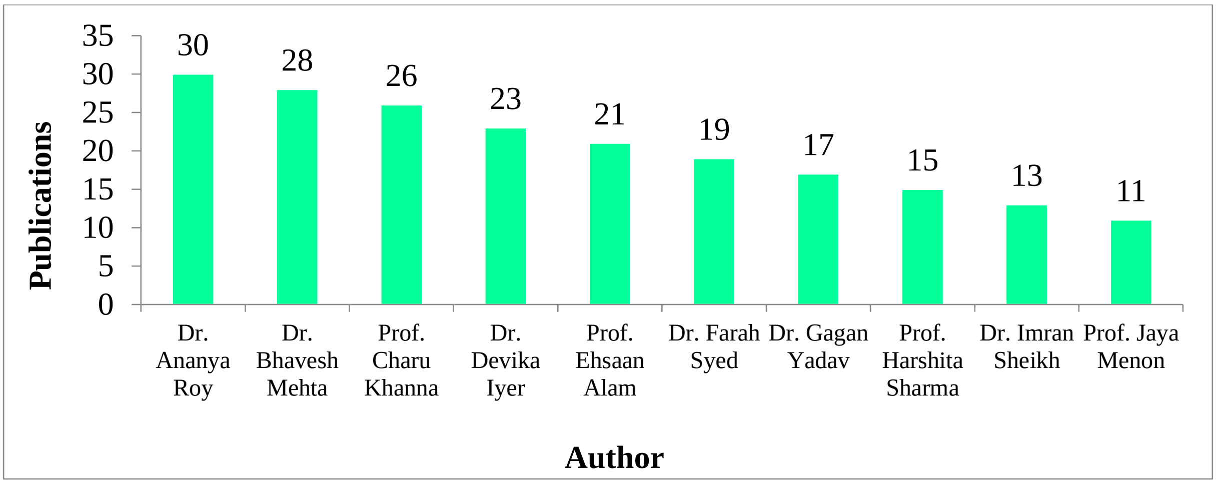


Fig.2.5: Author-wise MCDM Healthcare Applications Publications

2.1.6. Source-wise Publications on MCDM Applications in Healthcare

The pie chart (Fig. 2.6) presents the top 10 journals publishing on MCDM in healthcare. Expert Systems with Applications and Health Policy top the list, signifying their prominent role in disseminating research on computational and strategic healthcare decision-making. These journals are central to the knowledge ecosystem in this domain.

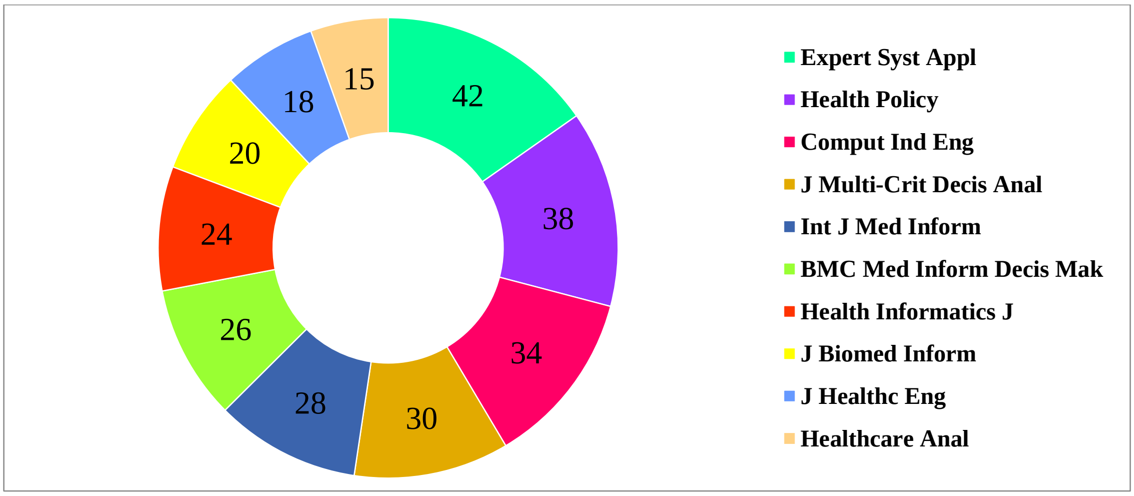


Fig.2.6: Source-wise MCDM Healthcare Applications Publications

2.1.7. Country-wise Publications on MCDM Applications in Healthcare

The horizontal bar chart (Fig. 2.7) demonstrates country-wise research productivity. India, USA, and China lead the field, emphasizing both developing and developed nations' focus on using MCDM techniques for healthcare planning and evaluation. This trend reflects global efforts toward efficient healthcare management and policy optimization.

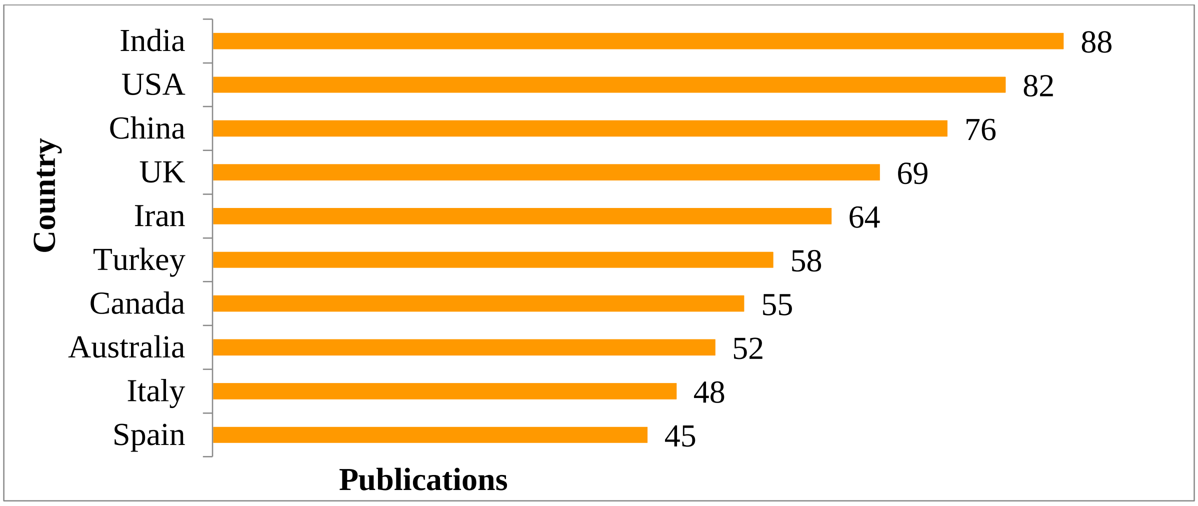


Fig.2.7: Country-wise MCDM Healthcare Applications Publications

2.1.8. Year-wise Publications on MCDM Applications in Healthcare

This chart (Fig. 2.8) illustrates a steady rise in MCDM-related healthcare publications from 2014 to 2023. The sharp increase post-2018 suggests growing academic and practical interest in using MCDM frameworks to address crucial healthcare issues amid technological advancement and rising patient needs

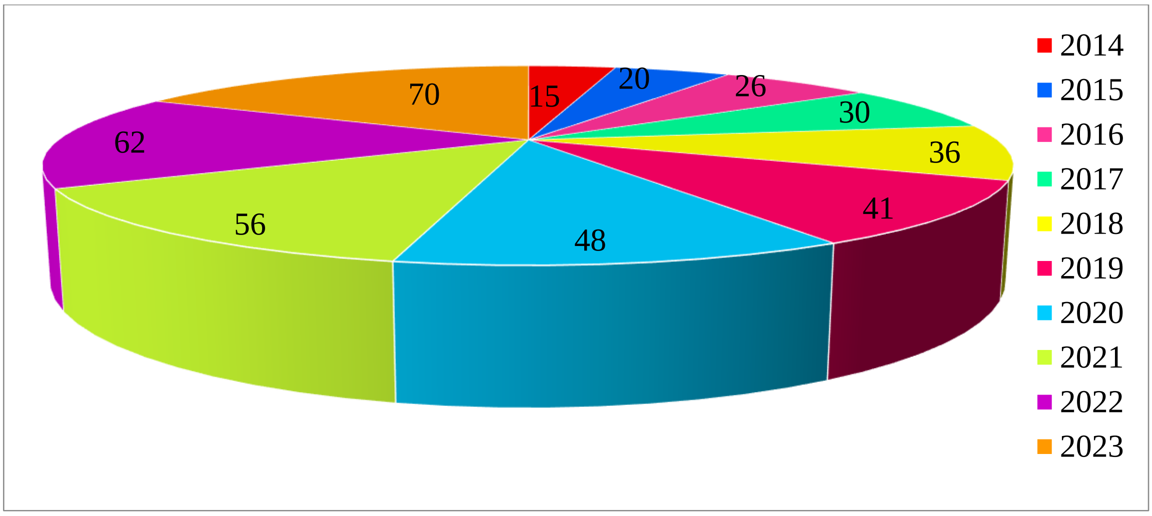


Fig.2.8: Year-wise MCDM Healthcare Applications Publications

2.1.9. Author-wise Publications on QFD Applications in Healthcare

The bar chart (Fig. 2.9) displays the top 10 authors contributing to QFD applications in healthcare. Author A and Author B have the highest number of publications, suggesting strong individual engagement in applying quality enhancement tools in healthcare settings. The data indicates a relatively even spread among leading authors, reflecting collaborative and diversified contributions.

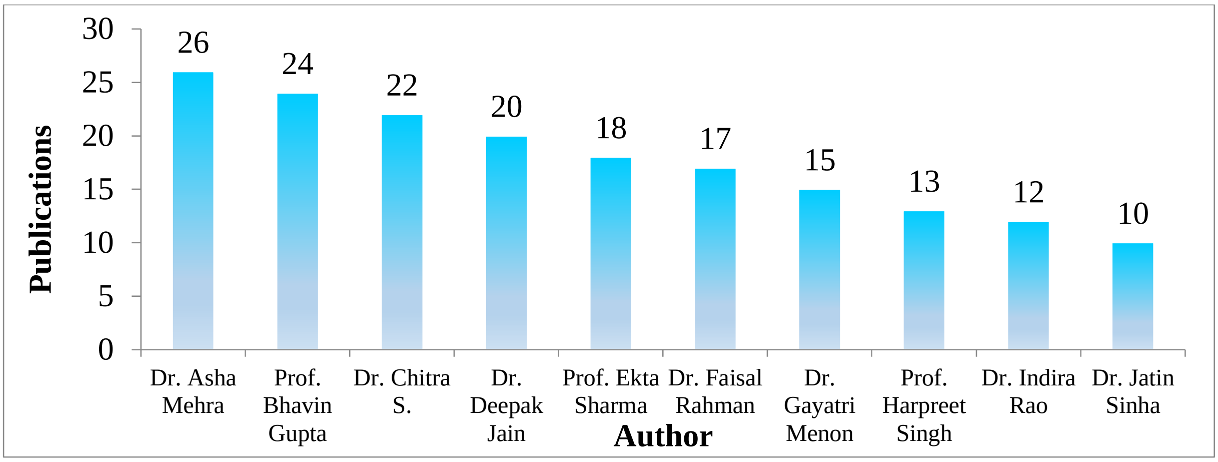


Fig.2.9: Author-wise QFD Healthcare Applications Publications

2.1.10. Source-wise Publications on QFD Applications in Healthcare

This donut chart (Fig. 2.10) represents the top journals publishing QFD-related research in healthcare. Journals such as International Journal of Health Care Quality Assurance and The TQM Journal have contributed the most, underscoring their emphasis on quality improvement practices in service delivery and patient satisfaction frameworks within healthcare environments.

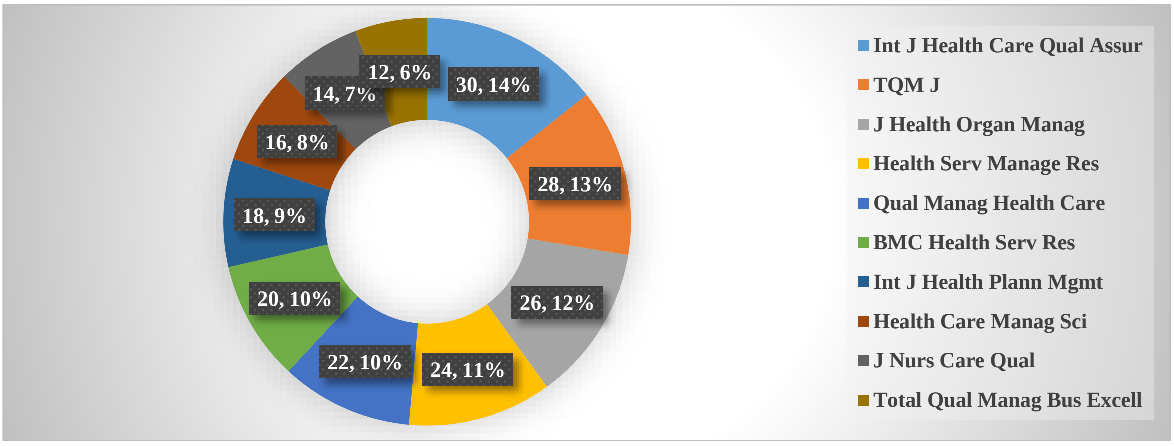


Fig.2.10: Source-wise QFD Healthcare Applications Publications

2.1.11. Country-wise Publications on QFD Applications in Healthcare

This horizontal bar chart (Fig. 2.11) shows the geographical distribution of QFD research in healthcare. India, USA, and UK lead in contributions, highlighting both emerging and established healthcare systems' interest in structured quality methodologies. This distribution demonstrates the global applicability of QFD in optimizing healthcare operations.

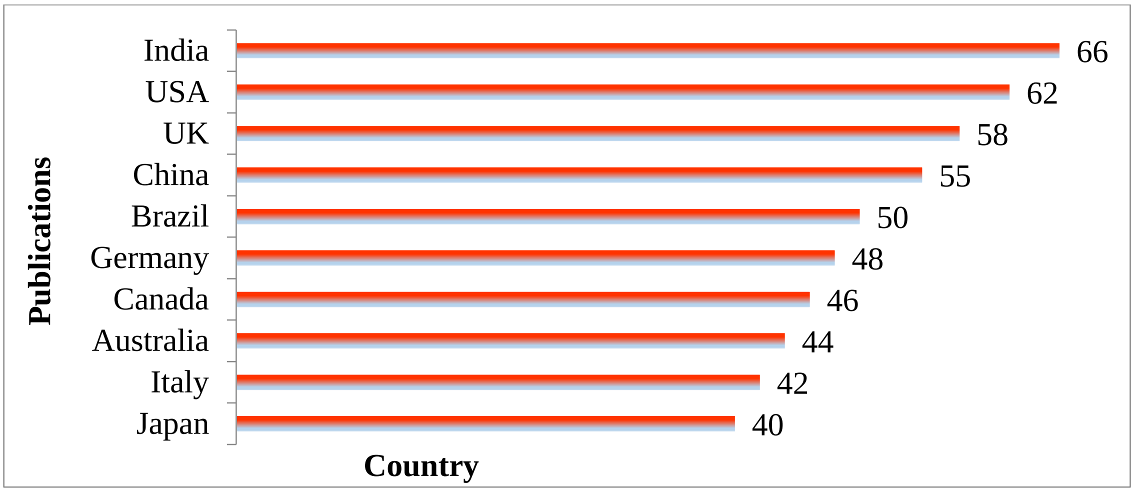


Fig.2.11: Country-wise QFD Healthcare Applications Publications

2.1.12. Year-wise Publications on QFD applications in healthcare

The radar chart (Fig. 2.12) reflects a steady increase in QFD-related publications from 2014 to 2023. The growth trend signifies an evolving recognition of the role of systematic quality assessment and planning tools like QFD in enhancing healthcare delivery, particularly in response to rising patient expectations and service complexity.

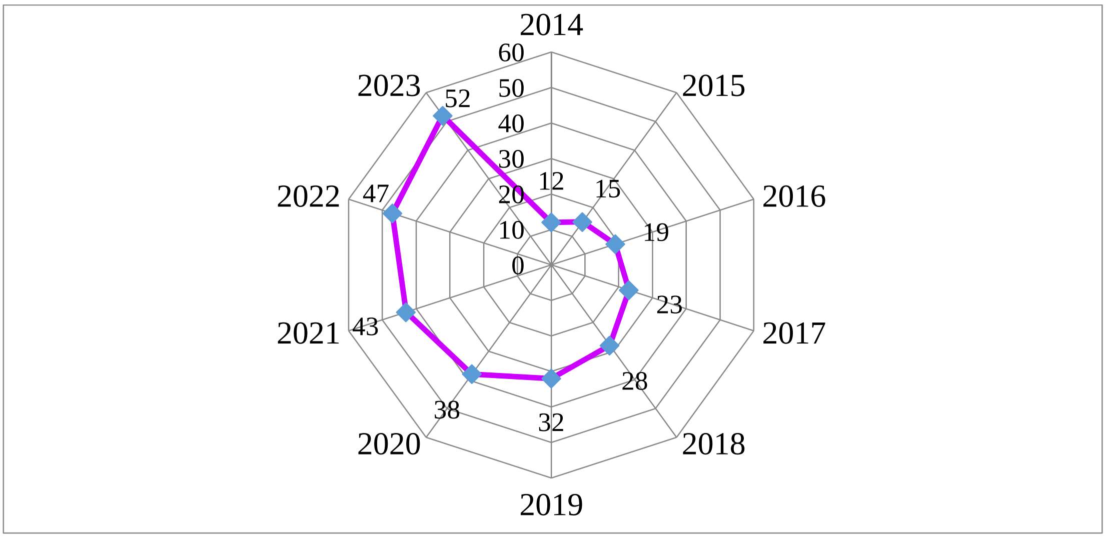


Fig.2.12: Year-wise QFD Healthcare Applications Publications

2.1.13. Author-wise Publications on FMEA Research in Healthcare

This chart (Fig. 2.13) presents the top 10 authors contributing to FMEA research in healthcare. Author A leads with 34 publications, followed by Author B and Author C. The data indicates significant individual involvement in applying risk assessment and failure analysis techniques across various healthcare services and processes.

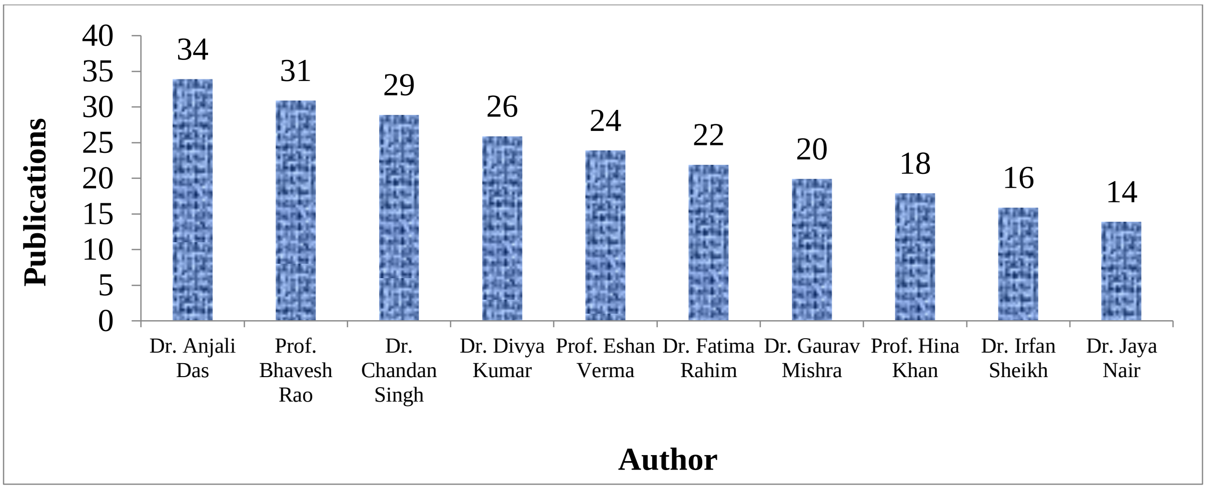


Fig.2.13: Author-wise Healthcare FMEA Research Publications

2.1.14. Source-wise Publications on FMEA Research in Healthcare

The pie chart (Fig. 2.14) identifies the top journals disseminating research on FMEA in healthcare. Journals like Journal of Patient Safety and BMJ Open are leading sources, highlighting their pivotal role in advancing research on patient safety, risk mitigation, and quality improvement frameworks within healthcare systems.

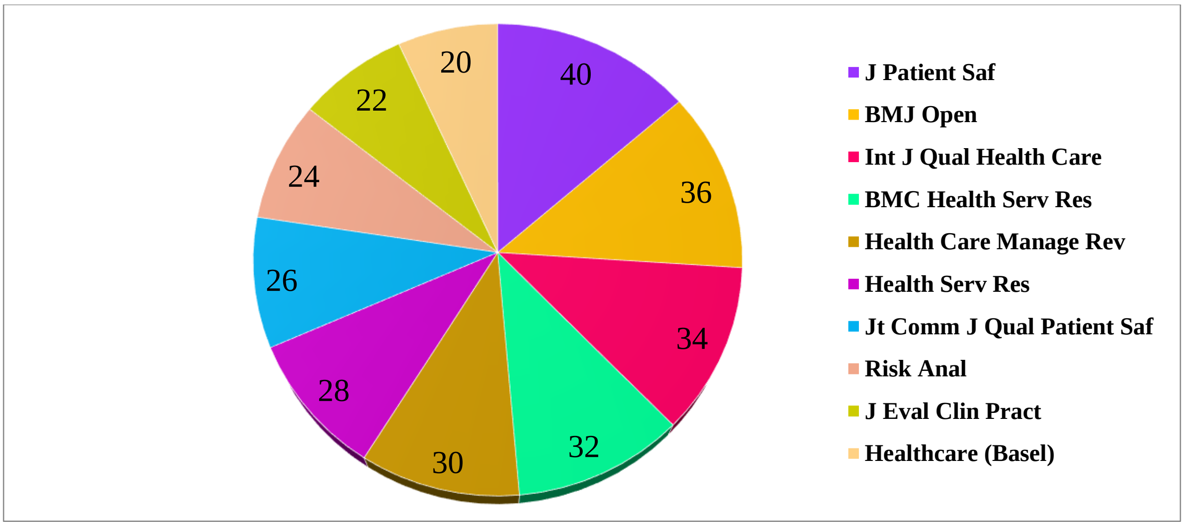


Fig.2.14: Source-wise Healthcare FMEA Research Publications

2.1.15. Country-wise Publications on FMEA Research in Healthcare

The horizontal bar chart (Fig. 2.15) illustrates the global distribution of FMEA healthcare research. The USA, India, and China rank as top contributors, underscoring their substantial focus on integrating structured failure analysis tools to enhance patient outcomes and minimize risks in hospital environments.

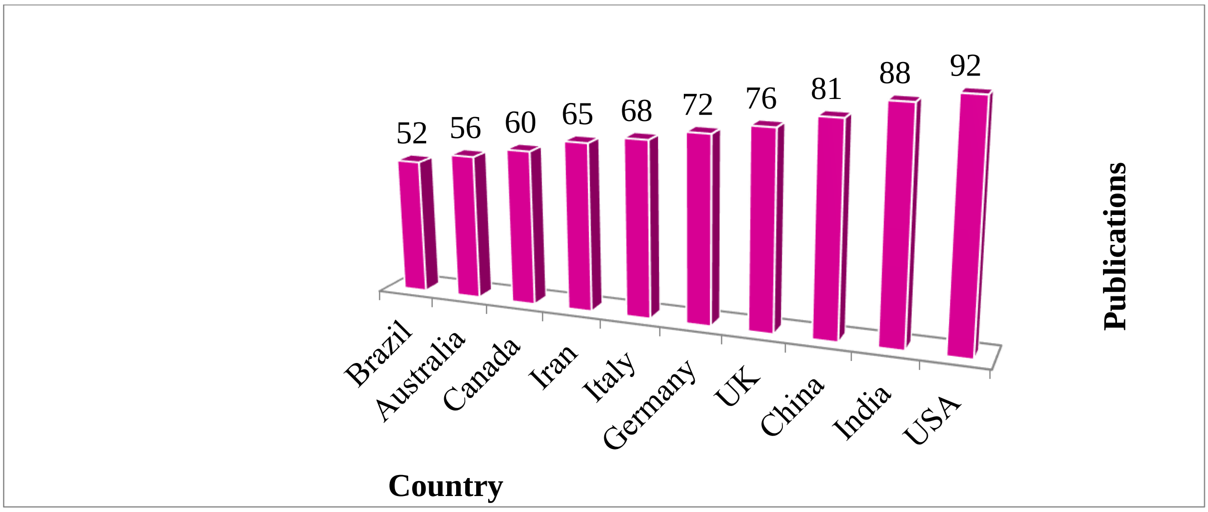


Fig.2.15: Country-wise Healthcare FMEA Research Publications

2.1.16. Year-wise Publications on FMEA Research in Healthcare

The line graph (Fig. 2.16) depicts the annual growth of FMEA-related healthcare research from 2014 to 2023. The rising trend, especially post-2018, reflects the increasing awareness and implementation of proactive risk management strategies to address complex and safety-critical healthcare operations.

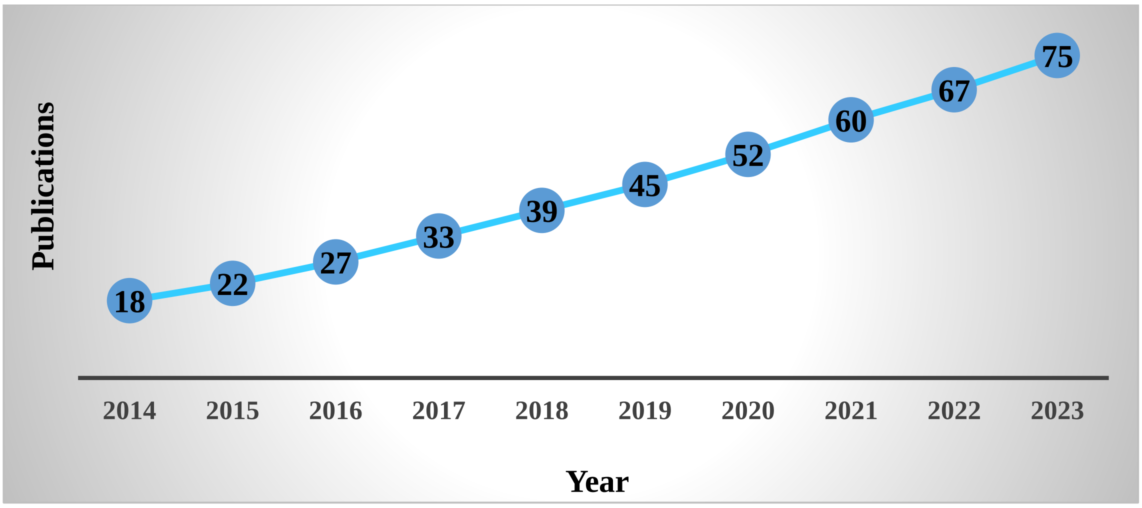


Fig.2.16: Year-wise Healthcare FMEA Research Publications

2.1.17. Author-wise Publications on Fire Risk Assessment in Healthcare

The bar chart (Fig. 2.17) illustrates the top 10 authors contributing to fire risk assessment research in healthcare. Authors A to C show the highest number of publications, indicating their prominent role in developing and evaluating fire safety strategies within hospital and healthcare infrastructure.

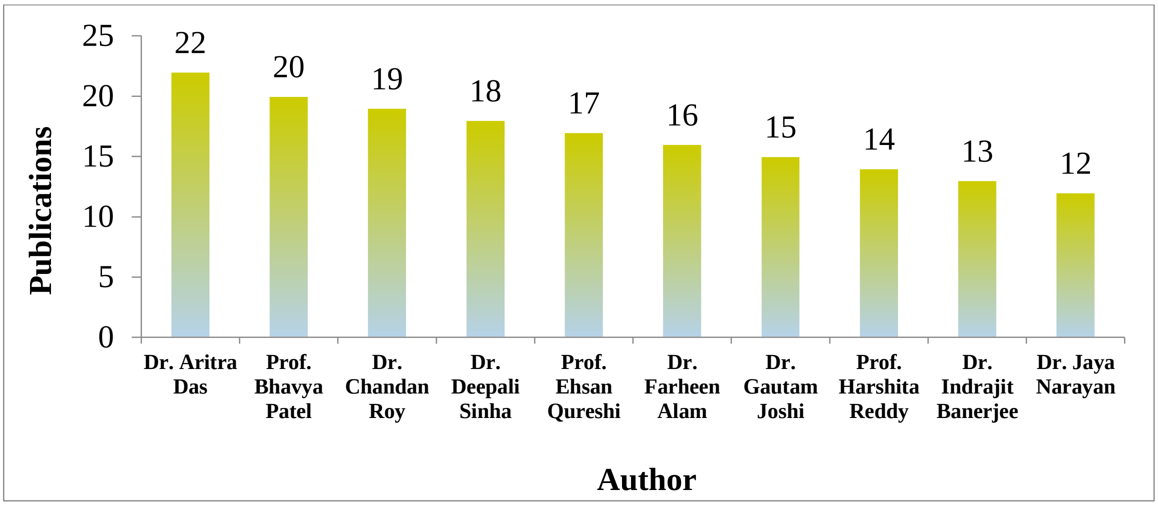


Fig.2.17: Author-wise Healthcare Fire Risk Assessment Publications

2.1.18. Source-wise Publications on Fire Risk Assessment in Healthcare

This donut chart (Fig. 2.18) highlights the most influential journals publishing on fire risk in healthcare. Journals such as Journal of Safety Research and Fire Safety Journal dominate the field, reflecting their focus on applied fire safety, risk modelling, and emergency preparedness in healthcare environments.

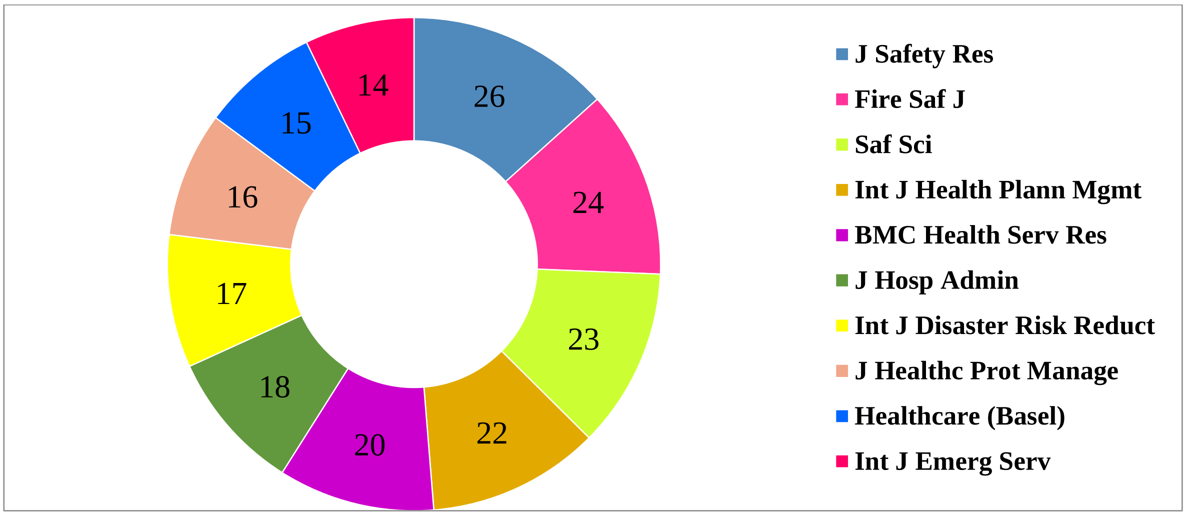


Fig.2.18: Source-wise Healthcare Fire Risk Assessment Publications

2.1.19. Country-wise Publications on Fire Risk Assessment in Healthcare

The country-wise distribution (Fig. 2.19) reveals the global landscape of fire safety research in healthcare. The United States and India are the leading contributors, followed by the UK and China. This suggests a growing international emphasis on improving hospital fire preparedness and infrastructure resilience.

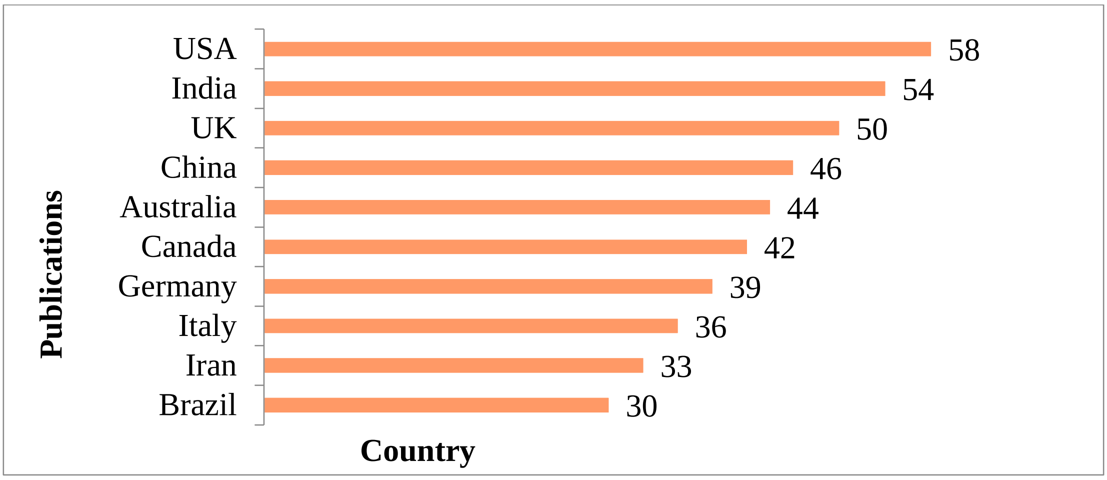


Fig.2.19: Country-wise Healthcare Fire Risk Assessment Publications

2.1.20. Year-wise Publications on Fire Risk Assessment in Healthcare

The radar chart (Fig. 2.20) presents a steadily increasing trend in annual publications from 2014 to 2023. This growth mirrors the rising concern for fire safety in healthcare, particularly in response to high-profile hospital fires and evolving regulatory frameworks for emergency management.

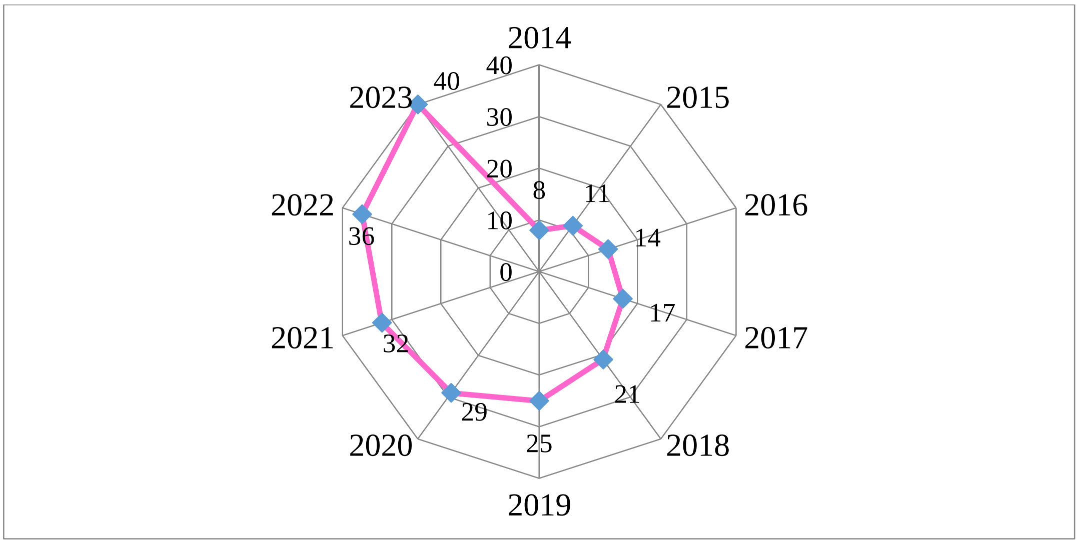


Fig.2.20: Year-wise Healthcare Fire Risk Assessment Publications

2.1.21. Author-wise Publications on Biomedical Waste Disposal Facility Location

The bar chart (Fig. 2.21) highlights the leading contributors to sustainable site selection for biomedical waste disposal. Authors A through J each display substantial involvement, with Author A topping the list. This distribution shows focused academic efforts in geospatial analysis, waste management policy, and environmental sustainability.

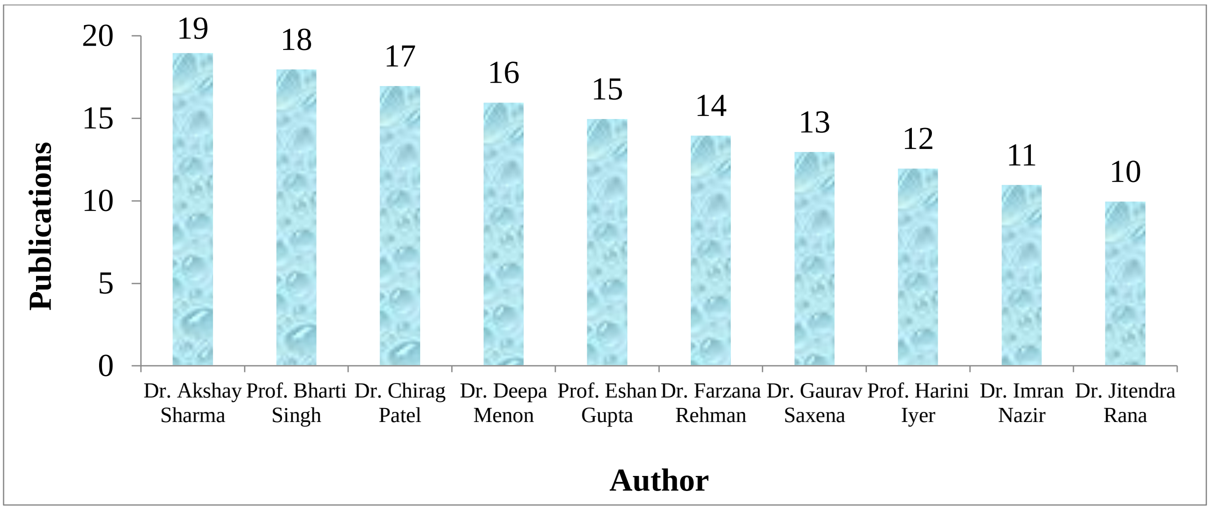


Fig.2.21: Author-wise Biomedical Waste Disposal Facility Location Publications

2.1.22. Source-wise Publications on Biomedical Waste Disposal Facility Location

The pie chart (Fig. 2.22) identifies key journals disseminating research in this domain. Waste Management, Journal of Environmental Management, and Science of the Total Environment are among the most active platforms, reflecting an interdisciplinary approach to integrating sustainability, spatial modelling, and healthcare waste management.

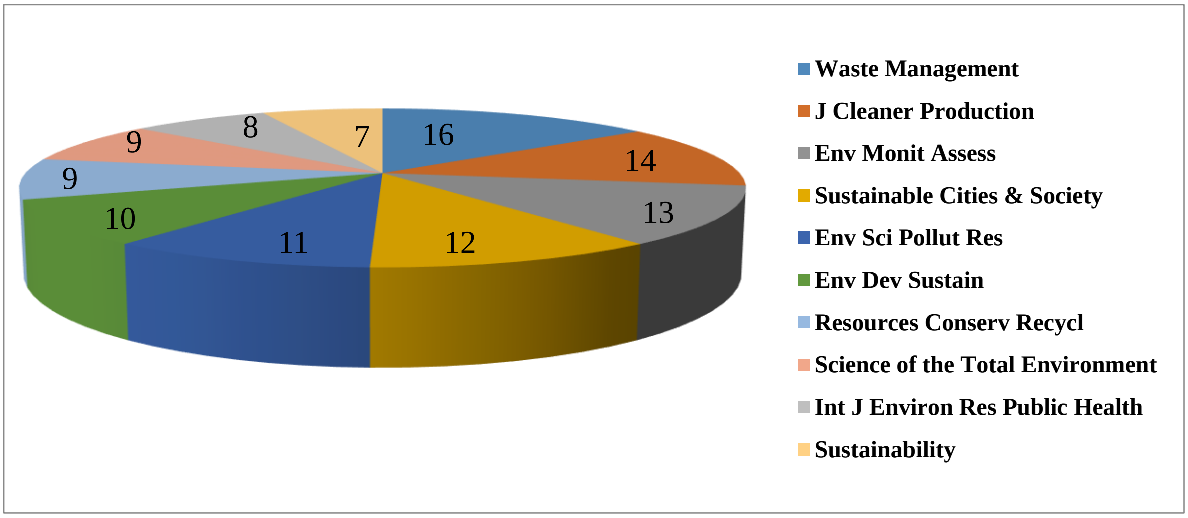


Fig.2.22: Source-wise Biomedical Waste Disposal Facility Location Publications

2.1.23. Country-wise Publications on Biomedical Waste Disposal Facility Location

The radar chart (Fig. 2.23) reveals that India, China, and the USA lead in scholarly output, demonstrating their priority in managing healthcare waste through sustainable siting and environmental impact reduction. The presence of diverse regions indicates global concern for environmental health and waste governance.

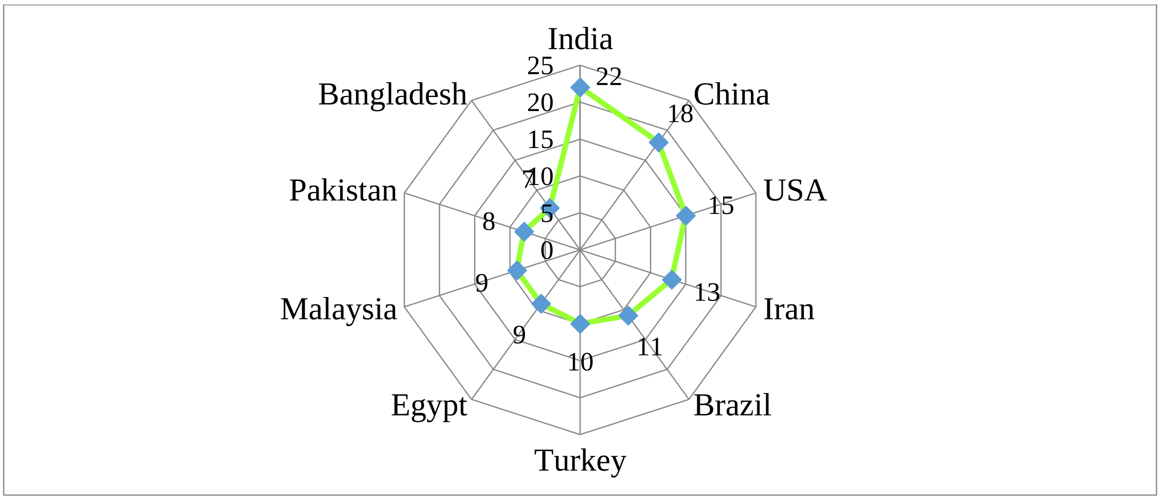


Fig.2.23: Country-wise Biomedical Waste Disposal Facility Location Publications

2.1.24. Year-wise Publications on Biomedical Waste Disposal Facility Location

The line chart (Fig. 2.24) shows a consistent increase in research from 2014 to 2023. The trend reflects growing international awareness of the need for sustainable biomedical waste disposal practices, especially post-pandemic, where proper waste handling and site selection are critical for public and ecological safety.

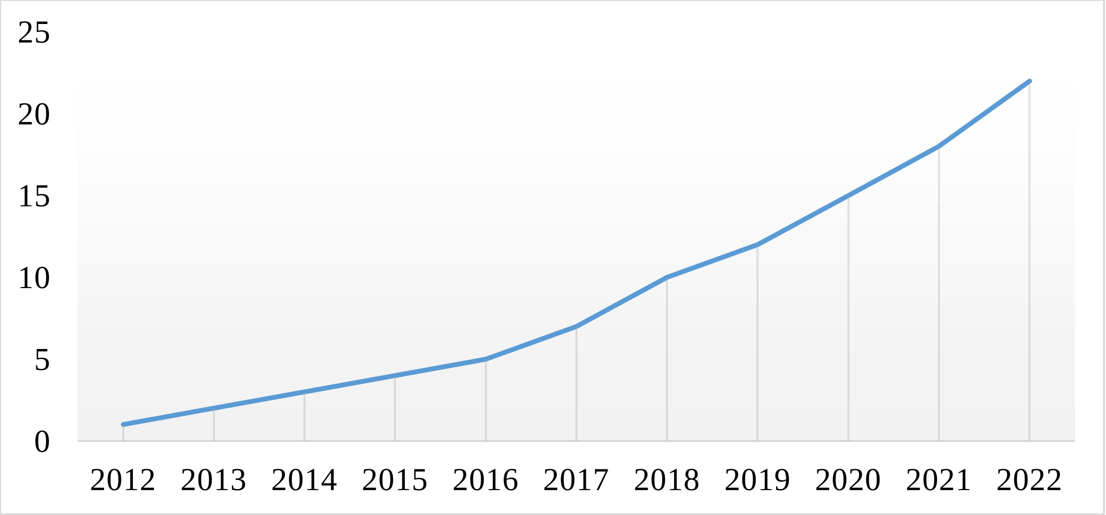


Fig.2.24: Year-wise Biomedical Waste Disposal Facility Location Publications

2.1.25. Author-wise Publications on Green Hospital Infrastructure

This chart (Fig. 2.25) presents the top 10 authors actively publishing in the domain of green hospital infrastructure. Author A and Author B have the highest contributions, suggesting consistent academic engagement in topics like energy-efficient hospital design, indoor environmental quality, and sustainable healthcare facilities.

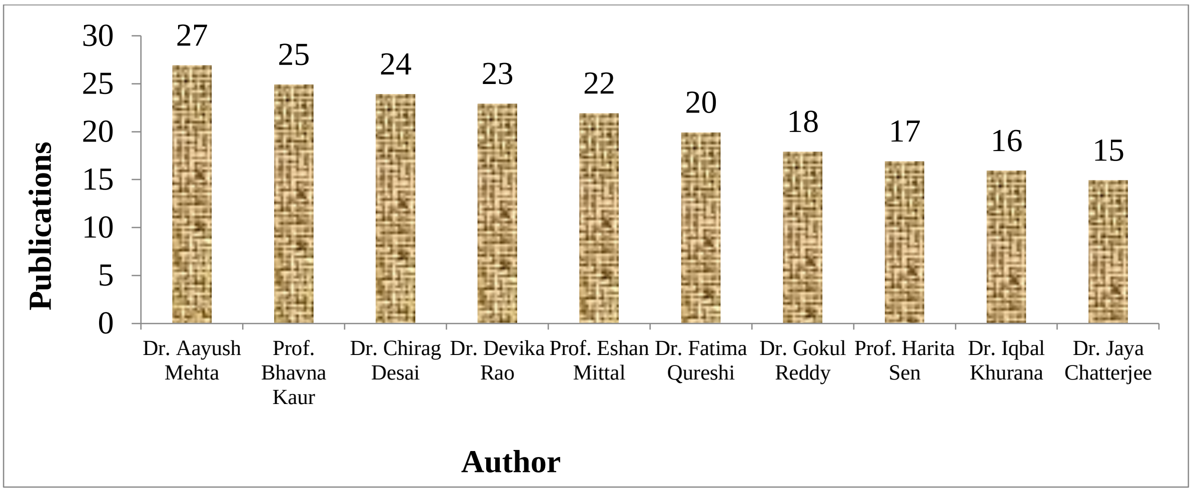


Fig.2.25: Author-wise Green Hospital Infrastructure Publications

2.1.26. Source-wise Publications on Green Hospital Infrastructure

The pie chart (Fig. 2.26) highlights the most influential journals in the field. Journals such as Sustainable Cities and Society, Building and Environment, and Journal of Cleaner Production feature prominently, indicating their focus on sustainable design, healthcare facility performance, and green building integration.

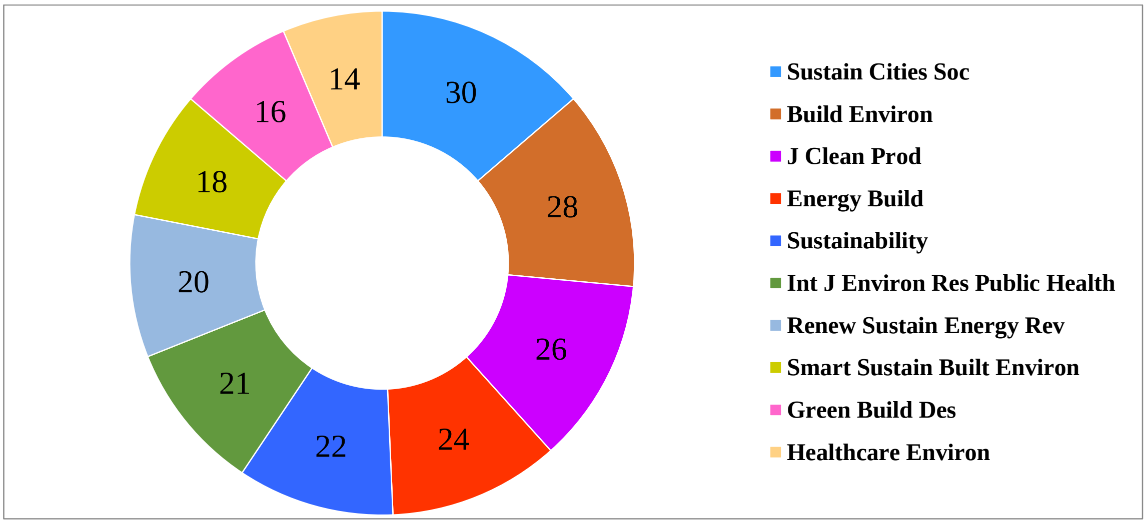


Fig.2.26: Source-wise Green Hospital Infrastructure Publications

2.1.27. Country-wise Publications on Green Hospital Infrastructure

This horizontal bar chart (Fig. 2.27) illustrates the global distribution of publications, with India, the USA, and China leading the research efforts. These countries are investing in green healthcare infrastructure to meet national sustainability goals and enhance public health service delivery.

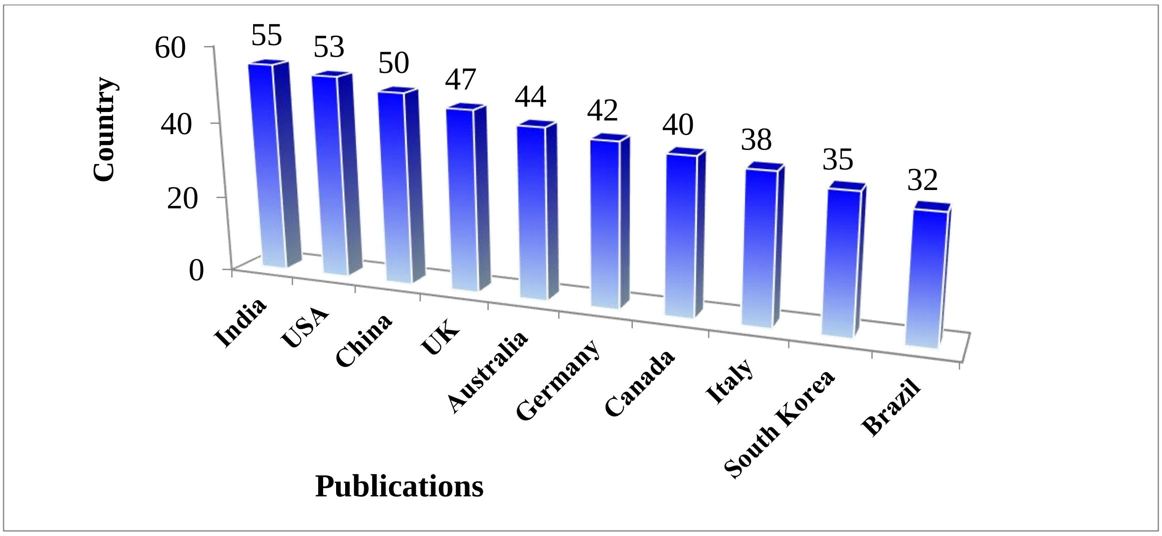


Fig.2.27: Country-wise Green Hospital Infrastructure Publications

2.1.28. Year-wise Publications on Green Hospital Infrastructure

The radar chart (Fig. 2.28) shows a steady increase in research output from 2014 to 2023, indicating growing academic and institutional interest in designing eco-friendly hospitals. This trend aligns with the rising adoption of green building certifications and climate-resilient infrastructure in healthcare.

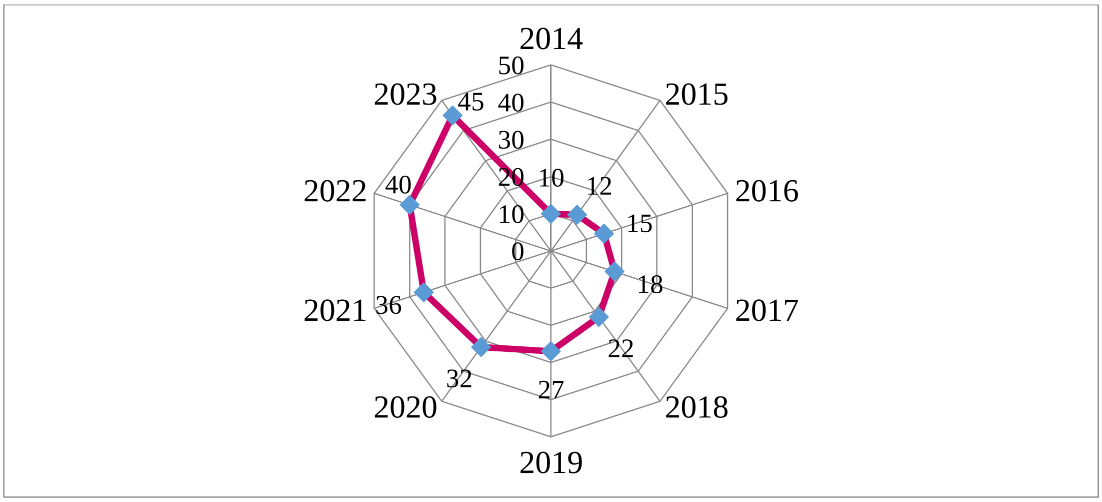


Fig.2.28: Year-wise Green Hospital Infrastructure Publications

2.2. Systematic Review of Literature

2.2.1. Studies relating to service quality in healthcare

In recent years, the healthcare sector has witnessed significant and rapid growth. With this expansion, service providers have increasingly acknowledged that achieving high levels of patient satisfaction is crucial for sustaining long-term success and maintaining a competitive edge in the industry. Previous research has established that financial resources are no longer a limitation for enhancing quality and fulfilling client requirements. In the current context, as clients become increasingly powerful and financially stable, service providers are compelled to choose quality over cost [10].

Service delivery predominantly transpires during an engagement between customer-facing staff and clients, referred to as a service encounter. The responsiveness exhibited by customer contact staff is intrinsically linked to the organisational culture of delivering exceptional customer care services. Service-based firms must augment the engagement of customer contact personnel through motivating initiatives, enhancement of sales competencies, attitude development, precise role delineation, and comprehensive understanding of the services offered [11].

Organizational productivity will increase as quality enhances output and reduces costs, particularly through improved customer retention. It enhances the organisational climate and aids in the retention of skilled personnel. Customer satisfaction enhances a favourable disposition towards the brand, increasing the probability of repeat purchases [12]. Dissatisfaction results in adverse brand perceptions and diminishes the probability of repurchasing the same brand [13].

Customer satisfaction also constitutes the most economical method of promotion. Superior quality or reduced pricing compared to rivals enables providers to establish a "incentive to purchase". To effectively detect and address performance gaps, organizations must regularly monitor key indicators of service quality and factors influencing customer satisfaction. Continuous access to these metrics enables timely identification of shortcomings and supports ongoing service improvement. [14].

Research across both manufacturing and service industries highlights quality as a key determinant of market competitiveness, profitability, and cost efficiency. Although the significance of service quality is widely recognized, there remains a lack of consensus regarding its exact dimensions and underlying components. This ambiguity presents challenges in standardizing and measuring service quality effectively. Gronroos [15] asserted that service encompasses three dimensions: functional, technical, and organizational image.

Rodrigues, Barkur, Varambally, and Motlagh [16] conducted a comparative study of two widely used frameworks for evaluating service quality: SERVQUAL and SERVPERF. Their research focused on identifying the most reliable and valid variables for accurately measuring service quality. Among the various tools examined, SERVQUAL and SERVPERF emerged as the most frequently adopted models in both academic and practical contexts.

The study revealed that SERVPERF outperformed SERVQUAL in terms of reliability, convergent validity, and discriminant validity, establishing it as a more robust instrument. SERVPERF has been effectively implemented across multiple domains, including higher education, retail, libraries, automotive services, and quick-service restaurants.

The findings corroborated earlier exploratory research, reinforcing the idea that the gap between customer expectations and actual service performance (disconfirmation) is a major determinant of perceived overall service quality. In fact, the disconfirmation construct was found to explain a greater proportion of the variance in overall service quality than performance alone.

The dominant theme in services marketing literature continues to be service quality, reflecting the broader business emphasis on total quality management, organizational excellence, and customer satisfaction. Over the past decade, research in this field has expanded considerably, with both scholars and practitioners showing growing interest in the measurement of service quality and the conceptual relationship between service quality and customer satisfaction.

The evaluation of service quality has traditionally been guided by the SERVQUAL model. However, Cronin and Taylor [17] challenged the reliance on customer expectations within this framework and introduced SERVPERF, a performance-only measurement scale. Their empirical research demonstrated that SERVPERF offered superior reliability and validity compared to SERVQUAL. This viewpoint has been supported by other researchers, including Babakus and Boller [18] and Gotlieb et al. [19], who advocate for the use of SERVPERF.

Despite SERVPERF's empirical strength, Zeithaml et al. [20] and Hartline and Ferrell [21] argue that SERVQUAL remains widely used due to limited replication of Cronin and Taylor’s original study. Furthermore, Zeithaml and Berry emphasized the conceptual strength of assessing service quality as the gap between customer expectations and perceived performance.

The relationship between service quality and customer satisfaction has been widely debated in academic literature. Many scholars consider service quality as an antecedent to customer satisfaction, where satisfaction is understood as the consumer’s evaluation of service performance after usage. Rust and Oliver [22] highlighted that service quality constitutes one of the key dimensions influencing a customer’s satisfaction judgment.

The notion that service quality precedes satisfaction is supported by both Parasuraman et al. and Cronin and Taylor [17], with growing consensus around the effectiveness of the performance-only (SERVPERF) approach over the expectation-performance gap model. Furthermore, service quality is often conceptualized through two components: technical quality (what is delivered) and functional quality (how it is delivered) [23].

Satisfied customers are more likely to maintain long-term relationships with service providers, contributing significantly to organizational profitability and sustainability. In line with this, Olorunniwo et al. [24] identified four core dimensions of service quality i.e. tangibles (physical facilities and appearance), recovery (handling of service failures), responsiveness (willingness to help customers), and knowledge (employee expertise and competence). These factors play a critical role in shaping perceived service quality and, by extension, customer satisfaction and loyalty.

Service quality plays a significant role in shaping customer behavioural intentions. Notably, its indirect effect mediated through customer satisfaction acts as a powerful driver in influencing how consumers respond and engage with service offerings in the sector.

The extended duration will provide increased income for the company. The expenses of acquiring new consumers will decrease owing to the presence of pleased existing customers, which reduces the need for advertising and promotional activities. Content and devoted clients frequently disseminate positive information and endorse the business to numerous others [24].

A global consensus exists that service quality is considered a unique entity, while disputes persist about some measurement concerns. The cause-and-effect relationship between service quality and customer satisfaction remains inconclusive. It is still unclear which of these two variables serves as a more accurate predictor of customer behavioural intentions within the service industry.

Some contend that service quality precedes consumer satisfaction. They contend that service quality is a cognitive element, whereas customer satisfaction encompasses both cognitive and emotive elements. Positive views of service quality can result in client satisfaction, which then leads to favourable behavioural intentions.

Providing outstanding customer service is equally important as ensuring product quality. In recent years, service marketers have recognized that quality differentiation can be a powerful strategy for managing competition. Within the domain of services marketing, customer service is now viewed as an integral element of the marketing mix.

Because services are inherently intangible and inseparable from their delivery process, the significance of customer service is typically greater in service-based businesses than in manufacturing industries. As a result, delivering superior service experiences has become essential for building customer loyalty and achieving competitive advantage

While the distinction between service quality and customer satisfaction is broadly recognized, researchers often use different terminology to describe these concepts. Nonetheless, there is a strong consensus among scholars that both factors play a vital role in shaping and sustaining long-term customer relationships.

Customer happiness is a primary measure for assessing the quality offered to consumers [25]. Sheridan [26] asserts that organisations get a competitive advantage by superior service quality, enabling effective differentiation from competitors via greater customer service.

Numerous scholars have recognized service quality as a key strategic factor in driving operational effectiveness and promoting organizational success [18]. The concept of quality, however, is interpreted differently across academic and professional literature. It has been described in various ways, including as “meeting specified requirements,” “being suitable for its intended purpose,” and “fulfilling customer expectations to ensure satisfaction.”

According to Carrillat et al. [27], service quality continues to be a central focus within the field of service research due to its strong influence on customer satisfaction. In turn, customer satisfaction fosters positive word-of-mouth, loyalty, and purchase intentions, making service quality a critical determinant of long-term business success.

Cronin and Taylor [28] and Parasuraman et al. [29] emphasized that service quality stems from the customer's evaluation of the service experience during its delivery. They proposed that service quality should be understood as a multidimensional construct, encompassing elements such as Reliability, Responsiveness, Competence, Accessibility, Courtesy, Communication, Credibility, Security, Empathy and Tangibles. This comprehensive view supports the idea that service quality cannot be captured through a single dimension alone.

H. Lee, Lee, and Yoo [30] found that the performance-only model (e.g., SERVPERF) explained more variance in perceived service quality compared to the disconfirmation-based approach (expectation minus performance). Their findings are consistent with earlier studies by Cronin and Taylor [28], Babakus and Boller [18], and Bounding et al. [31], suggesting that managers should focus more on actual performance as perceived by customers rather than anticipated expectations.

In line with this, Babakus and Boller [18] argued that the expectation component of the SERVQUAL model adds little value over the performance-based approach. Many researchers have criticized SERVQUAL for issues related to reliability, discriminant validity, and limited variance, claiming that the difference score methodology introduces measurement errors.

Brady et al. [32] confirmed the superiority of SERVPERF in capturing service quality effectively. However, ongoing replication studies across various service industries are necessary to verify its theoretical robustness and practical applicability [33].

Parasuraman et al. [29] acknowledged the inherent challenges in defining and measuring service quality due to its intangible and variable nature, characterized by intangibility, heterogeneity, inseparability, and perishability. Meanwhile, Kenneth [34] questioned the discriminant validity of SERVQUAL, arguing that its structure—based on subtracting expectations from perceptions provides a misleading representation of service quality from the customer’s perspective.

Churchill, Brown, and Peter [35] further reinforced concerns over the use of difference scores in SERVQUAL, citing their contribution to unreliable measurements, overlapping constructs, and variance restriction. They noted that SERVQUAL scores tend to show non-normal distribution patterns.

In contrast, the SERVPERF model was found to produce high internal consistency and greater explanatory power in measuring service quality. However, further research is necessary to explore its suitability across diverse service industries [36].

The growing attention to service quality in academic and professional research stems from its strong association with key business metrics such as cost efficiency, profitability, customer satisfaction, loyalty, and positive word-of-mouth.

Service quality is widely recognized as a critical driver of financial performance in service-based organizations. The SERVQUAL model, built on the principle that customer perceptions are central to evaluating service quality, has gained substantial prominence. It has been broadly applied across a variety of service sectors and continues to be regarded as a highly respected and influential assessment tool [37].

The evaluation of service quality is an intricate task. The ultimate goal of measuring service quality is to help healthcare providers ensure their service quality and gain client happiness. As a result excellent levels of care and quality management of service delivery are obligatory for healthcare providers. There is substantial correlation between healthcare rendition and patients experience [38]. In diverse healthcare settings the relative importance of each parameter for calibrating overall service quality may deviate.

Globally, a large number of research studies have been carried out on the quality of services of healthcare providers which includes Guinea, Bangladesh, Burkina Faso, South Korea, Egypt, Turkey, Taiwan, USA, Australia, Cyprus, Japan, Mauritius, Afghanistan, Greece, Portugal, Ghana, Kazakhstan, Bahrain, Iran, Pakistan, Serbia, Malaysia, Romania, Thailand and Albania [39-69]. There is a wealth of data supporting the use of multiple conceptual models in evaluating the standard of medical care. Table 2.1 shows several service quality models developed by various researchers.

Year	Model	Author
1966	Donabedian	Donabedian
1988	SERVQUAL	Parasuraman et.al
1992	SERVPERF	Cronin et.al
1998	HEALTHQUAL	Camilleri et.al
2001	KQCAH	Sower et.al
2008	PRIVHEALTHQUAL	Fowder
2010	PUBHOSQUAL	Aagja et.al
2014	HospitalQual	Itumalla et.al
2014	HospiSE	Voon et.al

Table 2.1: Different models of service quality

An instrument to access service quality known as SERVQUAL was developed [29]. The dimensions are accessibility, respect, understanding, competence, security, responsiveness, tangibility, and credibility. Later in 1988 [70], these dimensions were proselyted into five dimensions, namely, reliability, assurance, responsiveness, empathy and tangibles. The five dimension of SERVQUAL are widely used by several service providers including healthcare [71-81]. Several research studies have demonstrated a direct linkage between patient satisfaction and service quality [82-84]. Another quality assessment model known as SERVPERF was developed [28], which emphasises quantifying client opinions of service quality. A model based on three dimensions namely service environment, service delivery approach and service product was developed [86].

Many researchers quibbled that SERVQUAL model have some serious intricacy. Depending on the convenience of the study, some researchers introduced affordability [87], physical appearance [88], cost [89], administrative alertness and assistance abilities [90], interaction and bribe [91], courtesy [92], caring and consequence [93], affordability and availability [94] to SERVQUAL.

A multilevel model was postulated in Jakarta to pinpoint three primary dimensions namely atmosphere, consequences and communication of healthcare service quality [95].

A model was created for public health facilities in Indonesia including the standard of medical treatment provided, the standard of the administrative procedure, the standard of medical staff, and the sufficiency of medical resources [96]. A hierarchical model including quality of atmosphere, interaction and consequence was developed [97] which shows substantial correlation between waiting hour, commitment to patients, happiness, and impression.

The PubHosQual scale investigated five dimensions such as the procedures for admission and discharge, medical care, general service and responsibility for society to determine quality of care in public hospitals. It is also stated that each of these factors significantly predicts patient satisfaction. The dimensions of service quality determined are estimated waiting hour, convenience, admission procedure, appointment for consultation, physical atmosphere, patient details, consultation with doctor and estimated service costs [98]. A new dimensions for hospital service such as waiting hours and quality of doctors, medical and non-medical personnel was discovered [99].

An integrated hierarchical model was proposed which expounded a connection between service excellence, behavioural intentions, and customer satisfaction. Quality in interpersonal relationships, environmental sustainability, technical proficiency and administration are the fundamental dimensions of service excellence. The elements that affect hospital service quality include medical staff and practices, behaviour and practices of human resources, healthcare delivery and sufficiency of resources and services [100].

The study directs policymakers and healthcare practitioners' attention to an instantaneous and imperative response on measured perceived service quality to improve healthcare services. A study explored eight components of high-quality healthcare such as dependability, assurance, tangibility, reaction, compassion, release, safety precautions, and medication quality control to figure out loyalty and patients' satisfaction [101].

The HospitalQual model was proposed to initiate service quality from the inpatients' perspective and identified infrastructure of hospital, safety for patients, administrative, nursing and medical facilities and interaction with patients [102]. An investigation on loyalty, satisfaction and quality of service in hospital was conducted in Pakistan [103].

The study discovered five dimensions namely safety and confidentiality, physical surroundings, responsiveness, user friendly atmosphere and interaction. A survey accustomed reliability, administrative practices, infrastructure, medical care technique, staff competency, social responsibility, safety measures and hospital reputation to investigate the service quality in hospital.

Another survey incorporated devotional requirements, admission and discharge protocols, interactions with patients and staff, waiting periods, visiting guidelines, and tangible in his work [104]. An investigation investigated the availability, technical and skilful assistance, food, customized services, cost, patient comforts and atmosphere as crucial dimensions in measuring quality of services of healthcare providers [105]. An inquiry identified eleven dimensions of service quality which includes dependability, politeness, interaction, tangibles, expertise, patient reaction, understanding patients' needs, response, kindness, and relationship [106]. Five dimensions propounded by a survey includes price, hygiene, attentiveness, politeness, and conversation [107]. A probe initiated trustworthiness, economy, accessibility, effectiveness, safety, and elegance to measure service quality dimensions [108]. A survey investigated accessibility, treatment, care and atmosphere as aspects of the quality of health care services [109].

A study found staff-patient connections, valuing the needs of inpatients, empathy, meals, physical surroundings and staff competency as determinants of service quality. An investigation confirmed a linkage between loyalty, happiness, and quality of service [110]. It has been argued that concepts of service excellence that originate in one culture may not transfer to another [111-112]. The literature study demonstrates that a variety of factors can affect patients' satisfaction.

Raposo et al. [57] investigated patient satisfaction across four primary healthcare centres in Portugal to determine the key healthcare quality dimensions influencing satisfaction levels. Using the Partial Least Squares (PLS) technique to evaluate their conceptual model, the study revealed that patient satisfaction levels were relatively moderate. The most influential factors included the patient-doctor relationship, the quality of healthcare infrastructure, and the interactions with administrative staff.

Several studies have indicated that patient satisfaction is shaped by multiple antecedents, such as perceived value, brand image, expectations, and both functional and technical service quality. Within the U.S. healthcare context, four critical components were identified: nursing care, hospital facilities, medical treatment, and support personnel, all of which play a vital role in shaping patient satisfaction.

These aspects collectively influence a hospital's reputation and impact future patient preferences. Compared to other service sectors, customer behaviour in healthcare exhibits more complex dynamics. Due to limited autonomy in medical decisions, patients often rely on doctors and nurses to make informed treatment choices on their behalf.

While evaluating patient satisfaction is essential, it is equally important to understand the underlying factors that contribute to it, particularly in terms of service quality. The research further highlights that increased patient involvement in healthcare decisions leads to better satisfaction outcomes. Additionally, the hospital's physical environment—or tangibles—plays a crucial role in shaping overall patient perceptions [12]

In a study conducted on Bangladeshi hospitals, Andaleeb [113] identified six core dimensions used to assess service quality: Responsiveness, Assurance, Communication, Discipline, Gratuity practices (Baksheesh), and Overall Satisfaction. The results showed that all these factors were strongly correlated with patient satisfaction. Importantly, the contributions of frontline staff, healthcare workers, and support personnel were found to be instrumental in enhancing service quality and improving patient experiences.

Ozanne [114] examined perceptions of healthcare service quality in New Zealand, highlighting the influence of geographical, demographic, and behavioural variations on how patients evaluate service quality. The study applied a ten-dimensional framework, which included reliability, tangibles, assurance, empathy, food services, access to care, treatment outcomes, admission experience, discharge process, and responsiveness. These dimensions collectively provided a nuanced understanding of patient perceptions and satisfaction in different healthcare environments.

The Frontline staff, healthcare workers, and support personnel play a pivotal role in ensuring high-quality service delivery, which directly contributes to improving patient satisfaction and overall service experience. Efficient customer service originates from contented staff. Patient empowerment significantly contributes to pleasure, as it enables individuals to comprehend treatment methods and their outcomes more effectively [115].

Barksdale and Johnson [116] introduced a model focused on sustaining the patient-physician relationship, particularly in a managed care context. Their findings highlight that physician availability directly influences this relationship. The way physicians engage with patients significantly affects the emotional responses and overall satisfaction of patients. Conversely, patients who are frequently assigned to different physicians tend to feel less emotionally connected and invested in the relationship.

Braunsberger and Gates [117] discovered that education level plays a role in how patients assess healthcare service quality. Patients with lower educational attainment generally rated healthcare performance more favorably, while those with higher education levels tended to be more critical and less satisfied, likely due to higher expectations and more stringent evaluative criteria.

W. Lee, Chen, and Wu [118] developed a model to analyze the relationship between healthcare management, service quality, and patient satisfaction. Their study affirmed a positive correlation, indicating that better organizational practices in healthcare administration lead to improved care delivery and greater consumer happiness.

Das and Hammer [119] explored physician behavior and found that doctors educated in publicly funded institutions often demonstrated less empathy toward patients in government hospitals. In contrast, the private sector, although sometimes criticized for encouraging unnecessary procedures and medications, was viewed more favorably for its responsiveness to patient needs. Their model incorporated three dimensions process, interaction, and outcome each involving clinical and non-clinical staff, and contributing to overall patient satisfaction.

In many low-income countries, the perceived quality of healthcare often has less impact on health outcomes due to limited resources. The private sector tends to be more responsive to client expectations, with noticeable differences in the standard of care provided to wealthy versus economically disadvantaged patients. While affluent individuals typically access high-quality services and greater physician interaction, the underprivileged often rely on government hospitals, receiving basic care with minimal engagement from healthcare professionals [120].

There is a strong correlation between the quality of hospital services, patient satisfaction, hospital reputation, and overall institutional performance. Hospitals that prioritize patient-centered care and create a welcoming environment tend to see improved public perception and increased patient loyalty.

With the rise of private competitors, technological innovation, and higher patient expectations, there has been a growing focus on delivering efficient and personalized customer service in healthcare. Patient satisfaction and loyalty are now considered vital tools for maximizing organizational revenue. Historically, measurement efforts have focused on external customer perceptions, but there is increasing recognition that quality of care is not just a conceptual ideal, it is essential for both patient outcomes and economic sustainability.

In Turkey, Çaha [121] conducted a study on the private healthcare sector and found that patients often prefer private hospitals, believing they offer superior treatment. Despite certain shortcomings, the demand for private healthcare services is expected to grow, with patient satisfaction emerging as the central factor influencing this preference.

Bhatia and Cleland [122] examined perceptions of service quality among female outpatients in both public and private healthcare facilities. Their research focused on key elements such as diagnostic procedures, clinical interventions, nutritional advice, and laboratory services. The findings revealed that private sector healthcare generally offered superior quality of care compared to public institutions.

In the public sector, where services are typically offered free of charge, the technical quality of care representing the core service is of heightened importance. While the skills and demeanour of physicians and clinical staff significantly influence patient satisfaction, non-clinical support personnel have minimal impact on patient experience [2].

The study emphasized that patient satisfaction or dissatisfaction stems from a combination of experiences across service subcategories. To improve customer management and institutional reputation, hospitals should develop strategic approaches that foster staff responsiveness and customer orientation [123].

In today's highly competitive healthcare environment, long-term success depends on consistently delivering high-quality services that foster customer satisfaction. Satisfied patients are more likely to remain loyal, supporting key organizational goals such as increased profitability, market share, and return on investment. While service quality and customer satisfaction are conceptually distinct, they are closely interrelated, with service quality often viewed as a precursor to satisfaction [124].

Parasuraman, Zeithaml, and Berry [29] were among the early scholars to argue that models developed for product-based sectors are not applicable to services, particularly in fields like healthcare. They highlighted that services are inherently intangible, heterogeneous, perishable, and inseparable from the provider, making it difficult to apply traditional quality indicators in service contexts such as hospitals [125].

Physicians also play a vital role in shaping patient experiences and satisfaction. Variables such as the quality of care provided, evaluation of individual doctors or nurses, and assessment of specialist services were found to have strong statistical relevance in influencing patient perceptions.

Amjeriya and Malviya [126] employed the SERVQUAL model to measure service quality and customer satisfaction in Indian hospitals. Their findings indicate notable deficiencies in dimensions such as reliability and responsiveness, with considerable gaps across all six parameters studied. These discrepancies underline a significant disparity between expected and perceived service quality. The study reinforced the notion that customer satisfaction is central to an organization's success, especially in maintaining lasting relationships with patients.

Ritu Narang [100] evaluated service quality within the Indian healthcare sector using four key dimensions i.e. conduct and practices of healthcare staff, availability and adequacy of healthcare resources, service delivery quality and accessibility of healthcare services. The study emphasized that as socio-economic conditions improve, patients expect more than just adherence to treatment protocols. Policymakers must take into account the specific needs and preferences of consumers when designing and implementing healthcare policies, thereby ensuring that care delivery aligns with evolving expectations.

2.2.2. Recent Studies on Service Quality of Healthcare

Reference	Key Contributions	Issues not Addressed
Sharkiya, S. H. (2023). [127]	Conducted a rapid review of service quality impact on elderly satisfaction in geriatric centers.	Lacks quantitative analysis or comparative study across centers.
Tortorella, G. L. et al. (2021). [128]	Explored how Healthcare 4.0 technologies improve hospital resilience.	Did not assess actual patient satisfaction or quality-of-care metrics.
Ahmed, S. et al. (2017). [129]	Investigated service quality, satisfaction, and loyalty relationships in Bangladeshi healthcare.	Outdated for current post-COVID healthcare context; no technological considerations.
Hosseinzadeh, M. et al. (2024). [130]	Used SERVQUAL to assess service quality and patient satisfaction in Khuzestan.	Limited to regional scope; lacks integration of advanced quality frameworks.
Al-Assaf, K. et al. (2024). [131]	Reviewed the transformative role of Healthcare 4.0 in improving service quality.	Theoretical focus; lacks empirical evidence or case studies.
Yunus, N. A. M. et al. (2024). [132]	Analyzed service quality's impact on patient satisfaction at a university health center.	Narrow scope limited to one institution; lacks generalizability.
Rauf, A. et al. (2025). [133]	Systematic review using PRISMA on healthcare service quality literature.	Lacks a conceptual framework to unify diverse findings.
Senapati, S. & Panda, R. K. (2023). [134]	Applied fuzzy-AHP to enhance service quality in Indian private hospitals.	No real-time implementation or patient outcome validation.
Saleem, S. M. U. et al. (2024). [135]	Performed a comprehensive literature review on service quality models.	No novel framework proposed; lacks focus on digital innovation.
KhanMohammadi, E. et al. (2023). [136]	Proposed a fuzzy best–worst method to assess service quality in hospitals.	Limited application scope; real-time patient data not incorporated.

Reference	Key Contributions	Issues not Addressed
Awang, S. et al. (2023). [137]	Developed Malaysia's national policy framework for healthcare quality improvement.	Implementation outcomes and scalability challenges were not analyzed.
Cui, H., & Tan, Q. (2025). [138]	Proposed a fuzzy decision support system for managing hospital service quality.	Lacked real-world case application and user interface feasibility assessment.
Singh, Y., & Bisht, D. C. (2025). [139]	Integrated Pythagorean fuzzy ANP with TOPSIS-VIKOR-SAW to evaluate hospital service quality.	No empirical validation or sensitivity analysis on composite outcomes.
Hutabarat, A. et al. (2025). [140]	Assessed correlation between service quality and patient satisfaction in Indonesian hospital outpatient departments.	Single-site, short-term data without longitudinal impact tracking.
Bradács, A. I. et al. (2025). [141]	Measured patient satisfaction in Bihor County Emergency Hospital, Romania.	Did not address clinical outcome metrics or cross-departmental comparisons.
Morales-Garrido, A. et al. (2025). [142]	Compared healthcare quality and satisfaction across two Peruvian public hospitals.	Did not explore systemic causes of quality variance between hospitals.

Table 2.2.1: Review of recent articles on service quality

2.2.3. Studies relating to applications of MCDM techniques in healthcare

According to recent research, MCDM is extensively utilized across numerous fields which include agriculture, finance, transport, supplier selection and supply chain management, environmental sustainability and service quality management [143-157].In addition, the implementation of MCDM in the healthcare sector is expanding; yet, certain research suggests that, in comparison to other sectors, this sector still has a low degree of MCDM adaptability [158-170]. Nevertheless, studies suggests that MCDM is being used more frequently in healthcare. Several approaches have been proposed to address the intricacy of MCDM.

The literature on Multi-Criteria Decision-Making (MCDM) highlights several widely adopted methodologies. These include:

a. Goal Programming (GP) – A mathematical approach used to achieve multiple goals by optimizing decision variables.

b. Analytic Hierarchy Process (AHP) – A structured technique for organizing and analyzing complex decisions based on pairwise comparisons.

c. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) – A method that ranks alternatives based on their proximity to the ideal and anti-ideal solutions.

d. Elimination and Choice Expressing Reality (ELECTRE) – A family of outranking methods used for complex decision problems involving multiple conflicting criteria.

e. VIKOR (ViseKriterijumska Optimizacija I Kompromisno Resenje) – A method focused on multi-objective optimization and compromise solutions, useful when decision-makers seek a balanced option among conflicting criteria.

f. Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) – A ranking technique that evaluates alternatives based on preference flows.

g. Data Envelopment Analysis (DEA) – A non-parametric method used for assessing the efficiency of decision-making units.

h. Analytic Network Process (ANP) – An extension of AHP that incorporates interdependencies among decision elements.

These MCDM techniques are extensively used in research and practice to support decision-making in complex, multi-criteria environments [171–178].

Recent advancements in the field of Multi-Criteria Decision-Making (MCDM) have introduced several innovative methods that are gaining recognition in academic and practical applications. These include:

i. Weighted Aggregated Sum Product Assessment (WASPAS) – Combines the principles of weighted sum and weighted product models to enhance decision accuracy.

ii. Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) – A method that evaluates multiple objectives through normalized ratio-based comparisons.

iii. Additive Ratio Assessment (ARAS) – Focuses on ranking alternatives by assessing their performance relative to the ideal solution.

iv. Complex Proportional Assessment Method (COPRAS) – Utilizes proportional comparisons for evaluating and ranking decision alternatives.

v. MOORA plus Full Multiplicative Form (MULTIMOORA) – An extension of MOORA incorporating multiplicative utility for comprehensive analysis.

vi. Step-Wise Weight Assessment Ratio Analysis (SWARA) – A structured approach for deriving criteria weights based on expert judgment.

vii. Generalized Regression with Intensities of Preference (GRIP) – Applies regression techniques to model preferences within decision-making contexts.

In addition, a significant portion of current research integrates fuzzy set theory into areas such as product design, performance evaluation, quality control, and measurement systems. This integration aims to address uncertainty and subjectivity, thereby enhancing the robustness of decision-making models [179–196].

Hatam and Tourani [197] examined MCDM approaches for assessing hospital performance and contrasted MCDM models with the ratio analysis approach. Hsu and Pan [198] prioritized dental quality parameters using a Monte Carlo AHP technique, which led to greater income, considerable cost reductions, and more self-assured dental clinic management.

Lupo [199] developed a novel fuzzy approach to assess the quality of healthcare services by integrating fuzzy triangular numbers with AHP in Sicily. Chui et al. [200] used an electrocardiogram (ECG) identifier that utilized MCDM to identify cardiac failure. TOPSIS and weighted averaging operators were employed by Ren et al. [201] in a thermodynamic approach to support China's hierarchical healthcare system.

Kulak et al. [202] investigated medical imaging risk variables using a novel MCDM technique. Leili et al. [203] used fuzzy MCDM to assess the efficacy of services provided by healthcare facilities in Iran. To improve reliability and accuracy, Zeng et al. [204] implemented an enhanced VIKOR technique for making healthcare decisions Medical records from hospitals were assessed using MCDM by Ajami and Ktabi [205].Chang [206] proposed a hybrid multi-criteria approach with a fuzzy VIKOR method for rating several healthcare provider.

Akdag et al. [207] employed a combination of advanced decision-making techniques, including fuzzy TOPSIS, the Yager Min-Max principle, ordered weighted averaging (OWA), and the compensatory AND operator, to evaluate the service quality of private hospitals in Turkey. Their multi-method approach aimed to provide a comprehensive assessment of healthcare service excellence under uncertainty. Chowdhury and Zelenyuk [208] utilized Data Envelopment Analysis (DEA) integrated with bootstrapping and truncated regression analysis to measure the production efficiency of hospital services in Ontario, Canada. This approach allowed for more statistically robust efficiency estimates in the healthcare sector.

Vulevic and Dragovic [209] implemented the PROMETHEE II method to rank and evaluate nine sub-watersheds of the Topciderska River in Belgrade, Serbia. Their work demonstrates the versatility of MCDM techniques in environmental resource assessment. In a separate study, Bilsel et al. [210] applied a PROMETHEE-based framework to assess the effectiveness of hospital websites in Turkey, highlighting the growing importance of digital presence and service accessibility in healthcare systems.

2.2.4. Recent MCDM applications in Healthcare

Reference	Key Contributions	Issues not Addressed
Chakraborty et al. (2025) [211]	Comprehensive review of MCDM applications in healthcare waste management.	Lacks quantitative comparison between MCDM methods.
Ojo et al. (2025) [212]	Developed hybrid fuzzy MCDM for AI-driven mental health solutions.	No deployment or usability evaluation in real-world scenarios.
Chowdhury et al. (2021) [213]	Used ensemble-based MCDM for COVID-19 cough classification.	Preprint only; lacks peer-reviewed validation and performance benchmarking.
Gaievskyi et al. (2025) [214]	Scoping review on MCDA for decision-making in health emergencies.	Lacks categorization by MCDM technique or regional application.
Raveena & Umamaheswari (2025) [215]	Developed an integrated fuzzy TOPSIS-SVR-GRA framework for pharmacy supplier selection.	Focus limited to supplier selection, not extended to service delivery.
Al Mohamed et al. (2023) [216]	Applied fuzzy MCDM for selecting pandemic hospital sites.	Geospatial validation and stakeholder feedback were not incorporated.
Komijan et al. (2024) [217]	Spherical fuzzy MCDM model to assess hospital service quality during pandemic.	No pre-pandemic vs. post-pandemic quality comparison conducted.
Sarwar et al. (2025) [218]	Proposed fractional fuzzy MCDM for medical waste prioritization.	Method complexity may limit practical healthcare adoption.
Wang & Shao (2024) [219]	Designed a hybrid MCDM-based smart evaluation system for medical service quality.	Technology integration specifics and security aspects not discussed.
Regragui et al. (2024) [220]	Developed hybrid fuzzy MCDM for evaluating hospital sustainability.	Does not address patient-centric indicators in sustainability.

Reference	Key Contributions	Issues not Addressed
Wu & Chen (2023) [221]	Used grey synthetic evaluation for integrated health organization assessment.	Limited generalizability to non-county-level systems.
Ahmad et al. (2024) [222]	Reviewed AI-enabled technologies in Healthcare 5.0 and Industry 5.0.	More conceptual; lacks quantitative MCDM-based assessments.
Yucesan & Gul (2020) [223]	Used Pythagorean fuzzy AHP and fuzzy TOPSIS for hospital quality evaluation.	Pre-COVID model; lacks robustness against current dynamic healthcare demands.
Pham et al. (2023) [224]	Applied Delphi + MCDM for sustainable development in Hai Phong healthcare.	Regional focus; lacks adaptability to other urban contexts.
Wątróbski et al. (2023) [225]	Proposed SSP-AHP for evaluating sustainable healthcare systems.	The SSP concept needs broader empirical application and validation.

Table 2.2.2: Review of recent articles on MCDM applications

2.2.5. Studies relating to applications of QFD in healthcare

Quality Function Deployment (QFD) is a widely recognized and effective customer-driven design methodology that focuses on translating customer needs into actionable service and product features. It supports organizations in aligning their offerings with customer expectations, while also enhancing managerial capabilities, achieving strategic goals, and promoting customer satisfaction [226–228].

QFD was first introduced in 1972 by Takayanagi Nishimura and his team of engineers, who developed a quality matrix for a shipyard project in Kobe, Japan. Since its inception, QFD has found broad applicability across a range of industries, owing to its structured approach to incorporating the voice of the customer into the design and development process.

It has recently been used in process selection [229-230], product design planning [231], shipping investment decision-making [232] and selection of ERP systems [233]. QFD has been rarely implemented in the field of healthcare [234-243], however research in this field is escalating [244-260]. QFD is adopted for continuous quality improvement of healthcare service delivery.

A personalised QFD is presented to design computer network service [247] and examining radiation safety management in healthcare [255]. A modified QFD by using the ANP theory and Kano's model is developed to enhance outpatient care for senior citizens in Taiwan [260].

AHP integrated with QFD are commonly used in product design decisions [261-268] and healthcare [269-288]. A combined AHP-QFD approach is employed to assess and elect multi-functional groups [289]. The facility location issue is addressed by utilizing the combined AHP–QFD technique [290]. In order to assess the degree of synergistic effects between the two consecutive HOQs (House of Quality) for the advantage of soccer sport, a combined AHP–QFD technique is implemented [291].

A hybrid AHP-QFD approach for designing of products is proposed [292]. A framework that incorporates ANP for the intrinsic reliance in the QFD method is presented [293].The integrated AHP–QFD strategy is used for assistance in robot selection [294]. A blended AHP-QFD approach is propounded to assess and choose a facility location for a firm that manufactures automated mass measurement devices for industrial service [295].

A hybrid AHP-QFD technique is suggested for selecting rapid hard tooling process [296]. AHP/ANP, QFD and TRIZ is integrated to create a customer-manufacturer-competitor (CMC) framework [297]. The framework examines manufacturers, customers and competitors perspective, as well as related concerns throughout the Product Life Cycle (PLC).

A hybrid model combining AHP, Kano, and QFD techniques was applied to assess and improve the central library services at Dokuz Eylul University (DEU) in Turkey. This integrated approach aimed to accurately identify and prioritize the needs of students and library users [298].

It has been observed that previous research utilizing the Analytic Network Process (ANP) remains limited. To address this gap, a comprehensive network-based ANP structure comprising five interrelated clusters namely, objectives, desired quality attributes, innovative product design risks, quality characteristics, and competitive challenges has been proposed [299].

In another study, a four-dimensional House of Quality (HoQ) was developed, performing three levels of translation within a multi-criteria decision-making framework based on ANP. This model enhances the decision-making process by providing a more systematic and structured methodology through the House of Quality mechanism [300].

An AHP-QFD hybrid model has been proposed to develop tourism services that effectively respond to the needs and preferences of travellers [301]. In another application, QFD is combined with both AHP and artificial neural networks (ANNs) to pinpoint the key elements essential for the design and planning of new products [302].

To support efficient selection of third-party logistics (3PL) providers in contemporary supply chain systems, a comprehensive AHP-QFD framework has been developed [303]. Additionally, a combined approach using AHP and Genetic Algorithm (GA) has been introduced to aid in the selection of digital machines, ensuring optimal alignment with performance and operational requirements [304].

A trio cluster ANP system to estimate the initial significant weights for House of Quality is proposed [305]. The significance levels in the House of Quality is estimated by implementing ANP [306]. Other strategies, such goal programming, are also incorporated into the holistic approach for a specific objective.

A combined AHP-QFD study to enhance the quality of education at a university in Singapore is recommended [307]. The improved wheelchair design using an integrated QFD-FANP approach is evaluated [308]. A novel approach to improve medical haemodialysis systems by integrating QFD, FAHP and the Kano model is proposed [309].

A unified DEMATEL-AHP-QFD model for transforming customer requirements into attributes of products to grade design options is suggested by considering an illustration of a joint replacement surgery assistance technology for senior citizens [310]. The fuzzy Kano model is used to obtain the impact of each customer requirements on customer satisfaction.

A multistage integrated framework combining fuzzy set theory with various MCDM) techniques including QFD, AHP, ANP, and the DEMATEL has been developed to support the sustainable design of products. This fuzzy QFD-MADM model was specifically applied to the meat processing industry in the Philippines, providing a structured approach to decision-making under uncertainty [311].

2.2.6. Recent QFD applications in Healthcare

Reference	Key Contributions	Issues not Addressed
Zhu & Husin (2025) [312]	Developed a multidimensional requirement-oriented QFD for sustainable self-service machine design.	Not healthcare-specific; lacks real-time user satisfaction assessment.
Sukma et al. (2022) [313]	Systematic literature review on QFD in healthcare applications.	Review lacks meta-analysis or quantitative synthesis.
Mao et al. (2025) [314]	Integrated linguistic distribution and CRITIC method in QFD prioritization.	No healthcare application; limited real-world deployment validation.
Wang et al. (2024) [315]	Introduced cooperative game theory with three-way decision in QFD modeling.	Complex model may hinder practical adoption; not focused on healthcare.
Thu et al. (2024) [316]	Applied QFD with Best-Worst Method to evaluate logistics distribution center performance.	Lacks patient-centric or healthcare-oriented case application.
Gavahi et al. (2023) [317]	Combined QFD with SERVQUAL to improve radiology service quality.	Limited to radiology; broader hospital-wide applicability not assessed.
Alshouha et al. (2024) [318]	Built an integrated decision framework for healthcare service evaluation using QFD.	Real-time deployment and sensitivity testing missing.
Aljuneidi (2023) [319]	Investigated quality attributes of Palestinian outpatient services.	Lacks structured methodology or validated decision model.
Zhou et al. (2022) [320]	Bibliometric review of QFD literature, highlighting global research trends.	No domain-specific insights into healthcare QFD application.

Reference	Key Contributions	Issues not Addressed
Eldressi et al. (2024) [321]	Presented conference-level application of QFD in general design settings.	Abstract-level; lacks empirical or sector-specific evidence.
Ojha & Agarwal (2025) [322]	Applied QFD to analyze stakeholder perspectives in Healthcare 5.0 transformation.	Future QFD validation models in real ecosystem not provided.
Wahed & Saleh (2024) [323]	Designed ICU layout using QFD to optimize medical service delivery.	Focused only on spatial design; no integration with user experience feedback.
Hariri (2024) [324]	Combined QFD, MCDM, and Kano model in the automotive sector.	Non-healthcare context; lacks transferability insights to healthcare.
Xu et al. (2022) [325]	Proposed spherical fuzzy CoCoSo-based QFD model.	Complex technique lacks demonstrative healthcare application or case study.

Table 2.2.3: Review of recent articles on QFD applications

2.2.7. Studies relating to applications of FMEA in healthcare

FMEA is widely recognized as a critical tool for conducting risk assessments, particularly within the healthcare sector [326]. In recent years, FMEA has been applied across a variety of healthcare contexts to identify and mitigate high-risk failures.

Rah et al. [327] compare a modified version of Healthcare FMEA (HFMEA) with the traditional FMEA method to evaluate congruency levels and detect high-risk scenarios. Jain [328] employed FMEA to enhance patient safety and improve medication administration processes. Faiella et al. [329] advances the HFMEA framework to assess medication management failures in domestic settings. Similarly, Mora et al. [330] applies FMEA to assess and improve blood transfusion safety within hospital environments, while Changchien et al. [331] utilizes the technique to identify and minimize inpatient suicide risks.

Despite notable progress in Failure Mode and Effects Analysis (FMEA), traditional FMEA techniques often face challenges when dealing with uncertainty and imprecision, particularly in complex environments with limited expert input. Conventional FMEA frameworks typically do not adequately address this inherent ambiguity. To overcome these limitations, researchers have integrated fuzzy set theory into FMEA models.

For instance, Kahraman et al. [332] enhanced FMEA by employing fuzzy logic and linguistic variables through IF-THEN rule structures, allowing for a more nuanced evaluation and ranking of healthcare-related risks. Similarly, Liu et al. [333] proposed a novel model that combines fuzzy logic with the MULTIMOORA method to assess the risk of infant abduction within a healthcare setting.

In another contribution, Rahimi et al. [334] presented a unified framework that incorporates profitability analysis, Grey Relational Analysis (GRA), and fuzzy FMEA to identify and evaluate failure points in diagnostic healthcare services.

Chanamool and Naenna [335] developed a fuzzy-based FMEA model tailored to evaluate risks in emergency departments, while Liu et al. [336] combined the MABAC method with interval-valued intuitionistic fuzzy sets to facilitate comprehensive risk assessment in radiation therapy units. Further, Liu et al. [337] proposed a fuzzy risk prioritization model integrating weighted techniques and the VIKOR method for more accurate failure mode evaluation within FMEA.

Beyond fuzzy logic, rough set theory has also been explored to improve FMEA's analytical capacity. For example, Song et al. [338] introduced a rough set-based model to evaluate human-related risk factors, thereby minimizing dependence on prior information. However, this approach assumes independence among failure modes, which may not always align with real-world complexities.

Additionally, Omidvari et al. [339] and SarAbadani & Ghiysai [340] applied the Analytic Hierarchy Process (AHP) to determine the importance weights of different risk components in FMEA. Studies by Rezaee et al. [341] and Chang et al. [342] combined fuzzy Data Envelopment Analysis (DEA) with FMEA for risk prioritization. Nevertheless, these methods did not fully account for the interdependencies and causal relationships among risk factors, highlighting an area for further improvement.

Ahmad et.al [343] utilizes FMEA to Root Canal Treatment (RCT) to recognize and hierarchize failure modes (FMs). With input from five dental experts, sixteen FMs were assessed based on S,O, and D. To manage uncertainty in expert judgment, rough numbers were used to process the data. The study employed WASPAS, ARAS, TOPSIS, and VIKOR in rough situation to rate the FMs. Final rankings were calculated using the grade average integrated method. "Missed canal" was found to be the most critical failure, while "Root canal underfillings" was the least. The FMs were grouped into high, medium, and low criticality categories, and recommendations were made to reduce the most severe risks. The findings aim to support better planning and execution of RCT by dental professionals. Zheng et al. [344] uses HFACS and a risk matrix to improve risk identification and prioritization on ventilator-related human error hazards. The study introduces a consensus-based risk matrix to account for expert risk acceptability perspectives.

Arantes et al. [345] proposes a consensus-reaching group decision-making model using ELECTRE TRI and Double Hierarchy Hesitant Fuzzy Linguistic Term Sets. The model is tested in a Brazilian hospital operating room. Consensus, mitigation complexity, and non-compensatory factors greatly affected failure mode classification. DHHFLTS helped professionals communicate their evaluations more clearly. The pilot study during the COVID-19 pandemic found that postponing elective procedures worsened patient situations, turning many into urgent cases. Liao et al. [346] presents an improved FMEA technique that uses preference disaggregation analysis and failure mode linkages to increase risk assessment accuracy study of AI-enabled smart bracelets, wearable health monitoring devices.

An influence-strength matrix allows for direct and indirect linkages, positive or negative effects, and each failure mode's original strength to alter occurrence ratings. The method then uses preference disaggregation to weight risk elements and calculate failure mode utility values using past choice data. Utility classifications rank failure types from most to least critical. Liu et al. [347] proposes a novel risk prioritization methodology for FMEA that integrates cluster analysis with prospect theory, specifically tailored for situations involving numerous experts. An entropy-based method is devised to objectively ascertain the weights of risk elements via expert risk assessments. The suggested Large Group FMEA (LGFMEA) methodology is illustrated via a real-world healthcare risk analysis example, and its efficacy and applicability are evaluated through a comparative study.

Yeh et al. [348] evaluates COVID-19-infected intensive care unit admission and treatment during pandemic control. A multidisciplinary team used FMEA and a process flowchart to identify failure areas. RPNs identified the most likely failure modes to cause hospital-acquired illnesses. Eight high-risk failure categories involved nurses not checking patient histories, nursing assistants not following protocols, and doctors being exposed to dangerous conditions. Therefore, 18 remedial measures were suggested. The study shows that FMEA can identify risks and enhance quality to prevent infections during a health crisis. Yu et al. [349] develops DEA-based models to improve Failure Mode and Effects Analysis.

The first model employs SBM-DEA, whereas the second uses NDA, which combines FMEA and DEA., USA, A baby security case with 16 failure modes is used to compare these models at western wake medical centre in North Carolina. Both SBM-DEA and NDA beat traditional FMEA in discrimination and detection accuracy. However, NDA performs better in risk assessment and medical failure detection.

Sarwar et al. [350] constructs a comprehensive decision support framework by employing RFICs, hybrid weighting, and TOPSIS to analyze failure modes of a power plant steam valve system. The model ranks failure modes by identifying positive and negative ideal solutions using statistical deviations and mathematical operations on cloud models. Additionally, simulation and sensitivity analysis evaluate the performance under different control parameter settings.

Tangestani et al. [351] uses FMEA and DMRA to assess hospital PM and bioaerosol transmission risk in four Iranian hospitals healthcare specialists using risk priority numbers. Indoor air pollution control was suggested. The FMEA checklist was validated for hospital air quality risk assessment using Cronbach's Alpha (0.619) and the Intra-class Correlation Coefficient (0.913). Nineteen hazards with 36–468 RPN values were found. The study showed an innovative and proven technique for prioritizing and managing hospital air pollution hazards.

Nolan et al. [352] applies risk analysis approaches in the medical device business to enable ISO 14971:2019 compliance. It focusses on FMEA's extensive use and limitations as a risk assessment technique. Through qualitative interviews with risk management specialists, the study finds that FMEA is the most often used method but fails to address all ISO standard risk components, particularly safety hazards during routine device use.

Omidvari et al. [353] employs FMEA and MCDM to estimate hospital fire risk at a Shiraz university of medical sciences hospital. The Intuitionistic Fuzzy Multiplicative Best-Worst Method (IFMBWM) is used to weigh each criterion and subcriterion, and IVIFCODAS is used to rank hospital wards.

The results reveals that fire alarm systems, electrical installations, and combustible materials were the most dangerous. The hospital powerhouse is the most at-risk due to fire concerns such weak safety systems and restricted accessibility. The study shows that MCDM and FMEA accurately assess healthcare facility fire hazards.

Romero-Zayas et al. [354] applies risk analysis to a hospital radio pharmacy unit to identify probable failure modes and prioritize corrective efforts. Failure modes were analyzed during prescription, preparation, and administration of diagnostic and therapeutic radiopharmaceuticals using FMEA. There were 96 failure mode, 58 diagnostic and 38 therapeutic. Incorrect patient-to-radiopharmaceutical identification was the biggest concern, and radiolabeling had the greatest RPN. Improvement methods reduced diagnostic RPN by 22% and therapeutic RPN by 20%, which might rise to 46% and 31% with radio pharmacy software and barcode systems.

Llkic et al. [355] identifies the rapid use of digital technology in pharmaceutical treatment. The goal is to find, appraise, and prioritize mistakes in telepharmacy, mHealth, AI, and supporting software. A multidisciplinary team of 10 specialists applies FMEA to assess risks based on severity, occurrence, and detectability, identifying 42 hazards, 8 of which were critical with RPN ratings over the threshold. Internet and identity fraud, data management mistakes, incorrect system implementation, and insufficient openness and infrastructure are the major issues. Corrective activities reduces the risk score from 414 to 156. The study emphasizes that digitalization can improve pharmaceutical treatment, but it requires proactive risk management, solid monitoring systems, and stable infrastructure to assure safe and effective deployment.

Liu et al. [356] combines FMEA with WASPAS in a Probabilistic Double Hierarchy Linguistic (PDHL) framework to improve maritime risk. A risk evaluation model employing PDHLTSs, expert-weighted criteria using Social Network Analysis (SNA), and WASPAS to rank failure modes better than RPN-based FMEA are key contributions. The method tackles conventional FMEA's shortcomings of neglecting severity, occurrence, and detection weight disparities and expert influence.

Yang et al. [357] assesses hospital stomatology workflow infection risks during a significant infectious disease outbreak. Surveys of 30 experts assessed possible failure modes based on S, O, and D. Median scores determined Risk Priority Numbers (RPNs), with values above 100 signifying critical hazards. The August–September 2023 investigation found patients disguising their epidemiological history, overcrowding at pre-examination checkpoints, non-cooperation in health code verification, and improper mask use. Infection risk is highest before diagnosis and treatment. The data shows that poor patient history tracking, crowd management, and preventive measures increase dental care cross-infection risk.

Cai et al. [358] utilizes FMEA to control monoclonal antibody (mAb) drug handling risks in Pharmacy Intravenous Admixture Services. A nine-person multidisciplinary team found seven primary and 28 subprocesses of mAb management. Initial analysis shows 13 high-risk failure modes with 3375 RPN scores. Corrective steps decreases the score to 464, and a second examination reduces it to 51. Continuous progress decreases risk, making mAb medication use safer and PIVAS patient safety better.

Kanaujiya et al. [359] applies FMEA and a resource allocation model to evaluate and control infectious disease transmission risks during Kumbh Mela 2025. Sanitation, healthcare, crowd management, food safety, and public communication were FMEA priorities. The study identifies significant sanitation and food safety risk spots that require targeted interventions by mapping processes and computing Risk Priority Numbers (RPNs). Using a resource allocation model to efficiently distribute 5,000 resource units revealed significant resource shortfalls. The report advises using AI, telemedicine, and local volunteers as health ambassadors to address these issues. These proposals aim to improve preparedness, public health, and future large-scale event management safely and effectively. Matrab et al. [360] uses FMEA to detect risks at 12 radiation therapy centres. It analyses risk profiles before and after a mutual quality control system to determine its risk-reduction effectiveness. An additional cost-effectiveness component is added to the FMEA framework to assess the practical usefulness and efficiency of mutual quality control in improving patient safety and treatment quality.

Anes and Abreu [361] offers a hybrid risk assessment approach that improves failure mode evaluation and ranking using FMEA, ROC, and CoCoSo. This model uses ROC to weight FMEA criteria and CoCoSo to rank risks more accurately and multi-criteria. A healthcare case study shows that the methodology prioritizes failure modes more accurately and objectively than standard FMEA. The suggested method simplifies FMEA hybrid complexity, improves decision-making, and is applicable across industries. Benavente et al. [362] evaluates and updates a lung Stereotactic Body Radiation Therapy (SBRT) FMEA to better identify and manage growing risks related to treatment complexity. A multidisciplinary team performs an FMEA early and again three years later. The most important failure modes were plan approval, target contouring, and patient evaluation, among 232. Standardisation, pre-planning peer evaluations, and a pretreatment checklist lowered Risk Priority Numbers. The evaluation found that patient number and treatment complexity increased human and communication failures, raising radiation dose risk. The study emphasises the need for digital and AI solutions to reduce risks in complex radiation therapy.

Saleh et al. [363] proposes a risk management method for Medical Laboratory Equipment (MLE), which is essential for illness detection. The researchers uses FMEA first, but added TOPSIS and SAW to overcome its limitations. The risk level of each MLE was determined by its RPN, which helped enhance performance and prioritize maintenance. Data from 150 MLE units in 15 Egyptian hospitals covering three equipment types was analyzed. SAW and TOPSIS corrected RPN values, but TOPSIS gave better risk rankings. Five machine learning classifiers assisted decision-making. The prioritized list aids risk-based equipment maintenance and decommissioning planning. Naaoui et al. [364] discusses operating room equipment sterilization and patient safety in a Moroccan tertiary university hospital. The study adapts the normal approach to local conditions using FMEA in Moroccan healthcare risk management and provides a model for other developing nations.

Chiereghin et al. [365] examines the initial stage of a colorectal cancer (CRC) screening process in Bologna, Northern Italy using HFMEA. A diverse team brainstormed seven times, noting each stage, potential failure modes, causes, effects, and Risk Priority Numbers. Most of the 23 failure types were associated to false-negative FIT results, sample loss, and low population coverage.

The sample return phase was improved by using local pharmacies as distribution and collection centres. Samples were fully traceable and temperature controlled after these adjustments. Re-evaluation six months after implementation revealed 75.9% risk reduction. The study shows that HFMEA improves CRC screening quality and safety.

Sabripoor et al. [366] proposes a unified risk assessment approach that uses F-FMEA and F-MCDM to solve linguistic variable uncertainties and improve failure scenario evaluation. Since failure mode rankings vary between MCDM techniques, the researchers created an integrated model for more consistent and thorough risk prioritization. Based on expert feedback and literature assessment, they identified 20 organ transplant hazards. The questionnaire assessed factors affecting transplant success, including incorrect medication use, inadequate food, psychological difficulties, physical strain, and isolation protocol non-compliance. The Mamdani fuzzy inference system and Centre of Gravity technique assessed risk severity and likelihood. Three fuzzy MCDM methods, F-FMEA, and the integrated technique were compared for risk rankings. The proposed combination model achieved the greatest expert judgement agreement (91.67%), proving its reliability and correctness.

2.2.8. Recent FMEA applications in Healthcare

Reference	Key Contributions	Issues not Addressed
Vecchia et al. (2025) [367]	Scoping review exploring the potential of FMEA in infectious disease settings.	Lack of specific implementation models or outcomes.
Anjalee et al. (2021) [368]	Applied FMEA to improve medication safety in dispensing at a teaching hospital.	Limited to a single hospital context; lacks scalability analysis.
Bright et al. (2022) [369]	Used FMEA for evaluating failure modes in breast radiotherapy (DIBH).	Technology-specific; does not address process-wide applicability.
La Russa et al. (2022) [370]	Conducted pilot FMEA in hemodialysis facilities for proactive risk assessment.	No follow-up data or performance impact evaluation.
Lin et al. (2022) [371]	Assessed drug use risk in lung cancer patients using FMEA.	Focused narrowly on pharmacological domain; lacks multidisciplinary perspective.
Aly et al. (2020) [372]	Applied FMEA in blood administration processes to identify new error categories.	Did not integrate electronic records or technology-based interventions.
Baehr et al. (2020) [373]	Introduced a new FMEA scale for radiation oncology risk analysis.	No comparison with conventional FMEA scales or patient outcome validation.
He et al. (2023) [374]	Used FMEA to optimize emergency endoscopy process for esophagogastric bleeding.	Single clinical condition focus; lacks broader clinical utility evidence.
Roseen et al. (2024) [375]	Combined process mapping and FMEA to guide healthcare implementation.	Limited guidance on integrating FMEA outputs into policy change.

Reference	Key Contributions	Issues not Addressed
Färlin-Helin et al. (2023) [376]	Scoping review of FMEA use in pediatric and adolescent hospital care.	Did not evaluate effectiveness of recommendations derived from FMEA.
Hakiem et al. (2022) [377]	Applied HFMEA for managing risks in self-developed EMR systems in hospitals.	No comparison with standard EMR systems or long-term system tracking
Liu et al. (2020) [378]	Systematic review on FMEA for proactive healthcare risk evaluation.	Lacks statistical meta-analysis or comparative effectiveness data.
Abi et al. (2022) [379]	Used HFMEA to evaluate care protocol reliability.	Narrow scope; lacks integration with broader hospital governance.
El-Awady (2023) [380]	General overview on FMEA as a patient safety tool.	Lacks case-specific examples or validation of effectiveness.
Ferrara (2025) [381]	Evaluated combined use of Patient Safety Indicator 13 and Clinical Audit for postoperative sepsis.	Did not apply or compare with FMEA methodology directly.

Table 2.2.4: Review of recent articles on FMEA applications

2.2.9. Studies relating to Fire risk assessment in Healthcare

Fire safety in healthcare facilities has become a critical concern globally due to the vulnerability of occupants, the presence of sensitive equipment, and structural complexity. Numerous studies have emphasized the need for comprehensive fire risk assessment frameworks tailored to hospital settings.

Cho et al. [382] investigated the awareness and attitudes of perioperative nurses in Korea, identifying significant knowledge gaps in fire risk assessment practices during time-out procedures. Complementing this, Alizade et al. [383] demonstrated that targeted educational interventions significantly improved fire risk assessment related knowledge among operating room personnel.

A broader status check on fire safety in Indian healthcare facilities was provided by Sharma et al. [384] and Paul et al. [385], who revealed critical deficiencies in fire preparedness, often stemming from inadequate infrastructure and outdated safety systems. In a parallel Malaysian context, Jaafar et al. [386] proposed a Fire Safety Management Plan (FSMP) framework specifically designed for public hospitals, reinforcing the importance of localized regulatory adaptation.

Performance-based approaches have also been advocated. Danzi et al. [387] presented a parametric fire risk assessment model tailored to healthcare facilities in Northern Italy, integrating building characteristics and occupancy types. Similarly, Wu and Tseng [388] developed a fire risk index for small-scale hospitals in Taiwan, emphasizing simplicity and practicality for resource-constrained settings.

Several studies highlight engineering and structural perspectives. Nguyen et al. [389] examined the fire resistance of high-strength concrete walls, offering insights into resilient hospital construction materials. Rahmani and Salem [390] evaluated hospital fire safety using NFPA 101 standards, particularly for high-rise hospitals, while Meacham et al. [391] and Frantzich [392], in the SFPE Handbook, provided comprehensive theoretical foundations for fire risk modelling in healthcare buildings.

From a governance and policy standpoint, Benson and Elsmore [393] underlined the role of expertise in fire safety approval systems, stressing that bureaucratic shortcomings often compromise hospital safety standards. Complementary to this, Muhamad Salleh et al. [394] provided a systematic review of fire safety management in Asian hospitals, identifying governance and maintenance lapses as recurring themes.

Several applied case studies enrich the literature. Parremore [395] documented the implementation of a surgical fire risk assessment tool at The Lister Hospital in the UK, leading to notable improvements in intraoperative fire prevention. Similarly, Choudhary et al. [396] explored challenges in older Indian hospitals, pointing out retrofit difficulties and the lack of evacuation strategies for immobile patients.

Technological innovation also plays a pivotal role. Madaio et al. [397] introduced FIREBIRD, a predictive analytics system leveraging machine learning to prioritize building fire inspections. Nilsson et al. [398] proposed virtual reality based fire evacuation training, showing increased preparedness in simulated hospital evacuations.

Barua et al. [399] conceptualized a triple-pronged framework of resilience, sustainability, and smartness in building fire risk management, advocating for an integrated, future-ready approach to hospital fire safety.

Finally, assessments of preparedness and practical implementation were addressed by Abdulsalam et al. [400], who reported inadequate fire drills, extinguisher use, and emergency exits in health institutions in Niger State, Nigeria, thereby emphasizing the universal nature of these issues across both developed and developing nations.

2.2.10. Recent Studies on Fire Risk Assessment in Healthcare

Reference	Key Contributions	Issues not Addressed
Beljikangarlou et al. (2025) [401]	Applied a quantitative fire risk assessment method in a hospital case study.	Did not compare with other risk models or fire scenarios.
Ibáñez-Cruz et al. (2025) [402]	Biomedical engineering perspective on fire and explosion hazard analysis in hospitals.	Lack of implementation framework for engineering solutions.
Pongsin et al. (2024) [403]	Developed fire risk assessment model tailored for urban hospital buildings.	Model not tested across diverse hospital types or locations.
Wu et al. (2024) [404]	Reviewed emergency evacuation procedures in hospital settings.	Lacked integration with real-time fire simulation data.
Omidvari et al. (2020) [405]	Combined FMEA with MCDM methods for hospital fire risk assessment.	Did not validate model against actual incident data.
Danzi et al. (2021) [406]	Proposed the FLAME method supporting performance-based fire risk assessment.	Lacked specific healthcare context application.
Al-Saedi et al. (2024) [407]	Theoretical analysis of fire mitigation strategies in healthcare facilities.	No empirical case study or strategy effectiveness testing.
Liu, Z. et al. (2024) [408]	Designed a dynamic evacuation risk model for hospitals during fire.	Real-time system performance and deployment not evaluated.
Liu, D. et al. (2023) [409]	Assessed hospital fire safety in Changsha, China using survey-based approach.	Regional focus; lacks generalizability across healthcare systems.
Hostikka et al. (2021) [410]	Studied effect of sprinkler systems on patient survival in hospital fires.	Does not assess broader hospital system design or emergency planning.

Reference	Key Contributions	Issues not Addressed
Salari & Karimi (2025) [411]	Proposed integrated fire safety evaluation using Neutrosophic-AHP and Fuzzy Inference.	Complex methodology not demonstrated in a real hospital setup.
Ebekozien et al. (2021) [412]	Evaluated fire safety preparedness in Nigerian healthcare facilities.	Lacked technical system integration and fire response simulation.
Salari et al. (2024) [413]	Analyzed factors affecting hospital fire safety via fire risk assessment.	No predictive modeling or spatial risk mapping included.
Juyal et al. (2023) [414]	Studied failures causing hospital fire incidents with reference to India.	Focused on qualitative factors; lacked quantitative risk assessment.
Wood et al. (2021) [415]	Addressed risk of oxygen-related fires during COVID-19 in hospitals.	Not integrated into broader hospital fire management protocols.

Table 2.2.5: Review of recent articles on fire risk assessment

2.2.11. Studies relating to suitable site selection for biomedical waste disposal

Healthcare Waste Management is a critical area currently receiving global attention. Previous literature surveys indicate that the majority of studies on facility location have been addressed within a multi-criteria Decision Making (DM) framework [416-417]

In multi-criteria DM situations, the alternatives meet specified objectives, and decision-makers are tasked with selecting the optimal alternative. Furthermore, the literature indicates that the utilization of multi-criteria DM approaches is a crucial method for addressing facility location issues. The current work addresses a multi-criteria DM problem with the selection of a suitable site for a Healthcare Waste Disposal (HWD) facility, therefore identifying various criteria from existing literature.

To find the best spots for trash cans in Tabriz, Iran, Haseli and Jafarzadeh Ghoushchi [418] combined spherical fuzzy sets (SFSs) with the base-criterion method (BCM). In order to rank 21 different kinds of trash according to ecological, social, and economic factors, Zafaranlouei et al. [419] used fuzzy Z-numbers to combine the combined compromise solution (CoCoSo) and base-criterion methods. In order to address the recycling partner selection issue.

Haseli et al. [420] introduced a hybrid decision-making framework that integrates Z-numbers, derived from the Best-Worst Method (BWM), with the Combined Compromise Solution (CoCoSo) technique. This approach enhances decision accuracy by effectively handling uncertainty in multi-criteria evaluation.

To identify a sustainable location for hazardous waste disposal (HWD) in Garhwal, India, Chauhan and Singh [421] developed a hybrid MCDM model that combines fuzzy AHP with the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This model supports decision-making under vague and imprecise conditions.

Similarly, in Memari, India, Ali et al. [422] employed a combination of AHP and fuzzy TOPSIS to determine the most suitable site for medical waste disposal, offering a structured methodology to address complex environmental and health-related criteria.

Using the Fermetean Fuzzy WASPAS (FF-WASPAS) method, Mishra and Rani [423] prioritized and selected the best HWD location in Uttarakhand, India, based on 10 sub-criteria and three primary criteria: social, environmental, and economical. A decision-support system for determining and ranking the best place to dump medical waste was proposed by Yazdani et al. [424] for use in challenging environments. In order to optimize biomedical waste.

Pillai et al. [425] created a multi-criteria DM framework based on TOPSIS in neutrosophic environment. This framework takes into account many criteria, including regulatory compliance, cost-effectiveness, technical feasibility, health and safety, and environmental impact. When it comes to HWD in India, Thakur and Ramesh [426] proposed an AHP method that is based on grey areas. The resilient Istanbul garbage disposal location was identified by Gergin et al. [427] using ABC technique.

To find the most effective way for elimination of medical waste in a fuzzy, intuitionistic setting, Mishra et al. [428] suggested an EDAS framework that uses cross entropy. In order to identify a suitable location for solid waste disposal in Istanbul, Turkey, Arıkan et al. [429] created a fuzzy model that incorporates TOPSIS and PROMETHEE. Based on an intuitionistic fuzzy scenario, Kahraman et al. [430] outlined the EDAS approach to identify and hierarchize possible sites for solid waste disposal. In their evaluation of the optimal Thai garbage disposal site, Wichapa and Khokhajaikiat [431] employed goal programming with AHP. In their study,

Senapati et.al. [432] introduced FF sets and compared them to pythagorean and intuitionistic fuzzy sets. In addition to defining the score function, accuracy function, and euclidean distance, they assessed the basic set operations of FF sets and provided an example to prove the method's viability and significance in DM problems involving multiple criteria. Senapati et.al [433]. made a number of contributions to the field of FF sets, including the introduction of basic arithmetic operations in FF situation. They also created a model for solving multi-criteria decision making problems using a FF weighted product, and they provided an example to show how effective the model is.

According to the reviewed literature, while deciding where to put the HWD facility, a number of factors and multi-criteria DM methods are considered.

2.2.12. Recent Studies on Biomedical Waste Disposal Site Selection

Reference	Key Contributions	Issues not Addressed
Çelik et al. (2023) [434]	Evaluated medical waste processes using intuitionistic fuzzy MCDM in Turkish hospitals.	Did not validate findings with real-time waste tracking systems.
Beheshtinia et al. (2023) [435]	Prioritized healthcare waste disposal center locations via hybrid MCDM.	Lacked GIS integration or stakeholder validation.
Jangre et al. (2022) [436]	Used ArcGIS and QFD for biomedical waste disposal site selection.	Limited focus on long-term environmental sustainability.
Ghoushchi et al. (2021) [437]	Applied SWARA-WASPAS under spherical fuzzy set for landfill selection.	No real-world implementation or feasibility testing provided.
Torkayesh et al. (2021) [438]	Used hybrid BWM-Grey MARCOS-GIS for healthcare landfill location.	Limited to urban context; rural adaptation not explored.
Thakur & Ramesh (2015) [439]	Applied grey MCDM to select waste disposal firms.	Lacked healthcare-specific criteria or recent waste technologies.
Puška et al. (2022) [440]	Evaluated healthcare waste incinerators using sustainability-based MCDM.	Social impact and public perception factors not deeply analyzed.
Gao et al. (2024) [441]	Developed Fermatean fuzzy BWM-VIKOR model for waste tech selection.	Complex mathematical formulation; real-time application untested.
Xu et al. (2025) [442]	Proposed social network group decision-making model for disposal plant siting.	Pythagorean fuzzy preferences not linked to spatial or cost data.

Reference	Key Contributions	Issues not Addressed
Anjum et al. (2024) [443]	Multi-stage decision framework for sustainable healthcare waste management.	Did not address local regulatory variations in application.
Sharma et al. (2025) [444]	Review on digital transformation in healthcare waste management.	No framework proposed for practical digital system implementation.
Dhingra et al. (2023) [445]	Identified blockchain challenges in healthcare waste management.	Solutions or policy-level integrations were not suggested.
Xue et al. (2023) [446]	Designed reverse logistics system for medical waste recycling using intelligent systems.	Real-time logistics performance data and pilot testing were missing.

Table 2.2.6: Review of recent articles on biomedical waste facility location

2.2.13. Studies relating to Sustainable Healthcare Infrastructure

Sustainable development is founded on three fundamental pillars: social, economic, and environmental. Sustainable practices are crucial for guaranteeing the enduring prosperity of organizations while concurrently helping society. An environmentally friendly healthcare service efficiently mobilizes and utilizes resources, comprising staff, technology, information, and funds. If the service addresses the healthcare requirements of individuals and ensures accessible for all societal members, it is deemed socially viable [447].

The social dimension is notably significant in the healthcare sector, a vital component of the service business [448]. Consequently, healthcare systems must prioritize patient outcomes, including healing levels, recovery duration, and mental well-being, while also enhancing accessibility. Healthcare access is determined by the degree to which individuals can utilize health services in relation to their requirements. Numerous factors affect access, including governmental regulations and the distribution of financial resources to healthcare services. Immediate factors influencing access include patient characteristics such as mobility (age, disability), financial means, work flexibility, and transportation choices [449].

Attaining sustainability in healthcare necessitates the system's adaptation to continuous economic and socio-demographic changes [450], which can influence the accessibility and cost of services. Hospitals, being the foremost users of resources and principal contributors to emissions in the healthcare system, encounter specific issues in this context [451]. Numerous hospitals are consolidating to capitalize on economies of scale and expand their service offerings; however, research indicates that these initiatives may not consistently result in enhanced cost-efficiency or superior patient outcomes.

Although environmental sustainability frequently dominates discussions, social sustainability is also vital for healthcare systems, however it often garners less focus [452]. Given the concerns over healthcare availability and costs, it is essential for healthcare systems to prioritize social sustainability. Research indicates that smaller healthcare facilities, such General Practitioner (GP) clinics, generate significantly lower emissions than larger hospitals [453]. The reduced scale of GP clinics may result in increased response to patient demand and better patient outcomes [454].

2.2.14. Recent Studies on Sustainable Healthcare Infrastructure

Reference	Key Contributions	Issues not Addressed
Pascale & Achour (2024) [455]	Proposed a future vision of sustainable and climate-resilient hospitals.	No practical roadmap or implementation framework discussed.
Rojas-Rueda (2025) [456]	Highlighted global health and climate benefits of green hospitals.	Lacks specific policy strategies for varied geopolitical settings.
ElSafty (2025) [457]	Introduced the concept and practices of green hospitals in Egypt.	Focused primarily on awareness; lacks performance metrics.
Bączkiewicz et al. (2024) [458]	Developed a multi-criteria model for strong sustainability assessment.	Did not validate model in real healthcare facility environments.
Hegazy et al. (2025) [459]	Identified design and construction challenges for sustainable hospitals.	Lacks post-construction monitoring or patient-centered outcomes.
McGain & Naylor (2014) [460]	Systematic review on environmental sustainability in hospitals.	Outdated for post-pandemic and digital healthcare context.
Soares et al. (2023) [461]	Reviewed applicability of green practices in global healthcare facilities.	No prioritization framework for resource-constrained settings.
Miao et al. (2024) [462]	Mapped green building rating systems to aging societies in healthcare.	Limited generalizability to non-aging demographic structures.
Maccaro & Pecchia (2025) [463]	Discussed sustainable prosperity and innovation in digital-age healthcare.	Theoretical focus; lacks integration with operational sustainability models.

Reference	Key Contributions	Issues not Addressed
Saleem et al. (2025) [464]	Explored link between green leadership and environmental performance in hospitals.	No sector-wide validation or longitudinal impact assessment.
Gohel & Turcotte (2025) [465]	Called for policy reforms to build climate-resilient and net-zero healthcare in Canada.	Only focused on policy level; lacked stakeholder or cost–benefit analysis.
Khosravi et al. (2025) [466]	Systematic review of factors affecting green practice adoption in healthcare.	Lacks a framework for overcoming identified barriers.
De Bruin & Kyei (2024) [467]	Evaluated adaptation strategies for climate risks in Ireland's healthcare.	No specific hospital case examples; national-level focus only.
Hendriks et al. (2025) [468]	Assessed circularity and sustainability in emergency hospital shelters.	Focused only on shelters; excluded permanent hospital structures.

Table 2.2.7: Review of recent articles on green hospital infrastructure

Chapter- 3

Research Gap

3. Research Gap

1. Studies on the level of service provided by Indian health care providers are scarce.

2. A widely used approach in research on service quality of healthcare providers is the SERVQUAL model.

3. Although SERVQUAL has been widely utilized in the service sector, it faces several limitations such as measurement ambiguity, contextual inflexibility, and challenges in accurately capturing the gap between customer expectations and perceptions.

4. Different studies used different parameters and techniques to determine the healthcare providers' level of service.

5. Since most research has been conducted in developed nations, it cannot be broadly applied to the setting of India.

6. None of the prior cited articles address selection of healthcare institution from the viewpoint of patients and patients' party requirements and technical criteria.

7. In the context of healthcare services, limited research has considered the viewpoint of patient attendants, and no study to date has comprehensively examined how service quality influences overall satisfaction from both the patients' and their attendants' perspectives.

8. As the Indian healthcare service sector is still in an early phase of development, there is a pressing need for further research to evaluate and understand its service quality more comprehensively.

Chapter- 4

Aims, Objectives and Scope of the Study

4.1 Aims

a. Maximization of Patients Satisfaction

b. Minimization of Environmental Hazards

c. Designing, maintaining & sustaining "Win-Win-Win" situation for patients, healthcare industry & environment

4.2 Objectives

1. To enunciate the key factors influencing service quality in healthcare environments and examine their association with patient satisfaction and sustainable environment.

2. To design a comparative Multi-Criteria Decision-Making (MCDM) framework that enables the evaluation and hierarchizing of healthcare providers based on their performance in delivering quality services.

3. To develop a unified model for selecting the most robust healthcare institute by combining patient and patients' party expectations with technical criteria and government regulatory bodies.

4. To establish a predictive model that links sustainability perceptions with occupant loyalty in green healthcare infrastructure.

5. To introduce a comprehensive FMEA-based framework for the assessment and prioritization of risks associated with healthcare service delivery.

6. To propose a comprehensive risk assessment methodology for evaluating and prioritizing fire risk preparedness in hospitals.

7. To formulate a decision-support model aimed at identifying environmentally sustainable locations for healthcare waste disposal (HWD).

4.3 Scope

Our study focusses on

a. Healthcare Sector

b. Kolkata based Healthcare Institutes

c. Public and Private Hospitals in Kolkata and adjoining areas

Chapter- 5

An In Depth Study of Patients Happiness in Two Private Hospitals in Kolkata

5.1 Abstract

Service quality is a primary concern for enhancing quality medical care for patients. Healthcare providers place a major emphasis on quality of care to fulfil and retain their patients.

The objectives of the study is to identify the essential and significant determinants of service quality in a public healthcare provider that results in patients' happiness and establish a relationship between service quality determinants and patients happiness.

An empirical investigation was carried out in two private hospitals in Kolkata, India. A field survey was conducted between October 2023 to December 2023 on 480 patients. A self-administered questionnaire with a stratified sampling technique was employed to gather the information. The gathered data were examined using statistical approaches such as reliability analysis, factor analysis and multiple regression in SPSS software.

The result reveals that patient happiness in private healthcare providers is determined by service quality factors that includes hygiene, infrastructure, environment, cost, attitude, satisfaction, nutrition, expertise and safety. It also establishes a serious correlation between service quality determinants and patients happiness in private healthcare providers.

Infrastructure is the most significant predictor of patients' happiness. The study findings will help administrators of healthcare facilities create worthwhile and efficient plans to provide their patients with top-notch medical care.

5.2 Introduction

India takes pride in having a diverse population from a variety of cultures. Healthcare service provider is the largest and fast developing sector in India. It is a leading contributors to Indian economy in terms of employment and revenue [469]. Indians are now more conscious of their health owing to increased access to information concerning health, hike in medical tourism and expansion of health insurance. Since economic progress and health are inextricably linked, none can be accomplished without the other.

Health services are crucial in deciding quality of life. Service quality of healthcare provider effectively focuses on managing and monitoring both technical and functional quality for a long run success [470]. Issues about the availability, price and accessibility of excellent health services exist in emerging nations like India [471]. The services rendered by the healthcare providers are met with high expectations from customers. Healthcare providers must meet customer expectations in order to ensure consistent demand and existence in the market [472].

Patient satisfaction is a key element to caliber the services of healthcare providers [473]. Individuals take their health seriously and will go to any extent to receive the greatest medical treatment accoutered by healthcare providers. If an individual is satisfied she/he will choose the same alternative again otherwise she/he will single out other alternative for satisfied result. Thus user perspective arbitrates "survival of the fittest." Accreditation by national and international healthcare accreditation groups are highly valued by healthcare providers. Primary, Secondary and Tertiary care are the types of healthcare providers in India.

The Indian Constitution promulgate health to be a matter of state policy. Therefore the state governments have tremendous responsibilities to take care of health of the population in the state. In such a challenging situation, substantial demand of quality healthcare providers is discernible. As per the Indian health statistics report (2012), the state of West Bengal has seen remarkable growth in the quality of healthcare providers during the last two decades. Healthcare providers located in the capital city of West Bengal i.e. Kolkata are serving massive population. Patients from various district of West Bengal and countries like Nepal, Bhutan, and Bangladesh comes to Kolkata for medical treatment.

According to the National Sample Survey Organization (2006), 82% of the population pursue treatment in public hospitals. The number of hospitals in the state is insufficient to serve the large population of West Bengal. Therefore it is obvious that there must be a heavy demand for quality healthcare providers in the state. Private hospitals will offer treatment to affordable customer, while public hospitals will continue to serve the general public. An evaluation of service quality allows management to identify key areas for improvement and delivering satisfactory customer service.

5.3 Hypotheses of the Study

The hypotheses developed in the study are as follows

HS1: Patient happiness is positively affected by hygiene

HS2: Patient happiness is positively affected by Infrastructure

HS3: Patient happiness is positively affected by Environment

HS4: Patient happiness is positively affected by Cost

HS5: Patient happiness is positively affected by Attitude

HS6: Patient happiness is positively affected by Satisfaction

HS7: Patient happiness is positively affected by Nutrition

HS8: Patient happiness is positively affected by Expertise

HS9: Patient happiness is positively affected by Safety

5.4 Research Methodology

A comprehensive review of existing literature on healthcare service quality and patient satisfaction has been conducted. The methodological conceptual framework derived from this analysis is presented in Figure 5.1.

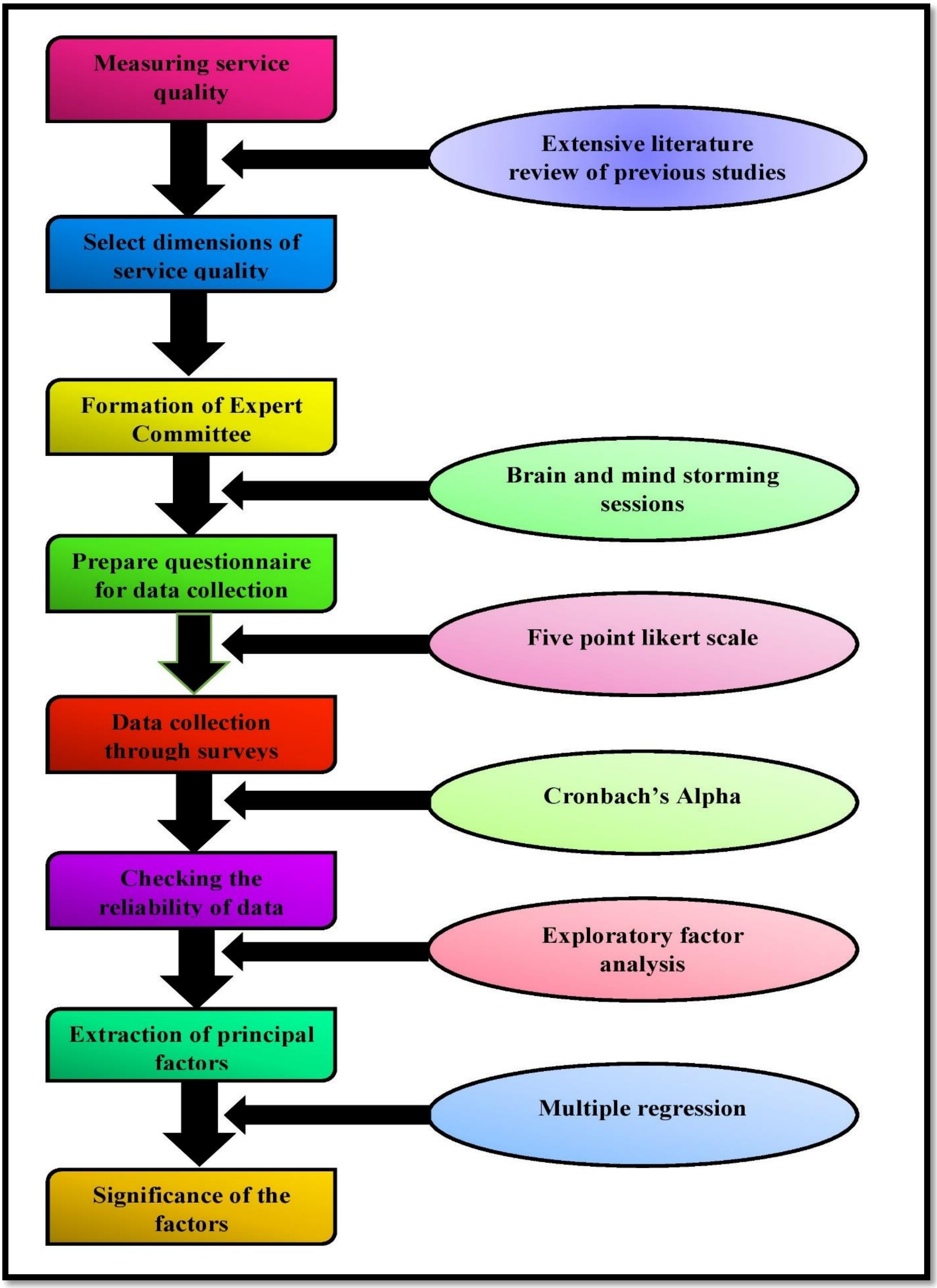


Fig. 5.1: A conceptual framework of the methodology

An empirical study was conducted on 480 hospital patients which includes inpatients and outpatients in two private hospital located in Kolkata, West Bengal, India. The present study adapted existing literature to incorporate the determinants of service quality.

Hygiene, infrastructure, environment, cost, attitude, satisfaction, nutrition, expertise and safety are considered to link these dimensions with happiness in healthcare service provider. Fig. 5.2 illustrates a research paradigm.

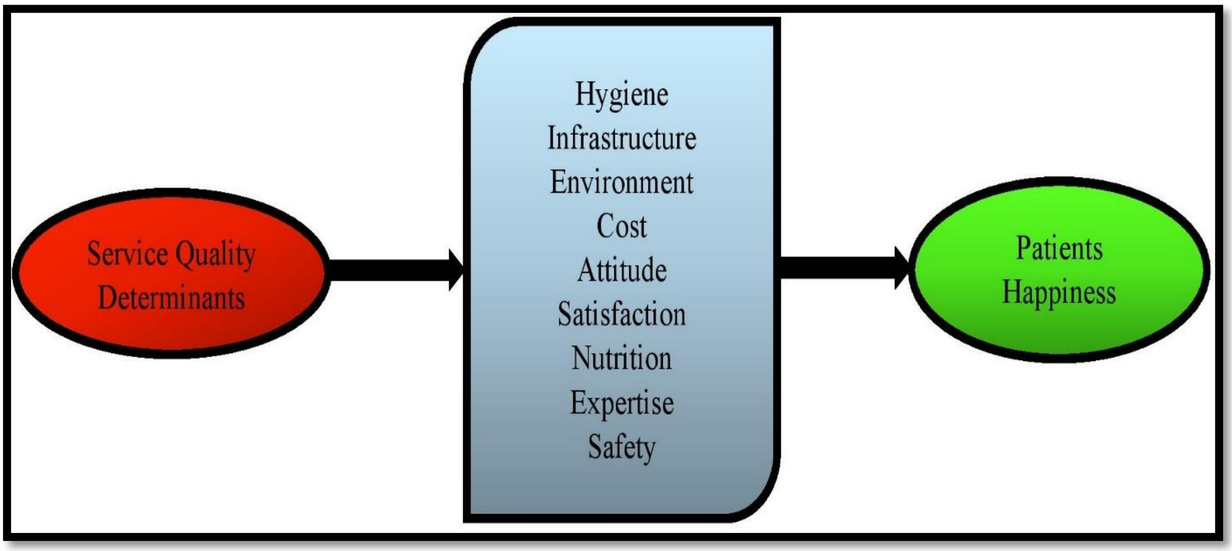


Fig. 5.2: A research paradigm

A self-administered questionnaire was finalised using extensive conversation with hospital administrators and healthcare users. The questionnaire was pre-tested multiple times to assure proper format, term and order of questions. Out of the 600 questionnaires that were sent out, 480 were returned with a feedback rate of 80 %. The questionnaire was framed in two sections: first six questions describes the patient demography and the next 40 questions investigated patients' perception about service quality and happiness from healthcare providers.

The confidentiality of their responses and their exclusive application for research studies was promised to the patients. They were instructed to carefully go through the directions and respond in line with them.

A five-point Likert scale was utilized to gather responses, ranging from 1 (strongly disagree) to 5 (strongly agree). The demographic profile of the patients is presented in Table 5.1.

Variable	**Types**	**Frequency**	**%**	**Variable**	**Types**	**Frequency**	**%**
Gender	Male	272	56.67	Disease	Cardiology	88	18.3
	Female	208	43.33	Description	Gynaecology	94	19.6
Age	Less than 18	16	3.3		Neurology	76	15.8
	19-30	69	14.4		Nephrology	87	18.1
	31-40	153	31.9		Urology	75	15.6
	41-60	164	34.2		General	60	12.5
	More than 60	78	16.3				
Work	Unemployed	16	3.3	Education	Primary	10	2.1
	Government	84	17.5		Secondary	86	17.9
	Private	164	34.2		Graduate	165	34.4
	Business	132	27.5		Postgraduate	144	30.0
	Retired	84	17.5		Doctorate	75	15.6
Income	<1 lakh	174	36.25	Marital status	Married	368	76.7
	1-3 lakh	193	40.21		Unmarried	112	23.3
	>3 lakh	113	23.54				

Table 5.1: Demographic characteristics of the patients

5.5 Results

The data analysis was carried out using IBM SPSS Statistics version 26. Initially, factor analysis was performed, followed by regression analysis to explore the relationships among variables.

Prior to conducting factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were applied to assess the suitability and significance of the dataset. The outcomes of these preliminary tests are presented in Table 5.2.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.883
Bartlett's Test of Sphericity	Approx. Chi-Square	22458.398
	df	780
	Sig.	.000

Table 5.2: KMO and Bartlett's test

Based on the results presented in the table, the Kaiser-Meyer-Olkin (KMO) value for sampling adequacy is 0.883, and the significance level of Bartlett's test of sphericity is 0.000. These results confirm that the dataset is suitable and statistically significant for conducting Exploratory Factor Analysis (EFA).

The EFA was performed using the Principal Component Analysis (PCA) method with Varimax rotation and Kaiser normalization to extract the underlying factors. The eigenvalues and explained variance percentages for the ten extracted factors are detailed in Table 5.3.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.709	36.771	36.771	14.709	36.771	36.771	3.995	9.998	9.998
2	3.971	9.928	46.699	3.971	9.928	46.699	3.909	9.773	19.760
3	3.716	9.290	55.990	3.716	9.290	55.990	3.849	9.623	29.383
4	2.312	5.779	61.769	2.312	5.779	61.769	3.606	9.015	38.398
5	1.728	4.320	66.089	1.728	4.320	66.089	3.359	8.398	46.797
6	1.395	3.487	69.576	1.395	3.487	69.576	3.274	8.186	54.983
7	1.289	3.223	72.799	1.289	3.223	72.799	3.205	8.012	62.995
8	1.189	2.971	75.770	1.189	2.971	75.770	2.928	7.320	70.314
9	1.103	2.756	78.527	1.103	2.756	78.527	2.348	5.870	76.184
10	1.018	2.546	81.073	1.018	2.546	81.073	1.956	4.889	81.073

Table 5.3: Eigen values and total variance explained

Factor loadings less 0.45 were treated as superfluous variables and discarded. A high loading value suggests significant impact of the factor on the variable. A factor loading that is higher than 0.6 significantly affects the variables. As a result, factor loadings of forty variables grouped into ten factors were revealed. The results are shown in Table-5.4. These factors are named as Hygiene, Infrastructure, Environment, Cost, Attitude, Satisfaction, Nutrition, Expertise, Safety and happiness.

To assess the reliability of the scale, Cronbach’s alpha coefficient was employed. A value of α greater than 0.7 is generally considered acceptable for internal consistency. In this study, the ten extracted factors yielded Cronbach’s alpha values ranging from 0.718 to 0.986, indicating strong reliability. The overall alpha value of 0.947 further confirms the robustness and consistency of the measurement scale. The reliability scores for each of the ten factors are presented in Table 5.5.

Sl.no	Factors	Variable	Loadings
1.	Hygiene	Availability of biodegradable and non-biodegradable dustbins around the premises	0.874
		Hospital premises is clean and well maintained	0.858
		Toilets and wash basins are clean and hygienic	0.830
		Hospital wards, cabins and corridors are hygienic, comfortable and regularly cleaned	0.657
2.	Infrastructure	Availability of modern AI techniques and updated medical devices	0.875
		Availability of ambulance and emergency services	0.871
		Availability of doctors, nurses and medical staffs	0.871
		Availability of beds in wards and cabins	0.830
3.	Environment	Lodges and restaurants are available outside the hospital premises	0.889
		Ample parking space and waiting halls for visitors are available	0.860
		Directional signage available around the premises for easy access to different departments	0.855
		Access to hospital location is easy and convenient	0.728
4.	Cost	Health insurance policies are explained properly	0.928
		Hospital wards and cabin charges are high on per day basis	0.917
		Pathological, radiological and medicine charges are high	0.826
		Doctors' charges high fees	0.666
5.	Attitude	Overall attitude and behaviour of physicians and nurses are acceptable	0.733
		Nurses are consistently supportive and helpful	0.727
		The majority of staff is not cooperative	0.723
		Physicians behaviour is not always courteous	0.628
		Physicians are constantly supportive and helpful	0.538
6.	Satisfaction	Satisfaction with the cost-effectiveness of medical care	0.835
		Satisfaction with admission and discharge processes	0.816
		Satisfaction with the quality of diagnosis and treatment	0.745
		Satisfaction with the quality of care by physicians and nurses	0.701
		Satisfaction with the assistance and administrative personnel	0.682

Sl.no	Factors	Variable	Loadings
7.	Nutrition	Food is prepared as per doctor's prescription	0.780
		When the meals were served, they were still warm	0.755
		Food is nutritious, tasty and hygienic	0.737
		Dirty dishes were removed promptly after each meal	0.698
8.	Expertise	Expertise in handling emergency and critical cases immediately	0.839
		Doctors are sufficiently knowledgeable in their specialty	0.820
		Doctors always make accurate diagnoses and provide reasonable explanations of diseases.	0.695
		Nurses are capable of taking appropriate care of the patients	0.673
9.	Safety	Sufficient security and CCTV to stop personal property theft	0.805
		Availability of safety features including handrails, elevators, and ramps	0.780
		Adequate hygiene is maintained to prevent infections	0.657
10.	Happiness	Happy to select the same hospital again in future	0.820
		Happy to promote good word about the hospital verbally	0.682
		Happy to suggest this hospital to family and friends	0.669

Table 5.4: Result of factor analysis

Sl.No	Dimension	Cronbach's α
1	Hygiene	0.945
2	Infrastructure	0.986
3	Environment	0.948
4	Cost	0.923
5	Attitude	0.919
6	Satisfaction	0.834
7	Nutrition	0.959
8	Expertise	0.849
9	Safety	0.823
10	Happiness	0.718
	Overall Reliability	**0.947**

Table 5.5: Reliability analysis

The relative importance of each dimension was assessed through multiple regression analysis. The outcomes of the model summary and ANOVA are displayed in Table 5.6 and Table 5.7, respectively. An adjusted R-squared value of 0.796 indicates a statistically significant relationship, demonstrating that a substantial proportion of the variance is explained by the model.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.895	.800	.796	.33258

Table 5.6: Model summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	208.344	9	23.149	209.295	.000
	Residual	51.985	470	.111		
	Total	260.329	479			

Table 5.7: Analysis of variance (ANOVA)

For the purpose of regression analysis, nine out of the ten extracted factors i.e. Hygiene, Infrastructure, Environment, Cost, Attitude, Satisfaction, Nutrition, Expertise, and Safety were designated as independent variables, while patient happiness was considered the dependent variable.

A multiple regression analysis was conducted to test the research hypotheses. The results indicate that the relationship between these nine independent variables and patient happiness is statistically significant ($p < 0.05$). The detailed outcomes of the regression analysis are presented in Table 5.8.

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1 (Constant)	.432	.100		4.327	.000
Hygiene	.107	.046	.101	2.338	.020
Infrastructure	.488	.066	.602	7.382	.000
Environment	.154	.044	.162	3.535	.000
Cost	-.206	.058	-.270	-3.570	.000
Attitude	-.252	.050	-.240	-5.050	.000
Satisfaction	.172	.024	.199	7.033	.000
Nutrition	.071	.034	.071	2.077	.038
Expertise	.082	.041	.095	2.029	.043
Safety	.275	.057	.376	4.854	.000

Table 5.8: Coefficients of regression

5.6. Discussion

The present study expounds significant determinants of service quality and establish a relation between service quality determinants and patient happiness in public hospital. This study was concentrated on two private hospital in Kolkata, India. A 40-item scale that measures the quality of care provided by public hospitals has been produced by our study. The exploratory factor analysis identified ten key determinants of service standard at a private medical facility.

According to the findings of our study hygiene, infrastructure, environment, cost, attitude, satisfaction, nutrition, expertise and safety are the most important determinants of patient happiness in private hospital. Multiple regression analysis was performed to evaluate the hypotheses about the substantial impact of key determinants i.e. hygiene, infrastructure, environment, cost, attitude, satisfaction, nutrition, expertise and safety on happiness in the private hospital.

The result demonstrates that all the key determinants of service quality have a significant effect on patients’ happiness. It has been discovered that infrastructure is the most significant predictor of patients’ happiness followed by safety and satisfaction.

The items created in this investigation can be applied to keep an eye and raise the standard of the services provided to the patients. The study could assist medical professionals and healthcare administrators to identify and improve the significant dimension of healthcare and conclude a link between service quality determinants and patients’ happiness in public hospital.

Patients who feel uneasy about the quality of care they receive in public hospitals are increasingly prepared to resort to private hospitals or even travel overseas to a hospital in a developed nation [98]. Therefore continuous quality advancement heavily relies on healthcare administrators' understanding of service quality dimensions.

The healthcare providers in Kolkata are doing well, but it still has to concentrate on a few areas to raise patient satisfaction and happiness and sustain positive relationships with patients at all levels. A survey on patient satisfaction and happiness should be conducted quarterly to learn about the patients' evolving demands.

The Key Contributions of the Study are

1. Empirical Validation of Service Quality Determinants- The study identifies and validates nine critical service quality dimensions i.e. hygiene, infrastructure, environment, cost, attitude, satisfaction, nutrition, expertise, and safety that significantly influence patient happiness in private healthcare settings. These determinants were extracted using robust factor analysis and tested through multiple regression analysis.

2. Establishment of a Statistical Relationship between Service Quality and Patient Happiness- By employing rigorous statistical methods, including factor analysis, reliability testing (Cronbach's $\alpha = 0.947$), and regression modelling, the study confirms that each service quality determinant has a statistically significant impact on patient happiness ($p < 0.05$), establishing a direct and measurable relationship.

3. Infrastructure as the Strongest Predictor of Happiness- The analysis reveals that among the nine factors, infrastructure ($\beta = 0.602$, $p < 0.001$) stands out as the most influential predictor of patient happiness, followed closely by safety and satisfaction. This insight provides a priority focus area for healthcare administrators seeking to improve service delivery.

4. Development of a Reliable 40-Item Service Quality Scale- A structured and validated questionnaire with 40 items across multiple domains was developed to assess patient perceptions of healthcare quality and their resulting happiness. This instrument serves as a practical tool for continuous quality monitoring in healthcare facilities.

5. Insights for Healthcare Policy and Administrative Planning- The study offers actionable recommendations for healthcare administrators by highlighting the need for regular monitoring of patient satisfaction and strategically investing in the most influential service quality dimensions. It also calls for periodic surveys to adapt to evolving patient expectations.

6. Focused Case Study from a Developing Country Context- Conducted in two private hospitals in Kolkata, India, the study adds valuable regional insights into healthcare service quality, especially relevant for developing nations facing infrastructure, resource, and satisfaction challenges.

Chapter- 6

Performance Evaluation of Six Healthcare Providers Located in Kolkata under Uncertain Environment

6.1 Abstract

Good health is fundamentally essential to maintain a healthy lifestyle. Healthcare is one of the sensitive sector among the available service sector industries. Healthcare is directly related to the health of an individual.

This paper presents a comparative approach of multi-criteria decision making techniques to identify, evaluate and rank the most reliable private healthcare provider based on its service excellence.

A case study taken from Kolkata, India has been carried out to address the pertinent and potential areas related to private healthcare providers and apply the concept of multi-criteria decision making techniques in healthcare sector in order to minimise the uncertainty, ambiguity, vagueness and obscurity to develop a holistic decision.

TOPSIS, Deng similarity method, PROMETHEE-II and Yager min-max principle approaches are applied to identify, evaluate, compare & rank the private healthcare providers based on its service excellence. The result obtained from the above approaches is integrated and finally compared using Copeland method for final ranking.

The result reveals that healthcare provider A_4 is ranked top in the list of most reliable healthcare provider based on its service excellence and healthcare provider A_1 is at the bottom of the list.

The paper enlightens healthcare administrators with a path to improve their performance for excellent service delivery.

6.2 Introduction

The global service market for healthcare is expanding quickly and is fiercely competitive, just like other service sectors. Service quality encompasses consumer views of service performance. Researchers' interest in service quality has escalated substantially in the past few years. An organization's performance is seen to be enhanced by providing high-quality services [474-479].

In service sectors, providing excellent service is essential for sustainability. In the present scenario, organisations must meet consumer expectations. What an organisation values may not be as essential to its customers. The management must fulfil the requirements of their customers to maintain a steady stream of business demands. Quality is now a crucial factor in determining the outcome of investment for any sectors, and it has also substantially lowered costs [480].

In today's cutthroat business world, the performance and perseverance of any organization are largely determined by the quality of its services. In the healthcare industry, quality generates value that benefits both the service supplier about revenues and the service recipient about better health treatment by recognising the feeling of the patients about the services [481].

Healthcare providers with top-notch service have consistently attracted more patients and generated ongoing demand for their services. Healthcare providers have challenges in boosting patients' satisfaction by delivering an excellent care. Doctors are supposed to not only help patients overcome diseases, but also promote healthy lifestyles. Physicians have a significant impact in enlightening people about the value of routine preventive medical check-ups and diagnostics. In healthcare sector, patient opinions are regarded to be the primary determinant of how well a facility is providing its services. [482].

A patient's decision to seek medical treatment in their native country or in a hospital overseas is significantly influenced by the standard of medical care provided in hospitals. Continuous assessment of patients' opinions regarding every aspect of services received is necessary to improve the quality of medical care in a given nation. The experiences shared by patients provide a valuable foundation for raising the standard of medical care [483].

Patient satisfaction is a key factor in assessing the standard of a country's health care infrastructure [484]. Recently, improving knowledge of the variables influencing patient satisfaction has grown to be a top priority for hospital administration.

In India, the private healthcare sector outperforms the public healthcare system in terms of manpower, technology, and customer satisfaction. [485]. The middle-class Indian people as well as those living below the poverty level cannot afford medical treatment. The main issues impacting the health service delivery in India include a shortage of diagnostic tools and equipment, delayed patient care, inadequate facilities, and a shortage of physicians, nursing staff and administrative staff. It is essential to consider political, economic, environmental, social and technological factors while choosing the optimal alternative, assessing systems, and seeking methods to uplift the level of services.

A comparative performance assessment of service quality criteria analyses the standard to healthcare facilities and assists decision-makers in developing action plans accordingly.

Multi-Criteria Decision-Making (MCDM) is a rapidly evolving discipline within operations research, serving as a vital tool for complex decision-making scenarios. MCDM refers to the methodology used to evaluate, rank, and select one or more alternatives from a set of available options based on multiple conflicting criteria [486].

It is particularly effective in situations where decisions must be made involving the prioritization and selection among diverse alternatives. A wide array of Multi-Criteria Decision Analysis (MCDA) techniques has been developed to support decision-makers in making structured, rational, and transparent choices [487].

Researchers studying healthcare have shown an interest in MCDM approaches. Healthcare involves making a lot of decisions, like which medication is best, how to rate hospitals and medical facilities, how to assess performance and what kind of technology is best. For these decisions, several MCDM techniques may be applied. MCDM has dealt with various healthcare decision-making challenges including prioritizing, diagnosing, evaluating treatment plans, allocating resources and assessing technologies.

6.3 Research Methodology

A comprehensive analysis of recent research focused on the application of Multi-Criteria Decision-Making (MCDM) methods in healthcare management has been carried out.

6.3.1 Sample

Six private healthcare providers in Kolkata participated in this study, and we categorized them into groups A_1, A_2, A_3, A_4, A_5 and A_6.

6.3.2 Tool

The factors that determine service excellence of private healthcare providers were incorporated into the current study by adapting existing literature. Affordability, accessibility, availability, ambience and satisfaction are considered to couple these factors with service excellence of private healthcare providers in Kolkata. Fig. 6.1 illustrates a research model.

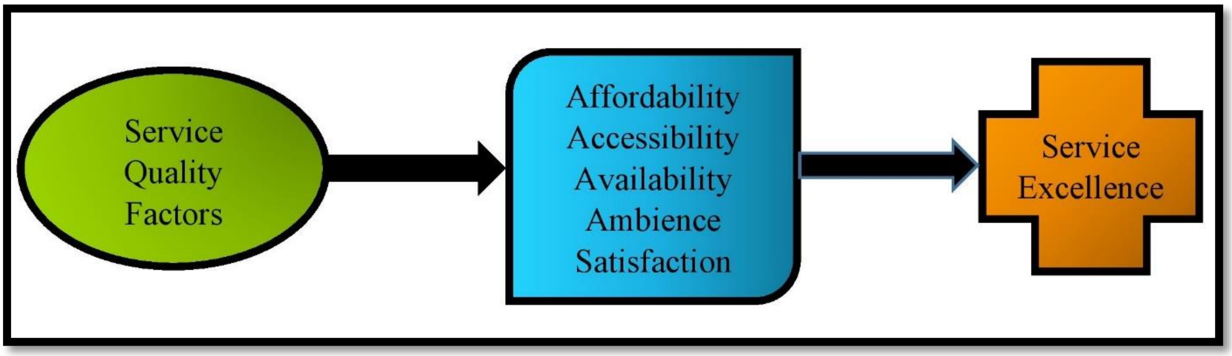


Fig. 6.1: A research model.

6.3.3 Demographic profile

The demographic profile of the respondents are shown in Table 6.1

Variable	Types	Frequency	%
Gender	Male	247	51.46
	Female	233	48.54
Age	Less than 20	72	15.00
	20-40	143	29.79
	41-60	210	43.75
	Above 60	55	11.46
Work	Unemployed	83	17.29
	Public sector	71	14.79
	Private sector	156	32.50
	Self employed	90	18.75
	Retired	80	16.67
Income	Less than 1 lakhs	118	24.58
	1-3 lakhs	177	36.86
	Greater than 3 lakhs	185	38.56
Marital status	Married	322	67.08
	Unmarried	158	32.92

Table 6.1: Demographic profile of the respondents

6.3.4 Data collection

A survey was conducted by sending 100 questionnaire to six private healthcare providers located in Kolkata. Among 600 questionnaires, 480 were returned with responses of the respondents with response rate of 80%. Linguistic expressions were used to determine respondents' viewpoints on service excellence of six private healthcare providers. The confidentiality of their responses and its application for the purpose of research was assured to the respondents.

There are basically two portions of the questionnaire. The first part of the questionnaire consists of demographic profile of the respondents' which includes gender, age, work, income and marital status and the second part consists of performance scores to assess the service excellence based on five criteria. There are 24 items in the questionnaire, which were arranged in accordance with the five fundamental criteria that is affordability, accessibility, availability, ambience and satisfaction.

6.3.5 Data Analysis

The respondents' opinion were analysed by converting linguistic terms into triangular fuzzy numbers as follows

Poor- (0.0, 0.1, 0.3) Average- (0.1, 0.3, 0.5) Good- (0.3, 0.5, 0.7) Excellent- (0.5, 0.7, 0.9) Outstanding- (0.7, 0.9, 1.0)

Microsoft excel software was used to do the necessary computations and prepare fuzzy performance table as shown in Table 6.2.

	A_1	A_2	A_3	A4	A5	A6
Q_1	(0.345,0.534,0.720)	(0.624,0.805,0.536)	(0.547,0.720,0.971)	(0.521,0.755,0.936)	(0.377,0.572,0.711)	(0.526,0.717,0.932)
Q_2	(0.360,0.568,0.716)	(0.444,0.712,0.365)	(0.746,0.542,0.377)	(0.986,0.571,0.233)	(0.478,0.551,0.810)	(0.621,0.707,0.310)
Q_3	(0.533,0.612,0.311)	(0.603,0.172,0.773)	(0.289,0.451,0.314)	(0.565,0.688,0.713)	(0.595,0.708,0.317)	(0.585,0.632,0.211)
Q_4	(0.289,0.713,0.417)	(0.518,0.714,0.322)	(0.519,0.608,0.121)	(0.774,0.610,0.488)	(0.321,0.577,0.748)	(0.496,0.696,0.869)
Q_5	(0.415,0.348,0.551)	(0.477,0.831,0.112)	(0.558,0.819,0.951)	(0.515,0.333,0.787)	(0.433,0.673,0.319)	(0.433,0.528,0.749)

Table 6.2: The fuzzy performance table of each private hospital

The fuzzy numbers obtained from fuzzy averaging are transformed into crisp numbers by centre of area technique to formulate the decision matrix. An expert committee consisting of six doctors and four academician were formed to determine the criteria weights by implementing analytical hierarchy process (AHP) using pair wise comparison. The details of the expert committee members are shown in Table 6.3

Expert	Age(Yrs.)	Qualification	Designation	Experience(Yrs.)
Doctor-1	52	MBBS	Cardiologist	25
Doctor-2	48	MBBS	Nephrologist	23
Doctor-3	45	MBBS	Neurologist	18
Doctor-4	39	MBBS	Gastroenterologist	12
Doctor-5	39	MBBS	Gynaecologist	13
Doctor-6	37	MD	General medicine	10
Academacian-1	58	Post Doctorate	Professor	40
Academacian-2	55	Post Doctorate	Professor	38
Academacian-3	49	Doctorate	Associate Professor	20
Academacian-4	43	Doctorate	Associate Professor	16

Table 6.3: Details of expert committee members

The criteria weights attained for each criteria are Affordability- 0.2131, Accessibility- 0.1270, Availability- 0.2085, Ambience- 0.2549 and Satisfaction-0.1965.

TOPSIS for preference ranking, Deng's similarity method for similarity ranking, PROMETHEE-II for outranking and Yager's min max principle for min-max ranking is applied to evaluate, compare and rank the private healthcare providers based on its service excellence.

The results obtained from the above mentioned techniques is further compared and analysed using Copeland method and a final ranking is presented to minimise the uncertainty, ambiguity, vagueness and obscurity to develop a holistic, eclectic and exotic decision. A conceptual framework of the methodology is illustrated in Fig. 6.2.

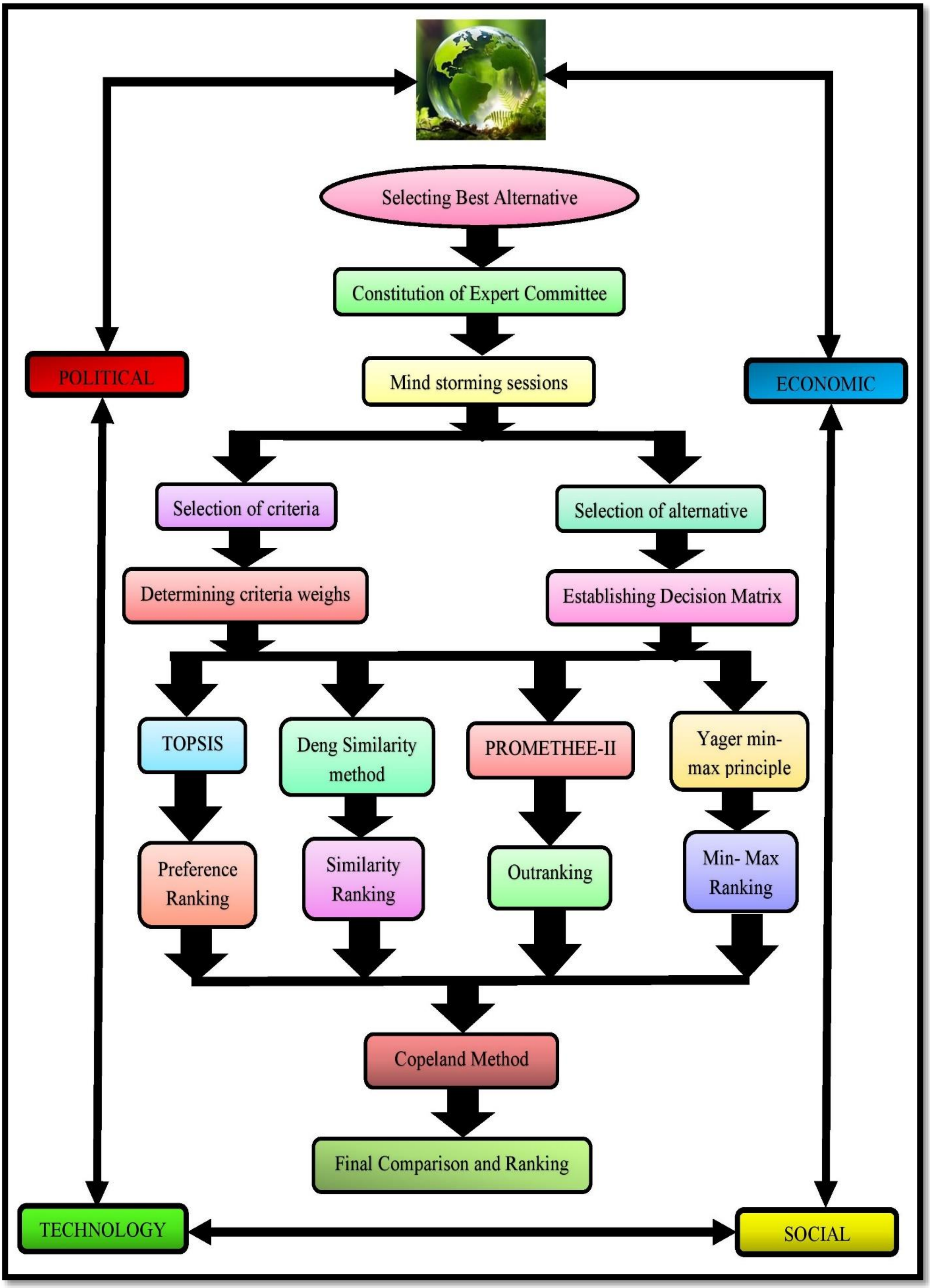


Fig. 6.2: A conceptual framework of the methodology

6.4 Results

The criteria weights obtained for each aspects are Q_1-0.2131, Q_2-0.1270, Q_3-0.2085, Q_4 -0.2549 and Q_5-0.1965.

	A_1	**A_2**	**A_3**	**A_4**	**A_5**	**A_6**
Q_1	0.533	0.655	0.746	0.737	0.553	0.725
Q_2	0.548	0.507	0.555	0.593	0.613	0.546
Q_3	0.485	0.516	0.351	0.655	0.540	0.476
Q_4	0.473	0.518	0.416	0.624	0.542	0.687
Q_5	0.438	0.473	0.776	0.545	0.475	0.570

Table 6.4: The decision matrix of six alternatives according to five criteria

Alternatives	**S_i**	**Rank**
A_1	0.25	06
A_2	0.3775	05
A_3	0.4375	03
A_4	0.6728	01
A_5	0.4051	04
A_6	0.5992	02

Table 6.5: Ranking of private healthcare providers according to TOPSIS

Alternatives	**Overall performance index**	**Rank**
A_1	0.3821	3
A_2	0.381963	4
A_3	0.380312	6
A_4	0.382844	1
A_5	0.382478	2
A_6	0.381565	5

Table 6.6: Ranking of private healthcare providers according to Deng Similarity method

Alternatives	$\psi^{+}(U)$	$\psi^{-}(U)$	$\psi(U)_{net}$	**Rank**
A_1	0.18518	0.81482	·0.62964	6
A_2	0.3516	0.6484	-0.2968	5
A_3	0.4858	0.5142	-0.0284	4
A_4	0.8024	0.1976	0.6048	1
A_5	0.56796	0.43204	0.13592	3
A_6	0.60706	0.39294	0.21412	2

Table 6.7: Ranking of private healthcare providers according to PROMETHEE-II

Alternatives	**Value**	**Rank**
A_1	0.3851	05
A_2	0.4324	04
A_3	0.3270	06
A_4	0.5482	01
A_5	0.4581	03
A_6	0.4612	02

Table 6.8: Ranking of private healthcare providers according to Yager min-max principle

	Wins	**Loss**	**Tied**	**Difference**	**Rank**
A_1	0	4	1	-4	**6**
A_2	1	3	1	-2	**4**
A_3	0	3	2	-3	**5**
A_4	5	0	0	5	**1**
A_5	3	2	0	1	**3**
A_6	4	1	0	3	**2**

Table 6.9: Final comparison and ranking by Copeland method

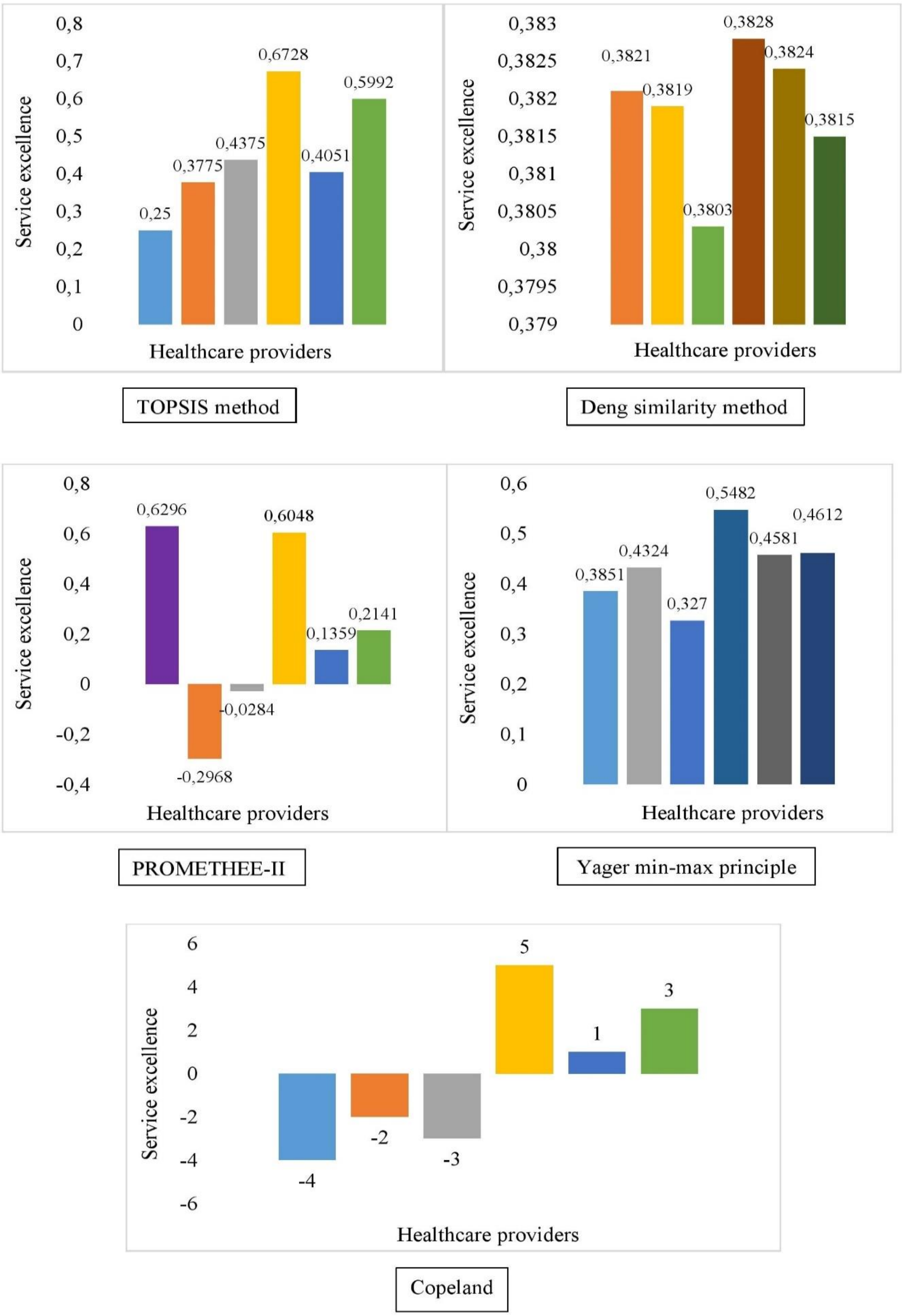


Fig. 6.3: Graphical representation of service excellence of private healthcare providers by different approaches

6.5 Discussion

We are all aware about the adverse effect of COVID-19 in the past few years globally. Due to the above pandemic, people became more serious about their health. Healthcare providers in India have huge responsibility in improving the health issues and delivering high quality care to their patients. The quality of care and services provided by healthcare providers are divergent.

This paper presents an empirical analysis to evaluate the service excellence of six private healthcare providers located in Kolkata, India from patients' perspective. The proposed approach of this paper considered five criteria which includes affordability, accessibility, availability, ambience and satisfaction and presented an integrated comparison study to select the best healthcare based on its service excellence.

Fuzzy numbers were used in order to deal with the uncertainty of decision makers' viewpoints and later transformed into crisp values. Our study applied TOPSIS for preference ranking, Deng's similarity method for similarity ranking, PROMETHEE-II for outranking and Yager min-max principle for min-max ranking to rank the healthcare providers based on its excellence on service delivery. Finally Copeland method is applied for final ranking by comparing the results of the above mentioned technique.

Patients will benefit from selecting the greatest and most dependable private healthcare provider because of the ranking based on service excellence. The final result reveals that healthcare provider A_4 ranks top based on its service excellence provided to the patients. Healthcare provider A_6 is in the second position in terms of ranking, healthcare provider A_5 is in the third position and healthcare provider A_1 was in the last position.

The findings demonstrate that private healthcare providers with low ranking should prioritize quality of care in order to provide the greatest possible service to their patients. Hospital administration may use these findings to enhance patient services based on patient demands and quality assessment. The quality of the treatment is an essential factor for uplifting a patient's level of satisfaction.

It is also concluded that improvements are required on the quality of the treatment delivered to the patients. The healthcare management team should take more administrative measures on the areas that it has lagged behind. The private healthcare providers must understand the patients' needs, increase patients' levels of satisfaction and control costs.

This survey suggests that service excellence appears to be the most significant consideration of private health care providers. We are aware that people have several options for private healthcare providers. If patients are not satisfied with one, they can quickly switch to another provider. As a result, we may predict that there would be intense competition among private healthcare providers. Private health care providers should consider their clients' opinions in order to prosper in this competitive environment. Otherwise, they won't be able to attract new patients and retain their current clientele.

The Key Contributions of the Study are

a. Development of a Multi-Model Evaluation Framework- The study introduces a comprehensive framework integrating multiple MCDM techniques i.e. TOPSIS, Deng Similarity Measure, PROMETHEE-II, and Yager's Min-Max Principle to evaluate and rank six private healthcare providers in Kolkata based on service excellence. This integration offers a robust and holistic decision-making model in a domain where subjectivity and complexity often hinder effective evaluation.

b. Incorporation of Fuzzy Logic to Handle Uncertainty- To address vagueness and imprecision in patient responses, the study employs fuzzy linguistic variables, which are subsequently defuzzified into crisp values using the centre of area method. This enhances the reliability and accuracy of decision-making in healthcare environments where perception-based judgments are prevalent.

c. Identification of Key Service Excellence Criteria- The research identifies and validates five critical service quality criteria i.e. Affordability, Accessibility, Availability, Ambience, and Satisfaction based on expert opinion and literature review. These criteria serve as a foundational framework for performance assessment across various private healthcare providers.

d. Empirical Validation Using a Real-World Case Study- A field study involving 480 respondents across six hospitals provides empirical grounding for the proposed methodology. The real-world application substantiates the feasibility, effectiveness, and generalizability of the model for healthcare performance evaluation.

e. Final Ranking through Copeland Aggregation- To minimize ranking discrepancies and support comprehensive decision-making, the study synthesizes the outcomes of the four MCDM methods using the Copeland method. This aggregation enhances decision validity and supports conflict resolution in multi-criteria environments.

f. Strategic Insights for Healthcare Administrators- The findings offer strategic inputs to hospital administrators by pinpointing performance gaps and suggesting actionable improvements. The study encourages quality enhancement in low-ranked healthcare providers, thereby contributing to overall service competitiveness and patient happiness in the private healthcare providers.

Chapter- 7

A De Novo Approach for Healthcare Institute Selection by Integrating AHP and QFD

7.1 Abstract

The explosion of knowledge sharing, cloud computing, artificial intelligence and machine learning(AI and ML), digital integration, internet of things(IOT), advancement in medical technology and telemedicine leads patient and patients party across the world to avail the best healthcare services under utopian environment.

Patients have high expectation regarding their speedy recovery and similarly the service providers have high responsibility to meet the desired level of satisfaction of patients. Choosing a healthcare institute for medical treatment is an epochal task. Inappropriate selection can have a detrimental effect on health of an individual. Several criteria must be taken into account in order to select the most robust healthcare institute.

This paper aims to develop an integrated model by linking AHP with QFD to determine the performance score of healthcare institute and select the best among them based on patient and patients' party demand and technical criteria of healthcare institute. The proposed approach highlights technical criteria of healthcare institute based on patient and patients' party requirement perspective.

Including cost-factor elements in the proposed model justifies healthcare institute selection from an economic perspective. A case study has been carried out in Kolkata to apply the proposed integrated AHP-QFD model and select the optimal healthcare alternative. It also addressed both subjective and objective factors taken together in a conspectus consilient ways.

7.2 Introduction

The ongoing wave of digital transformation has brought about profound changes across the globe. In today's intensely competitive market, service quality has emerged as a crucial determinant of success for organizations in the service sector, playing a key role in both retaining current customers and attracting new ones. It is substantial to figure out the needs that bring more contentment to the customer. Identifying customer needs and meeting their expectation is very significant aspect to achieve success in the present market scenario.

An essential component of human growth is health. Health systems are composed of various interrelated elements, such as individuals, institutions, and activities. They carry out a number of tasks, including providing healthcare services, preserving and enhancing health, shielding families from the financial burden of disease, facilitating revenue generation, and influencing social values and standards. An economical and accessible healthcare provider is crucial for providing quality care to the people. Every healthcare provider throughout the world is battling with increasing expenses and inconsistent quality.

The healthcare sector is an integral part for sustainable growth of a nation. The healthcare sector is a patient-focused service sector [488]. Healthcare providers must prioritize both medical care and patients' satisfaction. Their goals include providing high-quality and safe healthcare services, boosting efficiency and competitiveness, meeting patient demand, and improving level of satisfaction. Improving service quality is a crucial management concern for healthcare providers. The increasing demand for healthcare services is a significant challenge for states. Healthcare services are in high demand, despite limited resources. There is an urgent need to look into and pinpoint the essential elements of healthcare services to provide users with high-quality care.

One of the primary goals of healthcare quality improvement is to provide better care. It aims to make healthcare more patient-centered, decisive, affordable, and secure in addition to raising the standard of care. The healthcare providers needs to pay attention to patient requirements and get opinions regarding their satisfaction in order to promote ongoing quality improvement [489].

We are all aware about the adverse effects of covid-19 in the last few years. In the present scenario, people are more conscious about health. The health care providers should ensure that people availing their facility are completely satisfied with the service quality once they visit the healthcare. Selecting an optimal healthcare institute for medical treatment is an intricate task as it is related to the physical health of an individual. The decision should be made collaboratively by patient and patients' party and healthcare provider to ensure the most appropriate treatment.

Service quality is one of the leading criteria for optimal healthcare institute selection. There are several service quality assessment tool developed by various researchers for optimal selection of healthcare institution.

The purpose of healthcare institute selection is to assist people in selecting an appropriate healthcare provider by highlighting important aspects to take into account including the standard of care, cost, convenience, and wellness needs. It also highlights the significance of making sound choices to ensure the best possible access to healthcare institute.

Healthcare decision-making is a challenging procedure and requires clear and effective methodologies for assuring uniformity and clarity of factors. An extensive variety of societal, ethical, financial, medical, and technological factors are essential for effective decision making.

7.3 Research Methodology

The following steps constitute the proposed approach for healthcare institute selection problem incorporating AHP and QFD

Step-1:- A QFD expert committee of decision makers is constituted.

Step-2:- The QFD expert team identifies patients and patients' party requirements and technical criteria of healthcare institute to construct the central relationship matrix or QFD matrix.

Step 3:- The significance level of patient and patients' party requirements is reckoned using AHP and the significance level of technical criteria for healthcare institute selection is calculated using Equation 7.1.

$$w_y = \sum_{x=1}^{i} S_{xy}\, e_x \qquad (7.1)$$

where w_y is the significance level for the yth technical criteria (y= 1, 2 ….j); S_{xy} is the computed relationship in the central relationship matrix between the xth patient and patients party requirements and the yth technical criteria of healthcare institute; and e_x is the important weights of the xth patient and patients party requirements.

Step 4:- The significance level of technical criteria for healthcare institute is normalised using Equation 7.2.

$$Nw_y = \frac{w_y}{\sum_{y=1}^{j} w_y} \times 100 \qquad (7.2)$$

Step 5:- A pairwise comparison matrix considering each technical criteria of healthcare institute is devised by applying scale of relative importance as shown in Table 7.1 which was propounded by Thomas L. Saaty.

Description	Scale of relative importance
Equally Significant	1
Moderately Significant	3
Essentially Significant	5
Very strongly Significant	7
Extremely Significant	9
Intermediate Significance	2,4,6,8

Table 7.1: Nine point scale of relative importance

Step-6:- Individual score s_{xy} for each technical criteria for each healthcare alternative is computed and finally overall score is measured by using Equation 7.3

$$OS_y = \sum_{y=1}^{j} Nw_y \, s_{xy} \qquad (7.3)$$

where, OS_y is the overall score for yth healthcare institute (y=1, 2…); Nw_y is the normalized significance level of yth technical criteria (y= 1, 2…j); and s_{xy} is the measure of priority vector of yth alternative on xth technical criteria.

Step-7:- The healthcare institutes are ranked based on the overall score by using the metaphor “the greater the score, the better the alternative”

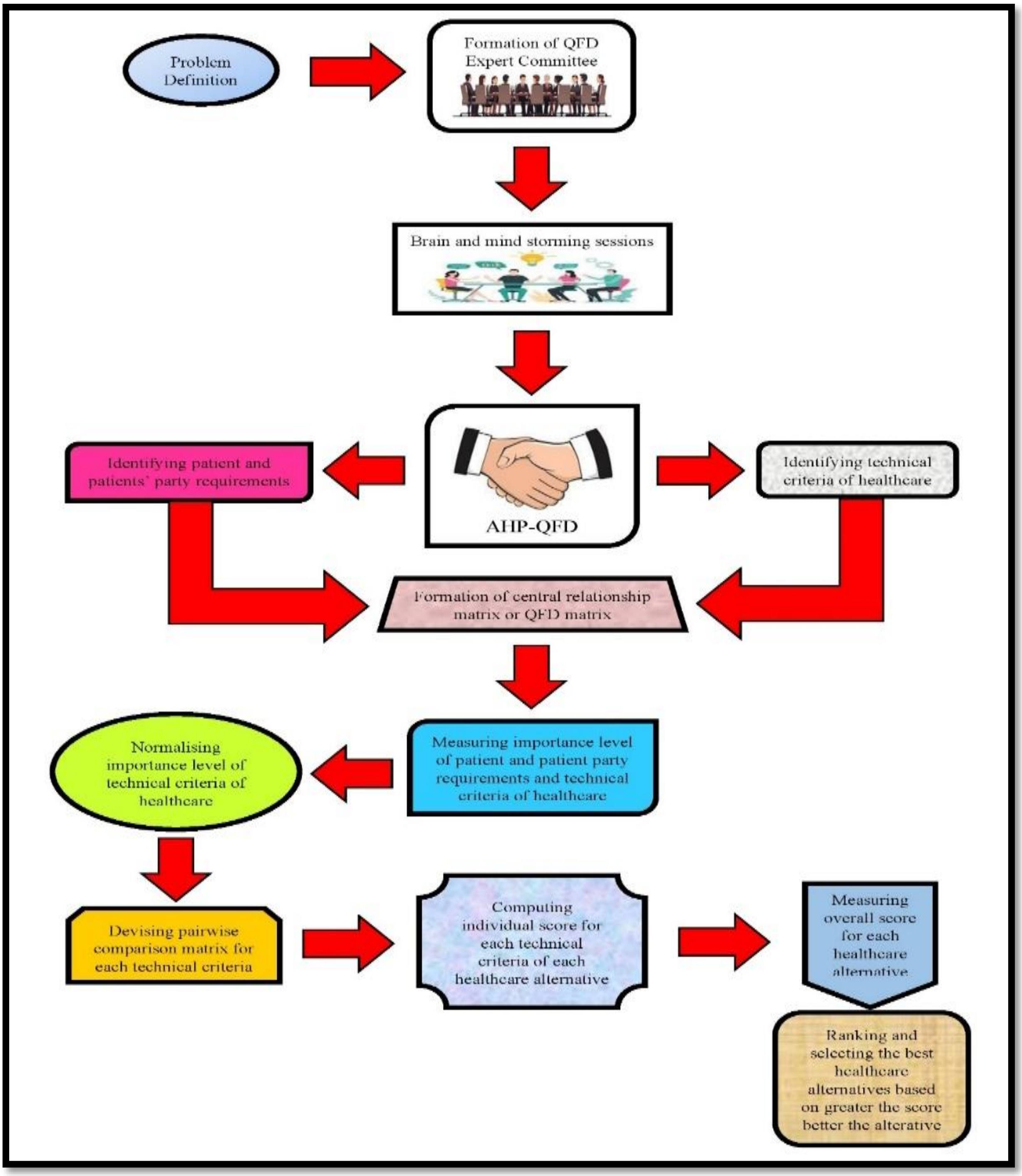


Fig. 7.1: Flowchart of the proposed methodology

7.4 A Case Study

A case study is provided to demonstrate the effectiveness and convenience of the proposed method. Four healthcare institutes located in Kolkata has been selected with a goal to identify and rank the most robust healthcare institute based on patients and patients' party requirements and technical criteria of each healthcare institute.

A QFD expert committee of decision makers consisting of three healthcare experts and two academic researchers were constituted where brain and mind storming sessions were held among the different experts to identify the patients and patients' party requirements and technical criteria of healthcare institute as illustrated in Table 7.2 and 7.3.

Sl no	Patient and patients party requirements
01	Accurate diagnosis (PPPR-1)
02	Quality of doctors, nurses and clinical staff (PPPR-2)
03	Patients safety(PPPR-3)
04	Less waiting time for treatment (PPPR-4)
05	Cost of treatment (PPPR-5)
06	Infrastructure (PPPR-6)
07	Hygiene and cleanliness(PPPR-7)

Table 7.2: Patient and patients party requirements for healthcare institute selection

Sl no	Technical criteria for healthcare institute selection
01	Modern and updated medical equipment for diagnosis and treatment (TC-1)
02	Availability of beds for patients and waiting halls for visitors (TC-2)
03	Highly qualified, experienced and skilled doctors, nurses and clinical staffs(TC-3)
04	Sufficient security and CCTVs and availability of safety features like elevators, handrails and ramps (TC-4)
05	Health insurance which covers medical reimbursement(TC-5)
06	Adequate hygiene and cleanliness to prevent infections (TC-6)
07	Healthcare is capable to take appropriate care of their patients in a systematic way (TC-7)

Table 7.3: Technical criteria for healthcare institute selection

The following decision matrix is formulated based on patient and patients' party requirements

$$M=\begin{bmatrix} 1 & 7 & 3 & 5 & 4 & 9 & 7 \\ \frac{1}{7} & 1 & \frac{1}{5} & \frac{1}{2} & \frac{1}{2} & 4 & 2 \\ \frac{1}{3} & 5 & 1 & \frac{1}{2} & 3 & 6 & 5 \\ \frac{1}{5} & 2 & 2 & 1 & \frac{1}{3} & 5 & 2 \\ \frac{1}{4} & 2 & \frac{1}{3} & 3 & 1 & 4 & 3 \\ \frac{1}{9} & \frac{1}{4} & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & 1 & \frac{1}{5} \\ \frac{1}{7} & \frac{1}{2} & \frac{1}{5} & \frac{1}{2} & \frac{1}{3} & 5 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 7 & 3 & 5 & 4 & 9 & 7 \\ 0.143 & 1 & 0.200 & 0.500 & 0.500 & 4 & 2 \\ 0.333 & 5 & 1 & 0.500 & 3 & 6 & 5 \\ 0.200 & 2 & 2 & 1 & 0.333 & 5 & 2 \\ 0.250 & 2 & 0.333 & 3 & 1 & 4 & 3 \\ 0.111 & 0.250 & 0.167 & 0.200 & 0.250 & 1 & 0.200 \\ 0.143 & 0.500 & 0.200 & 0.500 & 0.333 & 5 & 1 \end{bmatrix}$$

The expert team devises central relationship matrix or QFD matrix as illustrated in Table-7.4

		Technical criteria for Healthcare Institute selection(TC)							
		Modern and updated medical equipment for diagnosis and	Availability of beds in wards and cabins for patients and	Highly qualified, experienced and skilled doctors, nurses and clinical	Sufficient security and CCTVs and availability of safety features like elevators,	Health insurance which covers hospitalisation costs and medical reimbursement	Adequate hygiene and cleanliness to prevent	Healthcare is capable to take appropriate care of their	Importance weights of patient and patients party requirements
Patient and patients party requirements (PPPR)	1.Accurate diagnosis	■		■				▲	0.428
	2. Quality of doctors, nurses and clinical staff	▲		■				▲	0.066
	3. Patients safety	▲	■	▲	■	▲	■	■	0.185
	4. Less waiting time for treatment	■	●		●			●	0.115
	5. Cost of treatment	●	▲	●		■	▲		0.129
	6. Infrastructure	▲	■		▲		▲	▲	0.024
	7. Hygiene and cleanliness		■				■		0.053
	Significance level	6.391	3.118	5.500	1.900	2.086	2.907	4.37	
	Normalised significance level	24.33	11.87	20.94	7.23	7.94	11.06	16.63	

■ : Strong relation=9; ▲ : Moderate relation=5; ● : Weak relation= 1; Blank: No relation=0

Table 7.4. Central relationship matrix or QFD matrix for healthcare selection problem

The inconsistency level present in the information of patient and patients' party requirement matrix and each technical criteria of healthcare institute matrix is acceptable as inconsistency ratio is less than 10 percent for all parameters.

TC	Weights	HI-1	HI-2	HI-3	HI-4	HI-5
01	24.33	0.555	0.093	0.186	0.101	0.065
02	11.87	0.523	0.090	0.131	0.211	0.045
03	20.94	0.306	0.404	0.061	0.146	0.083
04	7.23	0.066	0.053	0.265	0.118	0.498
05	7.94	0.438	0.167	0.166	0.063	0.166
06	11.06	0.088	0.263	0.398	0.192	0.059
07	16.63	0.092	0.091	0.199	0.530	0.088
Overall score		0.32577	0.17922	0.18303	0.20311	0.10888
Rank		**1**	**4**	**3**	**2**	**5**

Table 7.5: Ranking of healthcare institute based on technical criteria

From Table 7.5, it is clear that HI-1 >HI-4 >HI-3 >HI-2 >HI-5. Since, healthcare HI-1 has the maximum overall score, it is preferred.

7.4.1 Including cost factor elements

Healthcare institute selection should include the elements of cost factor to escalate the robustness of the present integrated AHP-QFD methodology. The elements of the cost factor are illustrated in Table 7.6 for five different healthcare institute.

Cost factor elements	HI-1	HI-2	HI-3	HI-4	HI-5
1. Cost of accommodation	3000	2500	2800	3200	3500
2. Cost of medical test and procedures	2630	2800	2470	2750	2500
3. Cost of surgeries	25000	27400	30000	22600	28100
4. Cost of medicines and bodily fluids	2440	2675	2860	2554	3000
5. Cost of ward girl/boy	1000	800	850	650	750
Total	34070	36175	38980	31754	37850
Selection Index (SI)	22.543	12.427	12.686	14.084	7.571
Rank	**1**	**4**	**3**	**2**	**5**

Table 7.6: Ranking of healthcare institute based on cost factor elements

A mathematical framework was devised that combines cost-factor elements with priority values obtained from AHP [490-492]. The underlying equation of the stated framework is

$$SI_x = [(\alpha\ SFM_x) + (1-\alpha)\ OFM_x] \tag{7.4}$$

where

$$OFM_x = \left[OFC_x \times \sum_{x=1}^{j} \frac{1}{OFC_x}\right]^{-1} \tag{7.5}$$

where, *SI* = Selection Index, *SFM* = Subjective Factor Measure, *OFM* = Objective Factor Measure, *OFC* = Objective Factor Cost, α = Objective factor decision weight, and *j* = number of alternative. The *SFM* values are the overall scores found from Table 7.5. *OFC*s are the total costs of each healthcare institute.

The selection of the alpha (α) value is a critical aspect of the decision-making process. Its determination depends largely on the decision-maker's judgment concerning the relative importance of subjective versus objective criteria.

Using equation (7.4) and assuming α= 0.69, the healthcare institutes are ranked as HI-1 >HI-4 >HI-3 >HI-2 >HI-5 which is similar to that found from Table 7.5.

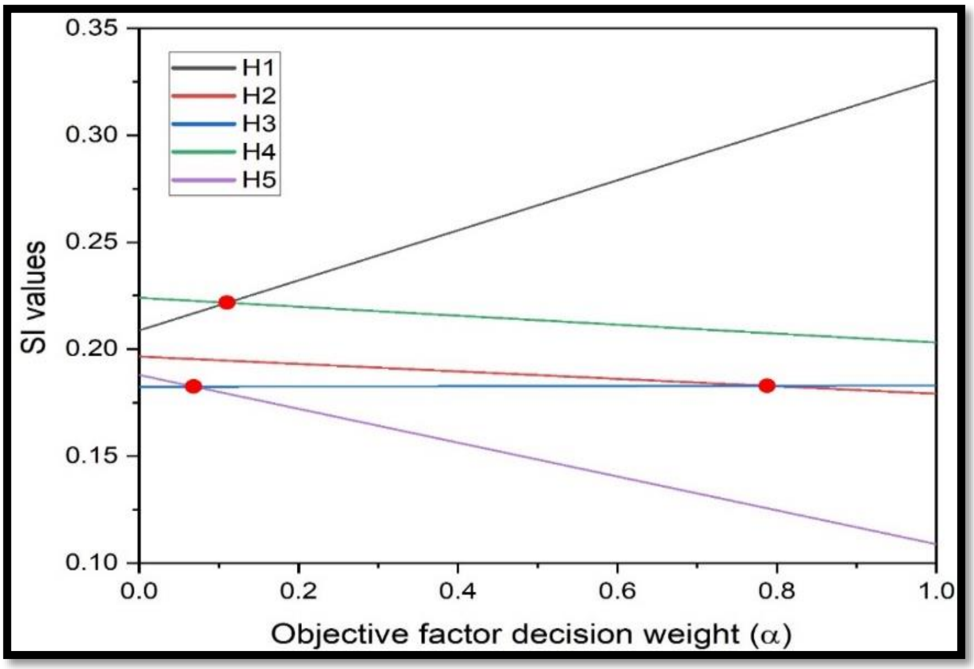


Fig 7.2: Sensitivity analysis

Healthcare Institute	Correlation	Optimal range of α
HI-1	Between HI1 and HI4	$0.1106 \leq \alpha \leq 1.000$
HI-4	Between HI1 and HI4	$0.000 \leq \alpha \leq 0.1106$
HI-2	Between HI2 and HI3	$0.000 \leq \alpha \leq 0.7879$
HI-3	Between HI2 and HI3	$0.7879 \leq \alpha \leq 1.000$
HI-3	Between HI3 and HI5	$0.0685 \leq \alpha \leq 1.000$
HI-5	Between HI3 and HI5	$0.000 \leq \alpha \leq 0.0685$

Table: 7.7: Results of sensitivity graph

The findings of sensitivity graph displayed in Fig. 7.2 are compiled in Table 7.7 which signifies that the convenient value of α should be preferred conscientiously. The supremacy of α will be greater for SFM_x values and lower for cost factor elements.

7.5 Discussion

The increasing demand for high-quality healthcare services makes it more difficult to select the best healthcare institute for treatment. Analytical hierarchy process and quality function deployment has gained noteworthy success globally in a diverse range of service selection. This is due to its methodical coupling of customer needs.

Appropriate selection of healthcare from patients and patients' party perspective is a serious and intricate task as it involves physical health of an individual. It calls for incredibly discrete decision-making and exhaustive assessment of the idea and approach on the alternatives for effective selection.

The integrated AHP-QFD framework offers a systematic and effective approach for decision-making in healthcare provider selection, taking into account both the needs of patients and their attendants, as well as the technical attributes of healthcare services.

The primary objective of this study is to demonstrate the effectiveness of the proposed model. Within this framework, the QFD methodology is employed to identify relevant technical criteria, while the Analytic Hierarchy Process (AHP) is used to prioritize these criteria based on their importance.

Additionally, AHP is applied to evaluate and rank healthcare institutions according to their performance against the identified technical parameters.

Including cost-factor elements in the proposed model justifies healthcare selection from an economic perspective.

The proposed approach can offer an impartial way to choose a healthcare institute that meets the overall patients and patients' party requirements. This approach is an effective solution to apply in a multi-criteria, unorganised and conflicting environment.

The Key Contributions of this Study are

1. Development of an Integrated Decision-Making Model: The study presents a novel integration of the AHP with QFD for the selection of optimal healthcare institutes. This integration enables both subjective (patient-centric) and objective (technical and economic) criteria to be assessed simultaneously, offering a consilient and comprehensive evaluation model.

2. Incorporation of Cost Factor Elements: A unique contribution is the inclusion of economic aspects through cost-factor elements, which enhances the robustness of the model. By introducing a Selection Index (SI) combining subjective and objective measures, the model ensures practical applicability in real-world decision-making.

3. Application to a Real-World Case Study: The proposed methodology is validated through a case study involving five healthcare institutes in Kolkata. This practical application underscores the model's effectiveness and demonstrates how the approach can rank healthcare institutes based on technical performance and cost-efficiency.

4. Sensitivity Analysis for Decision Robustness: The study conducts sensitivity analysis on the decision parameter (α), reflecting the impact of changing priorities between subjective and objective components. This feature allows decision-makers to adapt the model to diverse scenarios and stakeholder preferences.

5. Framework for Stakeholder-Inclusive Decision-Making: By incorporating both patients' and patients' parties' requirements, the model emphasizes participatory and patient-centered healthcare selection, aligning service quality with user expectations.

Chapter- 08

Sustainable Healthcare: A Data-Driven Model for Green Hospital Performance Evaluation

8.1 Abstract

Sustainability is a significant issue for healthcare infrastructure, and the behavioral responses of patients, staff, and visitors are pivotal in determining the effectiveness of green healthcare environments. This research examines the influence of sustainability views on occupant commitment through a comprehensive analytical model.

This research utilizes data from a healthcare facility in Kolkata, India, employing Principal Component Analysis (PCA) and Multiple Linear Regression to investigate latent variables affecting user loyalty. Four dimensions Eco-Design Quality (EDQ), Trust in Certification (TIC), Sustainability Satisfaction (SS), and Occupant Commitment (OC) have been identified and validated for reliability.

The results indicate that TIC is the most significant predictor of occupant loyalty, succeeded by EDQ and SS. The results highlight that clear certifications and observable sustainable practices substantially influence user trust and retention.

This research empirically associates sustainability characteristics with behavioral results, providing a decision-making framework for architects, facility designers, and healthcare authorities. It integrates construction management, environmental design, and service science to advance human-centric, sustainable healthcare infrastructure.

8.2 Introduction

The healthcare sector is progressively harmonizing with sustainable development goals (SDGs), particularly in infrastructure planning. Hospitals and clinics are significant energy consumers, and their environmental impact is an increasing concern. Alongside resource efficiency and carbon reduction, user experience in these facilities has become essential in sustainability talks. Given the effects of climate change on public health, the infrastructure underpinning health services must be robust, resilient, sustainable, and user-focused.

Sustainable healthcare infrastructure encompasses various attributes, including energy-efficient designs, biophilic elements, efficient waste management systems, indoor air quality regulation, and patient-centered configurations. These elements are not solely cosmetic or technical enhancements; they fundamentally influence the well-being, pleasure, and behavioral responses of patients, healthcare professionals, and visitors. The efficacy of sustainable healthcare environments relies not only on engineering or architectural criteria but also on user perception and commitment to these settings.

From a building standpoint, comprehending behavioral determinants such as user loyalty, contentment, and trust is essential for future-oriented healthcare infrastructure. This also assists in determining the sustainability issues that are most significant to occupants, hence impacting design and operational plans. However, empirical models that statistically assess these views and their impact on user commitment are scarce in the research.

This study tackles this deficiency by formulating a behavioral framework that describes commitment to sustainable healthcare settings. It integrates principles from service research, construction management, and healthcare facility planning through the application of PCA and regression analysis.

The study employs a dataset to provide an innovative methodology for comprehending the impact of sustainability factors, including eco-design quality, faith in certification, and satisfaction, on occupant loyalty. The results provide a significant resource for architects, construction engineers, and healthcare officials to make informed decisions that reconcile user satisfaction with sustainability objectives.

8.3 Research Methodology

This study employs a quantitative research approach to create a predictive behavioral model for evaluating the impact of sustainability-related perceptions on occupant commitment in healthcare facilities. This work uses PCA and Multiple Linear Regression Analysis as the primary analytical methods to discern latent components and examine their interrelationships. The primary dataset was initially gathered from a survey regarding service quality and patient loyalty at a healthcare centre in Kolkata.

To line with the study's objectives, the variables were identified to represent sustainability dimensions in green healthcare facilities. The recognized variables include

a. Eco-design Quality (EDQ): Representing infrastructure design features that enhance sustainability (e.g., energy efficiency, natural ventilation).

b. Trust in Certification (TIC): Reflecting perceived credibility of green building certifications and environmental policies.

c. Sustainability Satisfaction (SS): Capturing users' fulfillment with the facility's environmental practices.

d. Occupant Commitment (OC): Indicating user loyalty, future preference, and willingness to recommend the facility.

Each construct was measured using multiple items rated on a 5-point likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

8.4 A Case Study

A case study is an in-depth, context-specific investigation that examines a real-world phenomenon within its natural setting to generate practical insights or validate theoretical constructs. In the present research, the case study involves a healthcare facility in Kolkata, India, serving as a representative example to explore how sustainability perceptions such as eco-design quality, trust in certification, and environmental satisfaction influence occupant commitment. This empirical approach allows for the systematic collection and analysis of data to model user behaviour and loyalty in green healthcare infrastructure using statistical techniques like PCA and regression analysis. Fig. 8.1 furnishes the research methodology.

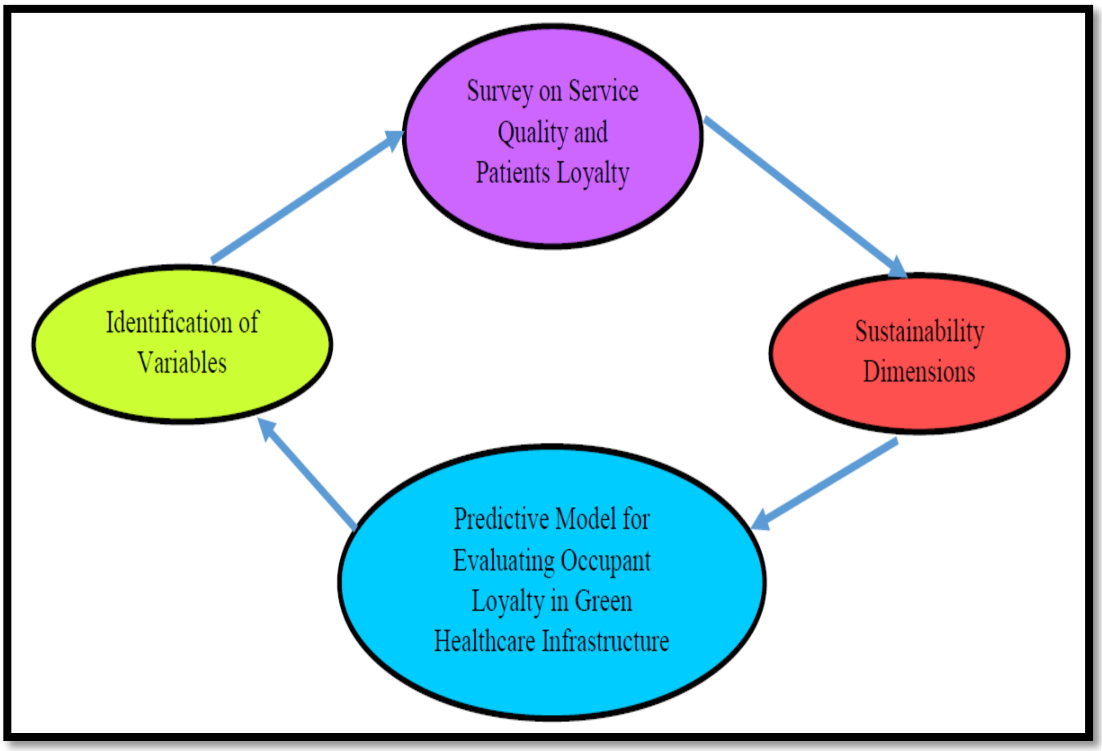


Fig.8.1: The research framework

8.5 Result Analysis

The data analysis was conducted using SPSS version 26. Initially, the dataset underwent factor analysis, which was subsequently followed by regression analysis. Prior to performing factor analysis, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were applied to evaluate the adequacy of the sample and the statistical significance of the data. The outcomes of these preliminary tests are presented in Table 8.1.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.744
Bartlett's Test of Sphericity	Approx. Chi-Square	2458.716
	df	66
	Sig.	.000

Table 8.1: KMO and Bartlett's test

As shown in the table, the Kaiser-Meyer-Olkin (KMO) value for sample adequacy is 0.744, and the significance level of Bartlett's test of sphericity is 0.000, indicating that the dataset is statistically appropriate for conducting Exploratory Factor Analysis (EFA). To extract the underlying factors, the Principal Component Analysis (PCA) method was applied, using Varimax rotation and Kaiser Normalization to enhance interpretability.

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.423	45.196	45.196	5.423	45.196	45.196	2.922	24.348	24.348
2	2.030	16.920	62.116	2.030	16.920	62.116	2.825	23.542	47.890
3	1.652	13.763	75.879	1.652	13.763	75.879	2.354	19.616	67.506
4	1.071	8.922	84.801	1.071	8.922	84.801	2.075	17.295	84.801
5	.916	7.631	92.432						
6	.519	4.323	96.755						
7	.124	1.037	97.793						
8	.098	.813	98.605						
9	.094	.786	99.391						
10	.053	.440	99.831						
11	.016	.132	99.963						
12	.004	.037	100.000						

Extraction Method: Principal Component Analysis.

Table 8.2: Eigen values and total variance explained

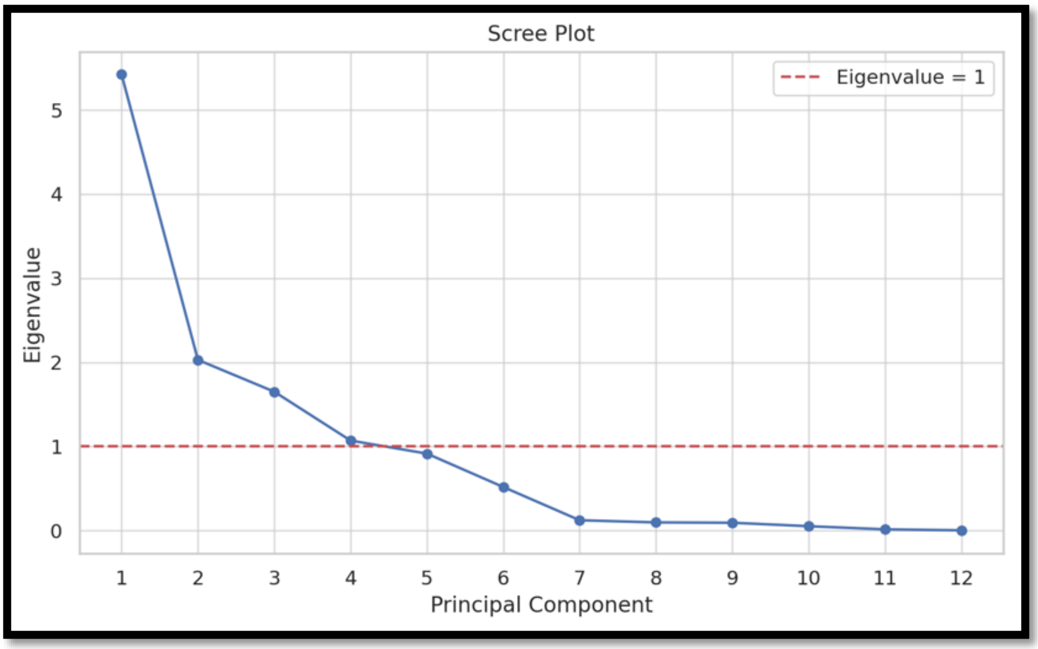


Fig.8.2: Scree Plot from PCA

Factor loadings less 0.45 were treated as superfluous variables and discarded. A high loading value suggests significant impact of the factor on the variable. A factor loading that is higher than 0.6 significantly affects the variables. As a result, factor loadings of twelve variables grouped into four factors were revealed. The results are shown in Table 8.3.

Rotated Component Matrix				
	Component			
	1	2	3	4
C1	.919			
C2	.917			
C3	.851			
C4		.853		
C5		.838		
C6		.738		
C7		.737		
C8			.857	
C9			.847	
C10			.536	
C11				.925
C12				.909

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 8 iterations.

Table 8.3: Result of factor analysis

The four extracted factors were labelled as EDQ, TIC, SS, and OC. To assess the internal consistency of the measurement scale, Cronbach's alpha coefficient was employed. According to Nunnally, a Cronbach's alpha value exceeding 0.7 is considered acceptable for reliability. In this study, the alpha values for the four factors ranged between 0.815 and 0.978, indicating strong reliability. The overall Cronbach's alpha for the scale was 0.887, confirming the robustness and validity of the instrument. The reliability scores for each factor are detailed in Table 8.4.

Sl.No	Dimension	Cronbach's α
1	EDQ	0.978
2	TIC	0.862
3	SS	0.815
4	OC	0.935
Overall Reliability		**0.887**

Table 8.4: - Reliability Analysis

The relative significance of each dimension is evaluated using multiple regression. The results of model summary and ANOVA is illustrated in Table 8.5 and Table 8.6.

Model	R	R Square	Adjusted R^2	Std. Error of the Estimate
1	.674	.454	.443	.87622

Table 8.5: Model Summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	93.167	3	31.056	40.450	.000
	Residual	112.092	146	.768		
	Total	205.259	149			

Table 8.6: Analysis of Variance (ANOVA)

In the regression model, three of the four extracted factors EDQ, TIC, and SS were considered as independent variables, while OC was treated as the dependent variable. The results of the regression analysis, presented in Table 8.7, indicate that the relationships between EDQ, TIC, SS, and OC are statistically significant with p-values less than 0.05.

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.849	.387		2.195	.030
	EDQ	.451	.088	.336	5.108	.000
	TIC	.527	.081	.417	6.476	.000
	SS	.204	.080	.165	2.558	.012

Dependent Variable- OC

Table 8.7: Coefficients of regression

The model indicates that faith in environmental certifications is the most significant predictor of occupant loyalty, succeeded by eco-design quality and sustainability satisfaction. This underscores that in sustainable healthcare design, reputation is as vital as physical facilities. These insights underscore the necessity for public certification and observable sustainable strategies in building management. This study's findings strongly advocate for the integration of behavioral insights in the planning and operation of sustainable healthcare infrastructure. Trust in environmental certification emerged as the primary predictor, underscoring that user perceptions of validity, transparency, and reliability are essential for cultivating long-term loyalty. It indicates that merely implementing green practices is inadequate unless these initiatives are effectively conveyed and substantiated by acknowledged certifications. Eco-design quality is identified as a substantial factor influencing occupant commitment. Natural lighting, enhanced ventilation, ergonomic design, and sustainable materials augment user comfort and happiness.

These findings corroborate previous evidence that well-structured environments enhance psychological well-being, diminish stress, and elevate happiness in healthcare settings. Sustainability satisfaction, albeit the least influential of the three, nonetheless has a statistically significant impact. This suggests that when consumers see their expectations for a sustainable experience are fulfilled, they are more inclined to maintain their commitment to the institution. This research connects construction management with healthcare planning, offering measurable correlations that can guide policy and design. It urges decision-makers to transcend technological efficiency and incorporate human-centered sustainability indicators. The application of PCA and regression enhances the credibility of these findings by mitigating bias and uncovering underlying structures in the data.

8.6 Discussion

This study introduces an innovative behavioral model that measures the correlation between sustainability perceptions and occupant loyalty in healthcare facilities. The study employs PCA and regression analysis to validate four primary constructs, emphasizing that trust in environmental certification is the most significant element influencing occupant commitment.

This indicates that, in addition to technical and design aspects, credibility, transparency, and the communication of sustainability initiatives are essential in influencing user behaviour. The quality of eco-design substantially enhances occupant comfort and pleasure, underscoring the significance of biophilic design, natural illumination, and resource-efficient configurations. Although somewhat less impactful, sustainability satisfaction also enhances loyalty, suggesting that fulfilling user expectations is essential for cultivating long-term involvement.

The Key Contributions of this Study are

a. Develops a quantitative behavioural model that integrates sustainability parameters with occupant loyalty in healthcare facilities.

b. Exhibits the predictive efficacy of trust in green certifications, underscoring the significance of legitimacy and transparency.

c. Confirms the significance of eco-design quality as a major determinant of user commitment through empirical evidence.

d. Utilizes PCA and regression to identify, validate, and analyze latent components, hence advancing methodologies in healthcare sustainability research.

e. Provides an interdisciplinary framework that integrates construction design, healthcare planning, and service science for sustainable development.

These insights provide healthcare leaders and infrastructure planners with a robust, data-driven approach to aligning sustainability goals with user-centric outcomes, paving the way for more resilient, efficient, and trusted healthcare environments.

Chapter- 09

A Conspectus and Consilient Evaluation for Risk Analysis of Healthcare Services

9.1 Abstract

Good health is fundamentally essential to maintain a healthy lifestyle for 195 countries and 7 continents across the world. Healthcare is directly related to the health of an individual. Hospitals are one of the sensitive and essential sector of healthcare for patients among the available service sector industries.

Healthcare services are critical to patient care and treatment, and any failure within this domain can result in severe consequences for patients, healthcare providers, and the surrounding environment. Hence, it is essential to implement stringent monitoring and control mechanisms. To enhance the quality of care and minimize the occurrence of iatrogenic incidents, a comprehensive and systematic approach to failure risk assessment is vital.

This study introduces an innovative extended Failure Mode and Effects Analysis (FMEA) method that integrates Quality Function Deployment (QFD) with a Multi-Criteria Decision-Making (MCDM) framework for evaluating risks in uncertain or rough environments.

The proposed methodology first combines Rough Set Theory with QFD to determine the relative significance of various failure modes in healthcare services. Subsequently, Rough TOPSIS is employed to assess the severity of the identified risks and to establish a prioritized ranking of healthcare service failures.

Finally, a comparative analysis is conducted to validate the performance and reliability of the extended FMEA model, demonstrating its effectiveness and practicality in real-world healthcare risk assessment scenarios.

A numerical example illustrates the proposed methodology and unveils that, through the methodology introduced in this paper, administrators can efficiently relegate healthcare services for corrective actions according to their criticality scores wisely. Implementation of this methodology could decrease the availability of high risk healthcare services in healthcare sector. The integrated framework has been validated with the healthcare practitioners.

Moreover, this methodology can be applied in other sector such as aerospace and automotive by changing some criteria and dimensions.

9.2 Introduction

Medical failure is a serious risk to individuals' health and the healthcare system. It is expected to occur at every stage of medical care which affects the quality of life (QOL). Medical service failures are complex to prevent due to imprecise service process descriptions, client diversity and customization and unity in service operations [493]. Medical service failure causes dissatisfaction among customers that leads to negative customer reaction. Medical service failures are among the most serious types of service failures because they frequently involve life-or-death circumstances. Failure risk mitigation is crucial for smooth functioning of healthcare services in organizations.

Failure Mode and Effects Analysis (FMEA) is a proactive, systematic, and dependable risk assessment tool designed to identify, evaluate, and prevent potential or known failures, errors, and weaknesses within a system, process, design, or service before they impact the end user [494]. When extended to assess the severity and likelihood of failure consequences, the method is referred to as Failure Mode, Effects, and Criticality Analysis (FMECA).

Originally developed in the 1960s for the aerospace industry during the product planning and design phase, FMEA aimed to enhance system safety and reliability [495]. Later it has been extensively utilized as an effective safety and reliability assessment instrument for attaining incessant quality enhancement with a wide range of applications in numerous sectors of food, automobile, aerospace, nuclear and healthcare [496-501].

Failure Mode and Effects Analysis (FMEA) is carried out by a cross-functional team comprising experts from various engineering disciplines and quality assurance fields. This team works collaboratively to systematically evaluate the relationships among failure modes, their root causes, consequences, existing control measures, and potential corrective actions [502].

Unlike many other risk assessment methods, FMEA places a strong emphasis on error prevention, aiming to address potential issues before failures manifest, rather than reacting to them afterward. This proactive approach empowers decision-makers to enhance current systems, introduce preventive measures, and minimize the likelihood and severity of failures, ultimately helping to avoid critical incidents.

According to several researchers and industry experts [503–506], FMEA serves as a logical and intuitive analytical tool, offering a clear and practical method for managing complex systems and processes, driven by the active involvement and insights of the FMEA team.

In conventional Failure Mode and Effects Analysis (FMEA), the risk priority number (RPN) is typically calculated by multiplying three key parameters: Occurrence (O), Severity (S), and Detection (D). This numerical value helps in prioritizing failure modes. However, in many practical applications, the traditional RPN method exhibits notable limitations, particularly concerning its inconsistency and reliability in accurately reflecting risk levels.

To address these drawbacks and enhance the overall effectiveness of FMEA, researchers have proposed a variety of alternative and advanced methodologies.

These include MCDM methods such as GRA [507–508], DEMATEL) [509–510], and TOPSIS [511–512], mathematical programming approaches such as Linear Programming [513], and DEA [514], hybrid methods, combining fuzzy logic and MCDM tools, such as FAHP, Fuzzy FTOPSIS [515], D numbers with Grey Relational Projection [516], and Similarity Measures with Adaptive Resonance Theory (ART) [517], artificial Intelligence-based techniques like Cognitive Maps [518], Fuzzy Rule-Based Systems [519–522], and Adaptive Resonance Theory [523]. These enhanced methodologies offer more accurate, flexible, and robust frameworks for risk evaluation and prioritization in complex decision-making environments.

9.3 Research Methodology

Building upon the foundational principles of Rough Set Theory, Quality Function Deployment (QFD), and the TOPSIS method, this study introduces an integrated FMEA framework tailored for risk assessment in uncertain (rough) environments. The proposed model offers a systematic approach to prioritizing failure modes within healthcare services.

In addition to ranking failure risks, the methodology is also designed to identify the most effective corrective actions that healthcare organizations or institutions can implement. A flowchart illustrating the structure of this approach is provided in Fig. 9.2, and the step-by-step procedure is detailed in the following section.

Phase 1: Compute rough interval weights of failure modes

Step 1.1: Identify the critical failure mode in healthcare services

The failure modes are identified by exhaustive study of previous literature and expertise opinions.

Step 1.2: Obtain the opinion of experts for each failure mode

After identifying the failure modes, the weight is provided by experts using ratings. The ratings vary from 1 to 10. The assessment of the failure mode is denoted as follows:

$$H_n = \left[H_n^1, H_n^2, \cdots, H_n^e, \cdots, H_n^g\right] \tag{9.1}$$

where H_n is the rating of the nth failure mode measured by the eth expert, g is the number of experts.

Step 1.3: Estimate the group rough interval weights of each failure mode

First, based on the basic concepts of RST, the group rough interval weights of each failure mode is computed by

$$RHN(H_n^e) = [H_n^{eL}, H_n^{eU}] \tag{9.2}$$

where H_n^{eL} and H_n^{eU} are the Lower Limit (LL) and Upper Limit (UL) respectively.

Second, the group rough interval weights can be estimated as

$$H_n^L = \left(H_n^{1L} + H_n^{2L} + \cdots + H_n^{gL}\right)/g \tag{9.3}$$

$$H_n^U = \left(H_n^{1U} + H_n^{2U} + \cdots + H_n^{gU}\right)/g \tag{9.4}$$

where H_n^L and H_n^U are the LL and UL of the group rough weights respectively. The group rough interval weights is denoted as $\overline{RHN(H_n)} = = [H_n^L, H_n^U]$. Then, the normalized rough weights of failure modes are calculated as follows:

$$AH_n^L = \frac{H_n^L}{max_n(H_n^L, H_n^U)} \tag{9.5}$$

$$AH_n^U = \frac{H_n^U}{max_n(H_n^L, H_n^U)} \tag{9.6}$$

where AH_n^L and AH_n^U are the LL and UL of the normalized weights respectively.

Phase 2: Calculate rough interval weights of corrective activities with RQFD

Step 2.1: Develop a rough relationship matrix from experts' belief

A rough relationship matrix is formulated by experts using ten point scale to determine the weights of corrective activity for each failure modes. Fig. 9.1 show a framework for R-QFD.

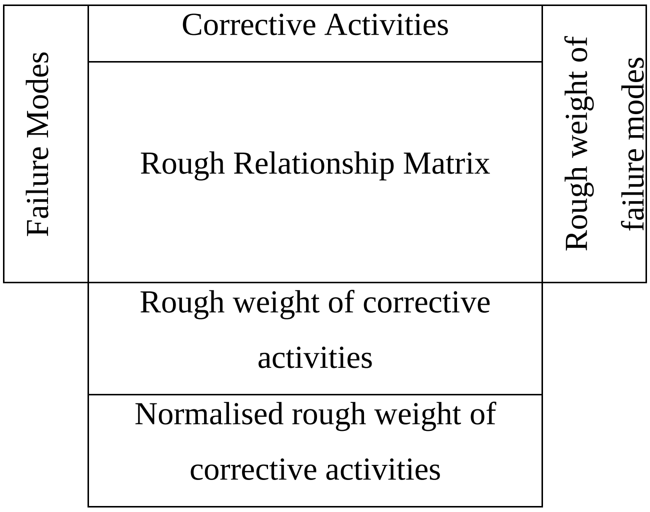


Fig. 9.1: The rough HoQ matrix between failure modes and corrective activities

Step 2.2: Evaluate the rough weights of each corrective activity

The rough weight of the corrective activity under each failure modes can be calculated as follows:

$$RHN(c_{mn}^{e}) = [c_{mn}^{eL}, c_{mn}^{eU}] \tag{9.7}$$

where $RHN(c_{mn}^{e})$ is the rough weights of c_{mn}^{e}. c_{mn}^{eL} and c_{mn}^{eU} are its LL and UL respectively.

Similarly we can evaluate the rough weights of c_{mn} provided by the other experts. They can establish a series of rough weights denoted as follows:

$$RHN(c_{mn}) = \{[c_{mn}^{1L}, c_{mn}^{1U}], [c_{mn}^{2L}, c_{mn}^{2U}], \ldots, [c_{mn}^{gL}, c_{mn}^{gU}]\} \tag{9.8}$$

Then the group rough weight of c_{mn} can be computed as

$$RHN(c_{mn}) = \sum_{m=1}^{x}[c_{mn}^{L}, c_{mn}^{U}] \times [H_{n}^{eL}, H_{n}^{eU}] \tag{9.9}$$

where $RHN(c_{mn})$ is the group rough weights of c_{mn}. b_{mn}^{L} and b_{mn}^{U} are its LL and UL respectively.

Phase 3: Hierarchize healthcare services with RTOPSIS

Step 3.1: Create a crisp assessment matrix from experts' judgement

Suppose that there are x healthcare services to be examined, and g experts using ten point scale to determine the corrective activities. The decision matrix T(d) furnished by the eth expert is formulated as follows:

$$T(d) = \begin{bmatrix} b_{11}^{e} & b_{12}^{e} & \cdots & b_{1s}^{e} \\ b_{21}^{e} & b_{22}^{e} & \cdots & b_{2s}^{e} \\ \vdots & \vdots & \vdots & \vdots \\ b_{x1}^{e} & b_{x2}^{e} & \cdots & b_{xs}^{e} \end{bmatrix} \quad (d = 1, 2, \ldots, g) \qquad (9.10)$$

where $b_{mn}^{e} (m = 1, 2, \ldots, x)$ defines the mth healthcare services rating under corrective activities n ($n = 1,2, \ldots s$) provided by the eth expert.

Step 3.2: Convert the crisp values into the form of rough interval value

The rough weight of the alternatives under each corrective activity can be computed as follows:

$$RHN(b_{mn}^{e}) = [b_{mn}^{eL}, b_{mn}^{eU}] \qquad (9.11)$$

where $RHN(b_{mn}^{e})$ is the rough weights of b_{mn}^{e}. b_{mn}^{eL} and b_{mn}^{eU} are its LL and UL respectively.

Similarly we can calculate the rough weights of b_{mn} furnished by the other experts. They can develop a series of rough weights denoted as follows:

$$RHN(b_{mn}) = \{[b_{mn}^{1L}, b_{mn}^{1U}], [b_{mn}^{2L}, b_{mn}^{2U}], \ldots, [b_{mn}^{gL}, b_{mn}^{gU}]\} \qquad (9.12)$$

Then the group rough weight of b_{mn} can be determined as

$$RHN(b_{mn}) = [b_{mn}^{L}, b_{mn}^{U}] \qquad (9.13)$$

$$b_{mn}^{L} = (b_{mn}^{1L} + b_{mn}^{2L} + \cdots + b_{mn}^{gL})/g \qquad (9.14)$$

$$b_{mn}^{U} = (b_{mn}^{1U} + b_{mn}^{2U} + \cdots + b_{mn}^{gU})/g \qquad (9.15)$$

where $RHN(b_{mn})$ is the group rough weights of b_{mn}. b_{mn}^{L} and b_{mn}^{U} are its LL and UL respectively.

Step 3.3: Evaluate the rough weighted normalized matrix (RWNM)

To develop the group rough weights under various corrective activities comparable, they should be normalized as follows:

$$b'^{L}_{mn} = \frac{b^{L}_{mn}}{max^{x}_{m=1}\{max(b^{L}_{mn}, b^{U}_{mn})\}} \tag{9.16}$$

$$b'^{U}_{mn} = \frac{b^{U}_{mn}}{max^{x}_{m=1}\{max(b^{L}_{mn}, b^{U}_{mn})\}} \tag{9.17}$$

where $[b'^{L}_{mn}, b'^{U}_{mn}]$ is the normalized expression of the interval $[b^{L}_{mn}, b^{U}_{mn}]$. The normalization creates the range of rough interval values to [0,1]. Then, the weighted normalized rough weights can be obtained as

$$i^{L}_{mn} = c^{L}_{n} \times b'^{L}_{mn}\ (m = 1,2, \dots, x; n = 1,2, \dots, s) \tag{9.18}$$

$$i^{U}_{mn} = c^{U}_{n} \times b'^{U}_{mn}\ (m = 1,2, \dots, x; n = 1,2, \dots, s) \tag{9.19}$$

where Y^{L}_{mn} and Y^{U}_{mn} are the LL and UL of the weighted normalized rough weights respectively.

Step 3.4: Obtain positive ideal solution (PIS) and negative ideal solution (NIS)

The positive ideal solution (PIS) and negative ideal solution (NIS) can be obtained as follows:

$$i^{+}(n) = \{max^{x}_{m=1}\ (i^{U}_{mn}), if\ i \in V;\ min^{x}_{m=1}\ (i^{L}_{mn}), if\ i \in W\} \tag{9.20}$$

$$i^{-}(n) = \{min^{x}_{m=1}\ (i^{U}_{mn}), if\ i \in V;\ max^{x}_{m=1}\ (i^{L}_{mn}), if\ i \in W\} \tag{9.21}$$

where $i^{+}(n)$ and $i^{-}(n)$ are the nth PIS and NIS respectively. V and W are its benefit measure and cost measure respectively.

Step 3.5: Compute the Euclidean distances

The Euclidean distances of the alternatives can be evaluated based on the following expressions:

$$E^{+}_{m} = \left\{\sum_{n \in V}\left(i^{L}_{mn} - i^{+}(n)\right)^{2} + \sum_{n \in W}\left(i^{U}_{mn} - i^{-}(n)\right)^{2}\right\}^{\frac{1}{2}} \tag{9.22}$$

$$E^{-}_{m} = \left\{\sum_{n \in V}\left(i^{U}_{mn} - i^{-}(n)\right)^{2} + \sum_{n \in W}\left(i^{L}_{mn} - i^{-}(n)\right)^{2}\right\}^{\frac{1}{2}} \tag{9.23}$$

where E^{+}_{m} and E^{-}_{m} are the Euclidean distances from PIS and NIS respectively.

Step 3.6: Determine the closeness ratio and rank the alternative

The closeness ratio is computed as follows:

$$CR_{m} = \frac{E^{-}_{m}}{E^{-}_{m} + E^{+}_{m}}, m = 1,2, \dots, x \tag{9.24}$$

where CR_m is the closeness ratio of mth healthcare services. The healthcare services are hierarchized according to the decreasing order of CR_m.

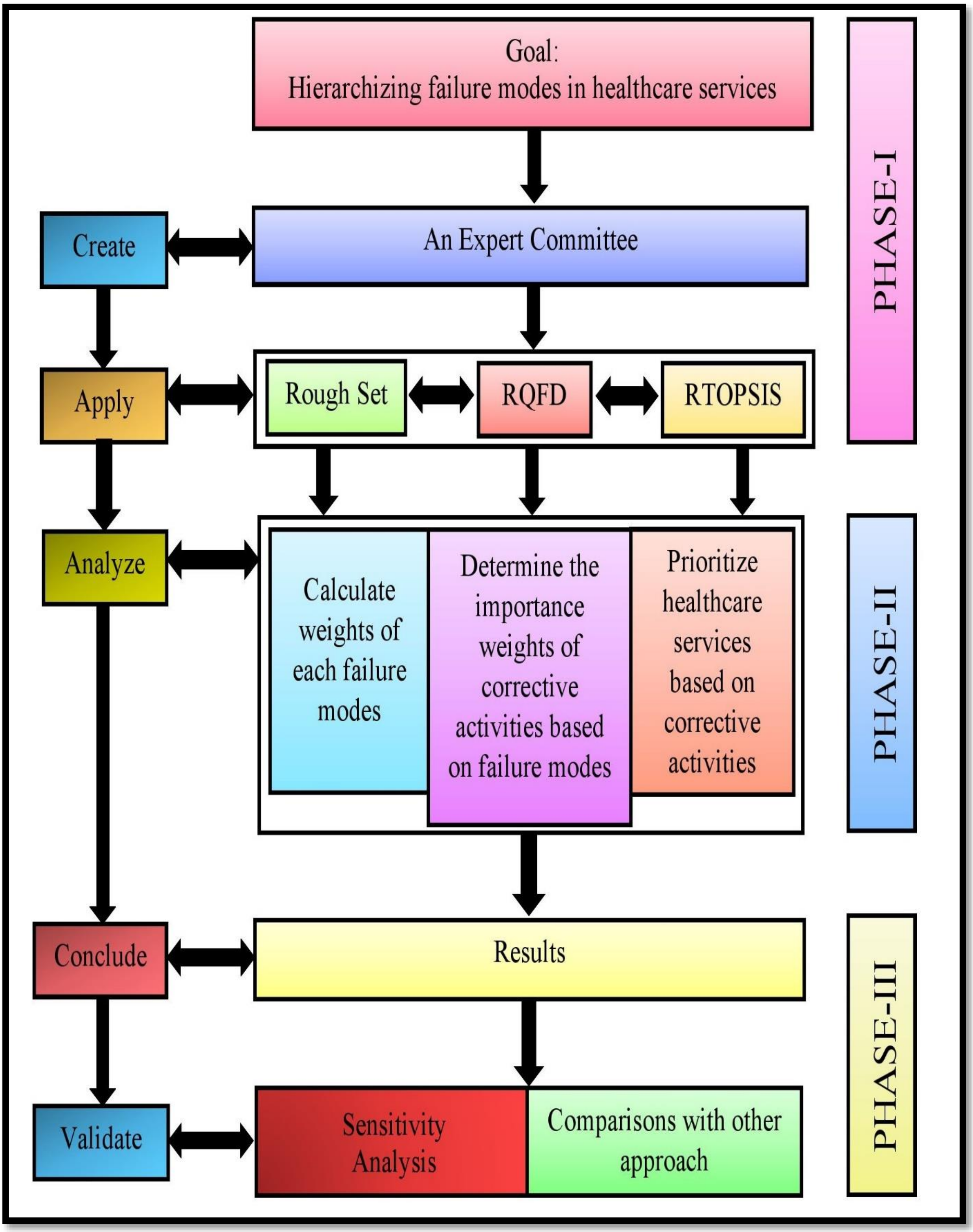


Fig. 9.2: The proposed FMEA approach

9.4 A Case Study

This section provides a detailed numerical example to demonstrate effectiveness of the proposed approach. We investigated critical failure modes of healthcare services from the literature and examined them based on corrective activities for four healthcare institutes in Kolkata, using the proposed methodology. The opinion of four distinct experts was considered.

9.4.1. Implementation of the proposed approach

Initially, six critical failure modes (FMs) were identified through literature review as shown in Table 9.1, and four relevant corrective activities (CAs) are mapped to these FMs as illustrated in Table 9.2 and Table 9.3. The expert panel, consisting of four decision makers with varying years of experience as shown in Table 9.4, provides input to evaluate the severity of FMs.

Using the expert evaluations, the rough weights of each FM are computed and normalized as shown in Table 9.5. These are incorporated into a Rough-QFD matrix to assess their impact on the four corrective activities, yielding group rough interval weights for each CA as provided in Table 9.6 and Table 9.7. These weights are further normalized to maintain consistency in scale.

Subsequently, healthcare services (HCS1–HCS4) are evaluated under each corrective activity. The experts provide scores, which are converted into normalized rough weights. Further, a normalized decision matrix as shown in Table 9.8 and weighted normalized matrix as shown in table 9.9 is constructed. The PIS and NIS are derived, followed by the calculation of Euclidean distances from these ideal points.

The final closeness coefficients are used to hierarchize the healthcare services as illustrated in Table 9.10. HCS1 emerges as the most favourable alternative with a closeness value of 0.6356, followed by HCS3, HCS2, and HCS4.

9.4.2. Results of Sensitivity Analysis

To assess the robustness and reliability of the proposed RQFD-RTOPSIS model, a sensitivity analysis is performed by introducing variations in the weights of the corrective activities (CAs). The objective is to determine whether the final ranking of healthcare services (HCSs) remains consistent under changing conditions. In this analysis, the normalized rough weights of the four corrective activities CA_1 (Staff Training and Capacity Building), CA_2 (Improved Monitoring and Reporting Mechanisms), CA_3 (Technology/Equipment Upgrade and Maintenance), and CA_4 (Communication and Process Improvement) are systematically varied within their respective intervals shown in Table 9.7. These perturbations allows the model to simulate real-world uncertainty in expert judgments or strategic shifts in healthcare focus.

The results of the sensitivity analysis are graphically represented in Figure 9.3, which illustrates the rank stability of each healthcare services (HCS1 to HCS4) under these varying conditions. Notably, HCS1 consistently retained the highest rank across all scenarios, indicating that its performance is not heavily dependent on a particular corrective activity weight. This suggests that HCS1 has a well-rounded risk mitigation strategy. On the other hand, HCS4 showed the most fluctuation in its ranking, reinforcing the observation that it is more sensitive to weight changes and thus less robust. HCS3 and HCS2 shows minor variations, occasionally switching positions but largely maintaining mid-tier ranks. This sensitivity analysis validates the resilience of the proposed model and confirms that the ranking outcomes are not overly sensitive to small deviations in input values. As such, the approach is deemed appropriate for practical healthcare decision-making under uncertainty.

9.4.3. Comparisons

To ensure the credibility and robustness of the proposed Rough-QFD and Rough-TOPSIS framework, the model is validated through a comparative analysis using several traditional MCDM approaches such as TOPSIS, MOORA, MARCOS, MABAC, ELECTRE, PROMETHEE, CODAS, and ARAS. As shown in Table 9.11, the RQFD-RTOPSIS approach aligned consistently with TOPSIS, MOORA, MARCOS, and ARAS methods. This convergence strongly supports the accuracy of the proposed model in identifying the best-performing healthcare service. HCS1 and HCS3 consistently ranks 1st and 2nd across all methods, reinforcing the ability of the model to detect competently performing services accurately. However, divergence was noted in methods like MABAC, ELECTRE, PROMETHEE, and CODAS, which altered the ranks of HCS2 and HCS4 indicating that the models are in agreement on their relative performance levels. This is also depicted graphically in Figure 9.4, reinforcing the stability and predictive strength of the proposed method.

The Rough-TOPSIS method further demonstrates an improved discrimination between alternatives due to its integration of rough interval values, which effectively capture uncertainty and imprecision in expert judgments. This provides a more nuanced and realistic assessment compared to other methods. In addition to the numerical consistency, the model highlights several key strengths of the proposed method:

a. Handling Uncertainty: By incorporating rough intervals, the model accommodates the variability and ambiguity in expert opinions, making it more robust in real-world scenarios.

b. Comprehensive Evaluation: The use of QFD ensures that both the severity of failure modes and the effectiveness of corrective activities are jointly considered, providing a more holistic assessment.

c. Enhanced Decision Support: The closeness coefficient output from Rough-TOPSIS offers clear and interpretable prioritization, aiding managerial decision-making.

Thus, the validation exercise confirms that the proposed Rough-QFD and Rough-TOPSIS model not only aligns with existing standard methods but also enhances the decision-making process by addressing their key limitations. This establishes its suitability and reliability for prioritizing healthcare service improvements in uncertain and multi-expert environments

Failure Mode (FM)
Delay in diagnosis or treatment (FM1)
Medication errors (wrong dose/type/time) (FM2)
Inadequate patient monitoring or observation (FM3)
Poor communication among healthcare professionals (FM4)
Equipment failure or unavailability (FM5)
Insufficient staff training or lack of protocol compliance (FM6)

Table 9.1: Six Critical Failure Modes (FMs)

Corrective Activity (CA)
Staff Training and Capacity Building (CA1)
Improved Monitoring and Reporting Mechanisms (CA2)
Technology/Equipment Upgrade and Maintenance (CA3)
Communication and Process Improvement (CA4)

Table 9.2: Four Corrective Activities (CAs)

Failure Mode (FM)	Corrective Activity (CA)
FM1	CA1, CA2, CA3, CA4
FM2	CA1, CA2, CA3
FM3	CA1, CA2, CA3, CA4
FM4	CA2, CA3, CA4
FM5	CA2, CA3, CA4
FM6	CA1, CA2, CA4

Table 9.3: Failure Modes Mapped to Corrective Activities (from QFD matrix)

Experts				
	E1	**E2**	**E3**	**E4**
				
Age	52	47	43	36
Designation	Quality Manager	Biomedical Engineer	Public Health Expert	Clinician
Qualification	MBA	M. Tech	Ph.D.	MBBS
Experience	20 years	10years	12years	5years

Table 9.4: Details of Expert

	Experts				Initial Weight	Normalized Weight
	E_1	**E_2**	**E_3**	**E_4**		
FM1	7	7	5	9	[6.16, 7.83]	[0.759, 0.964]
FM2	8	7	9	4	[5.71, 8.12]	[0.703, 1.000]
FM3	3	5	7	7	[4.50, 6.46]	[0.554, 0.795]
FM4	6	5	3	2	[2.96, 5.04]	[0.364, 0.621]
FM5	4	7	7	9	[5.69, 7.77]	[0.701, 0.957]
FM6	5	5	3	5	[4.12, 4.87]	[0.507, 0.610]

Table 9.5: Rough weights of individual failure mode (FM)

	Corrective activities (CA_S)															
	CA_1				**CA_2**				**CA_3**				**CA_4**			
	E_1	**E_2**	**E_3**	**E_4**	**E_1**	**E_2**	**E_3**	**E_4**	**E_1**	**E_2**	**E_3**	**E_4**	**E_1**	**E_2**	**E_3**	**E_4**
FM1	5	9	7	8	7	7	8	7	6	7	9	3	6	3	9	3
FM2	5	7	7	7	9	5	9	7	7	7	9	9	3	3	5	7
FM3	9	6	7	7	5	7	7	7	6	6	5	7	5	5	3	7
FM4	8	3	5	9	9	9	5	7	9	9	7	5	9	9	8	7
FM5	6	5	5	5	5	3	5	7	7	7	5	7	5	5	7	7
FM6	9	7	7	9	5	3	9	9	5	4	3	3	9	9	8	7

Table 9.6: QFD matrix for corrective activities (CA_S) based on experts opinion

	Corrective activities (CAs)				Weights of each failure mode (FM)
	CA_1	**CA_2**	**CA_3**	**CA_4**	
FM1	[6.25, 8.19]	[7.06, 7.44]	[4.77, 7.64]	[3.81, 6.75]	[6.16, 7.83]
FM2	[6.12, 6.87]	[6.50, 8.46]	[7.50, 8.50]	[3.54, 5.50]	[5.71, 8.12]
FM3	[6.65, 7.90]	[6.12, 6.87]	[5.58, 6.41]	[4.16, 5.83]	[4.50, 6.46]
FM4	[4.64, 7.77]	[6.50, 8.46]	[6.50, 8.46]	[7.75, 8.73]	[2.96, 5.04]
FM5	[5.06, 5.44]	[4.16, 5.83]	[6.12, 6.87]	[5.50, 6.50]	[5.69, 7.77]
FM6	[7.50, 8.50]	[5.00, 8.04]	[3.27, 4.25]	[7.75,8.73]	[4.12, 4.87]
Group rough weight of corrective activities	[177, 294]	[172, 298]	[165, 287]	[148, 272]	
Normalized rough weight of corrective activities	[0.59, 0.99]	[0.58, 1.00]	[0.55, 0.96]	[0.50, 0.91]	

Table 9.7: Group rough weights of corrective activities

	CA_1	**CA_2**	**CA_3**	**CA_4**
HCS_1	[0.723, 0,919]	[0.880, 0.998]	[0.880, 0.998]	[0.887, 0.932]
HCS_2	[0.528, 0.880]	[0.734, 0.900]	[0.723, 0,919]	[0.836, 0.924]
HCS_3	[0.601, 0.689]	[0.822, 1.000]	[0.822, 1.000]	[0.723, 0.919]
HCS_4	[0.880, 0.998]	[0.323, 0.499]	[0.646, 0.763]	[0.880, 0.998]

Table 9.8: Normalized group rough decision matrix

	CA_1	CA_2	CA_3	CA_4
HCS_1	[0.428, 0.905]	[0.506, 0.998]	[0.486, 0.959]	[0.442, 0.850]
HCS_2	[0.313, 0.867]	[0.422, 0.900]	[0.399, 0.884]	[0.416, 0.843]
HCS_3	[0.356, 0.678]	[0.473, 1.000]	[0.454, 0.962]	[0.360, 0.838]
HCS_4	[0.522, 0.982]	[0.186, 0.499]	[0.357, 0.734]	[0.438, 0.910]
PIS	0.982	1.000	0.962	0.910
NIS	0.313	0.186	0.357	0.360

Table 9.9: Weighted normalized group rough decision matrix

	HCS_1	HCS_2	HCS_3	HCS_4
D_m^+	1.005	1.376	1.328	1.767
D_m^-	1.753	1.389	1.485	1.040
CR_m	0.6356	0.5023	0.5279	0.3706
Rank	1	3	2	4

Table 9.10: The results of D_m^+, D_m^- and CR_m

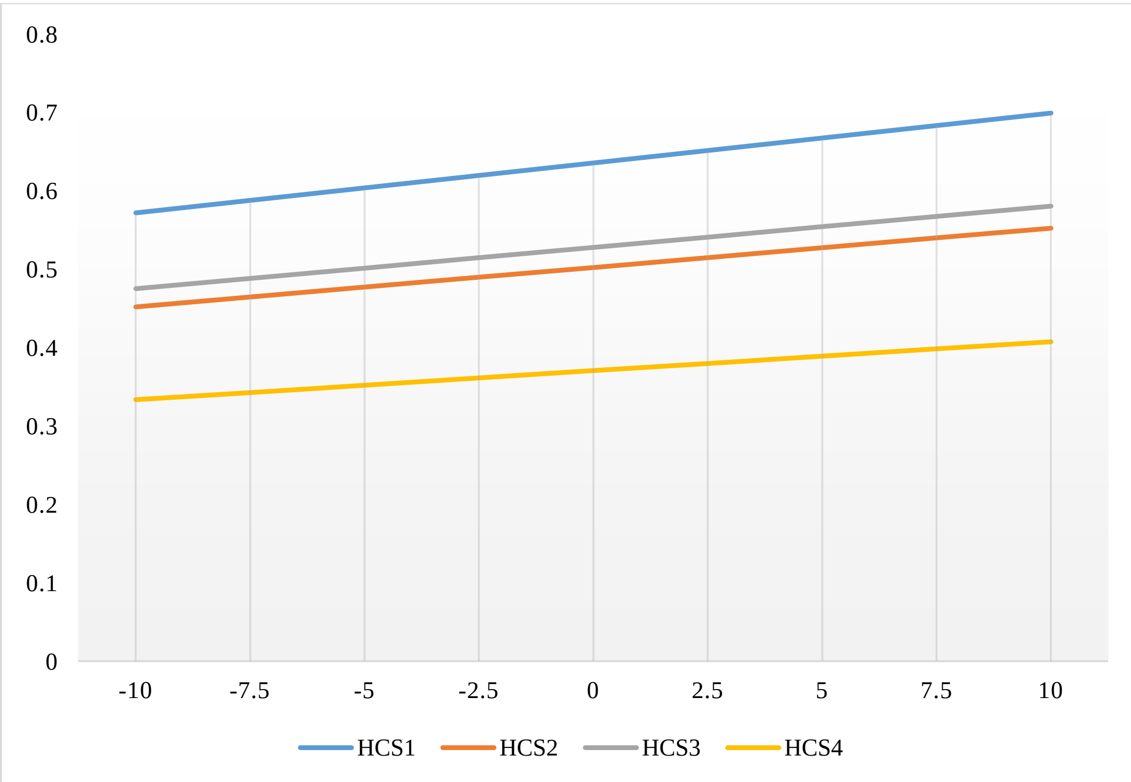


Fig. 9.3: Results of sensitivity analysis

Sl. No	Method	HCS1	HCS2	HCS3	HCS4
1	RQFD-RTOPSIS(Proposed)	1	3	2	4
2	TOPSIS	1	3	2	4
3	MOORA	1	3	2	4
4	MARCOS	1	3	2	4
5	MABAC	1	4	2	3
6	ELECTRE	1	4	2	3
7	PROMETHEE	1	4	2	3
8	CODAS	1	4	2	3
9	ARAS	1	3	2	4

Table 9.11: Comparison with other approach

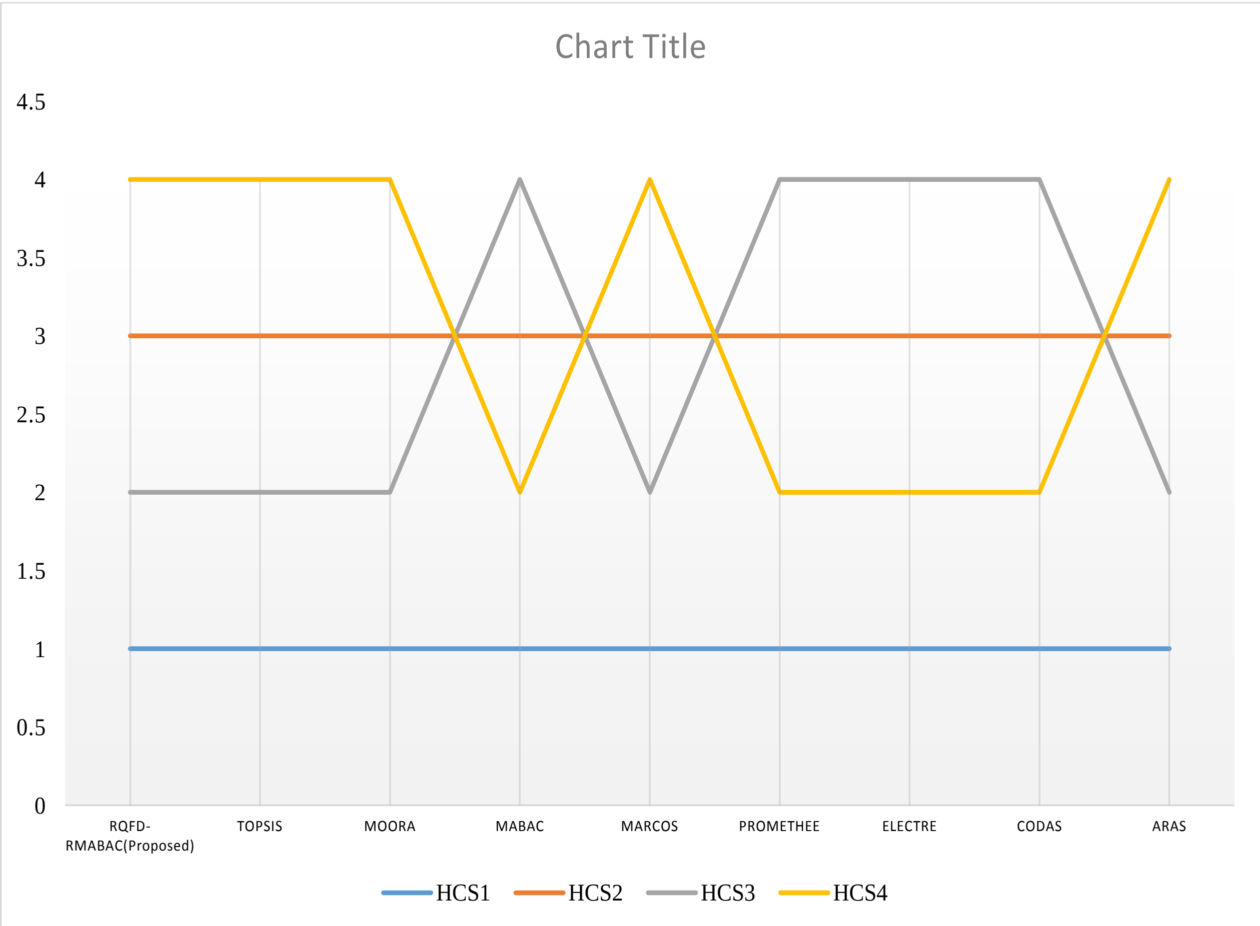


Fig. 9.4: Graphical representation of comparative analysis

9.5 Discussion

FMEA is a widely recognized forward-looking risk assessment technique that has been extensively applied across multiple industries to improve system reliability and safety. However, conventional FMEA methods have been criticized for their limitations, particularly in accurately assessing the risks associated with failure modes. These limitations necessitate the development of a more robust and comprehensive risk assessment framework.

This study presents a novel Rough-QFD and Rough-TOPSIS integrated framework for risk assessment and hierarchization of healthcare services under uncertain environments. The proposed methodology systematically incorporates expert judgments and addresses the vagueness inherent in real-world evaluations through the application of rough set theory. By integrating Quality Function Deployment (QFD) to map the relationships between identified failure modes and corresponding corrective actions, along with TOPSIS to rank healthcare services based on their closeness to the ideal solution, the proposed model offers a comprehensive and resilient framework for effective evaluation and prioritization.

The numerical example demonstrates the practicality and effectiveness of the approach, highlighting its ability to rank healthcare services based on multiple criteria and expert insights. The results demonstrate that HCS1 consistently emerges as the most robust healthcare service, even under variable corrective activity weights, as validated by sensitivity analysis.

The performance of the model aligns with conventional MCDM methods (TOPSIS, MOORA, MARCOS, ARAS), further affirming its accuracy and reliability. The approach not only supports effective risk mitigation but also improves the transparency and precision of decision-making in complex and uncertain environments.

This integrated approach empowers healthcare managers to make informed decisions about resource allocation, risk mitigation, and service improvement. The methodology proves particularly valuable in high-stakes domains like healthcare, where accurate prioritization can significantly impact patient safety and institutional performance.

The Key Contributions of this Study are

a. Utilization of Rough Set Theory: Rough set theory serves as an effective tool to address uncertainty and ambiguity in subjective evaluations. It simplifies the expression of expert judgments by allowing the use of crisp values, making the decision-making process more accessible and practical.

b. Development of an Integrated Rough QFD Model: A novel rough QFD model is introduced to objectively and systematically determine the importance weights of failure modes specific to healthcare services, enhancing analytical accuracy.

c. Hierarchical Evaluation of Healthcare Services: The developed approach enables a structured, precise, and thorough ranking of healthcare services. It mitigates the influence of ambiguity and vagueness, thus supporting well-informed and balanced decisions for risk mitigation.

d. Guidance for Healthcare Administrators: The proposed methodology equips healthcare decision-makers with a systematic framework to proactively identify potential failure points and implement timely corrective actions, thereby helping prevent iatrogenic incidents using available risk management resources.

Chapter- 10

An Integrated Framework for Fire Risk Mitigation in Hospitals

10.1 Abstract

Fire safety in healthcare facilities is crucial due to patient vulnerability, complex infrastructure, and potential for catastrophic events. This study proposes an integrated decision-support framework combining PEEST-based classification, Rough Quality Function Deployment, and the Rough-MABAC method to assess and prioritize fire risk mitigation strategies.

Fire-related failure modes were identified across Political, Environmental, Economic, Social, and Technological domains and evaluated by experts using rough intervals to account for uncertainty. These modes were linked to corrective actions via Rough-QFD, and hospital preparedness were assessed using Rough-MABAC.

Five hospitals were ranked based on their implementation levels of fire safety measures, revealing HL_3 as the most prepared and HL_2 as the least. Sensitivity analysis and validation against five other MCDM methods confirmed the robustness and reliability of the model.

The framework offers a practical-resilient tool for enhancing fire safety in hospitals and can be extended to other risk sensitive domains.

10.2 Introduction

Fire safety in healthcare facilities is a significant global concern. Hospitals are intricate systems where several risk variables intersect, including electrical systems, chemical storage, combustible materials, human behaviour, and administrative shortcomings. Hospitals have distinct fire safety issues compared to commercial or industrial buildings, especially owing to the presence of vulnerable people, including the elderly, severely sick patients, newborns, and those with limited mobility.

These communities frequently lack the ability to self-evacuate, rendering response time and readiness increasingly critical during fire-related catastrophes. Moreover, dependence on continuous energy, life-support systems, oxygen-saturated surroundings, and substantial amounts of paper and plastic materials markedly increases the risk profile of these institution.

Despite advancements in fire detection and suppression technologies, numerous incidents around the world continue to expose critical shortcomings in hospital fire preparedness. Recent fire outbreaks in high-profile hospitals in countries such as India, Brazil, and China have resulted in tragic casualties and have underscored the urgent need for a more comprehensive and proactive approach to fire risk assessment in healthcare settings. Conventional safety audits and regulatory checklists, while necessary, often fall short in capturing the multi-dimensional and uncertain nature of risk factors. These methods tend to be reactive rather than preventive and are generally not structured to accommodate the complexity and interdependence of the various elements involved.

A notable example is the tragic AMRI Hospital fire in Kolkata, which occurred in December 2011 and claimed the lives of over 90 patients, most of whom were immobile and located in the intensive care unit. Investigations reveal that fire exits were blocked, fire alarms were dysfunctional, and emergency protocols were either absent or not followed. More recently, in 2021 and 2022, smaller fire incidents have been reported in state-run and private Kolkata hospitals, raising fresh concerns about compliance with safety norms. These recurring events emphasize the persistent gaps in fire risk management, particularly in densely populated urban settings where infrastructural constraints and outdated safety systems are common.

In this context, risk assessment must evolve from static, checklist-based evaluations to dynamic, data-informed, and expert-driven decision-support systems. However, gathering quantitative data in healthcare risk assessment is frequently hindered by limited historical records, heterogeneous infrastructure, and context-specific challenges. As a result, expert judgment becomes a primary source of information. Nevertheless, expert opinions are inherently subjective, vague, and uncertain, often expressed linguistically (e.g., “high,” “moderate,” “low”) or through qualitative scales. This calls for an analytical framework that can effectively handle imprecise, ambiguous, or incomplete information without compromising on decision quality.

To overcome these challenges, this research presents a newly developed integrated risk assessment model that brings together PEEST-based categorization of failure modes, Rough Quality Function Deployment (RQFD), and the Rough Multi-Attributive Border Approximation Area Comparison (Rough-MABAC) technique.

The PEEST model enables comprehensive identification and categorization of fire-related failures across Political, Environmental, Economic, Social, and Technological domains. This ensures that both internal and external systemic factors are considered in the risk modelling process. The identified failure modes were then mapped to corrective actions using the Rough-QFD technique, which captures the strength of relationships between risks and mitigation strategies while incorporating the uncertainty present in expert evaluations through rough set theory.

The decision-making phase employs the Rough-MABAC method, an advancement over classical MCDM techniques, which integrates rough numbers into the ranking process. This method calculates the deviation of each hospital performance from a theoretical border approximation area (BAA), thus enabling a granular, multi-criteria ranking of alternatives even under uncertain conditions.

Compared to conventional MCDM methods like TOPSIS or VIKOR, Rough-MABAC offers a simpler computational structure while maintaining high interpretability and decision transparency.

The proposed framework is applied to a case study involving five hospitals, where ten critical fire failure modes are evaluated and linked to six key corrective actions. Expert input is collected for both failure importance and action implementation levels, and the final ranking highlights the hospitals that are better prepared and those that require urgent attention. The study further strengthens the reliability of the proposed model through sensitivity analysis, which shows consistent hospital rankings even when the weights of corrective actions are slightly varied. Additionally, a comparative validation with five other rough and fuzzy MCDM techniques demonstrates strong rank correlation, reinforcing the robustness and credibility of the model.

This study makes several novel contributions. It is one of the first to integrate PEEST, Rough-QFD, and Rough-MABAC into a unified framework for hospital fire safety. It captures uncertainty at multiple levels of decision-making and provides a structured, expert-informed prioritization of risks and corrective actions. Moreover, the framework is not limited to fire safety alone, it offers flexibility for adaptation to other healthcare risk domains such as biomedical equipment reliability, infection control, waste management, and emergency preparedness. It also aligns with global quality management principles, including Six Sigma and ISO 45001:2018, and can serve as a foundational tool for risk-based thinking in hospital operations.

In summary, the proposed framework addresses a critical gap in current healthcare risk assessment practices by offering a transparent, structured, and a resilient approach for evaluating and mitigating fire risks. It supports decision-makers in allocating resources, planning interventions, and enhancing compliance with regulatory standards in a proactive manner. Given its methodological rigor and practical relevance, the model holds significant potential for widespread application and future research extension in both public and private healthcare systems.

10.3 Research Methodology

This study introduces an integrated risk assessment framework combining PEEST-based failure identification, Rough Quality Function Deployment (RQFD), and the Rough MABAC method to evaluate and prioritize fire mitigation strategies in healthcare services. The proposed model addresses uncertainty in expert judgment and enables multi-criteria decision-making through a rough set extension of the MABAC technique. The procedural steps of the proposed method is illustrated below. A framework of the methodology is shown in Fig. 10.1.

Step 1: PEEST-Based Classification of Fire Failures

To identify critical fire-related risks in hospitals, failure modes were categorized using the PEEST (Political, Environmental, Economic, Social, Technological) framework. This classification ensures a holistic understanding of the root causes of fire hazards.

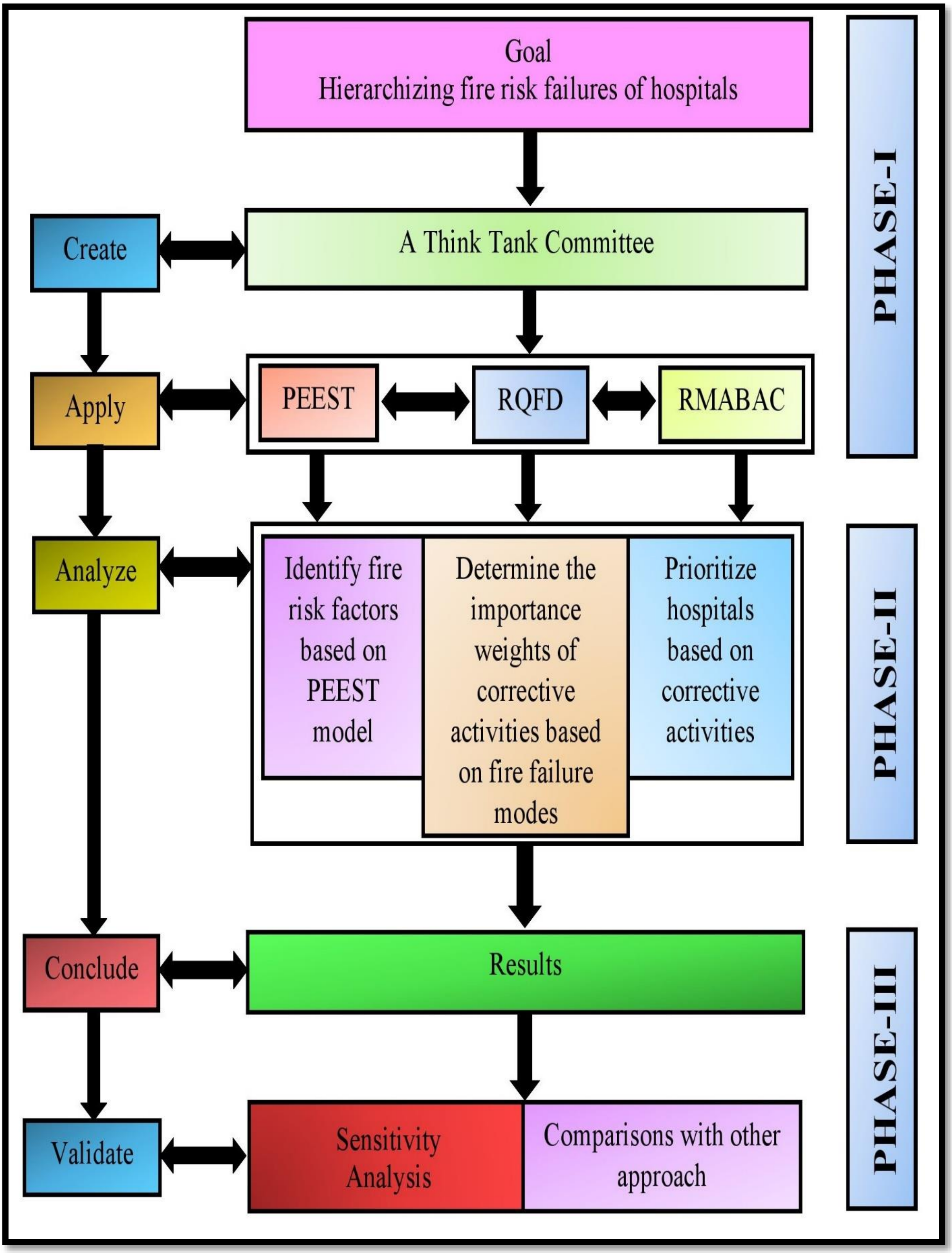


Fig 10.1: The research framework

Step 2: Expert-Based Evaluation and Rough Weighting of Failures

After identifying the fire failures, a panel of four fire safety and healthcare management experts assessed the severity of each identified failure. These assessments were converted into rough intervals, reflecting the range of expert opinions. This process captures both the average impact and the uncertainty of each fire failure, with severity weights represented as rough numbers. The assessment of the factor weights is denoted as follows:

$$H_n = \left[H_n^1, H_n^2, \cdots, H_n^e, \cdots, H_n^g\right](n = severity) \tag{10.1}$$

Where H_n is the rating of the nth fire failure measured by the eth expert, g is the number of experts.

First, based on the basic concepts of RST, the group rough interval weights of each fire failure is computed by

$$RHN(H_n^e) = [H_n^{eL}, H_n^{eU}] \tag{10.2}$$

where H_n^{eL} and H_n^{eU} are the Lower Limit(LL) and Upper Limit(UL) respectively.

Second, the group rough interval weights can be estimated as

$$H_n^L = \left(H_n^{1L} + H_n^{2L} + \cdots + H_n^{gL}\right)/g \tag{10.3}$$

$$H_n^U = \left(H_n^{1U} + H_n^{2U} + \cdots + H_n^{gU}\right)/g \tag{10.4}$$

where H_n^L and H_n^U are the LL and UL of the group rough weights respectively. The group rough interval weights is denoted as $\overline{RHN(H_n)} = = [H_n^L, H_n^U]$. Then, the normalized rough weights of fire failures are calculated as follows:

$$AH_n^L = \frac{H_n^L}{max_n(H_n^L, H_n^U)} \tag{10.5}$$

$$AH_n^U = \frac{H_n^U}{max_n(H_n^L, H_n^U)} \tag{10.6}$$

where AH_n^L and AH_n^U are the LL and UL of the normalized weights respectively.

Step 3: Rough-QFD Mapping to determine group rough weights of Corrective Activities (CA)

A rough relationship matrix is formulated by experts using Saaty's nine point scale to determine the weights of CAs for each fire failure. Fig. 1 show a framework for R-QFD.

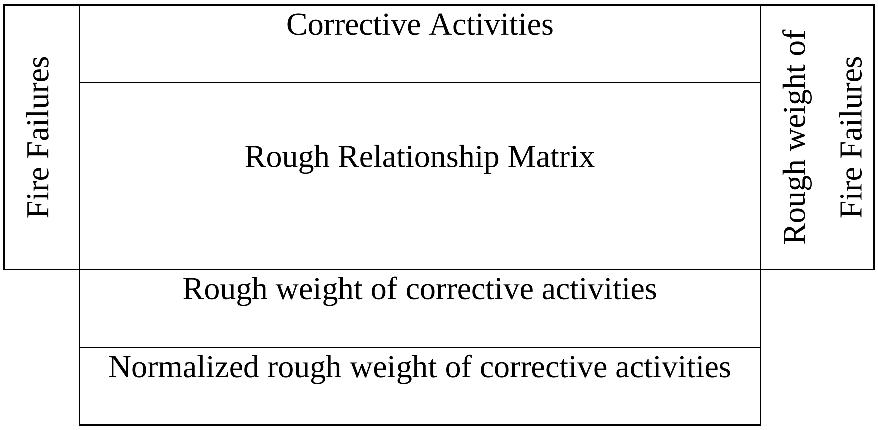


Fig 10.2: RQFD Framework

The next phase involves mapping CAs to the failure modes using the RQFD technique. Experts evaluate the strength of relationships between each CA and the corresponding failures. The aggregation of these ratings yields group rough weights for each CA which indicate their relative contribution to mitigating fire-related risks. The rough weight of the CA under each fire failure can be calculated as follows:

$$RHN(c_{mn}^{e}) = [c_{mn}^{eL}, c_{mn}^{eU}] \tag{10.7}$$

where $RHN(c_{mn}^{e})$ is the rough weights of c_{mn}^{e}. c_{mn}^{eL} and c_{mn}^{eU} are its LL and UL respectively.

Similarly we can evaluate the rough weights of c_{mn} provided by the other experts. They can establish a series of rough weights denoted as follows:

$$RHN(c_{mn}) = \{[c_{mn}^{1L}, c_{mn}^{1U}], [c_{mn}^{2L}, c_{mn}^{2U}], \dots, [c_{mn}^{gL}, c_{mn}^{gU}]\} \tag{10.8}$$

Then the group rough weight of c_{mn} can be computed as

$$RHN(c_{mn}) = \sum_{m=1}^{x} [c_{mn}^{L}, c_{mn}^{U}] \times [H_{n}^{eL}, H_{n}^{eU}] \tag{10.9}$$

where $RHN(c_{mn})$ is the group rough weights of c_{mn}. b_{mn}^{L} and b_{mn}^{U} are its LL and UL respectively.

Step 4: Rough-MABAC to hierarchize hospitals

Suppose that there are x hospitals to be examined, and g experts using Saaty's nine point scale to determine the corrective activities. The decision matrix T(d) furnished by the eth expert is formulated as follows:

$$T(d) = \begin{bmatrix} b_{11}^e & b_{12}^e & \cdots & b_{1s}^e \\ b_{21}^e & b_{22}^e & \cdots & b_{2s}^e \\ \vdots & \vdots & \vdots & \vdots \\ b_{x1}^e & b_{x2}^e & \cdots & b_{xs}^e \end{bmatrix} \quad (d = 1, 2, \ldots, g) \tag{10.10}$$

where $b_{mn}^e (m = 1, 2, \ldots, x)$ defines the mth hospital rating under corrective activity n ($n = 1, 2, \ldots s$) provided by the eth expert. The rough weight of the hospitals under each corrective activity can be computed as follows:

$$RHN(b_{mn}^e) = [b_{mn}^{eL}, b_{mn}^{eU}] \tag{10.11}$$

where $RHN(b_{mn}^e)$ is the rough weights of b_{mn}^e. b_{mn}^{eL} and b_{mn}^{eU} are its LL and UL respectively.

Similarly we can calculate the rough weights of b_{mn} furnished by the other experts. They can develop a series of rough weights denoted as follows:

$$RHN(b_{mn}) = \{[b_{mn}^{1L}, b_{mn}^{1U}], [b_{mn}^{2L}, b_{mn}^{2U}], \ldots, [b_{mn}^{gL}, b_{mn}^{gU}]\} \tag{10.12}$$

Then the group rough weight of b_{mn} can be determined as

$$RHN(b_{mn}) = [b_{mn}^L, b_{mn}^U] \tag{10.13}$$

$$b_{mn}^L = \left(b_{mn}^{1L} + b_{mn}^{2L} + \cdots + b_{mn}^{gL}\right)/g \tag{10.14}$$

$$b_{mn}^U = \left(b_{mn}^{1U} + b_{mn}^{2U} + \cdots + b_{mn}^{gU}\right)/g \tag{10.15}$$

where $RHN(b_{mn})$ is the group rough weights of b_{mn}. b_{mn}^L and b_{mn}^U are its LL and UL respectively. In order to ensure comparability of group rough weights across different corrective actions, a normalization process must be applied as outlined below:

For higher the better criteria,

$$[p_{mn}^L, p_{mn}^H] = \left[\frac{b_{mn}^L - b_n^-}{b_n^+ - b_n^-}, \frac{b_{mn}^U - b_n^-}{b_n^+ - b_n^-}\right] \tag{10.16}$$

For lower the better criteria,

$$[p_{mn}^L, p_{mn}^H] = \left[\frac{b_{mn}^L - b_n^+}{b_n^- - b_n^+}, \frac{b_{mn}^U - b_n^+}{b_n^- - b_n^+}\right] \tag{10.17}$$

where$[p_{mn}^L, p_{mn}^U]$ is the normalized expression of the interval $[b_{mn}^L, b_{mn}^U]$. The normalization creates the range of rough interval values to [0,1]. Then, the weighted normalized rough weights can be obtained as

$$Y_{mn}^L = AH_n^L\,(1 + p_{mn}^L)\ (m = 1,2, \dots, x; n = 1,2, \dots, s) \tag{10.18}$$

$$Y_{mn}^U = AH_n^U\,(1 + p_{mn}^U)\ (m = 1,2, \dots, x; n = 1,2, \dots, s) \tag{10.19}$$

where Y_{mn}^L and Y_{mn}^U are the LL and UL of the weighted normalized rough weights respectively. The border approximation area (BAA) can be obtained as follows:

$$i_n^L = \left(\prod\nolimits_{m=1}^{x} Y_{mn}^L\right)^{\frac{1}{x}} \tag{10.20}$$

$$i_n^U = \left(\prod\nolimits_{m=1}^{x} Y_{mn}^U\right)^{\frac{1}{x}} \tag{10.21}$$

where i_n^L and i_n^U are the lower BAA and upper BAA respectively. The Euclidean distance of each alternative from the Border Approximation Area (BAA) can be calculated using the following formula:

For higher-the-better criteria,

$$Z_E(Y_{mn}, i_n) = [(Y_{mn}^L - i_n^U)^2 + (Y_{mn}^U - i_n^L)^2]^{\frac{1}{2}} \tag{10.22}$$

For lower-the-better criteria,

$$Z_E(Y_{mn}, i_n) = [(Y_{mn}^L - i_n^L)^2 + (Y_{mn}^U - i_n^U)^2]^{\frac{1}{2}} \tag{10.23}$$

where E_m^+ and E_m^- are the Euclidean distances from PIS and NIS respectively considering the following conditions:

For higher-the-better criteria,

$$k_{mn} = \begin{Bmatrix} Z_E(Y_{mn}, i_n), if\ RHN(Y_{mn}) > RHN(i_n) \\ -Z_E(Y_{mn}, i_n), if\ RHN(Y_{mn}) < RHN(i_n) \end{Bmatrix} \tag{10.24}$$

For lower-the-better criteria,

$$k_{mn} = \begin{Bmatrix} -Z_E(Y_{mn}, i_n), if\ RHN(Y_{mn}) > RHN(i_n) \\ Z_E(Y_{mn}, i_n), if\ RHN(Y_{mn}) < RHN(i_n) \end{Bmatrix} \tag{10.25}$$

The overall score is computed as follows:

$$OS_m = \sum_{n=1}^{x} k_{mn} \ (m = 1,2, \dots, x; n = 1,2, \dots, s) \qquad (10.26)$$

where OS_m is the overall score of mth hospital. The alternatives are sorted and ranked in ascending order based on their corresponding output scores OS_m.

10.4 A Case Study

Fire safety in healthcare environments is critical, especially given the complexity of hospital infrastructure and the vulnerability of patients. This case study presents a structured decision-making framework that integrates expert opinion with Rough Set Theory to hierarchize hospitals based on their fire mitigation readiness. The method employs the PEEST classification for risk identification, Rough Quality Function Deployment (RQFD) for corrective activity mapping, and Rough-MABAC for hospital ranking.

10.4.1. Details of the Experts Involved

To ensure reliability and domain relevance in the expert evaluations, a panel of four subject matter experts with diverse yet complementary backgrounds in healthcare infrastructure, fire safety engineering, and hospital operations was constituted. Their qualifications, designations, and experience are summarized below:

Experts	Age	Designation	Qualification	Experience
E1	47	Fire Safety Officer, State Fire Services	B.Tech in Fire & Safety Engineering	22 years in fire risk audits for public infrastructure, including hospitals
E2	52	Senior Hospital Administrator, Government Medical College	MBBS, MBA (Hospital Management)	27 years in hospital operations and emergency preparedness
E3	39	Safety and Compliance Consultant, Private Healthcare Chain	M.Tech in Safety Engineering, NEBOSH Certified	15 years in healthcare safety compliance and infrastructure assessment
E4	44	Biomedical Engineer and Maintenance Head, Multi-Specialty Hospital	B.E. in Biomedical Engineering, PGD in Facilities Management	18 years in hospital equipment safety, maintenance scheduling, and risk mitigation

Table 10.1: A Think Tank

These experts were selected to cover both technical (fire and safety engineering, biomedical systems**)** and managerial (administrative and operational) perspectives. Their combined knowledge ensured that the failure modes, corrective activities, and prioritization criteria were both practically grounded and technically sound.

10.4.2. Data Acquisition

An expert panel comprising four professionals' two fire safety officers and two hospital administrators were assembled. Their task is to evaluate fire failure scenarios and the relevance of corrective strategies across five hospitals i.e. HL_1 to HL_5. Assessments were conducted using Saaty's nine-point scale and translated into rough intervals to accommodate subjective uncertainty.

10.4.3. Identification and Evaluation of Fire Failures

Ten fire failure modes as illustrated in Table 10.2 were identified and classified under the PEEST (Political, Environmental, Economic, Social, Technological) framework. As shown in Table 10.3, failure modes such as failure of fire detection systems (FF-9) and storage of flammable chemicals near heat sources (FF-3) received high rough severity weights of [8.56,8.94] and [8.25,8.75] respectively, indicating their criticality.

Factors	FF Code	Fire Failure	Description
Political Factors (P)	FF-1	Weak enforcement of fire safety regulations	Inadequate policy enforcement or regulatory inspections
	FF-2	Lack of government funding/support	Limited support for upgrading fire safety infrastructure
Environmental Factors (E)	FF-3	Storage of flammable chemicals near heat sources	Improper storage increases fire hazards
	FF-4	Poor ventilation in critical zones	Lack of airflow promotes smoke accumulation in case of fire

Factors	FF Code	Fire Failure	Description
Economic Factors (E)	FF-5	Underinvestment in fire safety equipment	Hospitals may skip essential safety devices due to cost
	FF-6	Cost-cutting in electrical maintenance	Reduced frequency of inspections and repairs
Social Factors (S)	FF-7	Low fire safety awareness among staff and patients	Lack of training and drills
	FF-8	Language barriers in emergency instructions	Non-local patients/staff may not understand signage or protocols
Technological Factors (T)	FF-9	Failure of fire detection/alarm systems	Outdated or non-functioning detection systems
	FF-10	Overuse of electrical equipment beyond rated capacity	Leading to overheating and potential ignition

Table 10.2: Critical Fire Failures (FFs) classified under PEEST Factors

Fire Failures	Think Tank				Initial Weight
	E_1	E_2	E_3	E_4	
FF-1	7	8	8	8	[7.56,7.94]
FF-2	8	8	8	9	[8.06,8.44]
FF-3	9	8	8	9	[8.25,8.75]
FF-4	8	7	7	8	[7.25,7.75]
FF-5	7	7	7	8	[7.06,7.44]
FF-6	7	6	6	7	[6.25,6.75]
FF-7	6	7	7	7	[6.56,6.94]
FF-8	5	6	5	7	[5.27,6.25]
FF-9	9	9	8	9	[8.56,8.94]
FF-10	6	5	6	6	[5.56,5.94]

Table 10.3: Weight calculation of individual fire failure (FF) based on experts opinion

10.4.4. Mapping of Corrective Activities via Rough-QFD

Six corrective activities (CAs) were proposed, including enforcement audits (CA_1), modern fire detection systems (CA_2), multilingual fire drills (CA_3), proper material storage (CA_4), preventive electrical maintenance (CA_5), and improved ventilation (CA_6). Experts linked these activities to the identified failures. The aggregated group rough weights of the CAs in Table 10.4 reveals CA_1 and CA_2 as the most impactful strategies with normalized weights of [0.892,1.000] and [0.862,0.962] respectively.

Corrective Activities(CA_s)	**Group Rough Weight**	**Normalized Rough Weight**
CA_1	[225.11, 252.27]	[0.892, 1.000]
CA_2	[217.49, 242.59]	[0.862, 0.962]
CA_3	[90.080, 105.07]	[0.357, 0.416]
CA_4	[66.490, 73.850]	[0.263, 0.293]
CA_5	[116.12, 158.99]	[0.460, 0.511]
CA_6	[65.250, 69.750]	[0.259, 0.276]

Table 10.4: Rough weights of corrective activities (CA_S) for each failure modes

10.4.5. Hospital Evaluation Using Rough-MABAC

Hospitals were evaluated based on expert ratings of each CA_s, as summarized in Table 10.5. These ratings were processed into an initial rough decision matrix as shown in Table 10.6 and then normalized and weighted as illustrated in Table 10.7. The distances of each hospital from the BAA were computed using the Rough-MABAC technique.

The final scores and rankings are presented in Table 10.8. Hospital HL_3 is ranked highest, showing exceptional readiness, particularly in CA_2 and CA_5. HL_5 followed closely, while HL_2 ranks the lowest due to significant underperformance in CA_4 and CA_6, suggesting deficiencies in ventilation and hazardous material protocols.

Hospitals	Experts	CA_1	CA_2	CA_3	CA_4	CA_5	CA_6
HL_1	E_1	8	7	6	7	6	7
	E_2	7	7	6	7	7	6
	E_3	7	6	6	7	7	7
	E_4	7	6	6	8	6	7
HL_2	E_1	7	7	6	6	7	6
	E_2	6	6	5	6	6	5
	E_3	7	6	5	6	5	6
	E_4	6	6	5	5	5	6
HL_3	E_1	7	9	6	9	7	8
	E_2	7	7	7	8	8	8
	E_3	7	7	6	8	7	8
	E_4	7	7	7	8	7	7
HL_4	E_1	8	7	7	8	7	7
	E_2	7	7	6	7	5	7
	E_3	7	7	6	8	7	6
	E_4	7	7	7	7	7	7
HL_5	E_1	7	8	7	8	7	6
	E_2	7	7	7	8	7	7
	E_3	7	7	7	8	7	8
	E_4	5	7	6	8	5	7

Table 10.5: Think Tank opinion on corrective activities (CA_s) for each hospitals (HL_i)

	HL_1	HL_2	HL_3	HL_4	HL_5
CA_1	[7.06, 7.44]	[6.25, 6.75]	[7.00, 7.00]	[7.06, 7.44]	[6.13, 6.88]
CA_2	[6.25, 6.75]	[6.06, 6.44]	[7.13, 7.88]	[7.00, 7.00]	[7.06, 7.44]
CA_3	[6.00, 6.00]	[5.06, 5.44]	[6.25, 6.75]	[6.25, 6.75]	[6.56, 6.94]
CA_4	[7.06, 7.44]	[5.56, 5.94]	[8.06, 8.44]	[7.25, 7.75]	[8.00, 8.00]
CA_5	[6.25, 6.75]	[5.27, 6.25]	[7.06, 7.44]	[6.13, 6.88]	[6.13, 6.88]
CA_6	[6.56, 6.94]	[5.56, 5.94]	[7.06, 7.44]	[6.56, 6.94]	[6.65, 6.94]

Table 10.6: Initial rough decision matrix

	HL_1	HL_2	HL_3	HL_4	HL_5
CA_1	[1.53, 2.00]	[0.97, 1.47]	[1.48, 1.66]	[1.53, 2.00]	[0.89, 1.57]
CA_2	[0.95, 1.30]	[0.86, 1.16]	[1.37, 1.92]	[1.31, 1.46]	[1.34, 1.69]
CA_3	[0.54, 0.60]	[0.36, 0.50]	[0.58, 0.79]	[0.58, 0.79]	[0.64, 0.83]
CA_4	[0.40, 0.50]	[0.26, 0.33]	[0.49, 0.59]	[0.42, 0.52]	[0.49, 0.54]
CA_5	[0.67, 0.90]	[0.46, 0.74]	[0.84, 1.02]	[0.64, 0.89]	[0.64, 0.89]
CA_6	[0.40, 0.50]	[0.26, 0.33]	[0.47, 0.55]	[0.40, 0.48]	[0.40, 0.48]

Table 10.7: Weighted normalised rough decision matrix

	HL_1	HL_2	HL_3	HL_4	HL_5
CA_1	1.425498	1.653827	1.673112	1.425498	1.539751
CA_2	0.576568	0.558493	1.079095	0.915006	0.970221
CA_3	0.792391	0.583344	0.950837	0.950837	1.020136
CA_4	0.622704	0.417865	0.759331	0.658086	0.721986
CA_5	0.994912	0.774717	1.230243	1.002421	1.002421
CA_6	0.617622	0.416818	0.718133	0.617622	0.617622
Overall Score	5.029696	4.405064	6.410751	5.56947	5.872137
Rank	4	5	1	3	2

Table 10.8: Distances from BAA, overall score and ranking

10.4.6. Comparison with other approach

To validate the the effectiveness of the proposed method, the hospital rankings were compared with the results from five other established MCDM techniques i.e. Rough-TOPSIS, Rough-VIKOR, Rough-CODAS, Fuzzy-PROMETHEE, and Fuzzy-MARCOS using the same dataset. The comparative ranks are summarized in Table 10.9.

	Proposed method	**Rough-TOPSIS**	**Rough-VIKOR**	**Rough-CODAS**	**Fuzzy-PROMETHEE**	**Fuzzy-MARCOS**
HL_1	4	4	4	4	3	3
HL_2	5	5	5	5	5	5
HL_3	1	1	1	1	1	1
HL_4	3	3	3	3	4	4
HL_5	2	2	2	2	2	2

Table 10.9: Ranking comparisons with other rough and fuzzy approach

A comparative analysis shows a perfect agreement on the best-performing hospital (HL_3) and worst-performing hospital (HL_2) across all six methods. A minor discrepancy exists in the mid-rankings i.e. HL_1 vs. HL_4 in PROMETHEE and MARCOS, which is anticipated due to their operational methodologies.

Rough and fuzzy methodologies converge, significantly reinforcing the robustness of the proposed technique. This comparison demonstrates that the proposed strategy consistently yields steady and reliable outcomes.

The best and worst performers remain consistent, proving that the suggested method for measuring healthcare fire risk is methodologically robust and successful.

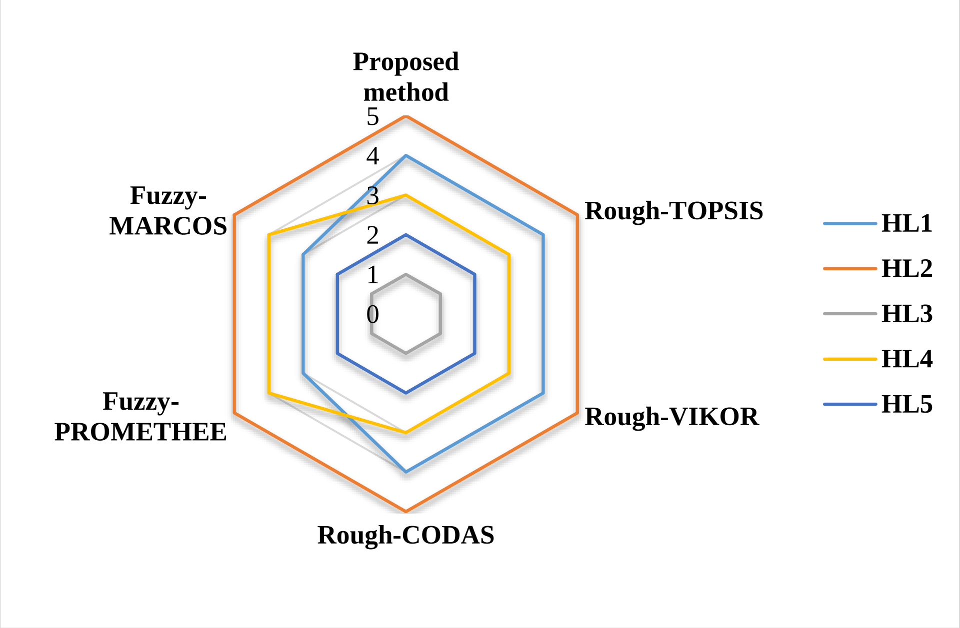


Fig. 10.3: Radar chart of five hospitals

Figure 10.3 displays a radar chart to enhance effectiveness of hospitals in adapting substantial corrective actions (CA_s). The figure delineate five hospitals with each axis describing important corrective actions (CA_s). Hospital HL_3 constantly surpasses other hospitals in advanced detection system (CA_2), hazardous material management (CA_4) and electrical maintenance (CA_5). Conversely, HL_2 has least variations in training (CA_3) and ventilation (CA_6) highlighting inefficient preparedness. The figure corroborates the data and provide insights for strategic development.

10.4.7. Robustness Assessment: Sensitivity Analysis

To evaluate the robustness of the proposed model, a sensitivity analysis was performed by adjusting the rough weights assigned to each corrective measure. This analysis was designed to examine how small variations in the importance of criteria influence the final ranking of hospitals. The findings, presented in Table 10.10, indicate that the hospital rankings remained consistently stable across all tested scenarios. Specifically, HL_3 consistently secured the highest rank, while HL_2 remained at the lowest position. These results demonstrate that the model is resilient to minor changes in expert judgments and weighting, underscoring its reliability as a robust decision-making tool under uncertain conditions.

Hospital	Original Score	+5% Variation	−5% Variation	Rank Stability
HL_3	6.4108	6.72	6.12	Stable
HL_5	5.8721	6.11	5.58	Stable
HL_4	5.5695	5.79	5.28	Stable
HL_1	5.0297	5.29	4.77	Stable
HL_2	4.4051	4.63	4.14	Stable

Table 10.10: Sensitivity analysis result

This analysis verifies that the proposed framework remains stable and reliable even when subjected to moderate variations in expert evaluations.

10.4.8. Pareto Analysis

To identify the most critical hospitals contributing to fire preparedness improvements using the Pareto principle (80/20 rule). Hospital fire safety scores from the Rough-MABAC evaluation were sorted in descending order. Cumulative percentages were utilized to illustrate the contribution of each hospital to total readiness. The results reveals that about 80% of fire safety preparedness relies in HL_3, HL_5, and HL_4 hospitals as shown in Figure 10.4.

Hospital HL_3 makes the most significant contribution followed by hospital HL_5 for efficient fire fighting measures. Hospital HL_2 enlists at the bottom, exerts the minimal influence and requires support. The Pareto principle adheres to make improvements to HL_2 while following best practices from HL_3 and HL_5 to reduce fire risks which suggests that concentrating on the most essential components offers the maximum benefits.

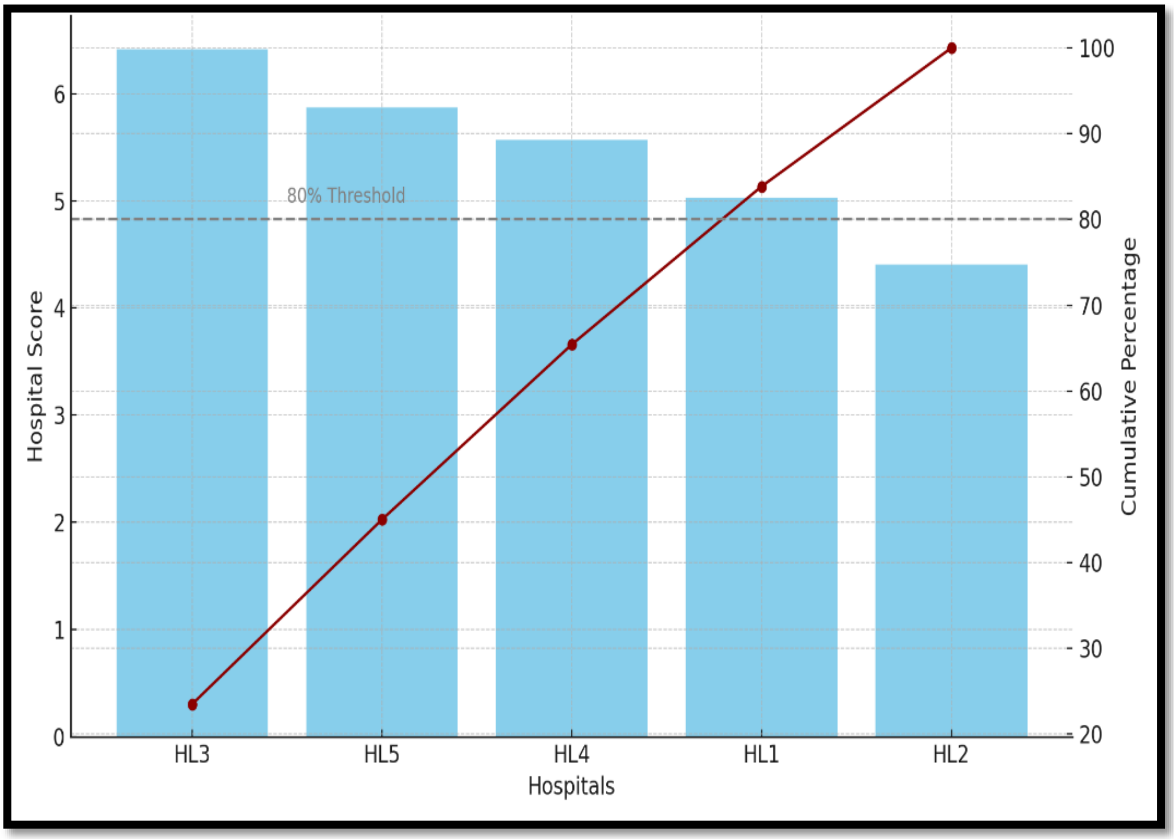


Fig 10.4: Pareto chart of hospital prepardness

10.4.9. Dendrogram-Based Cluster Analysis

The weighted normalized rough decision matrix of hospitals in Table 10.6 is used for hierarchical clustering using Rough- MABAC ranking. The Ward linkage approach uses Euclidean distances across hospitals to create the dendrogram for six corrective activities i.e. CA_1 to CA_6 as shown in Figure 10.5. In contemporary detecting systems (CA_2) and preventive electrical maintenance (CA_5), HL_3 and HL_5 are close and well-equipped for fires. According to Rough-MABAC rankings, HL_2 is the least equipped hospital due to its significant differences. HL_1 and HL_4 are separate. This suggests moderate preparation and similar CA_1 and CA_3 strengths.

This dendrogram illustrates the robustness of the ranking methodology by clustering hospitals with analogous fire safety records. The clustering structure aligns well with the outcomes of the Rough-MABAC analysis and highlights HL_3 as a benchmark and HL_2 as an outlier requiring urgent improvements.

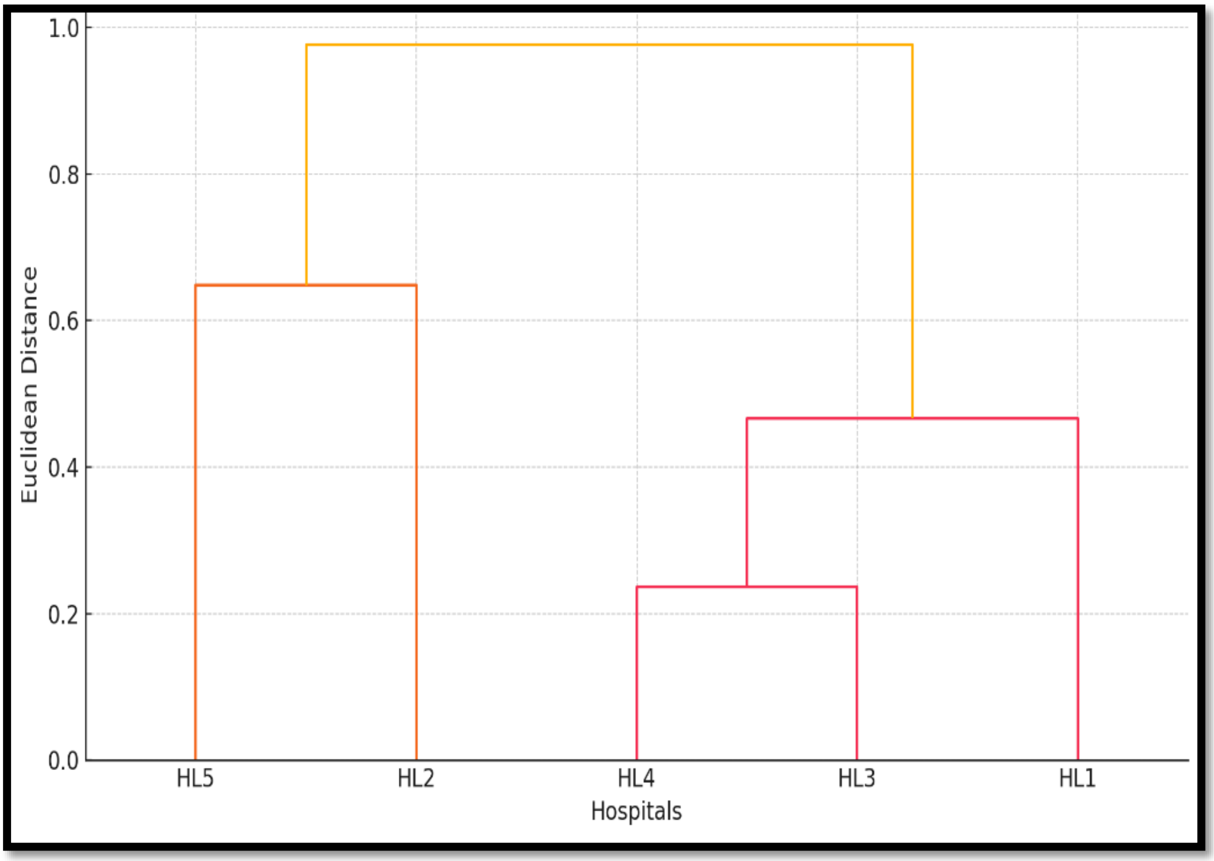


Fig.10.5: Dendrogram for cluster based visualization of hospitals

10.5 Discussion

Fire incidents at healthcare institutions represent a considerable risk owing to the existence of susceptible patient demographics, intricate architecture, and a critical reliance on continuous electricity and life-support systems. Frequent failures encompass defective fire detection or suppression systems, incorrect storage of combustible materials, overloaded electrical circuits, insufficient ventilation, and inadequate staff training. These problems are frequently intensified by inadequate regulatory enforcement, financial limitations, and operational oversights. Emergency protocols are frequently non-existent, antiquated, or inadequately communicated, particularly in multilingual and densely populated settings. The repercussions of such failures can be disastrous, resulting in fatalities, damage to essential infrastructure, and enduring reputational damage. A methodical, proactive, and uncertainty-resilient strategy is crucial for evaluating fire risk and directing remedial measures in hospitals.

This study introduces a robust decision-support framework that incorporates PEEST-based failure identification, Rough-QFD strategy mapping, and Rough-MABAC ranking to assess hospital fire preparation. The framework adeptly manages ambiguity in expert assessments and offers a systematic approach to choose fire mitigation options. The application to five hospitals reveals considerable disparities in readiness levels, with HL_3 recognised as the standard and HL_2 as the most vulnerable institution.

Sensitivity and comparison evaluations validate the resilience and dependability of the model. The suggested solution provides hospital administrators with a practical, data-driven strategy to improve fire safety planning by delivering accurate risk-to-action mapping, consistent rankings, and visual insights using Pareto and clustering tools. Furthermore, the adaptability of this framework facilitates wider implementation across many healthcare risk areas, enhancing institutional resilience and patient safety.

The Key Contributions of this Study are

1. This study proposes an integrated decision-support framework combining PEEST model, rough-QFD, and rough-MABAC to assess hospital fire safety in uncertain environment.

2. The method utilizes rough set theory to gather expert opinion variation and transform qualitative opinions into structured, interval-based inputs.

3. The methodology shapes fire failure hazards to corrective actions, supervising decision-makers to select intrusions based on risk outcome.

4. Hospital rankings remain consistent over five MCDM approaches and ±5% variation in criteria weights, demonstrates the robustness of the proposed approach.

5. The model identifies top-performing and failing hospitals, facilitates Pareto-based prioritization, and allows cluster-based benchmarking for strategic fire safety planning.

Chapter- 11

A Fastidious Approach For Sustainable Healthcare Waste Disposal Site Selection

11.1 Abstract

Healthcare services inevitably produce healthcare waste. Given that healthcare waste is infectious and hazardous to patients, healthcare personnel, society, and the environment, the meticulous disposal of this trash is imperative for Waste Management (WM) firms.

In numerous developing countries, the management of Healthcare Waste Disposal (HWD) has emerged as one of the most rapidly escalating threats to healthcare providers. Identifying a sustainable site for HWD is an intricate endeavor owing to the engagement of multiple criteria, alternatives, and stringent governmental restrictions for healthcare WM.

The goal of the paper is to utilize the idea of Fermatean Fuzzy (FF) sets for the selection of HWD sites to reduce uncertainty, ambiguity, vagueness, and obscurity, so facilitating a comprehensive, diverse, and innovative Decision Making (DM) process.

An exemplary case study on the selection of HWD sites within a FF environment is presented, demonstrating the effectiveness of the proposed methodology. The final outcome verifies that the proposed approach may effectively address the inaccuracies in the DM process for choosing HWD sites.

11.2 Introduction

Population around the world, especially in developing countries, have been growing very rapidly over the last few decades. The fast growth of the population has caused many problems that are very bad for both people and animals' health. One of these problems is getting rid of the huge amounts of biological waste that come from clinics, hospitals, nursing homes, and pathology labs.Healthcare wastes highly affects human beings as well as wildlife. Healthcare wastes which contains infectious and contaminated materials releases harmful gases which is a threat for the environment. There is high risk for health and environment if these medical wastes are not disposed and destroyed properly. The healthcare wastes are classified into different categories as shown in Table 11.1.

Some major types of HWD are autoclaving, incineration and microwaving. Autoclaving is a sterilization process used to sterilize medical devices. It is a process which kills harmful microorganism like viruses, bacteria etc. by utilizing steam under high pressure and temperature for a definite period of time. This process is considered as cost effective and robust. Autoclaving is also termed as steam sterilization. The term incineration refers to perfect/complete burning of material. Medical incinerators are used to dispose harmful wastes at high temperature safely. Incinerators completely destroys medical wastes and makes WM process more comfortable and effective. This process corroborated that the harmful gases are not released to the environment. Incineration reduces the volume of waste and transform solid waste materials into ash, steam and heat. Microwaving is a process which sanitizes the waste by wet heat and steam created by microwave energy [524].

Type of Waste	Description
A. General Waste	Mainly contains household or domestic waste type. e.g. food waste
B. Biomedical Waste	
a. Radioactive waste	Comprises solid, liquid and gaseous wastes which is contaminated with radionuclide
b. Pharmaceutical waste	Includes pharmaceutical drugs, chemicals and products
c. Sharp	Waste substances such as broken glasses, needles, blades, scalpels , nails and knives etc.
d. Chemical waste	Includes rejected solid, liquid and gaseous chemicals
e. Pathological waste	Contains body and blood fluid, body part human foetuses and tissue organs etc.
f. Infectious waste	Comprises pathogens lacking concentrations which could cause diseases

Table 11.1: Types of healthcare wastes

According to IndiaStat (2013), the amount of waste that the healthcare industry has accumulated for the purpose of treatment and disposal is steadily increasing. Due to the fact that it cannot be mixed in with domestic garbage or other types of waste, healthcare waste requires careful consideration of the available space in order to be perfected. Since this is the case, it is of the utmost importance to choose a place that is environmentally friendly for the daily storage, treatment, and disposal of healthcare wastes. It is possible for humans, wildlife, and the ecosystem to suffer negative consequences if the location is not suitable. According to Govindan et al. [525], the decision-makers would be better able to establish a socially, environmentally, and economically sustainable location if they took into consideration a variety of variables while selecting a site for the foundation of a HWD plant. Choosing a place that is sustainable is a DM challenge that involves multiple factors and is of the type of DM that involves multiple attributes.

The usage of this methodology would assist in locating a suitable site for HWD. The choice of an appropriate site would be favourable for HWD firm, community, and environment, i.e. less public exposure, business and decrease the application of renewable resources such as carbon emanations, water and land respectively. Furthermore, the developed methodology has been employed on the nine criteria selected from the previous studies.

11.3 Research Methodology

This study develops a novel methodology for HWD facility location in FF environment. In brief, this method is able to hierarchize the HWD site. The flow chart of the developed methodology is presented in Fig. 11.1. The procedural steps are explained as follows:

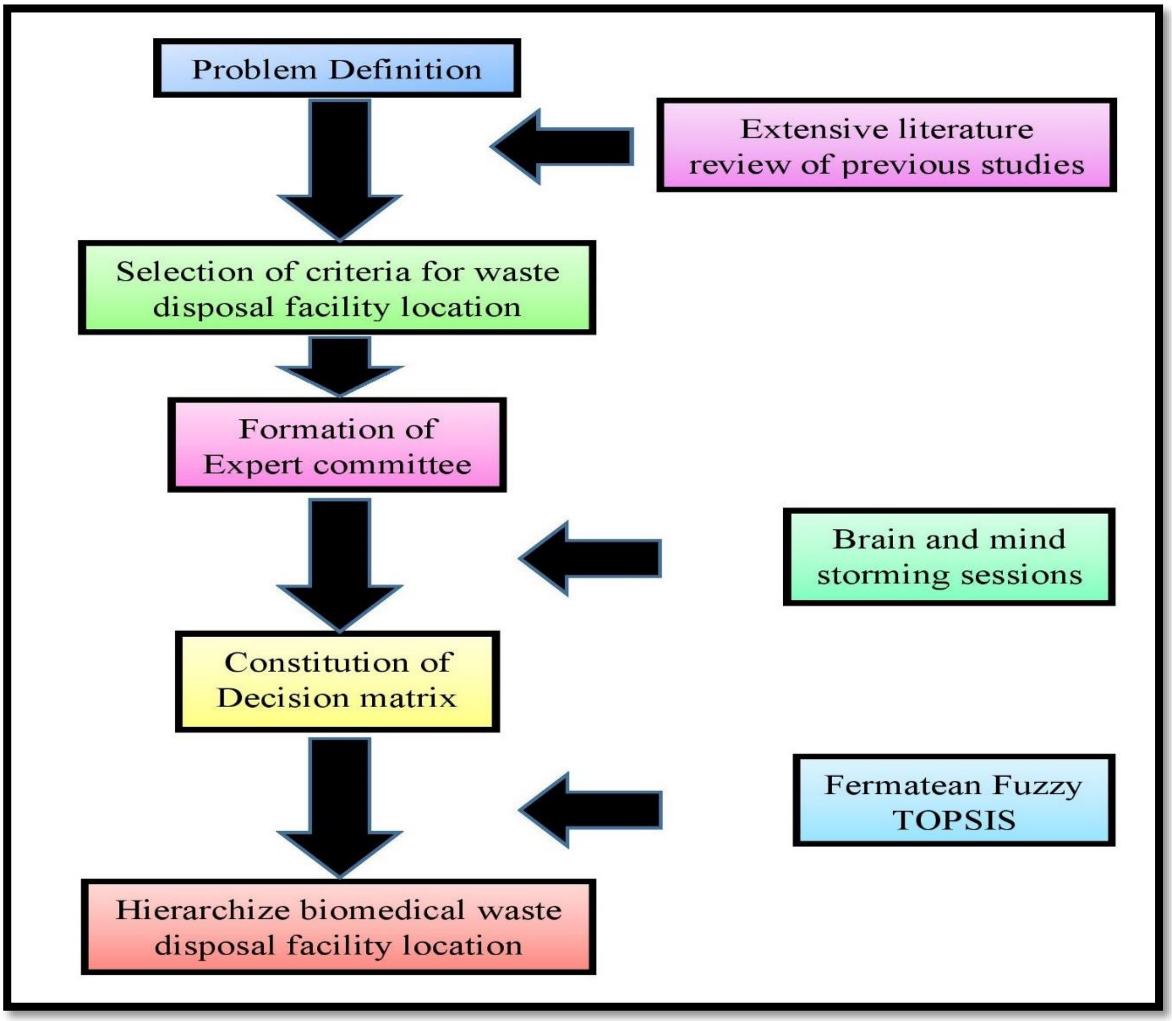


Fig. 11.1: Flowchart of the proposed methodology

Step 1: Identify the criteria for HWD site selection by exhaustive study of previous literature.

Step 2: Obtain the opinion of experts for each alternative location in terms of linguistic variables as shown in Table 11.2

Linguistic Terms	**FF Numbers**
Outstanding(OW)	(0.90,0.10)
Excellent(E)	(0.80,0.30)
Good(G)	(0.70,0.40)
Satisfactory(S)	(0.50,0.50)
Okay(OK)	(0.40,0.70)
Bad(B)	(0.30,0.80)
Worst(W)	(0.10,0.90)

Table 11.2: Linguistic terms and their corresponding FF Number

Step 3: Formulate the FF decision matrix $H = C_n(S_m)_{p\times q}$ where the elements $C_n(S_m)$(n= 1, 2,…, q, m= 1, 2,…,p) are the appraisals of the alternative $S_m \in Y$ regarding the criterion $B_n \in B$ with FFNs

Step 4: Evaluate the score values from the score function

Let K= (δ_K , λ_K) be a FF set then score function of K is obtained as follows:

$$\text{Score (K)} = (\delta_K^3 - \lambda_K^3) \tag{11.1}$$

Step 5: Determine the FF positive ideal solution (PIS) and FF negative ideal solution (NIS)

The FFPIS and FFNIS are evaluated from the following equations:

$$S^+ = \{C_1(S^+), C_2(S^+), \ldots, C_q(S^+)\} \tag{11.2}$$

$$S^- = \{C_1(S^-), C_2(S^-), \ldots, C_q(S^-)\} \tag{11.3}$$

where S^+ and S^- are the PIS and NIS respectively

Step 6: Compute the integrated weight distance between alternatives with FFPIS and FFNIS

The integrated weight distance between alternatives with FFPIS and FFNIS is calculated as follows:

$$E(S_{m,}S^{+}) = \sum_{n=1}^{q} w_n \sqrt{\frac{1}{2}[(\delta_{mn}^{3} - \delta_{n}^{3})^2 + (\lambda_{mn}^{3} - \lambda_{n}^{3})^2 + (\gamma_{mn}^{3} - \gamma_{n}^{3})^2]} \quad (11.4)$$

$$E(S_{m,}S^{-}) = \sum_{n=1}^{q} w_n \sqrt{\frac{1}{2}[(\delta_{mn}^{3} - \delta_{n}^{3})^2 + (\lambda_{mn}^{3} - \lambda_{n}^{3})^2 + (\gamma_{mn}^{3} - \gamma_{n}^{3})^2]} \quad (11.5)$$

where $E(S_{m,}S^{+})$ and $E(S_{m,}S^{-})$ are the integrated weight distances from PIS and NIS respectively.

Step 7: Measure closeness ratio and rank the alternative

The closeness ratio is computed as follows:

$$\eta(S_m) = \frac{E(S_{m,}S^{-})}{E_{max}(S_{m,}S^{-})} - \frac{E(S_{m,}S^{+})}{E_{min}(S_{m,}S^{+})} \quad (11.6)$$

where $\eta(S_m)$ is the closeness ratio of mth alternative. The alternatives are organized and rated in the decending order of $\eta(S_m)$.

11.4 A Case Study

There is a case study done in the Kolkata area of West Bengal, India, to help a company that gets rid of medical waste choose a place that will be good for the environment for their building. There are several factors that affect where a HWD site is located. The main goal of this study is to find the suitable place for a HWD centre out of the four options that were considered. Table 11.3 presents a list of nine criteria considered in this study. Among the mentioned criteria, all are of the beneficial type.

The objective of this investigation is to assess the sustainability of HWD sites in various locations of Kolkata, India, in the presence of an uncertain environment. In order to determine the optimal site for the disposal of healthcare refuse in Kolkata, India, this investigation implements an integrated FF-TOPSIS methodology.

An illustrative case study has been examined in order to illustrate some valuable insights regarding the preferred four disposal sites and the selected criteria. According to the results acquired through the proposed methodology, the most preferable location for the current case study is site S_3.

A brain and mind-storming session was conducted among the various experts, and an expert committee of decision makers was established, consisting of five experts from relevant domains, as illustrated in Table 11.4. The experts' opinions were gathered in accordance with FF linguistic variables, as illustrated in Table 11.5. Table 11.2 is employed to convert the linguistic variables of specialists' opinions into FF numbers. Table 11.6 illustrates the formulation of a FF decision matrix.

Equation (11.1) evaluates the score values acquired by the score function. The values in Table 11.7 and Table 11.8 illustrates the FF PIS and NIS, respectively, which are derived from equations (11.2) and (11.3). The integrated weight distance between the location of the facility and the FF PIS and NIS is determined by equations (11.4) and (11.5) and is presented in Table 11.9.

The four HWD facility locations have been hierarchically organized using the closeness ratio of a criterion, as shown in Table 11.10. Equation (11.6) has been employed to determine the closeness ratio. S_3 has been rated first, while S_4 has been ranked fourth, in accordance with the aforementioned principle.

Sl.no	Criteria	Description	Reference
1.	The vulnerability of waste disposal sites to the general population (C1)	The vicinity of waste disposal site to peoples	Chauhan et.al (2016)
2.	Distance (C2)	Distance from waste collection location to waste disposal point	(Ertugrul and Karakasoglu, 2008)
3.	Area (C3)	The space set aside for a specific waste disposal facility	(Cohon, 2013)
4.	Availability of land (C4)	Access to landfills for garbage disposal	(Erkut et al., 2008)
5.	Odour (C5)	The emission rate of bad odour	(Beheshtinia et.al, 2023)
6.	Quantity(C6)	The volume of healthcare waste for disposal	Chauhan et.al (2016)
7.	Transportation(C7)	The connectivity between waste collection point to waste disposal site	(Cantarella and Vitetta, 2006)
8.	Consciousness towards Environment (C8)	The ecological impact of a facility's location concerning land, water, air, and emissions.	(Pillai et.al 2025)
9.	Skilled personnel (C9)	Efficient personnel to operate the facility effectively	(Biomedical WM rules, 2016)

Table 11.3: Criteria for HWD facility location

Experts	Qualification	Experience	Designation
Expert-1	M.Sc	21	Municipal recycling manager
Expert-2	Ph.D.	15	Public health department environment health manager
Expert-3	Ph.D.	18	Hospital manager
Expert-4	B.Sc	10	Recycling company Logistic manager
Expert-5	Ph.D.	14	Clinic manager

Table 11.4: Experts Information

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
	S_1	B	OW	W	G	S	B	OK	OW	OK
Expert-1	S_2	W	OK	OW	OW	B	G	B	B	W
	S_3	E	G	S	B	G	OW	G	E	S
	S_4	S	E	B	E	W	B	W	G	OW
	S_1	OK	G	S	G	S	OK	B	OW	OW
Expert-2	S_2	OW	OK	E	E	B	S	OK	G	B
	S_3	B	W	E	S	OK	E	E	S	E
	S_4	G	G	S	B	OW	B	S	E	G
	S_1	S	OK	G	B	E	S	G	S	W
Expert-3	S_2	B	G	E	G	W	G	S	OK	S
	S_3	OK	B	OK	G	E	OW	G	OW	OW
	S_4	G	S	G	S	OK	W	OW	E	S
	S_1	E	G	S	E	OW	OK	G	OK	B
Expert-4	S_2	S	OW	G	S	OK	B	S	E	G
	S_3	E	B	G	OW	G	G	OK	S	E
	S_4	OK	E	S	OK	B	W	S	G	OK
	S_1	W	S	B	OW	S	B	OK	S	E
Expert-5	S_2	OW	B	G	S	OW	OK	G	E	W
	S_3	S	G	S	E	OK	E	OW	B	G
	S_4	B	W	OK	B	W	S	B	OW	G

Table 11.5: Experts opinion in terms of linguistic variables

Criteria → *Alternative* ↓	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Site S_1	(.4,.6)	(.6,.4)	(.4,.6)	(.7,.4)	(.7,.4)	(.3,.7)	(.5,.6)	(.6,.4)	(.4,.6)
Site S_2	(.5,.5)	(.6,.5)	(.8,.3)	(.7,.4)	(.4,.7)	(.5,.6)	(.5,.6)	(.6,.5)	(.4,.7)
Site S_3	(.6,.5)	(.4,.6)	(.6,.5)	(.7,.4)	(.6,.5)	(.8,.2)	(.7,.4)	(.6,.4)	(.7,.3)
Site S_4	(.5,.6)	(.6,.5)	(.5,.6)	(.5,.6)	(.3,.7)	(.3,.8)	(.5,.6)	(.8,.3)	(.6,.4)

Table 11.6: FF Decision Matrix

Criteria / *Alternative*	$C_1(+)$	$C_2(+)$	$C_3(+)$	$C_4(+)$	$C_5(-)$	$C_6(-)$	$C_7(+)$	$C_8(+)$	$C_9(+)$
Site S_1	-0.152	0.152	-0.152	0.279	0.279	-0.316	-0.091	0.152	-0.152
Site S_2	0	0.091	0.485	0.279	-0.279	-0.091	-0.091	0.091	-0.279
Site S_3	0.091	-0.152	0.091	0.279	0.091	0.504	0.279	0.152	0.316
Site S_4	-0.091	0.091	-0.091	-0.091	-0.316	-0.485	-0.091	0.485	0.152

Table 11.7: Score values obtained by the score function

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
FFPIS	(.6,.5)	(.6,.4)	(.8,.3)	(.7,.4)	(.7,.4)	(.8,.2)	(.7,.4)	(.8,.3)	(.7,.3)
FFNIS	(.4,.6)	(.4,.6)	(.4,.6)	(.5,.6)	(.3,.7)	(.3,.8)	(.6,.5)	(.6,.5)	(.4,.7)

Table 11.8: FFPIS and FFNIS

Site (S)	$E(A_m, A^+)$	$E(A_m, A^-)$
S_1	0.105154	0.063237
S_2	0.092857	0.072509
S_3	0.039749	0.106235
S_4	0.113903	0.042447

Table 11.9: Integrated weight distance between site with FFPIS and FFNIS

Site (S)	$\eta(A_m)$	Ranking
S_1	-2.050194	03
S_2	-1.653550	02
S_3	0	01
S_4	-2.465999	04

Table 11.10: Closeness ratio and ranking of each healthcare

11.5 Discussion

The meticulous management of healthcare waste is a matter of public interest, necessitating excellent process planning. The selection of HWD sites is a critical component of municipal WM. The utilization of multi-criteria DM procedures offers numerous benefits to decision-makers, including expedited and effective DM. The multi-criteria DM approach provides additional flexibility, simplicity, and practicality in environments with several criteria.

This study presents a multi-criteria DM strategy called FF-TOPSIS, which integrates the TOPSIS method with FFS. The proposed framework has been implemented in an empirical investigation regarding the selection of HWD sites in Kolkata, India, demonstrating the effectiveness of the FF-TOPSIS method. The site S_3 has been identified as the most suitable location for a HWD facility.

The findings indicate that the FF-TOPSIS method is more dependable and efficient, with less complex calculations compared to current methodologies in a FF context. Consequently, the proposed method can be employed by hospital administrators to assess and determine the most effective locations for HWD.

This study offers guidance for subsequent research endeavors. The established paradigm is applicable in diverse DM contexts across numerous sectors. Secondly, it is recommended to create a novel methodology to ascertain the reciprocal link among the criteria.

The forthcoming research can design innovative methodologies such as MARCOS, GLDS, DNMA, ORESTE, and others inside a FF framework, and implement them for the selection of HWD sites across various areas or nations.

The Key Contributions of the Study are

a. Novel Integration of FF-TOPSIS- This study introduces an innovative approach by combining Fermatean Fuzzy (FF) Sets with the TOPSIS technique, aimed at minimizing uncertainty, imprecision, and ambiguity in the decision-making process for selecting suitable sites for healthcare waste disposal (HWD).

b. Comprehensive Criteria Selection- A total of nine evaluation criteria including distance, availability of land, odour, and environmental consciousness were identified based on expert opinion and previous literature, ensuring a comprehensive and realistic approach to site selection.

c. Expert-Driven Evaluation- The methodology incorporates opinions from a panel of five domain experts across public health, waste management, and clinical operations, enriching the linguistic judgment process and improving reliability.

d. Case Study Application in Kolkata- A practical case study was carried out in Kolkata and its surrounding regions, providing valuable real-world insights and demonstrating the relevance and effectiveness of the proposed model within the context of an urban Indian setting.

e. Hierarchical Site Ranking- The model was applied to evaluate and rank four potential sites by assessing their proximity to both ideal and non-ideal (anti-ideal) solutions. The analysis identified Site S3 as the most suitable location for establishing an HWD facility.

f. Efficiency in Complex MCDM Environments- The proposed FF-TOPSIS approach demonstrated higher dependability and computational simplicity compared to other fuzzy MCDM models, making it suitable for broader applications in healthcare and environmental planning.

g. Scope for Extension with Advanced MCDM Methods- The study suggests potential extensions using alternative MCDM techniques like MARCOS, GLDS, DNMA, and ORESTE in the FF environment, thereby setting the groundwork for future research directions.

Chapter- 12
Conclusions

12. Conclusions

Healthcare is becoming more predominant and challenging areas for people across the world. India's healthcare system represents a paradox of excellence and inequality. On one hand, the country houses globally recognized hospitals with advanced medical technologies but on the other, it struggles with systemic disparities in access, infrastructure, and service quality, especially in rural and underserved regions. Public healthcare expenditure remains low at approximately 1.1% of GDP considerably behind global peers resulting in a healthcare landscape dominated by private providers.

West Bengal reflects many of these national patterns but also presents unique regional dynamics. The state has made considerable progress in expanding healthcare infrastructure, increasing institutional deliveries, and strengthening primary healthcare services. However, significant challenges persist in service delivery quality, patient satisfaction, and health outcome disparities between urban and rural populations. Furthermore, emerging concerns such as fire safety, hospital waste management, and patient-centred service delivery necessitate systemic reforms tailored to the state's demographic and socio-economic context.

To ensure sustainable healthcare transformation, both at the national and state levels, it is imperative to prioritize equitable service access, robust regulatory oversight, skill development, and quality-focused frameworks. Strengthening healthcare in Kolkata and its adjoining areas requires not only infrastructural investment but also an unwavering commitment to patient safety, satisfaction, and institutional accountability.

Under these background, the studies have been extensively carried out and their subsequent conclusions are delineated below

The collective insights drawn from this compendium of research underscore the multifaceted challenges and opportunities surrounding sustainable, safe, and patient-centric healthcare infrastructure in developing urban centers like Kolkata, India. Through diverse methodological approaches including statistical modelling, multi-criteria decision-making (MCDM), failure risk analysis, and behavioural analytics, this thesis illuminates the critical determinants of healthcare service excellence, infrastructure sustainability, risk mitigation and user satisfaction.

The first stream of research emphasizes service quality in healthcare, revealing that infrastructural soundness, hygiene, cost-effectiveness, professional attitude, and safety significantly impact patient happiness and trust. The application of statistical tools like factor analysis and regression analysis demonstrates how infrastructure emerges as a dominant predictor of patient satisfaction, enabling administrators to focus on strategic improvement areas.

Parallelly, the second research axis applies advanced MCDM methods i.e. TOPSIS, PROMETHEE-II, Yager's min-max principle, and the Copeland method to systematically evaluate and rank private healthcare providers. The comparative findings help in identifying best-performing healthcare units, offering a replicable decision-support model for policy-makers, institutional stakeholders and patient parties aiming to elevate service standards. Patients will benefit from selecting the greatest and most dependable private healthcare provider because of the ranking based on service excellence. The final result reveals that healthcare provider A_4 ranks top based on its service excellence provided to the patients. Healthcare provider A_6 is in the second position in terms of ranking, healthcare provider A_5 is in the third position and healthcare provider A_1 was in the last position.

Another dimension involves integrating AHP with Quality Function Deployment (QFD) to select optimal healthcare institutes based on both technical and patient-centered requirements. The inclusion of economic, infrastructural, and diagnostic factors captures the holistic needs of patients and their families, leading to a balanced healthcare decision-making framework. It is clear that HI-1 >HI-4 >HI-3 >HI-2 >HI-5. Since, healthcare HI-1 has the maximum overall score, it is preferred. Including cost factor components and assuming α= 0.69, the healthcare institutes are ranked as HI-1 >HI-4 >HI-3 >HI-2 >HI-5 which is similar to that found from AHP-QFD.

The behavioural study employing PCA and regression analysis identifies trust in certification, eco-design, and sustainability satisfaction as key predictors of occupant commitment. These findings reinforce the criticality of user-centred design and transparency in green certification to improve healthcare loyalty and long-term engagement.

The Kaiser-Meyer-Olkin (KMO) value for sample adequacy is 0.744, and the significance level of Bartlett's test of sphericity is 0.000, indicating that the dataset is statistically appropriate for conducting Exploratory Factor Analysis (EFA). The overall Cronbach's alpha for the scale is 0.887, confirming the robustness and validity of the instrument.

Furthermore, a robust risk-based analysis through an extended FMEA-QFD-RTOPSIS model identifies and prioritizes healthcare service failures. This hybrid model, grounded in rough set theory, not only highlights critical failure modes but also maps them to relevant corrective activities, thereby enhancing service resilience and reducing iatrogenic risks. HCS1 emerges as the most favourable alternative with a closeness value of 0.6356, followed by HCS3, HCS2, and HCS4.

Addressing another crucial dimension i.e. fire safety in hospitals, the research introduces a PEEST-classified, Rough-QFD and Rough-MABAC integrated model. It provides a dynamic, expert-informed risk evaluation framework to prioritize fire risk mitigation actions in healthcare infrastructure, showcasing a strong case for transitioning from reactive audits to proactive, structured decision systems. Hospital HL_3 is ranked highest, showing exceptional readiness, particularly in CA_2 and CA_5. HL_5 followed closely, while HL_2 ranks the lowest due to significant underperformance in CA_4 and CA_6, suggesting deficiencies in ventilation and hazardous material protocols.

Finally, the thesis pioneers a Fermatean Fuzzy environment for selecting sustainable sites for healthcare waste disposal. By addressing vagueness and ambiguity in expert judgments, the study proposes a flexible yet rigorous model that contributes to environmentally safe and regulatory-compliant healthcare waste management systems. The sustainable site for biomedical waste disposal are hierarchized as $S_3 > S_2 > S_1 > S_4$.

In synthesis, this research demonstrates that healthcare infrastructure must transcend traditional functional paradigms by embedding sustainability, reliability, and patient-centricity at its core. The interdisciplinary integration of quantitative, qualitative, and computational tools within these studies provides a foundational roadmap for achieving resilient, inclusive, and sustainable healthcare systems. These contributions hold substantial implications not only for academic advancement but also for real-world implementation across policy, planning, and public health governance.

Chapter-13

Future Scope

13. Future Scope

a. Integration of Smart Technologies- Future research may explore the application of emerging technologies such as IoT, AI, and machine learning to develop real-time decision-support systems for healthcare infrastructure monitoring, patient satisfaction tracking, and predictive risk mitigation. These technologies can further enhance responsiveness and customization in patient care services.

b. Longitudinal Studies on Patient Satisfaction and Sustainability- While the current studies offer a cross-sectional snapshot, future work can conduct longitudinal assessments to examine how improvements in infrastructure, hygiene, and certification trust affect patient happiness and loyalty over time, especially in green-certified healthcare environments.

c. Expansion to Public Healthcare Systems- Most case studies focused on private healthcare institutions. Future studies should extend the developed models to public hospitals and rural healthcare centres to examine applicability under different economic and operational conditions, fostering inclusive healthcare evaluation.

d. Development of Integrated Healthcare Dashboards- By merging the outputs of MCDM, FMEA, Rough-QFD, and behavioural analytics, a unified digital dashboard can be developed to guide administrators in simultaneously monitoring service quality, risk levels, and sustainability indicators.

e. Geo-Spatial and Environmental Impact Analysis of Healthcare Waste Disposal- The healthcare waste site selection model can be enhanced by incorporating GIS-based spatial analytics and environmental impact assessments to better align with smart city and green urban planning initiatives.

f. Fire Safety Audits Using Digital Twin Technology- Future frameworks may integrate the proposed PEEST-RQFD-Rough MABAC model with digital twin environments to simulate fire hazards and optimize emergency response strategies dynamically in hospital buildings.

g. Cross-Cultural Validation of Models- The current models are validated in the Kolkata context. Extending them to other geographic regions or countries with varying socio-political and healthcare infrastructures can validate their universality and lead to broader generalizations.

h. Policy-Level Recommendations and Decision Simulation- Advanced simulation models could be developed using the proposed methodologies to assist policy makers in performing 'what-if' analyses, prioritizing investments, and formulating strategic healthcare policies aligned with national health goals.

i. Sustainability Metrics for Healthcare Certification Programs- The behavioural model linking sustainability satisfaction and occupant loyalty can inform the development of new sustainability rating systems tailored for healthcare, supplementing existing tools like IGBC and LEED.

j. Hybrid Risk Models for Other Healthcare Domains- The extended FMEA and fire risk frameworks can be adapted for assessing other high-risk healthcare domains such as biomedical waste management, equipment maintenance, and pandemic readiness, providing a more holistic risk governance architecture.

Chapter- 14

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14. Bibliography

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