Study of Sustainability in Construction: A Consilient Conspectus Approach

Thesis submitted

by

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Doctor of Philosophy (Engineering)

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   i) **Deep Saha**, Biswajit Paul, Bijan Sarkar (2025). Revolutionizing Sustainable Construction through Predictive Modeling of Green Concrete. Published in Developments in the Built Environment Journal (Elsevier), Volume-23, Page 1-11.

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   v) Biswajit Paul, **Deep Saha**, Bijan Sarkar (2025). Sustainable Healthcare Infrastructure and Occupant Loyalty: A PCA and Regression-Based Model for Green Hospital Evaluation, Published in STAPS Journal, Volume-11, Issue-7, Page 98-111.

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5) Green Concrete Solutions: Revolutionizing the Future of Sustainable Construction. Presented at Third International Conference on Construction Materials and Structures, themed on Synergy of Materials and Structures held at IIT Tirupati from 03-05 July, 2025.
6) A De Novo Approach for Sustainable Site Selection for Healthcare Waste Disposal in Kolkata and its Adjoining Areas. Presented at 3rd International Conference on Data Analytics and Insights (ICDAI-2025) on August 28-30, 2025 at Techno International Newtown, Kolkata.

5) List of Patents: NIL

PROFORMA -1

"Statement of Originality"

I Deep Saha registered on 07 March 2022 do hereby declare that this thesis entitled "Study of Sustainability in Construction: 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.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 5%.

Deep Saha

Signature of Candidate

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25 May 2024

PROFORMA -2

CERTIFICATE FROM THE SUPERVISOR

This is to certify that the thesis entitled "Study of Sustainability in Construction: A Consilient Conspectus Approach" submitted by Shri Deep Saha who got his name registered on 07 March 2022 for the award of Ph.D.(Engineering) degree of Jadavpur University is absolutely 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 25 May 2026
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Signature of the Supervisor
and date with Office Seal

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Thanks & Regards,

Deep Saha

(Deep Saha)

This thesis is dedicated to

My Father, Mr. Debabrata Saha,

My Mother, Mrs. Anindita Saha,

My Wife, Mrs. Anushka Saha

My Brother, Mr. Deb Kumar Saha,

My Sir, Prof. Bijan Sarkar and

My Aunty Mrs. Nila Sarkar

Contents

Chapter 3: *Systematic Literature Study*

Chapter 4: *Research Gap, Aim, Objectives and Scope of the Study*

Chapter 5: *An In-Depth Study on Performance Evaluation of Civil Contractors*

Chapter 6: *A Decision Support Framework for Sustainable Waste Landfill Siting*

Chapter 7: *Predictive Modeling of Compressive Strength of Green Concrete*

Chapter 8: *Analysis on Sustainable Health Care Infrastructure Design*

Chapter 9: *A Diagnostic Approach to Risk Evaluation in Sustainable Construction Projects*

Chapter 10: *Geospatial Analysis for Waste Landfill Site Suitability*

References

ABSTRACT

The construction industry plays a pivotal role in global economic development but simultaneously contributes significantly to environmental degradation and social inequities. This research presents a comprehensive consilient approach towards sustainability in construction, integrating environmental, economic, and social dimensions through advanced decision-making frameworks, quantitative modeling, and geospatial analysis. The study aims to holistically evaluate and enhance sustainability in construction practices, with particular emphasis on contractor performance, waste management, green materials, healthcare infrastructure, and risk assessment.

A multi-methodological framework is developed across certain thematic domains. Contractor performance evaluation is carried out using Fuzzy AHP, Fuzzy TOPSIS, and K-Means clustering, followed by an intuitionistic fuzzy reliability-based analysis to incorporate risk considerations.

For sustainable waste management, the research employs Rough TOPSIS for municipal solid waste site selection, supplemented by GIS-based spatial suitability mapping.

The study of sustainable building materials involves comprehensive study on green concrete and development of strength prediction models for green concrete, contributing to circular economy practices.

Social sustainability is addressed through an assessment of green healthcare infrastructure using Principal Component Analysis and regression modeling.

Risk management in construction is further explored using an enhanced Failure Modes and Effects Analysis (FMEA) model tailored for development of sustainable construction projects.

This research contributes a unified sustainability assessment architecture, validated through real-world data and expert opinions. The outcomes provide actionable insights for policymakers, construction managers, and urban planners aiming to foster resilient, efficient, and socially responsible construction ecosystems.

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Introduction

The construction business is a major contributor to global economic growth, essential for infrastructural advancement, urbanisation, and job creation. Nonetheless, it is among the greatest users of natural resources and a significant emitter of greenhouse gases, resulting in a substantial and extensive environmental imprint. The extraction of raw materials, energy-intensive manufacturing, construction activities, and the lifecycle effects of buildings significantly contribute to environmental degradation, resource depletion, and climate change. Given the escalating environmental concerns and heightened cultural awareness of ecological responsibility, the need for sustainability in construction industry has become more essential and significant.

Sustainability in the construction sector pertains to the design, development, and operation of buildings and infrastructure that minimises environmental harm, conserves natural resources, promotes energy efficiency, and improves occupant health and well-being, while ensuring economic viability. It includes a broad range of techniques and beliefs designed to harmonise the triple bottom line of sustainability: environmental preservation, social equality, and economic efficiency. This encompasses the utilisation of sustainable materials, energy-efficient technologies, waste minimisation strategies, risk evaluation, and the implementation of green building standards.

The shift towards sustainable building is driven by a combination of legislative demands, stakeholder anticipations, and long-term economic factors. Governments and international organisations are progressively implementing rigorous environmental rules and climate policies that necessitate the building sector to transition to more sustainable options. Clients and end-users are seeking buildings that are not only economical and functional but also ecologically sustainable and conducive to health. Sustainable construction approaches have shown potential to save long-term operating costs, enhance building performance, and increase asset value, making them appealing from an investment standpoint.

Nonetheless, the shift to sustainable building presents problems. Obstacles include substantial initial expenses, insufficient knowledge and training, opposition to change, and the disjointed structure of the construction sector might hinder the extensive implementation of sustainable methods. Addressing these challenges requires a unified endeavour from policymakers, industry participants, educational entities, and the public to cultivate a culture of sustainability and to invest in creative solutions that may revolutionise the building sector. In summary, sustainability in the construction industry is an essential and transformational initiative that corresponds with the worldwide effort to combat climate change, save biodiversity, and create resilient and inclusive built environments. This is not just a trend or statutory obligation but a fundamental transformation in our conception in how we construct and manage our environment. In the context of rising urbanisation and environmental deterioration, adopting sustainability in construction is not just a requirement but also a duty and a chance for creating a better future.

In order to achieve sustainability in the construction industry, a multi-pronged strategy that incorporates strategic decision-making across the whole of the project lifespan is required and the present study is aimed at doing so.

1.2 Research Background

The construction industry has long been recognized not only as a driver of economic growth but also as a major contributor to environmental degradation and resource depletion. Due to its extensive use of raw materials, energy-intensive processes, and emission-heavy operations, the sector has significant environmental, economic, and social implications. Over the decades, researchers and practitioners have increasingly emphasized the need to improve the environmental performance of construction activities.

Sustainable construction aims to achieve a balanced integration of environmental, social, and economic goals throughout the lifecycle of buildings and infrastructure. This encompasses a wide array of practices including the use of green materials, energy-efficient design, effective waste management, and enhanced stakeholder engagement. The concept extends beyond mere compliance, advocating for resilience, inclusivity, and long-term performance.

Earlier studies (Pitney, 1993; Spence and Mulligan, 1995; Hill and Bowen, 1997; Ofori et al., 2000; Halliday, 2008) laid the foundation for defining sustainability in construction, while more recent efforts have concentrated on operationalizing these principles through frameworks, tools, and metrics [1-5]. Shen et al. (2010) advanced the notion of balancing the three dimensions of sustainability: economic viability, social equity, and environmental protection in real-world construction project execution [6].

In this context, the current study builds upon this foundation by adopting a comprehensive and consilient approach, addressing interrelated areas critical to achieve sustainability in construction. This integrative perspective is essential to develop actionable strategies that respond to both local and global sustainability challenges. The sustainable construction practices as depicted in Figure 1.1 aims at establishing an equilibrium among economic, social, and environmental performances in implementing construction projects [6].

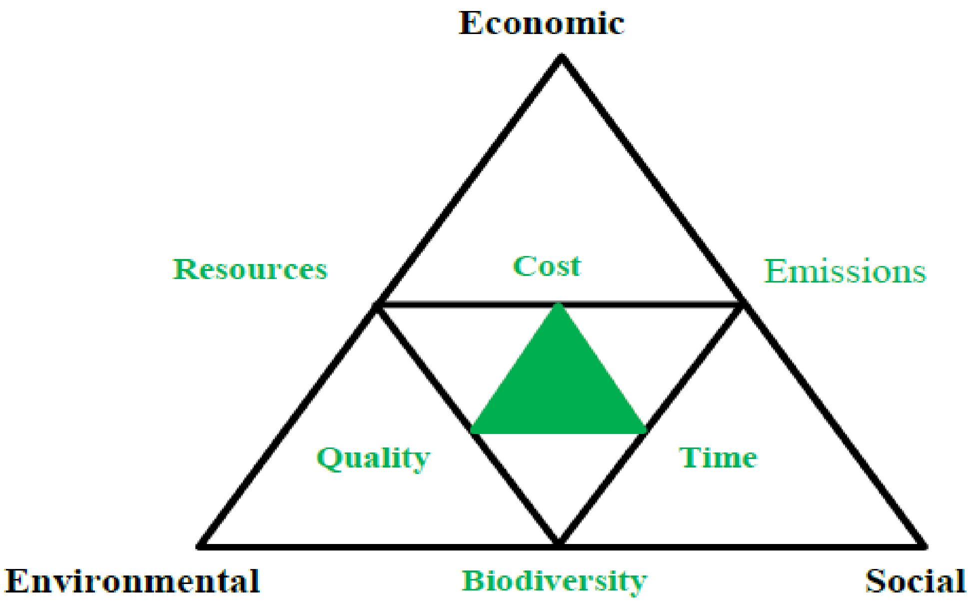

Figure 1.1 Sustainable construction strategy (Huovila, 2001)

1.3 Research Motivation

The motivation for this research stems from the fragmented and siloed nature of current sustainability efforts within the construction sector. Although individual domains such as green materials or risk assessment have seen considerable progress, a unified and integrated framework that holistically links all key pillars of sustainability remains underdeveloped. This study aims to bridge that gap by offering an interdisciplinary synthesis that connects technical, environmental, economic, and social dimensions. It is motivated by the need to provide actionable insights and scalable models that can support the transition to a more sustainable, resilient, and inclusive construction industry, especially in developing economies facing rapid urbanisation and ecological vulnerability.

Chapter 2

Bibliometric Literature Study

2.0 Introduction

The construction industry is undergoing a transformative shift toward sustainability, driven by global imperatives such as climate change mitigation, circular economy integration, and resilient infrastructure development. To understand the evolving research landscape across key thematic areas including contractor performance evaluation, waste management, sustainable materials, healthcare infrastructure and risk assessment a bibliometric analysis has been conducted using the Scopus database, one of the most comprehensive repositories of peer-reviewed literature. This study systematically examines publication trends, geographic and author-wise distributions, and keyword co-occurrence (through VOS viewer software) to identify influential contributors, research hotspots, and thematic evolutions.

2.1 Study on Performance Evaluation of Civil Contractor

The domain of civil contractor performance evaluation has attracted growing academic interest over the past two decades, reflecting its critical role in ensuring construction project success, sustainability, and risk mitigation. A bibliometric analysis has been conducted to examine the publication trends, key contributors, geographic distribution, and thematic evolution of research in this field.

2.1.1 Temporal Trends in Publication

As indicated in Figure 2.1, the number of scholarly publications on the performance evaluation of civil contractors has shown a marked upward trend, particularly in the last 10 years. This surge reflects a growing recognition of the need for structured contractor assessment methodologies to improve project outcomes in terms of time, cost, and quality.

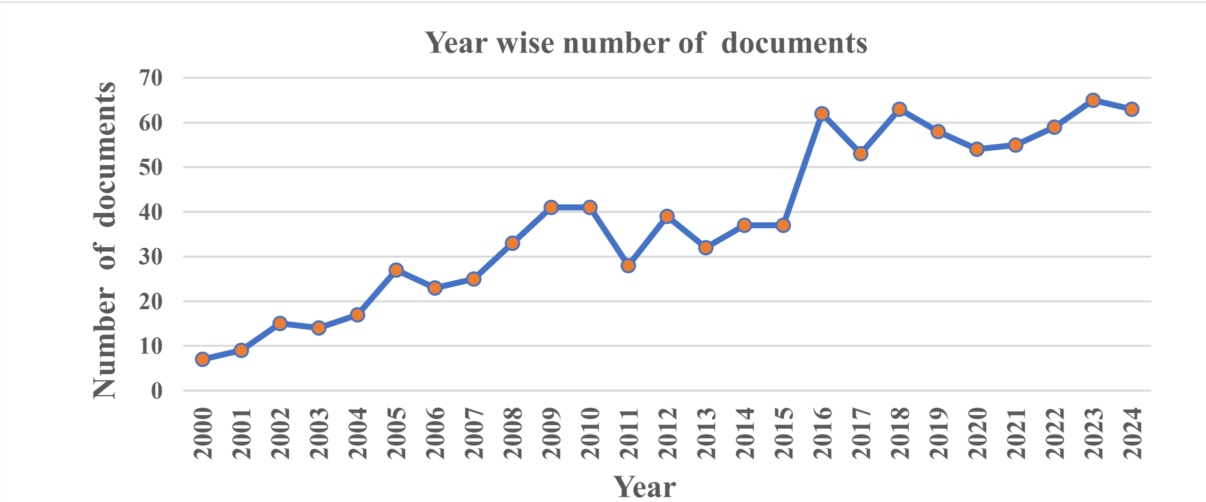

Figure 2.1 Year wise number of documents on performance evaluation of civil contractors

2.1.2 Geographic Distribution of Research

Figure 2.2 highlights the country-wise distribution of research output. The leading contributors include countries with robust construction industries such as, the United States, United Kingdom, China and India. India's significant contribution aligns with its rapid urbanization and the increasing demand for performance-driven public and private infrastructure projects.

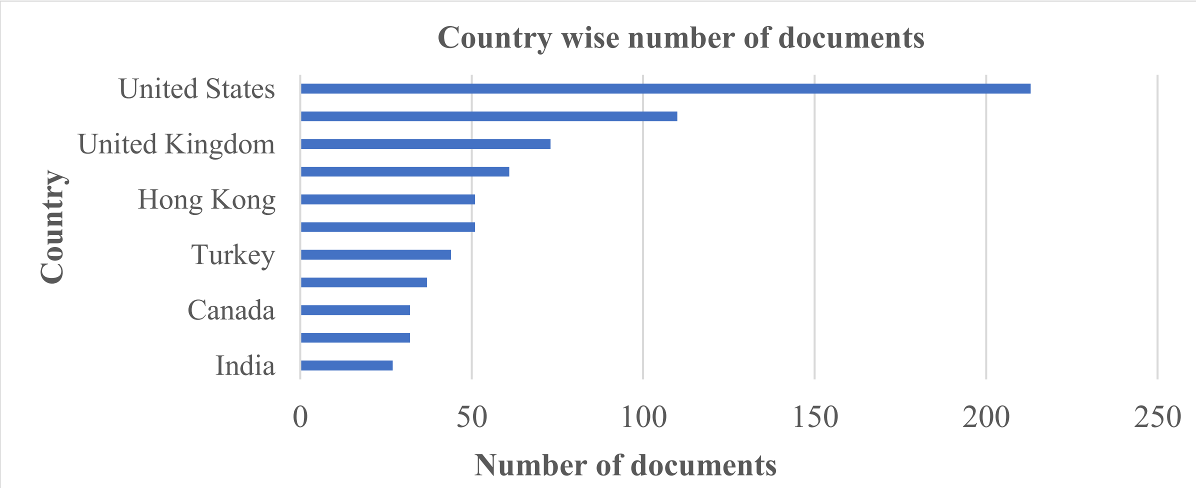

Figure 2.2 Country wise number of documents on performance evaluation of civil contractors

2.1.3 Author Contributions and Influential Researchers

As shown in Figure 2.3, a small cluster of authors dominates the publication landscape, indicating the presence of research hubs and thought leaders. These core authors often collaborate in developing hybrid Multi Criteria Decision Making (MCDM) models and reliability-based methods, reflecting a trend toward methodological pluralism in contractor performance evaluation.

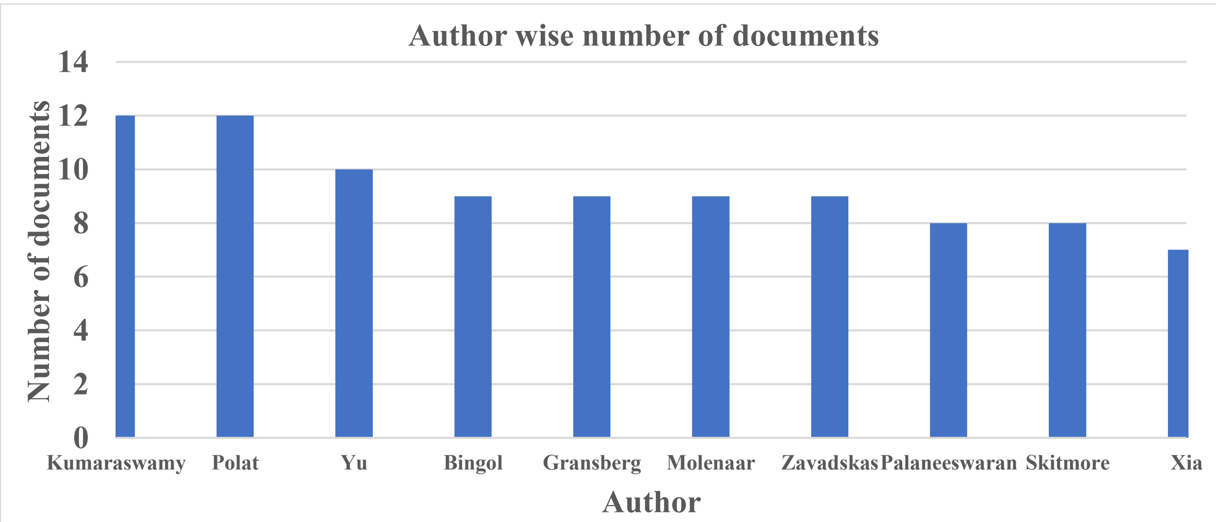

Figure 2.3 Author wise number of documents on performance evaluation of civil contractors

2.1.4 Thematic Clustering through Keyword Co-occurrence

The co-occurrence map in Figure 2.4 reveals several thematic clusters of keywords. Prominent themes include: Performance evaluation, MCDM, Fuzzy logic, Contractor selection, Risk analysis, Reliability and sustainability

These clusters demonstrate a convergence of interests around quantitative evaluation models, emphasizing not only technical capabilities but also sustainability, stakeholder satisfaction, and risk mitigation.

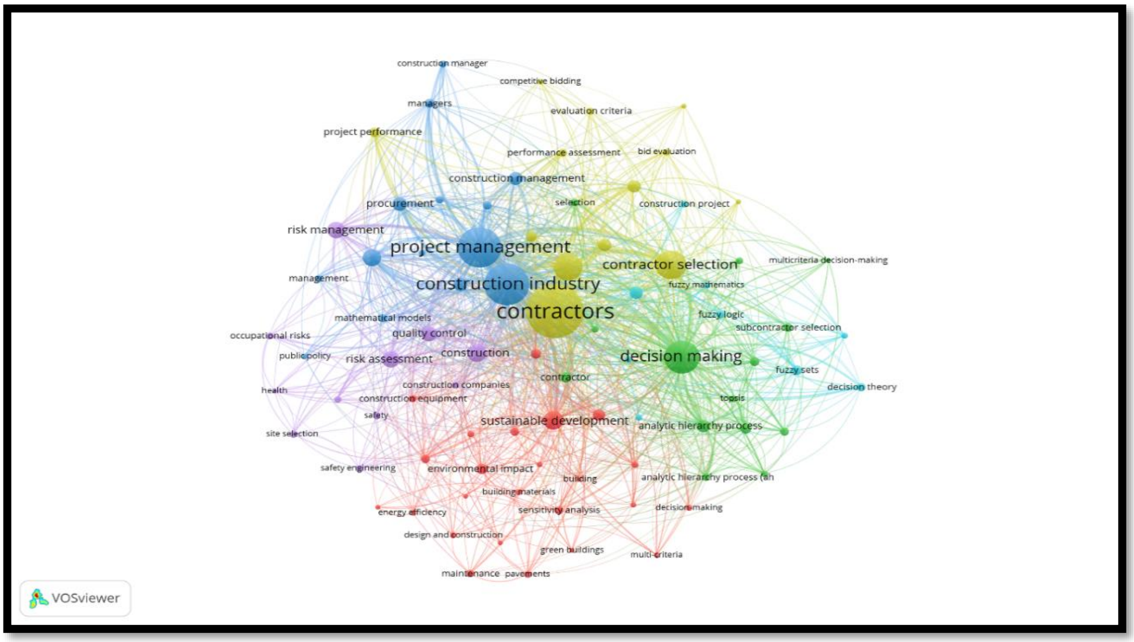

Figure 2.4 Co-occurrence of keywords on performance evaluation of civil contractors

The bibliometric insights confirm that the performance evaluation of civil contractors is an evolving interdisciplinary field with growing emphasis on quantitative, data-driven approaches. Future research should aim to unify the diverse methodological strands into robust, adaptive frameworks capable of responding to the complex, dynamic challenges of sustainable construction. There is also scope for expanding research to underrepresented regions and integrating real-time performance data using digital tools like Building Information and Modeling (BIM) and Internet of Things (IoT).

2.2 Study on Waste Management

The construction sector is one of the largest generators of solid waste globally, and the need for effective waste management has become increasingly urgent in the context of sustainable development. This bibliometric analysis provides a comprehensive overview of global research trends, intellectual contributions, and emerging themes in waste management within the construction industry.

2.2.1 Temporal Trends in Publication

According to Figure 2.5, the number of publications on waste management has steadily increased over the years, with significant growth observed in the last decade. This reflects a rising awareness of environmental sustainability and the economic impact of inefficient construction waste practices. The post-2015 surge aligns with the global implementation of the UN Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities) and SDG 12 (Responsible Consumption and Production).

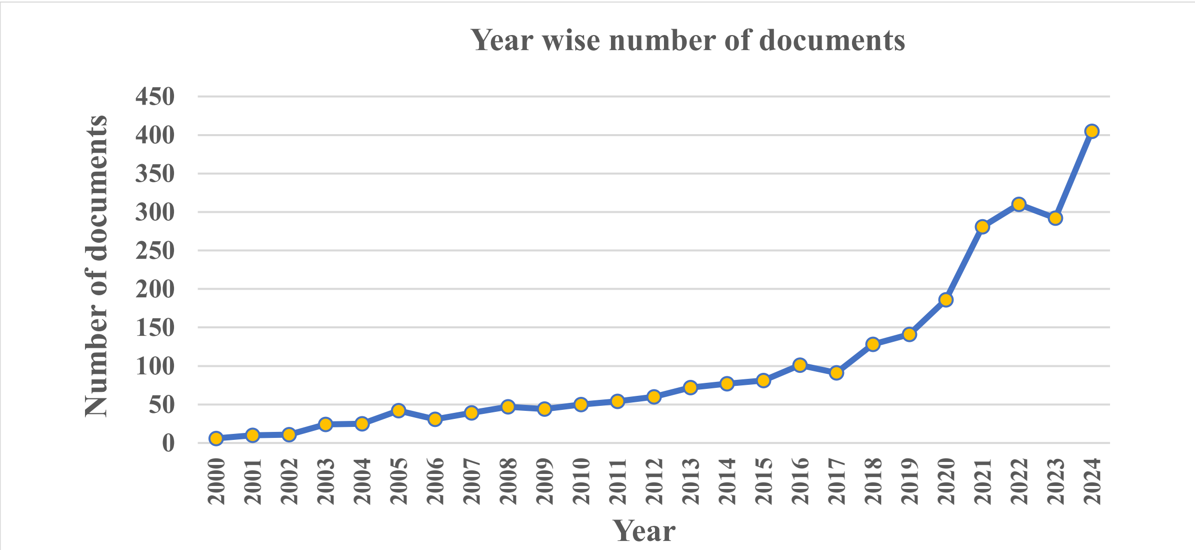

Figure 2.5 Year wise number of documents on waste management

2.2.2 Geographic Distribution of Research

As shown in Figure 2.6, the research output is geographically diverse, with leading contributions from the United States, China, India and the United Kingdom. The dominance of Asian countries like China and India is reflective of their booming construction sectors and the simultaneous pressure to manage construction and demolition (C&D) waste sustainably.

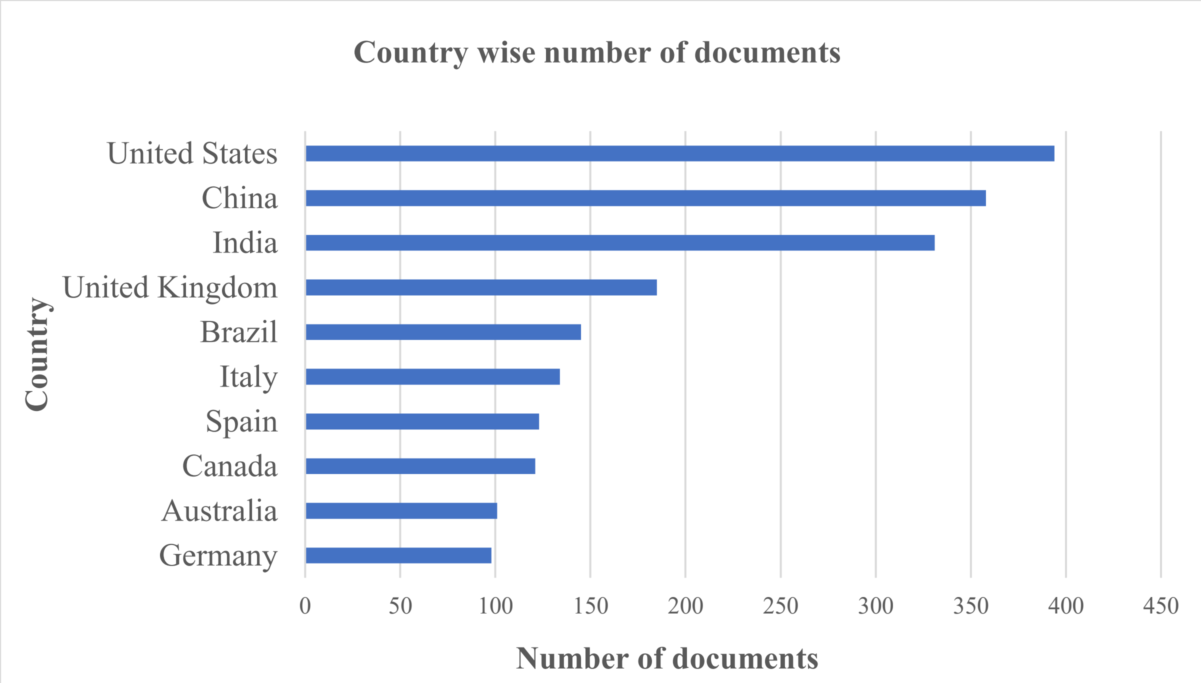

Figure 2.6 Country wise number of documents on waste management

2.2.3 Author Contributions and Influential Researchers

Figure 2.7 reveals a concentrated group of prolific authors who have contributed significantly to the literature. These researchers often collaborate on developing models for waste minimization, circular economy integration, and decision-support systems for waste management.

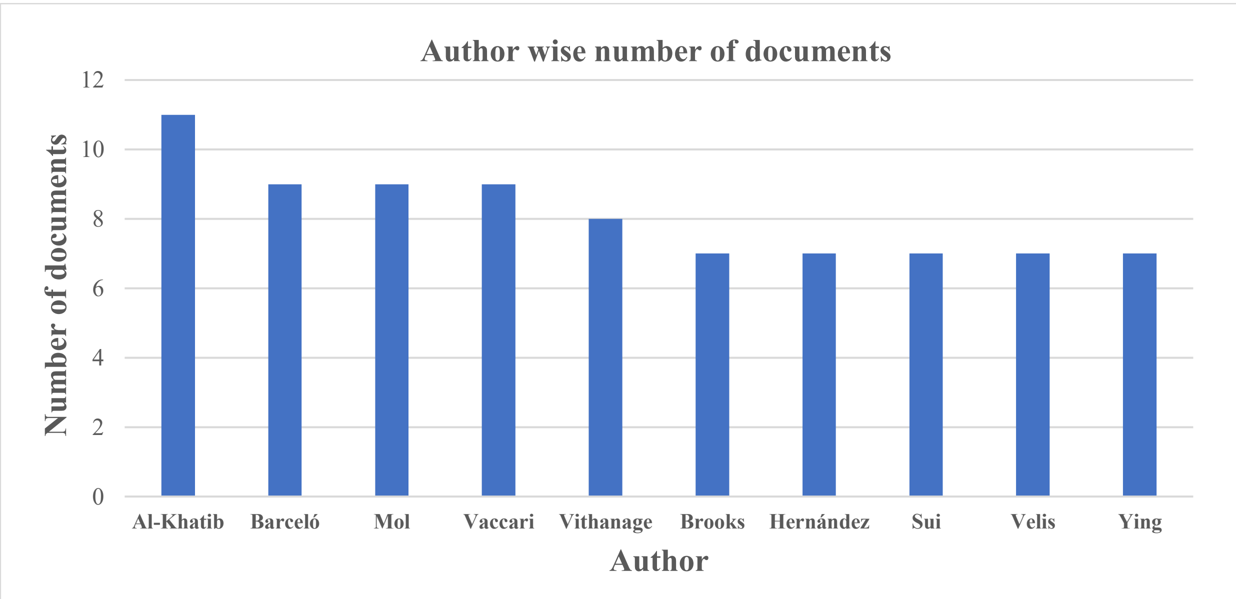

Figure 2.7 Author wise number of documents on waste management

2.2.4 Thematic Clustering through Keyword Co-occurrence

The co-occurrence of keywords in Figure 2.8 reveals four major thematic clusters:

Cluster A: Waste Minimization and Management Practices

Keywords: Waste management, construction waste, waste minimization, reduction strategies

Cluster B: Decision-Making Tools and Methodologies

Keywords: MCDM, Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Geographic Information System (GIS)

Cluster C: Sustainability and Circular Economy

Keywords: Sustainability, resource efficiency, recycling, circular economy

Cluster D: Environmental Impact and Policy Frameworks

Keywords: Life cycle assessment, environmental impact, regulations, policy.

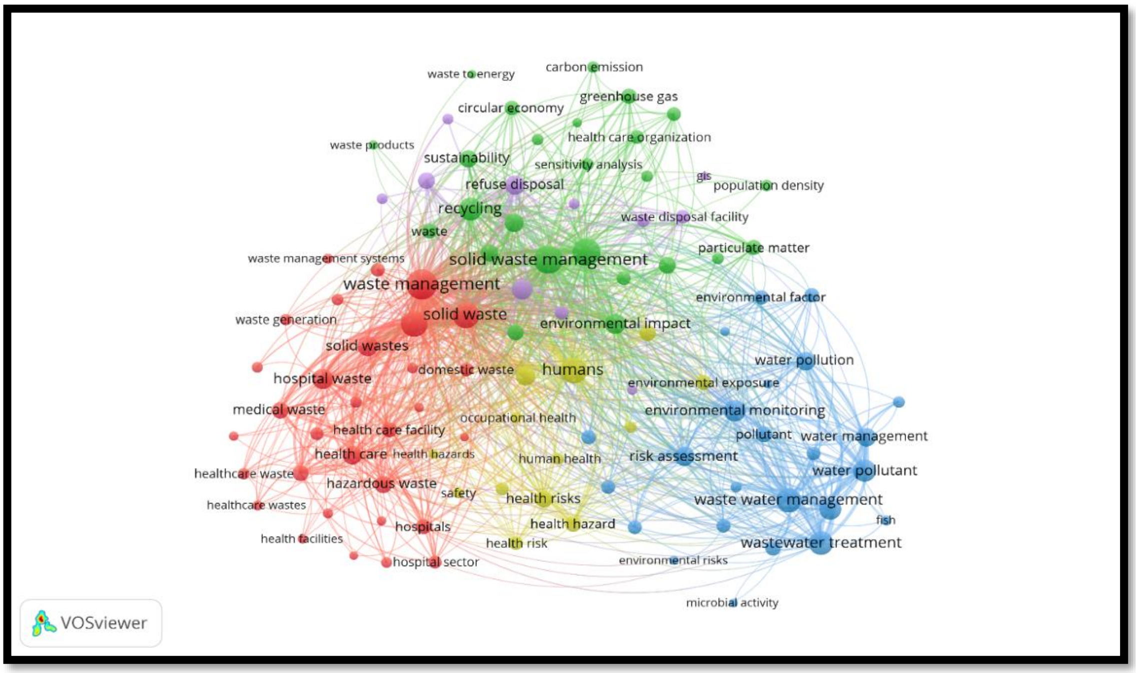

Figure 2.8 Co-occurrence of keywords on waste management

The bibliometric review illustrates that research on construction waste management is increasingly robust, interdisciplinary, and globally distributed. The field is evolving toward integrated systems that combine sustainability principles, advanced decision models, and policy-driven solutions.

2.3 Study on Sustainable Building Materials

The pursuit of sustainability in the construction industry has led to an increasing focus on sustainable building materials, particularly green concrete, which integrates recycled and eco-friendly components to reduce environmental impact. This bibliometric analysis offers insights into the global research landscape on sustainable building materials, identifying leading countries, authors, publication trends, and evolving research themes.

2.3.1 Temporal Trends in Publication

As shown in Figure 2.9, the volume of publications on sustainable building materials has grown steadily, especially after 2015. This aligns with increased global awareness of climate change, carbon footprint reduction, and the promotion of green certifications such as LEED, IGBC, and BREEAM. The growth trend confirms that sustainable materials, and specifically green concrete, have become a central research theme in sustainable construction.

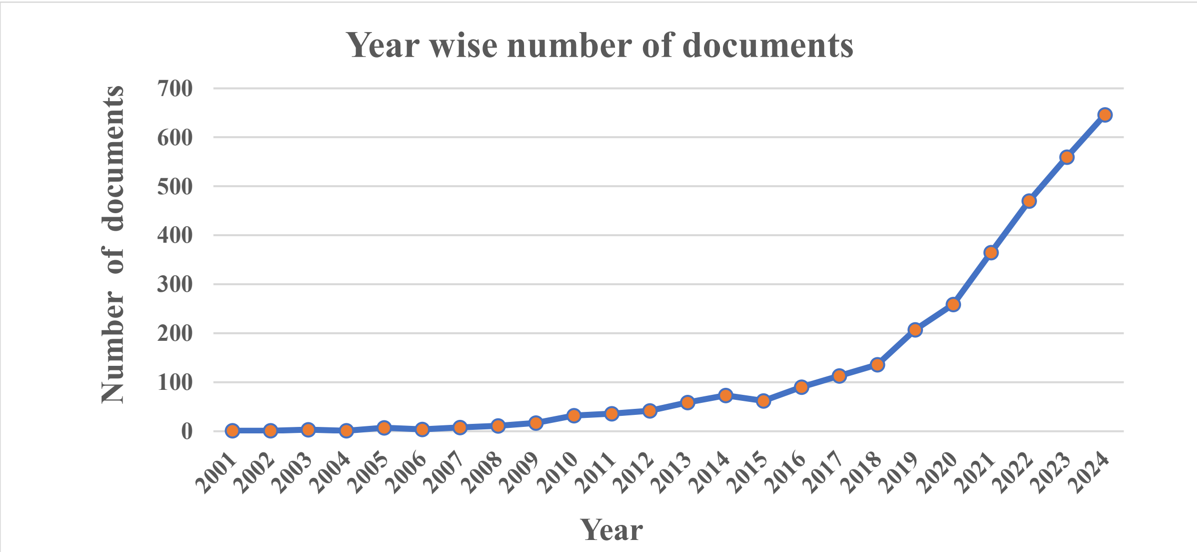

Figure 2.9 Year wise number of documents on sustainable building material

2.3.2 Country-wise Research Contributions

According to Figure 2.10, top contributing countries include China, India, the United States, Australia, and the United Kingdom. These nations are not only major players in global construction output but also face substantial environmental and waste-related challenges, making them natural leaders in the search for sustainable material solutions. India's strong research publication reflects its commitment to low-carbon infrastructure and the strategic reuse of C&D waste in concrete production.

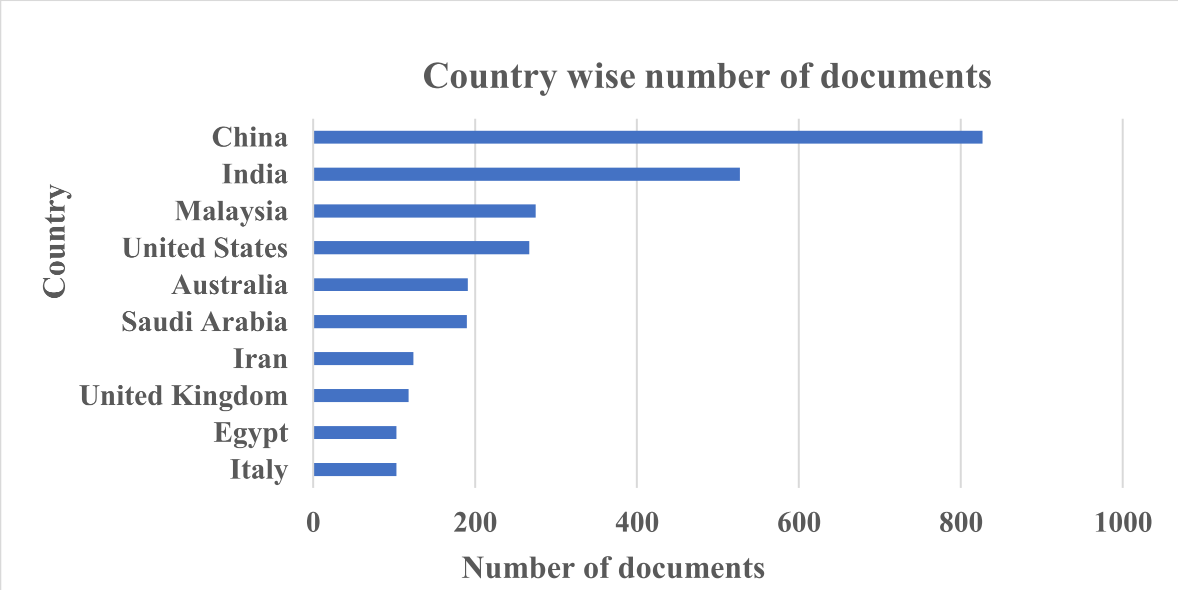

Figure 2.10 Country wise number of documents on sustainable building material

2.3.3 Author Contributions and Influential Researchers

Figure 2.11 identifies a core group of prolific authors who are shaping the discourse on green concrete and sustainable building materials. These researchers frequently collaborate on studies involving recycled aggregates, fly ash, silica fume, supplementary cementitious materials (SCMs) among others. The dominance of interdisciplinary collaborations signals a convergence of expertise in civil engineering, material science, and environmental studies.

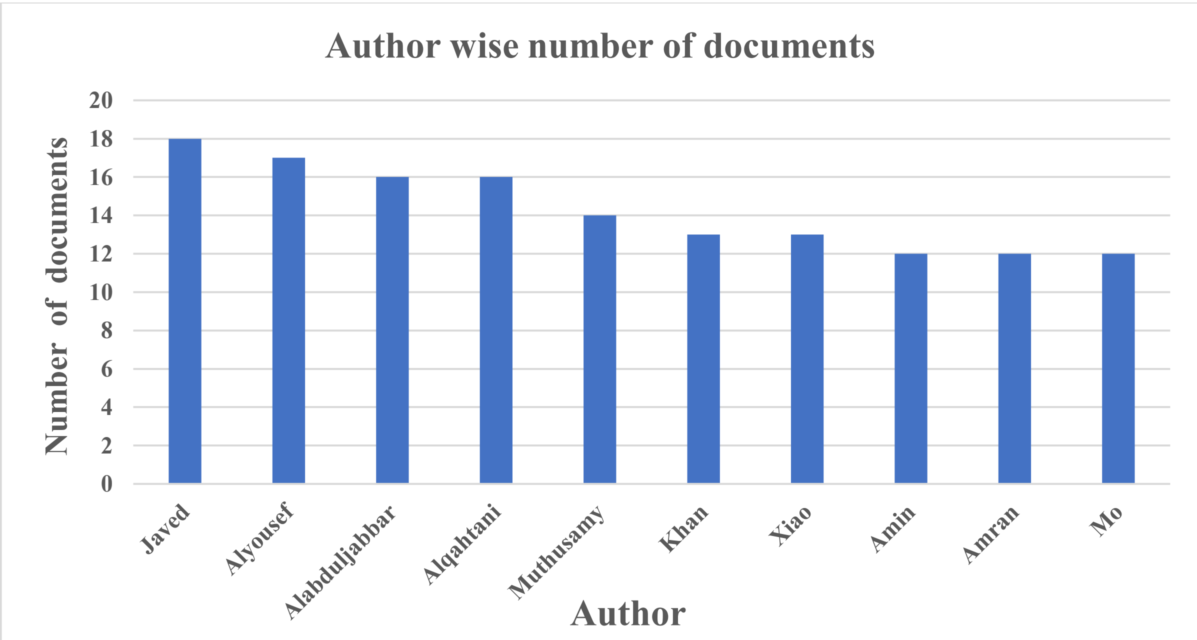

Figure 2.11 Author wise number of documents on sustainable building material

2.3.4 Thematic Clustering through Keyword Co-occurrence

The keyword co-occurrence map in Figure 2.12 reveals several dominant research themes:

Cluster A: Material Composition and Innovation

Keywords: Green concrete, fly ash, SCMs, recycled aggregates, geopolymer concrete

Cluster B: Environmental and Lifecycle Assessment

Keywords: Sustainability, life cycle assessment, carbon footprint, embodied energy

Cluster C: Mechanical and Durability Properties

Keywords: Compressive strength, durability, permeability, thermal resistance

Cluster D: Circular Economy and Waste Utilization

Keywords: Waste materials, reuse, resource efficiency, circular economy

This thematic map reflects the dual emphasis on technical performance and environmental impact, a key characteristic of current research on sustainable materials.

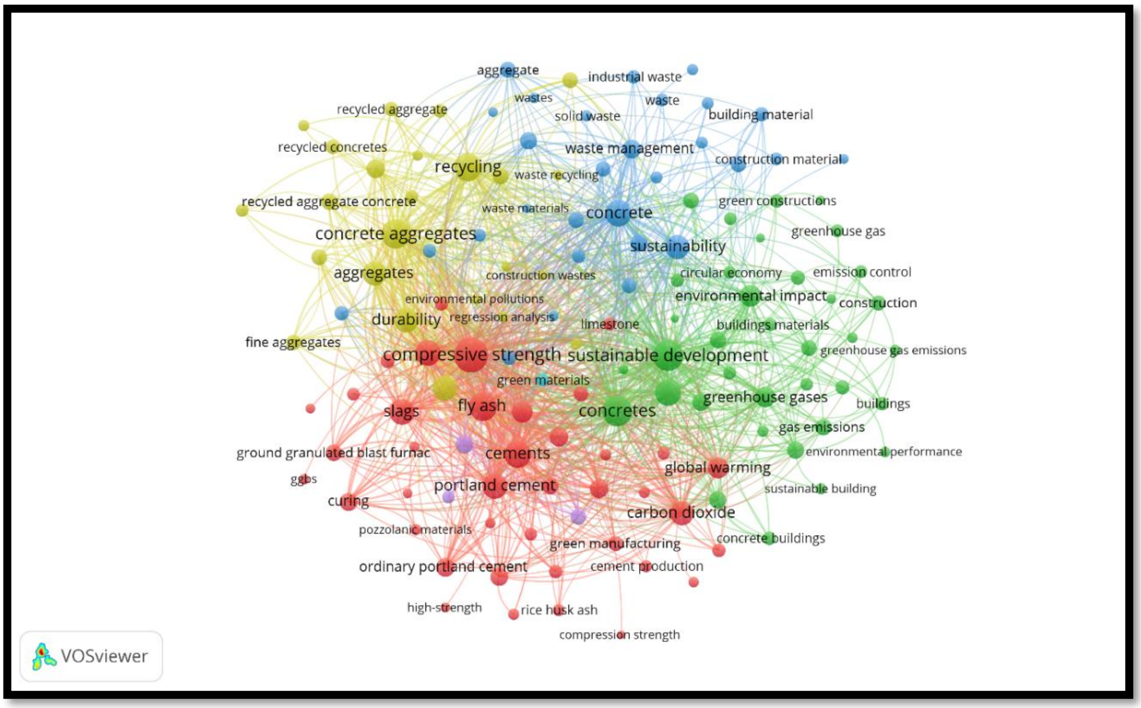

Figure 2.12 Co-occurrence of keywords on sustainable building material

The bibliometric profile confirms that sustainable building materials and green concrete are at the forefront of sustainable construction research.

2.4 Study on Sustainable Healthcare Infrastructure

The intersection of sustainability and healthcare infrastructure has gained prominence in recent years due to growing global health demands, climate change, and the imperative to reduce the environmental footprint of healthcare systems. This bibliometric review examines the evolution, contributors, and thematic development of research on sustainable healthcare infrastructure, particularly with a focus on risk assessment, environmental management, and facility performance evaluation.

2.4.1 Temporal Trends in Publication

As shown in Figure 2.13, there has been a noticeable increase in publications over the past decade. This upward trend corresponds with global efforts to promote green building certifications for hospitals, pandemic preparedness, and resilient infrastructure development. Notably, the post-2020 period has seen a surge in interest, likely driven by the COVID-19 pandemic and renewed attention on healthcare infrastructure capacity and safety.

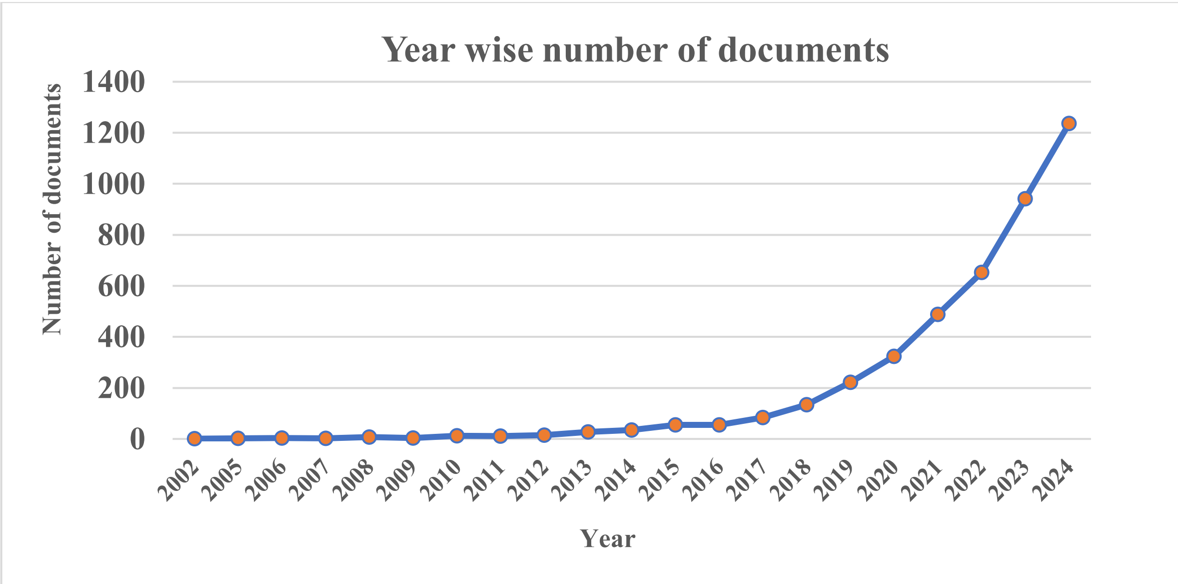

Figure 2.13 Year wise number of documents on sustainable health care infrastructure

2.4.2 Country-level Contributions

Figure 2.14 reveals that the United States, China, India, the United Kingdom, and Australia lead in publication output. The high contributions from developed nations reflect their investments in energy-efficient hospitals, carbon reduction mandates, and digital health infrastructure. Meanwhile, India’s rise highlights the dual challenge of expanding access to care while ensuring sustainability in rapidly urbanizing contexts

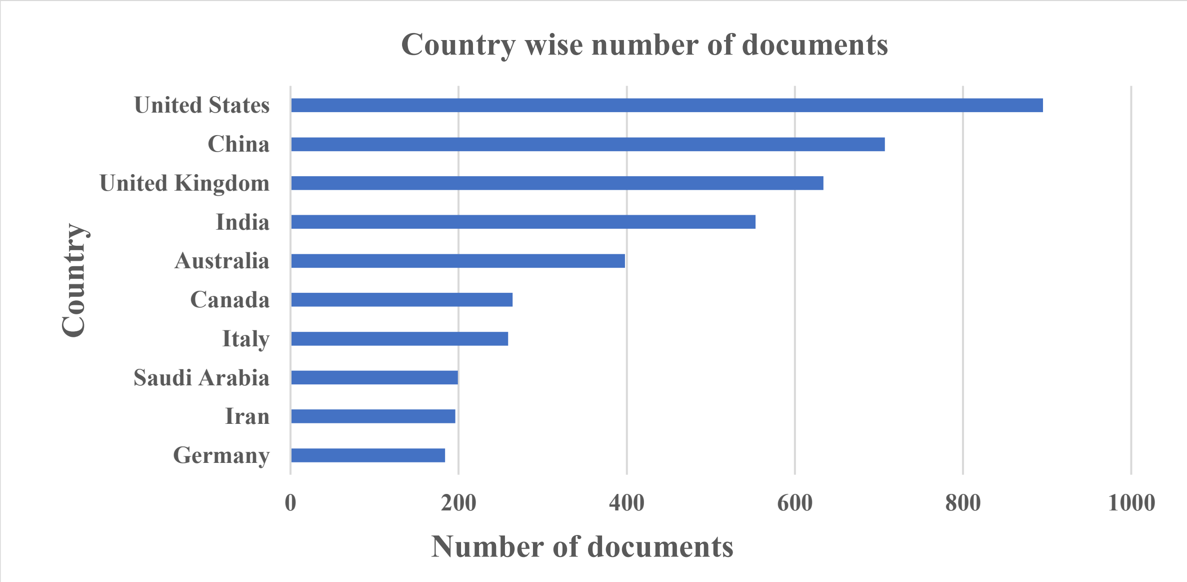

Figure 2.14 Country wise number of documents on sustainable health care infrastructure

2.4.3 Author Contributions and Influential Researchers

Figure 2.15 shows a concentration of active authors in this domain, many of whom are multidisciplinary researchers working across healthcare planning, environmental science, and systems engineering. These scholars have contributed extensively to areas such as green hospital design and certification, energy efficiency and waste management in healthcare, facility risk assessment and emergency preparedness. Their collaboration networks often intersect with studies on public policy, civil infrastructure, and healthcare systems modeling.

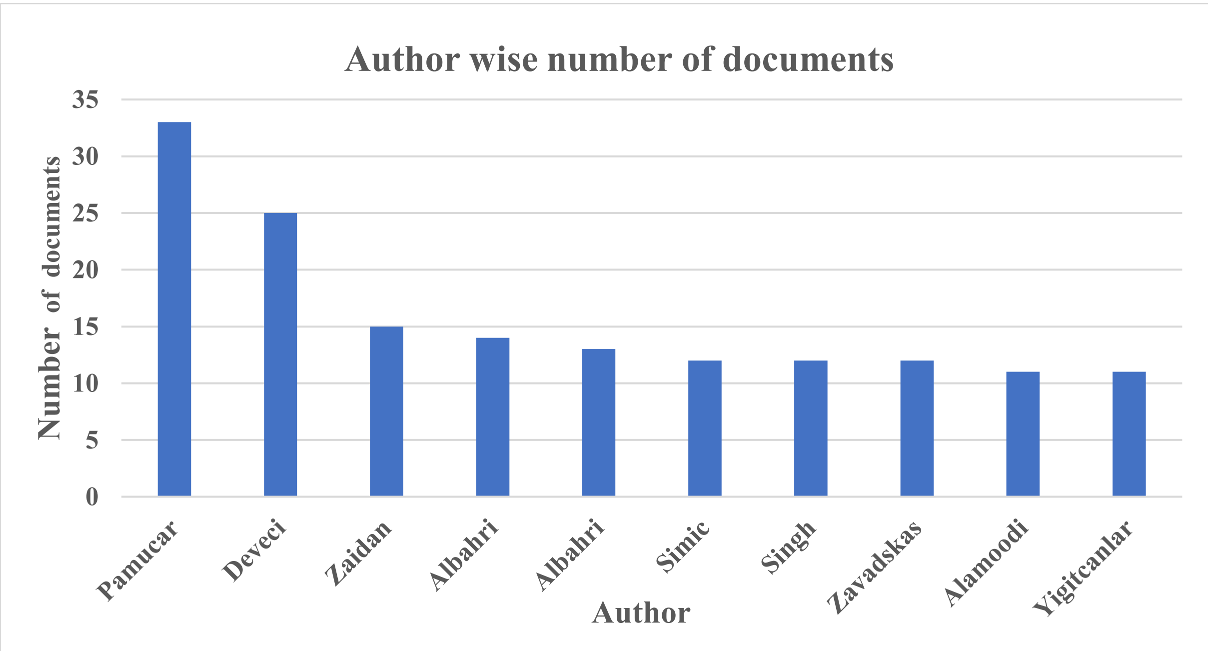

Figure 2.15 Author wise number of documents on sustainable health care infrastructure

2.4.4 Thematic Clustering through Keyword Co-occurrence

The analysis of Figures 2.16 and 2.17 (keyword co-occurrence and visual density) identifies four major research clusters:

Cluster A: Sustainable Design and Green Certification

Keywords:Sustainable healthcare, sustainable development, green buildings, energy efficiency, building design

Cluster B: Environmental and Resource Management

Keywords: Waste management, energy consumption, carbon emissions, lifecycle assessment, decision making

Cluster C: Healthcare Infrastructure Risk and Resilience

Keywords: Risk assessment, resilience, infrastructure planning, hospital safety, disaster preparedness

The visual density map further reinforces that risk assessment and infrastructure resilience are becoming increasingly dominant themes especially in the context of pandemics, climate-induced disasters, and urban emergency response systems.

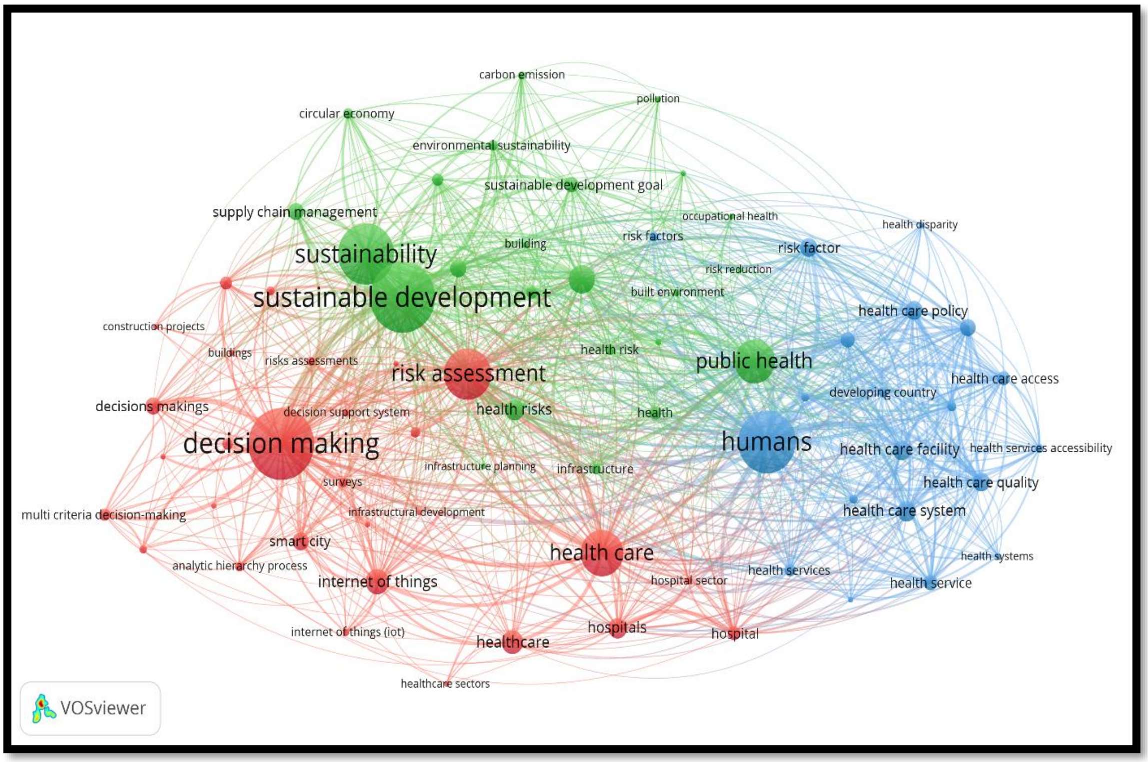

Figure 2.16 Co-occurrence of keywords on sustainable health care infrastructure

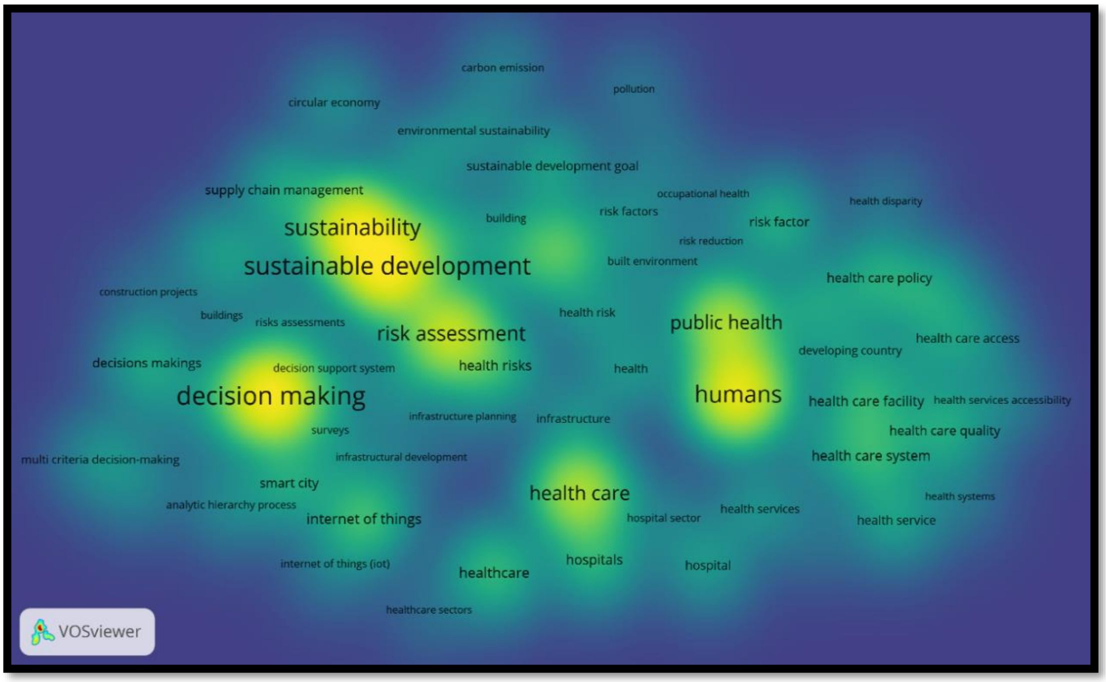

Figure 2.17 Co-occurrence of keywords visual density on sustainable health care infrastructure

The bibliometric landscape of sustainable healthcare infrastructure reveals a multidisciplinary and rapidly growing field. The convergence of sustainability, risk assessment, and health system resilience underscores the global recognition that hospitals must not only provide care but do so efficiently, safely, and sustainably. Future studies must embrace smart, patient-centric, and adaptive systems, especially in the face of emerging public health and environmental challenges.

2.5 Study on Risk Assessment in the Construction Industry through FMEA

The construction industry, inherently complex and dynamic, is exposed to a multitude of risks ranging from financial and operational to environmental and human factors. Over the last two decades, Failure Mode and Effects Analysis (FMEA) has emerged as a widely adopted tool for systematic risk assessment in construction projects. This bibliometric analysis maps the evolution, key contributors, and thematic structure of the global research on FMEA applications in construction risk management.

2.5.1 Temporal Trends in Publication

As shown in Figure 2.18, there has been a progressive rise in publications on FMEA in the construction sector, with sharp growth observed particularly after 2015. This reflects increasing concerns regarding project delays, cost overruns, safety hazards, and the need for proactive risk management approaches. The recent surge is also associated with advances in fuzzy extensions of FMEA, enabling better handling of uncertainty in risk prioritization.

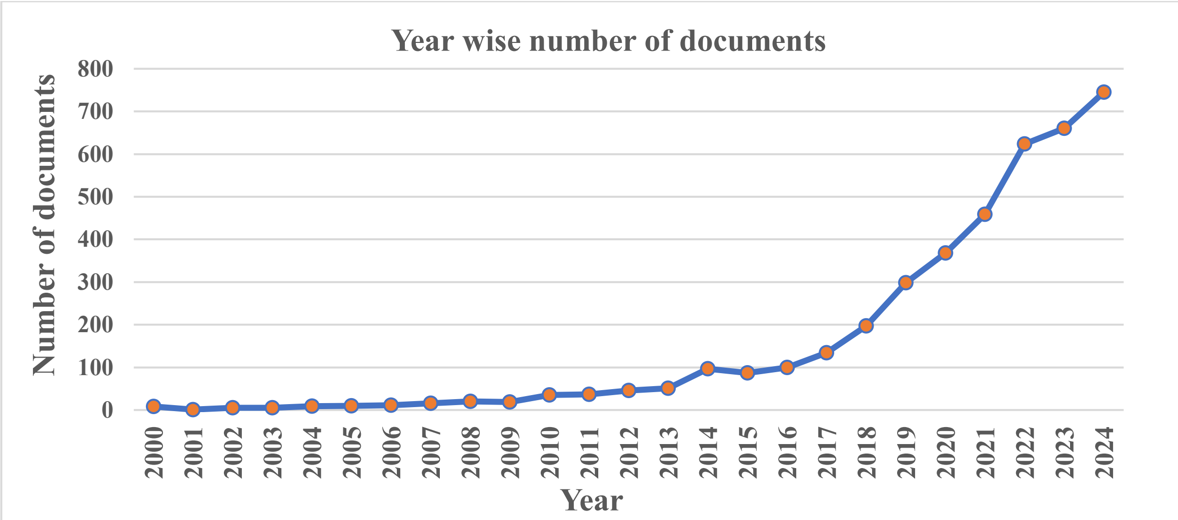

Figure 2.18 Year wise number of documents on risk assessment in construction through FMEA

2.5.2 Geographic Distribution of Research

Figure 2.19 highlights that leading research output comes from countries like China, India, Iran, the United States, and the United Kingdom. This distribution correlates with regions experiencing significant infrastructure expansion, regulatory emphasis on risk compliance, and academic interest in quantitative decision-making frameworks. India's prominent presence is noteworthy, reflecting its academic focus on construction risk mitigation under developing economy constraints.

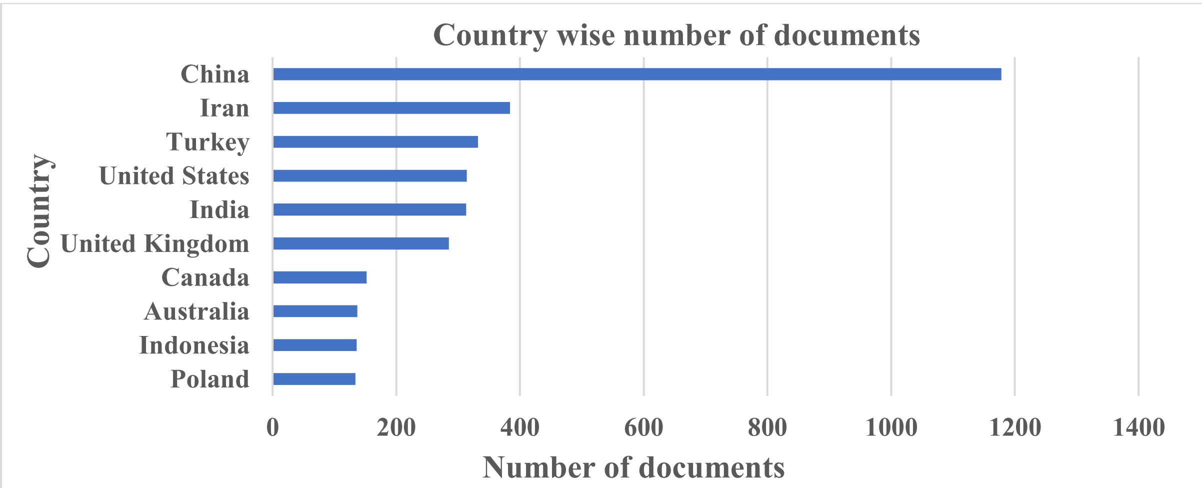

Figure 2.19 Country wise number of documents on risk assessment in construction through FMEA

2.5.3 Author Contributions and Influential Researchers

According to Figure 2.20, a selected group of authors has made consistent contributions in this domain. These researchers are often aligned with civil engineering, construction management, and industrial safety programs and have collaborated on applying FMEA to Contractor risk evaluation, Occupational health and safety (OHS), Environmental risk prioritization in sustainable projects, etc.

They frequently integrate FMEA with fuzzy logic, AHP, TOPSIS, and hybrid MCDM methods, indicating a methodological evolution from conventional FMEA to advanced, uncertainty-resilient models.

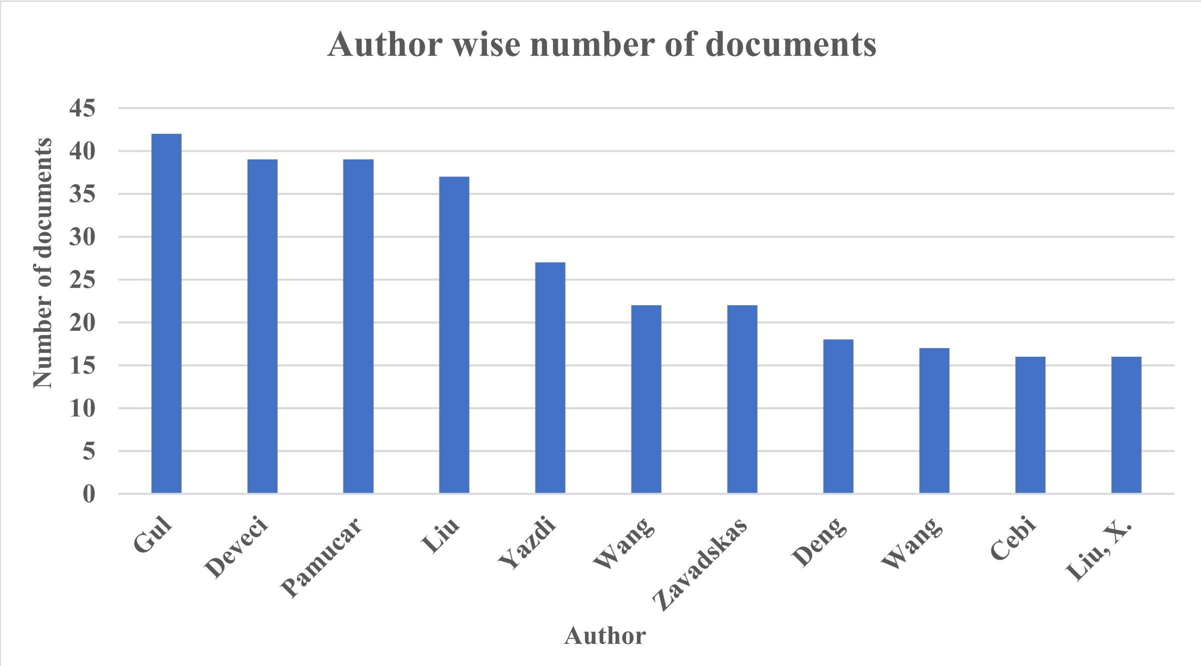

Figure 2.20 Author wise number of documents on risk assessment in construction through FMEA

2.5.4 Thematic Clustering through Keyword Co-occurrence

The analysis of Figures 2.21 and 2.22 reveals dense clusters of co-occurring keywords that highlight the interdisciplinary nature of this research field. Major clusters include:

Cluster A: Risk Management Frameworks

Keywords: Risk assessment, risk prioritization, construction risk, failure modes

Cluster B: FMEA and Hybrid Techniques

Keywords: FMEA, fuzzy logic, fuzzy FMEA, AHP, TOPSIS, MCDM

Cluster C: Safety and Occupational Health

Keywords: Safety risk, hazard identification, worker safety, accident prevention

Cluster D: Sustainability and Reliability

Keywords: Sustainable construction, reliability analysis, lifecycle cost, environmental risk

These themes indicate the transition of FMEA from a technical quality assurance tool to a holistic risk modeling framework for sustainable and safe construction environments.

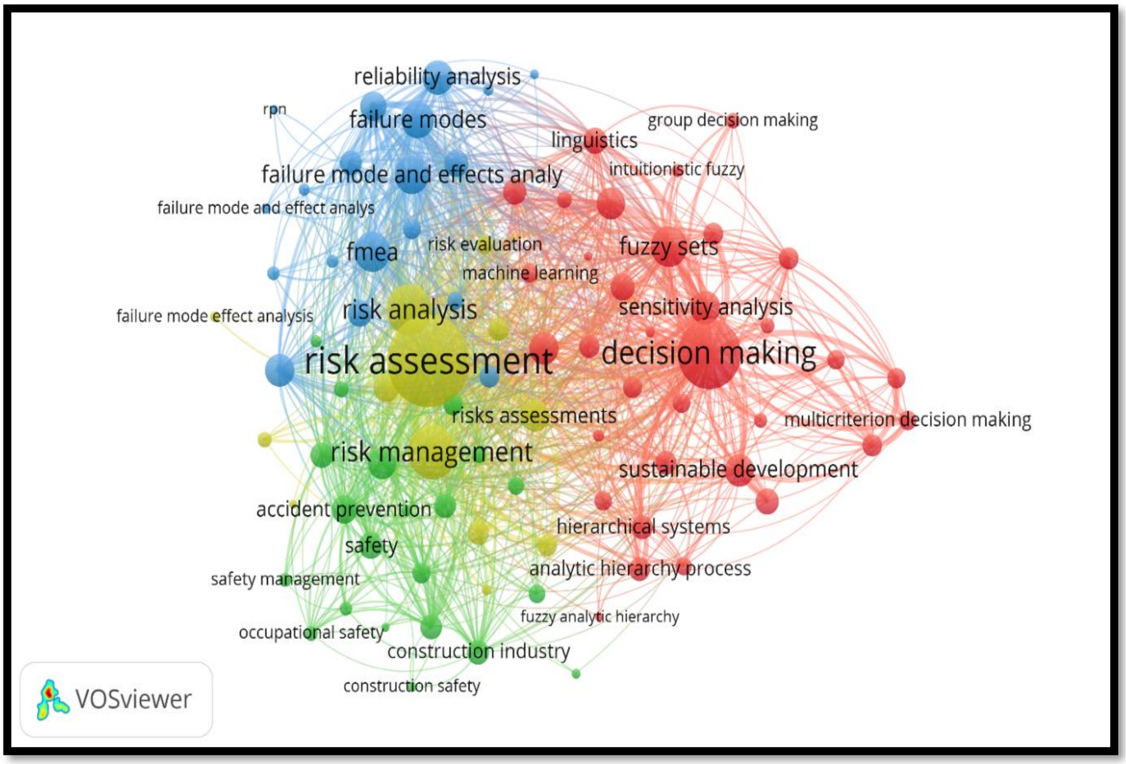

Figure 2.21 Co-occurrence of keywords on risk assessment in construction through FMEA

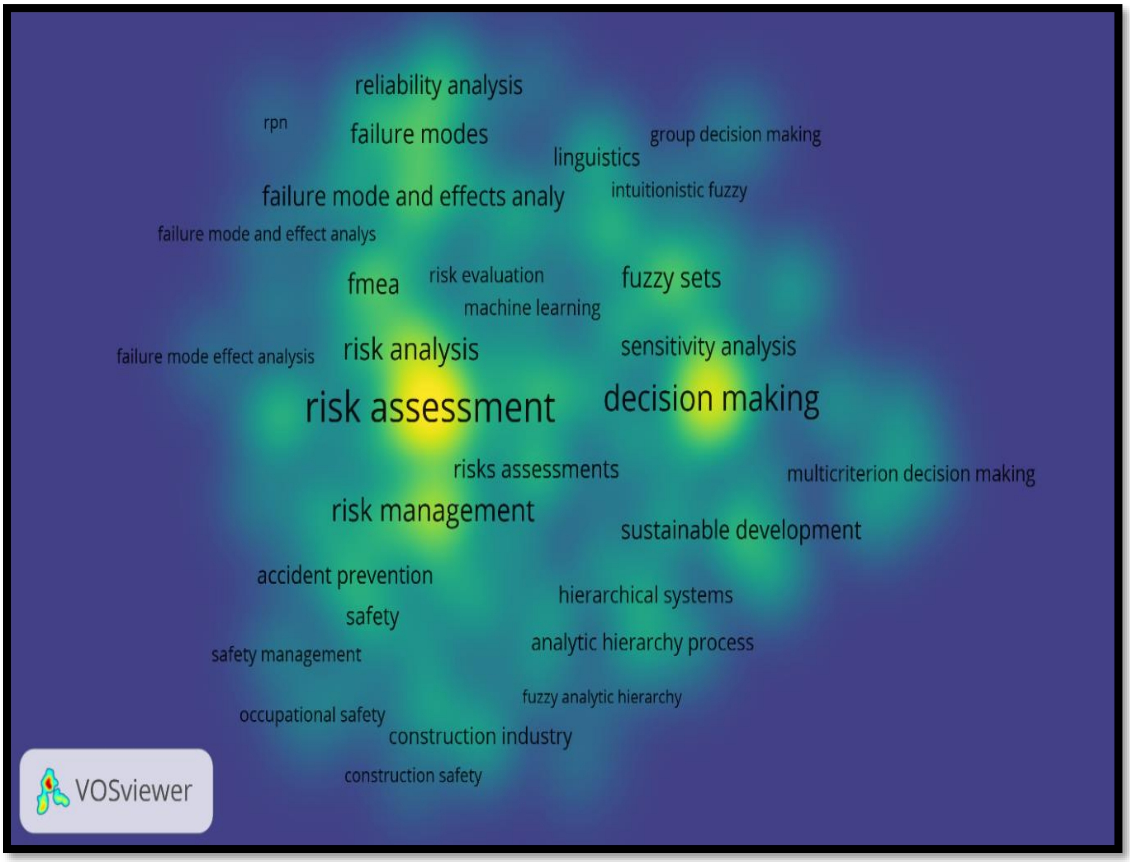

Figure 2.22 Co-occurrence of keywords density visual on risk assessment in construction through FMEA

FMEA has proven to be a critical tool in the construction industry's transition toward proactive and preventive risk management. Bibliometric trends show that the field is evolving through the incorporation of fuzzy logic, hybrid MCDM techniques, and sustainability considerations.

Chapter 3

Systematic Literature Study

3.1 Sustainability and Sustainable Development

The concept of sustainable development gained prominence in the 1980s as a strategic response to increasing concerns about the negative consequences of unchecked economic growth. It was formally introduced in the 1980 World Conservation Strategy by organizations such as UNEP, WWF, and IUCN. This initial framework emphasized that development should integrate ecological stability, economic growth, and social well-being to be considered truly sustainable.

A major turning point came in 1987 when the World Commission on Environment and Development (WCED) released the Brundtland Report. The report defined sustainable development as 'development that meets the needs of the present without compromising the ability of future generations to meet their own needs.' This definition gained global traction and provided the foundation for future sustainability agendas. The report also recommended strategic actions such as restoring economic growth, changing the quality of growth, meeting basic needs, and integrating environmental concerns into policy-making [7].

In 1992, the Earth Summit held in Rio de Janeiro further institutionalized the concept of sustainability through the adoption of the Rio Declaration on Environment and Development. Delegates from nearly 180 countries endorsed 27 principles and signed important international agreements, including the Framework Convention on Climate Change and the Convention on Biological Diversity. Agenda 21, a comprehensive plan of action to promote sustainable development at national and local levels, was also adopted during this summit [8].

The momentum continued with the 2002 World Summit on Sustainable Development (WSSD) in Johannesburg, where global leaders reaffirmed their commitment to sustainability. They prioritized goals such as halving global poverty by 2015, expanding the use of renewable energy, improving access to safe drinking water, and reducing biodiversity loss. These summits underscored the importance of sustainability as a guiding principle for global governance and development [9].

Today, sustainable development is viewed as a holistic approach to achieve long-term social, economic, and environmental balance. It encourages policymakers and practitioners to adopt strategies that go beyond short-term benefits and prioritize long-term ecological and societal resilience. By embedding sustainability into planning and governance, institutions aim to ensure equitable and viable futures for present and coming generations.

3.2 Mapping the Sustainable Development

Sustainable development, while widely recognized and advocated, continues to be interpreted in a multitude of ways depending on context, discipline, and stakeholder perspective. Its broad applicability has led to the creation of over a hundred definitions in literature, reflecting varying priorities such as environmental protection, economic growth, social justice, and ethical responsibility. This divergence in interpretation has been acknowledged by numerous scholars who argue that rather than striving for a singular definition, efforts should focus on practical implementation and contextual relevance. Some definitions emphasize minimizing environmental degradation and fulfilling essential human needs, while others broaden the scope to include cultural identity, ethical governance, and long-term resilience of systems [10-14].

Hill and Bowen (1997) describe sustainable development as an approach that reduces negative environmental impacts while satisfying societal demands [3]. Postle (1998) extends this perspective by incorporating elements like social welfare, cultural diversity, and infrastructure into sustainability discourse [15]. This evolving view acknowledges the interconnectedness of multiple dimensions like economic viability, environmental protection, and social inclusivity that must be addressed simultaneously.

The complexity of operationalizing sustainability lies in its requirement for balance among competing priorities. Authors like Lautso et al. (2004) and Ding (2005) emphasize that a truly sustainable development model must support harmony between ecological preservation, economic advancement, and social equity. These principles underscore the importance of intergenerational equity ensuring that current actions do not compromise the wellbeing of future populations [16,17].

Various global institutions, including the International Institute for Sustainable Development (IISD), stress the necessity of aligning economic improvement with sustainability goals. Economic growth remains a vital objective for governments as it contributes to enhanced quality of life, better access to resources, and greater institutional capacity. However, it must be pursued in conjunction with ecological responsibility and social welfare to achieve genuine sustainability [18-20].

In summary, the absence of a universally accepted definition of sustainable development underscores its inherent complexity and multidisciplinary nature. What is clear, however, is the growing consensus on the core principles of balance, equity, responsibility, and long-term thinking. This research adopts these principles to guide the assessment and implementation of sustainability within the construction sector, recognizing the need for sector-specific adaptations and practical frameworks.

3.3 Sustainable Construction Practices

Over the past three decades, sustainability has become a central theme in the construction industry due to its substantial influence on environmental quality, economic growth, and social development. Sustainable construction is understood as the application of environmentally responsible and resource-efficient processes throughout a building's entire life cycle from planning and design to construction, operation, maintenance, and eventual demolition [21].

The construction sector is one of the largest contributors to global energy consumption and greenhouse gas emissions. According to the International Energy Agency (IEA), buildings account for approximately 30% of global final energy consumption and nearly 40% of energy-related CO_2 emissions. This impact has prompted international efforts to reduce the sector's ecological footprint through the adoption of sustainable practices [22,23].

Sustainable construction practices aim to balance environmental performance, cost-efficiency, and social responsibility. This includes designing energy-efficient buildings, utilizing renewable energy sources, reducing construction waste, recycling materials, and selecting sustainable building products [24]. These strategies not only minimize negative environmental impacts but also enhance building performance, reduce operating costs, and support occupant well-being [25]. Numerous researchers have emphasized that sustainable construction should begin at the planning stage. Early-stage integration of sustainability principles can influence design decisions that promote passive energy use, efficient spatial planning, and material selection aligned with environmental goals [26,27]. Moreover, building performance assessments and life cycle evaluations are essential tools for quantifying environmental impact and informing sustainable choices. Social sustainability is also gaining prominence in construction literature. It addresses issues such as ensuring healthy indoor environments, improving safety and comfort, and considering the long-term impact of construction projects on communities [28]. When combined with environmental and economic considerations, these aspects contribute to a more holistic understanding of sustainable development in the built environment [29,30].

In essence, sustainable construction is more than a technical or regulatory requirement. It represents a shift in mindset toward systems thinking and long-term stewardship. Through a combination of innovation, policy support, and stakeholder engagement, the construction industry can evolve into a leading force for sustainable development globally [31].

3.4 Principles of Sustainable Construction

A number of scholars and international organizations have outlined key principles that underpin sustainable construction. These principles serve as a foundation for integrating environmental protection, economic feasibility, and social responsibility throughout the construction lifecycle [32,33].

Hill and Bowen (1997) proposed a framework dividing sustainable construction principles into three core dimensions: social, economic, and biophysical. Social principles focus on enhancing human health, safety, cultural preservation, and overall quality of life. Economic principles promote affordability, employment creation, fair trade, and long-term value. Biophysical principles emphasize responsible resource use, pollution prevention, and biodiversity conservation [3].

Similarly, Miyatake (1996) and the CIB (1999) recommend minimizing resource consumption, maximizing reuse, incorporating renewable and recyclable inputs, and ensuring a non-toxic, healthy environment. These practices aim to reduce environmental degradation while maintaining functionality and comfort [37,38].

Cole and Larsson (1999) place particular emphasis on indoor environmental quality, advocating for improvements in air purity, acoustic comfort, thermal conditions, and visual appeal factors that directly affect occupant well-being [39].

The UK Department of the Environment, Transport and the Regions (DETR, 2000) expand these ideas by incorporating profitability, stakeholder satisfaction, and competitiveness into sustainability goals. Their framework stresses energy efficiency, minimal environmental impact, and respect for social equity [36].

Collectively, these principles offer actionable guidelines for architects, engineers, contractors, and policymakers striving to implement sustainable practices. Adopting a life-cycle perspective, these frameworks encourage decisions that support long-term ecological balance, economic stability, and social inclusion in the built environment [34,35].

3.5 MCDM Methods Used in Construction Industry

MCDM methods have emerged as essential tools in the construction sector to support decision-makers in addressing complex problems involving conflicting and heterogeneous criteria. These methods have been extensively used for project selection, contractor evaluation, sustainable construction decisions, and material selection.

Among the most widely adopted techniques, TOPSIS and AHP dominate the landscape. For instance, TOPSIS has been applied in areas like construction project selection and sustainable investment evaluation due to its simplicity and computational efficiency [40]. Similarly, AHP has been instrumental in scenarios requiring hierarchical structuring of criteria, such as construction site selection and contractor assessment [41,43,44].

More advanced hybrid methods are also gaining traction. ANP (Analytic Network Process) and DEMATEL (Decision Making Trial and Evaluation Laboratory) have been used to identify and analyze critical success factors in project management and green material selection. Their integration captures both the interdependencies among criteria and feedback mechanisms [45].

Further, COPRAS (Complex Proportional Assessment) and ARAS (Additive Ratio Assessment) are applied in domains such as material selection and sustainable building assessment, highlighting their capacity to handle both quantitative and qualitative data. For strategic decision-making involving SWOT analyses, Goal Programming has shown efficacy in quantifying qualitative judgments [46].

Innovative models have also been explored. For instance, Step-wise Weight Assessment Ratio Analysis (SWARA) combined with Yin-Yang balance has been used in product design, reflecting cultural and philosophical factors in design criteria. Additionally, Qualification-Based Selection (QBS) and Best-Value Procurement models offer contractor evaluation frameworks that prioritize long-term value over low bidding strategies [42].

Khurana and Garg (2024) conducted a comprehensive systematic review focused on material selection within the construction industry using MCDM approaches. Their study found that traditional methods such as AHP and TOPSIS dominate, but recent research trends are gravitating toward hybrid techniques that integrate fuzzy logic to deal with linguistic variables and ambiguity in expert judgments [47].

Expanding into the domain of safety management, Khosravi et al. (2023) analysed how MCDM models, particularly fuzzy AHP(FAHP) and fuzzy TOPSIS(FTOPSIS), are being utilized for construction safety risk assessment. Their findings emphasized that MCDM offers a structured and quantifiable framework for prioritizing safety factors, assessing site-specific risks, and guiding policy implementation for safer construction practices [48].

Shahin and Elshaboury (2024) demonstrated the practical value of a hybrid fuzzy AHP–TOPSIS–VIKOR model in selecting sustainable structural materials. Their study showcased how combining these methods leads to a more robust ranking mechanism by balancing trade-offs among conflicting sustainability indicators such as cost, durability, and environmental impact [49].

A broader sustainability lens was adopted by Verma and Singh (2025), who reviewed the integration of MCDM techniques within circular construction frameworks. Their analysis revealed that AHP–TOPSIS hybrids are particularly effective in evaluating alternatives under environmental, economic, and technical criteria, promoting resource efficiency and lifecycle optimization [50].

For contractor evaluation, Hassan and Arefin (2024) proposed a Digital Weighted MCDM (DWMCDM) framework incorporating interval-valued fuzzy sets. Their model accounted for uncertainty in contractor attributes during both pre-qualification and bid evaluation phases, yielding more reliable and consistent decisions compared to conventional deterministic approaches [51].

Ali and Elkouny (2023) developed an integrated hybrid framework combining Fuzzy Foresight Systems (FFS), AHP, DEMATEL, and TOPSIS to evaluate electronic waste recycling facility locations—highlighting the applicability of advanced MCDM structures for infrastructure projects linked to sustainability and smart city planning [52].

On the frontier of probabilistic modeling, Minouei and AzariJafari (2025) introduced a probabilistic MCDM framework tailored for assessing circular Modern Methods of Construction (MMC). Their model integrated stakeholder uncertainty, performance variability, and lifecycle attributes—pushing the boundaries of conventional MCDM by incorporating probabilistic scenarios and risk propagation [53].

Together, these studies affirm that MCDM continues to evolve as a cornerstone in construction decision-making, with future research expected to integrate deeper uncertainty modeling, sustainability metrics, and digital technologies.

3.6 Need of Fuzzy Theory and its Application in Construction Industry

Construction projects involve multiple, often conflicting criteria such as cost, quality, time, safety, and sustainability and are rife with uncertainty and qualitative judgments (e.g., expert opinions, stakeholder preferences) that cannot be accurately captured by crisp numeric values. Fuzzy set theory (Zadeh, 1965) provides a mathematical framework to handle imprecision, vagueness, and linguistic variables, enabling better modeling of human judgment in MCDM contexts [54].

Chen et al. (2021) offered a systematic review of fuzzy MCDM (FMCDM) in construction management (2007–2017), identifying 165 FMCDM studies involving 37 single and 17 hybrid fuzzy methods. These primarily addressed material selection, risk assessment, contractor evaluation, and site planning. They emphasized that fuzzy techniques enhance robustness and applicability in uncertain environments [55].

Taylan et al. (2014) applied FAHP to weight project risk criteria (e.g., cost, time, safety), and used FTOPSIS for ranking construction projects under uncertainty. Applied to 30 projects at King Abdulaziz University, the hybrid method effectively identified the lowest-risk option in a fuzzy environment [56].

Hybrid FMCDM models combining FAHP and other methods (like DEMATEL, TOPSIS) have been used in location selection decisions for e.g., siting e-waste facilities or supply chain technologies demonstrating the flexibility of fuzzy logic in managing qualitative indicators across domains. FMCDM approach can make work a lot easier under uncertain situations. Application of FMCDM method requires proper selection of the method for a particular problem which includes various criteria like validity, suitability and intelligibility. FMCDM methods have the advantages of both Fuzzy Set Theory for dealing with uncertainty and MCDM for dealing with project decision complexity [57,58].

3.7 Fuzzy Theory and its Evolution

In 1965, Zadeh developed the Fuzzy Set Theory which is a branch of modern mathematics to model vagueness in human cognitive process [54]. Fuzzy Set Theory is used to address real world complex and ill-defined problems with incomplete information [59]. The application of the theory has its obstacle in attribution membership degrees to the elements which relies on the application and context. In 1971, Zadeh developed the concept of type-n Fuzzy Set including type-2 Fuzzy Set [60]. Since then, several types of Fuzzy Sets have been developed which has been discussed below.

The evolution of fuzzy set theory began in 1965 with Lotfi A. Zadeh's seminal work on fuzzy sets, introducing the foundational concept that laid the groundwork for subsequent developments in fuzzy logic [54]. Building on this, Zadeh extended the theory in 1971 by proposing the notion of Type-n fuzzy sets and specifically, Type-2 fuzzy sets, both of which allowed a more flexible representation of uncertainty and linguistic vagueness [60]. He further elaborated on Type-n fuzzy sets in 1975, defining their structure in more detail [61]. In 1976, Mizumoto and Tanaka mathematically formalized the definition and operational framework for Type-2 fuzzy sets, thus providing a deeper theoretical foundation [62].

The first known application of fuzzy theory occurred in 1980 when F. L. Smith Co. developed a commercial product, cement using fuzzy logic principles, marking a practical milestone in the field [63]. In 1982, Deng introduced Grey System Theory (GST), which enabled system analysis under conditions of incomplete information [64]. Later, in 1986, Atanassov defined the Atanassov Intuitionistic Fuzzy Sets (IFSs), adding another layer of richness to uncertainty modeling by including both membership and non-membership functions. He, along with Gargov, extended this in 1989 by introducing Interval-Valued Atanassov Intuitionistic Fuzzy Sets (IVIFSs), enhancing the flexibility of the model [65] .

Development continued into the 21st century with Torra's 2009 proposal of Hesitant Fuzzy Sets (HFSs), which allowed the representation of multiple potential membership values for a single element, better capturing hesitation in human judgment [66]. In 2014, Bedregal and colleagues defined Typical Hesitant Fuzzy Sets (THFSs), further extending the capabilities of hesitant fuzzy models [67]. Between 2014 and 2020, fuzzy set theory witnessed significant theoretical and application-oriented advancements. A major development was the emergence of Pythagorean fuzzy sets, which extended intuitionistic fuzzy sets by introducing a relaxed constraint of $u^2 + v^2 \leq 1$, thereby allowing more flexible representation of uncertainty. This innovation was soon followed by the introduction of q-rung orthopair fuzzy sets, where the condition became $u^q + v^q \leq 1$, providing greater freedom in modeling vagueness and enabling more accurate decision-making processes [68]. In addition, researchers proposed new fuzzy structures such as spherical fuzzy sets, picture fuzzy sets, and neutrosophic fuzzy sets, which offered multidimensional and more nuanced representations of uncertainty. These sets captured the concepts of membership, non-membership, indeterminacy, and neutrality more precisely, contributing to advancements in areas like environmental modeling, social decision-making, and medical diagnosis [69]. Another notable progression was the extension of hesitant fuzzy sets into type-2 hesitant fuzzy sets, dual hesitant fuzzy sets, and higher-order hesitant models, which accommodated more complex human hesitancy and fuzziness in multi-criteria decision-making scenarios [68,70]. During this period, researchers also integrated fuzzy logic with robust optimization techniques, leading to the formulation of robust fuzzy programming (ROFP) models, which ensured solution reliability under uncertainty in real-world supply chain and logistics problems [71]. These advancements reflect a growing interest in making fuzzy systems more adaptable, expressive, and robust for practical use across engineering, healthcare, and environmental applications.

3.8 Contractor Performance Evaluation

Selecting a suitable contractor is one of the most critical and complex aspects of a building project due to the inherent ambiguity and difficulty in formalizing contractor-related variables [72–74]. Historically, this decision-making process has often been undervalued, leading to negligence in evaluating essential factors [75]. The widely adopted practice of selecting contractors based on the lowest bid has come under increasing scrutiny in recent years, as it frequently results in negative outcomes stemming from inadequate consideration of other influential project dimensions [76]. Studies conducted in countries such as Canada, the United States, and Lithuania have documented instances where contractors were chosen solely based on the lowest price criterion [77]. However, reliance on this single metric has led to multiple project issues, including delays, substandard work quality, and financial losses [78], [80].

Hatush and Skitmore emphasized the importance of a comprehensive evaluation framework in contractor selection, identifying key parameters such as cost, time, quality, adaptability to project changes, uncertainty management, and the ability to handle complex project conditions. They illustrated this through a comparative analysis of four contractor alternatives using multiple decision variables [79]. To mitigate potential risks, Topcu proposed a structured prequalification process that incorporates a multi-attribute decision-making model, taking into account essential criteria such as cost, time, and quality [81].

Over time, several analytical techniques have been employed in contractor prequalification, including Multi-Attribute Analysis (MAA), Cluster Analysis (CA), Fuzzy Set Theory (FST), Multi-Attribute Utility Theory (MAUT), Multiple Regression (MR), and Multivariate Discriminant Analysis (MDA) [79,82,83]. An additional model incorporating risk assessment has been introduced using the Hodges-Lehmann Rule, where a project-specific risk coefficient (λ), ranging from 0 to 1, was used to quantify the level of risk associated with contractor decisions [84].In a broader context of supplier selection, Govindan et al. analyzed various decision-making methodologies and ranked them by usage frequency led with 27.78%, followed by ANP at 16.6%, Data Envelopment Analysis (DEA) at 11.1%, Linear Programming (LP) at 8.76%,TOPSIS at 5.56%, and Multi-Objective Optimization at 2.77% [85].

3.8.1 Contractor Performance Evaluation Considering Risk and Reliability

Choosing the right contractors for construction projects is very important for the project's success in terms of cost, quality, and schedule. Cost-based analysis and technical evaluations are two common ways to choose a contractor, but they frequently don't take into account the fact that contractor performance and data dependability are always unpredictable [86]. This is especially apparent when performance data might be self-reported, is unreliable, or is hard to check. Because of this, project managers and stakeholders can be making judgements based on data that isn't clear, which might lead to bad or unsafe choices. In real-life construction projects, data uncertainty typically shows up as things like changing prices, unsubstantiated project dates, or noise levels that aren't always the same throughout development. It's not always easy to measure these uncertainties using standard contractor selection frameworks, which usually put more weight on things like cost-effectiveness or historical performance without really knowing how accurate these data points are. Since of this, decision-makers face more risks since the information they have may not be accurate or may not have been verified [87]. There is a rising requirement to include risk awareness and data dependability in the process of choosing a contractor [88]. This has led to the creation of decision-making models that go beyond conventional trade-off analysis. Recent studies in MCDM have come up with strong ways to take into account uncertainty, dependability, health and safety making contractor assessment more thorough [89-94]. The Hodges-Lehmann rule is one of these methods that has worked well for making decisions that take risks into account. [84]. Table 3.1 below highlights the analysis of recent literatures on contractor performance evaluation.

Table 3.1 Analysis of recent literatures on contractor performance evaluation

Paper Title & Reference	Key Contributions	Issues Not Addressed
A Decision Model Proposal for Construction Contractor [81]	Proposes a contractor prequalification model using AHP and evaluation matrices to determine Global Prequalification Scores (GPSs).	Limited validation and refinement; excludes health, safety, environmental aspects; model tested on a limited number of cases.
Application of Graph Theory and Matrix Methods [95]	Introduces graph theory and matrix methods as an effective decision analysis tool for contractor selection, accounting for interdependencies among criteria.	Model lacks generalizability; specific to predetermined criteria; interactions not comprehensively validated.
Application of Type-2 Interval Fuzzy Sets [96]	Proposes an enhanced FAHP using Type-2 interval fuzzy sets to aggregate expert judgments with imprecise assessments.	Application limited to a single case; assumes homogeneity in decision-maker understanding; lacks scalability analysis .
Assessment of Contractor Selection Success Factors [97]	Uses ANP to assess and rank 31 contractor selection criteria considering interdependencies; provides data-backed prioritization.	Regional focus (Qatar); lacks comparative validation against other MCDM methods; environmental and safety criteria underexplored .
Assessment of Dispute Causes in Government Maintenance Projects [98]	Identifies and ranks 44 dispute causes using FAII and risk mapping; validated with real-world case studies.	Focused only on Saudi Arabia's context; does not explore dispute mitigation strategies in depth; lacks longitudinal data.
Analysis of Negative Impacts of BIM-Enabled Information Transparency [99]	Explores how BIM transparency can impair contractor interests; identifies key unethical practices affected by BIM.	Focuses only on contractor perspective; does not offer counterstrategies or involve broader stakeholder analysis.
An Empirical Study on Trust Between Owners and PMC Contractors [100]	Develops and validates a model linking trust antecedents and project performance in PMC projects using empirical data.	Case-specific to China; does not explore trust dynamics in multi-party or cross-cultural contexts; limited generalizability.
Fuzzy MCDM Model for Contractor Selection [101]	Integrates fuzzy set theory with multiple criteria to improve contractor ranking under uncertainty.	Limited comparison with other fuzzy-based models; lacks empirical testing with real-time data

Paper Title & Reference	Key Contributions	Issues Not Addressed
New Compromise Solution for Group Fuzzy Decision Making [102]	Proposes an enhanced fuzzy compromise ranking method for group decision-making with interval fuzzy environments.	Not directly tested in construction scenarios; lacks integration with contractor selection or real-world implementation.
Corporate Risk Management for Global Contractors [103]	Proposes a multi-criteria integrated portfolio model (Return, Risk, Efficiency); introduces corporate-level Value-at-Risk (VaR) assessment for project selection; validated with case study from global contractor	Limited to large contractors with multiple international projects; does not offer guidance for small/medium firms; lacks sequential modeling between project and corporate levels
Dynamic Selection of Risk Response Strategies [104]	Develops a simulation–optimization model combining system dynamics and resource allocation; addresses dynamic, cross-stage risk interactions in project portfolios	Assumes availability of reliable stage-wise project risk data; doesn't model organizational behavioral responses or uncertainty in RRS effectiveness
Decision Making Framework for Tender Evaluation [105]	Introduces a three-stage DMF using DEA, fuzzy logic, and MILP for public-sector contractor selection; explicitly considers risk in selection	Doesn't account for qualitative judgments or subjective bias in risk assessments; implementation feasibility in organizations with limited technical capacity is not addressed
A Type-2 Fuzzy Set Model for Contractor Prequalification [106]	Applies Interval Type-2 Fuzzy Sets (IT2FS) to model expert uncertainty and improve robustness of contractor ranking; handles subjectivity in group decision-making	High computational complexity; does not integrate time or cost risk post-selection; does not address feedback or iterative evaluation processes
Contractor Selection using Multi-Attribute Decision Making [107]	Combines cloud theory and utility theory for evaluating both qualitative and quantitative attributes in contractor selection	No risk modeling or probabilistic treatment of uncertainty; doesn't support dynamic updates or post-award performance feedback
Evaluation and selection of construction projects based on risk analysis [108]	Proposes a FAHP based strategy for project selection using risk factors; applied to HVAC projects in Egypt and Saudi Arabia.	Scalability to larger/more diverse project types; lacks validation across broader geographic or cultural contexts.

Paper Title & Reference	Key Contributions	Issues Not Addressed
Examining owners' and contractors' motivations to participate in CRM [109]	Develops a motivation framework using identity and interest logic; based on Hong Kong-Zhuhai-Macao Bridge case study.	Lacks empirical validation across multiple mega infrastructure projects; does not explore how motivations evolve over project stages.
Expertise-based bid evaluation with ELECTRE III [110]	Introduces GCLEs with ELECTRE III for imprecise bid evaluations; uses real-life contractor selection case.	High computational complexity; limited generalizability due to small case base.
Factors affecting contractors' risk attitudes [111]	Identifies four major factors influencing contractor risk attitude in China using factor analysis.	Geographically limited to China; influence of external economic variables not deeply analyzed.
Factors influencing sub-contractors' selection [112]	Identifies 46 influencing factors using surveys and SPSS; provides statistical analysis of factor significance.	Lacks modeling or decision framework; regional specificity not tested for generalizability.
Feature weights in contractor safety performance [113]	Compares machine learning and expert-based methods for safety performance assessment.	Limited dataset scope; effect of data distribution shift not fully resolved.
Fuzzy clustering validity for contractor performance [114]	Applies multiple clustering algorithms to contractor performance; identifies fuzzy C-means as most valid.	Limited to UAE dataset; real-time application feasibility not evaluated.
Housing refurbishment contractor selection using fuzzy-QFD [115]	Proposes hybrid fuzzy-QFD model for private refurbishment contractor selection.	Does not test model across public or commercial sectors; lacks real-time tool application.
Improving sub-contractor selection via WEBSES [116]	Develops web-based evaluation system (WEBSES) using combined criteria.	Technological scalability and cybersecurity of web tool not discussed; limited validation cases.
Integrating the group-based fuzzy best-worst method and MARCOS for selecting sustainable contractors [117]	Presents a hybrid group-based decision-making method combining fuzzy BWM and MARCOS for contractor evaluation under sustainability criteria.	Limited real-world validation and scalability across diverse regions or large contractor databases.

Despite significant advancements in contractor assessment problem using MCDM methodologies such as AHP, ANP, fuzzy sets, and ELECTRE, many critical issues still persist. Many current studies inadequately address occupational health concerns, particularly noise exposure, despite bibliometric research indicating its increasing significance in sustainable construction practices. Noise is a recognised workplace danger; yet, it is not often used as a decision criterion, making existing models less comprehensive. While some advanced MCDM methods consider risk attitudes or fuzziness in preferences, they typically treat risk and reliability as separate dimensions. There is no integrated approach that systematically adjusts contractor performance scores based on both decision-makers' risk preferences and data reliability simultaneously. The Hodges-Lehmann method, a non-parametric and outlier-resistant method, remains underutilized in contractor evaluation literature. Particularly, no existing study appears to have applied a modified Hodges-Lehmann approach that incorporates data reliability for contractor selection under uncertainty.

3.9 Waste Landfill Site Selection

In 2022 Paul and Ghosh attempted to investigate new dumping sites for the KMA taking into account 4 main parameters and 17 sub-parameters. FAHP and weighted linear combination model were used to calculate the ratings and weights for all the parameters. The use of GIS-based methods in selecting appropriate landfill locations was also highlighted in the current investigation [120].

In 2022 Guillermo and Garcia gave a detailed study of the most pertinent MCDM techniques and tools in this article with an emphasis on how well-suited they are for evaluating solid waste management systems. AHP, MAUT, Outranking methods, and TOPSIS have been recognized as the approaches that are most pertinent. The fact that decision makers typically select subjective evaluation criteria is a frequent shortcoming of these techniques [121].

In 2019 Shi et al. tried to reduce the expense and damaging impacts on the environment through their study. In order to determine the best method for tackling the problem of multi-objective function optimization, they put out a location-based multi-objective model that combined probabilistic robust optimization with evolutionary algorithms. The model employed a genetic algorithm to obtain an initial result before using probabilistic robust optimization to identify the best course of action. Significant clustering features were found in the Pareto optimum frontier, demonstrating the logic and viability of the site selection optimization model [122].

In 2014 Liua et al. suggested an attitude-based interval 2-tuple linguistic VIKOR (ITL-VIKOR) technique in order to choose the ideal MSW disposal location. An illustration of an RDF combustion plant location was used to better illustrate the viability and applicability of the suggested technique. The results demonstrated that, in the presence of ambiguous and partial information, the recommended method for group decision making may be able to address the challenge of selecting the MSW disposal location [123].

In 2022 Jinq et al. attempted to identify the most acceptable locations in Peninsular Malaysia for a permanent repository for radioactive waste used to dispose of sealed radioactive sources (DSRS). The possible locations were identified using a Weight Linear Combination (WLC) analysis based on GIS, which integrated methodologies from improved AHP and TOPSIS. The key contributing variables for the choosing of Peninsular Malaysia were determined using the sensitivity analysis. In the approximate criteria range, the model showed that the suitability ratings are inversely correlated with their area sizes [124].

In 2022 Süleyman Sefa Bilgilioglu aimed to choose the best RWDF locations for the Akkuyu Nuclear Power Plant. In order to do this, an MCDM model that combines GIS and AHP techniques to perform realistic and speedy evaluations was created. Twelve criteria were selected based on the features of the research area and the recommendations of subject-matter experts. The weights of each criterion and sub criteria were calculated using expert opinion to create a suitability map for selecting RWDF locations. Seven candidate regions were identified as a consequence of the study. Suitable sites for RWDF were identified on the outcome map. The outcomes show that GIS-based MCDM is a useful tool for site selection for RWDF [125].

Li et al. in 2022 took into account both financial (cost minimization) and environmental (emissions reduction) objectives. The optimum supply chain networks for sustainable MSW management were shown in this study using crisp and fuzzy optimization methods. The crisp model was used to examine the competing goals of reducing the total net cost and GHG emissions producing a number of Pareto ideal options. The fuzzy model was used to find a compromise solution that reduced costs by 21.6% and emissions by 28.4%. These outcomes showed how well the suggested methods work to address the MSW management issue [126].

Lee et al. in 2022 used a multi-criteria GIS framework in the study to handle a variety of difficult decision-making difficulties that when they worked on the selection of temporary disaster waste management sites (TDWMSs). The framework, which focused on post-flood situations, took into account possible restrictions on vehicle access and transportation depending on flood levels and road widths. Applying the framework to Seoul, South Korea, the case study's chosen location, allowed for an evaluation of the framework's usefulness. A weighted total analysis was used to assess the TDWMS' appropriateness using the fourteen criteria that were created. The results showed an increase in overall performance with respect to current situation in Seoul [127].

In 2018 Ding et al. studied to provide a framework that made it easier to choose a landfill for building trash. First, a literature analysis revealed a total of sixteen variables that might affect the choice of a landfill site. The weights and final comprehensive scores of the selected components were then determined using the combined AHP and entropy approach. The decision-making techniques suggested in this study might serve as a useful guide for choosing construction waste dump locations [128].

In 2022 Sondh et al. described the applicability and efficacy of each waste treatment technique by dividing them into conventional and non-traditional categories. Emphasizing waste-to-value, waste-to-energy (generating heat and electricity) and waste-to-material (creating value-added goods like slag, soil manures, bio-oils, etc.) have been further elaborated upon. The study provided insightful recommendations, such as new technological developments, to close the MSW management gap between high-income and low-income nations. The main goal of this review was to demonstrate how crucial an efficient MSW management system is to the global growth of sustainable nations [129].

In 2022 Kang et al. used cutting-edge technologies like the IoT to create a conceptual framework for the collection, maintenance, and analysis of comprehensive data through Smart BIM. A case study benefit-cost analysis based on three projected reuse and recycling-rate scenarios that describe off-site and on-site recycling techniques demonstrated the benefits of the suggested methodology. The findings demonstrated that by giving engineers and planners in the building sector technical and decision-making support functions, the suggested framework will open the door to developing sustainable waste disposal methods [130].

In 2022 Nimita et al. provided an overview of the various waste management strategies that various nations successfully employ, along with the necessary action plans. The current state of waste generation worldwide, its management strategies, and solid waste management's effects during COVID-19 were the main topics of this review. Relevant literature was included to provide updates on various waste management services, including collection and transportation, policies and legislation, various techniques adopted for waste management, and country investments in waste management processes. Asian nations must allocate additional funds for the management of solid waste. Zero waste cannot be achieved using the current waste management techniques so more innovative methods must be adopted [131].

In 2022 Roy et al. stated that the Government of Bangladesh (GoB) upgraded its e-waste policies, such as the Factory Act of 1965, to the Hazardous Waste (e-waste) Management of 2021.To gain a comprehensive understanding of the existing state of e-waste management in Dhaka and Chittagong, a field study was carried out, and the complete e-waste stream flow was given. The face-to-face questionnaire-based interviews investigated the consumption trends of electronic items, the average lifespan of these products, and understanding of e-waste. In Bangladesh, cell phones were determined to be the main source of e-waste. It is necessary to establish an integrated e-waste recycling facility using materials flow analysis (MFA) and life cycle analysis (LCA) [132].

In 2023 Wanore et al. determined the best choice for managing municipal solid waste (MSW) and then, utilizing integrated GIS and MCDA approaches, to choose the optimal landfill site in Hossana town. The relative weights of each criterion and the overall suitability map, where 10 criteria were taken into consideration within their respective limits, were analyzed using GIS coupled with MCDA. According to the study's findings, 20.8% of the solid trash was found to be recyclable, while the rest 7920% was not. Nineteen hectares of property located on the outskirts of the city to the north and south were selected as potential dump sites after a thorough appropriateness analysis was conducted, taking into account the projected trend of garbage output. Therefore, the combined use of MCDA and GIS could result in improved MSW management systems and optimum landfill site selection in urban and peri-urban settings [133].

In 2024 Bhowmick et al. determined the best place for the disposal and dumping of municipal waste. GIS and AHP were utilized to locate pertinent municipal waste disposal locations. Using ten functional parameters, the final result of the Waste dumping suitable sites was extracted. Legislators and urban planners may find this study useful in developing a resilient and environmentally responsible waste management infrastructure that minimizes negative environmental effects, safeguards public health, and maximizes resource utilization through the deliberate selection of appropriate locations [134]. Table 3.2 below summarizes each reference from the uploaded document, highlighting the specific work done and the corresponding research gaps or issues not addressed in each study.

Table 3.2 Analysis of recent literatures on waste landfill site selection

Reference	Work Done	Issues Not Addressed
Kapilan & Elangovan (2018) [136]	GIS and MCDA used for landfill site selection in India	Lack of integration with environmental risk assessment or public health considerations
Karimi et al. (2019) [137]	GIS-MCDA based landfill site selection in Javanrood, Iran	No stakeholder involvement or socio-political analysis
Zhai et al. (2009) [138]	Rough set based QFD for handling imprecise design info in product development	Not applied in environmental or landfill site selection context
Zhai et al. (2008) [139]	Rough set enhanced fuzzy QFD methodology	Lacks direct relevance to solid waste management or GIS applications
Ntagisanimana et al. (2021) [140]	Overview of solid waste management practices in East Africa and sustainability recommendations	No spatial or decision modeling techniques used for site selection
Pasalari et al. (2019) [141]	Hybrid AHP-Fuzzy-GIS for landfill site selection in Shiraz, Iran	Does not consider dynamic data or temporal changes
Rahimi et al. (2020) [142]	Hybrid BWM-MULTIMOORA-GIS for sustainable landfill site selection	Computational complexity and lack of real-time data usage
Rahmat et al. (2016) [143]	GIS and AHP used for landfill site selection in Behbahan, Iran	Limited to static criteria, no real-time monitoring
Sekulovic & Jakovljevic (2016) [144]	GIS and AHP applied to landfill site selection	No fuzzy or rough set integration to handle uncertainty
Vallner et al. (2015) [145]	Environmental risk management of oil shale landfill in Estonia	Focus on post-operation phase; no site selection modeling

3.10 Sustainable Building Material, Green Concrete

The use of urban garbage in concrete, as discussed by Chen et al. in 2022, has enormous promise as an alternative since it has positive effects on the environment, the economy, and technology. It also highlights the most recent advancements in this subject. Wasted glass, used motor oil and Plastic are the three primary types of rubbish generated in cities. These are the main areas of emphasis and can be utilized as models to incorporate urban waste into concrete with the right performance [146]. Recycled aggregate, fly ash, and circular economy are the three methods of manufacturing green concrete. The system energy flow for each method of production was compiled by Zhao et al. in 2020. They also presented emergy analysis methods for each mode [147]. Arora et al. conducted a review in 2022 wherein various waste materials were examined for potential substitution of cement. A comparison of the fundamental properties of key wastes such as fly ash, silica fumes, waste glass powder, and ceramic powder has been done to demonstrate how these wastes could be used to create value-added goods [148]. More cementitious and pozzolanic fly ash with a high calcium content has been investigated by Anish et al.Better results might be expected if the excess calcium from the C class fly ash is ingested by the pozzolanic material. Researchers have used silica fume as a substitute to study this effect [149]. Abdullah M. examined the viability of utilizing recovered wastewater as the foundation for green concrete in 2023. The chemical and physical characteristics of recycled wastewater were thoroughly examined in this research, with an emphasis on how they may be used in place of traditional freshwater during the concrete mixing process [150]. By employing a dry-mixed compaction process and waste glass cullet (WGC) and recycled concrete aggregate (RCA), Lu et al. created an environment friendly pervious concrete (PC) product in 2019. The PCs' mechanical attributes, thermal conductivity, water permeability behavior, and associated pore structure features were ascertained [151]. An investigation was done to assess the strength of green concrete by utilizing foundry by-products by Kazemiu et. al. in 2023[152]. A detailed analysis was conducted on the usage of steel slag as a hydration heat-controlling material in the production of green mass concrete that is sustainable in 2023 by Luo et al. The effects of high-volume fly ash and high-volume steel slag on the temperature rise and decrease of heat release, as well as the workability, strength, and durability of mass concrete, were compared and evaluated in this study. According to the results, the blended system's heat emission has effectively decreased with the inclusion of high-volume steel slag [153]. The effects of incorporating agricultural waste materials into concrete were assessed by Krishnan et al. in 2024. Green gram pod ash, an agricultural waste, has been used to make concrete with better engineering qualities and no negative environmental effect [154].Elaqra et al. (2021) looked at how changing the water to cement (w/c) ratios and the glass powder (GP) soaking period affected the mechanical properties of green concrete as well as the activation of the pozzolanic reactivity [155].The design of green concrete was presented by Khan et al. in 2020. Cement was partially replaced with fly ash, which was created by burning pulverized coal in power plants. Fine aggregate was completely replaced by glass powder and demolished debris, which was gathered from the construction site and processed into fine powder. In order to suggest using green concrete as a sustainable building material, a cost/benefit analysis was conducted and a comparison of the qualities of conventional and green concrete had been made [156]. A cutting-edge soft computing prediction model based on innovative genetic programming (GP) was proposed by Kumar et al. for the assessment of the compressive strength of concrete. Non-linear correlation makes it challenging for empirical relations and simple machine learning models to develop a trustworthy prediction model [157]. The sustainable benefits of using recycled materials, additional cementitious ingredients, and alkali-activated binders as raw materials in concrete were investigated by Sivakrishna et al. in 2020. This review has demonstrated that using novel materials can result in concrete that is both greener and has better qualities than conventional concrete [158]. A set of mixed recycled aggregate samples were examined in 2022 by Papi et al. for composition, density, fines content, water absorption, and freeze-thaw resistance. The process enhanced secondary material markets and the production of recycled aggregates, hence promoting a more circular economy [159]. Fernando et al. (2023) assessed the absorption and permeability capabilities of a blended fly ash-rice husk ash (RHA) AAC and compared the outcomes with 100% fly ash AAC. The outcomes demonstrated that the durability properties were negatively impacted by the inclusion of RHA [160]. A study on the financial and environmental advantages of using recycled spent foundry sand (SFS) in place of sand in concrete was presented by Siddique et al. in 2018.Strength and durability of green concrete were improved over control concrete's by up to 20% SFS incorporation as sand replacement [161]. Shen et al. in 2020 used TSTM to investigate the early-age cracking potential of high-performance concrete (HPC) with varying concentrations of ground granulated blast furnace slag (GGBFS) at adiabatic conditions with full uniaxial restraint degrees (0%, 20%, 35%, and 50%). The early-age cracking potential of HPC increased with increasing GGBFS content, according to the experimental results and related analysis; the ideal GGBFS concentration should not exceed 20% [162]. In 2022, Amiri et al. developed an artificial neural network (ANN) model based on the characteristics of the reference sample to predict the mechanical and durability qualities of waste, including concrete. According to the mechanical features, slag lessened the negative effects of using RCA in place of coarse aggregate when the samples were younger. Applying RCA accelerated the rate of chloride ion migration in concrete when it comes to durability. With the exception of the early phases, slag reduced the negative effects of recycled aggregate by improving hydration products [163]. These evaluations of the literatures offer insightful information about the developments and research in green concrete. They address a variety of subjects, such as the usage of waste materials [146-153], the addition of recycled aggregates [164-166], the collection and use of carbon [167-169], applications of nanotechnology [171,172], sustainable mix designs [156,170], life cycle assessment [173,174] and circular economy [175,176]. By reading these works, researchers can have a thorough grasp of the state of green concrete technology now and discover possible directions for future investigation.

3.10.1 Composition of Green Concrete

Supplemental cementitious materials (SCMs) derived from industrial processes, such as fly ash, slag, and silica fume, is an important component of green concrete. By substituting a substantial amount of Ordinary Portland cement (OPC) in concrete, these SCMs can lower the carbon emissions related to cement manufacture. Supplementary cementitious materials are byproducts of several industries and, depending on the desired qualities of the concrete, can replace OPC by around 10–50%. SCMs are waste products from a variety of sectors, such as fly ash from thermal power plants, rice husk ash from the agriculture sector, and slag from the metal sector [156]. Green concrete also uses recycled aggregates, including recovered asphalt pavement or broken concrete, which lessens the need for virgin aggregates and slows the loss of natural resources. Additionally, the addition of plastic wastes, motor oil, waste glass, urban garbage, and alkali activated binders somewhat alters the characteristics of green concrete. The mechanical qualities of concrete deteriorate as the amount of plastic wastes grows, yet they can be added to replace the demand for natural aggregates. According to studies, spherical plastic aggregates can increase the workability of concrete by up to 120% [176], while angular plastic wastes can reduce it by roughly 40% [175]. This occurs because angular wastes cause more friction than spherical wastes do. Because plastic wastes have a lower thermal conductivity than river sand, their addition to concrete also results in a drop in thermal conductivity. There is a loss in mechanical qualities such as modulus of elasticity and compressive strength, but an increase in sound-absorbing capacity. Weak interfacial bonding is the cause of the loss in mechanical characteristics [177-179]. The dosage of used engine oil (UEO) has a major impact on its results. According to studies, adding 0.5-0.8% mass UEO can improve concrete's workability by 0–100% [180]. Increased dosage causes the cement's degree of hydration to decrease, which in turn causes the strength to diminish. The addition of UEO can also lead to a number of health issues because it contains carcinogens including BTXs and PAHs [181]. Glass garbage is added to concrete to serve as an SCM and aid in cement replacement. Although replacement can be done up to an ideal level of 20-30%[183] any more than that may cause additional hydration products to form, which will weaken the cement's compressive strength[184] so it is recommended to keep the replacement to about 20%[182].The alkali-silica reaction between wasted glass and cement affects the durability performance of concrete highly[185].When alkali activated binders (AABs) are used in place of organic photocells, carbon dioxide emissions can be reduced by around 80%.Concrete's sustainability can be greatly increased by AABs, however some binders can negate this benefit. Thus, selecting the right AAB type is crucial [186]. Figure 3.1 indicates the various materials that can be used as a replacement of cement and other natural aggregates like sand and coarse aggregates to manufacture green concrete.

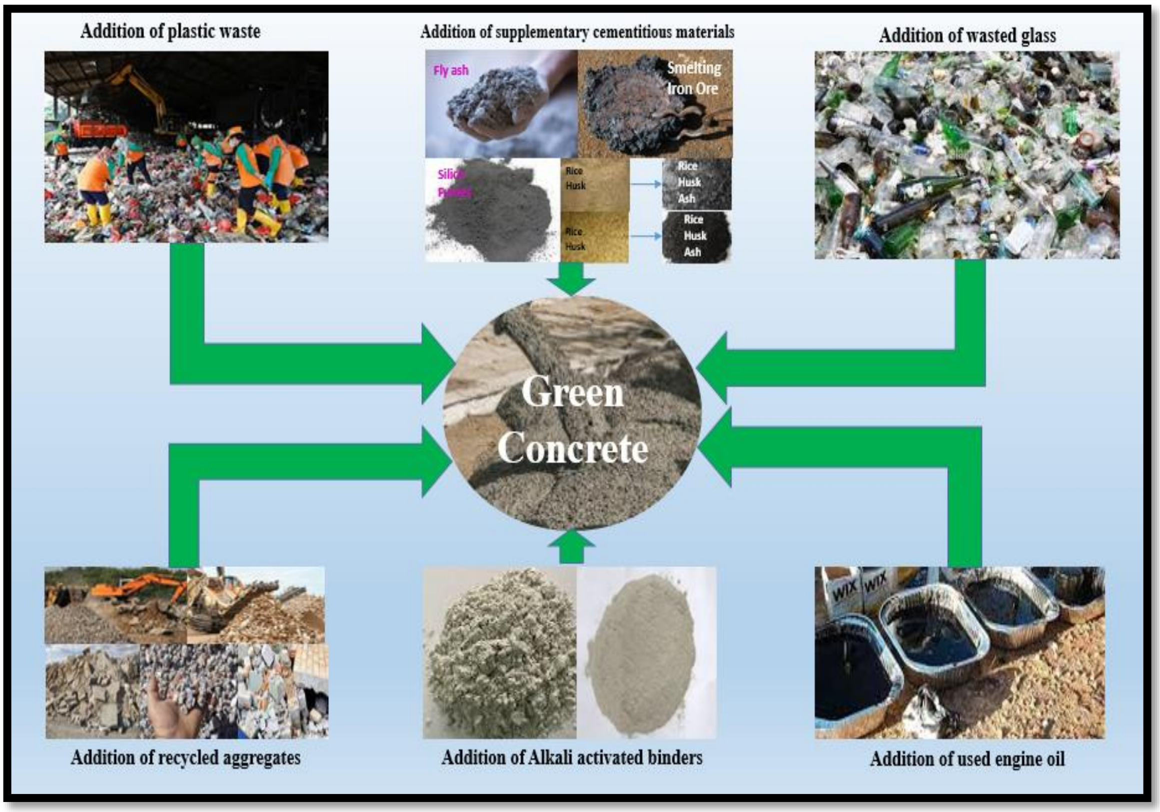

Figure 3.1 Different materials that can be added to replace cement and aggregates to obtain green concrete

3.10.2 Environmental Benefits of Green Concrete

Green concrete has major advantages for the environment. Because it uses more industrial byproducts and less cement than regular concrete, it can cut carbon dioxide emissions by up to 20–30%. Utilizing recycled aggregates lessens the burden on the environment, cuts down on trash going to landfills [187,188] and advances the ideas of the circular economy. Additionally, green concrete has exceptional thermal qualities that lower building energy use and increase energy efficiency. The environmental benefits of sustainable concrete are conspicuous in Figure 3.2.

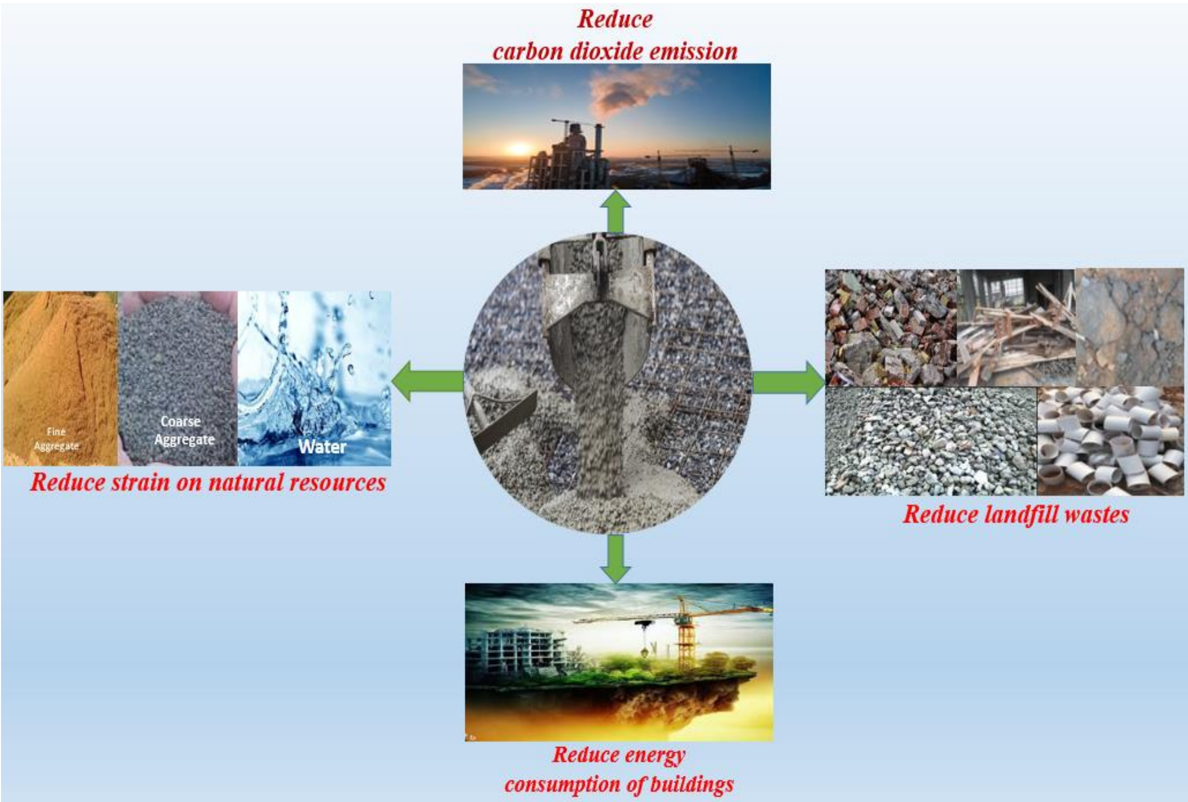

Figure 3.2 Environmental benefits of green concrete

3.11 Risk Assessment

Recently, risk analysis has garnered increasing attention. The Bayesian network (BN) is one of the more often utilized approaches. Numerous additional risk analysis methodologies have been employed, including the fuzzy Fault Tree Analysis (FTA) approach, the fuzzy inference system, and the Petri net method [189,195].

Apart from the techniques described before, FMEA is crucial in practically all sectors' risk and reliability initiatives because of its acknowledged great dependability and capacity to guarantee safety, particularly in many engineering disciplines and industrial sectors. Unlike other risk and reliability analysis techniques, FMEA is a proactive risk management tool that finds and evaluates the causes and consequences of possible failure modes and takes the required action to stop critical failure modes from happening[191,192]. FMEA, the most well-known way to examine and prevent failure modes in engineering, has not yet been substantially researched in contractors' failure risk assessment for construction projects [193,194]].

The drawbacks of conventional RNP techniques result in unsatisfactory and untrustworthy outcomes in the real world, particularly when decision makers face ambiguous data in their choices [195,196]. Many good ways have been created by academics throughout the past ten years to offset the drawbacks of conventional RNP approach and to enhance the precision and efficiency of failure mode risk assessments. The predominant methodology identified by Liu et al. is the fuzzy rule-based system [198,199]. Consequently, the subsequent section primarily examines the enhanced FMEA methodologies grounded in fuzzy set theory [200-202].

Many researchers have tried to formulate various fuzzy rules to address the qualitative and confusing data obtained from experts' risk assessments regarding failure types[203-205]. MCDM approaches are frequently integrated with fuzzy set theory to improve traditional FMEA. Song et al. presented a failure evaluation framework that employs fuzzy sets to address uncertainty, integrating them with the TOPSIS methodology. Liu et al. merged fuzzy and VIKOR methods; to address experts' subjective assessments and find out which failure modes have the highest risk priority. [206,207]. Chanamool and Naenna initially employed a fuzzy logic methodology to tackle the challenges associated with the reprioritization of the RPN, subsequently assigning priority and assessing the potential faults present in the operational processes [208]. In order to address the uncertainty and ambiguity that arises from the subjective evaluations of experts, Zhao et al. created a novel FMEA method that is based on interval-valued intuitionistic fuzzy sets. This method ultimately resulted in a more accurate ranking of failures that were found [209]. Additionally, Jiang et al. presented a fuzzy mapping technique in order to extract evidence information and quantify the risk of failure by employing fuzzy membership degree [210]. To address the limitations of the conventional RPN approach, Kerk et al. introduce a new RPN model that makes use of an interval fuzzy inference system to convert non-monotonic and incomplete fuzzy rules into interval-valued fuzzy rules [211].

In order to overcome the inherent uncertainty in expert evaluations, fuzzy set theory has been successfully employed in the aforementioned works. One drawback of fuzzy-based FMEA methods is that they rely on experts to predetermine membership functions before assessing the significance of risk factors and failure modes. This introduces subjectivity into the evaluation process. Another drawback is that the fuzzy-based RPN method requires experts to establish a large number of rules, which makes the process more complicated and requires them to make more judgement calls. A lot of effort and money are needed because of this. Type-1 fuzzy sets, upon which most prior fuzzy FMEA approaches have rested, also have a definitive membership degree for all values within a fuzzy interval, which can only take on the values from 0-1[212,213]. On the flip side, this is at odds with standard procedure and creates substantial doubts. The idea that something concrete can stand in for something vague is paradoxical. An improvement over type-1 fuzzy sets, interval type-2 fuzzy sets contain uncertainty in their interval-based membership grades [214,215]. This type of fuzzy set has been used by Bozdag et al. to prioritise failure mode risk over all other considerations; however, the uncertainty and unpredictability of the interval are ignored [216].

Rough set theory can address the issues of fuzzy set theory. In the absence of supplementary knowledge, rough set theory can reflect ambiguous information derived from expert evaluations. Therefore, the original data set defines the vagueness and subjectivity. Rough intervals reflecting experts' ambiguous information are more flexible and objective than fuzzy intervals. Rough theory is employed to address fuzziness, randomness, and their interrelationships, thereby resolving the limitations of type-1 fuzzy sets in accounting for membership degree uncertainty and type-2 fuzzy sets in managing randomness. Because of the benefits of rough set theory in managing uncertainties, some academics have used them separately to enhance the conventional FMEA approach. For instance, Song et al. integrate TOPSIS approach with rough set theory to get a more logical hierarchy of failure scenarios [217]. Based on cloud model theory, Liao et al. suggest an FMEA approach to give power transformer failures top priority, considering randomness and uncertainty and applying the conversion between qualitative and quantitative values [218]. An innovative FMEA model was presented by Wang et al. by incorporating the house of reliability (HoR) with rough number and VIKOR method [219]. For the purpose of addressing group behaviours in FMEA, Liu et al. included cloud model theory into PROMETHEE [220].

3.11.1 Risk Assessment in Construction Industry

The following Table 3.3 shows the application of FMEA in construction industry and their corresponding shortcomings obtained from literature study of the past decade.

Table 3.3 Application of FMEA in construction industry in recent literatures

Reference	Year	Work done	Issues not addressed
[221]	2025	Developed an FMEA model by integrating Fuzzy number with MABAC and GRA to enhance risk assessment for digital transformation in construction industry.	Though fuzzy theory deals with uncertainty, inherent subjectivity still persist. The study does not deal with sustainable construction.
[222]	2024	A new ranking method has been developed utilising Fuzzy numbers with FMEA for risk assessment in steel industry. Study has been done to find out the cause of potential accidents.	The corrective actions studied does not deal with sustainability. Environmental issues not addressed.
[223]	2023	The investigation was done to assess accidents occurring with construction equipment. Large group FMEA model has been formed to address the risks and behavioral TOPSIS method has been applied to rank the failure modes.	Though sensitivity and comparative analysis have been done but the model's capability to develop sustainable construction practices is a question mark.
[224]	2023	A model has been developed using Fuzzy FMEA and machine learning algorithm, CNN to predict project requirement prioritization.	Since the model has been trained with a fixed set of data from a certain firm, the model is not perfect for use in all real-world practical construction projects. The model is also not developed considering sustainability in construction.
[225]	2021	The research employs the Failure Mode and Effects Analysis (FMEA) technique, which has demonstrated efficacy in identifying accessibility-related deficiencies, their impacts, existing control measures, criticality levels, and action plans for modifying university environments to enhance usability for individuals with disabilities.	Uncertainty has not been addressed. Incomplete data not considered.

Reference	Year	Work done	Issues not addressed
[226]	2019	The work established a link between the maintenance ontology of historic structures and Building Information Modelling (BIM), while also proposing a cloud model-based knowledge mapping tool to assess the strength of this relationship. This work used FMEA to link ontologies and BIM, using grey relational analysis to assess the strength of the relationship.	Environmental factor not included in the study. Though cloud model can deal with uncertainty, yet it has to be feeded with prior information like Fuzzy theory which makes it a drawback. The model has not considered multidimensional approach to reach to the ultimate resolution.
[227]	2017	FMEA approach was used to identify significant elements contributing to cost escalations across the modular building life cycle from the viewpoint of the modular construction firm.	Uncertainty has not been involved. The study only dealt with cost cutting but its effects on other aspects of sustainability has not been studied.

3.12 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 [232]. The social dimension is notably significant in the healthcare sector, a vital component of the service business [233]. 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 [232,234]. Attaining sustainability in healthcare necessitates the system's adaptation to continuous economic and socio-demographic changes [235], 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 [236]. 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 [237]. 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 [238]. The reduced scale of GP clinics may result in increased response to patient demand and better patient outcomes [239]. Table 3.4 shows the recent studies carried out and their shortcomings in this domain.

Table 3.4 Comparative Analysis of recent literatures

Authors	Contribution	Issues not addressed
Lum et al. (2025) [240]	Describes implementation of system-wide decarbonization strategies using governance and internal capabilities in Singapore's NUHS.	Lack of behavioral model linking staff/patient engagement with sustainability outcomes; no quantitative framework for decision-making.
Luo et al. (2024) [241]	Explores facilitators and obstacles faced by medical trainees in advancing sustainable healthcare; emphasizes education, mentorship, and networks.	Lacks system-level policy integration; does not address infrastructural or operational sustainability metrics.
Watrobski et al. (2023) [242]	Proposes a multi-criteria evaluation method (SSP-AHP) for assessing social sustainability in healthcare across five domains.	Does not incorporate behavioral or psychological commitment factors of stakeholders (e.g., patients, employees).
Moya et al. (2024) [243]	Assesses waste generation and recycling strategies in ORs; identifies barriers (logistics, regulation, education).	Focused on waste; does not explore broader sustainability dimensions (e.g., energy, water, behavioral drivers).
Ma'in F. Abu-Shaikha (2025) [244]	Develops an AHP-based model for sustainable hospital planning; prioritizes site planning and energy efficiency.	Limited to infrastructure/design; no integration of occupant behavior, trust in systems, or satisfaction.

Authors	Contribution	Issues not addressed
Balay et al. (2024) [245]	Qualitative insights into student attitudes; identifies intrinsic motivation and interprofessional collaboration as key themes.	Does not provide actionable frameworks or link perceptions to operational design or loyalty outcomes.
Verdonck et al. (2025) [246]	Focuses on leadership, governance, and lean management; discusses procurement, energy, and supply chains.	Lacks quantitative models for evaluating sustainability impact on patient/staff behavior.
Hussain et al. (2024) [247]	Uses SEM to develop a framework addressing cost, policy, and management innovation for healthcare sustainability.	Economic and policy-focused; does not link sustainability perceptions with user loyalty or building design satisfaction.
Asperti et al. (2025) [248]	Developed a holistic framework integrating infrastructure, organization, and technology dimensions. Validated framework using Nominal Group Technique.	Lacks focus on economic and social sustainability. No integration with digital health or AI tools. Does not include performance benchmarks or KPIs for measuring progress.
Olawade et al. (2025) [249]	Addresses energy-efficient hospital design, green procurement, and low-carbon pharma. Reviews technological solutions (AI, green chemistry, HRES).	No empirical model or framework provided. Lacks policy integration strategies. Minimal focus on behavioral change or training of healthcare professionals.
Mathialagar et al. (2024) [250]	Applies Service-Dominant Logic and S-O-R theory. Explores social sustainability and patient co-creation in access-limited settings.	Focuses primarily on social aspects; minimal integration with environmental or technological sustainability.
Silva et al. (2024) [251]	Reviews energy efficiency strategies: passive & active design, smart systems and renewables. Classifies building strategies: sustainable vs. green vs. smart. Explores user behavior, IEQ, and HVAC system integration.	Lacks real-world implementation examples or case studies. No detailed economic analysis or regulatory insights. Limited discussion on stakeholder collaboration or healthcare staff roles.

Chapter 4

Research Gap, Aim, Objectives and Scope of the Study

4.1 Research Gap

Despite growing research in sustainable construction, significant gaps remain unaddressed. Firstly, contractor evaluation frameworks have largely ignored occupational health indicators such as noise, and seldom integrate fuzzy clustering with risk-reliability modeling. Secondly, solid waste disposal site selection studies often lack integration of rough set theory with GIS and seldom validate outputs with real-world dumping sites. Additionally, while green concrete is well-studied, there is limited work on predictive models that link compressive strength, cost, and environmental benefits within a circular economy framework. In healthcare, behavioral responses to green infrastructure are underexplored, particularly through PCA and regression models. Furthermore, traditional FMEA approaches in construction fail to manage uncertainty or prioritize sustainability-linked risks. Most importantly, literature lacks a region-specific, consilient framework that addresses environmental, economic, and social dimensions in construction sector collectively.

4.2 Aim of the Study

The aim of this research is to develop strategies that promote societal well-being, ensure socio-economic stability, and safeguard environmental integrity, thereby contributing to a resilient and equitable built environment.

4.3 Objectives of the Study

The primary objective of this work is to identify and implement key strategies that collectively enhance environmental performance, economic efficiency, and social responsibility in the construction process. The study focuses to develop an integrated framework for evaluating sustainability in construction by addressing environmental, social, and economic dimensions through a consilient and multi-methodological approach. Following are the objectives of this study:

1) To assess the performance of civil contractors using fuzzy-based multi-criteria decision-making (MCDM) techniques, incorporating clustering and risk-reliability analysis under uncertainty.

2) To identify and prioritize suitable waste disposal sites using rough set-based models, integrated with GIS-based spatial analysis for regional planning.

3) To investigate the potential of green concrete as a sustainable construction material, and develop predictive models for compressive strength and environmental performance aligned with circular economy principles.

4) To evaluate sustainable healthcare infrastructure by modeling the impact of green building attributes on occupant satisfaction, operational performance, and associated risks using Principal Component Analysis (PCA) and regression model.

5) To develop a comprehensive risk assessment framework for sustainable construction projects through the application of Failure Mode and Effects Analysis (FMEA) and its hybrid variants.

4.4 Scope of the Study

This research focuses on advancing sustainable construction practices within the urban and peri-urban context of Kolkata and its adjoining regions. The scope encompasses the identification, analysis, and implementation of key sustainability-driven strategies. The study investigates how these strategies can collectively enhance environmental performance, promote social equity, and support long-term economic viability in the construction sector. By addressing region-specific challenges such as rapid urbanization, environmental degradation, and resource constraints, the research aims to offer practical solutions tailored to the socio-economic and ecological landscape of the region. The outcomes of this study are expected to serve as a model for other developing urban centers striving for sustainable growth through responsible construction practices.

Chapter 5

An In-Depth Study on Performance Evaluation of Civil Contractors

5.1 Introduction

The effective selection and evaluation of civil contractors is pivotal to ensuring successful and sustainable construction outcomes. The most crucial stage of a building project is choosing the right contractor for the job after planning. The selection of contractors is getting harder as projects get more complicated and there are more factors by which a contractor must be chosen. The main construction part is totally dependent on the performance of the contractor and hence the selection of a capable contractor is essential for good performance of a construction project. Contractors have an impact on a project's supply chain management as well. A good, efficient contractor is essential to maintaining financial stability since building contracts have a large budget attached to them. To put it briefly, the contractor is at the center of every construction project, thus choosing the right contractor for a given project is one of the most significant issues that it will encounter [118,119]. The different types of structures built by civil engineers for development purposes are shown in Figure 5.1.

This study presents a dual-framework model for contractor performance evaluation that addresses both environmental sustainability and data-driven decision-making under uncertainty. The first model utilizes a hybrid fuzzy MCDM approach integrating FAHP [118] and FTOPSIS [206] to assess green contractor performance across eight key criteria, including technical expertise, green productivity, sustainable operations, and risk. In parallel, a second advanced framework incorporates occupational health dimensions by integrating noise impact, data reliability, and decision-maker risk preference through a modified Hodges-Lehmann rule supported by intuitionistic fuzzy logic.

Fifteen contractors have been evaluated using these complementary methodologies. FAHP determined criteria weights from expert judgments, while FTOPSIS ranked contractors based on their proximity to the ideal green contractor profile. Meanwhile, the Hodges-Lehmann model has been enhanced to incorporate both risk preferences and the reliability of contractor-reported data, offering robustness against uncertainty and subjectivity. A sensitivity analysis and Delphi-based validation confirm the consistency and effectiveness of both models. The integration of clustering algorithm (K-Means) further enable grouping contractors based on performance patterns.

The findings underscore that traditional contractor evaluation methods must evolve to reflect modern challenges, including environmental sustainability, occupational health, and data ambiguity. The proposed integrated framework offers a reliable, adaptable, and practical tool for sustainable contractor selection in high-risk, multi-criteria decision-making environments. This work contributes significantly to enhancing transparency, health-consciousness, and sustainability in civil construction projects.

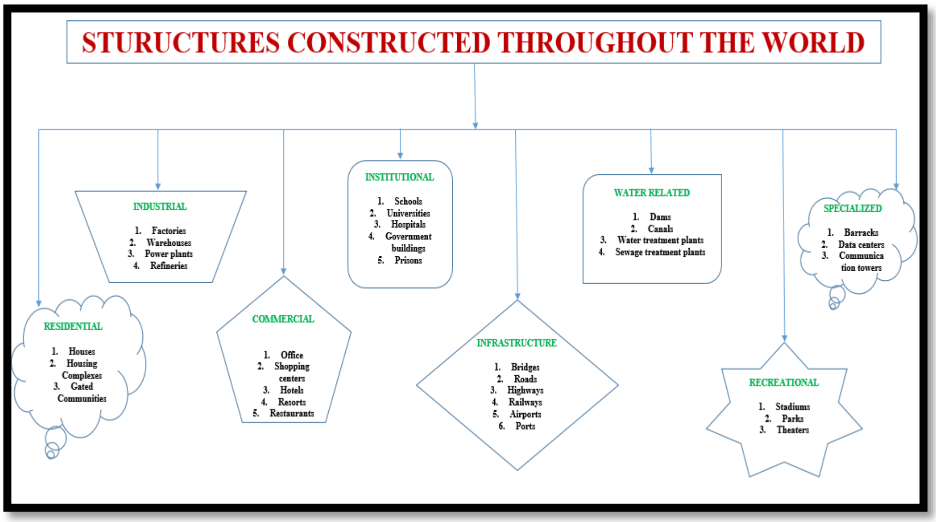

Figure 5.1 Different types of structures constructed throughout the world

5.2 Hierarchization of Contractors

5.2.1 Finding Criteria Weights Using FAHP

The process flow chart involved in finding the criteria weights using Fuzzy AHP is given below in Figure 5.2.

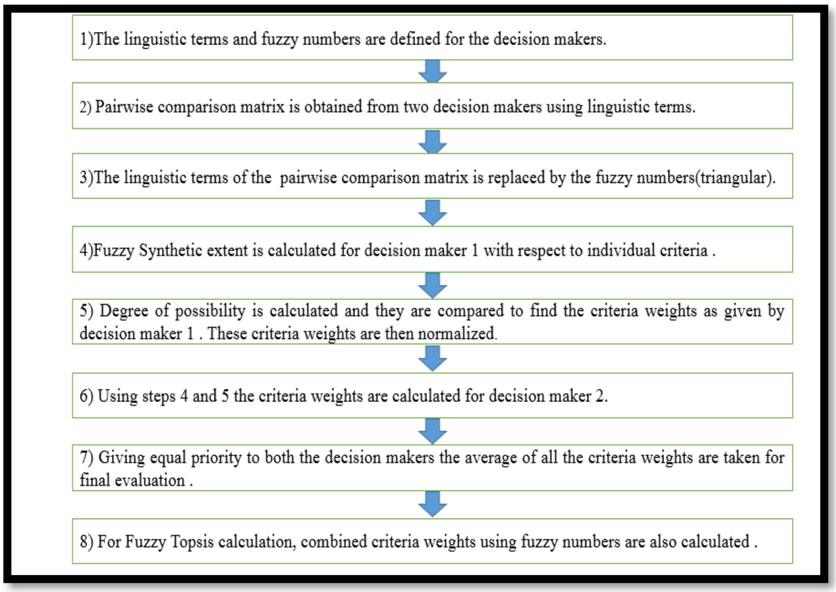

Figure 5.2 Process flow chart for Fuzzy AHP

5.2.2 Selecting the Best Alternative Using FTOPSIS

The process flow chart involved in selecting the best alternatives using FTOPSIS is given in Figure 5.3.

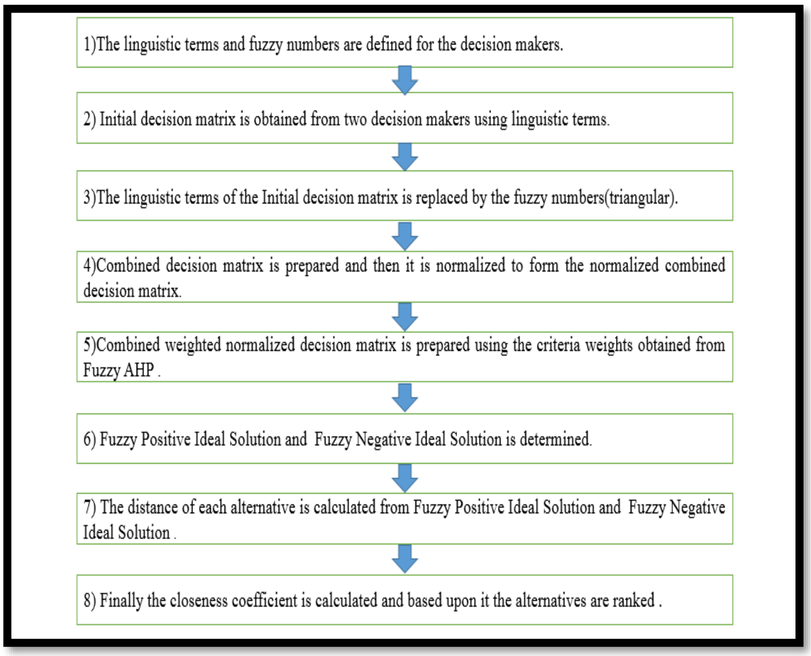

Figure 5.3 Process flow chart for FOPSIS

5.2.3 Clustering the 15 Contractors Using K-Means Algorithm

The process flow chart involved in clustering the contractors according to the given data using K-Means Clustering is given in Figure 5.4.

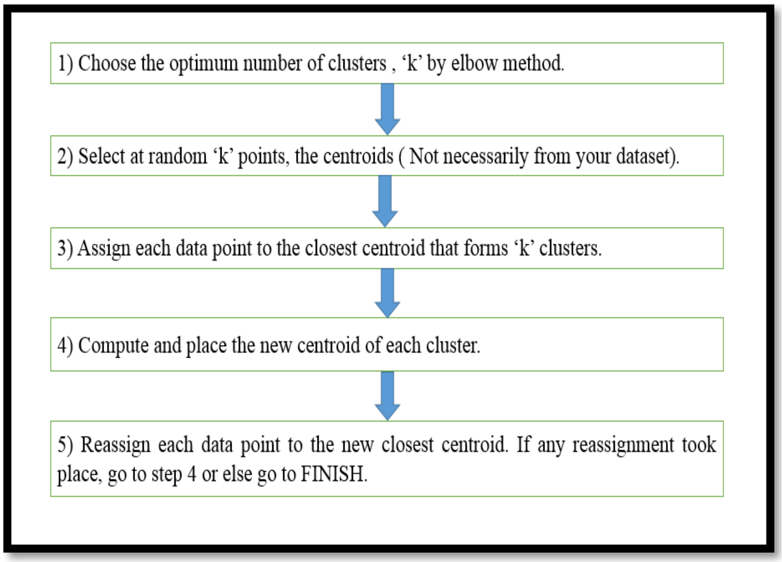

Figure 5.4 Process flow chart for K-Means Clustering

5.2.4 Preliminaries for FAHP and FTOPSIS

Given below are the preliminaries required for calculation and analysis of data. Table 5.1 shows the eight chosen selection criteria based upon which alternatives (15 contractors) have been ranked. The criteria have been chosen based on recent literature study and expert opinion during the mind storming session. Tables 5.2 and 5.3 gives the Fuzzy numbers for their corresponding linguistic terms for FAHP and FTOPSIS respectively.

Table 5.1 Eight criteria based on which contractor selection has been done

CRITERIA	CATEGORY	COMPARISON
Experience (C1)	Beneficial	Higher the better
Completed Projects (C2)	Beneficial	Higher the better
Communication Efficiency (C3)	Beneficial	Higher the better
Useful Life of Projects (C4)	Beneficial	Higher the better
Physical Resources (C5)	Beneficial	Higher the better
Green Strategy Implementation (C6)	Beneficial	Higher the better
Cost of Construction (C7)	**Non-Beneficial**	**Lower the better**
Construction Time (C8)	**Non-Beneficial**	**Lower the better**

Table 5.2 Linguistic terms and their corresponding triangular fuzzy number for FAHP

Linguistic values	Fuzzy numbers	Inverse of importance
Very high importance	(9,10,10)	(1/10,1/10,1/9)
High importance	(7,8,9,)	(1/9,1/8,1/7)
Fairly high importance	(5,6,7)	(1/7,1/6,1/5)
Equal importance	(1,1,1)	(1,1,1)
Fairly low importance	(3,4,5)	(1/5,1/4,1/3)
Low importance	(2,3,4)	(1/4,1/3,1/2)
Very low importance	(1,2,2)	(1/2,1/2,1)

Table 5.3 Linguistic terms and their corresponding Fuzzy numbers for FTOPSIS

Linguistic values	Fuzzy numbers
Very low (VH)	1,1,3
Low (L)	2,3,5
Average (A)	3,5,6
High (H)	5,7,9
Very high (VH)	7,9,9

5.2.5 Dataset Obtained from Expert Opinion

Tables 5.4 and 5.5 are the Pairwise Comparison Matrix (PCM) and Initial Decision Matrix (IDM) respectively obtained from the first decision maker. Similar opinion matrix has been obtained from the second decision during the mind storming session. Based on their expert opinion FAHP, FTOPSIS and K-Means Clustering algorithm have been applied following the steps depicted in Figures 5.2,5.3 & 5.4 respectively. The final results and discussion have been stated in the next section, 5.2.6 followed by the summary of the study in section 5.2.7.

Table 5.4 Pairwise comparison matrix for decision maker 1

	Technical knowledge	Green productivity	Green business operation	Management of project and employee	Operations and maintenance	Sustainable development	Bid estimate	Risk assessment and uncertainty
Technical knowledge	Equal importance	(1/7,1/6, 1/5)	(1/4,1/3,1/2)	Fairly high importance	Low importance	Fairly low importance	Very low importance	(1/4,1/3,1/2)
Green productivity	Fairly high importance	Equal importance	Low importance	Fairly high importance	(1/5,1/4,1/3)	Low importance	(1/4,1/3,1/2)	Fairly low importance
Green business operation	Low importance	(1/4,1/3, 1/2)	Equal importance	(1/5,1/4,1/3)	Low importance	Equal importance	(1/7,1/6,1/5)	Fairly low importance
Management of project and employee	(1/7,1/6,1/5)	(1/7,1/6, 1/5)	Fairly low importance	Equal importance	Equal importance	(1/5,1/4,1/3)	(1,1,1)	Fairly low importance
Operations and maintenance	(1/4,1/3,1/2)	Fairly low importance	(1/4,1/3,1/2)	(1,1,1)	Equal importance	Fairly low importance	(1,1,1)	(1/4,1/3,1/2)
Sustainable development	(1/5,1/4,1/3)	(1/4,1/3, 1/2)	(1,1,1)	Fairly low importance	(1/5,1/4,1/3)	Equal importance	(1/5,1/4,1/3)	Low importance
Bid estimate	(1/2,1/2,1)	Low importance	Fairly high importance	Equal importance	Equal importance	Fairly low importance	Equal importance	(1/2,1/2,1)
Risk assessment and uncertainty	Low importance	(1/5,1/4, 1/3)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	Low importance	(1/4,1/3,1/2)	Very low importance	Equal importance

Table 5.5 Initial decision matrix for decision maker 1

	Beneficial	Beneficial	Beneficial	Beneficial	Beneficial	Beneficial	Non beneficial	Non beneficial
	Technical knowledge	**Green productivity**	**Green business operation**	**Management of project and employee**	**Operations and maintenance**	**Sustainable development**	**Bid estimate**	**Risk assessment and uncertainty**
Contractor 1	VH	VH	VH	A	H	VH	H	A
Contractor 2	H	A	A	L	A	A	L	H
Contractor 3	H	A	A	A	A	A	L	H
Contractor 4	A	L	L	A	L	VL	A	H
Contractor 5	H	A	A	L	A	A	L	H
Contractor 6	VH	VH	VH	VH	H	VH	VH	L
Contractor 7	H	A	A	A	H	A	A	A
Contractor 8	H	A	A	A	H	A	A	A
Contractor 9	A	L	A	A	A	L	H	A
Contractor 10	H	A	A	L	A	A	H	A
Contractor 11	H	A	A	H	H	L	H	A
Contractor 12	A	A	A	A	H	L	H	L
Contractor 13	H	L	L	L	A	L	H	A
Contractor 14	H	H	H	H	A	L	VH	A
Contractor 15	H	H	H	VH	VH	H	VH	L

5.2.6 Results and Discussion

The final results have been obtained by utilising the steps of FAHP, FTOPSIS and K-Means Clustering algorithm as shown in the process flowcharts in Figures 5.2,5.3 & 5.4 respectively.

Table 5.6 Final criteria weights obtained by FAHP

	l	m	u
C1	0.084381	0.136227	0.229723
C2	0.108265	0.18313	0.324034
C3	0.066597	0.105864	0.180185
C4	0.060995	0.109154	0.18903
C5	0.064959	0.102164	0.162953
C6	0.055696	0.089573	0.140477
C7	0.113521	0.173363	0.280954
C8	0.048601	0.100525	0.170652

Table 5.7 Closeness co-efficient of the eight alternatives obtained by FTOPSIS

	(d_i*)	**(d_i^-)**	**Closeness Co- efficient**
Contractor 1	0.485701101	0.384488772	0.441844687
Contractor 2	0.67668437	0.260755182	0.278156796
Contractor 3	0.658145515	0.279605469	0.29816601
Contractor 4	0.449094477	0.083446469	0.156694935
Contractor 5	0.67668437	0.260755182	0.278156796
Contractor 6	0.403811997	0.452203352	**0.528265471**
Contractor 7	0.280360674	0.269495847	0.490120307
Contractor 8	0.280360674	0.269495847	0.490120307
Contractor 9	0.700945541	0.176478051	0.201132101
Contractor 10	0.685274345	0.183399109	0.211125491
Contractor 11	0.646560662	0.242477073	0.272741036
Contractor 12	0.655675296	0.208139659	0.240953989
Contractor 13	0.75166335	0.112555178	0.130239256
Contractor 14	0.577016607	0.309333522	0.348996985
Contractor 15	0.437667272	0.439268965	0.500913232

Table 5.8 Two clusters formed using K-Means algorithm

Contractor	**Cluster number**
1	1
2	2
3	1
4	1
5	2
6	1
7	1
8	1
9	2
10	2
11	1
12	1
13	1
14	1
15	1

At first criteria weights have been found out using FAHP method and then these weights have been utilized to evaluate the performance of the contractors to select the best contractor for assigning the project. The final criteria weights have been given in Table 5.6 and the performance of the contractors have been evaluated using the closeness co-efficient values as shown in Table 5.7. From Table 5.7, the best contractor under the given circumstances comes out to be the sixth contractor. The application of the Fuzzy Logic has helped the decision makers to give proper judgement under uncertain environment and this has also helped to form a robust model.

Finally, a study has been done using K-Mean Clustering Algorithm to identify some unknown pattern within the contractor data. The identification of pattern within the data helps to group the alternatives into clusters. The model has been developed in Google Colab using Python Language. This K-means Clustering Algorithm is very useful for clustering data which involves huge number of alternatives. The results of the algorithm have been shown in Table 5.8. Two clusters have been formed and they have been numbered as 1 and 2 respectively.

This study presents a structured and robust approach for green contractor selection by integrating FAHP and FTOPSIS. Given the increasing importance of sustainable practices in the construction industry, the proposed methodology provides a practical decision-making framework that incorporates both environmental and traditional evaluation criteria under uncertainty and vagueness.

The FAHP method determines the relative importance (weights) of criteria based on expert judgment, using fuzzy numbers to handle vagueness and linguistic uncertainty. The FTOPSIS model then ranks contractors according to their closeness to an ideal sustainable contractor profile.

Additionally, the study applies K-Means Clustering to group contractors based on performance patterns, revealing two distinct clusters that help decision-makers identify hidden trends and profiles among the candidates.

Contractor 6 emerge as the top-performing candidate based on the closeness coefficient from FTOPSIS.

The hybrid FAHP–FTOPSIS model successfully accommodates expert uncertainty and provides a robust framework for green contractor selection.

5.3 Reliable Risk-Aware Contractor Performance Evaluation through Modified Hodges Lehmann Algorithm

5.3.1 Motive of the Study

The primary motives of this study are:

a. To enhance the Hodges-Lehmann rule by using reliability-adjusted weighting to optimise contractor selection amid data uncertainty.

b. To evaluate contractor ranks using the Hodges-Lehmann model, both with and without reliability considerations, demonstrating the influence of reliability modifications on contractor assessment.

c. To do sensitivity analysis to evaluate the impact of differing risk preferences (λ) on the ultimate contractor rankings with reliability modifications.

d. To validate the proposed model using the Delphi methodology.

5.3.2 Study Methodology

This study introduces an innovative framework that incorporates reliability into the Hodges-Lehmann decision model. The technique provides a completer and more resilient decision-making tool for contractor selection by integrating weighted normalisation, reliability modifications, and robust aggregation. Sensitivity research evaluates the effects of variations in risk preference and data dependability on contractor rankings, offering insights into the trade-offs between certainty and uncertainty in actual building projects. This study employs a structured research technique that incorporates risk awareness, dependability, and sound decision-making in the selection of contractors. The procedure comprises many essential phases: establishing the choice criteria, normalising the decision matrix, including reliability modifications into the decision-making framework, and implementing the Hodges-Lehmann rule according to varying risk preferences. Finally, sensitivity analysis and validation using Delphi method have been done to check the robustness of the proposed model.

5.3.3 Criteria Selection

This contractor selection model includes nine evaluation criteria selected by expert opinion and recent literature study that provide a thorough assessment of contractors' performance. The criteria are classified into advantageous and disadvantageous categories as shown in Table 5.9. These criteria include economic, technical, and environmental dimensions of contractor performance, guaranteeing a comprehensive and equitable assessment. The selected criteria conform to established industry standards in contractor selection while enhancing traditional methods by including sustainability and environmental performance (C8 and C9).

Table 5.9 Details of the nine criteria chosen for contractor performance evaluation

Criteria	**Type**
C1: Cost of Construction	Non-beneficial
C2: Construction Time	Non-beneficial
C3: Experience	Beneficial
C4: Completed Projects	Beneficial
C5: Communication Efficiency	Beneficial
C6: Useful Life of Projects	Beneficial
C7: Physical Resources	Beneficial
C8: Green Strategy Implementation	Beneficial
C9: Noise Emission (New)	Non-beneficial

5.3.4 Data Collection

To ensure practical relevance and contextual accuracy, data for this study has been collected through structured expert opinion. A panel of 3 experts, comprising construction project manager, civil engineer, and Health & Safety Officer assembled for mind storming session. The experts have been selected based on their minimum 10 years of experience in public and private sector infrastructure projects as shown in Table 5.10. The data for the 15 contractors (A1 to A15) based on the criteria listed above have been obtained from expert opinion during mind storming session. These data points are like real-world performance ratings that have come from contractors' prior projects, bid submissions, or measures they provide themselves. To make sure they can be compared, the performance results for each contractor based on criteria have been normalised using equations 5.1 &5.2. For instance, the cost and time values are set as non-benefit criteria (where lower values are better), while the experience, projects finished, usable life, and green approach values are set as beneficial criteria (where higher values are better).

Table 5.10 Details of the experts involved in mind storming session

Expert ID	**Experience (Years)**	**Sector**	**Designation**
E1	15	Public	Senior Civil Engineer
E2	12	Private	Project Manager
E3	14	Public	Health & Safety Officer

5.3.5 Data Normalization

The data is normalized using the min-max scaling method using equations (5.1) & (5.2) as follows:

For beneficial criteria

$$\mathrm{Normalized}_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{5.1}$$

For non-beneficial criteria

$$\mathrm{Normalized}_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{5.2}$$

5.3.6 Intuitionistic Fuzzy Criteria Weighting

Linguistic Evaluations by Experts

Three experts who are construction practicians having more than 10 years of experience in the field have used a linguistic scale to rate each of the nine criteria (C1–C9). These language words have been connected to intuitionistic fuzzy numbers (IFNs) in the following way as shown in Table 5.11.

Table 5.11 Linguistic terms and their respective membership & non-membership

Linguistic Term	Membership (μ)	Non-membership (ν)
Very Low	0.1	0.8
Low	0.3	0.6
Medium	0.5	0.4
High	0.7	0.2
Very High	0.9	0.05

Each criterion has been averaged across experts for both μ and ν, and the Intuitionistic Fuzzy Score (IFS) has been calculated using equation (5.3). Table 5.12 gives the final criteria weights:

$$IF\,S_i = \mu_i - \nu_i \tag{5.3}$$

Table 5.12 IFS-Based Criteria Scores and Normalized Weights

Criterion	Avg μ	Avg ν	IF Score (μ−ν)	Normalized Weight
C1: Cost	0.767	0.150	0.617	0.171
C2: Time	0.567	0.333	0.233	0.065
C3: Experience	0.833	0.100	0.733	0.203
C4: Completed Projects	0.633	0.267	0.367	0.101
C5: Communication	0.433	0.467	-0.033	-0.009
C6: Useful Life	0.767	0.150	0.617	0.171
C7: Resources	0.567	0.333	0.233	0.065
C8: Green Strategy	0.767	0.150	0.617	0.171
C9: Noise Level (New)	0.567	0.333	0.233	0.065

In the above table, Communication (C5) yields a negative score and hence excluded.

5.3.7 Reliability Matrix

It is a table where each contractor's score based on each criterion is assigned a reliability value.

$$R = [R_{ij}], where\ R_{ij} \in [0,1]$$

If $R_{ij} = 1$: fully reliable, $R_{ij} = 0.7$: moderate confidence and $R_{ij} < 0.7$: unreliable.

This study's most important new idea is to include reliability in the process of choosing a contractor. The reliability matrix $[R_{ij}]$ is made to show how much faith or trust we may have in the data for each criterion. Each contractor has been given a reliability score for each criteria based on things like how well they verify data (for example, whether it was audited or self-reported), how well they have done in the past (for example, if they have consistently delivered projects on time), third-party certifications or external audits, and expert reviews. A reliability score may be anything from 0.7 to 1.0. A score of 1.0 means the data is very trustworthy (for example, it has been validated by someone else), while a score of 0.7 means the data is not very dependable (for example, it was reported by the person themselves without verification).An example of how reliability score have been provided to contractors by the experts have been elucidated in Table 5.13 for contractor A1.Similar scores have been given to all the contractors. The reliability scores are then used to change the contractor's normalised scores using the following formula:

$$x_{ij}^{\text{adjusted}} = x_{ij}^{\text{weighted normalized}} \times R_{ij} \tag{5.4}$$

Table 5.13 Reliability scores provided to contractor A1 by experts based on the eight criteria

Criterion	**Source of Data**	**Assigned Reliability**
C1 (Cost)	Audited reports from previous bids	High → 0.90
C2 (Time)	Company past projects (verified)	High → 0.90
C3 (Experience)	CVs cross-verified	Very High → 1.00
C4 (Projects)	Claimed with evidence	High → 0.90
C6 (Useful Life)	From technical specs	Medium → 0.80
C7 (Resources)	Site photos, equipment list	Medium → 0.80
C8 (Green Strategy)	Internal report only	Low → 0.70
C9 (Noise)	Self-reported, no certificate	Low → 0.70

This modification penalises contractors with poor dependability and guarantees that those with more dependable data get more consideration in the final selection.

5.3.8 The Hodges-Lehmann Method

The Hodges-Lehmann rule is a resilient decision-making technique used to consolidate the lowest and maximum weighted scores for each contractor across many parameters. The regulation alleviates the influence of extreme values or outliers in the data, yielding a more equitable evaluation of contractor performance [231].

The Hodges-Lehmann score,K_i for each contractor is computed using the following formula:

$$K_i = (1-\lambda).\sum_j x_{ij}^{min} + \lambda.\sum_j x_{ij}^{max} \tag{5.5}$$

Where,$\sum_j x_{ij}^{min}$is the sum of the minimum weighted scores (for cost criteria),$\sum_j x_{ij}^{max}$ is the sum of the maximum weighted scores (for benefit criteria),λ is the risk preference parameter, which can range from 0 (lowest risk) to 1 (highest risk).K_i=Hodges Lehmann score(higher the better).

The use of the $\sum_j x_{ij}^{min}$ and $\sum_j x_{ij}^{max}$ ensures that the decision model is not biased toward extreme values in either direction, making it more resilient to outliers.

5.3.9 The Proposed Hodges-Lehmann Method

The modified Hodges-Lehmann score (K_i) formula to account for reliability is derived as follows:

$$K_i = (1 - \lambda).\sum_j R_{ij}\,.x_{ij}^{min} + \lambda.\sum_j R_{ij}.x_{ij}^{max} \tag{5.6}$$

where R_{ij} is the reliability of contractor i on criterion j

5.3.10 Results and Discussion

The results of the proposed model are examined via three primary components: contractor ranking with and without reliability integration, sensitivity analysis with differing risk preferences (λ), and validation by expert consensus using the Delphi technique. The Hodges Lehmann scores have been obtained by the equations 5.5 & 5.6 based on the initial dataset obtained from expert opinion for the 15 contractors.

Table 5.14 Hodges Lehmann (HL) scores for all contractors without reliability adjustment

Contractor	**λ=0**	**λ=0.25**	**λ=0.5**	**λ=0.67**	**λ=0.84**	**λ=1.0**
A1	0.2092	0.2388	0.2684	0.2886	0.3087	0.3277
A2	0.0841	0.1359	0.1878	0.2230	0.2583	0.2914
A3	0.0776	0.1441	0.2106	0.2558	0.3010	0.3436
A4	0.1489	0.2217	0.2946	0.3441	0.3936	0.4403
A5	0.2513	0.2919	0.3326	0.3602	0.3878	0.4138
A6	0.2076	0.2838	0.3600	0.4118	0.4636	0.5123
A7	0.2759	0.2822	0.2886	0.2928	0.2971	0.3012
A8	0.0610	0.1328	0.2046	0.2534	0.3022	0.3481
A9	0.1112	0.1447	0.1782	0.2009	0.2237	0.2452
A10	0.0976	0.1609	0.2243	0.2674	0.3105	0.3511

Contractor	**λ=0**	**λ=0.25**	**λ=0.5**	**λ=0.67**	**λ=0.84**	**λ=1.0**
A11	0.1733	0.1976	0.2218	0.2383	0.2548	0.2703
A12	0.0601	0.1217	0.1834	0.2253	0.2672	0.3067
A13	0.1034	0.1065	0.1096	0.1117	0.1137	0.1157
A14	0.1540	0.2367	0.3193	0.3755	0.4317	0.4846
A15	0.2331	0.2753	0.3175	0.3462	0.3750	0.4020

Table 5.15 Hodges Lehmann (HL) scores for all contractors with reliability adjustment

Contractor	**λ = 0**	**λ = 0.25**	**λ = 0.5**	**λ = 0.67**	**λ = 0.84**	**λ = 1.0**
A1	0.4215	0.3831	0.3446	0.3184	0.2923	0.2677
A2	0.2356	0.2634	0.2912	0.3102	0.3291	0.3469
A3	0.2071	0.2360	0.2649	0.2846	0.3043	0.3228
A4	0.2108	0.2420	0.2731	0.2943	0.3155	0.3354
A5	0.2525	0.3138	0.3751	0.4169	0.4586	0.4978
A6	0.1881	0.2356	0.2832	0.3155	0.3479	0.3783
A7	0.2500	0.3600	0.4700	0.5447	0.6195	0.6899
A8	0.1189	0.1701	0.2213	0.2562	0.2910	0.3238
A9	0.1814	0.2474	0.3135	0.3583	0.4033	0.4455
A10	0.1698	0.2419	0.3140	0.3630	0.4120	0.4581
A11	0.3599	0.3378	0.3158	0.3008	0.2858	0.2716
A12	0.2722	0.3330	0.3938	0.4351	0.4765	0.5154
A13	0.2461	0.2323	0.2184	0.2090	0.1996	0.1907

Contractor	λ = 0	λ = 0.25	λ = 0.5	λ = 0.67	λ = 0.84	λ = 1.0
A14	0.2089	0.2368	0.2647	0.2836	0.3026	0.3204
A15	0.3812	0.4282	0.4752	0.5072	0.5391	0.5692

5.3.10.1 Hodges-Lehmann Scores without Reliability Adjustments

Table 5.14 shows the Hodges-Lehmann scores for each contractor for six distinct λ values, which range from 0 to 1. These scores are the result of a trade-off between minimising costs ($\sum_j x_{ij}^{min}$) and maximising benefits ($\sum_j x_{ij}^{max}$). varying values of λ show varying levels of risk tolerance. A6 always comes out on top at all risk levels, with scores going up from 0.2076 (at λ=0) to 0.5123 (at λ=1), as shown in Table 5.14 (without adjusting for reliability). A5 does a good job at lower risk, with scores going up from 0.2513 (λ=0) to 0.4138 (λ=1). A14& A4 perform well at high risk levels. The lowest scores for A2 are between 0.0841 (λ=0) and 0.2914 (λ=1). This first set of findings shows how important contractor A6 is as a consistently great performer, no matter what risk preference is used. The heatmap in Figure 5.5 shows how the contractors perform at different degrees of risk.

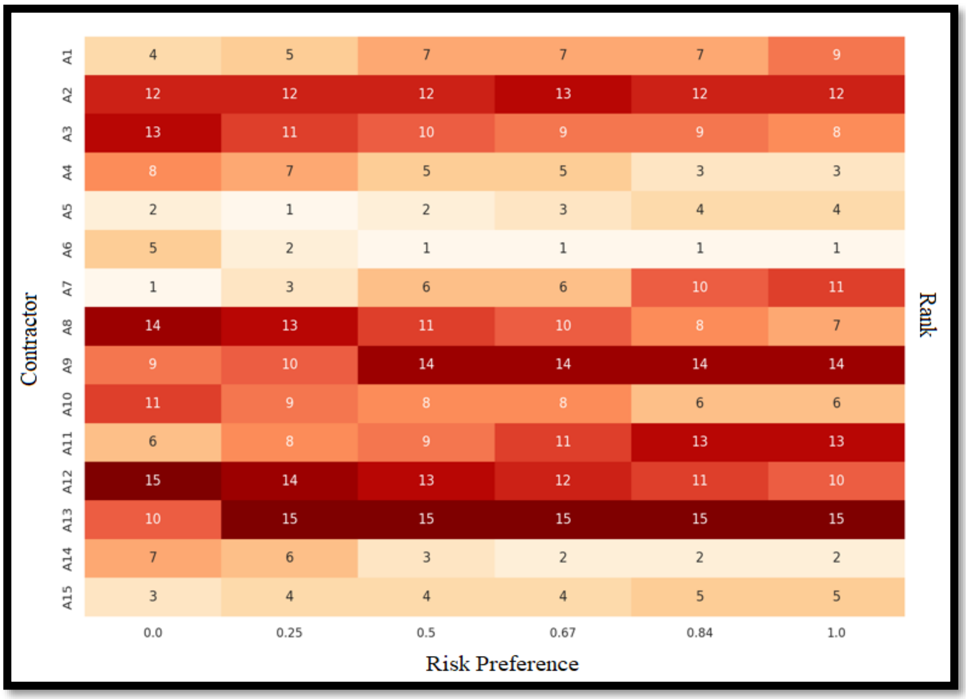

Figure 5.5 Heatmap for contractor ranking without reliability adjustment

5.3.10.2 Hodges-Lehmann Scores with Reliability Adjustments

The incorporation of the reliability matrix significantly alters the rankings, as seen in Table 5.15 The performance of each contractor is assessed based on the dependability of the data corresponding to each criterion. The heatmap in Figure 5.6 demonstrates how each contractor's performance has altered by incorporating reliability for degrees of risk. Contractors with more trustworthy data (i.e., those with higher reliability ratings) have more influence in the decision-making process. A7 excels at high risk level. The performance of the A15 has improved with adjustments, but that of the A14 has significantly declined. A12 remains highly ranked, despite a modest decline in ratings relative to the model without dependability improvements. This is due to enhanced confidence ratings for certain categories, which now affect its total ranking. A5 maintains its position, demonstrating elevated reliability-adjusted scores, particularly at increased λ values (0.4978 at λ=1). In contrast, A4, previously exhibiting good performance in the original model, demonstrates a decline in reliability-adjusted ranks, attributable to the poor reliability of its data in critical criteria. This investigation unequivocally illustrates that reliability modifications significantly influence contractor rankings, hence improving the decision-making process by favouring contractors that provide verifiable and credible data.

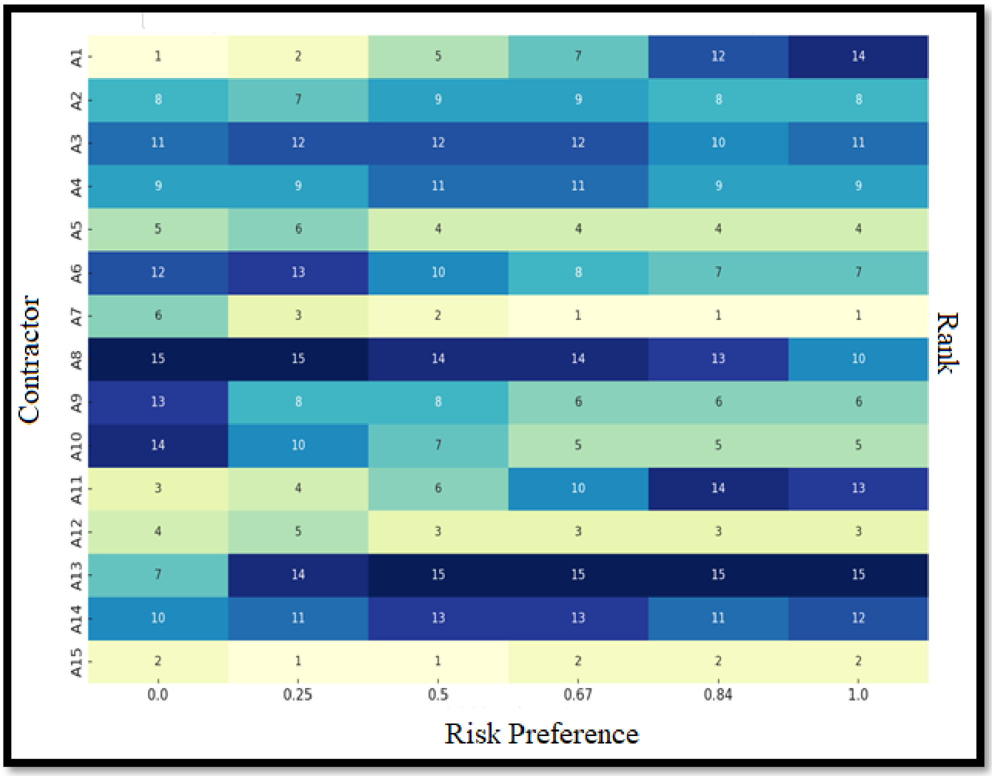

Figure 5.6 Heatmap for contractor ranking with reliability adjustment

5.3.10.3 Sensitivity Analysis: Impact of Risk Preferences (λ)

A sensitivity analysis has been conducted to assess the robustness of the contractor rankings by adjusting the value of λ from 0 to 1 shown in Figure 5.7. It enables to examine the alterations in rankings when the model transitions from a low-risk (λ = 0) to a risk-neutral (λ = 0.5) and high-risk (λ = 1) scenario. The sensitivity analysis is essential for comprehending the extent to which reliability changes impact contractor ranks across varying risk choices. The ultimate rankings have been determined by the computed Hodges-Lehmann scores, and variations in the rankings are examined to evaluate the influence of the reliability adjustment on the decision-making process. The sensitivity analysis conducted across several values of λ elucidates the impact of risk preferences on contractor selection. Low λ (approaching 0) signifies a more optimistic perspective, whereby more emphasis is put on benefit criteria (e.g., experience, resources, environmental strategy). Conversely, a high λ (approaching 1) prioritises cost minimisation and emphasises the mitigation of hazards, including noise emissions and construction duration. Contractor A7 is the most dependable performer at elevated λ values, continuously achieving good ratings in both cost and benefit metrics. The reduction in its score at lower λ values indicates the compromise between the significance of cost minimisation and the aggregate benefits. A15 demonstrates competitiveness across all λ values, indicating that its expertise and resources provide it an optimal selection in every scenario. A12 has uniform results across all risk parameters. Contractors like A9, which ranked lower in the baseline model, exhibit enhancement with reliability modifications at elevated λ values, where the weighting of benefits aids in balancing their lower cost against better benefit features. This investigation highlights the versatility and adaptability of the Hodges-Lehmann model, as it may modify contractor ranks according to varying degrees of risk tolerance and data dependability.

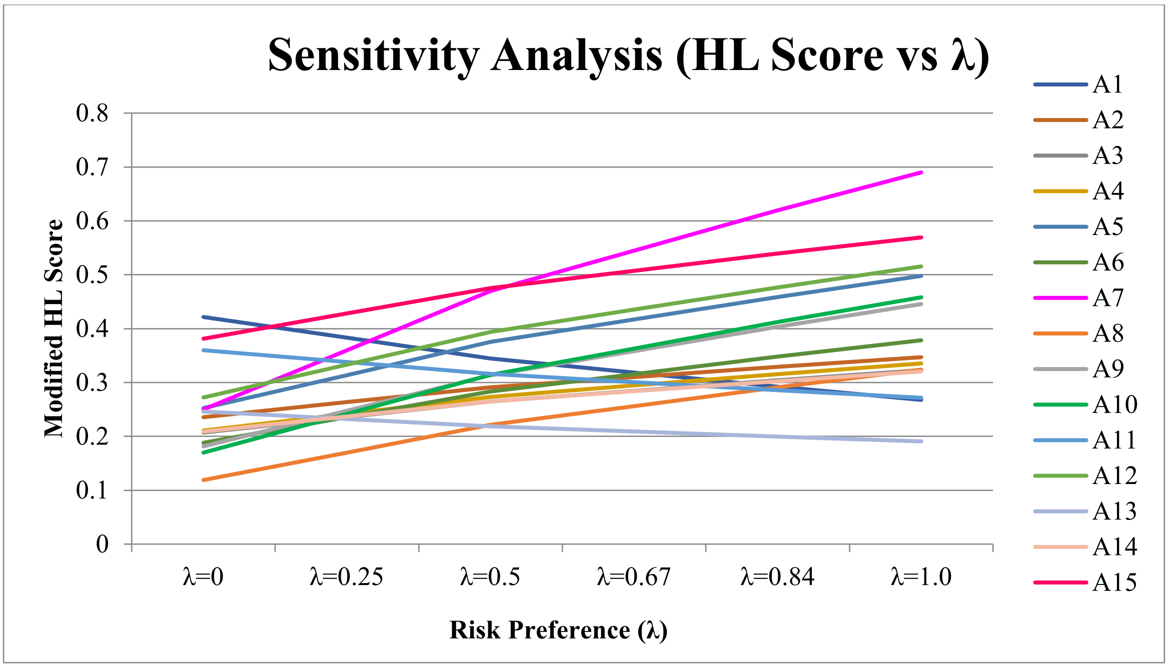

Figure 5.7 Sensitivity Analysis

5.3.10.4 Validation with Delphi Method

A Delphi panel including five experts in construction management and multi-criteria decision-making (MCDM) have been formed. Each expert has been requested to evaluate the contractors according to $\lambda = 0.5$ (risk-neutral scenario) from Table 5.15, a standard mid-value for assessing stability. Each expert individually evaluates and ranks the top 10 contractors according to their $\lambda = 0.5$ ratings as shown in Table 5.16. The final results obtained by validation has been shown in Table 5.17.

Table 5.16 Ranking of top 10 contractors by the Delphi expert panel for validation

Rank	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
1	A7	A7	A7	A15	A7
2	A15	A15	A5	A7	A15
3	A5	A5	A12	A5	A5
4	A12	A12	A15	A12	A12
5	A10	A10	A10	A10	A10
6	A11	A11	A11	A11	A11

Rank	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
7	A9	A6	A6	A6	A6
8	A6	A9	A9	A9	A9
9	A2	A2	A2	A2	A2
10	A3	A3	A3	A3	A3

Table 5.17 Results of Validation

Result	Value
Kendall's W (Concordance)	0.978
χ^2 Test (Significance)	44.01
Critical χ^2 ($\alpha = 0.05$, df=9)	16.92
Agreement Level	Excellent

Experts mostly agree on the rankings that the updated Hodges-Lehmann model provides with $\lambda = 0.5$. The Delphi panelists confirmed that the model is strong and has features that make it reliable. This validation shows that the proposed method may be used in real-world situations where contractors are chosen.

5.3.11 Summary

In the construction sector, assessing contractor performance with uncertainty poses a complex problem due to the intrinsic heterogeneity of project environments, inadequate or imprecise data, and varying risk preferences across stakeholders. Conventional approaches frequently depend on deterministic data, neglecting the subtleties of subjective assessments, variable data dependability, and occupational health hazards like noise exposure. Consequently, decision-makers risk choosing contractors based on potentially erroneous or unverifiable information, jeopardising project results regarding cost, quality, schedule, and sustainability. Recent methodologies have used MCDM techniques enhanced by fuzzy logic, risk modelling, and reliability assessments to mitigate these constraints, so ensuring more robust, transparent, and health-oriented contractor selection processes. In alignment with this evolving research direction, the present study introduces a comprehensive and risk-aware contractor performance evaluation framework that integrates noise impact and data reliability into a modified Hodges-Lehmann model.

This study establishes an innovative contractor performance evaluation system that directly integrates occupational noise exposure and data reliability into the decision-making process for sustainable construction. Fifteen contractors are evaluated based on eight criteria, encompassing economic, technical, environmental, and health factors, particularly noise emissions. The model is constructed on an extended Hodges-Lehmann principle, using intuitionistic fuzzy logic to represent uncertainty and expert assessment in criterion weighting. An essential innovation is the integration of a reliability matrix that modifies contractor scores according to the credibility of data sources. The research conducts dual ranking assessment (with and without reliability modification), sensitivity analysis utilizing a risk preference parameter (λ) ranging from 0 to 1 & validation employing the Delphi technique with five subject matter experts. Principal findings indicate that contractor rankings are markedly influenced by the incorporation of reliability scores and differing risk preferences. For example, contractors who were before rated highly on performance experienced a decline in ranking due to low data reliability. The incorporation of noise emission as a criterion underscores the increasing acknowledgement of health effects within sustainable frameworks.

This study offers a complete framework for evaluating contractor performance that takes into account occupational health issues, such as noise exposure, in a decision-making model that is more reliable and aware of risks. The study fills a major gap in the construction management literature by using intuitionistic fuzzy logic and a reliability factor to the modified Hodges-Lehmann approach. Its importance lies in dealing with performance data that is not clear, uncertain, or possibly unreliable in high-risk work environments.

The suggested model is new because it takes into account the different risk attitudes of decision-makers by adding a risk preference parameter (λ) and also reliability parameter. This lets the model change between maximizing benefits and minimizing costs. Also, it shows how contractor rankings can change a lot when the reliability of the data is taken into account. This system makes contractor selection more reliable and open, making sure that occupational health factors like noise pollution aren't pushed aside in favour of cost or schedule concerns.

This study enhances contractor assessment by encouraging decision-making that is cognizant of risks, attuned to health considerations, and grounded in trustworthy evidence. It promotes sustainable construction methodologies and offers a versatile framework that accommodates diverse risk tolerance levels and data reliability.

This research significantly contributes to environmentally friendly construction, improves decision-making clarity in complex project contexts and acts as an adaptable template for promoting sustainability, dependability, and worker well-being in industries characterised by uncertainty and risk. Future research can extend this model by incorporating additional occupational health parameters such as dust and vibration exposure to create a more holistic evaluation framework. Integration with real-time data analytics and machine learning can further enhance predictive accuracy and automate contractor assessment under dynamic site conditions.

Chapter 6

A Decision Support Framework for Sustainable Waste Landfill Siting

6.1 Introduction

Whenever we hear the term ‘waste’ we feel something unwanted and dirty that needs to be thrown away. In our daily life we come across numerous wastes that we just throw away without any care and awareness. But when the waste becomes too toxic or the amount is huge, we need to think of finding an appropriate place for disposing them. The production and management of enormous amounts of trash from numerous sources is one of the main issues faced by the modern world. Wastes can be classified into many types but in this study, we will deal with solid wastes. Solid wastes can also be further classified which has been shown in Figure 6.1. Rapid urbanization has increased the production of solid waste, and sustainable solid waste management is currently a prominent concern. Even though India's per capita garbage creation is lower than the worldwide average, the country still produces the most rubbish overall, even more than China [134]. It is widely acknowledged that the process of choosing a location for waste management systems is challenging due to numerous factors. To attain sustainability, environmental, sociological, and technological factors should all be thoroughly and methodically evaluated when choosing appropriate sites for garbage disposal. To find a suitable location for a landfill site, it is therefore essential to carefully review the siting criteria, including restrictions and legislation set by environmental agencies or local authorities. There have been initiatives to improve waste management techniques in India. As part of these efforts, the Central Pollution Control Board (CPCB) and the Central Public Health Environment and Engineering Organization (CPHEEO) have issued guidelines for the development of sanitary landfills [135]. Solid waste management is a critical environmental issue in rapidly growing urban areas, such as Kolkata and its adjoining areas. Appropriate site selection for waste dumping is essential to minimize environmental impacts and protect public health. The Rough Number-Based AHP (RAHP)is a tool that integrates rough number theory and AHP to evaluate and prioritize different waste disposal sites. Conventional methods for choosing sites frequently depend on deterministic techniques, which may ignore the uncertainties and variances that come with making decisions. As a consequence, this research presents a novel framework that improves the flexibility and robustness of site selection strategies for waste management by utilizing rough numbers, a mathematical tool that can handle inaccurate or partial information.

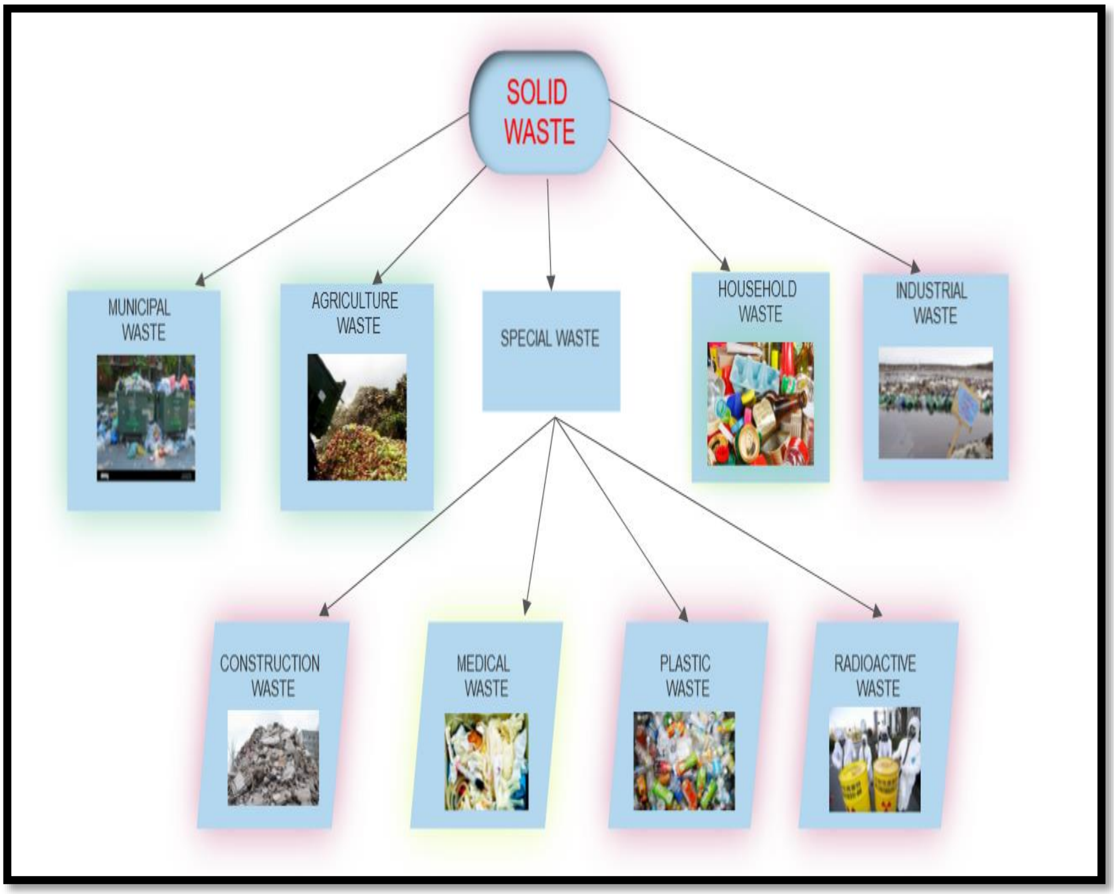

Figure 6.1 Different types of solid wastes

6.2 Research Methodology

The whole study can be broadly divided into 3 stages-

1) Preliminary stage- This includes the literature review, formation of the review committee who will assist in the process of decision-making and the brainstorming session to discuss upon the problem.

2) Intermediate stage- This includes the selection of appropriate criteria required for dumping site selection. Data collection and data analysis is done. RAHP has been used to evaluate the criteria weights. Using the criteria weights, alternatives have been ranked.

3) Final stage-Discussion of the results have been done.

The process flowchart showing the Research Methodology has been shown in Figure 6.2 below.

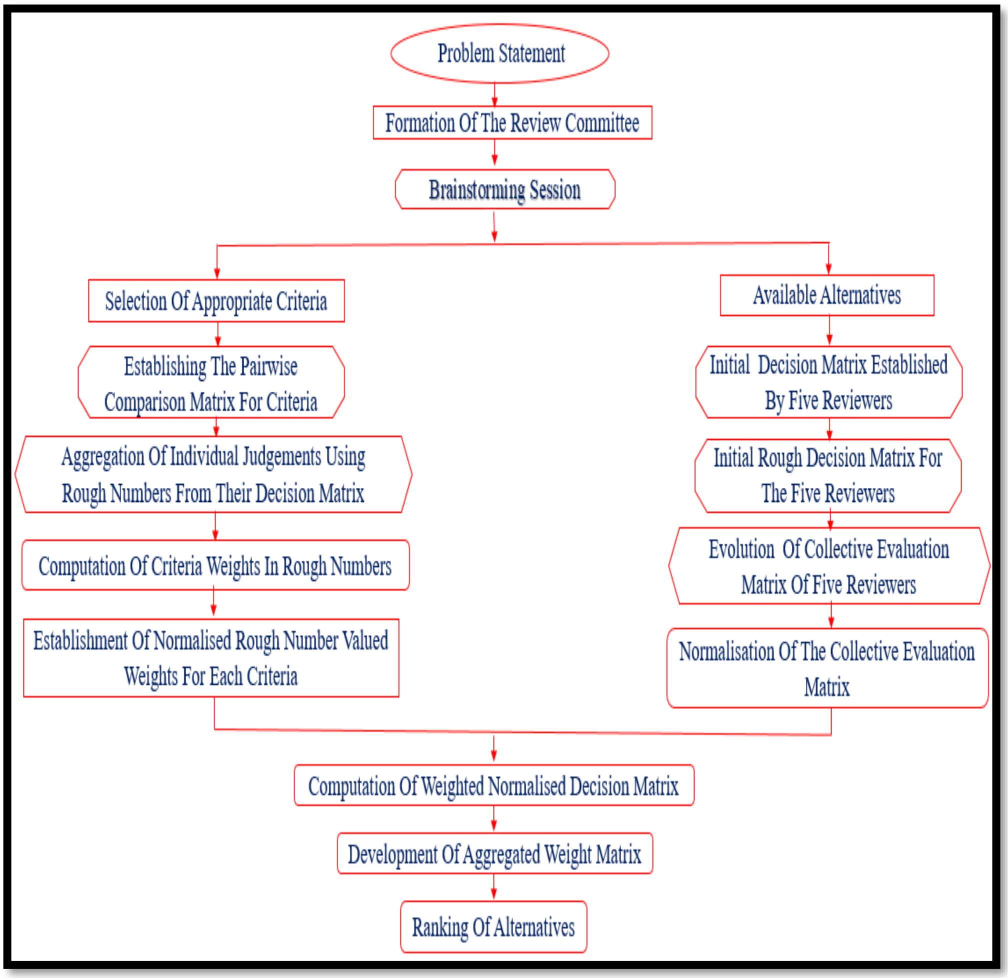

Figure 6.2 Process flowchart showing the research methodology

6.3 Study Area

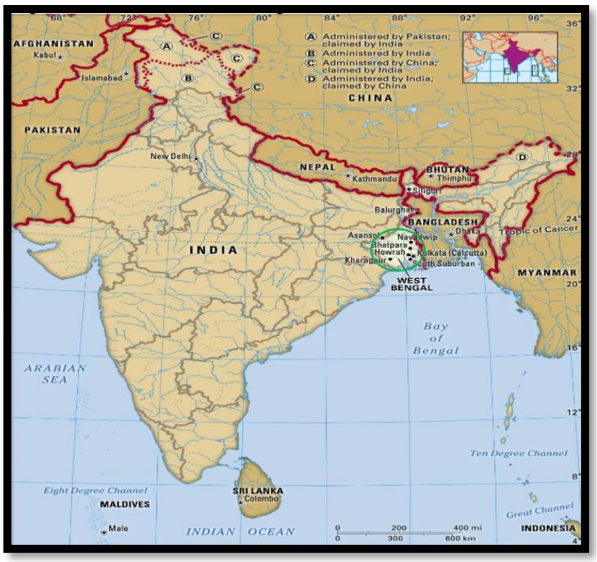

Figure 6.3 Showing the location of West Bengal

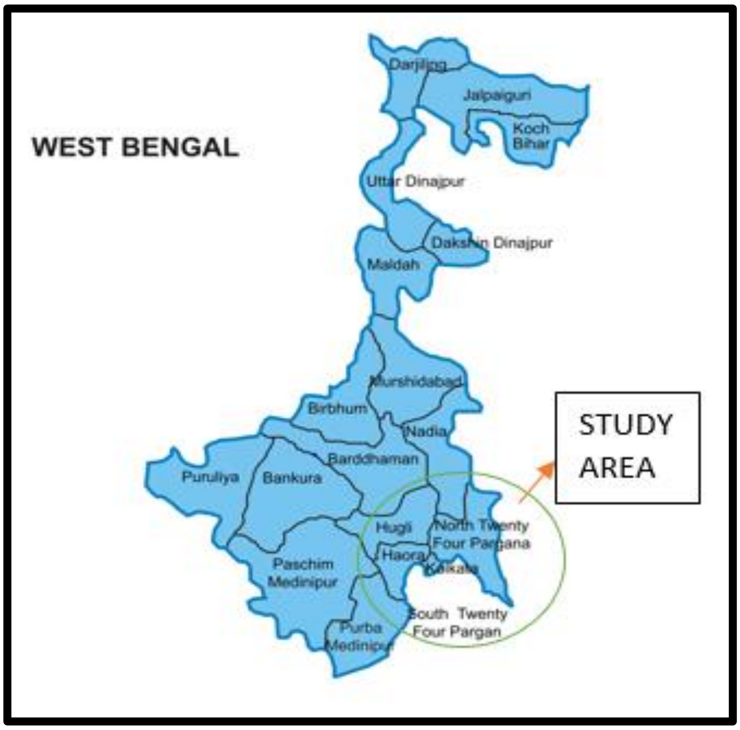

Figure 6.4 Showing Kolkata and its adjoining areas under study

The study area includes Kolkata (206.1Km^2) and its adjoining areas like Hooghly (3149Km^2), Howrah (63.55$Km^{2)}$, North 24 Parganas (4094$Km^{2)}$ and South 24 Parganas (9960Km^2) which roughly covers about 17472.65 Km^2 area and 19.7 % of the state of West Bengal, India. Figure 6.3 shows the location of West Bengal in India and Figure 6.4 shows the area of study under West Bengal.

6.4 Site Selection Criteria

For choosing the appropriate dumping site, six criteria have been chosen from literature survey based upon topological, environmental, social and economic aspect. The six criteria are explained below in Table 6.1. The (+) sign denotes beneficial criteria and the (-) sign denotes non beneficial criteria.

Table 6.1 Six criteria and their favourable conditions

Name of the criteria	Criteria group	Favourability	Reference
Distance from water bodies and urban area(+)	Topological	500metre at least (water body)	[144]
		1000 metre at least (water body)	[141]
		3 kilometre at least(urban)	[137]
Ground water depth(+)	Environmental	<4.5 mbgl is undesirable	[142]
Access to site(+)	Social	More the better	[123]
Slope (-)	Topological	<5.71° is highly desirable	[143]
		<26° may be suitable	[142]
Cost of site(-)	Economic	Lesser the better	[123]
Population density(-)	Social	<500/ km2 is mostly preferred.	[136]

6.5 Research Methodology

In this work, a case study has been conducted in Kolkata and its surrounding districts of West Bengal. A committee of five expert professionals had been established. Based on the literature analysis, six probable influencing elements (criteria) of site selection for solid wastes were determined keeping in view that they comply with sustainability. Eight potential dumping sites were identified in the study area to choose the best one. RAHP decides how much influence each component has on selecting the dumping site. Table 6.2 and Table 6.4 shows the linguistic and rough pairwise comparison matrix respectively of expert 1. Similar pairwise comparison matrix was obtained from other 4 experts. Combined pairwise comparison matrix of all the concerned 5 experts has been shown in Table 6.5. Then the rough aggregated matrix has been prepared as shown in Table 6.6. Finally aggregated and normalised weights of criteria has been shown in Table 6.10. An evaluation framework for solid waste dumping site selection is established using RAHP. Eight potential dumping sites have been identified in the study area and among them ranking has been done based on the rough scores. Initial decision matrix and initial rough decision matrix has been shown in Table 6.3 and Table 6.7 respectively. Normalised rough decision matrix and weighted normalised rough decision matrix has been shown in Table 6.8 and Table 6.9 respectively. Finally, the weights (rough score) of the alternatives and their ranking have been shown in Table 6.11. The linguistic terms L, M, H, VH stand for Low, Medium, High and Very High respectively and their values are taken as 3,5,7 and 9 respectively. Value of 1 is given for equal importance. In the Tables, C1, C2, C3, C4, C5 and C6 are the six chosen criteria and A1, A2, A3, A4, A5, A6, A7 and A8 are the eight alternative dumping sites that are under the present study chosen from Kolkata and its adjoining areas.

This model may be used to examine how social, economic, and environmental issues affect where to discard solid waste. The goal of this concept is to promote sustainability.

6.6 Dataset

Table 6.2. Linguistic Pairwise Comparison matrix of expert 1

	Distance from water bodies and urban area(+)	**Ground water depth(+)**	**Access to site(+)**	**Slope (-)**	**Cost of site(-)**	**Population density(-)**
Distance from water bodies and urban area(+)	1	M	VH	M		VH
Ground water depth(+)		1	H	L		H
Access to site(+)			1			
Slope (-)			H	1		M
Cost of site(-)	M	M	VH	VH	1	VH
Population density(-)			M			1

Table 6.3 Initial decision matrix provided by 5 experts

	C1	C2	C3	C4	C5	C6
A1	3,3,5,3,5	4,5,5,6,4	5,6,6,7,5	3,5,3,6,3	4,4,5,4,5	6,6,4,4,6
A2	5,6,4,4,5	5,5,6,7,6	3,4,4,6,5	4,6,4,5,5	3,3,4,5,5	4,3,3,5,4
A3	4,3,3,4,4	6,6,5,7,5	5,3,3,5,6	5,4,4,4,5	6,4,5,4,4	4,6,6,4,4
A4	3,5,5,3,4	5,5,3,5,4	5,3,3,5,4	4,6,4,5,5	5,6,7,6,5	4,5,3,4,3
A5	4,5,5,6,4	3,5,4,3,5	3,4,4,3,4	3,5,6,5,3	4,5,4,6,4	4,4,2,3,3
A6	3,4,6,5,4	5,6,5,7,6	4,4,3,3,4	4,6,5,5,5	5,5,3,4,5	4,3,3,4,5
A7	4,5,5,4,6	3,3,5,5,5	5,5,4,3,5	4,4,4,5,5	4,3,3,5,5	5,3,3,4,4
A8	5,5,5,4,3	6,5,5,3,4	3,6,3,5,5	5,3,3,5,4	4,3,3,4,4	2,3,3,4,4

6.7 Calculations

Table 6.4 Rough Pairwise Comparison matrix of experts 1

	Distance from water bodies and urban area (+)	Ground water depth (+)	Access to site (+)	Slope (-)	Cost of site (-)	Population density (-)
Distance from water bodies and urban area (+)	1	5	9	5	0.2	9
Ground water depth (+)	0.2	1	7	3	0.2	7
Access to site (+)	0.11	0.14	1	0.14	0.11	0.2
Slope (-)	0.2	0.33	7	1	0.11	5
Cost of site (-)	5	5	9	9	1	9
Population density (-)	0.11	0.14	5	0.2	0.11	1

Table 6.5 Combined pairwise comparison matrix for five experts

	Distance from water bodies and urban area	Ground water depth	Access to site	Slope	Cost of site	Population density
Distance from water bodies and urban area (+)	(1,1,1,1,1)	(5,7,5,9,5)	(9,9,9,7,9)	(5,5,5,7,7)	(0.2,0.2,0.2,0.14,0.2)	(9,9,9,9,9)
Ground water depth (+)	(0.2,0.14,0.2,0.11,0.2)	(1,1,1,1,1)	(7,7,7,7,7)	(3,5,3,3,3)	(0.2,0.14,0.2,0.2,0.14)	(7,7,5,7,9)
Access to site (+)	(0.11,0.11,0.11,0.14,0.11)	(0.14,0.14,0.14,0.14,0.14)	(1,1,1,1,1)	(0.14,0.11,0.14,0.14,0.14)	(0.11,0.11,0.14,0.11,0.14)	(0.2,0.2,0.14,0.2,0.2)
Slope (-)	(0.2,0.2,0.2,0.14,0.14)	(0.33,0.2,0.33,0.33,0.33)	(7,9,7,7,7)	(1,1,1,1,1)	(0.11,0.14,0.11,0.14,0.14)	(5,5,0.33,0.2,3)
Cost of site (-)	(5,5,5,7,5)	(5,7,5,5,7)	(9,9,7,9,7)	(9,7,9,7,7)	(1,1,1,1,1)	(9,9,9,9,9)
Population density (-)	(0.11,0.11,0.11,0.11,0.11)	(0.14,0.14,0.2,0.14,0.11)	(5,5,7,5,5)	(0.2,0.2,3,5,0.33)	(0.11,0.11,0.11,0.11,0.11)	(1,1,1,1,1)

Table 6.6 Rough aggregated matrix

	Distance from water bodies and urban area (+)	Ground water depth (+)	Access to site (+)	Slope (-)	Cost of site (-)	Population density (-)
Distance from water bodies and urban area (+)	[1,1]	[5.34,7.12]	[8.28,8.92]	[5.32,6.28]	[.1784,.1976]	[9,9]
Ground water depth (+)	[.149,.191]	[1,1]	[7,7]	[3.08,3.72]	[.1616,.1904]	[6.3,8]
Access to site (+)	[.1112,.1208]	[.14,.14]	[1,1]	[.1292,.1388]	[0.1148,.1292]	[.1784,.1976]
Slope (-)	[.1616,.1904]	[.2832,.3248]	[7.08,7.72]	[1,1	[.1208,.1352]	[1.1034,4.071]
Cost of site (-)	[5.08,5.72]	[5.32,6.28]	[7.72,8.68]	[7.32,8.28]	[1,1]	[9,9]
Population density (-)	[.11,.11]	[.1307,.1622]	[5.08,5.72]	[.6643,3.0544]	[.11,.11]	[1,1]

Table 6.7 Initial rough decision matrix

	C1	C2	C3	C4	C5	C6
A1	[3.7,4.85]	[4.36,5.25]	[5.44,6.41]	[3.3,4.7]	[4.16,4.64]	[4.72,5.68]
A2	[4.36,5.25]	[5.44,6.41]	[3.75,5.08]	[4.36,5.25]	[3.47,4.53]	[3.36,4.25]
A3	[3.36,3.84]	[5.44,6.41]	[3.68,5.04]	[4.16,4.64]	[4.17,5.06]	[4.72,5.68]
A4	[3.47,4.33]	[3.94,4.83]	[3.47,4.53]	[4.36,5.25]	[5.44,6.41]	[3.6,4.25]
A5	[4.36,5.25]	[3.47,4.33]	[3.36,3.84]	[3.68,5.09]	[4.17,5.06]	[2.75,3.64]
A6	[3.75,5.08]	[5.44,6.41]	[3.36,3.84]	[4.65,5.35]	[3.94,4.83]	[3.36,4.25]
A7	[4.36,5.25]	[3.72,4.68]	[3.94,4.83]	[4.16,4.64]	[3.47,4.53]	[3.36,4.25]
A8	[3.94,4.83]	[3.94,5.25]	[3.68,5.09]	[3.47,4.53]	[3.36,3.84]	[2.75,3.64]

Table 6.8 Normalised rough decision matrix

	C1		C2		C3		C4		C5		C6	
A1	0.58	0.76	0.68	0.82	0.85	1.00	0.51	0.73	0.65	0.72	0.74	0.89
A2	0.68	0.82	0.85	1.00	0.59	0.79	0.68	0.82	0.54	0.71	0.52	0.66
A3	0.52	0.60	0.85	1.00	0.57	0.79	0.65	0.72	0.65	0.79	0.74	0.89
A4	0.54	0.68	0.61	0.75	0.54	0.71	0.68	0.82	0.85	1.00	0.56	0.66
A5	0.68	0.82	0.54	0.68	0.52	0.60	0.57	0.79	0.65	0.79	0.43	0.57
A6	0.59	0.79	0.85	1.00	0.52	0.60	0.73	0.83	0.61	0.75	0.52	0.66
A7	0.68	0.82	0.58	0.73	0.61	0.75	0.65	0.72	0.54	0.71	0.52	0.66
A8	0.61	0.75	0.61	0.82	0.57	0.79	0.54	0.71	0.52	0.60	0.43	0.57

Table 6.9 Weighted normalised rough decision matrix

	C1		C2		C3		C4		C5		C6	
	0.55	0.56	0.23	0.26	0.03	0.04	0.11	0.15	1	1	0.08	0.11
A1	0.32	0.42	0.16	0.21	0.03	0.04	0.06	0.11	0.65	0.72	0.06	0.10
A2	0.37	0.46	0.20	0.26	0.02	0.03	0.07	0.12	0.54	0.71	0.04	0.07
A3	0.29	0.34	0.20	0.26	0.02	0.03	0.07	0.11	0.65	0.79	0.06	0.10
A4	0.30	0.38	0.14	0.20	0.02	0.03	0.07	0.12	0.85	1.00	0.04	0.07
A5	0.37	0.46	0.12	0.18	0.02	0.02	0.06	0.12	0.65	0.79	0.03	0.06
A6	0.32	0.44	0.20	0.26	0.02	0.02	0.08	0.13	0.61	0.75	0.04	0.07
A7	0.37	0.46	0.13	0.19	0.02	0.03	0.07	0.11	0.54	0.71	0.04	0.07
A8	0.34	0.42	0.14	0.21	0.02	0.03	0.06	0.11	0.52	0.60	0.03	0.06

6.8 Results and Discussion

Table 6.10 Final aggregated and normalised weights of criteria

Criteria	Rough weights	Normalised rough weights	Ranking of criteria
Distance from water bodies and urban area (+)	[2.69,2.99]	[.50,.56]	2
Ground water depth (+)	[1.22,1.40]	[.23,.26]	3
Access to site (+)	[0.186,0.198]	[.03,.04]	6
Slope (-)	[.592,0.8]	[.11,.15]	4
Cost of site (-)	[4.89,5.34]	[.92,1]	1
Population density (-)	[.42,.57]	[.08,.11]	5

Table 6.11 Aggregated weight matrix and ranking

Alternatives	Aggregated weights		Normalised aggregated weights		Ranking
A1	1.183120125	1.60798752	0.702849013	0.894194399	6
A2	1.167628705	1.652854914	0.69230836	0.919144949	3
A3	1.203307332	1.622371295	0.712669605	0.90219315	5
A4	1.328814353	1.79825	0.791754867	1	1
A5	1.176302652	1.629219969	0.701990145	0.906001666	4
A6	1.190655226	1.679407176	0.705729257	0.933910539	2
A7	1.103369735	1.566848674	0.656574244	0.871317278	7
A8	1.042043682	1.434212168	0.619885831	0.797558733	8

The use of AHP to solve the problem of choosing the best location for disposing of solid waste in Kolkata and its surrounding areas produces insightful findings that help choose the optimal location. The following sections outline the key findings and the subsequent discussion of the results.

Identified Best Site: Based on the evaluation using the RAHP model, a specific site (A4) emerges as the most suitable for solid waste dumping site as shown in Figure 6.6 and Figure 6.7. The selection process takes into account various criteria related to environmental, social, and economic factors. The chosen site exhibits the highest priority weight, indicating its superior suitability for waste disposal purposes. This result serves as a crucial outcome, guiding decision-makers in determining the optimal location for managing solid wastes in the study area.

Environmental Factors: The RAHP model enables the integration of environmental considerations into the site selection process. The criteria weights obtained using RAHP are shown in Figure 6.5 of which the distance of the site from any nearby water body or urban area emerges as the most important environmental factor. Criteria such as proximity to water bodies, air quality impacts, and ecological sensitivity play a significant role in determining the best site. The discussion delves into the importance of these factors and highlights how the chosen site aligns with sustainable waste management practices. Moreover, the results shed light on the potential environmental benefits that can be derived from the selected site, such as minimizing pollution and preserving natural resources.

Social Factors: Social considerations, including population density, proximity to residential areas, and public health impacts, are crucial for taking appropriate decisions. The discussion focuses on the implications of waste disposal on the surrounding communities and emphasizes the significance of selecting a site that minimizes adverse effects on public health and quality of life. Furthermore, the findings provide insights into the equitable distribution of waste management facilities, taking into account socio-economic factors and potential social inequalities associated with different site options.

Economic Factors: The economic viability of waste disposal plays a vital role in the decision-making process. The RAHP model incorporates economic criteria such as cost of site which appears to be the most important criteria for site selection as shown in Figure 6.5. The discussion examines the economic implications of the chosen site, considering factors such as operational costs, revenue generation potential, and long-term sustainability. Additionally, cost-benefit analysis and economic feasibility assessments may be conducted to evaluate the financial implications of the selected site over time.

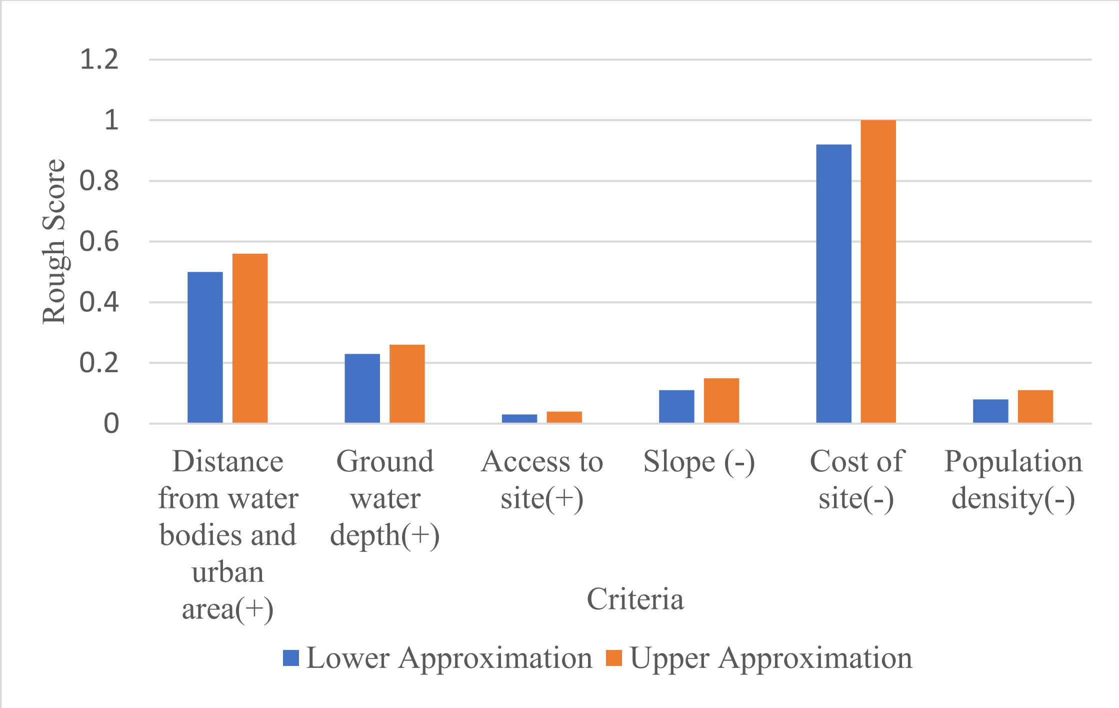

Figure 6.5 Criteria weights using rough number

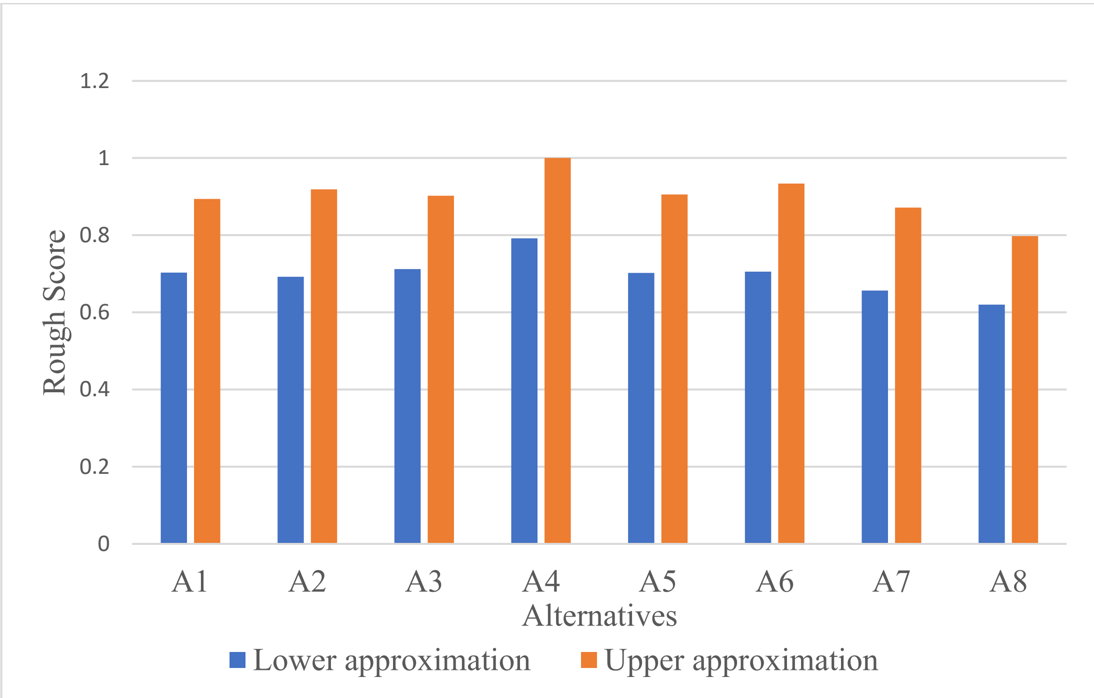

Figure 6.6 Alternatives with their final rough score

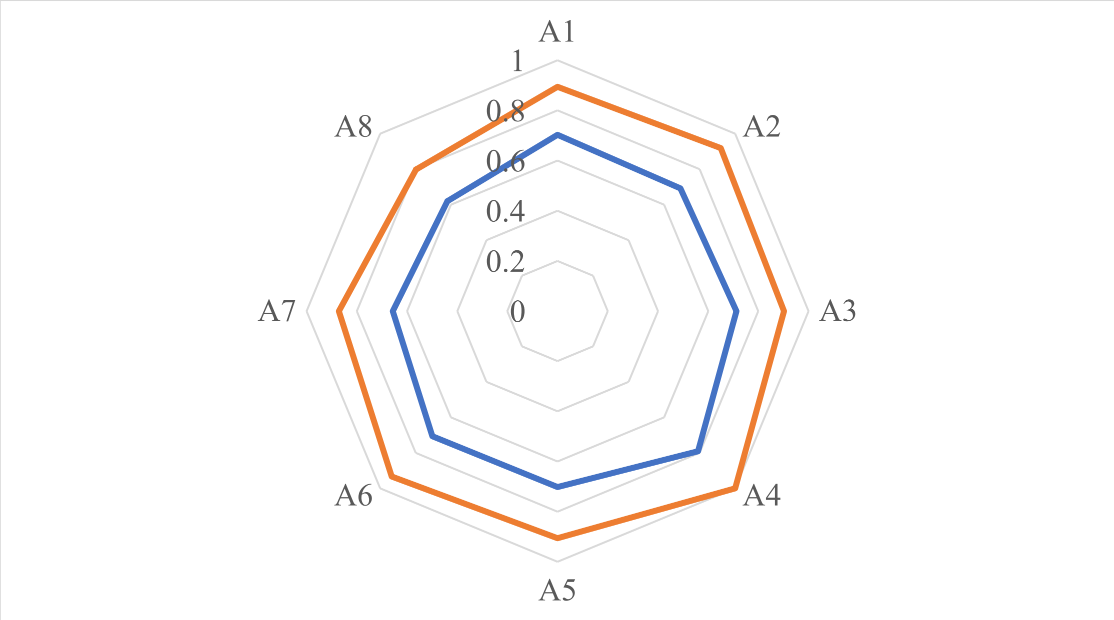

Figure 6.7 Normalized weights of 8 alternatives

6.9 Summary

At present, a significant amount of garbage is produced worldwide. Global trash creation in both urban and rural regions has increased in tandem with the world's population growth and improving living standards. Since established and developing countries face comparable obstacles to efficient waste management, the importance of this study transcends geographical boundaries to take a worldwide view.

The results and subsequent discussion offer a comprehensive understanding of the site selection process for solid waste dumping in Kolkata and its adjoining areas. This research offers a thorough analysis of current solid waste site selection approaches and identifies their shortcomings in terms of handling ambiguity and imprecision. It then presents the idea of rough numbers and clarifies how to use them when creating selection criteria and evaluating potential locations for waste management facilities. By considering the environmental, social, and economic dimensions, as well as incorporating uncertainties using the RAHP model, decision-makers have made choices that promote sustainable waste management practices.

Based on the chosen six influencing factors, the best site for dumping of solid wastes comes out to be the 4^{th} alternative and the most influencing factor turns out to be the cost of site. Rough number theory is very useful for difficult environmental management issues like solid waste site selection since it provides a methodical way to address imprecision and ambiguity in decision-making. This study has resolved inherent uncertainties in waste management planning from environmental to socioeconomic aspects, by introducing approximate figures into the decision-making process. The suggested method has successfully incorporated stakeholder preferences and expert knowledge into the site selection process by integrating qualitative and quantitative data. The results, thus obtained, have been validated with authoritative opinion. It is anticipated that future studies would incorporate advanced technology and data-driven approaches to maximize the precision and efficacy of site selection processes in determining suitable places for the disposal of municipal trash. Through the use of machine learning algorithms, remote sensing, Geographic Information System (GIS) mapping, and different spatial and environmental data analysis, a thorough understanding of possible sites can be attained.

Our goal has been effectively accomplished through the study. It is evident from this research that attaining sustainable urban expansion depends on pursuing such goals. The goal also set the foundation for long-term benefits in terms of the environment and public health. For the sustainable waste management projects to be implemented and completed successfully, ongoing community involvement and continuous monitoring are required. This study helps stop the careless disposal of municipal waste in ecologically sensitive areas by analyzing and allocating appropriate disposal locations in a methodical manner. Comprehensive environmental impact evaluations ensure that waste management practices don't compromise the health of ecosystems, water resources, or air quality. Additionally, it encourages appropriate land use planning by keeping garbage disposal sites from intruding on property designated for residential development, agriculture, or other necessary uses.

The findings contribute to the field of waste management and provide a valuable framework for similar site selection problems in urban areas.

Chapter 7

Predictive Modeling of Compressive Strength of Green Concrete

7.1 Introduction

Concrete is the most commonly used building material in the world, yet because of its enormous carbon emissions, other greenhouse gas emissions, and resource depletion during production, it has a major negative impact on the environment. In response, academic and business leaders have been creating cutting-edge substitutes for conventional concrete. Among them, green concrete has become a prominent sustainable option [255]. This study presents a comparative modeling framework for predicting the compressive strength development of normal and green concrete using both linear and exponential regression techniques. Experimental strength data at 7, 14, and 28 days were used to develop regression models for both concrete types. A linear regression model was constructed for normal concrete, yielding a strong correlation ($R^2 = 0.844$), whereas green concrete, characterized by the delayed pozzolanic activity of supplementary cementitious materials, was best represented by an exponential model. The exponential regression provided an excellent fit to green concrete strength data, capturing the nonlinear strength gain pattern typical of mixes incorporating fly ash and recycled aggregates. In addition, a Pareto analysis was performed to identify the most critical curing periods contributing to strength development. Results showed that approximately 86% of the 28-day compressive strength in green concrete was achieved within the first 14 days, emphasizing the importance of early-age curing and mix optimization.

7.2 Preliminaries

7.2.1 Linear Regression

Linear regression [252] is a statistical method used to model the relationship between a dependent variable (output) and one or more independent variables (inputs). In this case:

Dependent Variable (Y): Compressive strength (in N/mm^2)

Independent Variable (X): Number of curing days i.e. 7, 14 and 28

A linear relationship is assumed: $Y=\beta_0+\beta_1X$

Where, β_0= intercept (strength when curing time = 0)

β_1= slope (rate of strength gain per day)

X = number of curing days

Y = predicted compressive strength

7.2.2. Exponential Regression

An exponential relationship [253] is assumed: $y=a\cdot(1-e^{-b.x})+c$

Where, y=Dependent variable (e.g., compressive strength in MPa),

x= Independent variable (e.g., days of curing),

a, b and c are parameters to be estimated.

7.2.3 Pareto Chart

A Pareto chart is a special type of bar chart combined with a line graph that is used to identify the most significant factors in a dataset. It's based on the Pareto Principle (80/20 Rule), which suggests that 80% of outcomes come from 20% of causes. It helps us to prioritize which variables or time periods have the most impact and also focus on efforts where they will yield the greatest results [254].

7.3 Study Methodology

The flowchart of the developed methodology is illustrated in Figure 7.1

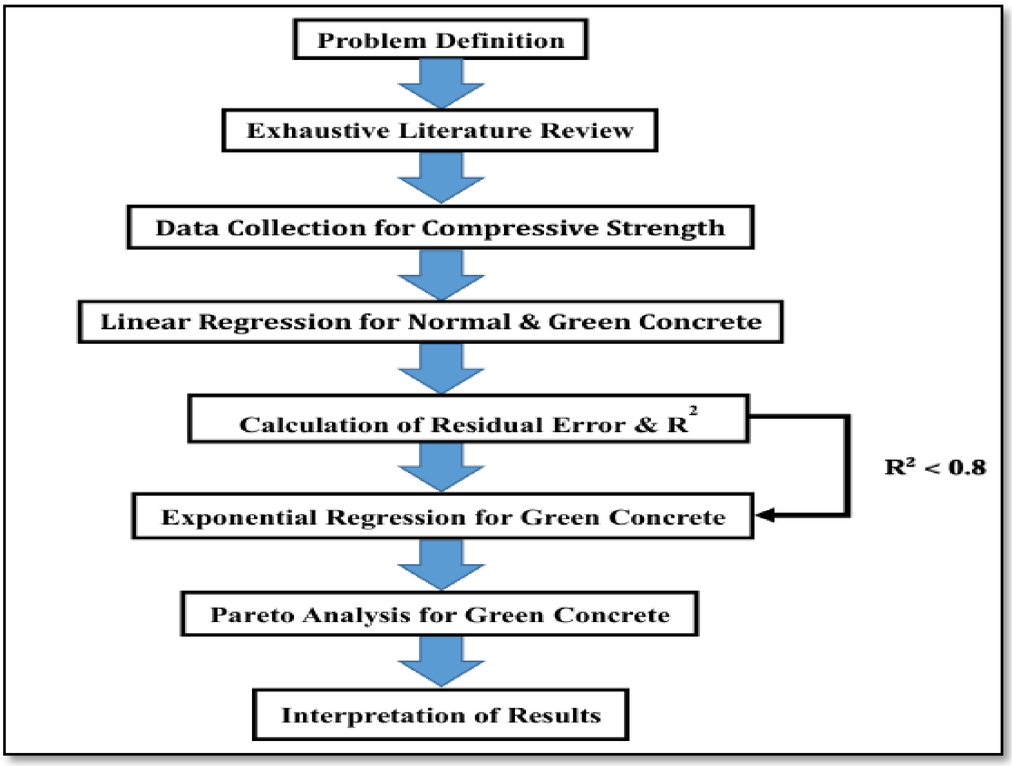

Figure 7.1 Flowchart for the research methodology

7.4 Materials Used and Mix Proportion

The experimental study involved the preparation and testing of two concrete mix types: normal concrete and green concrete, in accordance with IS 516:1959. For both mix types, M20 grade concrete has been designed as per IS 10262:2009 specifications. A total of nine cubes, each measuring 150 mm on all sides, have been cast for the normal concrete mix, and an equal number of cubes with identical dimensions have been prepared for the green concrete mix. The workability and consistency of the fresh concrete have been assessed using the slump test, following the procedure outlined in IS 1199:1959, prior to the setting of the mixes. After casting, the specimens have been demoulded after 24 hours and subsequently cured under room-temperature (27° C) conditions until testing. The mix proportions have been calculated with a water-to-cement (w/c) ratio of 0.5 being maintained throughout the design process for both kinds. In the normal concrete mix, the proportion of water, cement, fine aggregate, and coarse aggregate hasbeen maintained at 0.5:1:1.37:2.98 by weight. The corresponding material quantities used per batch included 24 kg of Ordinary Portland Cement (OPC), 32.88 kg of fine aggregate, and 71.52 kg of coarse aggregate. A total of 12 liters of water has been added to maintain the desired w/c ratio.

For the green concrete mix, a partial replacement strategy has been adopted to incorporate sustainable materials. The water content has been maintained at 0.5 parts, and the mix composition composed of cement, fly ash, glass powder, concrete detritus, and coarse aggregate in the following ratios: 1:1:2.1:2.49:5.96. Specifically, 12 kg of OPC has been replaced by 12 kg of fly ash, and the fine aggregate has been fully substituted with 25.2 kg of glass powder and 29.88 kg of recycled concrete and brick debris. Coarse aggregate content remained unchanged at 71.52 kg. Water content has been kept constant at 12 liters, ensuring a consistent w/c ratio across both mixes.

This material selection strategy highlights a comparative approach between conventional concrete and green concrete incorporating industrial by-products and recycled aggregates, aimed at promoting sustainability in concrete production.

7.5 Dataset

Experimental data for developing the model has been shown in Figure 7.2

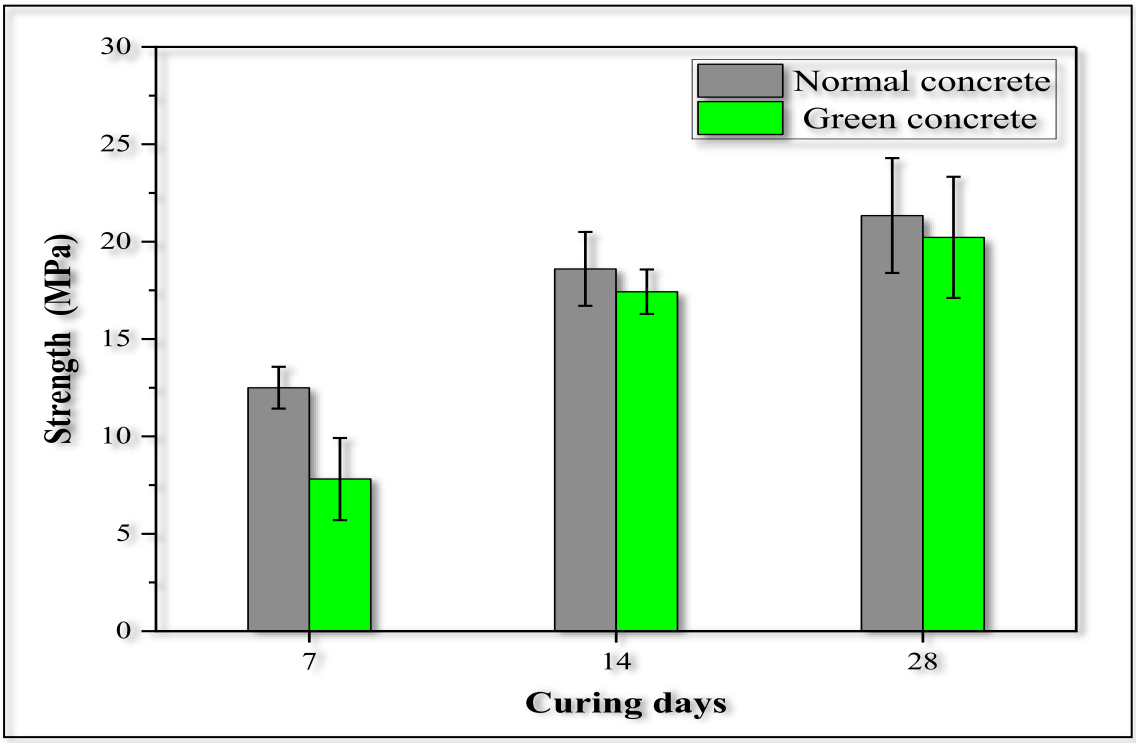

Figure 7.2 Data for model development

7.6 Results and Discussion

7.6.1 Linear Regression Output: Normal Concrete

The resulting equation obtained is: Strength=11.13+0.389×Days

Intercept (β_0 = 11.13) is the estimated strength at Day 0, slope (β_1 = 0.389) denotes that the strength increases by ~0.389 N/mm² for every extra curing day.

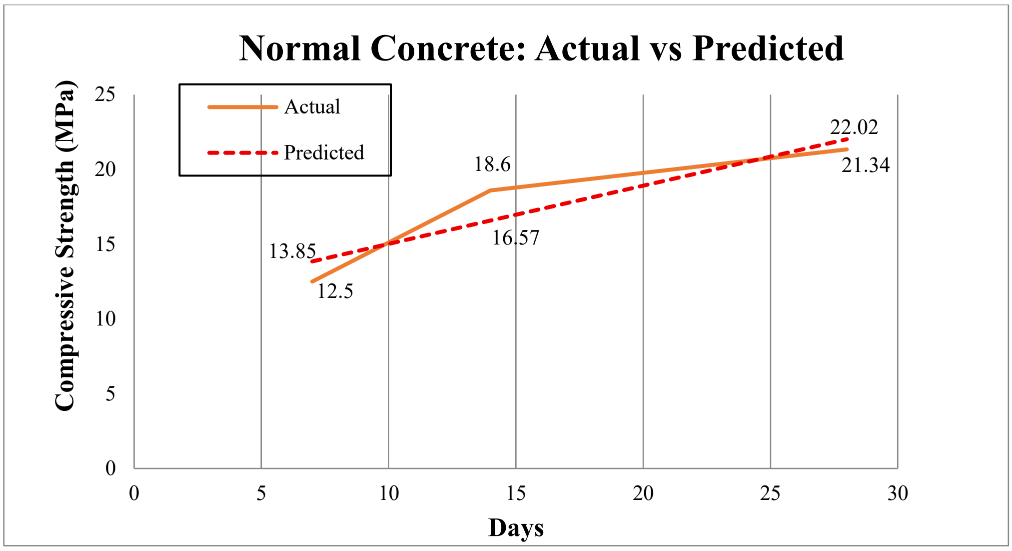

Figure 7.3 Comparison by linear regression for normal concrete

7.6.2 Linear Regression Output: Green Concrete

The resulting equation obtained is: Strength=6.42+0.535×Days

Intercept (β_0 = 6.42) is the estimated starting strength, slope (β_1 = 0.535) signifies that the strength gain rate per day is higher than normal concrete, which may be due to pozzolanic activity kicking in later.

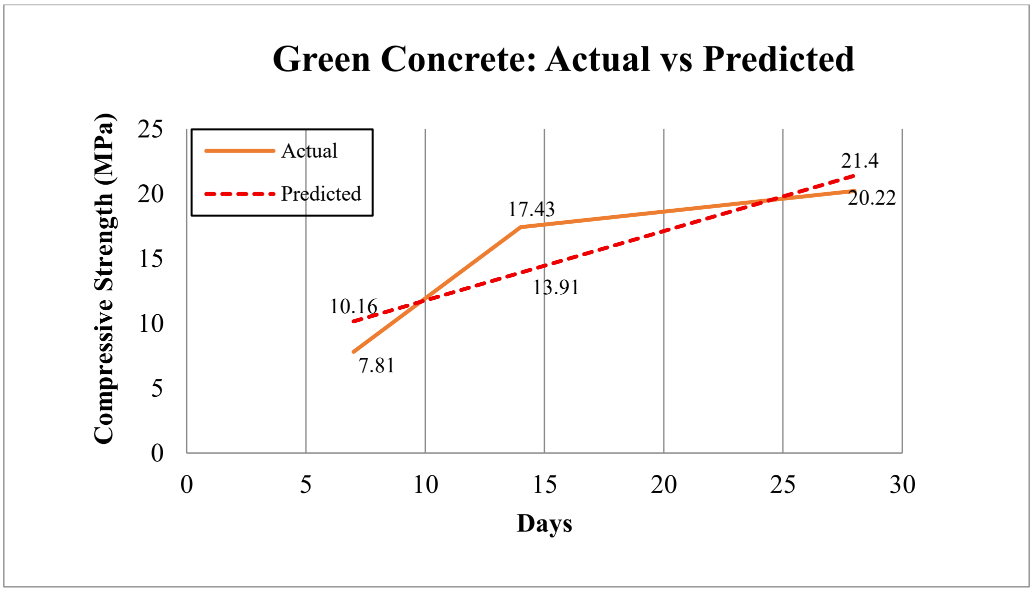

Figure 7.4 Comparison by linear regression for green concrete

7.6.3 Residual Error Analysis

Table 7.1 Calculation of residual error from linear regression

Normal Concrete				*Green Concrete*			
Days	**Actual (MPa)**	**Predicted (MPa)**	**Residual (Error)**	**Days**	**Actual (MPa)**	**Predicted (MPa)**	**Residual (Error)**
7	12.50	13.85	-1.35	7	7.81	10.16	-2.35
14	18.60	16.57	+2.03	14	17.43	13.91	+3.52
28	21.34	22.02	-0.68	28	20.22	21.40	-1.18

Residuals = Actual – Predicted values

Normal concrete has lower overall error (residuals range ~±2.0).

Green concrete shows slightly higher variation, especially on Day 14, which suggests non-linear gain.

7.6.4 Exponential Model for Green Concrete Compressive Strength

An exponential model of the form: Strength = $a\cdot(1-e^{-b.Days}) + c$ has been assumed.

Where, a = Asymptotic strength (≈ max strength),

b = Growth rate (start with ~0.1–0.2),

c = Offset (initial or residual strength).

Initial guess = [20, 0.1, 0]

Using nonlinear curve fitting (scipy.optimize.curve_fit in Python) to estimate parameters a,b,c.

```python
from scipy.optimize import curve_fit
params, _ = curve_fit(exponential_model, x_data, y_data, p0=initial_guess)
```

Fitted Parameters a = 53.53, b = 0.207 and c = −33.15

Final Equation: Compressive Strength (MPa) = $53.53\cdot(1-e^{-0.207.Days}) - 33.15$

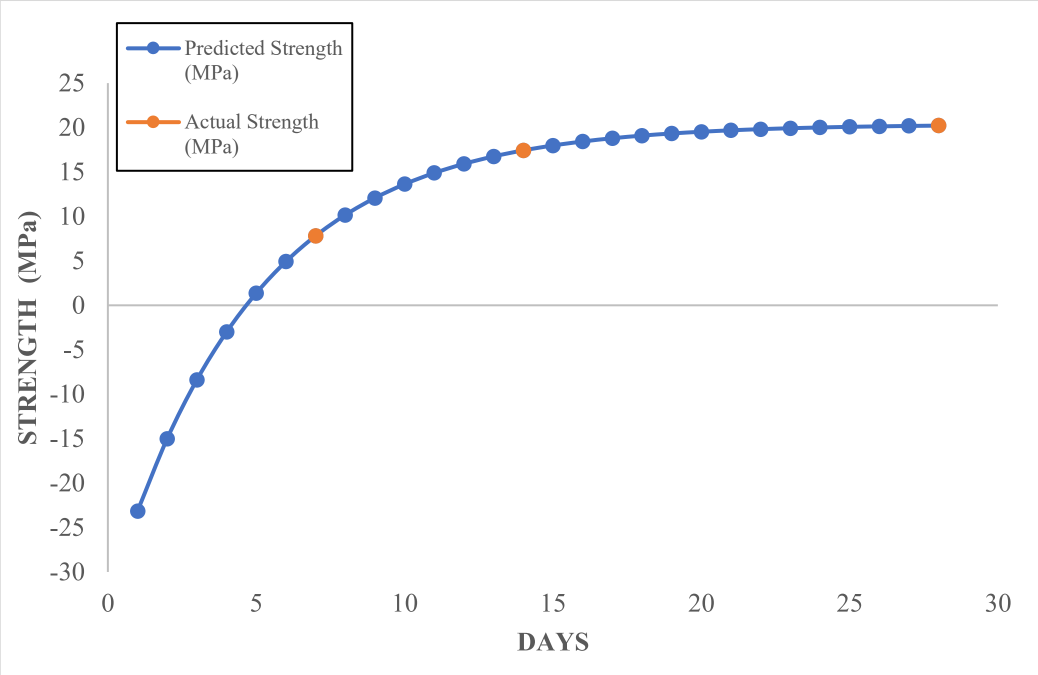

Figure 7.5 Comparison by exponential regression for green concrete

Table 7.2 Calculation of residual from exponential regression

Days	Actual (MPa)	Predicted (MPa)	Residual (Error)
7	7.81	7.81	~0
14	17.43	17.43	~0
28	20.22	20.22	~0

7.6.5 Pareto Chart of Strength Gain over Time for Green Concrete

Table 7.3 Cumulative percentage strength gain during the 28 days

Period (Days)	Strength Gain (MPa)	Cumulative %
0-7	7.81	38.6
7-14	9.62	86.2
14-28	2.79	100

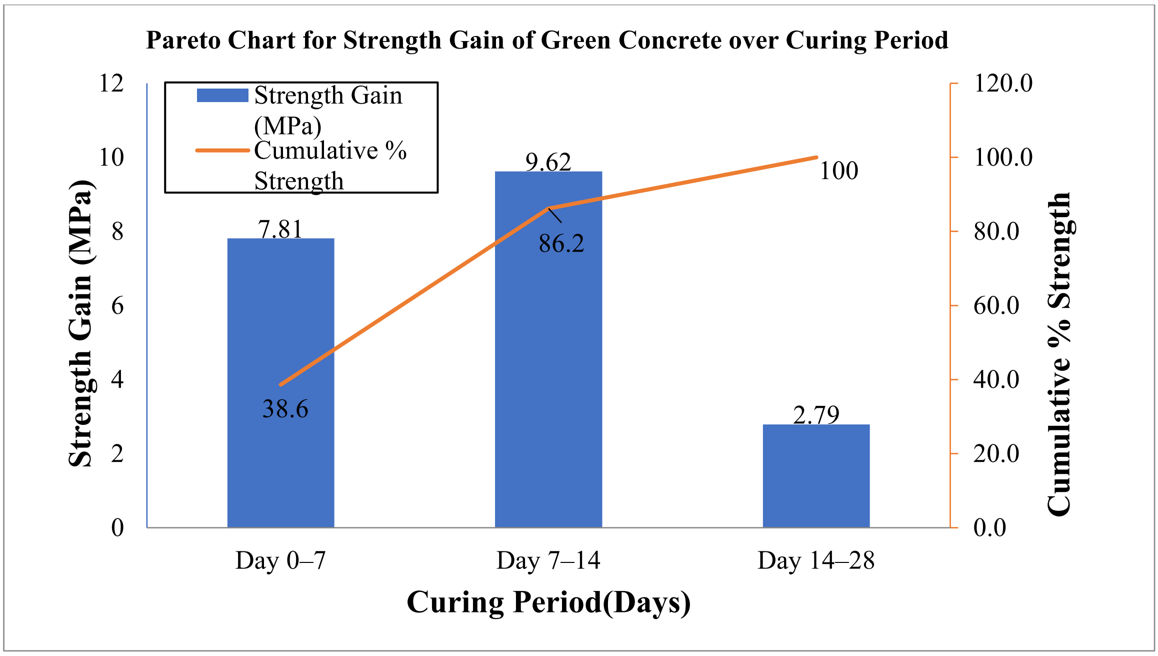

Figure 7.6 Pareto chart of strength (MPa) gain of green concrete over 28 days

A linear regression model has been developed using experimental compressive strength data of Figure 7.2 for normal concrete at 7, 14, and 28 days. The derived model equation is Strength (MPa) = 11.13+0.389·Days. This model yields a coefficient of determination R^2=0.844, indicating a good linear relationship between curing time and strength gain. The residual analysis from Table 7.1 shows in a minor deviation, with errors ranging from –1.35 MPa to +2.03 MPa, suggesting the model's suitability for early-age prediction.

For green concrete, a similar linear model has been developed using Figure 7.2 where Strength (MPa) = 6.42+0.535·Days. The model has an R^2=0.772, slightly lower than that of normal concrete, but still valid for prediction. The residuals as shown in Table 7.1 were more pronounced due to the nonlinear pozzolanic behaviour of fly ash, which often causes delayed strength development.

Figure 7.3 shows the actual compressive strength of normal concrete by an orange solid line and the red dashed line shows the predicted values obtained by linear regression. The predicted values are close, but there are small deviations (residuals). Figure 7.4 for green concrete has same pattern: actual vs. predicted comparison. It shows slightly larger deviation at day 14 which indicates that the predicted strength is underestimated with respect to the actual strength gain). The green concrete shows a higher slope, suggesting a faster gain rate post-initial set

To capture the nonlinear strength development more accurately, an exponential growth model has been fitted to the green concrete data where Strength (MPa) =53.53· ($1-e^{-0.207 \cdot \text{Days}}$). This model produces a perfect fit to the given dataset (zero residual error), capturing the rapid gain from 7 to 14 days and the plateauing effect after 21 days. The exponential form reflects the nature of strength development in concrete with supplementary cementitious materials, especially fly ash, which relies on pozzolanic reactions that activate slowly and accelerate with curing time. The model fits the existing data almost perfectly (zero residuals as shown in Table 7.2) as expected, since an exact 3- Point curve have been fitted as shown in Figure 7.5.

To identify the most critical period for strength development, a Pareto analysis has been conducted using cumulative strength gain data at different curing stages from Table 7.3. The chart in Figure 7.6 reveals that approximately 86% of the total 28-day strength is gained within the first 14 days, emphasizing the importance of controlling mix quality, curing practices, and material consistency during this period. The final 14 days (Day 14–28) contributed only ~14% to the overall strength, confirming that any improvement strategy should focus on early-age strength development.

7.6.6 Managerial Insights

The majority of strength gain (86%) occurs within the first 14 days. Strength gain after 14 days is only ~14%, suggesting that early curing is crucial. This analysis supports optimizing construction cycles by focusing on early-age strength development strategies like accelerated curing, applying additives, etc. This shows early curing period is most critical, and optimization of curing duration should be done based on this.

The outcomes of this study are crucial for ensuring sustainability and fostering future innovations in the construction industry. This study reviews recent advancements in green concrete technology, emphasizing its potential to meet future concrete demand and support sustainable urban development. The research highlights various materials, such as recycled aggregates and supplementary cementitious materials (SCMs), which can partially replace natural aggregates and traditional cement respectively. This substitution significantly reduces the need for fresh raw materials, effectively utilizing industrial waste and by-products, thus minimizing waste disposal issues and need for waste dumping sites. Furthermore, decreasing the cement content in concrete lowers CO_2 emissions. The study presents a comprehensive flowchart detailing the process of manufacturing sustainable green concrete, illustrating the connectivity between the necessary inputs and the beneficial outputs.

Recognizing the pillars of sustainability, this study integrates and addresses each one to enhance the quality of green concrete production. Ordinary Portland Cement (OPC) production accounts for 5-10% of global greenhouse gas emissions, making it a significant contributor to GHG emissions. Non-biodegradable waste materials such as glass, used motor oil, slag, and husk often occupy landfill space indefinitely, presenting a persistent global challenge. This study explores how this waste materials can effectively replace traditional concrete constituents to promote sustainability. While there are limitations to the usage of these waste materials, which are detailed in the study, some constraints remain to be identified. The replacement proportions of the waste materials and their subsequent effects on the concrete have also been detailed in this study. The research also presents an optimized green concrete production process and the composition of green concrete. Replacing various concrete constituents with waste materials can lower production costs, recycle waste, reduce the need for landfills, decrease CO_2 emissions, and improve public health and safety. The benefits of green concrete and the challenges associated with its adoption has also been discussed in this study.

7.7 Summary

The review of existing literature on green concrete underscores a significant and growing need for sustainable concrete solutions. As awareness of environmental issues intensifies, the demand for eco-friendly construction materials is poised to increase substantially. However, the current processes and design of mix proportions for green concrete remain in their infancy. Literature indicates that while substituting traditional cement or other constituents with sustainable alternatives can offer environmental benefits, these substitutions do not universally lead to improved performance. In some cases, they can have adverse effects, such as reduced mechanical strength, increased susceptibility to cracking, diminished thermal efficiency, and other performance-related issues. Therefore, further research and development are crucial to optimize the mix designs and production processes for green concrete to ensure it meets both environmental and structural standards. By synthesizing the knowledge from existing literature, the present study has identified and addressed the gaps in the field of green concrete.

This study successfully develop predictive models for the compressive strength of normal and green concrete using both linear and exponential regression techniques. While the strength gains in normal concrete follow a relatively linear trend, green concrete owing to the delayed reactivity of supplementary cementitious materials is more accurately captured using an exponential growth model. The exponential regression provides a high-fidelity representation of strength development and can serve as a robust predictive tool for pozzolanic concrete systems.

In parallel, a Pareto analysis of strength gain across different curing periods reveal that approximately 86% of the 28-day strength in green concrete is achieved within the first 14 days. This highlights the critical importance of early-age curing and mix control in achieving optimal performance. These findings provide actionable insights for sustainable construction practices, enabling more informed decisions in material design, quality control, and project scheduling. The integrated use of statistical modeling and Pareto optimization offers a comprehensive framework for advancing the performance and predictability of green concrete technologies.

Chapter 8

Analysis on Sustainable Health Care Infrastructure Design

8.1 Introduction

Sustainability has emerged as a critical consideration in the development and operation of modern healthcare infrastructure. The attitudes and behavioral reactions of patients, medical staff, and visitors significantly affect the overall success of environmentally responsible healthcare facilities. This study investigates how perceptions related to sustainability influence occupant commitment by developing an integrated analytical framework. In recent years, the healthcare sector has increasingly aligned its infrastructure strategies with Sustainable Development Goals (SDGs), emphasizing environmentally responsible and socially responsive healthcare systems. Hospitals and healthcare institutions are among the major consumers of energy and resources, making their environmental footprint an important concern in sustainable development discussions. Beyond energy conservation and emission reduction, improving the experience and well-being of facility users has become an equally important objective. Considering the growing challenges posed by climate change and public health risks, healthcare infrastructure must be resilient, sustainable, efficient, and centered on user needs.

Sustainable healthcare buildings incorporate several important dimensions, such as energy-conscious architectural planning, integration of natural and biophilic features, efficient waste handling mechanisms, superior indoor environmental quality, and patient-oriented spatial arrangements. These characteristics extend beyond technical or aesthetic improvements, as they directly influence user comfort, satisfaction, trust, and behavioral engagement. Therefore, the success of sustainable healthcare environments depends not only on engineering excellence or architectural innovation but also on how occupants perceive and respond to these sustainability initiatives.

From the perspective of healthcare facility planning and construction management, understanding behavioral indicators such as user satisfaction, loyalty, trust, and commitment is essential for designing future-ready healthcare infrastructure. Evaluating these behavioral dimensions also helps identify the sustainability aspects that users consider most valuable, thereby supporting more effective operational and design strategies. Despite the growing attention toward sustainable healthcare development, limited empirical research has quantitatively examined the relationship between sustainability perceptions and occupant commitment.

To address this research gap, the present study proposes a behavioral assessment framework for evaluating occupant commitment within sustainable healthcare facilities. The framework integrates concepts from healthcare management, sustainable construction, and service quality research using statistical techniques such as Principal Component Analysis (PCA) and regression modeling. The study analyzes the influence of major sustainability-related variables, namely Eco-Design Quality (EDQ), Trust in Certification (TIC), and Sustainability Satisfaction (SS), on Occupant Commitment (OC).

The findings reveal that Trust in Certification (TIC) exerts the strongest influence on occupant commitment, followed by Eco-Design Quality (EDQ) and Sustainability Satisfaction (SS). The results further indicate that visible sustainability practices and transparent environmental certifications play a major role in strengthening user confidence, satisfaction, and long-term attachment to healthcare facilities. The outcomes of this study provide valuable insights for architects, healthcare planners, construction professionals, and policymakers in developing healthcare environments that effectively balance sustainability objectives with occupant expectations and satisfaction.

8.2 Research Methodology

This research adopts a quantitative methodological framework to develop a predictive behavioral model for assessing how sustainability-oriented perceptions influence occupant commitment within healthcare environments. The study applies Principal Component Analysis (PCA) together with Multiple Linear Regression Analysis as the key statistical techniques for identifying underlying factors and investigating the relationships among them. The dataset utilized in this research was derived from a questionnaire survey associated with service quality and patient loyalty in a healthcare institution located in Kolkata.

In accordance with the objectives of the investigation, several variables were selected to characterize sustainability-related dimensions in environmentally responsible healthcare facilities. The identified variables are listed in details as follows:
a. Eco-Design Quality (EDQ): Represents sustainable infrastructure characteristics that improve environmental performance, such as energy-efficient systems and natural air circulation.
b. Trust in Certification (TIC): Denotes the perceived reliability and authenticity of green building certifications and institutional environmental commitments.
c. Sustainability Satisfaction (SS): Measures the degree of user satisfaction regarding the environmental initiatives and sustainable operational practices of the facility.

d. Occupant Commitment (OC): Reflects occupant loyalty, continued preference, and intention to recommend the healthcare facility to others.

Each construct was evaluated through multiple questionnaire items measured using a 5-point Likert scale, where 1 indicates "Strongly Disagree" and 5 represents "Strongly Agree."

8.3 An Empirical Investigation

A contextual investigation refers to a detailed and situation-oriented examination of a real-life phenomenon within its actual operational environment to derive meaningful insights and support theoretical understanding. In this study, the investigation focuses on a healthcare institution located in Kolkata, India, which acts as a representative setting for analyzing how sustainability-related perceptions, including eco-design quality, confidence in certification, and environmental satisfaction, affect occupant commitment. This practical research approach facilitates the organized collection and interpretation of data to evaluate user behaviour and loyalty within sustainable healthcare infrastructure through statistical tools such as PCA and regression analysis. Figure 8.1 presents the overall research framework.

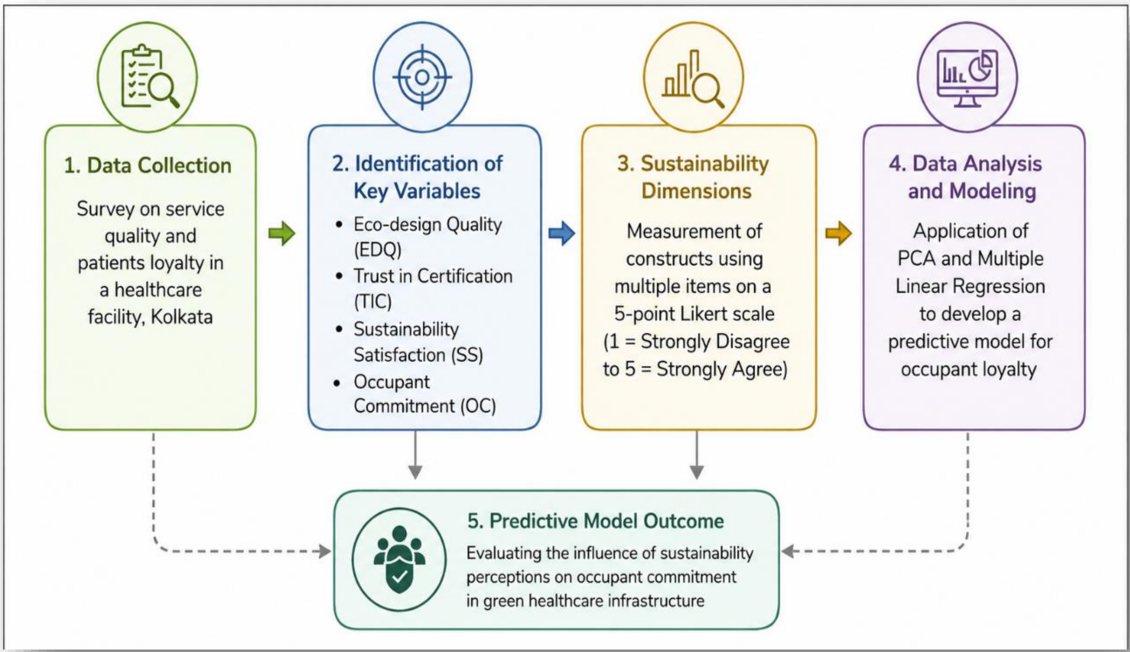

Figure 8.1 Conceptual Research Framework for Assessing Occupant Commitment in Sustainable Healthcare Facilities

8.4 Analysis and Interpretation of Findings

Data analysis was conducted using SPSS version 26. Initially, factor analysis was performed, followed by regression analysis. Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) test were applied prior to factor analysis to examine data significance and sampling adequacy. The corresponding results are presented in Table 8.1.

Table 8.1 Assessment of Sampling Adequacy and Sphericity Test Results

Statistical Test	Parameter	Value
Kaiser–Meyer–Olkin (KMO) Test	Sampling Adequacy Index	0.752
Bartlett's Test of Sphericity	Approximate Chi-Square	2471.384
	Degrees of Freedom (df)	66
	Significance Level (p-value)	0.000

Table 8.2 presents the eigenvalues and variance percentages of the four extracted factors, while Figure 8.2 illustrates the scree plot generated from the PCA analysis.

Table 8.2 Principal Component Extraction and Variance Distribution

Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)	Rotated Eigenvalue	Rotated Variance (%)	Cumulative Rotated Variance (%)
1	5.318	44.318	44.318	2.884	24.033	24.033
2	2.114	17.615	61.933	2.731	22.758	46.791
3	1.587	13.225	75.158	2.426	20.217	67.008
4	1.094	9.118	84.276	2.073	17.268	84.276
5	0.894	7.451	91.727	—	—	—
6	0.548	4.567	96.294	—	—	—
7	0.138	1.150	97.444	—	—	—
8	0.104	0.867	98.311	—	—	—
9	0.089	0.742	99.053	—	—	—
10	0.061	0.508	99.561	—	—	—
11	0.031	0.258	99.819	—	—	—
12	0.022	0.181	100.000	—	—	—

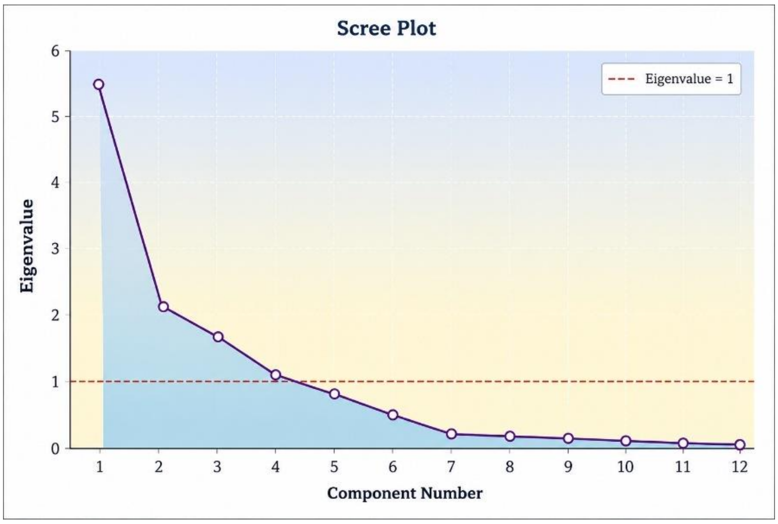

Figure 8.2 Scree Diagram of Principal Components

Variables with factor loadings below 0.45 were considered insignificant and excluded from the analysis. Higher loading values indicate stronger influence of a factor on a variable, while values above 0.60 represent substantial impact. Consequently, twelve variables were classified into four major factors. The detailed results are presented in Table 8.3.

Table 8.3 Rotated Factor Loading Matrix for Extracted Constructs

Variable Code	Factor A	Factor B	Factor C	Factor D
V1	0.912	—	—	—
V2	0.901	—	—	—
V3	0.846	—	—	—
V4	—	0.861	—	—
V5	—	0.824	—	—
V6	—	0.752	—	—
V7	—	0.729	—	—
V8	—	—	0.864	—
V9	—	—	0.839	—
V10	—	—	0.558	—
V11	—	—	—	0.918
V12	—	—	—	0.897

The extracted factors have been identified as EDQ, TIC, SS, and OC. Cronbach's alpha was used to evaluate the reliability of the scale, where values above 0.70 are considered acceptable according to Nunnally. In this study, the alpha values of the four factors ranged from 0.826 to 0.971, while the overall Cronbach's alpha value of 0.891 confirmed strong scale reliability. The reliability coefficients of the extracted factors are presented in Table 8.4.

Table 8.4 Internal Consistency Assessment of Extracted Constructs

Construct	Reliability Coefficient (α)	Consistency Level
EDQ	0.971	Excellent
TIC	0.874	High
SS	0.826	Good
OC	0.928	Excellent
Overall Scale Reliability	**0.891**	**Highly Reliable**

Multiple regression analysis was conducted to determine the relative importance of each dimension. The model summary and ANOVA results are presented in Tables 8.5 and 8.6, respectively.

Table 8.5 Regression Model Performance Indicators

Model No.	Correlation Coefficient (R)	Coefficient of Determination (R^2)	Adjusted R^2	Standard Error
1	0.682	0.465	0.451	0.854

Table 8.6 Variance Analysis of the Regression Model

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-Statistic	Significance (p)
Regression	95.284	3	31.761	41.236	0.000
Residual	109.846	146	0.752	—	—
Total	205.130	149	—	—	—

In the regression model, EDQ, TIC, and SS were considered independent variables, whereas OC was treated as the dependent variable. The regression results indicate that EDQ, TIC, and SS have statistically significant relationships with OC ($p < 0.05$), as presented in Table 8.7.

Table 8.7 Regression Coefficients for Occupant Commitment Prediction

Predictor Variable	Unstandardized Coefficient (B)	Standard Error	Standardized Coefficient (β)	t-Value	p-Value
Constant	0.832	0.372	—	2.236	0.028
Eco-Design Quality (EDQ)	0.438	0.084	0.328	5.214	0.000
Trust in Certification (TIC)	0.541	0.079	0.426	6.582	0.000
Sustainability Satisfaction (SS)	0.219	0.076	0.174	2.764	0.009

The regression model reveals that trust in environmental certification is the strongest predictor of occupant commitment, followed by eco-design quality and sustainability satisfaction. This highlights that, in sustainable healthcare infrastructure, institutional credibility is equally important as physical facilities. The findings emphasize the importance of transparent certification systems and visible sustainability practices in healthcare management.

The study further demonstrates that behavioral aspects should be integrated into the planning and operation of sustainable healthcare facilities. Trust in certification significantly influences user loyalty, indicating that green initiatives alone are insufficient unless they are properly communicated and supported by recognized certifications. Eco-design quality also plays a major role in enhancing occupant commitment. Features such as natural illumination, improved ventilation, ergonomic layouts, and sustainable construction materials contribute to user comfort and satisfaction.

These results align with earlier studies showing that well-designed healthcare environments improve psychological well-being, reduce stress, and enhance overall user experience. Although sustainability satisfaction showed comparatively lower influence, it remained statistically significant, suggesting that users are more committed when their sustainability expectations are fulfilled. The study also establishes a connection between healthcare planning and construction management by providing measurable relationships that support policy development and sustainable design strategies. The use of PCA and regression analysis further strengthens the reliability of the findings by reducing bias and identifying underlying data structures.

8.5 Summary

This study proposes a novel behavioral framework to evaluate the relationship between sustainability perceptions and occupant commitment within healthcare facilities. By applying Principal Component Analysis (PCA) and regression analysis, the study validates four major constructs and identifies trust in environmental certification as the most influential factor affecting occupant loyalty.

The findings suggest that, beyond technical efficiency and architectural performance, credibility, transparency, and effective communication of sustainability initiatives play a decisive role in shaping occupant behaviour and long-term commitment. Eco-design quality also demonstrates a substantial positive influence on user comfort and satisfaction, highlighting the importance of biophilic planning, natural lighting, efficient ventilation, and resource-conscious infrastructure design.

The major contributions of this study are summarized as follows:

a. Proposes a quantitative behavioral framework integrating sustainability dimensions with occupant commitment in healthcare infrastructure.

b. Demonstrates the strong predictive capability of trust in green certification systems, emphasizing the importance of transparency and institutional credibility.

c. Establishes eco-design quality as a key determinant of occupant satisfaction and loyalty through empirical validation.

d. Employs PCA and regression analysis to identify, validate, and interpret latent behavioral constructs, thereby enhancing methodological approaches in healthcare sustainability research.

e. Develops an interdisciplinary framework that combines sustainable construction, healthcare facility planning, and service science to support resilient and user-centered infrastructure development.

Chapter 9

A Diagnostic Approach to Risk Evaluation in Sustainable Construction Projects

9.1 Introduction

The construction sector has been experiencing a significant transformation as it seeks to reconcile economic advancement with environmental sustainability and social accountability. Sustainable construction, prioritising resource efficiency, environmental preservation, and long-term economic sustainability, has become an essential answer to the problems posed by unsustainable urban expansion. Construction projects concurrently encounter a diverse array of risks spanning financial, operational, environmental, and regulatory domains that jeopardise project performance and stakeholder goals. In this changing environment, a cohesive strategy that combines sustainable building principles with comprehensive risk assessment approaches is crucial. Failure Mode and Effects Analysis (FMEA) is a widely used technique for identifying potential failures, their causes, and impacts within systems and processes [256-259]. Usually the FMEA team decides their final consequences for every noted failure mode. Usually, the possible failure modes are graded by combining the risk elements, i.e., the severity (S), the occurrence (O), and the Detection (D), to produce a metric called risk priority number (RPN), the product of the three risk factors (RPN=O x S x D). The more RPN's value, the more the failure mode's risk influences the system dependability. Though widely employed in many sectors for its simplicity and ease, the RPN approach is nonetheless condemned for several flaws when applied in a real-world problem. [260-262]. Tables 9.1 & 9.2 depict some real-world construction failure examples. However, traditional FMEA has been criticized for its inherent limitations, including equal weighting of risk factors and its inability to effectively manage uncertainty. While various enhancements have been proposed using fuzzy set theory, these approaches often require extensive prior knowledge, complex rule development, and overlook the role of randomness in risk evaluation of construction projects. As on date no extensive work has been reported in the literatures on this area. To address these issues, this study presents an integrated approach that combines FMEA with rough set theory, enabling a more objective and flexible treatment of uncertainty without relying on prior information. Furthermore, the model incorporates environmental considerations to support sustainable construction practices. The methodology involves the use of Rough Analytic Hierarchy Process (RAHP) to determine the relative importance of risk factors, followed by Rough Technique for Order of Preference by Similarity to Ideal Solution (RTOPSIS) to prioritize failure modes. The model has been validated and corroborated by the construction industrial practitioners.

Table 9.1 Real world cases of occurrence of the failures and their insights

Failure Modes (FM)	Real World Case	Failure Incident	Impact of the Failure	Insights
Design Errors and Omissions(FM1)	Hyatt Regency Walkway Collapse (Kansas City, USA, 1981)	The contractor and engineer failed to adequately verify a design alteration during the building of suspended walkways.	During the incident, the walkways fell, killing 114 and wounding more than 200.	Even minor design modifications must be re-engineered and reapproved.
Poor Quality Control and Workmanship (FM2)	Sampoong Department Store Collapse (Seoul, South Korea, 1995)	Total collapse was caused by bad concrete quality, removal of structural columns, and incorrect load management.	More than 500 fatalities; still one of the deadliest contemporary building catastrophes.	Compromising on material quality and building requirements has disastrous effects.
Safety Incidents (FM3)	Qatar World Cup Construction (2010s-2022)	Many migrant workers died during stadium and infrastructure building. Investigations uncovered inadequate working conditions and absence of fundamental safety criteria.	Intense worldwide condemnation, labour changes mandated by outside influence.	Neglecting worker safety results in human tragedy, damage to reputation, and subsequent regulatory intervention.
Cost Overruns and Financial Mismanagement (FM4)	Boston Big Dig (Massachusetts, USA)	The underground highway project, initially projected to cost \$2.8 billion, ultimately incurred expenses nearing \$15 billion.	Litigations, contractor insolvencies, and quality concerns, including a lethal ceiling failure.	In the absence of robust cost controls, large-scale projects may lead to significant financial failures.
Schedule Delays(FM5)	Berlin Brandenburg Airport (Germany)	Originally scheduled to open in 2011, it was pushed back nearly ten years because of architectural problems, fire safety concerns, and project mismanagement.	Public shame, political repercussions, billions of euros lost.	Unreasonable timetables and inadequate coordination create huge delays and budget overruns.
Regulatory and Compliance Failures(FM6)	Grenfell Tower Fire (London, UK, 2017)	During the renovation, non-compliant cladding and insulation materials were utilized, facilitating the rapid spread of fire.	Seventy-two fatalities, significant public dissent, criminal enquiries, and regulatory changes.	Contractors are required to adhere to fire safety and building codes, as deviations can result in severe consequences.

Table 9.2 Occurrence of the failures in Indian construction projects and their insights

Failure Modes (FM)	**Indian Construction Case**	**Failure Incident**	**Insights**
Design Errors and Omissions(FM1)	Kolkata Vivekananda Road Flyover Collapse (2016)	A partially completed flyover collapsed, resulting in 27 fatalities. Subsequent investigations uncovered significant design deficiencies and expedited construction timelines.	Autonomous design evaluations, and a more deliberate, secure construction process could have averted the catastrophe.
Poor Quality Control and Workmanship(FM2)	Bengaluru Building Collapse (2018)	A five-storey structure under construction collapsed at Kasavanahalli, resulting in numerous fatalities. Reports indicated substandard concrete quality and unauthorized construction techniques.	It is essential to conduct regular site inspections and conduct appropriate material testing.
Safety Incidents (FM3)	Noida Twin Tower Demolition (2022)	Though the demolition was regulated, the incident drew attention to significant safety infractions during original construction—illegal floors installed without appropriate structural clearances.	By ignoring safety and structural norms in the name of profit, one exposes themselves to enormous hazards over the long run.
Cost Overruns and Financial Mismanagement (FM4)	Hyderabad Metro Rail Project	The largest public-private partnership metro project in India saw substantial cost overruns, with early estimates of ₹14,132 crore escalating considerably due to land complications, regulatory obstacles, and underappreciated urban intricacies.	There is a need for comprehensive risk-adjusted cost planning for urban megaprojects.
Schedule Delays(FM5)	Delhi Metro Phase III Extensions	Certain segments of Delhi Metro's Phase III experienced delays exceeding one year, primarily attributable to land acquisition challenges, contractor conflicts, and unanticipated complications, such as tunneling beneath densely populated regions.	In order to prevent falling behind schedule, it is vital to engage in comprehensive planning for the acquisition of land and utilities.
Regulatory and Compliance Failures(FM6)	Campa Cola Compound Case (Mumbai)	The Supreme Court mandated the destruction of many unauthorized storeys in the Campa Cola housing society due to building exceeding allowed plans.	Plans that have been approved and local building rules must be adhered to in a stringent manner by contractors and developers.

9.2 Preliminaries

9.2.1 Rough Set Theory

Rough Set Theory is an artificial intelligence method which has been applied to dimensionality reduction, pattern identification, classification and many other areas where data availability is difficult and there is vagueness and uncertainty.

Rough set theory served as the inspiration for Zhai et al.'s initial formulation of the rough number concept [228]. The benefit of rough numbers is that they may evaluate border intervals that are only dependent on source data and handle the subjective expert judgments. Rough number does not require additional information and takes real views of experts which improves the process of decision making. A rough number contains upper limit, lower limit and rough boundary interval.

9.2.1.1 Rough Number

Suppose U is the universe which contains all the objects, P is an arbitrary object of U; X is a set of y classes (S_1; S_2; ...; S_y) that cover all the objects in U; R = {S_1; S_2; ... ; S_y}. If these classes are ordered as $S_1 < S_2 < \ldots < S_t$, then $\forall P \in U$, $S_a \in X$, $1 \le a \le y$, the lower approximation ($\underline{Apr}(S_a)$), upper approximation ($\overline{Apr}(S_a)$) and boundary region ($Bnd(S_a)$) of class S_a are defined as:

$$(\underline{Apr}(S_a)) = U\ \{P \in U/X(P) \le S_a\} \tag{9.1}$$

$$(\overline{Apr}(S_a)) = U\ \{P \in U/X(P) \ge S_a\} \tag{9.2}$$

$$(Bnd(S_a)) = U\ \{P \in U/X(P) \ne S_a\} = \{P \in U/X(P) > S_a\}\ U\ \{P \in U/X(P) < S_a\} \tag{9.3}$$

Then S_a can be denoted using a rough number ($RN(S_a)$), which has a lower limit ($\underline{Lim}(S_a)$) and a upper limit ($\overline{Lim}(S_a)$), where,

$$\underline{Lim}(S_a) = \frac{1}{M_L}\boldsymbol{\Sigma}X(P)/P \in \underline{Apr}(S_a) \tag{9.4}$$

$$\overline{Lim}(S_a) = \frac{1}{M_U}\boldsymbol{\Sigma}X(P)/P \in \overline{Apr}(S_a) \tag{9.5}$$

$$RN(S_a) = [\ \underline{Lim}(S_a), \overline{Lim}(S_a)] \tag{9.6}$$

where M_L, M_U represent the quantity of items present in $\underline{Apr}(S_a)$ and $\overline{Apr}(S_a)$ respectively.

Obviously, the lower limit represents the average value of the components included in its equivalent upper approximation, and the higher limit does the same for the lower one.

Their difference is defined as rough boundary interval ($IRBnd(S_a)$):

$$IRBnd(S_a) = \overline{Lim}(S_a) - \underline{Lim}(S_a) \tag{9.7}$$

The rough border interval indicates how vague S_a is; a greater one indicates more ambiguity, while a smaller one indicates higher precision. Then an approximate number can be used to represent the subjective data. Consider the following data set: V = {3; 5; 7; 3; 7}, which consists of three classes, and X = {S1; S2; S3}, which is equivalent to {3; 5; 7}. Apply the equations 1-3, to S2 in order to provide an explanation of the definition of the rough number.

$\underline{Apr}(5)$=V {P ∊ V/X(P) ≤ 5} = {3,5,3}

($\overline{Apr}(S_a)$)= V {P ∊ V/X(P) ≥ 5}={5,7,7}

Bnd(5)= V {P ∊ V/X(P) ≠ 5}={3,7,3,7}

Consequently, the approximate value of S2 is determined using equations (9.4) – (9.6):

$$\underline{Lim}(5)= \frac{1}{M_L}\boldsymbol{\Sigma}X(P)/P \in \underline{Apr}(5) = \frac{1}{3} (3+5+3) = 3.67$$

$$\overline{Lim}(5)= \frac{1}{M_U}\boldsymbol{\Sigma}X(P)/P \in \overline{Apr}(5) = \frac{1}{3} (5+7+7) = 6.33$$

$$RN(5)=[\underline{Lim}(5),\overline{Lim}(5)] = [3.67,6.33]$$

The rough boundary interval of S_2 is defined as:

$$IRBnd(5) = \overline{Lim}(5) - \underline{Lim}(5) = 2.66$$

Finally, the number RN(5) = [3.67,6.3] stands for the part "5" in V.

The same method is used to determine the other elements of V. Due to their closeness to interval numbers, rough numbers may also be calculated using the interval numbers' arithmetic methods [228].

9.2.2 Rough AHP

Even though AHP has been used a lot as an MCDM method, this study uses AHP in a rough setting to figure out how well it can handle information that isn't precisely correct. The steps below were taken to reach the goal [229].

Step 1 Develop a pairwise comparison matrix (PWCM) for the assessment criteria, it is necessary to use the insights of k experts. This matrix should correspond to each individual expert (1≤f≤k) and should be constructed using Saaty's 9-point scale.

The PWCM for the k^{th} expert can be articulated as follows:

$$D_f = [d_{xy}^f]_{k*k} = \begin{bmatrix} 1 & d_{12}^f & \cdots & d_{1k}^f \\ d_{21}^f & 1 & \cdots & d_{2k}^f \\ \cdots & \cdots & \cdots & \cdots \\ d_{k1}^f & d_{k2}^f & \cdots & 1 \end{bmatrix} \tag{9.8}$$

Step 2: Generate k instances of PWCM. Assess the consistency ratio (CR) for each instance. If the CR is below 0.10, continue by accepting it.

Step 3: Form the integrated PWCM, as detailed below, by aggregating the opinions of all experts.

$$D_f = [d_{xy}]_{k*k} = \begin{bmatrix} 1 & d_{12} & \cdots & d_{1k} \\ d_{21} & 1 & \cdots & d_{2k} \\ \cdots & \cdots & \cdots & \cdots \\ d_{k1} & d_{k2} & \cdots & 1 \end{bmatrix} \tag{9.9}$$

where d_{xy}={ d_{xy}^{1} , d_{xy}^{2} , …. d_{xy}^{1k} }

Step 4: Convert the element d_{xy} into Rough Number, RN (d_{xy}^{e}) of d_{xy} as follows

$$\text{RN } (d_{xy}^{f}) = [\ d_{xy}^{fL}, d_{xy}^{fU}]\ , (1 \leq f \leq k) \tag{9.10}$$

Step 5: Determine average rough interval RN(d_{xy}) as,

$$\overline{[\text{RN (dxy)}]} = d_{xy}^L, d_{xy}^L \tag{9.11}$$

$$\text{where, } d_{xy}^{L} = \frac{\sum_{f=1}^{i} d_{xy}^{fL}}{i}\ ,\quad d_{xy}^{U} = \frac{\sum_{f=1}^{i} d_{xy}^{fU}}{i} \tag{9.12}$$

Now, the aggregated rough PWCM looks like

$$A = [a_{xy}]_{k*k}$$
$$= \begin{bmatrix} [1,1] & [d_{12}^L, d_{12}^U] & \cdots & [d_{1k}^L, d_{1k}^U] \\ [d_{21}^L, d_{21}^U] & [1,1] & \cdots & [d_{2k}^L, d_{2k}^U] \\ \cdots & \cdots & \cdots & \cdots \\ [d_{k1}^L, d_{k1}^U] & [d_{k2}^L, d_{k2}^U] & \cdots & [1,1] \end{bmatrix} \tag{9.13}$$

Step 6: Establish approximate criteria Weight W_x as the geometric mean of the aggregated rough PWCM.

$$B_x=[B_x^L, B_x^U]=[(\prod_{y=1}^{n} d_{xy}{}^{L})^{1/n}, (\prod_{y=1}^{n} d_{xy}{}^{U})^{1/n}] \tag{9.14}$$

Step 7: Normalize to get relative criteria weights which are expressed as

$$C_x=[C_x^L, C_x^U]=[\frac{C_x{}^L}{\max(C_x{}^U)}, \frac{C_x{}^U}{\max(C_x{}^U)}] \text{ , for all x} \tag{9.15}$$

9.2.3 Rough TOPSIS

The steps that are listed below have been carried out [230].

Step 1: Develop a Clear Evaluation Matrix

Upon calculating the weights of risk components, an assessment matrix must be constructed to delineate the performances of the failure types. Experts use numerical ranges ranging from 1 to 10 to assess the performance of each failure under P, Q, R, and S. As the scale increases, the impact of failure intensifies.

The matrix A supplied by an expert is as follows:

$$A = \begin{array}{c} \\ E_1 \\ E_2 \\ \vdots \\ E_x \end{array} \begin{array}{c} \begin{array}{cccc} RI_P & RI_Q & RI_R & RI_S \end{array} \\ \begin{bmatrix} t_{1P}^m & t_{1Q}^m & t_{1R}^m & t_{1S}^m \\ t_{2P}^m & t_{2Q}^m & t_{2R}^m & t_{2S}^m \\ \vdots & \vdots & \vdots & \vdots \\ t_{xP}^m & t_{xQ}^m & t_{xR}^m & t_{xS}^m \end{bmatrix} \end{array} \tag{9.16}$$

where E_x (x = 1, 2, ..., I) denotes the manner of failure x. RI_r (r = P, Q, R, and S) represents risk factor r. n represents the mth expert (m = 1, 2, ..., N). The initial judgement for the xth failure mode under the rth risk factor is denoted by the acronym $t_{xr}{}^m$. This judgement was supplied by the mth skilled individual.

Step 2: Obtain the vague intervals with rough set theory

During this stage of the decision-making process, rough set theory is also used in order to control the imprecision that is present.Then, $t_{xr}{}^m$ is converted into rough number RN ($t_{xr}{}^m$) following the equations (1)–(6).

$$RN(t_{xr}{}^m) = [t_{xr}{}^{mL}, t_{xr}{}^{mU}] \tag{9.17}$$

where $t_{xr}{}^{mL}$ and $t_{xr}{}^{mU}$ are the boundaries set by the approximate number RN($t_{xr}{}^m$).

At this point, the following is how all of the specialists' preliminary assessments on the y_i^r are expressed:

$$RN(t_{xr}) = \{[t_{xr}^{1L}, t_{xr}^{1U}], [t_{xr}^{2L}, t_{xr}^{2U}], ..., [t_{xr}^{NL}, t_{xr}^{NU}]\} \tag{9.18}$$

To calculate the average rough interval RN(txr), which is a representation of the group's rough performance, the following formula is used:

$$\overline{RN(t_{xr})} = [t_{xr}^{L}, t_{xr}^{U}]$$

$$t_{xr}^{L} = \frac{(t_{xr}^{1L}+t_{xr}^{2L}+\cdots+t_{xr}^{NL})}{N} \tag{9.19}$$

$$t_{xr}^{U} = \frac{(t_{xr}^{1U}+t_{xr}^{2U}+\cdots+t_{xr}^{NU})}{N} \tag{9.20}$$

where t_{xr}^{L} and t_{xr}^{U} are the boundaries set by the approximate number $\overline{RN(t_{xr})}$.

The crude decision matrix B is given as

$$B = \begin{bmatrix} [t_{1P}^{L}, t_{1P}^{U}] & [t_{1Q}^{L}, t_{1Q}^{U}] & [t_{1R}^{L}, t_{1R}^{U}] & [t_{1S}^{L}, t_{1S}^{U}] \\ [t_{2P}^{L}, t_{2P}^{U}] & [t_{2Q}^{L}, t_{2Q}^{U}] & [t_{2R}^{L}, t_{2R}^{U}] & [t_{2S}^{L}, t_{2S}^{U}] \\ \vdots & \vdots & \vdots & \vdots \\ [t_{xP}^{L}, t_{xP}^{U}] & [t_{xQ}^{L}, t_{xQ}^{U}] & [t_{xR}^{L}, t_{xR}^{U}] & [t_{xS}^{L}, t_{xS}^{U}] \end{bmatrix} \tag{9.21}$$

Step 3: Obtain the matrix that is weighted and normalised.

Normalisation and weighting of the rough matrix are both performed in this stage. First, the components of the decision matrix B are shown to be similar by the use of the following normalisation method:

$$t_{xr}^{L'} = \frac{t_{xr}^{L}}{\max_{x=1}^{I}\{\max[t_{xr}^{L}, t_{xr}^{U}]\}} \tag{9.22}$$

$$t_{xr}^{U'} = \frac{t_{xr}^{U}}{\max_{x=1}^{I}\{\max[t_{xr}^{L}, t_{xr}^{U}]\}} \tag{9.23}$$

where $[t_{xr}^{L'}, t_{xr}^{U'}]$ is a representation of the normalised bounds of the rough interval $[t_{xr}^{L}, t_{xr}^{U}]$ that has been processed using the normalisation procedure. After going through this normalisation process, the range of rough numbers will be contained inside the interval [0,1]. Second, the weighted normalized rough decision matrix is obtained by

$$y_{xr}^{L} = RW_r^{L} \times t_{xr}^{L'} \quad (9.24)$$

$$y_{xr}^{U} = RW_r^{U} \times t_{xr}^{U'} \quad (9.25)$$

where y_{xr}^{L} and y_{xr}^{U} are the boundaries of the rough assessments that are weighted and normalised

Step 4: Determine which options are the best

In this stage, the best solutions are identified by using the weighted normalised matrix as the basis.

$$y^{+}(r) = \{\max_{x=1}^{I}(y_{xr}^{U}), \text{ if } r \in Z; \min_{x=1}^{I}(y_{xr}^{L}), \text{ if } r \in P\} \quad (9.26)$$

$$y^{-}(r) = \{\min_{x=1}^{I}(y_{xr}^{U}), \text{ if } r \in Z; \max_{x=1}^{I}(y_{xr}^{L}), \text{ if } r \in P\} \quad (9.27)$$

where $y^{+}(r)$ and $y^{-}(r)$ denote the positive and negative ideal solutions for the risk factor r, respectively. Z and P denote the indices of benefit and cost, respectively.

Step 5: Determine the relative distances

After that, we will be able to determine the distances that separate the unsuccessful solutions from the perfect ones. It is necessary to apply the Euclidean distance in n dimensions in order to acquire the distances, which are presented in the following manner:

$$D_x^{+} = \{ \sum r \in Z(y_{xr}^{L} - y^{+}(r))^2 + \{ \sum r \in P\,(y_{xr}^{U} - y^{+}(r))^2]\}^{1/2} \quad (9.28)$$

$$D_x^{-} = \{ \sum r \in Z\,(y_{xr}^{U} - y^{-}(r))^2 + \{ \sum r \in P\,(y_{xr}^{L} - y^{-}(r))^2]\}^{1/2} \quad (9.29)$$

where the distances from failure mode x to the positive solution and the negative solution, respectively, are denoted by the symbols D_x^{+} and D_x^{-}, respectively.

Step 6: Using the proximity coefficient, determine the final outcomes

Finally, closeness coefficient (CC_x) represents failure mode x risk. Failure ranks start with it. Greater coefficients reduce failure risk.

$$CC_x = \frac{Dx^{-}}{Dx^{-} + Dx^{+}}, \quad x = 1, 2, ..., I \quad (9.30)$$

9.3 Study Methodology

The problem has been initially identified, and an extensive literature survey was undertaken based on it. A research framework has been established along with the PEEST (Political, Economic, Environmental, Social and Technological) analysis in consensus by the different experts to address the gaps identified from literature study. The study methodology has been separated into five phases as shown in Figure 9.1. In the initial step, various failure modes were identified, and expert assessments were conducted to evaluate severity (S), occurrence (O), detection (D), and environmental factor (E) which have been discussed in Table 9.4. In the second phase, rough weights of the risk assessment factors(O,S,D,E) have been determined utilising rough AHP using the equations 9.8 to 9.15 which are shown in Table 9.7.Initial PWCM for the four expert professionals based on Indian sustainable construction scenario as revealed in Table 9.2 have been shown in Table 9.55(a-d).Consistency Ratio(CR) of all the PWCM have been found to be <0.1 and hence all of them are acceptable for evaluation. In the third phase, all failure modes were assessed using rough TOPSIS using the equation 9.16 to 9.29, followed by prioritisation and risk ranking in the fourth phase to rank the failure modes based on the closeness coefficient using equation 9.30. Table 9.6 illustrates the performance of each failure mode based on individual risk factors as assessed by all four experts. Tables 9.8-9.10 provide the original group rough decision matrix, the weighted normalised rough decision matrix and closeness co efficient derived from Rough TOPSIS, respectively. The final phase involves a discussion of the results in section 9.6, culminating in a conclusion drawn from a comparison between the proposed model, Pythagorean Fuzzy TOPSIS(PFTOPSIS), Intuitionistic Fuzzy TOPSIS(HFTOPSIS), Neutrosophic Fuzzy TOPSIS(NFTOPSIS), and Hesitant Fuzzy TOPSIS(HFTOPSIS).

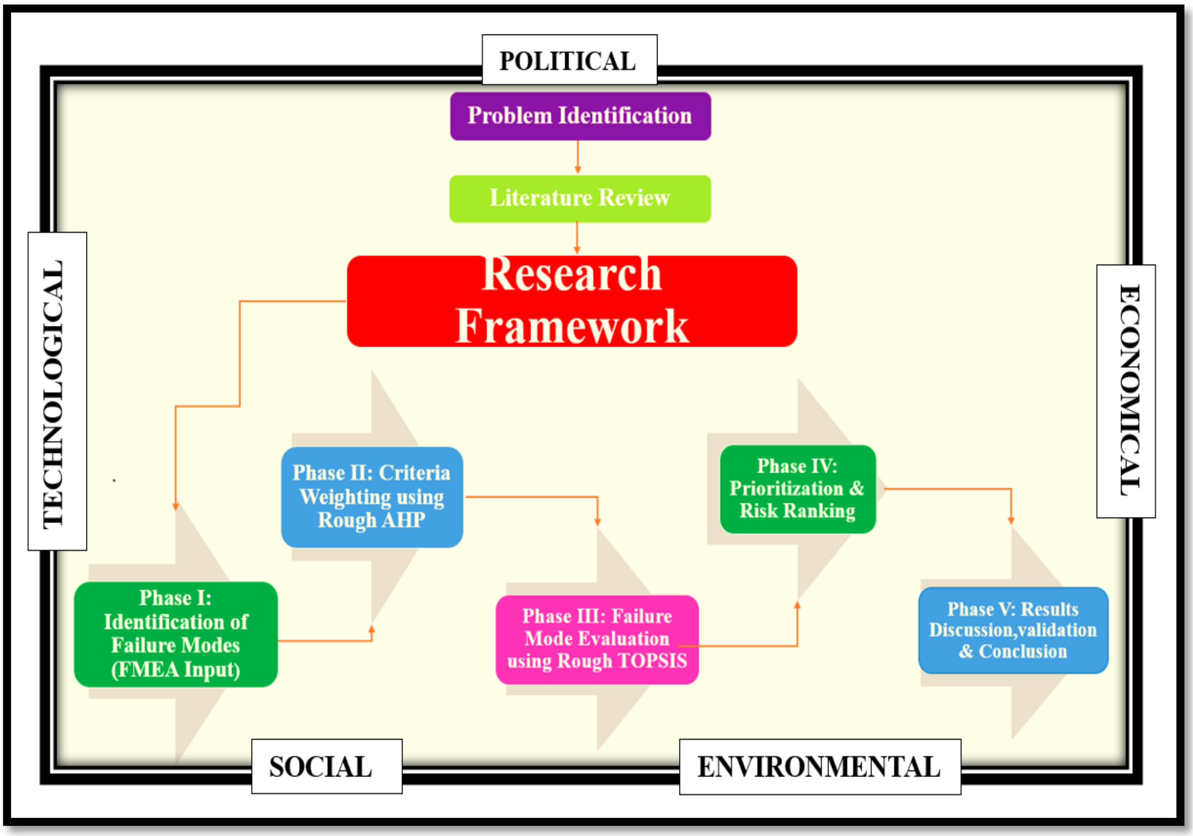

Figure 9.1 Flowchart of the proposed model

9.4 A Case Study

Construction contractors face many potential challenges and breakdowns that could delay, expense, and endanger the project. Major concerns include design and planning. Architectural, structural, and MEP designs that conflict or are incomplete can cause costly rework and delays. Poor discipline coordination sometimes causes construction-only problems. Permit and regulatory issues also cause problems. Delays in permissions, construction code changes, and zoning law violations can delay work or result in legal action. Site and ground characteristics are another major risk. Unexpected soil difficulties like low bearing capacity, high water tables, or contamination may necessitate redesign or stabilization. Environmental constraints like flood zones or seismic danger might make building harder. Materials and tool issues are also common. Material delivery delays, poor materials, and equipment breakdowns can delay construction and compromise structural integrity. Staff shortages, strikes, and poor training can limit production, create errors, and increase safety concerns. Construction projects are always risky since accidents or safety breaches could suspend work and hold contractors liable. Project management mistakes like scheduling, coordination, and budget mismanagement can cause delays, budget overruns, and resource inefficiencies.

The possible failures therefore have to be found beforehand to prevent the environmental and production losses. The iceberg model shown below in Figure 9.2 describes the Science of Motion (SOM) and Science of Emotion (SOE) where SOM denotes explicit knowledge like cost of resources, project progress and SOE indicates experts' intuition, contextual judgement, on-ground construction experience, etc. Risk mitigation in construction requires more than procedures, it demands interpretation of tacit knowledge.A team of experts including four personnel have been formed for identification of the failure modes. All of them are aware of the building procedures and have over ten years of work experience in their relevant fields which have been shown in Table 9.3. They come together to discuss and find the possible failures, their causes and detection techniques in the processes as displayed in Table 9.4. The identified most probable failure modes are Design Errors and Omissions (FM1), Poor Quality Control and Workmanship (FM2), Safety Incidents (FM3), Cost Overruns and Financial Mismanagement (FM4), Schedule Delays (FM5), Regulatory and Compliance Failures (FM6). Table 9.4 presents a detailed overview of the identified failure modes associated with a construction process, including their detection methods, underlying causes, and potential effects. Each failure mode is linked to already documented instances as given in Tables 9.2 & 9.3 of structural failures either temporary or permanent highlighting their practical significance. The risk of the indicated failure modes is assessed utilizing the proposed Rough AHP and Rough TOPSIS approach as given in section 9.2.2 and 9.2.3.

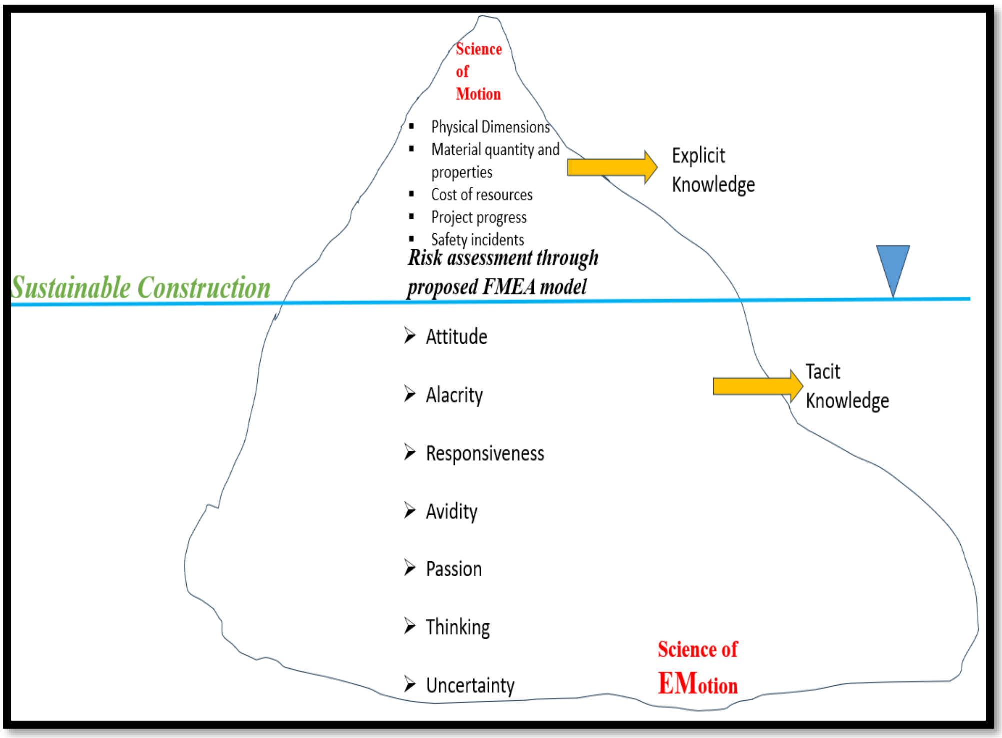

Figure 9.2 Iceberg model showing explicit and tacit knowledge of experts for risk assessment

Table 9.3 Experts' qualification and experience in their relevant fields

Experts →	E1		E2		E3		E4	
Age (in years)	43		48		52		55	
Gender	Male		Female		Male		Female	
Qualification	M.Tech in Architecture		Ph.D. in Material science and Engg.		Ph.D. in Civil Engg.		Ph.D. in Construction Engg	
Experience (in years)	Lab	Field	Lab	Field	Lab	Field	Lab	Field
	10	7	7	9	10	11	9	15

Table 9.4 Various construction failure modes, their detection, causes & effect

Failure Modes (FM)	Detection	Causes	Effects
Design Errors and Omissions(FM1)	1) Cross-discipline design reviews 2) Constructability reviews 3) Clash detection using BIM	Improper reading, application, or modification of the engineering design could result in expensive rework, dangerous buildings, or specification non-compliance.	1) Costly rework 2) Delay due to redesign 3) Safety risks if errors unnoticed
Poor Quality Control and Workmanship(FM2)	1) Site inspections (scheduled and surprise) 2) Material testing reports	Defects like cracks, uneven surfaces, water intrusion, or early material failure are frequently caused by insufficient supervision, qualified labour, or materials inspection.	1) Rework costs 2) Client dissatisfaction 3) Early deterioration (e.g., cracks, water leaks) 4) Possible structural failure
Safety Incidents(FM3)	1)Safety audit non-compliances 2) High absenteeism or turnover in labor 3) Workers ignoring PPE rules	Ignoring safety procedures, safe work practices, site security—can lead to accidents, injuries, deaths, lawsuits, and harm to reputation.	1)Injuries or fatalities 2) Work stoppages 3) Legal action and fines 4) Insurance premium hikes
Cost Overruns and Financial Mismanagement(FM4)	1)Variance between budgeted and actual cost (Cost Performance Index, CPI) 2) Frequent cash flow shortfalls 3) Rising number of unapproved variations 4) Supplier complaints over delayed payments	Ignoring expenses, bad budgeting, cash flow issues, or unanticipated changes (e.g., material price increases) could devastate a project or perhaps put a contractor out of business.	1)Project underfunding 2) Incomplete work 3) Contractor insolvency 4) Major claims and lawsuits

Schedule Delays(FM5)	1)Missed intermediate milestones 2) Look-ahead schedules slipping 3) Resource bottlenecks (labor or equipment shortages) 4) Frequent change orders without time adjustment	Poor management of project deadlines, lack of resources, equipment breakdowns, or weather effects can postpone project completion and result in fines and budget overruns.	1)Penalty payments (liquidated damages) 2) Overtime costs 3) Loss of contractor credibility 4) Client disputes
Regulatory and Compliance Failures(FM6)	1)Inspection failures (building, environmental, labor) 2) Permits pending for long periods 3) Contractor receiving compliance notices 4) Public or media scrutiny increases	Disregarding permits, environmental rules, zoning laws, or labour standards may result in fines, stop-work orders, or even litigation.	1)Stop-work orders 2) Fines and penalties 3) Reputation damage 4) Total project suspension

9.5 Dataset

Table 9.5 Initial Pairwise Comparison Matrix (PWCM) based on expert opinion

Expert 1				
	O	**S**	**D**	**E**
O	1	2	1/4	3
S	1/2	1	1/3	4
D	4	3	1	5
E	1/3	1/4	1/5	1

(a)

Expert 2				
	O	**S**	**D**	**E**
O	1	3	1/3	2
S	1/3	1	1/2	3
D	3	2	1	6
E	1/2	1/3	1/6	1

(b)

Expert 3				
	O	**S**	**D**	**E**
O	1	3	1/4	4
S	1/3	1	1/4	5
D	4	4	1	7
E	1/4	1/5	1/7	1

(c)

Expert 4				
	O	**S**	**D**	**E**
O	1	4	1/3	3
S	1/4	1	1/4	3
D	3	4	1	5
E	1/3	1/3	1/5	1

d)

Table 9.6 Failure modes performance under each risk factor based on expert evaluation

Factors	Experts	FM1	FM2	FM3	FM4	FM5	FM6
	E1	4	6	6	5	7	8
O	E2	4	6	5	5	6	6
	E3	5	7	5	4	5	6
	E4	3	5	4	4	5	7
	E1	6	3	4	8	8	7
S	E2	5	4	3	9	7	3
	E3	6	4	3	9	6	3
	E4	5	5	5	8	9	5
	E1	5	3	3	7	6	5
D	E2	5	3	4	9	6	4
	E3	4	4	3	7	7	2
	E4	6	5	6	6	8	4
	E1	2	5	6	3	5	7
	E2	4	7	4	2	5	7
E	E3	4	5	6	3	4	6
	E4	3	4	4	4	4	6

9.6 Results and Discussion

This study applies the proposed integrated Rough AHP–Rough TOPSIS framework to evaluate and prioritize contractor-related failure modes in sustainable construction projects. The analysis uses four key criteria Occurrence (O), Severity (S), Detection (D), and Environmental Impact (E) to assess six major failure modes (FM1 to FM6).

The resulting normalized rough weights (Table 9.7) indicate that Detection (D) carries the highest weight [0.86,1.00], followed by Occurrence (O), Severity (S), and Environmental factor (E). This outcome emphasizes that early identification of failures is the most critical factor in managing construction risk.The Initial group rough decision matrix & the Weighted normalised rough decision matrix are given in Table 9.8 and 9.9 respectively.

Table 9.7 Rough weights of the risk factors

	Rough weights	Normalised Rough weights
O	[1.18, 1.47]	[0.39,0.48]
S	[0.69, 0.85]	[0.23,0.28]
D	[2.62, 3.06]	[0.86,1.00]
E	[0.33, 0.39]	[0.11,0.13]

`

Table 9.8 Initial group rough decision matrix

	O		S		D		E	
FM1	3.59	4.41	5.25	5.75	4.59	5.42	2.75	3.73
FM2	5.59	6.41	3.58	4.42	3.27	4.25	4.64	5.89
FM3	4.59	5.42	3.27	4.25	3.33	4.75	4.5	5.5
FM4	4.25	4.75	8.25	8.75	6.65	7.89	2.58	3.58
FM5	5.27	6.25	6.75	8.25	6.36	7.25	4.25	4.75
FM6	6.44	7.25	3.27	4.25	3.1	4.35	6.25	6.75

Table 9.9 Weighted normalised rough decision matrix

	O		S		D		E	
FM1	0.193	0.292	0.138	0.184	0.500	0.687	0.045	0.072
FM2	0.301	0.424	0.094	0.141	0.356	0.539	0.076	0.113
FM3	0.247	0.359	0.086	0.136	0.363	0.602	0.073	0.106
FM4	0.229	0.314	0.217	0.280	0.725	1.000	0.042	0.069
FM5	0.283	0.414	0.177	0.264	0.693	0.919	0.069	0.091
FM6	0.346	0.480	0.086	0.136	0.338	0.551	0.102	0.130
PIS	0.193		0.086		0.338		0.042	
NIS	0.48		0.28		1.00		0.13	

The closeness coefficients in Table 9.10, derived using Equation (9.30), provide the final ranking of failure modes as follows:

Table 9.10 Closeness coefficient and final ranking

Failure Mode	Closeness coefficient	Rank
FM1	0.614	3
FM2	0.685	5
FM3	0.687	6
FM4	0.356	1
FM5	0.372	2
FM6	0.654	4

These results suggest that safety lapses and financial mismanagement pose the highest risks in the context of sustainable construction. Failure modes related to design flaws and regulatory violations also demonstrate moderate risk potential.

To validate the robustness and reliability of the proposed Rough-TOPSIS approach, it is benchmarked against four advanced fuzzy multi-criteria decision-making (MCDM) models: Pythagorean Fuzzy TOPSIS, Intuitionistic Fuzzy TOPSIS, Neutrosophic Fuzzy TOPSIS, and Hesitant Fuzzy TOPSIS. These models are widely acknowledged for their ability to handle uncertainty, hesitation, and ambiguity in expert evaluations. A comparative analysis in Table 9.11 reveals a strong concordance in the final rankings across all five methods, with FM4 and FM5 consistently emerging as the top-priority risks. The closeness coefficients varied within a narrow margin (±5%), suggesting that Rough-TOPSIS provides equivalent decision quality with reduced computational complexity. This validation confirms the credibility and practical utility of the proposed method, particularly in resource-constrained environments where expert opinions may be inconsistent or interval-based. Figure 9.3 furnishes the comparison analysis graphically.

Table 9.11 Comparison ranking with other techniques

Failure Mode	R-TOPSIS	PF-TOPSIS	IF-TOPSIS	NF-TOPSIS	HF-TOPSIS
FM1	3	3	3	3	3
FM2	5	5	5	5	5
FM3	6	6	6	6	6
FM4	1	1	1	1	1
FM5	2	2	2	2	2
FM6	4	4	4	4	4

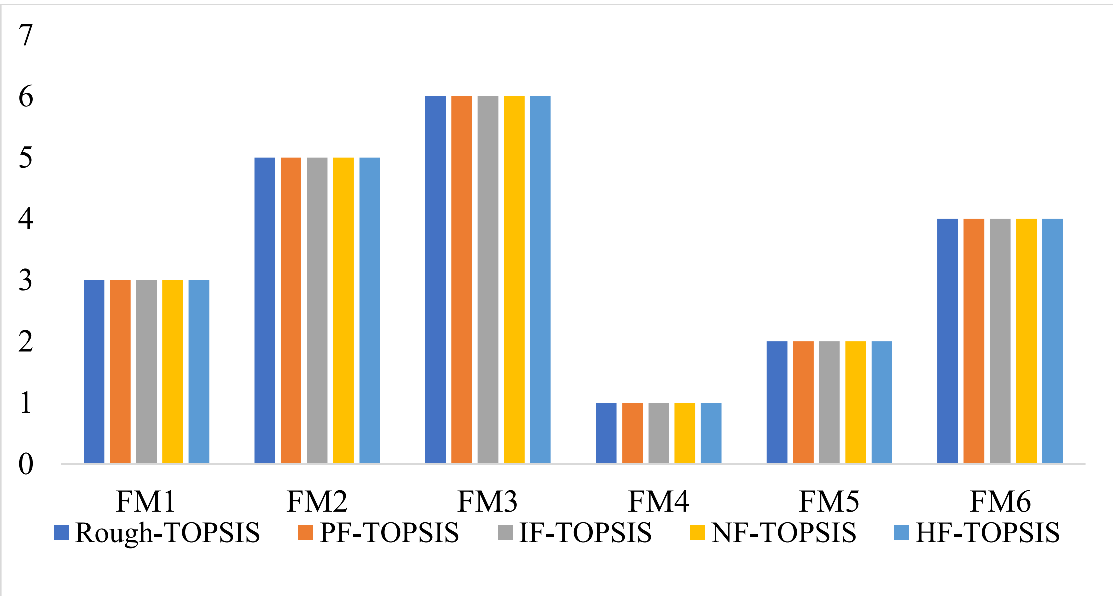

Figure 9.3 Graphical representation of comparative analysis

To further validate the grouping and prioritization of failure modes, Linear Discriminant Analysis (LDA) and hierarchical clustering were applied to the weighted decision matrix. Based on the Rough-TOPSIS rankings, failure modes were categorized into three classes: high-risk (FM4, FM5), moderate-risk (FM1, FM6), and low-risk (FM2, FM3). The LDA helps in dimensionality reduction and confirms that the failure modes can be clearly separated based on their risk attributes (Occurrence, Severity, Detection, and Economic impact). Additionally, the dendrogram produced from hierarchical clustering illustrated in Figure 9.4 reveals two major clusters one comprising high-risk modes (FM4, FM5), and the other grouping the remaining modes, indicating natural segmentation in the data. These findings reinforce the robustness of the Rough-TOPSIS-based prioritization, highlighting consistent patterns in risk categorization across multiple analytical methods.

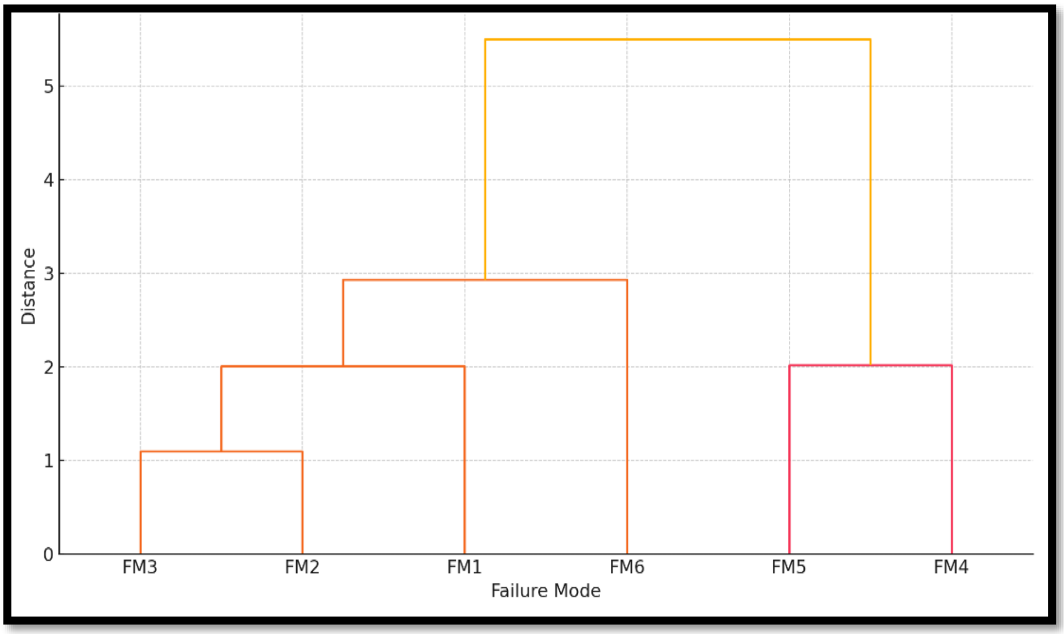

Figure 9.4 Dendrogram clustering of failure modes

9.6.1 Managerial Insights

The proposed framework generates critical insights for contractors, project managers, and policymakers striving for sustainable construction practices:

a. Prioritize Detectability: With Detection (D) having the highest weight, project managers must implement rigorous monitoring systems such as real-time safety dashboards, automated inspection tools, and BIM-integrated clash detection to catch failures early and mitigate their impact.

b. Enforce Safety Protocols (FM4): As safety emerges as the top-ranked risk, firms should strengthen their safety culture through frequent audits, training, and compliance checks. Ignoring safety can result in severe legal, financial, and reputational consequences.

c. Strengthen Financial Control (FM5): Given its second-highest risk ranking, it is essential to adopt dynamic budgeting tools such as Earned Value Management (EVM) and cost-performance indexes (CPI) to anticipate financial deviations and prevent contractor insolvency.

d. Reinforce Design and Regulatory Integrity (FM1, FM6): Design-related failures call for interdisciplinary design validation and automated plan checking. Regulatory compliance must be ensured through pre-permit reviews and digital regulatory compliance systems.

e. Account for Environmental Impact: The inclusion of Environmental Impact (E) as a key risk criterion ensures alignment with green building mandates and long-term sustainability goals. Contractors should be incentivized to adopt low-impact construction methods, sustainable materials, and energy-efficient processes.

f. Adopt Uncertainty-Based Decision Tools: Traditional models often overlook data vagueness and expert subjectivity. The current method offers an objective, flexible, and computationally simpler alternative, especially valuable in resource-constrained environments.

9.7 Summary

This study presents an integrated risk evaluation framework tailored for sustainable construction projects by combining FMEA with RAHP and RTOPSIS. The model successfully addresses the limitations of traditional FMEA—namely the equal weighting of risk criteria, inability to handle uncertain and imprecise expert inputs, and exclusion of environmental considerations. Using contractor-related risks as a real-world application, the proposed model identifies and prioritizes critical failure modes based on four dimensions: Occurrence (O), Severity (S), Detection (D), and Environmental impact (E). Among the six failure modes analyzed, Safety Incidents (FM4)and Cost Overruns (FM5) emerge as the highest risks, reflecting the urgent need for enhanced safety protocols and financial oversight in construction management. The comparative analysis with other fuzzy MCDM methods demonstrates the robustness, reliability, and reduced computational complexity of the proposed model. Additionally, the results from discriminant analysis and hierarchical clustering reinforce the consistency and classification capability of the proposed methodology. By including the environmental dimension, the model ensures alignment with global sustainability goals and supports eco-conscious decision-making in project risk governance.

The study makes several original and practical contributions to the field of construction risk management and sustainable project planning as

i. Methodological Innovation: It introduces a novel hybrid risk prioritization framework combining RAHP and RTOPSIS with FMEA, overcoming the subjectivity and rigidity of traditional and fuzzy-based approaches.

ii. Uncertainty Handling: The rough set theory effectively captures vagueness and inconsistency in expert opinions without requiring prior membership functions or fuzzy rules.

iii. Sustainability Integration: The model uniquely incorporates an Environmental Impact criterion into the conventional O-S-D structure, aligning the risk assessment with sustainable construction principles.

iv. Empirical Validation: The model is validated through a detailed case study of real-world contractor failures in Indian construction projects, offering practical insights for engineers, contractors, and policy-makers.

v. Comparative Robustness: It establishes the equivalence and computational efficiency of RTOPSIS compared to other fuzzy MCDM methods, with less complexity and higher adaptability.

vi. Managerial Utility: The ranking outputs, supported by discriminant and cluster analysis, help construction managers allocate resources to high-risk areas effectively and design proactive mitigation strategies.

The suggested approach provides a robust basis for sustainable risk assessment in construction; yet, several avenues for further study remain available. A possible expansion is the incorporation of multi-stakeholder viewpoints, integrating inputs from regulatory agencies, project owners, and community stakeholders to enhance the decision-making process and provide comprehensive risk assessments. The existing methodology functions within a static framework; incorporating real-time data via technologies like IoT sensors, drones, and BIM platforms may enable dynamic risk assessment and responsive decision-making. While the model is verified in the Indian construction setting, its applicability might be improved by empirical validation in other geographic locations and regulatory environments. Moreover, integrating this rudimentary set-based methodology with sophisticated predictive analytics, such machine learning or neural networks, may enhance early risk identification and forecasting precision. The creation of an intuitive decision-support tool grounded on this approach might facilitate broad acceptance among practitioners. Finally, integrating life cycle costing and environmental life cycle assessment (LCA) in subsequent iterations of the model will provide more thorough sustainability assessments over the whole duration of the building project.

Chapter 10

Geospatial Analysis for Waste Landfill Site Suitability

10.1 Introduction

The exponential rise in urban population and infrastructural development in the Kolkata Metropolitan Region (KMR) has significantly increased the volume of municipal solid waste (MSW), posing serious environmental and public health challenges. With limited availability of scientifically engineered landfills and increasing resistance from local communities, identifying appropriate landfill sites has become a pressing need for sustainable urban planning. Traditional site selection methods, often reliant on simplistic or static criteria, fail to incorporate the multifaceted nature of urban environments and stakeholder concerns. Hence, there is an urgent necessity for a spatially robust, environmentally sound, and socio-economically sensitive methodology for landfill site selection.

This study presents an integrated, geospatial approach for landfill site suitability analysis using Geographic Information System (GIS) and Rough Analytical Hierarchy Process (RAHP). The strength of this approach lies in its ability to combine quantitative spatial analysis with expert judgment, while also accommodating uncertainty and subjectivity through the use of interval-based weights. The selection of criteria is rooted in literature review, regulatory norms, and local contextual relevance, ensuring methodological rigor and practical applicability.

Six critical thematic criteria have been considered in this analysis: Slope, Average Annual Rainfall, Land Use Land Cover (LULC), Population Density, Distance to Roads, and Distance to Water Bodies. These criteria collectively account for environmental sensitivity, socio-demographic risk, infrastructural accessibility, and topographical constraints offering a comprehensive decision-support framework. Expert evaluations have been gathered and modeled through RAHP to derive relative importance weights, thereby minimizing bias in decision-making.

All spatial datasets have been preprocessed using ArcGIS software, reclassified on a standardized 1–5 suitability scale, and weighted using the derived RAHP weights. The final suitability map has been generated through weighted overlay analysis in ArcGIS, followed by classification using the natural breaks method to delineate four distinct suitability zones. These zones help visualize the spatial distribution of optimal locations, offering valuable insights for waste management authorities.

This methodological framework serves as a replicable tool for urban decision-makers and environmental planners, combining scientific rigor with real-world applicability. It supports the strategic siting of landfills in KMR and similar metropolitan areas, contributing to more effective and sustainable municipal solid waste management.

10.2 Study Area

The study focuses on the Kolkata Metropolitan Region (KMR), which includes major urban clusters such as Kolkata, Howrah, Chandannagar, Uluberia and Chunchura. Administratively, it spans parts of the districts of Kolkata, Howrah and Hugli. The region is characterized by dense population, urban sprawl, and proximity to the Hugli River, making landfill site planning both critical and complex. The spatial extent of the study area is illustrated in Figure 10.1, showcasing its nested location within India and West Bengal. The study area spans approximately from 87°30'E to 88°30'E and 22°15'N to 23°30'N as shown in Figure 10.1 (c).

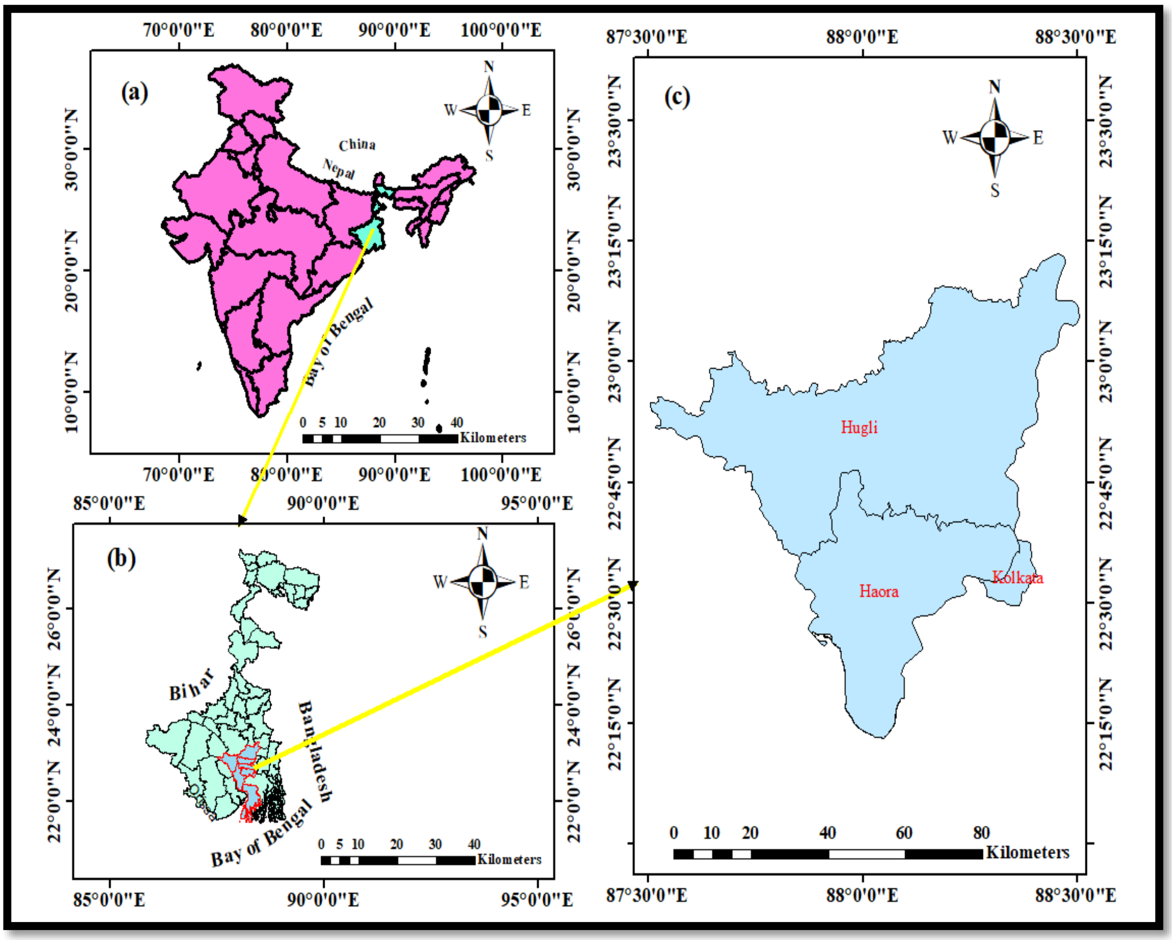

Figure 10.1 (a) Location of West Bengal in India, (b) Location of the study area in West Bengal and (c) Location of the study area including Kolkata, Howrah and Hugli region

10.3 Study Methodology

The following flowchart in Figure 10.2 illustrates the step-by-step methodology adopted for landfill site suitability analysis using RAHP and GIS. It includes 3 phases:

Phase 1: Criteria selection and expert judgment collection.

Phase 2: Data preprocessing through Arc GIS software and criteria weightage evaluation through RAHP.

Phase 3: Generation of a weighted landfill suitability map through weighted overlay method in Arc GIS and result discussion.

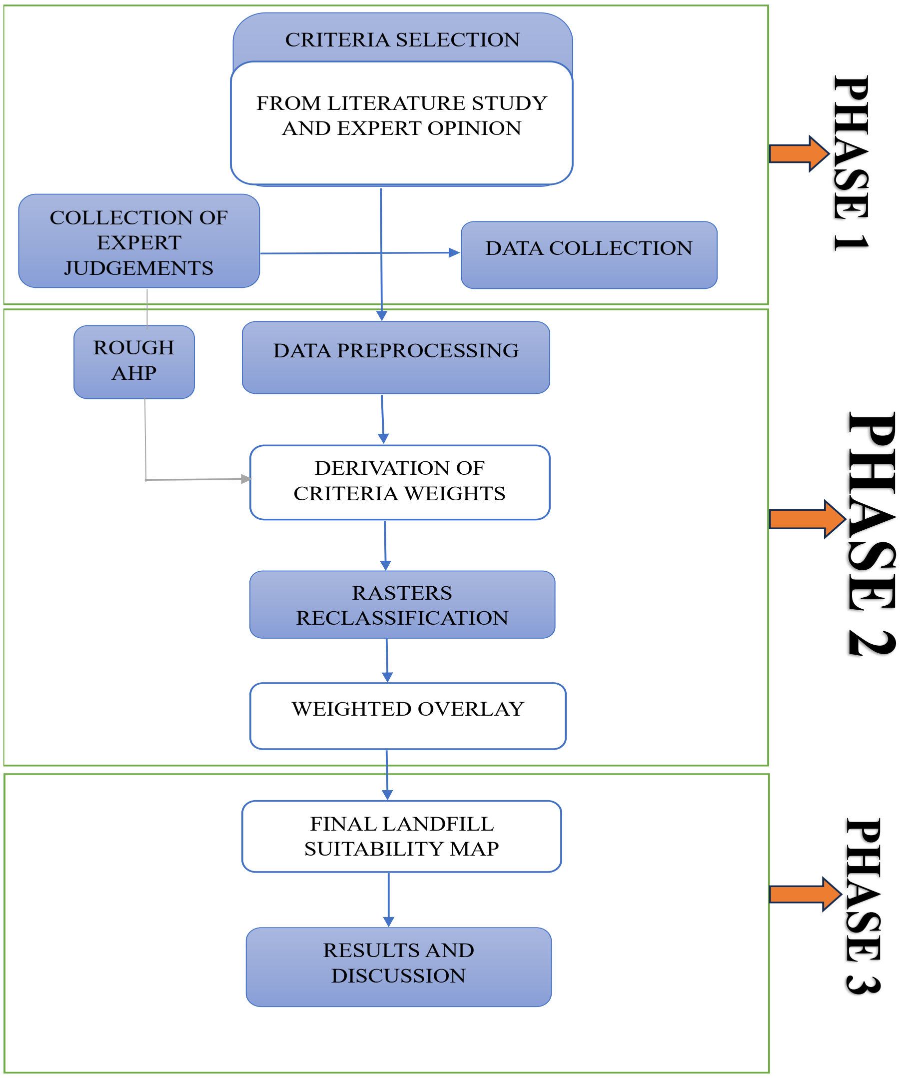

Figure 10.2 Flowchart showing the study methodology

10.4 Criteria Selection

In this study, six thematic criteria have been carefully selected for landfill site suitability analysis, guided by extensive literature review, prevailing environmental regulations, and expert consultations. The six criteria include slope, rainfall, land use land cover, population density, distance to road and distance to water bodies. All the thematic layers are illustrated from Figure 10.3 to Figure 10.8.

Collectively, these six criteria provide a balanced framework integrating topographical, environmental, social, and logistical dimensions for sustainable landfill site suitability analysis.

10.4.1 Slope

Slope influences the stability and drainage of a landfill site. Steep slopes can lead to erosion, leachate runoff, and slope failure, making flat or gently sloping areas preferable. It has been chosen to ensure safe and cost-effective construction and long-term operational stability. Figure 10.3 shows the slope map of the study area.

10.4.2 Rainfall

Rainfall determines the potential for leachate generation and flooding. Areas with high rainfall increase environmental risks through groundwater contamination and surface runoff. Hence, lower-rainfall zones are more environmentally sustainable for landfill siting. Figure 10.4 shows the annual average rainfall map of the study area from 2011-2020.

10.4.3 Land Use Land Cover (LULC)

LULC helps assess the existing land function and ecological sensitivity. Landfills should avoid built-up, agricultural, and forest areas to minimize social conflict and environmental degradation. It ensures the selection of compatible and low-impact zones like barren or scrub land. Figure 10.5 shows the Land Use Land Cover (LULC) map of the study area.

10.4.4 Population Density

Population density has been included to minimize health risks and public opposition. Densely populated areas are unsuitable due to higher chances of odour nuisance, disease transmission, and legal challenges. The criterion supports social sustainability and public acceptance. Figure 10.6 shows the population density map of the study area.

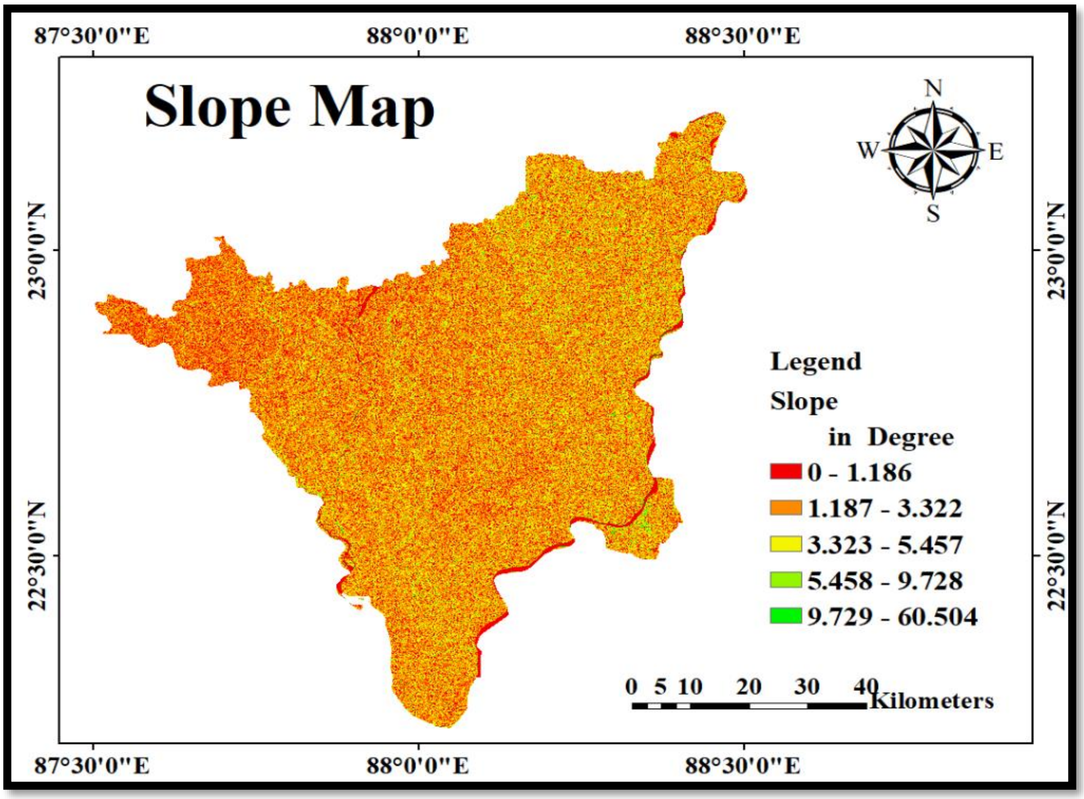

Figure 10.3 Slope map of study area

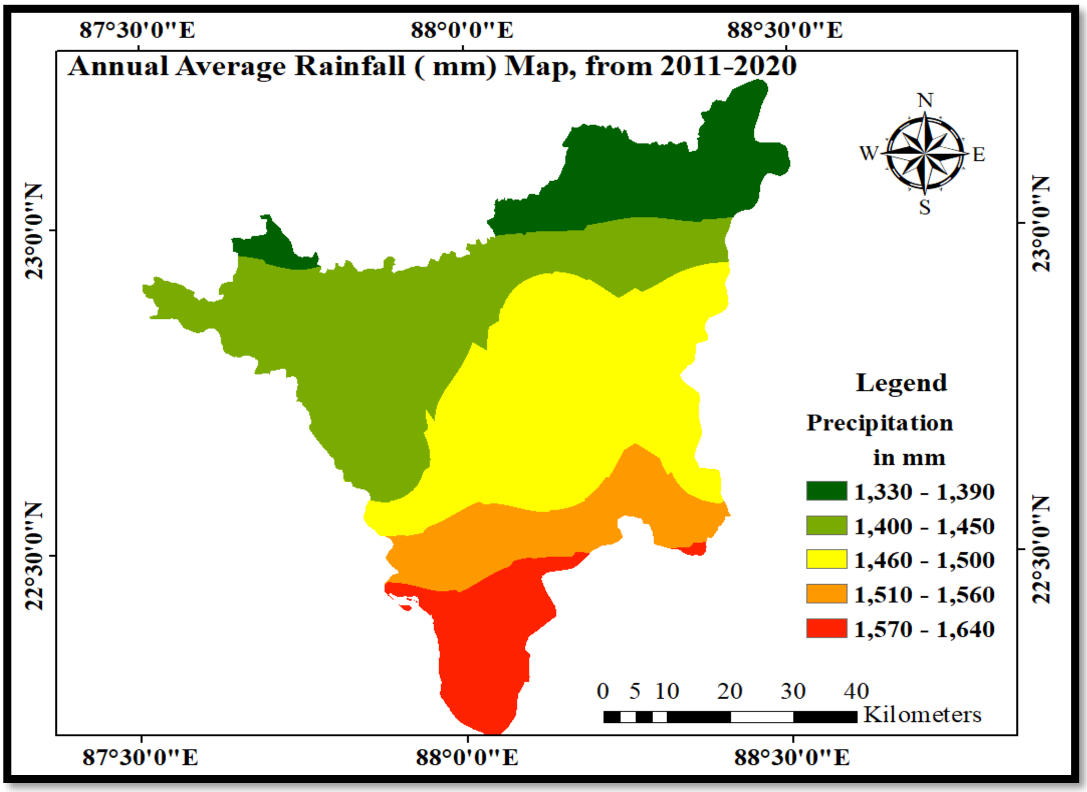

Figure 10.4 Annual average rainfall map of study area

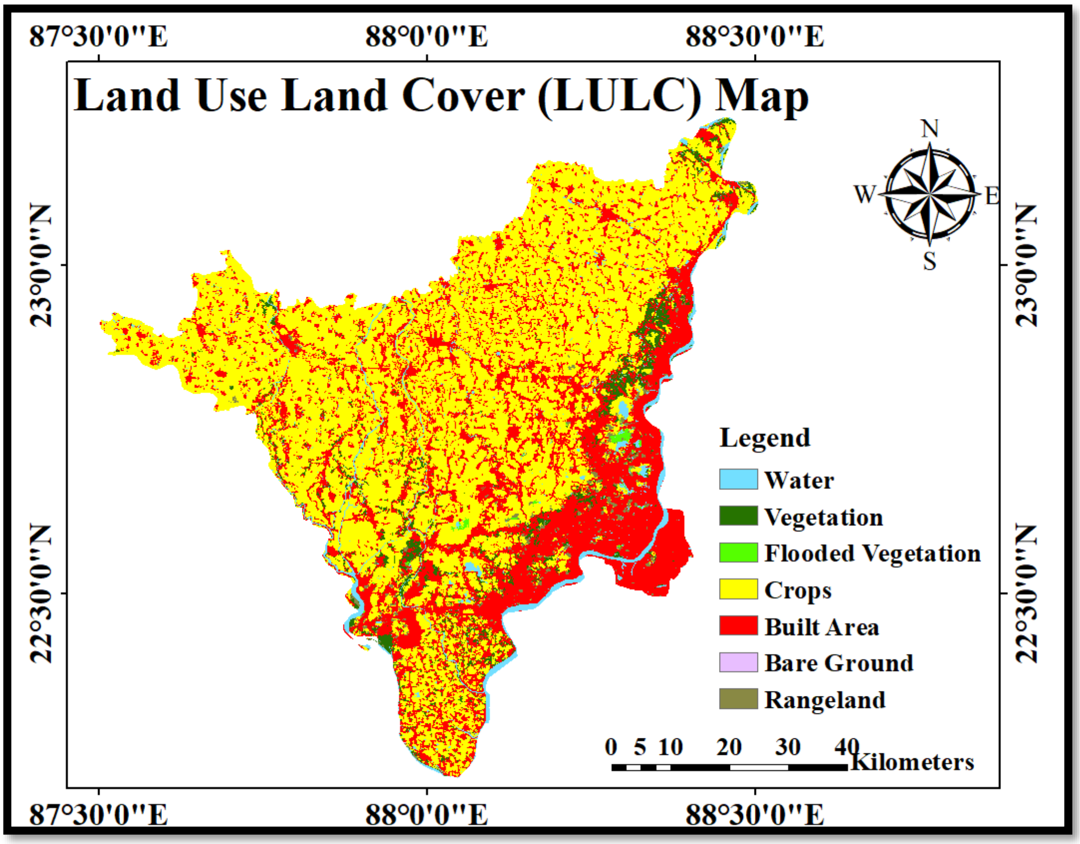

Figure 10.5 LULC map of study area

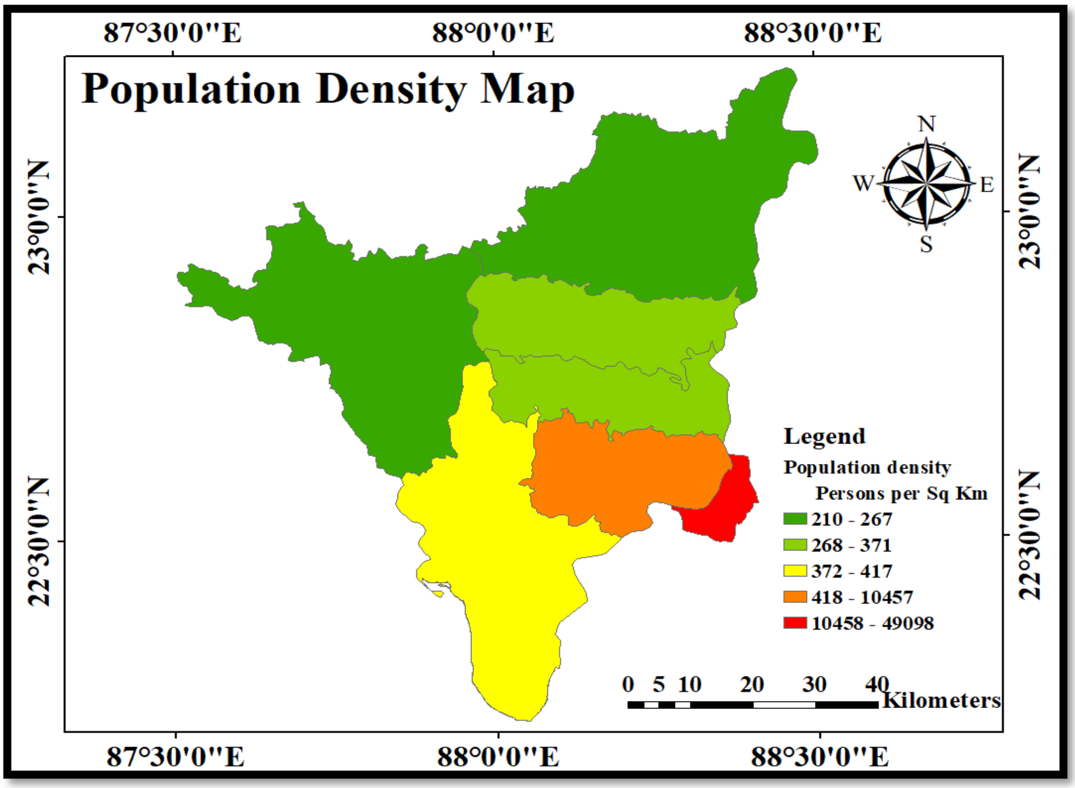

Figure 10.6 Population density map of study area

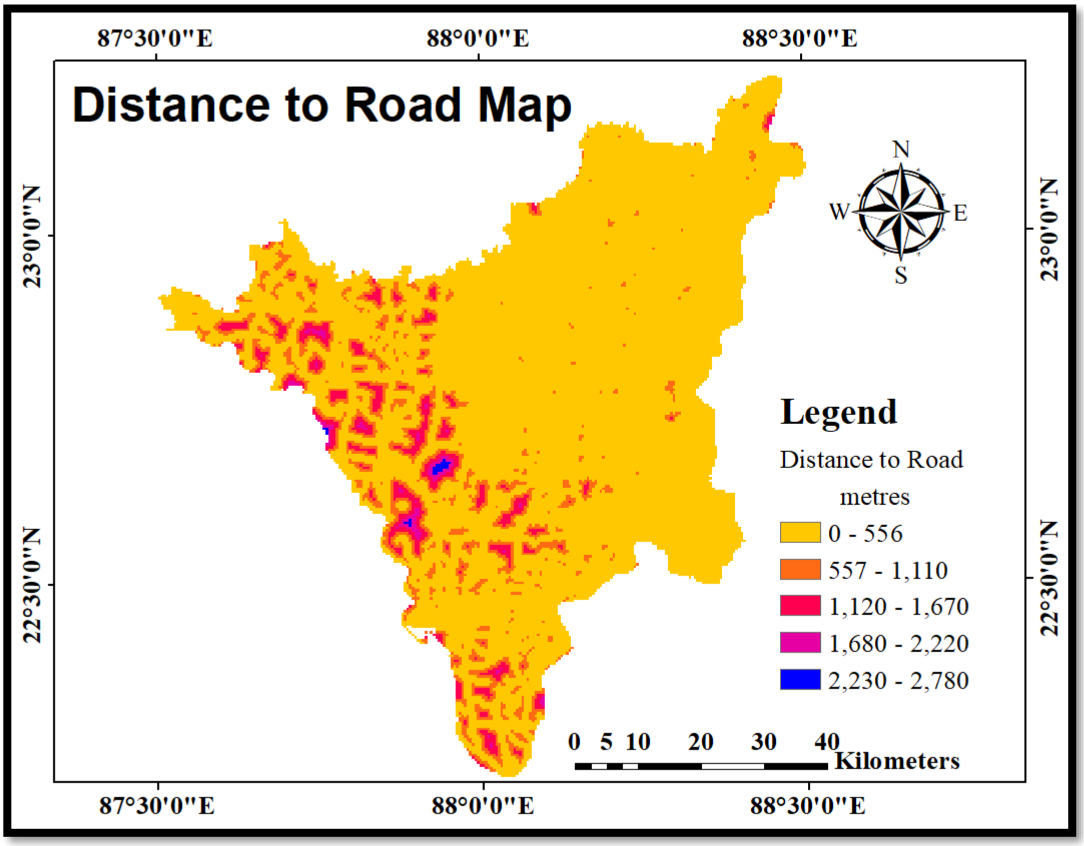

Figure 10.7 Distance to road map of study area

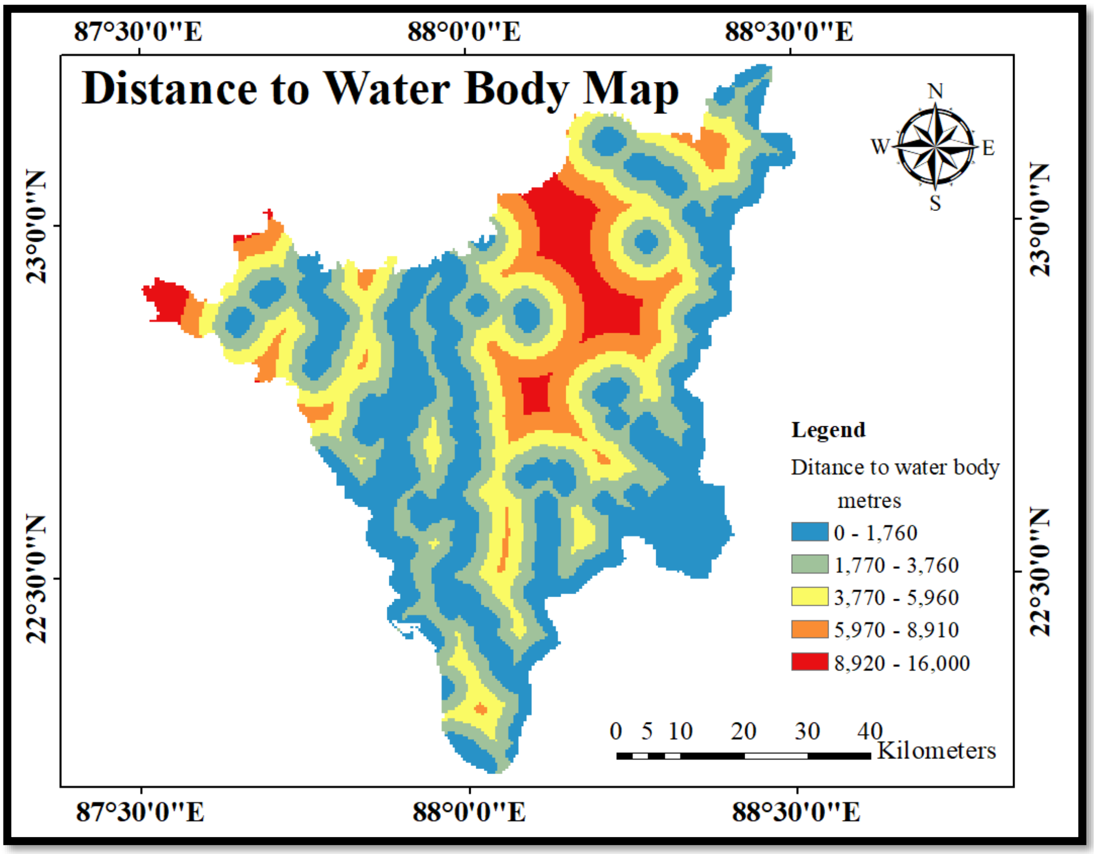

Figure 10.8 Distance to water body map of study area

10.4.5 Distance to Roads

Accessibility is critical for the efficient transport of solid waste. Sites close to major roads reduce transportation costs and environmental impact from fuel use. This criterion ensures logistical feasibility and economic efficiency of landfill operations. Figure 10.7 shows the distance to road map of the study area.

10.4.6 Distance to Water Bodies

Landfills near rivers, lakes, or wetlands pose severe contamination risks to surface and groundwater resources. Maintaining distance from water bodies is crucial to protect aquatic ecosystems and public health. This criterion ensures regulatory compliance and environmental safety. Figure 10.8 shows the distance to water body map of the study area.

All input data have been processed as raster layers (Geo TIFF format), clipped to the study area extent, and reclassified on a standardized suitability scale from 1 (unsuitable) to 5 (highly suitable).

10.5 Data Collection

The thematic data layers have been obtained from various data sources which are clearly depicted in Table 10.1.

Table 10.1 Details of data collection

Sl. No.	Data	Prepared Thematic Map	Source
1	Alos-Pulsar DEM with 12.5m Resolution	Slope	https://search.asf.alaska.edu/
2	Open Street Map (OSM)	Distance to road	https://www.openstreetmap.org
3	Open Street Map (OSM)	Distance to waterbody	https://www.openstreetmap.org
4	Climatic Research Unit (CRU) Data with 0.5° resolution	Rainfall	https://crudata.uea.ac.uk/cru/data/hrg/
5	Sentinel 2 with 10m Resolution	LULC	https://env1.arcgis.com/arcgis/rest/services/Sentinel2_10m_LandCover/ImageServer
6	2011 Census of India Csv file	Population Density	https://censusindia.gov.in/census.website/

10.6 Data Analysis

The data analysis phase of the study involves systematic integration of spatial data with multi-criteria decision-making (MCDM) technique to identify suitable landfill sites in the Kolkata Metropolitan Region. The workflow comprises of four major stages: spatial data preprocessing, raster reclassification, weight derivation using Rough AHP, and final weighted overlay to generate the suitability map.

10.6.1 Spatial Data Preprocessing

Thematic raster layers corresponding to the six selected criteria - Slope, Average Annual Rainfall, Land Use Land Cover (LULC), Population Density, Proximity to Road, and Proximity to Water Bodies have been acquired from remote sensing and open geospatial sources as stated in Table 10.1. All raster layers have been clipped to the study area boundary and resampled to a common resolution to ensure spatial alignment. A common Coordinate Reference System (CRS), UTM Zone 45N, has been assigned uniformly across all datasets.

10.6.2 Reclassification of Criteria Layers

To standardize the evaluation process, all input rasters have been reclassified into five suitability classes as shown in Table 10.2 on a scale from 1 to 5, where:

1 = Unsuitable

2 = Less Suitable

3 = Moderately Suitable

4 = Suitable

5 = Highly Suitable

Reclassification thresholds have been determined based on domain knowledge, environmental norms, and logical suitability.

Table 10.2 Criteria with their reclassification details

Criterion	Value/Range	Suitability Class	Justification
Slope (degrees)	0 – 5	5	Flat or gently sloped terrain is ideal for landfill construction
	>5 – 10	4	Slight slope; manageable with minor grading
	>10 – 20	3	May require slope stabilization measures
	>20 – 30	2	Increased risk of runoff and instability
	>30	1	Not recommended due to landslide/leachate risks
Rainfall (mm/year)	0 – 1000	5	Dry areas reduce risk of leachate formation
	>1000 – 1500	4	Moderate rainfall; some precautions required
	>1500 – 2000	3	Balanced, but increasing risk
	>2000 – 2500	2	High rainfall can cause leachate overflow
	>2500	1	Unsuitable due to excessive rainfall risk
LULC	Barren land / Fallow land	5	Ideal for landfill due to minimal use
	Scrub / Waste land	4	Acceptable with moderate risk
	Agricultural land	3	Less preferred due to food security conflict

Criterion	Value/Range	Suitability Class	Justification
LULC	Built-up area	2	Not recommended due to human exposure
	Water bodies / Forest / Wetlands	1	Environmentally sensitive zones
Population Density (people/km²)	0 – 50	5	Remote, sparsely populated – ideal
	>50 – 100	4	Rural regions – acceptable
	>100 – 500	3	Semi-urban; manageable with precautions
	>500 – 1000	2	Urban periphery – risk of opposition
	>1000	1	High public health risk – unsuitable
Distance to Road (meters)	0 – 100	5	Excellent access; minimizes transportation cost
	>100 – 300	4	Good access
	>300 – 500	3	Moderate access
	>500 – 1000	2	Poor access; increases logistic cost
	>1000	1	Very poor access
Distance to Waterbody (meters)	0 – 100	1	Very high contamination risk
	>100 – 300	2	Still at risk
	>300 – 500	3	Acceptable buffer
	>500 – 1000	4	Safer distance
	>1000	5	Low contamination risk; preferred

10.6.3 Derivation of Criteria Weights Using Rough AHP

To account for subjective variation in expert opinion, Rough AHP has been applied to derive the relative weights of the six criteria. Three independent experts have provided pairwise comparison matrices, which have been processed to compute lower and upper bounds for each comparison using rough set theory. The geometric mean method has been used to derive weights from both bounds, which have been averaged to obtain final crisp weights of the criteria as shown in Table 10.3.

10.6.4 Weighted Overlay Analysis

The reclassified raster layers have been multiplied by their respective Rough AHP weights using raster algebra. The results are then summed pixel-by-pixel to compute a composite suitability index:

Suitability Index= $\sum_{i=1}^{6}(\mathrm{R_i} * \mathrm{W_i})$

where R_i is the reclassified raster value and W_i is the weight of the i^{th} criterion.

The composite index has been then normalized and classified into final suitability classes using natural breaks methods.

The output raster, titled "Final Landfill Suitability Map" in Figure 10.9 is visualized with a blue to yellow gradient, where blue represented highly suitable zones and yellow indicates low suitability.

10.7 Results and Discussion

The study has been conducted for a comprehensive landfill site suitability analysis in the Kolkata Metropolitan Region, integrating geospatial method (GIS) and multi-criteria decision-making using RAHP. Six primary criteria—Slope, Average Annual Rainfall, Land Use/Land Cover (LULC), Population Density, Proximity to Roads, and Proximity to Water Bodies have been evaluated for their influence on landfill site selection. Raster and vector layers corresponding to each criterion have been standardized to a 1–5 suitability scale, taking into account local environmental, logistical, and social constraints.

10.7.1 Weights and Criteria Performance

Slope and LULC emerged as the most influential factors, jointly accounting for over 59% of the total decision weight. This emphasizes the necessity of siting landfills on gently sloped, non-sensitive land types such as barren or fallow lands where construction risk and ecological impact are minimal. Population density, rainfall, and infrastructure proximity, while still relevant, played secondary roles in influencing overall suitability.

Table 10.3 Final criteria obtained by Rough AHP

Criteria	Lower Bound	Upper Bound	Final Weight
Slope	0.2911	0.3363	0.3137
Rainfall	0.1390	0.1275	0.1333
LULC	0.2721	0.2869	0.2795
Population Density	0.1651	0.1315	0.1483
Road Proximity	0.0909	0.0774	0.0841
Water Proximity	0.0418	0.0403	0.0411

10.7.2 Suitability Mapping

The suitability mapping component of this study serves as a pivotal tool in visualizing and categorizing potential landfill sites across the Kolkata Metropolitan Region (KMR), based on the integrated analysis of six key criteria: Slope, Average Annual Rainfall, Land Use/Land Cover (LULC), Population Density, Proximity to Roads, and Proximity to Water Bodies.

After gathering and processing the spatial data layers for each criterion, they have been individually standardized to a common 1–5 suitability scale according to locally relevant thresholds as shown in Table 10.2. Each layer has been subsequently weighted using final values derived from expert analysis via Rough AHP, ensuring objective synthesis of both environmental and socio-economic considerations.

The weighted linear combination of criteria values produce a composite suitability index, which has been normalized and classified into distinct suitability classes using natural breaks in Arc GIS software. The mapping results indicate:

Highly suitable areas are predominantly found in the outer urban fringes, characterized by flat or gently sloped, sparsely populated, and non-productive lands with moderate access to road networks and safe distances from water bodies.

Moderate to low suitability areas correspond to peri-urban and semi-rural patches, where land use conflicts and population exposure become more significant.

Least suitable sites are concentrated within dense urban cores and environmentally sensitive zones, such as riverbanks, wetlands, forests, and high rainfall or steep regions. These locations score poorly due to elevated landslide, contamination, and public health risks.

Figure 10.10 illustrates the percentage distribution of the study area across four landfill suitability classes ranging from Highly Suitable to Unsuitable, based on the weighted overlay analysis using Rough AHP and GIS. This visual representation helps to quantify the spatial extent of each suitability zone for effective decision-making.

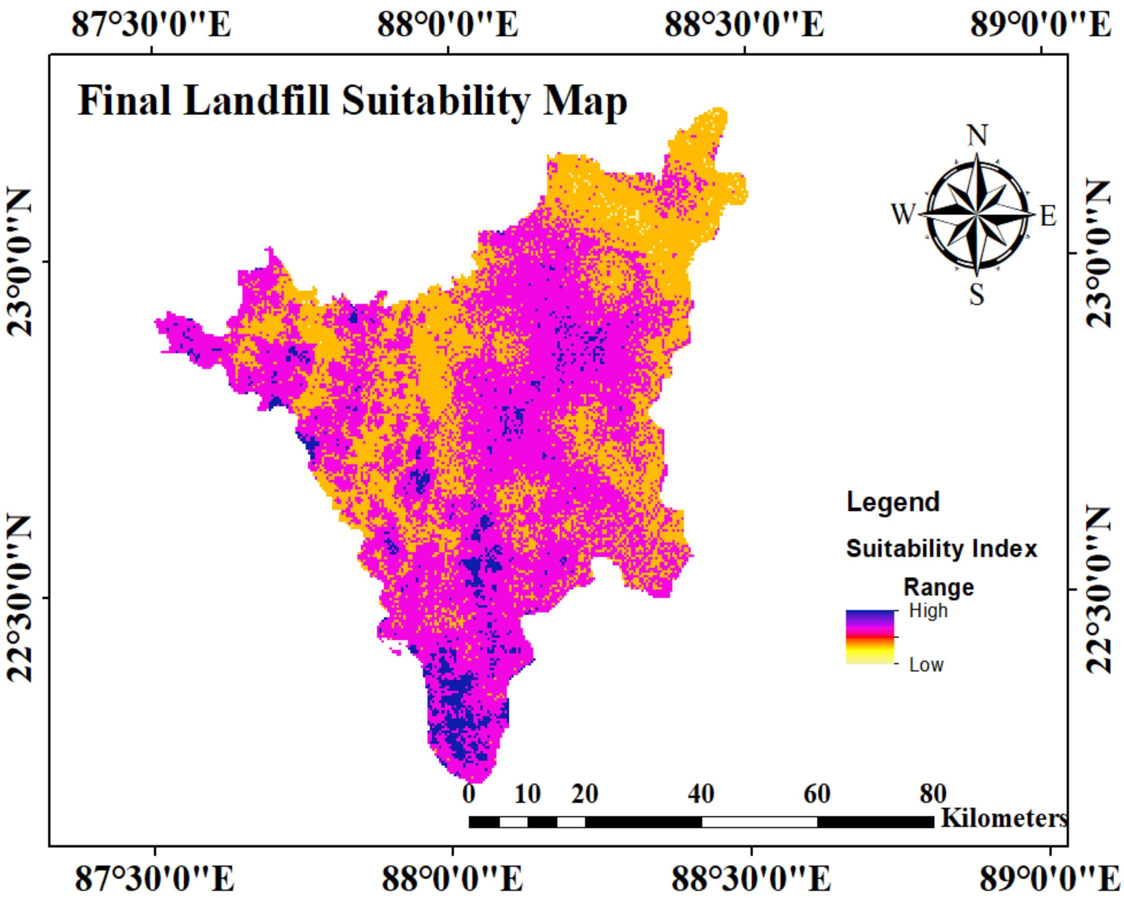

Figure 10.9 Final landfill suitability map of study area

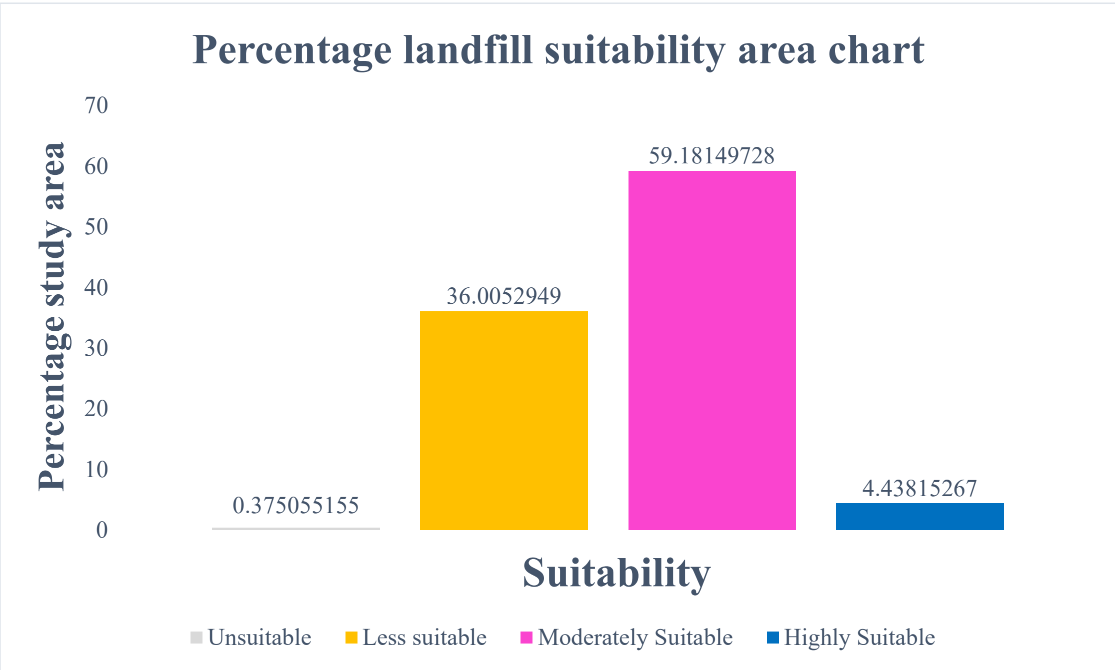

Figure 10.10 Percentage landfill suitability area

10.7.3 Methodological Strengths

Robust and Replicable Framework: The integration of GIS with Rough AHP enables systematic processing of multidimensional spatial data, accommodating uncertainty in human judgment, an often-overlooked aspect in environmental planning.

Environmental and Socio-Economic Balance: The criteria selection and their weights reflect a careful balance between minimizing environmental risks (e.g., leachate, runoff, contamination) and socio-economic costs (e.g., land use conflicts, transportation).

Interval-Based Weighting: Use of lower and upper bound weights from expert opinions ensures that recommendations are robust to subjective variability, increasing the reliability of site prioritization.

10.7.4 Implications for Urban Waste Management

Targeted Waste Infrastructure Planning: The identification of highly suitable outer fringe areas provides actionable guidance for municipal authorities, supporting the decentralization and distribution of waste disposal facilities away from population centres and sensitive environments.

Policy and Decision-Making Support: The approach offers a transparent, evidence-based tool for policymakers, potentially reducing site selection disputes and streamlining environmental clearance processes.

10.7.5 Limitations and Future Directions

Data Resolution: The spatial resolution of input datasets may limit micro-level precision of suitability predictions.

Dynamic Criteria: Urban expansion, demographic change, and climate variability may alter the relative importance of criteria over time; periodic updates and scenario planning are recommended for long-term relevance.

Broader Applicability: While tailored for the Kolkata and its adjoining regions, the methodology is generalizable to other metropolitan contexts with appropriate local customization of criteria and weights.

10.8 Summary

This investigation presents a GIS-based landfill site suitability analysis for Kolkata and its adjoining area, integrating six thematic criteria like slope, average annual rainfall, land use land cover (LULC), population density, distance to roads, and distance to water bodies which have been weighted using RAHP. All raster layers have been reclassified on a 1–5 scale and combined through a weighted linear overlay in ArcGIS, generating a composite suitability index which was normalized and categorized into four suitability classes using the natural breaks method.

The final suitability map revealed that outer urban fringes, including areas with gentle slope, low population density, non-urban LULC, and safe distances from sensitive hydrological features, have been classified as Highly Suitable. In contrast, densely urbanized and ecologically sensitive areas, especially central Kolkata and zones near the Hooghly River, were predominantly marked as moderately and less suitable. The corresponding percentage distribution of area under each suitability class is illustrated in Figure 10.10, offering a clear spatial interpretation of the landfill suitability landscape. The study demonstrates an effective, uncertainty-aware methodology for sustainable landfill planning in metropolitan regions.

Overall, the study demonstrates the effectiveness of combining spatial analysis and multi-criteria decision frameworks under uncertainty for sustainable landfill site selection, providing a critical foundation for improved solid waste management planning in rapidly urbanizing regions.

Chapter 11

Conclusions and Future Scope

11.1 Conclusions

Kolkata, a historic metropolis and one of India's major urban centres, founded by Job Charnock in 1690 has witnessed rapid infrastructural development over the past few decades. This growth, however, has often occurred in the context of environmental degradation, urban congestion, and socio-economic disparities. The construction sector in Kolkata and its surrounding regions such as Howrah, North and South 24 Parganas, Hooghly, and Nadia play a pivotal role in shaping the region's urban landscape and sustainability trajectory.

Environmental sustainability in Kolkata's construction sector is primarily driven by the need to tackle challenges such as urban heat islands, air pollution, and flood-prone zones issues exacerbated by unchecked construction and poor urban planning. Innovative approaches like rainwater harvesting, solar energy integration, vertical green walls, and sustainable drainage systems are gradually being adopted in new residential and commercial projects, especially in the New Town and Rajarhat areas.

From a social perspective, sustainable construction is influencing labour welfare, safety practices, and inclusive urban design. Projects now increasingly factor in affordable housing schemes under PMAY (Pradhan Mantri Awas Yojana), barrier-free access, and community facilities. The participation of local communities in planning and decision-making is gaining importance, aligning with the core principles of social sustainability.

Economically, the region's construction sector is being reshaped by cost-benefit analyses that incorporate life-cycle costing, energy savings, and waste reduction. A shift towards circular economy principles is noticeable, particularly in the reuse of demolition waste and fly ash-based concrete in infrastructure development. Additionally, green infrastructure investments are becoming attractive to both public and private stakeholders, ensuring long-term economic viability.

This research represents a comprehensive and interdisciplinary investigation into the multifaceted dimensions of sustainability within the construction sector. The thesis has addressed pressing global challenges related to environmental degradation, inefficient resource use, socio-economic inequity, and operational risks in infrastructure development by proposing a novel, consilient framework that integrates environmental, economic, and social sustainability in construction practices.

The term *"consilient conspectus"* within the title is not merely rhetorical,it embodies the unification of fragmented disciplines, approaches, and objectives into a single, coherent framework for sustainable construction. This approach has become essential in today's context where isolated efforts fail to address the complex, interdependent nature of sustainability challenges. Each thematic domain within this study like green contractor selection, sustainable waste landfill site selection, green concrete design, healthcare infrastructure evaluation, and construction risk assessment has been individually explored using robust scientific methods and yet collectively converges toward a unified goal: building an ecologically responsive, socially inclusive, and economically viable construction paradigm.

A significant strength of this research lies in its methodological plurality. The application of fuzzy logic (FAHP and FTOPSIS), Rough Set Theory, GIS-based spatial analysis, machine learning clustering (K-Means), intuitionistic fuzzy modeling,PCA, and Multiple Linear Regression models demonstrates a deep engagement with both quantitative rigor and qualitative insight. These tools were not used in isolation; rather, they were purposefully hybridized and tailored to suit the unique requirements of each research objective. This has enabled the study to traverse conventional analytical limitations and offer decision-making models that are not only computationally robust but also context-sensitive.

In the domain of contractor performance evaluation, the thesis introduces a dual-framework hybrid model. The first layer employs FAHP and FTOPSIS to rank contractors across green performance criteria. The second, more advanced model, integrates the Hodges-Lehmann rule with intuitionistic fuzzy reliability weighting—accounting for both the decision maker's risk preference (λ) and the trustworthiness of the data. This approach marks a novel contribution to the field by embedding occupational health indicators (noise emissions) and adjusting for data uncertainty, thus shifting contractor selection toward a more sustainable and health-aware direction. The model's validation using Delphi consensus confirms its applicability in real-world procurement scenarios.

For solid waste disposal site selection, a GIS-integrated RAHP model has been developed and applied to Kolkata and its adjoining urban-rural belts. Unlike earlier studies which relied heavily on subjective inputs or oversimplified spatial factors, this study introduced a multi-layered analytical process incorporating environmental sensitivity (rainfall, slope), socio-economic factors (population density, LULC) and topographical conditions (proximity to water bodies and urban areas). Potential landfill sites have been evaluated by suitability analysis through robust normalization and rough interval analysis, demonstrating a practical model for policymakers in urban planning and municipal solid waste management.

In the context of sustainable materials, particularly green concrete, the study provides both experimental and analytical contributions. Using a laboratory-prepared dataset, linear and exponential regression models have been formulated to predict compressive strength over curing periods. The exponential model, due to its superior fit for green concrete containing pozzolanic materials such as fly ash, glass powder, and demolition waste, has been found to be more appropriate in reflecting delayed strength gain characteristics. Moreover, a Pareto analysis revealed that over 86% of the strength was achieved within the first 14 days underscoring the importance of early-age curing strategies for optimal material performance. This research promotes the reuse of industrial by-products and urban waste in concrete production, aligning perfectly with the principles of a circular economy.

Another unique contribution of the thesis lies in its integration of behavioral and infrastructural sustainability, as demonstrated in the healthcare infrastructure case study. Using PCA and multiple regression analysis, the study identifies key latent variables like Eco-Design Quality (EDQ), Trust in Certification (TIC), and Sustainability Satisfaction (SS) that influence Occupant Commitment (OC) in green hospitals. The empirical findings reveal that user trust in green certifications is the most significant determinant of occupant loyalty, surpassing even infrastructure quality. This challenges the notion that infrastructure alone determines user satisfaction and instead brings to light the role of perceived authenticity, transparency, and user trust in sustainable service environments.

To strengthen the project management dimension, the study advanced construction risk modeling by developing an enhanced FMEA framework using Rough Set Theory and Rough TOPSIS. Common failure modes such as design errors, quality control lapses, safety hazards, cost overruns, and schedule delays have been systematically evaluated, and their risk priority rankings have been refined. By addressing traditional FMEA's weaknesses especially the inability to model uncertainty and equal-weighted factor biases,the study introduces a more responsive and granular model. This is especially important in high-risk construction environments where real-time decisions must be made with limited, ambiguous information.

11.1.1 Key Contributions of the Study

The present research makes several significant theoretical, methodological, practical, and interdisciplinary contributions toward advancing sustainability in the construction sector. The major contributions of the study are summarized as follows:

11.1.1.1 Development of a Consilient Sustainability Framework for Construction

One of the primary contributions of this research is the development of a comprehensive and consilient framework integrating multiple dimensions of sustainability in construction. Unlike conventional studies focusing on isolated sustainability aspects, the present work establishes an interdisciplinary analytical structure combining environmental, economic, social, technical, spatial, and risk-oriented perspectives within a unified sustainability assessment framework.

11.1.1.2 Advancement of Hybrid Fuzzy and Rough MCDM Approaches

The study contributes methodologically by integrating advanced Multi-Criteria Decision-Making (MCDM) techniques including Fuzzy AHP, Fuzzy TOPSIS, Rough AHP, Rough TOPSIS, clustering techniques, and modified FMEA models for sustainable construction decision-making under uncertainty. The integration of fuzzy and rough set theories improved the capability of conventional MCDM models in handling ambiguity, vagueness, and subjective expert judgments.

11.1.1.3 Reliability-Based Contractor Performance Evaluation Framework

A novel reliability-aware contractor evaluation framework has been developed by integrating intuitionistic fuzzy logic with a modified Hodges-Lehmann approach. The proposed model incorporates expert reliability and risk preference into contractor assessment, thereby improving the robustness and practical applicability of contractor ranking for sustainable construction projects.

11.1.1.4 Contribution toward Sustainable Waste Management and Landfill Site Selection

The research contributes significantly toward sustainable urban waste management by developing GIS-integrated landfill site suitability frameworks using Rough MCDM methodologies. The study demonstrates the effectiveness of combining spatial analysis with sustainability-based decision models for identifying environmentally suitable waste disposal zones while minimizing ecological and social risks.

11.1.1.5 Integration of Geospatial Intelligence with Sustainability Assessment

The study establishes an important linkage between geospatial analysis and sustainability evaluation through GIS-based landfill suitability mapping. By integrating spatial parameters such as slope, rainfall, land use, population density, road proximity, and water body buffers, the research contributes toward evidence-based environmental planning and sustainable urban infrastructure management.

11.1.1.6 Predictive Modeling Framework for Sustainable Green Concrete

The study contributes toward sustainable material research through predictive modeling of compressive strength development in green concrete. Regression-based modeling approaches were developed to evaluate the performance of green concrete incorporating sustainable material alternatives. The findings support the potential application of green concrete as an environmentally sustainable alternative to conventional concrete.

11.1.1.7 Contribution toward Sustainable Healthcare Infrastructure Assessment

The research extends sustainability assessment into healthcare infrastructure by developing a PCA and regression-based analytical framework for evaluating sustainable healthcare environments. The study identifies critical sustainability-related factors influencing occupant perception and institutional performance, thereby contributing toward socially sustainable infrastructure planning.

11.1.1.8 Enhanced Risk Assessment Framework for Sustainable Construction

An improved risk evaluation framework has been developed through the integration of Rough AHP, Rough TOPSIS, and FMEA approaches. The proposed methodology enhances conventional risk prioritization mechanisms by incorporating uncertainty handling capabilities and sustainability-oriented risk evaluation criteria for construction projects.

11.1.1.9 Contribution to Decision Support Systems for Sustainable Construction

The proposed models collectively contribute toward the development of intelligent and data-driven decision support systems for sustainable construction management. The frameworks developed in this thesis can assist policymakers, engineers, urban planners, project managers, and researchers in making scientifically informed sustainability decisions under uncertain environments.

11.1.1.10 Practical and Policy-Level Contributions

The findings of the study provide practical implications for sustainable contractor selection, environmentally suitable landfill planning, green material adoption, healthcare infrastructure improvement, and sustainability-oriented construction risk management.

The research also supports policy-level initiatives related to sustainable urban development, circular economy implementation, environmental protection, and resilient infrastructure planning.

11.1.1.11 Academic Contribution to Interdisciplinary Sustainability Research

The study contributes academically by demonstrating how interdisciplinary integration of construction engineering, sustainability science, geospatial analysis, decision science, risk assessment, and statistical modeling can collectively address complex sustainability challenges in the built environment. The proposed consilient approach offers a foundation for future interdisciplinary sustainability research in construction and infrastructure systems.

11.2 Future Work

While the current work lays a robust foundation, it also opens several promising avenues for future research. First, the models developed here particularly for contractor evaluation and green concrete performance can be scaled using AI and machine learning for predictive analytics across larger datasets. Second, the framework can be extended to incorporate life cycle costing (LCC), carbon accounting, and digital twin simulation for more holistic sustainability assessments. Third, the integration of real-time data streams (IoT sensors) in site selection, waste management, and health infrastructure can improve responsiveness and adaptability in decision-making.

The thesis serves as a blueprint for sustainable construction policy, particularly in developing regions where challenges are acute but opportunities for innovation are immense. It contributes not only to academic scholarship but also to practical policy, planning, and professional decision-making, bridging the gap between theory and application.

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