Implementing Fuzzy Analytical Hierarchy Process and Similarity Approach to Predict Health and Safety Incidents in Dubai Construction Projects

تنفيذ عملية التسلسل الهرمي التحليلي الضبابي ونهج التشابه للتنبؤ بحوادث الصحة والسلامة في مشاريع البناء في دبي

by

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ABSTRACT

With the benefit of improving and developing the construction business in the UAE, a smart and resilient system has been generated. The construction sector contributes 7.4% of Dubai's GDP and is highly exposed to hazards and uncertain events. Various types of risks can be obtained from the construction sites. Therefore, it is essential to explore and study strategies, logical methods and processes that save lives, increase profitability, reduce time, and enhance quality.

The chosen case studies of this research study are three innovative buildings established to attract residents and visitors to live in. The selected projects are related to the residential sub-community sector. Although the implementation of these projects was initiated and processed at high standards, unfavourable events occurred during the construction phase.

The developed MATLAB program is created to conduct the assessment method of the construction risks. The mathematical techniques utilised in the program are multi-criteria decision matrix, fuzzy analytic hierarchy process and similarity TOPSIS. The selected attributes which are used for the assessment are risks probability, health and safety severity, time delay, cost increment and productivity reduction. Besides, in order to promote accuracy and precision of output data, experts' decisions must be taken into consideration regarding the attributes ranking and hazards rating. Furthermore, three different ideal solutions criteria will be examined to select the most appropriate results.

By assessing and ranking the previous data of risks, project stakeholders will be able to predict future risks and apply mitigation responses prior to events occurrence. This research will propose mitigation plans to overcome uncertain events and reduce errors during the construction of projects.

الملخص

مع الاستفادة من تحسين وتطوير أعمال البناء في الإمارات العربية المتحدة ، تم إنشاء نظام ذكي ومرن. يساهم قطاع البناء بنسبة 7.4٪ من الناتج المحلي الإجمالي لدبي وهو معرض بشكل كبير للمخاطر والأحداث غير المؤكدة. يمكن الحصول على أنواع مختلفة من المخاطر من مواقع البناء. لذلك ، من الضروري استكشاف ودراسة الاستراتيجيات والأساليب والعمليات المنطقية التي تنقذ الأرواح وتزيد من الربحية وتقلل الوقت وتعزز الجودة.

إن دراسات الحالة المختارة لهذه الدراسة البحثية هي ثلاثة مبانٍ مبتكرة تم إنشاؤها لجذب السكان والزوار للعيش فيها. وتتعلق المشاريع المختارة بقطاع المجتمع الفرعي السكني. على الرغم من بدء تنفيذ هذه المشاريع ومعالجتها بمعايير عالية ، حدثت أحداث غير مواتية خلال مرحلة البناء.

تم إنشاء البرنامج المطور باستخدام "الماتلاب" لإجراء طريقة تقييم مخاطر البناء. الأساليب الرياضية المستخدمة في البرنامج هي مصفوفة قرار متعددة المعايير وعملية التسلسل الهرمي التحليلي الضبابي و تقنية ترتيب التفضيل عن طريق التشابه مع الحل المثالي. السمات المحددة المستخدمة في التقييم هي احتمالية المخاطر ، وشدة الصحة والسلامة ، والتأخير الزمني ، وزيادة التكلفة ، وخفض الإنتاجية. إلى جانب ذلك ، من أجل تعزيز دقة ودقة بيانات المخرجات ، يجب أن تؤخذ قرارات الخبراء في الاعتبار فيما يتعلق بترتيب السمات وتقييم المخاطر. علاوة على ذلك ، سيتم فحص ثلاثة معايير مختلفة للحلول المثالية لتحديد أنسب النتائج.

من خلال تقييم وتصنيف البيانات السابقة للمخاطر ، سيتمكن أصحاب المصلحة في المشروع من التنبؤ بالمخاطر المستقبلية وتطبيق استجابات التخفيف قبل وقوع الأحداث. سيقترح هذا البحث خطط التخفيف للتغلب على الأحداث غير المؤكدة وتقليل الأخطاء أثناء إنشاء المشاريع.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

WORD	**DEFINITION**
AI	Artificial Intelligence
BIM	Building information modelling
CNAE	National Classification of Economic Activities
DMRA	Decision matrix risk-assessment
FAHP	Fuzzy analytic hierarchy process
HS	Health and safety
ILO	International Labour Organization
IOT	Internet Of Thing
MCDM	Multiple-criteria decision-making
NIOSH	National Institute for Occupational Safety and Health
OHS	Occupational health and safety
OSHA	Occupational safety and health Administration
OHSMS	Occupational health and safety management systems
R&D	Research and development
SCAD	Statistic Centre Abu Dhabi
STPA	System-Theoretic Process Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

CHAPTER 1

INTRODUCTION

1.1 Study Overview

One of the critical success factors in worldwide industries is health and safety. In 2019, International Labour Organisation 'ILO' reported 2.8 million death cases yearly, recording more than 6,500 fatality cases from occupational diseases and 1,000 cases from occupational accidents (Warrier, 2019). The construction sector contributed around $12,744.40 billion to the global business in 2019, with an annual growth rate of 6.1% since 2015 (Global Construction Opportunities and Strategies Market Report, 2020). Regardless of the enormous research and efforts conducted to improve health and safety-related to the construction industry, construction workers are not immune to some occupational illnesses, injuries and accidents where the statistics don't represent enhanced performance in the past years.

The main reason for poor performance in health and safety in the construction sector is that several organisations are utilising a traditional approach in analysing occupational risks. Additionally, construction project sites have dynamic and complex nature in which there are limited techniques to detect health and safety risks and their causes. In contrast, other health and safety aspects are effectively controlled in construction sites, such as finance, accountability, and legal liabilities resulting from the occurred incidents. According to the increment of health and safety incidents, governments improve standards and engineering practices based on previous experiences. Depending on the historical data of construction projects, the weaknesses and threats caused by the accidents assist project managers to refine codes of practice. Applying new requirements in the design and planning phase will prevent risk events that arise from occupational incidents and their root causes. The causes of accidents and injuries are mainly due to the failure to adhere to health and safety standards or lack of risk communication among project stakeholders. Besides, health and safety developments can't be accomplished if labours and managers don't behave as per the work protocols. Accordingly, to improve health and safety performance, issues must be addressed and studied to examine if the risks will be dealt with as opportunities or threats (Cooney, 2016).

1.1.1 Health and Safety in the Construction Industry

The construction environment is highly exposed to risk and hazardous events; thus, workforce staff face critical site challenges during excessively long working hours. Occupational incidents are caused by various reasons, such as construction machines and equipment, which harm project operators and physical or mental health issues that arise from incorrectly assigning workers' duties. Additionally, project managers must effectively monitor employees' behaviours and adherence to health and safety standards. All stakeholders involved in the construction project should comply with occupational health and safety regulations illustrated at the workplace. In developing countries, numerous factors negatively impact health and safety management that contain insufficient communication among project teams, poor infrastructure, adherence to traditional approaches, lack of risk prevention systems, and inadequate codes of conduct. There will be additional costs associated with the unfavourable impacts of health and safety risks, which will reduce the overall project profit (Muiruri and Mulinge, 2014).

Every construction project has its opportunities and challenges, requiring risk identification, planning and management. With the purpose to reinforce risk mitigation and avoidance processes, firms must have the ability to identify, assess, monitor and control certain and uncertain risk events. Based on the organisations' capabilities, risk can be turned into opportunities or threats. Managing risks and turning them into opportunities will boost productivity and profits, create trustful relationships with key customers and expand business in the market. Project managers and directors examine all potential risks related to the construction project's operational, environmental, financial, and contractual aspects to make appropriate construction risk management. The construction risk management process involves identifying certain and uncertain risks assessing risk events based on their probability and outcomes. Risks are ranked as low, medium or high according to their impacts, and their probability is likely to occur. When a risk occurs, it will affect projects cost, time, and quality. The techniques developed against risk events are risks avoidance, mitigation, acceptance or transference. Risk avoidance can be performed by rejecting a contract or negotiating project terms and conditions to avert potential risks. Risk transfer is applied when a firm can't take the responsibility to manage a specific risk where the project owner can assign another firm capable of handling it. Moreover, the mitigation of risk contains reducing or eliminating. The decision will be based on comprehensive planning by segregating each risk into several segments and allocating an action to each segment. On the other hand, risk acceptance is usually made if the risk impacts are low or within the risk tolerance range (Jones, 2020).

1.1.2 Technology Development in the Construction Industry

For many decades R&D departments in construction organisations have been gathering several categorical data, integrating technologies in the process and implementing innovative strategies to improve the performance of construction projects. Recent studies in the construction industry are related to the fourth industrial revolution, which contains artificial intelligence 'AI', internet of things 'IOT', building information modelling 'BIM' and machine learning 'ML'. The main issues in the fourth revolution technologies are establishing and merging it in the business. Adopting these technologies requires a transparent cyclical model called ‘Labyrinth of Innovation’ consisting of six phases. The phases in sequence are need, creation, invention, innovation, diffusion and adoption. The key stakeholders in the construction sector's technology adoption cycle include owners, contractors, subcontractors, project management firms, engineers and designers, suppliers and manufacturers. The ‘Labyrinth of Innovation’ processes arises from market demands, competitive advantages, and changes in the business environment. Furthermore, the goals of developing the ‘Labyrinth of Innovation’ model are to satisfy stakeholders’ needs, increase profitability and enhance the performance of projects. Due to the complexity of innovation, the cyclical model will be continuously applied until getting the desired outcomes. Another challenging aspect is workers’ and managers' lack of knowledge and experience dealing with intelligent technologies (Tangkar and Arditi, 2000). To establish a smart and resilient innovative strategy, organisations integrate subsystems to design, simulate and illustrate best fit technologies to construction projects. Types of construction technologies that can be implemented during design and construction phases include real-time monitoring sensors, automated transportation systems of products and components, artificial intelligence systems for controlling construction procedures and BIM application to perform comprehensive designing and planning of projects before the construction stage.

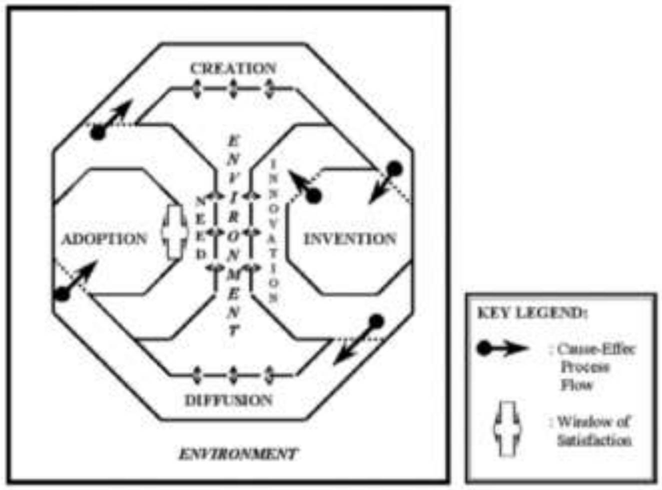

Figure 1.1: The six phases of the Labyrinth of Innovation source:
Tangkar and Arditi, 2000.

1.1.3 Health and Safety Management under Smart Construction

Managing health and safety in construction sites ensure safe and smooth business operations. Many construction project data related to accidents and death incidents have been generated in the last decades. Thus, the demand to apply big data technology has significantly increased. Analysing massive data incidents using computer data science will enhance health and safety management in the project sites. Examples of data science technologies are big data analysis that contains data collection, classification and storing processes; BIM technology which use 3-dimensional visual analysis, real-time site monitoring and controlling, and the internet of things that connect sensors and smart systems with each other to have better site management. Intelligent health and safety management provides early prediction and warning of potential incidents, promoting effective risk mitigation responses. Providing a guide to improve health and safety management in construction projects is the primary purpose of this research. Big data-based health monitoring and control systems have been applied to achieve the desired target. Researchers such as Wu Zhi Xia et al. established a bridge with considering health monitoring and maintenance platforms to collect and analyse big data. The platform has been used successfully during the construction phase of various bridge projects in Shanghai to enhance structural safety management (Wu et al., 2018). In another study, researcher Tu Chengfeng et al. developed a health big data monitoring and analysing platform by utilising a data mining engine, multi-scale correlation analysis and time-varying reliability (Yi and Wu, 2020). To establish a health and safety monitoring platform, the accumulative and development of big data have to be collected. Besides, these data will be stored, evaluated and analysed to facilitate the problem-solving and decision-making processes.

1.2 Research Problem Statement

According to worldwide statistics, around 25% to 40% of occupational deaths are related to construction incidents (Lingard, 2013). The impact of construction incidents resulted in massive financial losses and increased business threats. Therefore, it's essential to involve technology and cloud computing services in construction projects. The transformation of traditional construction to smart construction can be accomplished by digitalising the processes before and during the construction phase of projects. Collecting a vast amount of construction data and utilising them in smart technologies that continuously improve themselves will reinforce efficiency, facilitate the decision-making process and boost the profitability of construction projects. Critical issues will be covered in this dissertation as per the following:

i. What are the types of HS risks in UAE construction sites?
ii. What are the impacts of HS risks on the construction project quality, cost and time?
iii. How to reduce or eliminate HS uncertain events during the construction phase.

iv. How to predict HS risks before occurring using smart technology?
v. What are the key elements required to implement smart predictive system to mitigate HS risks?
vi. What are the challenges associated with implementing smart systems in the construction industry?

1.3 Research Aim and Objectives

1.3.1 Research Aim

This dissertation aims to implement innovative safety leading indicators in UAE construction sites to monitor safety, obtain risks associated with the projects' construction process and measure the effectiveness of risk control systems. The fuzzy analytical hierarchy process and TOPSIS technique will be applied as safety indicators due to the following reasons:

i. More flexible and realistic since it requires experts' knowledge and real-life cases to implement a smart predictive system.
ii. Ability to capture and process linear and non-linear relationships in significant safety data sets.
iii. Efficient prediction of outcomes and reduce errors.

1.3.2 Research Objectives

i. Obtain probability, causes, occurrence and impacts of health and safety risks on construction sites.
ii. Promote a risks analysis and ranking program based on MCDM, Fuzzy AHP and TOPSIS techniques.

iii. Acquire the fuzzy positive ideal solution, fuzzy negative ideal solution, and closeness coefficient values to rank the collected construction risks.

iv. Provide mitigation responses to mitigate the unfavourable events during the construction phase.

v. Develop a list of recommendations based on the study outcomes and findings in future research and projects.

1.4 Scope of Work

In this research, the three case studies were selected from various construction sites in Dubai, UAE. The initial two cases, Dubai Hills Business Parks and Smart City Silicon Park projects, are related to the residential sector. The third project is Creek Rise which belongs to the multi-use complex building sector.

The advantage of choosing these case studies is their importance as fundamental landmarks in UAE. Project stakeholders reported and recorded all uncertain events during the construction phase in research studies. The outcomes of this study might be applicable for several construction project types that share similar work environments and conditions.

In this study, health and safety reports are gathered from the mentioned construction sites and filled questionnaires by construction experts as inputs. It will assist in obtaining risk ranking, analysing and related mitigating responses. Additionally, computer programming software is utilised to apply machine learning algorithms to process and analyse the collected dataset. The chosen algorithms for risk ranking and classification will be multi-criteria decision making, fuzzy analytical hierarchy process and similarity TOPSIS. The results will prioritise construction events and assist in providing practical solutions to eliminate or reduce the threats.

1.5 Research Outline

To accomplish the objectives of this research, this dissertation study will be divided into seven chapters. The 1st chapter presented a brief introduction of the research's prime ideas related to health and safety uncertain events during the construction phase of the projects. Besides, it provides some definitions of machine learning, health and safety subjects' concepts.

The 2nd chapter includes two parts of the literature review. Each part has a comprehensive historical background and detailed health and safety studies in construction sites and machine learning algorithms in the construction industry. Additionally, the importance of health and safety in the construction business and machine learning algorithms to eliminate unfavourable events will be discussed in detail.

The 3rd chapter contains the algorithm approaches and data processing software to claim the desired outputs. Also, it presents other past research studies applied in the similar field of this study to clarify the selection of the best machine learning methodology and choosing the computer software.

The 4th chapter covers the procedure computer analytical program through MATLAB software. In addition, they will provide a comprehensive investigation of the input variables that will be utilised in different data processing logic to obtain the most accurate and precise outcomes. The output data and findings of the selected criteria will be implemented and criticised to choose the best performance.

The 5th chapter proposes several mitigation responses against each type of risk based on their ranking. It provides various insights for the concerned readers to act pro-actively prior to threats occurring.

The 6th chapter summarises all topics in the dissertation and introduces the research recommendations and limitations and future research recommendations.

1.6 Theme of the Research Study

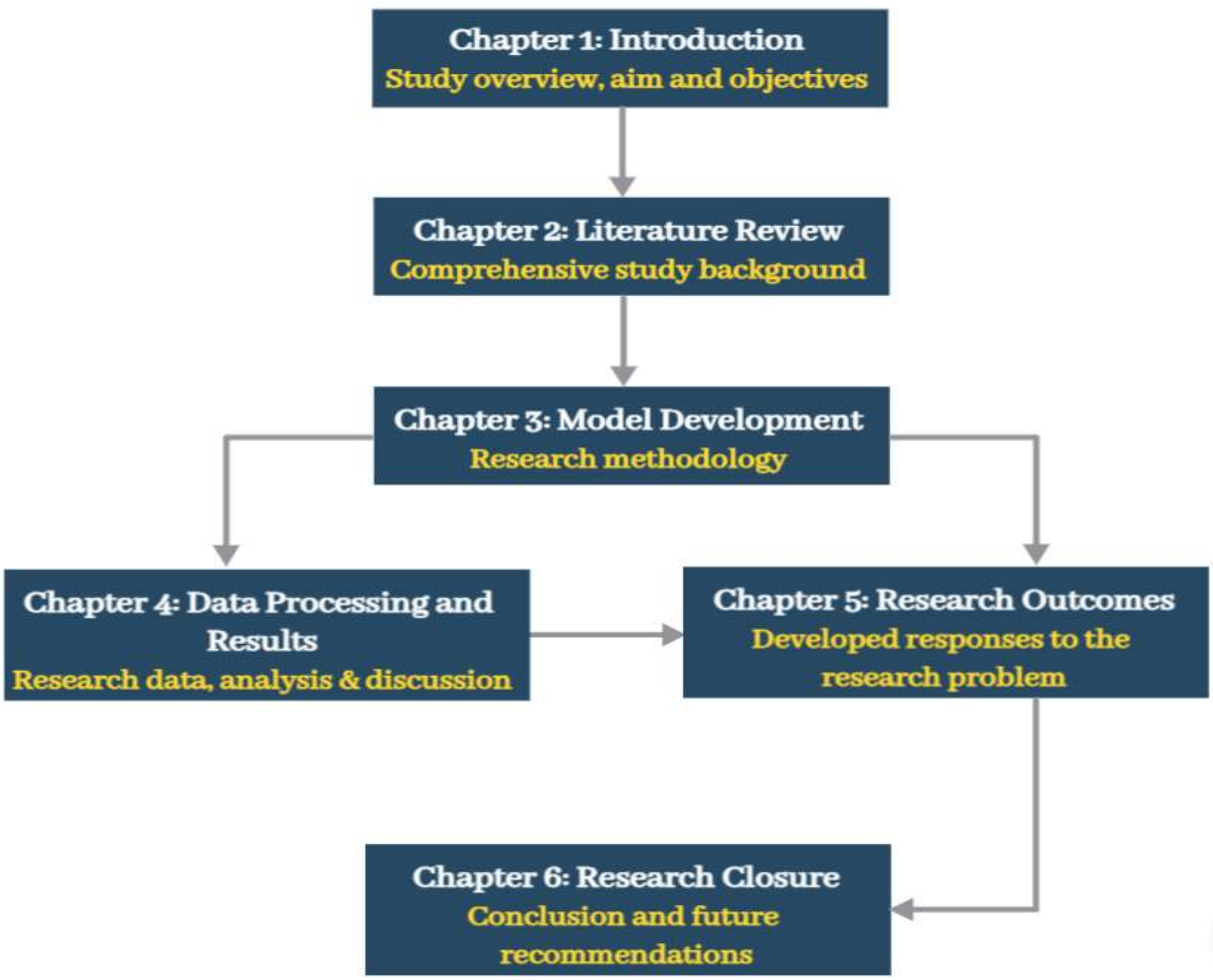

Figure 1.2: Theme of the research study.

CHAPTER 2

LITERATURE REVIEW

2.1 Health and Safety in the Construction Industry

2.1.1 Health and Safety Background

Occupational health and safety (OHS) is an entire area of study concerned about the health, safety, and welfare of people engaged in a workplace environment. The word ‘health’ is defined as the physical conditions of the human body and mind where it's essential to protect them from injuries, disease, or any form of harm in the workplace. Besides, the word ‘safety’ refers to the physical circumstances at the worksite in which damages must be eliminated or lessened to a tolerable level. The main objectives of health and safety platforms in a workplace are to foster a healthy and safe environment for employees and prevent or reduce hazardous situations.

2.1.1.1 History of Occupational Health and Safety

The definition of public health initially appeared in 1830 in the U.S. It refers to the science dedications in improving the HS of the human being. Public health was defined by Winston in 1926 as the applied science of art to prevent diseases, increase average life and reinforce the health of humans by organised efforts and practical choices of individuals, communities, and organisations. In 1999, Vetter and Mathews described public health as the process of prolonging life, restraining illness, promoting health and enhancing life quality by society efforts. Additionally, McKenzie in the year 2005 represented public health as the status of population health that contains governmental and authorities’ action in protecting, preserving and promoting people’s life and in 2009, Turnock argued that public health is a mutual effort to handle unfavourable events which lead to poor life outcomes. All of the previous definitions emphasise preventing health issues rather than curing them. Public health plays a significant role and involvement in all industries, where the main focus of this research will be in the construction workplace (Healey and Walker, 2009).

Since the beginning of the 20th century, worldwide developed countries started to focus on labourers' health and safety due to the significant increment of occupational injuries and diseases in the workplace. Governments developed occupational health and safety legislation and regulations to protect workers and save their lives. In 1970, the Occupational Safety and Health Administration (OSHA) was established to illustrate rules and regulations that reduce the morbidity and mortality of labours in their work environment. To improve the initial occupational health and safety (OHS), the OSHA settled the National Institute for Occupational Safety and Health (NIOSH). This firm established an investigation team and R&D departments to collect incidents details from several workplaces and organisations. These details assist in issuing recommendations to deal with the dangers associated with hazardous events in the workplace. By observing various injuries and illness cases and understanding the nature of occupational accidents, firms created real-time surveillance systems. They implemented primary preventions systems to monitor and detect workplace health and safety matters.

Health and safety agencies continuously improved the regulations and framework related to occupational risks. In September 1998, the International Labour Organisation (ILO), one of the United Nations agencies, published health and safety codes and frameworks to prevent occupational incidents and illnesses in worksites. The firm developed a pyramid structured in four parts where each part has specific measurements for occupational health and safety. The description of the pyramid parts is as per the following:

Part I is the basis of the pyramid that includes the general legal principles and frameworks. It provides the duties for stakeholders involved in the worksite.

Part II sets the elements of health and safety policy at the business process level of the organisation. The codes are applied in a management system to translate organisational procedures and regulations into daily practices.

Part III covers HS aspects related to the enterprise level of the organisation. Health and safety aspects include recruiting employees and workforce development. Besides, this level of the organisation must ensure that contractors, labours and supervisors have the required qualifications to meet enterprise missions and objectives. Also, it monitors the worksites to control risks and hazardous events.

Part IV is the most critical section since it provides guidance and technical details on the work planning, operation and management (ILO and IWCA sign MOU to improve occupational safety and health of women in the coffee sector, 2022).

Figure 2.1: Occupational safety and health model source: Improving occupational safety and health: the International Labour Organizations contribution - Peter Blombäck*, 2021.

Furthermore, in 2018 World Health Organization (WHO) and International Labour Organization (ILO) improved the occupational safety and health framework to be compatible with the unprecedented emergency risks. The developed framework consists of five stages: policy, organising, planning and implementation, evaluation and action. Workers' occupational and health approach is illustrated at the enterprise level. The organising stage is to determine and form the most effective mechanism response. The set of planning contains resources allocation and mobilisation such as personal protective equipment (PPE), medicines and vaccines, monitoring worksites and guidelines on OSH. In addition, it includes proactive plans and responses to hazardous and unfavourable events. Real-time monitoring and evaluating processes for risk assessments and reactions are managed in the evaluation stage. The final step includes the actions to prevent workplace risks and continuous modifications to risk responses (International Labour Organization, 2018).

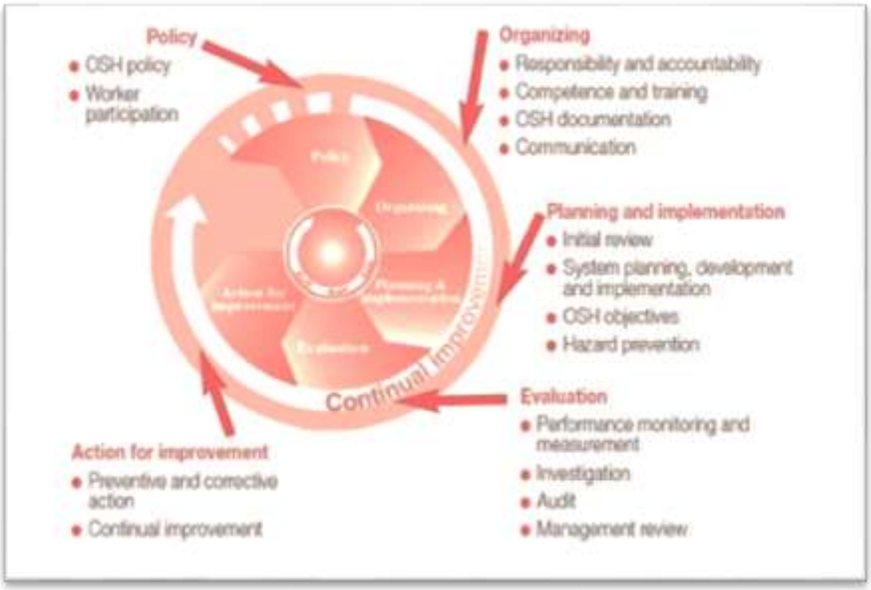

Figure 2.2: ILO occupational health and safety management system source: Labour administration and inspection, n.d.

2.1.1.2 The Importance of Health and Safety

The importance of health and safety in construction sites is critical to diminish social and economic issues related to labourers' physical damage and loss of life. The construction sector is considered one of the highest risks and unhealthy workplaces compared to other market sectors. Besides, the construction sector contributes to the worldwide economy by its high employment capacity and outstanding added value. If health and safety measurements are not followed in construction sites, diseases and physical damages are more likely to occur. The more occupational accidents happen, the less productivity and profitability result in the construction industry. Furthermore, when the organisations and stakeholders engaged in a construction project fail to implement proper HS protocols, they will be banned from operating in the sector, charged fines for breaking the law and face legal cases. Accordingly, organisations perform risk assessments and evaluations to minimise or eliminate construction threats (Yılmaz and Çelebi, 2015).

2.1.1.3 The Causes of Construction Accidents

The factors involved in incident causes should be examined to reduce construction sites injuries and accidents and develop risk prevention strategies. Furthermore, organisations increase their concentration in risks mitigations during the operational duration of the facility and construction phase. By gathering the historical data of health and safety incidents in several construction sites, project designers and managers initiated safe construction designs, operations and maintenance work before the construction phase. Additionally, IT support tools and technologies assist the project designers to make better decisions making and facilitate the communication process among project stakeholders. The radical enhancements in the initial design stage of construction projects support minimising the inevitable costs associated with health and safety risks (Manase, Mahdjoubi and Ahmed, 2004).

The consequences of occupational accidents are classified into minor, major, and deadly accidents. The measurements taken into consideration to specify the seriousness of an accident are the size of the workplace, climate zone, labours' age and health conditions, season and time of the accident, and the National Classification of Economic Activities (CNAE) code. From a different point of view, researchers classified health and safety accidents based on their causes into several categories. As per the Malaysian Journal of Civil Engineering, researchers categorised the reasons into six main categories with numerous examples (Abdul Hamid, Abd Majid and Singh, 2008).

Table 2.1: Health and safety accidents' types and causes

Category Ref.	Accident Causes	Examples
Category 1	Unsafe machines, tools and equipment	1. Equipment or machine failure 2. Without safety equipment or devices
Category 2	Construction sites conditions	1. Poor resources management 2. Site works noises 3. Slips and Trips in worksites
Category 3	Nature of construction industry	1. High elevation 2. Operations of work 3. Working area limitations 4. Natural Hazards
Category 4	Utilise dangerous methods	1. Low knowledge level 2. Improper work procedures 3. Not obeying HS standards
Category 5	Human aspects	1. Not wearing proper personal protective equipment 2. Personal attitude and emotions 3. Health conditions 4. Experience
Category 6	Construction industry management	1. Health and safety training 2. Incorrect safety policies 3. Poor safety monitoring system 4. Improper inspection programs

Concerning International Labour Organisation 'ILO' statistics, the most common injuries and death causes in the construction industry are as per the following:

i. Falls

Falling from high distance places such as ropes, ladders and scaffoldings lead to severe injuries. The avoidance of falls risk can be done by structuring a fall protection cover, wearing Personal protective equipment 'PPE', and training labourers on using the scaffoldings.

ii. Electrocution

Site workers who contact overhead power lines or work close to dangerous equipment and machines are exposed to electrocution risks. Thus, safety supervisors have to ensure that devices are appropriately geared up.

iii. Slips and trips

The loss of grip between labourers' shoe and the floor cause a slip, and when labour hits a low obstacle cause a trip. Slips and trips accidents can be eliminated by maintaining adequate light levels, providing proper storage facilities, and ensuring no holes in the floor surface.

iv. Crush Injuries

Building wreckages or structure slabs that fall into workers are among the most common causes of fatalities in construction sites. Workers should cover their heads with safety helmets to avoid head injuries from falling objects.

v. Fires

Due to the carelessness of labourers in using equipment or electrical machine, fires may start and spread all over the construction site. Besides, since there are combustible materials used in the building construction, such as fuel and wood, there will be many potential causes of fires. Hence, managers must provide health and safety training and illustrate influential organisational culture (Warrier, 2019).

2.1.1.4 Growth of Causation Models

To have better risk prevention at the construction sites, the causation of the incident must be examined. Accidents can be prevented by monitoring, controlling, and managing the worksites effectively. Thus, it's crucial to establish conceptual models for the causes of accidents. Accident causation models were initiated in the 1920s and developed through three phases. Each phase type is reinforced by certain assumptions and provides diverse outcomes. The first phase consists of several simple models called the simple linear models. The models are performed based on the belief that accidents are continuous series of circumstances or events that interconnect in a sequential arrangement that results in a linear pattern. The prevention of accidents series can be obtained by eliminating one of the causes linearly. One theory that applies the sequential accident model is Heinrich's Domino Theory. Heinrich's theory was implemented in 1931, and it proposed the thoughts where accident causes are lined up sequentially, such as the dominos. The leading five factors in Heinrich's theory are social environment, fault of the person, serious acts and physical hazards, accident, and injury. Based on Heinrich's Domino Theory, accidents will be prevented by removing one of the five factors. The main elements of Heinrich's theory are the fault of persons and unsafe acts since both cover 88% of the accident causes and are considered human factors. Therefore, removing or reducing the human failure factors will prevent accidents (Safety Institute of Australia, 2012).

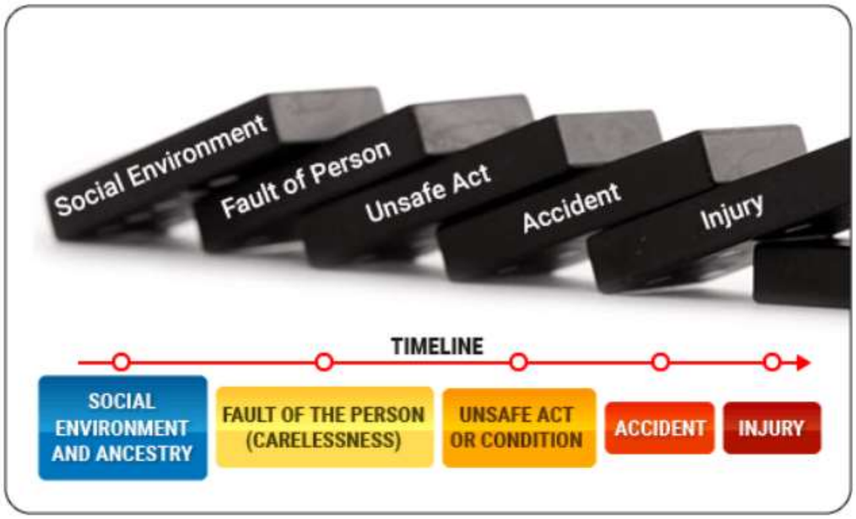

Figure 2.3: The domino model of accident causation source: Accident Causation | Understanding Safety, 2022.

The second phase of causation models consists of complex linear models. The intricate linear models pre-assumed the outcomes of the accident from unsafe acts and potential hazardous events within a linear system. The primary reason for accidents is human factors resulting from humans' close interaction with the accident. Other factors related to the organisation or surrounding environment are not significantly considerable in the complex linear models. The prevention criteria concentrate on causes and reduce their impacts by establishing barriers or eliminating them. An example of complex-linear models is the time sequence model. The time sequence model is a development of a domino type model to modify four main issues in the initial model. The four problems in the basic domino type model are related to accidents' beginning and end times, representation of the accident events in a sequential timeframe, structured process to find accident factors and defining events and circumstances using the charting method. The benefit of the time sequence model is its ability to analyse the events based on the sequence of occurrence-consequence, which provides specific opportunities to prevent the accident as per the time zone. The consequences of risk can be prevented in time zone 1 by eliminating the event occurrence.

Time zone 2 focuses on creating control mechanisms to reduce the threats and increase the likelihood of the risk. In zone 3, the consequences of the event or risk will be evaluated to make better decisions and perform effective responses (Viner, 1991).

Figure 2.4: Generalised time sequence model source: Viner, 1991.

Since accidents are the outcomes of integrated complex variables in the actual construction environment, linear causation models will not provide accurate results to prevent the accidents and their causes. Thus, non-linear causation models were developed by researchers to examine the accident complex factors and how they are affecting each other. One of the theories initiated by Perrow in the early 1980s called Perrow's standard accident theory argued that systems became inheritably complex due to the technological advances and correlation between multiple systems channels (Taylor, 1997). System-Theoretic Process Analysis (STPA) was created by Nancy Leverson, one of the paradigm types related to complex non-linear models. The model is an analysis technique for hazardous and unfavourable events. It identifies the potential risk events and their impacts, whether threats or opportunities. Besides, it assists in developing action plans, design controls and mitigation criteria. In addition, evaluate existing safety measures and improvement action plans (Safety Institute of Australia, 2012).

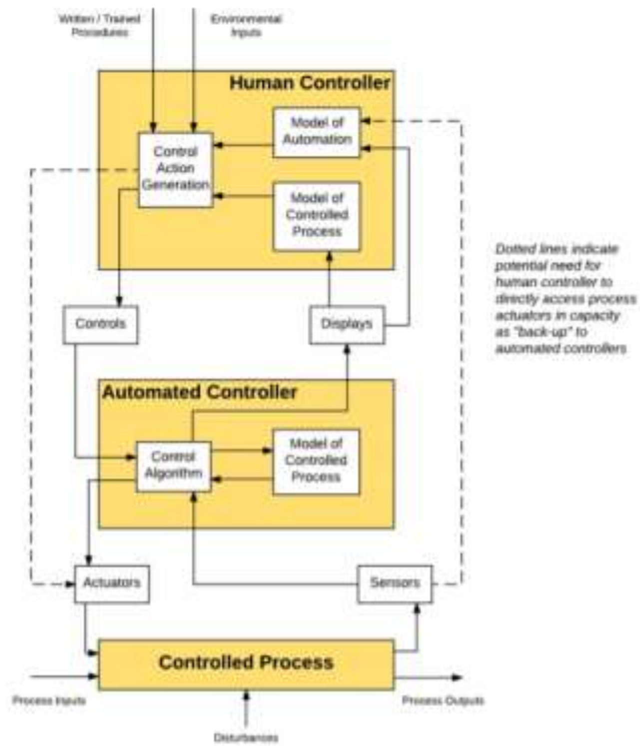

Figure 2.5: Non-linear causation model source: Safety Institute of Australia, 2012.

2.1.2 Cost of Work-Related Accidents, Injuries and Ill-health

Accident and injuries cost can be classified into direct costs and indirect costs. The direct costs are easily identified and associated with the compensation offered to workers and treatments for their injuries. Most of the direct expenses are covered by compensation insurance. Labours compensation insurance covers sick leave administration, medical expenditure and hospitalisation. On the other hand, indirect costs are expenses related to hidden costs resulting from occupational accidents. Indirect costs contain diminished productivity due to workers' shortage, project delay cost, clean-up and replacement costs. Generally, when an accident occurs, the associated indirect costs are significantly higher than the direct costs since indirect costs are sophisticated and can't be measured. The sorts of injuries and accidents cost that are not comprised in insurance are incident auditing costs, production loss, project handover lateness, tools and machines damages, legal expenses, etc.

As per the occupational health and safety data and statistics shared by Statistic Centre Abu Dhabi (SCAD) in UAE, the registered hazardous cases are 196 thousand. The construction industry represents 18% of the total cases. Moreover, the higher percentage of death cases is related to the construction sector, 47% of real 165 cases. The number of injuries that required medical treatment and first aid are 10,830 and 21,714, respectively. The significant number of injuries and death cases result in direct and indirect costs associated with these cases (Weerd, Barandiarán Irastorza and Elsler, 2014).

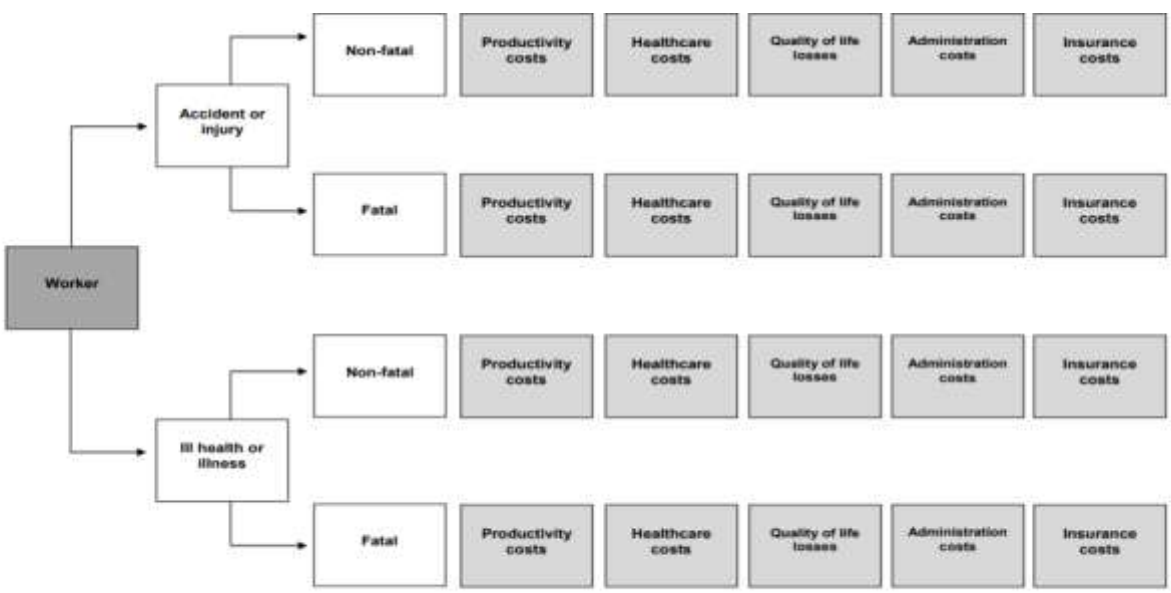

Figure 2.6: Conceptual framework of work-related accidents economic costs source: Weerd, Barandiarán Irastorza and Elsler, 2014.

2.1.3 Occupational Health and Safety Management Systems (OHSMS)

The general definition of occupational health and safety management is planning, managing and documenting processes created to monitor and control hazardous or unfavourable events. To strengthen the health and safety managing process, a systematic approach of planning, real-time monitoring, maintaining, evaluating, and correcting actions must be implemented. The management system assists the managers in allocating the resources, responsibilities, and accountabilities for employees, which will enable making effective decisions along with considering OHS standards. Workplaces' health and safety cultures are divided into two types; reactive approach and proactive approach. The reactive workplace culture deals with hazardous events and threats, lacking strategic planning and reviewing the controls after incidents. The reactive approach makes the firm more vulnerable to risks, weakening its performance. On the other hand, the proactive, systematic approach identifies risks or hazardous events, monitors and controls risk, integrates risk management in the firm system, and plans OHS activities.

The conceptual framework of OHSMS is illustrated in Figure 2.9. The organisations modify the framework to comply with their work environment. As per the ILO guidelines, the primary elements of successful occupational safety and health management system are policy and commitment, planning, implementation and operation, measuring performance, auditing and reviewing performance. Each firm at the corporate level must state occupational health and safety programmes and objectives. The policies provide clear directions for effective health and safety performance in the organisation's departments and business. Besides, health and safety policies assist in preserving company resources and that lead to minimising the financial costs and liability losses. Firms have to design and plan effective structures to accomplish structures and safety policies in the planning stages. Following to planning stage, the implementation and operation mechanisms should be executed to achieve the objectives and missions of the board level. An effective risk management system is implemented to reduce business threats and increase opportunities. The risk management system includes risk planning, assessments, monitoring, and control methods to prevent or mitigate hazardous events. The monitoring and controlling organisations are continuously measured and evaluated for further enhancements in the organisation's performance. Thus, if an accident occurs or control fails, the system will provide causes of the incident and proactively promote actions to mitigate the risks. Moreover, measuring the performance assist stakeholders in setting and achieving short term and long term objectives. Continuous auditing will improve health and safety management system performance constantly. Most organisations investigate OHS performance annually, generate safety statements for future developments, and adopt the new market changes (Health and Safety Authority, 2006).

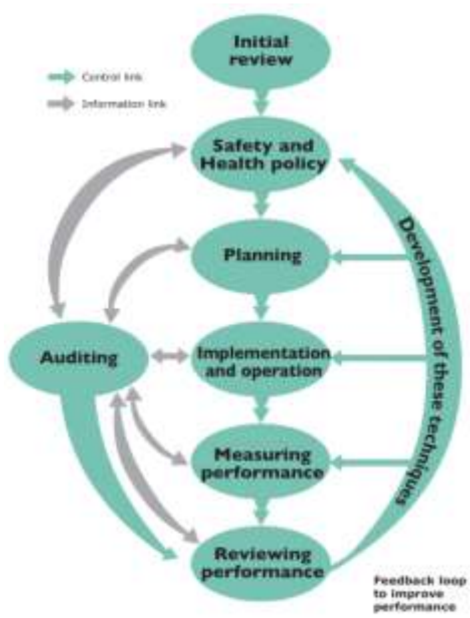

Figure 2.7: Key elements of OHS management source: Health and Safety Authority, 2006

The following schedule explains occupational health and safety system guidance.

Table 2.2: OHSMS key elements and guidances

OHSMS Model Levels	OHSMS Guidance
Health and Safety Policy	1. Commitment to protect workers from incidents and injuries associated with their activities. 2. Comply with health and safety code of practice and legislation. 3. Create a framework for measuring performance and conducting annual safety and health audits. 4. Illustrate health and safety rules and provide training for employees. 5. Allocate health and safety management responsibilities at all levels of the organisation.
Planning Stage	1. Adopt changing circumstances and new demands. 2. Establish favourable safety and health culture and improve performance. 3. Identify work objectives and programs. 4. Monitor and control risks and complies with the minimum safety and health laws.
Implementation and Operation	1. Issuing health and safety strategies for key high risks. 2. Allocating health and safety resources in workplaces. 3. Setting health and safety objectives for individuals. 4. Evaluate the effectiveness of OHSMS. 5. Ensure proper implementations of health and safety policies.
Measuring Performance	1. Generate annual assessments and reporting of health and safety performance. 2. Reflect board priorities in the safety statements. 3. Assign health and safety supervisors at the senior management level. 4. Ensure appropriate communication between departments at risk of occurrence or failure.
Auditing and reviewing performance	1. Conducting and documenting annual audits. 2. Track the implementation of newly modified recommendations. 3. Allocate responsibilities of audit findings to departments and individuals to correct actions and enhance health and safety performance.

2.1.4 Management of Health and Safety Risks in Construction Projects

The lack of knowledge and experience in determining the accident causes and insufficient safety indicators illustrated at construction sites to predict the risks restrict the sustainable developments of safety in the construction industry. When an organisation has a reactive approach to health and safety incidents, it will not insight the risks before their occurrence. As per the research, more than 90% of crucial safety accidents can be mitigated or eliminated in the pre-construction phase, such as the design stage, procurement operation or project planning. Thus, to improve the quality and performance of construction projects, health and safety risks and their causes must be identified by analysing the accidents and injuries reports that occurred at the construction sites and implementing proactive responses for future threats.

The life cycle of construction projects consists of five stages: initiation, planning, implementation, monitoring and performance, and closing. In the initial stage, project managers perform a feasibility study to decide whether it's worth it or not to undertake the projected deal. Besides, a project initiation document 'PID' must be implemented to manage the entire construction project life cycle. The second stage is planning, in which clear project objectives, procedures and deliverables along with allocating time, cost and quality must be identified. Thus, the critical factor for project success is to set smart, specific, measurable, and timely goals. The implementation stage includes resource allocation, tasks assignment, execution of management plan, monitoring and controlling progress, and project modifications. The project planning and execution performance will be monitored and measured through key performance indicators 'KPIs'. KPIs assist managers and the board of directors determine the project budget and controlling cost, monitoring progress, estimating deliverables quality, and ensuring achievement of objectives. The final stage is project closing, where construction processes review and lessons learned of previous project stages have to be documented for future projects. To summarise, the key factors of project success, objectives, planning and deliverables must be settled before the construction phase. Conducting precise planning in technical, operational and economic aspects at the early stages of the project influence the outcomes and increase opportunities. Furthermore, feasibility plans assist in creating detailed and accurate solutions that lead to making preferable decisions. One of the critical success factors is hazard or risk identification, which must be initiated in the pre-construction phase, monitored and controlled through construction and handover phases (PHOYA, 2012).

Figure 2.8: Life cycle of construction projects source: PHOYA, 2012.

There are two types of traditional indicators: the ‘lag’ indicator that measures the risks and installs controls after they occur. The other indicator is ‘lead’, which is developed to predict risks before their occurrence. The lag indicator concentrates on the preceding failures instead of present and future opportunities. The lead indicator is established based on systematic processes but doesn't identify crucial risk sources and challenging events. Furthermore, both traditional indicators can deal with known risks but not uncertainty in which recently uncertain events appear in all global businesses. Indicators must be designed and implemented to identify risk events and their causes to provide effective decisions prior, during and post the project lifecycle where the lag and lead indicators are inadequate to mitigate or eliminate risk challenges. The characteristics of a successful indicator are measured by their ability in providing real-time safety performance indications, assist in implementing the safety process and integrate the control of three elements; employees, procedures and systems. Besides, it focuses on giving insights to predict certain and uncertain risks, promote risk responses and support organisations to be proactive (Deloitte, 2014).

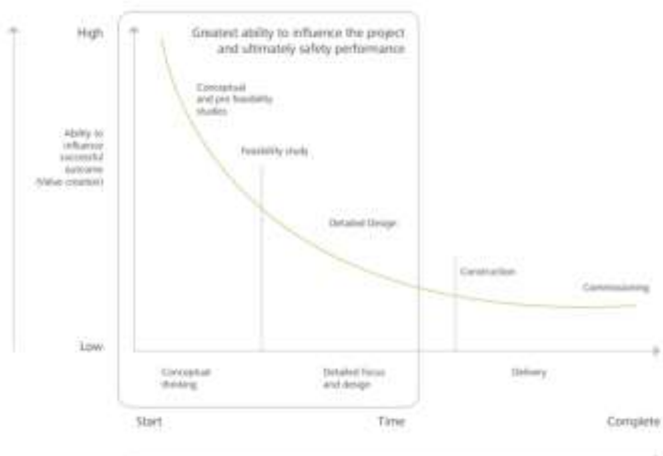

Figure 2.9: Relationship between project success and project stages lifecycle
source: Deloitte, 2014.

According to the competitive market and new challenges associated with the businesses, several factors drive the need to change occupational health and safety frameworks. The following points are the change drivers:

i. Government policy and regulations in OHS

ii. Stakeholders liabilities in safety governance

iii. Modern operationaeconomicomical risks

iv. Technoladvancesaces

v. Integrating health and safety elements in project deliverables

Project stakeholders require early indicators to foresee safety risks and systematic processes to recognise the impacts of risk occurrence on the project. To achieve efficient safety performance during the life cycle, organisations involved must predict what may go wrong and what should go right. Government and private firms can apply potential risk prevention criteria to reinforce project effectiveness.

i. Establish an intelligible safety system

Real-time controls are essential to monitoring project operations, and site works. Effective accountability mechanisms must be implemented to allocate responsibilities and resources, manage risks and monitor project tasks performance before and during the construction phase. Furthermore, leaders continuously measure safety strategies and decisions performed at the construction site by evaluating the project.

ii. Benefit from preceding projects’ data

Organisations leverage previous construction project data by analysing the risk causes and impacts on the project life cycle. Predicting risks based on past knowledge and experience motivate project managers to design safety indicators and construct critical safety activities. The performance of safety is evaluated by counting the number of lost workdays, the number of injuries and death cases, and financial expenses. Thus, to avoid losing these simple measurements, accurate, robust and reliable safety indicators are installed in the construction sites. Besides, intelligent IT systems facilitate the vast amount of risks data analysis.

iii. Predict incidents and prevent them from an occurrence

As discussed earlier in the research study, incidents are a series of failures generated from insufficient processes, decisions and systems. The ‘swiss cheese’ incident causation model highlights the prevention criteria utilised to combat occupational risks. The ‘Swiss cheese’ model is considered one of the most functional risk management models that illustrate an effective combination of risk controls in the construction sector. To eliminate or reduce risks occurrence, organisations are required to develop intervention strategies that focus on the causes of the incidents.

iv. Benchmarking in the construction sector

Examining the construction market and learning from other organisations’ experiences in dealing with risks and hazardous events assist managers to establish health and safety activities in the pre-construction phase. Studying the sophisticated risk data analysed from the market improve health and safety strategies for current and future projects. In addition, enhancing health and safety projects performance result in gaining a competitive advantage in the market.

v. Evaluate safety performance by measuring the return of investment

One of the main advantages of implementing a health and safety system at construction projects is saving costs from preventing the incidents. Although the safety system and intelligent indicators add expenses to overall project costs, they assist managers in making more effective decisions and reducing health and safety threats and their related costs (Deloitte, 2014).

2.1.5 Risk Management Processes for Construction Projects

Due to economic crises and market challenges, R&D departments worldwide focus on improving project risk management strategies. The heterogeneous and complex nature of the construction industry increased the demand to monitor and control the uncertain events during construction project phases. Following the project management institute (PMI), project management's main nine knowledge areas are integration management, scope management, time management, cost management, quality management, human resource management, procurement management, communications management, and risk management. All of these areas are equally essential but depending on the critical outcomes of each project case, project managers will focus more on specific key areas. Nevertheless, risk management is the most crucial aspect because of its uncertain and ambiguous characteristics. Through the comprehensive systematic methodology, project stakeholders can identify the root causes of risk events and their consequences with the best possible effective responses. The methodical technique utilised by several authors includes risk identification, risk assessment, risk mitigation and risk monitoring. The identification stage is an iterative process in which new risks are recognised, and their effective responses will become known. The previously identified risks become more flexible and easier to deal with. The identification process supports project stakeholders in selecting significant risks to make further analysis and preferable decisions. The assessment stage of risk is divided into quantitative and qualitative research. The risk factors are specified by illustrating checklists, brainstorming and interviews ‘qualitative’ study or through numeric data “quantitative” analysis. The assessment process evaluates risk by analysing its consequence as insignificant, minor, moderate, major and critical, and its probability of occurrence as rare, unlikely, possible, likely and almost certain. In construction projects, the quantitative methodology requires advanced techniques such as machine learning algorithms ‘ML’, multi-criteria decision making ‘MCDM’ and Monte Carlo Simulation to examine and investigate the consequences and likelihood related to the occurred risks. These techniques assist project managers and engineers select the most efficient risk strategy among risk mitigation, risk avoidance, risk transfer or risk acceptance strategies (Cooney, 2016). An essential procedure after the risk assessment is to rank the risks based on the probability and consequences of their occurrence. A common and straightforward ranking mechanism is to use risk matrices. The matrix is divided into column ‘likelihood/ probability/ frequency’ and rows ‘severity/ consequence/ impact’, forming a block of risk that increases radically from insignificant to the extreme. Additionally, a colour-coding technique is added to seek the attention of project stakeholders for the importance of danger. The main concept of the matrices is to level and prioritise identified risks to plan for risk responses and facilitate the decision-making process. There are three different types of risk matrices. The first type is a qualitative matrix where its blocks represent descriptive terms, the second type is quantitative, and the blocks have measurable terms or numerical scale. The third is a hybrid type described as semi-qualitative and semi-quantitative matrix and illustrated measurable and descriptive words (Elmontsri, 2014).

2.1.6 The Fundamentals of Health and Safety Standards in UAE

The economic growth of the United Arab Emirates (UAE) expands annually; thus, the demand for health and safety standards have increased to manage occupational health and safety (OHS) risks and protect the workforce. The importance of OHS developed by the UAE government affirmed to reduce risks at the workplace, prevent accidents and facilitate occupational health and safety management for individuals, organisations and government entities. The standard of Occupational Health and Safety Management System (OHSMS) followed by UAE is national standard AE/NSCS/NCEMA 71000:2016. The standard was developed based on studies applied in UAE workplace incidents and injuries cases. According to UAE law, all government and private sectors must implement OHS standards among their organisations. The fundamental causes of health and safety incidents in UAE are insufficient safety planning, inadequate safety culture and improper safety governance. The causes are related to poor safety planning due to inappropriate conduction of OHS risk assessments. Besides, the lack of safety governance is because of inadequate supervision at work operations and inadequate knowledge of safety systems. Additionally, the poor safety culture arises from a lack of safety awareness and improper safety behaviours and attitudes (AE,NSCS&NCEMA, 2016).

The occupational health and safety management systems (OHSMS) performed in UAE organisations assign the requirements for establishing, assessing and evaluating occupational risks. Furthermore, it assists the organisations in complying with UAE regulations, ensuring achievements of OHS objectives, and integrating OHS protocols in organisations’ business processes and departments.

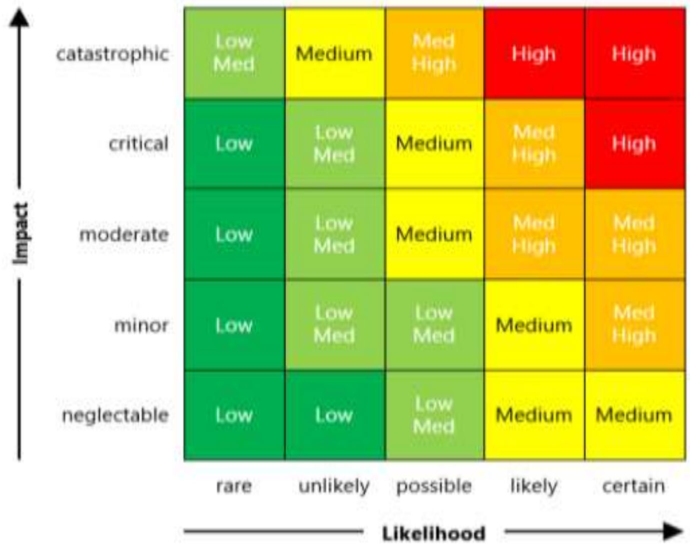

Figure 2.10: Classic 5x5 risk matrix source: Risk Matrices, n.d.

2.1.6.1 UAE OHSMS Framework

The critical stakeholders among UAE organisations and National Crisis & Emergency Management Authority (NCEMA) collaborated to establish and evolve the OHSMS framework. The framework layouts the structure of OHS standards and guides organisations to perform a comprehensive OHSMS. It includes five essential elements: governance, OHS culture, personnel management, OHSMS and OHSMS performance management. The governance indicates an organisational structure that supports assigning employees, managers, and corporate responsibilities to implement and develop OHSMS. The culture of OHS refers to the individuals and group attitudes, values and commitments to the organisation's OHSMS. Additionally, personnel management emphasises if the employees can utilise OHS procedures and processes in their functions. OHSMS define risk management methodology and required systems to identify and manage risks. Besides, the OHSMS performance management measures and continuously monitor the performance of tactical and operational levels (AE,NSCS&NCEMA, 2016).

Figure 2.11: UAE OHSMS Framework source: AE,NSCS&NCEMA, 2016.

2.2 Machine Learning Algorithms' their Role in the Construction Industry

2.2.1 Introduction

The industrial revolutions were developed through four eras; the first phase is steam/water the power, the second one is electricity, the third is computing, and the fourth phase is driven by artificial intelligence and big data algorithms. The industrial 4.0 revolution or intelligence revolution focuses on providing smart machines such as robots, cloud computing and drones the ability to 'think' and 'act'. The concept of artificial intelligence 'AI' indicates the machines' capability to learn and understand from human experience, identify objectives, analyse data, make decisions and solve issues. Integrating artificial intelligence in all types of businesses makes the marketplace smarter. AI and big data revolution insight the organisations to rethink and modify strategies related to manufacturing products using more innovative technologies, offer better services, facilitate business processes and develop effective business models.

The second part of this chapter provides a general background of artificial intelligence and machine learning algorithms, examines different types of ML algorithms and their working methodology, illustrates a few examples of business sectors that require ML algorithms and focuses on the construction business with discussing the impacts on construction projects health and safety, time, quality and cost of ML applications. Additionally, it summarises the common challenges faced in implementing and adopting machine learning algorithms.

2.2.2 Artificial Intelligence and Machine Learning

Innovative solutions should be evolved and integrated within organisations ' systems to improve the sustainability and quality of business activities and reduce costs. Artificial intelligence is defined as the science and engineering utilised to make machines more intelligent and efficient. The driven 16 smart technologies produced from AI are data mining, reasoning, genetic algorithms, systems, programming, artificial life, distributed AI, expert systems, constraint satisfaction, belief revision, theory of computation, theorem proving, natural language understanding, machine learning ‘ML’, enetic algorithms and neural networks. Machine learning is one of the methods created in 1959 to assist the implementation of artificial intelligence. It’s defined as the field of study which provides machines with the ability to learn and understand without being programmed. Both AI and ML techniques have critical advantages such as solving critical issues, enhancing global sustainability and predicting the changes of the business processes in the future age.

Machine learning was generated from artificial intelligence to deal with the computational data complexity related to various work fields. Thus, machine learning algorithms are developed in intelligent machines to resolve high degree polynomial datasets. The complication of machine learning methods is due to time consumption in training the machines to rapidly adapt the algorithms and detect specific test points among many analysed datasets. Machine learning algorithms' main problems are network analysis, regression, classification, and segmentation. The criteria utilised to select the best fit solution depend on nominating data features, analysis method, data size and association between different data features. The algorithms of machine learning used as solutions consist of four types: supervised learning, unsupervised learning, reinforcement learning, and evolutionary learning. The supervised learning algorithm is established based on prepared exemplars and training sets in which it generates correct responses to possible inputs. The unsupervised learning algorithm doesn't have a set of valid responses where it recognises the similarities between several inputs by categorising them into their standard features. The density estimation statistical approach detects the similarities of the input. The reinforcement learning algorithm can identify wrong responses but can't provide methods to correct or improve them. It keeps generating various possibilities until it figures out the most proper answer. The evolutionary learning algorithm uses a similar idea of biological organisms' learning process where it adopts the new environment, keeps improving its res, and continuously measures the current solution's effectiveness. Each algorithm can solve certain types of business issues (Zicari, 2018).

2.2.3 Machine Learning Algorithms

As discussed earlier, the theory of machine learning was obtained from the human mind's thinking process. Human beings continuously enhance their methods in tackling the issues they face by learning from their previous experiences and mistakes. The domain of machine learning determines critical problems and promote effective solutions by utilising computer programs that can learn, enhance their performances and adopt new changes by gathering information and data. Machine learning algorithms were classified based on several strategies, types of input data and computer program models. Traditional computer programs can't perform any data inference, and their knowledge is only implemented by software programmers and developers since the system can't conclude from given information. This sort of strategies called rote learning. Another machine learning strategy that evolves to rote learning is transforming information and instructions from given input language to internal computer coding. The transformation combines both programmers' coding and built-in forms of inference. Conversely, learning by analogy provide machines and computers with the ability to adopt changes, develop new functions and skills and create combinations of a knowledge set. This type of machine learning requires many inferences. Additionally, the most common machine learning strategy is learning from examples known for their flexibility, among other strategies. It enhances the capability of computer programs to develop unknown skills or generate various structures and patterns from a set of data. The tasks related to data mining and data classifications are performed by learning from examples technique which assists in predicting the new input data using a dynamic set of recognised examples. In the following section, the most common systems of machine learning algorithms will be examined (Poh, Ubeynarayana and Goh, 2018).

2.2.3.1 Artificial Neural Networks

Singh and Chauhan founded the Artificial Neural Networks technique. It is defined as the mathematical model established based on the biological neural networks where it can be considered a simulation of the biological neural system. The self-organising nature and simple structure features of Artificial Neural Networks facilitate addressing and solving a broad range of problems without programmers' interventions.

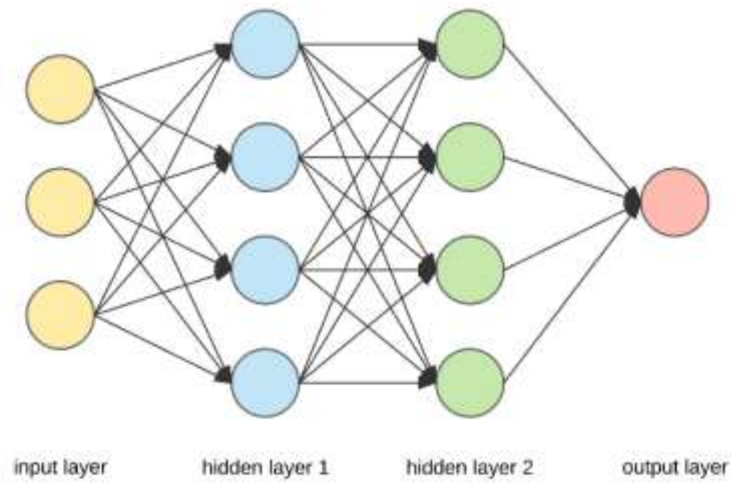

Figure 2.12: Artificial Neural Networks technique source: LUCKERT and KEHNERT, 2015.

The architecture of an Artificial Neural Network contains neurons or called nodes. The connections between these nodes determine the output value based on input values and designated functions. Each neural network has several layers where each layer combines various nodes. External sources of information and data, such as the data entry for attributes value, are received in the input layer. The output layer includes the outcomes of the neural network, and hidden layers link the input layer with the output layer. The measurement of input value in each node results from the sum of incoming nodes' values multiplied by the respective weight of the correlation between the nodes.

Moreover, the primary neural networks types are recurrent and feedforward networks. The recurrent networks represent all networks that include feedback options and can reapply the data from later phases in the earlier phases of the learning process. The nodes' outcomes are determined in a neural network by utilising input values on a predefined function. Besides, the feedforward networks contain all the networks with no feedback gained from the network itself. This type of neural network data flows in one direction from the input node to the output node through '0' to 'n' hidden nodes. Unlike the recurrent type, the information doesn't flow backwards from later stages to earlier stages (LUCKERT and KEHNERT, 2015). The following equation represents the new weight of connection in a neural network.

$$W = l \times \varepsilon + m \times W_P$$

Where

W : new weight change.

l : learning rate.

ε : minimal error.

m : momentum.

W_P: the weight change of the previous cycle.

The main parameters utilised in neural network learning and training processes are learning rate, momentum and minimal error. Learning rate identifies the speed of an executed learning process, and the rate value lies between 0 and 1, which will be multiplied by the local error for each output result. When the learning rate value is set at a high value, the weights will fluctuate and complicate the process of optimal values finding. Conversely, setting a low value for the learning rate will reduce the weight of the errors and get stuck on the local maxima. Additionally, the momentum is used to soften the optimisation process by utilising a fraction of the last weight change and adding the new weight change. The minimal error represents the stopping standard for the learning process in which if the error value falls under the threshold value, the learning process stops (Zicari, 2018).

2.2.3.2 Decision Tree

A decision tree is one of the common classification techniques used in machine learning algorithms. Attribute vectors are sort of the data sets that decision trees process, consisting of classification attribute categories. These categories represent the vector and a class feature where the data entry will be assigned to a specific class. The decision tree technique divides data into various existing types built on each category based on a specific common attribute. The advantage of the decision tree form is that it represents summarised overview of data using a simple structured tree format to support stakeholders illustrating successful decisions.

The first decision tree algorithms, Iterative Dichotomiser 3 (ID3) and the C4.5 algorithms were developed by Ross Quinlan in 1986 and 1993. The decision tree consists of a root node that indicates the begging of the decision support process, inner nodes with one entry edge and two or more outgoing edges, and end nodes or leaf nodes representing the decision process's closure. Internal nodes are highly fundamental in the decision tree technique since they include a test applied on a data set based on a specific attribute. Furthermore, solutions to the decision problem are provided in the leaf nodes with only one incoming edge and no outgoing edges. The purposes of a decision tree are to make data set classification then to predict the result of a certain attribute from a group of input attributes (Charbuty and Abdulazeez, 2021). A training set with supervised scenarios must be implemented to figure out the patterns of data and establish a decision tree.

Besides, a set of past examples and experiences support in predicting the attribute value. The data set is recorded in the form of the below equation.

$$(\vec{x}, Y) = (x_1, x_2, x_3, \ldots, x_n, Y)$$

Where

Y : the target attribute value.

x : vector containing n input values.

n : number of performed attributes in a data set.

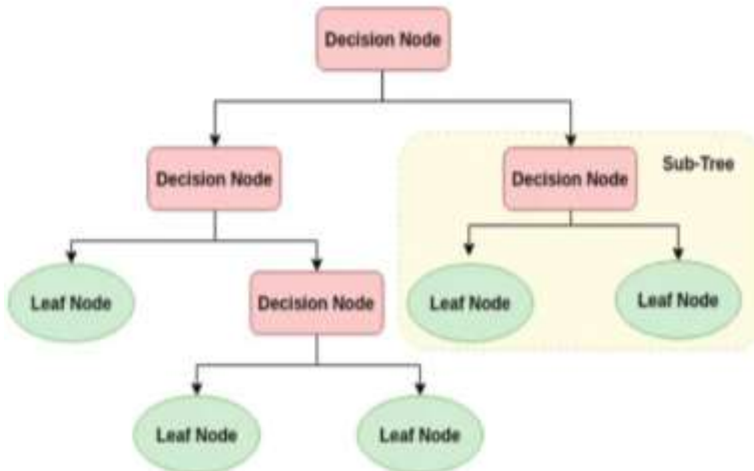

Figure 2.13: Decision Tree technique source: Charbuty and Abdulazeez, 2021.

2.2.3.3 Random Forest

Random forests 'RF' technique collects numbers 'n' of decision trees 'DT'. Each decision tree has a diverse set of dynamic parameters and is trained based on different functions and subsets of data. Consequently, the outcome predictions or decisions vary among several decision trees. For example, if one test data is performed over a significant number of decision trees, the result will be selected depending on the similar majority outcomes. In addition, the random forest is one of the supervised learning algorithms that can be utilised for data classification and regression tasks. The fundamental advantage of the random forest method is that it processes the data in a simple, stable, and reliable manner. The random forests technique randomly selects x number of features represented in the ‘columns’ and y number of examples that illustrate in the ‘rows’ of a subset of original data. Compared to the decision tree ‘DT’ algorithm, random forest ‘RF’ votes are based on iterative output decisions rather than accepting one output decision (Random Forests in Machine Learning | Random Forests for Data Science, 2020).

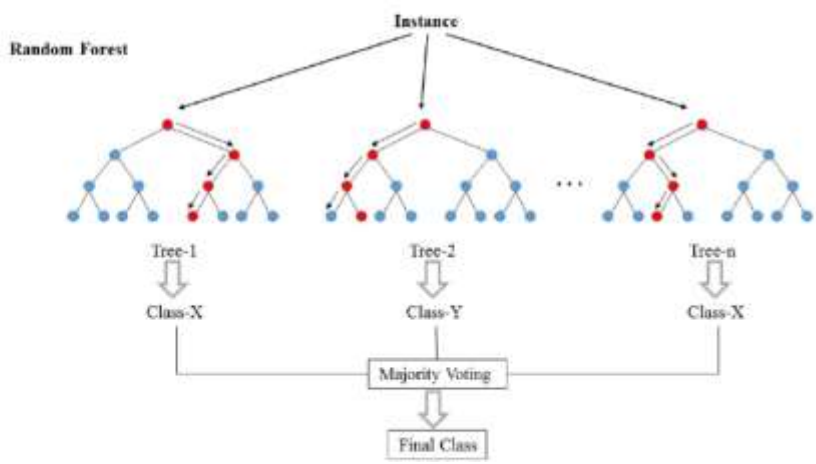

Figure 2.14: Random Forest technique source: Random Forests in Machine Learning | Random Forests for Data Science, 2020.

Regression problems can be solved using a random forest algorithm by calculating the mean square error ‘MSE’ as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2$$

Where
MSE: mean square error.
N : number of data points.
f_i : returned value by decision tree model.
v_i : actual value for data point *i*.

The distance between each node is calculated from the predicted actual value. The output value support selects the best branch that gives the most effective decision among other branches in the forest. Additionally, along with solving regression problems, RF can solve classification problems by implementing the Gini index. The following Gini index equation assists users to make data classifications by determining the class and probability of each branch to know which one is more likely to occur (Random Forest Algorithm for Machine Learning, 2019).

$$Gini = 1 - \sum_{i=1}^{c} \left(P_i\right)^2$$

Where
P_i: relative frequency of the class.
c : number of classes.

2.2.3.4 Support Vector Machines

An additional type of machine learning related to supervised learning is the support vector machines 'SVM' method. The approach of support vector machines technique initiates by labelling known data and classifying the data based on the created function that separates the data points to their corresponding labels. Data points splitting process is performed either by considering the least feasible amount of errors or the highest possible margin. Since there are many cases when data sets separate properly without any mistake arising using multiple functions, an additional parameter, the margin, is utilised to evaluate the quality of the splitting process. In n-dimensional space, the support vector machines technique formalises one or multiple hyperplanes to split data set into categories linearly. The two main focuses founded by Steinwart and Christmann are the non-linearity of data separation and the potential overfitting of SVM. All the cases in the real world generate non-linear inseparable data since the same attribute vector might have various labels. This issue can be overridden by implementing the kernel trick that maps data from a specific n-dimension into a larger dimensional space. Furthermore, the SVM overfitting can be avoided by pre-processing the data to remove the noises and accept certain tolerance of misclassifications (LUCKERT and KEHNERT, 2015).

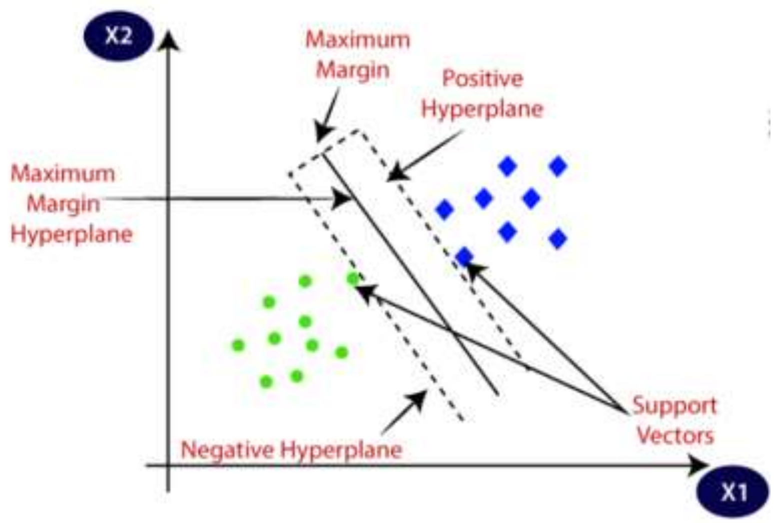

Figure 2.15: Support Vector technique source: Support Vector Machine (SVM) Algorithm - Javatpoint, 2022.

2.2.3.5 Instance-Based Learning (KNN)

The instance-based learning, also called the K-nearest neighbour 'KNN' learning, explains solving issues based on known problems. The main parameters of instance-based learning are the distance function which measures the similarity between data or problems inputs to obtain the closest neighbours, the number of neighbours determined to tackle a new problem. This weighting function assists in predicting the nearest neighbours and increase learning quality. Evaluation criteria to provide a methodology for solving the new problem using selected neighbours. This machine learning technique is considered a static learning method since it doesn't calculate the data before any request is provided to the system (LUCKERT and KEHNERT, 2015).

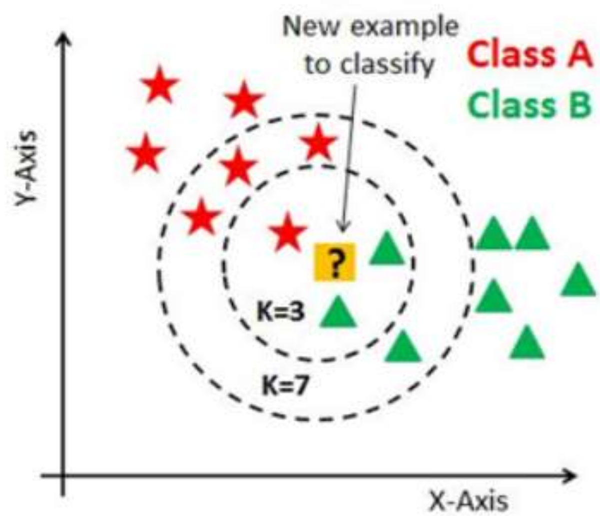

Figure 2.16: Instance-Based Learning (KNN) technique source: Shaier, 2019.

2.2.4 Applications of Machine Learning Algorithms

Machine learning applications utilise algorithms to learn from data sets obtained in a business continuously. With every iteration, the system will collect new data, compare it with past data entries and separate it into further enhancements. Algorithms will enable the system to have better insight and interconnect random new information to previously known data. The primary benefit of machine learning algorithms is that programmers don't need to program and constantly interfere with making system improvements explicitly. In addition, the algorithms are used to develop business operations and scalabilities in worldwide organisations. The main enhancements provided by machine learning algorithms are data collection, storage of data, efficient and quicker data processing, and improved work execution quality. Other fundamental advantages of implementing machine learning algorithms are extracting essential information from many raw data sets and providing diverse solutions to complicated businesses and customers. The following points represent the positive consequences of machine learning.

i. Remove manual entry and process of data

Machine learning applications continuously detect data by monitoring the work progress, classifying the data into labels, and processing them automatically without human interventions.

ii. Lifetime value prediction

Customers' behaviour and purchase pattern can be predicted using machine learning algorithms. It provides the preferable offers to customers by analysing their previous purchases.

iii. Reinforcing cyber security

To improve the performance of cybersecurity systems, machine learning algorithms eliminate or reduce systems vulnerabilities, potential spyware, and malware depending on the user data.

iv. Boost customer satisfaction

Enhancing the performance and quality of work will increase customer satisfaction. Customers' calls are recorded to obtain their behaviour and predict their requirements to improve customer service execution.

v. Maintenance prediction

The risks associated with maintenance business are unforeseen failures and unnecessary expenses that can be effectively reduced or eliminated by executing machine learning algorithms. The prediction of maintenance data is initiated by reviewing previous data, implementing workflow visualisation tools, analysing the surrounding environment, and evaluating the feedback from the process.

vi. Image recognition

Numeric and symbolic data of images and multidimensional data are produced using computer vision, database knowledge detection, pattern recognition, and data mining, which are machine learning techniques.

vii. Financial analysis

In the finance sector, machine learning assists managers in detecting frauds, underwriting loans and algorithmic trading. As well as improvements in banking security systems and customer service.

viii. Medical diagnosis

The Healthcare industry is one of the critical businesses which requires innovative prediction systems. Artificial intelligence and machine learning foresee readmissions, identify potential threats, and select the most proper decisions based on documented patients' records (Imran, 2019).

2.2.5 Smart Construction using Machine Learning Algorithms

There are many areas of improvement in occupational health and safety despite the advanced techniques and robust technology used in health and safety management. Occupational risks are analysed and studied through software modelling and simulation. The relationship between health and safety performance and other project factors such as quality, productivity, duration, direct and indirect costs is examined by researchers. The fuzzy qualitative risk management model is a social science technique that combines case-oriented and variable-oriented analysis to reduce occupational risks. Another model is the real-time risk evaluation which assists in reinforcing the quality of construction projects. Additionally, the iceberg theory has been performed to analyse the indirect cost. Besides, the cost-benefit analysis quantify the direct and indirect costs related to health and safety accidents in the construction sector. With the benefit of improving the performance metrics in the construction field, several techniques and simulations of health and safety risks are conducted (Alkaissy et al., 2020).

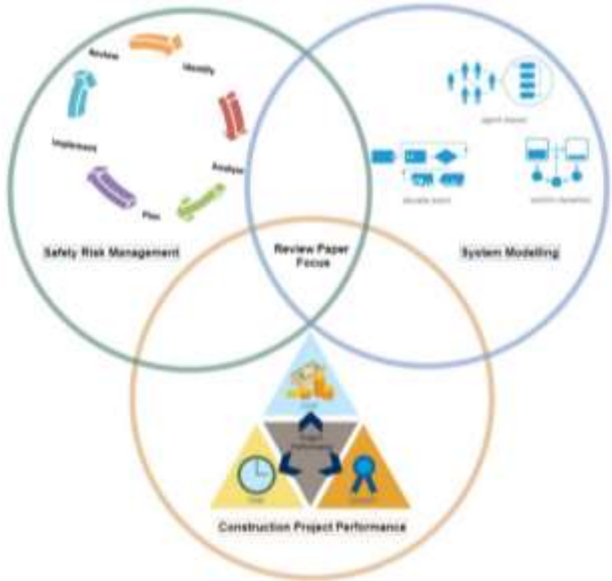

Figure 2.17: Integration of smart construction and risk management source: Alkaissy et al., 2020.

Business entrepreneurs integrate artificial intelligence and machine learning in worldwide businesses and operations due to its positive impacts and valuable achievements. Since the construction industry computes 7% of the global workforce, intelligent systems and developed technologies reinforce business productivity and quality. The growth of the construction industry is relatively low compared to other industries, where it accomplished 8% of the annual growth between 2014 and 2019. To increase the annual growth of the construction industry, artificial intelligence and machine learning are merged in the business operation and strategy. Both artificial intelligence and machine learning algorithms can transform traditional construction into intelligent construction. The benefits of machine learning algorithms in the construction industry will be explained in the following part.

2.2.5.1 Project Health and Safety

Over decades of experience and statistics, researchers studied and examined the incidents and their causes in the construction sites. The significant difficulties in the construction business involve several stakeholders who are highly exposed to various risks. Furthermore, Human mind capabilities are limited to the number of details they can handle and process. Thus, machine learning algorithms will process and analyse significant amounts of data from previous projects' incidents to assist the project team in health and safety risks prediction. Most construction accidents result in fatal outcomes. To create better health and safety accidents prevention, organisations from the construction industry gather and study previous incidents data to learn from past experience and improve health and safety systems. Moreover, along with the last short-term goals, long-term objectives can be achieved using machine learning algorithms, such as increasing the value of customers and boosting the company's production. Among worldwide firms, Autodesk company applies machine learning algorithms in real projects to improve risks detection and mitigation through project IQ management software. This type of software has the accessibility to millions of construction data and the ability to predict risks and classify them into categories. Contrary to traditional risk techniques, the smart construction attribute-based approach describes the incidents and injuries as the consequence of mutual occurrence and interactions between workers' behaviour and the surrounding environmental conditions. Extracting the data features from incidents and injuries reports can illustrate the constitution of a structure and generate a prediction mechanism based on discovered knowledge. The effectiveness of the health and safety framework is based on several methodological factors: define specific data attributes, qualify and quantify the incident reports, develop a technique for attributes extraction, and use machine learning algorithms in the prediction paradigm (Alkaissy et al., 2020).

2.2.5.2 Project Quality

The quality and productivity of construction projects can be improved by integrating machine learning algorithms in their construction management software. The monitoring and controlling processes of the construction process are tracked through management software. The monitoring process includes observing flooring, plumbing setup, electrification and brickwork. If any risk occurs before or at construction projects, the system releases alerts, and managers and engineers can take corrective actions. Eliminating or reducing project threats will save time throughout the project procedures, make workers focus on their respective rules, and decrease cost overruns. Additionally, applying artificial intelligence and machine learning algorithms will reinforce the risk assessments in more accurate and faster methods. Due to the machine learning capability in gathering and processing significant amounts of data, risk events will be monitored, assessed and mitigated. The productivity of risks will be highly increased by monitoring and controlling the risks and their potential causes (AI and machine learning: What's in it for the construction industry?, 2019).

2.2.5.3 Project Time

Almost 70% of the construction projects experienced time overruns in which real projects failed to comply with the time frame designed in the pre-construction stage of the project. The delay of the projects will lead to cost increment and reputation losses. Digitalising the construction projects by training the machine learning algorithms based on the past data establishing realistic time schedules will optimise the ability to plan projects effectively and improve the project performance. Besides, algorithms will promote time reliability that assists in reducing certain and uncertain risks and their effects on both the organisations and the stakeholders.

2.2.5.4 Project Cost

One of the crucial threats in the construction sector is its low margin and profitability and its high exposure to risks. Due to these reasons, the industry endures several obstacles. In the construction design phase, most projects' procedures and associated costs are effectively planned using innovative systems despite predictable or unpredictable events. The improvements in project planning and cost prediction can be achieved by training the machine learning algorithms to recognise projects' input and output data that determine cash flow through all project processes and decrease the probability of financial risks. The elimination of cost overrun is obtained by machine learning techniques to reduce accidents occurrence and causes, boost the manufacturing process and meet the project time frame without diminishing the quality. Figure 2.42 displays the construction project phases and which stage is more effective to reduce the cost overrun (Tixier, Hallowell, Rajagopalan and Bowman, 2016).

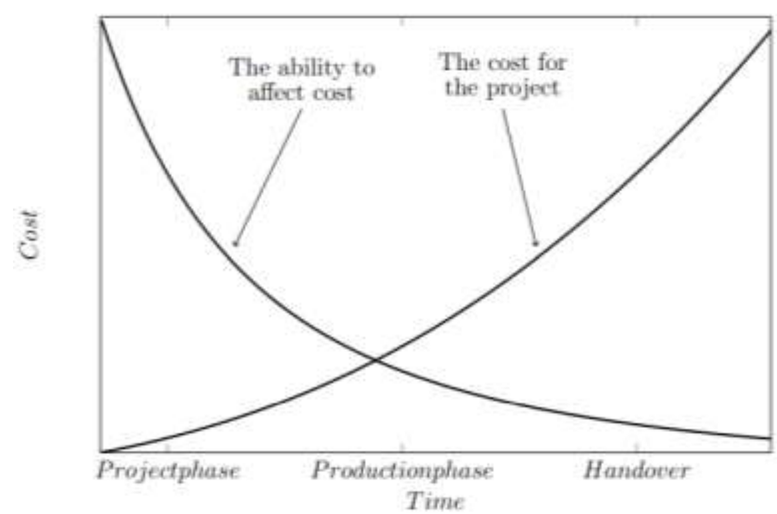

Figure 2.18: Cost during construction project phases source: Tixier, Hallowell, Rajagopalan and Bowman, 2016.

2.2.6 Challenges of Machine Learning Implementation in Industry

Machine learning solutions are developed to provide better insights, develop innovative solutions and overcome business challenges. Thus, the challenges of implementing and adopting machine learning techniques must be examined. Machine learning supports organisations in understanding the occupation data sets, automating business procedures, and improving productivity and revenue. Most organisations struggle at the early stage of nominating machine learning algorithms. The most frequent machine learning challenges faced by the majority of firms are related to business objectives alignment and persons' attitudes. The main six challenges associated with integrating machine learning algorithms with organisation systems are demonstrated in the below list of points.

i. Robust business models

To facilitate the implementation of machine learning systems, business agility, innovation and resilience should be merged in the organisation policies at the corporate level. Additionally, the firm attributes include flexible infrastructure, employees' behaviours and skills, and internal culture. Nevertheless, machine learning implementation is not the main struggle where prompt and flexible experiments must be conducted to improve the data learning process performance and to guarantee the success of adopting the algorithms. Even though the machine learning strategy failed in some cases, it enables the organisation to learn from the outcomes and initiate correction criteria in structuring a new design for robust machine learning. The iterative process of learning from past data or failures boosts the chances of adopting machine learning.

ii. Lack of knowledge and experience

The high-risk challenge of adopting machine learning is a lack of knowledge and talent. Since technology developers create several machine learning systems in all businesses, it will take some time for workers from various sectors and industries to be experts in using the machine learning systems. Machine learning is one of the complex IT systems that evolved in the 4th generation of the IT industry, where the number of experts is limited. If employees don't have the sound capability in dealing with IT systems, they will not be able to use machine learning applications. Due to the importance of machine learning in business developments, the demand for field experts has increased dramatically. Therefore, data scientists' average salaries are considered one of the highest paying careers among others. Two solutions can be provided to overcome the lack of knowledge: partnering up with organisations specialised in illustrating ML systems that fulfil organisations' goals and training stakeholders to use ML applications based on their assigned tasks.

iii. Lack of appropriate infrastructure

Not all companies are established on a robust technology basis. Poor technological infrastructure will fail to implement data learning, modelling, and reusability. In contrast, robust infrastructure assists in implementing and testing ML algorithms using various tools. Besides, it enables organisations to generate frequent tests to develop the best ML solutions that provide desired outcomes. Therefore, to overcome the lack of infrastructure issue, firms can consult ML system specialists to establish proper IT infrastructure and obtain suitable data models. Moving forward, they can compare the outcomes produced by implementing various scenarios where according to the results, the best design will be applied and adopted. The ML testing method called stratification draws a random sample from a data set representing the actual population. The concept stratification refers to randomly separating the dataset into specific categories and representing the resulting subsets. The standard practice is to split the dataset group based on the stratified method (Challenges faced by businesses in adopting Machine Learning, 2022).

iv. Data inaccessibility and security

Data availability is one of the critical challenges in the construction industry due to its importance in implementing machine learning applications and training the algorithms to fit corporate strategy. Few data will generate sufficient models; therefore, data gathering, storing and categorising are essential processes in construction projects. Besides, data security is an important aspect to differentiate between insensitive and sensitive data that will be utilised to apply efficient machine learning. Organisations tend to store sensitive data by encrypting it in several fully secured and monitored servers. Trusted stakeholders can access common company data since confidentiality is not required (Barriers to AI adoption: challenges faced and ways to overcome, 2022).

v. Time-consumption of ML implementation and adoption processes

Many organisations consume a lot of time and effort in integrating and adopting machine learning algorithms in their procedures. The business board of managers always expect rapid outcomes and efficient problem solving from initiating the process of ML applications. The implementation of ML algorithms is highly complicated compared to traditional software installation. It contains diverse techniques such as data collection, categorisation and processing to train ML algorithms and make it learn from the data developed to fit the company goals. It includes several complex planning and detailed task execution. Due to uncertain events and multiple procedures that impact the fashion of ML algorithms, the actual planning and execution time doesn't usually meet the estimated time provided by the project team for the completion date. Thus, managers and employees must have the patience and proper technical approaches to engage ML applications in their projects to solve this issue.

vi. Finance affordability

To effectively adopt machine learning in projects, project managers and data engineers can assist in the adoption process rather than utilising a data science team since start-ups and small firms can’t afford the high cost. The adoption of machine learning requires various plans wherein the plans fail to provide desired outcomes; another project will be operated to achieve the desired results. Furthermore, to know the most suitable algorithm for a specific business operation that aligns with the organisation's mission and objectives, the organisation has to perform several experiments to accomplish the desired findings. It’s essential to recognise the company's financial position to decide if it has a budget to either assign a third-party machine-learning consultant with the experience and expertise or train certain employees or managers to deal with ML algorithms. Machine learning consultants provide effective solutions that support making rapid decisions and improving productivity (Challenges faced by businesses in adopting Machine Learning, 2022).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter aims to examine previous research studies and describe the adopted research strategy in this study. The chapter reviews the standard research approaches, including quantitative, qualitative, and mixed methods. The represented qualitative method contains literature review and survey techniques. The quantitative method is applied in the form of simulation and computer science algorithms techniques, where the combination of quantitative and qualitative methods is the mixed method. After that, the selection of research methodology, its justification and the associated software required to illustrate a dissertation study will be discussed. In addition, the work progress, improvements, and a detailed framework will be implemented to demonstrate the data processing phases gradually. To conclude this chapter, an overview of real-life case studies related to the health and safety sector of construction projects in the UAE is implemented.

3.2 Methodology Selection and Justification

To fulfil the aim of this dissertation, a mixed research methodology that covers both inductive 'subjective' and deductive 'objective' approaches are utilised. To establish a database for a hybrid method, there are two types of data to be collected either sequentially or simultaneously: numeric 'quantitative' and text information 'qualitative'. Researchers considered the mixed method as the preferable approach in resolving research complications. It expands the research area of a specific problem by involving expertise and analysing the collected real data. Information and data are gathered from actual case studies executed in UAE projects. A case study is defined as a strategical approach intended to recognise real-life circumstances in which researchers have no control over it. Furthermore, it assists in addressing the research questions and related possible solutions that can be traced over a particular duration of time. The collected information and data used in the dissertation support the researchers in investigating the risk of health and safety in construction projects or sites. The qualitative data were gathered by providing three experts in the construction project field a risk assessment based on their experience and knowledge. Health and safety risk reports collected from previous project sites executed in UAE are considered apart from the qualitative data. On the other hand, the number of risk occurrence times and the duration to mitigate the risks are numeric values deemed a form of quantitative data. Nevertheless, to facilitate the data analysis procedure, qualitative information will be converted into normalised numeric values to provide the desired output information. Construction of certain and uncertain incidents frequently produces significant data that takes a long time for manual or regular computer software processing. Therefore, the new technology of artificial intelligence and machine learning conserve project construction time, reduce the cost, improve the quality, and save stakeholders' effort. The unique feature of machine learning is its ability to educate the machines to automatically analyse real-time qualitative input data and transform it into quantitative values that will be analysed using coding systems to obtain the output results. The discussed mixed method aimed to evolve a comprehensive understanding in managing health and safety risks at construction sites through assessing, evaluating, controlling and communicating the expected and occurred risks. The case study target is to provide safety analysts with the big picture of the event. The author will implement the mixed research approach and real case studies to tackle the following issues in this research study.

i. Significance level determination of the risk parameters, probability, and severity, while assessing health and safety risks in construction sites.

ii. The value of construction health and safety risks by evaluating both risk parameters.
iii. Classifications of conducted risk assessment that should be provided to analysts.
iv. The selection of the evaluation strategies for risk analysis, identifying risk controlling techniques and their priorities.

The implementation of the mixed research methodology in this study is as per the subsequent pattern. The literature review covers several topics related to the construction industry, health and safety management and machine learning algorithms. The research literature review aims to provide a comprehensive overview in simple phrasing to understand the study's importance. The significance of the construction industry, health and safety management and machine learning algorithms topics appears from various perspectives. Business specialists are concerned about the construction industry due to its significant contribution to the economic growth among worldwide nations. Health and safety management essence arise by preserving labours life, reducing project costs, saving construction duration, and enhancing quality and performance. Furthermore, machine learning and artificial intelligence are the current and future technology where R&D departments in companies have a high interest to develop and utilise in their business. Moving forward, real case studies and survey methodologies are used in health and safety data collection, risks identification, assessment, and evaluation to reduce or eliminate construction project threats.

3.2.1 Decision Matrix Risk-Assessment

The risk registration and categorisation process are performed by gathering health and safety reports from various construction sites in UAE. These reports contain qualitative information that requires smart technological solutions. The risk assessment and ranking process is executed using the decision matrix risk-assessment 'DMRA' technique. Risk assessment is defined as a systematic approach that utilises valid data and information to determine the frequency of events occurrence and the severity of risks. The risk assessment process is considered the fundamental element among risk management procedures. It assists project stakeholders in creating proactive health and safety strategies by inspecting potential risks. Construction project health and safety are assessed by nominating severity and likelihood parameters as scoring systems to categorise several types of hazards.

The frequency of risk occurrence is defined as the likelihood where severity indicates the level of people injured, the value of project time loss, and the amount of property and equipment damages. By implementing the DMRA method, the rank of severity and probability will reduce risk impacts to an acceptable level. The output result of risk assessment in certain projects will be documented to facilitate future risk prediction in other projects within similar circumstances. One of the most efficient risk assessment approaches is the DMRA systematic method. DMRA technique has been widely used in the occupational health and safety field. It utilises severity and likelihood parameters to ease the decision-making process related to project risk management. Each risk value is measured by multiplying the frequency of risk occurrence and its impacts as per the equation below.

$$R = P \times S$$

Where

R : risk.

P : probability of risk.

S : severity of risk.

The severity and likelihood categorisation ratings are as per the below tables 3.1, 3.2, 3.3, 3.4 and 3.5.

Table 3.1: Likelihood ratings (P)

Hazard likelihood ratings (*P*)	Description of likelihood
Rare	Occur in exceptional circumstances only
Unlikely	Not likely to occur within the project lifecycle
Possible	May occur within the project lifecycle
Likely	Likely to occur within the project lifecycle
Almost certain	Very frequent to occur within the project lifecycle

Table 3.2: Health and safety severity ratings (S)

The severity of consequences ratings (*S*)	Description of consequences
Insignificant	No treatment required
Minor	Minor injury requiring first aid treatment
Moderate	Injury requiring medical treatment
Major	Severe injury that requires special medical treatment or hospitalisation
Critical	Death, permanent disability or multiple serious injuries

Table 3.3: Time severity ratings (T)

The severity of consequences ratings (*S*)	Description of consequences
Insignificant	Within a duration of 1 day
Minor	Less than 1 week
Moderate	Within a duration of 2 weeks
Major	More than 2 weeks and less than 1 month
Critical	More than 1 month

Table 3.4: Production/Quality decrement severity ratings (Q)

The severity of consequences ratings (*S*)	Description of consequences
Insignificant	High productivity
Minor	Normal productivity
Moderate	Slight decrement in the productivity
Major	Minor decrement in the productivity
Critical	Major decrement in the productivity

Table 3.5: Cost severity ratings (C)

The severity of consequences ratings (*S*)	Description of consequences
Insignificant	Less than 500 AED
Minor	Between 500 – 5,000 AED
Moderate	Between 5,000 – 25,000 AED
Major	Between 25,000 – 100,000 AED
Critical	More than 100,000 AED

The risk management matrix is established as per table 3 to determine the level of risk acceptability. According to the occurred risk types, their impacts on the project, and control criteria required to mitigate these risks, decision makers' priorities and rank them. Thus, multi-criteria decision making is applied to the DMRA matrix to accomplish the risk ranking process. The fundamental goal of the MCDM method is to classify risk criteria using a numerical scale that has been established from the experts' perceptions (Bao, Li and Wu, 2016).

Table 3.6: Decision Matrix Risk Assessment (DMRA)

Severity (*S*)	**Likelihood (*P*)**				
	Rare	**Unlikely**	**Possible**	**Likely**	**Almost certain**
Insignificant	Insignificant	Low	Low	Low	Medium
Minor	Low	Low	Medium	Medium	High
Moderate	Low	Medium	Medium	High	High
Major	Low	Medium	High	High	Extreme
Critical	Medium	High	High	Extreme	Extreme

Risk matrices are considered qualitative research tools that value the risk by words. The consequences of occurred threat may appear in various aspects such as projects fund, duration of work execution, and resources allocation. Since decision-makers evaluate risk impacts from different perspectives, the output of risk severity will be formed as a relative rather than a magnitude result. Hence, the qualitative description of consequences collected from construction projects will be normalised from 0 to 1 relative to facilitate comparing occurred risk types. Furthermore, normalising diverse dimensions of risk impacts will eliminate risks aggregation irrespective of having similar or different consequences measured by the risk matrices. On the other hand, utilising the numerical interval method instead of a particular magnitude may lose some risks located in the interval. Therefore, in this study, a fuzzy analytic hierarchy process (FAHP) approach is performed to achieve the desired output in making effective health and safety risk management decisions in construction projects.

3.2.2 Fuzzy Analytic Hierarchy Process (FAHP)

Fuzzy AHP is defined as a decision support approach developed to deal with multi-criteria decision-making problems in uncertain and ambiguous environments. The prime input for an AHP method is experts' viewpoints within the same field. Two essential factors that must be considered in the fuzzy APH process are the subjectivity in retrieval decisions and data validity. Since part of the assessment depends on human knowledge and experience, the accuracy percentage of the collected data and obtained results will be scaled down. Thus, to increase the accuracy of results, a sufficient amount of risk data should be collected from construction projects and implemented in the analysis. The main benefits of the FAHP-fuzzy TOPSIS hybrid method are averting the lack of crisp risk score measurements and reducing the decision-making inconsistency. Aside from the classic DMRA approach, experts modified the weight criteria using the multi-criteria decision matrix technique of FAHP for the risk assessment process. Additionally, the risk evaluation process of probability and severity parameters is performed by utilising linguistic variables assigned from experts' opinions. To summarise, the advantages of the promoted DMRA method based fuzzy technique are as follows.

i. The risk is assessed by a group of experts' not individual points of view.
ii. Risk ranking is executed by employing probability and severity parameters relative importance in the multi-criteria decision matrix.
iii. Both parameters S and P are precisely evaluated by applying linguistic terms in the developed technique.

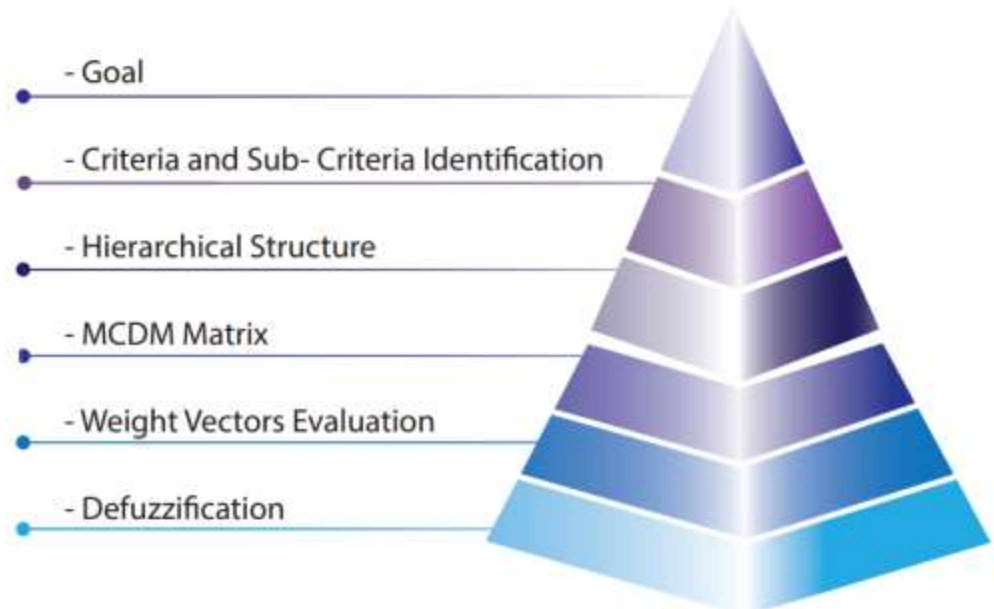

Figure 3.1: Structure of fuzzy analytic hierarchy process (AHP) algorithm

3.2.3 Integration of DMRA and Fuzzy AHP Techniques

The integrated procedure of DMRA and Fuzzy AHP techniques are illustrated in the following steps.

- Step 1: Establishing the MCDM technique for the parameters criteria in the dimension of the hierarchy structure. Linguistic terms are assigned to the decision matrix elements by nominating the intensity of importance among selected elements (Gul and Guneri, 2016).

$$\widetilde{M} = \begin{pmatrix} 1 & \widetilde{a}_{12} & \cdots & \widetilde{a}_{1n} \\ \widetilde{a}_{21} & 1 & \cdots & \widetilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{a}_{n1} & \widetilde{a}_{n2} & \cdots & 1 \end{pmatrix} = \begin{pmatrix} 1 & \widetilde{a}_{12} & \cdots & \widetilde{a}_{1n} \\ 1/\widetilde{a}_{21} & 1 & \cdots & \widetilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\widetilde{a}_{n1} & \widetilde{a}_{n2} & \cdots & 1 \end{pmatrix} \qquad (1)$$

$$\widetilde{a_{ij}} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & \textit{criterion i is of relative importance to criterion j} \\ 1 & i = j \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1} & \textit{criterion j is of relative importance to criterion i} \\ \tilde{2}, \tilde{4}, \tilde{6}, \tilde{8} & \textit{Intermediate values between both criterions i and j} \end{cases}$$

- Step 2: Implementing the geometric mean technique on the risk matrix. The equation of fuzzy geometric mean:

$$r_i = \left(a_{i1} \times a_{i2} \times a_{i3} \times \ldots \times a_{in}\right)^{1/n} \tag{2}$$

Where

r_i : fuzzy geametric mean.

a_{in} : the elements of risk matrix.

n : number of criteria.

- Step 3: The fuzzy weights are calculated for each criterion. Hence, $\widetilde{w}_i$ represents the fuzzy weight of criterion i.

$$w_i = r_i \left(r_1 + r_2 + r_3 + \ldots + r_n\right)^{-1} \tag{3}$$

Where

w_i : fuzzy weight.

r_i : fuzzy geametric mean.

n : number of elements.

The fuzzy weight of criterion lower, middle and upper values justify me.

- Step 4: Determining the weight of decision matrix criteria w_i by assigning a group of 3 experts' assessment and implementing an alternative matrix $x_{ij}$of the decision matrix as per the following equations.

$$\text{Criteria weight } w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_3 \end{bmatrix} \tag{4}$$

- Step 5: The aggregated fuzzy weight $\widetilde{w}_j$ of each criterion will be calculated as per the next formulas.

$$w_j = \left(w_{j1}, w_{j2}, w_{j3}\right) \tag{5}$$

$$w_{j1} = min_k \left\{w_{jk1}\right\} \tag{6}$$

$$w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{jk2} \tag{7}$$

$$w_{j3} = max_k \left\{w_{jk3}\right\} \tag{8}$$

Where

w_{j1} : the minimum value of weighted attributes.

w_{j2} : the average value of weighted attributes.

w_{j3} : the maximum value of weighted attributes.

- Step 6: Normalising the fuzzy decision matrix. The normalising rates are illustrated as per the following equations.

$$r = \left[\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right] \tag{9}$$

Where

r : normalisation rate.

c_j^* : $\max_i c_{ij}$ if $j \in benefit\ criteria$.

$$r = \left[\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}}\right] \tag{10}$$

Where

r : normalisation rate.

a_j^- : $\min_i a_{ij}$ if $j \in \cos t\ criteria$.

- Step 7: To transform the criteria scales to a comparable scale using TOPSIS, the following normalised fuzzy decision matrix R has developed.

$$Alternative\ fuzzy\ R_{ij} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{11}$$

Where
$i = 1, 2, \ldots, m$
$j = 1, 2, \ldots, n$

The weighted normalised ratings are calculated below the equation.

$$v_i = r_{ij} \cdot w_j = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_3 \end{bmatrix} \tag{12}$$

$$w_j = \frac{1}{k}(w_j^1 + w_j^2 + \ldots + w_j^k) \tag{13}$$

$$r_{ij} = \frac{1}{k}(r_{ij}^1 + r_{ij}^2 + \ldots + r_{ij}^k) \tag{14}$$

Where
$v_i =$ weighted normalisation rating.
$r_{ij} =$ normalisation rate.
w_j = weight of criteria.

- Step 8: The Ideal solution measurements have to be defined since the distance of each alternative will be calculated from the fuzzy positive ideal point and the fuzzy negative ideal point. Additionally, it can be estimated through several logics to obtain the proper reasonable evaluation. Implementing the three ideal solution logics follows where $(FPIS, A^*)$ is the fuzzy positive ideal point is, and $(FNIS, A^-)$ is the ideal negative point (Kaur, 2010).

i. Utilise the crisp values presented in the fuzzy method rather than the fuzzy values. The $FPIS$ will be configured by finding the maximum values, and $FNIS$ will be found by the minimum values from the fuzzy decision matrix to chosen attributes. In $FPIS$, a and b values will be replaced by c values wherein $FNIS$ b and c values will be replaced by a value. Chen et al develop this logic.

$$FPIS = A^* = \left\{\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right\} \tag{15}$$

$$\tilde{v}_j^* = max_i(v_{ij3})$$

$$FNIS = A^- = \left\{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right\} \tag{16}$$

$$\tilde{v}_j^- = min_i(v_{ij1})$$

Where
FPIS : fuzzy positive ideal solution.
FPIN : fuzzy negative ideal solution.

ii. In reference to Alidoosti, Yazdani, Fouladgar, and Basiri, both points $FPIS$ and $FNIS$ are derived as per the below formulas and depend on the weighted normalised fuzzy decision matrix values. The results will exist within the range of the close interval $[0,1]$.

$$FPIS = A^* = \left\{\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right\} \tag{17}$$

$$\tilde{v}_j^* = (1,1,1)$$

$$FNIS = A^- = \left\{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right\} \tag{18}$$

$$\tilde{v}_j^- = (0,0,0)$$

Where
FPIS : fuzzy positive ideal solution.
FPIN : fuzzy negative ideal solution.

iii. The third logic is promoted by Hwang and Yoon, 1981. $FPIS$ and $FNIS$ are measured by finding the maximum and minimum values of a fuzzy decision matrix, respectively, to select and rank the alternatives in a multi-criteria decision problem.

$$FPIS = A^* = \left\{ \tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^* \right\} \tag{19}$$

$$\tilde{v}_j^* = max_i (v_{ij})$$

$$FNIS = A^- = \left\{ \tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^- \right\} \tag{20}$$

$$\tilde{v}_j^- = min_i (v_{ij})$$

Where
FPIS : fuzzy positive ideal solution.
FPIN : fuzzy negative ideal solution.

- Step 9: The distance of each alternative is calculated from the fuzzy positive ideal solution and fuzzy ideal solution, or it can be explained as the distance from the $FPIS$ and $FNIS$ among the other options.

$$S_i^* = \sum_{j=1}^{n} d(v_{ij}, v_j^*),\ j = 1, 2, \ldots m \tag{21}$$

Where
S_i^* : distance of each alternative from FPIS

$$S_t^- = \sum_{j=1}^{n} d(v_{tj}, v_j^-),\ j = 1, 2, \ldots m \tag{22}$$

Where
S_t^- : distance of each alternative from FNIS

- Step 10: The defuzzification separation process is performed by utilising graded mean integration-representation distance (GMIR). The closeness coefficient CC_i^* to the ideal solution is calculated per the following formula.

$$CC_i^* = S_j^- \Big/ (S_j^* + S_j^-) \ , i = 1, 2, \ldots, m \tag{23}$$

Where

CC_i^* : closeness coefficient value.

- Step 11: Create a similarity matrix by calculating the similarity of each risk. The types of risk will be assessed and ranked depending on the average similarity value (Zhang, Ma and Chen, 2014).

$$S_i = \frac{1}{2}\sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_{ij}^*) \tag{24}$$

Where

$S_i =$ average similarity value.

3.3 Software Selection and Validation

MATLAB is the most effective and efficient software among several computer programs for data science and artificial intelligence (AI) implementation. It contains a programming language specialised in technical computing and mathematical algorithms. Mathematical matrices, linear algebra, data analytics, control design, image and signal processing applications are forms of MATLAB functions to analyse real-time data. Furthermore, the integrated support tools facilitate data exploration and tasks for less time. MATLAB allows researchers and engineers to visualise the output result of data processing while applying machine learning classification, surface fitting algorithm or filter design technique. The iteration of data processing can be done automatically until the desired data is produced.

3.4 Process Improvement Methodology

The main purpose of organisations' performance management is to set a proactive, systematic approach to simplifying decision-making. Therefore, to improve the methods of this research and reduce the margin of error, data management plays a significant role in quality improvement (QI). Data quality enhancements require data gathering, tracking, interrupting, analysing, and acting on. QI team is concerned about opportunities identification and implementation in which its progress will be monitored while applying the changes. In this research, the author concentrates on the performance improvements related to occupational health and safety management in UAE projects. All government and private sectors set an indicator to continuously monitor, analyse and control the OHSMS performance management using Key Performance Indicators (KPI). The KPI indicators come in two forms lagging and leading. Lagging safety performance indicators depend on historical data by tracking occurred incidents, safety issues and implementation of corrective actions where leading indicators set policies, procedures and practices to control the incidents prior, during and after the occurrence. Although the UAE government set comprehensive health and safety regulations, many project contractors are not applying them during construction. Therefore, the solution is to assist organisations in developing a leading indicator that continuously measures, monitor, and control health and safety performance. Additionally, it facilitates identifying future health and safety risks and proactively mitigating them. An intelligent, cost-effective, thorough system that includes sensors, machine learning algorithms and cloud computing storage must be integrated and implemented to execute leading indicators in UAE construction projects. Furthermore, an internal audit to review and modify the implemented process of the OHS management system has to be applied to ensure that construction risk events are managed accurately. The internal audit consists of setting the objectives, developing a schedule, designing the audit template, recording and documenting the results, and examining corrective actions status. While the risk management procedures are controlled and modified, additional parameters can be inspected to precisely review the performance of construction projects. The main three parameters to measure the success of any project are time, quality and cost. Additionally, some parameters such as planning, communication, etc., have less attention by contractors in UAE. Therefore, it’s essential to develop a historical database and a real-time intelligent analytical system to overcome the insufficiency of construction projects (AE,NSCS&NCEMA, 2016).

3.5 Methodological Frameworks

3.5.1 The Framework of Construction Risks Research

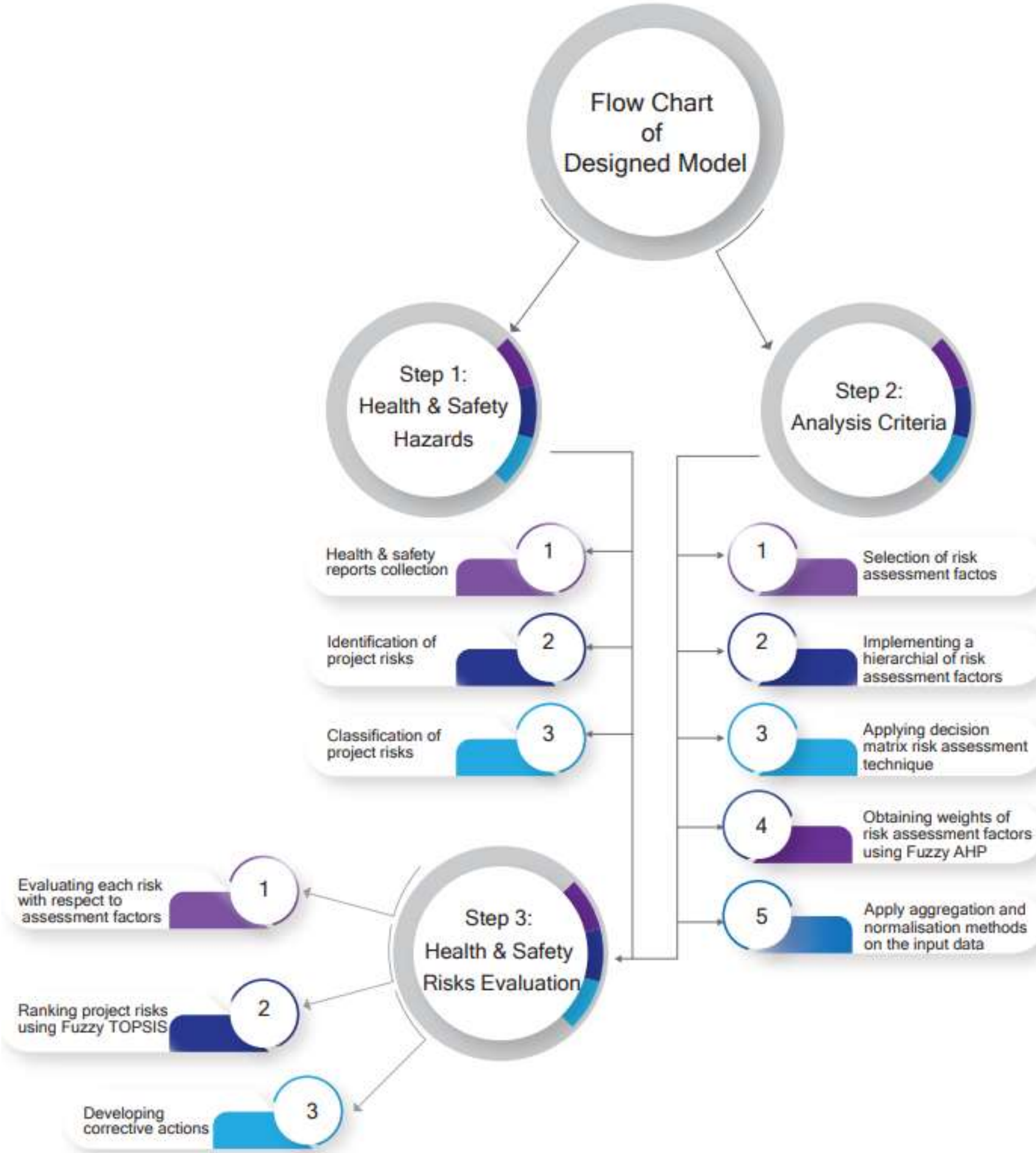

Figure 3.2: The Framework of Construction Risks Research

3.5.2 Main Four Categories of the Collected Risk Types

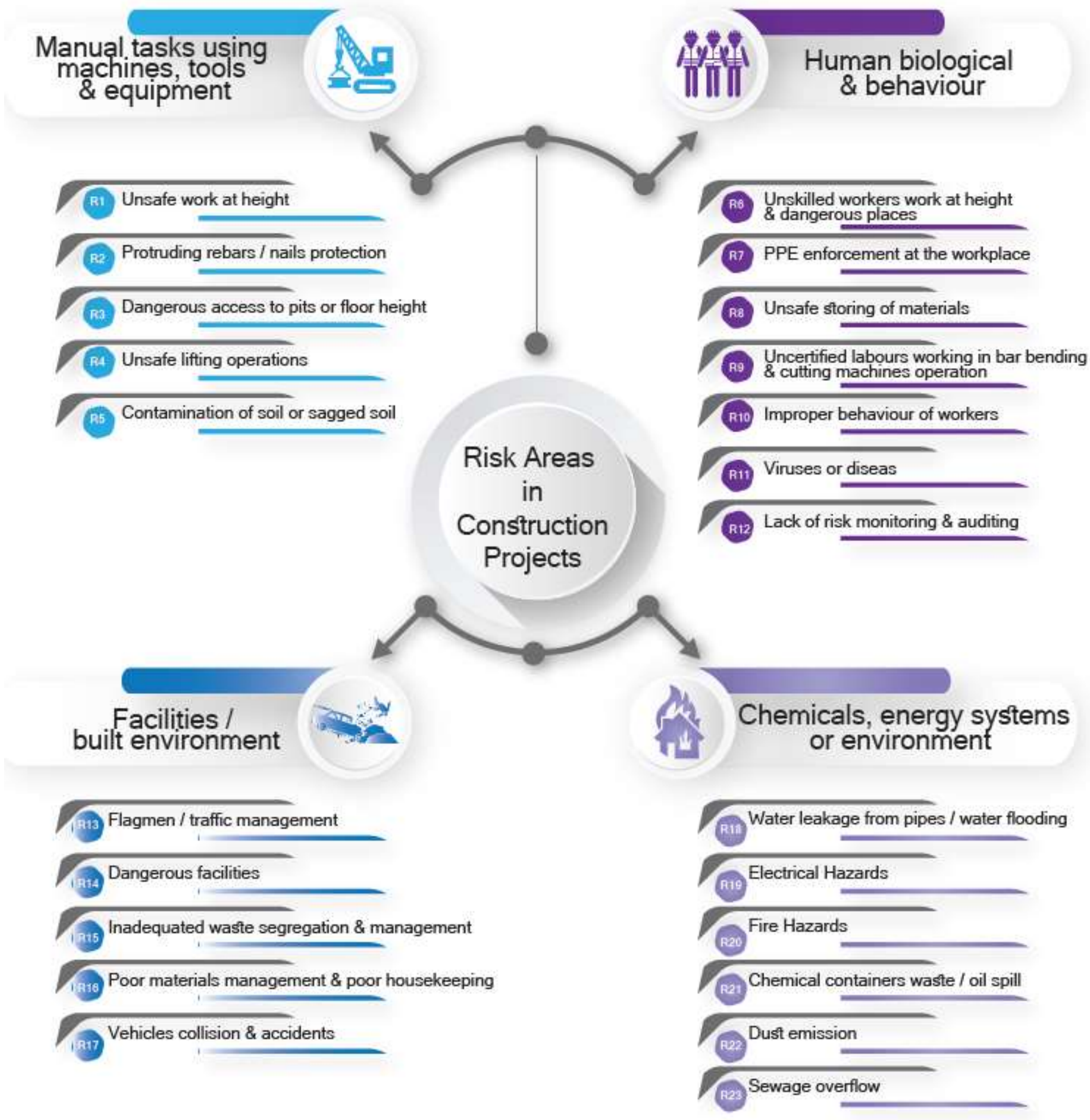

Figure 3.3: The main four categories of construction risks.

3.5.3 Schematic flowchart of Fuzzy AHP and TOPSIS Procedures

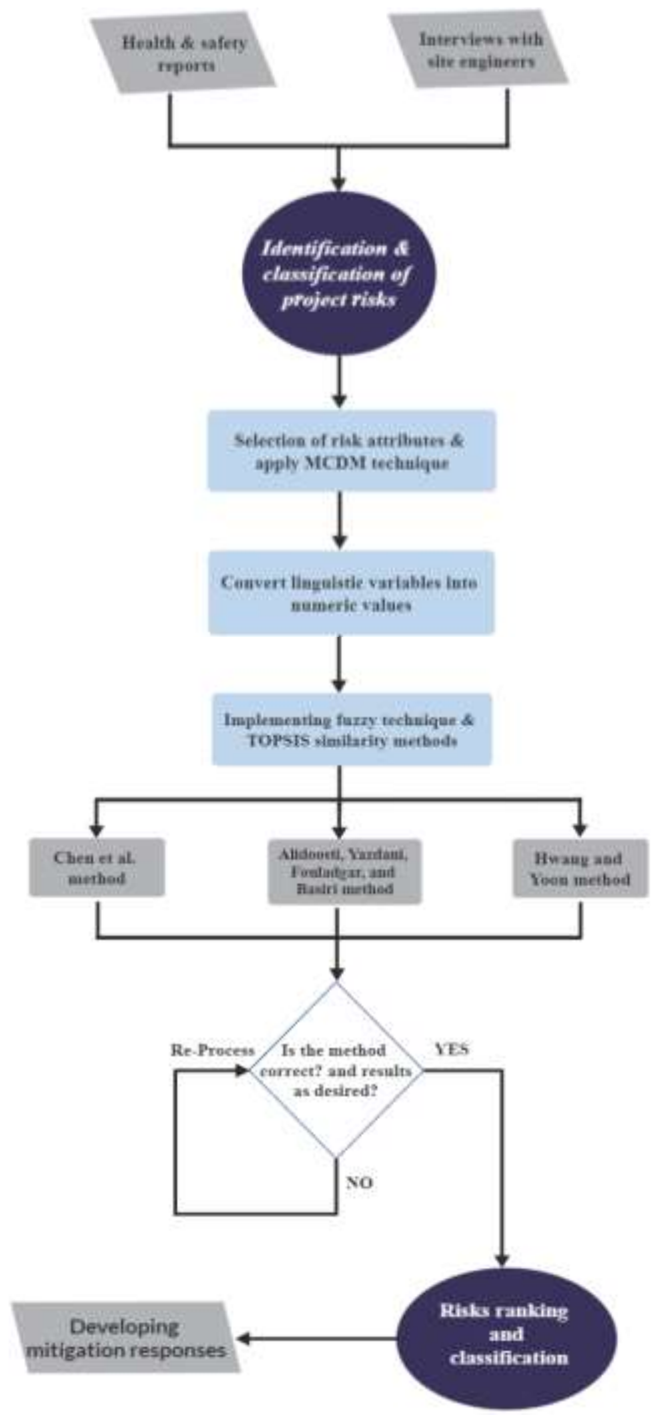

Figure 3.4: Schematic flowchart of Fuzzy AHP and TOPSIS procedures

3.5.4 Schematic of MATLAB Program

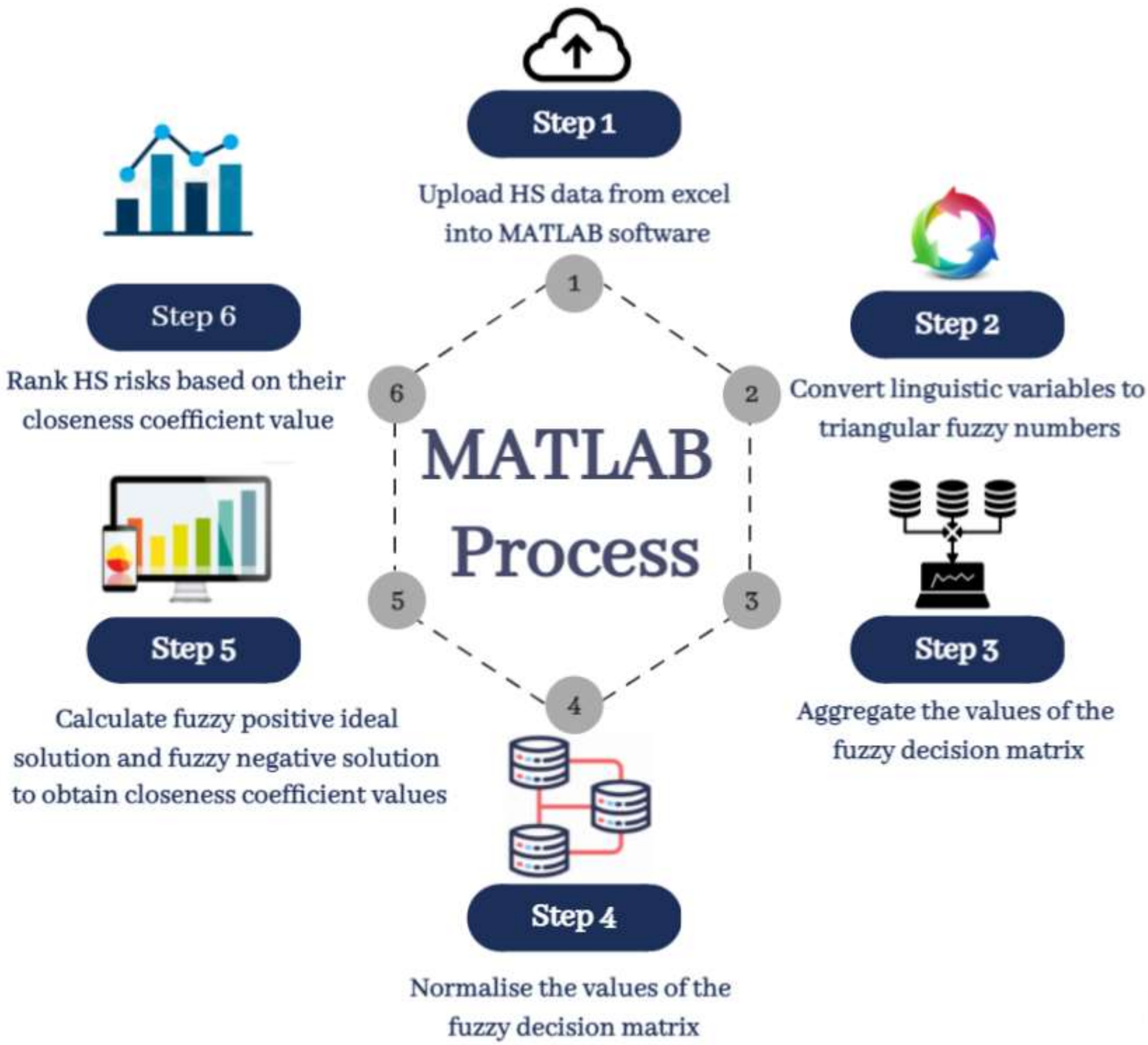

Figure 3.5: MATLAB programming of Fuzzy AHP and TOPSIS procedures

3.6 Applications of the Proposed Methodology

This section of chapter 3 will demonstrate a background of case studies from UAE construction sites. The selected construction projects are randomly picked as samples to represent the performance of construction projects in the UAE. It provides equal chances for each construction project to be chosen, and it has less margin of error upon analysing the data. This study's targeted construction projects are Dubai Hills Business Parks, Smart City Silicon Park and Creek Rise projects.

3.6.1 Case Studies Justification and Selection Criteria

The criteria and consideration of selecting the research case studies must be discussed. Since several projects got established at the same duration of time, it's essential to choose the projects' samples carefully. One of the vital parameters in the selection criteria is to nominate case studies belonging to UAE construction sites. The most effective outcomes for expressing a business performance appear from selecting samples from the same surrounded circumstances. Each case study is an actual project constructed in different locations in Dubai city. In addition, two projects, Dubai Hills Business Parks Smart City Silicon Park projects, are related to the residential sub-community sector, where Creek Rise belongs to the multi-use complex building sector.

The differences among the three projects are in the occurred risk type, its severity, and the number of occurrences. Each risk type is precisely investigated to assist in developing effective and efficient control responses. The more successful projects are constructed with minimum risk events, the newer projects will be executed, which will lead to an increase in the population in UAE as well. Furthermore, since risk impacts will be eliminated or reduced, the cost and time duration of the project will be decreased, and the quality will be improved.

3.6.2 Construction Health and Safety in Dubai

Dubai city has the second biggest area among the seven Emirates of UAE with the highest population of 46.0%. The people of Dubai are expected to increase for the following decades, reaching 3.42 million inhabitants as per the year 2021. The Emirate of Dubai is distinguished by its rapid developments and ability to adapt to market changes (UNITED ARAB EMIRATES POPULATION STATISTICS 2022, 2022).

For two decades, UAE has been the most significant construction market measured by awarding contracts in the Middle East. It covers at least 41.0% of all GCC construction contracts since 2004. The construction contracts include both building and infrastructure projects. The investments of the Dubai construction field have massively increased where 57.0% of UAE projects are constructed in the Emirate of Dubai. Additionally, Dubai's real estate sector has the ultimate concern since it dominates around 81.0% among other tasks (THOMPSON, 2020).

Considering the previous statistics, it’s essential to monitor internal and external events or risks that affect the construction project’s performance. During 2007, the Emirate of Dubai recorded 249 incidents in construction sites. The major types of accidents are falling from heights, violating health and safety regulations, and wearing PPE kits at the workplace. The associated health and safety fines applied against the accidents reached AED 1.5 million. Accordingly, a code of practice that includes occupational health and safety requirements has been issued by the municipality of Dubai (249 Dubai construction site accidents in a year, 2008).

3.6.2.1 Dubai Hills Business Park Project

The first case study that collected health and safety data is the Dubai Hills Business Park project. The project is related to the residential sub-community of the Dubai Hills Estate district and is located at Umm Suqeim Street (D63) and Al Khail Road (E44). It was developed by Emaar properties, launched in the year 2017 and completed by the year 2021. The project's total area is 150,000 m2 that includes office buildings consisting of seven floors, ground level and six floors of parking constructed in the fifth building. The entire community of Dubai Hills Estate contains a shopping mall, bicycle routes, a championship golf course, play areas, landscape walkways, schools and pools.

The project aims to allow the clients to design their own luxurious houses within Dubai's social and economic developments standards. In addition, the community was designed to fulfil the highest standards of sustainability to enhance the building performance and improve the city's tourism sector (Dubai Hills Business Park Guide | Propsearch.ae, 2021).

Figure 3.6: Dubai Hills Business Park project aerial view source: Google Earth, 2022

Figure 3.7: Dubai Hills Business Park project design source: Dubai Hills Business Park Guide | Propsearch.ae, 2021. https://propsearch.ae/dubai/dubai-hills-business-park accessed 7 November 2021.

3.6.2.2 Smart City Silicon Park Project

The second construction project selected for this research is Smart City Silicon Park- DSOA. The project was established in 2014 and completed in 2019 by Dubai Silicon Oasis Authority and is located in Dubai Silicon Oasis. The area comprises 71,000 m^2 for offices, 46,000 m^2 for the residential sector, and 25,000 m^2 for the commercial sector. The project is divided into two phases; the first phase contains 20 buildings, and the second consists of Radisson Red hotel, conference centre and furnished residential apartments.

The crucial value for Smart City Silicon Park project is to develop an innovative, sustainable and healthy city for intelligent initiatives and projects. All facilities and buildings are linked through an integrated building management system by utilising intelligent sensors and IoT based technology. The process of data monitoring and controlling will be executed by installing the detectors in several locations. The receiving, processing and transmitting of data are achieved through computer programs, control centres, and intelligent innovation platforms (Silicon Park, Dubai's first smart city, on track for handover in Q2 2019, 2019).

Figure 3.8: Smart City Silicon Park project aerial view source: Google Earth, 2022

Figure 3.9: Smart City Silicon Park project design source: Silicon Park, Dubai's first smart city, on track for handover in Q2 2019, 2019. https://www.khaleejtimes.com/business/silicon-park-dubais-first-smart-city-on-track-for-handover-in-q2-2019 accessed 7 November 2021.

3.6.2.3 Creek Rise Towers Project

The third case study is related to a complex mixed-use development building, the Creek Rise residential towers project. It was launched in the year 2017 and completed by the year 2020. It consists of Creek Rise Tower 1 and Creek Rise Tower 2. Tower 1 comprises 42 floors, and Tower 2 contains 33 floors. Both include basement level, ground level, mezzanine, and podium levels, and each tower has 1-3 bedroom apartments with an area varying from 72 m^2 to 152 m^2. The facilities in both towers are a gymnasium, sports court, play area and swimming pools (Creek Rise Guide | Propsearch.ae, 2022).

Figure 3.10: Creek Rise Towers Project aerial view source:
Google Earth, 2022.

Figure 3.11: Creek Rise Towers Project design source: Creek Rise Guide | Propsearch.ae, 2021. https://propsearch.ae/dubai/creek-rise accessed 7 November 2021

Chapter 4

Research Data, Analysis and Discussion

4 MATLAB Programming

4.4.1 Introduction

The definite aim of the health and safety management system is to establish safe workplace conditions for workers. Various factors such as resources allocation, HS policies implementation, management commitments, and communications impact the performance of the HS management system. In the construction field, the size and type of project parameters play a major role in identifying the complexity and scope of the HS management system. The desired outcomes of the system are to increase the productivity of workers, reduce the cost of losses, enhance the quality, and reduce the duration of project construction. Accordingly, HS risks of construction sites in Dubai, UAE, will be analysed and discussed using machine learning algorithms and computer programming.

This chapter illustrates the mathematical algorithms and MATLAB coding of the proposed fuzzy analytical hierarchy process and similarity to the ideal solution (TOPSIS) model based on previous chapters' literature review and research methodology findings. In the earlier stage of the conventional AHP technique, the challenging aspect required a decision-making process from several decision-makers with diverse project experiences and backgrounds. Hence, the arising vagueness of decision makers' judgement may affect the precision and accuracy of the decision-making process.

To overcome the fuzziness issue, a new realistic approach combining fuzzy AHP technique, linguistic assessment and TOPSIS ideal solutions are applied to this research to predict and analyse the risks of construction projects as per the following segments.

4.4.2 Construction Risk types, Probability and Severity

Dubai is considered one of the best-growing economical countries in the construction industry. It’s the city of skyscrapers and high-rise buildings that attract tourists and residents to visit and live in it. The growth of the construction industry will lead to improving real estate and tourism businesses. Therefore, it’s essential to reduce or eliminate uncertain events prior to and during the construction phase of projects.

With the benefit to improve construction sites’ health and safety management, 188 total risks related to 23 different risk types and four primary sections were collected from Dubai Hills Business Parks, Smart City Silicon Park and Creek Rise project sites in Dubai. The main four categories of risks are human biology and behaviour, manual tasks or ergonomics using machines, tools and equipment, facilities or built environment, chemicals, energy systems or environmental hazards. The sub-categories of each risk category, along with risk causes, risk owners, safety measurements and time scale to mitigate the risk, are presented in table 4.1.

As per the initial observation from the collected data, the unsafe works at height risk event has the highest probability of occurrence, significant consequences on health and safety, cost, time and quality, among other risk types. On the other hand, dust emission risk event has the minimum impacts on health and safety, cost, time and quality of the project with a less rate of occurrences.

Thus, it’s fundamental to predict uncertain events and establish proper mitigation responses before their occurrences.

Table 4.1: Human biological and behaviour risk types

Ref.	Main Risks' Types	Owner of risk	Reasons / Causes	Effects	Level of Risk	Safety Measurements	Time Scale for mitigation responses	Number of occurrence
A. Human biological and behavior								
R1	Unskilled workers works at height and dangerous areas	Labours and operators	1. Lack of knowledge and skills 2. Violating PPE rules 3. Drop objects from height	Minor / Major Injuries and death cases	Meduim	Requires hospitalization	< 1 week	5
R2	PPE enforcement at the workpla	construction site team and HR	1. Labours and visitors are not wearing basic PPE's inside the site such as hard hat, Hi-Viz jackets and safety shoes 2. HSE Policy was not displayed and communicated in multi languages	Minor / Major Injuries	Meduim	> 1 day work lost	2 weeks > & < 1 month	16
R3	Unsafe storing of materials	Workers	Improper stacking of plywood	No damages	Insignificant	Non-injury accident	< 1 week	2
R4	Uncertified labours working in bar bending and cutting machines operation	Consultant	Lack of experience	Minor / Major Injuries	Low	Requires medical attention	< 1 week	3
R5	Improper behaviour of workers	HR and Supervisors	1. Violating code of practice at sites 2. Smoking at construction zones 3. Lack of awareness about electrical hazards 4. Fighting between workers	Minor / Major Injuries	Meduim	Requires hospitalization	< 1 week	9
R6	Virus or disease	Workers & construction team	1. COVID-19 Pandemic 2. Gastric Issues caused by virus	Minor / Major Injuries and death cases	Meduim	Requires hospitalization	2 weeks > & < 1 month	4
R7	Lack of Risk monitoring and auditing	HR and Supervisors	1. Temporary work method statement and risk assessment was not conducted. 2. Insufficient risk registration, assessment and communication. 3. Improper documenting for internal and external audit. 4. Lack of risk management trainings.	No damages	Low	Non-injury accident	< 1 week	4

Table 4.2: Manual tasks or ergonomics using machines and equipment risk types

Ref.	Main Risks' Types	Owner of risk	Reasons / Causes	Effects	Level of Risk	Safety Measurements	Time Scale for mitigation responses	Number of occurrence
B. Manual tasks or ergonomics using machines and equipment								
R8	Protruding rebar / nails protecti	Construction team	1. Unsafe work sites 2. No designated nail removing area 3. Constantly occurs at sites	Minor / Major Injuries	High	Requires hospitalization	2 weeks	8
R9	Unsafe work at height	Workers & construction team	1. Using unsafe scaffold with missing ladder or bad platform. 2. Using unsafe & incomplete scaffolding. 3. Poor standard of barricade. 4. Insufficient working platform at height works (columns beans extension concert casting works) 5. Fall from Height 6. Weak edge protection system 7. Poor fall protection system	Minor / Major Injuries and death cases	Extreme	> Fatality	1 month	31
R10	Dangerous access to pits or floor holes	Construction team	1. Inadequate access to lower pits 2. Falling hazards 3. Slip or trip hazards	Minor / Major Injuries and death cases	Meduim	Requires hospitalization	2 weeks	5
R11	Unsafe lifting operation	Construction team	1. Riggers are not fully trained and aware of load tied and load limit. 2. Slings and tag lines are not properly used. 3. Loose load are not wrapped properly.	1. Minor / Major Injuries and death cases 2. Major damages for property	High	Requires hospitalization	< 1 week	8
R12	Contamination of soil or Sagged soil	Construction team	1. Poor Concrete Casting 2. Soil contaminated	1. Minor / Major diseases 2. Major damages for property	Low	Requires medical attention	2 weeks	5

Table 4.3: Facilities / built environment risk types

Ref.	Main Risks' Types	Owner of risk	Reasons / Causes	Effects	Level of Risk	Safety Measurements	Time Scale for mitigation responses	Number of occurrence
C. Facilities / built environment								
R13	Flagmen / traffic management	Workers	1. Insufficient traffic control 2. Mobile cranes parked at wrong location	No damages or injuries Work delay	Low	Non-injury accident	1 day	9
R14	Vehicles collision and accidents	Construction team	1. Drivers are not following site speed limit 2. Vehicles and people accidents 3. Vehicles struck the properties or barriers at site	Minor / major damages and injuries	Meduim	> 1 day work lost	1 day	6
R15	Inadequate waste segregation and management	Construction team	1. Ineffective waste management 2. No segregation policy implemented 3. Concrete / plywood's / others waste are dumped 4. Materials buckets were used for food waste 5. Improper stacking and storage of materials such as steel rebar, metal scraps and cement bricks	Minor / major damages and injuries	High	> 1 day work lost	2 weeks > & < 1 month	19
R16	Dangerous facilities	Site Subcontractors	1. Rest at unhygienic and dangerous facilities 2. High chance of materials falling 3. Parking at undesigned / danger areas 4. Chemical containers parked at danger zone 5. Materials stacked near to edge of high building	Minor / Major injuries and diseases	High	> 1 day work lost	2 weeks > & < 1 month	18
R17	Poor materials management and poor housekeeping	Workers	1. Dumping formwork of materials unsafely	Minor property damages	Low	Requires medical attention	< 1 week	10

Table 4.4: Chemicals, energy systems or environment

Ref.	Main Risks' Types	Owner of risk	Reasons / Causes	Effects	Level of Risk	Safety Measurements	Time Scale for mitigation responses	Number of occurrence
D. Chemicals, energy systems or environment								
R18	Water leakage from pipes / Water flooding	Site consultant	Poor maintenance and lack of monitoring	No damages or injuries	Insignificant	Non-injury accident	< 1 week	6
R19	Electrical hazards	Site consultant and subcontractors	Improper installation of electrical cables and find damaged cables at site	Property / equipment damages Injuries and death cases	High	> 1 day work lost	< 1 week	7
R20	Fire hazards	Site consultant and subcontractors	1. Unsafe hot work welding / cutting / fire hazards 2. Use highly combustible materials in storage areas 3. Poorly maintained fire protection equipment 4. Poor maintenance and lack of monitoring	Critical property / equipment damages and major injuries	High	> 1 day work lost	2 weeks	5
R21	Chemical containers waste / Oil	Site consultant and subcontractors	1. Compressed chemical foam sprays were allowed to be mixed with others waste 2. Lack of environmental awareness	Health issues and labours illness	Meduim	Requires hospitalization	2 weeks	4
R22	Dust emission	Construction team	1. Environment Impacts 2. Lack of dust control system in site	No damages	Insignificant	Non-injury accident	1 day	3
R23	Sewage overflow	Construction team	1. Insufficient tank capacity 2. Detector systems and alarms are not installed to avoid overflow	Property / equipment damages and workers diseases	Low	Requires medical attention	1 day	1

4.4.3 Selection of Decision-Makers and Criteria Evaluation

Human judgements significantly contribute to the multi-criteria decision-making processes in all real-life situations. Making wrong decisions against specific business issues will create incorrect assessments and solutions due to the fuzziness feature of human judgements. The selection of decision-makers includes criteria that must be considered, such as their knowledge, experiences, skills, and abilities.

In this research, three experts were chosen to rate the risk criteria and evaluate risk types' probability and severity. The background of the decision-makers is implemented in table 4.2.

Table 4.5: Decision-makers knowledge and experience

Experts' Name	Area of Specialisation	Company	Qualification	Years of Experience
Assessor X	Project Manager	Dar Al-Handasah	Bachelor's Degree	21
Assessor Y	Civil Engineer	ALEC	Bachelor's Degree	8
Assessor Z	Architecture Engineer	LACASA	Master's Degree	5

The selected five standards to assess and evaluate various risk types are events probability, health and safety severity, time severity, quality reduction impact and cost severity. The assessors filled out health and safety assessments based on their knowledge, experience and skills with nominal data, converted into numerical values. The conversion procedure requires linguistic variables to weigh the verbal expressions. The following two tables, 4.6 and 4.7, contain the linguistic terms with corresponding fuzzy values for criteria evaluation and the linguistic terms with corresponding fuzzy values for hazard ranking.

Table 4.6: Linguistic variables for criteria evaluation

Linguistic variables for criteria evaluation	Fuzzy Values
Absolutely Strong “AS”	(0.9, 1, 1)
Very Strong “VS”	(0.7, 0.9, 1)
Slightly Strong “SS”	(0.5, 0.7, 0.9)
Medium “MM”	(0.3, 0.5, 0.7)
Slightly Weak “SW”	(0.1, 0.3, 0.5)
Very Weak “VW”	(0, 0.1, 0.3)
Absolutely Weak “AW”	(0, 0, 0.1)

Table 4.7: Linguistic variables for hazards ranking

Linguistic variables for hazards ranking	Fuzzy Values
Extremely High “EH”	(7, 9, 10)
Very High “VH”	(5, 7, 9)
Medium “M”	(3, 5, 7)
Very Low “VL”	(1, 3, 5)
Extremely Low “EL”	(1, 1, 3)

MATLAB code:

In many real-life cases, the amount of input data is enormous and collected over a long duration of time. Additionally, since data gathering can be executed through sensors, surveys, interviews and reports, it's necessary to simplify the data entry into MATLAB software. The collected construction risks data are stored in an excel spreadsheet which is transmitted in the MATLAB program, and verbal terms are converted into numerical values as per figure 4.1. The linguistic variables relevance to the critical weight of the five chosen criteria is demonstrated in figure 4.2.

```
for i=1:row
    for j=1:col
        %Extremely Low
        if strcmp(cell2mat(FDMX{i,j}),'EL')
            FDMX{i,j}={[1,1,3]};
        %Very Low
        elseif strcmp(cell2mat(FDMX{i,j}),'VL')
            FDMX{i,j}={[1,3,5]};
        %Medium
        elseif strcmp(cell2mat(FDMX{i,j}),'M')
            FDMX{i,j}= {[3,5,7]};
        %Very High
        elseif strcmp(cell2mat(FDMX{i,j}),'VH')
            FDMX{i,j}= {[5,7,9]};
        %Extremly High
        elseif strcmp(cell2mat(FDMX{i,j}),'EH')
            FDMX{i,j}= {[7,9,10]};
        end
    end
end

FDMY = table2cell(FDMX);
FDM1 = FDMY(1:23,1:5);
FDM2 = FDMY(1:23,6:10);
FDM3 = FDMY(1:23,11:15);
FDM={FDM1;FDM2;FDM3};
```

Figure 4.1: Matlab coding to insert the input data from Excel spreadsheet.

```
%Needed linguistic variables for importance weight of each criterion
%as generalized fuzzy numbers:
 AS = [0.9,1,1];          %Absolutely Strong
 VS = [0.7,0.9,1];        %Very Strong
 SS = [0.5,0.7,0.9];      %Slightly Strong
 MM  = [0.3,0.5,0.7];     %Meduim
 SW = [0.1,0.3,0.5];      %Slightly Weak
 VW = [0,0.1,0.3];        %Very Weak
 AW = [0,0,0.1];          %Absolutely Weak
```

Figure 4.2: The assigned scale for Linguistic Variables.

4.4.4 Multiple-Criteria Decision Making (MCDM) Implementation

This research is highly dependent on the experts' decision making; therefore, the multi-criteria decision-making process is an advanced approach to deal with the AHP technique. As illustrated in the previous section, it utilises a triangular membership function to scale the linguistic variables. The experts ranked the five attributes based on their personal decision by preferring one criterion over the other as per table 4.8 to achieve the main aim of predicting construction risks. The method of dividing a system's input and / or output into one or more fuzzy sets is known as 'Fuzzification'. The weight of assigned criteria is represented in figure 4.2.

Table 4.8: Experts' ratings for risks attribues

Risk Management Matrix (MCDM) Fuzzification - FAHP					
Experts Judgement	**Probability**	**HS Severity**	**Time Severity**	**Quality Severity**	**Cost Severity**
Assessor 1	MM	AS	VS	SW	AS
Assessor 2	SS	AS	VS	MM	AS
Assessor 3	SS	VS	SS	MM	AS

MATLAB code:

```
%Importance weights from decision makers related to the assigned criterias:
%The assigned criterias are {C1 C2  C3  C4  C5};
%where C1=Probability C2=H&S C3=Time C4=Quality C5=Cost Consequences
        WD1={MM AS VS SW AS};
        WD2={SS AS VS MM AS};
        WD3={SS VS SS MM AS};
        WD={WD1;WD2;WD3};
```

Figure 4.3: Importance weights rated by decision-makers.

4.4.5 Aggregation and Normalisation Methods

In following to MCDM, the desired output results of the criteria weight matrix and fuzzy decision matrix are obtained using the aggregation procedure. The mathematical equations of the aggregated fuzzy ratings are described in chapter 3 section 3.2. The next step is normalising the aggregated matrices to have the output values between 0 and 1. Considering the importance of each criterion, the weighted normalised fuzzy decision matrix is expressed by $V_i = r_{ij}\ X\ w_i$.

<u>MATLAB code:</u>

i. The aggregation process of the weighted attributes matrix.

```
function W=aggregatew(WD,k,n)
%The aggregation process of weight
for i=1:n
    tmp1=[];     tmp2=[];     tmp3=[];
    for j=1:k
        tmp1=[tmp1 WD{j}{i}(1)];
        tmp2=[tmp2 WD{j}{i}(2)];
        tmp3=[tmp3 WD{j}{i}(3)];
    end
    Wj1a(i)=min(tmp1);
    Wj2a(i)=1/k*sum(tmp2);
    Wj3a(i)=max(tmp3);
end

W=[Wj1a;Wj2a;Wj3a];

%Here we just take transpose to get them in more suitable form.
for i=1:n
    Wa(i,:)=W(:,i)';
end
W=Wa;
```

Figure 4.4: Aggregation process of the weighted attributes.

ii. The aggregation process of fuzzy decision matrix

```
function FDM=aggregateFDM(FDM,m,k,n)
%The aggregation process of fuzzy decision matrix
for i=1:n
        tmp1=[];      tmp2=[];      tmp3=[];
    for j=1:k
        tmp1=[tmp1 FDM{j}{m,i}(1)];
        tmp2=[tmp2 FDM{j}{m,i}(2)];
        tmp3=[tmp3 FDM{j}{m,i}(3)];

    end
   Wj1a(i)=min(tmp1);
   Wj2a(i)=1/k*sum(tmp2);
   Wj3a(i)=max(tmp3);

end
FDMtmp=[Wj1a; Wj2a; Wj3a];
for i=1:n
    FDM2{:,i}=FDMtmp(:,i)';
end
FDM=FDM2;
```

Figure 4.5: Aggregation process of fuzzy decision matrix.

iii. Forming normalised aggregated fuzzy decision matrix

```
%Forming normalized aggregated fuzzy decision matrix FDM_N:

for j=1:n
    for i=1:m
        matrixB(i,j)=FDMA{i,j}(3);  %getting cij's
        matrixC(i,j)=FDMA{i,j}(1);  %getting aij's
    end
end


    dividerB=max(matrixB);    %c plus for benefit criterias
    dividerC=min(matrixC);    %a minus for cost criterias


for i=1:m
    for j=1:n
        if criteria(j)==1
            FDMN{i,j}(1:3)=FDMA{i,j}(1:3)./dividerB(j); %Benefit Criteria
        elseif criteria(j)==2
            FDMN{i,j}(1:3)=dividerC(j)./FDMA{i,j}(3:-1:1); %Cost Criteria
        end
    end
end
```

Figure 4.6: Normalisation procedure of aggregated values.

iv. Weighting the normalised fuzzy decision matrix

```
%Weighted normalized fuzzy decision matrix:

for i=1:m
    for j=1:n
        FDMNW{i,j}(1:3)=FDMN{i,j}(1:3).*Wagg(j,:);
    end
end
```

Figure 4.7: Weighted normalised fuzzy decision matrix.

4.4.6 Ideal Solutions and Similarity Measures

To expand the research findings, three different ideal solution techniques are included in determining the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS). The MATLAB code for each technique is shown in 4.8, 4.9 and 4.10.

MATLAB code:

i. Chen et al. ideal solution.

```
if ideal==1
    %First possible criteria for positive and negative ideal solutions:
    for i=1:m
        for j=1:n
            maxi(i,j)=FDMNW{i,j}(3);
            mini(i,j)=FDMNW{i,j}(1);
        end
    end
    FPIStmp=max(maxi);
    FNIStmp=min(mini);
    for i=1:n
        FPIS{i}(1:3)=FPIStmp(i)*ones(1,3);
        FNIS{i}(1:3)=FNIStmp(i)*ones(1,3);
    end
```

Figure 4.8: Chen et al. Ideal solution coding.

ii. Alidoosti, Yazdani, Fouladgar, and Basiri's ideal solution

```
elseif ideal==2
    %Second possible for positive and negative ideal solutions:
    for i=1:n
        FPIS{i}(1:3)=ones(1,3);
        FNIS{i}(1:3)=zeros(1,3);
    end
```

Figure 4.9: Alidoosti, Yazdani, Fouladgar, and Basiri's ideal solution coding.

iii. Hwang and Yoon’s ideal solution

```
elseif ideal==3
    %Third possible criteria for positive and negative ideal solutions:
    for j=1:n
        for i=1:m
            maxi2(i,:)=FDMNW{i,j}(1:3);
        end
        FPIS{j}(1:3)=max(maxi2);
        FNIS{j}(1:3)=min(maxi2);
    end
end
```

Figure 4.10: Hwang and Yoon’s ideal solution coding.

As explained earlier, the similarity method is essential for obtaining the base of analogical reasoning among two fuzzy triangular numbers based on their distance. The MATLAB code presenting the similarity functions are illustrated in figure 4.11. Moving forward, the closeness coefficient will be calculated to rank the risks as per figure 4.12.

MATLAB code:

i. Similarity measurements

```
%Calculating fuzzy similarities between
%the weighted normalized decision matrix and FPIS:
for i=1:m
    Spos(i,:)=fuzzsim(FDMNW(i,:),FPIS,n);
end

%Aggregating over the criterias:
SposAgg=sum(Spos,2)/n;
Spos=SposAgg';

%Calculating fuzzy similarities between
%the weighted normalized decision matrix and FNIS:
for i=1:m
    Sneg(i,:)=fuzzsim(FDMNW(i,:),FNIS,n);
end
SnegAgg=sum(Sneg,2)/n;
Sneg=SnegAgg';

function Spos=fuzzysimveca(FDMNW,FPIS,n)

for i=1:n
    Spos(i)=fsimil([FDMNW{i}(1:3) 1],[FPIS{i}(1:3) 1]);
end

function [Simil]=fuzzysimil(A,B)
%Below function is called GMIR method to obtain the similarity
PA=(A(1)+4*A(2)+A(3))/6;
PB=(B(1)+4*B(2)+B(3))/6;
dAB=abs(PA-PB);
Simil=1/(1+dAB);
```

Figure 4.11: Similarity measurements code.

ii. Closeness coefficient and risks order.

```
%Closeness coefficient:
for i=1:m
    CCS(i)=SposAgg(i)/(SposAgg(i)+SnegAgg(i));
end
[Y,I]=sort(CCS,'descend');

%Order of the Risk types:
Order=I';
```

Figure 4.12: Closeness coefficient coding.

4.4.7 Risks Classification

The assessment status of construction risks will be evaluated in an additional method by subtracting the interval of [0, 1] into five sub-intervals. Each sub-interval determines a class of risk along with the corresponding decision rule. The following table 4.6 demonstrates the ranges of the five categories and related decisions.

Table 4.9: Decision rules against risks' classes

S_i or CC_i Value	Assessment Status
S_i or $CC_i \in [0.0, 0.2)$	Insignificant Risk
S_i or $CC_i \in [0.2, 0.4)$	Low Risk
S_i or $CC_i \in [0.4, 0.6)$	Medium Risk
S_i or $CC_i \in [0.6, 0.8)$	High Risk
S_i or $CC_i \in [0.8, 1.0]$	Extreme Risk

i. If $S_i \in [0.0, 0.2)$, then risk A_i belongs to class I, and the assessment status of risk A_i is an insignificant risk.

ii. If $S_i \in [0.2, 0.4)$, then risk A_i belongs to class II, and the assessment status of risk A_i is low risk.

iii. If $S_i \in [0.4, 0.6)$, then risk A_i belongs to class III, and the assessment status of risk A_i is medium risk.

iv. If $S_i \in [0.6, 0.8)$, then risk A_i belongs to class I$\mathcal{V}$, and the assessment status of risk A_i is high risk.

v. If $S_i \in [0.8, 1.0]$, then risk A_i belongs to class $\mathcal{V}$, and the assessment status of risk A_i is extremely high risk.

5 Research Results

4.5.1 Introduction

By the end of the computer programming of Fuzzy AHP and TOPSIS analysis, the results were assembled to identify the order of the risk and perform effective mitigation. This chapter will display the outcomes produced by MATLAB software and the analysis of Fuzzy TOPSIS in the earlier chapters, followed by a discussion of the most appropriate solutions for each health and safety risk in terms of the probability of occurrence, time loss, quality reduction and cost severity.

The initial section of the chapter starts with finding the outputs, which are similar values with respect to attributes and FPIS, similarity value with respect to features and FNIS, closeness coefficient and risks ranking through three different criteria of the ideal solution. Afterwards, a comprehensive comparative study among the three ideal solutions will be conducted to detect the best risk analysis criteria. The second section contains responses and proposed solutions to uncertain events.

This chapter aims to respond to the main research questions and accomplish the study's objectives. Study recommendations and construction risk prediction guidelines will be carried out for current and future construction projects.

4.5.2 Fuzzy AHP and TOPSIS Program Results

The data processing method has been established depending on the collected data and experts' opinions selected from the same field to fulfil the desired outcomes. The construction health and safety database characteristics combine qualitative and quantitative inputs to develop a comprehensive health and safety analysis program. Furthermore, the utilised program must function correctly under various circumstances in construction sites.

As discussed in section 4.1.7, the output data and risks classification differ concerning the utilised ideal solution criteria. The three types of ideal solutions operate with the same inputs and provide exceptional results based on the used mathematical logic. The main objective of ideal solution comparison is to demonstrate the strengths and limitations of the three methods. The health and safety data analyses are illustrated in sections 4.2.3 to 4.2.7.

4.5.3 Decision Maker's Evaluation of Risks

The three assessors evaluated the risk types as per the following table based on their knowledge and experience. The benefit of the experts' long experience is due to the lack of health and safety uncertain events recorded in UAE construction sites. Linguistic variables are utilised to convert the verbal expression into numerical values. The leading five attributes, which are probability, health and safety severity, time severity, quality or production reduction, and cost severity, are represented in consistence as 'P', 'S', 'T', 'Q' and 'C'.

Table 4.10: Decision-makers’ risk evaluation

Risks Ref.	P1	S1	T1	Q1	C1	P2	S2	T2	Q2	C2	P3	S3	T3	Q3	C3
R1	M	VH	M	M	VL	EL	VH	M	M	VL	VL	EH	M	M	EL
R2	VH	VH	EL	VH	EL	M	M	EL	M	EL	VL	M	EL	EL	EL
R3	M	EL	EL	VL	EL	VH	M	EL	VL	EL	EL	M	EL	VL	EL
R4	VH	VH	M	M	M	VH	M	M	EL	VH	M	M	M	VL	M
R5	M	VL	EL	M	EL	M	M	EL	M	EL	EL	VL	EL	M	EL
R6	M	VH	M	M	M	VH	M	VH	VL	M	VH	M	VH	VL	VH
R7	EL	M	M	VL	M	EL	VH	VH	M	M	VL	M	EH	M	VL
R8	EH	M	VL	M	VH	VH	M	M	VL	M	EH	VH	M	VH	M
R9	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH	EH
R10	EH	VH	M	M	M	VH	VH	M	M	M	VH	EH	M	VL	M
R11	VH	VH	M	VL	EH	VH	EH	M	M	EH	VH	EH	M	M	VH
R12	M	M	M	VL	EL	M	VH	VL	VL	EL	VL	M	M	VL	EL
R13	EL	M	M	EL	EL	VL	VL	VH	M	EL	EL	VL	VH	EL	EL
R14	EH	VH	M	M	M	EH	M	EL	M	M	VH	VH	M	M	VL
R15	M	M	M	EH	VH	M	VH	M	M	EH	M	M	M	M	VH
R17	VH	VH	M	EH	VL	EH	EH	EL	VH	VL	VH	VH	M	VH	M
R17	M	M	M	VL	EL	M	M	VL	M	EL	M	VH	M	VL	EL
R18	M	VL	EL	VL	EL	M	EL	EL	VL	EL	M	VL	EL	M	EL
R19	EL	EH	VH	EH	EH	VH	EH	VH	VH	VH	EL	EH	EH	VH	EH
R20	VL	EH	VH	EH	VH	M	EH	VH	EH	EH	EL	EH	EH	EH	VH
R21	VH	M	M	EH	VH	M	VH	M	M	EH	M	M	M	M	VH
R22	VH	VL	EL	VL	VL	VH	EL	M	EL	EL	VH	VL	EL	EL	EL
R23	EL	VL	M	VH	M	VL	M	VL	EL	VL	VL	M	M	EL	M

4.5.4 Aggregation Procedure of Fuzzy Decision Matrix 'FDM'

The data aggregation process has been utilised to compile and organise a significant amount of data stored in a database to facilitate data processing in real-life applications.

Table 4.11: Data aggregation process

Risks / Criteria	Probability	Health & Safety Severity	Time Severity	Productivity-Quality Reduction	Cost Severity
R1	[1,3,7]	[5,7.67,10]	[3,5,7]	[3,5,7]	[1,2.33,5]
R2	[1,5,9]	[3,5.67,9]	[1,1,3]	[1,4.33,9]	[1,1,3]
R3	[1,4.33,9]	[1,3.67,7]	[1,1,3]	[1,3,5]	[1,1,3]
R4	[3,6.33,9]	[3,5.67,9]	[3,5,7]	[1,3,7]	[3,5.67,9]
R5	[1,3.67,7]	[1,3.67,7]	[1,1,3]	[3,5,7]	[1,1,3]
R6	[3,6.33,9]	[3,5.67,9]	[3,6.33,9]	[1,3.67,7]	[3,5.67,9]
R7	[1,1.67,5]	[3,5.67,9]	[3,7,10]	[1,4.33,7]	[1,4.33,7]
R8	[5,8.33,10]	[3,5.67,9]	[1,4.33,7]	[1,5,9]	[3,5.67,9]
R9	[7,9,10]	[7,9,10]	[7,9,10]	[7,9,10]	[7,9,10]
R10	[5,7.67,10]	[5,7.67,10]	[3,5,7]	[1,4.33,7]	[3,5,7]
R11	[5,7,9]	[5,8.33,10]	[3,5,7]	[1,4.33,7]	[5,8.33,10]
R12	[1,4.33,7]	[3,5.67,9]	[1,4.33,7]	[1,3,5]	[1,1,3]
R13	[1,1.67,5]	[1,3.67,7]	[3,6.33,9]	[1,2.33,7]	[1,1,3]
R14	[5,8.33,10]	[3,6.33,9]	[1,3.67,7]	[3,5,7]	[1,4.33,7]
R15	[3,5,7]	[3,5.67,9]	[3,5,7]	[3,6.33,10]	[5,7.67,10]
R16	[5,7.67,10]	[5,7.67,10]	[1,3.67,7]	[5,7.67,10]	[1,3.67,7]
R17	[3,5,7]	[3,5.67,9]	[1,4.33,7]	[1,3.67,7]	[1,1,3]
R18	[3,5,7]	[1,2.33,5]	[1,1,3]	[1,3.67,7]	[1,1,3]
R19	[1,3,9]	[7,9,10]	[5,7.67,10]	[5,7.67,10]	[5,8.33,10]
R20	[1,3,7]	[7,9,10]	[5,7.67,10]	[7,9,10]	[5,7.67,10]
R21	[3,5.67,9]	[3,5.67,9]	[3,5,7]	[3,6.33,10]	[5,7.67,10]
R22	[5,7,9]	[1,2.33,5]	[1,2.33,7]	[1,1.67,5]	[1,1.67,5]
R23	[1,2.33,5]	[1,4.33,7]	[1,4.33,7]	[1,3,9]	[1,4.33,7]

4.5.5 Normalisation Procedure of Fuzzy Decision Matrix 'FDM'

The term "normalisation" refers to the process of minimising data redundancy in a database. Normalisation is an effective strategy to utilise when designing and revamping a database.

Table 4.12: Data normalisation process

Risks / Criteria	Probability	Health & Safety Severity	Time Severity	Productivity-Quality Reduction	Cost Severity
R1	[0.1,0.3,0.7]	[0.5,0.77,1]	[0.3,0.5,0.7]	[0.3,0.5,0.7]	[0.2,0.429,1]
R2	[0.1,0.5,0.9]	[0.3,0.57,0.9]	[0.1,0.1,0.3]	[0.1,0.43,0.9]	[0.33,1,1]
R3	[0.1,0.43,0.9]	[0.1,0.37,0.7]	[0.1,0.1,0.3]	[0.1, 0.3,0.5]	[0.33,1,1]
R4	[0.3,0.63,0.9]	[0.3,0.57,0.9]	[0.3,0.5,0.7]	[0.1,0.3,0.7]	[0.11,0.177,0.33]
R5	[0.1,0.37,0.7]	[0.1,0.37,0.7]	[0.1,0.1,0.3]	[0.3,0.5,0.7]	[0.33,1,1]
R6	[0.3,0.63,0.9]	[0.3,0.57,0.9]	[0.3,0.63,0.9]	[0.1,0.37,0.7]	[0.11,0.177,0.33]
R7	[0.1,0.17,0.5]	[0.3,0.57,0.9]	[0.3,0.7,1]	[0.1,0.43,0.7]	[0.143,0.231,1]
R8	[0.5,0.83,1]	[0.3,0.57,0.9]	[0.1,0.43,0.7]	[0.1,0.5,0.9]	[0.11,0.177,0.33]
R9	[0.7,0.9,1]	[0.7,0.9,1]	[0.7,0.9,1]	[0.7,0.9,1]	[0.1,0.11,0.143]
R10	[0.5,0.77,1]	[0.5,0.77,1]	[0.3,0.5,0.7]	[0.1,0.43,0.7]	[0.143,0.2,0.33]
R11	[0.5,0.7,0.9]	[0.5,0.83,1]	[0.3,0.5,0.7]	[0.1,0.43,0.7]	[0.1,0.12,0.2]
R12	[0.1,0.43,0.7]	[0.3,0.57,0.9]	[0.1,0.43,0.7]	[0.1, 0.3,0.5]	[0.33,1,1]
R13	[0.1,0.17,0.5]	[0.1,0.37,0.7]	[0.3,0.63,0.9]	[0.1,0.23,0.7]	[0.33,1,1]
R14	[0.5,0.83,1]	[0.3,0.63,0.9]	[0.1,0.37,0.7]	[0.3,0.5,0.7]	[0.143,0.231,1]
R15	[0.3,0.5,0.7]	[0.3,0.57,0.9]	[0.3,0.5,0.7]	[0.3,0.63,1]	[0.1,0.13,0.2]
R16	[0.5,0.77,1]	[0.5,0.77,1]	[0.1,0.37,0.7]	[0.5,0.77,1]	[0.143,0.273,1]
R17	[0.3,0.5,0.7]	[0.3,0.57,0.9]	[0.1,0.43,0.7]	[0.1,0.37,0.7]	[0.33,1,1]
R18	[0.3,0.5,0.7]	[0.1,0.23,0.5]	[0.1,0.1,0.3]	[0.1,0.37,0.7]	[0.33,1,1]
R19	[0.1,0.3,0.9]	[0.7,0.9,1]	[0.5,0.77,1]	[0.5,0.77,1]	[0.1,0.12,0.2]
R20	[0.1,0.3,0.7]	[0.7,0.9,1]	[0.5,0.77,1]	[0.7,0.9,1]	[0.1,0.13,0.2]
R21	[0.3,0.57,0.9]	[0.3,0.57,0.9]	[0.3,0.5,0.7]	[0.3,0.63,1]	[0.1,0.13,0.2]
R22	[0.5,0.7,0.9]	[0.1,0.23,0.5]	[0.1,0.23,0.7]	[0.1,0.17,0.5]	[0.2,0.6,1]
R23	[0.1,0.23,0.5]	[0.1,0.43,0.7]	[0.1,0.43,0.7]	[0.1,0.3,0.9]	[0.143,0.231,1]

4.5.6 Ideal Solutions Criteria

Since several ideal solution methods have been applied in previous studies, it's essential to test all of them on construction health and safety application. The output data against each ideal solution criteria are determined in sections 4.2.6.1, 4.2.6.2 and 4.2.6.3.

4.5.6.1 Method 1: Chen Et Al. Ideal Solution

The ideal solution of Chen et al. alternates the 'a' and 'b' values of a fuzzy triangle with 'c' value in the positive ideal solution 'PIS'. In the negative ideal solution, 'NIS' the 'b' and 'c' values are replaced by the 'a' value in a fuzzy triangle 'abc'. The "FPIS" will be utilised with benefits criteria, and "FNIS" will be used with cost criteria.

Table 4.13: Risks ranking as per Chen et al ideal solution

When ideal solution = 1						
Risks Group	**Construction Risk Types**	**Similarities w.r.t. attribute & FPIS "Spos"**	**Similarities w.r.t. attribute & FNIS "Sneg"**	**Risks Order**	**Risks order in each group**	**Closeness values with similarity "CCS"**
Human biological and behaviour	R1	0.6709	0.7405	9	2	0.4753
	R2	0.6884	0.7497	17	5	0.4787
	R3	0.6630	0.7846	16	4	0.4580
	R4	0.6406	0.7796	12	3	0.4511
	R5	0.6659	0.7798	20	7	0.4606
	R6	0.6515	0.7661	19	6	0.4596
	R7	0.6479	0.7709	2	1	0.4566
Manual tasks/ergonomics using machine, tools and equipment	R8	0.6545	0.7637	1	1	0.4615
	R9	0.7358	0.7041	13	4	0.5110
	R10	0.6712	0.7489	10	2	0.4727
	R11	0.6675	0.7640	14	5	0.4663

	R12	0.6926	0.7330	11	3	0.4859
Facilities / built environment	R13	0.6806	0.7553	8	5	0.4740
	R14	0.6643	0.7449	5	2	0.4714
	R15	0.6426	0.7807	6	3	0.4515
	R16	0.6890	0.7198	3	1	0.4891
	R17	0.6993	0.7220	7	4	0.4920
Chemicals, energy systems or environment	R18	0.6590	0.7930	21	4	0.4539
	R19	0.6942	0.7440	18	3	0.4827
	R20	0.6971	0.7422	15	2	0.4843
	R21	0.6475	0.7741	4	1	0.4555
	R22	0.6352	0.7913	22	5	0.4453
	R23	0.6175	0.8044	23	6	0.4343

In accordance to output data in table 4.13, the initial five risks of Chen et al ideal solution approach are ‘R8’ protruding rebar and nails protection, ‘R17’ Poor materials management and poor housekeeping, ‘R16’ dangerous facilities, ‘R21’ chemical containers waste or oil spill, and ‘R14’ vehicles collision and accidents. Although the output ranking of ‘R8’, ‘R17’, ‘R16’, ‘R21’ and ‘R14’ indicates that these risk types are the majorly important ones. Still, the probability and the consequences of health and safety, cost, time and quality expand among all risks. Construction health and safety risks are not evaluated precisely. Therefore, other ideal solution approaches will be examined to achieve the desired result. On the other hand, the program's lowest risk type is accurately selected, which is ‘R23’ sewage overflow and is considered a low risk referring to health and safety reports and experts’ evaluation. The author considers this approach as the least preferable technique to analyse health and safety risks in construction applications.

4.5.6.2 Method 2: Alidoosti, Yazdani, Fouladgar, and Basiri Ideal Solution

Alidoosti, Yazdani, Fouladgar, and Basiri ideal solution defined as the perfect values of zeros and ones where the positive ideal solution ‘PIS’ is represented as [1, 1, 1] and the negative ideal solution ‘NIS’ as [0, 0, 0]. This technique is deemed a crisp logic in which the statements are either true or false to handle the uncertainty in risk events. This method is distinguished by its simplicity in using the logical sense to process the data without applying any complex design method. Depending on the program results, this technique will be compared and criticised based on the experts’ opinions on health and safety reports.

Table 4.14: Risks ranking as per Alidoosti, Yazdani, Fouladgar, and Basiri ideal solution

Ideal Solution = 2						
Risks Group	**Construction Risk Types**	**Similarities w.r.t. attribute & FPIS "Spos"**	**Similarities w.r.t. attribute & FNIS "Sneg"**	**Risks Order**	**Risks order in each group**	**Closeness values with similarity "CCS"**
Human biological and behaviour	R1	0.6409	0.7163	9	2	0.4722
	R2	0.6575	0.7251	17	5	0.4755
	R3	0.6346	0.7579	16	4	0.4557
	R4	0.6106	0.7500	12	3	0.4488
	R5	0.6358	0.7529	20	7	0.4578
	R6	0.6210	0.7374	19	6	0.4572
	R7	0.6192	0.7439	2	1	0.4543
Manual tasks/ergonomics using machine,	R8	0.6209	0.7344	1	1	0.4581
	R9	0.6970	0.6769	13	4	0.5073
	R10	0.6393	0.7214	10	2	0.4698
	R11	0.6361	0.7346	14	5	0.4641

	R12	0.6645	0.7108	11	3	0.4832
Facilities / built environment	R13	0.6534	0.7314	8	5	0.4719
	R14	0.6313	0.7185	5	2	0.4677
	R15	0.6096	0.7496	6	3	0.4485
	R16	0.6527	0.6948	3	1	0.4844
	R17	0.6697	0.7001	7	4	0.4889
Chemicals, energy systems or environment	R18	0.6294	0.7648	21	4	0.4515
	R19	0.6603	0.7155	18	3	0.4800
	R20	0.6619	0.7137	4	1	0.4812
	R21	0.6139	0.7433	15	2	0.4523
	R22	0.6063	0.7632	22	5	0.4427
	R23	0.5891	0.7749	23	6	0.4319

As per table 4.14, the highest five risks belong to ‘R8’ protruding rebar and nails protection, ‘R10’ dangerous access to pits or floor holes, ‘R16’ hazardous facilities, ‘R20’ fire hazards, and ‘R14’ vehicles accident types. These risks' health and safety consequences vary between insignificant to high levels. Hence, the author cannot rely on these results. In addition, the lowest risk type is ‘R23’ sewage overflow which matches the development of Chen et al.’s ideal solution. Moving forward, the third approach will be tested to achieve the goal of this study.

4.5.6.3 Method 3: Hwang and Yoon’s Ideal Solution

Hwang and Yoon’s ideal solution has been developed to simplify the ranking method in scientific applications. The logic of this ideal solution maximises the benefit criteria. It reduces the cost criteria in the positive ideal solution ‘PIS’ where on the other hand, the negative ideal solution ‘NIS’ minimises the benefit criteria and maximises the cost criteria. This technique uses triangle values rather than crisp values. The maximum and minimum fuzzy magnitudes will be obtained from the fuzzy decision matrix. The following tables represent the aggregated and normalised fuzzy decision matrix and output data.

Table 4.15: Risks ranking as per Hwang and Yoon's ideal solution

Ideal Solution = 3						
Risks Group	**Construction Risk Types**	**Similarities w.r.t. attribute & FPIS "Spos"**	**Similarities w.r.t. attribute & FNIS "Sneg"**	**Risks Order**	**Risks order in each group**	**Closeness values with similarity "CCS"**
Human biological and behaviour	R1	0.7996	0.7972	9	1	0.5008
	R2	0.8183	0.8108	16	4	0.5023
	R3	0.7829	0.8548	20	7	0.4780
	R4	0.7662	0.8384	17	5	0.4775
	R5	0.7874	0.8492	19	6	0.4811
	R6	0.7826	0.8234	12	3	0.4873
	R7	0.7719	0.8341	10	2	0.4806
Manual tasks/ergonomics using machine, tools and equipment	R8	0.7902	0.8190	2	2	0.4911
	R9	0.9130	0.7481	1	1	0.5496
	R10	0.8101	0.8012	14	5	0.5028
	R11	0.8045	0.8170	11	3	0.4961
	R12	0.8219	0.7936	13	4	0.5088
Facilities / built environment	R13	0.8065	0.8250	8	4	0.4943
	R14	0.8004	0.7992	6	2	0.5004
	R15	0.7707	0.8386	21	5	0.4789
	R16	0.8352	0.7693	5	1	0.5205
	R17	0.8325	0.7804	7	3	0.5162
Chemicals, energy systems or	R18	0.7794	0.8673	15	3	0.4733
	R19	0.8433	0.7955	3	1	0.5146
	R20	0.8483	0.7938	4	2	0.5166

	R21	0.7787	0.8307	18	4	0.4839
	R22	0.7543	0.8634	22	5	0.4663
	R23	0.7293	0.8734	23	6	0.4550

According to table 4.15, the maximum five risk types are ‘R9’ unsafe work at height, ‘R8’ protruding rebar and nails protection, ‘R19’ electrical hazards, ‘R20’ fire hazards and ‘R16’ dangerous facilities. The results are intensely close to health and safety risks reports and experts’ judgements. Furthermore, all risk types are within the range of high and extreme risk levels. In addition, the lowest risk type is ‘R23’ sewage overflow, which matches the previous ideal solutions criteria outputs. Hwang and Yoon’s ideal solution appears to be the most realistic. It involves genuinely employing fuzzy triangle numbers rather than displaying crisp numbers in a fuzzy manner to achieve a reasonably high similarity rating.

4.5.7 Output Data of Risks Classification Procedure

By applying the data classification procedure presented in section 4.1.7, the outputs vary among the three criteria based on the utilised one. Table 4.16 contains the output of risk classification.

Table 4.16: Risks classification results

Risk Types	S_id1	Class	S_id2	Class	S_id3	Class
R1	0.6709	IV	0.6409	IV	0.7996	IV
R2	0.6884	IV	0.6575	IV	0.8183	V
R3	0.6630	IV	0.6346	IV	0.7829	IV
R4	0.6406	IV	0.6106	IV	0.7662	IV
R5	0.6659	IV	0.6358	IV	0.7874	IV
R6	0.6515	IV	0.6210	IV	0.7826	IV

R7	0.6479	IV	0.6192	IV	0.7719	IV
R8	0.6545	IV	0.6209	IV	0.7902	IV
R9	0.7358	IV	0.6970	IV	0.9130	V
R10	0.6712	IV	0.6393	IV	0.8101	V
R11	0.6675	IV	0.6361	IV	0.8045	V
R12	0.6926	IV	0.6645	IV	0.8219	V
R13	0.6806	IV	0.6534	IV	0.8065	V
R14	0.6643	IV	0.6313	IV	0.8004	V
R15	0.6426	IV	0.6096	IV	0.7707	V
R16	0.6890	IV	0.6527	IV	0.8352	V
R17	0.6993	IV	0.6697	IV	0.8325	V
R18	0.6590	IV	0.6294	IV	0.7794	IV
R19	0.6942	IV	0.6603	IV	0.8433	V
R20	0.6971	IV	0.6619	IV	0.8483	V
R21	0.6475	IV	0.6139	IV	0.7787	IV
R22	0.6352	IV	0.6063	IV	0.7543	IV
R23	0.6175	IV	0.5891	III	0.7293	IV

The Chen et al. method categorised all risk types in class IV, which indicates 'high risk'. In Alidoosti, Yazdani, Fouladgar, and Basiri's ideal solution method, all risks belong as well to class IV "high risk" except the last ranking risk 'R23' is related to class III 'medium risk'. The final criterion is Hwang and Yoon's ideal solution, segregating the risks into class IV 'high risk' and class V 'extremely high risk'. Project stakeholders have to immediately act once a risk is classified under ‘extremely high risk’ and ‘high risk’ categories. The neglecting in any of the risks will cause dramatic losses of workers’ lives, delay project completion and reduction in project profit.

6 Research Discussion

This research employed an innovative approach to rank the uncertain events from the highest to lowest risk. It utilises MCDM, Fuzzy AHP, and TOPSIS methods to facilitate the decision-making process depending on the weights of the experts’ rated attributes.

The selected five parameters used to evaluate risk events are the probability of occurrence, health and safety severity, time consumption, quality reduction, and cost increment consequences. Choosing these specific parameters is vital to all parties and stakeholders working on the same project. The better the site team’s performance creates, the more profitability the project results, the better the performance created by site teams, the more profitability results are generated in the project.

A comparison between the three ideal solutions criteria results of the registered risks was conducted. The optimum ideal solution criteria were selected depending on experts’ opinions provided in the risk assessment literature review's risk assessment and global classification rved that the results of the two ideal measures were declined since they didn’t give the desired data to specialists’ perceptions. The results of the third ideal solution comply with the experts’ judgement and worldwide statistical data. The utilisation of fuzzy values obtains more realistic output data.

The classification of the twenty-three risk types was performed correctly by measuring the similarity values concerning attributes and FPIS. The grouping of certain risk events facilitates promoting adequate solutions against each group.

The developed program was established based on mathematical algorithms, health and safety reports and experts' judgements. The output data and comparison criteria present the ranking of the unfavourable construction events along with the efficient mitigation plans.

The gain extracted from developing a real-time MATLAB program is to continuously detect, rank and priorities the favourable and unfavourable events at construction sites. The adequate mitigation responses provide an insight for the readers to eliminate or reduce the unfavourable scenarios. Besides, it diminishes the fuzziness caused by the construction workplace surrounding environment and operations.

In addition to the above, the promoted program operates properly with various scenarios of real-life events. In many cases, two or more threats occurred together. The program will be able to rank and categorise them into risk levels. Additionally, as per schedules 4.1, 4.2, 4.3 and 4.4, the owner of the occurred risk may not be the same in all cases; thus, the responsibilities will be segregated among the project stakeholders.

CHAPTER 5

5.1 CONCLUSIONS AND RECOMMENDATIONS

Concerning worldwide statistics, the construction sector contributes to occupational accidents among other industries. The consequences of OHS incidents are divided into illness, injuries and fatalities. In 2019, construction sites had 195,600 workplace injuries and 3,600 workplace illnesses. As observed by OSHA, the leading fatal four causes of HSE hazards cover 58.6% and belong to working at height hazards with 33.5%, 11.1% for falling objects, electrical risks with 8.5%, and 5.5% is for sticking in things (Workplace Injury Statistics - 2021 UPDATE | WorkInjurySource.com, 2021).

The impacts that appear from the individuals or team on health and safety disasters include workdays' losses, production reduction, health damages, and cost increment. These outcomes will decrease the labourers' performance and overall project quality. Thus, health and safety officers must register all minor and major risks, measure the probability and consequences, and prevent threats and weaknesses.

In the UAE market, the construction sector forecast has an annual average growth of 3.9% between the duration of the year 2022 and the year 2025 (WIRE, 2021). Since the construction industry is one of the profitable industries in UAE and has a high potential of risks, the author established a health and safety leading indication program using machine learning algorithms and MATLAB computer software. Both mathematical logic and computing systems were developed based on collected data containing health and safety reports and assessors' filled questioner.

The benefits of utilising machine learning algorithms in the business are their ability to keep learning, improve the results and eliminate the causes of unfavourable events. The inputs used in the program assessed 188 different risk types presented as linguistic variables by the experts and the importance weight of parameters. The linguistic variables were represented with fuzzy numerical values to ease the data processing and analysis. The selected five parameters are the probability of occurrence, health and safety threats, duration of the incidents and their corrective actions, productivity losses, and total accident cost. Additionally, the 188 risk kinds were categorised into four prime groups: human biology and behaviour, manual tasks or ergonomics using equipment, facilities or built environment, and chemicals or energy systems.

The weighting procedure was performed by utilising a multi-criteria decision-making matrix. It facilitates the assessors' decision-making process to precisely evaluate the risk events. Besides, input data aggregation and normalisation processes were applied after converting the linguistic variables into fuzzy numerical values. The normalisation adjusted the range for data to be within 0 and 1 to obtain data consistency within the database and generate a flexible database design.

All analytical processes were conducted to attain finding the similarities concerning attributes, FPIS and FNIS. Three theories of ideal solutions were tested to choose the most effective and efficient health and safety risks ranking. As observed from data processing through different criteria, Hwang and Yoon’s proposed approach is reliable and reasonable. Furthermore, a mathematical GMIR function was performed to obtain the similarities values. Another classification technique was applied by promoting a set of rules represented in a range of values. In addition, the closeness coefficient was calculated to rank and classify risks depending on a set of rules determined by the author and experts’ judgments.

Risks ranking was obtained among all types and as per risk causes categories. Depending on the rating sequence, the responses of risks were determined by applying avoidance, acceptance, mitigating or transferring strategies. Professional construction contractors act proactively and take safety measurements before unfavourable events occurrence. The rectified actions were implemented to correct labourers' behaviours, establish a safe working environment, and prevent fire and electrical hazards.

The main advantage of gathering and analysing uncertain events is to act proactively and execute proper mitigation plans prior to an incident occurring. Monitoring and controlling the risk will lead to saving protect peoples' lives and providing them with a healthy work environment. In addition, it will assist project decision-makers in evaluating health and safety damages and apply it to project time, cost and quality.

5.1.1 Research Recommendations

Ultimately, the study presented several criteria of fuzzy AHP ideal solutions that project owners and stakeholders could use to establish healthy and safe work conditions and construct an efficient construction project.

Creating a real-time program to detect, evaluate, and analyse unfavourable events will prevent the threats and allow opportunities to occur, which will maximise the project profit and improve construction sites' health and safety environment.

A significant amount of risks in UAE construction sites are not properly detected and analysed; therefore, the margin of the construction projects is estimated to be 10%-15%. Additionally, the completion date of projects is getting delayed for more than 6 months, resources are consumed, and workers' productivity is decreased. Since UAE business is highly dependent on the construction industry, an intelligent, proactive risk indicator program has to be implemented and utilised to eliminate or reduce construction sites' threats.

In conclusion, the research findings comply with the prime research question and accomplish the aim and objectives by providing intelligent indicators to predict health and safety incidents in construction projects.

Research Limitations

The proposed study was concentrating on the construction industry where it may not fit exactly other business applications. Machine learning models can’t be isolated from real recorded business data and experts’ judgement specialised in the same field. Furthermore, in order to improve the accuracy and precision of the results, a significant amount of datasets must be collected from different construction sites prior to new construction project implementation. Besides, although in UAE it’s mandatory to investigate and record all uncertain events at construction sites, not all consultants were willing to provide health and safety reports for the study. As well as there is a limited time duration of the research study to be performed. Thus, it’s challenging to collect a sufficient amount of data, develop a program to process them and analyse the findings.

Future Recommendations

The findings of this study are considered as an essential basis for future research, which leads to improving and upgrading the outputs of the research. The area of improvement of future studies are:

i. Install sensors and CCTV systems to detect unfavourable events on a real-time basis.
ii. Transfer the data continuously into the fuzzy TOPSIS program to have updated data analysis.
iii. Implement MCDM, fuzzy AHP and TOPSIS methodologies at risk mitigation responses to rank and classify them based on their performance.

iv. Comparing the research results with other countries sharing the same environment and procedure of UAE construction sites to affirm the efficiency of results.

v. Investigate other machine learning theories at different stages of the construction business such as the construction phase and design phase.

CONSTRUCTION RISKS MITIGATION RESPONSES

The core benefit of ranking criteria is facilitating risk mitigation responses and dividing related tasks among concern teams. The major categories that cause uncertain events to arise at sites are human biology and behaviour, manual tasks, facilities environment, chemicals, energy systems, etc. Based on the ranking of Hwang and Yoon's ideal solution against each category, risk responses will be determined.

5.2.1 Human Biological and Behaviour Risk Responses

One of the critical tasks in construction projects is to prevent workers' misunderstanding and errors. Construction projects combine workers with different mentalities, capabilities and experiences. Depending on the size of the project, the percentage of workers at the site is 70%-75% for labours and 25%-30% for engineers, supervisors and managers. Usually, most workers come from basic knowledge, various cultures and limited experiences. Therefore, the possibility of having unfavourable or catastrophic events is high. Additionally, Projects stakeholders have to accept that workers make mistakes and support them in fixing the situation before the accident occurs. According to the following analysis, the causes of human errors in a workplace have to be addressed and ranked in sequence from highest to lowest. Moreover, mitigation responses will be provided.

5.2.1 Unskilled workers work at height and dangerous areas

Knowledge, ability and experience are three significant parameters for human success. Recruiting unskilled employees or providing insufficient instructions can lead to minor or major injuries. The following proposed solutions can be employed to eliminate or reduce this type of event.

Mitigation plan:

i. Comprehensive practical training to be conducted for workers.
ii. Re-allocation of employees' tasks based on their capabilities.
iii. Strict training and examination for the advanced tasks.
iv. Develop a fall protection system by the consultant.
v. Educate labours with health and safety instructions which the HSE department promotes.
vi. Immediate reporting for the case to health and safety supervisors.

5.2.2 Lack of Risk Monitoring and Auditing

Project monitoring is a necessary procedure that must be performed from the initial planning stage until the handing over of the project phase. Risks monitoring allow project stakeholders to act before and during unfavourable events. Additionally, it impacts the project performance positively by reducing the cost and the duration of the mitigation responses.

Mitigation plan:

i. Install sensors and CCTVs to cover the construction area.
ii. Implement HSE awareness training sessions.

iii. Communicate injury cases or accidents to HSE supervisors.

Virus or Disease

The struggle of having an illness worker at a workplace is the considerable possibility of spreading the virus or disease, among others. This type of risk damages the project's progress harshly. It results in a time delay, high cost and low productivity, as happened during the pandemic situation of Covid-19 from the end of 2019 until today. Thus, it's essential to plan for mitigation actions properly.

Mitigation plan:

i. Develop protocols and contingency plans in case a confirmed case.

ii. Isolate sick employees and provide them with the necessary treatment.

iii. Utilise the minimum required workforce and supervisors to keep essential operations running.

iv. Conduct virtual meetings to reduce the number of employees and make social distancing

v. Ensure medical treatments, masks and gloves are available all the time at site.

vi. Regular cleaning and sanitising of the accommodations and gathering area.

PPE Enforcement at the Workplace

Each consultant and contractor have to supply protection equipment for their employees. Since not all labours can adopt the culture of the construction site and apply health and safety regulations, project supervisors have to provide them with clear leads to comply with UAE site culture and legislation.

Mitigation plan:

i. Consultant HR department should provide practical training for PPE usage.
ii. Consultants and contractors must purchase a sufficient amount of PPE products for workers.
iii. Arrange a storage area for personal protective equipment.
iv. Violators to be penalties as per HR and HSE department's code of conduct.

Uncertified Labours Working in Bar Bending and Cutting Machines Operation

Although using machines at site operations conserve a significant amount of time, it contains several dangerous areas. Hence, workers who operate the machines must be chosen wisely to ensure risk elimination or reduction.

Mitigation plan:

i. Competency training to be arranged by the manufacturing companies to ensure the safety of site workers.
ii. Continuous monitoring during machines operation.
iii. Health and safety supervisors to ensure that protective equipment is worn.
iv. Safety system to be activated on the used machines.

Improper Behaviour of Workers

Another impact of cultural difference results in some workers' improper behaviours when communicating or working with each other. In many previous cases, labours fought with their colleagues or supervisors due to disagreements on personal or work matters. In addition, many of them violate the code of practice or smoke and eat in improper locations at the site.

Mitigation plan:

i. Locate a smoking area for workers on site.
ii. Prevent workers from using cooking gas or accommodating on-site.
iii. Identify offices and rest areas by signs for better usage.
iv. Eliminate any conflict or issue among workers.

Unsafe Storing of Materials

This type is not one of the top harmful events on human health and safety compared to the others. Nevertheless, improper staffing or storage can lead to minor injuries or disease spreading since dangerous animals may live or hide in the storage area. In addition, it will lead to physical defects, and materials will be wasted.

Mitigation plan:

i. Site management to implement safe and proper criteria of materials arrangement.
ii. Assign storekeepers to monitor and control the storage area.
iii. Regular cleaning of the storing area.
iv. Implement CCTV to facilitate the monitoring process.

Manual Tasks or Ergonomics Using Equipment Risk Responses

Manual handling tasks are significant causes of injuries or death cases on construction sites. The type of activities included in manual tasks is pulling, pushing, holding, lifting and carrying. These tasks are not considered unfavourable events at standard conditions, but due to environmental, workplace conditions and machine operation, they will be transferred to hazardous events. The prevention of manual handling functions will be explained according to risk ranking from high to low.

Unsafe Works at Height

Dangerous areas or heights are the two significant locations on-site for extreme risks. During the occurrence of the risk, it's extremely tough to avoid it. It results in major injuries and death cases. The main tasks at height are aligned with utilising the scaffolding and ladders. Furthermore, there are no safe barricades at the edges or good platforms for the structure. Thus, it's essential to consider the following mitigation responses.

Mitigation plan:

i. Instruct supervisors and foremen to ensure that trained people erect scaffolding.
ii. Cranes shall contain barricades with suitable signs to make the operators and drivers aware.
iii. Edge protection barriers on the construction building has been established with caution signage.
iv. Real-time monitoring is applied to make safe working procedures.
v. Regular maintenance for construction tools and machines.
vi. Use ropes and PPE equipment to overcome falling incidents.
vii. Extensive training for labours to practice working at heights.

Protruding Rebar or Nails On-Site Areas

In addition to the machines usage, nails and protruding rebar equipment are tremendously required in buildings construction. Constantly, having workers stepping on a nail or protruding rebar is happening among all construction sites.

Mitigation plan:

i. Place the steel caps on the steel and protruding rebar wherever required at the site.
ii. Open floors or floors with nails to be barricaded properly.
iii. Easy access for medical treatments.
iv. Immediate reporting for health and safety supervisors.

Unsafe Lifting Operation

In many cases, labours overload the lifts with heavy substances or make the lifting operations during unstable weather conditions. Or else, the loads may fall if materials wrapping, and packing are not correctly done. Falling objects over people lead to significant injuries or immediate death.

Mitigation plan:

i. Warning signs near the lifting operations.
ii. Ensure labours are not walking or working close to the loaded lifts.
iii. Immediate reporting for any case of falling objects.
iv. Ensure efficient load wrapping and connecting load with slings.
v. Monitor workers upon loading the substances and don’t exceed the limit.
vi. Train labours in conducting the lifting operations.

Contamination of Soil or Sagged Soil

As mentioned in the previous sections, labourers' behaviour affects the work progress and surrounding area. Soil gets contaminated because labours commonly throw out chemical waste or harmful materials. In addition, soil sagging is happening due to poor concrete casting.

Mitigation plan:

i. Contractors to train their engineers and supervisors for environment-friendly concrete casting.
ii. Prepare environment safety procedures to control contamination of soil.
iii. Violators to be penalties as per HR and HSE departments code of conduct.
iv. Locate a particular area for dangerous wastes.

Dangerous Access to Pits or Floor Holes

When workers don't comply with health and safety regulations on wearing the PPE on-site, it results in slip and trip hazards. Furthermore, in other scenarios, the labours construct unsafe access to lower pits which harm their health.

Mitigation plan:

i. Ensure that labours wear PPE during the site work.
ii. Provide sufficient numbers of ladders for accessing the pits.
iii. Keep the floor free of obstacles and dry as much as possible.
iv. Immediate reporting of the hazards when they occur.
v. Add warning signs next to floor holes and pits.

Facilities or Built Environment Risk Responses

Facility management contains all managerial services that facilitate business processing and completion. It manages physical work, administrative tasks, and engineering processes. The main target of facility managers is to accomplish the construction tasks with exceptional performance and high quality. It’s essential to understand the risk kinds of facility management to ensure smooth operation and completion of project construction.

Dangerous Facilities

Several features represent dangerous facilities such as unhygienic areas, high buildings and scaffolding locations, chemical containers zones, and problematic parking areas. The critical issue with this kind of risk is its negative impact on a significant amount of labour. Thus, mitigation actions are developed to overcome these events as per the following.

Mitigation plan:

i. Locate eating and resting areas for labour.
ii. Regular cleaning and sanitising of indoor areas.
iii. Supervisors must conduct training to prevent resting in dangerous areas.
iv. Arrange suitable parking zones for heavy vehicles and plant machines.
v. Avoid poor management and engineers' adequate, effective work system.
vi. Add labels and signs around dangerous areas.

Vehicles Collision and Accidents

The causes of vehicles collision arise from the drivers’ poor attention, erratic driving and irresponsible behaviour. Whether they are walking or inside the vehicle, construction workers will be under extensive risks due to the lack of protection. In addition, construction vehicles are distinguished by their heavyweight and big size than regular vehicles; therefore, their collision will result in vast inflict.

Mitigation plan:

i. Specific emergency plan to deal with potential vehicle fires.
ii. Vehicle movements must be controlled under the supervision of a flagman.
iii. Locate loading, unloading, and parking areas for vehicles delivery and collection.
iv. Establish barricades around the parking and materials loading or unloading lots
v. Traffic marshals shall be easily identifiable.
vi. Traffic control measures shall be provided at pedestrian crossings, junctions, and other hazardous areas.

Poor Materials Management

A total project cost is related to the necessary construction materials. The squandering of materials will add additional costs to contractors, decrease the profit margin and delay the tasks completion dates. Inadequate storage of materials leads to physical damages or stealing cases, and both will cause a reduction the profitability. To accomplish the contractors', aim of delivering the maximum profit of the project under safe conditions and seeking client satisfaction, below mitigation responses should be considered.

Mitigation plan:

i. Employ a contractor specialising in the housekeeping process.

ii. Avoid materials stacking on high shelves.
iii. Reorganise all construction materials with properly stacking.
iv. Materials labelling, counting, and registering for ease accessing and picking up.
v. Install CCTV for real-time monitoring and recording.

Traffic Management

The coordination of vehicles movements and parking requires flagman support to be achieved. Traffic supervisors are obligated to regulate traffic flow and eliminate vehicle collisions by providing them with training and safety awareness sessions. Furthermore, it's essential to give a strategy to protect the lives of flagmen or traffic controllers while doing their tasks.

Mitigation plan:

i. Establish clear traffic instructions for flagmen and vehicles drivers at the construction site.
ii. Flagmen should be provided with adequate shelter from the sun or rain when working at fixed locations.
iii. Selection of safe positions for traffic supervisors during their operations.
iv. Penalties should be applied upon violating the rules.
v. Instant reporting of any unanticipated event.

Inadequate Waste Segregation and Management

With the benefit of maintaining the construction site safe and clean, waste has to be appropriately managed and segregated. In several events, workers dump steel rebar, metal scraps, cement bricks, concrete, and chemical wastes in different construction site areas. Moreover, some labours use buckets for food waste, which is considered an improper attitude.

Mitigation plan:

i. Develop a waste segregation policy based on site conditions.
ii. Ensure waste collection and disposal regularly.
iii. Immediate disposal of unwanted steel, rebar, and chemical wastes.
iv. Hire pest control to expel dangerous animals.
v. Set special containers for each waste type.

Chemicals, Energy Systems or Environment Risk Responses

Stakeholders must consider adequate tactical precautions to protect site workers from environmental hazards. An example of energy systems, chemical and environmental hazards are electrical and fire disasters, chemical containers, water leakage, sewage overflow and dust emission, which can harm the personnel in a workplace. Health and safety officers continuously monitor potential environmental and energy hazards to overcome unfavourable events. An ecological and power-controlled system is evolved to protect people's lives and reduce project losses.

Electrical Hazards

Various forms of electrical hazards cause explosions, shocks, burns and fires. Inadequate wiring, damaged equipment and tools, and wet conditions are the common reasons for electrical disasters. Project consultant assigns a particular person to examine all electrical equipment, cables and switches to ensure that they are operating safely. Electrical hazards significantly impact human lives, tasks performance, and project cost.

Mitigation plan:

i. Remove all unwanted or damaged cables from the site
ii. Follow manufacturer instructions while using electrical appliances or connecting cables.
iii. Guide site workers to use safe working power tools.
iv. Improve site team awareness and provide them training programs.
v. Implement over-voltage and over-current protection devices.
vi. Instant reporting for health and safety officers and technical engineers to fix the issues.

Fire Hazards

Construction sites are one of the highest areas to initiate a potential fire hazard. Various sources increase fire hazards' probability and impacts, such as flammable waste substances, explosive materials, improper wiring, and deficient electrical system. Additionally, poor equipment maintenance and lack of monitoring will maximise the risk of catastrophic fire.

Mitigation plan:

i. Extensive training is conducted regularly for MEP workers.
ii. Issue clear policies and instructions to control workers' behaviour on site.
iii. Implement firefighting systems in various zones on site.
iv. Install fire detection sensors among site areas.
v. Issue warning notes and penalties for the violators of safety laws.
vi. Collect, segregate, and get rid of the flammable wastes.

Water Leakage or Water Flooding

The consequences of water leaking or flooding led to dramatic losses to construction business shareholders during the site erection. The water leakage and flooding are caused by the damages of the plumbing systems or heavy rain entering the site. Although the insurance company covers part of the unfavourable event cost, project owners are responsible for most of the cost, which will reduce the profit margin of the business. Furthermore, such a type of risk will ruin the reputation of the stakeholders' companies.

Mitigation plan:

i. Arrange regular inspection to maintain the pressure of the underground water lines.
ii. Regular walk-through inspection on-site to identify water damages on site.
iii. Utilise sensors to facilitate monitoring and controlling procedures.
iv. Install water leak detection system.
v. Prompt repairing of water system while problems are detected.

Chemical Containers Waste or Oil Spill

In the case of a chemical container spill on a construction site, the team who caused this event has to be in charge of prompt clean-up and immediate reporting. Appropriate tools and personal protective equipment have to be utilised in chemicals refining. Furthermore, supervisors have to prevent mixing compressed chemical sprays with other wastes.

Mitigation plan:

i. Prepare a list of hazardous chemicals used at the site.
ii. Labelling all chemical containers and arranging specific areas for storing them.
iii. Develop a communication strategy to perform immediate cleaning of chemical spills.
iv. Prompt evacuation plan on-site upon spilling of flammable chemicals.

Dust Emission

All activities in construction sites play a significant role in generating dust emissions. The main tasks of dust sources include ground excavation, wall drilling, blasting, and cutting operations. According to the prevailing meteorological conditions and execution level, dust emissions vary among the days.

Mitigation plan:

i. Materials prefabrication based on precise drawings before the installation process.
ii. Implement dust suppression measures by utilising equipment that minimises dust emissions.
iii. To reduce dust from cutting machines and drilling operations, use water sprays.
iv. Install ventilation system, Fans and filters to ensure smooth operation.

Sewage Overflow

The sewage overflow is caused by roots, breakage and debris blocking the sewer lines. Or else the insufficient tank capacity. Sewage overflow damages the property, harm people's health and increases water lines or soil contamination.

Mitigation plan:

i. Contractor must arrange adequate sewage tank capacity for the human resources on site.

ii. Install protection and detector systems for sewage overflow.

iii. Hire a cleaning company to hygiene the site after the overflow incident.

iv. Immediate reporting in case of property damages or health illness.

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