PREDICTIVE MODELLING OF INCIDENT RISK TO PREEMPT RISK IN HIGHWAY OPERATIONS: A MACHINE LEARNING APPROACH

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Predictive Modelling of Incident Risk to Pre-empt Risk in Highway Operations: A Machine Learning Approach

by

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ABSTRACT

Highway traffic officers (HTOs) operate in complex and hazardous environments, yet transportation safety research has predominantly focused on drivers, pedestrians, roads, and vehicles, with limited attention to HTOs' safety. In the UK, National Highways currently employs traditional statistical methods to mitigate safety risks post-incident, a reactive approach that does little for risk prevention. This thesis proposes a proactive approach by developing a machine learning (ML) prediction model to forecast incidents such as injuries, incursions and environmental hazards, assess risk levels, and predict the body parts likely to be affected in injurious events. The aim is to provide highway safety authorities with predictive insights for timely interventions and enhanced risk management. Despite the growing application of ML in safety risk prediction, there is limited evidence on the reliability of variables used as indicators of safety performance. To address this gap, this study develops a conceptual framework for selecting optimal safety indicators (SIs) and formulating input variables that enhance ML-based risk prediction. A three-stage, multiphase mixed-methods research design was employed: i) developing the conceptual framework; ii) constructing the proof-of-concept ML model; and iii) validating the model's performance. The conceptual framework was established through a systematic literature review using PRISMA-based bibliometric search, scientometric and cluster analysis to identify significant SIs and grounded theory analysis was used for synthesis. The ML model development phase applied supervised learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), Deep Neural Networks (DNN), Ensemble Learning (EL), and Recurrent Neural Networks (RNN). The models were trained using secondary data from a highway incident database and three data balancing techniques were tested to address the class imbalance. Model validation employed a stratified k-fold cross-validation approach, evaluated based on AUROC, precision, recall, and accuracy.

The study identifies key considerations for selecting SIs, emphasizing the integration of leading and lagging indicators to enhance system adaptability and resilience. A novel conceptual framework is presented that guides the selection of robust indicators for ML-based risk modelling. Empirical findings indicate that the SVM model with a polynomial kernel, combined with the SMOTE algorithm, outperforms other models in predicting incident types, risk levels, and affected body parts, whereas Random Under-sampling (RU) was the least effective. Critical factors influencing highway incidents, including weather conditions, visibility, age range and location, were identified and analysed.

This research makes several novel contributions: i) a novel conceptual framework integrating resilient SIs for predictive modelling; ii) a systematic approach to combining leading and lagging indicators for enhanced safety performance; and iii) the first study to use an incident database dedicated to HTOs for predictive risk modelling. The developed ML model provides actionable insights for safety officers, enabling proactive risk mitigation through targeted training and preparedness strategies for HTOs. This ultimately improves workplace safety in highway operations.

DEDICATION

In loving memory of Faustina Aforkor Lomotey (my mother) and Victoria Akonnor Borketey (my grandmother). This work is dedicated to the ever-present memory of these two women who taught me to be a warrior, never to give up and to always aim for the best. ‘Mummy, Grandma, I did it!’

SPECIAL DEDICATION

I cannot complete this section without mentioning my darling husband, Steve Kubate Salifu: I would like to express my deepest gratitude and appreciation for your unwavering support, love, and understanding. Your sacrifice and encouragement have been the cornerstone of this journey. Thank you for your endless patience, for believing in me, and for encouraging me every step of the way. I do not take for granted your persistent love and support. I am forever grateful for your steadfast presence in my life.

To my beloved son, you have been a source of joy and inspiration throughout this process. Your constant need for attention, fighting over my laptop and sometimes going a little hungry especially when I spend long hours working on this thesis, have meant the world to me. They are memories I hold dear and will cherish for the rest of my life. Thank you for your sweet smiles, your warm hugs and your dedication which have provided me with the strength and motivation to persevere.

This thesis would not have been possible without the incredible support of my family and friends. To my husband and son, I dedicate this work to you, with all my love and gratitude.

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LIST OF ACRONYMS

AI – Artificial Intelligence

DDA – Descriptive Data Analytic.

H&S – Health and Safety.

HSE- Health and Safety Executive

HTO- Highway Traffic Officer

ML – Machine Learning.

SI- Safety Indicator.

UK – United Kingdom

SRN – Strategic Road Network

IPV – Impact Protection Vehicle

FAL- Functional Analytical Layer

LIST OF PUBLICATIONS

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CHAPTER 1 - INTRODUCTION

The construction industry is arguably one of the most dangerous sector in the world in terms of safety (Dong *et al.,* 2018). Globally, available evidence suggests that the accidents on construction sites claim the lives of over 60,000 workers annually (Golizadeh *et al.,* 2018, Lingard, 2013). In other countries such as the United States, construction fatalities account for 19.09% of all occupational injuries (Golizadeh *et al.,* 2018). China reported an injury mortality rate of 46.90 per 100,000 people, accounting for 6.61% of the overall deaths in the year 2021 (Duan *et al.*, 2023). Health and safety (H&S) hazards are the potential harm that workers are exposed to within the workplace (cf. Carter & Smith, 2006) and have the likelihood of causing adverse effects known as risks. Risk and risk management concepts have been studied extensively in the construction industry owing to the nature of work carried out; the vagaries of a dynamic working environment; and the plethora of machines and equipment employed (cf. Zheng *et al.*, 2019). The Health and Safety Authority (HSA, 2020) defines risk as the likelihood that a person may be harmed or suffer adverse health effects if exposed to a hazard. This definition considers the existence of hazards and the probability that a person will interact with these hazards which may have a negative impact on their safety.

Within the United Kingdom (UK), construction workers are five times more at risk of being killed than in other industries combined (Cater and Smith, 2006). According to the Health and Safety Executive (HSE), the fatality rate of construction workers in 2019/2020 was three times that of all other industry fatal injuries (HSE, 2020) albeit, the construction industry accounts for only 7% of the national workforce. Also, a study conducted by Behm and Schneller (2013) on understanding accident causation and prevention in the UK cited the construction industry as the sector that kills and injures most people. Furthermore, a recent report by the HSE rated *'construction'* as the third most dangerous work in the United Kingdom (HSE, 2019).

Several industries (Tiwary *et al.*, 2012; Chapman *et al.*, 2017) fall under the construction sector including the highway industry (Valiante *et al.*, 2004) which design, plan, construct and maintain highways. The highway industry is prone to encounter various health and safety risk which could result in the occurrence of incidents, accidents, or injuries due to the nature of work operations (Mendeloff and Staetsky, 2014, Eseonu *et al.,* 2018). Such operations include: constructing roads (Rashid *et al.,* 2019); expanding and refurbishing surfaces clearing and levelling sites preparing ground (Cattermole *et al.*, 2013); fixing potholes and addressing cracks (Howell *et al.,* 2024); crushing and screening various materials (Khankelov et al., 2021); installing pavements and curbs (Veneziano et al., 2023); and upkeeping roadside verges and central reservations (Howell *et al.,* 2024). H&S risks are a major concern in the highway industry because of the staggering number of omnipresent fatal and non-fatal incidents which occur and result in high compensation claims and significantly exorbitant mitigation costs (Waehrer *et al.,* 2007). The cost of non-fatal occupational injuries in the UK has been estimated by the HSE to be approximately £4.8billion (HSE, 2016). Although the UK has significantly lower reported fatality rates than other jurisdictions such as China and the US in a comparative study by Mendeloff and Staetsky (2014), it is imperative that more work is undertaken to encourage an incident-free work environment as the life of every worker is valuable. This is made possible via an enormous repository of data (held by National Highways) to support and facilitate proactive measures such as risk prediction and prevention (Ayhan and Tokdemir, 2019). Such work (*ibid*) aimed at predicting incident risks could have implications in areas such as safety decision making, resource prioritisations and risk awareness thereby creating a learning organisation.

1.1 PROBLEM STATEMENT AND MOTIVATION OF STUDY

In the ever-evolving landscape of road construction and transportation operations, ensuring the safety and wellbeing of highway workers is paramount (Rashid *et al.,* 2019). Due to the nature of operations carried out on the highway and proximity to live traffic, highway workers are prone to encounter various health and safety (H&S) risk which could result in the occurrence of incidents, accidents or injuries (Mendeloff and Staetsky, 2014, Eseonu *et al.,* 2018). Worker traffic incidents which occurs on the highway include incursions, injuries and the emission of hazardous substance (Rogovski, *et al.,* 2021) – each requires prompt and precise reactions from workers responsible for safety on the highway. Furthermore, to address safety risks in highway operations, it is essential to gather data that specifically addresses the risks associated with these operations. Highway projects, incidents and operations generate substantial data, offering the potential to reduce the probability of incidents (DeLisle, 2020). Nevertheless, there is currently a lack of guidance and evidence regarding safety-oriented data that can serve as an indicator of impending risks (Dolan, 2008).

To proactively improve the situation, judicious identification of event/incident types likely to occur on the highway is critical for deploying suitable resources, optimising traffic flow and ultimately, saving lives (Eseonu *et al.,* 2018). By proactively identifying incidents beforehand, many incidents could be checked and prevented in time before they metamorphose into fatal accidents and complete systems shutdown (Rashid *et al.,* 2019). Incidents therefore could be prudently detected through projections and predictions (Zhang *et al.*, 2019). A study by Bortey *et al.* (2022) revealed that the unit of highway workers who have received scant attention in the safety prediction area are highway traffic officers (HTOs). HTOs are the highway workers responsible for resolving and responding to incidents on the highway, carrying out highway safety and maintenance inspections, traffic management and reporting faults on the road network.

Several efforts have been made by highway safety mangers to prevent incidents and accidents on the road network (Zhao *et al.*, 2016). However, for HTOs in the UK, traditional analytical methods are being used currently to mitigate risk after they have occurred (Tam *et al.*, 2020). However, traditional analytical methods of incident classification are incapable of handling the volume of incident data being churned out as well as the complexities of modern highway operations (George and Hautier, 2021). Another limitation with this conventional method, is its failure to predict and pre-empt accident risk from happening in the first place since it is more reactive than preventive (Costanza *et al.*, 2017). Hence, a more complex tool and approach are needed for predictive modelling of incident risk to ensure the proper health and safety of HTOs.

Machine learning (ML) has proven to be very relevant in identifying hidden trends and patterns which gives insight into the available data (Witten and Frank, 2002). The ascendency of ML algorithms allows it to capture the nuances of the multifaceted and uncertain nature of incidents (Zhang *et al.,* 2019). The ability of ML to discern intricate patterns when processing large volumes of data is a desirable quality that makes it preferable for incident prediction (Alawad *et al.,* 2019). For instance, some studies (cf. Matías *et al.*, 2008; Sarkar *et al.*, 2019; Theofilatos *et al.*, 2019) have used ML techniques to analyse accidents that occur in the workplace based on its prediction ability and the capacity to be detailed than descriptive (Matías *et al.*, 2008). Studies which use historical data from accidents have all proposed the use of ML as a better solution as compared to the traditional and conventional analytical methods (Tixier *et al.,* 2016; Zhang *et al.,* 2019; Goh *et al.,* 2018). Other characteristics of ML that makes it advantageous is its predictive ability, enabling pre-emptive measures to be taken, and the ability of finding relationships between the variables and how they influence accidents (Zhai *et al.,* 2021).

1.2 AIM AND OBJECTIVES

This thesis aims to uncover how diverse data sources from the highway industry and from literature could aid in developing a safety risk predictive model specifically tailored for HTOs..

To achieve this, it is first necessary to critically examine existing literature on safety indicators to establish their relevance and effectiveness in ML-based risk modelling. Through a systematic review and scientometric analysis, this thesis identifies and categorises leading and lagging indicators to create a resilient framework for safety prediction. Using the identified indicators, input variables for ML models are formulated and assessed to determine their impact on prediction accuracy and reliability. This process extends beyond conventional safety risk literature to incorporate interdisciplinary perspectives, including transportation safety, occupational risk assessment and machine learning methodologies, to ensure a comprehensive understanding of risk factors influencing HTO safety. Finally, the developed ML models are empirically tested and validated using highway incident data to evaluate their effectiveness in predicting incidents, risk levels and body parts most likely affected in injuries. This helps to provide actionable insights for proactive safety management.

1.2.1 Research objectives

The following objectives were established to accomplish the aforementioned aim:

i. To identify how various previous and existing models and theories underpinning safety risk management within construction and other industries could be tailored towards highway operations.
ii. To identify and analyse contributions of existing safety indicator data which informs the selection safety-oriented variables for highway traffic operations.
iii. To develop a conceptual model based on identified standardised safety indicator data tailored for highway traffic operations.
iv. To establish a robust framework for the success of a similar prediction or classification proof-of-concept model in literature.
v. To build a proof-of-concept ML predictive model which can be used to predict risk level, body parts likely to be affected and incident types for effective decision making.
vi. To validate and identify significant parameters within the model and assess the accuracy and precision of the model using standard evaluation metrices.

1.3 THE THESIS

This section details the scope of the research, the research questions and a brief summary of the methodology and research design adopted.

1.3.1 Scope

The research presented in this thesis is not a fully developed and deployed safety prediction model but instead focuses on developing a conceptual framework and proof-of-concept ML model for risk assessment in HTO operations. The study exclusively integrates selected safety indicators SIs derived from systematic literature analysis and applies them to predictive modelling using historical incident data from a highway incident database. The performance of the ML models is assessed under controlled conditions using standardised evaluation metrics without real-time deployment or integration into existing highway safety management systems. The following list outlines the study limitations:

i. The study utilises historical incident data recorded by National Highways for HTOs. However, real-time data collection or live streaming data integration was not within the scope of this research.

ii. While a broad range of SIs were reviewed, only those identified as most relevant through bibliometric analysis, scientometric clustering, and grounded theory synthesis were incorporated into the model. Some potential indicators may have been excluded due to data availability constraints.

iii. Three data balancing techniques (SMOTE, Random Under-sampling, and a hybrid approach) were tested to address class imbalance. However, alternative advanced data augmentation methods were not explored in this study.

iv. The ML models were validated using stratified k-fold cross-validation within the dataset but were not externally validated against independent datasets from different regions or agencies.

v. The conceptual framework for safety indicators is designed to be broadly applicable to HTO safety risk assessment. However, the predictive model’s performance may vary across different operational contexts and geographical locations due to differences in reporting standards, environmental conditions and workforce demographics.

vi. While safety risk prediction inherently involves human factors, this study did not explicitly model behavioural aspects such as decision-making, reaction times, or situational awareness of HTOs due to the complexity of quantifying such variables in an ML model.

While these limitations define the scope of the study, the research provides significant contributions by presenting a structured approach to integrating SI in ML-based risk prediction, offering new insights into proactive safety management for highway operations.

1.3.2 Research questions

i. What are the most explored theories and models underpinning the safety risk management and their contributions in the construction industry?

ii. What are the relevant safety indicators necessary towards the development of a prediction model?

iii. What are the factors within the highway industry that are significant to the prediction or classification of accident risk?

iv. How can ML and deep learning models be successfully adopted in predicting health and safety risk?

v. What are the significant parameters, accuracy, and precision level of the prototype model?

1.3.3 Research methodology and design

The research methodology and design adopted outlines the processes employed in this thesis as proposed by Saunders *et al.* (2016). This consists of: i) philosophical selection; ii) reasoning approach; iii) choice of method; iv) determination of research strategies; v) identification of time horizon; and vi) techniques and procedures employed. A concise summary of the techniques, methods and approaches adopted for this research is therefore explained in intricate detail below. Chapter 2 which is the methodology chapter presents a more granular description and contextualisation of these methods and approaches in significant details.

1.3.3.1 Philosophy

Adopting research philosophical approaches allows the reconciliation of philosophy, methodology and the research problem (Holden *et al.,* 2004). Answers to important questions are captured under philosophical underpinnings – viz. what the reality of knowledge is (ontology), how the knowledge is acquired (epistemology), the values and ethical considerations of knowledge acquisition (axiology), how the language is designed to present the impact of knowledge (rhetoric) and the outline or framework for how the knowledge is obtained (Creswell, 2003). However, mixed philosophical stance which include positivism, interpretivism and postpositivism are adopted for this thesis due to the interdisciplinary nature of this research. This thesis therefore recognises the significance of factual knowledge while acknowledging that the conclusions mined from facts could still be influenced by a researcher's experiences and values. This thesis also attempts to interpret and analyse knowledge obtained objectively.

1.3.3.2 Reasoning approach

The establishment of or validation of a particular theory is the primary objective for which a research approach is adopted (Cargan, 2007). To accomplish this, several types of reasoning such as i) critical thinking; ii) cause and effect reasoning; iii) intuition; iv) inductive; v) abductive; vi) deductive and vii) counterfactual reasoning which could aid in gathering knowledge and developing theories (Wilson, 2010).

The most commonly used reasoning approach however includes inductive, deductive and abductive reasoning (Fellows and Liu, 2015; Saunders *et al.*, 2016) although each of these reasoning approaching including those less often adopted presents a different approach to research with a common objective centred on the idea of theory (Wilson, 2010). The choice of methodology is directly influenced by the reasoning approach utilised; hence, it is imperative to carefully consider the appropriate application of reasoning approach when selecting one (Cargan, 2007).

1.3.3.3 Choice of method

There are two main methods that can be used in data collection, namely: i) qualitative; and ii) quantitative (Fellows and Liu, 2015). After determining the research philosophy(ies) and approach(es), the subsequent phase of decision making is the methodological choice (Saunders *et al.*, 2016). The choice of method for data collection be it qualitative, quantitative or a combination of both determines which data collection technique to employ (Creswell, 2003). A researcher can choose between a mono-method which is a single data collection technique, a multi-method or a mixed-method which is a combination of qualitative and quantitative analytical approaches and data (Harden and Thomas, 2010). This research employs mixed method approaches to deliver a comprehensive study on how safety risk and accidents can be prevented by utilising predictive models.

1.3.3.4 Time horizon

Time horizon refers to the duration of the study or the period over which data is collected (Rose *et al.,* 2015). It is a key element in planning and conducting research because it can have a significant impact on the research design, data collection methods, sample size, and analysis techniques (Dolan *et al.,* 2008). This present thesis employs exclusively a retrospective time horizon to analyse data from past safety incidents and draw lessons from events that have occurred in the past.

1.3.3.5 Strategies, techniques and procedure

The research strategy provides a connection between the research philosophy(ies) and the method(s) of data collection, outlining how the study objective will be accomplished (Saunders *et al.*, 2016). The techniques that the researcher employs are the specific, detailed approaches to gathering information (Fellows and Liu, 2015; Saunders *et al.*, 2016). This thesis sourced secondary data from existing literature by using databases such as Scopus and google scholar. Bibliometric analysis which is a computer-aided, scientific methodology was used to review literature by finding the main authors, their primary research and the relationship that exist between them, through broadly reporting on the majority of research publications associated with a specific field or topic (De Bellis, 2009). Also, secondary data was obtained from a highway incident database that details the characteristics of events that lead to an incident occurrence and the characteristics of individuals involved. In this present thesis, RF, SVM and NB algorithms were applied to an already labelled incident dataset to generate incident predictions. The model was trained with labelled data and by learning the patterns in the incident dataset, the model was able to predict the different types of incidents likely to occur, the risk levels and the body parts likely to be affected. Five metrics of accuracy, sensitivity (recall) , precision, and F1-score were proposed based on the four outcomes of a confusion matrix and utilised in this present thesis.

1.4 THESIS STRUCTURE

Figure 1.1 outlines the specific research process flow, precisely the parts, items and outputs for the various stages of the research. This consists of three stages that cumulatively progresses from a *conceptual model* premised upon literature (Stages 1), to a *proof-of-concept model* in Stage 2 and subsequently validated in Stage 3 – thus, constituting the *final validated model*.

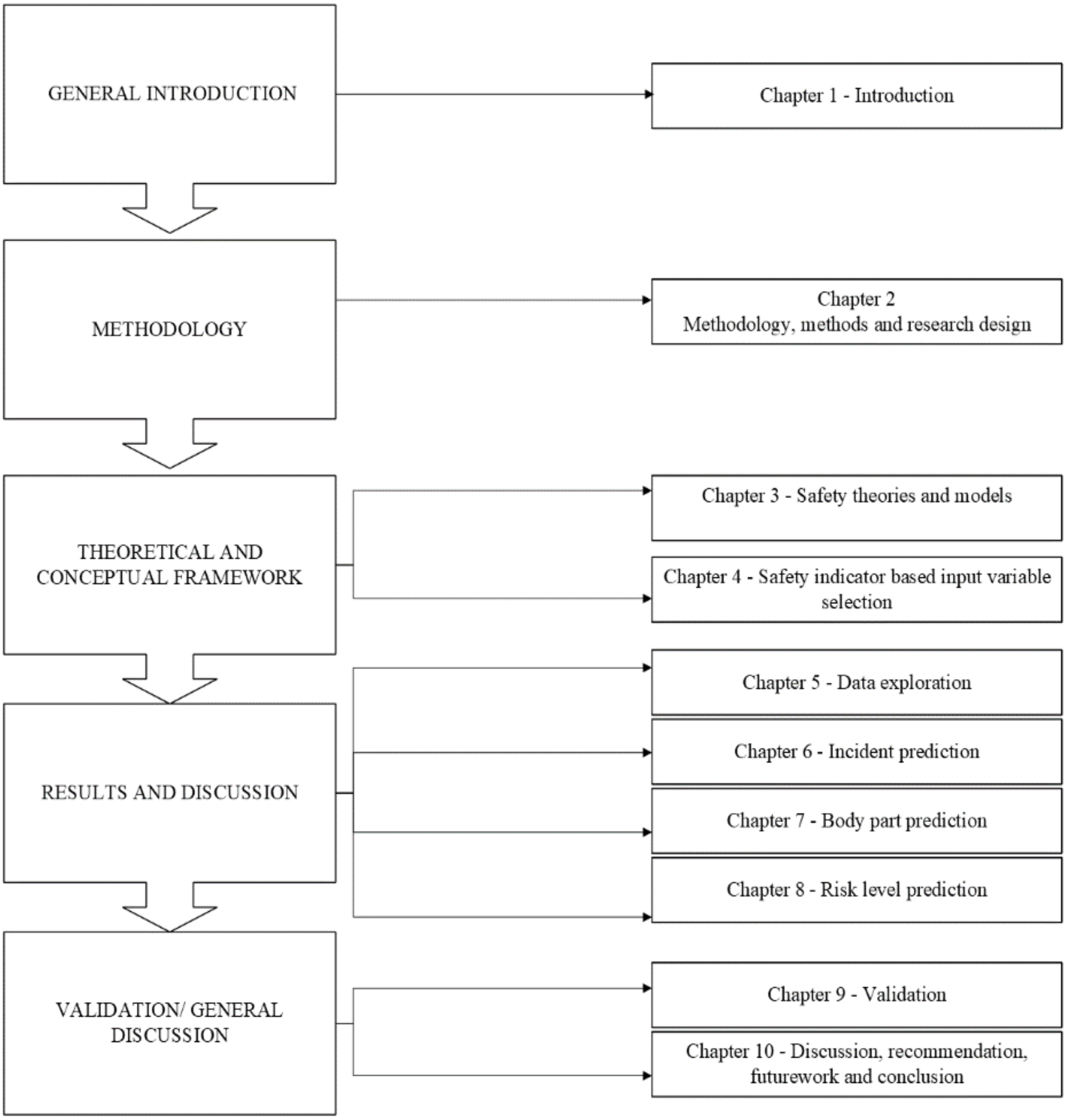


Figure 1.1 - Research Process Flow Diagram

Chapter 1- Introduction

Chapter one presents the study background, research challenge, and goals and objectives are all presented in the first chapter of this thesis. Accompanying these are remarks on the following: i) the research's importance; ii) the research aim; iii) the research scope; iv) a synopsis of the research techniques used; and v) the study's ethical considerations. The chapter concludes by providing an overview of the research's general organisation and a synopsis of each chapter.

Chapter 2- Methodology

Chapter Two has been divided into two sections. The first section gives a detailed summary of the methodology chosen and used for the research, based on Saunders *et al.* (2016) Research Onion. This chapter covers the following topics in more detail: 1) philosophical choice; 2) research methodologies; 3) temporal horizons; 4) general specific procedures used; and 5) ethical considerations. The section focuses on the particular research design that was used for this thesis and provides a guide through each of its three phases (see Figure 2.1 in Methodology Chapter 2). In order to confirm that a strong scientific approach was taken when carrying out the task, choices have also been justified.

Chapter 3- Safety theories and models (Literature review I)

This chapter reviews safety risk models and theories by summarising and comparing them to identify the best strategies that can be adopted in a *'conceptual'* safety risk model for highway workers' safety. Research findings illustrate that existing models reviewed were built on earlier safety risk models with minor upgrades. However, human elements (human errors, human risky behaviour and untrained staff) remained a constant characteristic which contributed to safety risk occurrences in current and future trends of safety risk. Therefore, more proactive indicators such as risk perception, safety climate and safety culture have been included in contemporary safety risk models and theories to address the human contribution to safety risk events. Furthermore, the findings revealed that, highway operation safety risk literature is scant and consequently, comprehensive risk prevention models have not been well examined in this area. Premised upon a rich synthesis of secondary data, a conceptual model was recommended which proposes infusing ML predictive models (augmented with inherent resilient capabilities) to enable models to adapt and recover in an event of inevitable predicted risk incident.

Chapter 4- Safety indicator input data for ML (Literature review II)

This chapter identifies safety leading indicators which justify and influence the type of incident data considered necessary for building a proof-of-concept incident risk prediction model for the highway sector and provide a standardised approach to selecting safety indictor data. Research findings indicated that current research focuses on leading and lagging indicators for risk modelling while leading indicators were the most preferred in predictive modelling.

However, an emerging use of resilient indicators was evident as a cushion for systems where in the unfortunate event of an incident occurring, the indicators could help the system adapt and adjust. Leading, lagging and resilient indicators were however considered individually in existing literature rather than combining the strengths of these safety indicators in a holistic research design to proffer solutions. The lack of a standardised approach to selecting safety indicators necessary for predictive modelling of risk was also noted in this chapter. Hence a more robust theoretical framework which combines leading, lagging and resilient indicators holistically is developed.

Chapter 5 – Data exploration and visualisation

A comprehensive incident data exploration for HTO was performed in this chapter to uncover patterns and correlations that can inform future safety strategies. To enable insight discovery and better understanding of the data, descriptive data analysis, frequency distribution assessments and statistical tables for numerical values were adopted as methods for exploring the data. Emergent findings showed significant correlations between the input variables utilised. the results showed, a relationship exists between average traffic rate and incident occurrence. The tendency of an increase in incident rates for times with high traffic volumes was revealed. Furthermore, a correlation between injury and age was found, which shows that certain age groups are more susceptible to injuries than others. The study also mapped incidents by location to obtain insights into work areas with higher incident rates. Risk levels across different times of the day were further examined to uncover specific periods with elevated risk, which can shape the roll out of targeted interventions. By projecting risk levels, future trends can be anticipated and resources can be prioritised and allocated more efficiently. The distribution analysis of various types of incidents provided a detailed understanding of the most common incident categories, aiding in the development of focused safety measures. In summary, this chapter strived to provide valuable insights that are consistent with findings in the literature, supporting the effectiveness of data-driven approaches in enhancing highway safety and traffic management.

Chapter 6- Incident type prediction

This chapter develops a robust mathematical model which enables highway safety authorities to: predict various incidents; respond effectively to diverse safety risk incident scenarios; and assist in proactive safety precautions to reduce Highway Traffic Officer (HTO) incidents.

Using data obtained from a highway incident database, a supervised ML method that employs three algorithms (viz. Support Vector Machine (SVM), Random Forests (RF) and Naïve Bayes (NB)) was applied and their performances were comparatively analysed. Three data balancing algorithms were also applied to handle the class imbalance challenge. A five-phase sequential method which includes i) data collection; ii) data preprocessing; iii) model selection; iv) data balancing and v) model evaluation was implemented. Findings indicated that although the model produces a high accuracy score of SVM (96%), RF (97%) and NB (94%), the individual classes of the target variable perform poorly with the original data. This can be attributed to the high-class imbalance which causes the model to learn that it can obtain high accuracy by constantly predicting the majority class. SVM with a polynomial kernel combined with the SMOTE algorithm is the best model in predicting the various safety incident and the Random Under-sampling (RU) algorithm was the most inefficient in improving model accuracy. The Random Oversampling algorithm resulted in overfitting in the model. The NB model is unable to handle the high dimensionality of the target classes hence, performs poorly irrespective of whichever balancing algorithm is applied.

Chapter 7- Prediction of body part likely to be affected by an injury.

This chapter focuses on a crucial aspect of this research, investigating the prediction of the body part likely to be affected in the event of an injury. The objective is to enhance the granularity of the safety risk ML model, providing valuable insights for emergency response planning and medical intervention strategies. This chapter begins by reviewing existing literature on injury prediction models and methodologies employed in similar domains. The chapter then outlines the specific objectives related to predicting affected body parts, ensuring a targeted and focused exploration. Data collection procedures are detailed, encompassing diverse datasets that include information on historical accidents, injury types and associated variables. Methodological considerations involve the selection and implementation of ML algorithms tailored to accurately predict the body part likely to be affected, with a keen emphasis on model interpretability. As the chapter progresses, an overview of the results obtained through initial analyses is provided. Insights into the model's performance, validation metrics and potential areas for optimisation are highlighted. This summary serves as a precursor to subsequent chapters, where detailed discussions and in-depth analyses of the prediction of affected body parts will be advanced, contributing valuable knowledge to the field of highway safety.

Chapter 8- Risk level prediction

This chapter implements DL models in predicting the level of risk involved in a highway operation so safety officers could prioritise resources and effectively make timely decisions to avert any disaster from occurring. Although incidents can be quantified and modelled using ML methods, traditional ML methods, have not been as effective because meticulous engineering is needed to convert data into appropriate formats. In order to address this issue, a cutting-edge ML technique (boosted trees and deep learning) is built and evaluated against other traditional approaches through the examination of incident events from a top UK highway organisation. By comparing the observed and anticipated values statistically, the created models' predictive ability was evaluated. The use of deep feedforward neural networks produced the best predictions, according to the results.

Chapter 9- Validation of proof-of-concept model

This chapter validates the proof-of-concept model. Results reveal that not only is the model reliable in terms of its ability to forecast outcomes, but it also offers a highly generalisable risk management algorithm that makes it possible to effectively predict and visualise risk-related occurrences.

Chapter 10- Discussion and conclusion

This chapter first presents an overview of the study's main conclusions. Major knowledge contributions are then delineated and this leads into a discussion of the study's recommendations and limitations. The study concludes with a set of research questions that provide several avenues for future investigation and a wealth of connections to themes and research fields that follow.

1.5 SIGNIFICANCE OF STUDY

This thesis applies the use of ML models in safety risk prevention by predicting risks and pre-empting them before they occur. Specifically, a conceptual model for safety risk prediction and prevention tailored to the safety characteristics of highway operations is developed based on literature. A proof-of-concept model is then built with real world incident data sourced from a highway agency in charge of road workers in the UK. Lastly, the model is validated with unseen data to enhance the effectiveness of the model and reinforce trust in the model performance. Such a model could aid in predicting and preventing unwanted incidents and accidents which are detrimental to the health, safety and wellbeing (HSW) of workers. The ambition is to provide a robust datum for safety managers to engage in evident-based decision making. Safety officers can also be equipped with enough information to educate and train HTOs on impending risks predicted by the model thereby equipping workers with resilient cushions needed to adapt and adjust in situations where predicted incidents are unavoidable. Furthermore, the model will allow better prioritisation and allocation of safety resources, preventing wastages. To build the conceptual model, this thesis employs various analytical methods and techniques to investigate existing safety risk theories and models, as well as current safety risk indicator applications and their contributions towards safety risk management. The significance of the conceptual and proof of concept models developed in this thesis is that, they satisfies the need for a robust system capable of identifying various safety risk incidents in time to provide adequate solutions to prevent them. Moreover, the conceptual model developed helps to identify safety-oriented input variables deemed essential for developing a risk prediction model in the highway sector; and present a robust set of influential variables which contributes to a more accurate prediction model, thereby saving lives on the highway. This thesis further introduces a system which can also build shocks for adaptation to minimise impact of incidents in cases where these incidents cannot be prevented. This thesis therefore contributes to risk management research by providing a practical and relevant proof of concept model for application based on a holistic study of: i) existing literature on safety risk theories and models; ii) studies on safety risk indicators and their applications; iii) applications of ML model in safety predictions; and iv) validation of the prediction model.

1.6 SUMMARY

This chapter established a comprehensive foundation for the research endeavour, focused on developing a safety risk ML Model for predicting risk levels, incident types and affected body parts in the domain of highway safety. The primary aim of this thesis is to address critical gaps in existing road safety models and contribute innovative insights to enhance predictive capabilities. The objectives outlined guides the research journey which aims to develop a ML model capable of predicting risk levels, classifying incident types and identifying likely affected body parts. The scope of this thesis encompasses a thorough exploration of literature, extensive data collection, and the implementation of cutting-edge methodologies.

Contributions to knowledge for this present thesis lie in the development of a novel robust predictive model that integrates risk level prediction, incident classification, and identification of affected body parts for HTOs using an incident database dedicated to HTOs. This novel work for HTOs is the first of its kind. By addressing limitations in current approaches and making use of advanced ML algorithms, this research seeks to provide a meticulous and accurate tool for improving highway safety. The research scope includes an extensive review of existing literature, comprehensive data collection, methodological approaches, and the integration of the predictive model into highway incident management systems. This chapter has set the stage for subsequent detailed analyses and model development.

CHAPTER 2 RESEARCH METHODOLOGY (I)- A REVIEW OF RESEARCH METHODOLOGIES

2.1 INTRODUCTION

This chapter provides a justification for the methodological framework (following a specified methodological path for its design and analysis) which is implemented to attain the research aims and objectives previously delineated. It therefore introduces the research process and strategies adopted including the research paradigms, methodology and methods implemented. This methodology presents the connection between the research method, the objectives, the collection of data, methods of sampling and data analysis techniques implemented. Ethical considerations and the credibility, validity and reliability of the results obtained are clearly justified and highlighted herein.

This research methodology adopts the *'research onion'* concept which was proposed by Saunders *et al.* (2007). Akin to the layers of an onion, Saunders (*ibid*) posits that the research process is layered and the structured process of peeling away each layer (with the outer layer as the starting point) will eventually allow access to the core of the research undertaken. The research process starts from topmost layer of the research onion which consist of the research philosophies before iteratively progressing through the middle layers which comprises of the approaches, strategies, choice of methods and the time horizon before finally arriving at the core of the onion which highlights the data collection process, techniques and the advances for the data analysis procedure. In this section, each layer of the onion is addressed through a review of different types of research philosophies, approaches, strategies, choices of data, time horizons and techniques and procedures. A research design was then fashioned to include the various layers chosen from the review which was most appropriate for the type of research being undertaken. First, a conceptual model was developed based on a body of knowledge sourced through bibliometric and systematic review, second, a proof-of-concept model was developed using real life data sourced from incident database National Highways and analysed using ML models such as SVM, BN, RF and DL. The model is then evaluated based on performance metrics such as the confusion matrix, precision, recall, F1-score and the AUROC curve. Finally, the product of the work is presented as a system shell and validated through a series of semi-structured interviews using a case study strategy that employs HTOs.

2.2 RESEARCH PHILOSOPHIES

Adopting research philosophical approaches allows the reconciliation of philosophy, methodology and the research problem (Holden *et al.,* 2004). Answers to important questions are captured under philosophical underpinnings – *viz.* what the reality of knowledge is (ontology); how the knowledge is acquired (epistemology); the values and ethical considerations of knowledge acquisition (axiology); how the language is designed to present the impact of knowledge (rhetoric); and the outline or framework for how the knowledge is obtained (Creswell, 2003). Establishing a relationship between the research and the philosophical stance or assumptions enables the clarification of theoretical frameworks (Cohen and Maldonado, 2007). Contrary to frequent practice, Creswell (2003) proposes that research design extends beyond research methods and approaches implemented but also the reasoning and philosophical foundations that constitute assumptions made in the study. These assumptions could be classified into two categories, i.e. the ontological and epistemological stance of philosophy (Scotland, 2012). Aliyu *et al.* (2014) proposes that ontology is not independent of epistemology hence, there exists a relationship between ontology and epistemology. Conversely, Guba and Lincoln (1994) state that any attempt to link the two philosophies will result in a grievous error as the meta-theoretical assumptions that characterises of ontology and epistemology are extremely distinct and could alter their foundation. However, other researchers believe in the likelihood of adopting the philosophy of one approach and implementing the methods of another approach (Sale *et al.,* 2002; Cook and Reichardt, 1979). In this thesis, given that the focus is directed toward the creation of new knowledge (i.e. nature, origin and scope) (Farrell *et al.,* 2017; Fellows and Liu, 2015) epistemology will constitute the main branch adopted although various significant philosophies are discussed in detail below. Fig (2.1) represents the research onion as proposed by Saunders *et al.* (2007).

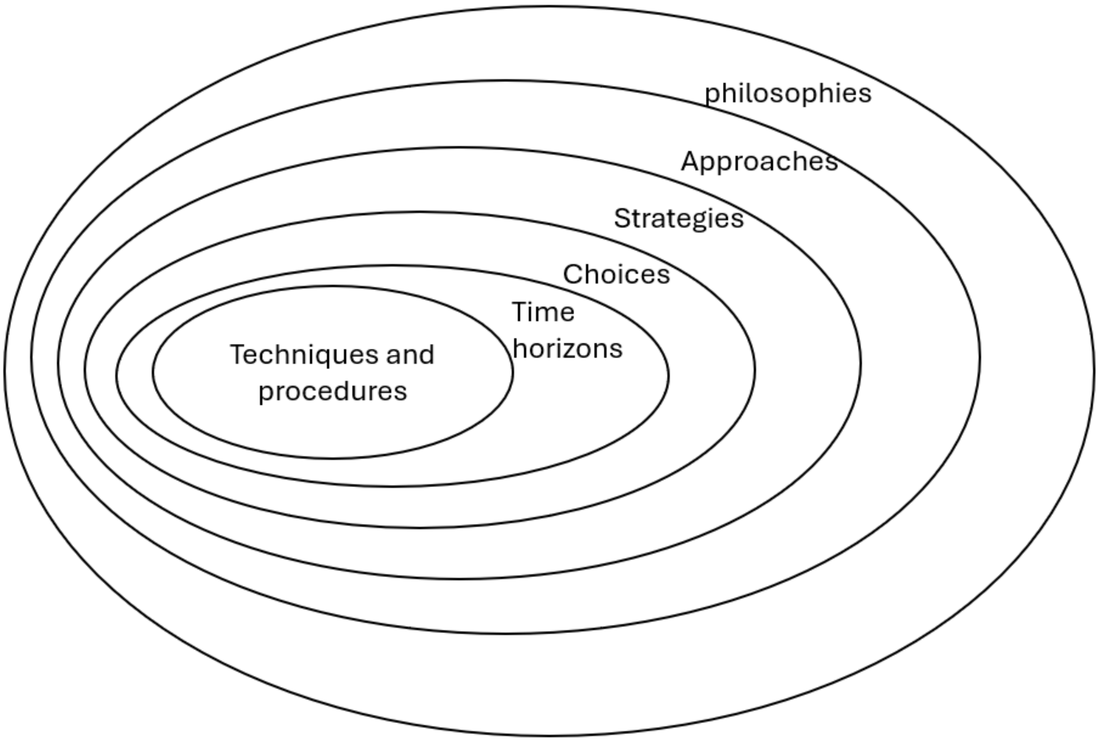


Figure 2.1 - The Research Onion (Saunders, 2007)

2.2.1 Ontology

Grenon and Smith (2011), defines ontology as *'assumptions made about the nature of reality'*: where realism and relativism are two types of ontology research. Ontological realism assumes that the external world is made up of established physical structures (Liu, 2014). Thakurta (2015) proffers that an important characteristic of realism is the disclosure of the truth about reality and the presence of objects are independently predominant in the human mind. Ontological realism aims to detail the nature of scientific practice (Bryman, 2008). Relativism on the other hand is more practical than idealistic (Kinzel, 2019). It focuses on pragmatic structures rather than intangible views of life (van Dijk, 2021). From the lens of relativism, all opinions are valid from a specific context of perspective (Sherratt and Leicht, 2020). Although ontological relativism is mainly associated with the truth, knowledge and morality (Rassokha, 2022), there are two viewpoints that question what the nature of reality really is, i.e. objective and subjective viewpoints. Objectivists believe that reality exists and is thus tangible, complete and independent of a given individual's understanding (Dainty, 2008) while subjectivists believe an individual's own reasoning is the only sacrosanct fact of experiences (Crotty, 1998).

2.2.1.1 Applications of ontology

Grossmann (2019), Van Inwagen (2014) and Açıkgenç (2020) have argued that ontology provides a strong philosophical backing for management studies because it tackles the nature of existence and categories of existence by addressing the distinction between what exists and what appears to exist. It takes the unique experiences of different actors and strives to theorise what reality is according to their experiences (Baskerville *et al.,* 2019).

In construction risk management, Xing *et al.* (2019) proposed the use of ontology to formalise safety risk knowledge in metro construction to provide support for decision making in safety risk identification. In similar research which utilises ontology for structuring of safety risk knowledge, for easy identification and reuse, Jiang *et al.* (2020) developed a decision method for construction safety risk management. Through an ontological approach, Aziz *et al.* (2019) formulated a knowledge-based tool for process industries to identify and screen hazards as well as conduct rapid risk estimation by mapping out possible pathways to an incident occurrence, linking causation to the transition of states. Notably the prevalent issue that ontology tackles it risk management domain is mostly decision making and knowledge-based challenges (Aziz *et al.,* 2019; Xing *et al.,* 2019; Jiang *et al.,* 2020) therefore it is not mere coincidence that, in a review of the myriad of construction related ontology research literature using scientometric methods, Zhong *et al.* (2019) discovered that the keyword *'knowledge management'* was predominantly adopted.

In a social science setting, Elder-Vass (2015) addresses how critical realism affect the practice of social science by suggesting some methodological implications of the realist theory of emergence as a method for social ontology. However, Thomasson (2003) finds that the construction of social reality is too narrow to determine how a reality of facts and objects genuinely created by human intentionality exists. Hence, a more detailed social ontology can be built by acknowledging the various rules for constructing social reality. Therefore, to study the nature and properties of the social world, it is pertinent to explore the different entities that can be deduced from social interactions. Taking into consideration, all the instantiated social properties that are irreducible and ineliminable at the time of examination (Elder-Vass, 2015).

In the context of computer and information sciences (specifically, ML), an ontology defines a specification of a conceptualisation or a group of representational attributes according to which a domain of knowledge or discourse can be modelled (Guarino,1980; McCarthy, 1995; Day,2019; Kasirzadeh and Smart, 2021). The representational attributes are normally characterised as features (or properties), classes (or groups) and relationships (or relations among class members) (Wang *et al.,* 2011). Definitions of the representational primitives include information about their meaning and constraints on their logically consistent application (Day, 2019). Early Artificial Intelligence (AI) researchers (cf. Hayes, 1985; Guarino,1980) adopted the philosophical term ontology, after identifying the relevance of mathematical logical research and made the case that new ontologies may be developed as computer models to support certain types of automated reasoning (Wang *et al.,* 2017). The word *'ontology'* was then used by the AI community in the 1980s to describe both a theory of a modelled world such as a Naive Physics (Guarino,1980) and a component of knowledge systems (Hayes, 1985). Some scholars considered computational ontology to be a form of applied philosophy, gaining influence from philosophical ontologies (Al-Fedaghi, 2020; Smith 2021). Gradually, ontological positioning has been widely applied in the AI community in a plethora of studies (cf. Wang *et al.,* 2017; Iliadis, 2019; Smith 2021;). Wang *et al.* (2019) developed an Algorithm of Formal Ontology Generation (AFOG) based on the most recent developments in cognitive knowledge learning and formal semantic analyses whereby the AFOG technique enables autonomous development of quantitative ontologies through deep ML for knowledge engineering and semantic understanding. The implementation of a methodological approach for studies in sociotechnical dimensions of data driven ontology work was proposed by Iliadis (2019) to demonstrate how applied ontologies are constituted communicatively with ethical implications. Smith (2021) argues that a counterfactual approach in ML fairness and social explainability can require an incoherent theory of what social categories are. Through a review of papers from philosophy and social ontology Smith (2021) explores the use of counterfactuals when the facts to be considered are social categories such as race or gender. These aforementioned studies reiterate the applications of ontology in the computer and information science space.

2.2.1.2 Benefits and limitations of ontology

With any philosophical stance, there are inherent benefits and limitations. Within ontology, one of the major benefits derived is clarity (Açıkgenç, 2020). By providing a framework that enables deep insights into the fundamental nature of reality, a better understanding into the existence of things in the world (Grenon and Smith, 2011). In a study which develops an ontology to formalise safety risk knowledge, Xing *et al.* (2019) specifies clarity as one of the features provided in the study whereby the intended meaning of concepts can be expressed effectively without ambiguity. The significance that clarity brings in an ontological setting is the prevention of any misinterpretation or misrepresentation which could lead to an erroneous conclusion for a research or study. Similarly, another benefit of ontology is the consistency of thoughts, that it promotes (Xing *et al.*, 2019; Bravo *et al.,* 2019). Ontology helps to establish a consistent way of thinking about the world. It provides a set of concepts and categories that help to organise our knowledge and understanding of the world (Yamagata *et al.,* 2014). In a study which presents systematic evidence maps as a tool to support evidence-based decision-making in chemicals policy and risk management, Wolffe *et al.* (2019) proposes that openly accessible ontologies may be used for coding to promote consistency and interoperability for systematic evidence map used in responding to risk management needs. The nature of ontological studies enables individuals to stimulate innovation and new ways of thinking, which is also a benefit derived from ontology (Riedl *et al.,* 2011). It encourages people to question assumptions and to explore new possibilities for understanding the world (Courvisanos, 2007).

While ontology has many benefits, it also has its limitations. The subjective viewpoint (cf. Crotty, 1998) of ontology (whereby different individuals may have different views on the fundamentals of reality (Guba, 1990)) can make it complex and abstract (Zhe *et al.,* 2006). Hence, a high level of philosophical knowledge may be required to fully comprehend what reality is and how it exists (Ratner, 2002). However, ontology may not provide a complete understanding of the world (Al-Ababneh, 2020). It is limited by human knowledge and understanding (Hathcoat *et al.,* 2019), which is constantly evolving thereby creating a limitation in its application (Osborne, 1997). Ontology may not be applicable to all areas of knowledge as it is primarily concerned with abstract concepts (Drolet, 2014) and categories and may not be relevant to more practical areas of knowledge.

2.2.2 Epistemology

Epistemology studies the relationship between knowledge and how it is acquired - in other words, the way that people eventually know the things they know (Crotty, 2003, p.3). Epistemology also provides philosophical underpinnings to the decision on the type of knowledge that could be adapted and how to guarantee the veracity, authenticity and legitimacy of this knowledge (Maynard, 1994 in Crotty, 2003, p8). A myriad of studies use epistemology as a criterion for classifying what constitutes knowledge and what does not constitute knowledge (Hallebone and Priest, 2008; Nurasyiah *et al.,* 2021; Couso and Simarro, 2020). In terms of epistemology, this thesis discusses postpositivism and interpretivism as a philosophical medium for knowledge acquisition considering an objectivist viewpoint of ontology (Chowdhury, 2014; Alharahsheh. and Pius, 2020).

2.2.2.1 Applications of epistemology

Due to the nature, scope and justification of how knowledge is obtained being the main purpose of epistemology (Crotty, 2003; Nurasyiah *et al.,* 2021; Couso and Simarro, 2020), various research has sought to apply epistemological positioning in different scientific fields (Bishop and Trout 2005; Fagan, 2010; Mascolo and Kallio 2020). Hacking (1992) explores the relationship between epistemology and scientific practice, arguing that scientific knowledge is shaped by the practices and methods used by scientists. Therefore, knowledge acquisition is largely influenced by the researcher's methods or techniques. In a similar vein, Fagan, (2010) sought to marry epistemology and scientific practice by arguing that although scientific practice seeks to typically evaluate and explain scientific inquiry, epistemological rules are required for such evaluations. Therefore, a type of social constructivism which focuses on epistemic justification can be the foundation for critical epistemology of scientific practice (*ibid*). Bishop and Trout (2005) examined the relationship between epistemology and psychology, arguing that the two fields are deeply interconnected and that a better understanding of epistemology can lead to a better understanding of psychological phenomena. In this thesis (*ibid*), a cost-benefit analysis approach was used to tackle reasoning challenges and provided a framework for resolving normative disputes in psychology. Mascolo and Kallio (2020) also in an intersubjective epistemology for psychology and argue that intersubjective processes between individuals, rather than subjectivity or objectivity, are the source of psychological knowledge. Hence, knowing *'self'* and other things is not only through intersubjective engagements but also verifying and validating psychological knowledge through that same intersubjectivity.

2.2.2.2 Benefits and limitations of epistemology

Epistemology could be explored either through (for example) interpretivist, postpositivist, phenomenology, feminism, postmodernism and pragmatism philosophies (Al-Ababneh, 2020; Dindjer, 2020; Irshaidat, 2022). However, no matter how epistemology is examined, it still presents its own problems and prospects (Brady and Pritchard, 2005). For instance, interpretivist researchers assume that one can access reality only through social constructs

(Berger and Luckmann, 2016). Meaning, rules and societal values are created through social interactions and are followed because they eventually become habits. The limitation of this argument is the assumption that people will form habits once rules are created and would follow them because they have become a lifestyle, which is not necessarily the case (Haslanger, 2012). Furthermore, it is difficult to generalise findings made from epistemological considerations because, the researchers' personal values and views could influence how they perceive the nature and scope of knowledge gained (Kiernan and Hill, 2018). Moreso, epistemology is often wholly independent of empirical evidence and requires only analysis of constituent terms to support its claims, which can make it difficult to test its theories and evaluate their validity (Tunc *et al.,* 2021).

Epistemology, however, allows access to gaining deeper understanding of what knowledge is, how it is acquired and how it can be used to advance intrinsic understanding of the world (Kubota, 2020). Similarly, identifying the different sources of knowledge, such as perception, memory, testimony and reasoning (Spear, 2023) is another pertinent prospect of epistemology that allows a proper evaluation of the reliability and credibility of different types of knowledge (Jope, 2021). Table 2.1 outlines the nature of reality the philosophies present and their individual features.

Table 1.1 - The nature and features of ontology and epistemology

		Ontology: study of reality		
Philosophy	**Theory**	**Nature of reality**	**Feature**	**Citations**
Objectivism	Knowledge is true and factual.	Reality is not dependant on any social actors.	Focuses on hard facts and what is.	Pölzler et al., (2019); Davis (2021); Vrhovski (2021).
Constructivism	Knowledge is constructed based on experiences.	Reality is dependent on social actors.	Characterised by creation of perspectives through human interactions.	Brau (2020); Merve (2019); Pande and Bharathi, (2020).
pragmatism	Incorporates social and environmental perspectives of knowledge.	Finds connection between reality and practice.	Combines both objective and subjective theories and investigates questions been asked.	Allemang et al. (2022); Elder-Vass (2022); Kelly and Cordeiro (2020).
		Epistemology: study of knowledge		
	Theory	**Nature of knowledge**	**features**	**citations**
Positivism	Scientific knowledge is true.	Knowledge is derived from existing theories and can be replicated.	Characterised by the testing of the hypotheses or research question.	Patton (2015); Park et al., (2020); Alharahsheh and Pius (2020).
Realism	Question's reliability of scientific knowledge.	All knowledge can be revised and optimised.	Characterised by continual research and application of new research methods.	Reed and Jones (2019); Tonkin (2021); Harris (2021).
Interpretivism	Incorporates human experiences into scientific knowledge.	Interprets data subjectively.	Characterises the use of qualitative analysis to answer research questions.	Dindjer (2020); Irshaidat (2022).

2.2.3 Positivism

Guba (1990) asserts that positivism establishes a claim for reality to be depicted, studied and understood. Positivists are concerned with reality and how it is perceived (Denzin and Lincoln, 1998). It is through scientific means that positivist philosophies can be verified. However, Egan (1997) makes a case for Plato's description of dispute between philosophy and poetry as the origin of positivism where early poets have made the claim that access to truth and knowledge was not only gained through science and reason but also through poetic justice. This had sparked the debate on which discipline deserved more attention in respect to the subject of development of the mind - the humanities or the science (Egan 1997). Cohen and Maldonado (2007) describe August Comte's (1798-1857) work on positivism which posits that the physical world runs on general laws as the empirical goals of sociological methods. Comte believed that just as the natural and physical sciences employed scientific analysis, the social realm could also do same precisely the same way (Comte, 1844). In contrast to Comte's ideology, Durkheim (2014) who's work was first published in 1895, proposed that having a unique scientific methodology for sociological study was a better alternative. The philosopher of the *'Vienna circle'* (cf. Hanfling, 1981; Patton, 2015) combined Comte's (1844) work with logically based rational thoughts which they termed *'rigorous and systematic application of rational thought based in logic'* leading to the birth of 'logical positivism'. However, because of how superficially logical positivism defined knowledge and science, it became redundant in research applications such as nursing research (cf. Patton, 2015; Corry and McKenna, 2019). Positivism is a paradigm that relies on measurement and reason that, knowledge can be obtained from a neutral and measurable (quantifiable) observation of activity, action or reaction therefore, it favours quantitative approaches over qualitative methods to identifying explanatory associations or causal relationships through empirically based research (Park *et al.,* 2020). Alharahsheh and Pius (2020) believe that the positivist paradigm has the prospect of equipping researchers with major statistical reliance and generalisation leading to the development of universal laws and findings.

2.2.4 Postpositivism

A postpositivist stance holds the view that it is impossible to fully understand reality, nevertheless it can be approximated (Guba, 1990, p.22). Miller (2007) discusses the basic components of postpositivism. Robert Dubin (Dubin, 1970) explains these components as building blocks of ideas, interests, rules of how these interests interacts. While positivism asserts that research and the researcher are independent and have no influence on each other, postpositivism contends that the researcher's background and their worldviews, could influence the object of research (Miller, 2007). Postpositivist achieve objectivity by actively recognising the impact of biases (Robson, 2002). Postpositivist legitimises both qualitative and quantitative approaches unlike positivism which predominantly recognises mainly quantitative approaches (Taylor *et al.,* 2011). Therefore, a postpositive research paradigm adopts a variety of methods in its quest to describe reality in the most accurate terms (Denzin and Lincoln, 1998). Although postpositivism posits that knowledge can be influenced by human conjecture, it is however noteworthy that it is not a type of relativism. Rather, postpositivism encourages the pursuit of objective truth - i.e. postpositivists strive to be objective by recognising and addressing the possible influence of biases (Philips and Nicholas, 2000)

2.2.5 Interpretivism

Interpretivism is an epistemological theoretical positioning that proposes that the approaches and techniques used to investigate a phenomenon within the natural science context cannot be applied to the social context therefore, investigation within the social realm involves distinct epistemology (Crotty, 1998; Matthews and Ross, 2010; Irshaidat, 2022). Other research (cf. Giedymin, 1975; Stockman, 2013; Dindjer, 2020) use the term antipositivism to describe interpretivism. The belief that language and concepts of a research used by individuals influences their perception of the social phenomena under investigation is fundamental to interpretivist epistemology (Macionis and Gerber, 2011). Unlike the postpositivist who believes that objective truth can be obtained from research, interpretivists believe that research cannot produce objective results hence, instead of objectivity, interpretivists derive meaningful insights from subjective experiences of each research participant (Matthews and Ross, 2010). Therefore, the use of interpretivism acknowledges certain limitations such as the possibility of researcher's biases being introduced into the research which can be presented by omitting certain research during literature searching or through translation errors (cf. Mallett *et al.,* 2012). Also, interpretivists follow the assumption that reality can only be accessed through social constructs hence allows the use of a qualitative method. However, qualitative methods are a medium for researchers to induce their own values and views into the research due to their subjective nature (Symon *et al.,* 2016).

2.3 RESEARCH APPROACH

The research approach presents the strategy that is adopted in reasoning to derive a result when conducting research. There are several types of reasoning (Walliman, 2011; Marin *et al.,* 2020;

Pellegrino and Glaser, 2021) which leads to knowledge acquisition however, this thesis will limit its discussion to the three approaches usually adopted in health and safety management (Holt, 2016), i.e. inductive (Pellegrino and Glaser, 2021), deductive (Marin *et al.,* 2020) and abductive (Upmeier zu Belzen *et al.,* 2021) approaches. Other less common approaches that could be used include: i) critical thinking; ii) cause and effect reasoning; iii) intuition; and iv) counterfactual reasoning which provide unique ways by which knowledge could be unravelled through theories (whether the theories are before or after conclusions are drawn) (Wilson, 2010). The selection of a reasoning approach often depends on the aim, objectives, research questions or hypothesis previously established in the research.

2.3.1 Inductive

Inductive reasoning is employed in establishing factually generalised analysis derived from scattered facts obtained from patterns and trends in an ostensibly dispersed compilation of observations or data (Medin *et al.,* 1983). Inductive reasoning strives to construct new theories from obtained data rather than using an existing theory to interpret data (Lichtman, 2006; Ekinci, 2015). An inductive approach is based on learning from experience in the sense that the researcher is constantly gaining knowledge while collecting data. Patterns, conflicts and relationships are sought from collected data in order to compose a conclusion or theory, at the end of research (Wilson, 2010; Dudovskiy, 2016). This form of reasoning is more qualitative in character and includes strategies such as grounded theory to formulate new theories or conceptualisation (Goel *et al.*, 1997; Dudovskiy, 2016). Research questions are used in inductive reasoning to provide a focus for the research design and conceptualisation (Farrugia *et al.*, 2010). A proposed theory presented is considered credible if it details the facts and conditions that provoked the research questions asked. Based on existing knowledge, inductive references can be made from a specific assumption or an analogy and implemented in finding accurate generalisation for a similar basis (Goswami, 2011). Inductive reasoning is predominant in human thinking.

2.3.1.1 Inductive reasoning in health and safety management

Inductive reasoning is a positive approach in the incident investigation field to answering the question what happened? and why did it happen? Generally, inductive reasoning is an important tool for identifying and mitigating potential hazards and risks in health and safety management (Stemn *et al.,* 2020). By drawing conclusions based on observations and experiences, informed decisions about how to protect the health and safety of workers can be taken. When an incident occurs in the workplace, inductive reasoning can be employed to investigate the incident and identify the root cause(s) that led to it. Stemn *et al.* (2020) explored five Ghanaian large-scale mines and used inductive reasoning to identify incident investigations improvement opportunities from the perspective of mine workers. In a similar study, DeLisle *et al.* (2020) demonstrates how big data such as crime incident reports can support inductive reasoning that can lead to enhanced real estate decisions.

Risk analysis and risk assessment is another area where inductive reasoning is often used in the health and safety management domain (Hadj-Mabrouk, 2020). Potential hazards and risks in the workplace could be identified by analysing past incidents and near-misses, identifying patterns and trends, and drawing conclusions about the likelihood and consequences of future incidents (Hadj-Mabrouk, 2020). Furthermore, inductive reasoning is an effective approach to developing practical health and safety training programs (Loosemore and Malouf, 2019). By analysing past incidents and identifying common causes and contributing factors, training programs can be developed to address those specific issues and reduce the likelihood of similar incidents occurring in the future (*ibid*).

2.3.2 Deductive

Deductive reasoning involves starting with a general principle or assumption and using logical arguments to arrive at a specific conclusion (Goswami, 2011). Although deductive reasoning can also reach new specific conclusions, unlike inductive reasoning, deductive reasoning presents only a single logically valid answer (Goswami, 2011). The flow of this research approach tends to stem from more generic ideas to a specific conclusion by drawing inferences (Leedy and Ormrod, 2010). A deductive research approach begins with a theory then to a hypothesis which is tested with data collected afterwards (Elo and Kyngäs, 2008). The results from the data collected would inform the validity or invalidity of the hypothesis propounded (Goel *et al.,* 1997). Hence, confirming or rejecting the premise made. A valid deductive reasoning argument is characterised by the ability to specify exact premises for which conclusions formed can be accepted (Goswami, 2011). Logically valid deductive conclusions are significant in establishing research hypothesis and testing theories (Leedy and Ormrod, 2010). In situations where existing data would be retested in a new context, the deductive research approach can also be implemented (Elo and Kyngäs, 2008).

2.3.2.1 Deductive reasoning in health and safety management

In the context of health and safety, this might involve starting with a well-established safety principle or regulation, and then using logical reasoning to determine how that principle applies to a specific situation (Boadu *et al.,* 2020). For example, a safety professional might start with the general principle that workers should be protected from exposure to hazardous chemicals, and then use deductive reasoning to determine the appropriate safety measures that should be taken when working with a particular chemical (Boadu *et al.,* 2020).

In a review of methodologies adopted for incident investigations performed by Salguero-Caparros (2019), deductive reasoning was found to be a requirement when performing event and causal factor analysis because it helps to determine which events and/or conditions were contributing factors in an accident. Deductive reasoning is therefore a pertinent tool in health and safety management decision making because it enables logical conclusions to be drawn based on well-established principles and regulations (Caparros, 2019).

2.3.3 Abductive

Abductive reasoning is a type of artificial assumption which highlights consequential fundamental patterns of a given event to give meaning to complex reality and develop scientific knowledge (Raholm, 2010). By considering a range of possible explanations for the event, including both obvious and less obvious factors, investigators can gain a more complete understanding of what went wrong and develop more effective strategies to prevent similar incidents in the future. Abductive reasoning serves as a guide in initiation of hypothesis, with its implications clarified logically through a deductive approach and explicated empirically by inductive approach (Eriksson and Lindström, 1997). Abduction allows for a precondition to be inferred from a consequence given (Doven, 2021). It begins with an observation and then finds the highest probability of consequence as the most likely conclusion obtained from the observation (Haig, 2018). Although abductive reasoning can also reach conclusions from observations, these conclusions are not positively verified (Sober, 2013). Hence, there exist elements of uncertainty in abduction which is presented as ‘most likely’ or ‘best case scenario’ (Sober, 2013).

2.3.3.1 Abductive reasoning in health and safety management

In managing health and safety risks, abductive reasoning can be used in the process of incident investigation to generate hypotheses about the underlying causes of the incident, based on the available evidence and information. Spring and Pym (2018) established a logic capable of expressing decision-making during incident analysis by expressing abductive hypotheses in machine readable and precise language than ordinarily an analyst would. Ghiafehdavoudi and Vaillant (2020) also utilised abductive reasoning in investigating success factors of safety performance and explore the digital transformation of the construction worksite, more specifically to the impacts of artificial intelligence (AI) for workers and work-environment safety. When evaluating potential hazards and risks in the workplace, abductive reasoning can be an effective tool, used to identify all of the possible scenarios or outcomes that could result from a given hazard or risk (Schoenfisch *et al.,* 2016). By considering a wide range of possibilities, health and safety managers can develop more comprehensive risk assessments and make more informed decisions about how to mitigate and manage risks.

2.4 CHOICE OF METHODS

A robust methodological process must be followed after research philosophies and approaches are finalised. There are two main methods that can be used in data collection, namely: i) qualitative; and ii) quantitative (Fellows and Liu, 2015). How these two main methods are used determines the type of the methodological path a researcher decides to take (López-Robles, 2020). It could be the selection of a single data collection method which is referred to as the mono-method or the choice of several data collection method which is known as the multi-method (Vizcarguenaga-Aguirre and López-Robles, 2020). However, when one decides to use both qualitive and quantitative data collection techniques, it is referred to as mixed method (Salmons 2015). The difference between the multi-method and mixed-method research lies in how the data collection technique is combined (López-Robles, 2020). Multi-method uses more than one approach within a qualitative or quantitative paradigm, while mixed methods studies uses both qualitative and quantitative approaches (Salmons 2015).

2.4.1 Qualitative

Qualitative research is used to explore and understand people's experiences, beliefs, attitudes and behaviours (Tenny *et al.,* 2017). It is based on collecting and analysing non-numerical data, such as observations, interviews and textual data, to generate insights and develop theories (Creswell, 1994; Tenny *et al.,* 2017). Qualitative research involves the use of description, explanation and interpretation in analysing data (such as textual data from interviews and questionnaires) collected using different techniques and strategies (Leedy and Ormrod, 2001). The use of ethnography, phenomenology, case studies, grounded theory and content analysis are common strategies employed in the qualitative research (Creswell, 2003; Nobel *et al.,* 2011). Inductive reasoning is often utilised because researchers attempt to answer questions posed by observations and experiences (Dudovskiy, 2016).

The interpretive nature of qualitative research allows researchers to explain the trends and themes found in the data from their point of view (Patton, 2015). Creswell, (2006) proposed a process that can be employed in data interpretation as: describing the phenomena under investigation based on a particular context; classifying data into themes and categories also known as coding (Gibbs, 2007); and then theoretically interpreting meaning derived from data and drawing personal conclusions. Since the use of personal observations and interpretations are unavoidable in a qualitative study, it is significant that multiple methods of interactive and humanistic reality and knowledge are captured to enable broader enquiry and much more useful results (Creswell, 2006; Han *et al.,* 2009).

Qualitative studies have been extensively employed in predictive modelling (cf. Ndjaboue *et al.,* 2020; Aggarwal *et al.,* 2019; Graves, 2012). For example, Ndjaboue *et al.* (2020) used qualitative approaches to evaluate and synthesise quantitative estimates for predictive models of diabetes complications. Graves (2012) used qualitative approaches to interpret geographic information system-based, quantitative archaeological predictive models through case study research. Narrowing down specifically to the use of qualitative research in risk prediction models, Barda *et al.* (2020) carried out qualitative research in clinical prediction tools to explain the factor that causes an increase in adverse risk outcomes through user-centred displays. Burkov *et al.* (2018) used qualitative research to undertake risk assessments in project management in construction industry. Pinto *et al.* (2011) also presented an occupational risk assessment traditional method for the construction industry using qualitative methods.

2.4.2 Quantitative

Quantitative studies allow information to be derived from data collected by quantifying the data and exposing it to statistical analysis through investigating the association between variables to prove or disprove a hypothesis (Creswell, 2003, p.153). Qualitative studies make room for the utilisation of observation, measurement and testing of theory as a way of experimenting with variables to investigate the problem (Creswell, 2006). Historically, qualitative research has seen trends in measurement procedure, test, statistical analysis and research design (Creswell, 2003). An initially formulated hypothesis is either validated or refuted based on tests conducted, using statistical analysis and measurement procedures on data collected (Creswell, 2006).

Inquiry methods are employed to ensure that statistical analysis methodologies are aligned with tests carried out. These inquiry strategies include surveys, experiments and data collected on predetermined instruments which produces statistical data (Creswell, 2003). Quantitative research can be classified into descriptive, experimental, correlation and causal comparative (Leedy and Ormrod, 2001). Each of these research methods uses a different kind of inquiry strategy to collect data therefore, the most suitable approach must be selected based on the kind of inquiry to be undertaken.

2.4.3 Mono-method

The mono method in research refers to the use of a single method or approach to gather and analyse data in a research study (Vizcarguenaga-Aguirre and López-Robles, 2020). This means that the researcher relies solely on one method to collect and interpret data, rather than using multiple methods to triangulate findings (Heale and Forbes, 2013). The mono method approach is often used in research studies that aim to investigate a specific research question or hypothesis using a particular method that is best suited for that question or hypothesis (Tashakori and Teddlie, 2009). For example, a researcher might use a survey to gather quantitative data from participants about their attitudes or behaviours (Vizcarguenaga-Aguirre and López-Robles, 2020).

While the mono method approach can be useful in certain contexts, it has some limitations. One limitation is that relying on a single method may result in limited data that may not capture the complexity or richness of the research question or phenomenon being studied (Kelle, 2006). It may also lead to biases in the data or limitations in the types of conclusions that can be drawn from the data (Harden and Thomas, 2010). It is therefore pertinent that carefully consideration of the advantages and disadvantages of using a mono method approach is taken to ensure that the chosen method is appropriate for the research question or phenomenon being studied (Vizcarguenaga-Aguirre and López-Robles, 2020).

2.4.4 Mixed method

Mixed method is a combination of qualitative and quantitative analytical approaches and data (Harden and Thomas, 2010). It is the crucial point between the two major research methodological approaches (Creswell, 2003). Within a single paradigm, the mixed method approach involves the constructivist elements of quantitative methods and the positivist element of qualitative research (Hayvaerts *et al.,* 2016). The mixed method study could have different purposes which includes completeness, complementarity, expansional, developmental, confirmatory, compensation or diversity (Tashakori and Teddlie, 2009; Creswell, 2006). The purpose for which a mixed method approach is adopted must be completely met for the research to be considered of high quality (Hayvaerts *et al.,* 2016). If the study is expansional (i.e. when the breadth and the range of the research is expanded by employing different methods for different lines of enquiry), it must fully interrogate and explain the significance of the understanding gained in a previous study (McLaughlin *et al.,* 2016), or if the purpose of the study is complementary, then it must enable access to complementary views about the same phenomenon than a single approach of either qualitative or quantitative nature can produce. This is known as the utilisation quality (Greene and Caracelli, 1997).

The research objective directs the type of research approach to adopt (Jankowicz, 2000). When the aim of the research is to develop a framework or a theory, it is more appropriate to employ mixed method approach rather than just choosing either qualitative or quantitative method (Saunders *et al.,* 2007). As the quantitative methods help provide answers to the 'how' questions of the research, such as 'how much' and 'how many' (Biggam, 2015), qualitative research will complement it in answering 'why' and 'what' questions to investigate the perspectives of participants and meaning they attach to value (Hammarberg *et al.,* 2016). The mixed method approach only becomes useful when a single approach has certain limitations that could influence the outcome of the research negatively. For example, the biases that might exist in a qualitative approach stemming from interpretation based on a researcher's perspective could be mitigated by adopting a mixed method study (cf. Creswell 2006). Heale and Forbes (2013) propose a triangulation process as a way of merging quantitative and qualitative methods.

There are different types of mixed method approaches which allow researchers to gain insights into the nuances of each method and make informed decisions when designing their own studies (Leech *et al.,* 2010). These types of mixed method include:

Sequential Explanatory (Othman *et al.,* 2020): in this design, the researcher collects and analyses quantitative data first, followed by qualitative data gathering and analysis (Ivankova *et al.,* 2006). The goal is to explain or investigate surprising or contradicting quantitative findings (Bowen *et al.,* 2017). This approach prioritises quantitative data, with qualitative data utilised to give additional insights or explanations (Othman *et al.,* 2020). The researcher may begin with a large-scale quantitative survey and then follow up with interviews or focus groups to investigate participants' experiences or the reasons behind the quantitative results (Ivankova *et al.,* 2006).

Sequential Exploratory (Doyle *et al.,* 2016): in this approach, the researcher first collects and analyses qualitative data before proceeding to gather and analyse quantitative data (Cabrera, 2011). The goal is to investigate a phenomenon in depth using qualitative methods, followed by quantitative approaches to validate or generalise the findings. This design emphasises the priority of qualitative data, with quantitative data utilised to give confirmation or greater generalisability (Doyle *et al.,* 2016). The researcher may begin with interviews or observations to gather rich insights before moving on to quantitative surveys or experiments to test hypotheses or evaluate the prevalence of specific qualities or behaviours (Cabrera, 2011).

Sequential Transformative: this design integrates both qualitative and quantitative data collecting and analysis, but with a transformative goal (Bremser *et al.,* 2021). The goal is to employ a variety of ways to promote social change, empower individuals, or question established assumptions or power systems (Subedi, 2016). The purpose of this design is to answer research questions on equality, social justice or transformation (Bremser *et al.,* 2021). The researcher may employ qualitative approaches to investigate lived experiences before employing quantitative methods to assess changes in behaviour or outcomes as a result of an intervention or social programme (Subedi, 2016).

Convergent: in this design, qualitative and quantitative data are gathered concurrently and analysed independently, followed by a comparison or integration of the results (Doyle *et al.,* 2016). The goal is to offer a thorough grasp of the study issue by investigating various aspects or dimensions via both qualitative and quantitative perspectives (Moseholm and Fetters, 2017). The value of both qualitative and quantitative data is emphasised in this design as the researcher might gather survey and qualitative interview data simultaneously and compare the findings to detect trends, differences or convergence (Doyle *et al.,* 2016).

Embedded: in this method, one form of data (qualitative or quantitative) takes precedence, with the other type of data embedded inside it to provide extra insights or context (Izgu and Metin, 2020). The goal is to use one form of data as the major emphasis, while the second type of data supplements or enhances the conclusions (Tunji-Ajayi *et al.*, 2020). Using the embedded data, researchers may go further into certain areas of the research issue. The researcher might perform a quantitative survey first, followed by qualitative interviews to comment on or offer examples that elucidate the survey findings (Izgu and Metin, 2020).

Multiphase: With this approach, qualitative and quantitative research are conducted separately, with each phase influencing the one that follows (Pardede, 2019). The overall design is characterised by an iterative and cyclical process, and each step could entail a new research or sample (Van Lith *et al.,* 2023). Throughout the many phases, the goal is to build on prior discoveries and improve the research questions, procedures or metrics (Pardede, 2019). A qualitative exploratory phase may be used by the researcher to establish initial hypotheses, and a quantitative confirmatory phase might be used to evaluate and validate those concepts (Van Lith *et al.,* 2023).

These various mixed method research design techniques provide flexibility in conducting studies by allowing modifications to research methodologies in accordance with the research questions, context, and objectives (Doyle *et al.,* 2016; Van Lith *et al.,* 2023).

2.4.5 multi-method

The multi-method approach to research involves using more than one research method to investigate a research question (Salmons 2015). This approach allows researchers to triangulate their findings by collecting and analysing data from different sources and using different methods (Heale and Forbes, 2013). By doing so, researchers can increase the validity and reliability of their findings, as they are not relying solely on one method or one source of data.

There are several benefits to using a multi-method approach. One is that it can help to overcome the limitations of individual research methods (Kelle, 2006). For example, a quantitative survey might provide valuable information about people's attitudes towards a particular issue, but it might not provide any insight into why people hold those attitudes (Salmons 2015). By using a qualitative method like interviews or focus groups in addition to the survey, researchers can gain a more meticulous understanding of the issue (Kelle, 2006). Furthermore, a multi-method approach can help to mitigate the biases that can arise from using a single method (Harden and Thomas, 2010). For example, if a researcher only collects self-report data, they may not secure an accurate picture of people's behaviour (Kelle, 2006). However, by also using observational or behavioural data, the researcher can cross-check the self-report data and gain a more complete understanding of the phenomenon under investigation (Salmons 2015). Generally, the multi-method approach is an effective means of increasing the rigor and comprehensiveness of a research study (Salmons 2015). By combining multiple methods and sources of data, a more viable conclusion about the research question can be reached (Harden and Thomas, 2010).

2.5 TIME HORIZONS

Time horizon refers to the duration of the study or the period over which data is collected (Rose *et al.,* 2015). It is a key element in planning and conducting research because it can have a significant impact on the research design, data collection methods, sample size and analysis techniques (Dolan *et al.,* 2008). The time horizon in research can be broadly classified into three categories: cross-sectional, longitudinal and retrospective (Dolan *et al.,* 2008).

2.5.1 Longitudinal

A longitudinal study involves the collection of data over an extended period, with multiple measurements taken at different points in time (Staub-French *et al.,* 2022). The aim of a longitudinal study is to analyse how a phenomenon changes over time and to identify trends and patterns in the data (Staggs *et al.,* 2022). This type of study is useful in situations where the research question is about the cause-and-effect relationship between different variables over time (Dolan *et al.,* 2008).

2.5.2 Cross-sectional

In a cross-sectional study, data is collected at a single point in time, and the focus is on analysing the characteristics of a population or a sample at that particular moment (Lavrakas, 2008). A cross-sectional study aims to provide a snapshot of a particular situation or phenomenon (Roberts, 2020). This type of study is useful in situations where the research question is about the prevalence of a particular phenomenon or characteristic in a population (Saunders *et al.,* 2016). A questionnaire is an example of data collection tools that can be used for cross-sectional study as it samples the views of participants in a particular moment in time

(Tavory, 2020), These views might differ at a different time based on different experiences participants may have encountered later on (Roberts, 2020).

2.5.3 Retrospective

In a retrospective study, data is collected from the past, and the focus is on reconstructing events that have already occurred (Dolan *et al.,* 2008). This type of study is useful in situations where the research question is about the effects of a particular event or intervention on an outcome (Shi *et al.,* 2021).

2.6 STRATEGIES, TECHNIQUES AND PROCEDURES

Research strategies are the plans put in place to attain the research goal (Saunders *et al.,* 2016). The type of research strategy to adopt is dependent on the kind of research to be undertaken (Hasanova *et al.,* 2021). These might include the types of data that was collected, the sources of that data, the methods of analysis and the expected outcomes. Common research strategies include experimental, survey, case study, ethnographic and action research. Table 2.2 presents some of the types of research strategies that can be adopted, their strengths and their weaknesses.

Table 2.2 - Types of research strategies and their strengths and weaknesses

Research strategy	**Choice of method**	**Question rhetoric**	**Strength**	**weakness**	**Citations**
Experiment	Quantitative	How, why?	Allows the exploration of relationship between variables. Can be applied widely in various domains. Allows access to and control of factors that may affect results.	It is time-consuming and costly. Over manipulation of variables could produce inaccurate results.	Rogers and Revesz (2019); Ledyard (2020); Mattila *et al.,* (2021).
Survey	Quantitative	Who, what, where how many, how much?	Close-ended questions allow easier analysis of data. Allows datasets to be directly compared. Gives a general perspective to an event under scrutiny.	Rigidity of design prevents alterations during data collection. Poor design can result in invalid conclusions. Answers given may not reflect reality as a little detail is given.	Story and Tait (2019); Wagner *et al.,* (2020); Griffin *et al.,* (2021).
Case studies	Qualitative or quantitative	How, why?	It is detail oriented. Helpful in generating and verifying hypothesis. Direct observation of data allows broader knowledge acquisition.	Subjective nature of data could present errors. Presents the possibility of unintentional bias.	Forrest-Lawrence (2019); Schoch (2020); Takahashi and Araujo (2020).
Ethnography	Qualitative or quantitative	How, what, why?	It is detail oriented. Helpful in generating and verifying hypothesis. Direct observation of data allows broader knowledge acquisition,	It is time consuming and costly. Highly dependent on situational events.	Sharma and Sarkar (2019); Hirsch and Gellner (2020); Pink *et al.,* (2022).
Interview/ focus group	Qualitative	Who, what, where, how, why?	Encourages capturing of verbal and non-verbal responses more accurately. Researcher has more control on shaping the focus of discussion,	Subjective nature of data could present errors. Presents the possibility of unintentional bias.	Gray *et al.,* (2020); Tavory (2020); Roberts (2020).
Archival research	Qualitative or quantitative	Who, what, where how many, how much?	Data collection is cheaper and time effective as no addition data collection process is required. Rare behaviours can be studied. Allows for longitudinal studies over a life span. Minimises response biases.	Causal conclusions cannot be accurately made. Limitation on the availability of appropriate records. No control over data collection process. There is also no guarantee of consistency between the records from one source to another.	Velte (2021); Hanlon (2022).
Action research	Qualitative	How, why?	Tackles social problems and proposes social interventions. It is easy to conduct.	Research biases are eminent. It is time consuming. Generalisability of results is limited.	Mac Naughton (2020); Banegas and de Castro (2019).

2.6.1 Bibliometric Network Analysis

The manual method of reviewing literature presents challenges which includes: researchers' bias; inaccurately capturing meaning of information and limited number of publication sampling due to the time and resource restraints; and limited ability of the human mind to process large amount of information (He *et al.,* 2017). Bibliometric analysis is a computer-aided, scientific methodology used to review literature by finding the main authors, their primary research and the relationship that exist between them, through broadly reporting on most research publications associated with a specific field or topic (De Bellis, 2009). The ability of bibliometric analysis to capture and present a visual overview of a large body of literature has made it a desirable option for literature review across multiple fields (Van Eck and Waltman, 2010). Bibliometric analysis gives an in-depth understanding of the general intellectual landscape of a body of literature by providing several relational information on the given field or subject (Iqbal *et al.,* 2019; Churruca *et al.,* 2019). Software such as VOSviewer (Van Eck and Waltman, 2010; Edwards *et al.,* 2017; Roberts *et al.,* 2021; Posillico *et al.,* 2022) or Gephi (Bastian *et al.,* 2009) are used to generate a network map which illustrates the relationships between data sourced from literature databases such as Scopus, Web of Science etc.

2.6.2 Case studies

A case study research approach allows generation of comprehensive, multi-faceted understanding of dense issues in its real-life context (Cousin, 2005). A case study enables contemporary phenomena to be investigated as a way of shedding more light on problems and concerns for a better understanding of any prevailing issues or phenomenon under investigation (Yin, 2012). If the real-world problems presented can better be appreciated in a given context, then a case study is the approach to be adopted (Gillham, 2005).

In other instances where cause-effect relationships are complex and unidentified, case study research can be presented as an approach for delivering information which reveals causal links and relationships to enhance decision making based on relevant information discovered (Yin, 2012). The multi-method approach, also referred to as 'chain of evidence' was proposed by Gillham (2000) as a significant approach to undertaking case study research. The chain of evidence accumulates a variety of various sources of evidence, with diverse methods of collection of evidence but relates to the same point (*ibid*).

Stake's (1995) art of case study research proposes three categories of case studies *viz*: i) intrinsic; ii) instrumental; and iii) collective case studies which are represented in Table 2.3 below.

Table 2.2 - Categories of case studies

Case study approach	Description	References
Intrinsic	This type of research focuses on the case at hand. It is often suitable for evaluation research due to its ability to reveal the value attached to specific activities or events. It seeks to derive generalisation from focusing on the singularity of a case under study. It attempts to generalise within a case.	Hamilton *et al.,* (1977); Simons (1980); Parker (2016).
Instrumental	It investigates cases as an instance of a class to reveal issues pertaining to the class. In this type of research, attention must be given to any local effects that might present uncertainties and prevent accurate generalisations being made. It attempts to generalise from a case.	Fuller *et al.,* (2003); Wasburn, (2007).
Collective	It explores several selections of cases for a particular class in order to attain some sort of representation.	Au and Blake (2003); Bray, (2011).

2.6.3 Primary Data

Primary data is original information gathered particularly for a research project, typically by direct observation, questionnaires or experiments (Heap and Waters, 2019). Primary data is utilised to address research questions that have not previously been published or obtained from other sources (Kara, 2023). Surveys, focus groups, experiments and observational studies are all approaches for gathering primary data (Mazhar *et al.,* 2021). Surveys are a popular way of gathering primary data in which participants are asked to answer a series of questions about the study topic (Kara, 2023). Focus groups include a small group of people delving deeply into the study issue, whereas experiments and observational studies entail modifying factors and evaluating their effects (Mazhar *et al.,* 2021).

One of the fundamental benefits of primary data is that it is personalised to the specific research subject under consideration (Saleem *et al.,* 2014). Researchers may tailor their data gathering methods to capture only the information they want, ensuring that the information gathered is relevant and correct. Moreover, primary data helps researchers to regulate the research process and reduce the influence of confounding variables, thereby boosting the study's validity (Nayak and Narayan, 2019). Another benefit of original data is that it is frequently more up to date and reliable than secondary data sources (Saleem *et al.,* 2014). Secondary data sources, such as published reports and data sets, may be out of date or irrelevant to the phenomenon under consideration. Primary data collection guarantees that the information gathered is current and pertinent to the subject of study (Nayak and Narayan, 2019). Yet, gathering primary data may be time-consuming and costly, which limits the scope of many research investigations (Mazhar *et al.,* 2021). Moreover, the data obtained may contain biases and mistakes, such as response bias or observer bias, which might restrict the study's validity and reliability (Kara, 2023). While collecting primary data can be time-consuming and costly, it is personalised to the individual research subject being researched and can be more accurate and up to date than secondary data sources (Saleem *et al.,* 2014). Therefore, to ensure the validity and trustworthiness of a study, researchers must be aware of the limits and inherent biases of primary data gathering techniques (Heap and Waters, 2019).

2.6.4 Secondary Data

Secondary data is information that was gathered by someone else for a different reason but can be utilised for a research study (Heap and Waters, 2019). Secondary data is frequently accessible from a variety of sources, including government organisations, research institutes and private businesses (Rabinovich and Cheon, 2011) and may include government statistics, reports and publications. There are two forms of secondary data viz.: internal and external (Sarker *et al.,* 2013). Internal secondary data refers to information gathered within a company, such as sales records or customer information (Sarker *et al.,* 2013). This information may help firms monitor their operations, performance and consumer behaviour. External secondary data refers to information gathered from sources outside than the organisation, such as government or research agencies. This data is useful for researchers in analysing trends and making comparisons across different populations (Boslaugh, 2007).

Secondary data has the benefit of being both cost-effective, time efficient, frequently easily available and can save time and resources that would otherwise be spent gathering fresh data (Saleem *et al.,* 2014). Secondary data can also give a historical perspective, allowing researchers to look at trends and patterns across time. Another benefit of secondary data is its high sample size, which allows for more precise and dependable results (Heap and Waters, 2019). Secondary data can also give access to populations that are difficult to contact or research directly, such as historical populations or rural communities (Boslaugh, 2007). However, secondary data has significant limitations that researchers should be aware of. One restriction is that secondary data may not be customised to the unique situation or may not be customised to the researcher's individual study topic or objectives (Cole and Trinh, 2017). Furthermore, the quality of secondary data might vary and researchers may need to examine the data's reliability and validity before using it in their research (Johnston, 2014). Therefore, to effectively use secondary data, researchers should consider several factors, including the relevance of the data to the research question, the reliability and validity of the data, and ethical considerations related to data use and confidentiality.

2.6.5 Sampling

Sampling is a research strategy that is used to select a representative group from a larger population to examine that community (Naoum, 2019). Due to logistical, budgetary or time restrictions, it is sometimes difficult or impossible to examine a whole population and that is where sampling becomes a necessity. Choosing an appropriate sampling technique depends on various factors such as research objectives, population size, availability and resources (Taherdoost, 2016). Two main branches of sampling exist- this includes probability and non-probability sampling (Saunders *et al.,* 2016).

Probabilistic sampling is a technique which selects people at random from a broader group and is considered the most rigorous sampling method (Farrell *et al.,* 2017). Every member of the population will have an equal chance of being chosen., Probability sampling, yields a sample of the population that is representative of the whole and can be expensive and time-consuming (Sharma, 2017). Stratified sampling is a sort of probability sampling in which the population is divided into subgroups or strata and then participants are chosen from each subgroup in proportion to their representation in the population (Parsons, 2014). This method assures that the sample is representative of the population while also allowing researchers to concentrate their efforts on certain subgroups of interest. Cluster sampling is another type of probability sampling which involves grouping the population into clusters or groups and then choosing randomly which clusters will take part in the research (Berndt, 2020). When the target demographic is geographically distant or challenging to reach, this strategy might be helpful.

Unlike probability sampling, non-probability sampling involves choosing individuals using factors other than chance (Bae *et al.,* 2022). Purposive, convenient and snowball sampling are all part of this method (Parker *et al.,* 2019). Non-probability sampling is less accurate than probability sampling, but it can be beneficial and cost-effective in cases when it is challenging to reach the target population (Bae *et al.,* 2022). Quota sampling however, is a sort of non-probability sampling in which participants are chosen based on defined quotas (Zhang *et al.,* 2020). A researcher, for example, may wish to recruit a specified number of volunteers from various age groups, genders or socioeconomic backgrounds. Although this approach assures that the sample is representative of the target population, it is not as trustworthy as probability sampling (Bhardwaj, 2019). Snowball sampling is also another non-probability technique, the researcher identifies a few participants who meet certain criteria and then asks them to refer other participants who also meet the criteria (Parker *et al.,* 2019). This technique is useful when the population is hard to reach or when the characteristics being studied are rare (Ruel *et al.,* 2016). Using the researcher's discretion, purposive sampling, a non-probability sampling strategy, selects certain examples from the target population that will help answer the research question(s) (Bhardwaj, 2019). When working with restricted target populations, this kind of sampling is typical (Farrell *et al.,* 2017). Further aiding the researcher in acquiring a representative sample for the study are various subsets of purposive sampling, such as crucial case, typical case, extreme case, heterogeneous and homogeneous (Adabre *et al.,* 2022; Jupp, 2006).

2.6.6 Machine learning

ML is a methodology that has various methods of inquiry (models) that enables systems to learn from a set of available data and improve from experience without it being programmed to do so (Carbonell *et al.,* 1983; Jordan and Mitchell, 2015; Ghahramani, 2015). There exists a relationship between ML and research methodologies (Jordan and Mitchell, 2015; Moosavi *et al.,* 2020) because it can be linked to quantitative research due to the similarities between choosing a hypothesis and model selection in ML (Zhang and Feng, 2021). The process of establishing a hypothesis based on existing proof is similar to selecting a model based on available data (Shi *et al.,* 2022). The process of validating a hypothesis can also be linked to the process of validating a model selected. Lastly, the decision of which experiments to perform and which observation are to be made is much like ML (Poggi *et al.,* 2017). ML is a computational modelling technique that can be likened to theorising (Körner and Schoop, 2013). The reasoning approach it adopts has been characterised as abductive (Raholm, 2010). However, ML methods can also perform a wider and a more iterative task of working through evidence to theory, to new evidence to new theory and this has been referred to as induction (Pierce, 1984; Shrestha *et al.,* 2021). Induction however, is more associated with qualitative research as it attempts to generalise observations on a population based on inference made from an observed sample. This is a more accurate description of ML as it extracts rules from a set of training data and uses those rules to process the test data (Shrestha *et al.,* 2021).

One major outcome of hypotheses and model inferences is prediction (Tredennick *et al.,* 2021). Rules inferred from training data can be induced on new data (test) to predict future events (Hohwy, 2020). In contrast to just building new theories as a research focus, ML focuses on building predictive models (Mosavi *et al.,* 2019). This process is therefore known as modelling (Ayodele, 2010). ML can combine both qualitative and quantitative data to build both prediction or classification models (Mosavi *et al.,* 2019). Where the models define the classes or group of the possible predictions, the model becomes a classification model nevertheless if the model fits into a shape as close to the data as possible it is prediction (Song and Ying, 2015).

Several ML techniques have been adopted to predict HS risks (Papazoglou *et al.,* 2015; Tsoukalas and Fragiadakis, 2016; Debnath *et al.,* 2016;). Fuzzy methods (Ahmed *et al.,* 2021) were also employed by Rastogi and Gabbar (2013) to analyse risk in a nuclear plant. Tsoukalas and Fragiadakis (2016) used multivariable linear regression and genetic algorithm analysis to predict occupational risk in the ship building industry. Similarly, decision trees have been utilised in exploring contributing factors to occupational risk in the Taiwan construction industry (Cheng, *et al.,* 2012), while Debnath *et al.,* (2016) used a fuzzy inference model to examine occupational risks in construction sites. In other examples, Esmaeili *et al.,* (2015) predicted attribute-based safety outcomes using generalised linear models; Zhang *et al.,* (2016) used fuzzy Bayesian networks to access risk of pipeline damage; and Englehardt *et al.,* (2003) and Papazoglou *et al.,* (2015) used Bayesian networks extensively in the risk prediction domain.

With ML techniques, features that were used for prediction must be manually extracted from the pool of numerous features obtained - which requires a considerable amount of effort and could be time consuming as these features usually exist in large database (Esmaeili *et al.,* 2015). However, ML techniques provide a higher prediction accuracy and are more efficient as compared to traditional statistical models due to the large amount of data being processed (Shin *et al.,* 2021; Hale *et al.,* 2018; Farooq *et al.,* 2020). The problem of manual extraction of significant features can however be addressed with deep learning (DL) techniques (Hwang *et al.,* 2020; Han *et al.,* 2020). DL is a subfield of ML which permits computational models that comprises several processing layers to learn data representations with multiple levels of abstraction (LeCun *et al.,* 2015; Bengio *et al.,* 2017).

The ability of DL models to discover complicated data structures and continuously build novel task-specific features from high dimensional data coupled with its high learning capacity makes its performance superior to existing ML techniques (LeCun *et al.,* 2015). DL enables the challenges of nonlinear relationships between dependent and independent attributes to be addressed hence, has been employed in the prediction of short-term traffic (Zhao *et al.,* 2017) and the prediction of building cooling load (Fan *et al.,* 2017).

Unsupervised Learning

Unsupervised learning is a type of ML technique in which an algorithm learns from an unlabelled dataset to discover patterns or structure within the data (Berg-Kirkpatrick *et al.,* 2010). In contrast to another type of ML known as supervised learning, unsupervised learning has no explicit output or target variable that the algorithm is trying to predict (Celebi and Aydin, 2016). Instead, the algorithm learns to identify underlying patterns and relationships among the input data (Berry *et al.,* 2019). Unsupervised learning algorithms can be broadly categorised into two types *viz.*: clustering and dimensionality reduction (Celebi and Aydin, 2016). In clustering, the algorithm groups similar data points into clusters or subgroups based on some similarity metric while in dimensionality reduction, the algorithm reduces the number of features in the input data while still retaining as much information as possible (Palacio-Niño and Berzal, 2019). The most commonly used clustering algorithms are k-means, hierarchical clustering and density-based clustering (Sinaga and Yang, 2020). In dimensionality reduction, principal component analysis (PCA), t-distributed stochastic neighbour embedding (t-SNE) and autoencoders are commonly used (Mahesh, 2020). Clustering is useful for grouping similar images or texts together based on some similarity metric, which can be useful in recommendation systems or image retrieval while dimensionality reduction techniques such as PCA and t-SNE are useful for visualising high-dimensional data in a lower-dimensional space.

K-means is a simple yet powerful clustering algorithm that groups the input data into a predefined number of clusters based on their similarity to a set of cluster centroids (Sinaga and Yang, 2020). Hierarchical clustering, on the other hand, builds a tree-like hierarchy of clusters, where each node represents a cluster that can be further divided into smaller clusters (Nielsen and Nielsen, 2016). Density-based clustering algorithms, such as DBSCAN, identify clusters based on areas of high density within the input data (Campello *et al.,* 2020). In the area of dimensionality reduction, PCA is a widely used algorithm that identifies the most important features in the input data by projecting it onto a lower-dimensional space (Karamizadeh *et al.,* 2013). t-SNE is also a non-linear dimensionality reduction technique that preserves the local structure of the input data in the lower-dimensional space, making it particularly useful for visualising high-dimensional data (Wattenberg *et al.,* 2016). Unsupervised learning also includes autoencoders which are neural network-based algorithms that can learn a compressed representation of the input data by reconstructing it from a lower-dimensional latent space (Liu *et al.,* 2018).

Unsupervised learning has been applied in several areas, including anomaly detection, image and text data clustering and data visualisation (Campello *et al.,* 2015; Hasan *et al.,* 2019; Wang *et al.,* 2021). Anomaly detection involves identifying data points that are significantly different from most of the input data, which can be useful in fraud detection or cybersecurity (Campello *et al.,* 2015). Hasan *et al.* (2019) applied anomaly detection in the internet of things (IoT) domain to predict attacks and anomalies on the IoT systems accurately. In similar research, Wang *et al.* (2021) used data-driven clustering for anomaly detection of industrial control systems based on transfer learning. Unsupervised learning has been of tremendous help in data-driven research especially when data is unlabelled, through the kind of pattern it helps generate to provide insight into the available data (Wang *et al.,* 2021).

Supervised Learning

Supervised learning is a type of ML technique which uses an algorithm to learn from a labelled dataset in order to generate predictions or choices (Singh *et al.,* 2016). A model is trained on a collection of input-output pairs in supervised learning, where the input is a set of features and the output is a label or target variable. This training data is then used by the model to create predictions about new, unforeseen data usually referred to as test data (Vrigazova, 2021). Various fields, including image classification (Ma *et al.,* 2017), audio recognition (Akbari *et al.,* 2021), natural language processing (Chowdhary and Chowdhary, 2020) and recommendation systems (Ko *et al.,* 2022), have made extensive use of supervised learning. The two main categories of supervised learning algorithms are classification and regression (Choudhary and Gianey, 2017). While the output variable in regression is a continuous value, it is a discrete label in classification (Matloff, 2017). Support vector machines (SVM), decision trees, random forests, logistic regression and artificial neural networks techniques (ANN) are the most widely used classification (Choudhary and Gianey, 2017). Regression analysis frequently employs linear regression, decision trees, random forests, SVM and ANN (Freund *et al.,* 2006).

Binary classification problems are frequently solved using logistic regression which is a straightforward yet an effective classification approach (Menard, 2002). To determine the likelihood that the output variable would fall into one of two groups, a logistic function is fitted to the input data in this algorithm. This can be done using a sequence of if-else statements, tree-based algorithms such as decision trees and random forests to make decisions about the input data (Kudryashov, 2015). SVM is an effective method that may be applied to classification and regression issues (Vapnick, 1999). It functions by identifying the hyperplane that best categorises the input data into distinct groups or forecasts the regression's output variable (Noble, 2006). The ANN deep learning algorithm has transformed several industries, such as computer vision and natural language processing (Choudhary and Gianey, 2017). To identify intricate patterns in the input data, it employs numerous layers of linked neurons (Ingre and Yadav, 2015). Recurrent neural networks (RNN) and convolutional neural networks (CNN) are an example of ANN that are commonly used in speech recognition which involves converting spoken words into text and image classification (Akbari *et al.,* 2021). RNN and transformer models, such as the popular Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT) models, are commonly used in natural language processing (Chowdhary and Chowdhary, 2020) which involves analysing and understanding human language. Recommendation systems involve suggesting products or services to users based on their past behaviour or preferences and supervised learning is a commonly used technique for such systems (Shani and Gunawardana, 2011; Das *et al.,* 2017; Ko *et al.,* 2022). Collaborative filtering and matrix factorisation are commonly used in recommendation systems.

Although supervised learning comes with significant benefits it requires certain levels of expertise to structure accurately. Training supervised learning models can be very time intensive and datasets can have a higher likelihood of human error, resulting in algorithms learning incorrectly (Muhammad and Yan, 2015). This is why, various metrices such as accuracy score, f1 score, confusion matrix etc. are employed to evaluate the model’s performance.

2.6.6.1 Random forest

Random forest (RF) is a ML classification method that comprises of an ensemble of uncorrelated decision trees (forest of trees) which unanimously determine how new objects are classified (Kuncheva *et al.,* 2011). Each individual decision tree present in the random forest has a vote and can make prediction on classes. The class with a majority of votes becomes the model's prediction. Decision trees employ binary splits to iteratively split the predictor space by determining the areas (leaf) that respond homogeneously to predictors (Elith *et al.,* 2008). A constant is then locally fitted to the individual final leaf (*ibid*). The constant for a target variable of a categorical nature is the most possible category of outcomes while the same equation applies to the whole data space for global models (Kuncheva *et al.,* 2011). For example, because the trees for logistic regression are local models rather than global models, they can adapt to the several explicit domain components that identifies the connection between input and output attributes (Boz, 2002).

RF have proven to have reliable performance when employed in regression and classification tasks (Liaw and Wiener, 2002; Breiman, 2001) as well as anomaly detection (Liu, 2012). It also has the advantage of identifying complicated non-linear first-order functions among predictors, to tackle the challenge of high dimensionality of data due to its voluminous nature. This advantage allows outliers to be efficiently handled and insignificant features captured (Sutton, 2005; Timofeev, 2004). Labelled objects that are characterised as a feature vector with fixed sizes are used to train each of the individual trees. To prevent over fitting and reduce variance, some randomness is introduced into the training which is known as bagging or bootstrap aggregation (Thelen and Riloff, 2002). Bagging is the process of creating new multiple samples of dataset from a single sample of data (Banea *et al.,* 2008). By resampling the original dataset and creating new distinct trees (subsets of the input variable) from random selection of observations, the random forest attains a higher predictive accuracy as compared to a single decision tree. The bootstrapping aggregate (Rigatti, 2017) method is applied in training RF algorithms therefore, to present the algorithm for RF the algorithm for bootstrapping aggregate is elucidated upon (Rigatti, 2017) *viz.*:

Given a training dataset $D = d_1 \ldots\ldots d_n$ with responses $R = r_1 \ldots\ldots r_n$

Bagged iteratively (B times), random samples of the original training dataset D are selected with replacement (WR- an observation may occur multiple times in the selected sample)

for $b = 1, \ldots., B$

Select sample (WR)
n training samples from *D, R*; refer to as $\boldsymbol{D_b}, \boldsymbol{R_b}$
training of regression or classification tree (t_b) on D_b, R_b

Now, predictions for test samples d' can be carried out by finding the average of predictions made from all the different regression tree on d' or selecting the most votes with classification. This can be mathematically represented as:

$$\hat{t} = \frac{1}{B}\sum_{b=1}^{b} t_b\,(d') \tag{1}$$

The uncertainty in the predictions can also be estimated as the standard deviation of the predictions obtained from each of the regression trees combined on d':

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum_{b=1}^{b}(t_b(d')-\hat{t})^2}{B-1}} \tag{2}$$

The algorithm for RF employs a non-parametric method of ML which requires no assumptions of relationship between predictor variables and target variables (Rigatti, 2017). The RF algorithm involves an ensemble of *N* trees with its corresponding N outputs for each individual tree. RF employs another version of the original bagging algorithm above known as feature bagging (Sutton, 2005). Feature bagging is similar to the original bagging method. However, with feature bagging, random samples of the predictor variable are selected from the pool of data attributes with replacement (WR) for each individual algorithm (Ho, 1998; Bryll, 2003). This process prevents individual algorithms from excessive concentration on attributes which are only effective predictors for the training data but fail to perform as effectively when applied to data points that do not exist in the set (Skurichina, 2002).

The algorithm for RF (Kuncheva *et al.,* 2011) can be expressed as follows:
number of training samples = S;
number of attributes in the training data = P;
number of individual models in the ensemble = M;
therefore, for every single model (m):
select s_m (where s_m<S) as the total input sample for m;
for all the individual models, s_m could have a single value.
For every single model m;

Draw p_m attributes from P (WR) to build a training set;
Train the models m;
For data which exist outside the training set; and
Merge the results of each individual model M by majority votes.

Random forests can be implemented using Scikit-learn which is a ML library that makes available a range of supervised and unsupervised learning algorithms including random forest algorithms. Random forest is made up of many decision trees and for each decision tree, scikit-learn calculates the importance of a node using the Gini Importance (GI) (Sandri and Zuccolotto, 2008) - which measures the average gain of purity by splits of a given variable. If the variable is relevant, the GI will divide the mixed labelled nodes into pure single class nodes. For example, with a binary tree where we have nodes i and j,

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \quad (3)$$

Where:

ni_j = Node j's importance;
w_j = weighted number of samples (node j);
C_j = impurity value (node j);
Left(j)= left split child node; and
Right (j)= right split child node.

When using random forest for classification tasks, the Gini index (which is a measure of the inequality among values of a variable (cf. Miao *et al.,* 2022)) is often used. It is necessary to find the variable significance in random forest as this gives clarity to which features in the sample space are very pertinent in the prediction task. Unique features (variables) are used in determining the classification of the target variable hence, the significance of each variable on a decision tree needs to be determined (Miao *et al.,* 2022). It is the calculated as:

$$Vi_i = \frac{\sum_{j:node\ j\ splits\ on\ variable\ i} ni_j}{\sum_{k \in all\ nodes} ni_k} \quad (4)$$

Vi_i = Variable i's significance
ni_j= node j's significance

During data preparation in ML, the dataset is normalised (Singh and Singh, 2020) so numerical values in the data set could have a common scale without losing any information or distorting the values. Hence, by dividing variable significance by the sum of all the variable significance values, the variable's significance can be normalised to a value between 0 and 1.

$$normVi_i = \frac{Vi_i}{\sum_{j \in Variables} Vi_j} \tag{5}$$

Finally, at the random forest (RF) stage, the decisive variable significance is the average of the variable significance divided by all the trees (T). The values of all the variable significance on each tree are added and divided by the total number of trees (Zhao *et al.,* 2022) presented as:

$$RFVi_i = \frac{\sum_{j \in all\ trees} normVi_{ij}}{T} \tag{6}$$

$RFVi_i$ = the significance of Variable i deduced from total trees present in random forest model
$normVi_{ij}$ = normalised variable significance for node i in tree j;
T= total number of trees; and
The number of trees (n) in the forest and at each split and the number of predictor variables (P) selected randomly are the tuning parameters of the RF (Xie *et al.,* 2009).

2.6.6.2 Support vector machine

Support vector machine (SVM) is a mathematical operational concept that was derived from statistical learning theory (SLT) (Vapnick, 1999; Noble, 2006). SLT which is mathematically profound computational method, enables the learning of dependencies from predictable experiments. Furthermore, the use of SLT enables a comprehensive knowledge gain from exploring several learning techniques ranging from neural networks, statistics, signal processing etc. (Cristianini and Shawe-Taylor, 2000). The ability of SVM to manage extremely large feature spaces is one of the characteristics that makes SVM a preferred choice by many studies (Friedrichs and Igel, 2005; Yu *et al.,* 2013). SVM training allows classified vectors (CV) to be dimensional in such a way that the classified vectors do not directly influence the performance of the SVM. However, the CV's influence is predominant in the execution of the conventional classifier (Friedrichs and Igel, 2005). High dimensional classification problems can therefore be efficiently handled by SVM and perform effectively in fault classification due to its ability to accommodate an enormous number of variables which might contribute to the effective classification of faults (Cristianini and Shawe-Taylor, 2000). In SVM, the number of features that exist in a dataset determines the dimensional space available for plotting individual observations, for example, if there exists F number of features in the dataset, then each observation is plotted as a point in an F-dimensional space (Bhavsar and Panchal, 2012). SVM also consist of two classes present in the feature space, i.e. the F-dimension where features used to characterise the data, excluding the target variable, exists (Sun *et al.,* 2010).

The presence of a hyperplane in SVM serves as a decision boundary which distinguishes the two classes in the feature plane (Mun *et al.,* 2017). A data point located either side of the hyperplane can be recognised as a distinct class (Ding *et al.,* 2014). The data points closest to the hyperplane are known as the support vector, which has influence on the orientation and positioning of the hyperplane (Cortes and Vapnik, 1995; Ding *et al.,* 2014). If the data can be classified into two using a single straight line, then it is termed a linear support vector machine problem.

For a linear SVM, given a training data with S data inputs of the form,
$\boldsymbol{x_i}$ where i=1,2, …, S and S the number of samples.
Assumption: two classes exist, i.e., positive (P+) and negative(N-) class.
$\boldsymbol{x_i}$ is an F-dimensional vector
Hence if, each class associates with a label y, then,
Let y_i= 1 for P+ and y_i = -1 for N-
A hyperplane can be expressed as
$m^T x - c = 0$
where m is an F-dimensional vector and c is a scalar
Given a linear data, the hyperplane $f(\mathbf{x})$= 0 differentiating the given data can be expressed as
$$f(x) = m^T x + c = \sum_{j=1}^{S} m_j x_j + c = 0 \quad (7)$$

Two parallel hyperplanes that differentiate the classes can be selected such that the largest possible distance can be created between them. A margin, which is the area bordered by the parallel hyperplane can find its maximum known as the maximum margin, when it lies halfway between the two hyperplanes. For a standard normalised dataset, the hyperplanes can be expressed as:

$$m^T x - c = 1 \tag{8}$$

where the area bordered on or above this hyperplane belongs to a particular class, and…

$m^T x - c = -1$ where the area bordered on or below this hyperplane belongs to a particular class

The distance between a hyperplane and its origin is expressed as $\frac{c}{\|m\|}$

∴ the distance between the two parallel hyperplanes can be expressed as $\frac{2}{\|m\|}$

Hence, to create a maximum distance between the hyperplanes $\|m\|$ must be minimised, the distance can be calculated using the formular for distance between a point and a plane.

$$(x, y, z) = \sqrt{x^2 + y^2 + z^2} \tag{9}$$

however, the condition below must be satisfied, i.e., data points must be prevented from falling into the margin.

$$\forall 1 \leq i \leq S, \quad y_i f(x_i) = y_i(m^T x + c) \geq 1 \tag{10}$$

An optimisation problem can be derived from the above equation where to minimise $\|m\| \; \forall 1 \leq i \leq S, \quad y_i f(x_i) = y_i(m^T x + c) \geq 1$, the value of m and c can determine a classifier $\boldsymbol{x}$ when a sign function is applied. This can be expressed as.

$$\boldsymbol{x} \rightarrow \boldsymbol{sgn}(m^T x - c) \tag{11}$$

For a nonlinear SVM, a hinge loss function can be applied,

$$\boldsymbol{max}(0,1 - y_i(m^T x - c)) \tag{12}$$

The optimisation objective will then be to reduce C, which is a parameter that influences the exchange between maximising the size of the margin and locating $\boldsymbol{x_i}$ on the right side of the margin when C>0.

$$C\|m\|^2 + \frac{1}{S}\sum_{i=1}^{S} \max\,(0,1 - y_i(m^T x - c)) \tag{13}$$

The multiclass SVM

The previous discussion on SVM has focused on binary classification using SVM where the class labels are only two values, either 1 or -1. However, this present research uses a dataset that presents a multi classification task of classifying risk levels as either high, medium, or low.

This presents a 3-dimensional problem hence, the use of a plane, rather than a line will be more appropriate.

1. One vs. one SVM (OvO)

OvO is an empirical method of applying binary classification algorithms to multi-class classification. A $k(k-1)/2$ classifiers are constructed where each classifier is trained on data extracted from the two classes (Mat Yusoh *et al.,* 2020). OvO splits the classifier into a binary classification problem. The data set is split into one set of data for each class against every other class (Liu, 2022). For instance, Figure 2.2 demonstrates a case where there are three class labels of high, medium and low, this could be divided into five binary dataset classification problem (BCP) as follows:

BCP 1; high vs medium
BCP 2; high vs low
BCP 3; medium vs. low

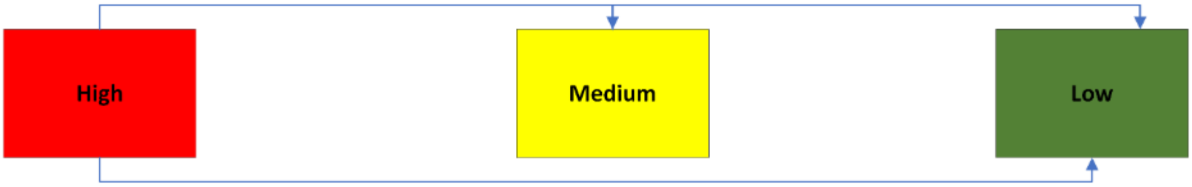


Figure 2.2 - A binary dataset classification problem

A single class label could be predicted by each binary classification model and the OvO strategy predicts the model with majority votes or predictions. The Max Win strategy (Duan and Keerthi, 2005) could be used as the voting approach. Here, if by the sign function, $((\mathbf{m}^{ij})^T\varphi(\mathbf{x})+c^{ij})$ proposes that an input variable x is in the ith class, it is considered a vote for the ith class hence, one vote is added to the class. If not, then one vote is rather added to the jth class. The largest vote is therefore used to predict the class of **x.**

2. One-vs-All (OvA)

OvA is a heuristic approach for employing binary classification algorithms for multi-class classification (Mishra *et al.,* 2021). The multi-class dataset is divided into several binary classification problems. Each binary classification problem has a binary classifier trained on it to make predictions by applying the most assertive model (Utami *et al.,* 2021).

Using the same example previously used in OvO, for a multi class problem of classifying variables into high, medium, and low, the problem is split into three binary classification datasets as follows:

BCP 1: high vrs (medium, low)
BCP 2: medium vrs (high, low)
BCP 3: low vrs (medium, high)

A training dataset is created for each of the labels, then a classifier model is given to each of the labels which trains the model by application of an algorithm (Mishra *et al.,* 2021). After the model is trained, a test data is provided for the model which predicts the right class. Only the correct label will be assigned a positive score (Mishra *et al.,* 2021; Utami *et al.,* 2021).

2.6.6.3 Bayesian Networks (BN)

Thomas Bayes empirical formula for defining conditional probability (Niedermayer, 2008) is the foundation for BN which are efficiently employed in revealing complicated relationships that exist between variables (Korb, 2004). BN are particularly significant in determining probabilistic relationships and can effectively handle incomplete and insufficient data sets (Tran, 2013; Korb, 2004). BN is capable of combining several sources of information to model causal relationships among data features, communicates and illustrates decision scenarios which are characterised by uncertainty thereby tackling uncertainty problems efficiently and significant in successfully predicting useful outcomes (Uusitalo,2007; Hanninen, 2014). It has been extensively adopted in solving probabilistic problems in different domains. In construction, BNs have been used to: predict and control project cost (Hwang, 2016; Leu *et al.,* 2015); analyse building safety controls and accidents (Nguyen *et al.*, 2016; Jitwasinkul *et al.,* 2016); and analyse risk in construction projects (Zhang *et al.,* 2014; Zhang *et al.,* 2016). For an accident to occur, several factors come together to influence it. Consequently, traditional statistical methods such as analysis of variance (ANOVA), factor analysis and multiple regression (Aksorn *et al.,* 2008; Cheng *et al.,* 2010) have been employed to investigate the relationship between the variables and the outcome. However, this conventional method overlooks the interdependencies of the causal factors while exploring their relationships (Leu and Chang, 2013). Its limitation is conspicuous in determining complicated cause-effect interdependencies which is a characteristic of a prediction model for safety risk in construction (Zhang, 2014). Although structural equation models (SEM) have been adopted in determining linear cause-effect relationships between variables, SEMs perform abysmally when applied to non-linear relationships (Siu *et al.,* 2004). In contrast, BNs, handle non-linear relationship modelling better as it constructs joint probability distributions which can determine the value of child nodes based on each fluctuation of the parent node (Korb, 2004). Specifically in the domain of safety risk prediction, Nguyen *et al.* (2016) used BNs to predict the safety risk involved in working at height and Deublein *et al.,* (2015) used BNs to predict accidents on Swiss highways.

2.6.6.4 Deep neural network (DNN)

A DNN is a type of artificial neural network trained to function like the human brain by mapping and input vector to an output vector (LeCun *et al.,* 2015, Schmidhuber, 2015). For instance, a DNN model trained to identify the features of a particular gender (say a female), will study the attributes associated with being female and estimate the probability that a given classification task, will produce a female based on the given features (Schmidhuber, 2015). Results can be reviewed to choose which likelihoods the network should present and produce the proposed class. neurons, weights, synapses, functions and biases make up the components of a DNN (Tanaka *et al.,* 2020). The multiple number of layers, nodes and the depth of a DNN is what makes it complex and termed as “deep” (Aggarwal, 2018). DNN has been successfully applied in: intelligent transportation systems (Wang *et al.,* 2018); segmentation of images (Dou *et al.,* 2016); facial recognition (Sun *et al.,* 2014); and in the classification of images (Krizhevsky *et al.,* 2012). In the field of risk prediction, deep neural networks have been used to: forecast risk with electronic health records (Cheng *et al.,* 2016); predict the risk of breast cancer (Yala *et al.,* 2019); and in the prediction of accidents (Cheng *et al.,* 2012; Ren *et al.,* 2018; Moosavi *et al.,* 2019).

For tasks with complex non-linear relationships, DNNs are effective at modelling such relationships. The DNN architecture produces hierarchical models which presents objects as layered structure of standard data types (Szegedy *et al.,* 2013). The composition of characteristics from the basic layers is supported by the extra layers, which models complex data with less components as compared to a shallow network with similar performance. Rolnick and Tegmark (2017) demonstrated the power of DNN in easily calculating multivariate polynomials as compared to a shallow network. DNN are usually feedforward networks although they can be trained to test for errors from the output node to the input node through a back propagation method (Lee *et al.,* 2019). The data flow begins from an input layer where a map of virtual neurons created by the DNN allocates random weights to the links between them. The input is then multiplied by the weight and generates a result between 0 and 1. The weights are adjusted by an algorithm in the case where a specific pattern is not recognised accurately by the network (Talaat, 2022). Hence, the algorithm has the flexibility to increase or decrease the influence of certain parameters (hyperparameters) until it figures out the ideal mathematical tuning which can accommodate the processing of the data fully (Kumar *et al.,* 2021). This is process is also known as hyper parameter tuning (Wang *et al.,* 2017).

The factors below contribute to the performance of a well-trained DNN model and determines the success thereof:

- ***Architecture***: the denser the layers of a DNN, the better it is at capturing invariant characteristics of data in contrast to a shallow NN (Rolnick and Tegmark, 2017). It generates a compositional model which allows primitive data types to be presented as layered objects (Hu *et al.,* 2020). The architecture of a NN comprises of neurons which possesses its own weight, activation function and bias. It has an input layer which does not perform any computations on the data but takes it in its raw form and passes it on to the hidden layer which provides a form of abstraction to the NN and executes the computations on the data provided by the input layer (Zhang *et al.,* 2016). The outcome of the computation is then passed on to the output layer which in turn displays the results obtained from the hidden layer as its final outcome (Hu *et al.,* 2020).
- ***Optimisation algorithm***: this algorithm allows a set of inputs to an objective function to be discovered so a minimum or maximum function evaluation can be presented (Simon, 2013). The classical approach to training NN presents a problem of non-convexity however, optimisation algorithms (ReLu, SGD) have proved to have a positive impact on convexity problems (Ruder, 2016). There are several optimisation algorithms to choose from (such asReLu, SGD), nevertheless, the quantity of information available about the target function being optimised could determine the approach to grouping

optimisation algorithms. Effectively using available information about the target function can make the function easier to optimise (Vidal *et al.,* 2017).

- ***Regularisation techniques:*** overfitting is one of the challenges that confronts the use of NN models (Papernot *et al.,* 2016). This causes the models to perform well on trained data but abysmally on test data (Ying, 2019). Regularisations helps to tackle this problem by changes to the learning algorithm in a way that allows a more acceptable generalisation (Hammerla *et al.,* 2016). It penalises the weight matrices of the node by optimising the regularisation coefficient.

Although DNN has chalked many successes in its several applications, it is confronted with the challenge of its inputs having adversarial perturbation (Papernot *et al.,* 2016). These alteration in the data distribution could cause the variables to become weaker which could then result in minor performance deterioration and eventually lead to the DNN making incorrect predictions with high confidence (Nguyen *et al.,* 2015). Therefore, the use of DNN in safety related model predictions must be critically examined with these adversarial challenges addressed (Mustafa *et al.,* 2019). Several methods for handling adversarial challenges have been used and addressed in literature. Papernot *et al.,* (2016) used distillation as a measure against adversarial perturbation. An ensemble method was also proposed and used to reduce adversarial challenges (Strauss *et al.,* 2017). Mustafa *et al.* (2019) used the restriction of hidden spaces of DNN as an adversarial defence in its study. Denoising autoencoders could also be applied to pre-process the data (Gu and Rigazio, 2015).

DNN could be empirically represented as follows:
Given H hidden layers.
Let $h \in (1 \ldots H)$
Let $V^h = vector\ of\ input\ into\ the\ layer\ h$
$j^h = vector\ of\ output\ from\ the\ layer\ h$
$j^0 = x \ \rightarrow input$
For a standard NN, the feedforward task for its hidden layers $h \in (1 \ldots H)$ and any hidden layer (i) where the weighted matrix is W^h and the bias is b^hcan be expressed as:
$v_i^{(i+1)} = W_i^{(i+1)} j^h + b_i^{(i+1)}$
$j_i^{(i+1)} = f(v_i^{(i+1)})$

Where f is the activation function employed to add non-linearity between the input and output. Example, a tan function represented as $f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$ or a rectified linear unit function most commonly referred to as ReLu function expressed as $f(x) = \max(0, x)$

The problem of training the NN weights is usually expressed as an optimisation problem.
$\min \beta\big(J, \emptyset\,(X, W^{1} \ldots W^{H})\big) + \gamma\theta(W^{1} \ldots W^{H}), \{W^{h}\}_{h=1}^{H}$
where a loss function $\beta(J, \emptyset)$is applied to an input data X and its weights W to estimate the relationship between the real outcome J, and predicted outcome $\emptyset(X, W)$. A hyper parameter $\gamma > 0$ is added which can be tweaked to optimise results and to handle the problem of overfitting, a regularisation function θ is introduced.

2.6.6.5 Predictive modelling (deterministic vs. stochastic modelling)

Generally, modelling is said to be a process that produces a basic representation of a how a real-world system could operate or function (de Dios Ortúzar and Willumsen, 2011). Predictive modelling therefore is a mathematical technique which uses statistical methods to forecast events (Ajiboye *et al.,* 2015). When building a predictive model, a significant factor worth exploring is the ability to incorporate existing data and predict with rational accuracy the possibility of the system being involved in unplanned or foreseen stress (Carrera *et al.,* 1987). Making reasonable meaning from data to explain past observations aid in forecasting future events when insight is derived from the existing data (Hämäläinen, 2006). The evolution of predictive models and its significance in achieving effective results has made its application essential in various industries including the construction industry. In construction research, predictive modelling has been employed to enhance open-pit excavations by modelling the blasting-induced vibrations (Choi and Lee, 2021); Guo *et al.* (2016) used predictive models to forecast safety behaviour in the construction industry and Stančič *et al.,* (2016) sought to enhance highway operation planning by employing archaeological predictive modelling.

Predictive modelling uses mathematical models to define a system by a collection of variables and a collection of equations that determine the relationship existing between the variables and the principal parameters governing them (Aragón *et al.,* 2016). Predictive models could be denoted analytically when several simplifications are required before the equations can be susceptible to solutions (Veltzke and Thöming, 2012) or numerical when the models employ computers in the equation solutions and are more versatile (Errera *et al.,* 2020). Mathematical models employed in predictive modelling could either be deterministic or stochastic (Paulo *et al.,* 2011).

For a given set of inputs, the outcomes produced by deterministic models are uniquely determine by the state of the variable and are consistent irrespective of the number of times the deterministic model is recalculated (Artzrouni, 2005). The characteristic of randomness is not attributed to deterministic models because, its peculiar features are known and for every specific input, there exist only one solution or answer to that specific input (Kirchsteiger, 1999). Deterministic models leave little or no room for errors because it specialises in definitive outcomes. For a given set of parameters and previous conditions, deterministic models will have the same performance with unique solutions (Theis *et al.,* 2005). However, deterministic models can sometimes be unstable, such that a slight disturbance or shift from initial set conditions or parameters could result in a major change in the final solution (Lorenz, 1963). Hence, although unique solutions would be produced, largely different solutions can be obtained if a governing parameter is slightly altered at any point in the domain. A deterministic model can be adopted in instances where outputs can be accurately ascertained where randomness or uncertainty does not exist within a recognised relationship between states and events (Kirchsteiger, 1999). For example, if a recognised condition that running '*x*' miles a day could burn '*y* kg' of body weight, then the value of *y* can always be determined precisely by identifying the value of *x*. When developing a ML deterministic model, the relationship between the target variable and the factors affecting the outputs should be displayed thus, the relationship between the variables must be known and determined.

Stochastic models in contrast however can be intrinsically unpredictable therefore, the unidentified elements are incorporated into the model (Mesbah, 2016). The model produces a pool of outcomes, estimates and solutions in the same way variables can be incorporated into an equation and tweaked iteratively in diverse ways to determine its effect on the final outcome generated (Voskoglou, 2007). The stochastic characteristic of ML algorithms is highly apparent in complex and nonlinear methods applied to resolve classification and regression predictive modelling problems (Zhang *et al.,* 2015). These techniques utilise randomisation in the model building procedure by using randomised training data to construct the model, which results in a different model fitting each time the same algorithm is executed on the same data (Levin *et al.,* 2000).

Although historical data could give insight to past events and produce an understanding to why certain events occurred in the past, it does not precisely guarantee a direction for the future as certain events likely to occur in the future might not have presented itself yet. In safety risk modelling, stochastic predictive modelling (Zhang *et al.,* 2021) presents a mechanism for simulating future events that are likely to arise based on scientific evidence. These mechanisms could be incorporated into risk assessment to address the challenges posed by the limitations of historical data (Li *et al.,* 2016). In the case of risk modelling, adopting deterministic models might not be sufficient in addressing the challenges that arise from modelling risk as deterministic models do not consider the complete scope of possible outcomes, likely to result from event occurrences and does not quantify the probability of each of these outcomes (Zhang *et al.,* 2021). Hence, adopting a deterministic approach could result in underestimating the magnitude of the likely risk.

2.6.7 Model Evaluation

The predictive accuracy and model evaluation for each model is measured to ascertain their generalisability (LeCun *et al.,* 2015). Model evaluation is the practice of employing several evaluation measures to comprehend the performance, strengths and weaknesses of a ML model (Raschka, 2018). With the early stages of research, it is crucial to evaluate a model's effectiveness. Model evaluation also significantly aids in model monitoring by serving as an indicator of how well a model performs when new data is introduced (McAvaney *et al.,* 2001). Although several metrices can be adopted in measuring model performance, the ones discussed in this chapter includes the confusion matrix, accuracy score, AUROC and the classification report.

2.6.7.1 Confusion matrix

A confusion matrix (CM) is a group of actual and predicted outcomes for a classification task carried out in a particular system (Visa *et al.,* 2011). An evaluation is done on the data derived from such a system for an analysis of its performance (Deeks *et al.,* 2005). A matrix known as the confusion square matrix which comprises both true and false (positive and negative) outcomes is built while performing predictive analysis (Lewis and Brown, 2001). The matching outcome for all the cases is calculated individually for each case. Then from the true and false rates, an evaluation can be made for the sensitivity, accuracy, specificity and null error rate (Deeks *et al.,* 2005). The peak signal-to-noise ratio (PSNR) and the mean square error can be used to compute the figure of merit. The layout of Table of a CM allows the performance of an algorithm to be properly visualised. The Table is made up of rows and columns and each row signifies a sample in a target outcome while the column signifies the real outcome or vice versa (Chicco *et al.,* 2021). Table 2.4 depicts the layout of a CM. The four cells that make up the output matrix include, true negative (TN), true positive (TP), false negative (FN) and false positive (FP). If the real value and the target (predicted) value both turn out to be positive, then a TP is obtained, else if the real value is meant to be positive but rather, a negative is predicted, then the outcome is FN (Wang *et al.*, 2022). In the case where a negative value is supposed to be the real value but a positive is predicted then that is known as a FP and, finally, the actual value is correctly predicted as negative, then that is a TN.

Table 2.3 - A 3x3 confusion matrix

		Predicted value		
		A	B	C
Actual value	A	AA	AB	AC
	B	BA	BB	BC
	C	CA	CB	CC

In the 3x3 confusion matrix above, the diagonal AA, BB and CC represents the TP (Wang *et al.*, 2022). When the predicted label matches the true label, it appears on the diagonal of the confusion matrix (Deeks *et al.*, 2005). Off-diagonal elements represent misclassifications made by the classifier. Higher values along the diagonal of the confusion matrix indicate more correct predictions, reflecting the model's accuracy (Chicco *et al.*, 2021).

2.6.7.2 Classification report

The classification report presents a breakdown of the individual class performances based on confusion matrix. This is an essential approach for evaluating a model's classification effect (Krstinić *et al.,* 2020). True positives (TPs), true negatives (TNs), false positives (FPs) and false negatives (FNs) are the four types of classification outcomes in the frequently employed two-class confusion matrix (Xu *et al.,* 2020). Five metrics of accuracy, sensitivity (recall), specificity, precision and f1-score were proposed based on the four outcomes (Yacouby and Axman, 2020). These five metrics were employed in this thesis. The following equations are indicative of the metrices used for performance evaluation in this research (Krstinić *et al.,* 2020) *viz.*:

Precision: measures the number of correctly predicted positive instances.

$$precision = \frac{TP}{TP+FP} \quad (8)$$

Recall: measures the model's ability to predict positive samples. It is the ratio of positive samples that were accurately classified as positive to the entire number of positive instances.

$$recall = \frac{TP}{TP+FN} \quad (9)$$

Specificity: measures the number of actual negative instances correctly predicted as negative.

$$specificity = \frac{TN}{TN+FP} \quad (10)$$

F1-score: The harmonic mean of precision and recall is the F1-score. It offers a balanced evaluation of precision and recall, which is particularly valuable when classes are imbalanced.

$$F1 - score = \frac{2(precision*recall)}{precision+recall} \quad (11)$$

Accuracy score: measures the total accurate predictions (both true positives and true negatives) out of all instances.

$$accuracy = \frac{TP+TN}{TP+TP+FP+FN}$$

2.6.7.3 Accuracy score

The accuracy score is also a performance metric in ML used to evaluate classification models (Ravuri and Vinyals, 2019). A prediction is said to be accurate when the target (predicted) value is the same as the real value. Accuracy score can be referred to as the fraction or percentage of predictions a model correctly forecasts (Sokolova *et al.,* 2006). For a binary classification task accuracy can be expressed as:

$$accuracy = \frac{number\ of\ accurate\ predictions}{total\ number\ of\ predictions} = \frac{TP+TN}{TP+FP+TN+FN} \quad (14)$$

However, the risk level prediction, injury body part prediction and event prediction task of this research are multiclass task therefore, true and false binary definitions are not enough to address this task (Romero-Brufau *et al.,* 2021). The problem must be expressed in a more general form given a_i as the actual value, p_i as the predicted value, *n* as the of samples and the inversion bracket [[…]] which returns a value 1 when the expression inside it is true and 0 if its false.

$$accuracy\ (a_i, p_i) = \frac{1}{n}\sum_1^n [[a_i == p_i]] \quad (15)$$

Computing the total accuracy metric supresses class-level problems which also exist in the multiclass case; therefore, it is imperative to investigate class-level predictions. Interpreting accuracy can be a complex task for individual classes in a multi-class task therefore other metrices such as statistical tests, precision, recall and averaging techniques can be employed to handle the limitations of using accuracy score for a multi-class problem.

2.6.7.4 Area under the receiving operating characteristic (AUROC)

The AUROC is a performance metric that is adopted in model evaluation to empirically evaluate classification models (Bewick *et al.,* 2004). It is also known as a performance metric for 'discrimination' because it exhibits the ability of a model to discriminate between events (positive cases) and non-events (negative cases) (Hossin and Sulaiman, 2015). For example, for a safety risk prediction model, an AUROC can help determine the probability that a randomly selected worker on a particular project has a higher chance of experiencing an incident event than another worker on the same project or another project. Having an AUROC of 0.7 and above indicates the strength of a model's discriminatory ability. This means that 70% of the time, the model will accurately determine the class of an event (Fan *et al.,* 2017). Figure 2.3 is a representation of an AUROC curve.

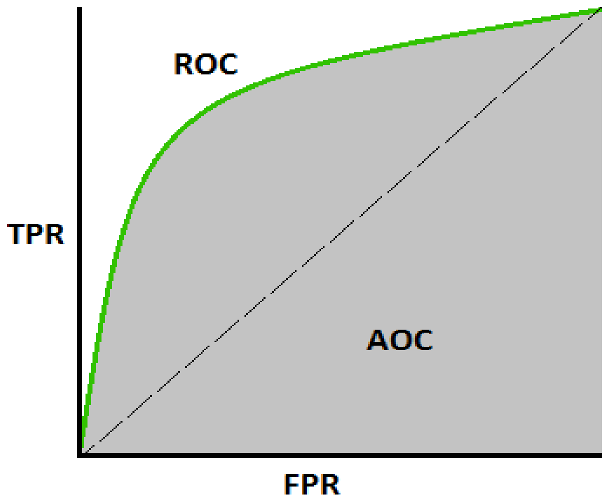


Figure 2.3 - The AUROC curve (Bowers and Zhou, 2019)

The AUROC is estimated to be the area under the ROC curve (Narkhede, 2015). When there are true positive rates (TPR) and false positive rates (FPR), the ROC curve illustrates the trade-off between them across distinct decision levels (thresholds) (Marzban, 2004). The decision threshold for a plotted ROC curve is implicit and are not displayed as an axis. The AUROC is also implied from the graph as the area under the presented ROC curve, but it is not explicitly displayed. The FPR forms the x-axis of the ROC curve and the TPR form the Y-axis of the curve (Narkhede, 2015). The lower left corner of the curve is the starting point (TPR=0, FPR=0) which maps to a decision threshold of 1 where all the cases are classified as negative due to every predicted probability being <1. The ROC curve then terminates at the top right spot (where TPR=1 AND FPR=1) with a 0-decision threshold mapping. In this case, all the instances fall under a positive classification because every predicted probability is > 0 (Marzban, 2004). The FPR and TPR for different decision thresholds which fall between 1 and 0 are computed to find the middle points forming the curve. Less decision thresholds are employed in building rough steep curves as compared to several decision threshold used in creating smooth ROC curves (Bowers and Zhou, 2019).

CHAPTER 3- RESEACH METHODOLOGY (II)- RESEACH DESIGN

3.1 THE RESEARCH DESIGN ADOPTED FOR THIS THESIS

A mixed philosophical paradigm that used both interpretivism (Edwards *et al.,* 1998; Edwards *et al.,* 2017; Roberts *et al.,* 2021; Edwards *et al.,* 2020) and postpositivism (Roberts *et al.,* 2018; Al-Saeed *et al.,* 2020; Spellacy *et al.,* 2020) was adopted for the literature review which focuses on theory and *'conceptual model development'* as this research considers existing theories subjectively while utilising an objectivist epistemological perspective (Annells, 1997). Interpretivism adheres to a post-foundational epistemology with a purpose of interpreting and establishing facts within the context of the subject and experience being researched (Edwards *et al.,* 2017). Postpositivism assumes that an approximation of phenomena under investigation could be objectively made, subject to individual researcher bias (Edwards *et al.,* 2019). This was to answer the research questions: *"what are the most explored theories and models underpinning the safety risk management in the construction industry?"* and *"what are the most significant safety indicators that can be used as input variables to predict incidents and the level of risk associated to the various incidents."* This mixed philosophical approach has been widely used in literature (cf. Roberts *et al.,* 2019; Oshodi *et al.,* 2020; Ghosh *et al.,* 2020) and therefore, its use is justified in the present research setting. This is due to the goal of this research to interpret and understand safety risk models and theories subjectively from diverse sources while also pursuing objectivity through postpositivism to minimise the possible impact of the researchers' bias.

Table 3.1 describes the methods adopted for each research phase based on the methodology used to fulfil the research questions attached to each phase. The entire research is based on a multi-phase mixed method approach whereby, each phase influences the one that follows (Van Lith *et al.,* 2023). The bibliometric analysis phase used a sequential explanatory mixed method (Berman, 2017) whereby a quantitative analysis of academic publications is performed followed thematic and content analysis, using inductive reasoning and interpretivism to qualitatively explain the quantitative data. The ML predictive modelling phase uses both qualitative and quantitative data however, quantitative analysis is performed using descriptive statistical methods such as frequency, mean, median to analyse trends and patterns as well as perform predictions. This approach helps to establish a *'proof of concept model'* (which also includes the system shell architecture viz. hardware and software adopted). The validation phase which is the final phase is a critical component of the development process, which intends to ensure that the model performs accurately and reliably in predicting safety risks. In the context of safety risk prediction, validation serves multiple purposes *viz*: i) it verifies the model's ability to generalize to unseen data; ii) assesses its effectiveness against various conditions; and iii) provides confidence in its practical applicability. Figure 3.1 presents a more detailed overview of the processes involved in each stage of the research design.

Table 3.1 - The multiphase mixed method and types of data sources

2	Research Questions addressed	Data source	Data types	Choice of method
Stage 1-Bibliometric analysis – [*building a conceptual model*].	What are the most explored theories and models underpinning the safety risk management in the construction industry? What are the most significant safety indicators that can be employed in ML for safety risk incident prediction	Secondary data (Scopus)	Qualitative and Quantitative	Explanatory sequential mixed method
Stage 2 - ML predictive modelling – [*developing a proof-of-concept model*].	Can ML and deep learning models be successfully adopted in predicting health and safety risk? What ML and deep learning models can be applied effectively in safety risk prediction What are the significant parameters, accuracy, and precision level of the prototype model?	Secondary data (National highways incident database)	Quantitative	Quantitative
Stage 3 – Validation – [*testing the final model's validity*].	How well does the model perform in predicting safety risks	Secondary data (National Highways incident database)	Quantitative	Quantitative a

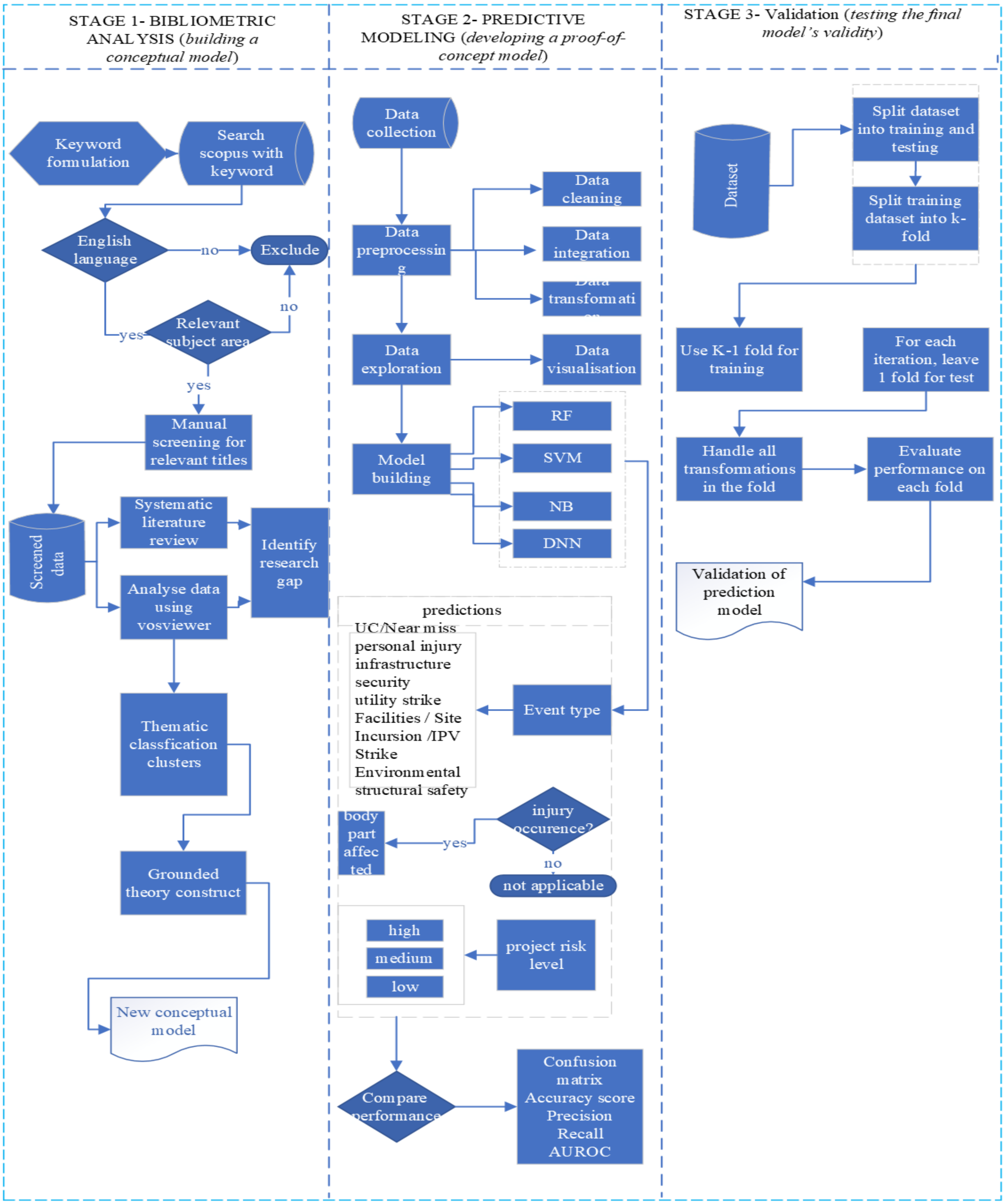


Figure 3.1 - The three-stage research design adopted.

3.2 Stage One - bibliometric analysis of safety risk theories and models to build a new conceptual model.

A bibliometric analysis is conducted to determine pertinent theories, past research undertaken and relevant discourse so that a conceptual model for the prediction of health and safety risk could be determined. Using extant literature to build new theory is a basic premise upon which all research is built (Rowlands, 2005; Solinger *et al.,* 2023; Siregar, 2023). Positioning within a general context of risk modelling in the highway industry, predictive modelling helps to forecast future events and provides the advantage of early decision making that could avert any impending misfortunes before they happen (Shen *et al.,* 2020; Chen *et al.,* 2018). Risk modelling also provides safety leaders, the ability to learn from past mistakes and positive safety performances through the use of past data for predictive modelling (Bortey *et al.,* 2022; Tian *et al.,* 2021). Such lessons equip safety practitioners with practical knowledge they can employ in effective decision-making when designing future safety procedures and improving existing safety systems to increase safety performance (Mohammadi *et al.,* 2018).

An interpretivist paradigm was adopted (Edwards *et al.,* 1998; Edwards *et al.,* 2017; Roberts *et al.,* 2021) couched within an inductive reasoning approach (Edwards *et al.,* 2017) which adopts mixed methods of systematic review of relevant literature. The literature is analysed qualitatively and visually represented using VOSviewer, a quantitative bibliographic software. To identify gaps within a body of knowledge, employing a mixed method systematic review is one of the most effective ways (Oraee *et al.,* 2017). In contrast to mono-method systematic review, mixed method systematic review employs multiple steps in developing protocols that effectively identify gaps in knowledge. In this thesis, bibliometric analysis uses qualitative data mainly sourced from: i) titles; ii) abstracts; and iii) keywords. With VOSviewer, the network mapping consisting of nodes which represents an item of interest in the analysis. These nodes are linked to show the relationship that exists between them and other nodes and could be measured in terms of weight and strength (Newman *et al.,* 2020). The greater the word frequency, the larger the node becomes (Van Eck *et al.,* 2019), and the stronger the connection of nodes, the thicker the line (link) between them (Chamberlain *et al.,* 2019). The number of publications in which a keyword appears is also known as occurrence in VOSviewer and contributes to the weight of the node of item. The presence of a weak link between two keywords (or the total absence of it) could be interpreted as this relationship being under explored. Different colours are assigned to nodes/clusters within a visualisation, to distinguish it from other nodes/clusters. The distance between nodes/clusters gives a better indication of the strength of relationship between these items when compared to graph-based maps (Waltman *et al.,* 2010). VOSviewer was adopted for this thesis due to its ability to display large quantities of data in an easy-to-interpret format (Waltman *et al.,* 2010). Such a visual interpretation of the relevant literature can allow for the identification of emergent common themes and relationships between the themes' elements.

The bibliometric review process consisted of a three-phase process (refer to Figure 3.2). **Phase one** focuses on a detailed review of existing safety risk theories and models that exist and have been applied in various fields ranging from: aviation (Mohaghegh-Ahmadabadi); maritime (Awal, and Hasegawa, 2017); and shipbuilding (Tsoukalas and Fragiadakis, 2016) and how they can be adopted in the construction and highways industries, particularly tailored for HTOs and inspectors. A rich synthesis is therefore undertaken on the strengths and weaknesses of these models and theories. The literature review identifies safety indicators (both leading and lagging) which are adopted as input variables in the risk modelling process (cf. Bayramova *et al.,* 2023a; 2023eb). These safety indicators justify the reason such variables were selected as input data for the model built. The second part of this stage which consist of qualitative research using bibliometric analysis is conducted in three phases. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was used in the search strategy to obtain bibliometric data on the diverse application of risk models and theories to systematically review extant literature and combine all relevant knowledge in this subject area (Grant and Booth, 2009); where each article constituted secondary data and a unit of analysis. The Scopus journal database was implemented utilising keywords such as "*occupational and health or safety risk and accident theories or models.*" Only relevant subject areas and papers written in English were considered for this thesis.

In **phase two**, a bibliometric analysis of bibliometric data extracted from Scopus was performed using VOSviewer software. A network map of keyword co-occurrence (Chabowski *et al.,* 2013) and hierarchical cluster analysis were used to analyse the pertinent keywords and data clusters which represented major themes in the literature (Samiee and Chabowski ,2012). Suitable themes were found for the clusters based on the concept of the items each cluster presented. Based on the themes discovered interpretivism and inductive reasoning were used to ascertain which factors and preconditions needed to be considered when selecting safety indicators as input variables for a ML risk model. The biblioshinny function of the bibliometrix software (cf. Aria *et al.,* 2017) was also used to perform document analysis to determine the outcomes of applying safety indicators in risk modelling. The most cited and relevant documents were analysed using thematic maps created by the bibliometrix software as well as the most influential journals in the field. A comparative review of industry-based safety indicators applied in the document reviewed was performed to ascertain the most relevant input variables and ML models adopted in risk modelling. A variety of suitable input variables that could be employed in ML risk model building for highways industry were found which were justified by safety indicators presented in the literature (Zhang *et al.,* 2019; Grabowski *et al.,* 2007)

In **phase three**, grounded theory analysis (cf. Roberts *et al.*, 2019; Bayramova *et al.*, 2021; Oshodi *et al.*, 2020) afforded greater synthesis of the literature and provided an avenue to develop a novel conceptual framework which addresses the challenges presented in this thesis

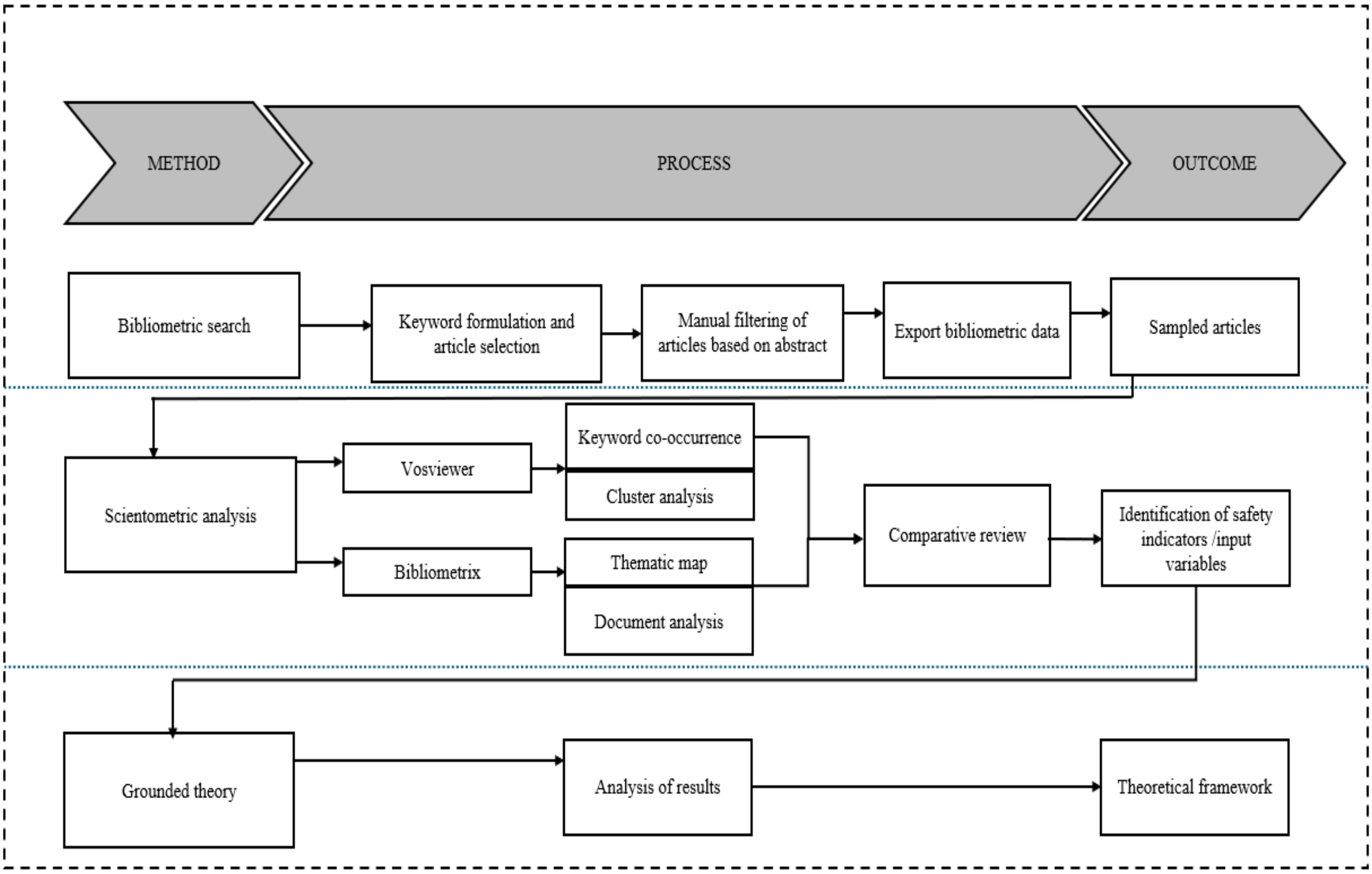


Figure 3.2 - The methodological process

3.2.1 Conceptualisation of safety indicator- based input variables

An interpretivist and pragmatic mixed philosophical stance were adopted to build the theoretical framework proposed (Edwards *et al.*, 2017; Roberts *et al.*, 2021; Posillico *et al.*, 2022). Within this overarching epistemology, an iterative three-phase ‘waterfall’ process was adopted to critically analyse academic discourse within pertinent literature to provide a solid basis for knowledge advancement – refer to Figure 3.3 (Edwards *et al.*, 2020). First, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), secondary data was sampled from existing literature on SI and ML research premised upon an interpretivist approach (Roberts *et al.*, 2019). Second, inductive reasoning was employed to obtain common themes, relationships and ideas from bibliographic maps which were created with the secondary data sampled through scientometric analysis (Van der Meij *et al.*, 2021; Posillico, 2023). Third, grounded theory afforded greater synthesis of the literature and provided an avenue to develop a novel conceptual framework which addresses the challenges presented in this thesis. A plethora of literature (cf. Roberts *et al.*, 2019; Bayramova *et al.*, 2021; Oshodi *et al.*, 2020) have adopted the mixed philosophical paradigm in research to provide a foundation for generating new knowledge hence, its use is justified in the present research setting. This is because this research seeks to understand and interpret literature on SI adoption for ML risk modelling subjectively from multiple perspectives while also pursuing objectivity through pragmatism to minimise researcher bias. Inductive reasoning couched within a thematic analysis setting was employed to answer the research questions: i) what factors should be considered when selecting SI? and ii) what SI data is significant to build ML prediction models?

Bibliometric search

Using PRISMA, the literature search was conducted (refer to Figure 3.3). Articles selected were published between 2005 and 2023 to ensure that the latest and most impactful literature was included. Literature review papers were retrieved from the Scopus database which covers almost all journals and publications when compared to alternative digital repositories (Aghaei Chadegani *et al.*, 2013; Chamberlain *et al.*, 2019; Nazir *et al.*, 2020). To search for journal articles, keywords included in the search were obtained from the study’s title using search rule: ‘TITLE-ABS-KEY (safety AND indicators AND risk AND prediction AND model). The terms leading, lagging, ML and resilience were omitted from the search to ensure that if the terms emerge in the keyword analysis, their presence is not solely attributable to their inclusion in the search criteria. Rather, it is anticipated that these terms hold intrinsic significance, warranting independent consideration for analysis purposes. A total number of 1,765 articles were sampled from this initial search. The search was then refined to exclude irrelevant subject areas such earth science, veterinary medicine and material science. Only articles from relevant disciplinary domains such as engineering, computer science, mathematics, construction and environmental science were included in the subsequent analysis. Consequently, 701 papers were extracted from the database and manually screened by reading their abstracts to remove superfluous articles which provided little or negligible contribution to the knowledge gained or duplicates. This led to a final dataset of 516 papers obtained for analysis.

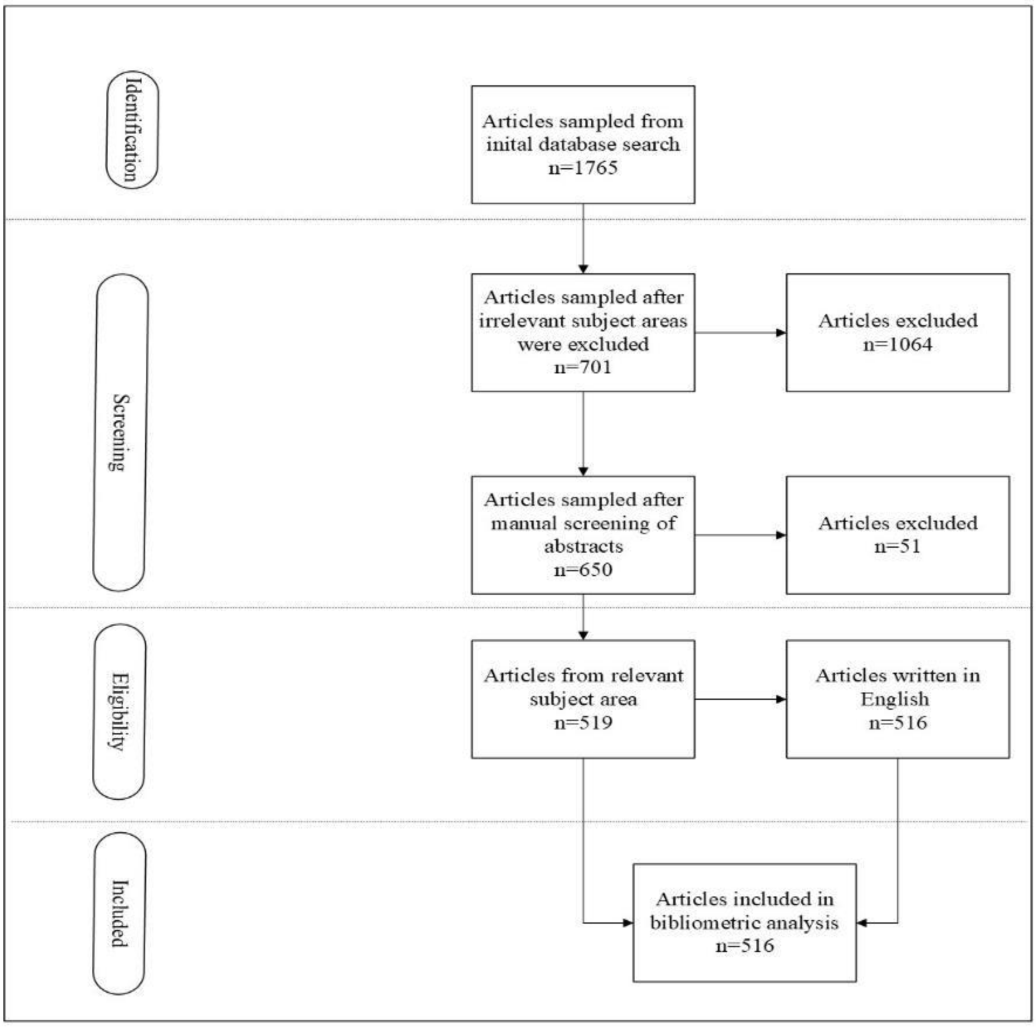


Figure 3.3 – The PRISMA diagram for bibliometric search

Scientometric analysis technique

Scientometric analysis was performed using VOSviewer (Newman, 2020), software and the "Biblioshiny" function in the "bibliometrix" package (Aria *et al.*, 2017). VOSviewer bibliometric analysis measures the impact of research and is widely utilised in several academic fields (Cobo *et al.*, 2011; Bayramova *et al.*, 2021; Posillico *et al.*, 2022). A network map of keyword co-occurrence (Chabowski *et al.,* 2013) and hierarchical cluster analysis were used to analyse the pertinent keywords and data clusters which represented major themes in the literature (Samiee and Chabowski, 2012). Suitable themes were found for the clusters based on the concept of the items within each cluster presented. Based on the initial findings, interpretivism and inductive reasoning were used to ascertain what these themes meant and establish their contributions to theory building.

Biblioshinny is the web interface version of the bibliometric software and is useful for comprehensive science mapping analysis (Aria *et al.*, 2017). The most cited and relevant articles and the most influential journals in the field were analysed using thematic maps created by the bibliometrix software. The thematic map categorises the keywords into research themes based on their development and impact (Derviş, 2019). The four thematic map categories are: i) *niche themes* that have a relatively narrow focus; ii) *basic themes* which are well established and extensively studied; iii) *emerging* or *declining themes* which represent the relatively new or fast developing (or declining) themes within the research area; and iv) *motor themes* which represent the influential or innovative themes shaping the direction of contemporary research in the field (Radha and Arumugam, 2021).

Based on the document analysis findings, a manual review of relevant journals was performed to derive factors that required consideration when combining leading and lagging indicators to form resilient indicators. Also, a comparative review of industry-based SI applied in the document reviewed was performed to ascertain the most relevant input variables and ML models adopted in risk modelling across various industries. A variety of suitable input variables that could be employed in ML risk model building for highways industry were found which were justified by SI presented in the literature (Zhang *et al.*, 2019; Grabowski *et al.*, 2007).

Grounded theory

Grounded theory is a well-known research technique in safety management, with applications such as: analysis of occupational H&S management modes in supply chain (Zhou *et al.*, 2023);

analysis of factors affecting unsafe behaviours in Iranian workers (Malakoutikhah *et al.*, 2021); and the development of maturity model for construction safety culture (Olugboyega and Windapo, 2019). Post cluster analysis (performed during the scientometric stage), axial coding was implemented to establish correlations between the various themes developed in the cluster analysis (Vollstedt and Rezat, 2019). A saturation test was then performed to ensure the validity and comprehensiveness of the conceptual framework development (Olugboyega and Windapo, 2019). A conceptual framework is logically saturated if the ideas or categories formed utilising the obtained data are assimilated into existing concepts or categories and no novel themes or categories develop (Vollstedt and Rezat, 2019).

3.3 Stage Two – Building a highway safety prediction 'proof of concept' model (HSPM)

The second stage of this thesis adopts a positivist philosophical stance and deductive reasoning as an overarching epistemological stance to build a new proof of concept model for predicting health and safety risk in the highways industry. The proof-of-concept model combines variables sourced from literature with data sourced from National Highways and then builds model architecture (hardware and software) to predict health and safety risk on the highway. Within contemporary construction management literature, such an approach has been extensively used to, for example: build ML predictive model based on national data for fatal accidents of construction workers (Choi *et al.,* 2020); estimate the challenges of smart city development in developing countries (Aghimien *et al.,* 2020); and measure hand-arm vibration exposure risk in the UK utilities sector (Edwards *et al.,* 2020). The fundamental body of research serves to substantiates the suitability of the current study. This section of the research focuses on the predictive modelling of accident risks using ML algorithms which inculcates data from past incidents and events using incident reports gathered in the highways accident report database. The data consist of variables representing safety indicators identified during the literature review stage, which are combined and input into ML and DL algorithms to enable prediction of risk levels beforehand, for better decision-making when a highway task or operation is going to be executed. This thesis employs ML models and DL models to classify risk level of an intended task into three classes, i.e., high risk, medium risk and low risk. Despite the availability of highways H&S event data sourced from National Highways and literature, the data is voluminous, diverse and imbalanced with notable missing values. Hence, analysing and identifying significant patterns will be challenging to the human eye, and less efficient with traditional qualitative techniques. Therefore, three different ML techniques (SVM, RF and BN) will be employed in conjunction with deep neural network (DNN) to make predictions (refer immediately below).

From a research approach perspective, an iterative three-phase process was adopted. *Phase one* describes the data collection and preparation stages. It focuses on data description, methods used to process the data (handling missing values, label encoding, feature extraction etc. before performing an initial data exploration. *Phase two* develops a novel proof of concept model to predict i) the level of risk involved in a project (low, medium, high), ii) the type of incident event possible to arise from a project going to be undertaken, and iii) if an injury occurred, the body part likely to be affected if an accident occurred. *Phase three* compares the performance of the models used in this thesis and selects the model with the best performance based on the accuracy score, confusion matrix, classification report and the AUROC as a means of validating the final model selected for application in practice. This process serves as a validation of the final model produced within the system shell created. It will also serve to identify how the model (and its predictive power) could be improved in future research.

3.3.1 The data

In the general construction industry, the operations or tasks attributed to the most dominant safety risks and hazards include working at height, movement of plants, vehicles and excavations (Hinze and Teizer, 2011). However, although the highway industry is involved in certain construction tasks, the HTO perform certain tasks and operations which are only peculiar to the highways industry. Such tasks include, highways maintenance, winter maintenance, highways Act enforcement as well as minor highways and environmental improvements (HSE, 2014). These tasks are prone to certain peculiar risks such as impact protection vehicle (IPV) incursion risks and security risks when highway officers conduct highway act enforcements on drivers etc. (Fowler *et al.,* 2011). Furthermore, the work force for the highway industry is dynamic, with complex supervision relationships as the workforce comprises of contractors, sub-contractors and employees (Mohan and Zech, 2005). Therefore, when building prediction models for highway industry workers, although variables attributed to construction health and safety risks are significant, the prediction models will require additional characteristics when it comes to the highway industry.

The Reporting of Injuries, Diseases and Dangerous Occurrences Regulations (RIDDOR) is a UK legislative framework that mandates the reporting of workplace injuries, diseases, and hazardous occurrences (Wheeler, 2024). It provides a structured approach for documenting incidents that could pose risks to workers, including HTOs. National Highways, as the governing body responsible for HTO safety, adheres to RIDDOR requirements by systematically recording incidents that result in injuries or pose significant risks.

The data used in this study is largely influenced by RIDDOR-compliant reporting mechanisms. These reports form the foundation for identifying patterns in workplace hazards, injuries, and risk factors. The thesis applies ML techniques to predict the likelihood of various safety-related occurrences, moving from a reactive reporting approach to a proactive risk prevention strategy. Variables attributed to health and safety risk modelling include, weather, work pressure, project location, vehicle involvement in project and human error (Törner and Pousette, 2009). Other significant variables that have been employed include experience of worker, employment type and location of the project (Zhang *et al.,* 2014; Zhang *et al.,* 2016). Certain variables like the sex, age, experience, time and day could be used to ascertain and explore the demography of workers or the distribution of work accidents (Cheng *et al.,* 2012).

3.3.2 The data profile.

The dataset used in this research are historical past data of highway incident reports recorded and stored on HART database which is dedicated to incident and accident reporting. The data comprises of 23 features signifying the characteristics and nature of incidents that have occurred on past highway projects. 20 of these features are independent variables while three of these are the target variables.

72,811 incident cases reported between 2017 and 2022 were selected from the database with nine different classes of various incidents (event types), three classes of project risk level (high, medium, low) and ten classes of part of body affected, which are the target variables already classified by National Highways. The various event types include, personal illness/injury, undesirable circumstance/near miss, security, environmental, infrastructure, facilities/site, structural safety, utility strike and incursion/IPV strike. The class distribution for the target variables is noted to be imbalanced which can result in biased classifications if not handled. Table 3.2 shows the variables used in building the prediction model in this thesis and indicates the independent and dependent variables respectively.

Table 3.2 - Description of variables used in modelling.

Independent Variable	Data Type	Meaning	References
PublishedRecordId	Int	ID number for data point	Törner and Pousette, (2009)
Region	Categorical	The region where project is based	Zhang *et al.,(*2014)
Site/Project'	Categorical	The site where project is based	Hinze and Teizer, (2011)
Date and Time of Event	Datetime	The date and time incident occurred	Esmaeili *et al.,* (2015)
vehicles involved?	Categorical	Are there vehicles involved in the project (yes/no)	Chang and Chen (2005),
Type of Person	Categorical	The status of the individual's employment or visit (employee, contractor, member of public, customer)	Cheng *et al.,* (2012)
Location	Categorical	The location of the project site	Tixier *et al.,* (2016)
Did this event occur on the SRN (strategic road network)?	Categorical	Is incident a strategic road network related? (Yes/No)	Namian *et al.,* (2016) Poh *et al.*, (2018)
Experience in Current Role	Integer	The number of years worker has been working in that position	Kashani and Mohaymany (2011)
Age Range	Integer	The age of the worker	Ajayi *et al.,* (2021)
Weather / Visibility	Categorical	The visibility at time of incident (rainy, stormy, clear, windy)	Sadeghi *et al.,* (2015)
Potential Severity Rating	Integer	What the possible impact of incident could be (1-25)	Zhang *et al.,* (2019)
Actual Severity Rating	Integer	What the actual impact was (1-25)	Tixier *et al.,* (2016)
Month	Integer	The month of incident	Rivas *et al.,* (2011)
Season	Categorical	The season of the incident (winter, summer, spring, and autumn)	Mistikoglu *et al.,* (2015)
Type_of_work	Categorical	The type of work being undertaken (traffic management, highway operation, not applicable)	Zhang *et al.,* (2016)
Year	Categorical	Year of incident	Moh *et al.,* (2018)

Day_of_week	Categorical	The day of the week incident happened (Monday-Sunday)	Oyedele *et al.,* (2021)
Time_of_day	Categorical	The time of the day (morning, afternoon, evening, and night)	Zhang *et al.,* (2016)
‘Injury occurrence	Categorical	The likelihood of an injury occurring (True/ False)	Ajayi *et al.,* (2021)
‘Injury Type’	Categorical	The types of injury that could occur (cut/laceration/ sprain/strain, bruising, amputation. Musculoskeletal, abrasion)	Tixier *et al.,* (2016)
Dependent variables			
Project risk level’	Categorical	The likely severity of project risk (high, medium, low)	Rivas *et al.,* (2011)
Event Type’	Categorical	The kind of incident likely to occur (Personal illness/injury, undesirable circumstance, security, environment, infrastructure)	Tixier *et al.,* (2016)
‘Part of Body Affected’,	Categorical	The part of the body likely to be affected (head, hand, waist, leg etc)	Ajayi *et al.,* (2021)

3.3.3 Data pre-processing

Figure 3.4 depicts the process for the data-pre-processing stage. The dataset which was selected from the HART system which is the incident database for National Highways is made up of 72,811 data entries collected from 2017 to 2022. The data comprises of thirty features signifying the characteristics and nature of incidents that have occurred on past highway projects. These features were chosen based on safety indictor literature which presented various variables adopted for building ML risk prediction models (Törner and Pousette, 2009; Zhang *et al.,* 2014; Zhang *et al.,* 2016). Data preprocessing and manipulation was done using Jupyter notebooks, a web-based Interactive development environment which presents an interface for coding and configuring workflows. Python libraries and functions were employed in exploring the data. First, the Python library Pandas was used to upload the data from the cloud storage into Jupyter notebooks to allow other libraries access the data for its operations. As a means of processing the data, data cleaning techniques (Xu *et al.,* 2016) were used to identify and amend errors presented in the data.

The first task was managing missing data. Columns which had less than 50% of data required in it were dropped from the dataset. Missing data from rows were filled in with data using information from the rows they have similar and corresponding features with. Rows which did not have 50% or more of the data present and had no corresponding row with similar features were dropped completely. Certain features such as ‘age’ and ‘experience’ which has missing data were simulated by giving them random number to ascertain the effects of these feature on the model Outliers in the data were identified by employing histogram and boxplots as well as mean/mode attributions which allows the use of binning techniques and transformations in removing outliers. Other features which would be pertinent in deriving insights from data exploration were extracted based on existing features. For example, the variables, ‘day of week’ and ‘month’ of incident were extracted from the variable, ‘time of event.’ These derived variables will help explain what has happened in the past and what is happening now as a means of performing descriptive analytics through data exploration.

For a prediction model to attain an elevated level of performance, the data inputs are incredibly significant (Xu *et al.,* 2016). The input of the dataset employed in this research possess several features, all of which might not be relevant in the model development, hence might retard the efficiency of the prediction model. Therefore, a subset of the features considered to be most significant were adopted as inputs for the prediction model. This was done using a feature selection method known as recursive feature elimination (RFE) as well as a univariant statistic (US) (correlation and chi-squared) method (Xu *et al.,* 2016). This approach will allow the ML models to have a better prediction accuracy. The final dataset after the cleaning task was made up of 62,912 data entries which was made up of twenty-five attributes with twenty independent attributes and three dependent/target outcomes (project risk level, event type, body part affected). The 'project risk level' independent variable prioritises risk of individuals interacting with hazards present in a project (high, medium, and low), the 'event type' is also a multiple variable outcome which tells of incidents likely to occur because of a task being undertaken. The 'actual risk severity' column which ranges from 1-25, is used to compute and classify the project risk level into high (19-25), medium (10-18) and low (1-9). The 'injury occurrence' target outcome is a binary variable with true if the 'event type' is a personal illness or injury and false if no injury occurred. The type of injury presents what kinds of possible injuries such as cuts/lacerations, sprain etc. may occur and the 'body part affect' presents various parts of the body that might be exposed to risks during the project that must be prioritised for protection. The categorical variables are then transformed to numerical variables using the label encoding, an encoding technique for handling categorical variables (Lazzeri *et al.,* 2015)

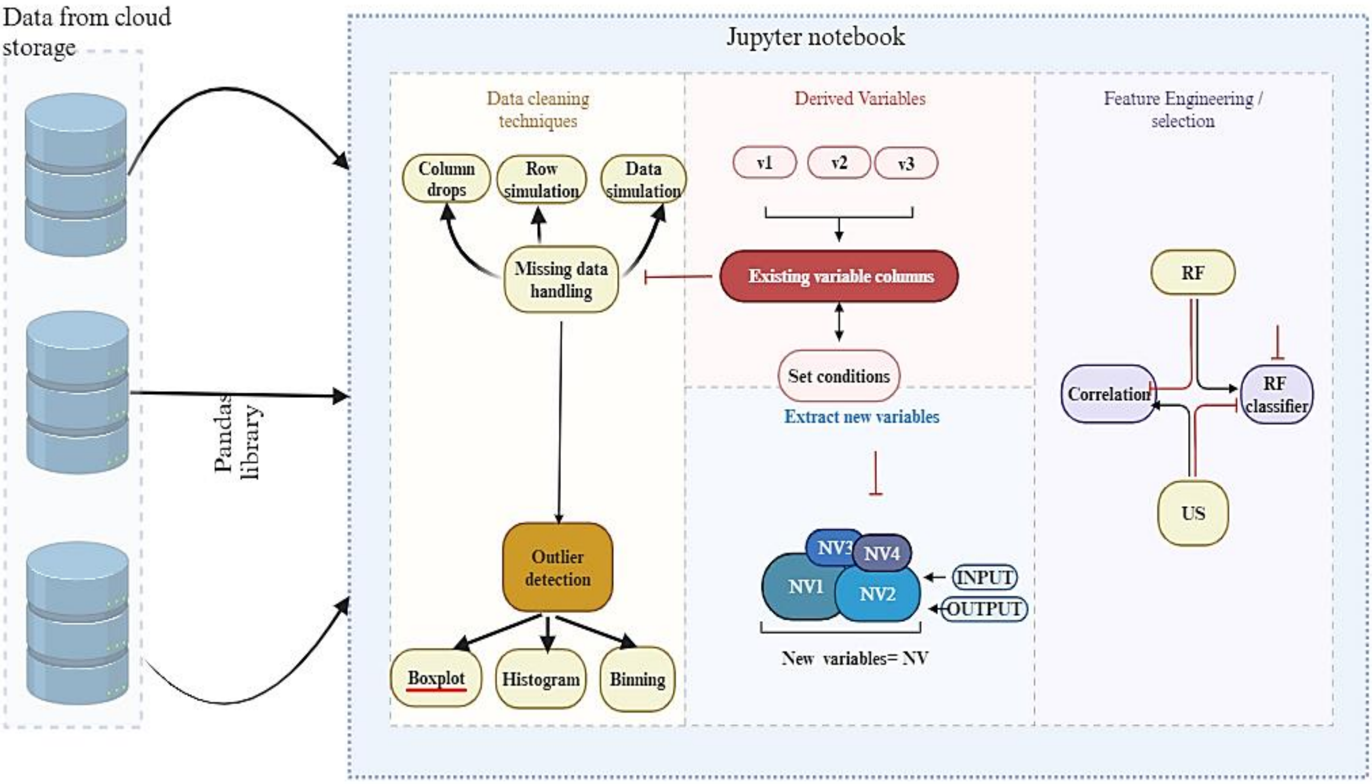


Figure 3.4 - The data pre-processing process

3.3.4 Feature importance and selection

The term 'feature importance' refers to strategies that assess and allocate a score to input variables by considering their predictive power against a target variable (Sattar *et al.*, 2023). Although there are numerous various kinds and sources of feature importance scores, often used examples include permutation importance scores, decision trees, statistical correlation scores and coefficients computed within the framework of linear models (Parr *et al.*, 2024). In the development of predictive models, feature importance scores are crucial due to their ability to present an empirical understanding of the data and the model (Molnar *et al.*, 2023). Feature importance ratings also serve as the foundation for feature selection and dimensionality reduction, which can increase a predictive model's effectiveness and efficiency in solving the problem (Parr *et al.*, 2024).

Reduction in the criterion used to choose split points such Gini or entropy provides the basis for the feature importance scores presented by decision tree algorithms (Rahmati *et al.*, 2022). The random forest, stochastic gradient boosting techniques and the classification and regression trees (CART) are some examples of decision tree ensembles that can be used to compute feature importance score (Zhou *et al.*, 2020; Saarela *et al.*, 2021).

The RF classifier was used to determine the relevance of each attribute in the predictive model. In a study to predict types of occupational accidents at construction sites, Kang and Ryu (2019) used RF method to determine the most important features that contribute to the prediction. In a similar study to assess accident prediction accuracy for highway-rail grade crossings Zhou *et al.* (2020) proposed the use of the RF method for feature importance evaluation. These studies justify the use of RF method in the current setting.

RF has an embedded feature importance score and could be adopted for classification and regression tasks (Li *et al.,* 2019). The Gini Importance (GI) is the specific feature importance indictor that is utilised in this thesis. When splitting the data at a feature's values within the decision trees of a RF, GI quantifies how much each feature contributes to the decline in impurity (i.e. the degree of disorder in a dataset) or the rise in purity (i.e. the degree of certainty in a dataset) (Nembrini *et al.,* 2022). The value of the GI sums up to one - the higher the value of the GI, the greater its significance at the node.

3.3.6 Dimensionality reduction (Chi-square test)

To identify the most significant variables relevant in classifying the body part likely to be affected, one commonly used method for feature selection is the Chi-Square test (Bahassine *et al.*, 2020). The Chi-square test is a statistical test that measures the independence between two categorical variables (Sikri *et al.*, 2023). A test of association was conducted between the categorical independent variables and the target variable. A contingency table which shows the frequency of observations for each combination of independent and target variable was computed. To visualise the results of the chi-square test, a heatmap was created by sorting the chi-square statistic in descending order to visualise the variables with the highest chi-square values first.

3.3.7 Architecture of Proposed Highway Safety Risk Prediction Model (HSPM)

The proposed architecture for the HSPM is based on the idea of a layered architecture (cf. Westfechtel *et al.,* 2001; Savolainen and Myllarniemi, 2009; Richards, 2015). A layered architecture organises components and parts of a system which possess similar functionalities into horizontal layers (Westfechtel *et al.,* 2001). Therefore, individual layers within the system have particular roles they perform within the application and aim to promote the idea of partitioning points of concerns. Partitioning points of concern allows easy updates to the system and promotes unproblematic division of workload among teams (Marmsoler *et al.,* 2015). The view of a layered architecture provides an abstraction of a complete system as it stipulates in detail, the characteristics, features and responsibilities of each layer and how they interact with each other (Benito *et al.,* 2014). The layers of the HSPM architecture include: i) the application layer; ii) functional and analytics model layer; iii) the data access layer; and iv) data storage layer (database sources) which are represented in Figure 3.5 and discussed in subsequent subsections.

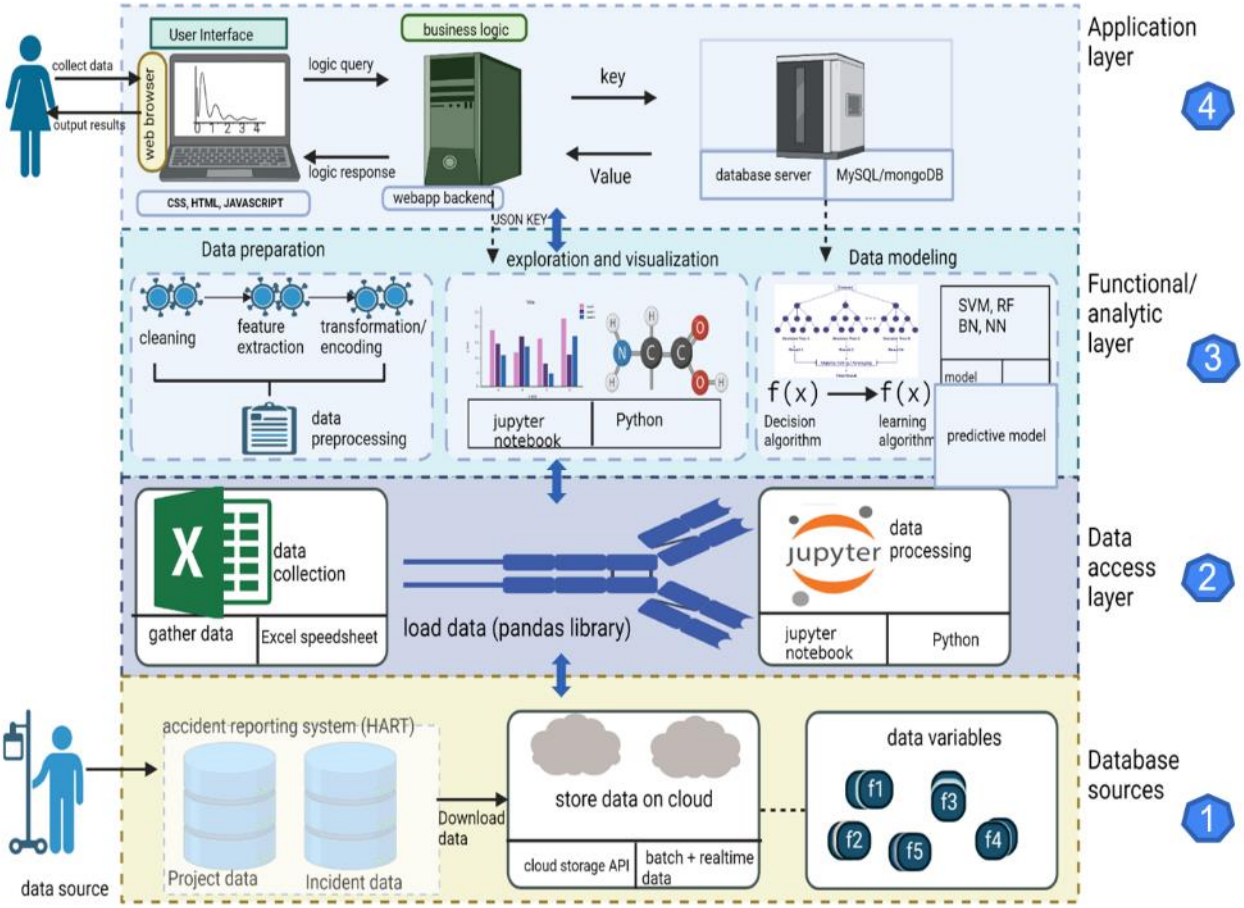


Figure 3.5 - Proposed HSPM architecture

Database Sources (The Data Storage Layer)

This layer represents the sources of data (project data and incident data) which are required to effectively build and run the HSPM and perform exploratory analysis for creating descriptive analytical models for organisational purposes (Avci *et al.,* 2020). The data consist of information such as project region, project type, project location and the exact project or site.

The incident data also contain historical information about any event that occurred that either resulted in an accident or could have resulted in an undesired event. These include, event type, injury type, potential and actual severity of event, the part of body affected etc. The diverse nature of data stored in this layer has been presented in a graphical interface on the HART system for easy accessibility.

The Data Access Layer

This layer presents an opportunity for computer programs to have simplified access to data stored in an obstinate database such as an entity-relational database (Merzky *et al.,* 2015). The data access layer can return rows of field from a database table or a reference to an object furnished with its features when dealing with object-oriented programming (Russel, 2008). This allows a detailed presentation of components to be created. This kind of abstraction seeks to mask the complexity of the nature of data storage beneath it. This layer also provides a common data format for exchanges in the entire system data (Peres *et al.,* 2016) through data provisioning and exchange formatting. The application layer which is at the topmost end of the architecture can also have access to the databases through the data provisioning functionality (Stach *et al.,* 2021). This research uses the Pandas library to upload the dataset from an excel spreadsheet on the cloud storage into a data frame well suited for referencing and manipulating the data.

The Functional/Analytic Layer (FAL)

This layer is the programming that controls services responsible for returning data when a query is made. It is also known as the business logic layer (Litvinov, 2020) The FAL provides the presentation layer with access to services which enables the display of data or to query a business process. There is also an additional independent business logic in the application layer which manages the interaction between the end user interface and the databases by transforming messages to name value pairs (JSON) for processing (Hnatkowska and Kasprzyk, 2009). Health and safety data is characterised by its high volume and complexity (Gershon *et al.,* 2005); therefore, it is imperative that it possesses the ability to efficiently analyse and swiftly act when queried.

In this research, this layer consists of one functional model responsible for H&S data pre-processing and three analytical processes, being the exploratory, descriptive and the predictive analytical process all of which make up the HSPM system. For this research, python libraries such as sklearn, matplotlib, numpy and pandas were used to build the analytical and exploratory models in the jupyter notebooks. However as mentioned, H&S model building is highly data-driven, therefore in future models where the data volumes require higher computation capacity, Apache spark engine and pySpark (Ryza *et al.,* 2015) can be configured in the jupyter notebooks to increase its in-memory storage capacity to efficiently handle the high volumes of data and for effective computation.

For data exploration: Exploratory data analysis (EDA) forms a critical part of the ML workflow because it provides insight into the data being worked with. It provides an opportunity to make sense of the data before modelling it (Idreos *et al.,* 2015). EDA allows recognition of patterns that exist within the data, enables an understanding of relationships between data variables and the identification of probable outliers as well as missing values within the data. NumPy and pandas' libraries (McKinney, 2012), provide data structures and analytical tools which enables effortless extract-transform-load (ETL) processes such as data cleansing. Pandas provides useful functions for column and row operations and data transformation. It also provides certain functions that could otherwise been accessed using SQL such as join, merge etc. other libraries such as matplotlib and sklearn provides useful functions for visualisations. Being able to visualise H&S data helps to tell a better story and improves the understanding of non-technical decision-making stakeholders in the H&S domain.

For predictive modelling: predictive modelling of data allows the forecasting of future events based on trends and patterns found in historical data. Python provides libraries for predictive model such as Sklearn which has methods like the RandomForestClassier, SVM and the Tensorflow library which has the DNNClassifier method for deep neural networks. These methods provide easy access to building models with data (Mosavi *et al.,* 2019). The cleaner the data, the more effective the models are and increases the prediction ability of the models (Zhang *et al.,* 2013).

The Application Layer

The application layer provides an abstraction which stipulates the communication between the user interface and the databases. This is the shell which would employ graphic user interface (GUI) in communicating the system's functions to the end user (Avci *et al.,*2020). It ensures that information send out from the other layers passes through communication protocols which makes it readable to end users and the application layer of other systems (binti Ayob *et al.,* 2009). Powerful application programming interfaces (APIs) can be accessed in building this layer. The end users for this tool include, workers, safety officers, site managers and supervisors employed by National Highways. The descriptive variables for a highway project are input into the system through the user interface provided and loaded onto a file system and a database through an intermediary business logic. The input data then triggers the analytic pipeline to predict safety risk events that could occur, the possibility of an injury occurrence and the body part to be affected prior to a worker going on a project site. These predictions are then communicated through the interface to the end user for effective decision making before embarking on the project.

3.3.8 The modelling processes.

Python 3.0 (Anaconda) was the platform used in model building (Blagus *et al.,* 2013). Figure 3.6 presents an overview of the process involved in building and evaluating the performance of the incident prediction model.

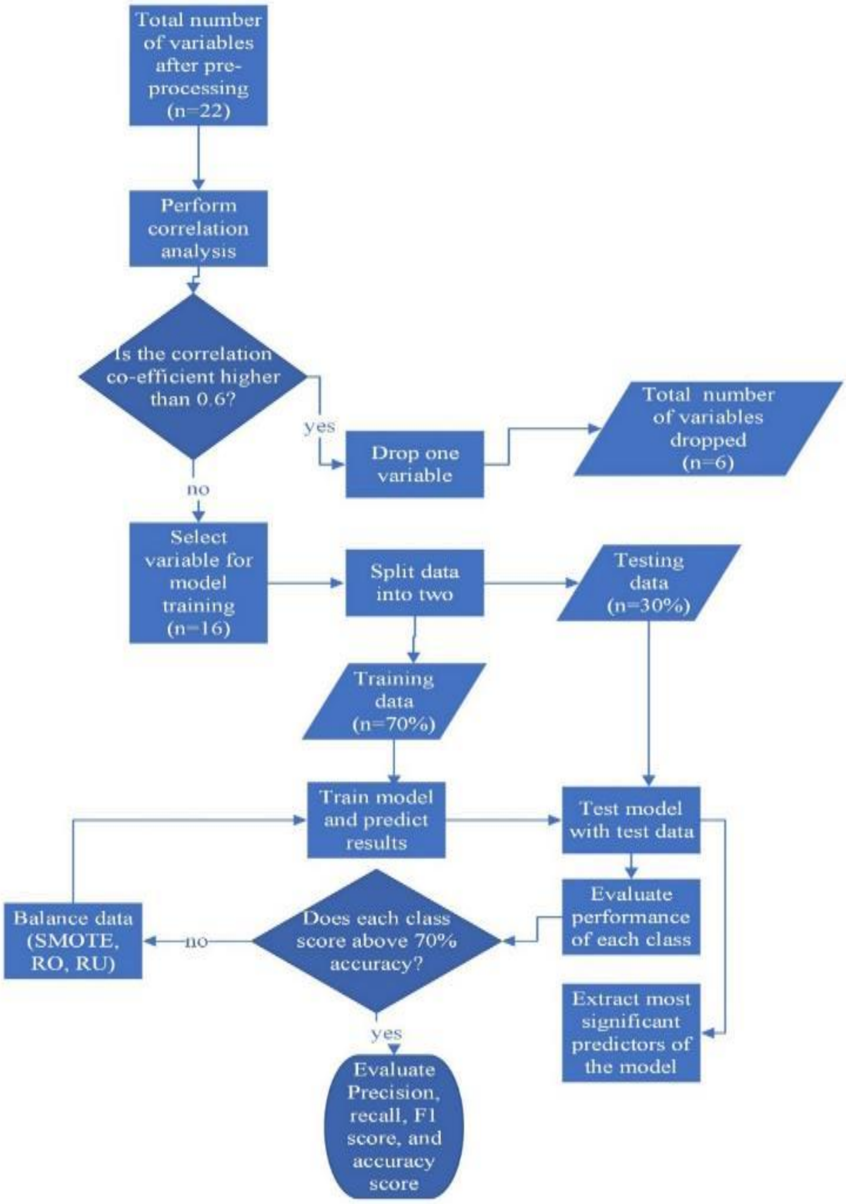


Figure 3.6 - Flowchart of model building experiment

3.3.8.1 Support vector machine (SVM)

The data points nearest to the hyperplane are referred to as the support vector, which has influence on the orientation and positioning of the hyperplane (Ding *et al.,* 2014). If a straight line can be used to categorise the data into two sets, then the task is termed a linear support vector machine problem. According to the original formulation for SVM (Cortes and Vapnik, 1995).

A hyperplane can be expressed as:

$$m^T x - c = 0 \tag{1}$$

where m is an F-dimensional vector and c is a scalar.

Given a linear data, the hyperplane *f(***x***)*= 0 differentiating the given data can be expressed as:

$$f(x) = m^T x + c = \sum_{j=1}^{s} m_j x_j + c = 0 \tag{2}$$

However, this present research presents a multi classification task whereby the target variable has nine classes hence, the use of a plane rather than a line is more appropriate (Mun *et al.,* 2017). SVMs were initially intended for binary classification however, complex distributed real-world data cannot be distinguished using traditional linear SVMs (Borovikov, 2014). SVM therefore uses the kernel technique to generalise it to a nonlinear hyperplane (Guo *et al.,* 2021). The resultant algorithm is similar, but each scaler product is changed to a nonlinear kernel function (Scetbon and Harchaoui, 2021). Moreover, the maximum-margin hyperplane could be fitted in a modified feature space using the kernel SVMs (Islam and Kim, 2019). The modified space is high dimensional and the transition might be nonlinear. As a result, in the higher-dimensional feature space, the classifier is a hyperplane, despite perhaps being nonlinear in the original input space. (Jha and Swami, 2021). The selection of an appropriate kernel function however affects how well an SVM classifier performs (Tharwat, 2019). There are several kernels that can be used for SVM classification tasks *viz.*: Gaussian Kernel, Polynomial Kernel, Radial Basis Function (RBF), Sigmoid Kernel and Anove RBF Kernel (Tharwat, 2019).

The kernel technique

The kernel algorithm is a mathematical technique that enables SVM to classify an ensemble of initially one-dimensional data in a 'two-dimensional' manner (Han *et al.,* 2012). The four kernel functions adopted for this thesis, given a kernel 'W' are:

i. Polynomial kernel

Expressed as:

$$W(v_i, v_j) = (\beta {v_i}^T v_j + 1)^{\circ}, \beta > 0 \qquad (3)$$

Where $W(v_i, v_j)$ is the value of the kernel function for two input data points, v_i, v_j;β is the constant that determines the scaling of the dot product between v_i, v_j; and ° is the degree of the kernel function and an adjustable parameter which makes the kernel flexible.ii. Linear Kernel

Expressed as:

$$W(v_i, v_j) = {v_i}^T * v_j \qquad (4)$$

iii. Gaussian Radial Basis Function (RBF) Kernel

Expressed as:

$$W(v_i, v_j) = \exp(-\beta \left\| v_i - v_j \right\|^2) \qquad (5)$$

Where $\left\| v_i - v_j \right\|$ is the the Euclidean distance between vectors $v_i \; and \; v_j$; β is the positive constant which controls the shape and reach of the RBF kernel function. A broader, more dispersed kernel results from smaller gamma values, whereas a more localised, sensitive kernel results from greater gamma values.

iv. Sigmoid kernel function

Expressed as:

$$W(v_i, v_j) = \tanh(\beta {v_i}^T v_j + c) \qquad (6)$$

Where β is the adjustable parameter that establishes the weight or relevance of the dot product of the input vectors $v_i, and \; v_j$

3.3.8.2 Random Forest classifier

For the 9-class multiclass problem in this thesis, the equation for a RF model can be represented as:

$$C^i = Mode(f_1(x_i), f_2(x_i), \ldots, f_9(x_i)) \quad (7)$$

Where: C^i is the predicted class for the i-th sample; N is the number of trees in the random forest; $f_N(x_i)$ is each individual decision tree; and Mode: For the i-th sample, the Mode function determines the predicted class that is used the most frequently across all decision trees.

3.3.8.3 Bayesian classifier (Gaussian Naïve Bayes)

NB classifiers are a type of simple probabilistic classifiers that use Bayes' theorem with a high degree of independence across the features (Li *et al.,* 2022). Although NB could be deemed one of the most basic Bayesian network models, they have the ability perform exceptionally, with high accuracy levels when they are merged with kernel density estimation (Wahbah *et al.,* 2022). To train the model for each given class, the class probability and conditional probabilities are calculated for each feature while taking into consideration the NB hypothesis that the features are conditionally independent given the class label (Farid *et al.,* 2014). Using the Bayes theorem and the conditional probabilities computed during the training, the likelihood that a data point is affiliated to each of the nine classes is calculated and the one with highest calculated probability will be the predicted class.

3.3.8.4 Event type prediction

A positivist philosophical stance (Park *et al.,* 2020; Alharahsheh and Pius, 2020) couched within an abductive approach (Posillico, 2023) was adopted for event type prediction. Within contemporary safety management literature, such an approach has been extensively used to, for example: to build ML predictive model based on national data for fatal accidents of construction workers (Choi *et al.,* 2020) and measure hand-arm vibration exposure risk in the UK utilities sector (Edwards *et al.,* 2020). Although it is through scientific means that positivist philosophies can be verified, combining positivist philosophies with an abductive approach allows room for elements of uncertainty which is presented as 'most likely' or 'best case scenario' (Sober, 2013). Such elements of uncertainty could be encountered in stochastic prediction models developed this thesis which justifies the adoption of abductive reasoning for this present research (Mesbah, 2016; Kläs and Vollmer, 2018). Moreover, abduction has been extensively used in a plethora of ML research (cf. Dai *et al.,* 2019; Crowder *et al.,* 2020), therefore adding further validity to this choice.

To predict incident risks ML algorithms were developed using data from past incidents and events recorded in incident reports recorded on the UK's highways accident report database. The data consist of variables representing safety indicators (Bayramova *et al.*, 2023a), which are combined and input into ML algorithms to enable pre-emptive prediction of incidents, for improved decision-making when a highway task or operation is going to be executed.

A sequential explanatory mixed method (Roberts *et al.,* 2021) which employs both qualitative and quantitative data (Roberts *et al.*, 2019) was adopted for this thesis. This sequential method comprises five phases *viz.*: i) data collection; ii) data preprocessing; iii) model selection; iv) data balancing; v) model evaluation – refer to Figure 3.7. The *data collection* phase identified 22 independent variables such as region, site/project, location, weather / visibility and season and the dependent variable which is 'event type' includes nine different classes namely, personal illness/injury (PI) type, undesirable circumstance/near miss (UN), security (SC), environmental (EN), infrastructure (IF), facilities/site (FS), structural safety (SS), utility strike (US) and incursion/IPV strike (IS). The data was then cleansed as part of the data pre-processing phase to improve data accuracy and quality. Investigations carried out during the *model selection* phase were: analysis of the correlation of feature variables and analysis of feature importance using RF. These analyses were carried out to ascertain which independent variables were most influential in the performance of the classification model. The *data balancing* phase also evaluated and compared data balancing algorithms and their impact on model training. The final *model evaluation* stage involved a performance evaluation and comparison of the performance of the three ML models employed.

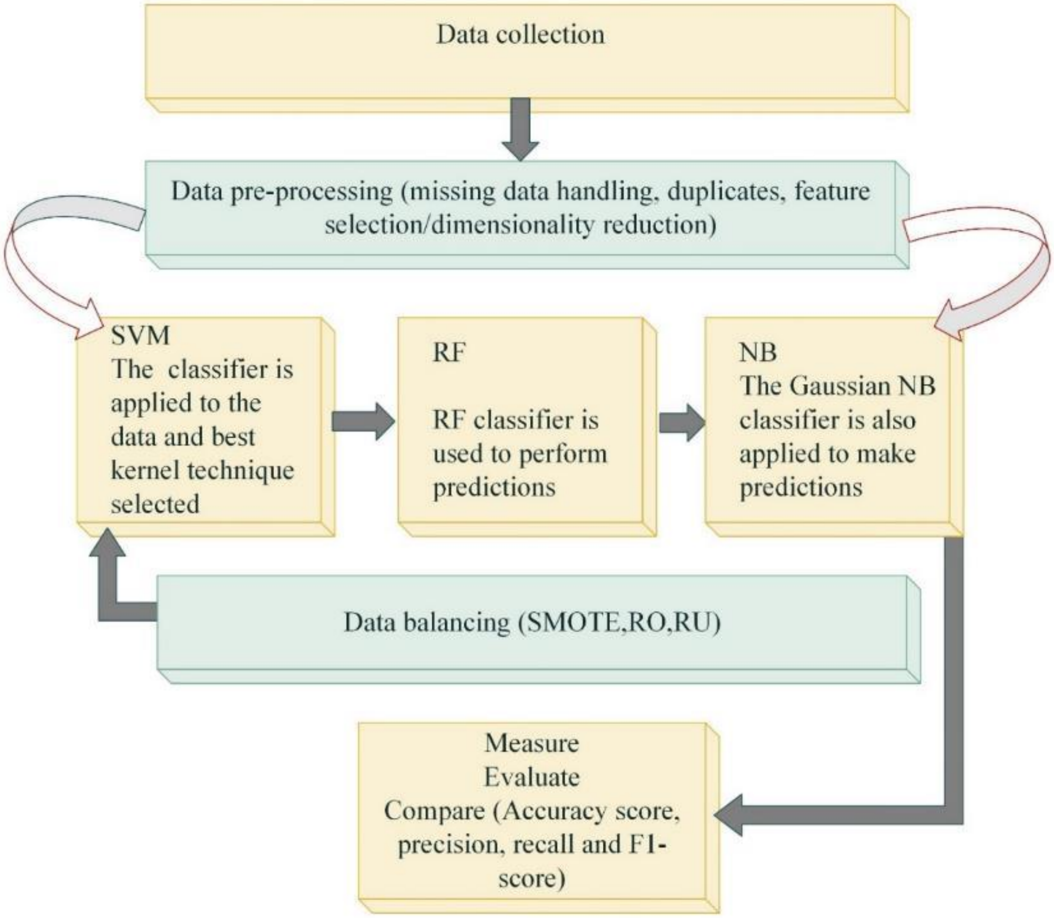


Figure 3.7 - The sequential method adopted.

In a bibliometric review of ML models most utilised in the safety risk assessment domain, Bortey *et al.,* (2021) discovered that SVMs were the most explored ML models while BN were the least utilised. This could be due to restrictive data availability in safety management previously (Eseonu, 2018) as BN require voluminous data sets (as compared to SVM) to train and test classification models (Zhang *et al.,* 2013). However, as the data available for this thesis is considered voluminous as it consists of 64,000 data entries. SVM and BN are both adopted to explore any significant differences in model performance that could be observed. According to Sanchez *et al.* (2011) SVMs are advantageous because they simultaneously reduce the empirical classification error and increase the geometric margin – SVMs can also manage small sample problems with high precision (Cortes and Vapnik 1995). These features may explain why their usage predominates in the safety literature. However, Matías *et al.* (2008) talks about the discriminative nature of SVM and other tree-based classification algorithms and proposes

BN as a more robust alternate due to its generalisability and ability to model joint probability distribution for variables in resolving problems.

3.3.8.5 Risk level prediction

The second classification task involves predicting the class of the risk level for a safety risk event. RF algorithm will be the primary algorithm used to predict the risk level of a safety risk event. Based on the 'actual severity rating score' column which ranges from 1-25, a 'project risk level' column is created which classifies the risk level involved into high, low and medium based on the severity score associated. A severity score between 1-9 is rated low, between 10-18 is rated medium and between 19-25 is rated high (Zhang and Mahadevan, 2019; Kleinberg *et al.,* 2016. The labelled 'project risk level' column then becomes the target variable. The RF model is then applied to the labelled data to classify the different event occurrences into risk levels. The data is divided into 70:30 training and testing data respectively and trained. New data which is the testing data is then introduced to the model to classify. The accuracy of the model's classification is then evaluated based on four metrices *viz.*: the confusion matrix, the accuracy score, the confusion matrix, the classification report and the AUROC. The DL algorithm is then applied to the data in the same way and evaluated based on the same metrices. The performance of the ML models is then compared and contrasted with the DL models based on the specified metrices to determine the best performing model for the risk level classification task.

The Python programming language presents a 'randomForest' package which was used to develop the RF models in this thesis. RF was implemented using a Scikit-learn library. RF was employed in this thesis to predict the risk level involved in a project due to its successful application in prediction for other domains. Zhou *et al.* (2019) used RF to predict the safety risk level of deep foundation pits in subway stations. Rebollo and Balakrishnan (2014) used RF to predict the risk level of air traffic lags in the transportation sector and Lessmann *et al.,* (2010) predicted the outcome of competitive events using horse racing as a case study. These aforementioned studies show the feasibility of using RF to predict risk levels and hence justifies its use in the present setting.

3.3.8.6 Body part affected

To develop predict models for classifying body parts likely to be affected in the event of an injury, the cleaned data was randomly divided into 70% training and 30% testing data. The training data is used to train and optimise the model. SVM model was created and fit to the training data in the model experiment. The kernel applied was the polynomial kernel, the probability was set to ‘True’, with a random state of ‘42’. Different experiments were also conducted for three other ML models namely, RF, NB and the ensemble learning method to compare their performance against that of SVM model. A DL model known as Recurrent Neural Network (RNN) was also used to perform classification to ascertain whether a neural network would have a better performance on the data as compared to ML models. The models were then validated using a technique called k-fold cross-validation (Malakouti *et al.*, 2023) that involved using the procedure in k number of tests and randomly dividing the data into k folds. The value of k in this experiment was ten. The precision, recall, F1-score, kappa statistic and accuracy score were the best evaluation metrics (Borovikov, 2014) utilised to determine how well the model performed. The performance of each model was then compared, and the top performing model was identified.

Several preprocessing techniques were applied to enhance the efficiency and facilitate the modelling process. Initially, to address missing values, the ‘*SimpleImputer’* class from scikit-learn library provided a strategy parameter, which enabled the specification of variables to impute missing categorical values with the mode. This method significantly bolstered the predictive power of the final models despite its computational demands. The simple imputation method has been used by several studies to fill in missing data in ML tasks (Chheda *et al.,* 2020; Rezaei *et al.,* 2020; Abd Halim *et al.,* 2020)

The values in the ‘body part affected’ column had duplicate entries which posed challenges for data analysis and interpretation. For example, entries such as ‘back/spine', 'lower arm, hip, hand, back/spine', ‘hip’ were observed. In this example, the values, back/spine and hip can be seen to have been duplicated leading to an inaccurate representation of the true count of unique values. To address the duplicate entries, the first four letters of each entry was examined, and the same value was assigned to entries with identical prefixes. The observation made by examining the first four letters of the duplicate entries was that they possessed common prefixes. Therefore, by focusing on the first four letters, the commonalities were effectively captured and consolidated. Hence, the unique values were reduced from 179 to 14 unique entries. Assigning the same value to entries sharing a common prefix resulted in the reduction of the unique values in the ‘body part affected’ column without any loss of essential information conveyed by the original values. Consolidating duplicate entries enhanced the clarity and interpretability of the data, thereby facilitating meaningful insights and promoting reliable analysis results. Subsequently, the SMOTE technique (Blagus and Lusa, 2013) was selected to rectify class imbalances within the dataset.

3.3.8.7 Training and testing

The dataset was split into two sets at random: the training set, which was used to train the model and rank the significance of the variables for the feature selection process (70%); and the test dataset, which was used to verify the performance of the prediction model (30%). After the data was pre-processed, a correlation test was performed to determine the correlation rating of all the variables. If two features were found to have a high correlation co-efficient (CC) (Zhou *et al.*, 2022), one of the features is dropped in a process known as dimensionality reduction (Huang *et al.,* 2019). This is because, the complexity of the model increases with a high dimensional feature set. Also, some of the variables due to high correlation may be redundant and might exhibit multicollinearity, thereby undermining the statistical significance of the independent variables. (Huang *et al.,* 2019).

3.3.8.8 Data balancing

For a major difference in the amount of data allocated to each class of the target variable, the challenge of class imbalance arises (Sarkar *et al.,* 2020). This type of data set is known as an imbalanced dataset (Sarkar *et al.,* 2020). To handle the issue of data imbalance in this thesis, three balancing algorithms namely: SMOTE (Chawla *et al.,* 2002); Random Undersampler (RU) (Estabrooks and Japkowicz, 2001); and Random Oversampler (RO) (Shelke *et al.,* 2017) were applied to each of the three ML models used in the experiment (SVM, NB and RF) separately.

Random oversampling is the process of enhancing training data with multiple replications of some minority classes (Shelke *et al.,* 2017). Using an unbalanced dataset, SMOTE is an oversampling approach that creates artificial samples for the minority class (Chawla *et al.,* 2002), while the RU is a non-heuristic approach that attempts to balance desired distributions rather than removing instances at random from the majority class (Estabrooks and Japkowicz, 2001). Although SMOTE and RO are oversampling techniques, in contrast to RO, the SMOTE algorithm oversamples the minority class by creating artificial cases as opposed to oversampling by substitution (Fernández *et al.,* 2018). Instead of using data space, the SMOTE algorithm generates counterfeit instances depending on the feature space (Blagus and Lusa, 2013).

3.3.9 Performance evaluation

The confusion matrix is an essential approach for evaluating a model's classification effect (Krstinić *et al.,* 2020).. Five metrics of accuracy, sensitivity (recall), specificity, precision and F1 were proposed based on the four outcomes (Yacouby and Axman, 2020). These five metrics were employed in this thesis. The following equations are indicative of the metrices used for performance evaluation in this research *viz.*:

Precision: measures the number of correctly predicted positive instances.

$$precision = \frac{TP}{TP+FP} \quad (8)$$

Recall: evaluates the predictive ability of the model for positive samples. It is the proportion of positive samples to total positive cases that were correctly categorised as positive.

$$recall = \frac{TP}{TP+FN} \quad (9)$$

Specificity: measures the number of actual negative instances correctly predicted as negative.

$$specificity = \frac{TN}{TN+FP} \quad (10)$$

F1-score: it is the harmonic mean of recall and precision. It offers a balanced evaluation of precision and recall, which is particularly valuable when classes are imbalanced.

$$F1 - score = \frac{2(precision*recall)}{precision+recall} \quad (11)$$

Accuracy score: measures the total accurate predictions (both true positives and true negatives) out of all instances.

$$accuracy = \frac{TP+TN}{TP+TP+FP+FN} \tag{12}$$

The data is cleaned and prepared for the model building in a process known as data pre-processing. Figure 3.8 below presents an overview of the three-phase process adopted for this stage of the research and the model building process is explained subsequently.

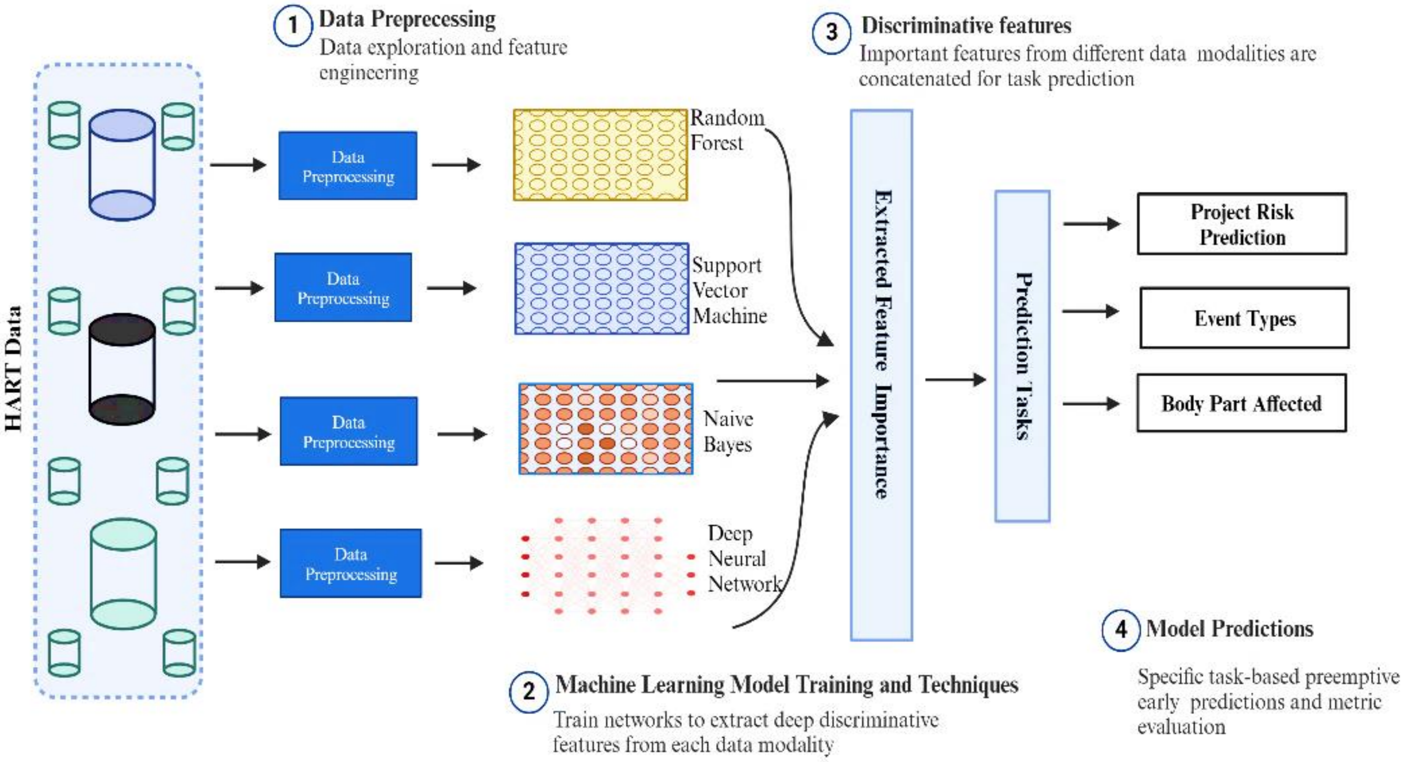


Figure 3.8 - The process adopted for building the HSPM.

3.4 Stage Three – Validation of the Prediction Model.

The validation stage in ML is an important stage which intends to guarantee a model's stability and efficiency (Malakouti *et al.*, 2023). This stage tackles the approaches used to validate the model, including the evaluation metrics utilised, the results obtained, and the test on the effectiveness of the model (Maleki *et al.*, 2020). To determine the generalisability of the safety risk prediction model, a k-fold cross-validation with k=10 was employed (Nti *et al.*, 2021). This method was also used to validate the model by randomly dividing the data (selected features) into ten folds and applied in 10 experiments. In each experiment, the data is divided into training and test datasets. The model was then trained, and the accuracy of each model was determined by averaging the accuracy across the ten experiments. This method intends to reduce the variation associated with a single train-test split and enables a more complete evaluation of model performance (Tan *et al.*, 2021). Therefore, a simple train-test split process was performed in addition to the cross-validation procedure. 70% of the data was allocated for training and 30% for testing. This split ratio was chosen in accordance with previous studies (Nguyen *et al.*, 2021; Bichri *et al.*, 2024) to ensure that model is given sufficient data to learn and also reserve a significant portion for an unbiased evaluation.

Table 3.3 details the research objective, it's associated research questions and the methods that were adopted to address the research objectives.

Table 3.3 - Research methods adopted.

Objectives	Research questions	Research Methods						
		Bibliometric Analysis	Analysis techniques			Data analysis	ML Predictive modelling	Discussion\ Evaluation
			Document analysis	Grounded theory	Thematic analysis			
1.To conduct a bibliometric literature review to identify how various previous and existing models and theories underpinning safety risk management within the construction industry could be tailored towards highway operations.	What are the contributions of the most explored theories and models underpinning the safety risk management in the construction industry?	M	S	S	S			
2. To identify and analyse contributions of existing safety indicators which informs the selection safety-oriented variables for highway traffic operations.	What are the most significant safety indicators that can be employed in ML for safety risk incident prediction	M			S	S		S
3. To develop a conceptual model based on identified safety indicator variables tailored for highway traffic operations.	What input variables (derived from safety indicators) are most significant in predicting the risk and incident outcomes?	M	S		M			S
4. To establish a robust framework for the success of a similar prediction or classification proof-of-concept model using data exploration.	What insights can be derived from the data?		S			M		S
5. To build a ML predictive model which can be used to predict risk level, body parts likely to be affected and incident types for effective decision making.	What ML and DL models can be applied effectively in safety risk prediction	S				S	M	S
6. To validate and identify significant parameters within the model and assess the accuracy and precision of the model using standard evaluation metrices.	What are the significant parameters, accuracy, and precision level of the prototype model?					M	M	S

*Key: M – Main method, S – Secondary method

3.5 Ethical Considerations

The information and data collected does not contain any personal details of participants of the organisations supporting this work. No data which could be traced back to individuals (such Name, National Insurance, specific job positions) was collected. All data collected was generalised. Information from data coding and interpreting was used to create a research paper and PhD thesis with no reference to any personal details of participants from the organisations supporting this work. All information was electronically stored on the University's secure 'One Drive'. At the end of the study, all information and data were securely disposed of (including raw data) and only anonymised data was used for publishing the findings as part of this dissertation study. At no time will any data be passed to a third party (willingly or otherwise) – these conditions are stipulated in the contract agreed with National Highways and they reserve the right to be acknowledge (or not) in the final report and research papers produced (Petrova *et al.,* 2016). Indeed, all papers proposed are agreed with them in advance of write-up and a suitable acknowledge given for their support. National Highways reserve the right to withhold data that is commercial and in confidence (Rustad and Koenig, 2019).

The research ended in November 2024 hence data was kept until final submission of thesis and oral defence is done. Personal questions posed to participants could trigger psychological stress from memories hence no personal questions were included in interview. Participants still had the option of not answering questions they were uncomfortable with. Participants were exposed to no intended risk as risk within the built environment tend to be limited (Heggen and Guillemin, 2012). The various data processing methods were handled independently from participants hence this cannot be traced back to any individual (Heggen and Guillemin, 2012). Research method classes and further instruction and guidance was given by the supervisory team (which has a staff from National Highways). This combination of experience and support adequately prepared this researcher and was equipped with sufficient information to detect unforeseeable ethics breeches and take appropriate mitigation action to avoid them (Petrova *et al.,* 2016).

3.5.1 Ethics of AI

The application of AI in safety risk prediction introduces several ethical considerations that must be acknowledged to ensure responsible use. Akinrinola *et al.* (2024) postulates that, AI systems, especially those applied to workplace safety, must adhere to principles of fairness, transparency, privacy, and accountability. In this thesis, the dataset used for training ML models does not contain any personal details of participants of the organisations supporting this work. However, complying with GDPR (General Data Protection Regulation) is a significant step taken to prevent unauthorised access or misuse of all incident data used. All personal attributes in the data were therefore removed to protect individual identities while still maintaining the integrity of the data for the modelling process.

The ML models employed were susceptible to bias due to the class imbalances that were present in the dataset (Estabrooks and Japkowicz, 2001). Hence, to prevent the model predictions skewing towards a particular class, different data balancing techniques such as SMOTE, random oversampling and random undersampling (Blagus, 2013) were used to handle the class imbalance and improve fairness in the risk assessment process. Furthermore, this thesis is not an exception to the 'black box' nature of ML models which makes it difficult for humans to comprehend the inter-relationship between variables (Ahmed *et al*., 2023). To address this, interpretable ML techniques such as feature importance analysis (Li *et al.,* 2019) were employed to provide insights into how predictions were made. The models used in this thesis is to complement human safety expert decision making and not to replace them in safety risk management. Hence, the research emphasises the capacity of the safety risk prediction system as a decision support tool rather than an autonomous risk mitigation system.

CHAPTER 4 - SAFETY THEORIES/MODELS: A SYNTHESIS FOCUSING ON DEVELOPMENT OF NEW RISK THEROY FOR A PREDICTIVE MODEL

4.1 INTRODUCTION

To determine the most effective tactics that can be used in a "*conceptual*" safety risk model for the safety of highway workers, this chapter summarises and compares current safety risk models and theories. As a measure to minimise accidents and injuries in the highway operation industry, methods for gaining insights have depended on a variety of models and theories for creating suitable risk mitigation plans (Liu *et al.*, 2023). These have been used in various situations, such as occupational health (Leveson, 2017; Huang *et al.*, 2023), worker safety practices (Mohammadfam *et al.*, 2017), and emergency safe haven construction (Wu *et al.*, 2011). Numerous high-risk industries, including mining, aviation, oil and gas, and medical, have utilised theory and model application, according to a review of various health and safety risk models and theories (Rasmussen, 1980; Swuste *et al.*, 2014; Adelani *et al.*, 2024). However, considering the construction industry, scant research has been undertaken on the effective application of these theories and models in a highways setting hence, neglecting safety risk prediction research in this field (Hancher *et al.*, 2007). The various types of safety risk models and theories adopted in other fields could be applied to highway operation safety strategies by making use of their most useful characteristics (Leveson, 2004; Ali *et al.*, 2023).

This chapter's contents have been subject to peer review thereby validating its findings for publication in a scientific journal. The research paper, titled ' A Review of Safety Risk Theories and Models and the Development of a Digital Highway operation Safety Risk Model', was published in the Digital journal of Multidisciplinary Digital Publishing Institute (MDPI) in May 2022 (Bortey *et al.*, 2022).

4.1.1 Safety risk theories and models

The modern approach to model driven development creates a pivotal concern for an acceptable notion and consensus of what a model is and what it is not (Nilsen, 2020). A model can be defined as an informative representation of a system or an object (Epstein, 2008; Esmail *et al.*, 2020). Models enable the simplification of ideas, provides information, creates a mental picture and characterises and evaluates communication remedies(Kjellén, 2000). These models can manifest visually, mathematically or through description. Nilsen (2020) however, theorises that a model is a notion or a collection of ideas that attempts to provide clarification on facts, observations, data, realities or happenings and are generally tested and recognised scientific hypothesis. While models are conceptual depictions of reality or an individual's vision of a potential future, created to enhance comprehension and/or enable forecasting, theories are tenable explanations developed to establish a connection between potential causes and their consequences (Ali *et al.*, 2023). For the purpose of this thesis, models represent the concepts and framework by which safety techniques are implemented.

This section explores potential strategies of improving safety on highway operational sites by evaluating early and anachronistic risk theories and models to illustrate the evolution and re-evaluation of these concepts over the years. The levels of models consist of descriptive, analytical, domain specific and system models with descriptive models at the highest level (Husung *et al.*, 2022). Normally diagrammatic or visual rather than the comprehensive quantitative and mathematical models are employed in domain specific analytical purposes (Banerjee, 2021). Models are applied and used contextually hence, identifying the differences the model's description and its application is highly significant (Underwood and Waterson, 2014). Identifying the details of the specific application of a model helps to tackle the weaknesses that are inherent in high level models (Nilsen, 2020).

4.1.2 Early safety risk theories

Early studies on risk theories made significant strides in proposing measures to minimise risks (Heinrich, 1931; Reason, 1990). Evidence in support of risk theories, however, remain mixed (Esmail *et al.*, 2020) hence the need to design a study which assembles the most significant theories together and critically analyses them using a resilient methodology. A thematic analysis of these theories and assumptions they make could help in discovering new ways to develop novel theoretical models (Bortey *et al.*, 2022).

4.1.2.1 Heinrich Domino's theory

Herbert William Heinrich proposed a risk theory in 1931 which went on to be validated and improved by other researchers over the years (Heinrich, 1931). According to Heinrich (Avwata *et al.,* 2021), unsafe acts of workers contributed to 88% of occupational accidents and therefore proposed that there is sequence of factors which leads to injury occurring and if this sequence is interrupted by even missing a step, an accident will not occur (cf. Avwata et al., 2021). Heinrich (*ibid*) considers an accident as just one factor in the sequence. The sequence presented by this theory are: i) ancestry and social environment; ii) worker fault; iii) unsafe acts together with mechanical and physical hazard; iv) accident and damage or injury.

i. **Ancestry and social environment**: the social environment of an individual characterises their attitude and behaviour and this could bring out traits such as laziness, carelessness, bad anger management etc (Aven, 2022). Heinrich believes that some of these traits could even be hereditary or ancestral hence, are inherent in humans (*ibid*). These characteristics are present in humans even in the process of training or acquiring knowledge in the field of work and can influence an individual's approach to using knowledge acquired (Cozzani *et al*., 2009). Such influence could lead to the second step which is the "worker fault".

ii. **Worker fault:** this is mainly characterised by carelessness and negligence of workers (Leveson, 2015). Undesirable personality traits of workers could result in holding the worker responsible for any action that results in an injury (Schulman, 2004). This specifically focuses on the negative actions of workers when handling tasks.

iii. **Unsafe acts working with physical and mechanical hazards:** Unsafe acts and conditions lie at the center of the domino sequence (*ibid*). It is said to be the easiest the eliminate in the sequence and also the most efficient in preventing the next domino which is accident (Sabet *et al*., 2013).

iv. **Accident:** this is known as an unfortunate incident that happens unexpectedly and unintentionally, typically resulting in damage or injury (Wang *et al.,* 2023). Unsafe acts results in accidents and the main factor that causes damage either to humans, properties or image (Sabet *et al*., 2013)..

v. **Injury**: is a general term that refers to harm caused by e.g. accidents, falls and hits etc (Intini *et al*., 2024). An injury in this instance is said to be caused by an accident (c.f.). Injuries could be in different forms ranging from mild to fatal andfatal injury is one of leading causes of death in the construction industry (HSE, 2020).

Any process that has the likelihood of causing harm is known as risk (Burt, 2001) and as such the uninterrupted sequence proposed by Heinrich is the risk in focus. This theory presents a risk with the probability of not occurring if one of the dominos stated is eliminated. This means there is certainty that if all the dominos are kept in place, an injury is going to occur. However, there is not much proof that eliminating one of the dominoes in the sequence could prevent an accident from happening (Suraji and Arman, 2023). Taking worker fault domino as an example, unsafe acts could still exist even if workers are careful and prudent because of unidentified hazards which no one knew existed due to routine steps carried. The Esso gas explosion at Longford (Hopkins, 2000) is a classic case of unidentified hazards which could lead to unsafe acts. The gas piping which is usually hot to touch had ice visible on it, hours before the incident which was an antecedent to the accident (*ibid*). This is an unusual incident which rarely happened hence, workers instructions and training did not include handling ice on piping.

The domino theory focused on human errors and negatives. It puts responsibility for the accidents that happened on workers rather than management, responsible for not preventing the accidents from happening. Other researchers have questioned the efficacy of this theory regarding the role management plays in preventing these accidents (Chen *et al*., 2023; Khakzad, 2023). These are the improvements to the domino theory also referred to as the management models (Hosseinian *et al.*, 2012)

Improvements To Domino Theory

Unlike the original theory proposed by Heinrich which apportions 88% of accident causes to unsafe act of workers, the management model places most responsibility for accidents that occur on management. A new sequence was proposed (Bird and Loftus 1974) which included lack of management, basic causes, immediate causes, the incident and loss.

Failure of management to plan, control and organise constitutes a lack of control on the part of management (Katsakiori *et al.*, 2009). This is a prerequisite for preventing an incident from happening (Bird and Loftus, 1974). Employee factors and work factors made up the *'basic causes'* domino (Vincoli, 1994). An example of these employee and work factors could befactors such as no motivation to perform safe work (Helander, 1991). In a survey to determine why employees risk safety (Zin and Ismail, 2012), reasons such as "accident will not happen to me syndrome", not being aware of OSHA act (OSHA, 1994), or the discomfort and difficulty in following rules were stated as factors preventing workers from working safe. Job factors includes inadequate personal protective equipment, faulty machines etc.

The earlier research of Wearver (1971) threw light on operational errors and the role of management in risk identification and why unsafe acts continued to persist. In this regard, Weaver questioned (*ibid*) underlying risks and the knowledge deficit in safety by management. According to Abdelhamid (2000) answering Weavers' question can clarify the fundamental operational errors and risks that end up in accidents.

4.1.2.2 Normal accident theory (NAT)

On the 28th of March 1978, what begun as failures in the non-nuclear secondary system of a nuclear reactor became the most significant accident in the commercial nuclear power plant history (Batur and Alkan, 2023). This was known as the three-mile island disaster (Marguet, 2023). Charles Perrow (1999) attempted to understand this disaster via the development of the normal accident theory (NAT): a condition whereby the elements involved were so complex such that an accidental outcome was inevitable. According to this theory, it is unrealistic for safety to be given the utmost priority among the organisational objectives. NAT claims that fatal accidents are unavoidable over time and theories mostly create blueprintsfor much more organised and effective institutions rather than focusing on more complex organisations and real-world situations (Muecklich et al., 2023). Two factors were proposed by Perrow (*ibid*) for analysing safety and organisations.

- Interactions: linear to complex.
    a. Linear systems are characterised by features such as effortless accessibility, replacing equipment, isolating subsystems, dedicated connections, little attention on feedback circuits, dedicated communication and a comprehensive understanding of the system.
    b. Complex systems are characterised by closeness, few replacements, interconnected subsystems, feedback circuit, dedicated information and a restricted level of understanding.
- Coupling: loose to tight
    a. Tight coupling prevents delays, supply shortage where redundancies and buffer are incorporated and supplies are replaced.
    b. With loose coupling, there is a probability of process delay with alternations in the order of process succession, the availability of different methods, shortages in supply are possible and there are buffers, redundancies and replacements available.

The system constructed to handle fast-paced coupling have a reaction speed that is parallel to any possible developing incident. For example, when one fire fighter is taking all significant decisions and fighting a raging fire at the same time, by the time information about people inside the building reach the fire fighter, people will already be dead by the time they take a decision on the next course of action before going ahead to act. A solution for such problems to loosen such organisations is the '*subordinateness*' approach where lower-level workers are allowed to partake in decision making while being coordinated by the required top management experts (Wang *et al.,* 2022). This encourages training of all organisation staff irrespective of their level to be confident enough to take critical decisions (Kessler *et al*., 2020).

4.1.2.3 Goals Freedom Alertness Theory (Kerr 1957)

This theory reflects that an undesirable psychological occupational environment will result in low-quality events with accidents included. In effect, psychologically gratifying and pleasant occupational environments increases organisational safety performance (Jha,2011). Workers pay more attention to tasks and activities therefore enhancing safe work and resulting in accident-free occupational environments. Worker incentives and support, rewarding of worker initiative, coordinating attainable goals and planning groundbreaking ways of attaining such goals are all characteristics of a psychologically gratifying work environment (Abdelhamid and Everett, 2000). Here, workers have the freedom to create new initiatives which could aid in problem solving. Management could then help shape these initiatives by establishing a mission and vision for workers, permitting participatory techniques and acknowledging the efforts of their workers (Abdelhamid and Everett, 2000; Jha,2011).

4.1.2.4 Ferrel Theory

Russel Ferrel (1997) proposed this theory based on a sequence of human factors. Ferrel theory posits that humans are the primary source of accidents and they interact with other factors which results in accidents (Jhamb and Jhamb, 2003; Taylor *et al*., 2004). These factors include:

- Overload: this factor indicates that the capacity of humans is sometimes irreconcilable with the load and tasks to be carried out. This results in incompatibility which creates pressure, anxiety, tiredness, and psychological triggers which could be optimised by physical factors such as noise, smoke, light, dirt etc. where the task is taking place.
- Response error: this could be caused by the inefficiency of workers, haphazard routines, and inability of workers to follow instructions. When the instance of work is incompatible with the training of the worker.
- Improper activities: when one indulges in activities they are not trained for or lack knowledge about, this could result in avoidable accidents. Sometimes this could be because of inadequate resources, lack of training or even deliberately taking risk in some cases to either beat time or save scarce resources.

4.1.2.5 Risk Homeostasis theory.

The risk homeostasis theory was based on an idea generated by Wilde (1976;1978) to model passenger- vehicle- driver behaviour which was known as the risk compensation theory. This model proposed incentives and rewards for safety behaviours, initiated by a seeming inconsistency between the perceived and accepted levels of risk. This model was expanded to risk homeostasis (Wilde, 1982a) which posits that, rather than the desired risk level, drivers (workers) should intuitively sustain best possible level of tolerated risk. Wilde (1982a) says that, on average, an erratic risk level only complements a specific level of risk targeted. Risk homeostasis is however different from isostasis which is an invariant risk level and unlike homeostasis, isostasis does not fluctuate. Risk homeostasis theory is based on the general concept of perception evaluation with feedback loop to control and modify behaviour based on unique individual abilities and circumstances (*ibid*). An application in construction is when workers halt climbing tasks in foggy weather until visibility improves and then continue with this task. Wilde (1985a,1988a) espoused that until the consequences of an accident is well understood by a driver, an engineered safety measure such as anti-lock braking system or seatbelts can only do much.

However, these safety enhancements could incentivise drivers to improve their performance once they feel safer with measures instituted. Incentivised systems have been proven to be a robust technique in reduction of injury rates (Grant and Smiley, 1993; Fosser *et al.*, 1996). Although risk homeostasis was primarily developed and validated in the area of road safety for drivers, this theory can be adopted in the area of construction worker safety also. An example is when construction workers are not allowed to carry out operations in situations where safety resources such as personal protective equipment are not available

4.1.3 Early safety risk models

4.1.3.1 Swiss Cheese model

Reason (1990), posits that, defences, barriers and safeguards present within the safety framework of an organisation still have weakness. These weaknesses within the system are presented as ‘holes within a Swiss cheese which changes location, opens up and shuts continually and never remains in the same position (as shown in Figure 4.1). This model states that, although these holes (weaknesses) exist, it only leads to an unfortunate event when the holes line up and permits a trajectory of opportunity for an accident to occur. Two reasons were given for the presence of these holes.

- Active failure: this is because of unsafe acts such as procedural violations, mistakes etc. that are caused by humans in direct contact with the system. Their specific forms are usually hard to predict and creates opportunity for adverse events occurring.
- Latent conditions: these are the inevitable lapses in the system caused by designers, builders or top management. This is in sharp contrast to active failures as they can be identified and resolved before any unfavourable condition occurs. This leads to a more proactive approach to risk management.

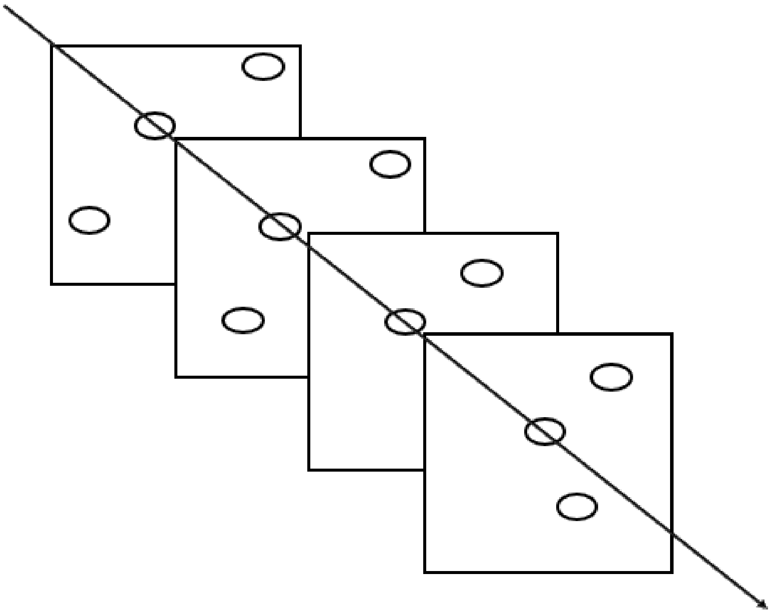


Figure 4.1 - Swiss cheese model (Reason, 1990)

4.1.3.2 Embrey's M.A.C.H.I.N.E model

Embrey's model of accident causation (using hierarchical influence network (Machine)) postulates that an accident could occur due to human errors, hardware failures and external events (Embrey, 1992). This is then broken down into:

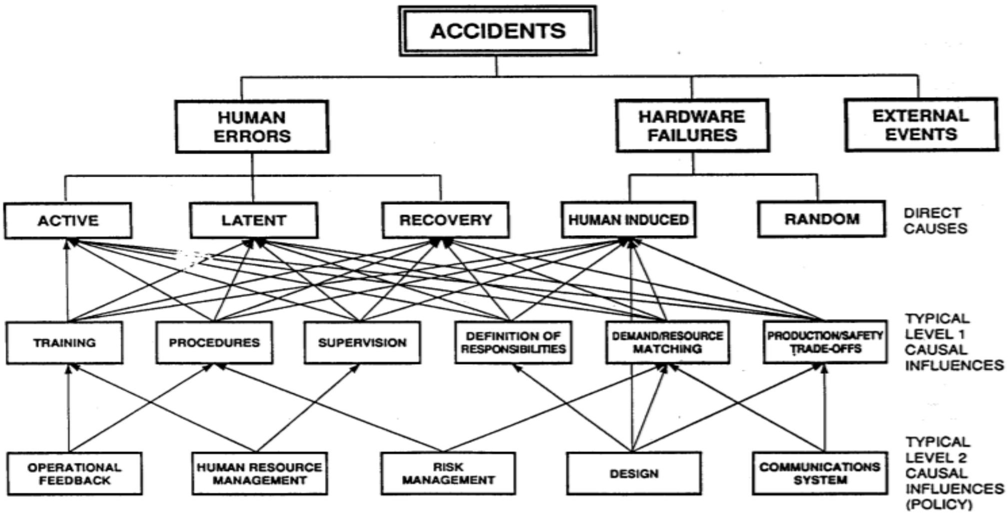
- Direct causes such as inability to follow laid down rules and/or regulations are well as failure to perform maintenance and checks on equipment.

- Level one causal influences such as ambiguous description of job roles and obligations, inadequate training of personnel or uncertainty in systems and practices.
- Level two causal influences, which deals with inherent errors in the system design, lack of proper human management or inefficiencies in the risk management process.

Embrey (*ibid*) based this model (refer to Figure 4.2) on the Clapham Junction disaster which occurred in the United Kingdom in 1988. This was caused by wiring errors made while constructing relay control signals (Swuste *et al.,* 2020). The errors caused signal failures resulting in the collision of a train whereby 21 people died (Morse, 2023). The direct cause in such a situation was the failure of supervisors in carrying out laid down wiring checks procedures hence, wiring faults were not detected (*ibid*). The level one and two causal influences occurred due to the inefficiency of technician workers who left old live wires in contact with relay terminals and the inability of drivers to report observed signal irregularities due to time constraints. These errors and omissions boil down to lack of proper human resource management training and failure to identify inefficiencies in the risk management process.

Embrey’s model also recognises that the implementation of an efficient human resource management could increase the likelihood of effective distribution of demands, resources and adequate training. However, the existence of this does not give an absolute guarantee that resources will be complemented or that training will be enhanced. This model however acknowledges the complex nature of the accident process as several elements including management and organisational elements could impact it. Hence, combining these elements quantitatively creates a total approximation of accident probability.

Figure 4.2 - Embrey's generic model of accident causation (Embrey,1992)



4.1.3.3 Rasmussen risk management model

Rasmussen's (1980) risk management model conceptualises the negative effect of stretching or stressing a system beyond its capacity or elastic limit (Little and Graves, 2008). This model proposed behavioural restructuring models which focuses on qualitative guiding principles to substitute the focus on sequences of actions and sporadic digressions in the form of human errors in accident analysis. Precisely identifying boundaries would revolutionise risk management and enhance safe work (ibid). These boundaries must be clearly evident to workers to provide them an opportunity to continuously become skilled at adapting to the boundaries (c.f. Little and Graves, 2008).

Creating effective systems is one major benefit of making boundaries visible (Rasmussen, 1982). Workers who work close to margins they understand and are familiar with may be safer than operating on unknown boundaries with the possibility of weakening under volatile conditions when stressed (Tozlu, 2023). The boundaries proposed by Rasmussen include:

- **Work system constraint**: losing control of the work system could lead to injuries, financial loss, environmental contamination or property damage hence, the need to maintain boundary of restraint (Reason, 1990). The sequence of events that lead to accidents is influenced by human activities which could either initiate a chain of risky events resulting in accidents or change the normal flow of events also leading to accidents (Dekker, 2011). Therefore, instituting a work system constraint enables safer operations by avoiding accidental outcomes which has negative impact on people, the environment and investments (Rasmussen, 1997). Instructions, laws or rules are sometimes put in place to control worker activities which could be hazardous (Hollnagel, 2014). Other constraints put in place include equipment design, which controls worker behaviour that could be harmful hence, improving safety of operations (Hollnagel, 2014).

- **The economic boundary:** describes the operating envelope in which a business is profitable and cost effective (Dekker, 2011). If normal operations are still running smoothly then the organisation is still operating within its economic boundary although there is always pressured to cut down costs while still operating an effective organisation and competing with others in the same industry (Rasmussen, 1997). This can be problematic because it opens the organisation to ignoring pertinent safe practices and equipment needed to enhance safety as a way of being cost effective.
- **Acceptable performance boundaries:** In a competitive environment, economic success means moving beyond the usual operational boundaries considered as acceptable practices and exploiting its benefits (Reason, 1990). Nevertheless, this could result in crossing limits on safe work and practices. This, however, is directed towards naturally migrating towards acceptable performance boundaries as opposed to high productive target. Due to the unpredictable nature of human behaviour, objectives and constraints need to be enforced and followed by management and workers respectively to enhance work performance (Hollnagel, 2014). Having high productive targets would mean exploiting the boundaries of freedom by leaving them open while being guided by certain principles such as cost effectiveness, workload, risk of failure and joy of exploration.

The capacity of humans in the system is reflected by the performance boundary (Hollnagel, 2014). Due to the large amount of work that needs to be completed with a stipulated time to drive productivity, humans tend to take shortcuts to minimise the amount of work to be done (Dekker, 2011). The boundary of acceptable performance when crossed, tend to push back, sometimes more aggressively against the economic and work system constraint boundaries (Woods *et al.,* 2017). The acceptable boundary includes a marginal boundary which alerts or signals closeness to disaster (Leveson, 2011). This serves as a safety margin which offers some leeway in the system (Snook, 2000).

The likelihood of an accident occurring is lower if the safety margin is wider (Perrow, 1999). Creating robust, measurable key performance indicators (KPIs) could serve as a safety margin (Hopkins, 2009). However, since these safety margins are artificially created, they generate extra costs which causes actors to push against the margins from time to time to save cost (Weick and Sutcliffe, 2001). Most often, it is successful hence, actors continuously challenge the marginal boundary with the intention of pushing it further permanently (Turner & Pidgeon, 1997). However, over time, as accidents do not occur, actors would become oblivious of the accident boundary and a sequence of low probability events could push the system into the accident boundary leading to injuries and other consequences (Reason, 1997).

4.1.3.4 The structural equation model (SEM)

The adequacy of SEM was evaluated (Tomas et al.,1999) to control occupational accidents. This approach suggested that accidents result from a complex chain of events hence the introduction of a SEM to control this complexity. Although most accidents are attributed to human errors, there is a need to analyse this deeper by investigating significant risk factors such as insufficient attention to details, worker behaviour towards safety, lack of training and the processes employed by management in investigating unsafe worker behaviour (Dekker, 2008). The proposal of the use of safety-indicator questions such as appropriate operation of plant and machinery, whether safety rules were followed, intake of alcoholic substance while at work etc., to assess safety behaviour on site can be adopted in construction (Guo *et al.,* 2016). The assessment made resulted in the following assumptions:

- That workers' behaviour is majorly impacted by attitude towards safety.
- Accident occurrence is because of safety behaviour.
- The ability of workers to manage inherent hazards is not the determinant of accident occurrence however, the primary source is the hazard itself.

After statistical assessment, these assumptions lead to the conclusion that:

- There exists a chain of substantial illustrations that linked safety climate, to co-workers, site leads and worker behaviour towards disaster and safety performance.
- The impact of safety climate on safety behaviour or co-workers' response was negligible.

- The response of leaders had significant impact on attitude and safety behaviour as well as co-workers' response.
- Well trained and resourced staff are capable of managing hazards hence, the influence of hazards on accident occurrence was not immediate.
- The attitudes of workers create behavioural patterns which in turn affects the likelihood of an accident occurrence.

In conclusion, this model posits that the number of accidents is insufficient in measuring safety however, merging it with how severe the three previous accidents were, is a better alternative (Hollnagel, 2014). Unsafe worker behaviour, lack of hazard alert and proper preparation for hazards, contribute to eventual accident occurrence in contrast to the idea that hazardous effects on workers causes accidents (Reason, 2006).

4.2 RESULTS FOR SAFETY RISK MODEL DEVELOPMENT

The articles selected for this review were published between 1990 and 2022. The year 1990 is selected as the starting point because the articles sourced from previous years were observed to have limited impact on the research. Using VOSviewer, analysis of all keywords present in the selected literature was conducted by selecting keywords which occurred at least five times. Of all keywords (i.e. 2,593), only 162 keywords met this threshold. 'All keywords' was used as a criterion in keyword selection instead of 'author keywords' or 'index keywords' to present a more detailed and comprehensive picture of the prevailing academic discourse on the phenomena under investigation. Selecting 'all keywords' prevented bias when viewing topics within the subject based on the authors' perspective and knowledge. However, it was recognised that this could result in superfluous information within the visualisation making it complex and difficult to interpret or manipulate (Van Eck *et al.*, 2019). Therefore, keywords that had little impact in terms of weighting, synonymous terms (such as 'human' or 'humans'), and uninfluential keywords such as male female, article, priority journal etc. were manually screened out, resulting in sampling 141 keywords for analysis.

4.2.1 Co-occurrence of keywords

The network visualisation (refer to Figure 4.3) uses an overlay illustrating eleven prominent keywords that indicates topical areas where risk theories and models have been applied. These include 'occupational risk' (frequency(*f*)= 121); 'accident prevention'(*f*= 108); 'safety' (*f*= 63);

‘human’ (*f*= 82); ‘risk assessment’ (*f*= 64); ‘accident’ (*f*= 63); ‘occupational accident (*f*= 56)’; ‘occupational safety’ (*f*= 55); ‘risk management’ (*f*= 31); ‘safety management’(*f*= 42); and, from a wider perspective, the ‘construction industry’ (*f*= 43). The predominance of these keywords highlights the adoption of theories and models for enhancing occupation health and safety to prevent accidents. Furthermore, the green and yellow color-coded nodes illustrate the keyword ‘human’= (*f*=82) is predominantly used between 2013 and 2014, ‘construction worker’ (*f*=13) and ‘worker’ (*f*=7) which is more recently adopted between 2018 and 2021 has the same meaning. This could imply that the focus on the human element in theory and model building remains prominent in literature. The keywords in yellow shows the most recent trends and direction of models in safety focus on: ‘prediction’ (*f*=7); ‘project management’ (*f*=9); ‘human resource management’ (*f*=23), ‘construction worker’ (*f*=13); ‘occupational injury’ (*f*=7); ‘construction equipment’ (*f*=5); ‘procedures’ (*f*=5) and ‘risk perception’ (*f*= 9). This trend suggests a shift from reactive systems such as ‘laws and legislation’ (*f*=8) and ‘risk reduction’ (*f*=9) between 2010 and 2012 to more proactive systems such as ‘prediction’(*f*=7) and human resource management during 2016-2018.

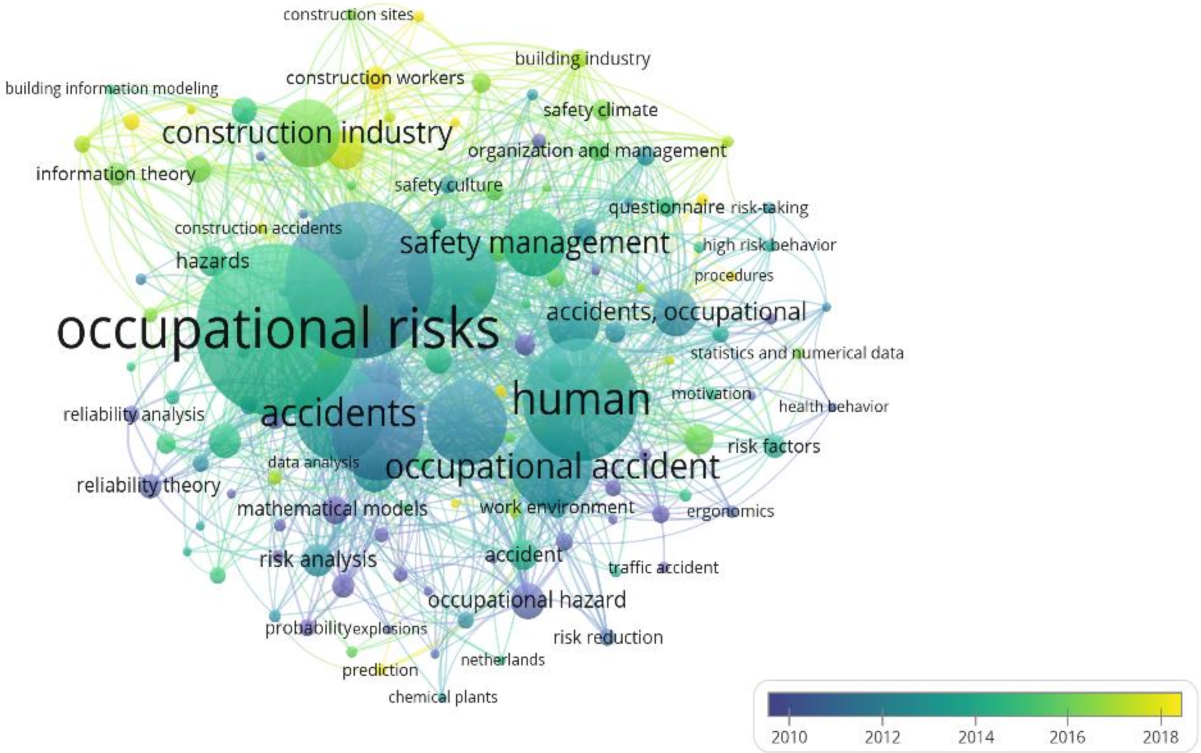


Figure 4.3 - Network map of keyword co-occurrence

4.2.2 Existing safety risk theories and models

The purple, blue and deep green nodes show a trend of keywords that dominated between 2010 and 2015. This trend displayed keywords such as ‘risk analysis’ (*f*=12), ‘occupational hazard’ (*f*= 20), ‘occupational risk’ (*f*=121), ‘occupational accident’ (*f*=56), ‘human’ (*f*=82) and ‘safety management’ (*f*=42). These keywords demonstrate the focus of existing theories and models of safety risk. In comprehending and significantly influencing safety risk challenges, theories and models have been developed to effectively explore occupational safety risk problems in terms of occupational accidents and occupational hazards. For example, Lees (1996) justified the effectiveness of models and theories in the investigation of safety risk incidents and accidents. Investigating an incident is essential to understand why it occurred in order to forestall future occurrence. Early theories and models have seen several researchers propose theories and techniques to aid this process (Embrey,1992; Booth,1980; Rasmussen, 1980; Rasmussen, 1982; Gordon, 1949). For example, Heinrich (1941) proposed a domino theory where the central premise focused on human behaviour. A modification to Heinrich’s theory (*ibid*) was proposed by Bird *et al.* (1974) by including management and organisational aspects in the causal factors in incidents. Whittington *et al.* (1992) discovered the role of management errors as major contributors to incidents in the construction industry. On the issue of worker distractions, Hinze (1996) proposed a distraction theory where the risk of a construction incident increased due to worker distractions.

Abdelhamid and Everett (2000) developed a model for identifying root causes of construction incidents as worker attitudes, training and procedures. The limitation with this model however, is attributed to the fact that it ignores systemic root causes that might explain why procedure, for example, failed and caused an incident. Following this limitation, Gibb *et al.* (2004) proposed additional inquiries targeted at leadership, culture, project management decisions and design inadequacies. Proximal and distal factors in construction incidents were identified and proposed by Suraji *et al.* (2001) as an incident causality method. While factors directly related to the incident cause was termed as proximal factors, the research (*ibid*) defined distal factors as those which lead to introduction of proximal factors, such as design complexity and time constraint.

According to Reason (2016), contradiction incident causation theories can be encapsulated by the ‘systems approach’ and ‘person approach.’ The person approach centres on the errors of individuals such as inattention, forgetfulness, or moral weakness, whereas the system approach focuses on conditions under which the individual works and attempts to build defences to avert errors or mitigate their effects. A comprehensive management program aimed at several different targets such as the person, task, team, workplace and the institution as a whole is needed to make the systems approach work effectively (Reason and Reason, 1997). According to Burgoyne (1982) maximum attention to detail must be placed on investigating an incident with the aim of extracting the highest amount of knowledge from the experience and to disseminate the knowledge in the way that forestalls future occurrences and ensure personnel safety. The term 'root cause' is widely used in practice and must be explored to the point where there is nothing further to investigate. Investigators often find difficulty in reporting deep-rooted findings of incidents which are as a result of organisational policy or culture and hence, mostly settle at employee-based causes (Kletz, 2002).

4.2.3 The trend and future direction of theory and model building

The keywords in yellow show the most recent trends and direction of models in safety risk focus on: 'project management' (*f*=9); 'human resource management' (*f*=23), 'construction worker' (*f*=13); 'occupational injury' (*f*=7); 'construction equipment' (*f*=5); 'procedures' (*f*=5) and 'risk perception' (*f*= 9); 'prediction'(*f*=7). Recently, the disintegrated nature of construction work activities has made it imperative that safety risk is considered on a project basis instead of the previously generalised sole safety considerations made for the entire organisation (White and Fortune, 2002; Demirkesen and Ozorhon, 2017). Safety risk is now managed on a project basis as a divide and conquer approach highlighting the influence of project management on safety risk management (Badri *et al.*, 2012; Manu *et al.*, 2014). The models and theories reviewed predominantly focus on human error as a major cause of accidents and it is not coincidental that 'construction worker' and 'human resource management' feature as trends within model building. Human resource management is a vital contribution to a developing domain such as safety cultures, which requires a modification in staff safety perception and work behaviour to prevent occupational injury (Palmieri *et al.*, 2010). The procedure involved in task performance and the equipment used is another trend considered. Although human errors are considered a root cause of accidents, in some instances, human errors are only a reflection of system lapses.

Any ambiguity in the description of work procedure (Embrey, 1992), inadequate personal protective equipment or faulty machines could cause human errors which result in accidents or injury. Hence, the requirement to investigate these factors and include them within theory and model building. One major change of safety risk management in current trends is a notable shift from reactive systems such as ‘laws and legislation’ (*f*=8), ‘risk reduction’ (*f*=9) between 2010 and 2012 to more proactive systems such as ‘prediction’ (*f*=7) (Zhang *et al.*, 2019). Thus, prediction of safety risks and accidents before they occur (via lead indicators) as a preventive method rather than existing mitigation methods which are more reactive.

4.2.4 Categorisation of significant keywords

The clustering of the keywords displayed in the map projected certain keywords which highlighted a number of perspectives on the trend of theory/model adoption and application. These conspicuous keywords were grouped and interpreted in Table 4.1 as: the prominent theories most considered; the domains these theories/models have been applied most; the key safety-indicators presented within the map; and what data collection methods have been applied most frequently. Another noticeable element within the map was the various keywords used to describe workers. This could stem from how significant human elements are considered in safety model building. The highway operation industry is also not featured in the domain area for model application. This could support the proposition that scant research has been done on highway worker safety (Hancher *et al.*, 2007) - at least in academia. Instead published papers analysed showed that health and safety of workers has been generalised to encompass all construction activities and consequently, the term ‘construction worker’ is the generalised term used to describe the staff in construction industry with no mention of highway workers specifically.

Table 4.1 – Keyword Categorisation

Category	Keywords	Frequency (f)	Percentages (%)	Citations
Prominent Theories/ models	Information theory	13	8.8	Akaike (1973), Bauk *et al.*, (2017)
	System theory	25	17.0	Embrey, (1992), Rivas *et al.*, (2011)
	Theory of planned behaviour	11	7.5	Heinrich (1941), Grant and Smiley (1993)
	Reliability theory	14	9.5	LaPorte and Consolini (1991), Roberts (1990)
	Mathematical models	16	10.9	Kjellen and Sklett (1995), Wells *et al.*, (1992)
	statistical models	5	3.4	Johnson (1980), Munteanu and Aldemir (2003)
	bayes theory	5	3.4	Alizadeh *et al.*, (2015), Amiri *et al.*, (2016)
	Bayesian network model	9	6.1	Eleye-Datubo *et al.*, (2006), Gerassis *et al.* (2017)
	Fuzzy set theory	9	6.1	Ardeshir and Mohajeri (2018), Nieto-Morote and Ruz-Vila (2011)
	Structural equation model	11	7.5	Tomas, Melia, and Oliver, 1999
	Regression analysis	8	5.4	Rivas *et al.*, (2011)
	Decision theory	13	8.8	Ehrenberg *et al.*, (2000), Eleye-Datubo *et al.*, (2006)
	Laws and legislations	8	5.4	Perneger (2005), Rasmussen (1980)
Domain	Construction industry	43	36.4	Azmy and Zain (2016), Hallowell and Gambatese (2009)
	Building information modelling	14	11.9	Al-Saeed *et al.*, (2000)
	Tunnel construction	11	9.3	Choudhry, Fang, Mohamed, 2007
	Coal mines	7	5.9	Wu *et al.*, (2011)
	Traffic accident	6	5.0	Booth (1980)
	Transportation	5	4.2	Fosser *et al.*, (1996)
	Building industry	10	8.4	Al-Saeed *et al.*, (2020), Roberts *et al.*, (2021)
	Mining	7	5.9	Donoghue (2004)
	Agriculture	6	5.0	
Definition words for	Operatives	8	24.2	Choudhry *et al.*, (2008)
	Worker	13	39.4	Johnson (1980), Newnam and Watson (2011)

human factor	Construction worker	5	15.2	Mohammadfam *et al.*, (2017)
	Employee	7	21.2	Carter and Smith (2006)
Key Safety-Indicators (factor)	Safety climate	12	12.6	Teo and Feng (2009),
	Safety culture	11	11.5	Choudhry *et al.*, 2007, Ardeshir and Mohajeri (2018)
	High risk behaviour	7	7.4	
	Risk	25	26.3	Choudhry *et al.*, (2008)
	perception/perception.	10	10.5	Chen *et al.*, 2018
	Safety behaviour	5	5.3	Mohammadfam *et al.*, (2017)
	Task performance	20	21.1	Embrey (1992), Reason and Reason, (1997)
	Industrial hygiene	5	5.3	
	Construction equipment			

4.2.4.1 Information Theory, Technology, and safety models

Information theory is an emerging area in the health and safety domain with an average publication year of 2016 and f=13 occurrences in the keyword analysis and represents encapsulates the study of storing, measuring and transmitting digital information (Riaz *et al.*, 2011). This is of particular interest because it encapsulates all the prominent theories and models including statistical models, bayes theorem, Bayesian models etc. listed in Table 4.1 (Shannon, 1940). The type of information that this theory handles are uncertainty based, hence, it is considered a useful component in influencing highway operation safety that are characterised by fuzziness and uncertainty. Information theory has recently become prominent in the occupational health and safety domain. For example, Zhuang *et al.*, (2016) implemented information theory in investigating safety passage planning for system shoring supports with building information modelling (BIM). Bauk *et al.*, (2017) adopted it for communication to increase occupational safety at a seaport and enabling a powerful marine and offshore decision-support solution through a Bayesian network technique (Eleye-Datubo *et al.*, 2006). The impact of information theory has been crucial to its application in areas such as: model selection (cf. Burnham and Anderson, 2002); data analysis (cf. Akaike, 1973); pattern recognition; and anomaly detection (cf. Howard, 2007). Information technology advancements such as BIM have been influential in safety management (Tixier *et al.*, 2016) and has required the digitisation and digitalisation of safety related data. The close relationship between ontology and information technologies can be explored to develop knowledge-based safety models (Guo and Goh, 2017, Lu *et al.*, 2015) that could analyse and predict safety risks and accidents (Rivas *et al.*, 2011). Data analytics could also be adopted in implementing safety leading indicators useful in safety risk prediction (Salas and Hallowell, 2016).

4.2.4.2 The relationship between human element (human resource management), key safety indicators and domain application

Theories and models have focused on human centred themes to continually investigate and provide measures for errors (Choudhry *et al.*, 2008; Johnson,1980; Newnam and Watson, 2011). This is evident in the various keywords used in emphasising human involvement in safety risk literature such as operatives, workers etc. However, humans remain versatile and constantly alter their actions based on situations rather than procedures (Edwards and Holt, 2014). These actions could be influenced by key safety indicators such as worker perception about risk, behaviour, the safety climate and safety culture (Edwards and Holt, 2008; Ardeshir and Mohajeri, 2018; Chen *et al.*, 2018). Therefore, focus on human errors have been expanded to include more proactive indicators such as risk perception, safety climate and safety culture in contemporary safety risk models and theories to address the human contribution to safety risk events. The different ways workers perceive risk, their performance and their attitudes create behavioural patterns, which can be associated with their demography (Lyu *et al.*, 2018) and safety climate factors like co-worker attitude and safety awareness (Choudhry and Fang, 2008). Other studies reveal the integral part safety climate plays in safety culture (Guldenmund, 2000, Marquardt *et al.*, 2012). Safety climate has a situational, behavioural and psychological influence on safety climate (Teo and Feng 2009) hence, analysing safety climate could enable the prediction of safety culture and further impact safety performance. Human resource management is also an emerging trend noted between 2018 and 2021. This is particularly important given that highway operation is characterised by different groups of contract workers and contingent workers such as highway engineers, road maintenance operatives, traffic officers and inspectors.

4.2.4.3 Predictive safety models

Predictive models provide insight into future events (Oloke *et al.*, 2006). From the scientometric analysis and categorisation of the keywords, it is inferred that safety risk management is moving from a reactive approach to a more proactive approach through prediction for prevention. The trend in using prediction in safety management provides a proactive approach to handling risks and accidents. Predictive models and frameworks are associated with planning and strategy with specific emphasis on foreseeing future disruptions in a system (Rivas *et al.*, 2011; Salas and Hallowell, 2016). Safety risk data in construction is characterised by its large volume, velocity, value and variety which are all features of big data (Huang *et al.*, 2018). Therefore, big data analytics can be used in building ML predictive models based on existing and historical data available with a more robust storage facility. Gerassis *et al.* (2017) used data mining and attribute selection techniques to identify the main predictors of accidents related to embankment construction, then built Bayesian networks to predict the individual causes of various accident types. Amiri *et al.* (2016) employed decision trees, association rule and multiple-correspondence analysis which resulted in identifying a significant relationship between time of accident, accident location and the part of the body impacted by the accident. Workers who are mostly prone to fatal accidents have also been identified and classified using Bayesian theory where, by ranking the risks involved, the result was applied to training workers to reduce accidents and safety risk issues on site (Alizadeh *et al.*, 2015). Knowledge from these previous works could be employed in building an accident prediction model for highway workers.

4.2.5 Classification of models

From the classification analysis technique and grounded theory analysis, the reviewed models and theories were categorised into seven thematic classifications based on their features, processes, domain, idea and application; each category's benefits and limitations were also compared to reveal the strengths and weaknesses of these classified theories and models (refer Table 4.2). The dearth of studies reviewed demonstrates the benefits and limitations of each of the seven model categories presented.

Table 4.2 - Model classification.

Thematic Classification of Model/ Theories	Features	Benefits	Limitations	Authors
Element Theories/Models	Characterises the unique participating elements and components that make the model	Its holistic nature allows individual weakness and solutions to be identified. Reveals individual parts' contribution to model. Enables proper distribution of human resources and structures.	Does not identify the interconnection between components. May not reveal political or representational elements. Analysing actions and processes are challenging. 4.Results are difficult to describe.	Embrey (1992), Burns and Machado (2009), Booth (1980), McGraw et al. (2008), Rasmussen (1980), Rasmussen (1982), Rasmussen (1997), Gibson (1961), Gordon (1949)
Incentive Theories/Models	Characterises the actions and initiatives that enhances safety with feedback elements	Identifies the role management can play to enhance safety. Highlights contributions and responsibilities of workers and management Enables proper distribution of human resources and structures. Robust insight into results	1. Does not identify the interconnection between components. 2. May not reveal political or representational elements 3. Its focus on specificity may make it unable to be applied holistically	Rasmussen (1980), Kerr (1957), Wilde(1985a), Johnson (1980), Newnam and Watson (2011)
Quantitative Or Statistical	identifies the connection between events and incidents by quantifying data and finding patterns.	It has evident based outcomes Decisions taken are backed by evidence Gives insight into results and relationships	Its focus on specificity may make it unable to be applied holistically Does not recognise all components 3. Contextual considerations need to be made when in use	Kjellen and Sklett (1995), Kjellen (1995), Wells et al., (1992), Johnson (1980), Munteanu and Aldemir (2003)
Sequential	Identifies a chain of events that leads to an accident	Gives insight to causes of failure At micro level, provides good examination Relationships between causal components are described explicitly Focuses on human error and how it could be prevented	Does not reveal contributions to success At strategic level, it is challenging to apply to more complex systems Effects are not identified May not reveal political or representational elements	Heinrich (1931), Haddon(1968a), Cameron (1992)
Behavioural	Identifies the unsafe behaviour and attitude of workers as leading causes of accidents	Normally based on safety climate Could be generally applied to several situations General focus on parts and purpose Reveals human resource management qualities	Its generalization feature may prevent it from being used in specific instance May not reflect on all connections Challenging to recognize all chances for solutions Guidance on specific activities and situation is scarce	Brown et al. (2000), Tomas et al. (1999)

Barricade	Safety is measured based on the effectiveness of barriers erected.	Provides defences against failure Gives insight to causes of failure At micro level, provides good examination Relationships between causal components are described explicitly	Does not reveal contributions to success At strategic level, it is challenging to apply to more complex systems Effects are not identified	Reason 1990, Hopkin (2007), Bellamy et al., (2008), Ekanem and Mosleh, (2014)
Resilient Models	Focuses on the ability of a system to handle varying conditions and the how long it takes to be restored to normal conditions after a disturbance occurs	Gives insight to contributing successes Provides shocks for the system 3. Allows system to return to normal functions after failure	1. Cannot predict future situations 2. Only focuses on present The magnitude of relationships and components could make it too complex for application.	Hollnagel et al. (2006); Wood and Wrethall (2003); Woods et al. (2010); Hollnagel (2017)

All models and theories identified in this review could potentially be applied to highway worker safety risk mitigation however, many components characterise highways construction and although these components work comparatively independently, they interact closely with each other over a period. Therefore, individual purposes and context determine which model or theory will be applicable. Comparing models' features based on resilience theory (Hollnagel *et al.*, 2006; Woods *et al.*, 2010) with the models classified in Table 4.2, found that the variety of models classified are not entirely independent of each other and demonstrate features that other models possess also. While all of these different models propose different means for safety risk mitigation, only models based on resilient theory provide alternatives for adaptability and recovery even if incidents or accidents occur. The resilience theory approach has the ability to inculcate all significant factors, elements and results of the other models classified if thoroughly applied to highways construction.

4.2.6 Resilient predictive models

Resilience is the inherent capability of a system to adapt its operation before or after any modifications and disruptions to carry on with performing its functions when hit by a major catastrophe (Hollnagel *et al.*, 2006). This is based on the resilience theory (Woods and Wreathall, 2003). Resilience promotes a holistic view of how a system adjusts dynamically and changes to promote the continuity of safer operations (Hollnagel, 2015). It focuses on effectively using resources to proactively anticipate and manage risks (Chen *et al.*, 2018). This however is not the same as predictive modelling although there are similar characteristics (Imani *et al.*, 2021). While predictive models handle future disruptions and focuses on planning for these, resilience engineering (resilient models) focuses on the current system and its response to disturbances, its adaptability and the pace for recovery back to normal activities. The resilient measures (data) generally recognised include awareness, safety culture, anticipation, management commitment, flexibility, reporting culture and safety climate (Woods and Wreathall, 2003; Azahdeh *et al.*, 2014; Ferreira, 2011). Adaptability, response to incidents and system recovery are gaps in predictive models which could be addressed by introducing resilient features into the predictive models. This chapter therefore presents a predictive model which has resilient capabilities. This model will predict the probability of safety risk events occurring and if unavoidable, resilient features will provide shocks to enable recovery.

4.3 DISCUSSION

Early safety risk theories and models (Heinrich 1941; Whittington *et al.*, 1992) focused on human errors and behaviour as the major risk contributors in an organisation. Others (cf. Bird *et al.*, 1974) later included lack of or inadequate management responsibilities in their models. Several other safety risk models were developed based on earlier models proposed and irrespective of improvements made, the human factor in safety risk management was not made redundant (Hollnagel, 2015). This demonstrates how indispensable humans are in safety risk model/ theory building therefore any model developed to address safety risk challenges should consider human factor elements and include key leading indicators that proactively measure human involvement in safety risk events (Grabowski, 2007).

A trend in future direction represented in the keyword co-occurrence analysis showed that the focus of safety risk research is moving towards ‘project management’ (Ershadi *et al.,* 2020), ‘human resource management’ (Liang et al., 2020), ‘construction worker’ (Palmieri *et al.*, 2010), ‘risk perception’ (Ardeshir and Mohajeri, 2018) and ‘prediction’ (Tixier et al., 2016). The literature reveals that, safety risk challenges are being handled on project basis to personalise safety risk measures and solutions put in place (Ershadi *et al.,* 2020). The keywords ‘human resource management’ and ‘construction worker’ (Singh et al., 2020) highlights that concentration on the human factors in safety risk and this is emphasised by the different terms used to describe humans in the categorised keywords section. Theories and models have focused on human centred themes to continually investigate and provide measures for errors. However, the versatility of humans remains constant such that, they respond to situations rather than procedures and this has led to varying human safety indicators to look beyond error to including leading indicators such as risk perception, safety climate, safety culture and worker behaviour (high risk behaviour). The keyword ‘prediction’ was also presented as a recent trend and future direction for safety risk models and theory research (Pavlou, 2015). Existing models and theories focus more on a reactive mitigation of risk after it has occurred rather than proactive prevention of risk before they occur (Blismas *et al.*, 2005). Yet, predicting safety risk could help avert misfortunes and accidents.

Inculcating information technology into safety risk model research and digitalisation has been seen in current trends (Lee *et al.,*2019). Keywords such as ‘bayes theory’ (Alizadeh *et al.*, 2015), ‘Bayesian network model’ (Zhang et al., 2013), ‘fuzzy set theory’ (Ardeshir and Mohajeri, 2018) and ‘regression analysis’(Freund *et al.,* 2006), indicate the presence of technology in the field of ML and data analytics in safety risk model research. Information theory and fuzzy sets have been widely used to identify patterns in data for analytical insight (Hüllermeier, 2011) while Bayesian network models, and regression analysis models have predictive abilities that can be applied to predict safety risk levels before they occur (Zhang et al., 2013).

Based on similar features, processes, domains, ideas and applications, the various models identified were classified. Comparing the strengths and limitations of the models and theories revealed that the variety of models classified are not entirely exclusive and demonstrate features that are inherent in other models. However, individual purposes and context determine which model or theory will be applicable. From the literature, it was discovered that only models based on resilient theory (resilient models) had the ability to adapt and recover after an incident occurs. Predicting safety risk incidents or safety risk levels is a huge step toward prevention of an accident or loss occurrence in an organisation, nonetheless, predicting future occurrences only helps in anticipating and planning for these risks without any provision for adaptability and recovery in the event that the risks predicted are unavoidable. This leaves a gap for predictive models which have inherent resilient features capable of recovery in event of an inevitable predicted safety risk.

Premised upon the analysis of literature, this section proposes a concept of a digital predictive model enhanced with inherent resilient features (refer to Figure 4.4) to develop a conceptual framework known as a resilient predictive model (P_r). The resilient measures (data) generally recognised from the literature include awareness, safety culture, anticipation, management commitment, flexibility, reporting culture and safety climate. This data will be collected through secondary data such as worker satisfaction surveys, accident data and primary data collection through interviews with highway workers. This data will be added to variables that will be incorporated in building a predictive ML model. The types of models studied have provided diverse knowledge in the field of safety risk mitigation. While some have taken a holistic approach towards mitigation and control of construction risk, others have dealt specifically with other domains such as mining, coal mining, tunnel construction etc. However, no presently available model has adopted a predictive model fused with resilient capabilities in the highway operation domain.

The data collected will be pre-processed and cleaned through data transformation and reduction techniques such as normalisation and attribute selection. This process is to decrease the size of data and limit it to only the most important information and increases the accuracy and efficiency of ML models. ML models such as Bayesian models, SVM, RF, and DL models such as ANN and RNN will be applied to the data to build different predictive classification models. The model building process will involve a random selection of 70% of the data for training and 30% for testing and verification. the different models built will be compared, evaluated and validated. Metrices that will be used to evaluate the ML and deep learning algorithms include classification accuracy, confusion matrix, f1-score, and AUROC. K-fold cross validation and bootstrapping will then be employed in validating the results of the model to properly understand the model and estimate an unbiased generalization performance.

Figure 4.4 - A schematic diagram of the resilient predictive conceptual model

4.4 SUMMARY

Safety and risk are omnipresent challenges confronting the construction industry, despite the health and safety improvements that have been made. Previous research undertaken has provided numerous insights into fostering construction safety performance including the construction of models and theories which guide safety activities. This section adopted a bibliometric mapping approach by conducting a comprehensive keyword analysis to identify new trends in model building using the VOSviewer software and was based on 607 papers extracted from Scopus. The methods employed included keyword co-occurrence analysis, classification techniques where models and theories were categorised based on similar themes and ideas. Based on the screening of topics and abstracts, areas of active research endeavour were identified namely, ‘prediction’, ‘project management’, ‘human resource management’, ‘construction worker’ ‘occupational injury’, ‘construction equipment’, ‘procedures’, and ‘risk perception’ with prediction and human resource management being prominently investigated during 2018 and 2021. Further analysis of keywords through categorisation further revealed five prominent clusters which included ‘prominent theories/models’, ‘domains’ (where models/theories have been applied), ‘definition of worker’ (terms used to describe worker), ‘key safety indicators’, and ‘data collection methods’ employed. This thesis identified research gaps which included:1) the information theory and technology gap has not been well exploited in building theories and models for safety; 2) the under exploration of theories and models for highway operation as these have been normally generalised to encompass all construction industry activities hence, leaving highway workers vulnerable; and 3) the need for a resilient prediction model that inculcates leading safety indicator and technology such as ML (pattern recognition and prediction), data analytics and the way digitised data is stored. The scientometric keyword analysis provided insight for the future research direction such as applying big data technologies (data analytics, ML, data storage) in safety management.

‘Key safety indicator’ was another influential category which included keywords such as ‘safety climate’, ‘safety culture’, ‘risk perception’ which suggests emphasis on moving towards leading safety indicator as proactive measurements. The emerging trend of leading indicator data such as ‘safety climate’, ‘safety culture’, ‘risk perception’ and reactive safety indicator data such as ‘high risk behaviour’, ‘safety behaviour’, ‘task performance’ were inculcated into building a resilient model. This was done on the basis of resilience theory, while big data technologies such as data analytics and pattern recognition were inculcated into building a predictive model based on information theory principles. These two concepts were combined to create a resilient predictive safety model which was proposed in this chapter, as an alternative in handling highway operation risks. This will help management in making safer decisions based on empirical knowledge.

This chapter begins the early conceptual stages of a proposed prediction model with resilient features. This concept does not evaluate the most significant factors of resilience and prediction that has major impact on highway operation safety. This is a conceptual model under development. Ensuing chapters will build a prototype model by exploring in-depth, the proposed model by investigating various ML architecture that could be employed in building predictive models with resilient model data through deductive and stochastic modelling to test the new emergent model presented. Also assessing the user adaptability and acceptance as well as industry readiness of employing various big data technologies in construction safety management.

CHAPTER 5- A CONCEPTUAL FRAMEWORK FOR SAFETY INDICATOR-BASED INPUT VARIABLE SELECTION FOR MACHINE LEARNING RISK PREDICTION MODELS.

5.1 INTRODUCTION

The transportation sector is an inherently dangerous industry (Smirnova, 2021). HSE records indicate that in the five years before 2003, 60 sector employees lost their lives, nearly 5,000 severely wounded, with an additional 23,000 sustaining injuries severe enough to require a three-day absence from work (HSE, 2003). The highway industry (an integral part of the transportation sector) is prone to encounter various elevated health and safety (H&S) risks due to the nature of work conducted and proximity to live traffic which could result in incidents, accidents or injuries (Mendeloff and Staetsky, 2014, Eseonu *et al.*, 2018). These risks constitute a major concern in the highway industry because of the staggering number of omnipresent fatal and non-fatal incidents which carry concomitant high compensation claims and exorbitant mitigation costs (Eseonu *et al.*, 2018). According to Highways England (2018), over 300 incidents of incursions and verbal abuse on highway workers are recorded each week with circa 150 workers involved in serious injuries.

Traffic operations play a significant role in highway operations, maintenance and management and the on-road HTOs are critical workers who have a quintessential role in ensuring that traffic operations are handled smoothly (Cattermole *et al.*, 2013). Motorists and other road users' safety is significantly enhanced by HTOs who conduct periodic traffic stops, enforce traffic regulations and aid drivers and road users when their vehicle has broken down (Marsh, 1927; Pollitt, 2009). Despite the HTOs' vital role in traffic management, they are often exposed to various H&S hazards while executing their daily duties (Eseonu *et al.*, 2018). Typical H&S risks faced by HTOs include physical and mental health hazards often attributed to contact with hazardous materials, stress and fatigue (Pollitt, 2009). In some cases, HTOs face certain less controllable events such as verbal abuse and physical assault while performing their duties, particularly during traffic stops, responding to accidents or while patrolling the roads (Cattermole *et al.*, 2013). Other safety challenges which compromise the safety and effectiveness of HTOs include inclement weather-related dangers such as extreme heat, cold, rain and snow (Cattermole *et al.*, 2013).

Various methods have been adopted to mitigate risk incidents on work sites and locations. However, current approaches towards managing safety risk in the highway sector are currently more 'reactive' rather than 'proactive' (Ranasinghe *et al.*, 2020). Reactive approaches are shaped by retrospective past historical data to mitigate future occurrences and thus, fail to address future accidents already in gestation (Yorio *et al.*, 2020). Consequently, reactive measures create ‘blind spots’ which provides little or no insights into the factors or events that could engender a future incident (i.e. leading indicators) (Hallowell *et al.*, 2013). To offer insight into accident causes that are developing in real time and to inform site management before the accident happens, a proactive approach to risk management is required which entails assessing risk levels using leading indicators. Grabowski *et al.* (2007) defines leading indicators as events that occur prior to an incident and are important for incident prediction while Hinze *et al.* (2013) refers to them as the foundation of organisational safety culture. Hollnagel *et al.* (2007) also proposed resilience engineering which moves beyond prevention to encapsulate how a system adapts and/or adjusts in the event of an incident occurring. Although early safety risk level detection is made possible by leading indicators, it is imperative to move beyond merely identifying and developing leading indicators, to combining leading, lagging and resilient (Ranasinghe *et al.*, 2020) safety indicators (SI) to build robust risk prediction models capable of predicting incipient incidents and accidents (Bortey *et al.*, 2021; 2022). Such a development would provide an avenue for control systems to adapt and adjust to mitigate risk before an anticipated incident occurs.

A risk prediction model is a statistical model that merges data from various attributes to forecast future events (Pavlou, 2015). Examples include logistic regression models, classification trees or classification neural networks which produces a predicted risk using information input into the model (Cobbinah *et al.*, 2022). Past studies have proposed traditional statistical models for risk predictions and analysis (Mariano and Ozmucur, 2020; Kattan and Gerds, 2020) and although useful, they do contain certain limitations which reduce their predictive capability. For example, when employing traditional statistical modelling techniques, assumptions made about how data is distributed is usually a linear function between independent and dependent variables (Hocking, 2013). These fundamental assumptions made may not always be true and when breeched, inaccurate assessments and erroneous deductions are generated (Hocking, 2013). Furthermore, traditional statistical approaches often fail because they use a selection of variables under consideration instead of employing all the available information on a particular subject (Bhattacharjee *et al.,* 2019). In addressing this challenge, ML methods offer a suitable alternative for identifying complex and non-linear patterns that may be challenging for traditional statistical methods (Poh *et al.*, 2018). Typical examples include: the generalised linear model (Hocking, 2013), Bayesian networks (Tang *et al.*, 2022), multivariable linear regression (Tsoukalas and Fragiadakis, 2016) and decision trees (Zhou *et al.,* 2020). These risk prediction models have been built and applied across various industries ranging from medicine

(Roelen *et al.*, 2018), shipbuilding (Tsoukalas and Fragiadakis, 2016) and construction (Poh *et al.,* 2018). However, a customised prediction model tailored for highway sector's unique characteristics (e.g. incursions, project locations and working close to live traffic) remains elusive (Hancher *et al.*, 2007; Pollitt, 2009). Such unique characteristics are not considered in generalised prediction models built for other industries therefore, justifying the need for a specialised accident risk prediction model tailored for the highway industry.

Given the prevailing knowledge gap, this chapter focuses on the development of a new conceptual framework that offers a strategic approach for combining leading and lagging indicators to create resilient indicators; where the latter delineate the optimum types of input variables selected for highways risk prediction. Associated chapter objectives are to: identify safety-oriented input variables deemed essential for developing a risk prediction model in the highway sector; and present a robust set of influential variables which contributes to a more accurate prediction model, thereby saving lives on the highway.

5.2 RESULTS FROM SCIENTOMETRIC ANALYSIS AND ML SAFETY INDICATOR LITERATURE

Results are presented in a sequential iterative stage order so that the findings of the previous stage, inform the investigation taken in the following stage. Key stages are: i) overlay visualisation of keyword co-occurrence; ii) a detailed overlook of the major SIs discovered from the keywords (leading and lagging); iii) combining leading and lagging indicators to develop resilience; iv) findings from clusters presented by keywords; and v) a comprehensive document analysis using bibliometrix software to unearth specific input variables that can be formulated from SIs.

5.2.1 Overlay visualisation of keyword co-occurrence

An overlay visualisation presents a narrative of the evolution of research within specific areas or fields over time. It visually highlights the progression of years alongside research fields using colour-coded nodes. Blue nodes denote keywords prevalent before 2013, green nodes indicate keywords prevalent between 2013 and 2017, and yellow nodes represent more recent focus areas emerging after 2017 (Posillico *et al.*, 2022).

An overlay visualisation of keywords (Figure 5.1) displays sixteen prominent terms that indicates topical areas where SI have been adopted and applied. These include: risk assessment (frequency (*f*)=189), accident prevention (*f*=119), leading indicators (*f*=150), lagging indicators (*f*=47), safety engineering (*f*=85), key performance indicator (*f*=29), SI (*f*= 20), risk management (*f*=58), safety (*f*=51), health (*f*=32), humans (*f*=59), security systems (*f*=20), safety professionals (*f*=20), managers (*f*=21), professional aspects (*f*=20), safety culture (*f*=25). The predominance of these keywords contextualises the use of key performance indicators which could either be leading or lagging in major H&S subject areas such as risk management, safety engineering, risk assessment and accident prevention.

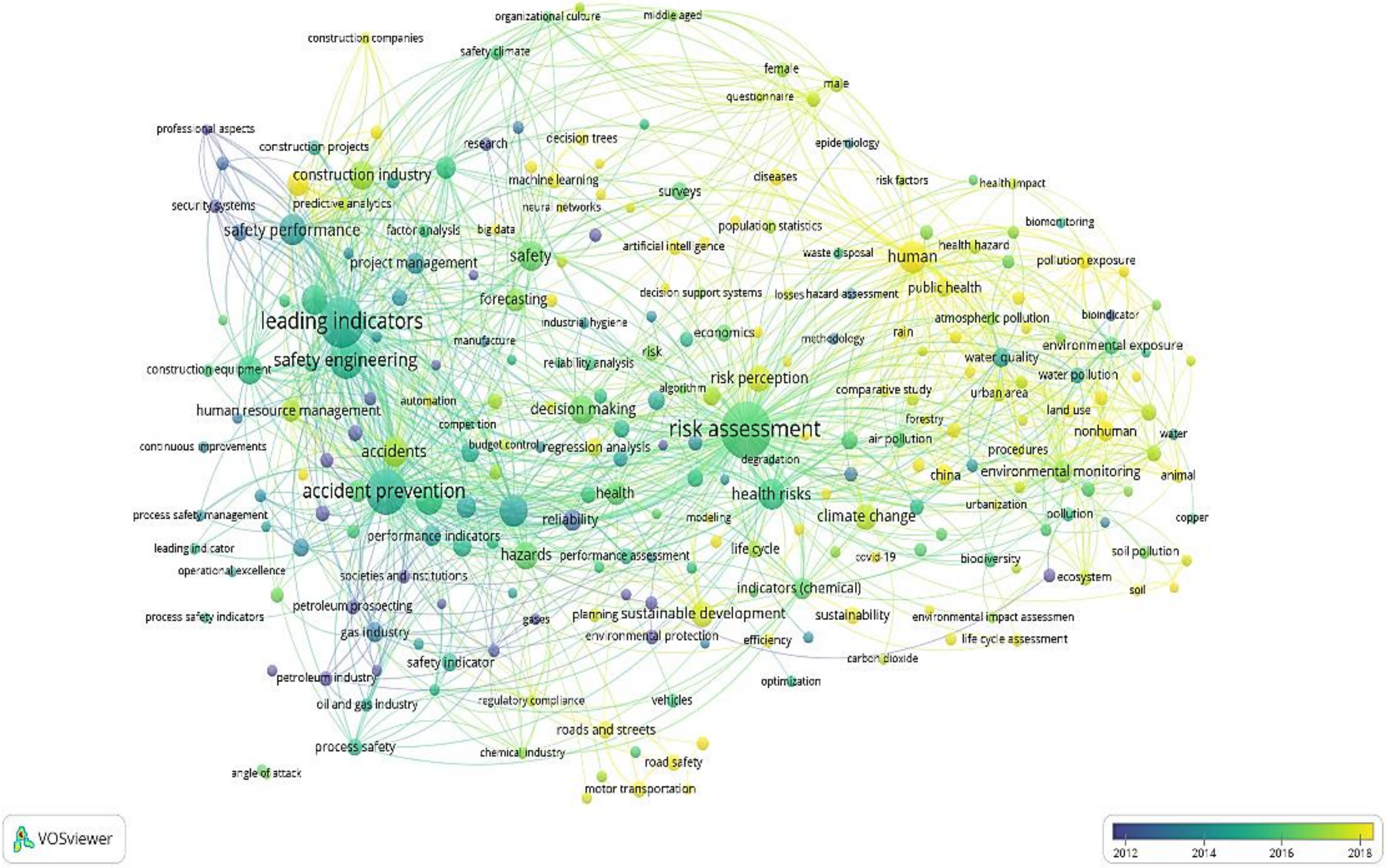


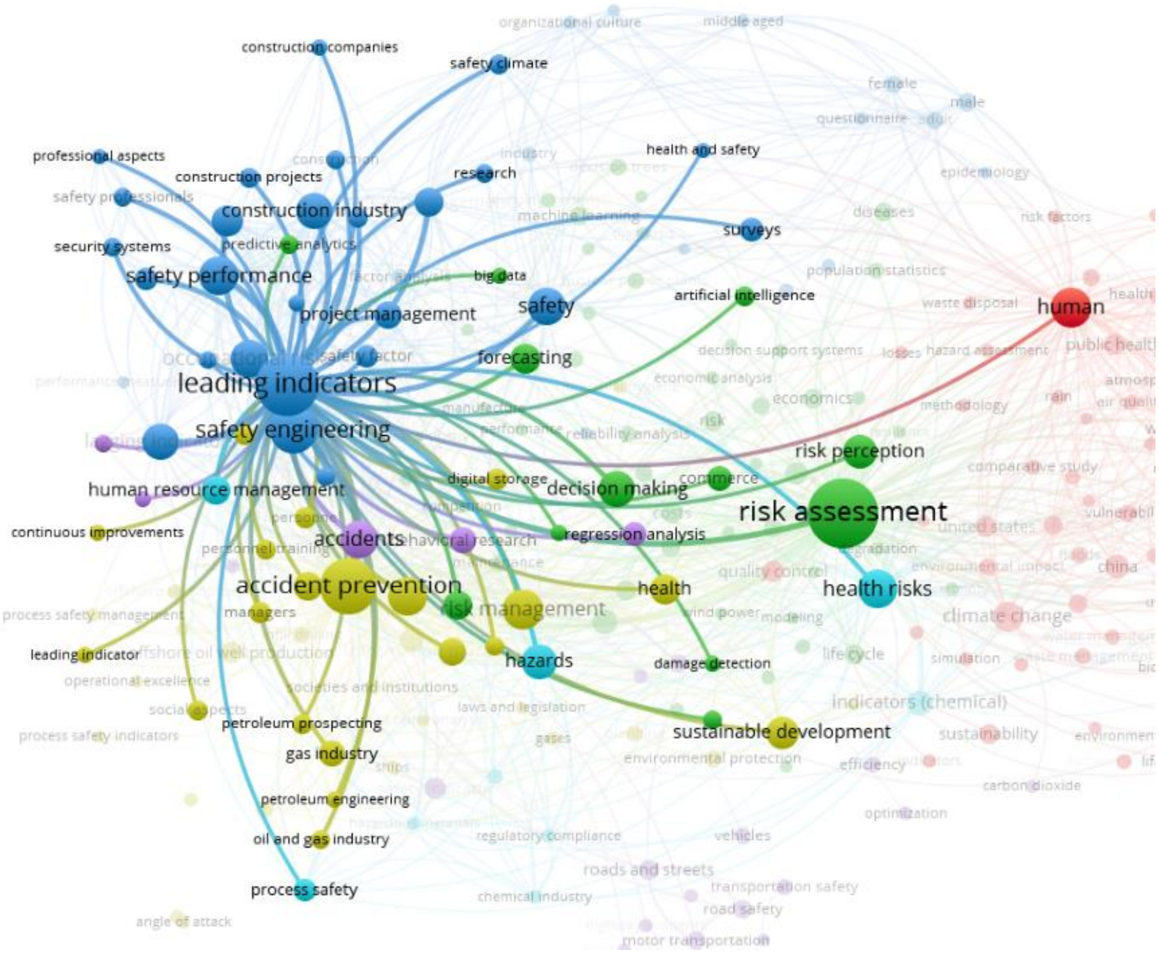
Figure 5.1 - Overlay visualisation of keywords

The most dominant keywords in the articles selected (based on the year of publication) not only display the frequency of terms but also the research direction and trend SI studies have taken over the years through colour coded nodes. Violet nodes present the research direction between 2008 and 2012. Notable keywords include 'managers' (*f*= 16), 'personnel' (*f*= 16), 'security systems' (*f*= 12), 'reliability' (*f*= 27), 'professional aspects' (*f*= 17), 'environmental protection' (*f*= 13), petroleum industry (*f*= 14), petroleum engineering (*f*= 8), petroleum prospecting (*f*= 13). It could be inferred that the research on SI between 2008-2012 was targeted towards improving the reliability of security systems and environmental protection with employees (personnels and managers) as the major focus (Makin and Winder, 2008; Kalantarnia *et al.*, 2010; O'Connor and Kleyner, 2012). The prominent appearance of petroleum in the violet nodes indicates that the petroleum sector had more engagement in terms of SI research during the period of 2008-2012 (Øien *et al.*, 2011; Skogdalen *et al.*, 2011). Major safety events such as the deepwater horizon oil spill in the Gulf of Mexico in 2010 (Upton, 2011) could account for a surge in safety research papers in the petroleum sector during this period. This is because this event drew intense international attention to safety issues in the petroleum industry, prompting increased research and regulations to prevent similar incidents occurring (Beyer *et al.,* 2016). Furthermore, the global financial crisis that began in 2008 also caused an increased scrutiny and re-evaluation of the petroleum sector (Mohan, 2009). Therefore, companies and regulatory bodies may have heightened their focus on safety to ensure operational resilience during challenging economic times (Bouslah *et al.,*2018).

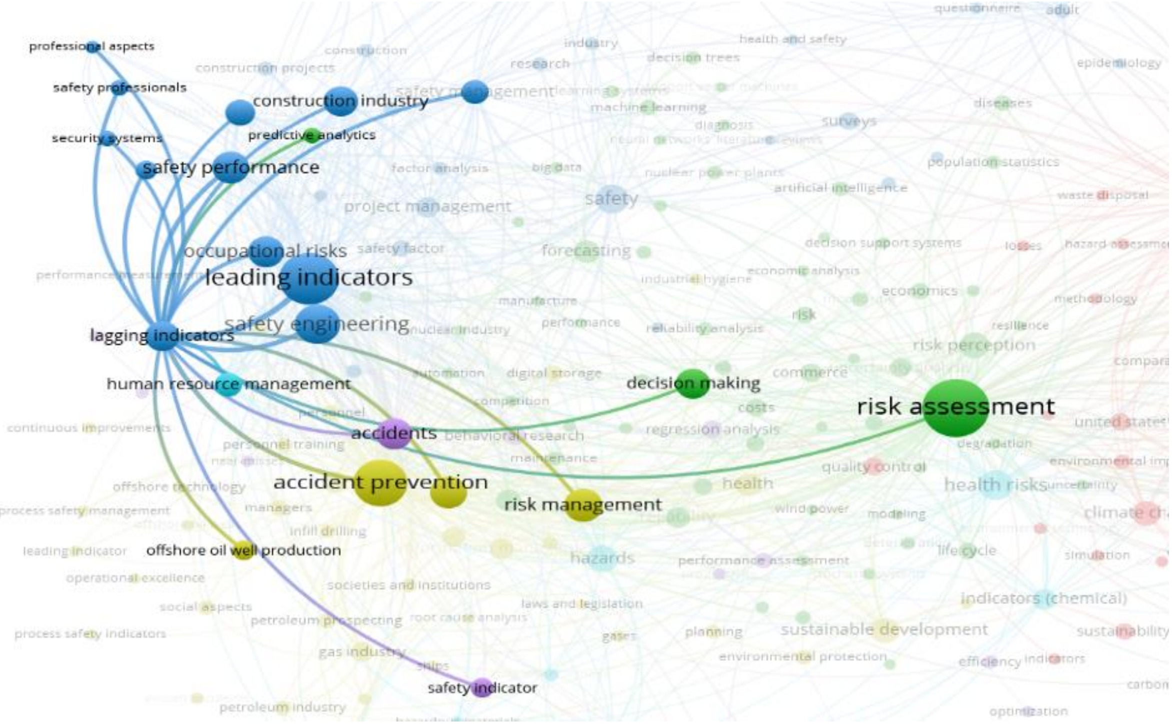
The green nodes illustrate the keywords 'risk assessment' (*f*=189), 'accident prevention' (*f*= 119),' leading indicators' (*f*=150), 'lagging indicators' (*f*=47), 'health' (*f*=32), 'safety' (*f*=51), 'health risk' (*f*=55), 'risk management' (*f*=58), safety engineering (*f*=85), 'occupational risk' (*f*=51), 'behavioural research' (*f*=25) and 'laws and legislation' (*f*=28) are predominant between 2013-2016. These keywords indicate a trend in the adoption of SI (both leading and lagging) in risk management, safety engineering and accident prevention through the use of behavioural research and implementation of laws and legislations. For instance, Leveson (2015) provided a systems approach to risk management through leading SI and Niciejewska and Obrecht (2020) evaluated the use of SI in modifying unsafe behaviours. However, a shift in research trend towards the adoption and application of technology in SI development is observed between 2016 and 2023. This shift is evident in the yellow nodes which illustrates keywords such as 'machine learning' (*f*=16), 'artificial intelligence' (*f*=14), 'learning systems' (*f*=10), 'decision trees' (*f*=7), 'big data' (*f*=9), 'predictive analytics' (*f*=11), 'neural networks' (*f*=7), 'support vector machine' (*f*=7), 'automation' (*f*=9) and 'regression analysis' (*f*=20). For example, Poh *et al.* (2018) used ML to develop SI for construction sites and Jafari *et al.* (2019) also adopted leading indicators in a ML model for evaluating safety performance.

5.2.2 Leading and Lagging indicators

It is noteworthy that although the terms, ‘leading’ and ‘lagging indicators’ were excluded from the search terms, they still emerge conspicuously in the keywords obtained. Figure 5.2 a and b present a network visualisation of the selected keywords ‘*leading indicator’* and ‘*lagging indicator’* and displays other words linked to them. Examining the selected keywords, provides a deeper insight into the contextual association of linked words and reveals a more detailed understanding of the broader field of study or discussion around the chosen keyword (Roberts *et al.,* 2019). Furthermore, the linked words provide a picture of the topics or subtopics associated with the selected keyword. Such a snapshot helps in exploring different facets of a subject and discovering key themes within the literature (Bortey *et al.*, 2021).



a.



b.

Figure 5.2 - Visualisation of leading and lagging indicator

The connected keywords were categorised into themes based on similar ideas they represented. The themes were then examined to determine the type of knowledge they indicate or contribute to the research. Table 5.1 details the connected keywords and the themes that emerged from them.

Table 5.1 - Categorisation of keywords connected keywords into themes.

Lagging indicators	
Keywords connected	Theme
Leading indicator, safety indicator, accidents.	Definition
Construction industry, offshore oil well production.	Industry
Accident prevention, risk mitigation.	Action
Predictive analytics, decision making, risk assessment, risk management, safety performance, safety management, occupation safety, safety engineering, security systems.	Utility
Professional aspect, safety professional, human resource management.	People

Leading indicators	
Safety, safety factor, health risk, health and safety, occupational risk, leading indicator, lagging indicators, accidents.	Definition

Forecasting, behavioural research, decision making, commerce, risk assessment, damage detection, performance measurement, safety performance, predictive analytics.	Utility
accident prevention, mitigation	Action
Construction equipment, personnel training, risk perception, social aspect.	Focus
Digital storage, artificial intelligence, big data, deep learning, machine learning.	Technology
Continuous improvement, sustainable development, information management.	Feedback
Survey, research, instruments, regression analysis.	Measurability
Professional aspect, safety professionals, personnel, managers, human, human engineering.	People
Petroleum prospecting, gas industry, petroleum engineering, oil and gas, process safety, civil engineering, construction, construction project, construction companies.	Industry

For both 'leading indicators' and 'lagging indicators' keywords, nine common themes were found running through the connected keywords. These include: i) definition; ii) focus; iii) industry; iv) technology; v) people; vi) accountability/feedback; vii) utility; and viii) measurability; ix) action. These themes obtained state factors that should be considered when selecting the type of safety indicator to employ in a field (Guo *et al.*, 2016; Yorio *et al.*, 2020). Based on these factors, a decision could be made on whether leading indicators or lagging indicators or the combination of both will best serve an intended safety operational purpose. For example, for a factor such as 'action', if the safety operation to be undertaken is to prevent incidents, then leading indicators will be the preferred option but if the purpose is mitigation, then lagging indicators could rather be adopted.

Table 5.2 outlines the considerations to be taken into account through a series of questions and elucidates when and how each factor can be utilised.

Table 5.2 - Overview of factors for consideration

Factors	Question	Leading indicator	Lagging indicator	references
Definition	How will you express the type of indicator needed?	Leading indicators are proactive measures that are used to anticipate and prevent safety incidents.	lagging indicators are reactive measures that are used to track and analyse past safety incidents.	Grabowski *et al.*, (2007), Swuste *et al.* (2017).

Focus	What is the goal for indicator selection?	Focus on the activities and processes that are likely to lead to safety incidents, such as safety training, equipment maintenance, and safety audits.	Focus on the outcomes of safety incidents, such as injury rates, lost workdays, and workers' compensation claims.	Johnsson *et al.* (2018), Øien *et al.* (2011).
Measurability	How and when will the indicator be measured?	Measured in real-time or near-real-time.	Measured after the incident.	Sadeghi *et al.*, (2015), Lingard *et al.* (2017)
Accountability/feedback	What type of response is required?	Leading indicators are considered to be more predictive of future safety performance.	lagging indicators are reactive and provide a retrospective view of safety performance.	Bellamy and Sol (2012), Jafari *et al.* (2018).
People	What human factors contribute to unsafe acts?	Encourage a proactive safety culture.	Reflect the outcomes of safety practices and the impact on employee well-being.	Reason (2016), Tomlinson *et al.* (2016).
Technology	How can technology augment the efforts of precursors?	Enables the implementation of innovative safety measures.	Improves incident reporting and investigation processes.	Aversano *et al.* (2022).
Industry	What type is industry will the indicators be used?	Reflects an industry's potential growth.	Reflects an industry's historical efficiencies.	Neill (2011).
Action	What action needs to be taken? Prevention or mitigation?	Leading indicators are more actionable because they provide information that can be used to identify potential safety hazards and take corrective actions to prevent safety incidents.	Less actionable because they provide information after an incident has already occurred.	Leveson *et al.* (2015), Sultana *et al.* (2019).

Utility	What is the application of the indicator?	Leading indicators are more useful for identifying trends and making proactive safety decisions.	More useful for evaluating the effectiveness of safety programs and policies.	Oswald *et al.* (2018), Song *et al.* (2019)

The *definition* of SI is dynamic and could be expressed in terms of safety, accidents, health or occupational risk (Grabowski *et al.*, 2007; Swuste *et al.*, 2017). Studies such as Johnsson *et al.* (2018); Øien *et al.* (2011) and Bayramova *et al.* (2023) identify various definitions of SI and how they are expressed in literature justifies the dynamism of SI definitions. Therefore, when selecting a type of SI, it is pertinent to take into account how the definition could impact the results. It is also pertinent to determine the *focus* of the SI (cf. Johnsson *et al.* 2018) which reflects on systems vs outcomes (cf. Øien *et al.* 2011). Safety leading indicators focuses on the effectiveness of safety systems while lagging indicators concentrates on the outcomes of such systems (Bayramova *et al.*, 2023). Therefore, depending on the focus of a safety operation, a leading or lagging indicator could be adopted. Furthermore, how and when an indicator could be measured determines whether its leading or lagging (Sultana *et al.*, 2019). The Organisation for Economic Co-operation and Development (2003) described SI as measuring the level of changes in safety performance for an organisation over time. Leading indicators are measured before incidents or in real-time while lagging indicators are measured after an incident occurs (Lingard *et al.* 2017). This makes the quantification and *measurability* of leading indicators more challenging especially because they evaluate potential future events (Bellamy and Sol, 2012). Conversely, lagging indicators are easy to measure, thereby making data from lagging indicators easily accessible due to its availability (Lingard *et al.* 2017).

Additionally, if a safety system requires retrospective *feedback* on safety performance, a lagging indicator will be best suited as leading indicators deal with predictive use cases of safety performance (Baker *et al.*, 2007). With leading indicators, the predictive outlook could enable potential safety issues to be identified and addressed proactively, thereby enhancing safety via performance feedback (Baker *et al.*, 2007). Also, various safety models have emphasised the role of human elements in an incident (Rasmussen *et al.*, 1981; Reason, 2006; Odumodu, 2023), hence the need to consider *people* in selecting SI. Dekker (2014) proffered that when considering human factors, trust should be imposed in humans instead of bureaucracy hence, the proposal of safety differently. Leading indicators therefore encourage a positive safety culture to preventing incidents while lagging indicators rely on safety practices and their impact on employees (Dekker, 2001). Keywords such as artificial intelligence, ML and big data point to the significance of *technology*. Technological advancements can contribute to leading indicators by enabling the implementation of innovative safety measures such as ML to predict safety incidents while lagging indicators could be influence by technology by improving incident reporting and investigation processes (Aversano *et al.*, 2022).

Furthermore, every *industry* has unique characteristics that are peculiar to that industry only (Zhen *et al.*, 2022). Hence, it is necessary to consider the type of industry SI are to be applied and inculcate industry-specific metrices (Leveson *et al.*, 2015). The *action* to be taken (i.e. either prevention or mitigation) also informs the selection of either leading or lagging indicators (Sultana *et al.,* 2019). Finally, it is also pertinent to consider the usefulness or *utility* of the SI (Song *et al.*, 2019). Leading indicators are more useful for identifying trends and making proactive safety decisions while lagging indicators are more useful for evaluating the effectiveness of safety programs and policies (Oswald *et al.*, 2018).

5.2.3 Combining leading and lagging indicators to form resilient indicators.

Although the nexus between leading and lagging indicators are apparent, Øien *et al.* (2011) posits that, the discussion on the differences between leading and lagging indicators should be managed in a way that, it does not obstruct the establishment of practical indicators that can offer (early) warnings about impending catastrophic events. While the purpose of safety leading indicators has been established as a means of proactively preventing incidents and accidents, Hollnagel (2015) still posits that, even the adoption of safety leading indicators and resources could be "*stretched to the limit"* hence, the proposal of resilience engineering (Dekker *et al.*, 2008) whereby systems could adapt and bounce back in the event of an accident occurring. The need for safety systems to adjust in the event of unplanned disturbances, has resulted in the necessity of resilient safety indicator development (Baud a*et al.*, 2013). The strategic combination of both leading and lagging indicators could be a *terminus a quo* to the development of resilient indicators for organisations (Tjandra and Shimko, 2016). However, studies on how both indicators can be integrated to form resilient indicators reside within an incipient stage (Ranasinghe *et al.*, 2020).

A plethora of studies have proffered various methods in identifying safety indicator (Swuste *et al.*, 2016; Tjandra and Shimko, 2016; Sultana *et al.*, 2019), but these studies have linked safety indicator identification to safety performance and not resilience. For example, Kongsvik *et al.* (2010) proposed the use of safety climate and risk analysis in identifying organisational safety indicator, Sultana *et al.* (2019) also proposed a system engineering perspective in identifying safety indicator. Consequently, it has become essential to establish a relationship between safety indicator identification and resilience, thereby facilitating a comprehensive elucidation of the manner in which the former influences the development of resilience. To establish a relationship between leading and lagging safety indicator, some studies suggested an empirical link between these two safety indicator types (Sheehan *et al.*, 2016), Yorio *et al.* (2020) also discovered a temporal relationship between leading and lagging indicators which suggests the possible use of lagging safety indicator in incident anticipation. Anticipation, however, is a characteristic of resilience which alludes the necessity of establishing relationships between the two safety indicator in building resilience (Chen *et al.*, 2018). Other studies have also proposed the use of triggers in developing resilience (Man *et al.*, 2019; Ayhan and Tokdemir, 2019). Furthermore Hallowell *et al.* (2013) have suggested monitoring and responding to safety indicator as a means of building resilience and Leveson *et al.* (2017) recommends the implementation of feedback loops to enhance resilience. All these considerations (safety indicator identification, relationship establishment, triggers, monitoring and feedback loops) are therefore regarded as necessary steps in augmenting the strengths of leading and lagging indicators to create resilient indicators.

Figure 5.3 therefore demonstrates an approach for the integration process for a resilient indicator development. These include: i) identifying the safety indicator; ii) establishing a relationship between the indicator; iii) establishing threshold and triggers; iv) continuous monitoring; and v) development of feedback loop. The figure was developed based on the methods previously listed and discovered in literature and illustrates the interconnection and relationship between these methods. Establishing a relationship between leading and lagging safety indicator becomes the pivot of setting threshold and triggers by which the identified safety indicator can be measured.

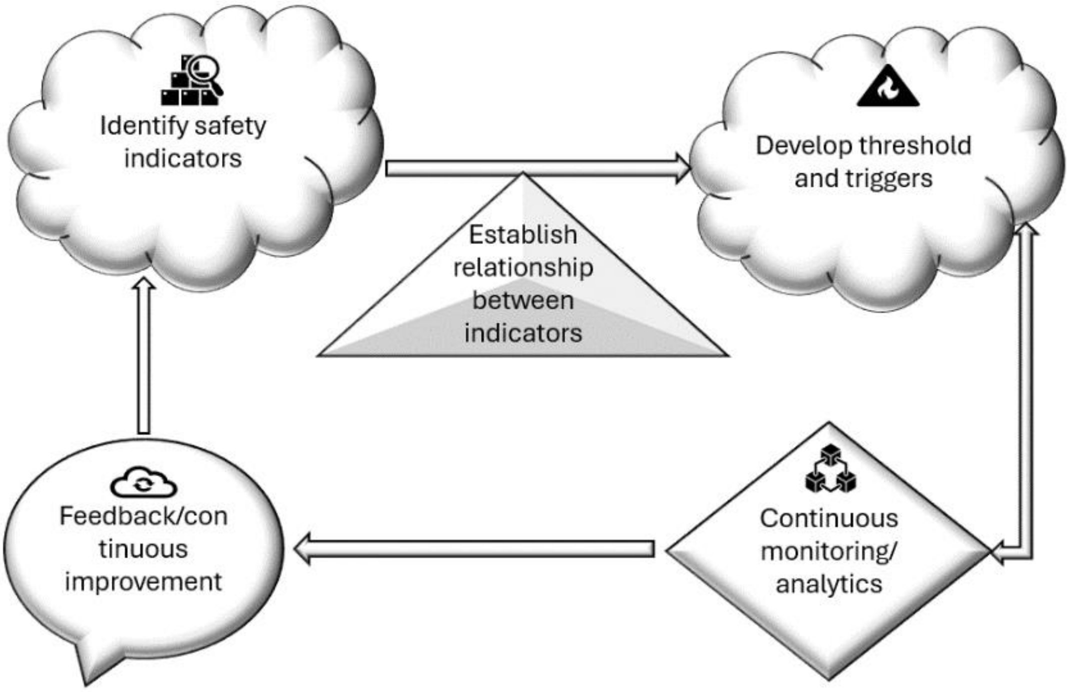


Figure 5.3 - Resilient indicator development

5.2.4 Cluster analysis.

Figure 5.4 presents a view of how keywords were clustered. Cluster 1 (red nodes) is centred on themes around environmental application of safety indicator. Cluster 2 (light green) is concerned with topics connected to technological and economic applications in safety indicator research, the pertinent subject areas these technologies have been applied, the types of analysis undertaken using these technologies and the economic application areas of safety indicator. Cluster 3 (blue) highlights the institutional, demographic and research methods of safety indicator and how they are used to evaluate safety. Cluster 4 (yellow) is focused on matters around industry-specific safety indicator research. Cluster 5 (purple) brings together topics concerning behavioural, agent-based and spatial temporal safety indicator. Finally, Cluster 6 (deep green) focuses on safety integration and the importance of a unified approach in managing aspects of safety. In general, the clusters presented a viewpoint of the different types of leading and lagging indicators that inform the selection of input variables.

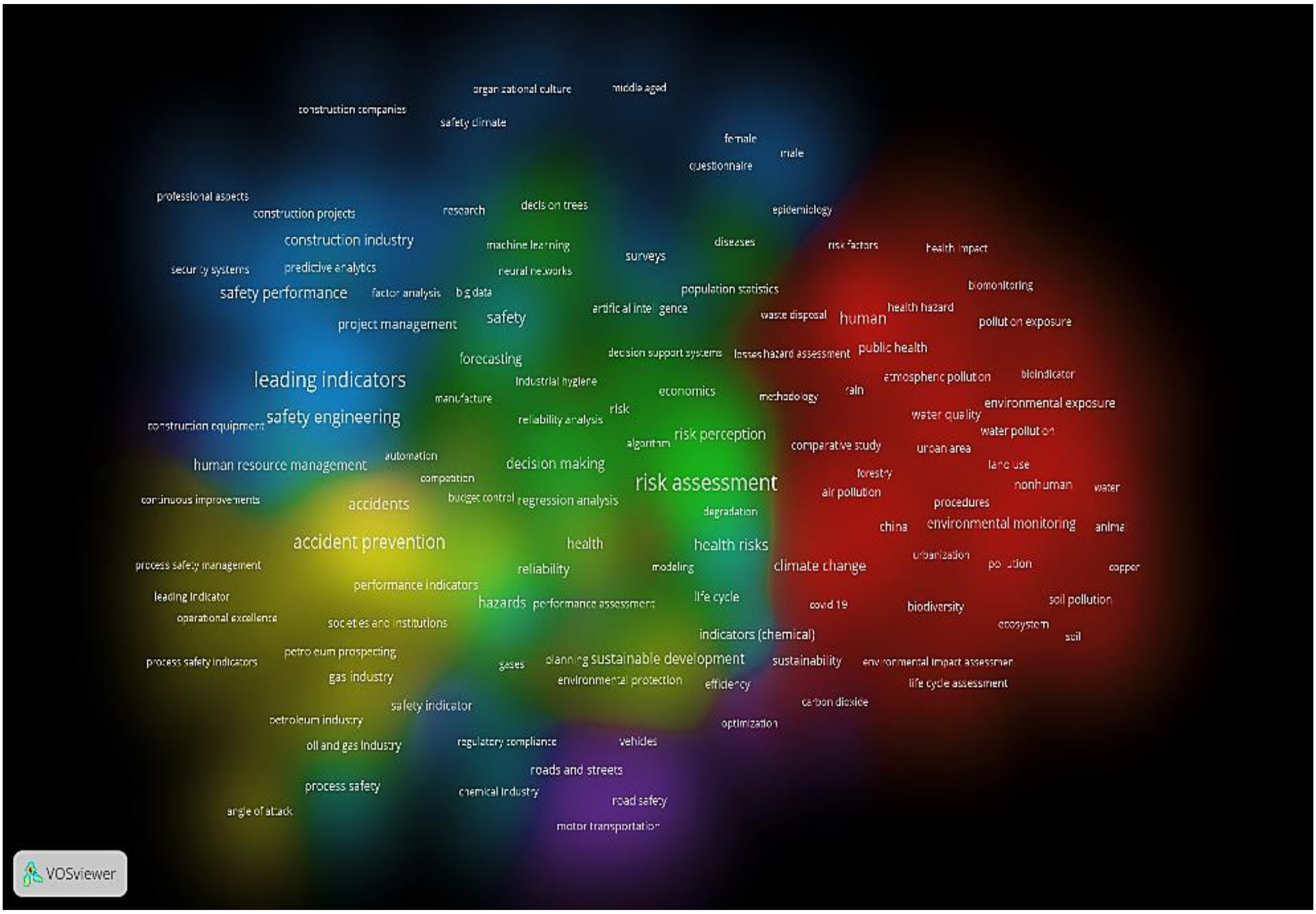


Figure 5.4 - Cluster density view of concept visualisation

5.2.4.1 Cluster one (red): environmental applications of safety indicator.

Safety indicators have been used as metrics to monitor and evaluate environmental performance and identify areas where improvements can be made (Rogovski *et al.*, 2021). Cluster one presents certain prominent keywords such as 'pollution exposure (*f= 15*)', 'air pollution (*f=15*)', 'atmospheric pollution (*f=12*)', 'soil pollution (*f=25*)' and 'water pollution (*f=16*)'. These keywords strongly indicate the role of safety indicator in assessing safety performance of environmental control systems such as air pollution control, hazardous waste management and water treatment (Ilyichev *et al.*, 2015; Rogovski *et al.*, 2021). The work of HTOs involves the use air quality monitoring equipment to measure levels of pollutants such as carbon monoxide, nitrogen oxides, and particulate matter emitted by vehicles on the highway (Ferrero *et al.*, 2016). This data can be used to identify locations where air pollution is a problem and to enforce regulations related to emissions standards for vehicles. HTOs may also monitor water quality in rivers, streams, and other bodies of water near highways to identify potential pollution sources and to enforce regulations related to water quality (Fu and Gu, 2017). Other keywords such as environmental exposure (*f*=17), environmental impact (*f*=14), environmental impact assessment (*f*=8), environmental monitoring (*f*=30), environmental risk (*f*=7) and environmental technology (*f*=9) also emphasise the use of safety indicator in monitoring environmental risk and exposure through the use of certain environmental technologies to minimise environmental exposure as assess environmental impacts (Sumampouw and Risjani, 2014).

5.2.4.2 Cluster two (light green): technological and economic applications of safety indicator.

Cluster two presents certain pertinent keywords such as ‘machine learning (*f*=16)’, ‘algorithms (*f*=14)’, ‘artificial intelligence (*f*=14)’, ‘data mining (*f*=11)’, ‘big data (*f*= 9)’, learning systems (*f*=10) which indicates the adoption of big data technologies in safety indicator research. This could be either using ML for developing safety indicator (Poh *et al.*, 2018) or using safety indicator to develop ML models to predict safety risk (Koc *et al.*, 2022). Notable in the cluster items are ML algorithms which have been applied in different safety indicator studies, which include, ‘neural networks (*f*=7)’ (Gohand Chua, 2013), ‘decision trees (*f*=11)’ (Kim *et al.*, 2008), ‘time series analysis (*f*=9)’ (Commandeur *et al.*, 2013), ‘support vector machine (*f*=25)’ (Suárez-Sánchez *et al.*, 2011), ‘random forests (*f*=14)’ (Tixier *et al.*, 2016), ‘fuzzy sets (*f*=7)’ (Lin *et al.*, 2021). These algorithms have been applied in prominent fields such as ‘condition monitoring’, damage detection and forecasting which are displayed prominently in the cluster. This cluster also gives an indication of the types of analysis carried out in aforementioned field which includes, ‘failure analysis (*f*= 10)’, ‘uncertainty analysis (*f*= 21)’, ‘sensitivity analysis (*f*=9)’, ‘reliability analysis (*f*= 11)’, ‘cost benefit analysis (*f*=8)’ and ‘predictive analytics (*f*=11)’.

Prominent keywords such as ‘budget control (*f*= 12)’, ‘economic and social effects (*f*=16)’, ‘economics (*f*=22)’, ‘economic analysis (*f*=9)’ and ‘investments (*f*=11)’ indicate the economic application of safety indicator. The cost associated with implementing safety measures, such as providing training, purchasing safety equipment, or upgrading facilities, can influence the extent to which these measures are implemented (López-Alonso *et al.*, 2013). Organisations with budget constraints may face challenges in allocating resources to robust safety programs

(Korchagin *et al.*, 2018). That is why economic safety indicator such as safety investments and budget control are necessary in safety indicator selection.

5.2.4.3 Cluster three (blue): institutional and demographic applications of safety indicator

Cluster 3 is centred on themes around the institutional metrices that have been applied in measuring safety performance and accident prevention and the inculcation of demographic data to evaluate human influence. The keywords, 'leading indicator (*f*= 150)' and 'lagging indicators (*f*=47)' are some of the most predominantly strong nodes in cluster 3. These are evaluation metrics used to measure the effectiveness of measures adopted to manage safety risk (Grabowski *et al.*, 2007). Cluster items such as 'safety climate (*f*=14)', 'safety culture (*f*=18)', 'safety management systems (*f*=30)', 'organisational culture (*f*=10)' and 'personnel training (*f*=14)' are linked to some of the most predominant nodes in the network such as 'safety performance (*f*=54)', 'safety engineering (*f*=85)', 'accident prevention (*f*=119)' and 'project management (*f*=27)'. This suggests that institutional leading indicators such as safety climate, organisational culture, personnel training and safety systems (Grabowski *et al.*, 2007) have been used mostly as metrices for evaluating pertinent aspects of safety such as safety engineering, accident prevention safety performance and project management. The use of leading indicators offers a more proactive approach to safety evaluation unlike lagging indicators (Lingard *et al.*, 2017) therefore as organisations shift towards safety risk prevention rather than mitigation after risk occurs (Sadeghi *et al.*, 2015), it is important to include leading indicators in any proposed model. Proper leading and lagging indicators could be adopted as evaluation metrics for measuring safety.

The presence of keywords such as 'adult (*f*=14)', 'male (*f*=10)', 'female (*f*=12)', 'middle-aged (*f*=8)' indicates the inculcation of demographic data in evaluating safety. Demographic data helps to analyse the characteristics of the worker population and their influence on safety risk management (Yembi *et al.*, 2021). For example, Marinaccio *et al.* (2013) explored the use of demographic data in investigating workers' perception on work related stress and found that female workers had a more negative perception about relationships and change at work as compared to their male counterparts which reveals the relevance of the inclusion of demographic data in safety indicator development.

5.2.4.4 Cluster four (yellow): industry-specific safety indicator and research methods

Issues concerning various industry domains and research methods used in safety indicator development can be found in this cluster based on the keywords presented. The keyword, ‘petroleum industry (14)’, ‘petroleum prospecting (*f*=13)’, ‘petroleum engineering (*f*=8)’, ‘oil and gas industry (*f*=12)’, ‘gas industry (*f*=24)’, ‘process safety management’, ‘nuclear industry (*f*=9)’, ‘chemical industry (*f*=8)’, ‘offshore oil well production (*f*=20)’, ‘construction industry (*f*=48)’ indicates some of the prominent domains that safety indicator development and applications have been used. For example, Skogdalen *et al.* (2011) conducted a study which uses safety indicator to monitor and prevent offshore oil and gas deepwater drilling blowout. Many safety indicator studies have been conducted in the construction industry (Oswald *et al.*, 2018; Li and Leung, 2017), the petroleum industry (Øien *et al.*, 2011; Zhen *et al.*, 2019), the chemical industry (Leveson, 2015) and the process industry (Swuste *et al.*, 2016). It is also interesting to note the relationship between the featured industries and keywords such as ‘laws and legislations (*f*=7)’, ‘key performance indicators (*f*=29)’, sustainable development (*f*=37), ‘operational excellence (*f*=9)’ and ‘continuous development (*f*=10)’. These keywords suggest relevant objectives which shapes the focus for domain application of safety indicator (Hosseini *et al.*, 2016; Li and Leung, 2017; Oswald *et al.*, 2018).

Additionally, the keywords ‘literature review (*f*= 11)’, ‘surveys (*f*=10)’, ‘questionnaire (*f*=9)’, ‘research (*f*=12)’, ‘comparative study (*f*=9)’, ‘quantitative analysis (*f*=8)’, suggests the use of certain research methods in mining safety indicator and in its continuous development. Guo *et al.* (2016) used surveys containing organisational and individual factors, safety behaviour and demographic information to develop an integrative model of construction workers’ safety behaviour. Ranasinghe *et al.*, (2020) also performed a comparative study on resilient engineering safety indicator and found 28 indicators commonly used in the domain of workplace safety based on the research aim, complexity, and the nature of the industry. Furthermore, Hosseini *et al.* (2016) performed a literature review using 150 articles to determine the future direction of safety indicator. Therefore, based on the aim, nature and domain of research, an appropriate research method can be used in develop customised safety indicator for specific industries.

5.2.4.5 Cluster five (purple): agent-based and spatial-temporal indicators.

Cluster 5 brings together topics concerning agent-based and spatial-temporal application of safety indicator in transportation research. Agent-based safety indicator focuses on behaviour and actions of individuals or entities within a system (Blom *et al.*, 2013). In the context of safety, agents typically refer to individuals, workers, or components that can influence safety outcomes through their actions, decisions, and interactions within a given environment (Walsh and Sawhney, 2004). The presence of agent-based keywords such as ‘behavioural-based safeties (*f*= 8)’, ‘behavioural research (*f*=25)’, ‘vehicles (*f*=12)’, ‘construction equipment (*f*=10)’, ‘carbon dioxide (*f*=7)’ and ‘near miss (*f*=9)’ could reflect their influence on ‘performance assessment’, ‘productivity’, ‘accidents’ and ‘highway accidents’ which are also keywords in this cluster. For example, behavioural-based safety observation which is a systematic process of observing and evaluating individual behaviours could help identify potential safety risks and unsafe practices (Niciejewsk and Obrecht, 2020). This process could thereby provide targeted interventions through performance assessment to improve safety performance and productivity (Zerguine *et al.*, 2016). Also, a high near-miss reporting rate may indicate an active safety culture where workers are encouraged to report incidents, helping identify and address potential risks proactively (Van der Schaaf *et al.*, 2013).

Spatial-temporal indicators incorporate both spatial (location-based) and temporal (time-based) dimensions to analyse and understand safety-related events or patterns (Liu *et al.*, 2020). Keywords such as ‘traffic control’, ‘traffic safety’, ‘road and streets’, ‘road safety’, ‘year’ and ‘location’, present a cross section of such spatial-temporal safety indicator. For example, analysing the interactions between traffic patterns during specific hours could provide a comprehensive view of safety incidents that occur at specific locations (Sánchez González *et al.*, 2021).

Nevertheless, a notable gap is found when it comes to accident prevention for traffic control. The keyword traffic control is not linked any other keywords in the network as shown in figure 5.5, which could suggest that unlike other sub-domains in transportation safety research, traffic control which is performed by highway workers is under explored. This supports Hancher *et al.* (2007) in a review conducted which found that highway workers are neglected when it comes to health and safety research. A review of transportation safety research found that studies on safety focused more on the safety of pedestrians, drivers, and the general public as compared to highway workers (Goodwin *et al.*, 2015; Stern *et al.*, 2019; Mannering *et al.*, 2020). Hence, the need for a study on development of safety indicator to help prevent highway worker accidents.

Figure 5.5 - Non-existent relationship between traffic control and other keywords

5.2.4.6 Cluster six (deep green): safety integration.

The presence of keywords such as ‘hazard’, ‘hazardous materials’, ‘human resource management’, ‘regulatory compliance’ and ‘cost effectiveness’ emphasise the interconnectedness of these concepts and the importance of a unified approach in managing various aspects of safety, compliance, materials, costs and human resources within an organisation (Ghemraoui *et al.*, 2009). The interconnectedness of these keywords suggest that a well-integrated system is more robust, efficient and effective in addressing complex challenges (Houssin and Coulibaly, 2011). For example, integration of human resource management programs such as safety training, the amalgamation of strategies that balance safety and financial considerations and the introduction of policies that enhance regulatory compliance could encourage a holistic approach to safety and enhance the effectiveness of safety systems (Ghemraoui *et al.*, 2009).

5.2.5 Document analysis with bibliometrix software.

To further understand the focus areas of safety indicator in safety risk ML prediction research, document analysis was performed to provide a thematic map which highlighted the development and impact of research themes shaping the direction of research within the ML safety risk prediction field. The analysis also presented the most relevant articles in terms of their total citations and the most relevant journal sources.

4.2.5.1 Thematic Map

Figure 5.6 displays a thematic map with keywords classified under themes. Keywords such as ‘human’, ‘article’ and ‘humans’ were between niche and motor themes which makes them influential topics although scarcely reviewed in the research field. This finding reiterates human protection being the predominant focus of safety management (Hollnagel *et al.,* 2015). The keyword ‘safety’ that was present in motor themes also suggest groundbreaking and impactful research undertaken over the years due to the how crucial the topic is to general wellbeing of employees and employers combined. ‘Regression analysis’ and ‘statistical models’ which are presented as basic themes reflect the foundational concepts of the risk prediction field. As basic themes pinpoint to extensively researched or fundamental topics established in a research field, it is notable that the literature highlights statistical models as the basis for risk prediction research. Even before the advent of ML (which is based on statistical models (Kattan and Gerds, 2020), traditional statistical models such as regression were used as basis for prediction models – e.g. the Klein–Goldberger model (Giorgio, 1979; Mariano and Ozmucur, 2020). However, emerging or declining themes which represent topics that are under current exploration or have growing interest displays themes such as ‘risk assessment’ (Smirnova, 2021), ‘forecasting’ (Koc *et al.*, 2022) and ‘safety engineering’ (Ranasinghe *et al.* 2020). Thus, researchers are starting to discuss these issues in the *‘ML SI for prediction’* context. To contextualise emerging themes, consideration could be given to SI usage in building ML models for risk assessment, prediction (forecasting) and safety engineering (Koc *et al.*, 2022; Dekker *et al.*, 2008).

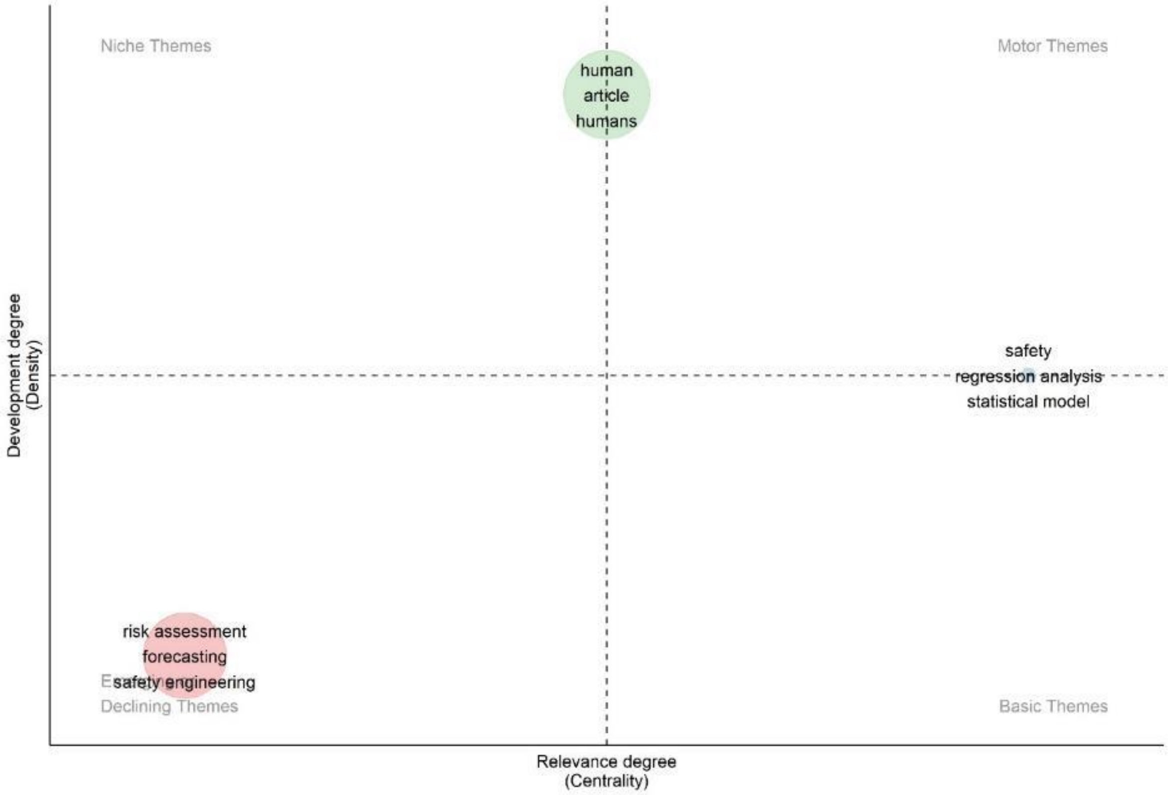


Figure 5.6 - Thematic map

5.2.5.2 *Citation documents*

Table 5.3 presents the top 10 most cited documents among publications analysed to determine what SI are commonly adopted in high-risk industries. The table also indicates three prominent research areas these articles have focused on based on the themes found in the thematic map *viz.* forecasting, risk assessment and humans.

Table 5.3 - Top 10 most cited documents.

Authors	**Title**	**Source**	**Year**	**Total citations**	**Total citations per year**	**Forecasting**	**Humans**	**Risk assessment**
Shi Q; Abdel-Aty M.	Big data applications in real-time traffic operation and safety monitoring and improvement on urban expressways.	Transportation Research Part C: Emerging Technologies	2015	298	31.444	✓	✓	
Poh C.Q.X; Ubeynarayana C.U; Goh Y.M.	Safety indicators for construction sites: a machine learning approach.	Automation in Construction	2018	135	22.500	✓		✓
Erdogan S.	Explorative spatial analysis of traffic accident statistics and road mortality among the provinces of Turkey.	Journal of Safety Research	2009	109	7.267	✓	✓	✓
Zhang L; Wu X; Ding L; Skibniewski M.J; Yan Y.	Decision support analysis for safety control in complex project environments based on Bayesian Networks.	Expert Systems With Applications	2013	89	8.091	✓		
Morrow S.L; Kenneth Koves G; Barnes V.E.	Exploring the relationship between safety culture and safety performance in US nuclear power operations.	Safety Science	2014	82	8.200	✓	✓	✓
Schneidewind N.F.	Reliability modelling for safety-critical software.	IEEE Transactions on Reliability	1997	75	2.778	✓		✓
Chen T; Shi X; Wong Y.D.	Key feature selection and risk prediction for lane-changing behaviours based on vehicles' trajectory data.	Accident Analysis and Prevention	2019	63	12.600	✓	✓	✓

Alruqi W.M.; Hallowell M.R.	Critical success factors for construction safety: review and meta-analysis of safety leading indicators.	Journal of Construction Engineering and Management	2019	55	11.000	✓	✓	✓
Wang J; Huang H	Road network safety evaluation using Bayesian hierarchical joint model.	Accident Analysis And Prevention	2016	51	6.375	✓	✓	✓
Rostamabadi A; Jahangiri M; Zarei E; Kamalinia M; Alimohammadlou M.	A novel fuzzy Bayesian network approach for safety analysis of process systems; an application of HFACS and SHIPP methodology.	Journal of Cleaner Production	2020	51	12.750	✓		✓
Meng X; Chen G; Zhu G; Zhu Y	Dynamic quantitative risk assessment of accidents induced by leakage on offshore plat forms using dematel-bn.	International Journal of Naval Architecture And Ocean Engineering	2019	50	10.000	✓		✓

For each paper assessed on risk prediction modelling using SI, three key focus areas were identified. The models were either for forecasting or predicting a phenomenon (Erdogan, 2009; Zhang *et al.*, 2013; Poh *et al.*, 2018), assessing risk levels (Kim *et al.*, 2018; Wang *et al.*, 2021; Ma *et al.*, 2022) or evaluating human factors on safety (Boer, 2006; Shen *et al.*, 2022). Analysis results indicates that 57% of all publication on using SI to build risk prediction models indexed in the Scopus database were aimed at evaluating human influence on safety risk prediction, 27% of the publications aimed to forecast events, while 15% focused on risk assessment. Shi and Abdel-aty (2015) (298 citations) was the most cited article in the analysed research field and focused on reducing congestion and crash risks on urban expressways. Poh *et al.* (2018) (135 citations) was the second most cited and proposed a ML model for developing safety leading indicators for the construction industry. Erdogan (2009) (109 citations) was the third most cited and presented a spatial analysis using two different risk indicators to evaluate the road safety performance. Notably two of the top three most cited papers (*viz.* Erdogan, 2009; Shi and Abdel-aty, 2015) in the field of SI of risk modelling centred on the road safety however, these papers were focused on the general population of drivers and pedestrians rather than the road workers. The absence of road workers in safety risk studies extends beyond these two papers, as observed in numerous other studies analysed in this research. These studies either generalise models to encompass all construction workers or concentrate on drivers, pedestrians, or the general public (Holló *et al.*, 2010; Dell'Acqua *et al.*, 2013; Dadashova *et al.*, 2016; Čubranić-Dobrodolac *et al.,*2017).

5.2.5.3 Comparative review of industry adopted safety indicator-based machine learning variables

Table 5.4 presents a comparative review of some input variables applied in ML safety prediction research for different industries with SI used as their basis. SI are the metrices used to evaluate safety performance while input variables are the parameters that the model analyses to make predictions (Chen *et al.,* 2018). The three types of SI sourced from the literature (i.e. leading, lagging and resilient indicators (Woods and Wreathall, 2003; Poh *et al.*, 2018; Koc *et al.*, 2022)) were examined for the types of input variables that have been derived from them in various studies. It was discovered that the type of indicators adopted is dependent on the research aim, the complexity and the nature of industry these indicators are being adopted for (Ranasinghe *et al.*, 2020). Although various SI have been adopted in a plethora of research (Poh *et al.*, 2018; Zhang *et al.*, 2019; Ajayi *et al.*, 2021), Table 5.4 provides a justification for the types of SI selected as input variables in this thesis based on: i) industry domain; ii) types of input variables that have been derived in previous studies; and iii) ML methods that have been employed in similar studies. Documents reviewed revealed that when selecting SI, researchers have relied on characteristics peculiar to the industry they are working with (Zhang *et al.*, 2019; Poh *et al.*, 2018). Indicators used in one industry domain have therefore been eliminated from another study domain due to their ineffectiveness based on the context in which they are being used. For example, although similar attributes such as weather, experience and time of day can be used for both construction and aviation safety risk prediction, other attributes such as type of building and flight phase will be peculiar to only construction and aviation respectively (Poh *et al.*, 2018; Zhang and Mahadevan, 2019). Therefore, in assessing which SI will be appropriate for highway risk prediction, it is pertinent to consider attributes that are peculiar to the highway industry such as incursions. It is also noted that despite resilient indicators being adopted widely by researchers in different fields (Pillay *et al.*, 2010; Ferreira, 2011; Shirali *et al.*, 2018), the highway industry is underexplored in risk prediction using resilient indicators and leading indicators. The highway industry has relied more on lagging indicators which are more reactive rather than proactive (Choudhry and Iqbal, 2013). Concerning resilient indicators, while the petroleum industry has focused on awareness, flexibility and anticipation (Øien *et al.*, 2011), the construction industry has paid less attention to flexibility and awareness, and has instead focused on anticipation, management commitment, reporting culture and learning culture (Ranasinghe *et al.*, 2020). This is because the construction industry does not deem flexibility as an appropriate indicator due to its unique characteristics (cf. Chen *et al.*, 2018). This difference in adoption of resilient indicators also implies that the focus on what resilient indicators should be adopted for, vary based on the industry. It is therefore imperative that when selecting indicators for a safety risk model, the industry's unique characteristics and domain specific attributes must be taken into consideration.

Across the various industries, SVM, DT, RF and DNN were the most commonly used ML method for safety risk prediction (Tixier *et al.*, 2016; Oyedele *et al.*, 2021; Ajayi *et al.*, 2021). Considering the aim, outcome and nature of selected variables, studies employed diverse ML methods suited to analyse attributes and either produce an assessment model, a forecasting model or a risk assessment model (Wang *et al.*, 2022).

Table 5.4 - Input variables derived from safety indicators.

Safety indicator	Input variable	Industry							MLM	Author
Leading		CI	PI	O&G	HC	E&P	TI	HI		
Near-miss reporting.	Frequency of near miss, project location and experience.	*			*	*			SVM, RF	Sarkar *et al.*, 2019; Kurian *et al.*, 2020
Safety training completion rates	Safety training participation, aggregated training effectiveness score, Training policy, training program and project type.	*	*	*		*	*	*	RF, DT, SVM,	Namian *et al.*, 2016; Mo *et al.*, 2018
Hazard identification and risk assessments	Type of work undertaken, type of hazards, project type, project manpower, accident frequency (per year), types of equipment, project location, season and weather.	*		*				*	SVM, CART	Chang and Chen (2005), Kashani, and Mohaymany (2011)
Safety audits and inspections	Frequency of safety violations, number of inspections, operating procedures, management of change records, incident investigations and emergency response plan.	*		*	*		*		RF, DT, SVM, LR, KNN	Poh *et al.*, 2018; Birkmire *et al.*, 2007
Employee engagement and participation in safety programs	Attendance per month/year, employment type, safety outcomes and employee engagement index.	*		*	*				PCA, NB, DNN	Peña-Alcántara, 2020; Golestani *et al.*, 2018
Safety culture assessments	Safety perception surveys, schedule delays, safety committees, meeting effectiveness, safety education, workers' involvement, competence and safety training.	*			*				RF, BN, DNN	Shirali *et al.*,2012; Poh *et al.*, 2018

Environmental conditions	Temperature, humidity and air quality.	*	*		*	*		*	RF, DT, SVM, LR, KNN	Tam *et al.,* 2004; Poh *et al.*, 2018; Oyedele *et al.*, 2021
Equipment	Machineries (i.e. elevators, drills, hammers and winches).	*	*	*		*		*	NLP, SVM, RF	Tixier *et al.*, 2016; Oyedele *et al.*, 2021
lagging										
Injury and illness rates	Number of injuries and injury type.	*	*	*		*	*	*	ANN, MAR, SVM	Koc *et al.*, 2022; Tixier *et al.*, 2016
Time factors	Time of incident, day of incident. month, season, age.	*		*	*		*	*	SVM, DT, DNN	Oyedele *et al.*, 2021; Ajayi *et al.*, 2021
Lost time injury frequency rates	Number of lost time injuries and magnitude of delay.	*				*	*		DNN, SVM	Zhang *et al.*, 2019; Ajayi *et al.*, 2021
Days away from work rates	Number of sick days off and lost time.	*	*	*		*	*		BN, RF	Sadeghi *et al.*, 2015
Property damage costs	Cost of each infrastructure damage and contract sum.	*				*			PCA, DT, KNN	Birkmire *et al.*, 2007; Peña-Alcántara, 2020;
Workers' compensation claims	Amount of compensation and project cost.	*			*	*			RF, SVM	Erdogan; 2009; Morrow 2014
Resilient measures										
Awareness	Frequency of safety briefings, safety knowledge score and near-miss awareness index.		*		*				SVM, DNN	Shirali *et al.*, 2012
Anticipation	Hazard identification rate, proactive safety suggestions and composite anticipation index score.	*	*	*					SVM, RF, DNN	Ferreira, 2011; Woods and Wreathall, 2003;
Management commitment	Managerial support score, safety budget/ resources allocation, frequency of managerial presence, frequency of safety inspection, provision of safety equipment, number of safety	*			*				RF, DT, XGBoost	Reason, 2016

	programs introduced and post-incident approach (blame or solution).									
Reporting culture	Percentage of incidents, near-misses, or safety concerns reported by traffic officers compared to the total number observed, openness to feedback index and trust in reporting systems.	*		*	*				SVM, BN, RF, DNN, SVM	Morrow 2014
Flexibility	Variability in response times to incidents, percentage of traffic officers trained in multiple roles and adaptability index.		*		*				BN, DNN	Woods and Wreathall, 2003
Learning culture/ Response	Number of implemented continuous improvement initiatives, frequency of changes based on lessons learned from incidents or near-misses, training participation rate and frequency of knowledge-sharing sessions.	*		*		*			PCA, DT, RF	Woods and Wreathall, 2003
safety climate	Safety perception score, safety leadership effectiveness and safety communication effectiveness.	*				*			KNN, SVM, DNN	Ferreira, 2011; Odumodu, 2023

CI: Construction Industry , PI: Petroleum Industry, O&G: Oil and Gas industry, HC: healthcare, E&P: Electricity and Power, TI: Transportation industry, HI: Highway Industry, MLM: ML method, SVM: Support Vector Machines, RF: Random Forest, KNN: K-Nearest Neighbour, BN: Bayesian Networks, PCA: Principal Component Analysis, DT: Decision Trees, LR: Logistic Regression, CART: Classification and Regression Trees, NB: Naïve Bayes Multinomial classifier, ANN: Artificial neural network, MAR: Multi-variate adaptive regression, NLP: Natural language processing

5.3 DISCUSSION

The result of this chapter shows a shift in focus in recent years (2016-2023) highlights the adoption and application of technological methods such as ML in the bid to model risk accurately using safety indicator (Zhang *et al.*, 2019; Poh *et al.*, 2018). Existing literature presents two main safety indicator that are considered in risk modelling which are the leading and lagging indicators (Grabowski *et al.*, 2007; Swuste *et al.*, 2017). The leading indicators focus on the activities and processes that are likely to lead to safety incidents, such as safety training, while the lagging indicators focus on the outcomes of safety incidents, such as injury rates and are therefore reactive indicators which lead to reactive measures (Johnsson *et al.*, 2018; Øien *et al.*, 2011). However, in selecting what type of safety indicator would be appropriate in measuring safety performance, it is necessary to consider attributes such as the definition, focus, measurability, people, technology, industry, utility, action and feedback. What these two main safety indicators do not provide however, is the mechanism for an organisation to adjust or adapt to changes in the event that an incident occurs. Dekker *et al.* (2008) therefore proposed resilient engineering, a mechanism whereby systems could adapt and bounce back when they are stretched to their limit (Hollnagel, 2015). Hollnagel (2014) posits that, it is not enough to either select leading indicators over lagging indicators or vice versa however, the combination of both concepts presents a better future for safety management and providing resilience. This thesis therefore provided a mechanism for how both concepts can be integrated to form resilient indicators.

5.3.1 New theoretical framework

Premised upon the rich synthesis of literature previously analysed, Figure 5.7 (entitled the efflorescent framework) depicts the formulation of ML input variables derived from safety leading, lagging and resilient indicators delineated within a novel theoretical framework. The framework inculcates elements of resilience within the process of choosing the input variables which are depicted with blue buttons. The framework is named ‘the efflorescent’ due to its inherent design, commencing internally and expanding outward like a blooming flower. This configuration serves to illustrate the sequential progression of steps to be pursued in safety indicator-based input variable formulation.

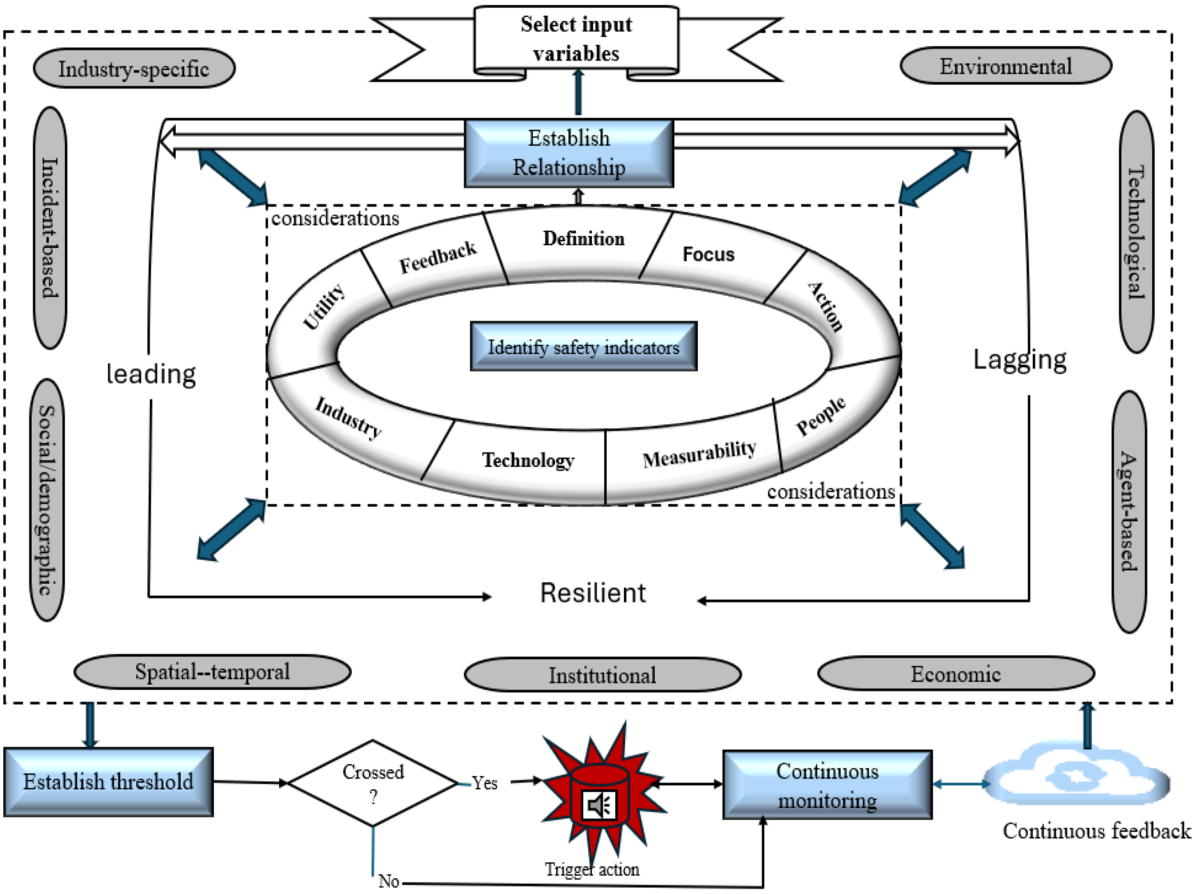


Figure 5.7 - The efflorescent framework

Proceeding with the identification of the type of safety indicator to adopt (depicted as the innermost blue button), certain factors (illustrated in the oval button) need to guide the type of safety indicator to be utilised. For example, if the input variable is supposed to offer information that can be used to identify potential safety hazards and take corrective actions (as the consideration factor) to prevent safety incidents in the future, then an input variable such as *'frequency of near-miss'* derived from a leading indicator such as *'near miss reporting'* can be used. Premised on the factors identified, either safety leading or lagging indicators could be selected or both can be combined to form resilient indicators by establishing the relationship between them. For example, establishing a correlation between safety training completion rates (leading indicator) and incident rate (lagging indicator) can reveal a positive correlation where increased training completion aligns with a decrease in incident rates due to resilient indicators such awareness or anticipation. The grey buttons are the themes that can inform the type of input variables to obtain. For example, environmental indicators could include weather, road surface conditions and location (Rogovski *et al.,* 2021); social/demography indicators could include age, income, driving culture (Alizadeh *et al.,* 2015) and institutional indicators could include drivers' education and licensing, policing practices (Namian *et al.,* 2016) which can be leading or lagging indicators depending on whether the data is collected before or after an incident.

Based on the data collected, thresholds can be defined for safety indicator that, when crossed could signal potential risks or opportunities. Hence, triggers (depicted by red button) a prompt for a closer examination or action can be introduced. For example, set a threshold for equipment reliability and maintenance (leading indicator), such as achieving a mean time between failures (MTBF) above a specified value. If the MTBF consistently falls below the threshold (lagging indicator), it may indicate an increased risk of equipment failures hence a trigger action of thorough equipment inspection, implementation of preventive maintenance measures, and consideration of equipment upgrades or replacements could be implemented to ensure operational safety. While the leading indicator helps in anticipating risks, the lagging indicator provides feedback and triggers actions to address actual incidents, forming a comprehensive approach of introducing resilience into the safety framework. Furthermore, the framework incorporates the concept of continuous monitoring for both leading and lagging indicators by regularly assessing their performance and updating them based on their unique circumstances to ensure accuracy and relevance. The last button (depicted by blue cloud) signifies the establishment of feedback loops that connect the insights gained from lagging indicators back into the decision-making process for leading indicators. This closed-loop system enables continuous improvement and adaptability.

The proposed framework offers a number of practical implications. First, owing to the substantial volume of data generated in highway operations (big data), safety officers may encounter challenges in discerning the most pertinent data for assessing safety performance. Hence, the proposed framework deals with the real-world complexity of organisational safety management decision making, by establishing precise and detailed criteria for risk modelling, thereby improving the reliability of safety assessments. Consequently, when constructing ML models to predict safety incidents, the optimal selection of safety variables may remain ambiguous. Presently, there is a lack of a systematic framework to guide the identification of crucial data for developing risk prediction models specific to HTOs. As a result, the proposed framework could be used to provide guidance to safety officers by elucidating the significance of specific data elements in the context of enhancing safety assessments. Hence safety officers will have a basis for selecting input variables for a ML risk prediction model. Lastly, the created framework identified several forms of safety indicator to suit the needs of various safety issues. As a result, it might be used not only to solve individual safety problems, but also in multiple-purpose safety challenges such as safety incident types, risk level prediction and injury type predictions.

5.3.2 Limitations and future work

The limitation of this seminal work must however be noted. The nature of an interpretivist philosophical stance presents a challenge of researcher induced bias for a study, hence, pragmatism and meticulous data analysis was adopted to mitigate the extent of bias introduced (Posillico *et al.*, 2023). Also, the keywords used in the bibliometric search was narrowly focused (*viz.* safety indicator and risk prediction). However, conducting a more extensive literature search which incorporates a broader spectrum of keyword terms, might introduce additional perspectives into the theoretical framework presented in the current research (Roberts *et al.*, 2020). Furthermore, this chapter does not incorporate ML algorithms in the theoretical framework. The goal is for the input variables outlined in the framework to remain open for exploration with various algorithms, in order to determine which, yields the most favourable results.

As various safety indicator-based input variables have been identified in this work, ensuing chapters will explore their application with various ML models such as RF, SVM and NB as identified in literature (Zhang *et al.*, 2019; Tixier *et al.*, 2016). Also, the framework could be applied by collecting relevant data on identified safety indicator areas to set thresholds and triggers on key variables. For example, set a threshold for the frequency of safety audits and inspections, such as daily or monthly inspections for high-risk areas. If the inspections are not conducted as per the schedule, it may indicate a lapse in monitoring. If threshold is consistently exceeded, trigger an immediate response, such as investigation, urgent review of the inspection process, assign responsibility, and implement corrective measures to ensure timely and thorough inspections. Adjustments to these thresholds and triggers could be made based on highway industry standards, regulatory requirements, and the organisation's specific risk tolerance. This application can be done through action research.

5.4 SUMMARY

Safety indicators are a useful source of information for selecting input variables for a safety prediction ML model. They can help identify relevant input variables and prioritise them based on their influence on safety outcomes. However, there are challenges and limitations to using safety indicators, such as the lack of a standard approach to selecting relevant safety indicators for risk modelling. This thesis performed content analysis and examined the state of art in safety indicator research using co-occurrence of keywords and their influence from VOSviewer, to derive thematic factors which reveals preconditions and factors various industries considered when selecting safety indicators as input variables for ML models. Document analysis performed using bibliometrix software revealed thematic maps which suggest ML models for risk assessment, prediction (forecasting) and safety engineering should be built on safety indicator (Koc *et al.*, 2022; Dekker *et al.*, 2008). Journals were evaluated based on the most cited documents, most influential authors and the most relevant journal sources to inform the types of industries safety indicators have been used as bases for input indicators. Accident prevention and analysis was found to be the most relevant journal source in this area and 'big data applications in real-time traffic operation and safety monitoring and improvement on urban expressways' (Shi and Abdel-aty, 2015) was found to be most cited document in this area. A comparative review of the industries revealed was performed and SVM, RF, DT, DNN were found to be the most influential ML algorithm applied in risk modelling. Leading, lagging and resilient indicator variables were also identified.

Based on these findings, a theoretic framework for a standard approach to selecting safety indicators was developed and relevant safety indicators accompanied with their appropriate input variable that could be employed in building ML models for highway industry were identified. However, with this research as a foundation, a robust ML model using safety indicators identified in this thesis will be developed in ensuing chapters.

CHAPTER 6- DATA EXPLORATION

6.1 INTRODUCTION

Data exploration is a critical component of any ML project because it lays the foundation for the entire project (Idreos *et al.,* 2015). Data exploration focuses on understanding the data, identifying patterns and trends, and preparing the data for further analysis (*ibid*). Various pertinent tasks such as data cleaning, data visualisation, and statistical analysis were performed during the data exploration stage to better understand the data and identify any issues or inconsistencies (Zuur *et al.,* 2010). Cumin *et al.* (2017) proposed a rewriting technique that enables a rapid and intuitive exploration of big data ML techniques.

One of the key tasks undertaken in the data exploration stage is data cleaning (He *et al.,* 2016). This entails locating and correcting any missing or incorrect data points, as well as ensuring that the data is in the proper format and consistent across all variables (Idreos *et al.,* 2015). Ilyas *et al.* (2019) suggests that specific data cleaning methods are applied to parts of the data to save time and maximise the performance of ML models. The data cleaning stage is critical for assuring the accuracy and dependability of the ML model constructed with the data. Tae *et al.* (2019) proposes a unified data cleaning framework that combines data cleaning techniques to improve the training accuracy of models. Once the data is cleaned, it is important to perform initial exploratory analysis to get a better understanding of the data (He *et al.,* 2016). This includes performing descriptive statistics, data visualisation and identifying potential outliers or anomalies (Ilyas *et al.,* 2019). Since discovering intriguing patterns or relationships within the data is one of the major objectives of data exploration, various statistical techniques, such as histograms, scatterplots and correlation analysis are sometimes employed to achieve this goal (Idreos *et al.,* 2015). These techniques help to identify underlying patterns and relationships within the data, which can then be used to inform the development of predictive models.

Data visualisation is also another crucial technique in data exploration (Sadiku *et al.,* 2016). Patterns and correlations in the data could be identified by plotting it in different ways. Visualisations may also assist in identifying outliers and abnormalities that may need to be addressed during data cleaning (Zuur *et al.,* 2010). Statistical analysis is also an essential part of data exploration which provides a better understanding of the distribution of the data and detection of any anomalies (Manikandan, 2011) such as skewed or imbalanced data could be discovered by computing summary statistics such as mean, median and standard deviation (Rana *et al.,* 2012). Another important aspect of data exploration is featuring engineering (Nargesian *et al.*, 2017), which involves transforming and selecting relevant features from the raw data. This can include techniques such as normalisation, scaling, and dimensionality reduction to improve the quality of the data and reduce the computational complexity of the model (Heaton, 2016). Dong *et al.* (2018) illustrates the importance of feature engineering in data analysis and ML and explains the application of feature engineering techniques for building ML models. This chapter therefore aims to explore the incident data of HTOs, uncover pertinent trends and patterns that will provide evidence-based information that describe contributory factors to incident occurrences and visualise findings to make its interpretations easier to communicate.

This chapter's contents have been subject to peer review thereby validating its findings for publication in a scientific journal. The research paper, titled ‘Hidden in Plain Sight: A Data Driven Approach to Safety Risk Management for Highway Traffic Officers’ was accepted for publication in the Buildings journal of Multidisciplinary Digital Publishing Institute (MDPI) in September 2024

6.2 DESCRIPTIVE DATA ANALYSIS (DDA) AND VISUALISATION

Data communicates useful information when explored and studied judiciously (Chen *et al.*, 2008; Mehta *et al.*, 2023). When exploring raw data, it is important to convert it into a structure (i.e. ordering, rearranging and manipulating) that presents an easy method of comprehension and interpretation to provide useful information about the data in use (Mehta *et al.*, 2023).

Descriptive data analysis (DDA) enables the illustration of data intricacies through a presentation and summarisation of data points methodically such that, it might highlight trends and patterns that fulfil the conditions of the data (Thompson, 2009; Soneson *et al.*, 2023). Conclusions on how the data is distributed can be obtained from carrying out DDA to aid in outlier detection, identification of duplicated data etc which are pertinent in conducting further statistical analysis (Lawless and Heymann, 2010). Techniques such as construction of statistical tables of means (Rana *et al.,* 2012), quantiles and mode of distributions such as standard deviation, variance and cross tabulations can be adopted in forming several distinct hypotheses which often highlights the disparities among the variable subcategories. The two main techniques adopted in this thesis to perform DDA includes: i) the measure of frequency and distribution; and ii) the measure of central tendency. DDA is performed in this section to improve the neutrality and objectivity of the research by providing statistical inferences of data which allows conclusions and generalisations to be derived from it (Kemp *et al.,* 2018). DDA provides a broader picture of a phenomenon due to its ability to employ several variables in conducting its investigation (Zook and Pearce, 2018). Therefore, trends and patterns found in performing DDA can be related to the real-life behaviour and occurrences of data allowing informed decisions and actions to be taken based on insights derived (Soneson *et al.*, 2023).

6.2.1 The Measure of Central Tendency and Position

Central tendency can be defined as: *"the statistical measure that identifies a single value as representative of an entire distribution"* (Gravetter and Wallnau, 2000). It significant in expressing the characteristics of the data accurately. In contrast to merely examining individual variables of the data to obtain the required understanding, central tendency provides insights more quickly and accurately (Manikandan, 2011). The measure of central tendency can be determined using the mean (Rana *et al.,* 2012), median (Manikandan, 2011) and mode (Bickel, 2003). The position of a specific data point or value falls in a data sample can be determined using the measure of position. This metric helps determine whether a data point is in the average or either oddly higher or lower than the rest of the values in the sample, which in this case was considered an outlier (Vinutha *et al.,* 2018). The measure of central tendency was used to identify the presence of outliers or skewed data that may impact upon the results of a predictive model. Table 6.1 is a descriptive statistical table for the central tendency and position of the numeric data present in the dataset.

Table 6.1 - Descriptive statistic table generated in Jupyter notebook.

	Experience in Current Role	**Age Range**	**Potential Severity Rating**	**Actual Severity Rating**	**Month**	**Year**	**Time**
count	64912.000000	64912.000000	64912.000000	64912.000000	64912.000000	64912.000000	64912.000000
mean	11.945804	36.558156	12.398062	11.498875	6.542750	2020.190674	12.671863
std	6.625666	11.043887	6.892359	3.074048	3.444392	1.168804	6.394766
min	1.000000	21.000000	1.000000	1.000000	1.000000	2018.000000	0.000000
25%	6.000000	27.000000	6.000000	11.000000	3.000000	2019.000000	7.000000
50%	12.000000	36.000000	12.000000	11.000000	7.000000	2020.000000	13.000000
75%	18.000000	45.000000	18.000000	11.000000	10.000000	2021.000000	18.000000
max	23.000000	59.000000	25.000000	25.000000	12.000000	2022.000000	23.000000

Sample size

The total sample size (count) of the distribution is 64,912 with no missing values after data cleansing.

Average, min, max.

The mean or median values give insights into what the average datapoint looks like. Table 6.1 shows that, the average number of years of experience a worker possess is 12 years with a minimum of 1 year and a maximum of 23 years. The average age range for workers normally involved in incident occurrences is 36 years with a minimum of age of 21 years and maximum age of 59 years. What this means is, should an incident occur, workers involved in that incident would likely be between the ages of 21 and 59 years however, the average age of workers involved in the incident is 36 years. The average severity rating for events is 10 with a minimum of 1 and maximum of 25. This therefore, means the average incident which occurs on a project site is normally of low risk. Considering the years from 2018-2022, the average year with incident occurring frequently is 2020. Also, considering a 24-hour working window, the average working time when incidents normally occur is 1pm.

Mean and median (50%)

Although the mean and the median are both a measure of central tendency, the difference between the mean and the median could offer insight into how the data is distributed (Rana *et al.,* 2012). If the mean is greater than the median it could be inferred that the data is rightly skewed whereas, if the median is higher than the mean it is likely the data is left-skewed (Doane and Seward, 2011). However, if the difference between the mean and the median is same, then the data has a normal distribution (Dean and Illowsky, 2018). From Figure 6.1, the mean and median for age range, potential severity, actual severity rating and year are the same, hence it could be inferred that the data for these variables are normally distributed. However, the median for experience in current role, month and time are slightly higher than the mean therefore, the data could be said to be marginally left-skewed.

Boxplot for outlier detection

A boxplot was plotted for the interquartile range presented in the summary statistic in Figure 6.1 to visualise any outliers that may be present in the numeric variables. However, no outliers were detected in the data. These also illustrate normal distributions.

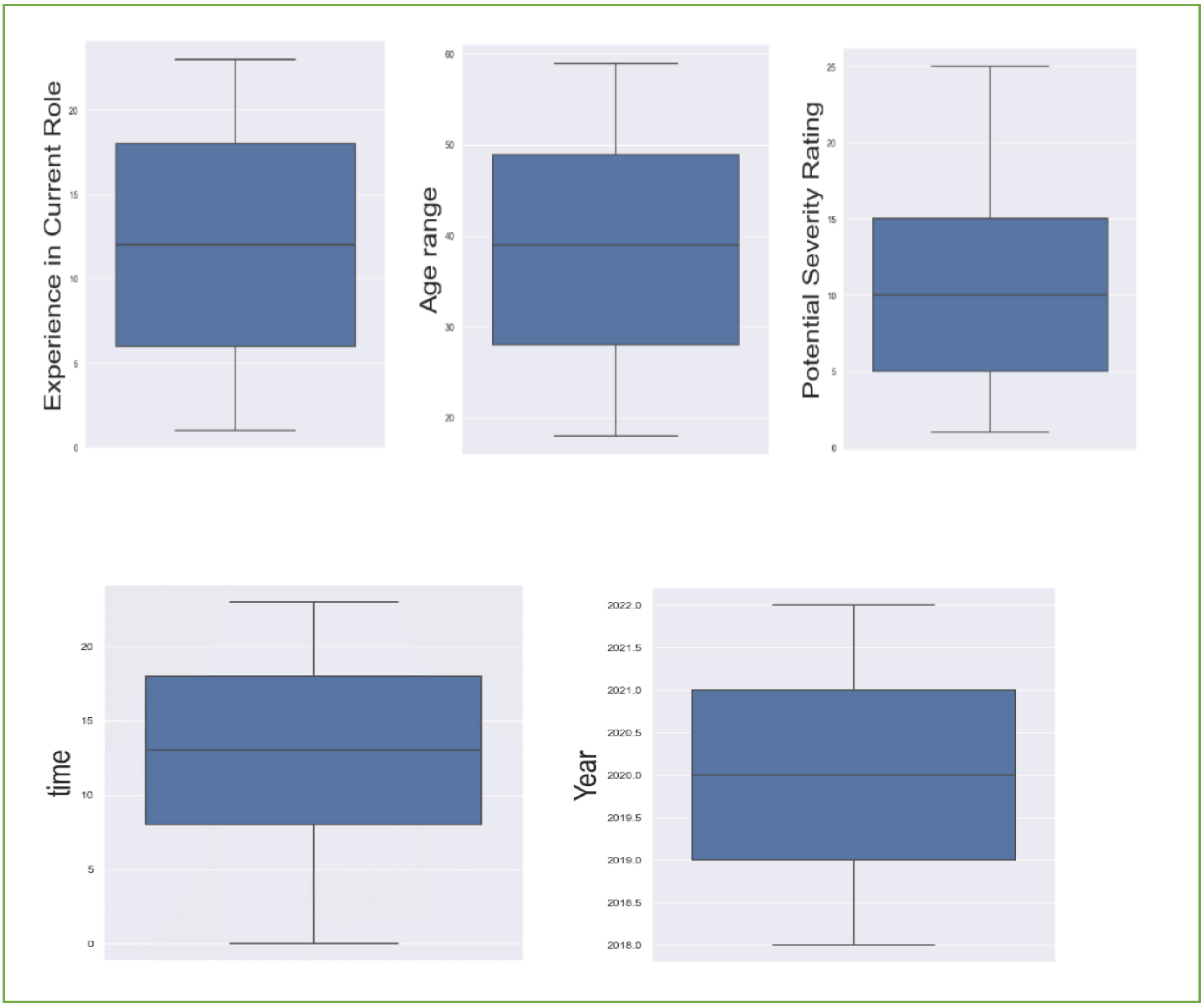


Figure 6.1 - Boxplots for numeric variables

6.2.2 The Measure of Frequency

Knowing how frequently a particular event occurred or is likely to occur is an essential feature of DDA (Cooksey, 2020). The measure of frequency can be used to represent personal information variables or variables that has discrete values, i.e. there are various categories that could be represented in the variable. In this section, the frequency statistics is used to explore data variables such as: i) the distribution of the types of events (incidents) likely to occur; ii) the distribution of event by location; iii) the distribution of injuries by season; iv) the distribution of events per year; v) the distribution of injuries per year; vi) the distribution of injuries by day of the week; and vii) the distribution of injuries by time of the day (morning, afternoon, evening and night).

6.2.2.1 The distribution of the types of events (incidents) likely to occur.

The events (incidents) that often occur in the highway industry has been categorised into nine unique values namely, utility strike (frequency (*f)*=0.43%), security (*f*=0.53%), structural safety (*f*= 0.53%), environmental (*f*=0.69%), facility/site (*f*=1.05%), incursion/IPV strike (*f*=1.58%), infrastructure/ asset (*f*=2.25%), personal illness or injury (*f*=2.55) and undesired circumstances/near miss (*f*=74.55%). Figure 6.2 shows the percentage of how frequently each of these incidents occur individually. From the diagram, it is noted that distribution of undesired circumstances/near miss occurs most among the incidents recorded. Workers are 74.55% more likely to encounter an undesired circumstance/ near miss in a typical highway project than any other incident. Secondly apart from an undesired circumstance/ near miss, personal illness/injuries are also more likely to occur than other incidents, while utility strikes are the least likely occurring incident. This type of insight gives an understanding on the distribution of incidents when prioritising probable incidents on a highway project and making decisions of possible measures to control the likelihood of an event occurring.

A near-miss is described by National Highways as an occurrence that, while not actively causing harming, has the potential to hurt by inflicting injury or resulting in poor health (FAME health and safety guide 1, 2022). Additionally, they describe undesirable circumstances as a collection of conditions or circumstances that have the potential to cause harm or ill-health (*ibid*). Even though it might seem clear, failing to notify a near-miss can result in more serious or dangerous occurrences later. This may be the result of employees not knowing how to report a near-miss or not understanding the protocol (Van der Schaaf *et al.,* 2013). However, other reasons why near-misses go unreported include: fear of disciplinary actions for the near-miss or getting a co-worker reprimanded; excessive documentation needed in reporting; fear of tarnishing a clean event record and potential rewards for maintaining it; the incident seems amusing and not serious; or a bad experience in the past when disclosing an incident (Jones *et al.,* 1999). Workers must be incentivised and encouraged to report near misses and undesirable circumstances to allow more proactive measures to be put in place to effectively curb future harm.

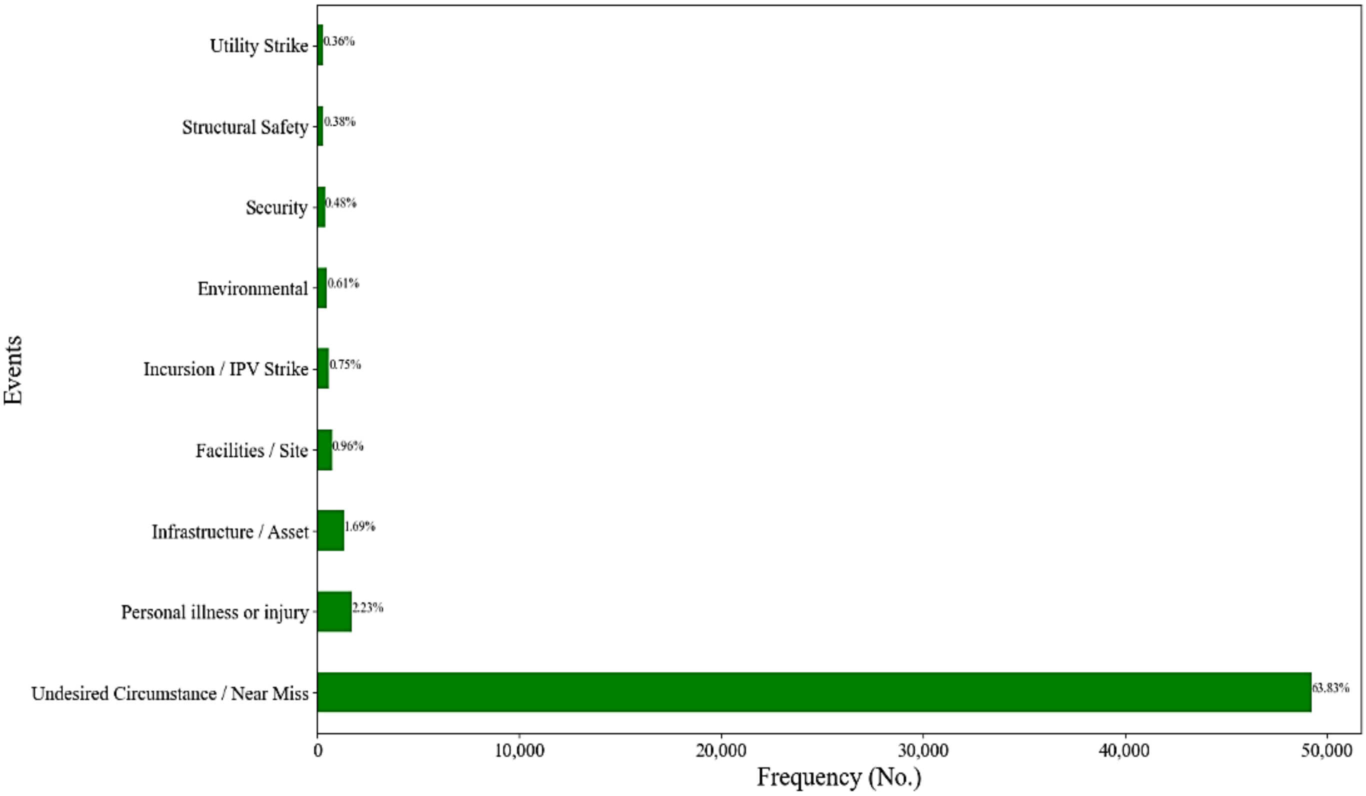


Figure 6.2 - Categorisation of event occurrence

6.2.2.2 The distribution of project risk levels

Considering the different levels of risk associated to highway operations undertaken by HTOs, it is crucial to assess the severity of the risk associated with incidents when they occur (Eseonu *et al.*, 2018). The highway incident data acquired from HART presents severity ratings for incidents which are further classified as high, medium and low risk incidents. Figure 6.3 shows a visualisation of the most frequently occurring risk level. This is examined to gain valuable insights into the level of risk HTOs are usually exposed to and the detrimental impacts of project risk levels on HTOs. The level of risk or risk severity associated with an incident is often linked to various factors, such as time of incident, location and site/ project (Intini *et al.*, 2024). Therefore, analysing how severe a risk could be will aid in exploring the relationship between the risk levels and the associated variables (Zhang *et al.,* 2019). Understanding how these variables contribute to increased project risk levels allows for deeper exploration of injury patterns and the implementation of safety improvement initiatives based on evidence.

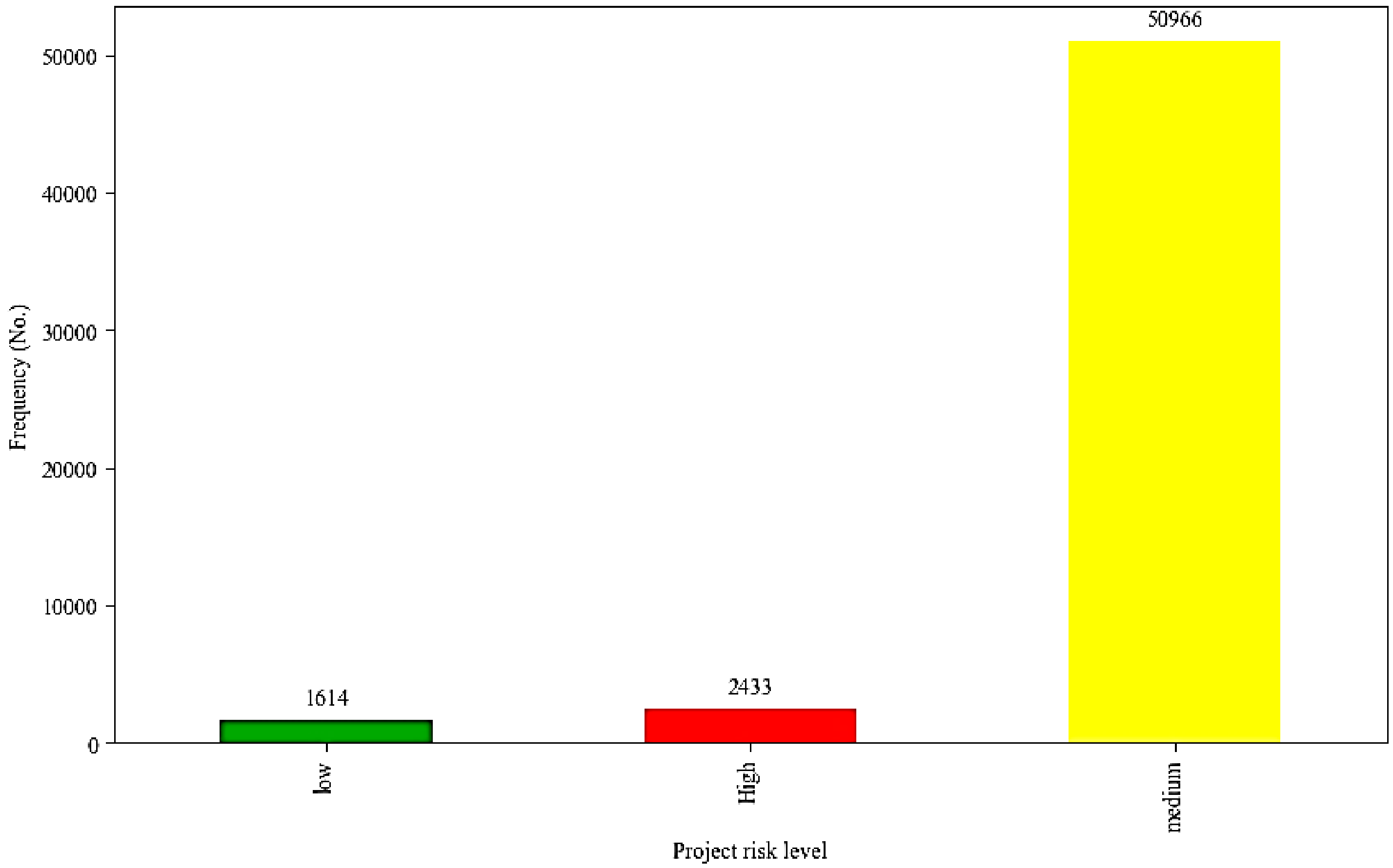


Figure 6.3 - Visualisation of project risk levels

Figure 6.3 shows that majority of the operations undertaken by HTOs have a medium risk level, followed by high risk and low risk respectively with little difference between the frequency of high risk and low risk operations. However, it could be inferred from the diagram that there is an extreme likelihood of a medium risk event occurring for any highway operation undertaken by HTOs. This finding is consistent with Sharaf and Abdelwahab (2015), who using Egypt as a case study, found that the overall risk in the highway projects is considered medium level.

6.2.2.3 The distribution of project risk level per time of day

The time of incident occurrences were divided into four periods i.e. morning (7:00- 11:59 am), afternoon (12:00- 15:59pm), evening (16:00- 20:59pm) and night (21:00pm-6:00am). Figure 6.4 presents the project risk levels for individual times of the day. For each time of the day, it is observed that the most prevalent risk level was the medium risk level, followed by the high-risk level and low risk level respectively. Furthermore, it is notable that night shift presented a major challenge in terms of risk followed by morning, afternoon and evening respectively. This finding is consistent with the claims made by Thokala *et al.* (2023) that most accidents occur during the nighttime. Moreso, Simončič (2001) found that accidents which occur on the road at nighttime were more serious than those which occurred during the day or other times

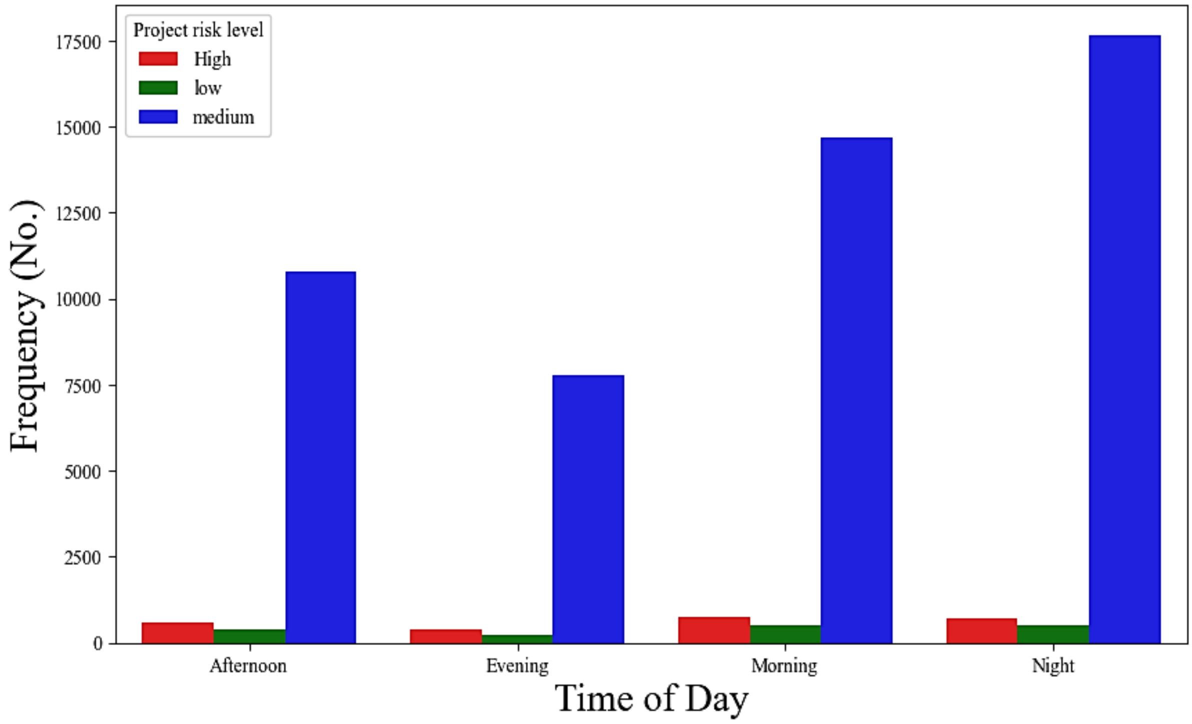


Figure 6.4 - Project risk level at various times

From the results, working during the night (night shift) posed the greatest risk in highway operations. This is because, people who work night shifts risk falling asleep and making mistakes at work due to a disrupted circadian rhythm and staying awake for a lengthy period prior to their shift (Maltese *et al.*, 2016). Also, the intensity of light at night is less than other times of the day therefore, it becomes more difficult for drivers to see road workers or road markings (cf. Thokala *et al.*, 2023). It is also difficult for HTOs to see incoming vehicles and other dangerous objects such as animals, falling debris, moving objects or equipment etc. leading to struck by accidents, slip and falls or even severe vehicle crashes (Yeole *et al.*, 2023).

6.2.2.4 The distribution of events by location

The location of a highway project or task could give an indication of the level of safety risk event likely to transpire based on how frequently incident have occurred at that location in the past. Previous incident locations for on-road HTOs were analysed and considered. 20 locations were realised from the dataset where incidents often transpired. From the distribution (refer-Figure 6.5), the number of events that occurred at the location provides a basis to rank the top

10 locations with most event occurrence as: carriageway A (*f*=198); traffic management enclosure (*f*=119); carriageway B (*f*=119); within works area / safety zone (adjacent to a live carriageway) (*f*=84); off network e.g. local authority road footpath marine (*f*=46); carriageway slip road J (*f*=27); outside works area- adjacent environment (*f*=26); works area/ safety zone access or exit point (*f*=24); working on SRN (*f*=21); carriageway hard shoulder (*f*=19).

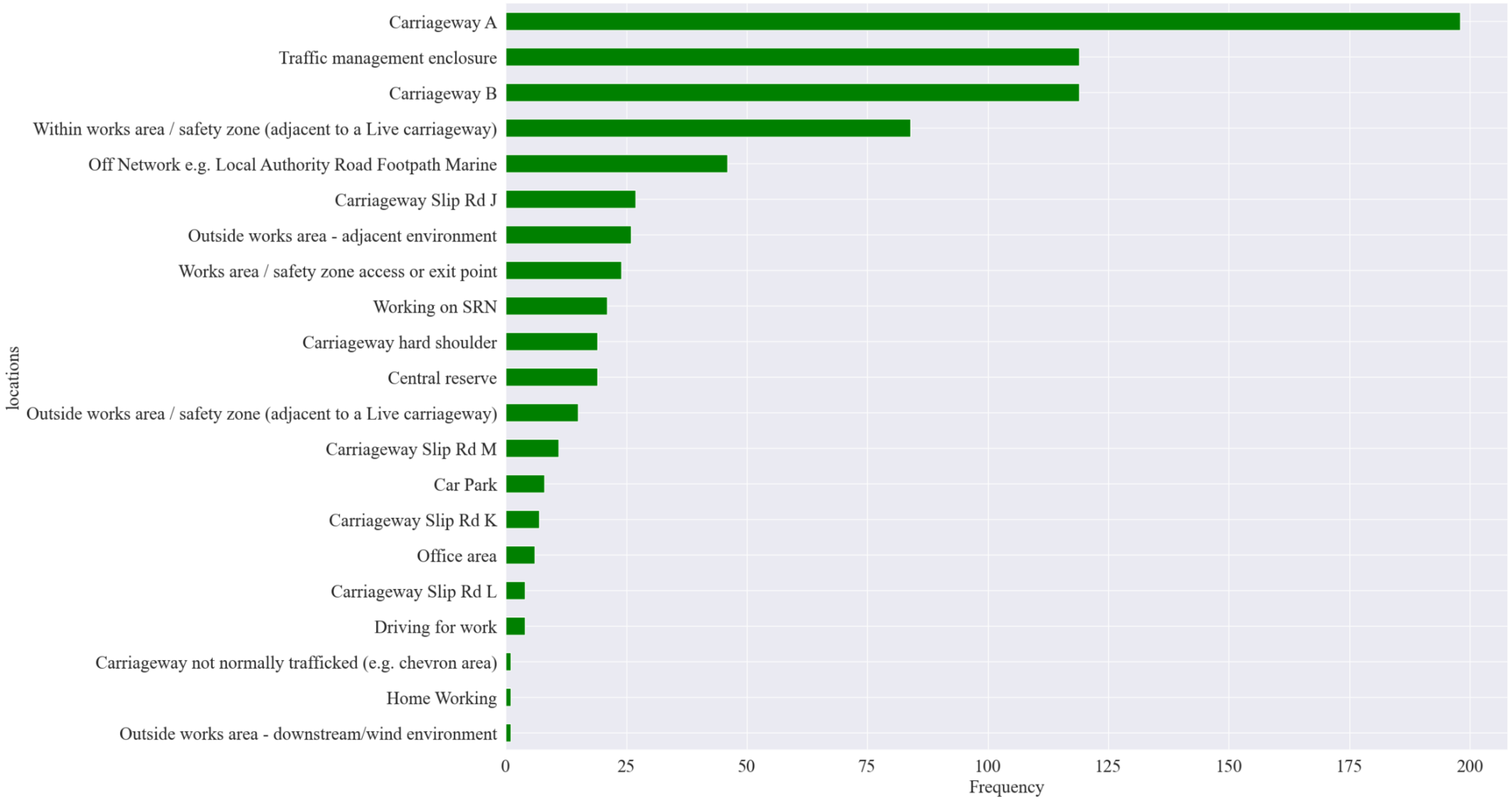


Figure 6.5 - Frequency of incidents by location

Safety decision makers would therefore have to prioritise and pay more attention to workers embarking on projects or operations on the carriageway (carriageway A and B). A carriageway is a roadway where a vehicle is free to proceed laterally over a width of road without encountering any physical obstructions or division (Taylor *et al.,* 2002). National Highways term any road, including expressways, smart motorways and motorways, where opposing flows are separated as dual carriageways (The Traffic Signs Regulations and General Directions, 2016). The primary carriageway is designated as 'A' in one direction (such as clockwise, or away from London) and 'B' in the opposite direction (e.g. anti-clockwise or the direction heading towards London), depending on the direction the road user is traveling, according to the carriageway identifier (CD 193 Driver location signs, 2020).

It is interesting to note that, 'outside work areas (*f*=2)'; 'home working (*f*=3)' and 'carriageways not normally trafficked (*f*=4)', were some of the locations with the least reported incident occurring. This understanding could be a basis for encouraging working from home where possible. For example, on days when HTOs might need to write reports or perform other administrative tasks assigned to them, they could work from home instead of working from the office area. Also, for 'carriageways not normally trafficked' to have less reported incidents, it could be inferred that, traffic congestion and other related issues are a major cause of accidents on the highway for HTOs. This is consistent with the findings of Yeole *et al.* (2023) who revealed that the congestion of vehicle on road (known as mixed flow traffic) is a major factor which leads to accidents on the highway.

6.2.2.5 The relationship between average traffic flow and incident occurrence.

The nature of highway operation is such that work is carried out every day of the calendar week. However, some workers could work on the weekdays while others work on the weekends. From the data, injuries have occurred on every day of the week with some days recording higher rates than others. Equipping safety managers with such information could enable management to take H&S decisions which could minimise factors that contribute to high injury rates on specific days. The annual daily traffic flow and distribution data (Road Traffic Statistics, 2022) from the Department of Transport UK, was used to analyse the average traffic flow daily and compared to the average daily incident recorded by employees on road (refer to Figure 6.6). From the Figure, it is observed that the average traffic flow between Monday (*f*=106.78) and Tuesday (*f*=108.07) was close, although Tuesday had a higher traffic flow rate. This reflects in the frequency of event occurrence on Monday (*f*=15616) and Tuesday (*f*=17129). It can be seen that event occurrence on Tuesdays are also slightly higher than Mondays. The average traffic flow for Thursday (*f*=114) was also slightly higher than Friday (*f*=113). Coincidentally, the incident rate for Thursday (*f*=16080) was also higher than Friday (*f*=14504). In addition, Saturday (*f*=85.22) and Sunday (*f*=74.19) had the least recorded average traffic flow and inadvertently the least recorded incident recorded. The days with least number of incidents recorded are notably the tail end of the week, i.e. Friday Saturday (*f*=9760) and Sunday (*f*=9314) with Sundays having the least recorded injuries. In contrast, more incidents are recorded on the weekdays. This finding aligns with findings made by Híjar *et al.* (2000) who stipulates that accidents on the highway occurs more frequently on the weekdays. This trend indicates a correlation between traffic flow and incident occurrences. However, this trend could also be due to other factors, such as the number of workers who report to work on weekends, the type of work carried out during weekends or the extra safety measures put in place during weekends to prevent accidents on the work sites (Eboli *et al.*, 2020). The details of such information could contribute to developing a resilient H&S best practice measure for specific days of the week based on the type of operation to be carried out and traffic flow during those days.

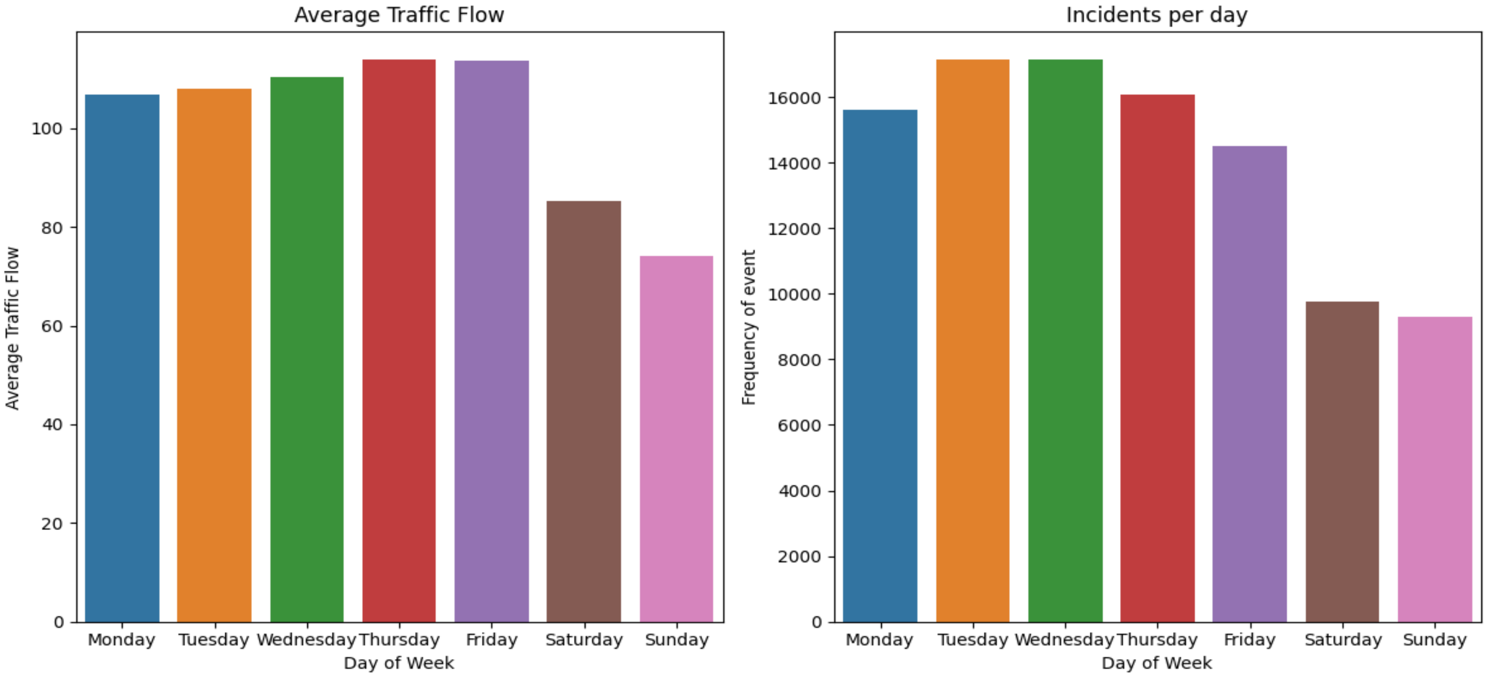


Figure 6.6 - Average traffic flow per day

6.2.2.6 The relationship between age and injuries

The 2021 census defines the working population in the UK as people between the ages of 16 to 64 years (Gov.uk, 2024). However, the incident data analysed showed that, HTO incidents reported normally involved workers between the ages of 20 to 60 years. Several studies have researched the impact age has on a workplace injury (Breslin and Smith, 2005; Frank-Neuhauser *et al.*, 2013; Bravo *et al.*, 2022). Some studies have concluded that older worker are more likely to have injuries (Rogers and Wiatrowksi; Bravo *et al.*, 2022) while others have proven the contrary (Smith *et al.*, 2005). Such conflicting conclusions show that the relationship between age and injuries of workers is subjective to individual industries or domains. Figure 6.7 presents the relationship between age and injuries for HTOs in the highway industry. The findings concur with those made by Smith (2005) which found injury rates to decrease with increasing age. From the results, it is seen that, younger HTOs are involved in more injuries when compared to older colleagues. This could be due to several reasons including the fact that the number of younger HTOs are more as compared to older ones. From the data, 72% of the HTO population fall between the ages of 23 and 49 years. It could be inferred from the result that; it is more likely for an HTO between the ages of 20 to 40 to be involved in an injury causing incident than older HTOs.

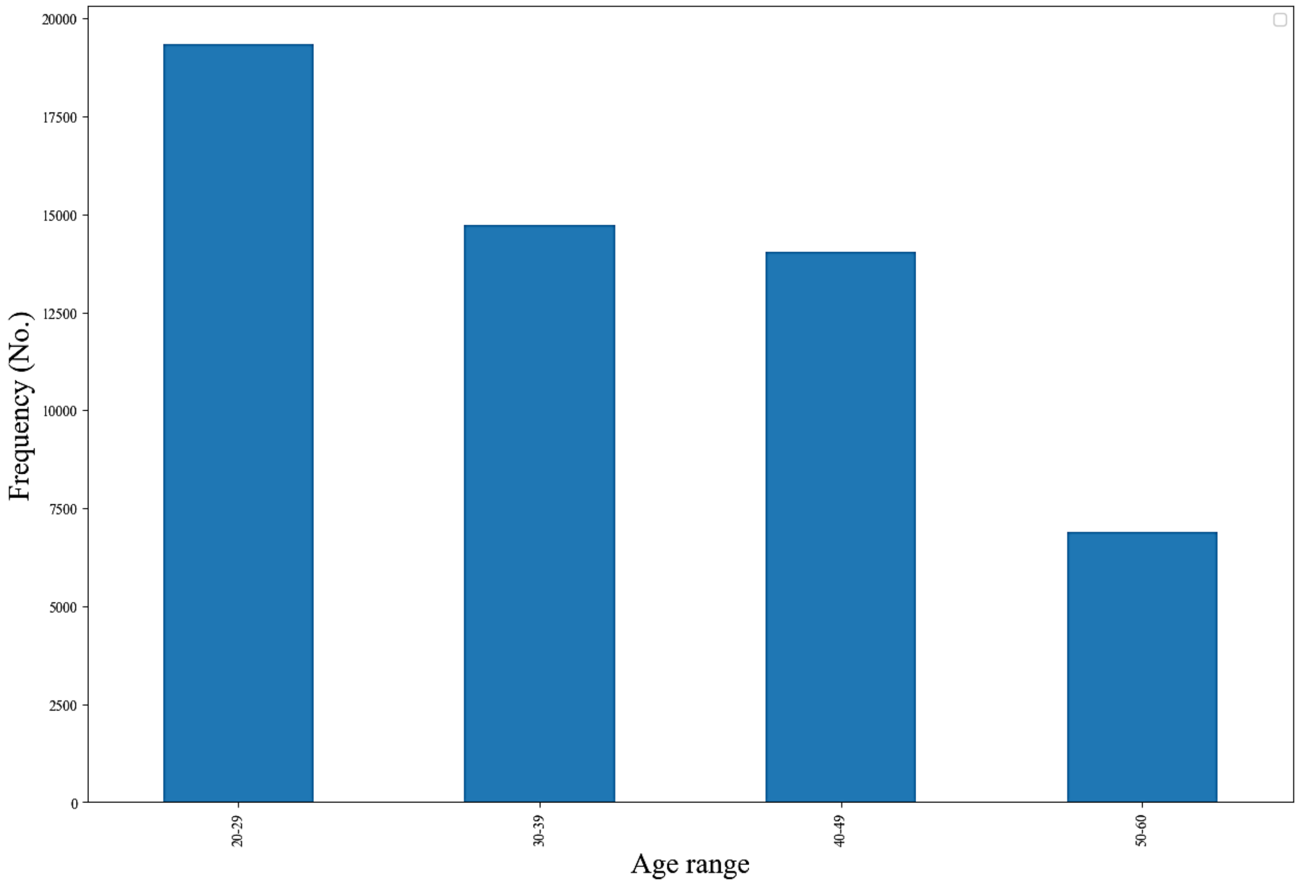


Figure 6.7 - The injury rate of HTOs according to age range

6.3 SUMMARY

A comprehensive incident data exploration for HTO was performed in this chapter to uncover patterns and correlations that can inform future safety strategies. To enable an insight into discovering and better understanding of the data, descriptive data analysis, frequency distribution assessments and statistical tables for numerical values were adopted as methods for exploring the data. Findings made showed significant correlations between the input variables utilised. The results indicated, a relationship exists between average traffic rate and incident occurrence. Clearly, the tendency of an increase in incident rates for times with high traffic volumes was revealed. Furthermore, a correlation between injury and age was found, which shows that certain age groups are more susceptible to injuries than others. The chapter also mapped incidents by location to obtain insights into work areas with higher incident rates. Risk levels across different times of the day were further examined to uncover specific periods with elevated risk, which can shape the roll out of targeted interventions. By projecting risk levels, future trends can be anticipated, and resources can be prioritised and allocated more efficiently. The distribution analysis of various types of incidents provided a detailed understanding of the most common incident categories, aiding in the development of focused safety measures. In summary, this chapter strived to provide valuable insights that are consistent with findings in the literature, supporting the effectiveness of data-driven approaches in enhancing highway safety and traffic management.

CHAPTER 7- BUILDING THE HIGHWAY SAFETY PREDICTION MODEL: INCIDENT TYPE PREDICTION

7.1 INTRODUCTION

To augment safety, judicious identification of event/incident categories likely to occur on the highway is critical for deploying suitable resources and optimising traffic flow (Eseonu *et al.,* 2018). It is imperative that workplace H&S teams can recognise and understand possible safety incident infractions that could be detrimental to workplace safety before highway personnel are deployed to work zones (Goh and Soon, 2014).

Through rigorous experimentation and analysis of primary data, this chapter develops a robust predictive framework which will enable highway authorities to prioritise resources, respond effectively to the diverse safety scenarios and enhance proof-driven safety precautions to minimise HTO incidents. Such a framework will be particularly useful during safety risk assessments meetings conducted prior to HTOs resuming operations on the highway (Jørgensen, 2011). Safety officers can then educate and train (Tong *et al.,* 2015) HTOs on impending risks predicted by the model thereby equipping workers with resilient shocks such as: awareness of risks (Shirali *et al.,* 2018); anticipation of the risks (Azahdeh *et al.*, 2014); and response and flexibility to make important safety decisions (Woods and Wreathall, 2003).

Three ML algorithms were explored in chapter, by making use of their inherent strengths to enhance the validity, veracity and efficiency of incident classification (Zhai *et al.,* 2021). The algorithms used are, Random Forests (RF), Naïve Bayes (NB) and Support Vector Machine (SVM) classifiers (Tixier *et al.,* 2016; Zhang *et al.,* 2019; Goh *et al.,* 2018). Associated objectives are threefold, namely to: 1) present a comparative analysis of SVM kernels by evaluating how well they performed using metrics such as precision, accuracy score, recall and F1-score; 2) apply original data to three ML algorithms (i.e., SVM, RF and NB) and evaluate these based on a comparative analysis of the overall accuracy score of each model, the precision, recall and F1-score of each class for the target variable; and 3) apply balancing algorithms to the original data and compare their performance to that of the unbalanced data.

This chapter's contents have been subject to peer review thereby validating its findings for publication in a scientific journal. The research paper, titled 'Unravelling Incipient Accidents: A Machine Learning Prediction Of Incident Risks In Highway Operations' was accepted for publication in the Smart and Sustainable Built Environment of Emerald Group publishing in September 2024.

7.1.1 Description of target variable

The class distribution for the target variable is imbalanced (i.e. classes are not equally represented in the data) with undesired circumstance/near miss being the class with the most occurrence. Table 7.1a describes the classes of the target variable and Table 7.1b presents the independent variables used in modelling.

Table 7.1a - Description of target variable classes

Target variable	Description	Examples
Personal illness/injury (PI)	Situation where an HTO experiences a medical issue or sustains an injury while on duty.	Fell, slipped or tripped from height or the same level, attacked by an animal, collision, hit by a moving object/plant/vehicle or falling object.
Undesirable circumstance/near miss (UN)	Events that have the potential to cause harm but are narrowly avoided or stopped before any adverse consequences occur.	Security threat, technology failure, contact with hazard, slips, trips and falls without injuries.
Security (SC),	Events that compromise the safety and well-being of HTOs due to intentional or malicious actions.	Intimidating behaviour, physical assault, racial abuse, verbal abuse or insult, object(s) thrown at road worker, vehicle driven at road worker.
Environmental (EN)	Events that affect the natural surroundings or the external conditions in which HTOs operate.	Disturbance of natural site/ecology, heritage / archaeology, land contamination, nuisance (noise, light, odour, vibration, dust, steam), spill, leak or uncontrolled discharge, weather.
Infrastructure (IF)	Incidents related to the physical structures, technology and components of the transportation system.	Failure or damage of technology, communication and signals, hard shoulder misuse, cone strike, live carriageway crossing.
Facilities/site (FS)	Hazards associated with the specific location or site where HTOs are stationed.	Cable management, car park, cleaning, fire evacuation, grounds maintenance, temperature, housekeeping, pest control and waste management.
Structural safety (SS)	Risks associated with the integrity of buildings, bridges, or other structures in the highway environment.	Collision with superstructure, substructure, parapet or vehicle containment barrier, bridge – fire, flood, scour, bridge component – steel failure, corrosion, component loss, concrete deterioration/damage, post tensioning.

Utility strike (US)	Incidents where underground utilities, such as gas, water, or electrical lines, are accidentally damaged or struck during highway activities.	Utility / Service Strike CCTV, electricity, gas, oil, drainage, telecom, other cables or pipelines, water.
Incursion/IPV strike (IS)	Events where unauthorised vehicles enter restricted areas or where HTOs' vehicles are struck.	incursion; intentional - because of breakdown, breach of rolling roadblock, to seek benefit incursion, to seek information, blue light incursion incursions. incursion: unintentional - driver confused, follow in incursion, result of accident, IPV strike.

Table 7.1b - Description of variables used in modelling.

Indicators	Independent Variable	Data Type	Meaning	References
	PublishedRecordId	Integer	ID number for data point.	Zhang *et al., (*2016)
Environmental indicators	Region	Categorical	The region where project is based.	Zhang *et al.,* (2012)
	Site/Project'	Categorical	The site where project is based.	Sarkar *et al.*, (2020)
	Location	Categorical	The location of the project site. .	Tixier *et al.*, (2016)
	Did this event occur on the SRN?	Categorical	Is incident a strategic road network related? (Yes/No).	Tixier *et al.*, (2016)
	Weather / visibility	Categorical	The visibility at time of incident (rainy, stormy, clear, windy).	Ajayi *et al.*, (2020)
	Season	Categorical	The season of the incident (winter, summer, spring, and autumn).	Rogovski *et al.,* (2021)
Social/demography indicators	Experience in current role	Integer	The number of years worker has been working in that position.	Sarkar *et al.*, (2020)
	Age Range	Integer	The age of the worker.	Alizadeh *et al.*, (2015)
Time-based indicators	Month	Integer	The month of incident.	Meng *et al.*, (2020)
	Date and time of event	Datetime	The date and time incident occurred.	Tsoukalas and Fragiadakis, (2016)
	Year	Categorical	Year of incident.	Chiang *et al.*, (2018)
	Day_of_week	Categorical	The day of the week incident happened (Monday-Sunday).	Sanchez *et al.*, (2015)
	Time_of_day	Categorical	The time of the day (morning, afternoon, evening, and night).	Namian *et al.*, (2016)
Agent-based indicator	Vehicles involved?	Categorical	Whether a vehicle was a party to incident (Yes/No).	Kidando *et al.*, (2021)
Incident-based indicators	'Injury occurrence	Categorical	The likelihood of an injury occurring (True/ False).	Cheng *et al.,* (2012)
	'Part of body affected',	Categorical	The part of the body likely to be affected (head, hand, waist, leg etc.).	Ajayi *et al.*, (2020)
	Project risk level'	Categorical	The likely severity of project risk (high, medium, low).	Meng *et al.*, (2020)
	Actual Severity Rating	Integer	What the actual impact was (1-25).	Tixier *et al.*, (2016)
	Potential Severity Rating	Integer	What the possible impact of incident could be (1-25).	Sanchez *et al.*, (2015)
	Dependent variable			
	Event Type'	Categorical	The kind of incident likely to occur (personal illness/injury, undesirable circumstance, security, environment, infrastructure).	Sarkar *et al.*, (2020)

7.2 RESULTS FOR INCIDENT RISK PREDICTION

Through statistical analysis, the prediction models allow the extraction of patterns from the variables that relates to the different types of incident risk occurrences (Tixier *et al.,*2016). Hence the result in this section provides evidence- based information for making safety-related decisions for HTOs. The results therefore obtained for the predictive modelling experiments performed indicated a potential feasibility of applying ML models in accurately predicting incidents risk occurrences in highway operations for HTOs.

7.2.1 Dimensionality reduction and feature selection

Pearson's correlation analysis was used to determine which features have the most significant impact on the performance and validity of a predictive model - refer to Figure 7.1 (Liu *et al.,* 2020; Yin *et al.,* 2013). Correlation analysis renders each input variable relatively independent by removing redundant data (Saccenti *et al.,* 2020).

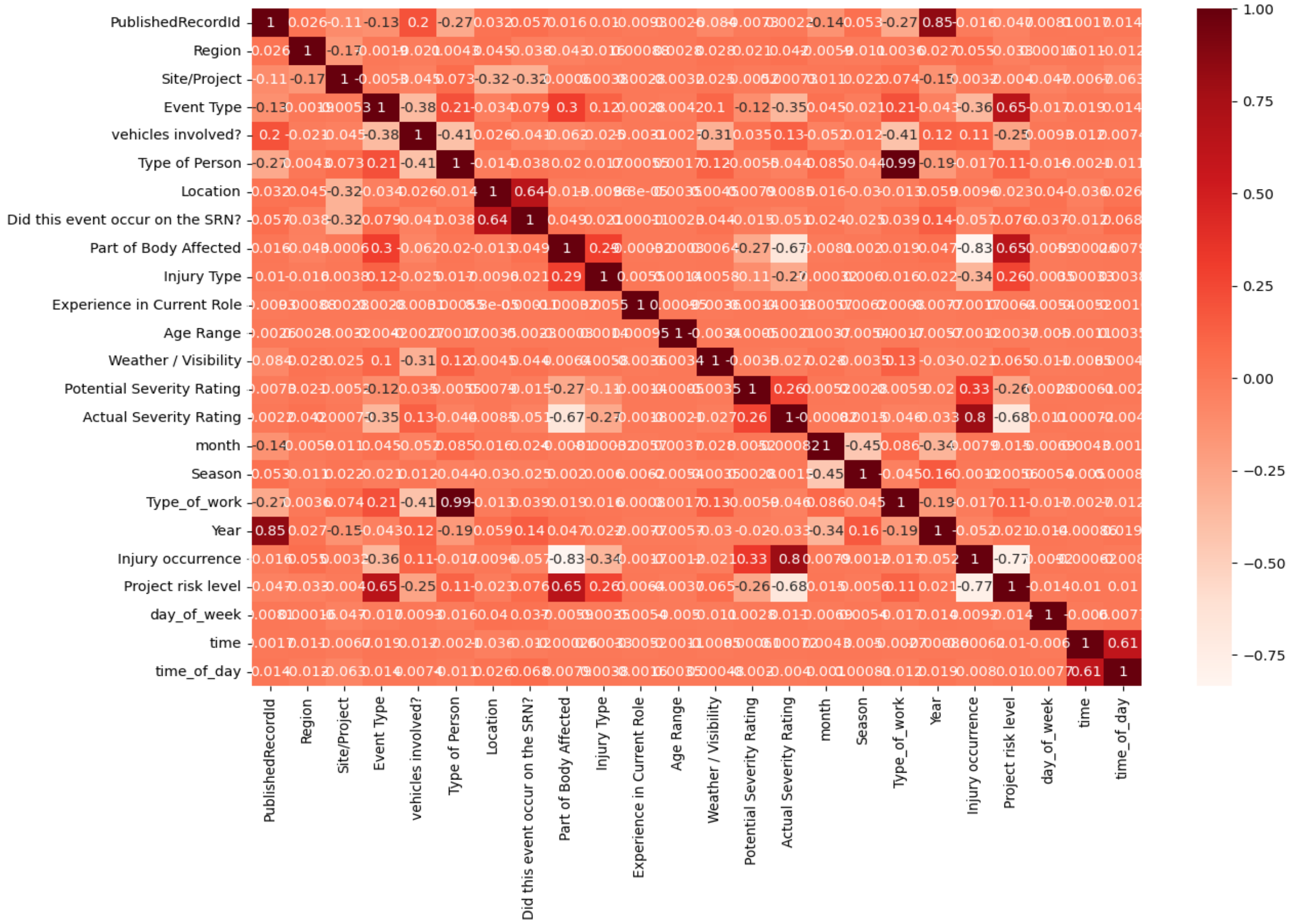


Figure 7.1 - Correlation matrix

Correlation coefficients (CCs) >-0.6 or 0.6 are considered strong correlations. In a horizontal alignment, the CC between the 'PublishedRecordId' and 'year' is noted as 0.85, this can be translated as a strong correlation between the two variables, hence since the 'publishedrecordID' has little impact on the entire analysis, it is dropped. The CC between 'type_of_person' and 'type_of_work' is 0.99 which is extremely strong, therefore, 'type_of_person' which describes the type of employment contract an individual has was dropped from the list since its impact is deemed less significant than the kind of work an employee is going to undertake when predicting an incident. The variables: 'location' and 'did this event occur on the SRN?' had 0.64 CC therefore 'Did this event occur on the SRN?' was excluded. 'part of body affected' also had a negative CC of -0.67 and -0.83 with 'actual severity rating' and 'injury occurrence' respectively and a CC of 0.65 with 'project risk level'. Since 'project risk level' also has a strong negative correlation with 'injury occurrence' (-0.77) and 'actual severity rating (-0.68), all the three variables are dropped and 'part of body affected' is maintained. The variable 'date and time of event' was also dropped since other variables such as 'day_of_week', 'month' and 'year' were already derived from it. In total, seven independent variables were eliminated leaving 15 feature variables.

7.2.2 Feature importance in prediction model

The RF classifier was used to determine the relevance of each attribute in the predictive model (refer to Figure 7.2). In a study to predict types of occupational accidents at construction sites, Kang and Ryu (2019) used RF method to determine the most important features that contribute to the prediction. In a similar study to assess accident prediction accuracy for highway-rail grade crossings Zhou *et al.* (2020) proposed the use of the RF method for feature importance evaluation. These studies justify the use of RF method in the current setting.

RF has an embedded feature importance score and could be adopted for classification and regression tasks (Li *et al.,* 2019). The Gini Importance (GI) is the specific feature importance indictor that is utilised in this thesis. When splitting the data at a feature's values within the decision trees of a RF, GI quantifies how much each feature contributes to the decline in impurity (i.e. the degree of disorder in a dataset) or the rise in purity (i.e. the degree of certainty in a dataset) (Nembrini *et al.,* 2022). The value of the GI sums up to one - the higher the value of the GI, the greater its significance at the node. Based on the trained model, feature importance analysis was performed – refer to Figure 7.2.

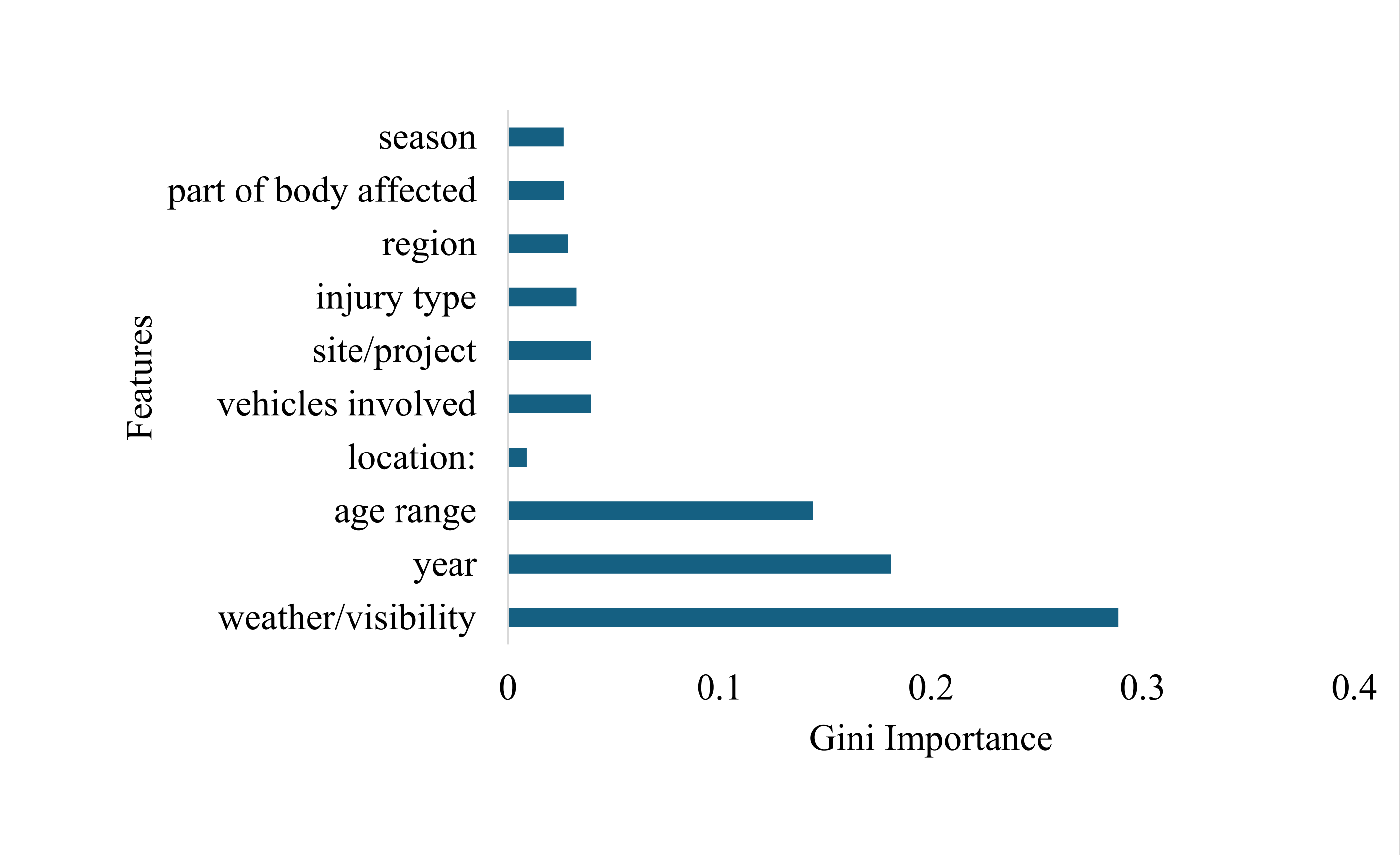


Figure 7.2 - Feature importance analysis with RF

From Figure 7.2, it could be inferred that the top 10 predictors of incidents in highway operations are: weather/visibility: (*GI*= 0.2886); year: (*GI*= 0.1810); age range: (*GI*= 0.1443); location: (*GI*= 0.0878); vehicles involved: (*GI*= 0.0393); site/project: (*GI*= 0.0391); injury type: (*GI*= 0.0324); region: (*GI*= 0.0283); part of body affected: (*GI*= 0.0266); and season: (*GI*= 0.0264). This implies that, the features mentioned contributes the most to the accuracy of the prediction model hence, these features are the most influential in predicting model outcomes and could therefore help reduce the dimensionality of the model without losing significant predictive power.

7.2.3 Class imbalance handling

70% of the selected sample chosen as training data yielded a total of 38,509 data entries from the initial dataset. Each class had the following data entries. ‘UN’ (f=34,491 or 89.57%), 'PI' (f=1,188 or 3.08%), 'IF' (f=933 or 2.42%), 'FS' (f=545 or 1.42%), 'IS' (f=389 or 1.01%), 'EN' (f=312 or 0.81%), 'SC' (f=265 or 0.69%), 'SS' (f=203 or 0.53%), and 'US' (f=183 or 0.48%) The under-sampling, over-sampling and synthetic sampling balanced dataset were created utilising three distinct resampling strategies to solve the imbalanced dataset problem. The totals from all employed datasets and their distribution among various incident type classes are shown in Table 7.2 Evidently, all the methods were successful in balancing the data because they all introduced diversity by creating new instances, thereby, potentially improving the model's generalisation ability (Sarkar *et al.,* 2020).

Table 7.2 - Distribution of classes in target variable

Dataset	Balancing algorithm	Total	UN	PI	IF	FS	IS	EN	SC	SS	US
Original dataset	N/A	38509	34491	1188	933	545	389	312	265	203	183
Synthetic sampling	SMOTE	310419	34491	34491	34491	34491	34491	34491	34491	34491	34491
Under-sampling	RU	1,647	183	183	183	183	183	183	183	183	183
Oversampling	RO	310419	34491	34491	34491	34491	34491	34491	34491	34491	34491

7.2.4 Performance evaluation of classifiers

Each model's predicted accuracy on test data is examined in order to determine how generalised it is. The accuracy score, recall, precision and F1-score are the metrics that are employed. These metrics are frequently used to assess how well a model predicts the ground truth (Yacouby and Axman, 2020). For a multi-class performance evaluation, it is best practice to evaluate the performance of individual classes to ascertain how best the model performs for each class (Farid *et al.,* 2014).

7.2.4.1 Experiment 1: choosing a kernel for SVM.

The SVM algorithm's performance is heavily influenced by the kernel that is used however, there is currently no common guideline regarding which kernel should be utilised (Patle and Chouhan, 2013). In the first experiment session, four individual kernel types (i.e. polynomial kernels, RBF kernels, linear kernel and sigmoid kernel) were examined and applied separately to the SVM model. This was to compare which kernel had the best performance on the original dataset. Table 7.3 presents the results from the individual kernels and shows the different target classes of the dependent variable being classified, the kernel function name from which classification task perform, the precision, the recall, the F1-score and the overall accuracy score for each of the kernels. The experimental results presented in Table 7.3 show that the polynomial function performed better in terms of accuracy score to all the other kernels. Furthermore, only the polynomial kernel was able to predict classes of each data entry albeit, the classification precision was extremely poor. The other kernels were unable to predict some of the classes. The polynomial kernel SVM is a proficient technique capable of handling high-dimensional datasets and capturing non-linear relationships between input data (Patle and Chouhan, 2013). It is therefore selected and applied as the preferred kernel technique for this thesis. Comparatively therefore, the polynomial kernel is preferred for the SVM model in this thesis.

Table 7.3 - Comparative analysis of SVM kernel performance

	Target class	EN	FS	IS	IF	PI	SC	SS	UN	US
Kernel										
POLYNOMIAL	Precision	0.24	0.37	0.79	0.50	1.00	0.57	0.27	0.99	0.38
	Recall	0.09	0.42	0.74	0.69	1.00	0.15	0.04	1.00	0.19
	F1-score	0.13	0.39	0.77	0.58	1.00	0.24	0.07	1.00	0.26
	Overall accuracy score	**0.96**								
RBF	Precision	0.33	0.34	0.83	0.44	1.00	0.00	0.00	0.98	0.29
	Recall	0.03	0.39	0.68	0.67	1.00	0.00	0.00	1.00	0.02
	F1-score	0.05	0.37	0.74	0.53	1.00	0.00	0.00	0.99	0.04
	Overall accuracy score	**0.95**								
LINEAR	Precision	0.00	0.30	0.80	0.40	1.00	1.00	0.00	0.99	0.00
	Recall	0.00	0.28	0.71	0.72	1.00	0.01	0.00	1.00	0.00
	F1-score	0.00	0.29	0.75	0.52	1.00	0.02	0.00	0.99	0.00
	Overall accuracy score	**0.95**								
SIGMOID	Precision	0.00	0.00	0.38	0.01	0.79	0.00	0.00	0.93	0.00
	Recall	0.00	0.00	0.12	0.00	0.82	0.00	0.00	1.00	0.00
	F1-score	0.00	0.00	0.18	0.00	0.80	0.00	0.00	0.96	0.00
	Overall accuracy score	**0.92**								

7.2.4.2. Experiment 2: comparing the performance with unbalanced and balanced data.

The three algorithms are applied to the dataset independently in experiment two. Performance metrics of each of the three classifiers are evaluated using the unbalanced (UB) and balanced datasets. First, the ML classifiers were applied on the original unbalanced data. The results of the experiment with the imbalanced data are detailed in Table 7.4 and Figure 7.3 for visual comparison. The different balancing algorithms were then applied separately to the data and then analysed using the three different classification algorithms separately. Results for the precision of each target class are presented in Table 7.4 and the percentage accuracy score has been presented for comparison in Figure 7.4. Table 7.4 shows the comparative results of all these algorithms on unbalanced dataset and the three balancing datasets (SM, RO and RU). In all the cases for the unbalanced dataset, it is observed that RF (97%) performs better than the others based on the accuracy score metric, followed by SVM (96%) and NB (94%).

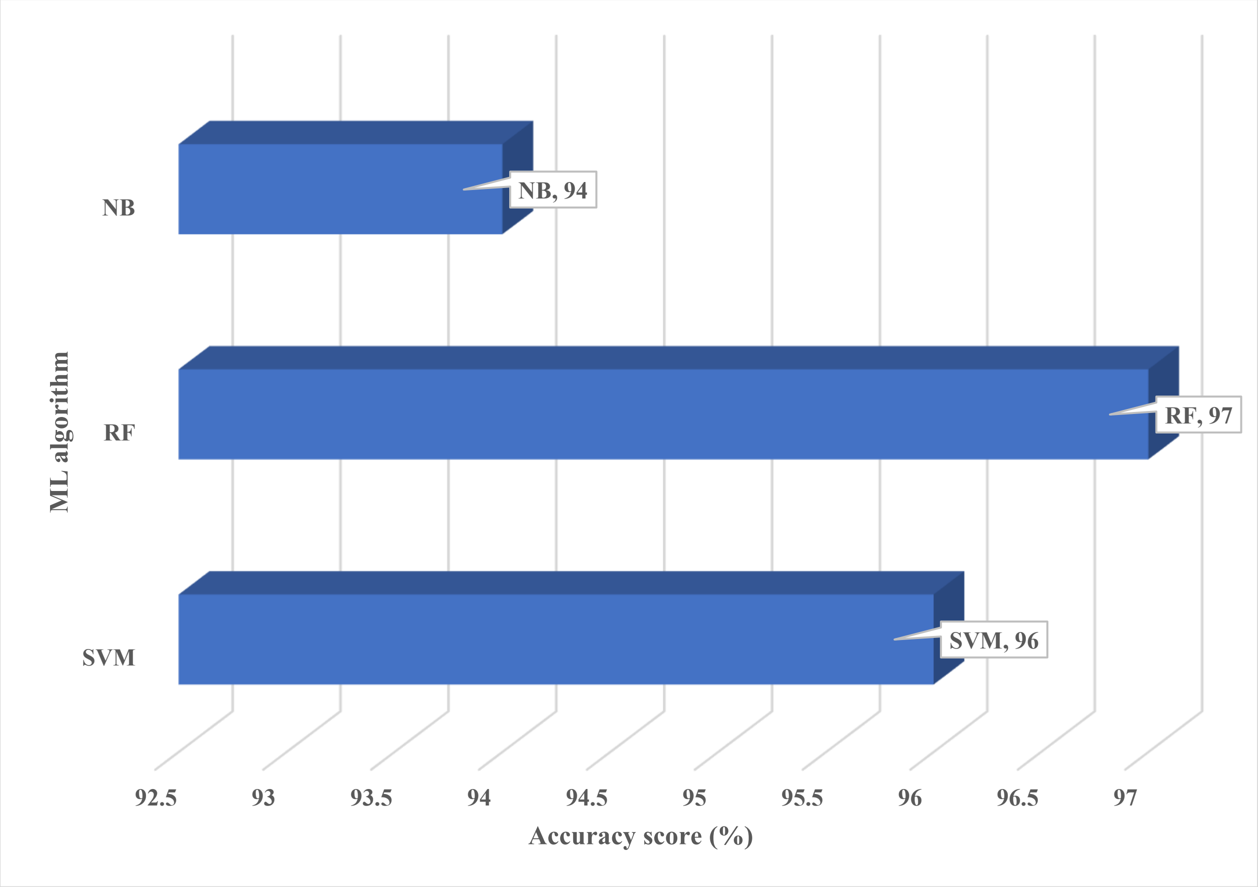


Figure 7.3 - Accuracy score comparison for imbalanced data

The high percentage of accuracy score for the models indicates good performance. Nevertheless, although accuracy score is mostly used to judge model performance, it might suffer an anomaly when classes are imbalanced (Sarkar *et al.,* 2020). The individual classes are therefore evaluated based on the precision, recall and f1-score to ascertain how each class performed in the model. The balancing algorithms are then applied to the dataset for further analysis – refer to Figure 7.4.

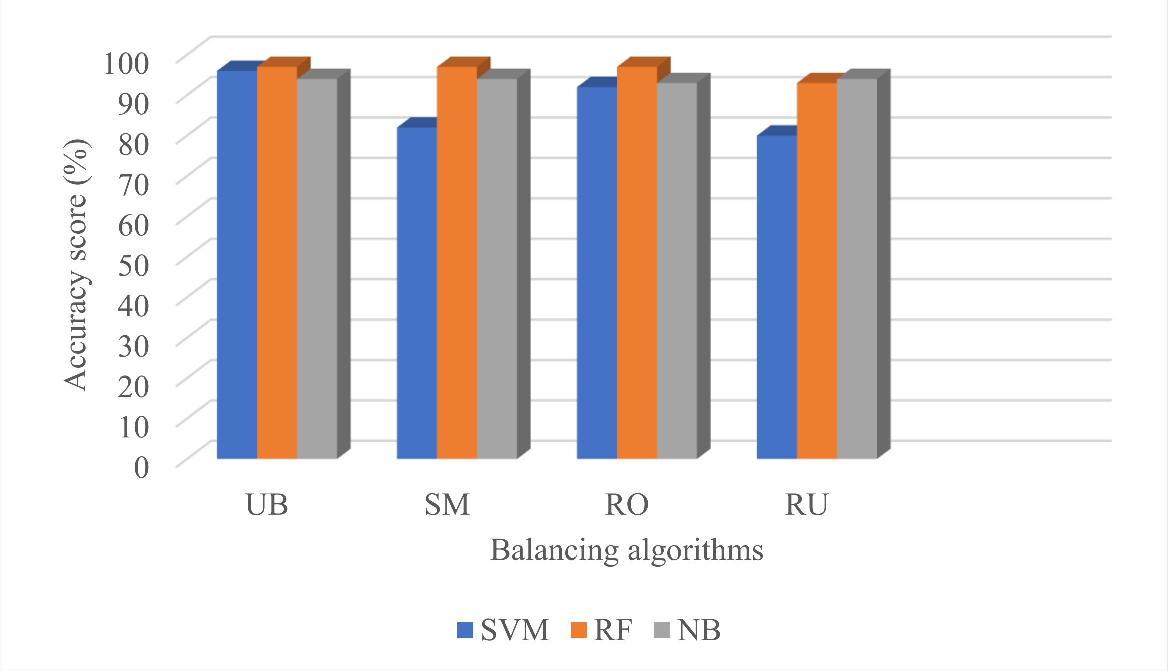


Figure 7.4 - Accuracy scores for the three models with the unbalanced and balanced data

It is observed that, although the accuracy scores decreased for SVM (82%), the individual classes had much better performance in classifying classes correctly when the SM algorithm is applied. A model which has performance of 70% and above is considered a good performing model (Krstinić *et al.,* 2020) therefore, an accuracy score of 82% is satisfactory. Some classes still performed poorly with NB and RF classifier when the SM balancing algorithm was applied.

Table 7.4 - Comparative analysis of three ML algorithms and balancing algorithms.

	Target class	**EN**				**FS**				**IS**				**IF**				**PI**				**SC**				**SS**				**UN**				**US**			
Model	(%)	UB	SM	RO	RU	**UB**	SM	RO	RU	**UB**	SM	RO	RU	**UB**	SM	RO	RU	**UB**	SM	RO	RU	UB	SM	RO	RU	UB	SM	RO	RU	UB	SM	RO	RU	UB	SM	RO	RU
SVM	Precision	24	71	00	07	37	71	00	09	79	94	38	47	50	73	01	17	100	100	79	100	57	83	00	07	27	78	00	06	99	80	93	99	38	83	00	06
	Recall	09	66	00	14	42	68	00	27	74	95	12	82	69	58	00	27	100	100	82	100	15	75	00	26	04	86	00	28	100	97	100	83	19	91	00	52
	F1-score	13	69	00	09	39	69	00	13	77	94	18	60	58	65	00	20	100	100	80	100	24	79	00	11	07	82	00	10	100	88	96	90	26	87	00	10
	accuracy score	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80	96	82	92	80
RF	Precision	27	38	53	26	53	56	62	41	78	76	80	49	58	61	60	52	100	100	100	100	43	41	49	24	31	17	33	21	100	100	99	100	51	47	51	23
	Recall	18	20	19	18	70	75	74	62	84	87	85	89	73	73	78	39	100	100	100	100	19	21	19	33	11	08	12	39	100	100	100	97	19	34	43	69
	F1-score	22	26	28	21	60	64	67	49	81	81	83	63	64	67	68	45	100	100	100	100	27	28	27	28	16	11	18	28	100	100	100	98	28	39	47	34
	accuracy score	97	97	97	93	97	97	97	93	97	97	97	93	97	97	97	93	97	97	97	100	97	97	97	93	97	97	97	93	97	97	97	93	97	97	97	93
NB	Precision	15	14	16	23	00	00	00	24	53	47	46	57	00	00	00	67	100	100	100	100	57	59	53	50	12	12	11	15	100	100	100	100	44	38	44	22
	Recall	25	19	20	07	00	00	00	58	88	88	66	86	00	00	00	03	100	100	100	100	07	09	07	09	84	90	87	70	99	99	99	99	11	08	11	02
	F1-score	19	16	18	11	00	00	00	34	66	61	80	69	00	00	00	05	100	100	100	100	13	15	13	16	20	21	19	25	99	99	99	100	18	13	18	04
	accuracy score	94	94	93	94	94	94	93	94	94	94	93	94	94	94	93	94	94	93	94	94	94	94	93	94	94	94	93	94	94	94	93	94	94	94	93	94

7.3 DISCUSSION

The number of features, attributes or variables used for input in ML is referred to as its dimensionality (Jia *et al.,* 2022). Therefore, dimensionality reduction is essentially the technique of decreasing the number of variables in a dataset while retaining as much variance as possible in the original dataset (Zebari *et al.,* 2020). Several ML studies have leveraged the proficiency of dimensionality reduction in handling multicollinearity, reducing training time and prevent overfitting (Huang, 2019; Zebari *et al.,* 2020; Hasan and Abdulazeez, 2021). However replete the literature is on the several techniques that can be employed in dimensionality reduction - such as factor analysis (Ali *et al.,* 2017; Gogtay and Thatte, 2017; Tharwat, 2017; Huang, 2019), principal component analysis (Hasan and Abdulazeez, 2021), correlation analysis (Gogtay and Thatte, 2017) and linear discriminant analysis (Tharwat, 2017) - there is no specific technique recommended for a particular ML task. For instance, Zhang *et al.* (2012) used Pearson correlation to examine the relationship between categorical and continuous auxiliary variables of soil organic matter. The Pearson CC was used in this thesis to select certain variables significant for the classification model. 15 variables were obtained while seven variables were dropped based on the strong correlations they had with other variables. The variables selected for the model building include; 'type_of_work', 'year', 'day_of_week', 'location', 'age range', 'weather / visibility', 'month', 'season', 'time of day', 'site/project', 'part of body affected', 'experience in current role', 'injury type', 'region' and 'vehicles involved?' hence, the dimensionality of the dataset was reduced from 22 to 15,

To further investigate the significance of the variables selected, the RF method was used to probe which variables had the strongest GI (Nembrini *et al.,* 2022). Notably, variables selected based on the correlation analysis, were confirmed as important variables by the RF method. None of the variables dropped during the correlation analysis were deemed important by the RF method which confirms the variables dropped were less significant. Also, the variables found to be significant in predicting safety incidents indicates that it is imprudent and insufficient to solely rely on only safety related data when predicting safety incident types. Rather, project related data such as the project location, site/project and demographic data (such as age of workers) could have substantial impact on prediction outcomes.

The original dataset after pre-processing was imbalanced. Some of the classes of the target variables has more entries than the others. The challenge with imbalanced data is (when a model is trained on imbalanced data) it learns that it can obtain high accuracy by constantly predicting the majority class, irrespective of whether recognising the minority class is equally or more significant when applied to a real-world scenario (Sarkar *et al.,* 2020). The three balancing algorithms namely SMOTE (Chawla *et al.,* 2002), RU (Estabrooks and Japkowicz, 2001) and RO (Blagus and Lusa, 2013) were therefore applied to each of the three ML models used in the experiment (SVM, NB and RF) separately. This resulted in having the same number of data entries for each class. Hence, there was no majority and minority class which could cause bias in prediction.

Due to the high dimensional nature of the dataset, SVM was primarily chosen for the prediction task due to its ability to manage extremely large feature spaces (Yu *et al.,* 2003). In choosing the best kernel for SVM in this task, four different kernels were applied to the ascertain which one had a better performance on the data. The polynomial kernel was found to have the best results for this thesis.

In the experiments to explore the performance of the ML classifiers when certain balancing algorithms are applied, it is observed that, with the imbalanced dataset, for all three algorithms, only the classes, IS, PI and UN could be correctly classified while the rest of the classes performed poorly and failed to classify any of the instances correctly. This could be attributed to these three classes being part of the top four classes with the majority of data. Sarkar *et al.* (2020) explains how a model constantly exhibit bias towards majority classes for imbalanced datasets, leading to poor predictions. This bias is evident in the results presented by the original imbalanced dataset for all the three classes.

When the SMOTE algorithm was applied to all three classifiers, it was observed that, the SVM classifier could predict accurately 70% and above all the classes present. For a model to be deemed as useful, it must have a minimum precision between 70-80% (Juba and Le, 2019) hence, the SVM+SMOTE algorithm can be considered as a useful model for predicting incident types. However, it is worth noting that the accuracy of the SVM+SMOTE algorithm was 82% which is less than the accuracy score of the SVM algorithm alone. The SVM classifier with the SMOTE balancing algorithm outperformed all the other balancing algorithms (i.e. RO and RU) with 72% being the least precision recorded for a class (0). This result is a clear indication that accuracy score alone is not a good enough metric to evaluate imbalanced classes (McNee *et al.,* 2006). For RF+SMOTE, although the accuracy score was 97% (same as with the original data), some of the classes could not be correctly classified. Some classes such as ‘EN’ had precision as low as 38% which is considered a very poor model. NB+SMOTE had not shown much promise either. The accuracy score was 93% which indicated a good performance but the precision and recall of the individual classes showed very poor performance (the lowest precision and recall being 0%). Therefore, with the SMOTE experiment, SVM is considered the best classifier for incident types.

The RO algorithm achieved an accuracy score of 92%,97% and 93% for SVM, RF and NB respectively. However, SVM+RO had the worst performance among the three classifiers. Except for ‘PI’ and ‘UN’ which were the top two majority classes, none of the other classes could be classified by the SVM+RO algorithm. The other classes achieved a 0% performance. Comparatively, RF+RO had a better performance among the three classifiers although some classes had precision and recall as low as 49% and 19% respectively. These were the lowest for the RF+RO. The NB+RO algorithm also had some classes recording precision and recall as low as 0%. Therefore, although not a good performance, RF+RO is the better performing model among the three algorithms.

The RU algorithm achieved the least performance both in terms of accuracy score and individual precision and recall for the class. SVM+RU was the worst performing algorithm among the three RU models with precision and recall as low as 06% and 14% respectively. It was also observed that, NB had a better performance with RU as compared to all the other balancing algorithms. Unlike the other algorithms where it had recorded 0% precision and recall, it had no record of a 0% performance with RU. Although RF+RU algorithms had also performed poorly by recording precision and recall as low as 26% and 18% respectively, the RF+RU algorithm has a comparatively better performance among the RU algorithms.

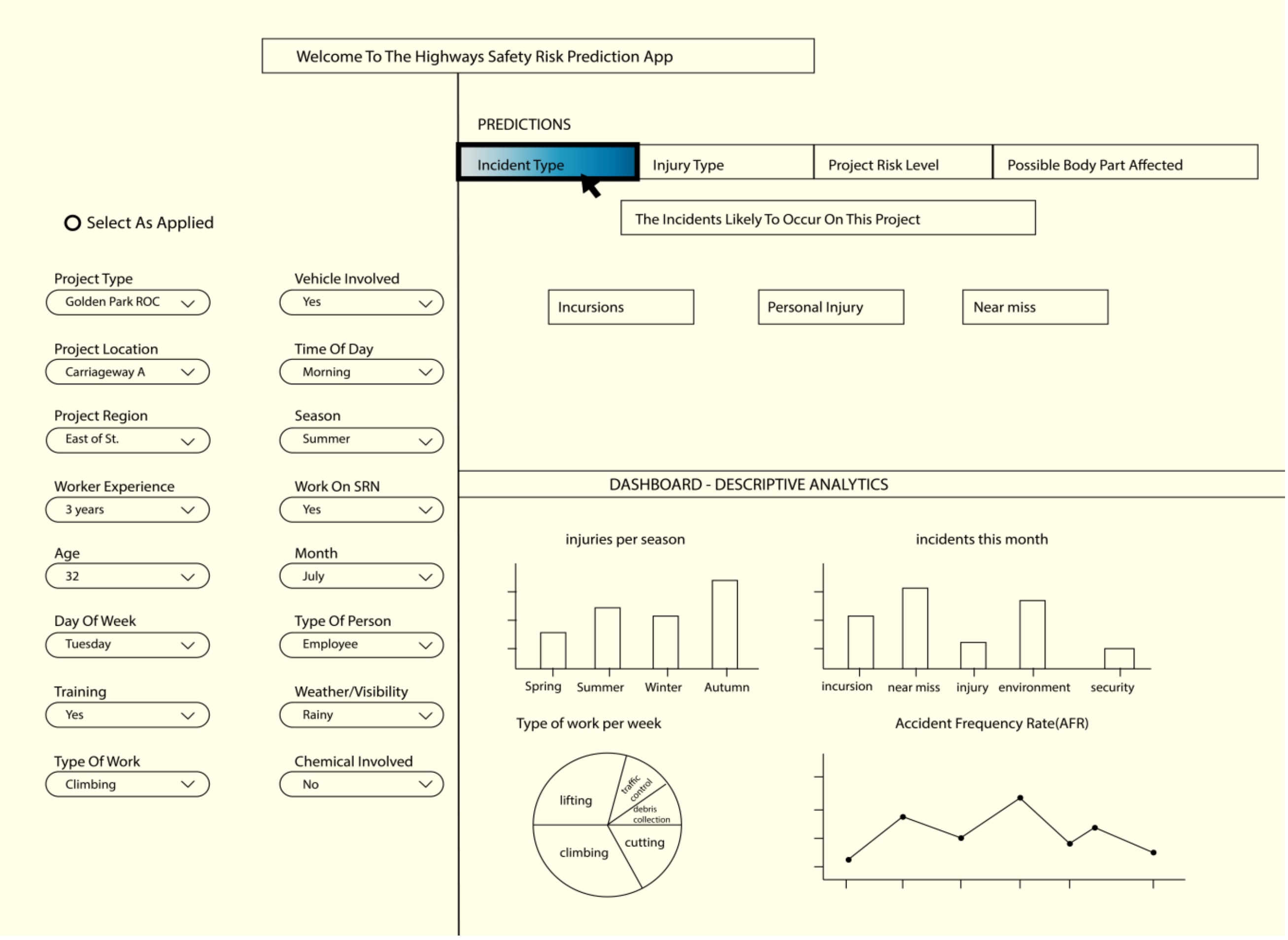
Premised upon the analysis of the results from the experiment, it can be concluded that, SVM+SMOTE is the best performing model among the models used and should therefore be considered as a prime ML model for predicting various incident types in highway operations. These findings demonstrate the model's ability to generalise: the model could reasonably predict the dependent variables that can identified events in highway operations for a given set of inputs. The result of this model indicates the possibility of predicting incidents even with imbalanced datasets. Zhang *et al.* (2015) had performed a similar study using SVM to forecast the profitability of a project with an imbalanced dataset which resulted in an accuracy score between 0.74 and 0.91. However, all predicted values were from the majority class which presented a challenge that the proposed model in this thesis remedies. Augmenting SVM with balancing algorithms such as SMOTE helps to ensure that the individual predicted values of a class are the true reflection of the high accuracy score a model presents. Furthermore, this thesis demonstrates that the occurrence of incidents are not random events but rather, there are underlying trends or pattern based on features found to be significant in predicting incident outcomes that could indicate an incident occurrence in time.

This thesis models incident type predictions using input variables that reflects safety indicators adopted in the highway industry. However, the entirety of significant input variables were not utilised due to its unavailability. It is recommended that, future work explores other significant indicators highlighted in literature such as: economic indicators e.g. road budgets; technological indicators e.g. vehicle fleet quality and composition; and road infrastructure characteristics and spatial-temporal indicators such as real-time traffic congestion to assess the impact of these variables on the outcome of the predictions. Furthermore, this research only employs three ML models based on their significance in literature. It is recommended that ensemble learning algorithms such as AdaBoost, Gradient Boosting, and XGBoost could be adopted by making use of their ability to combine the strengths of multiple ML model and compensate for the weaknesses of the individual models used, leading to more accurate predictions. Another notable limitation of this thesis is that although mental health and wellbeing is a severe challenge in the highway industry, this thesis focuses on other incident types such as injuries and accidents only. Future work could explore how mental health and wellbeing challenges can be incorporated into the model. Lastly, this thesis is not an exception to the ‘black box’ nature of ML model which makes it difficult for humans to comprehend the inter-relationship between variables. It is therefore recommended that further steps such as obtaining expert feedback should be taken to validate the model.

Despite the limitations of this research, the study provides a foundation for using ML models to develop a customised safety risk incident prediction model for HTOs. This is the first study that uses data solely sourced from a database dedicated to HTOs and considers factors peculiar to HTOs in forecasting risk events. This thesis therefore forms a solid basis for future works various incidents HTOs are exposed to or adapt the findings to suit other industries.

7.3.1 Proposed user interface for the model and practical implications.

Given the complexity of modelling developed and big data set involved, this thesis proposes the future development of web-based graphical user interface (GUI) software for safety officers working for highway projects. Such software will inspire knowledge-based decision making backed by evidence and encourage the emergence of a learning organisation. The software will enable users enter input variables concomitant to the project operation and then send instructions to the ML model to forecast the type(s) of incident likely to occur during that operation – refer to Figure 7.5. Hence, safety officers can prioritise H&S risk elements based on their probability of occurrence. Consequently, proper consideration is given to these risk variables while limiting occurrences in order to deliver a safer environment.



Welcome To The Highways Safety Risk Prediction App

○ Select As Applied

Project Type
Golden Park ROC

Project Location
Carriageway A

Project Region
East of St.

Worker Experience
3 years

Age
32

Day Of Week
Tuesday

Training
Yes

Type Of Work
Climbing

Vehicle Involved
Yes

Time Of Day
Morning

Season
Summer

Work On SRN
Yes

Month
July

Type Of Person
Employee

Weather/Visibility
Rainy

Chemical Involved
No

The Incidents Likely To Occur On This Project

Incursions

Personal Injury

Near miss

Figure 7.5 - Proposed Highway Incident Prediction Model (HSPM)

Currently, the highway risk identification and assessment stage in UK practice, focuses on using traditional statistical methods to mitigate risks after they have occurred (Lopez *et al.,* 2018). Moreover, the process of risk assessment relies heavily on the subjectivity of human judgement, perception and human lived experiences when an incident is to be predicted (Goodwin *et al.,* 2015). ML's innate ability to analyse large data sets (a limitation for traditional statistic approaches and human centred processes (Kang and Ryu, 2019)) enables the model developed in this thesis to offer an objective alternative to predicting and visualising incident scenarios that may occur during highway operations. In addition, the model presents an efficient approach to learning and discovering meaningful patterns and trends that lead to the various types of incidents occurring.

A key implication of this thesis is the opportunity it offers safety officers to train HTO and educate them on impending risks, provide needed resources (e.g. personal protective equipment (PPE)) and pre-emptively address impending risks before they occur. The model also unearths important attributes or indicators that safety officers should cogitate on when implementing safety risk prevention strategies. The GUI also allows organisations to collect new data which would help address the challenges of insufficient data for the organisation. Data collected can be analysed for deeper insights into why incidents occur, how they occur and what can be done to prevent them from occurring.

Furthermore, a major implication of this thesis is the resilience that this model brings to organisations. Some indicators of resilience according to Chen *et al.* (2018) include awareness, anticipation, management commitment, response and reporting culture. This model enables all these measures to be attainable i.e., predicting incidents beforehand will allow workers to be aware of impending risks, anticipate the incident, thereby providing enough time to respond to the incident with proactive measures to pre-empt it. Entering data variables through the GUI instead of reporting to management directly also promotes reporting culture which will encourage employees to record indicators without fear of being sanctioned. This is because, the data variables required do not have any personal identification indicators.

7.4 SUMMARY

HTOs face an omnipresent risk of being involved in several incidents that could endanger their lives and prevent them from returning home safely after work. For highway authorities to establish an efficient and reliable solution for these incidents, the probability of their occurrence must be predicted accurately as a first step towards risk mitigation measures being implemented. The current traditional statistical methods used to mitigate risk by UK highway authorities are more of a reactive approach which needs to be tackled. ML algorithms provide an effective technique to analysing complex data, identifying the nuances of highly complicated patterns in the data and making predictions based on these patterns.

Therefore, by comparatively analysing the performance of three ML algorithms and three balancing algorithms, this thesis developed a novel model for classifying incident risks in highway operations. This thesis has shown that year, weather, age, type of work, vehicles and project location play an essential role in predicting incident types. In this thesis, 16 variables out of the 22 variables presented were retained after correlation analysis was used for dimensionality reduction. 10 out of the 16 variables were found to have a high contribution to predicting incident types. The polynomial kernel of SVM had the best performance measure for the SVM classifiers among the other kernels.

The SVM classifier with the SMOTE algorithm demonstrated the best performance for each class of the target variable as compared to the other algorithms. The RF algorithm combined with the RO algorithm also had a good performance but was not better than SVM. The predictive model developed in this thesis has shown sufficiently accurate results which can be reliable for preventing safety incidents in highway operations. Therefore, practical implications can be accorded to the results of this thesis. Namely, the predictive model can augment the efforts of safety officers by establishing which incidents need more resources and attention at a particular time for effective decision making. Preventing incidents will also enable highway operations to run within budget, encourage timeliness and prevent waste of resources. Above all, avoiding such incidents could save lives.

Although the impact of these findings on existing highway safety risk prevention is important, this thesis has some limitations. First, the safety indicator data used in this thesis is imperfect. Other indicators such as economic (Ajayi *et al.,* 2020) (e.g. road budgets, safety investments), technological (Nnaji *et al.,* 2020) (e.g. vehicle fleet quality and composition, road infrastructure characteristics) and spatial temporal (Meng *et al.,* 2020): e.g. real time traffic volumes, congestion, incident clusters and emergency response will be incorporated in the model. In the future, this thesis also proposes an integrated model that combines the strengths of these algorithms (SVM, RF and NB), aiming for an ensemble approach that outperforms individual models. Deep learning models such as deep neural networks and artificial neural networks will also be applied in ensuing chapters to ascertain their impact on the model. Ensuing chapters will also incorporate models which can rate the risk level associated with an operation and body part likely to be affected by an injury.

CHAPTER 8- BUILDING THE HIGHWAY SAFETY PREDICTION MODEL: BODY PART AFFECTED

8.1 INTRODUCTION

Project sites and locations for highway operations normally present certain hazardous elements which could be detrimental to the safety of highway workers (Eseonu *et al.,* 2018). However, there is the probability that exposure to such hazardous elements could result in body part injuries (e.g. arms, head, legs or torso) which could impact the overall wellbeing of workers (Rogovski *et al.,* 2021). In several instances, injury occurrences on highway project locations have rendered victims incapacitated hence, exposing employers to cost of compensation claims and dent in organisational reputation (Giummarra *et al.,* 2020). Such negative consequences present a need for drawing insights from factors that contribute to injury occurrences and proffering tailored solutions to proactively prevent such incidents (Bucsuházy *et al.,* 2020). In a survey conducted by Headway (2020), head injuries accounted for 20% of all workplace injuries. According to Eurostat (2023) injuries to the upper limbs (shoulders, arms and hands) accounted for 38.3% of the total number of non-fatal accidents at work while the lower limbs (hips, legs and feet) recorded 29.1% of body parts affected in injuries.

Incident data from the highway accident reporting tool database in the UK presents a number of reported injury events with the associated body parts that were affected during the injury (Bortey *et al.,* 2024). These injuries when analysed, could provide an understanding of the most frequent body part affected in injuries cases, which could in turn present an indication of the type of work or activity that causes such body parts to be inflicted (Lo *et al.,* 2021). Furthermore, the body part affected could give insight to which injuries were more likely to be fatal and has the potential of resulting in more grievous consequences (Park *et al.,* 2024). For example, an injury to the head could result in a more fatal outcome as compared to an injury to leg (Dumrak *et al.*, 2013).

Although a few studies have sought to uncover the determinants of injuries affecting various body part (cf. Bucsuházy *et al.,* 2020; Lo *et al.,* 2021; Dumrak *et al.*, 2013), the insufficiency of data and absence of detailed comprehension of the relationships that exist between these factors have impeded the development of predictive models that could classify these injuries into body parts likely to be affected (Kashani *et al.,* 2022). In cases where data could be accessed, the quality of existing data is sub-optimal (Xu and Zou, 2021). However, data is crucial in the development of predictive models (Bortey *et al.,* 2022).

Understanding significant factors that are essential to injury occurrences and developing predictive models which could identify underlying patterns and trends prior to an injury occurring is a crucial step in enhancing safety risk management (Zhang *et al.*, 2019). Such a model would enable evidence-based decision making and contribute to prioritising and maximising the utility of resources (Alawad *et al.,* 2019). This chapter therefore aims to develop a predictive model capable of classifying body part injuries. Associated research objectives are to find the most efficient ML algorithm and the most suitable parameters for body part injury classification. Also, this chapter uses statistical tests such as chi-square test to investigate the most pertinent variables which influences the classification of body part injuries. The research questions that this chapter seeks to answer are i. '*what are the most important predictors of body parts likely to be affected in an injury*?' and ii. '*what is the most effective ML model for classifying body parts likely to be affected?'*

8.2 RESULTS FOR BODY PART AFFECTED CLASSIFICATION

Data for the target variable was explored and visualised to aid in obtaining a better understanding of the structure and nature of data. Also, the visualisation sought to help uncover an trends and patterns that may be hidden in the data. Figure 8.1 presents the distribution of body part affected from various personal illness and injury incidents. Not applicable which represents incidents which did not lead to injuries were the most occurring. However, for incidents which injuries had ensued, the most frequently reported body part affected on highway project site/locations was the leg/knee (*f*=338 or 17.2%). This was followed by lower arm including wrist and hand (*f*=275 or 14%), head (*f*=207 or 10.5%), ankle/foot (*f*=204 or 10.3%), finger/thumb (*f*=198 or 10.1%), mental/psychological (*f*=163 or 8.3%), back/spine (*f*=156 or 7.9%), neck/shoulder (*f*=126 or 6.4%), upper arm including elbow (*f*=97 or 4.9%), chest/stomach (*f*=74 or 3.8%), eye/ear (*f*=58 or 2.9%), hip (*f*=21 or 1.1%), lungs/throat (by chemical) (*f*=16 or 0.8%). Evidently, the chest/stomach area, eye/ear, hips and lungs/throat were the least recorded body part involved in injuries.

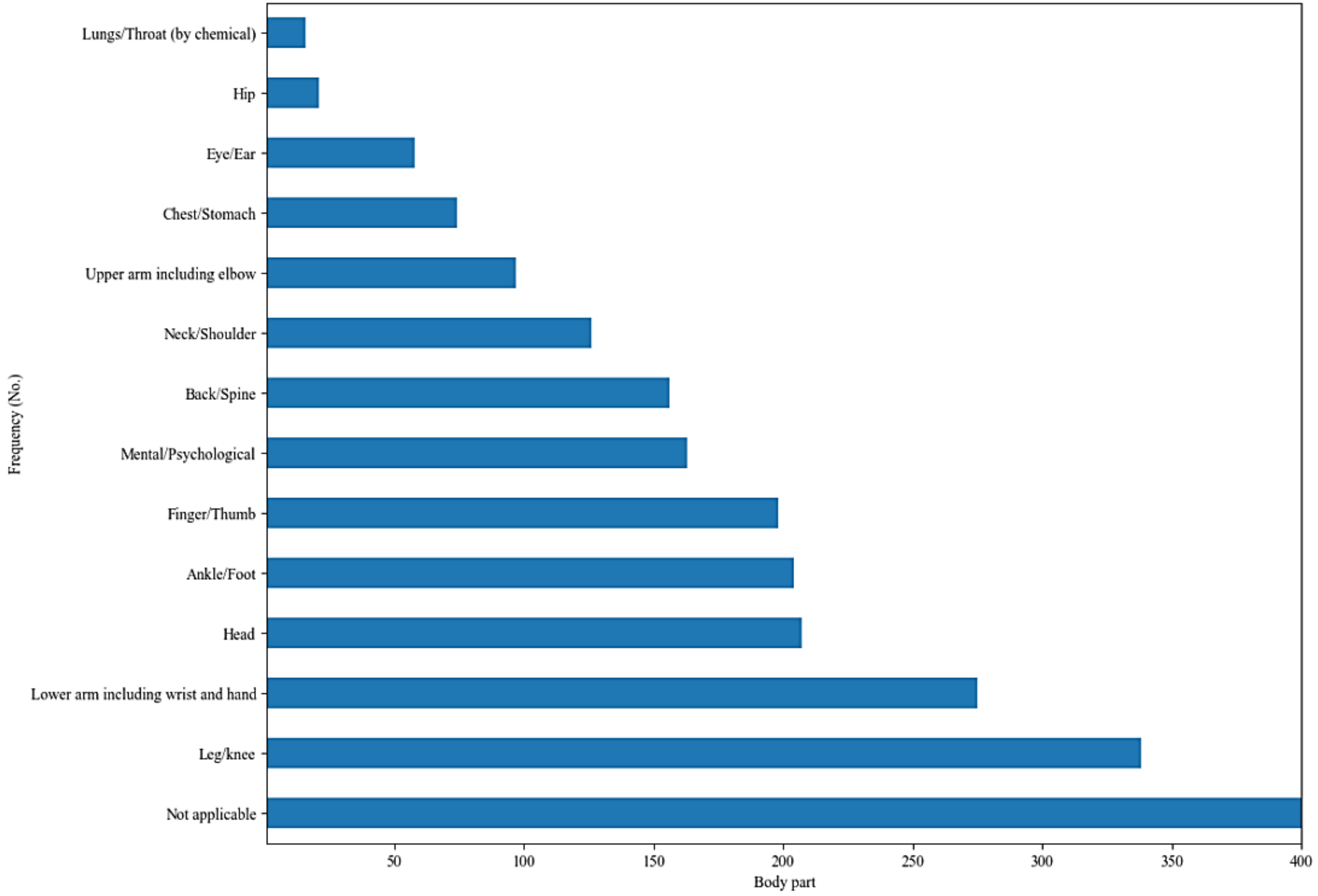


Figure 8.1 - Distribution of body parts affected by injuries.

8.2.1 Dimensionality reduction (Chi-square test)

Table 8.1 presents the independent variables and their associated chi-square statistic and p-value. The chi-square statistic measures the difference between the observed frequencies and the expected frequencies if two categorical variables were deemed associated. The greater the difference between observed and expected frequencies, the greater the values of the chi-square statistic. Therefore, a high chi-square value indicates an association between the variables while a low value indicates independence. In contrast, the smaller the p-value (i.e. <0.05), the greater the chance of an association between the variables, hence rejecting the null hypothesis of independence.

Table 8.1 - Chi-squared table

Variables	Chi-square (CS)	P-value (PV)
Region	2197.618813	5.218114e-259
Site/Project	15773.829953	0.000000e+00
Event Type	51244.164903	0.000000e+00
Vehicles involved	1093.540835	1.392244e-225
Type of Person	34.574609	6.718692e-01
Location	2774.114106	0.000000e+00
Did this event occur on the SRN?	179.344500	2.308856e-31
Injury Type	114009.334610	0.000000e+00
Weather / Visibility	248.317880	3.150706e-23
Season	39.119176	4.645261e-01
Type_of_work	34.574609	1.211591e-01
Injury occurrence	50650.254417	0.000000e+00
Project risk level	35544.383540	0.000000e+00
day_of_week	77.599370	4.915031e-01
time_of_day	77.518971	1.241510e-02

Two separate heatmaps (refer to Figure 8.2a and 8.2b) were created for the chi-square statistics and the p-values with each heatmap displaying the values for each variable, with annotations showing the numerical values. A cool warm colour map was used to represent the values, with blue colours indicating lower values and red colours indicating higher values.

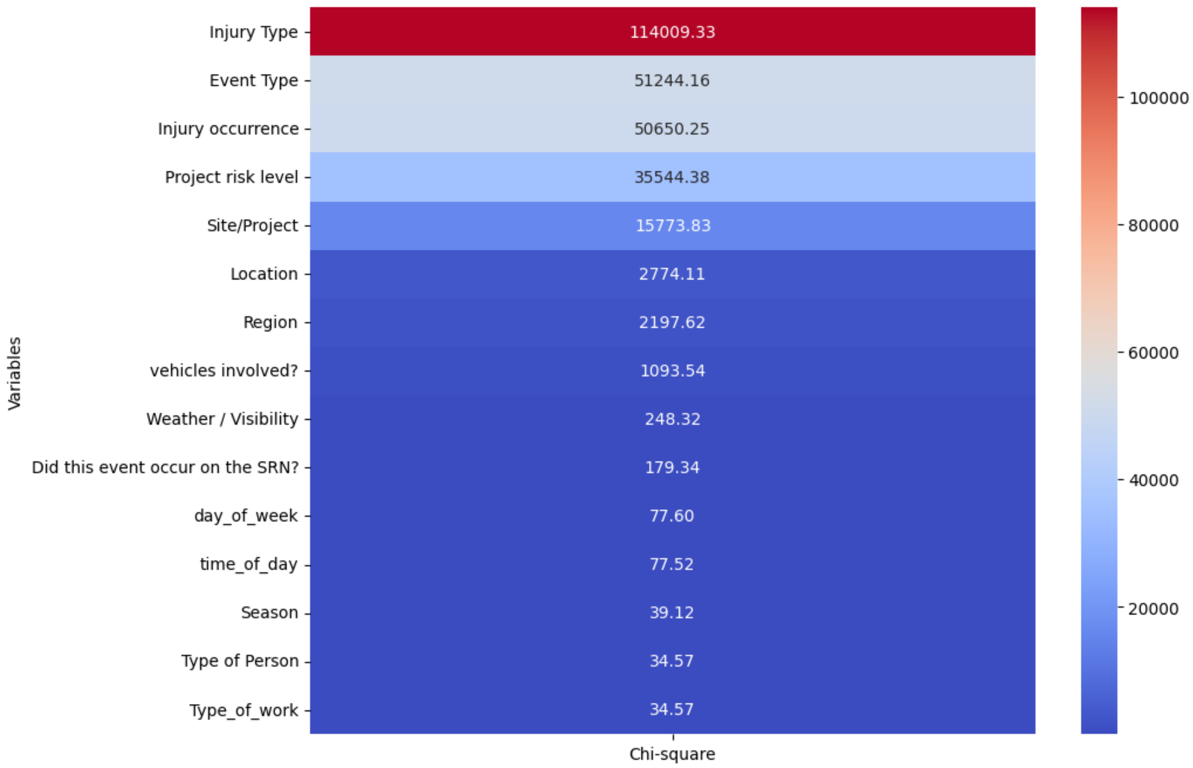


Figure 7.2a - Chi-square Statistics for Categorical Variables.

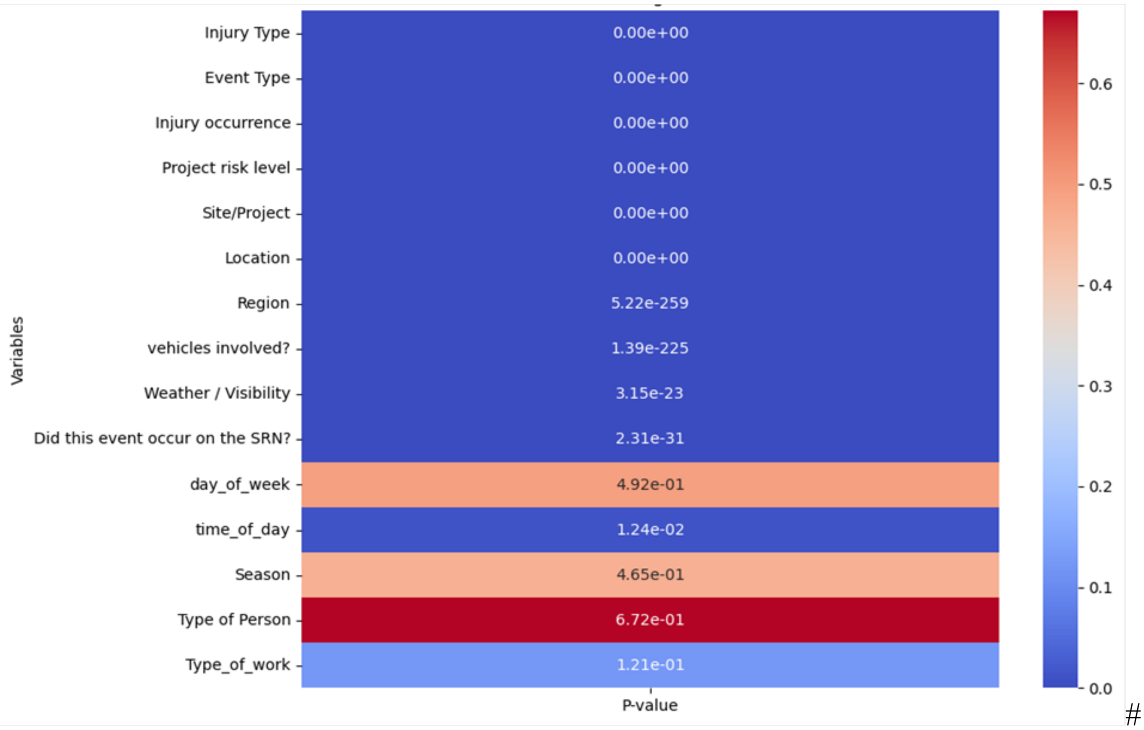


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Figure 8.2b - P-value for Categorical Variables

The variables 'Type of person (*PV*=0.67)'; 'day of week (*PV*=0.49)'; 'season (*PV*=0.46); 'type of work (*PV*=0.12)' had p-values greater than the significant level of 0.05. Similarly, the variables with higher p-values, also had relatively very small chi-square statistic value indicating that there is no statistically significant association between the 'type of person', 'season', 'day of week' and 'type of work' variables and the target variable (body part affected). Therefore, the null hypothesis of non-association is not rejected.

However, the variables, 'region', 'site/project', 'event type', 'vehicles involved?', 'location', 'did this event occur on the SRN?', 'injury type', 'weather / visibility', 'season', 'injury occurrence' and 'project risk level' had large chi-square statistic which indicates a substantial discrepancy between observed and expected frequencies, and a very low p-value which suggests that this association is highly unlikely to be due to chance alone. Therefore, the null hypothesis of non-association is rejected.

8.2.2 Model performance.

Table 8.2 presents the performance metrics, including precision, accuracy, recall, F1-score and AUROC, for different ML models used to classify the part of body likely to be affected in the event of an injury occurrence. The results showed that SVM outperformed all the other models in terms of accuracy.

Table 8.2 - Classification results.

Model	Accuracy score (%)	Precision (%)	Recall (%)	F1-score (%)	AUROC (%)
SVM	99	98	97	97	98
RF	96	94	94	94	95
NB	91	92	91	92	91
EL	98	97	98	98	97
RNN	95	94	92	94	94

Based on the overall performance of the models presented in Table 8.2, SVM is the best performing model in terms of accuracy (99%), AUROC (99%), indicating a an almost precise level of consistency in classification. Ensemble learning had the second highest performance with an accuracy (98%) and AUROC (97%). RF ranked third with an accuracy (96%), AUROC (95%), followed by RNN, with accuracy (95%), AUROC (94%). NB was the least performing model with accuracy (91%) and AUROC (91%).

8.2.2.1 Performance of each class using ROC curve

Figure 8.3 presents the ROC curve which describes how well each class of the target variable performed in the experiment for the best performing algorithm which was the SVM algorithm. Using the one-vs-rest multi-class algorithm, the results show that, each class of the target variable had near perfect prediction for body part likely to be affected. This shows, the accuracy of 99% for the SVM was not influenced by biased prediction of the majority class, but rather has a balanced high prediction ability across each of the classes.

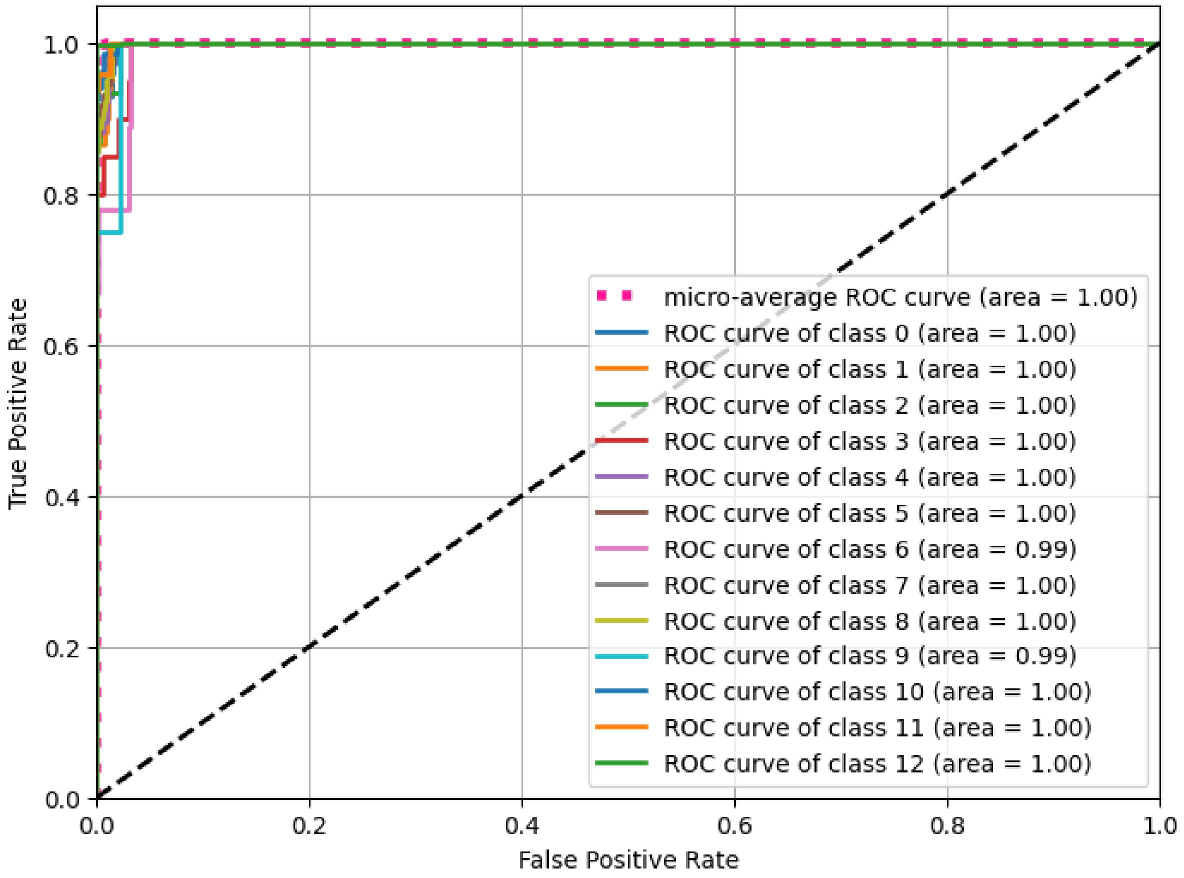


Figure 8.3 - ROC curve for body part affected

8.3 DISCUSSION

An exploration of the target variable presented the top five body parts usually impacted in an injury as: i) leg/knee; ii) lower arm including wrist and hand; iii) head; iv) ankle/foot; and v) finger/thumb. This could give an indication of the type of activities or incidents that must be carefully considered, prioritised and evaluated during highway operations. The type of incident or activity that leads to an injury can be inferred from the body part affected (Oyedele *et al.*, 2021). Injury prevention resources must be prioritised for these areas to proactively pre-empt these injuries (cf.). Table 8.3 provides details of such incidents which could affect the body part stated.

Table 8.3 - Inferred incidents from body part injured.

Body part	Incident/activity	References
Leg/Knee	Slips, falls or trips on uneven surfaces. Falls from heights. Struck by falling objects. Twisting or hyperextension during physical activities. Overuse injuries from repetitive motions.	Tahir *et al.*, 2023; Pillai *et al.*, 2020
Lower arm including wrist and hand	Accidents involving machinery or tools. Impact injuries from heavy objects. Repetitive strain injuries from typing or manual labour. Cuts or lacerations from sharp objects. Fractures or sprains from falls or collisions.	Sehsah *et al.*, 2020; Sundstrup *et al.*, 2020
Head	Falls from heights or slips. Struck by moving objects or equipment. Vehicle accidents. Impact injuries from falling debris and equipment.	Abukhashabah *et al.*, 2020
Ankle/foot	Twisting or rolling the ankle on uneven ground. Falls or slips on slippery surfaces. Dropping heavy objects on the foot. Crushing injuries from machinery or equipment. Sprains or strains from sudden movements.	Ahuja *et al.*, 2024
Finger/thumb	Pinching injuries from closing doors or machinery. Cuts or lacerations from sharp objects. Crush injuries from heavy objects or equipment. Impact injuries from striking objects Fractures or dislocations from accidents or falls. Climbing scaffolds/ladder	Alessa *et al.*, 2020

Abukhashabah *et al.* (2020) found that, falling equipment caused 27% of head injuries at the workplace hence, the provision and use of appropriate PPEs was pertinent to reducing such injuries. Ahuja *et al.* (2024) also recognised that big objects falling on the foot, or heavy machinery running over the foot could be some examples of incidents that could cause injuries to the ankle or the foot with severe damages to the muscle or tissues. Alessa *et al.* (2020) found that handling equipment and climbing scaffolds are activities which could contribute to finger/thumb injuries. These studies support the postulations of incidents likely to be the causes of body part injuries in this thesis.

Analysis of association conducted using the chi-square test of association showed that, the independent variables 'region', 'site/project', 'event type', 'vehicles involved?', 'location', 'did this event occur on the SRN?', 'injury type', 'weather / visibility', 'season', 'injury occurrence' and 'project risk level' were the most significant variable in predicting a body part likely to be affected by an injury. This finding answers the research question '*what the most important predictor of body parts are likely to be affected in an injury*?' The finding is consistent with findings of other studies that showed that 'project type', 'location', 'experience', 'day' and 'season' were influential to predicting body part injuries (Ajayi *et al.*, 2019; Oyedele *et al.*, 2021).

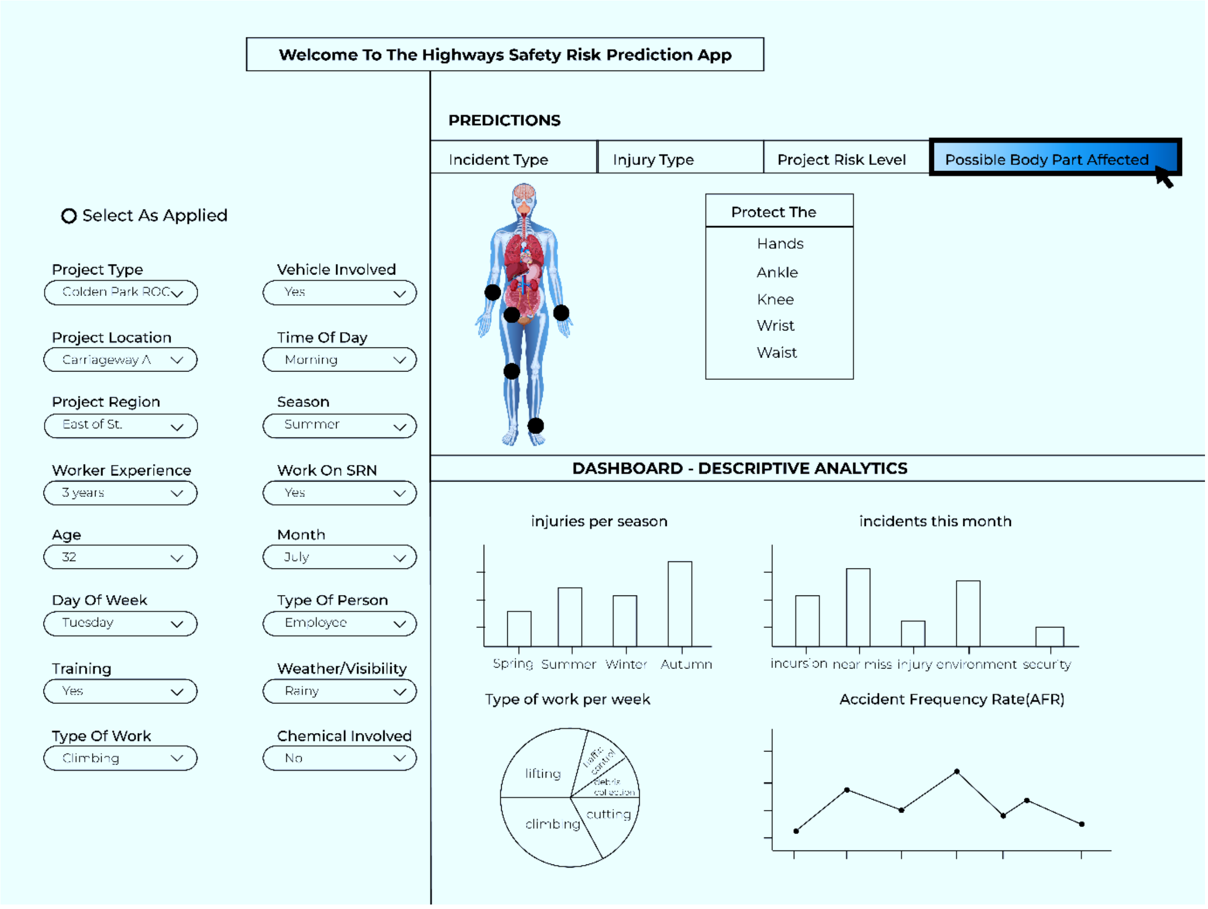
The results for model development indicate that SVM achieved the highest accuracy score of 99%, followed closely by Ensemble Learning (EL) with 98%. Random Forest (RF) and RNN attained accuracy scores of 96% and 95%, respectively, while Naive Bayes (NB) achieved an accuracy score of 91%. Across precision, recall and F1-score metrics, SVM consistently demonstrated strong performance, maintaining precision, recall and F1-score values above 97%. RF, EL and RNN also exhibited competitive performance across these metrics, with precision, recall, and F1-score values ranging from 94% to 98%. NB, while slightly lower in performance compared to other models, still demonstrated reasonable precision, recall, and F1-score values of around 91% to 92%.

The SVM outperforming all other models could be due to its ability to effectively model linear decision boundaries and handle high-dimensional feature spaces (Park *et al.*, 2020). In this thesis, SVM could have utilised the intrinsic linear separability of the data, resulting in robust predictions (Guan *et al.*, 2022). EL, which combined multiple models (SVM, RF, NB) to improve performance, also demonstrated a strong performance by making use of the diverse strengths the of individual models to enhance prediction accuracy (Mienye *et al.*, 2020). Random Forest and Recurrent Neural Network, while slightly lower in accuracy compared to SVM and Ensemble Learning, still exhibited competitive performance, indicating their capability to capture complex patterns in the data (Jung *et al.*, 2020). This could also be attributed to SVM having fewer hyperparameters to tune as compared to RNN and ensemble learning, which can simplify the model selection and tuning process. In the experiment, the hyperparameters of SVM were well-optimised for the data by exploring different combinations of hyperparameters to demonstrate which combination was most effective. The superior performance of SVM compared to RNN and Ensemble learning, could therefore be attributed to the optimal hyperparameter utilised as RNN and ensemble learning are more sensitive to hyperparameter settings (Farsi, 2021; Mohammed and Kora, 2023).

8.3.1 Practical implications and proposed user interface

In highway operations, accurate prediction of body parts which potentially could be injured is a significant measure for a learning organisation (Oyedele *et al.*, 2022). Such a prediction could influence the implementation of preventive measures and could be pertinent in developing tailored interventions to reduce highway safety injuries. The high accuracy of the ML models presents robust and effective decision-making tools which will enable safety managers prioritise resources and implement safety protocol which will significantly minimise injurious incidents. Using ML to analyse body part injuries in a predictive model could offer insights into the relationship between certain variables such as environmental, demographic, traffic patterns or location and specific types of injuries such as spine/back injuries, head trauma etc. a detailed understanding of such relationships enable proactive measures which facilitates the prevention of such injuries.

In the highway industry, contractors and subcontractors are often engaged by highway agencies to undertake various projects, yet they operate independently of direct oversight by these agencies (Kshraf *et al.*, 2022). Consequently, ensuring consistent safety standards across all contracted entities poses a challenge, as each contractor may adhere to varying safety policies and practices (Mbachu, 2008). Nonetheless, insights gained from body part injury prediction endeavours can be disseminated to contractors, serving as foundational knowledge for the development of principal safety guidelines applicable to all contractor companies. Relevant information such as anonymised injury prediction data and best practices could be obtained and can enhance collaboration between highway industry stakeholders by sharing insights derived from the data in the bid to improve safety efforts (Deep *et al.*, 2022). Figure 8.4 gives a representation of the proposed user interface for the body part prediction.



Project Type: Colden Park ROC

Vehicle Involved: Yes

Project Location: Carriageway A

Time Of Day: Morning

Project Region: East of St.

Season: Summer

Worker Experience: 3 years

Work On SRN: Yes

Age: 32

Month: July

Day Of Week: Tuesday

Type Of Person: Employee

Training: Yes

Weather/Visibility: Rainy

Type Of Work: Climbing

Chemical Involved: No

Protect The
Hands
Ankle
Knee
Wrist
Waist

Figure 8.4 - Proposed user interface for body part prediction model

8.4 SUMMARY

In contemporary times, ML has become an indispensable technique and has proved to be of utmost significance in curtailing injuries in various fields of occupational H&S. This chapter proposes a novel computational and ML model for determining body parts likely to be affected in an injurious incident. Five different algorithms (namely, SVM, RF, NB, EL, RNN) were employed to classify the body parts. The performance of each model was evaluated and compared based on five metrices (*viz.* accuracy score, precision, recall, F1-score and AUROC). The data is balanced using the SMOTE algorithm to prevent the models from being biased towards the majority class, which can affect performance accuracy. The parameters of each model are tuned to optimise their performance and evaluated with a train test split technique which reserves 30% of the data for testing purposes. The experimental results show that, SVM performed better than the three other ML algorithms i.e. RF, NB and EL. EL however had a slight advantage over RF and NB because it leveraged the strengths of both models to achieve a slightly better performance. Consequently, the RNN model although had a competitive performance, was the least performing algorithm. This was because RNN compared to the other algorithms, is more sensitive to hyperparameter settings (Farsi, 2021). A limitation of this work is that, other different hyperparameters could have performed better for RNN which were not explored. Future work will explore these other hyperparameters to ascertain their effectiveness on the model. A practical implication of accurately predicting body parts which potentially could be injured is the significant milestone of transforming an organisation into a learning organisation (Oyedele *et al.*, 2022). Such predictions could influence the implementation of preventive measures and could be pertinent in developing tailored interventions to reduce highway safety injuries. The ensuing validation chapter will further investigate the performance of the models by validating the model using a stratified k-fold cross validation technique (Prusty *et al.*, 2022). This will further strengthen the reliability of the model making it more robust.

CHAPTER 9- BUILDING THE HIGHWAY SAFETY PREDICTION MODEL: RISK LEVEL PREDICTION.

9.1 INTRODUCTION

Based on findings from the HSE’s labour force, it was discovered that the transportation sector had lost approximately 2 million working days to workplace illness and injuries, with workplace injuries accounting for 21% and work-related illnesses for 79% of these absences (HSE, 2023). On average, this translates to each worker losing approximately 1.4 working days, which is statistically similar to the overall industry average of 1.1 days (HSE, 2023). Although several attempts have been made by various studies (Huang *et al.,* 2008; Fowler *et al.,* 2011) to capture the notion of risk in a meaningful way, eventual incident occurrences that has led to fatal outcomes reiterate the difficulty in capturing the complex nature of risks and its uncertainties in a formula (Nilchiani, 2023).

For safety risk research in the transport sector, a plethora of studies have sort to develop prediction models for various categories of stakeholders such as drivers, pedestrians and passengers (Li *et al.,* 2020; Porcu *et al.,* 2020; Azadani and Boukerche, 2021). Li *et al.* (2020) developed a traffic crash prediction system for drivers to detect real time traffic crashes, Porcu *et al.* (2020) attempted to evaluate the severity of bus accidents and Azadani and Boukerche, 2021 analysed the effects of various risk factors on drivers’ behaviour. However, none of these studies have investigated safety risk and its severity on HTOs. Although HTOs play a crucial role in the road safety, the primary focus of previous research has been on road users and the road itself with little attention given to HTOs (Bortey *et al.*, 2024). Silva *et al.* (2020) in a review of how ML is applied in road safety, postulated that the three types of application in this area include the use of ML techniques to analyse crash data, predict crash frequency, and classify severity.

Considering the different degrees of risk faced by HTOs during incidents occurrences, it is crucial to assess the severity of the risk associated with these incidents when they occur (Eseonu *et al.*, 2018). As a result, the highway incident data acquired from HART is examined to gain valuable insights into the level of risk HTOs are usually exposed to and the detrimental impacts of project risk levels on HTOs. The level of risk or risk severity associated with an incident is often linked to various factors, such as time of incident, location, site/ project etc. (Intini *et al.*, 2024) therefore, analysing how severe a risk could be will aid in exploring the relationship between the risk levels and the associated variables (Zhang *et al.,* 2019). Understanding how these variables contribute to increased project risk levels allows for deeper exploration of injury patterns and the implementation of safety improvement initiatives based on evidence. This chapter therefore explores the use of DNN models in the classification of risk severity (levels) of incident occurrences.

9.2 RESULTS FOR PROJECT RISK LEVEL CLASSIFICATION

In this section, the results of the developed ML models are presented, highlighting the performance of the best model generated for predicting project risk levels from the input variables. Hyperparameters were determined through a fine-tuning process to ensure reproducibility. Additionally, model evaluation results are provided to compare the performance of various models. Table 9.1 indicates the risk matrix used in this work. The risk level was calculated using the actual risk severity rating and potential severity rating (likelihood). Risk was defined as:

Risk = actual severity rating * potential severity rating.

The resulting matrix is rated as follows (refer to Table 9.1):

Table 9.1 – The risk matrix

Risk rating	Risk level	Impact category	Definition
19-25	High	Fatal/serious	An incident that will cause major harm if it occurs.
10-18	Medium	Moderate	An incident that can cause moderate harm if it occurs.
1-9	Low	Minor	An incident that might cause little harm and will not have any physical impact on individuals or systems.

9.2.1 Feature importance and selection

A feature importance experiment was carried out for each of the ML models using the ‘feature importance’ package offered by the models. This process involved computing Gini importance scores for all input variables used in modelling to ascertain the significance of each variable in the decision-making process of the classification model (Molnar *et al.*, 2023). A higher score for a variable indicates a more substantial influence on the model's ability to predict a particular target variable (Parr *et al.*, 2024). Although RF was used to assess the feature importance of the most influential variables in the ML models, a separate analysis was conducted to evaluate the feature importance of the variables used in the DNN model. This allowed for a comparison between the feature importance in both the ML and DNN models to determine which features played a significant role in the predictions made by each model. Figure 9.1 a and b presents the most significant variables in the prediction model for both RF and DNN classifiers.

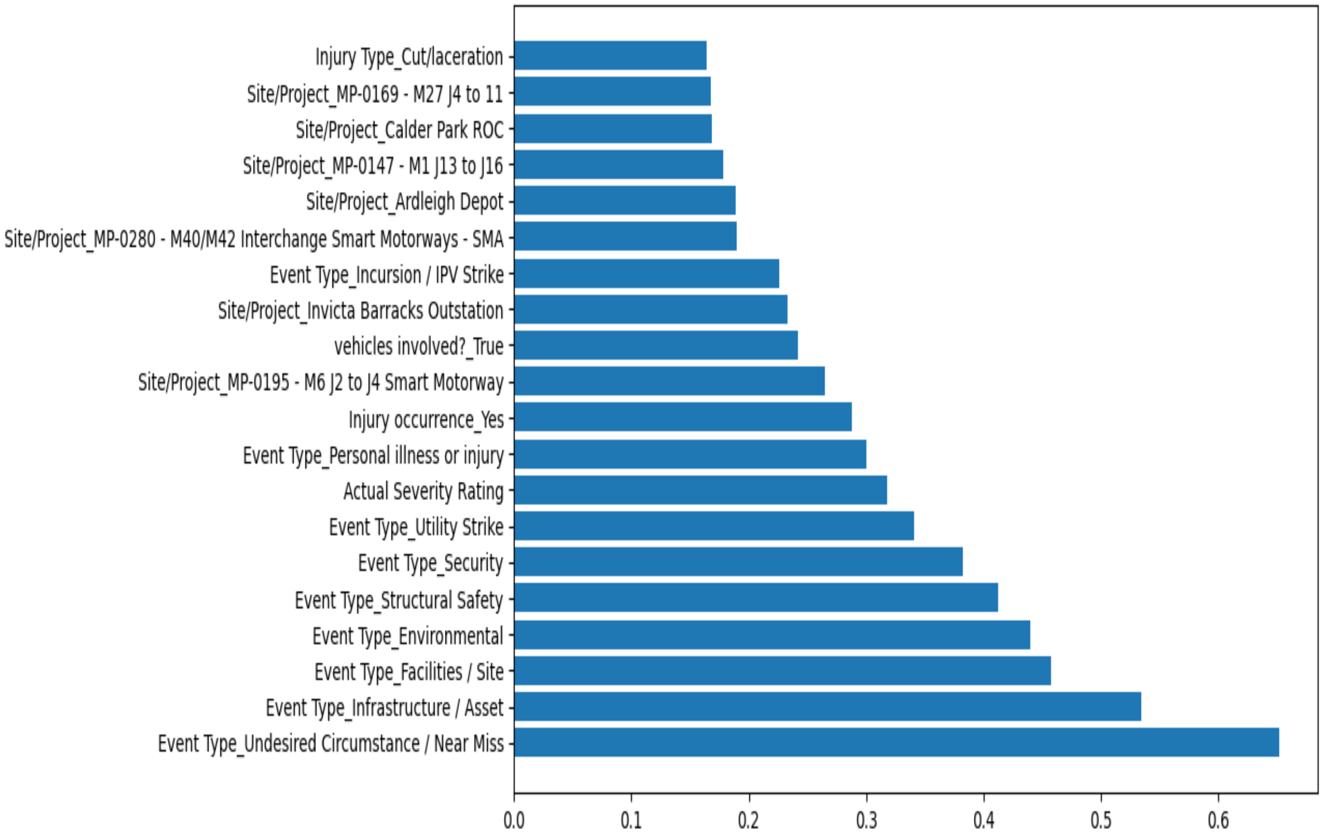


Figure 9.1a - Feature importance (RF)

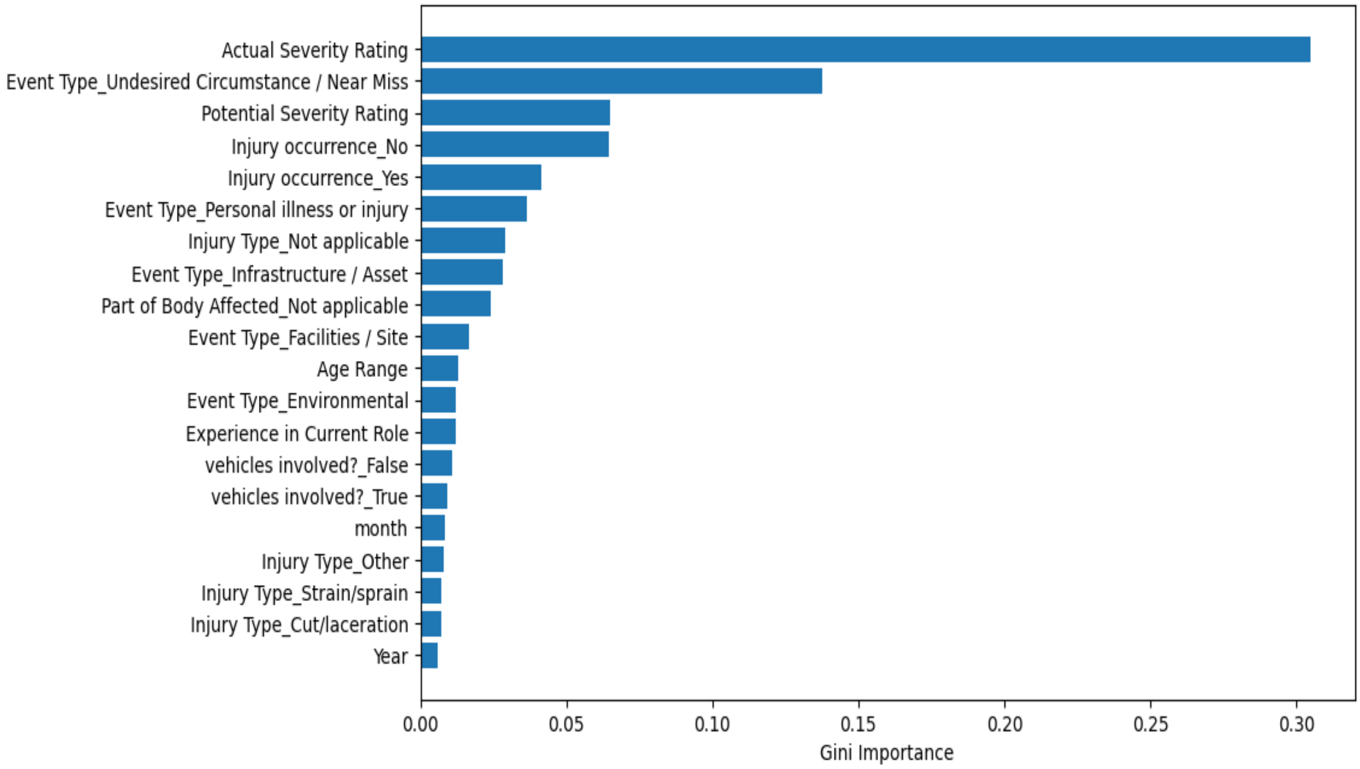


Figure 9.1b - Feature importance (DNN)

The variables injury type, site/project, event type, vehicles involved, injury occurrence and actual severity rating were the most influential features in the RF prediction. The results reveal variations in the contribution from different classes of the variables site/ project, event type, vehicle involved, injury occurrence and injury type to the classification of risk levels in the model. This observation indicates that while the variables were influential in risk classification, certain classes within these variables had a more significant impact on the classification process than others.

The DNN ML model also had the following variables as the most influential features of the classification model *viz.* actual severity rating, event type, potential severity rating, injury occurrence, injury type, part of body affected, vehicle involved, experience in current role, and age range, month and year. It is observed that the DNN model captured more important variables than the RF model. This is because DNN models can detect complex non-linear relationships between variables more effectively than RF models (Thakkar and Lohiya, 2023). Hence, DNNs may identify a larger number of significant variables, especially in datasets with complex patterns.

9.2.2 Model performance evaluation.

The various ML models and the DNN model employed are evaluated using the AUROC, the confusion matrix and the classification report of each of the target variables according to their precision, recall and F1-score. Figure 9.2 shows the feed-forward DNN architecture used in the experiment.

Figure 9.2 – The DNN architecture

9.2.2.1 AUROC results

Figure 9.3a, b, c and d present the ROC curve for each ML model employed in the experiment. The performance of the average AUROC and for the individual classes of the dependent variable is detailed in Table 9.2. The results of the average AUROC score indicates the resultant models are effective and they are generalisable. This means, the model can be applied to similar unseen data and the predictions made will still be reliable.

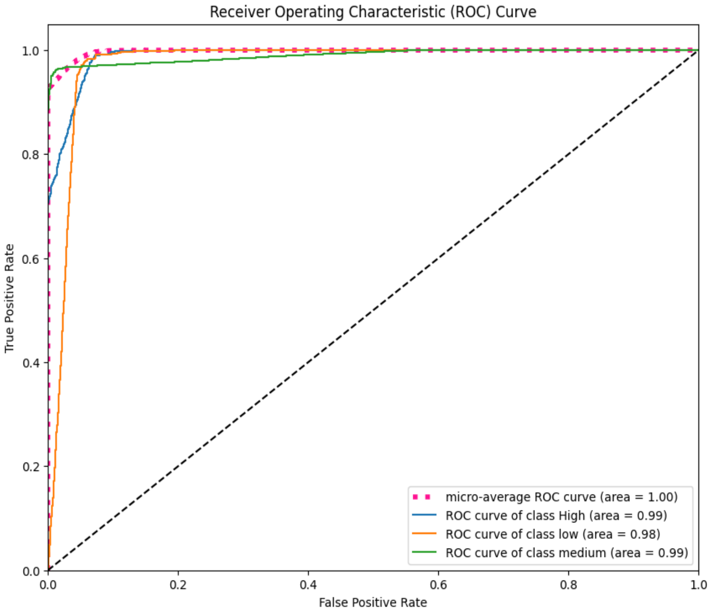


Figure 9.3a - AUROC for SVM

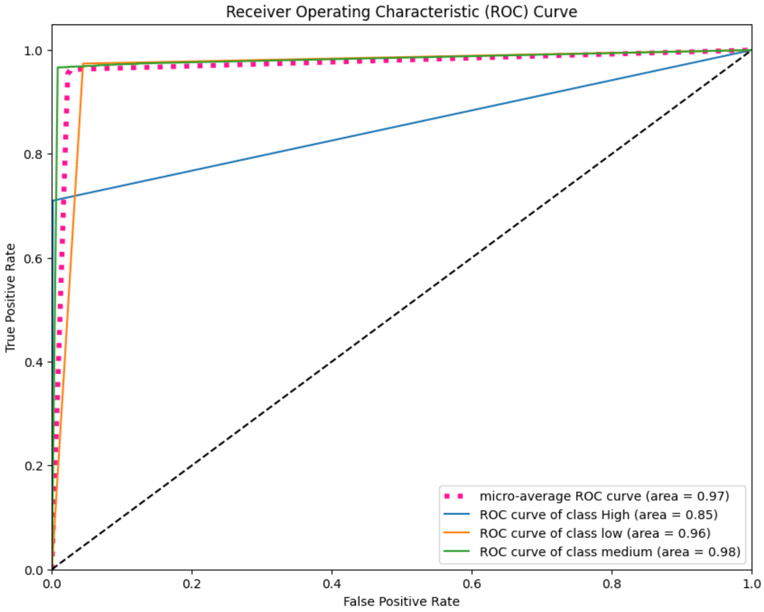
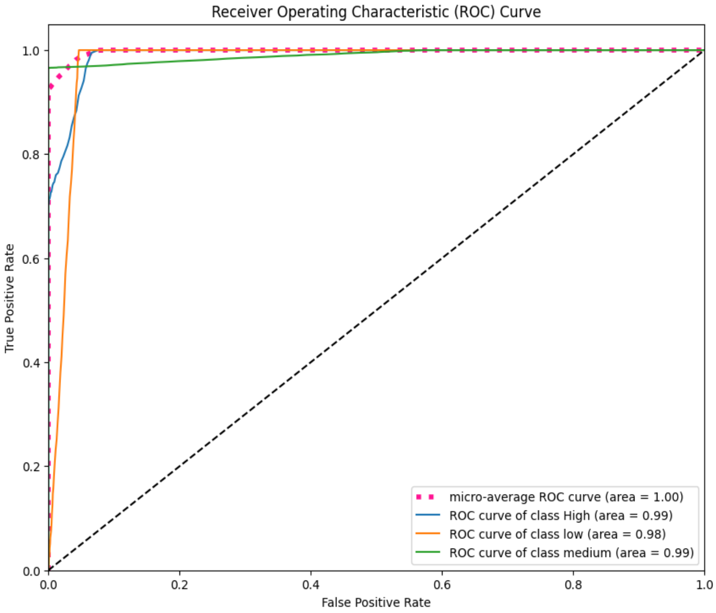


Figure 9.3b - AUROC for NB



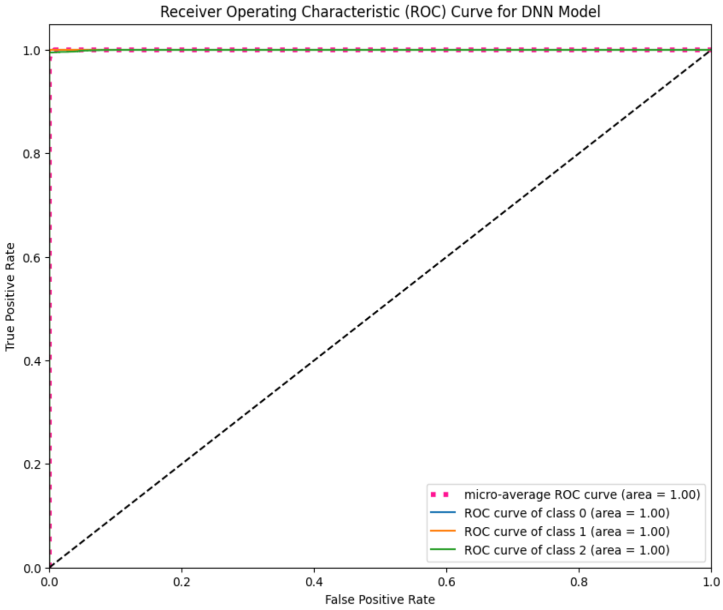


Figure 9.3c - AUROC for RF

Figure 9.3d - AUROC for DNN

Table 9.2 - AUROC results

		AUROC for individual classes (%)		
ML models	**Average AUROC (%)**	**High**	**Medium**	**Low**
SVM	100	99	99	98
RF	100	99	99	98
NB	97	85	98	96
DNN	100	100	100	100

All the models utilised in the experiment performed exceptionally well, with average AUROC scores exceeding 97%. Particularly noteworthy is the DNN model, which achieved the best results with an AUROC score of 100% for all the risk classes. This indicates the high predictive capability of the DNN model in accurately classifying project risk levels. The performance of the DNN model although exception, such performances are rare and may indicate overfitting (Ying, 2019) therefore, further analysis and experimentation is deemed necessary and investigations into the individual performance of each class of the target variable (Guo *et al.*, 2020) to ascertain the model's generalisability.

9.2.2.2 Classification report of each class

To further investigate and analyse the results of the models, the classification report for each class is evaluated due to its ability to provide detailed information about the model's performance for each individual class (Agarwal *et al.*, 2021). Analysing the performance of each class reveals whether the model is performing well for all classes or if it is biased towards certain classes. Table 9.3 shows the classification report of the individual classes.

Table 9.3 - classification report table

	Precision (%)			Recall (%)			F1-score (%)			Accuracy score (%)
Model	High	Medium	Low	High	Medium	Low	High	Medium	Low	
SVM	100	97	39	71	99	35	83	98	37	96
RF	97	97	41	71	99	30	82	98	35	96
NB	96	100	40	71	97	97	82	98	57	95
DNN	100	100	96	91	100	100	95	100	98	99

The individual precision, recall and F1-score of each class shows that, although the ML models had a high accuracy score, there were biases towards the ‘high’ and ‘medium’ class, whereas the ‘low’ class performed poorly as compared to the two other classes. However, it is notable that, a high precision, recall and f1-score (>70) was obtained by the DNN model. The high accuracy score of the models however show that they are reliable and effective for prediction tasks (Tixier *et al.*, 2016). Therefore, based on the results obtained, the DNN models are deemed the most effective algorithm.

9.2.2.3 Confusion matrix

From the classification report and the AUROC results, the DNN model was the best performing model for predicting project risk levels, therefore, a further investigation of the results obtained using the confusion matrix was conducted. The confusion matrix (refer to Figure 9.4) depicts the outcomes of actual classification compared to predictions, represented by a K*K matrix, where K denotes the number of individual classes the target variable has (Wang *et al.*, 2022).

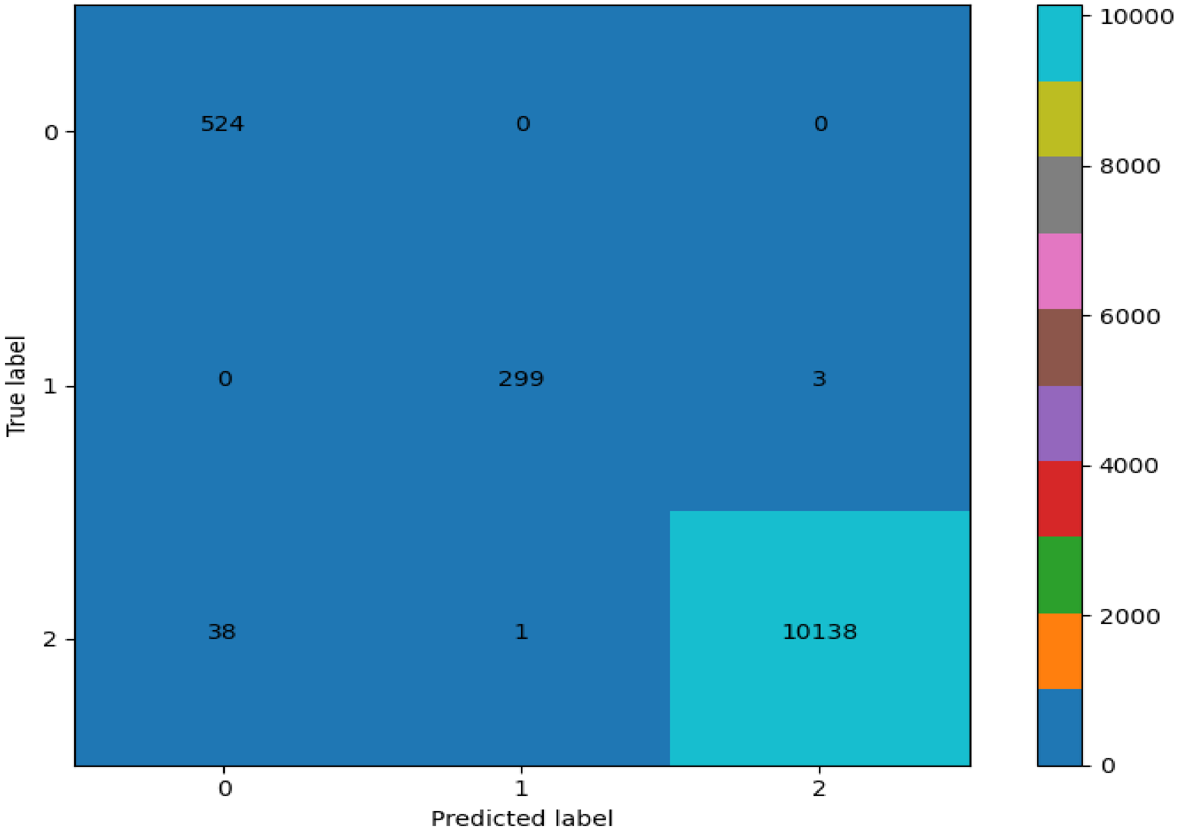


Figure 9.4 - Confusion matrix for DNN model

On the confusion matrix above, the labels 0,1 and 2 corresponds to the target classes high, low and medium respectively as assigned by the label encoding algorithm. From the visualisation, all the 'high' labels were predicted accurately, 299 out of 302 'low' labels were predicted accurately and 10,138 'medium' labels were predicted accurately out of the total 10,177 'medium' labels. This result indicates a superior performance of the DNN model.

9 SION

The findings on important features in classifying risk levels were consistent with findings in existing literature (Alizadeh *et al.*, 2015; Debnath *et al.*, 2016; Choi *et al.*, 2020; Ajayi *et al.*, 2020). For example, Choi *et al.* (2016) found that features such as 'age', 'month', and experience had significant impact on accident occurrence. However, the model discovered new significant features which were very influential in determining accident severity for HTOs such as potential severity rating, actual severity rating, event type, injury occurrence and vehicle involvement. The findings suggest that traditional factors alone may not sufficiently capture the complexity of accident severity for HTOs. The model provides a more thorough knowledge of the elements determining accident risk severity by including more variables related to the severity of possible and actual outcomes, event features, injury occurrence, and vehicle involvement. These results align with the practicality of current theoretical frameworks (Tixier *et al.,* 2016*;* Zhang *et al.,* 2019) by emphasising how crucial it is for accident severity prediction models to take a wider range of factors into account. The addition of these new features emphasises the necessity of an all-encompassing method for evaluating the severity of accidents. Features that consider not only the accident's specific characteristics but also its possible aftereffects and contributory causes.

The prediction accuracy of the three ML model was comparatively lower than that of the DNN model. The ML approaches achieved a prediction accuracy between 95% and 96%, whereas the DNN outperformed the other predictors with an accuracy score of 99%. Thus, the system selected the DNN model for severity prediction while noting its performance in terms of accuracy (99%), precision (98%), recall (98%), F1 score accuracy (97%) and AUROC (100%). The performance of the predictive model indicates its generalisability and reliability when implemented and introduced to new data. Based on the findings, highway safety management 'safe systems of working' (SSoW) can be developed and implemented. SSoW can be used in highway project sites and locations to identify workers/factors that are mostly prone to high risk levels which could eventually lead to fatalities and consequently, implement practical control measures to mitigate them. The analysis results can also be applied in effectively characterising root causes of fatal accidents and proactively tackling them before they result in unplanned incidents. This is a diametrically opposed contrast to reactive controls measures that implement change after an event – by which time the control has failed to prevent injury or save a life.

9.4 SUMMARY

The objective of this chapter was to present a novel synergistic ML and statistical approach for developing prediction models for classifying the severity of risk levels. Previous research has looked into the relationship between incident variables and injury severity, as well as the injury mortality rates (Tixier *et al*., 2016; Zhang *et al.,* 2013). This thesis classifies not just the severity of injuries, but also distinct event risk categories, utilising a variety of incident factors, including injury occurrences. Previous research has also looked into the relationship between injury severity and standard statistical procedures and techniques (Huang *et al.,* 2008; Fowler *et al.,* 2011), but it has not addressed the prediction of this condition in relation to other episodes such as incursions, environmental incidents, security risk, etc. The direction of research explored in this chapter will aid in prioritising risky incidents and help to make effective decisions in allocation of resources to prevent these incidents from occurring through prior prediction.

CHAPTER 10 - VALIDATION OF THE HIGHWAY SAFETY RISK PREDICTION MODEL

10.1 INTRODUCTION

For the purpose of developing optimised predictive models for incident classification, risk level classification and body part classification, it is necessary to validate the highway safety risk prediction model to ensure that, results obtained are reliable and effective (Prusty *et al.*, 2022). Similar data with same variables were selected between 2023 to 2024 to validate the prediction models built. The introduction of new data in the validation stage is to access the generalisability of the model. The generalisability of the prediction models (refer to chapter 7,8 and 9) were also assessed based on a technique which divides the entire dataset into '*k*' (where k=10 in this thesis) equal parts and uses k-1 part of the data for training the rest for testing. This technique is known as the k-fold cross validation (Nti *et al.*, 2021). The process is iterated ten times, and each fold becomes a test set once for each process. The 10-fold cross validation process is used to augment the train test split technique employed where the dataset is split into 70% training data and 30% testing data. This is to reduce any variance that might be produced by performing a simple train test split (*ibid*). The 70-30 split was chosen to ensure that the model has sufficient data to learn from while reserving a significant portion for an unbiased evaluation. To optimise the performance of the models, the values of the parameters for each of the algorithms were controlled by suitably chosen grids. The accuracy score, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUROC) were the evaluation metrics chosen to provide a comprehensive overview of the model's overall performance. Because this is a classification task, it is pertinent to select an appropriate threshold that balances recall and specificity (Roelen *et al.*, 2018). Therefore, the ROC curve was adopted. The chapter then concludes with a discussion of the model's limitations and potential areas for future work.

10.2 RESULTS OF VALIDATION

The results obtained from the classification of incidents, risk levels and body parts are validated and presented in this section. The validation process involved a detailed comparison of predicted versus actual outcomes, ensuring the robustness and reliability of the model. These results provide critical insights into how different factors contribute to incident occurrence, risk level and the specific body parts most frequently affected in such incidents.

10.2.1 Validation results of incident classification results

A grid search was performed to find the best parameters which will optimise the performance of the models. Table 10.1 presents the results for model performance on the test data and the hyperparameter used.

The results shows that the RF classifier had a slight advantage over the SVM for the validation stage of the incident risk classification.

Table 10.1 - Model performance evaluation

	SVM (%)	RF(%)	NB (%)
Metrics			
Accuracy score	96	96	94
Precision	95	96	93
Recall	95	96	93
F1-score	95	96	93
AUROC	98	99	96
Hyperparameter tuning			
	Kernel= polynomial	n_estimators= 100	Var smoothing=1e-9
	Decision function shape= ovr	Random state =42	Priors =None
	Maximum iteration (Max_iter) = 1	max_depth=None	
	Probability= True	max_leaf_nodes= None	

10.2.1.1 Performance validation using ROC curve

A one vs rest classifier (ovr) was used to initialise each model to handle the muti-class classification. The k-fold cross validation was set up and for each fold, the model was fit to the training data and the probabilities for the test data were predicted. The ROC curve and AUROC for each class and the micro-average were then calculated. The average (mean) TPR and AUROC were calculated across all the folds and the AUROC values and standard deviations were used to plot the ROC curve for each model. Figure 10.1 presents the ROC curve for each model which allows a visual comparison of the cross validated results for each model. The curve shows that, for the evaluation dataset, although all the models have great prediction results, RF had 99% which was considered the best performance. This deviates from the previous performance of the RF model in chapter 7. This performance improvement is attributed to the optimised hyperparameter tuning performed in this experiment. This shows that using a k-fold cross validation technique significantly enhanced the model's performance making it more sophisticated.

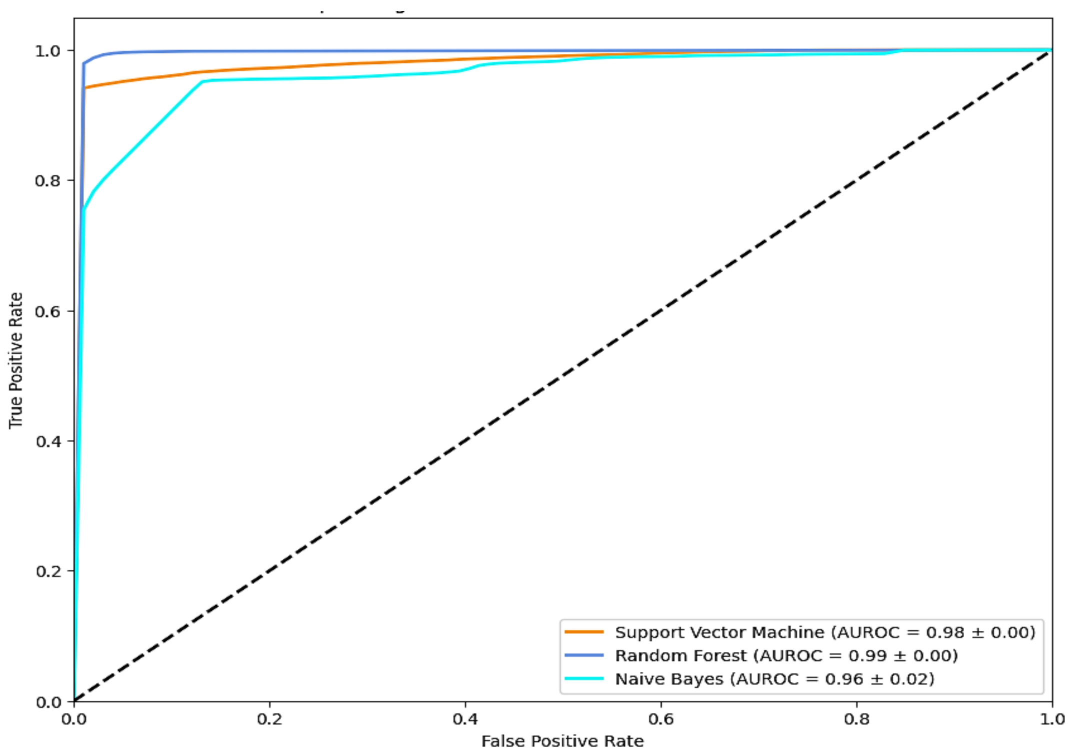


Figure 10.1- ROC curve with cross-validation

10.2.2 Validation results for project risk level

Table 10.2 presents the results for the individual models used in the validation of the project risk level classification task. The stratified k-fold cross validation was also employed and the average accuracy score, precision, recall and AUROC were computed and detailed.

Table 10.2 – Model validation performance

	SVM (%)	RF(%)	NB(%)	DNN(%)
Metrics				
Accuracy score	96	96	94	96
Precision	95	96	93	96
Recall	95	96	93	96
F1-score	95	96	93	96
AUROC	99	99	93	99
Hyperparameter tuning				
	Kernel= polynomial	n_estimators= 100	Var smoothing=1e-9	Optimiser= adam Activation function= Relu
	Decision function shape= ovr	Random state =42	Priors =None	Number of layers-=3 Epoch = 5
	Maximum iteration (Max_iter) = 1	max_depth=None		Learning rate =0.001 Dropout =0.5

	Probability= True	max_leaf_nodes = None		Loss function = 'sparse_categorical_crossentropy

10.2.2.1 Performance validation using ROC curve

Figure 10.2 shows the ROC curve for each model evaluation results. The models validated for the project risk level classification included SVM, NB, RF and DNN model. The models were initialised and assigned significant parameters to optimise their performance. A stratified K-fold cross validation technique was then used to split the data into 10 folds while preserving the class distribution. The training and validation datasets were extracted for each fold and stored. For each model, the training dataset is used to train the model within each fold and the validation dataset is then used to evaluate it. The AUROC scores for each class of the target variable were computed separately and averaged. The mean AUROC curves are then computed across folds for each model.

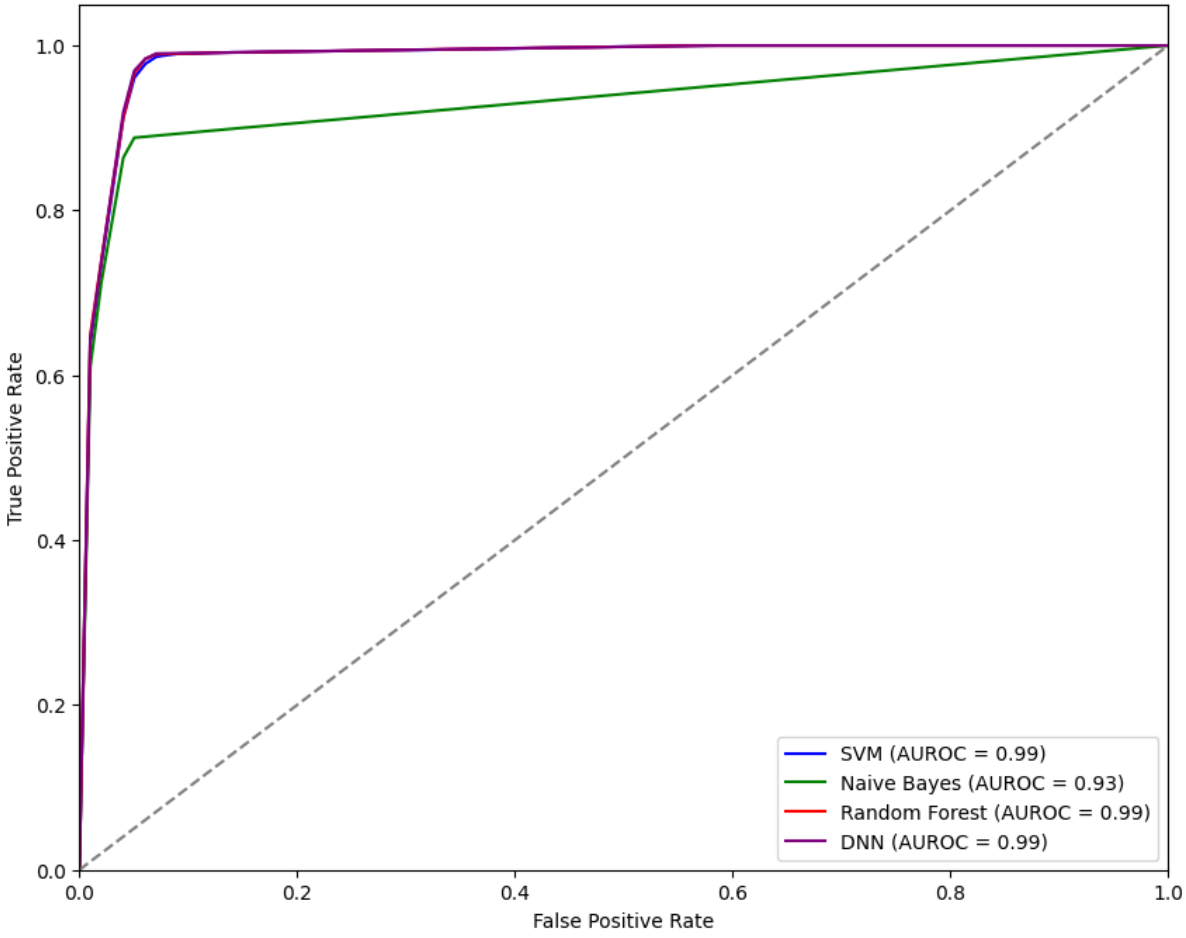


Figure 10.2 – AUROC curves for each model evaluated

The performance of SVM, DNN and RF models were at par. This shows that the optimisation techniques used to enhance model performance is a crucial step in building more reliable and generalisable models. The NB however still remained the least performing model in the validation stage although it was optimised. NB however has very few parameters that can be optimised as compared to the other models evaluated and this could account for its unchanging sub-par performance.

10.2.3 Validation results for body part affected

Table 10.3 shows the results from the modelling task. Although the accuracy, precision and recall show SVM has the best performance, the AUROC which considers the overall performance and overall possible classification threshold, indicates RNN has the best overall performance.

Table 10.3 - Model performance evaluation

	SVM	RF	NB	EL	RNN
Metrics (%)					
Accuracy score	99	98	94	98	96
Precision	99	98	93	97	94
Recall	99	98	93	98	97
F1-score	99	98	93	98	95
AUROC	97	91	65	96	98
Hyperparameter tuning					
	Kernel= polynomial	n_estimators= 100	Var smoothing=1e-9	individual classifiers= SVM, RF and NB	
	Decision function shape= ovr	Random state =42	Priors =None		
	Maximum iteration (Max_iter) = 1	max_depth=None			
	Probability= True	max_leaf_nodes = None			

10.2.3.1 Performance validation using ROC curve

Figure 10.3 compares the overall performance of each of the models using the ROC curve. The RNN and SVM had a competitive performance. Although the RNN was the best performing model, its performance was not overly different from the SVM model. The NB also remains the least performing model. Although the EL algorithm combines the strength of its individual classifiers, it is noted that, SVM (one of the EL classifiers) still performs better. This could be because EL also inherits the weakness of the NB classifier which is part of the EL classifiers.

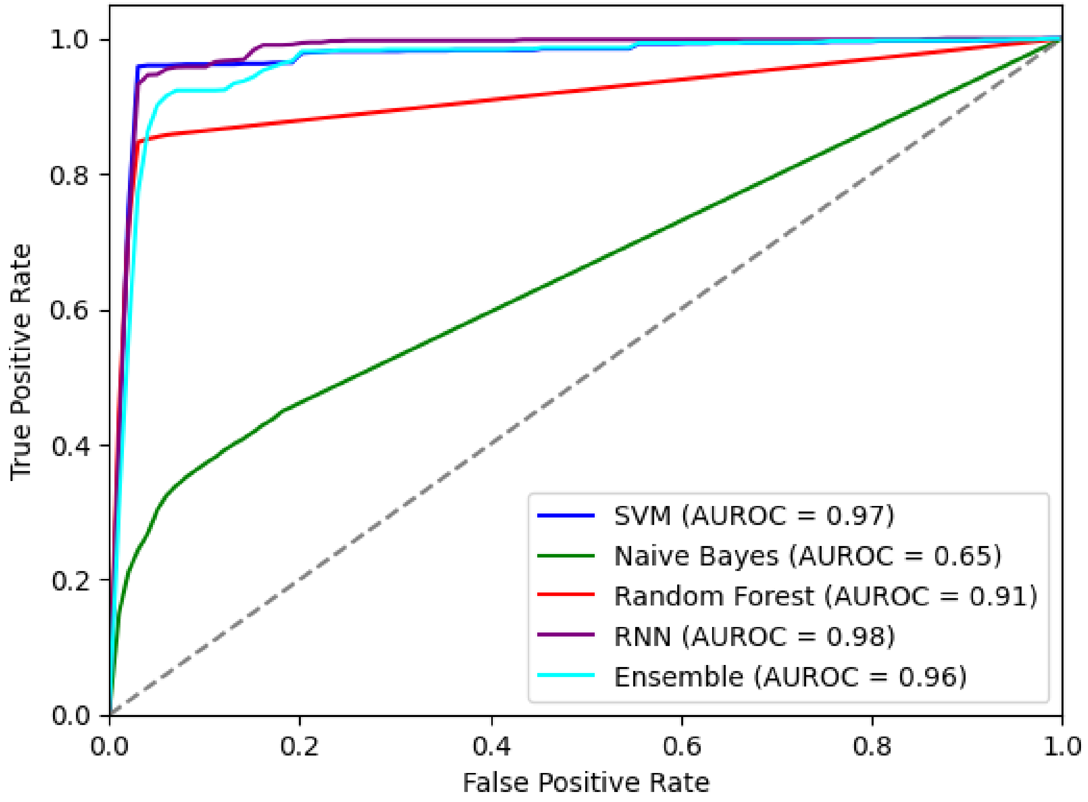


Figure 10.3 – AUROC for different models

10.3 DISCUSSION

The performances of the three classification tasks undertaken in previous chapters (refer to chapters 7,8 and 9) were validated to evaluate how well the models employed will perform on unseen data (Prusty *et al.*, 2022). This is because, models that perform well on training data, might not necessarily have a good performance when new similar data is introduced to it (Nti *et al.*, 2021). Models underperforming on unseen data could be due to many reasons including overfitting (Ying, 2019), underfitting ((Papernot *et al.,* 2016) or non-optimal hyperparameters (Hammerla *et al.,* 2016). When the model learns the noise and other details in the training data such that, it is becomes overly familiar with the training data used in modelling, it might have a negative bearing on the model, leading to overfitting challenges (Ying *et al.*, 2019). The k-fold cross validation technique ensures that the model is tested on various fold of the data to confirm its validity and prevent the issue of overfitting. Also, different sets of hyperparameters may have different effects on the model. Hence, it is essential to validate the optimal hyperparameter which works best for the model's performance. For this reason, the grid search technique was used to evaluate the efficiency of different hyperparameter settings on the model.

Various models were used to train the data for each of the classification tasks (i.e. incident type classification, project risk level classification and body part classification). The k-fold cross validation technique was employed not only as a confirmatory method but also to improve the performance of the models. For the categorisation of incident types, SVM, NB and RF classifiers were used to train the incident data. For the initial results, the SVM with a polynomial kernel had the best performance among the models, the RF classifier indicated a strong potential in being able to capture the pattern complexities that exist in the data, thereby, having a competitive performance also. Although the NB classifier was the least performing model, it served as a significant baseline for comparing the models employed in training. A significant improvement in the computational time and model performance is observed after the k-fold cross validation technique was applied to the models. It is therefore inferred that the challenge of overfitting was mitigated by the cross-validation technique employed, hence a more precise evaluation of the model's performance on new set of data was obtained. The average AUROC scores obtained for the models indicates that, the models are more reliable and effective in predicting various incident types that can occur on the highway for HTOs.

In the second task which was classify the project risk levels, an additional model (i.e. DNN) was included to further test how best the data could be utilised in deep learning frameworks. Similarly, the performance of each model was significantly improved as compared to the initial results (refer to chapter 9). Specifically, the DNN model had a better performance in terms of AUROC, precision and accuracy, and its enhanced architecture enabled it to effectively capture the trends in the dataset. The configuration of the number of layers, dropout rate and learning rates using the grid search also helped to develop a more robust architecture, capable of classifying the project risk levels more effectively.

An RNN model and an ensemble algorithm comprising of SVM, NB and RF, were added to the models to help classify the body parts likely to be affected in an injurious incident.

Compared to the initial results (refer to chapter 8), the models, specifically the RNN model, performed better in terms of AUROC and accuracy score. The ensemble learning approach although combines the inherent strengths of its individual models, failed to perform better than the SVM model. This could be attributed to the RNN also inheriting the weakness of NB model which was the least performing model. This indicates that, ensemble learning does not necessarily increase model's performance. If there are weak learners like NB in this case, it might impact the performance of the model, leading to subpar results.

Comparatively, the three classification tasks show improved consistency in the performance of the models when the k-fold cross validation technique is applied. The validation process also confirms the generalisability, reliability and effectiveness of model in real world applications as real-world data was used in the validation process.

10.4 SUMMARY

A ML model might have a good performance on training data but might poorly perform on unseen or real-world data due to many reasons such as overfitting or underfitting (Prusty *et al.*, 2022). It is therefore essential to employ validation techniques in a ML task to improve model accuracy, avoid overfitting, find the optimal hyperparameter setting and assess the models' strengths and weaknesses. One of the most commonly employed technique in validating and measuring ML model performances is the k-fold cross validation (Nti *et al.*, 2021). This chapter therefore explored the impact of applying the cross-validation technique to the models to ascertain their reliability and reaffirm their accuracy

The validation technique was successfully implemented in this chapter for the three classification tasks undertaken in this thesis (refer to chapters 7,8 and 9). The results obtained indicated a significant improvement in the accuracy and generalisability of the ML models employed. This chapter has highlighted the critical role of model validation and optimisation, providing insights into best practices for ML in safety risk prediction.

CHAPTER 11 - DISCUSSIONS, RECOMMENDATIONS AND CONCLUSIONS

11.1 INTRODUCTION

This chapter synthesises the thesis findings and their implications and summarises the limitations and ideas for future work. The significance of the thesis results in presented in a broader context and holistically connected to the original objectives of the research to reaffirm the significance of the study and its contributions to the field of safety risk management. This chapter is crucial in capturing the substance of the research discussion and demonstrates how the findings contribute to the existing body of knowledge. Hence, the impact of the study is clearly articulated, paving the way for continued research discoveries. The conceptual model obtained from the synthesis of literature provided a basis for the development of a ML solution that addresses the challenges of safety risk prediction and pre-emption. The validation of the ML model enabled the provision of a more reliable solution capable of being generalised for unseen data. This chapter therefore expresses a balanced interpretation of the conclusions and deductions drawn from the findings discovered in this thesis.

The final chapter of the thesis therefore includes: i) the key findings or results that have emerged from the study; ii) recommendations for HTOs, highway safety officers, and safety managers; iii) an unambiguous discussion of the different contributions to knowledge that have been produced from the thesis; iv) domains that warrant further research and investigation; and v) the main conclusions of the entire study. The initial research objectives are restated and associated to the exact thesis chapter(s) that satisfy these objectives.

11.2 SUMMARY OF MAJOR FINDINGS

The research objectives discussed in Chapter 1 are recapitulate in Table 11.1a and Table 11.1b associates the thesis chapters that fulfil each research objective.

Table 11.1a – Research objectives.

No.	Research Objectives
1	To conduct a bibliometric literature review to identify how various previous and existing models and theories underpinning safety risk management within the construction industry could be tailored towards highway operations.
2	To identify and analyse contributions of existing safety indicator data which informs the selection of safety-oriented variables for highway traffic operations.
3	To develop a conceptual model based on identified standardised safety indicator data tailored for highway traffic operations.
4	To establish a robust framework for the success of a similar prediction or classification proof-of-concept model.
5	To build a ML predictive model which can be used to predict risk level, body parts likely to be affected and incident types for effective decision making.
6	To identify significant parameters within the model and assess the accuracy and precision of the model using standard evaluation metrices.

Table 11.1b- Research objectives addressed per thesis chapter.

Chapter No.	Chapter Title	Research Objectives					
		1	2	3	4	5	6
2	A review of methodologies				✓		
3	Research methodology and design				✓		
4	A review of safety theories and models	✓					
5	A theoretical framework for safety indicator-based input variable selection for ML risk prediction models.		✓	✓			
6	Data exploration		✓		✓		
7	Building the highway safety prediction model: incident type classification					✓	✓
8	Building the highway safety prediction model: body part affected					✓	✓
9	Building the highway safety prediction model: risk level classification					✓	✓

11.2.1 A review of safety risk theories and models

The first research objective was to investigate the contributions of existing risk theories and models and how lessons from previous models could be adopted in highway operations to inform the development of a novel theory and model tailored for highway workers. Theories and models within safety risk research have been adopted and tailored to suit particular domain areas based on the generic early theories and models developed. This is evident in the prominent display of keywords such as construction, mining and agriculture. However, the conspicuous absence of highway operations, specifically operations of highway workers indicate a research gap must be filled. The various types of safety risk models and theories adopted in other fields could be tailored to highway operation safety strategies by making use of their most useful characteristics. Currently, safety theories and models prioritise retrospection over prediction. This inclination is observable in models like the Swiss cheese model, normal accident theory and the domino theory, which retrospectively examine past accidents and dissect them into a series of factors that if addressed individually, could have potentially prevented the accidents. However, these models do not significantly contribute to risk prediction. Consequently, this thesis analysed the factors proposed by these theories—including human, environmental and systemic factors - and utilised them to develop a predictive model specifically tailored for highway operations. Although various models offer diverse strategies for safety risk mitigation, only those grounded in resilient theory, referred to as "resilient models," offer solutions for adaptability and recovery in the event of incidents or accidents. Consequently, resilient factors inherent in these resilient models are suggested to be integrated with the predictive factors to develop a resilient prediction model. Predicting safety risk incidents or safety risk levels is a huge step toward prevention of an accident or loss occurrence in an organisation, nonetheless, predicting future occurrences only helps in anticipating and planning for these risks without any provision for adaptability and recovery in the event that the risks predicted are unavoidable. This leaves a gap for predictive models which have inherent resilient features capable of recovery in event of an inevitable predicted safety risk. A conceptual model was developed to address this gap.

11.2.2 The contribution of safety indicators in predictive modelling

The second objective was to identify and analyse how existing safety indicators can inform the selection of safety-oriented variables necessary for building a prediction model for highway operations. Currently, there is a shift in research trend towards the adoption of technology such as ML, artificial intelligence and predictive analytics in safety research. Also, the key words leading and lagging featured conspicuously in the literature findings because they were the two major types of safety indicators being used to measure safety performance across various industries. The literature on leading and lagging safety indicators identified nine main features that need to be considered when deciding on the type of safety indicator to select for risk modelling. Findings reveal that due to the proactive nature of leading indicators, they were more significant in risk prediction while lagging indicators were more useful for risk mitigation. Also, leading and lagging indicators could be combined to form resilient indicators which has the ability to introduce adaptability into the safety system thereby increasing safety performance. The cluster analysis unearthed various themes under which input variables derived from safety indicator can be classified. A comparative review across various industries reveals several input variables that can be formulated from safety indicators and adopted for

ML risk prediction. A notable gap was discovered which suggests the under exploration of ML risk prediction in the highway sector particular for HTOs.

11.2.3 Data exploration

The data exploration stage helped to fulfilled objectives two and four. The data derived from safety indicators which became input variables were analysed to establish their contributions towards the development of similar classification models in literature. The analysis performed gave insights into contributory factors to incident and injury occurrences. It was found that, certain factors such as time of day of an operation, either day, afternoon, evening or night, played an influential role in incident occurrences. Consistent with findings in literature, the data showed that, incident occurrences at night were more rampant and fatal than other times of the day. The results also showed a positive relationship existed between average traffic flow per day and incident occurrences i.e. the higher the average traffic flow, the higher the frequency of incidents. Findings also highlighted project locations which had higher frequency of incidents. It was interesting to note the relationship between age and injuries. It was found that, the younger population of employees were involved in more injurious incidents as compared to the older population. These findings will arm safety authorities with evidence-based information that they can rely on to make proactive safety decisions.

11.2.4 Incident type classification.

The fifth objective was to build a proof-of-concept model which can classify incident types. This is because judicious identification of event/incident categories likely to occur on the highway is critical for deploying suitable resources and optimising traffic flow. The most influential and significant variables in the classification of highway incidents were found to be weather/visibility, year, age range, location, vehicles involved, site/project, injury type, region, part of body affected and season. Although the model produces a high accuracy score of SVM (96%), RF (97%) and NB (94%), the individual classes of the target variable perform poorly with the original data. This can be attributed to the high-class imbalance which causes the model to learn that it can obtain high accuracy by constantly predicting the majority class. To handle class imbalances in complex data such as the one employed in this thesis, the SMOTE algorithm was found to be the most effective in efficiently balancing the data for modelling. The SVM with a polynomial kernel combined with the SMOTE algorithm is found to be the best model in predicting the various safety incident and the Random Under-sampling (RU) algorithm was the most inefficient in improving model accuracy. The Random Oversampling algorithm resulted in overfitting in the model. The NB model is unable to handle the high dimensionality of the target classes, hence, performs poorly irrespective of whichever balancing algorithm is applied. This explain why Bayesian models are the least used models in safety risk predictions.

11.2.5 Risk level classification.

To satisfy the fifth objective of classifying risk levels, a risk level classification model was developed. The most significant features in risk level classification were actual severity rating, event type, potential severity rating, injury occurrence, injury type, part of body affected, vehicle involved, experience in current role, and age range, month and year. The DNN model was able to capture more significant features as compared to ML models. This was due to the ability of DNN models to handle more complex relationships than ML models. Using the AUROC, confusion matrix and classification report metrices, the DNN model outperformed all the other models (SVM, RF, NB) which were employed in the model development.

11.2.6 Body part affected classification.

Research findings demonstrate that ‘region’, ‘site/project’, ‘event type’, ‘vehicles involved?’, ‘location’, ‘did this event occur on the SRN?’, ‘injury type’, ‘weather / visibility’, ‘season’, ‘injury occurrence’ and ‘project risk level’ were the most significant factor variables when predicting the body part likely to be affected by an injurious accident. Although ensemble learning methods combine the strengths of the individual models, they consist of to improve predictive performance, the SVM outperformed it. The ensemble learning method in handling complex relationships in the data and can often outperform individual models like SVMs, especially in scenarios with large datasets and high-dimensional feature spaces. However, in this thesis, the SVM captured the relationships between the data better than the other models due to the optimal hyperparameter utilised. It was found that, in cases where the data is sensitive to hyperparameter tuning, SVM could present better results as compared to more complex algorithms like the RNN and the ensemble method.

11.3 RECOMMENDATIONS

Certain recommendations were distilled from the findings of each chapter of this research. These recommendations underscore the critical importance of incorporating resilience, advancing collaboration between industry and academia, and refining safety prediction models to encompass a comprehensive range of safety indicators.

The first recommendation advocates for the integration of resilient features or variables into the prediction model, thereby equipping it with adaptability and the ability to withstand unforeseen shocks. Recognising the intrinsic unpredictability of highway incidents, this approach acknowledges the need for models that not only forecast potential incidents but also possess the ability efficiently respond to emergent situations. By incorporating resilience into the predictive framework, highway safety officers can better prepare for and mitigate the impact of incidents that defy anticipatory measures. As this research has shown (refer to chapters 4 and 5), predicting future occurrences only helps in anticipating and planning for these risks without any provision for adaptability and recovery in the event that the risks predicted are unavoidable. It is therefore vital to inculcate resilient features to overcome such uncertainties.

Second, it is imperative to build stronger connections between industry and academia in the health and safety research domain. Specifically, the application of ML techniques for predicting safety risks should be firmly rooted in practicality. Academic experiments must yield actionable insights with tangible practical implications essential for advancing industry practices. Adopting ML in highway operations presents a bright opportunity to augment the efforts of highway safety officers. As shown in this research (refer to chapter 7), through collaborative partnerships, industry practitioners can leverage the expertise and innovation of academic researchers to develop innovative predictive models capable of identifying and pre-empting potential safety hazards on the highways. This synergistic approach holds the potential to revolutionise the field of highway safety by harnessing the power of data-driven insights to proactively safeguard HTOs and mitigate the occurrence of incidents.

The third recommendation underscores the necessity of refining safety prediction models to incorporate a detailed and meticulous selection of leading and lagging safety indicators. By capturing the multifaceted challenges that exist in the highway industry, these indicators serve as metrics of safety performance, thereby enabling more accurate predictions of potential incidents. By meticulously identifying and selecting a diverse set of safety-oriented data which encompasses both predictive and retrospective metrics, safety prediction models can better encapsulate the dynamic complexities of the highway environment. A detailed exploration of the data (as shown in chapter 6) could uncover various patterns and hidden information that otherwise were unknown. Armed with this granular understanding of safety dynamics, HTOs can proactively identify risk factors, implement targeted interventions, and ultimately enhance the safety and well-being of HTOs.

Although the findings presented in this thesis focuses on safety risk predictions for HTOs in the UK, it is applicable beyond this specific context. The proposed ML framework can be tailored to other high risk occupations such as highway workers in general, construction workers, emergency responders and other law enforcement officers, where the nature of prevalent safety risk is similar to that of HTOS. Furthermore, the methodological approach, specifically the incorporation of leading and lagging safety indicators provides a framework that can be transferable and customised for various industries to improve their risk assessment strategies. The application of AI in enhancing workplace safety allows policymakers, safety managers and organisations make decisions based on well researched evidence- which has gradually become a significant tool for decision making globally. However, the generalisability of the models is dependent on the availability and quality of contextual data and future research should explore adaptations across different geographical and industrial settings to validate the robustness of the approach.

11.4 LIMITATIONS

There are significant philosophical limits with this approach. First, research bias is an inevitable bone of contention when employing an interpretivist and/or pragmatist philosophical approach because of the philosophy chosen. To provide the most objective perspective possible, the research has acknowledged this constraint and provided a wealth of academic sources, empirical clarifications, effects and outcomes. Different philosophical positions and quantitative methods (inferential statistics, bibliometrics, descriptive statistics, scientometric, and sections of content analysis) have been established by the research to counteract this. Furthermore, the notion of grounded theory is quite broad and has inherent limitations depending on the approach used.

Although secondary data presents a wealth of information for training prediction models, the limitations and potential constraints of using secondary data to train ML models must be examined. The potential for variation in the accuracy and reliability of secondary data is one of its primary limitations. Secondary data, as contrast to primary data that is gathered expressly for research, typically comes from multiple sources using a range of standards and collection techniques. The dependability and resilience of the ML models trained on the secondary datasets may be compromised as a result of inconsistencies, errors, and missing values that may permeate them. Furthermore, there exist data integration and compatibility challenges when employing secondary data in ML modelling. Datasets sourced from different domains, time periods or geographical regions may exhibit varying data formats, structures, and semantics. Therefore, achieving seamless compatibility and harmonisation across such heterogeneous datasets requires substantial preprocessing efforts, which can introduce additional complexities and potential errors into the modelling pipeline.

The scope of ML algorithms employed in the modelling process was restricted, primarily focusing on a select few, including SVM, RF, NB AND DNN. However, a plethora of alternative algorithms exists, each with its unique strengths and characteristics. For instance, k-Nearest Neighbors (kNN), K-Means clustering, and advanced Gradient Boosting techniques such as XGBoost and CatBoost represent just a fraction of the diverse algorithmic landscape available for predictive modelling tasks. Expanding the repertoire of algorithms tested can provide valuable insights into their comparative efficiency and performance in developing predictive models with the given dataset. While the algorithms utilised may have demonstrated satisfactory performance, it remains plausible that alternative algorithms could exhibit superior predictive power and generalisability. By conducting comprehensive experiments across a broader spectrum of algorithms, a more meticulous understanding of the data could be obtained and hidden patterns that may have eluded simpler models could be uncovered.

Moreover, the selection of algorithms plays a pivotal role in determining the model's robustness and applicability to real-world scenarios. Different algorithms excel in different contexts, depending on factors such as data complexity, feature interactions, and the presence of nonlinear relationships. Therefore, the exclusion of certain algorithms from consideration may inadvertently limit the model's capacity to capture the full complexity of the underlying data generating process.

Large Language Models (LLM) and Large Language Processing (LLP) are two examples of how recent developments in AI have greatly improved data processing abilities. They are useful for predicting safety risks in high-risk occupations such HTOs because they use deep learning techniques to process and analyse massive amounts of text data. A key limitation of this thesis is that it did not explore the use LLM and LLP for analysing the incident data. While the study focused on traditional machine learning techniques for safety risk prediction, LLMs could enhance the analysis of incidents by extracting deeper insights from unstructured text. A significant quantity of safety-related data is available in unstructured formats, including incident reports, maintenance logs and employee feedback, however, the traditional machine learning models used for safety prediction often rely on structured data. Hence, by extracting valuable insights from these textual datasets, LLMs such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-training Transformer (GPT) models can improve the precision of the safety risk assessment models.

Future research can therefore explore the use of LLMs to analyse the vast amounts of historical safety reports, identifying key risk factors, trends, and correlations that may not be immediately evident through traditional statistical methods. Also, by processing natural language data, the LLMs can be used to generate new safety indicators from unstructured text, hence, improving the model's input variables for risk prediction. However, this thesis contributes to the foundation for such advancements by establishing a structured, data-driven approach that can be further augmented with natural language AI capabilities.

11.5 CONTRIBUTIONS TO KNOWLEDGE

This thesis advances some United Nations Sustainable Development Goals (UNSDGs**)** by integrating predictive analytics into safety decision-making. The ability to anticipate workplace hazards and prevent injuries fundamentally redefines occupational safety strategies. Such a framework helps to bridge the gap between reactive policy frameworks and AI-enhanced risk prevention. This aligns with UNSDG3: Good Health and Well-being, particularly target 3.6, which aims to halve global road traffic deaths and injuries.

Furthermore, this thesis challenges conventional occupational risk assessment methodologies by demonstrating how AI can optimise safety interventions at the intersection of SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure)

The model's ability to process complex, multi-variable incident data and extract meaningful insights contributes to workplace safety resilience**.** This ensures that highway operations become increasingly adaptive to emergent risks.

The implication of this thesis also extends into SDG 11 (Sustainable Cities and Communities) from an infrastructure perspective. By reducing the frequency and severity of safety incidents, the proposed ML model enhances transportation system sustainability, ensuring that both road workers and the general public benefit from improved safety outcomes. The broader contribution to knowledge lies in its integration of leading and lagging indicators, an approach that has been underexplored in prediction-based safety modelling.

Throughout the entire research lifecycle, each chapter has also made significant contributions to knowledge by addressing existing gaps and offering solutions to the challenges identified in the study. Table 11.2 provides a detailed overview of these contributions, specifying the chapters responsible for advancing particular areas of knowledge.

Table 11.2 – Contributions to knowledge.

Chapter No.	Chapter title	Overview of Results
4	Safety theories/models: a synthesis focusing on development of new risk theory for a predictive model	Proposing models and theories which focus more on a proactive risk prevention. Highlighting the impact of human factors in safety risk prediction. Inculcating information technology into safety risk model/theories. Proposal of conceptual predictive models which have inherent resilient features capable of recovery.
5	A theoretical framework for safety indicator-based input variable selection for ML risk prediction models.	Identification of defined leading, lagging and resilient safety indicators tailored for highway risk prediction. Development of resilient indicators from the integration of leading and lagging safety indicators The adoption of technological trends in the application of safety indicators. Development of prediction model which combines leading, lagging, and resilient safety indicators. Conceptual model developed outlining input parameters and model architecture
6	Data exploration and analysis	Identification of trends and patterns in the incident data Visualisation of data insights

7	Building the highway safety prediction model: incident type prediction	Analysis of the correlation of feature variables Analysis of feature importance Comparison of data balancing algorithms and their impact on model training Evaluation and comparison of the performance of the ML models employed.
8	Building the highway safety prediction model: risk level prediction (proof of concept)	17. Identification of high-risk areas and factors contributing to accidents. 18. Implementation of targeted safety measures to address specific risk factors. 19. Optimisation of resource allocation for law enforcement, emergency response and infrastructure improvements based on predicted risk levels.
9	Building the highway safety prediction model: body part/injury type prediction	20. Approach to incidents with a heightened awareness of potential injuries, facilitating a more informed and efficient response. 21. Inform the optimisation of personal protective equipment (PPE) for traffic officers
10	Proof-of-concept model validation	22. Successful validation of the model.

11.6 FUTURE WORK

This thesis presented a detailed analysis on the theories and models underpinning safety and their contributions to the development of a proof-of-concept ML model for safety predictions. However, a number of future research avenues have emerged which could further enhance and validate the findings made. First, the data exploration carried out in chapter 6, answers the question ‘what is happening’? Potential future research which explores obtaining insights from HTOs, highway supervisors, safety officers or managers about the reasons behind certain trends and patterns emerging from the findings in the data will help answer the question of ‘why is this happening’. For example, findings were made which points to under reporting of incident occurrences (refer to chapter 6). Therefore, future research could include surveys and questionnaires to understand the reasons for workers under reporting incidents. Also, insights could be gathered on why certain day, times or locations posed higher risks in highway operations than others (refer to chapter 6).

Furthermore, a number of emergent themes under which input variables can be classified were identified through the scientometric analysis stage (refer to chapter 6). In future work, data on these identified themes can be collected and analysed to ascertain their impact on safety for HTOs. Also, an expert interview or focus group on the developed ML model will be a further step in validating the developed model. Expert contributions could help shape and refine the model better to suit highway operations without deviating from useful safety practice. Furthermore, future work could explore the development of a software user interface for the prediction model developed (refer to chapter 7). This will be a pragmatic way of deploying the prediction model for human use.

11.6.1 Survey and questionnaire to understand incident trends

The objective of this future work is to gather insights from workers about the reasons behind emerging trends found in the data analysis, exploration and visualisation such as underreporting safety incidents, distribution of incidents and injuries per age, location, time, etc. The perceptions of worker on current safety practices and the effectiveness of existing incentives for enhancing safety could be obtained.

A purposive non-probability sampling of HTOs and safety officer could help shed light on diverse issues. A structured questionnaire with both closed and open-ended questions could be developed to probe into issues. Topics such as reasons for underreporting incidents (e.g. fear of retribution, lack of awareness, inconvenience), workers' perceptions of safety culture within their organisation, evaluation of current incentives for reporting incidents, suggestions for improving incident reporting and safety incentives etc. could be considered in the questionnaire.

With such surveys or questionnaires, insights could be obtained from workers' attitudes towards safety and the safety culture/ climate within the organisation. This investigation will help to evaluate key factors that prevents a successful implementation of risk models and leads to an eventual occurrence of the safety risk incidents. Therefore, the questions, ‘how did this incident occur and why did this incident occur’ could be answered. The objective is also to identify the triggers of these events and why these triggers are successful in causing incidents despite existing barriers and measures put in place. It is pertinent to identify triggers as it helps validate the input variables necessary for prediction of event occurrences. The primary data collected from this stage could help safety managers formulate more targeted interventions to enhance safety performance. Understanding the underlying reasons for incident occurrences can help organisations design better policies and programs to improve overall workplace safety. For example, instituting policies which enhance incident reporting can lead to more accurate data, which is critical for effective safety management and the refinement of predictive models.

11.6.2 Interviewing experts on the developed ML model

Further research can be carried out to validate the proof-of-concept ML model developed in this research through expert feedback and gather insights for improving the model and its practical application. Experts in ML, safety management, occupational health, highway safety managers and policy formulators could be included in the interview process to obtain a more detailed and expert opinion on highway safety risk predictors. The inclusion of safety managers is also to ascertain what key safety risk factors are considered in practice when managing safety risks and any resilience measures currently in place.

The interviews are also aimed at decoding the real-life occurrences on real highways projects which contributes to findings obtained from analysing the data. A method of nonprobability purposive sampling can be used to recruit experts using the Cochran formula. Demographic criteria can be set based on its impact on the research to help obtain more relevant information. For example, only participants with a specified years of experience can be selected for the interview. Due to the qualitative nature of interviews, responses are open to interpretation based on the researcher's viewpoint and also based on the experts' experiences and personal observations.

Whilst the experiences of participants might be profound, there may be aspects of safety risk models in which they have not experienced or experienced in a limited scope therefore, a sample size of participants can be selected based on Mason's analysis (Mason's 2010; Morse, 2000) which suggests the most common sample sizes, in the case of qualitative research, were twenty and thirty. A saturation test can then be performed to ensure the validity and comprehensiveness of the interview responses (Olugboyega and Windapo, 2019). A thematic analysis can logically saturated if the ideas or categories formed utilising the obtained data are assimilated into existing concepts or categories and no novel themes or categories develop (Vollstedt and Rezat, 2019). The interviews can be conducted online using MS Teams in order to provide flexibility for respondents (Harrison *et al.,* 2019). Furthermore, due to its simplicity of use, availability and dependability, electronic and online dissemination tends to provide a greater response rate (Saleh and Bista, 2017).

A series of predetermined questions could be sourced from literature and the emergent findings of previous stages (refer to chapters 7, 8, 9 and 10) in this research will be the basis for which questions will be headlined. For example, questions could be based on: i) model understanding, use cases and model outputs; ii) model performance, accuracy and reliability; iii) data quality and availability; iv) user interface, accessibility and integration with existing systems; v) training, privacy and ethics; vi) potential improvements in data input, feature selection and algorithmic approaches; vii) recommendations for integrating the model into existing safety management systems; viii) future enhancement/ overall satisfaction; and ix) open ended closing thoughts. Detailed discussions of the research, analysis, and proof-of-concept model can be conducted before recording the interview. This is because, besides gaining background information on the research topic, such an approach will provide an opportunity to verify participant's understanding, as well as an opportunity for both parties (researcher and participant) to practice various conversational norms (greetings, familiarisation of speech patterns, pace of speech, annunciation, etc).

Expert feedback will be invaluable for refining the ML model, ensuring it is robust, reliable, and applicable in real-world settings. This iterative improvement process is essential for transitioning from a proof-of-concept to a deployable solution that can effectively enhance workplace safety.

11.6.3 Determining thresholds and triggers

The efflorescent framework developed in this research (refer to chapter 5) could be applied by collecting relevant data on identified safety indicator areas to set thresholds and triggers on key variables. For example, a threshold for the frequency of safety audits and inspections could be pegged for daily or monthly inspections for high-risk areas. In the event that inspections are not conducted as per the schedule, it may give an indication of a lapse in monitoring. If the threshold is consistently exceeded, an immediate response, such as investigation or an urgent review of the inspection process could be trigger. This allows the implementation of corrective measures to ensure timely and thorough inspections. Adjustments to these thresholds and triggers could be made based on highway industry standards, regulatory requirements and the organisation's specific risk tolerance.

This application can be done through action research. Action research allows for a more collaborative and iterative approach to planning, observing and brainstorming to find practical solutions to problems. This approach ensures that threshold and triggers set are continuously improved based on stakeholder feedback, observations and evidence-based data. First, the conceptual framework proposed in this research (refer to chapter 5) can be used to identify and collect key safety indicators relevant to HTO safety. The data collection can be both primary and secondary data collection. For primary data collection, stakeholder consultations with HTO, safety experts and policy makers can be adopted to obtain information on pertinent safety indicators such as incident response time, frequency of accidents, near-misses, and compliance with safety protocols. Secondary data from historical past incidents can be sourced from relevant databases and reports. This will help to further improve the safety framework (refer to chapter 5) proposed in this thesis by developing a comprehensive list of safety indicators that are significant for monitoring and improving HTO safety.

The data can then be analysed to identify pattern and trends which can inform the setting of baseline performance levels. Statistical methods can be used to also detect outliers, variance and average values to understand the distribution of the data. After analysing the data, seminars or symposiums could be conducted to discuss the results obtained with experts. Feedback on the results could help define premiere thresholds and triggers. The thresholds will represent acceptable performance baselines while the triggers will indicate actions needed to be performed. Existing industry standards and practices could be used to shape the thresholds and triggers in a realistic and achievable manner.

11.6.4 Development of a software user interface for the prediction model

ML applications could often have functionalities which could be complex for non-technical users. GUI therefore become a critical necessity in the deployment and utilisation of ML applications. Future work therefore proposes the development of a user-friendly software interface for the ML prediction model (refer to chapters 8,9,10), which will make the underlying algorithms and models accessible and practical for safety managers and decision-makers.

The first stage will be to comprehensively analyse user needs and the system requirements. Inputs from potential users such as safety officer, managers, supervisors etc. could be obtained through focus groups or interviews. Key functionalities such as dashboard presentation, data inputs, prediction visualisation and generation of reports need to be considered. The development of the software interface will allow targeted users to easily navigate the software, input data, see predictions made, visualisations from the dashboard and also generate reports. Developing a well-designed interface for the ML model will allow practical applications of the software and encourage the use of predictive and descriptive analytics for a more proactive approach to safety and risk management.

11.7 SUMMARY

The aim of this thesis was to effectively utilise data from the highways industry through analytics and predictive modelling. This is to inform proper safety policies and evidence-based decision making to enhance safety prevention for HTOs in the highway and transportation industry. Safety predictive modelling studies in the highway industry is an intertwined discipline of computer science, safety and transportation research. As all predictive models will have it, data is an essential part of the modelling process. However, data employed in safety prediction modelling especially in the highway industry is highly discombobulated, broadly non-cohesive and has no evidence of being safety oriented. Unfortunately, this situation is replicated and remarkably exacerbated in safety research for HTOs specifically due to lack of comprehensive research in this field. Safety research in highway and transportation industry have largely focused on pedestrians, drivers, the road and passengers to the neglect of HTOs. However, from an industry perspective, the role of HTOs is tremendously essential in the day-to-day tasks in highway operations. Building a safety prediction model tailored to the unique characteristics of HTOs is therefore a significant step in enhancing safety in the highway industry. Utilising data from a highway's agency in the UK (National Highways), a highway safety risk prediction model was developed using ML to predict various HTO incidents, project risk levels and body parts likely to be affected by injuries.

Numerous findings were revealed in this research. First, due to the lack of standard framework to guide the collection of pertinent safety-oriented data for safety predictive modelling, safety prediction models are being developed with data with no evidence of their significant contribution to the performance of prediction models. Also, the question *'what kind of data do we need to collect'* still lingers for many organisations in the highway industry. Second, safety resilience or resilience engineering have been proposed as an alternative technique for safety management in contemporary literature. However, there have been little, or no mention of how existing safety indicators could be used to create resilience in safety management. This therefore begs the question, *'how do we create resilience from the existing indicators available'?* and *'do we need to start from scratch'?* the lack of a foundational guide to creating the resilience required by highway organisations leaves room for formulating a conceptual framework which addresses this void. Third, current literature focuses on predicting accidents and injuries instead of various incidents. Some incidents may not be classified as accidents or may not cause injuries, but they might still be grievous or detrimental to the general safety of worker. For example, a security safety risk incident where HTOs are verbally assaulted by pedestrians or an environmental safety incident where there are chemical spillages may not be captured in accidents or injury predictions although they still remain grievous. Therefore, having a prediction model which captures the intricacies of various incidents, whether injurious or not is very essential in the safety management process. The lack of research on prediction models for incidents could be attributed to the unavailability of data necessary for developing such predictions.

This thesis therefore advances the research in safety risk predictive modelling in three phases to address the gaps and findings made via two phases. In the first phase, a theoretical and conceptual model was developed to serve as a data collection guide for highway authorities. the conceptual framework also inculcated techniques which integrated existing indicators (leading and lagging) to form resilient indicators required by highways organisations. Based on findings from literature on significant safety indicators, input variable data was derived from state of art safety indicators, thereby providing evidence that, these variables were safety oriented and markers of safety. In phase two, the features of the variables presented in the conceptual framework were then used to collect real world data from a highway agency and used to build a highway safety prediction model capable of predicting various highway incident, project risk levels and body parts likely to be affected by an injury in situations where an incident resulted in an injury. Phase three used a 'hold out' data with same features to validate the prediction model developed. This was to ascertain the generalisability and the performance of ML models employed when introduced to unseen data. The results from the validation stage reemphasised the effectiveness of the proposed prediction models.

Through the development of a safety prediction model, it is hoped that a central guide and a foundational framework for acquiring and utilising safety-oriented data, capable of enhancing the prediction abilities of safety prediction models can be accessed. Furthermore, it is hoped that this thesis provides evidence-based information highway safety management that can be shared, not only for the modification of current safety practices, but also for the benefit of highway safety managers and authorities.

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