Analyzing the risks associated with railway transportation of hazardous materials and developing process models for railway incidents with high potential for release using machine learning and data analytics

by

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Abstract

The Canadian economy relies heavily on its transportation network. It supports hundreds of thousands of jobs, contributes billions to the economy, and facilitates the movement of goods within the country as well as internationally. Railways provide affordable and efficient transportation to over 84 million passengers each year, and they transport approximately 70% of all intercity surface freight and half of Canada's exports. Rail transportation of hazardous materials is an activity that is important to most industries but is commonly associated with the oil and manufacturing sectors. Hazardous materials (hazmat) are defined as explosives, flammable and combustible substances, toxic substances, oxidizing substances, and corrosive substances, among others. Between 2011 and 2017, the quantities of fuels and chemicals transported by Class 1 railways (Canadian National Railway, CN, and Canadian Pacific Railway, CP) increased by 42.5%. Railway incidents transporting hazmat can have severe consequences for people that require mitigation, especially in areas where there is a high population density. In order to prevent and minimize the negative impacts of railway incidents, risk assessment is key to planning and improving safety. Several factors contribute to the risk analysis of hazmat transportation, such as hazmat-related incident rates in transport infrastructure, the consequences of hazmat release, and the probability of hazmat release. The objectives of this study are developed based on these factors of the risk assessment.

The primary objective of this study is to identify the impact of human factors on the likelihood of railway incidents and to identify the leading factors and their associations. It is determined that most deficiencies occurred in the areas of organizational oversight, supervision, and organizational culture. In addition, supervisory and organizational factors are highlighted as important factors in the prevention of railway loss incidents. The second objective of this study is to develop and

illustrate with a case study a methodology for developing enhanced risk maps. According to the risk maps, land-use planning should consider the appropriate allocations of hospitals, medical centers, route access, and emergency services to reduce and prevent future losses. As a third objective of the study, a prediction model is developed to predict evacuations in railway incidents and to identify their causes, and contributing factors using text mining and co-occurrence analysis. It is determined that Random Forest (RF) is the most accurate model for predicting evacuations. Furthermore, the type of incident (i.e., leak and spill), the action on means of contaminant (MOC)(i.e., overturning and derailment), the railyard operation and loading operations (i.e., loading, unloading, transloading, and handling), and the type of hazardous material (i.e., petroleum crude oil, diesel fuel, sulfuric acid, nitrate ammonium) are considered as contributing factors to evacuation. Finally, the study aims to develop a machine learning model capable of predicting the probability of hazmat release, identifying the underlying causes and contributing factors, and evaluating these factors in an effort to reduce hazmat release. There are many factors that can contribute to hazmat release incidents, including the location of tank cars within a train, the derailment of tank cars, the speed of the train, and the test year of the last tank. Analyzing the reports of the railway incidents using text mining indicate that the primary contributors to hazmat releases are the type of incident (i.e., release, leaking), the action on MOC (i.e., derailment, strike, puncture), and the type of hazmat involved (i.e., methanol, propane, aviation fuel).

Preface

This thesis is an original work by Hadiseh Ebrahimi. Chapter 2 of this thesis has been published as H. Ebrahimi, F. Sattari, L. Lefsrud, R. Macciotta, "*Analysis of train derailments and collisions to identify leading causes of loss incidents in rail transport of dangerous goods in Canada*", Journal of Loss Prevention In the Process Industries. Chapter 3 of this thesis has been published as H. Ebrahimi, F. Sattari, L. Lefsrud, R. Macciotta, "*Human vulnerability modeling and risk analysis of railway transportation of hazardous materials*", Journal of Loss Prevention In the Process Industries. Chapter 4 of this thesis has been submitted as "*Machine learning and data analytics approach for predicting evacuation and identifying contributing factors during hazardous materials incidents on railways*". Chapter 5 of this thesis has been submitted as "*An analytical approach to identifying the probability and contributing factors of hazmat release in Canadian railway incidents based on data-driven machine learning and text mining*".

Dedicated to My Beloved Family

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Chapter 1

1.1 Introduction

Hazardous materials (hazmat) include chemicals or substances that can potentially pose a significant threat to the safety and health of the surrounding population and property (Moradi Rad, 2020). The production, transportation, and use of hazmat are necessary for the economy of North America (Ebrahimi et al., 2021). Rail transportation of hazmat in North America is identified as one of the safest methods of moving large quantities of chemicals over long distances (Iranitalab, 2018). Since hazmat has special physical and chemical properties, especially the potential risk of fire, explosion, and leakage during an incident, hazmat rail incidents are often described as low-probability, high-consequence incidents (Zhou et al., 2020). Railway incidents transporting hazmat can pose serious threats to people, especially when the train crosses highly populated areas (Ebrahimi et al., 2022). Several railway incidents with catastrophic consequences have occurred in the past. In 2005, a train derailment in Wabamun (Canada) resulted in 800,000 liters of oil leakage into Alberta Lake (Transportation Safety Board of Canada, 2005). In 2013, the Lác-Megantic railway derailment (Canada) caused 6 million liters of crude oil leakage and 47 fatalities (Généreux et al., 2020). In 2021, as a result of a train derailment transporting ammonium nitrate and other chemicals in Iowa (the USA), over 3,000 people were evacuated from their homes (Changing America, 2021). To minimize the negative consequences of railway incidents, risk assessment is critical to planning and improving safety (Huang et al., 2020).

1.2 Literature review

Safe transportation of hazmat has been a topic of research for decades. Risks associated with hazmat transportation can generally be defined as the function of the probability that an incident would occur involving the release of hazmat and the consequences of that event (Iranitalab, 2018).

Most of these definitions share some common components, and numerous studies have attempted to quantify these components. There are a number of components to consider in the risk analysis of hazmat transportation (Iranitalab, 2018), including hazmat-related incident rates in the transportation infrastructure (Liu et al., 2012; Anderson & Barkan, 2004), the release consequences (Saat et al., 2014), and the probability of hazmat release (Treichel et al., 2006).

As a component of hazmat transportation risk, incident rates are examined per unit of transportation infrastructure (e.g., highway segments, rail segments, routes, etc.). Based on a combination of federal and state truck accident databases, Harwood et al. (1990) calculated truck accident rates and hazmat-released truck accident probabilities. The authors observed that area type (urban/rural), road type (multilane undivided/divided, and freeway), and truck ADT had a significant impact on accident rates, as well as the type of incident (collision/non-collision, single/multiple vehicles, run-offs/overturns, etc.) is a significant factor in hazmat release probability. Using fuzzy logic and negative binomial models, Qiao et al., (2009) developed hazmat transportation incident frequency models for trucks. It was assumed that the former covered route-dependent variables (population, number of lanes, and weather), and the latter covered route-independent variables (truck configuration, container capacity, and driver experience).

The severity of incidents may also be one component of the hazmat transportation risk, which could be useful in predicting the consequences of hazmat release. The number of released tank cars is one of these severity measures. Using a generalized probabilistic model, an estimation of the number of tank cars releasing hazmat during a train derailment was made by Liu et al., (2013). Several factors were considered as potentially effective factors, including the train length, the derailment speed, the cause of the incident, the position of the first car to derail, the number and placement of tank cars in the train, and the design of tank cars. Based on the number of tank cars derailed, Liu & Hong, (2015) estimated the number of tank cars released.

According to Liu & Hong, (2015), the number of released tank cars is a function of the number of derailed cars. Therefore, some studies have attempted to model the number of derailed cars. Based on track class, method of operation, and annual traffic density, Liu et al., (2013) used negative binomial models to estimate the number of derailed tank cars. There was a link between higher track classes and more frequent signal operations, and a decrease in the size of derailments (Liu et al., 2017). An analysis of derailments, the most common type of freight train accident in the United States, was conducted by Liu et al., (2013). To estimate the conditional mean of the size of train derailments, a zero-truncated negative binomial regression model was developed. To estimate the size of derailments at different quantiles, a quantile regression model was developed in recognition that the mean is not the only statistic used to describe data distribution. By combining the two models, the authors were able to obtain a better understanding of train derailment severity distributions.

The Bayes Theorem and Logical Diagrams were used by Verma et al., (2011) to develop a risk assessment methodology for hazmat rail transportation. Based on the results of a case study, the implementation of the method revealed that transportation risk depended on the length of the train, the position of the hazmat railcar within the train decile, and the number of intermediate handling points. For freight trains of any length, the front of the train was found to be more dangerous, and the 7th–9th train deciles were the most appropriate for moving hazmat railcars. Moreover, it was found that rail-track risk can be minimized by strategically distributing hazmat railcars across trains.

An additional component of hazmat transportation risk is the probability of hazmat release following an incident involving a hazmat-carrying truck or train. A logistic regression model was used by Treichel et al., (2006) to estimate the probability of lading loss (given a derailment) for various tank car specifications. Several factors affected the probability of a tank car release, including the type of shield, the thickness of the shield, the tank insulation, the thickness of the shell, the pressure on the tank car, as well as the yard/mainline. Additionally, they investigated the effect of train speed on lading loss probability and the distribution of quantities of lading lost given a release of lading. Several machine learning models have been developed by Iranitalab & Khattak, (2020) using data from US traffic accidents in order to estimate the probability of hazmat release from railroad accidents. They provided recommendations regarding the application of machine learning models in accordance with the purpose of the analysis.

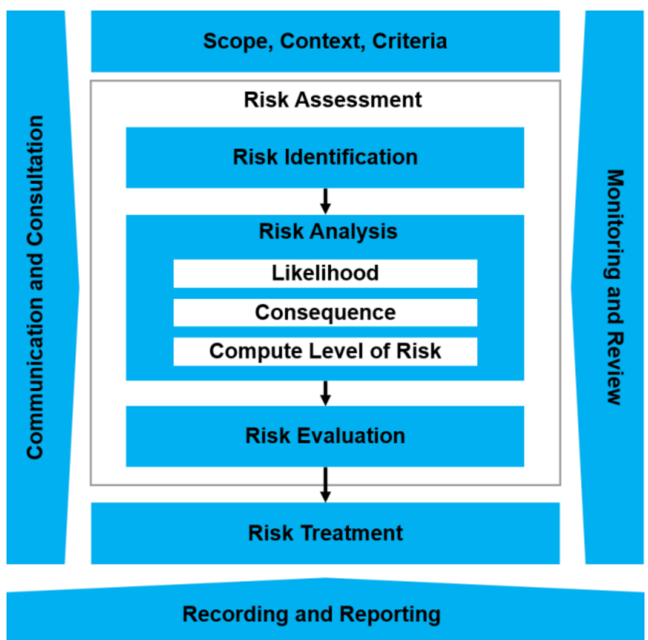


Fig. 1.1 Risk Assessment Process (ISO 31000) as the outline for this dissertation.

The objectives of this study are defined in accordance with the elements of risk assessment. In the first objective, the causes of railway incidents are identified in detail and the influence of each factor on railway incident rates is examined (this objective is highlighted as risk identification in Fig. 1.1). In the second and third objectives, the consequences of railway incidents are discussed and the ways of reducing the severe consequences of railway incidents are examined, such as developing enhanced risk maps to provide better emergency responses (e.g. evacuation) and land use planning (these objectives are highlighted as consequence and compute the level of risk in Fig. 1.1). In the final objective, the probability of hazmat release is evaluated and methods for reducing this probability are discussed (this objective is highlighted as likelihood in Fig. 1.1).

1.3 Research objectives

As mentioned in section 1.2, risk analysis of hazmat transportation includes several components, such as hazmat-related incident rates in the transportation infrastructure, the consequences of hazmat release, and the probability of hazmat release. Based on these main components of the risk assessment, the following objectives have been developed:

- Investigating the human factors involved in railway incidents in order to identify the leading human factors and their associations, and to enhance the effectiveness of risk mitigation measures.
- Developing a methodology for preparing enhanced risk maps and illustrating it with a case study in order to provide recommendations aimed at improving land-use planning, enhancing the safety of residents in high-risk areas, and prioritizing emergency responses.
- Developing a machine learning model to predict evacuations during railway incidents and identifying their causes, contributing factors, and dependencies.
- Predicting the probability of hazmat release using supervised machine learning models and identifying the contributing factors, as well as suggesting ways to reduce their impact.

In Canada, the safety of the rail system has been improved during the last decade, particularly in main-track derailments, which have the greatest potential to cause environmental damage and human fatalities (Railway Association of Canada, 2018; Sattari et al., 2020). Main-track derailments caused by equipment or track failures have decreased due to a sustained focus on inspections, compliance, and enforcement, as well as technological advances and investments in rail infrastructure. It is anticipated that this trend will continue, considering that the railways continue to invest in infrastructure as well as Transport Canada's increased compliance monitoring and enforcement efforts (Transport Canada, 2018; Macciotta et al., 2018). In contrast, the number of main-track derailments caused by human factors has remained unchanged (Transport Canada, 2018). Non-main track derailment accidents caused by human factors have consistently remained the most significant cause of non-main track derailments with no sign of improvement (Transport Canada, 2018). The first objective of this studyaims to analyze human factors as an important contributor to railway incidents and provide suggestions for reducing incidents related to human factors (chapter 2).

Some studies have been conducted to develop risk maps and provide recommendations to reduce the severity and consequences of hazmat release as part of the risk assessment for the transportation of hazmat. However, most of these studies (CCPS, 2021; Landucci et al., 2017; Ovidi et al., 2020; Anjana et al., 2018) focused on the number of people (population density) who may be exposed to hazmat releases. If incidents affect vulnerable people who have limited ability to protect themselves in emergency situations, the consequences may be more severe (Bondžić et al 2021). This highlights the importance of studying population vulnerability based on the different characteristics of the people exposed to hazards. In addition, due to the lack of meteorological information at the time of incidents, the hazard maps in the studies above were mostly prepared based on a number of assumptions. The second objective of this study is to provide a procedure that can be used to estimate the risk of hazmat railway transportation in densely populated areas by taking into account the relationships between meteorological variables and the sociodemographic characteristics of the population (chapter 3).

Depending on the severity of the railway incident and/or hazmat release, evacuation may be required. Researchers are primarily focused on implementing emergency evacuation orders efficiently during incidents. The decision to issue emergency evacuation orders before they have been implemented is also of concern (Phark et al., 2018). By predicting evacuation orders on time and accurately, the negative consequences of railway incidents involving hazmat may be minimized. The third objective of this study is to develop a model for predicting evacuations following railway incidents as one of the emergency responses. In addition, a combination of text mining and co-occurrence analysis is used to analyze incident reports in order to identify contributing factors that led to the evacuation and develop strategies for risk mitigation (chapter 3).

One of the components of hazmat transportation is the probability of hazmat release. A few studies (Treichel et al., (2006), Iranitalab & Khattak, (2020)) have been conducted to examine the effects of various factors, such as train speed, length, and derailment point, and determine the probability of hazmat release. As a final objective, this study examines and incorporates the effects of variables not previously considered in predicting the probability of hazmat release. As part of the project, text mining is utilized to extract simple patterns from reports of railway incidents and identify and evaluate the causes and contributing factors to hazmat release in order to reduce their probability (chapter 4).

1.4 Thesis outline

As described in the introduction, it is essential to study the concept of risk assessment to improve the safety of railway transportation of hazmat. Reviewing the literature shows that although promising studies have been conducted on the different components of risk assessment, there is still room for improvement in this area. This report consists of six chapters and its structure is briefly described in the following paragraphs.

Chapter 2, titled "*Analysis of train derailments and collisions to identify leading causes of loss incidents in rail transport of dangerous goods in Canada,*" provides an analysis of the role of human factors in railway incidents through the Human Factors Analysis and Classification System (HFACS) approach. Using statistical techniques, an association between different human factors is analyzed, and leading human factors are identified.

Chapter 3, titled *"Human vulnerability modeling and risk analysis of railway transportation of hazardous materials," discusses* population vulnerability assessment as an essential parameter for developing risk mitigation strategies to prevent negative consequences of hazmat transportation incidents. In this chapter, the risk maps are generated to prioritize emergency response decisions and to improve land-use planning based on population vulnerability.

Chapter 4, titled "*Machine learning and data analytics approach for predicting evacuation and identifying contributing factors during hazardous materials incidents on railways,"* provides a reliable model to predict evacuation on time and accurately to save people's lives in the aftermath of railway incidents. Further, text mining is employed in this chapter, which provides valuable insights for risk analysis by identifying causes, and contributing factors of the evacuation.

Chapter 5, titled "*An analytical approach to identifying the probability and contributing factors of hazmat release in Canadian railway incidents based on data-driven machine learning and text mining*". To predict the probability of hazmat release in railway incidents, supervised machine learning models are employed, and the best model is identified. In addition, text mining through Natural Language Processing (NLP) and co-occurrence network analysis are performed to determine the causes and contributing factors of hazmat release and their dependency. As a result of the models and recommendations developed in this chapter, railway transportation of hazmat could be made safer.

In Chapter 6, a summary of the finding of this study is represented, and some new ideas are proposed for the continuation of this study. Finally, the references used in this thesis are reported in alphabetical order.

Chapter 2

Chapter 2 of this thesis has been published as Hadiseh Ebrahimi, Fereshteh Sattari, Lianne Lefsrud, Renato Macciotta, "*Analysis of train derailments and collisions to identify leading causes of loss incidents in rail transport of dangerous goods in Canada*", Journal of Loss Prevention In the Process Industries. Contributions of the authors are listed below:

Hadiseh Ebrahimi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Fereshteh Sattari:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Supervision, Project administration**. Lianne Lefsrud:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Renato Macciotta:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

2.1 Introduction

Canada has the third-largest railway network and transports the fourth-largest volume of goods in the world (Leishman et al., 2017). Canada's railway transportation network plays an important role in the national economy, as approximately half of Canada's exports (by volume) are transported by rail (Macciotta et al., 2018; Rudin-Brown et al., 2019). Different types of goods, including dangerous and non-dangerous goods, are transported by rail. Dangerous goods include explosive, flammable and combustible, toxic, oxidizing, corrosive, and nuclear substances (Huang et al., 2020). These goods are necessary for maintaining Canadians' quality of life, as they provide fuel for vehicles and homes and facilitate manufacturing and industrial processes (Macciotta et al., 2018). According to Transport Canada, in 2011, approximately 70% of all dangerous goods (by weight) were transported by road, 24% by rail, 6% by vessel, and less than 1% by air (Transport Canada, 2013).

The Canadian railway industry has improved safety performance in the last decade as measured by freight loss incidents per billion gross ton-miles (Railway Association of Canada, 2018; Sattari et al., 2020). These improvements are a result of enhancing oversight, regulations and using more effective safety technologies (TransportCanada, 2018a). However, while the incidents per gross ton-miles have decreased, the number of loss incidents has not. The increase in the number of loss incidents is due to the increased rail activity on the main track (Transport Canada, 2018b). In 2018, there were 1172 reportable rail occurrences (including near misses and loss incidents leading to a loss in terms of people, environment, equipment, infrastructure, or fluid operations) were reported to the Transportation Safety Board of Canada (TSB) (Fig. 2.1), representing a 7% increase from 2017 and a 10% increase from the previous 10-year (2008–2017) average of 1067.

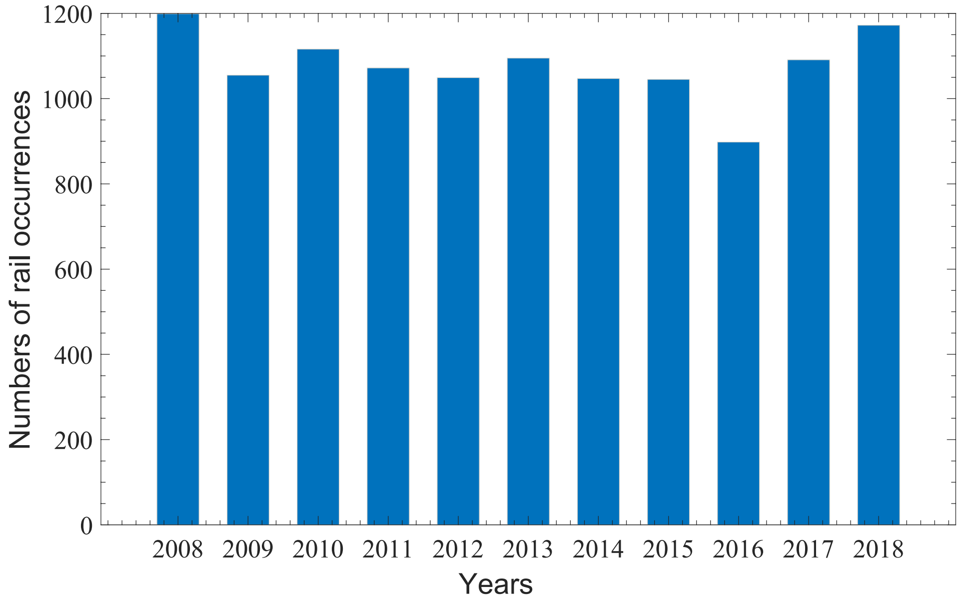


Fig. 2.1 The number of rail occurrences that occurred between 2008 and 2018 (Transport Canada, 2018b).

Although a very small fraction of occurrences leads to severe losses, a larger fraction would have the potential for such an outcome. Main-track collisions and derailments accounted for a small percentage of loss incidents (approximately 9% between 2007 and 2017). Nevertheless, main-track collisions and derailments can have serious consequences for people, the environment, and transport operations, especially if dangerous goods are involved (Macciotta et al., 2018). Numerous factors affect the severity of main-track derailments, such as car mass, derailment speed, residual train length (the number of cars after the point of derailment), derailment cause, ground friction, rail friction, and the proportion of loaded railcars in the train (loading factor) (Li, 2017; Woodward, 1989). Some guidelines, including (Association of American Railroads, 2019) have been published in recent years, which cover the methods for loading cargo in detail. These guidelines would help reduce the probability of the main-track derailment and its severity. Causes that contribute to the occurrence of railway loss incidents can be classified into five groups of factors: environment, equipment failure, track failure, human factors, and others (Liu et al., 2012).

This is consistent with the latest statistical analyses of rail incidents and immediate causes in Canada by Sattari et al., (2020). Fig. 2.2 shows the number of times that causes within each factor group was assigned for main-track derailments that occurred between 2008 and 2018 (Transport Canada, 2018b). Causes in the equipment and track failure factor groups are the most frequent; however, they are trending downward due to advancements in technology and larger investment in infrastructure by the Canadian railway industry (TransportCanada, 2018a). In railways, technologies used to decrease safety risks are but not limited to ultrasonic detectors to recognize rail defects under the surface, electrical and mechanical equipment to forecast rockfall in mountainous areas, and equipment to recognize movements as a result of joint rail problems or track geometry (Miller, 2015; Railway Safety Act Review, 2017).

The causes part of the environmental factors group and the "others" group show the lowest frequencies and have kept relatively constant at 10 or less per year. However, the frequency in which human actions are associated with main-track derailments has remained constant to a slightly increasing trend at about 20 to 25 counts per year, making them now as frequent as track and equipment groups. According to the Canadian Pacific Railway (CPR) (TransportCanada, 2018a), technological progress led to a 65% decline in railway loss incidents caused by equipment failure and a 35% decline in track-related loss incidents between 2005 and 2015. Technological progress includes using inspection imaging systems to detect different items such as tie plates and bolts, using wheel profile detectors to evaluate wheel integrity, and using ultrasonic detectors to identify rail issues (TransportCanada, 2018a; Railway Safety Act Review, 2017). However, loss incidents resulting from human actions increased by 11%. These trends indicate that human errors are having an increasing relative influence on railway loss incident frequencies. In the railway industry, some typical human errors are signal passing, train speed, and signaling or dispatching (Dhillon, 2007; Hill, 2007).

Some investigations were conducted in Canada to analyze the role of human factors in the railway industry. In 2002, Carid quantitatively and qualitatively analyzed the reasons for grade crossing accidents and evaluated driver behavior at a crossing (Caird, 2002). (Caird, 2002). English et al., (2007) analyzed train collisions and derailments in North America involving stationary railway cars carrying dangerous goods. Their study evaluated the risks associated with train collisions and derailments, including human factors, and provided recommendations to prevent them. Brown et al., (2014) mentioned those collision accidents between road vehicles and trains in passively controlled rural areas, where there is no sign to alert the vehicles' drivers about the presence of a train, increase safety concerns about human factors. Their study analyzed the role of human factors in crossing accidents using quantitative analysis and found leading human factors in crossing accidents. Despite the studies conducted in Canada to reduce human failures in the railway industry, the frequency of human failures has remained unchanged between 2008 and 2018 (see Fig. 2.2), which further motivated us to investigate this area.

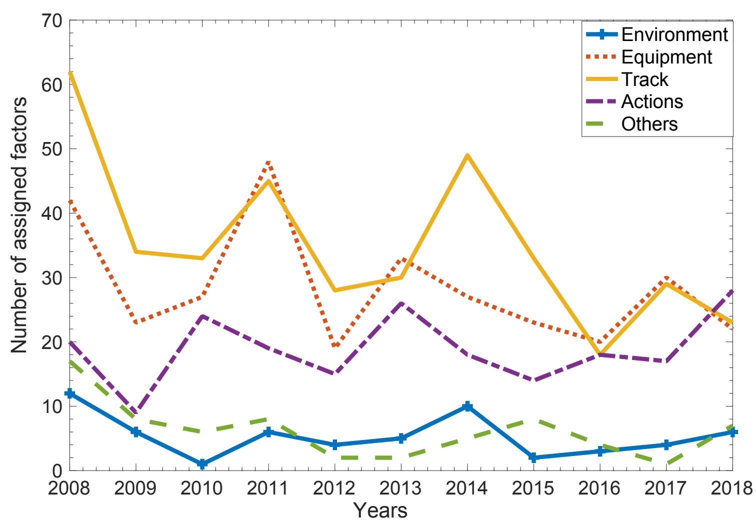


Fig. 2.2 The number of causes in each factor group assigned for main-track derailments between 2008 and 2018 (Transport Canada, 2018b).

To have a better understanding of the number of failures and the areas in which these failures occurred, a comprehensive model is required to analyze the entire system. Therefore, the Safety Management System (SMS) framework was selected to meet this task. SMS obtains a complete study of the process, equipment, procedures, and organizational factors to ensure all the hazards are identified and the most frequent failures of the system are categorized (Baybutt, 2014; Shamim et al., 2019).

After using SMS and realizing that human factors are responsible for numerous failures in the system, the HFACS model, which is one of the most powerful models in analyzing human factors (Dekker, 2002), is used in this study. In recent years, the HFACS model has been widely used in various fields to analyze human factors due to its high-reliability (Olsen, 2011). Finding human factors from accident reports and categorizing them using the HFACS model can not specify the main reasons for the accidents (Zhou & Lei, 2018). As mentioned by Chen & Yang (2004), the safety levels of high-risk operational systems are interrelated, and variation in one factor can change other factors. Therefore, safety assessment should be performed using comprehensive methods. In this study, the Chi-square test and Goodman and Kruskal's lambda analysis are used to find the relationship between the adjacent levels of the HFACS model. Using the Chi-square test and Goodman and Kruskal's lambda analysis reveals how decisions and actions of upper-level managers can affect the employees at a lower level of the system or how the conditions of the system may result in unsafe acts of front-line operators. However, it is not enough to simply correct the unsafe acts of employees and their preconditions or correct the unsafe acts of supervisors, their upper-level managers, and the organization. Instead, other quantitative assessments should be used to consider the whole organization and find the interrelationships between all the human factors in the system (Zhou et al., 2014).

Therefore, the Analytic network process (ANP), one of the most popular methods in decision-making problems, is used in this study to reveal the interdependencies between all the human factors and find leading human factors in railway accidents (Chemweno et al., 2015). Then, the Decision-making trial and evaluation laboratory (DEMATEL) method is used to depict the relationships between different human factors. The DEMATEL technique not only can visualize the cause-and-effect relationships between human factors but also can reveal the degree to which human factors affect each other (Tzeng et al., 2007). The combination of the DEMATEL method and the ANP (referred to as DANP) is used in this study to analyze human factors and find the core causation of railway accidents. Finally, to evaluate the leading causes of railway accidents, the results of this study were compared with some studies conducted to analyze human factors in other countries.

2.2 Material and Methods

2.2.1 Database

Information on railway incidents in Canada, including location and time, track and train type, train speed, injuries and fatalities, and a summary of each; is available through the Transportation Safety Board (TSB)'s Railway Occurrences Database System (RODS). RODS includes reportable near misses and loss incidents for federally regulated operations. The TSB further conducts detailed investigations of a subset of these incidents. This study analyzes 42 main-track derailments and collisions, that involved the transport of dangerous goods in Canada and were investigated in detail by the TSB. This work represents a snapshot of the state of current practice in the industry based on TSB investigation reports. The reports correspond to accidents between 2007 and 2018; therefore, we understand this is valid for the current operational context.

2.2.2 Safety Management Systems (SMS)

SMS allows for comprehensive evaluations of the process, equipment, procedures, and organizational factors of an organization to ensure all the hazards are recognized and managed (Baybutt, 2014; Yasir et al., 2019). Lefsrud et al. (2020) discussed the advantages of SMS systems in rail operations, and how performance-based regulations for SMS compliance can provide a comprehensive framework for rail safety improvements. SMS for rail safety in Canada is regulated through the Railway Safety Management System Regulations (SOR/2015-26, available at https://laws-lois.justice.gc.ca/eng/regulations/SOR-2015-26). This SMS has been tailored towards rail transport. To analyze the specifics of dangerous goods (DG) transportation, an SMS tailored to the production, storage, management, and transportation of dangerous goods was adopted. The SMS adopted in this study consists of 12 elements and their components and was originally proposed by the Center for Chemical Process Safety (CCPS) of the American Institute of Chemical Engineers (AIChE) in 2007 (Baybutt, 2014). Table 2-11 presents the SMS elements and definitions used in this study. The SMS was used as a framework for incident classification in this study, and the insights from the review are general in the sense that they do not refer to any particular SMS and are easily associated with any specific SMS adopted by rail operators on the basis of the regulation.

2.2.3 Accident Causation Models

Many accident causation models have been developed and modified to understand how and why accidents happen (Katsakiori et al., 2009). The first accident causation model is the Domino theory introduced by Heinrich in 1931. This theory portrays accidents as an outcome of a series of incidents, which is assumed to be a series of dominos. If one domino falls, the other dominos will fall eventually, and an accident will happen (Heinrich, 1941). The SHEL model was developed by

Edward in 1972. There are four elements in the SHEL model: Software, Hardware, Environment, and Liveware. If one element does not work appropriately, safety errors will happen in the system (Molloy & O'Boyle, 2005).

The Normal Accident Theory (NAT) was proposed in 1984. NAT is used to describe potential failures within complex systems that are interconnected and coupled (Sammarco, 2005; Chera et al., 2015). In 1983, Rasmussen developed the "SRK" model, in which human actions are classified into skill-based, rule-based, and knowledge-based actions (Drivalou & Marmaras, 2009). Then, Reason developed (Embrey & Lane, 1990) Generic Error Modeling System (GEMS) to describe the changes between the levels (skill, rule, knowledge) of the "SRK" model. The SLIM model was proposed in 1984. This model can handle all human error forms and does not need task decomposition or task analysis (Kyriakidis, 2013). However, this model is subjective, which can influence its reliability and consistency (Embrey, 1984). In 1998, the Cognitive Reliability and Error Analysis Method (CREAM) model was introduced by Hollnagel. The CREAM model is a well-structured and systematic model for categorizing human errors. As the model is comprehensive, more time and additional resources are required to perform and analyze (Hollnagel, 1998).

At the end of the1980s, the Swiss Cheese Model was presented by Reason (Reason, 2000). This model is shown as slices of cheese with some holes that show the failures of the system (Reason, 2000). In this model, the meaning of the holes in the slices is not clarified. Therefore, applying the model is difficult (Zhan et al., 2017). Human Factors Analysis and Classification System (HFACS) was developed by Shappell and Wiegmann in 2000 (Shappell & Wiegmann, 2001). The HFACS model defines the holes in the slices of the Swiss Cheese Model; therefore, the HFACS model can be used easily in practice. Also, the HFACS model considers the role of management and organization in the system (Shappell & Wiegmann, 2001), which is the most important difference between the HFACS model and other accident causation models (Shappell & Wiegmann, 1997; Shappell & Wiegmann, 2001). Lastly, Dekker (Dekker, 2002) mentioned that the HFACS framework is the most powerful model for analyzing human factors in different accidents. Due to these reasons, the HFACS model is selected to analyze human factors in this study. There are various accident causation models aside from the ones explained earlier. However, the application of these models for a particular case should be investigated further.

2.2.4 Human Factors Analysis and Classification System (HFACS)

HFACS is a broad human error framework that was originally used by the US Air Force to investigate and analyze human factors in relation to aviation (Shappell & Wiegmann, 2001). HFACS is a widespread tool employed by different industries, such as mining (Patterson & Shappell, 2010), aviation (Olsen & Shorrock, 2010), maritime (Wang et al., 2013), and process industries (Zarei et al, 2019; Wang et al., 2020). HFACS is a stand-alone approach that considers the role of management and the organization in the occurrence of loss incidents and identifies latent errors. More importantly, HFACS aids in understanding the relationships between failures at different levels of a system. This method can help organizations identify weaker areas in their safety systems and implement targeted, data-driven interventions (Ergai et al., 2016; Huang et al., 2020). Fig. 2.3 shows the HFACS model from Shappell and Wiegmann (2001). It consists of four levels of potential failures in the organization (Unsafe acts, Preconditions for unsafe acts, Unsafe supervision, and Organizational influences). At least one failure is required at each level for a loss incident to occur. If the failures in the organization are corrected at any level, the loss incident would be prevented. However, it is still reported as a near miss in the system. A near miss is an incident that initiates a loss under slightly different situations (Gnoni & Saleh, 2017).

Each level of the HFACS is divided into subcategories, which are associated with a set of criteria to aid in grouping the causes associated with human factors within the organization (Punzet et al., 2018; Yıldırım et al., 2019; Zarei et al, 2019). The main levels of the HFACS are described in the following sections and a brief explanation of the HFACS categories is listed in Table 2-12.

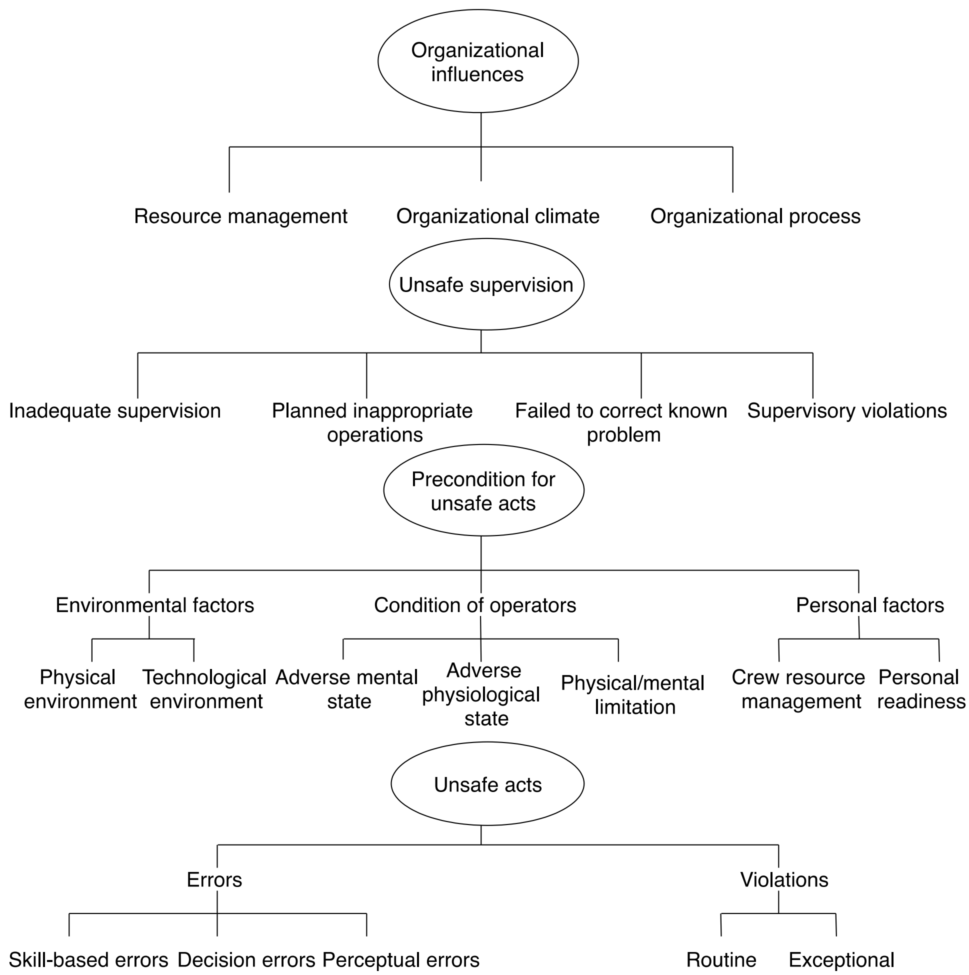


Fig. 2.3 The HFACS Framework (modified from Shappell & Wiegmann, 2001).

2.2.4.1 Bottom level: Unsafe acts

Unsafe acts are classified into two categories, namely errors and violations. Errors are classified into three subcategories: Skill-based errors, decision errors, and perception errors. Skill-based errors tend to happen during routine activities. These errors occur when the individual has the right knowledge, skills, and experience to do the task correctly, but the focus is diverted from the task.

Decision errors are associated with an individual's wrong judgment on specific situations and wrong responses to emergency situations. Perceptual errors occur if an operator’s perception is degraded and a decision is made based on the wrong information. Violations are categorized into two subcategories, namely routine and exceptional. Routine violations are common actions of the operator, and they are tolerated by the organization (Normalization of Deviance). On the other hand, exceptional violations are not acceptable by the organization (Punzet et al., 2018; Yıldırım et al., 2019).

2.2.4.2 Second level: Precondition for unsafe acts

Preconditions for unsafe acts are grouped into three categories, namely environmental factors, personal factors, and the condition of operators. Environmental factors refer to the physical and technological environment. Physical environment refers to the characteristics of the location of operations. Technological environment refers to the design of equipment and controls, characteristics of user interphases, degree of automation, etc. Personal factors refer to crew resource management and personal readiness. Crew resource management includes poor communication, organization, and teamwork problems. Personal readiness contains inadequate training, and inadequate capabilities to handle emergency situations. The condition of the operator includes adverse mental states, physical/mental limitations, and adverse physiological states. Stress, mental fatigue, incompatible physical abilities, and physical fatigue of the operator are examples of the condition of the operator (Punzet et al., 2018; Yıldırım et al., 2019; Wang et al., 2020).

2.2.4.3 Third level: Unsafe supervision

Unsafe supervision is grouped into four categories: inadequate supervision, failure to correct known problems, planned inappropriate operations, and supervisory violation. Inadequate supervision means providing inadequate training, leadership, and management. Plan inappropriate operation includes decisions, which might be acceptable during extraordinary situations, but are not acceptable during normal operations. Failure to correct a known problem includes situations in which deficiencies are identified but no action is taken to correct them. Supervisory violations are situations in which rules and regulations are disregarded intentionally by supervisors (Punzet et al., 2018; Yıldırım et al., 2019).

2.2.4.4 Top-level: Organizational influences

Organizational influences are grouped into three categories: resource management, organizational climate, and organizational process. Resource management refers to organizational decisions about the maintenance and distribution of assets. Organizational climate describes the working environment of the organization. Organizational process discusses the organizational decisions and rules that govern the routine activities in an organization (Punzet et al., 2018; Yıldırım et al., 2019).

2.3 Statistical Analyses

Knowing the frequency of human errors, which is identified using the HFACS model in this study, cannot specify the fundamental causes of accidents (Wang et al., 2020). Therefore, in this study, the relationships between different human factors are studied quantitively to find the main causes of accidents. Different statistical tests are used to determine the association between variables including Pearson correlation, which is used with continuous variables, Spearman correlation is used with ordinal variables, and Chi-square tests which can find the significance of the association between two categorical (nominal) variables (Dixon & Charles, 1972).

There are some statistical tests used to find the strength of the association between the variables. Kruskal's lambda analysis, for instance, is used to find the strength of the association between nominal variables. The Gamma test is used with ordinal variables, and Pearson's r is used with continuous variables (Dixon & Charles, 1972). As human factors are categorical (nominal) variables, Kruskal's lambda analysis is coupled with the Chi-square test to analyze human factors in this study. The limitation of the Chi-square test and Kruskal's lambda analysis lies in the fact that these analyses reveal the relationships between the human factors in adjacent levels of the HFACS and do not provide any information about the relationships between the human factors at different levels of the HFACS (Zhou et al., 2014). To determine, how human errors can initiate and propagate, it is necessary to find the relationships between all the human factors at different levels of the HFACS model. Therefore, the DEMATEL method was combined with the ANP method to further analyze human factors in this study.

The first advantage of the DEMATEL method is that it can find cause-and-effect relationships in decision-making problems. The second advantage is that the DEMATEL can visualize the interrelationships between factors and help decision-makers to realize which factors have mutual impacts on another factor. Furthermore, the DEMATEL is used to evaluate the ranking of alternatives, and calculate the weights of evaluation factors (Tzeng & Huang, 2012; Gölcük & Baykasoılu, 2016; Si et al., 2018).

The ANP is selected to analyze human factors in this study, as the hierarchical framework of the HFACS model is strongly aligned with the ANP method. Furthermore, the ANP can simplify complex problems, include intangible and tangible factors, and can prioritize indicators (Gu et al., 2018). Also, the ANP avoids the unrealistic hypothesis of the AHP, in which each factor within the same level is independent (Yeh & Huang, 2014).

2.3.1 Chi-square test and Kruskal's lambda

A Chi-square test measures the similarity of two random samples (Diaconis and Efron, 1985) of categorical variables. The null hypothesis (H_0) of the Chi-square test indicates no relationship between different categorical variables in the HFACS framework (i.e., the variables are independent). The alternative hypothesis (H_1) shows that the different factors of HFACS are associated with each other. By calculating the Chi-square test for a significance level (α) of 0.05 (adopted here), the limit value $\chi_{\alpha}^{2} = 3.84$ (Jankov Maširević, 2017). If the data renders a test value of χ^2 greater than χ_{α}^{2}, the null hypothesis is rejected and H_1 is accepted, which means that there is a correlation between the sub-categories of the HFACS framework.

Kruskal's lambda (λ) is usually used to calculate the proportional reduction in error with nominal variables to determine an asymmetrical (directional) degree of association (Goodman and Kruskal, 1954). Lambda ranges between 0 (no association or very weak association) and 1 (significant association). Also, Lambda has the advantage of being a directional statistic (Goodman and Kruskal, 1954), which is consistent with the HFACS framework.

2.3.2 The DEMATEL method

DEMATEL is mainly used to visualize the relationships between the sub-categories of the HFACS framework, which is done through a causal relationship diagram (Tzeng et al., 2007). In DEMATEL, the relationships are not necessarily reciprocal (e.g., the effect of a variable A on variable B can be different than the effect of variable B on variable A). This makes DEMATEL suitable for investigating directional cause-effect relationships (Yang & Tzeng, 2011). The DEMATEL method can be summarized as follows (Zhan et al., 2017; Zhou et al., 2011; Akyuz & Celik, 2015):

Step 1. Define a direct-relationship matrix through expert elicitation. A total of P experts rank the degree to which criterion i affects criterion j, for all the subcategories of the HFACS framework. The ranking consists of five levels: 0 (no influence), 1 (low influence), 2 (moderate influence), 3 (high influence), and 4 (very high influence). The elicited matrices for each expert elicitation exercise, are the following:

$$A^k = \left[a^k{}_{ij}\right]_{n\times n} \tag{2.1}$$

In which ($1 < k < P$) and n is the number of subcategories of the HFACS framework. The average matrix, x, is known as the initial direct-relationship matrix:

$$\left[x_{ij}\right] = \frac{1}{P}\sum_{k=1}^{P}\left[a_{ij}^{k}\right]_{n\times n} \tag{2.2}$$

Step 2. Normalize the average direct-relationship matrix to obtain matrix D, through the calculation of the parameter lambda:

$$\lambda = \min\left(\frac{1}{\max_{1\le i\le n}(\sum_{j=1}^{n} x_{ij})}, \frac{1}{\max_{1\le j\le n}(\sum_{i=1}^{n} x_{ij})}\right) \tag{2.3}$$

$$D = \lambda \times X \quad D = \lambda \times X \tag{2.4}$$

Step 3. Calculate the total-relationship matrix as follows:

$$T = \lim_{k\to\infty}(D + D^2 + \ldots + D^k) = D(I - D)^{-1} = \left[t_{ij}\right]_{n\times n} i, j = 1, 2, ..n \tag{2.5}$$

where I represents the identity matrix.

The sum of the rows (R) and the sum of the columns (C) of the total-relationship matrix T can be calculated as:

$$R = \left[r_i\right]_{n\times 1} = \left(\sum_{j=1}^{n} t_{ij}\right)_{n\times 1} \tag{2.6}$$

$$C = \left[c_j\right]_{1\times n} = (\sum_{i=1}^{n} t_{ij})_{1\times n} \quad \text{s} \tag{2.7}$$

The “centrality”, caluclated as $R+C$, indicates the relative importance of each subcategory of the HFACS framework. The “causality” calculated as $R-C$, allows grouping the subcategories into causes (positive values) and effects (negative values). Therefore, the DEMATEL categorized the sub-categories of the HFACS (human factors) into causes and effects. The DEMATEL not only identified direct and indirect relationships between the sub-categories at the same level of the HFACS but also identified the interaction between sub-categories at different levels of the HFACS (Yang & Tzeng, 2011).

Step 4. Define a threshold to eliminate relationships of negligible significance. Relationships below this threshold are eliminated (changed to zero) to reduce the complexity of the matrix.

2.3.3 The ANP method

The ANP method is commonly employed to solve MCDM problems as it has been shown to be a more robust approach than the Analytical Hierarchy Process (AHP) for these types of problems (Zhan et al., 2017). The ANP method considers the dependency within each subcategory of the HFACS framework (inner dependency) and between different categories of the HFACS framework (outer dependency). The approach consists of the following (Zhan et al., 2017; Khakzad et al., 2017):

Step 1. Establish a pairwise comparison matrix. A pair-wise comparison matrix (A) is made to provide a network among the subcategories of the HFACS framework. The comparison is performed between the subcategories of the HFACS framework using Saaty's scale (Table 2-1).

Table 2-1 Saaty's 1–9 pairwise comparison scale (Saaty, 1996).

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Absolute extreme importance
2,4,6,8	Intermediate values

The eigenvector (also referred to as the priority vector) for each subcategory of the HFACS framework is calculated from this equation:

$$A \times W = \lambda_{\max} \times W, \qquad a_{ii} = 1, \qquad a_{ji} = \frac{1}{a_{ij}}, \qquad a_{ij} \neq 0 \tag{2.8}$$

where A, W and $\lambda_{\max}$ are the pairwise comparison matrix, eigenvector (priority vector), and the largest eigenvalue, respectively (Khakzad et al., 2017; Zhan et al., 2017). Then, a Consistency Ratio (CR) is calculated to measure the consistency of the answers of the expert (one person or a team of persons) who completed the pairwise comparison:

$$CR = ((\lambda_{\max} - n)/(n-1))/RCI \tag{2.9}$$

Where n, λ_{max} and RCI are the size of the matrix A, the largest eigenvalue of the matrix A, and the Random Consistency Index (RCI), respectively. RCI depends on the size of the matrix A and is calculated from Table 2-2.

Table 2-2 Random Consistency Index (Saaty, 1996).

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RCI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

The answers are consistent if CR is equal or less than 0.1.

Step 2. Construct a super-matrix. The eigenvectors (priority vectors) are placed into the super-matrix W using Eq. 10:

$$W = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \\ e_{11}\cdots e_{1m_1} & e_{21}\cdots e_{2m_2} & & e_{n1}\cdots e_{nm_n} \end{array} \\ \begin{array}{c} C_1\begin{array}{c} e_{11} \\ e_{12} \\ \vdots \\ e_{1m_1} \end{array} \\ C_2\begin{array}{c} e_{21} \\ e_{22} \\ \vdots \\ e_{2m_2} \end{array} \\ \vdots \\ C_n\begin{array}{c} e_{n1} \\ e_{n2} \\ \vdots \\ e_{nm_n} \end{array} \end{array} & \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix} \end{array} \tag{2.10}$$

In the super-matrix, C_n $(n = 1, 2.., n)$ represents the clusters of the HFACS framework, and e_{nm} represents the m^{th} subcategory of the HFACS framework in the n^{th} cluster. W_{ij} represents the eigenvector (priority vector) of each subcategory in the jth cluster to the ith cluster. If there is no relationship between these, $W_{ij} = 0$.

Step 3. Calculate the weighted super-matrix by multiplying the total-relationship matrix (T) from the DEMATEL method and the un-weighted super-matrix from Step 2.

In traditional ANP, the matrix is normalized by dividing each subcategory in a column by the sum of the corresponding column. Therefore, each column sums to unity, which means that each cluster has the same weight. The disadvantage is that clusters that may have different influences on other columns are not considered. To address this shortcoming, the total-relationship matrix T from DEMATEL is used. To normalize the total-relationship matrix (T), the value for each subcategory of the HFACS framework in the matrix is divided by the sum of each row $s_n(n=1,2,...,n)$ in the matrix using Eq. (11):

$$T_{normalized} = \begin{bmatrix} t_{11}/s_1 & t_{12}/s_1 & \cdots & t_{1n}/s_1 \\ t_{21}/s_2 & t_{22}/s_2 & \cdots & t_{2n}/s_2 \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1}/s_n & t_{n2}/s_n & \cdots & t_{nn}/s_n \end{bmatrix} \tag{2.11}$$

The normalized matrix is transposed using Eq. 12:

$$T'_{normalized} = \begin{bmatrix} t_{11}/s_1 & t_{21}/s_2 & \cdots & t_{n1}/s_n \\ t_{12}/s_1 & t_{22}/s_2 & \cdots & t_{n2}/s_n \\ \vdots & \vdots & \ddots & \vdots \\ t_{1n}/s_1 & t_{2n}/s_2 & \cdots & t_{nn}/s_n \end{bmatrix} \tag{2.12}$$

Then, the transposed matrix is multiplied with the un-weighted super-matrix (W) to obtain the weighted super-matrix Q:

$$Q = \begin{bmatrix} t_{11}/s_1 \times w_{11} & t_{21}/s_2 \times w_{12} & \cdots & t_{n1}/s_n \times w_{1n} \\ t_{12}/s_1 \times w_{21} & t_{22}/s_2 \times w_{22} & \cdots & t_{n2}/s_n \times w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{1n}/s_1 \times w_{n1} & t_{2n}/s_2 \times w_{n2} & \cdots & t_{nn}/s_n \times w_{nn} \end{bmatrix} \tag{2.13}$$

Step 4. Obtain the limited super-matrix to find the final priority weights of the subcategories. The weighted super-matrix (Q) is multiplied by itself sequentially until the resulting matrix (Q') becomes stable (no variability in the matrix elements):

$$Q' = \lim_{n \to \infty} Q^n \tag{2.14}$$

The final priority weights of the subcategories are obtained from the relative rows of the limited super-matrix Q'. In this study, MATLAB was used to code these procedures, and subcategories with the highest weights in Q' were identified as key leading indicators for rail transport safety. A flowchart of the methods described is presented in Fig. 2.4.

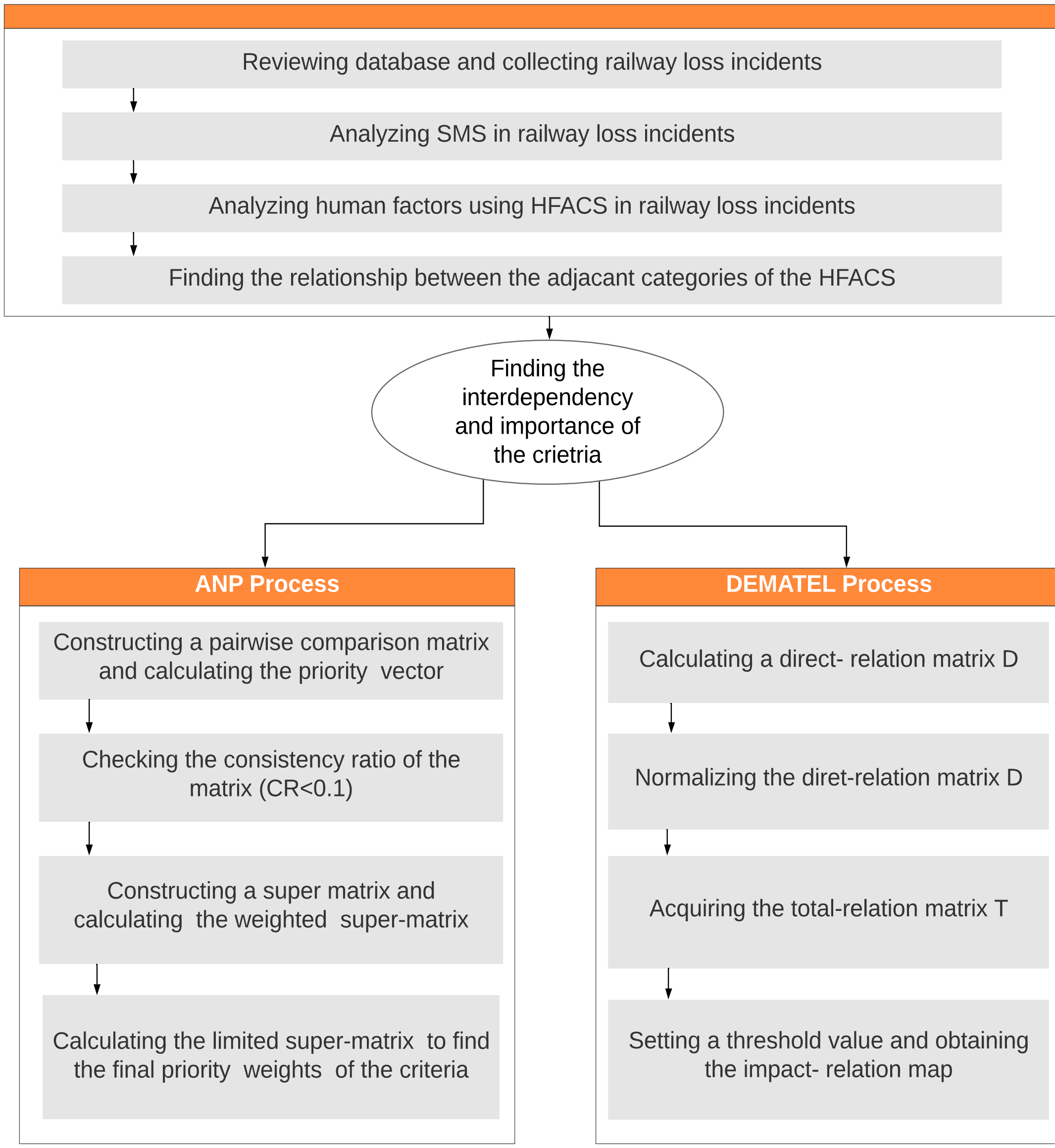


Fig. 2.4 Flowchart of the steps described in the proposed methodology.

2.4 Results and discussion

2.4.1 Safety Management Systems approach to main-track train derailments and collisions

The causes of main-track derailments and collisions between 2007 and 2018, inclusively, were classified using the SMS elements and components. An example of the classification is shown in Table 2-3 for TSB incident Report No: R14W0256. This incident occurred on October 7, 2014. Freight train A40541-05 was heading west on the main track. The train derailed at Mile 74.58 near Clair, Saskatchewan. 26 cars, including 6 tank cars filled with dangerous goods, derailed. An unexpected failure of the south rail due to the transverse defect, which had been unrecognized, was reported as the reason for the derailment of the train. Two of the tank cars loaded with petroleum distillates (UN 1268) released their product and caught fire (Transport Canada, 2014).

Table 2-3 SMS classification of latent errors for incident Report No. R14W0256.

SMS element	Justification
Process risk management	
a) Hazard identification	a) The absence of thermal protection was an unseen hazard.
b) Analyzing the risk of operation	b) Plans in place to analyze the risk of operations were insufficient, as there was no thermal protection for tank cars.
c) Reduction of risk	c) As a result of not identifying the hazard, there were no solutions to reduce the risk of the operation.
Audits and corrective actions	Robust auditing would have identified the problem of the tank cars' thermal protection.
Process and equipment integrity	
a) Reliability engineering	a) For monitoring and inspection of tank cars. Robust inspection programs could have allowed cost-effective correction of lack of thermal protection.
Capital project review and design procedures;	
a) Hazard reviews	a) The potential risks were not identified for the transportation of dangerous goods with these tank cars and mitigation strategies were not identified and implemented.
b) Process design and review procedures	b) A Robust review of processes and procedures by upper management and supervisors would have identified deficiencies and solutions to mitigate potential risks of tank cars without thermal protection.

This methodology was applied for the 42 detailed TSB loss incidents investigations and the frequency of latent error classification per SMS element is presented in Table 2-4 and illustrated in Fig 2.5.

Table 2-4 Frequency of latent error classification per SMS element.

Elements of SMS	Frequency	Percentage (%)
Process risk management	77	19
Audits and corrective actions	66	16
Process and equipment integrity	54	13
Accountability	51	12
Human factors	43	10
Capital project review and design procedures	35	9
Company standards, rules, and regulations	23	6
Process knowledge and documentation	22	5
Training and performance	19	5
Management of change	10	2
Enhancement of process safety knowledge	8	2
Incident investigation	3	<1
Total	**411**	

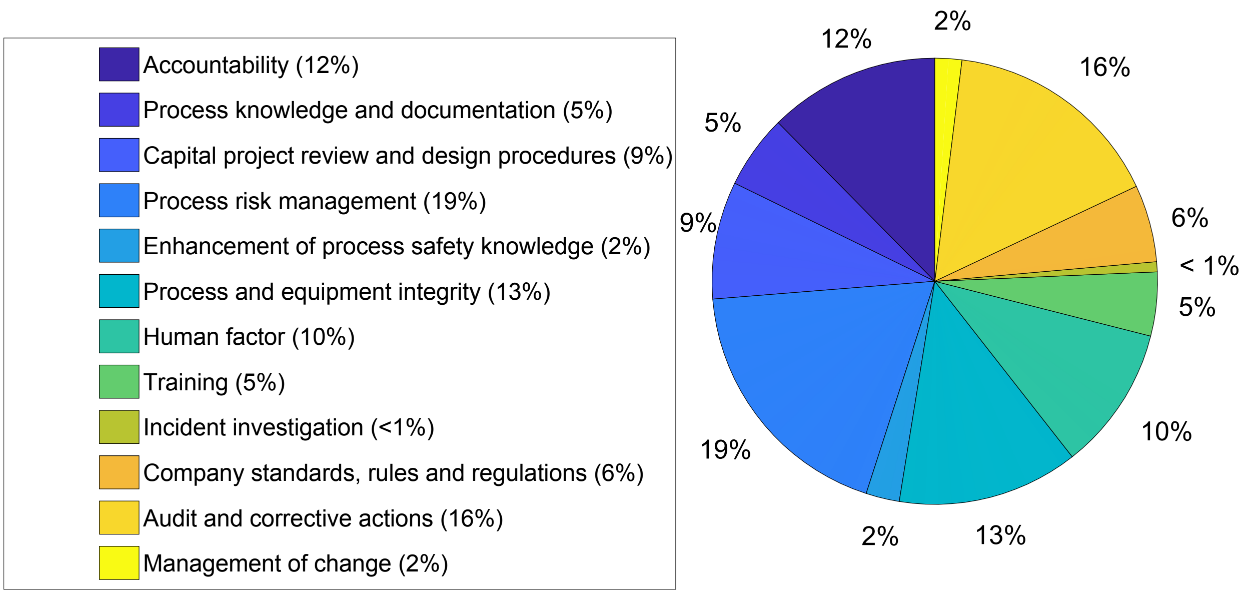


Fig. 2.5 Distribution of errors for each SMS element.

The results of classifying the causes of main-track derailments and collisions within the SMS approach indicate that process risk management, audits and corrective actions, and process and equipment integrity are the main elements where latent errors occurred.

Table 2-4 and Fig. 2.5 show that latent errors are most frequent in Risk Management, accounting for approximately one-fifth of all latent errors. This provides clear direction for managers to allocate resources towards enhancing the procedures associated with the identification, assessment, and control of risks associated with the rail transport of dangerous goods.

Table 2-4 and Fig. 2.5 indicate that latent errors in Audit and Corrective Actions are responsible for approximately 15% of all latent errors. Safety audits are planned processes to record, assess, and report information about the safety of an organization (Baybutt, 2014). Effective audits can capture compliance with the regulations and find areas for enhancements in the system (Birkmire et al., 2007; Lindsay, 1992; Guldenmund et al., 2006). The proportion of latent errors in Audit and Corrective actions is considerable. Therefore, some actions, such as hiring, training, and assessment of employees for taking ownership of performing these tasks and continuous follow-up of the implementation of recommendations, can substantially improve the performance of auditing and corrective actions.

Latent errors in Accountability are approximately 12% of all latent errors. The goal of a safety accountability system is to develop safety behaviors using standards, assessments, and consequences (Baybutt, 2014). Improving safety behaviors in employees across the organization will enhance safety performance, reducing the opportunity for loss incidents involving the rail transport of dangerous goods. Actions toward improving safety behaviors might include providing feedback and comments on the performance of the employees, developing a culture of trust and communication in the work environment, and specifying the outcomes and consequences of risky behaviors in the organization (Huang et al., 2019).

Most latent errors in the safety management system were identified as related to human factors. However, the exact contribution of human factors in the safety management system is difficult to identify (Jo & Park, 2003). Therefore, the application of HFACS is intended to clarify these contributions in order to enhance rail transport safety strategies.

2.4.2 Human factor analysis for main-track train derailments and collisions through HFACS

Examples of human factor classifications in the HFACS framework, and the justification for the classification, are presented in Table 2-5. Application of HFACS to the TSB rail incident reports reveals that organizational oversight, inadequate supervision, and lack of positive safety culture are the main areas in which the reported human errors are classified.

At Level 1, Unsafe Acts, the most frequent unsafe acts are decision errors (38%) and skill-based errors (35%). In the next level, Precondition for Unsafe Acts, the most frequent classifications are crew resource management (29%), which is typically related to good communication skills and team coordination, and personal readiness (29%), which is mainly due to inadequate training. At level 3, Unsafe Supervision, the most frequent classification is inadequate supervision (50%). At the top level, Organizational Influences, oversight (31%), and culture (22%) are the most frequent classifications.

Table 2-5 Examples of human factor classifications in the HFACS framework on railway loss incidents.

Causes of loss incidents	HFACS classification	Justification
The engineer did not remember the previous signal. Also, the conductor was not in their place when the train passed. Therefore, the crew could not recognize the signal and stop before the next signal using	Unsafe act; a) Skill-based errors	a) The engineer did not remember the previous signal. This unsafe act is a skill-based error due to memory failure.

Dynamic Brakes. (Report No: R10T0213)	b) Routine violation error	b) The conductor was not in the right place when the train passed.
Sufficient skills and experience are necessary for conductors in the work environment. However, there was not adequate training and assessment in handling yard movements for Conductor trainees. (Report No: R07T0270)	Precondition for unsafe acts; a) Personal readiness Unsafe supervision; a) Inadequate supervision Organizational influences; a) Human resources	a) Absence of training for new personnel, new conductors not qualified for the operation. a) It happened due to inappropriate training and guidance for the employees. a) The organization did not provide appropriate training time for supervisors

Classifications into the HFACS categories and sub-categories were performed by the members of the research team and showed a strong agreement between them. The frequency and percentage of human factor categories and sub-categories are shown in Table 2-6 and illustrated in Fig. 2.6.

Table 2-6 Frequency and percentage of human factor categories for rail derailments and collisions investigated.

Error Type	Frequency	Percentage (%)
Unsafe acts	**29**	**6**
Decisions errors	11	38
Skill based errors	10	34
Routine	5	17
Perceptual errors	2	7
Exceptional	1	3
Precondition for unsafe acts	**49**	**13**
Crew resource management	14	29
Personal readiness	14	29
Physical environment	9	18
Technological environment	7	16
Adverse mental states	4	8
Adverse physiological states	0	0
Physical/mental limitation	0	0
Unsafe supervision	**112**	**30**

Inadequate supervision	56	50
Failed to correct a known problem	21	19
Planned inappropriate operations	20	18
Supervisory violation	15	13
Organizational influences	**195**	**52**
Oversight	60	31
Culture	42	22
Procedures	26	13
Equipment/facility resources	24	12
Structure	24	12
Human resources	17	9
Operations	1	1
Monetary/budget resources	1	1
Policies	0	0
Total	**385**	

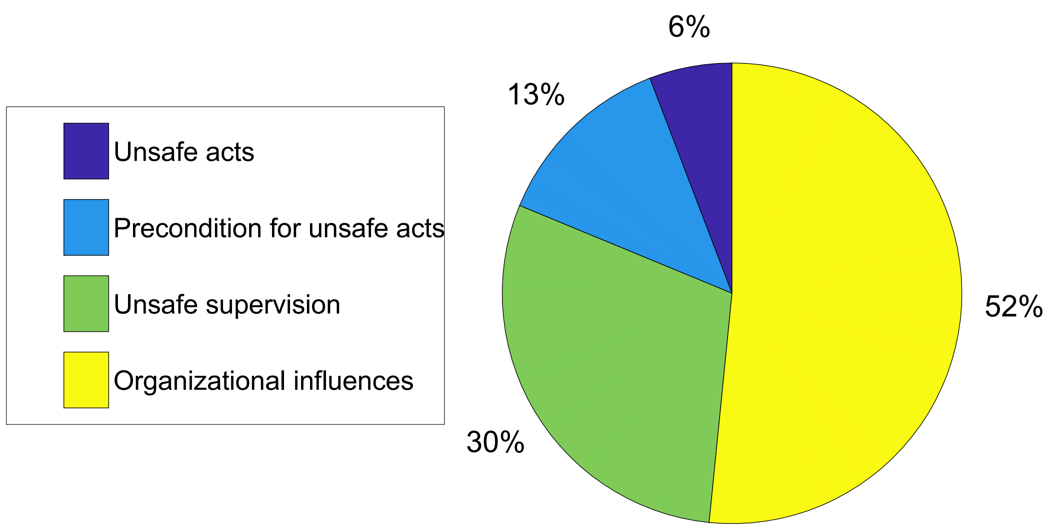


Fig. 2.6 Percentage of human factor categories for rail derailments and collisions investigated.

Table 2-6 and Fig 2.6 show that the latent errors associated with organizational influences account for over half of all latent errors. In this regard, Shappell et al. (1998) hypothesized that insufficient decisions of upper managers negatively affect supervision activities, which may influence the behaviors of front-line operators.

Table 2-6 and Fig 2.6 clearly show that latent errors in supervision are responsible for approximately 30% of all latent errors. According to the HFACS framework, supervision is the intermediate layer in the system, which is influenced by upper-level managers and has influences on lower levels of the system. This result suggests that enhancing the performance of upper level-managers regarding adequate feedback, training, and resource facilitation to front-line workers can substantially reduce the frequency of latent errors in the lower levels of the system.

Furthermore, Table 2-6 and Fig. 2.6 show that latent errors in Precondition for unsafe acts and Unsafe acts account for approximately 18% of all latent errors. Unsafe acts are the first layer of the HFACS framework and are associated with the actions of front-line operators.

2.4.3 Association analysis for main categories and their interdependency

Using the Chi-square distribution and adequate degree of freedom (degree of freedom (df)=1), the significance level is selected as $\alpha = 0.05$ (Roscoe & Byars, 1971) and the limit value (χ_α) obtained is 3.84. If the value of χ^2 is greater than the calculated limit value (χ_α), the null hypothesis is rejected and the alternative hypothesis is accepted meaning that the human factors are dependent (Roscoe & Byars, 1971; Maširević, 2017). If the lambda value is greater than 0.5, the relationship is considered significant (Goodman et al, 1954). The results are presented in Table 2-7 for all pairs with Chi-square values greater than 3.84 (18 relationships). The lambda value was zero in one relationship and greater than 50% in nine other relationships of the 18.

Table 2-7 Chi-square and lambda values for the relationships between the HFACS sub-categories.

The significant correlation among human factors in the HFACS framework	**Chi-square**	**Lambda**
HFACS level 4 association with level 3 categories		
Resource management to supervisory violation	34.314	0.848

Resource Management to Planned inappropriate operations	34.650	0.868
Resource management to Failed to correct known problem	31.500	0.821
Organizational climate to Inadequate supervision	6.735	0.000
Organizational climate to planned inappropriate operations	50.217	0.818
Organizational climate to Failed to correct known problem	53.90	0.867
Organizational climate to supervisory violations	33.971	0.538
Organizational process to inadequate supervision	21.672	0.034
Organizational process to planned inappropriate operations	60.930	0.723
Organizational process to Failed to correct known problem	64.946	0.771
Organizational process to supervisory violations	42.524	0.452
HFACS level 3 association with level 2 categories		
Planned inappropriate operations to crew resource management	5.367	0.250
Supervisory violations to personal readiness	7.467	0.333
Supervisory violation to crew resource management	7.467	0.333

HFACS level 2 association with level 1 categories		
Physical environment to skill-based errors	3.93	0.333
Physical environment to Decision errors	4.95	0.333
Technological environment to skill-based errors	7.467	0.600
Personal readiness to decision errors	3.94	0.250

The strength of the relationships, based on the lambda values, is illustrated in Fig. 2.7.

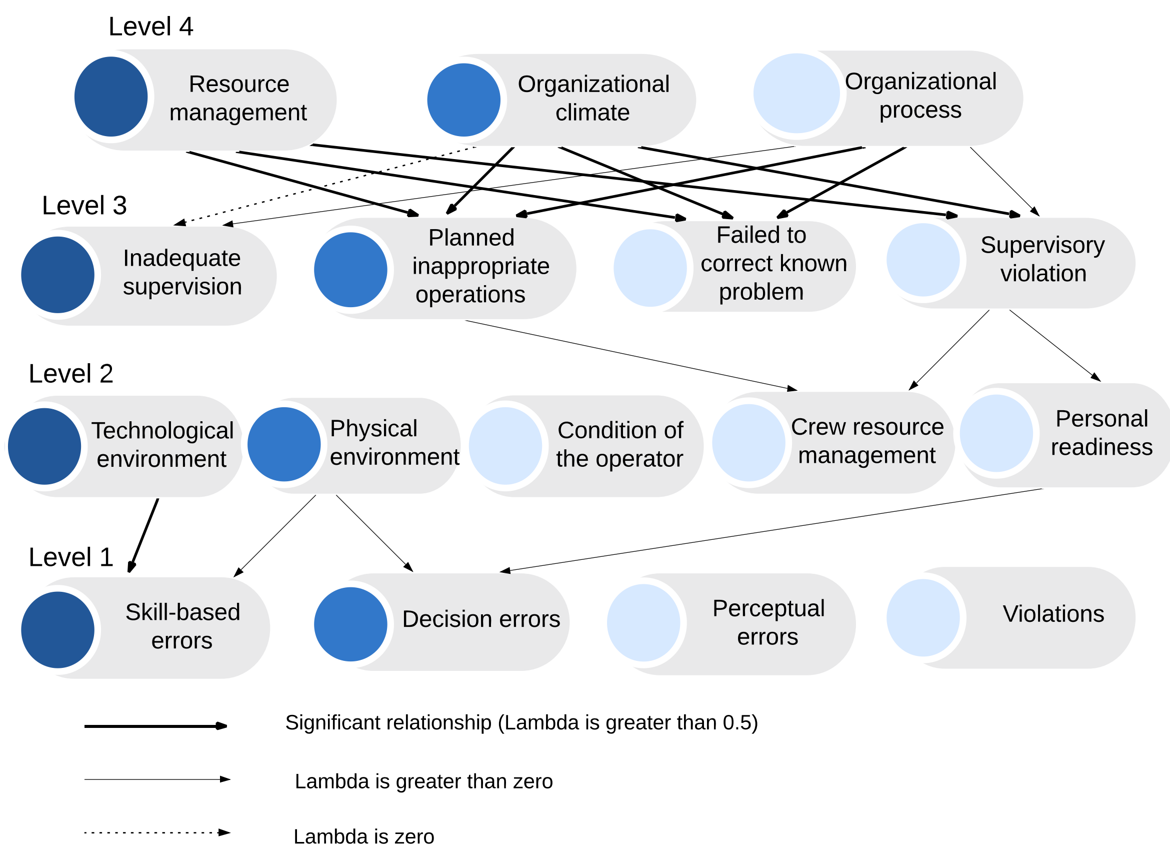


Fig. 2.7 Strength of the relationships between different levels in the HFACS framework based on the lambda values.

At the top level (level 4 – Organizational Influences) of HFACS, errors classified as Resource Management (human resources, budget resources, and equipment resources) were strongly identified as frequently leading to errors at level 3, classified as Supervisory Violation, Planned Inappropriate Operations, and Failed to Correct Known Problems. Increasing resourcing and improving the effectiveness of resources available (e.g., improving training and auditing) are potential approaches to reducing errors in this category. Errors classified within Organizational Climate (structure, policy, and culture of the organization) were strongly identified as frequently leading to errors classified within Planned Inappropriate Operations, Failed to Correct Known Problems, and Supervisory Violations, within level 3. There is a very weak correlation between errors in the category leading to errors classified as Inadequate Supervision. A positive and robust safety culture, including effective communications and well-developed organizational learning, would address these errors. It is acknowledged that culture change in an organization is a challenging task, however, the results of our analysis indicate that the benefits would outweigh the efforts. A robust safety culture would be required at each level of the organization; however, it stems from the top level of the HFACS framework, is driven by upper levels of management, and spreads throughout the organization (Gao et al., 2019).

At level 4 of the HFACS, errors classified as Organizational Processes (standards, procedures, risk management programs, etc.) were strongly identified as frequently leading to errors classified within Failed to Correct Known Problems and Planned Inappropriate Operations. There were weak to moderate correlations to errors classified as Inadequate Supervision and Supervisory Violations. It is common that errors classified within Organizational Processes are associated with system failures in all subcategories of level 3 (Unsafe Supervision) (Li et al., 2008). This was also the case for the rail transport incidents investigated here, although stronger correlations were found for errors classified as Failed to Correct Known Problems and Planned Inappropriate Operations. Therefore, corrective actions can be targeted to reduce errors in this category. These actions can include a combination of changes in procedures, standards that reflect the physical environment of rail transport operations, and more robust methods for training and inspecting.

At level 3 of the HFACS (Unsafe Supervision), Planned Inappropriate Operations (e.g., inadequate operation sequence design, crew scheduling or selection, inadequate supervision) were weak to moderately identified as leading to errors classified as Crew Resource Management failures at level 2 (Preconditions for Unsafe Acts). A potential situation may include a rail conductor and an engineer with no experience along a particular region, or rail corridor, being paired to operate a train in the new environment. In the last few years, due to the extensive turnover of employees in the railway industry, it is common for two employees with low experience to be paired and to work together, especially during night shifts (Transport Canada, 2016). Errors classified as Supervisory Violation were weak to moderately identified as leading to errors classified as Crew Resource Management and Personal Readiness at level 2. Examples would include inadequate instructions to crew members or inadequate scheduling.

At level 2 (Preconditions for Unsafe Acts), errors classified as Personal Readiness were weak to moderately identified as leading to errors classified as Decision Errors at level 1 (Unsafe Acts). A common example in the context of main-track train movements is conductors, engineers, maintenance crews, and field and track supervisors without proper rest or going through personal situations that impede them from focusing on their tasks. Errors classified within Physical Environment (e.g., weather, physiography, lighting, equipment, and infrastructure conditions) were weak to moderately identified as leading to errors classified as Skill-based Errors and Decision Errors at level 1. Common examples include errors associated with operational pressures under extreme weather conditions (e.g., the application of hand brakes under Canadian winter conditions). Errors classified within the Technological Environment category (e.g., inadequate design of equipment and controls, displays, interfaces, checklist layouts, automation, etc.) were strongly identified as frequently leading to errors classified as Skill-based errors. Common examples include errors that arise from complex equipment operations or unclear user interphases for semi-automated tasks.

2.4.4 DEMATEL applied to the HFACS classification of rail transport derailments and collisions

Following the procedures detailed in the previous section, the initial direct-relation matrix D was elicited for the subcategories of the HFACS framework (Fig. 2.8). Then, the matrix D was normalized using Equations (2) and (3), and the total-relation matrix was derived using Eq. (4), as shown in Fig. 2.9. Sum of the rows and columns were used to calculate the centrality ($R+C$) and causality ($R-C$). These are presented in Table 2-8.

	A_1	A_2	A_3	B_1	B_2	B_3	B_4	C_1	C_2	C_3	C_4	C_5	D_1	D_2	D_3	D_4	Row sum
A_1	0	0	0	0	3	3	3	0	0	0	0	0	0	0	0	0	9
A_2	0	0	0	1	3	3	3	0	0	0	0	0	0	0	0	0	10
A_3	0	0	0	2	3	3	2	0	0	0	0	0	0	0	0	0	10
B_1	0	0	0	0	1	1	0	0	0	0	2	0	0	0	0	0	4
B_2	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	3
B_3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
B_4	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	1	5
C_1	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	3
C_2	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	4
C_3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	0	3
C_4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
C_5	0	0	0	0	0	0	0	0	0	0	2	0	0	2	0	0	4
D_1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2
D_2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2
D_3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
D_4	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2
Column sum	0	0	0	3	10	10	8	0	0	0	10	2	7	11	2	1	

Fig. 2.8 The initial direct-relationship matrix *D*. Elements A_i correspond to HFACS level 4 (Organizational Influences), Elements B_i correspond to HFACS level 3 (Unsafe Supervision), Elements C_i correspond to HFACS level 2 (Preconditions for Unsafe Acts), and Elements D_i correspond to HFACS level 1 (Unsafe Acts).

	A_1	A_2	A_3	B_1	B_2	B_3	B_4	C_1	C_2	C_3	C_4	C_5	D_1	D_2	D_3	D_4
A_1	0	0	0	0	0.3	0.3	0.3	0	0	0	0.1620	0.06	0.0134	0.0669	0	0.03
A_2	0	0	0	0.1	0.31	0.3	0.3	0	0	0	0.1850	0.06	0.0141	0.0703	0	0.03
A_3	0	0	0	0.2	0.32	0.32	0.2	0	0	0	0.1840	0.04	0.0130	0.0650	0	0.02
B_1	0	0	0	0	0.1	0.1	0	0	0	0	0.23	0	0.0069	0.0344	0	0
B_2	0	0	0	0	0	0	0	0	0	0	0.2	0	0.0250	0.1250	0	0
B_3	0	0	0	0	0	0	0	0	0	0	0.1	0	0.0021	0.0104	0	0
B_4	0	0	0	0	0	0	0	0	0	0	0.24	0.2	0.0175	0.0875	0	0.1
C_1	0	0	0	0	0	0	0	0	0	0	0	0	0.3125	0.0625	0	0
C_2	0	0	0	0	0	0	0	0	0	0	0	0	0.2500	0.2500	0	0
C_3	0	0	0	0	0	0	0	0	0	0	0.1	0	0.0063	0.0313	0.2	0
C_4	0	0	0	0	0	0	0	0	0	0	0	0	0.0208	0.1042	0	0
C_5	0	0	0	0	0	0	0	0	0	0	0.2	0	0.0458	0.2292	0	0
D_1	0	0	0	0	0	0	0	0	0	0	0	0	0.0417	0.2083	0	0
D_2	0	0	0	0	0	0	0	0	0	0	0	0	0.2083	0.0417	0	0
D_3	0	0	0	0	0	0	0	0	0	0	0	0	0.0208	0.1042	0	0
D_4	0	0	0	0	0	0	0	0	0	0	0	0	0.0417	0.2083	0	0

Fig. 2.9 The total-relationship matrix T . Elements A_i correspond to HFACS level 4 (Organizational Influences), Elements B_i correspond to HFACS level 3 (Unsafe Supervision), Elements C_i correspond to HFACS level 2 (Preconditions for Unsafe Acts), and Elements D_i correspond to HFACS level 1 (Unsafe Acts).

Table 2-8 Values of *R*, *C*, Centrality and Causality in the DEMATEL approach.

	R	C	$R+C$	$R-C$
A_1	1.2323	0	1.2323	1.2323
A_2	1.3794	0	1.3794	1.3794
A_3	1.3620	0	1.3620	1.3620
B_1	0.4713	0.3	0.7713	0.1713
B_2	0.3500	1.0300	1.38	-0.68
B_3	0.1125	1.0300	1.1425	-0.9175
B_4	0.6450	0.8	1.445	-0.155
C_1	0.375	0	0.375	0.375
C_2	0.5	0	0.5	0.5
C_3	0.3376	0	0.3376	0.3376
C_4	0.125	1.601	1.726	-1.476

C_5	0.475	0.36	0.835	-0.115
D_1	0.25	1.0399	1.2899	-0.7899
D_2	0.25	1.6992	1.9492	-1.4492
D_3	0.125	0.2	0.325	-0.075
D_4	0.25	0.18	0.43	0.07

A threshold value of 0.56 was selected from the total-relationship matrix to differentiate the impact among main HFACS categories and define the Network Relationship Map (NRM) of the main categories (Fig. 2.10). The causal diagram according to the DEMATEL approach is shown in Fig. 2.11.

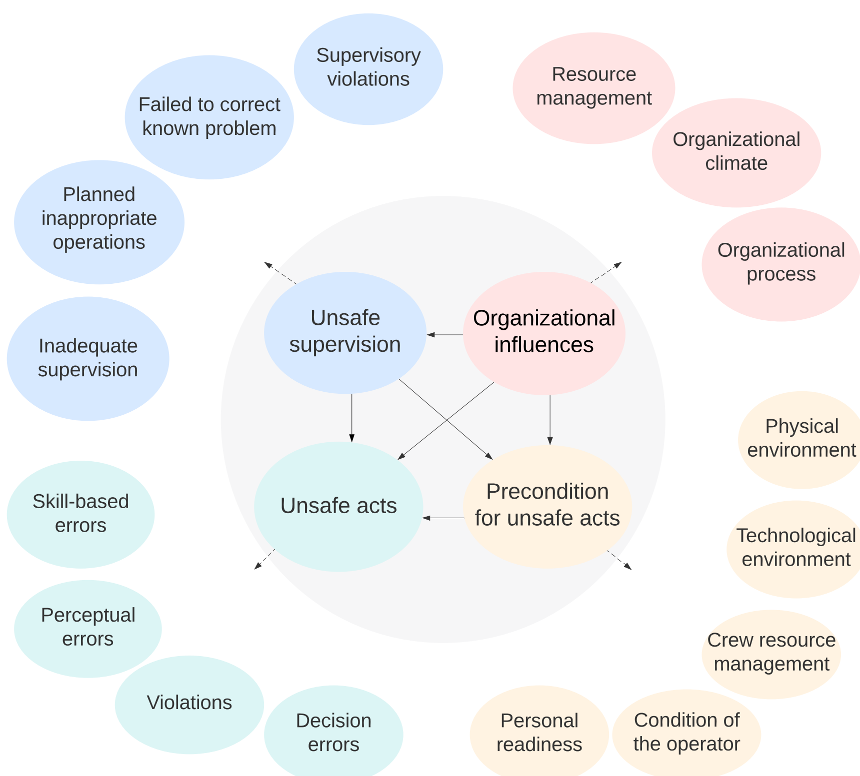


Fig. 2.10 NRM of main categories. Arrows show the causal relationship between the main categories of the HFACS as applied for rail transport of dangerous goods in Canada.

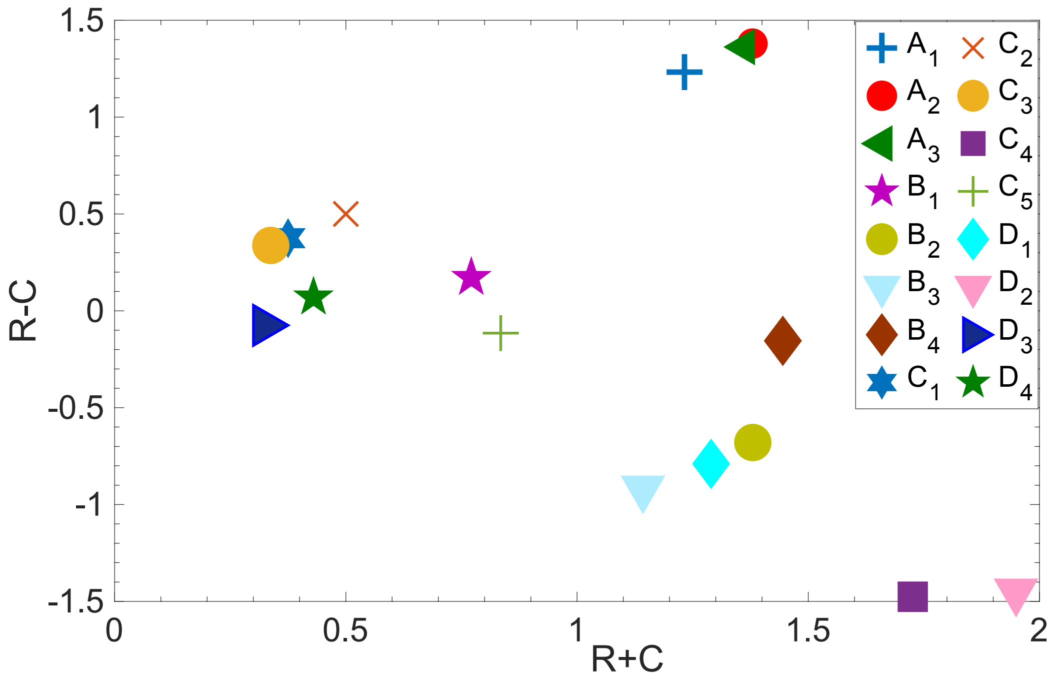


Fig. 2.11 The causal relationship diagram for the subcategories of the HFACS framework.

Positive values of $R-C$ for A_1, A_2, A_3, B_1, C_1, C_2, C_3, and D_4 classifies them as causes leading to the occurrence of errors classified as other subcategories of the HFACS. Negative values of $R-C$ for B_2, B_3, B_4, C_4, C_5, D_1, D_2, and D_3 classifies them as effects. Fig. 2.11 shows that A_2 (organizational climate), A_3 (organizational process), and A_1 (resource management) have the highest Causality values ($R-C$). Therefore, they have the highest effect on other subcategories, and the improvement of these subcategories would lead to enhanced incident prevention. Fig. 2.11 also shows positive values of $R-C$ for D_4 (violations), C_3 (condition of the operator), and C_1 (technological environment). However, they do not have a remarkable effect on the adjustment and optimization of the whole system because the values of R_i and C_i are low.

B_4 (Crew resource management) is classified within the effects group. The Causality value ($R-C$) for B_4 is slightly less than zero, and the Centrality value ($R+C$) is 1.445. Although B_4 is categorized as an effect, this analysis suggests that it has a strong influence on the occurrence of other errors in rail operations that lead to loss incidents. In this regard, assuring adequate scheduling, skills, training, etc., as part of the management of rail conductors, engineers, maintenance of way crews, etc.; gains significant importance for reducing train derailments and collisions.

2.4.5 DANP applied to the HFACS classification of rail transport derailments and collisions

In this step, pair-wise comparison matrices were elicited using expert judgment and reviewed by the authors. Four experts were invited to participate in this study. In addition to three experts with doctoral degrees in engineering, one expert also holds a master's degree in engineering. All of the experts had experience in academia and industry (railway transportation) and had a visible approach to the project. Two criteria were compared in a group under the influence of another criterion with respect to the 1–9 Saaty's linguistic scale (Saaty, 1996). Then, the eigenvectors (priority vectors) were calculated to build the super-matrix. Fig. 2.12 shows an example of a pair-wise comparison matrix for the category of Unsafe supervision under the influence of Resource management (A_1). In this Table, B_1 (Inadequate supervision), B_2 (Planned inappropriate operations) B_3 (Failed to correct known problem), and B_4 (Supervisory violations) were compared under the influence of A_1. In the ANP method, the subcategories of the HFACS framework have reciprocal values (e.g., in comparison to B_1 , the intensity of importance level of B_2 is 9 under the influence of A_1 in accident, therefore, in comparison to B_2 , the intensity of importance level of B_1 under the influence of A_1 in accident is 1/9). After preparing the pairwise comparison matrices, the Consistency Ratio (CR) was calculated for all the matrices to make sure the responses are consistent. Then, the eigenvectors (priority vectors) were calculated for all the subcategories of the HFACS framework.

	B_1	B_2	B_3	B_4	**Priority vector**
B_1	1	0.11	0.14	0.11	0.0363
B_2	9	1	3	3	0.5033
B_3	7	0.33	1	0.33	0.1660
B_4	9	0.33	3	1	0.2950

CR= 0.09

Fig. 2.12 An example of a pair-wise comparison matrix for the subcategories of the Unsafe supervision under the influence of the Resource Management (A_1).

The eigenvectors (priority vectors) were sorted into the super-matrix using Eq. (10) to obtain the unweighted super-matrix (Fig. 2.13).

	A_1	A_2	A_3	B_1	B_2	B_3	B_4	C_1	C_2	C_3	C_4	C_5	D_1	D_2	D_3	D_4
A_1	0.6823	0.5677	0.1923	0	0	0	0	0	0	0	0	0	0	0	0	0
A_2	0.1021	0.6932	0.2704	0	0	0	0	0	0	0	0	0	0	0	0	0
A_3	0.2156	0.2303	0.5373	0	0	0	0	0	0	0	0	0	0	0	0	0
B_1	0.0363	0.0494	0.4611	0.9880	0.2749	0.1375	0.0416	0	0	0	0	0	0	0	0	0
B_2	0.5033	0.2996	0.3736	0.5230	0.5254	0.0559	0.2256	0	0	0	0	0	0	0	0	0
B_3	0.1660	0.4972	0.3700	0.1298	0.0540	0.6008	0.1562	0	0	0	0	0	0	0	0	0
B_4	0.2950	0.6788	0.2053	0.0734	0.1522	0.3751	0.5760	0	0	0	0	0	0	0	0	0
C_1	0.0610	0.0675	0.1475	0.0567	0.0591	0.1229	0.0602	0.5000	0.0370	0.1079	0.0632	0.0776	0	0	0	0
C_2	0.0440	0.0675	0.0612	0.0567	0.0544	0.0417	0.0473	0.0525	0.3618	0.0967	0.0525	0.0776	0	0	0	0
C_3	0.1034	0.1128	0.1045	0.1179	0.1071	0.0574	0.1423	0.0705	0.0877	0.4126	0.1988	0.1948	0	0	0	0
C_4	0.2910	0.5326	0.1989	0.3063	0.5529	0.3799	0.3751	0.1937	0.3067	0.1053	0.4600	0.2972	0	0	0	0
C_5	0.4876	0.2195	0.4714	0.4661	0.2260	0.3981	0.3751	0.1937	0.2061	0.2821	0.2225	0.3588	0	0	0	0
D_1	0.4116	0.0900	0.3125	0.2461	0.1135	0.2350	0.1052	0.5272	0.1477	0.0690	0.3324	0.3904	0.5362	0.1213	0.1049	0.1932
D_2	0.1619	0.2913	0.3125	0.0915	0.4341	0.1848	0.2016	0.2554	0.3916	0.3916	0.2908	0.1503	0.3900	0.5967	0.1049	0.1932
D_3	0.0546	0.0442	0.2500	0.0540	0.0495	0.0565	0.0340	0.1512	0.3916	0.3900	0.0860	0.0689	0.0420	0.0678	0.6752	0.5338
D_4	0.0130	0.5751	0.3125	0.6083	0.4038	0.5229	0.6302	0.0663	0.0691	0.1477	0.2908	0.3904	0.0930	0.2142	0.1150	0.5453

Fig. 2.13 The un-weighted super-matrix defined for the subcategories of the HFACS for train derailments and collisions.

The next step was to transpose the total-relationship matrix obtained through the DEMATEL method (Fig. 2.9) and combine it with this un-weighted super-matrix (Fig. 2.13) to calculate the weighted super-matrix, following the steps detailed in the previous section. The weighted super-matrix was normalized (Fig. 2.14) and multiplied by itself iteratively until a stable super-matrix was achieved.

	A_1	A_2	A_3	B_1	B_2	B_3	B_4	C_1	C_2	C_3	C_4	C_5	D_1	D_2	D_3	D_4
A_1	0.0734	0.0918	0.0653	0.0739	0.0533	0.0815	0.0872	0.0143	0.0186	0.0170	0.0220	0.0234	0.0076	0.0103	0.0072	0.0122
A_2	0.0687	0.0857	0.0675	0.0890	0.0538	0.0779	0.0812	0.0139	0.0182	0.0160	0.0216	0.0226	0.0071	0.0096	0.0067	0.0112
A_3	0.0642	0.0772	0.0712	0.1070	0.0554	0.0734	0.0696	0.0128	0.0170	0.0140	0.0203	0.0201	0.0065	0.0087	0.0058	0.0091
B_1	0.0714	0.0881	0.0598	0.0840	0.0766	0.0806	0.0745	0.0309	0.0448	0.0258	0.0564	0.0483	0.0094	0.0120	0.0069	0.0080
B_2	0.0600	0.0809	0.0525	0.0635	0.0861	0.0707	0.0781	0.0612	0.0809	0.0653	0.0879	0.0750	0.0458	0.0587	0.0337	0.0393
B_3	0.0666	0.0979	0.0448	0.0804	0.0960	0.0847	0.0941	0.0526	0.0774	0.0418	0.0995	0.0852	0.0119	0.0152	0.0088	0.0102
B_4	0.0697	0.0775	0.0677	0.1048	0.0720	0.0890	0.1020	0.0489	0.0611	0.0652	0.0752	0.0935	0.0211	0.0311	0.0262	0.0550
C_1	0.0876	0.0241	0.0663	0.0621	0.0300	0.0534	0.0322	0.1232	0.0468	0.0392	0.0733	0.1046	0.1319	0.0531	0.0787	0.0917
C_2	0.0679	0.0372	0.0663	0.0475	0.0492	0.0495	0.0408	0.1000	0.0670	0.0734	0.0702	0.0807	0.1194	0.0950	0.0787	0.0917
C_3	0.0334	0.0415	0.0513	0.0383	0.0423	0.0395	0.0404	0.0461	0.0899	0.0956	0.0496	0.0448	0.0183	0.0259	0.3087	0.1602
C_4	0.0482	0.0503	0.0663	0.0330	0.0685	0.0456	0.0493	0.0769	0.0872	0.1077	0.0670	0.0568	0.1068	0.1370	0.0787	0.0917
C_5	0.0569	0.0729	0.0561	0.0555	0.0815	0.0641	0.0705	0.0653	0.0826	0.0765	0.0824	0.0702	0.0618	0.0793	0.0455	0.0530
D_1	0.0482	0.0503	0.0663	0.0330	0.0684	0.0456	0.0493	0.0769	0.0872	0.1077	0.0670	0.0568	0.1068	0.1370	0.0787	0.0917
D_2	0.0876	0.0241	0.0663	0.0621	0.0300	0.0534	0.0322	0.1232	0.0468	0.0392	0.0733	0.1046	0.1319	0.0531	0.0787	0.0917
D_3	0.0482	0.0503	0.0663	0.0330	0.0685	0.0456	0.0493	0.0769	0.0872	0.1077	0.0670	0.0568	0.1068	0.1370	0.0787	0.0917
D_4	0.0482	0.0503	0.0663	0.0330	0.0684	0.0456	0.0493	0.0769	0.1077	0.0670	0.0568	0.1068	0.1370	0.0787	0.0917	0.5453

Fig. 2.14 The normalized weighted super-matrix defined for the subcategories of the HFACS for train derailments and collisions.

The stable super-matrix represents the relative importance of each subcategory of the HFACS in the occurrence of train derailments and collisions. A summary of the relative weights and overall importance ranking is presented in Table 2-9. The most influential subcategories within Unsafe Acts are D_1 (Skill-based errors) and D_4 (Violations); within Preconditions for Unsafe Acts are C_4 (Crew resource management) and C_3 (Condition of the operator); within Unsafe Supervision are B_2 (Planned inappropriate operations) and B_4 (Supervisory violations), and within Organizational Influences are A_1 (Resource management) and A_2 (Organizational climate).

Table 2-9 DANP relative weights and overall importance ranking for the subcategories of the HFACS.

Main categories of the HFACS	Sub-categories	ANP evaluation weight	Ranks
Organizational influences	A_1 (Resource management)	0.0349	14
	A_2 (Organizational climate)	0.0343	15
	A_3 (Organizational process)	0.0329	16
Unsafe supervision	B_1 (Inadequate supervision)	0.0439	13
	B_2 (Planned inappropriate operations)	0.0655	10
	B_3 (Failed to correct known problem)	0.0581	12
	B_4 (Superviory violations)	0.0643	11
Precondition for unsafe acts	C_1 (Technological environment)	0.0721	7
	C_2 (Physical environment)	0.0755	6
	C_3 (Condition of operator)	0.0785	5
	C_4 (Crew resource management)	0.0789	1
	C_5 (Personal readiness)	0.0690	9

Unsafe acts	D_1 (Skill-based errors)	0.0788	2
	D_2 (Decision errors)	0.0720	8
	D_3 (Perceptual errors)	0.0786	4
	D_4 (Violations)	0.0787	3

These results identify that Skill-based errors have a strong influence on train derailments and collisions within Unsafe acts. This further supports our previous findings that training programs and qualifications, as well as their associated causes identified through DEMATEL, should be prioritized, including how the organization and supervisors need to prepare appropriate work scheduling for crews. Violations were identified as the second-highest influence within Unsafe acts. To decrease violations, employees need to know their tasks accurately and understand the outcomes of unauthorized behaviors. In addition, high-quality training, particularly in their trade and in hazard identification and control, is also of utmost importance.

Crew Resource Management was identified as the top in importance within Preconditions for Unsafe Acts. Failure to communicate and engage in effective teamwork is more likely to occur as a result of inadequate Crew Resource Management. To improve communication and teamwork, regular and effective meetings are required where ideas are shared and feedback is welcomed and encouraged. Condition of the Operator, including mental fatigue, stress, and a loss of situational awareness, has the second-highest rank of influence within Preconditions for Unsafe Acts. The railway industry and Transport Canada have recognized that fatigue has been a problem for over 20 years, and some actions have been taken to address this issue; however, fatigue is still one of the challenging issues in the railway industry (Rudin-Brown et al., 2019; Scyoc & Hughes, 2009). The Institute for Work and Health (IWH) reported that incident likelihood increases during the night, evening, rotating, and irregular shifts. Incident reports increased on the 4th successive night shift when compared to the first night shift, with the least incident reports during morning shifts. (CCOHS, 2021). The increased incident likelihood is associated with mental or physical fatigue near the end of a working shift and as a consequence of long working hours, less supervision and peer support, inadequate rest, and sleep disorder (Dembe et al., 2005; Shen & Dicker, 2008; Lerman et al., 2012; Theron & van Heerden, 2011). The HFACS approach differentiates between physical fatigue, which is the transient incapability of muscles to keep optimum physical performance, and mental fatigue, which is a transient decline in maximal mental performance after long periods of mental activity (Marcora et al., 2009). However, HFACS does not differentiate between fatigue as a result of long working hours at the end of the shifts and fatigue associated with a sleep disorder or lack of rest at the beginning of a shift (Alexander, 2019; Lenné et al., 2012). Effective fatigue management has been challenging because of unpredictable start times in freight operations, long duty hours, and rotating day and night shifts (Wong et al., 2018). Fatigue management plans need to consider the nature of the operations (e.g. the freight trains work in a particular territory) also traffic density, traffic patterns, run length, and geographical considerations are the items that need to be considered (Railway Association of Canada, 2011). A fatigue risk management system uses several overlapping and redundant defenses against the hazard in a system including training employees to handle fatigue and sleep disorders, optimization of shift schedules, developing alertness strategies for employees, and proper design of rest environment in the workplace (Transport Canada, 2007).

Planned Inappropriate Operations was identified as having the most influence on the occurrence of errors within Unsafe Supervision. Supervisory Violations were identified as the second most influential factor. As supervisors' roles are key for successful crew performance and successful operations; the organization needs to ensure that supervisors understand their responsibilities to the regulatory environment and to their crew members, the tasks at hand, the importance of robust safety culture, and the importance of all risk controls in place. Simultaneously, senior management needs to evaluate supervisors for performance and engagement regarding safety culture.

Resource Management was identified as having the most influence on errors within Organizational Influences. Resource management includes hiring, rewarding, and training employees at all levels of the organization. Hiring and training priorities need to meet the organization's requirements at different levels, therefore minimizing the potential for employees to perform tasks they do not feel qualified for or perform tasks in excess of their capacity (Banbury & Baker, 2015; Chidambaram, 2016). Organizational Climate was identified as having the second most influence on errors within Organizational Influences. Establishing clear values and objectives allows employees to understand the expectations of the organization. This, together with consistent behavior from management and supervisors, as well as empowering employees to take responsibility for safety; enhances trust amongst employees at different levels and improves the organizational culture.

2.5 Comparison between our findings and findings elsewhere

A comparison was made between this study and three other studies that focused on the relationships between active and latent errors in the railway industry in other countries through the application of the HFACS. Table 2-10 shows the list of studies reviewed for this comparison.

A study was performed in the UK (Madigan et al., 2016) using Chi-Square analysis (χ^2) and Adjusted Standardized Residuals (ASR). The ASR is a measure of the strength of the difference between observed and expected values (Sharpe, 2015). This study highlighted the need for the rail industry to consider latent errors at the Unsafe Supervision and Organizational Influences levels, as they can create situations that promote the occurrences of active errors leading to loss incidents.

Their results also highlighted the importance of the operational Environment, including unusual operating conditions, which have the potential to distract train conductors.

One study on human factors for high-speed railway incidents in China proposed a new framework for the application of HFACS, named "HFACS-RA" (Zhan et al., 2017). In their study, the ANP method was combined with Fuzzy-DEMATEL to investigate the leading causes of a loss incident. Their study showed that Inappropriate Organizational influences, in the form of internal regulations, and Unsafe Supervision, in the form of ineffective supervision, were causes of railway loss incidents that have been ignored in the past. Their study further proposed that improving the Organizational Climate, in terms of working conditions, and the behavior of shop-floor staff can reduce railway loss incidents.

Table 2-10 List of studies reviewed that focused on the relationship between latent and active errors through the HFACS in the railway industry in other countries.

Study	**Country**	**Method**
Application of Human Factors Analysis and Classification System (HFACS) to UK rail safety of the line incidents (Madigan et al., 2016)	UK	ASR, χ^2
A hybrid human and organizational analysis method for railway accidents based on HFACS-Railway Accidents (HFACS-RAs) (Zhan et al., 2017)	China	Fuzzy-DEMATEL-ANP
Paths between latent and active errors: Analysis of 407 railway accidents/incidents' causes in China (Zhou et al., 2018)	China	λ, χ^2

Another study on Chinese rail transport (Zhou et al., 2018) found that the most frequent organizational failures are in the areas of Organizational Influences, in terms of processes, inadequate supervision, personal readiness, and skill-based errors. Their study found the relationships between active and latent errors, which showed the importance of supervision and organizational influences on reducing active errors and railway loss incidents.

The results of these studies are consistent with the findings in our study for the Canadian railway industry. All studies show the importance of latent errors at the supervisory and organizational levels. This suggests that the characteristics might be endemic to rail industries evaluated in these studies and not only within the Canadian industry. In this regard, the comparison validates insights regarding leading indicators of safety performance from these studies as potentially applicable to the Canadian context. The work in this paper, therefore, becomes a step towards developing such leading indicators and effective controls to minimize the frequency of active errors, and therefore, train derailments and collisions.

2.6 Limitations and research assumptions

Due to the complexity and uncertainty of accident analysis, human factors, and the type of data (which is in text format), expert judgment is necessary for this study. Although the people who participated in this study are well-educated and experienced, experts' biases are one of the assumptions of this study that should be considered in both qualitative and quantitative analyses (Lee, 2016; Ergu et al., 2011). The other assumption is that after classifying the accidents using the HFACS framework, the inter-rater reliability is evaluated for each category of the HFACS framework using Cohen's Kappa (Mackinnon, 2000). The Kappa value is used to find the consistency between the results released by expert judgment. In this study, the consistency is greater than 0.5, which indicates acceptable reliability (Ergai et al., 2016; Landis & Koch, 1977). The next assumption is that we limited the number of experts who participated in this study. Although, the experts should be trained, and the agreement between the experts should not be random as there is a clear definition for each category of the HFACS (Olsen, 2011). However, having a small number of experts may increase a potential bias in the decision-making process (Zhou & Lei, 2018). At the same time, increasing the number of experts also lengthens the process and increases the difficulty of finding agreement between experts (Zhan et al., 2017). The other assumption is that the quantitative analysis was dependent on the quality of the accident reports (Lenné et al., 2012). This study examined accident reports collected by the TSB. The current dataset may be complemented with other databases, such as those provided by the Federal Railroad Administration (FRA), in future studies. The last limitation is that conventional DEMATEL and ANP seem to be insufficient to capture inherent fuzziness or uncertainty in judgment during the pairwise comparison. The use of a 1-9 scale to show verbal judgment in pairwise comparisons makes the comparison easier; however, it does not consider the uncertainty associated with the expert judgment of a number. In fact, the decision-makers could be uncertain about their own level of preference because of incomplete information, or uncertainty within the decision environment (Liou et al., 2011). Fuzzy logic is introduced to cover the deficiency associated with the conventional MCDM methods (Zhou, 2012; Kyriakidis, 2013; Fahad & Maghrabie, 2018). Therefore, fuzzy numbers can be used in future work to capture the uncertainty associated with the calculations.

2.7 Conclusions

The safe transportation of dangerous goods by railway is essential for the sustainability of the industry. Human failure has been identified as accounting for a substantial portion of these, either as immediate or latent errors. In this study, an analysis of safety weaknesses at an organizational level was performed to analyze the latent errors leading to main-track derailments and collisions. A large portion of the latent errors in the safety management system was recognized as related to human factors. However, the exact contribution of human factors in the safety management system is difficult to identify. To analyze the exact contribution of human factors in railway loss incidents, HFACS, and an analytical framework was employed. The results demonstrated that the most deficiencies are in the areas of organizational oversight, supervision, and the culture of the organization.

The Chi-square test and Kruskal's lambda analysis were employed to find an association between adjacent sub-categories of the HFACS. The results indicate the importance of making decisions at higher managerial levels and the way these decisions indirectly affect the actions of front-line operators and cause railway loss incidents. The DEMATEL method was performed to map the causal relationships between the subcategories of the HFACS framework and determine the importance of each subcategory. Then, the DEMATEL was combined with the ANP method to measure the weight of each subcategory and categorize the leading human indicators of railway loss incidents. The results of DEMATEL show that Organizational climate, Organizational process, and Resource management have the highest effect on other subcategories, and the enhancement of these subcategories would lead to the prevention of railway loss incidents in the future. Furthermore, we have identified potential groups of leading indicators in railway loss incidents. These include Crew-resource management, Skill-based errors, and Violations. Then, some recommendations were provided according to the priority of the leading indicators. The studies conducted in the railway industry were compared to find out the agreement between these studies and evaluated the leading indicators in the world. The results were in good agreement and highlighted the importance of supervision and organizational factors for reducing railway loss incidents. The results of this work provide valuable insight for decision-makers to define effective leading indicators that can help enhance the current safety performance of the Canadian railway industry.

Table 2-11 Description of SMS categories used in this study (Baybutt, 2014)

a. Accountability
- Continuity of operation
- Continuity of system
- Quality process
- Control of exceptions
- Continuity of organization
- Alternative methods
- Management accessibility
- Company expectations

b. Process knowledge and documentation
- Process definition and design criteria
- Process and equipment design
- Protective system
- Process risk management decisions
- Company memory
- Normal and upset conditions
- Chemical and occupational health hazards

c. Capital project review and design procedures
- Hazard review
- Process design and review procedures
- Plot plan
- Project management procedures and control
- siting

d. Process risk management
- Hazard identification
- risk analysis of the operation
- Reduction of risk
- Residual risk management
- Encouraging client and supplier companies to adopt similar risk management practices.
- Process management during emergencies

e. Management of change
- Change of process technology
- Change of facility
- Change of organization
- Permanent changes
- Temporary changes

f. Process and equipment integrity
- Reliability engineering
- Material of construction
- Preventive maintenance
- Maintenance procedures

- Alarm and instrument management
- Process hardware, system inspection, and testing
- Fabrication and inspection procedures
- Installation procedures

g. Human factors

- Operator-process/equipment interface
- Administrative control versus engineering control
- Human error assessment

h. Training and performance

- Definition of skill and knowledge
- Instructor program
- Records management
- Ongoing performance and refresher training
- Design of operating and maintenance procedures
- Initial qualification assessment
- Selection and development of a training program

i. Incident investigation

- Major incidents
- Communication
- Incident recording, reporting, analysis
- Third party participation
- Follow-up and resolution
- Near miss reporting

j. Company standard, codes, regulation

- Internal standard
- External codes/ regulations

k. Audits

- SMS system audits
- Process safety audits
- Corrective actions
- Compliance reviews
- Internal/external auditors

l. Enhancement of process safety knowledge

- Quality control program and process safety
- Professional and trade association program
- Technical association program
- Research development, documentation, and implementation
- Improved predictive system

Table 2-12 Brief description of HFACS categories (after Punzet et al., 2018; Yıldırım et al., 2019; 2018; Wang et al., 2020).

Main categories	Sub-categories	Description
Organizational influences	Human resources	Hiring, training, background check

	Budget resources	Lack of funding
	Equipment resources	Inappropriate design, failure to correct design problems
	Structure	Chain of command, communication
	Policies	Hiring and firing
	Culture	Value, beliefs, and attitude
	Operations	Time pressure, schedules
	Procedure	Performance standards, procedures
	Oversight	Organization's monitoring, checking of the resources, climate, and process to ensure about safety
Unsafe supervision	Inadequate supervision	Failed to provide appropriate training and guidance, track qualification, and performance
	Planned inappropriate operations	Poor crew pairing, failed to provide suitable Guidance and oversight
	Failed to correct known problem	Failed to correct unsuitable behavior, failed to correct safety risk, failed to start corrective actions
	Supervisory violations	Failed to implement rules and regulations, inadequate documentation, violated procedures
Precondition for unsafe acts	Adverse mental states	Loss of situational awareness, stress, alertness, mental fatigue, distraction
	Physical/mental limitation	Insufficient experiences for complex Situations, incompatible physical abilities
	Adverse physiological states	Medical illness, physical fatigue
	Crew resource management	Lack of teamwork, poor communication
	Personal readiness	Inadequate training, failure to follow the crew rest requirement
	Physical environment	Weather, altitude, lighting

	Technological environment	Equipment/control design, display/interface characteristics, automation
Unsafe acts	Skill-based errors	Inadequate technique, failure to prioritize attention Distraction, omitted step in procedures
	Decisions errors	Insufficient knowledge of procedures, wrong response to emergency
	Perceptual errors	Due to visual illusion, due to misjudge distance
	Routine	Violation of rules
	Exceptional	Accepted unnecessary risk, unauthorized Behavior

Errors on the first level of the HFACS (unsafe acts) are considered active errors, whereas errors on the other levels of the HFACS (precondition for unsafe acts, unsafe supervision, and organizational influences) are considered latent errors.

Chapter 3

Chapter 3 of this thesis has been published as Hadiseh Ebrahimi, Fereshteh Sattari, Lianne Lefsrud, Renato Macciotta, "*Human vulnerability and risk analysis of railway transportation of hazardous materials*", Journal of Loss Prevention In the Process Industries. Contributions of the authors are listed below:

Hadiseh Ebrahimi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Fereshteh Sattari:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Supervision, Project administration**. Lianne Lefsrud:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Renato Macciotta:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

3.1 Introduction

Railways transport a large volume of hazardous materials (hazmat) in Canada (Ebrahimi et al., 2021; Macciotta et al., 2018). The amount of hazmat railway transportation in Canada has increased by an average of 25% since 2004, with a 42.5% increase in fuels and chemicals shipped between 2011 and 2017 (Sattari et al., 2021). As a result of hazmat railway incidents, severe consequences to people are a possibility that requires mitigation, especially when the trains cross highly populated areas (Bersani et al., 2016; Landucci et al., 2017). Several railway incidents with significantly negative consequences on people, the environment, and infrastructure occurred in the past. For instance, in 1979, the rail accident in Mississauga (Canada) resulted in chlorine leakage and, consequently the evacuation of 200,000 people (Inanloo & Tansel, 2015). In 2005, the train derailment in Wabamun (Canada) caused 800,000 liters of oil leakage into Alberta Lake (Transportation Safety Board of Canada, 2005). A train derailment and LPG spill into the environment in Viareggio (Italy) resulted in 32 fatalities in 2009 (Landucci et al., 2011). In 2013, the train derailment in Lác-Megantic (Canada) resulted in 47 fatalities and the evacuation of 2000 people (Généreux et al., 2020). In 2021, over 3,000 people were evacuated from their homes as a result of the derailment of a train transporting ammonium nitrate and other chemicals in IOWA (the USA) (Changing America, 2021). These incidents are some examplesindicating the need for risk assessments in railway transportation.

3.1.1 Risk assessment in hazmat transportation

Risk assessment of hazmat transportation is a well-known practice that is applied to prevent severe consequences of incidents (Huang et al., 2020). Various risk assessment methods have been developed to estimate the risk of hazmat transportation in terms of human or economic loss (Landucci et al., 2017). For example, Huang et al. (2018) proposed a methodology to analyze the risk of hazmat transportation incidents in the areas along highways. The authors considered the maximum temperature and wind speed which may occur in the incident location, to prepare hazard maps. Social vulnerability indicators, including population density, hospital locations, and fire station locations, were considered to prepare the vulnerability maps in their study. With the aid of the risk maps obtained from the combination of hazard and vulnerability maps, they provided recommendations for emergency management in hazmat transportation incidents occurring along highways. Mohammadi et al. (2017) analyzed the risk of hazmat road transportation and concluded that risk depends on the distance from the hazmat source, the number of people exposed to hazmat, the number of hazmat shipments passing the road, the characteristics of the road, and the probability of an incident. Anjana et al. (2018) developed a risk assessment method by considering four different scenarios of ammonia release between 8.30 a.m. and 5.30 p.m. in the winter and summer seasons to prepare hazard maps. The authors indicated that stability class, wind speed, and wind direction are the most important factors for preparing the hazard maps. They also evaluated the population vulnerability in terms of population density and the number of evacuees in emergency situations. Ovidi et al. (2020) analyzed the risk of a railway accident that occurred in Tilburg, (the Netherlands) and proposed recommendations for emergency planning in railway incidents. The authors considered two meteorological conditions with the stability class D and F to prepare hazard maps and estimate the probability of death without considering the characteristics of the affected population. Bondžić et al. (2021) developed an integrated risk assessment method by considering that the highest temperature and lowest wind speed in a particular month (January 2016) can create the worst meteorological condition for hazmat dispersion. The authors also considered that the lowest temperature and highest wind speed in January 2016 can create the best meteorological condition for hazmat dispersion. They evaluated the vulnerability of disabled people in hazmat road incidents and provided recommendations for reducing the risk of hazmat road incidents.

Although various studies have been conducted to analyze the risk of hazmat transportation, many of these studies (CCPS, 2021; Landucci et al., 2017; Ovidi et al., 2020; Anjana et al., 2018) focused on the number of people (population density) who are in danger of hazmat release, and a few studies considered the characteristics of the population exposed to hazmat transportation incidents (Huang et al., 2018; Guan et al., 2022). Incidents may lead to more severe consequences if they affect vulnerable people with less ability to protect themselves in emergency situations (Bondžić et al., 2021). Therefore, it is of utmost importance to study population vulnerability based on the different characteristics of the people exposed to hazards (Huang et al., 2018). Additionally, due to the lack of meteorological information at the time of incidents, the hazard maps in the above mentioned studies were mostly prepared by considering some assumptions to cover this lack of information (Sanchez et al., 2018; Sengupta et al., 2016; Anjana et al., 2018; Ovidi et al., 2020). To process the metrological variables for preparing the hazard maps, a procedure should be developed. This study aims to provide a procedure to estimate the risk of hazmat railway transportation in densely populated areas to help land-use planning and emergency management. In this procedure, meteorological variables are processed based on the relationship between the variables to identify the most probable and the most dangerous meteorological conditions and to create hazard maps. Then, different sociodemographic characteristics of the population (15 characteristics), which have a great influence on the population vulnerability, are identified and ranked to create a vulnerability map. The risk map is generated by superimposing the hazard and vulnerability maps using ArcGIS software, taking into account the intensity and nature of the hazards and the demographic characteristics of the population (Beneventti G et al., 2019). Based on the most probable and the most dangerous meteorological conditions, this procedure is designed to determine the extent of railway incidents, but not the probability of the incident. Thus, the meteorological conditions of the region are used in order to identify the consequences of the incidents (Hirst & Carter, 2002; Miñarro, 2004).

3.2 Methodology

The characteristics of communities (e.g., population density) and climate conditions (e.g., wind direction) change with time. As a result, the risk does not remain unchanged. To consider this issue, the factors changing with time should be identified and considered (Federal Emergency Management Agency, 2018). This study considers different scenarios to cover the changes in the communities and climate for calculating the risk maps in an efficient way. To acquire the risk maps, the steps indicated in Fig. 3.1 were followed.

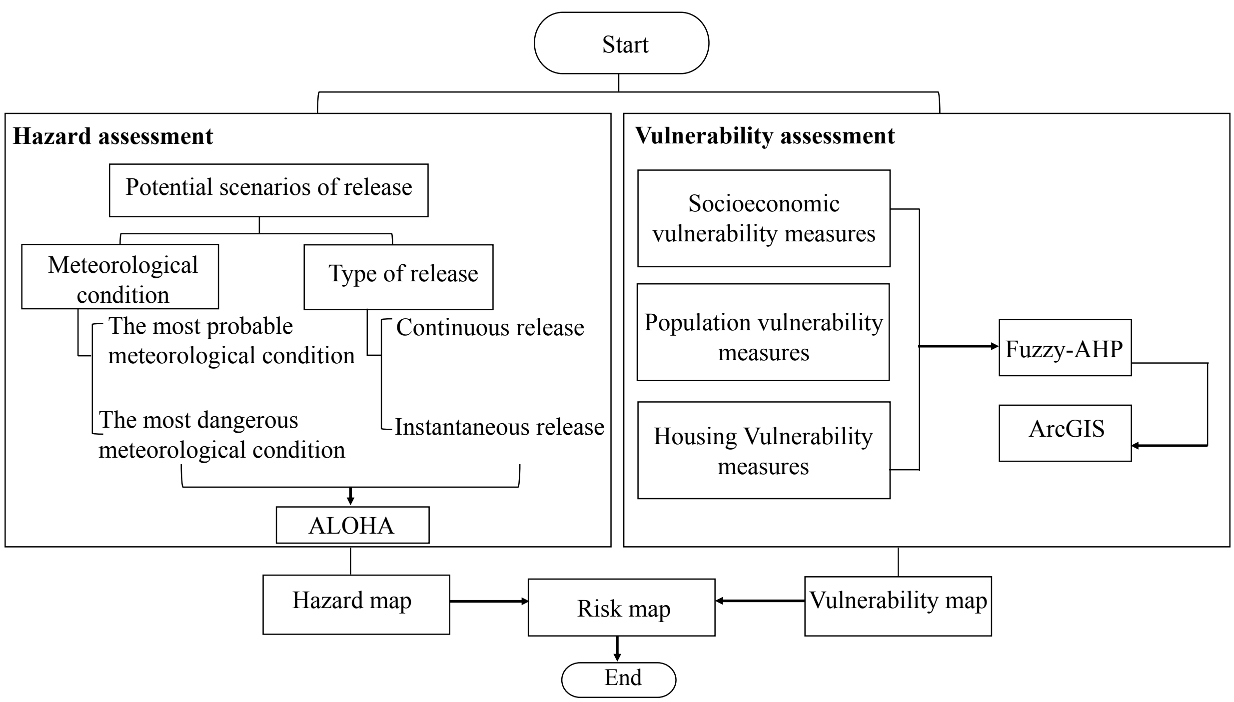


Fig. 3.1 The steps followed to calculate a risk map.

3.2.1 Hazard assessment

Hazard maps represent the threat zones in an area in which hazards (i.e., toxic radiation or thermal radiation) have exceeded a threshold value (Miñarro, 2004; Tseng et al., 2012). To determine the threat zones and create a hazard map, an appropriate software (e.g., ALOHA (United States Environmental Protection Agency, 2021) or PHAST (DNV, 2021)), which accurately simulates the threat zones, is required (Jabbari et al., 2020). As ALOHA (Areal Location of Hazardous Atmospheres) software has been widely used to simulate threat zones (Aquino-Gaspar., 2021), it is employed to model hazard maps in this study. To model the threat zones using ALOHA, the chemical properties of hazmat, type of hazmat release, time and location of the incident, and meteorological variables (e.g. stability class, wind speed, wind direction, temperature, humidity, ground roughness, cloud cover, and solar radiation) are required (AlRukaibi et al., 2018). ALOHA enables modeling different physical effects of hazmat release, including pool fire, vapor cloud explosion, flashfire, toxic release, and boiling liquid expanding vapor explosion (BLEVE) using input data and incorporated equations, (Mannan, 2012). The output results are three threat zones, the areas in which the ground-level hazmat concentration can exceed the level of concern (LOC) at a specific time after the beginning of the hazmat release (Chakrabarti & Parikh, 2013). LOC shows the threshold concentration of exposure to the hazmat that can hurt people if they inhale it for a certain amount of time (Chakrabarti & Parikh, 2013; Chakrabarti & Parikh, 2011). The threat zones are differentiated using different colors (i.e., yellow, orange, and red) in the hazard maps in ascending orders (Guan et al., 2022). The threat zones indicated in red show the worst hazard level, in which life-threatening conditions could happen to people. The threat zones indicated in orange and yellow reveal that people could experience serious health problems and discomfort symptoms, respectively (Hoscan & Cetinyokus, 2021; Horng et al., 2005).

3.2.1.1 Construction of hazard scenarios

To develop hazard scenarios and generate hazard maps, the types of hazmat release and meteorological conditions need to be considered. The type of hazmat release and meteorological conditions directly influence the dispersion of hazmat and hazard mapping (Ovidi et al., 2020). According to the Purple Book (U. De Haag & Ale, 2005) and the Railway Association of Canada (2017), Loss of Contaminant is classified for tank cars into two groups, namely instantaneous release (rupture of the tank car) and continuous release (leakage from a 3" hole in the tank car). These two types of release are considered to model the hazard maps in this study. As predicting the exact time and atmospheric conditions for incidents is hardly possible (Landucci et al., 2017; Sengupta et al., 2016), two general meteorological conditions, the most probable and the most dangerous meteorological conditions, are proposed and evaluated in this study based on the reports released by Federal Emergency Management Agency (2018) and Miñarro (2004). The type of stability class and wind speed are two notable factors compared to other factors (i.e., cloud cover, solar radiation, temperature, and humidity in the dispersion of hazmat release (Anjana et al., 2018; Joaquim, 2008; Sanchez et al., 2018; Miñarro, 2004; Kallos et al.,1993)). Atmospheric stability identifies the degree to which vertical mixing in the lower troposphere is repressed or increased in a specific region under certain meteorological conditions (Bulko et al., 2018). Atmospheric stability classes are listed in Table 3-1, which reveals that wind speed and solar radiation during the daytime and wind speed and cloud cover overnight are required to find the stability class (Essenwanger & Stewart, 1978; Kahl & Chapman, 2018).

Table 3-1 Atmospheric Stability Classes for use with the Pasquill-Gifford Dispersion Model (Turner, 1994), (The classes A, B, and C stand for very unstable, unstable, and slightly unstable conditions, class D stands for a neutral condition, and class E and F stand for stable and very stable conditions).

	Day	Night
	Incoming Solar Radiation	**Thinly Overcast**

Wind speed 10 m (m/sec)	Strong	Moderate	Slight	> 4/8	< 3/8
				Low Cloud	Cloudiness
<2	A	A-B	B	F	F
2-3	A-B	B	C	E	F
3-4	B	B-C	C	D	E
4-6	C	C-D	D	D	D
>6	C	D	D	D	D

With that said, all the meteorological variables required for the hazard mapping are processed in Fig. 3.2.

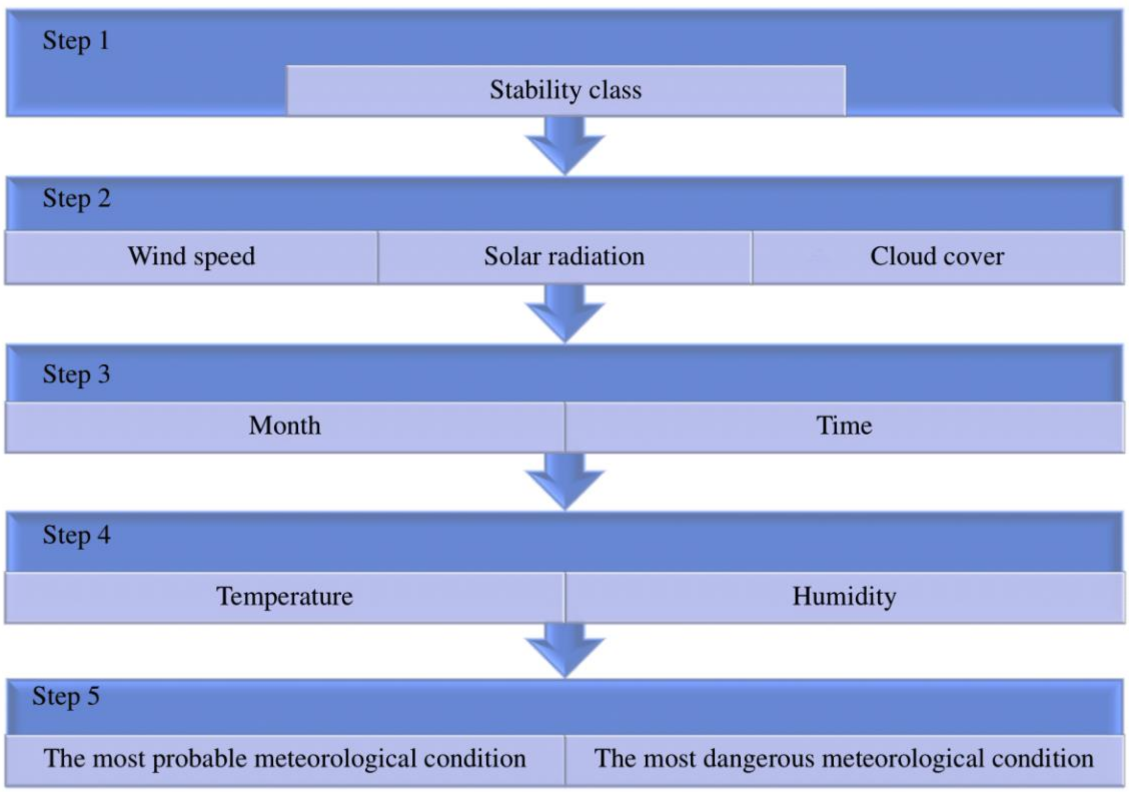


Fig. 3.2 The steps are taken to obtain the most probable and the most dangerous meteorological conditions.

As shown in Fig. 3.2, the first step in obtaining the most probable meteorological condition is to identify the most probable stability class using the regional meteorological data. Then, the most probable wind speed and solar radiation during the daytime and cloud cover overnight are obtained for this stability class. The most probable months and times in which the most probable stability class, wind speed, solar radiation, and cloud cover happened are identified using the steps shown in Fig. 3.2. Finally, the values of temperature and humidity are found for these months and times using the regional meteorological data. The most dangerous meteorological condition in terms of hazmat dispersion happens in stability class F (Zawar-Reza & Spronken-Smith, 2005; McCormick, 2013; Sanchez et al., 2018), which is very stable. Stable air, for example, means that the weather is calm and it does not change quickly (Bubbico & Mazzarotta, 2008). Dispersion of hazmat is worse during stable atmospheric conditions, as the amount of vertical mixing is reduced, and pollutants released in stable atmospheric conditions tend to spread horizontally rather than vertically (McCormick, 2013; Havens et al., 2012). The steps indicated in Fig. 3.2 are taken to obtain the meteorological variables required for the stability class F. This procedure creates more than one scenario for each meteorological condition. To cover all possibilities, all scenarios are modeled to find the greatest threat zones, which are selected as the worst-case scenario. The worst-case scenarios are then used to model the hazard maps for the most probable and the most dangerous meteorological conditions. Although hazmat is dispersed across the wind direction and occupies a part of the location where the hazmat is released (Nguyen et al., 2022), all wind directions (represented as 8 wind directions for calculation purposes) are considered to prepare a hazard map, which helps reduce possible errors in risk analysis. The change of wind direction with ground roughness (Z0) is also considered to model the hazard maps, as the earth's surface applies a frictional drag on the air moving above it, and this friction can change the direction of the wind (Mousavi & Parvini, 2016).

3.2.2 Population vulnerability assessment

Population vulnerability assessment is also required to develop emergency response plans and prevents severe consequences of incidents on people (Gai et al., 2020; Glade, 2003). Population vulnerability describes the population's characteristics to cope with hazards. Social vulnerability depends on the structure of society. Also, the reasons for social vulnerability are the economic, demographic, and political processes that affect the distribution of resources between different groups of people (Martins et al., 2012; Golovanevsky, 2007). Inadequate access to resources (knowledge, hazard information, education, and well-being) and physically or mentally vulnerable people (children, elders, females, and disabled individuals) are some sociodemographic characteristics that influence the population vulnerability reported by the social science community (Tahmid et al., 2020). These social vulnerability indicators affect the severity of the risk in different ways. For example, females are more vulnerable to toxic exposure due to the size of their body, physical strength, and hormonal differences (Vega et al., 2004). Children do not have adequate knowledge and ability to deal with hazards, and they also have immature organs with high metabolic rates that make them more vulnerable to toxic exposure (Ngo, 2001). Elders who have physical and cognitive difficulties due to old age are more vulnerable in emergency situations (Rosenkoetter et al., 2007). The people living in densely populated areas (e.g., crowded residential areas, workplaces, schools, hospitals, etc.) and people living in low-quality housing need immediate help and attention during accidents (Sengupta et al., 2016). Low-income people have barely access to communication technologies, and they may not be able to be prepared well in emergency situations (Ruiz et al., 2018). Illiterate people do not have adequate knowledge about hazards, and they may not be able to get ready and prepared in emergency situations quickly (Tierney, 2006). Finally, minorities (i.e., people with different religions, national origins, races, and colors) are more vulnerable to accidents as they might be exposed to social and economic discrimination (Payne-Sturges & Gee, 2006). These examples illuminate the importance of these social vulnerability indicators in preparing a vulnerability map.

3.2.2.1 Selection of social vulnerability indicators

In this study, the selection of social vulnerability indicators is based on the literature review (Cutter, 1996; Füssel, 2007; Kates & White, 1978; Robert W Kates, 1985; Cutter et al., 2003; Blaikie et al., 2014; MacEachren et al., 2006; Government of Canada, 2016) and expert opinions that aimed to find the most important social indicators and to include those that have not been studied previously. In addition, data availability also affected the selection of social vulnerability indicators.

The vulnerability indicators are considered as income (the population at the age of 15 and older with a total income lower than the society's median), labor (the population of unemployed people at the age of 15 years and older), education (the population of people at the age of 15 and older with no certification, diploma, or degree), children (the population of people at the age of 14 and younger), older people (the population of people at the age of 65 and older), aboriginals and visible minorities (aboriginal residents), language (the population of people with little to no knowledge of speaking the official languages of Canada (English and French), immigrants (the population of new immigrants), occupied private dwellings conditions (the population of people, living in the dwellings that require major repairs), dwelling characteristics (the population of people, living in movable dwellings), housing (the population of people, living in housing units with more than one person per room), private households by the number of household maintainers (the population of people, living in the houses with three or more household maintainers, private households conditions (the population of people, living in non-suitable housing conditions), female population, and the population density of the hazmat release location.

3.2.3 Population vulnerability map drawing

To optimize the process of creating vulnerability maps and to find the weight of each social vulnerability indicator, the Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) method is employed (Li & Zhu, 2019). AHP is a method for multicriteria decision-making that helps select an option between alternatives. As AHP does not consider vagueness for personal judgment, the fuzzy logic approach is used. In the Fuzzy-AHP method, the pair-wise comparisons of social vulnerability indicators are performed using the linguistic variables, which are shown by triangular numbers (triangular fuzzy numbers are used to represent uncertain and incomplete information in decision-making, risk evaluation, and expert systems). The steps taken in the Fuzzy-AHP method are as follow: (Yariyan et al., 2020; Gulum et al., 2021; Ekmekcioğlu et al., 2021).

Step 1): Experts compare the social vulnerability indicators using linguistics variables listed in Table 3-2:

Table 3-2 Linguistic terms and triangular fuzzy numbers.

Saaty scale	Description	Fuzzy Triangular Number
1	Equally important	(1, 1, 1)
3	Weakly important	(2, 3, 4)
5	Fairly important	(4, 5, 6)
7	Strongly important	(6, 7, 8)
9	Absolutely important	(9, 9, 9)
2		(1, 2, 3)
4	Values between two	(3, 4, 5)
6	adjacent scales	(5, 6, 7)
8		(7, 8, 9)

The pair wise comparison matrix is calculated as:

$$A^k = \begin{bmatrix} d_{11}^k & d_{12}^k & \dots & d_{1n}^k \\ d_{21}^k & \dots & \dots & d_{2n}^k \\ \dots & \dots & \dots & \dots \\ d_{n1}^k & d_{n2}^k & \dots & d_{nn}^k \end{bmatrix} \tag{3.1}$$

Where d_{ij}^{k} indicates the k^{th} expert's preference of i^{th} criterion over j^{th} criterion through fuzzy triangle numbers. A pairwise comparison matrix is made to determine the relative importance of different social vulnerability indicators with respect to the goal. This matrix clarifies which vulnerability indicator is more important for assessing the overall vulnerability of the population. This approach is taken for all possible pairs of indicators.

Step 2: If there is more than one expert, the average of the expert's preference is calculated as:

$$d_{ij} = \frac{\sum_{k=1}^{K} d_{ij}^{k}}{K} \tag{3.2}$$

Step 3: The geometric mean of fuzzy comparison values of each criterion is calculated as:

$$r_i = \left[\prod_{j=1}^{n} d_{ij}\right]^{\frac{1}{n}} \qquad i = 1, 2, \ldots n \tag{3.3}$$

Step 4: The fuzzy weight of each criterion is calculated using the next 3 sub-steps:

Step 4a: Calculate the vector summation of each r_i **.j**

Step 4b: Calculate the (-1) power of the summation vector.

Step 4c: Multiply each r_i with the reverse factor (see Eq. 4) to calculate the fuzzy weight of the criterion i ((w_i)):

$$w_i = r_i \otimes (r_1 \oplus r_2 \oplus \ldots \oplus r_n)^{-1} = (lw_i, mw_i, uw_i) \tag{3.4}$$

Step 5: To de-fuzzified w_i, the following equation is used:

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \tag{3.5}$$

Step 6: To normalize M_i as a non-fuzzy number, the following equation is used:

$$N_i = \frac{M_i}{\sum_{i-1}^{n} M_i} \tag{3.6}$$

To calculate the normalized weights of the social indicators, these steps are taken using MATLAB software. A geoprocessing model is designed using ArcGIS software, which uses the weights of the social vulnerability indicators. The model runs the calculations using the geospatial data for the social indicators and develops a vulnerability map. The vulnerability map reveals the location where a large hazmat release could cause severe consequences. The ArcGIS software then categorizes the location of the incident into different vulnerability levels (i.e., very low, low, medium, high, and very high).

3.2.4 Risk assessment

In risk-informed land-use planning, two methodologies have become popular: consequence-based and risk-based methodologies. Consequence-based approaches are based on assessing the consequences of potential accidents without taking into consideration their likelihood. Risk-based approaches consider both the probability and consequences of accidents (Tahmid et al. 2020). In this study, an integrated risk assessment procedure is developed by considering the possible consequences of incidents and the vulnerability of people living close to the hazmat release location. The social vulnerability indicators and the hazard levels of each geospatial zone are combined using a double-entry matrix (risk matrix in Fig. 3.3). The risk matrix was developed based on the studies conducted by Tahmid et al. (2020), Leśniak & Janowiec. (2019), Markowski & Mannan. (2008), and Federal Transit Administration. (2019). To develop this risk matrix, the direct sum of the variables is used, as the risk matrix is rectangular (5 levels of vulnerability and 3 levels of threat). This matrix is color-coded and is the central tool used for risk assessment. Levels of hazard and vulnerability are categorized into verbal and numerical scales. Hazard categories are high (3), medium (2), and low (1). These three levels correspond to the three output categories from the hazard analysis tool adopted in this study (ALOHA software). Vulnerability categories are very high (5), high (4), medium (3), low (2), and very low (1). These five levels correspond to the five output categories from the human vulnerability analysis in ArcGIS software. This matrix only shows the development of the methodology presented in this study, and each organization needs to develop a risk matrix based on the characteristics of their operations, their risk appetite, and their risk tolerance.

		Hazard level		
		High (3)	Medium (2)	Low (1)
Vulnerability level	Very high (5)	(8)	(7)	(6)
	High (4)	(7)	(6)	(5)
	Medium(3)	(6)	(5)	(4)
	Low (2)	(5)	(4)	(3)
	Very low (1)	(4)	(3)	(2)

Fig. 3.3 Risk matrix for risk assessment.

In this risk matrix, the higher the risk score, the greater the overall risk is. To evaluate the risk levels around the hazmat release location, the vulnerability of the surrounding population and the impact of different accident scenarios (each scenario has a different probability, which is indicated by regional meteorology) should be calculated.

The hazard and vulnerability maps are superimposed in ArcGIS, and the risk map is developed using the study performed by (Tahmid et al., 2020). The study area is divided into grid cells using ArcGIS. A grid cell is assigned a hazard and vulnerability score, and these two scores are combined to determine a risk score for that grid cell, as risk is defined as the function of hazard and vulnerability. Hazards are classified into three levels (low, medium, and high) and vulnerabilities into five levels (very low, low, medium, high, and very high). In cases of overlapping, the worst-case scenario is considered, for example, if a low hazard level for one scenario overlaps with a high hazard level for another scenario in a grid cell, the hazard score will be high in that grid cell. With the aid of the risk matrix shown in Fig. 3.3, 15 cases of possible combinations of hazard and vulnerability scores are obtained, and a risk score for each grid cell can be calculated. The risk score for each grid cell of the study area is displayed to model the risk map using ArcGIS.

3.3 Case study: Hazmat transportation and train derailment in a small Canadian city

3.3.1 Selection of the train derailment and research area

The procedure proposed in this study is tested in a small city in Canada. The data required for this case study are taken from a rail incident investigated by the Transportation Safety Board of Canada. This case study considers a potential train derailment of the tank cars loaded with Bakken crude oil, a light, low-density, very flammable crude oil. In this case study, the hazmat was released in a place with a few buildings and cultivated lands. The population of the place where the hazmat release occurred is estimated at around 65,000, and the land area is estimated at 50 square kilometers. The nearest road to the city is 1.28 km away from and toward the south of the release location. The nearest hospital is 14.8 km away from and towards the southwest of the release location, and the nearest residential area is 0.96 km away from and towards the southeast of the release location.

3.3.2 Modeling hazard scenarios

To model the threat zones in the ALOHA software, a horizontal cylindrical tank is considered with a length and volume of 51.3 feet and 30,079 gallons, respectively. The oil chemical mass is 70.3 tons, and the tank is 85% full. Two types of crude oil release are also considered, namely instantaneous release (rupture of the tank car) and continuous release (leakage from a 3" hole in the tank car).

The meteorological data of the incident location are obtained for a period of time between January 1, 2016, and December 31, 2017 (Government of Canada, 2021b). The frequency of the stability classes for this period of time (Government of Canada, 2021b) is shown in Fig. 3.4.

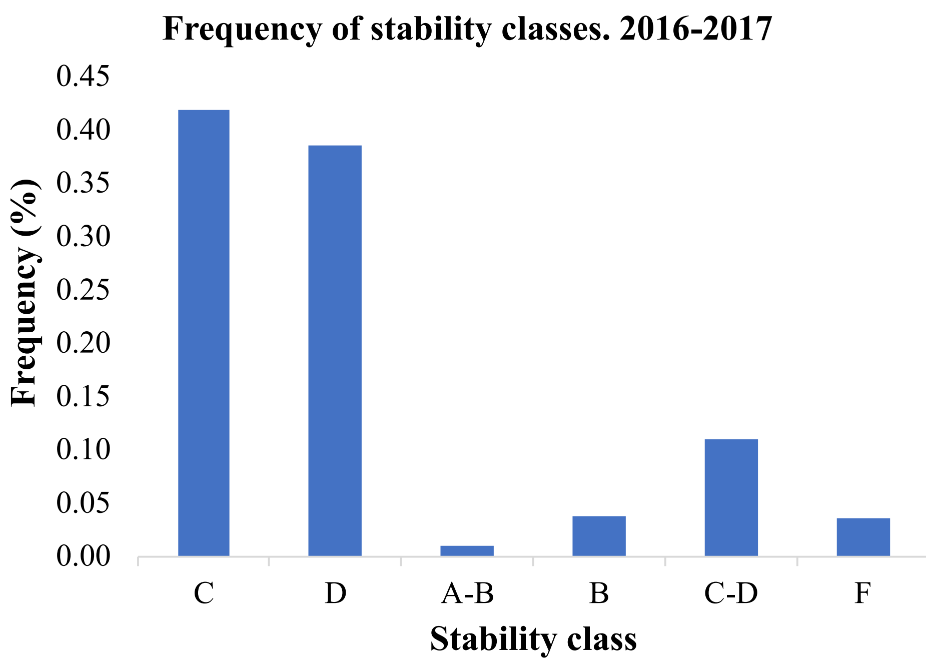


Fig. 3.4 Frequency of stability classes.

As shown in Fig. 3.4, the stability class C is reported for 153 days out of 365 days (42%). Stability class C is the most probable stability class compared to other stability classes in this location. The most probable wind speed and solar radiation are calculated in stability class C using the steps shown in Fig. 3.2. The wind speed greater than 6 m/s and strong solar radiation are the most probable conditions in stability class C (40 days out of 153 days have these conditions) as listed in Table 3-3. As mentioned, wind speed and solar radiation during the daytime and wind speed and cloud cover overnight are required to find the stability class. Stability class C happens during the daytime; therefore, solar radiation is considered in this procedure.

Table 3-3 Frequency of solar radiation and wind speed in stability class C (2016-2017).

Solar radiation / **Wind speed**	**Slight**	**Moderate**	**Strong**
2-3 m/s	13	0	0
3-4 m/s	36	0	1
4-6 m/s	0	12	39
>6 m/s	1	11	**40**

To reduce the number of scenarios that need to be modeled, the next step is to find the most probable times and months in which the most probable stability class, wind speed, and solar radiation happened. In June, 5 days out of 40 days have the most probable meteorological conditions between 9 am and 12 pm as listed in Table 3-4. To consider all the meteorological variables required for threat zones modeling, the humidity and temperature are also obtained for these 5 days.

Table 3-4 Frequency of months and times in stability class C, wind speed > 6 m/s, and strong solar radiation (2016-2017).

Time / **Month**	**6-9am**	**9-12pm**	**12-3pm**	**3-6pm**
March	0	1	0	0
April	0	1	2	2
May	1	3	3	0
June	1	**5**	3	2
July	1	3	2	2

August	1	1	2	1
September	0	2	1	0

The same procedure is repeated to find the most dangerous meteorological condition, and five scenarios are identified to be modeled. All the scenarios, which should be modeled to find the worst-case scenario with the greatest threat zones for the most probable and the most dangerous meteorological condition, are listed in Table 3-5.

Table 3-5 The most probable and the most dangerous meteorological variables (2016-2017).

ID	**Stability class**	**Wind speed (m/s)**	**Cloud cover (Tenths)**	**Solar radiation (W/m^2)**	**Month**	**Time**	**Humidity (%)**	**Temperature (°C)**	**Wind direction**
1	C	7.22	-	334.1	6	9-12	44.68	21.9	W
2	C	7.64	-	341.7	6	9-12	47.18	21.9	SW
3	C	8.25	-	439.7	6	9-12	49.29	22.4	W
4	C	7.19	-	447.2	6	9-12	45.65	28.9	SE
5	C	9.25	-	453.5	6	9-12	33.21	30.4	SE
6	F	2.47	6.5	-	12	21-00	52.2	4.5	SW
7	F	2.9	6.8	-	12	21-00	79.44	-8.5	SW
8	F	2.22	8.8	-	12	21-00	76.5	-5.5	SW

9	F	2.55	11.5	-	12	21-00	75.53	-11.1	S
10	F	2.97	13.7	-	12	21-00	76.02	-19.4	S

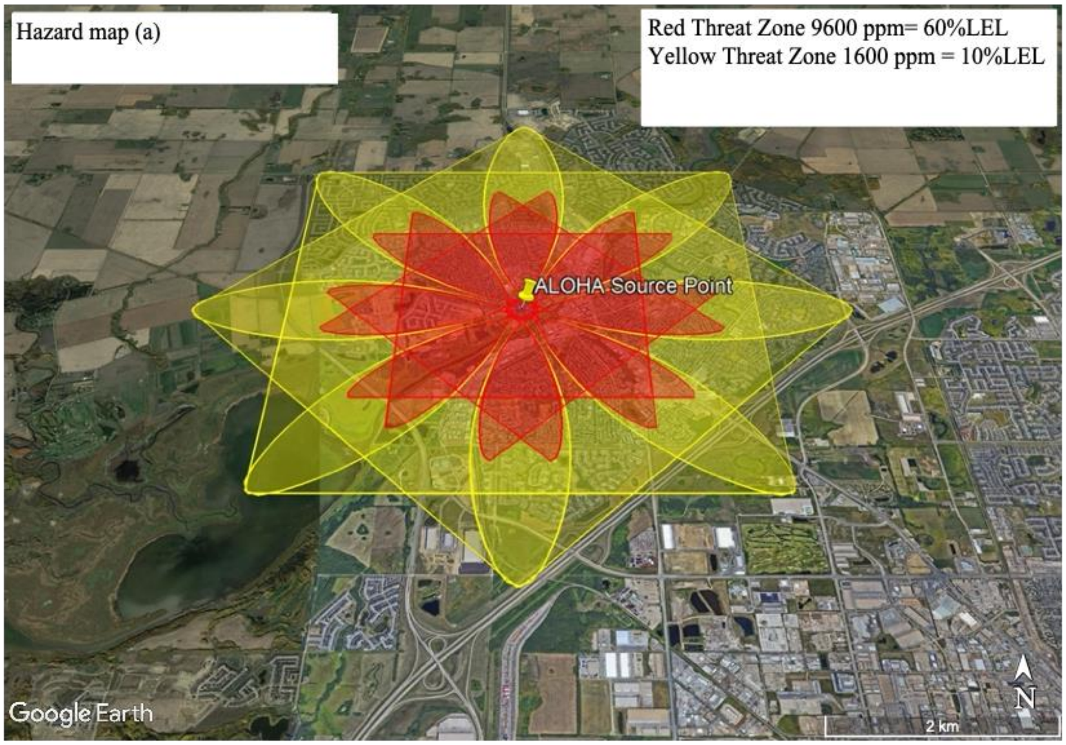
Table 3-5 only displays the variables necessary for modeling the hazard maps for the most probable and the most dangerous meteorological conditions. According to Table 3-1, stability classes C and F occur during the daytime and nighttime, respectively. If the stability class is C, solar radiation must be considered to determine the most probable meteorological condition and model hazard maps. To determine the most dangerous meteorological condition and model hazard map when stability class is F, cloud cover must be taken into consideration. The threat zones created due to different physical effects of hazmat release are modeled for all the scenarios listed in Table 3-5. Table 3-6 illustrates that Case IDs 4 and 7, whose type of release is rupture, create the greatest threat zones for the most probable and dangerous meteorological conditions. Additionally, flash fire threat zones are used in the preparation of hazard maps because they represent greater threat zones than other threat zones in Table 3-6 (bold values indicate the greatest threat zones). The red threat zone demonstrates the area with the highest hazard, and the orange and yellow threat zones demonstrate the areas with medium and low hazards, respectively.

Table 3-6 The greatest threat zones for the most probable and the most dangerous meteorological conditions (Red=R, Orange=O, Yellow=Y).

Meteorological condition / Threat zones (m) for each physical effect	The most probable meteorological condition (ID=4)		The most dangerous meteorological condition (ID=7)	
	3 inches hole	Rupture	3 inches hole	Rupture
Toxic dispersion	R:65.8 O:122.5 Y:224	R:282.5 O:470 Y:817.5	R:332.8 O:575.1 Y:954.6	R:655.6 O:1178.6 Y:1.9 km
Flash fire	R:165.5 Y:448	**R:620.9** **Y:1506**	R:745.2 Y:1.6km	**R:1539.8** **Y:3.05 km**
VCE	O:126.2 Y:191.1	O:484.6 Y:669.3	O:531.3 Y:652.9	O:1250.9 Y:1396.3
Pool/Jet fire	R:50.3 O:74.1 Y:117.04	R:145.4 O:225.9 Y:363.2	R:38.4 O:57.6 Y:91.4	R:117.9 O:178.4 Y:286.3
BLEVE/Fire ball	R:542.3 O:766.3 Y:1194.2	R:542.3 O:766.3 Y:1194	R:542.3 O:765.3 Y:1192.4	R:542.3 O:765.3 Y:1192.4

3.3.3 Hazard mapping

To prepare hazard maps for the most probable and the most dangerous meteorological conditions, the greatest threat zones are combined with the satellite maps obtained using Google Earth in eight wind directions (see Fig. 3.5). Fig. 3.5 illustrates that the default LOC for the red and yellow threat zones is 60% and 10% of the Lower Explosive Limit (LEL), respectively. LEL is the lowest concentration of a gas or vapor that will ignite in the air. It varies from gas to gas considering that most flammable gases have an LEL of less than 5% by volume (Bhaduri et al., 2021). If the intensity of the physical effects is uniform in all directions, the hazard maps may be circular, but if it varies in direction, they may be irregular (Sanchez et al., 2018).



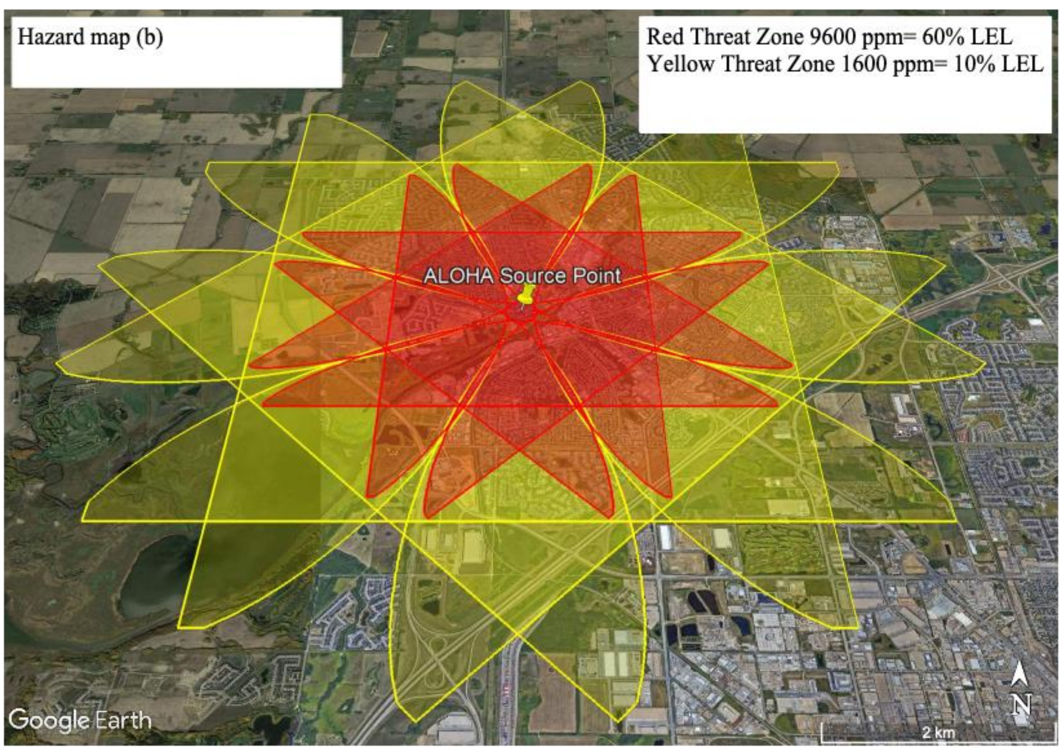


Fig. 3.5 (a) The hazard map of the most probable meteorological condition and (b) the hazard map of the most dangerous meteorological condition created by implementing the greatest threat zones in Google Earth (GoogleEarth, 2021).

3.3.4 Population vulnerability mapping

To find the weights of social vulnerability indicators, expert elicitation is employed with the Fuzzy-AHP method (see Table 3-7). More descriptions about the social indicators are provided in Table 3-8.

Table 3-7 The weights of social vulnerability indicators calculated using the Fuzzy-AHP method.

Social vulnerability indicator	Weight	Rank
Population at the age of 15 years and older with a total income lower than the society's median	1.2%	15
The population of unemployed people at the age of 15 and older	1.2%	14
The population of people at the age of 15 and older with no certification, diploma, or degree	1.8%	12
The population of people at the age of 14 and younger	17.3%	2
The population of people at the age of 65 and older	12%	3
Aboriginal residents	1.6%	13
The population of people with little to no knowledge of speaking the official languages of Canada (English and French)	7.7%	5
The population of new immigrants	1.9%	11
Female population	8.4%	4

The population density at the hazmat release location in 2016	21%	1
The population of people, living in dwellings that requires major repairs	5.9%	7
The population of people, living in movable dwellings	6.5%	6
The population of people, living in housing units with more than one person per room	3.8%	9
The population of people, living in houses with three or more household maintainers	3.8%	9
The population of people, living in non-suitable housing conditions	5.8%	8

The weights of social vulnerability indicators are entered into the ArcGIS software to create vulnerability maps based on the census information in the hazmat release location. The vulnerability map for each social vulnerability indicator is shown in Figs. 3.6 (a) aboriginal residents, (b) the population of people at the age of 14 and younger, (c) the population of people at the age of 15 and older with no certification, diploma, or degree, (d) the population of people at the age of 65 and older, (e) female population, (f) the population of new immigrants, (g) the population of people at the age of 15 and older with total income lower than the society's median, (h) the population of people with little to know knowledge of speaking the official languages (English and French), (i) the population of people, living in the housing units with more than one person per room, (j) the population of people, living in movable dwellings, (k) the population density in 2016, (l) the population of people, living in dwellings that require major repairs, (m) the population of people, living in unsuitable housing conditions, (n) the population of people, living in the houses with three or more household maintainers, and (o) the population of unemployed people at the age of 15 and older.

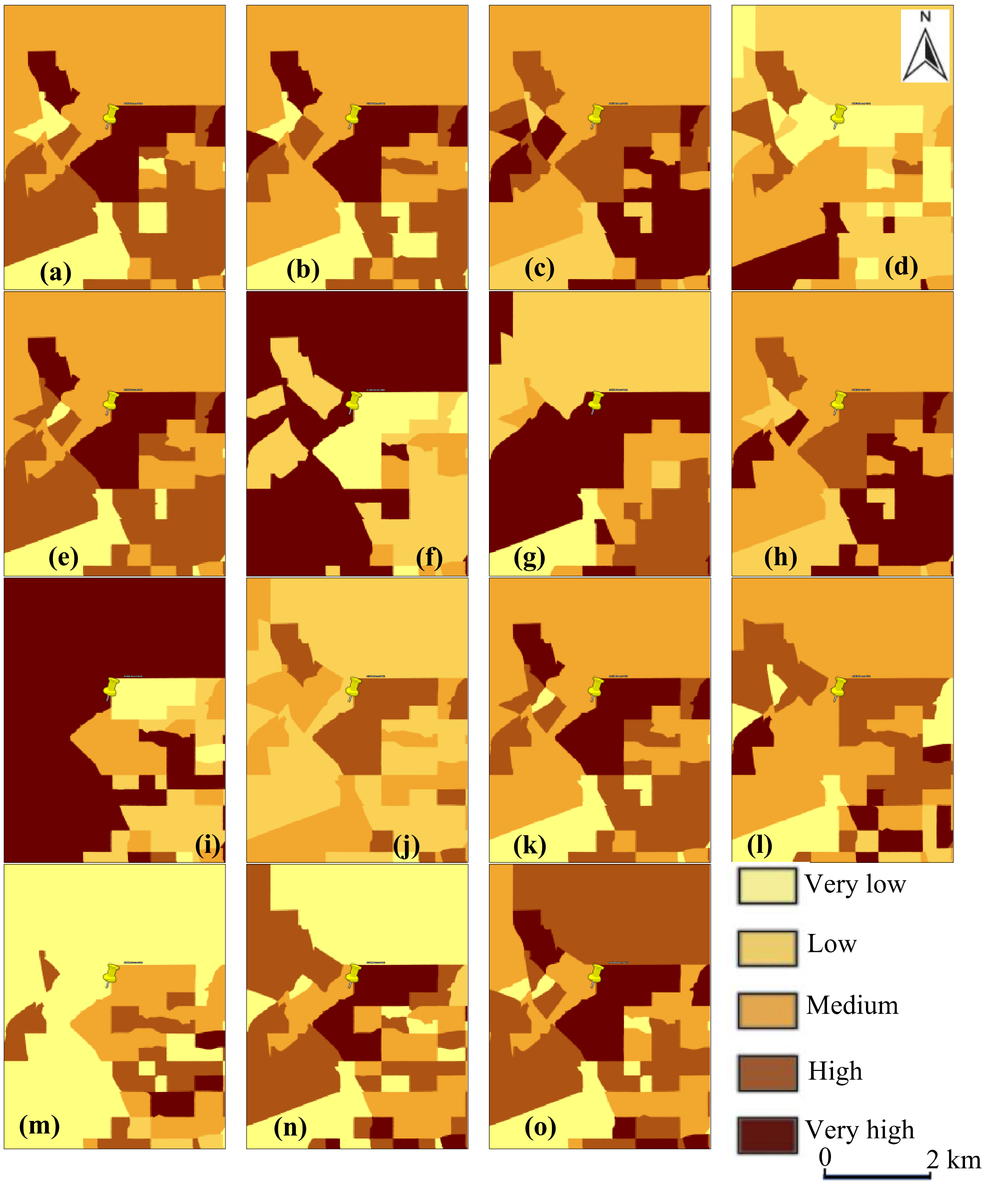


Fig. 3.6 The vulnerability maps of different social vulnerability indicators.

All the social vulnerability indicators are also combined to generate a general vulnerability map as shown in Fig. 3.7. It is observed that the vulnerability changes widely across the entire area, and the south and east sides of the hazmat release location are more vulnerable than the other sides

(Fig. 3.7). However, the road accessibility on the south side provides easier transportation in the case of hazmat release (the nearest road to the city is 1.28 km away from and toward the south of the release location). By contrast, population vulnerability is lower in the north and southwest (Fig. 3.7), which is mostly related to the lower population density in these locations (see Fig. 3.6 (k)). Population density is recognized as one of the most important social vulnerability indicators for creating the vulnerability maps in Table 3-7. Although population vulnerability in the southwest is low, the availability of a hospital in this area (14.8 km from the hazmat release location) makes this location even less vulnerable. Population vulnerability is affected by many factors, and considering various factors create more accurate vulnerability and risk maps.

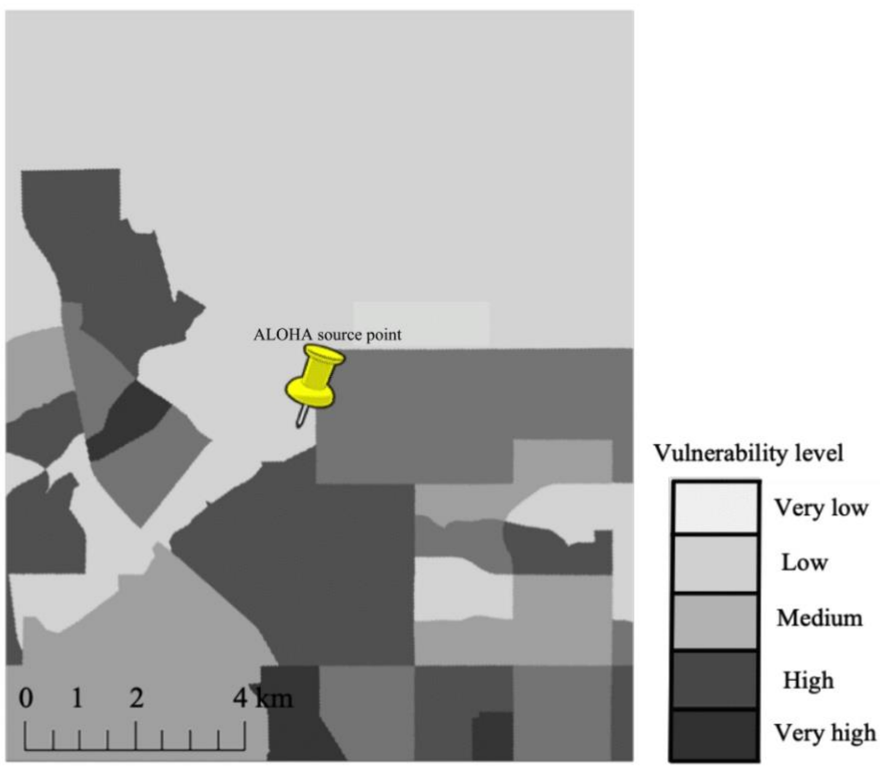


Fig. 3.7 The vulnerability map generated by combining all the social vulnerability indicators.

3.3.5 Risk mapping

The risk scores for the hazmat release location are identified using the risk matrix shown in Fig. 3.3, and the risk maps are generated for the most probable and the most dangerous meteorological conditions (Fig. 3.8). A risk map is an overlay analysis of hazard and vulnerability maps, which reflects hazard and vulnerability at the same time (Fengying Li et al., 2010).

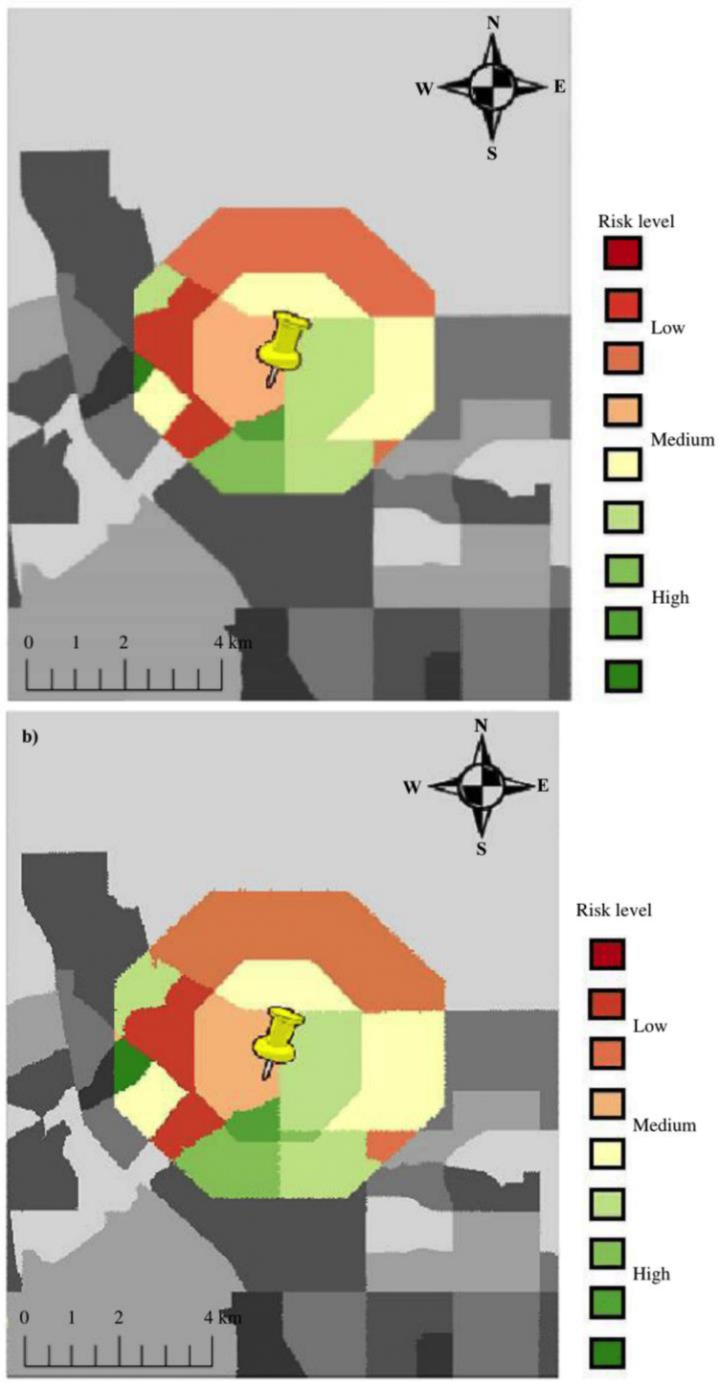


Fig. 3.8 (a) The risk map of the most probable meteorological condition and (b) the risk map of the most dangerous meteorological condition.

Not all the areas with high hazards indicated in Fig. 3.5 are considered as the areas with high risks, as shown in Fig. 3.8. For instance, the west side of the release location close to the hazmat source is found as the area with the highest hazard on the hazard maps (see Fig. 3.5). However, this area is considered with moderate risk on the risk maps (see Fig. 3.8) as the population vulnerability is low on the west side. Hazard maps only display the footprint for lethality and injuries; however, risk maps consider the vulnerability of people in assigning the risk values. The vulnerability-risk-based approach provides more accurate results in terms of land-use planning and emergency management.

3.4 Discussion

Risk maps can provide adequate guidelines for emergency management and land-use planning, as they consider the characteristics of the people living close to the hazmat release location (Meteoblue, 2021). Improving the distribution of health and medical supplies and paths dredging in extremely populated areas are examples of risk maps application in emergency management. From the land-use planning viewpoint, a safe distance between the railway track and residential areas should be considered in the future. Also, hospitals, medical centers, route access, and emergency services need to be considered in land-use planning to reduce and prevent the losses of future incidents. For instance, the population of people at the age of 14 and younger (i.e., children) is very high on the south and east sides of the hazmat release location compared to other locations (see Fig. 3.6 (b)), and consequently the risk is also high in these areas (see Fig. 3.8). Thus, risk managers should consider that children are not able to escape these risky areas as quickly as adults, and children are more vulnerable in the case of an emergency evacuation. Higher priority should be given to them in emergency management in terms of medical and health supplies. The vulnerability of this group of people is further increased, as no medical unit exists in the south and east sides of the hazmat release location. People must go to the nearest hospital in the southwest, which is 14.8 km away from the release location. Improvements in the healthcare distribution network need to be considered to reduce the risk of hazmat railway incidents. Also, the population of people living in houses with unsafe structures is high on the south and east sides (see Fig. 3.6 (m)), and risk maps indicate them as high-risk areas (see Fig. 3.8). These houses cannot protect the people in the case of toxic release, which makes them more vulnerable, and consequently, more attention to these people is required from emergency responders. Lastly, adequate distribution of health and medical supplies and better allocation of medical units need to be evaluated. These examples reveal that social vulnerability indicators play an important role, which should be considered in developing risk maps and optimizing emergency management and land-use planning.

3.5 Limitations and research assumptions

To prevent the severe consequences of hazmat incidents on people, population vulnerability should be assessed (Tahmid et al., 2020). The population affected by the consequences of hazmat release is a function of population density, the characteristics of the people living in the hazmat release location, the population of the group of people hospitalized, living in nursing homes, etc. The purpose of this study was only to generate vulnerability and risk maps based on the sociodemographic characteristics of people. Some of these vulnerability factors (e.g., distance to institutions for people with disabilities, distance to road networks, escape areas, etc.) have not been considered in this study as these data were not available in our current database; however, the procedure presented can implement these factors for areas with information availability.

The population of people and meteorological conditions change with time; however, the risk assessment method used in this is static. To consider the change of risk over time, the current risk assessment model could be combined with dynamic models. Deciding to implement a dynamic risk estimate approach, however, would need to balance comprehensiveness and applicability for emergency response purposes.

Lastly, although ALOHA software is a widely used software, it has some limitations, such as the estimation of hazard threat zones for a maximum of 10 km or 1 hour, and the inability to simulate threat zones for very stable atmospheric conditions or during wind speeds less than 1 m/s. (Guan et al., 2022). The PHAST software provides a suitable alternative, and the procedure presented here allows for the use of this or other software packages.

3.6 Conclusion

Hazmat railway incidents can pose threat to the people living in the areas close to railway tracks. Risk assessments are necessary to reduce the severe consequences of hazmat release on people. In this study, a procedure was developed to analyze the risk of hazmat railway incidents, and then applied to a small city in Canada. The meteorological variables (e.g., stability class, cloud cover, wind speed, solar radiation, etc.) were processed to create hazard maps for the most probable and the most dangerous meteorological conditions. The sociodemographic characteristics of people were identified and ranked to simulate the vulnerability map in the ArcGIS software. Risk maps were generated by superimposing the hazard and vulnerability maps in the ArcGIS software, which indicate a risk range from low to high, using a double-entry risk matrix. Risk maps reflect both hazard and vulnerability maps, which reveal that the areas with high hazards shown on the hazard maps are not necessarily the areas with high risks shown on the risk maps. The risk maps can be used to prioritize emergency response decisions and to improve land-use planning based on population vulnerability. They can also be used to improve the quality of life of the people living in higher-risk areas by boosting education, quality of housing, wellness, etc. This risk assessment method along with other quantitative methods (i.e., decision tree and Bayesian network analysis) can be a great help to evaluate and reduce the risk of hazmat railway incidents. It is worth mentioning that this risk assessment method can also be applied to different types of railway incidents in various locations or incidents occurring in other industries if the required data are available.

Table 3-8 The association between social vulnerability indicators calculated using Chi-Square analysis.

Social vulnerability indicator	Chi-Square
The population at the age of 15 years and older with a total income lower than the society's median to the population of unemployed people at the age of 15 and older.	12.33
The population of people at the age of 15 and older with no certification, diploma, or degree to the population of people with little to no knowledge of speaking the official languages of Canada (English and French)	8.33
The population density at the hazmat release location in 2016 to female population.	11.4
The population density at the hazmat release location in 2016 to the population of new immigrants.	6.7
The population density at the hazmat release location in 2016 to aboriginal residents.	6.2

The population of people, living in dwellings that requires major repairs to the population of people, living in housing units with more than one person per room	5.3
The population of people, living in houses with three or more household maintainers to the population of people, living in non-suitable housing conditions	7.4

Although the social indicators in this study are derived from literature reviews and expert analysis, Table 3-8 indicates that they are related based on information provided in section 2.4.3. Table 3-8 does not include indicators with weak associations because their Chi-Square was below 3.84.

Chapter 4

Chapter 4 of this thesis has been published as Hadiseh Ebrahimi, Fereshteh Sattari, Lianne Lefsrud, Renato Macciotta, "A machine learning and data analytics approach for predicting evacuation and identifying contributing factors during hazardous materials incidents on railways". The contributions of the authors are listed below:

Hadiseh Ebrahimi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. Fereshteh Sattari: Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Supervision, Project administration. Lianne Lefsrud: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. Renato Macciotta: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

4.1 Introduction

Natural (i.e., tornadoes and severe storms, floods, and earthquakes) and human-caused (i.e., hazmat releases, airline disasters, and biological agents) disasters have the potential to cause catastrophic loss of life and physical destruction (Ahmadi Rad et al. 2023; Gai et al. 2018). Before, during, and after a hazard impact, actions are taken to prevent death, reduce economic losses, and alleviate suffering from the hazard impact. Evacuation of threatened populations, opening shelters, providing medical care, firefighting, and urban search and rescue are all possible response actions (Oh & Lee, 2020). Emergency evacuation is often ordered as a precautionary measure to safeguard the health and safety of people after natural and human-caused disasters. The purpose of emergency evacuation plans is to provide logical procedures for responding to an emergency (Yoo & Choi, 2019).

This article develops a framework to predict evacuation after railway incidents and identify the contributing factors to the evacuation. By drawing from emergency evacuations in natural disasters, especially for vulnerable populations, this article also uses machine learning to examine the relevant factors for emergency evacuations following the release of hazmat.

4.2 Literature review

4.2.1 Emergency evacuation in natural disasters

Extensive research has been conducted to provide emergency evacuation plans to reduce the impact of natural hazards. For instance, Dulebenets et al. (2019a) present a mixed-integer programming model that assigns vulnerable individuals to emergency shelters using evacuation routes during available evacuation periods in coastal areas prone to natural hazards. The results indicate the proposed heuristic algorithms can provide high-quality solutions within a reasonable time frame. Dulebenets et al., (2019b) explore the effects of a variety of factors on driving performance indicators under emergency evacuations caused by natural hazards. The results indicate age, gender, visual disorders, lane size, and space headway substantially impact individuals' driving abilities. Using a driving simulator, Abioye et al. (2020) emulate realistic emergency evacuation scenarios and quantify the perceived driving difficulties of a vulnerable population under emergency evacuation caused by natural hazards. The analysis shows age, gender, education, race, chronic diseases, and self-reported driving ability significantly influence the performance indicators considered. Abdulhalim et al. (2021) analyze the pedagogical and behavioral considerations for Deaf and Hard of Hearing (DHH) children in the school context and their connections to the Disaster Risk Reduction (DRR) framework. They propose a strong theoretical basis for enhancing the post-earthquake evacuation preparedness of DHH children in schools. He (2021) develops a fully random evacuation model to analyze the evacuation of multi-story buildings during earthquakes. This model simplifies the simulation of pedestrian dynamics in three dimensions, couples the evacuation processes for emergency situations with the damage processes for structures, and incorporates randomness in pedestrian dynamics, structural damage, and seismic excitation. Based on a survey conducted in 2015, Dhellemmes et al. (2021) explore tsunami awareness, preparedness, and evacuation intentions among residents of the East Coast of the North Island of New Zealand. Despite knowing that their region is tsunami-prone, coastal residents were relatively unprepared and had unrealistic expectations regarding evacuation procedures.

4.2.2 Emergency evacuation in human-caused disasters

The emergency evacuations caused by human-caused disasters have been the subject of numerous studies. For instance, Gai et al. (2018) provide and validate an assessment framework for the dissemination of evacuation warnings and the calculation of health consequences based on regional evacuation modeling for toxic-cloud releases. Regional evacuation modeling incorporated several actual phases, such as a division called an evacuation unit, a way to calculate movement time quickly through the evacuation unit, loading of evacuation flows, and warning diffusion. Yoo & Choi (2019) develop a real-time risk analysis tool based on a geographic information system (GIS) to plan for emergency evacuation in hazardous chemical leakage accidents. As an alternative to an outdoor evacuation plan that is outside the range of damage, this study recommended developing an indoor/outdoor evacuation plan. Li et al. (2022) develop a multiagent-based model for simulating the evacuation processes of a chemical plant and assessing the effectiveness of optimization strategies for the original evacuation plan. They find optimized evacuation routes reduce the risk of gas exposure during the evacuation of some evacuation sub-areas. Hazardous chemicals are often transported through densely populated areas, which can pose serious problems to the public if leaks occur (Salarian et al. 2020). Failure to take effective emergency measures, such as evacuation in the event of hazmat release, can result in secondary accidents, such as fire, explosion, and poisoning (Hou et al., 2021).

4.2.3 Emergency evacuation in railway incidents

Hazmat rail incidents are described as having low probability and high consequences due to their specialized physical and chemical properties, especially their tendency to cause fires, explosions, and leaks during incidents (Ebrahimi et al., 2022). In the aftermath of a railway incident, response and recovery are required (Saat et al., 2014). In response to a railway incident, an emergency evacuation order might be issued to minimize the casualties and the severity caused by the consequences (Phark et al., 2018). Several studies have been conducted to facilitate emergency evacuations. Dunning & Oswalt (2007) examine the railroad chlorine spill in Graniteville, South Carolina, as a case study to illustrate the issues related to the capacity of the small town to handle no-notice evacuation. The results indicate the necessity of railway incident prevention using rail safety signal technology, enhancing public education on hazmat, and providing a comprehensive emergency response training program even for towns with a small population. Using a risk analysis model coupled with an optimization technique, Kawprasert and Barkan (2008) discuss how risk can be reduced through rationalization of the rail route structure for hazmat transportation. A risk metric was defined as the number of people who may need to be evacuated or sheltered in place because of hazmat release. Their results show route rationalization can reduce the risk of population exposure and evacuation. Zografos & Androutsopoulos (2008) describe a decision support system for assessing alternative distribution routes and coordinating emergency response deployment decisions with hazmat routes in terms of travel time, risk, and evacuation implications. They identify evacuation routes from the impacted area to designated shelters and estimate evacuation times. Kecklund et al. (2012) examine various situations that may occur in railway accidents using a systems safety perspective to address the interaction between humans, technology, and organizations and identify areas for improvement. They report that a few areas need improvement, including communication, reducing the time required to decide regarding evacuation and enforcing the decision, and training the staff. Saat et al. (2014) provide a methodology for estimating the costs of railroad transportation of hazmat. An estimation of evacuation costs was made based on the possible human exposure. The authors find chemicals transported along routes with higher-density populations tend to incur higher costs. To reduce the evacuation cost, the authors suggest a detailed track-segment-specific GIS analysis to prioritize infrastructure improvements along a rail network. Liu (2017) evaluates the relationship between rail failures and hazmat transportation risk. They analyze the potential number of people who need to be evacuated as a measure of risk. Their analysis suggests inspecting a small number of high-risk segments on a regular basis, improving rail defect detection, and improving tank car safety design can reduce the overall route risk**:** Iranitalab et al. (2019) examine different types and consequences of crude oil release from trains and evaluate response/cleanup costs and evacuation costs. Their results indicate the tank car head puncture resistance system and the tank car insulation are directly associated with the likelihood of gas dispersion. People near railroads face risks related to toxic gas dispersal from crude oil-carrying trains, and a resulting possible explosion with no time to evacuate. Salarian et al. (2020) simulate different solutions to reduce the evacuation time from a railway station in the event of a fire. Several scenarios were simulated based on (1) the number of gates and exit doors, (2) gate width, (3) obstacles, (4) the priority of the exit doors, and (5) the safe zone to reduce evacuation times. The results reveal that increasing the number of exit doors from two to four and considering a safe zone at the same time results in the fastest time for evacuation. Tang et al. (2020) estimate the implicit cost of derailments caused evacuations by depressing the value of residential properties. According to their results, prices are significantly different between houses outside vs. within around one mile of derailment sites (the evacuation zone). The results of this study provided evidence for evaluating the economic costs of rail shipping and for considering policy options in the current era of U.S. energy transformation. Schneller et al. (2020) evaluate railway incidents caused by failures in railway infrastructure and resulting in evacuations. Interviews, surveys, GIS mapping, and archival data analysis show the public was unaware of oil shipments and evacuation plans, and the perceived risk was high. Information about crude oil shipments and evacuation routes should be communicated (by mail) to potential impact zones. Kang et al. (2023) propose a risk assessment methodology that includes both mainline and yard operations to compare shipments with unit trains and manifest trains. Considering evacuation response time, risks were estimated as the total number of expected casualties. The evacuation time of nearby buildings was 4 minutes, and the maximum fire event duration was 120 minutes. Their results indicate that placing all tank cars in the positions with the lowest likelihood of derailing and switching tank cars alone in the classification yards results in the lowest risk.

The literature reviewed in this study reveals that evacuations have been evaluated from a variety of perspectives, including efficient implementation of emergency evacuation by identifying evacuation routes, training people, etc. (Dunning & Oswalt, 2007), reducing the risk of railway incidents based on the number of people that need to be evacuated (Kawprasert & Barkan, 2008), estimating evacuation times for escaping the impacted area (Zografos & Androutsopoulos, 2008), calculating evacuation costs (Saat et al., 2014), and determining the impact of the evacuation on the value of properties (Tang et al., 2020). To the best of the authors' knowledge, no studies in the literature aim to predict immediate evacuation orders in case of a railway incident. Obtaining more data for a decision on an evacuation order results in more accurate results. However, it takes time to collect and analyze this new information, which prevents prompt decision-making with respect to evacuation.

In fact, a prompt and accurate evacuation order is imperative to save people's lives in the case of hazmat release close to populated areas (Phark et al., 2018; De Silva, 2001). A high level of accuracy is essential: issuing unnecessary emergency evacuation orders can lead to the loss of time and resources, but failure to issue emergency evacuation orders can result in an injury or fatality. Similarly, speed is extremely critical when making a decision regarding an evacuation order. A delayed decision can result in severe consequences for people that are extremely difficult to alleviate (Phark et al., 2018). As an example, a hazmat release accident occurred in the Republic of Korea in 2015. Two and a half hours after the accident, risk managers decided an emergency evacuation order was not necessary. Initially, 15 people were injured, but this number increased to 105 due to poor evacuation decisions (Baek et al., 2022). Due to the complexity of railway incidents involving hazmat, making an accurate and timely decision regarding evacuation can be very challenging. Implementing a method that can quickly and accurately predict evacuation orders with limited data is imperative.

Although accurate decisions for evacuation can minimize the casualties by moving people who are close to the incident area to a safe place, a better understanding of the causes and factors contributing to the evacuation, as one of the emergency responses, can provide insights into disaster risk reduction (Liu et al., 2021; Halim et al., 2018). Numerous studies have been conducted on evacuations caused by railway incidents transporting hazmat, as mentioned earlier. However, to the best of the authors' knowledge, no study has examined the underlying causes and factors contributing to the evacuation. The major causes of railway incidents are usually selected from a predefined list, which includes equipment failure, track failure, the environment, etc. (Ebrahimi et al., 2021). Detailed information about the latent causes and contributing factors to the incidents and evacuations can only be addressed in incident reports (Pyun et al., 2020). Using incident reports, operators may provide a narrative description of the incident, from which any additional contributing factors can be extracted to create a more comprehensive causation model. The unstructured nature of the incident description and comment section necessitates applying an appropriate method to extract hidden information (Liu et al., 2021).

Due to the high speed of data processing and the high accuracy of data prediction, machine learning models have been extensively used in transportation safety research (Xuecai et al., 2022). Machine learning models have been utilized in predicting evacuation in various fields, such as construction accidents (Zhu et al., 2021; Zhao et al., 2020), chemical accidents (Phark & Jung, 2017), natural disasters (Roy et al., 2021; Burris et al., 2015), and pedestrian movement (Wang et al., 2019; Dong et al., 2019). Yet, little to no research has evaluated the effectiveness of machine learning models for predicting evacuations in railway incidents transporting hazmat. In the first part of this study, a machine learning model is developed to predict accurate and timely decisions regarding evacuation to reduce the number of people who might be affected by the consequences of railway incidents transporting hazmat.

An incident description can be a valuable tool for identifying the underlying causes and contributing factors. It is not only time-consuming but nearly impossible to search through thousands of such descriptions. Currently, no system exists that offers automated solutions to extract causations and identify contributing factors from the large quantity of text data (Liu et al., 2021; Naghavi-Konjin et al., 2020; Adedigba et al., 2016). In the second part of this study, brief descriptions of railway incidents were analyzed to provide insightful information regarding the factors contributing to the evacuation using natural language processing (NLP) and co-occurrence network analysis. Besides providing a cause-and-effect explanation of the incident, this method also identifies knowledge accumulated in the incident narratives. In addition to the potential for turning incident text data into valuable knowledge, the complexity of the network structure can facilitate the identification of a hierarchy of causal relationships using the co-occurrence analysis. Also, this work may improve automated risk and accident modeling analysis in the railway industry.

4.3 Materials and methods

Fig. 4.1 summarizes the methodological approach used in this study.

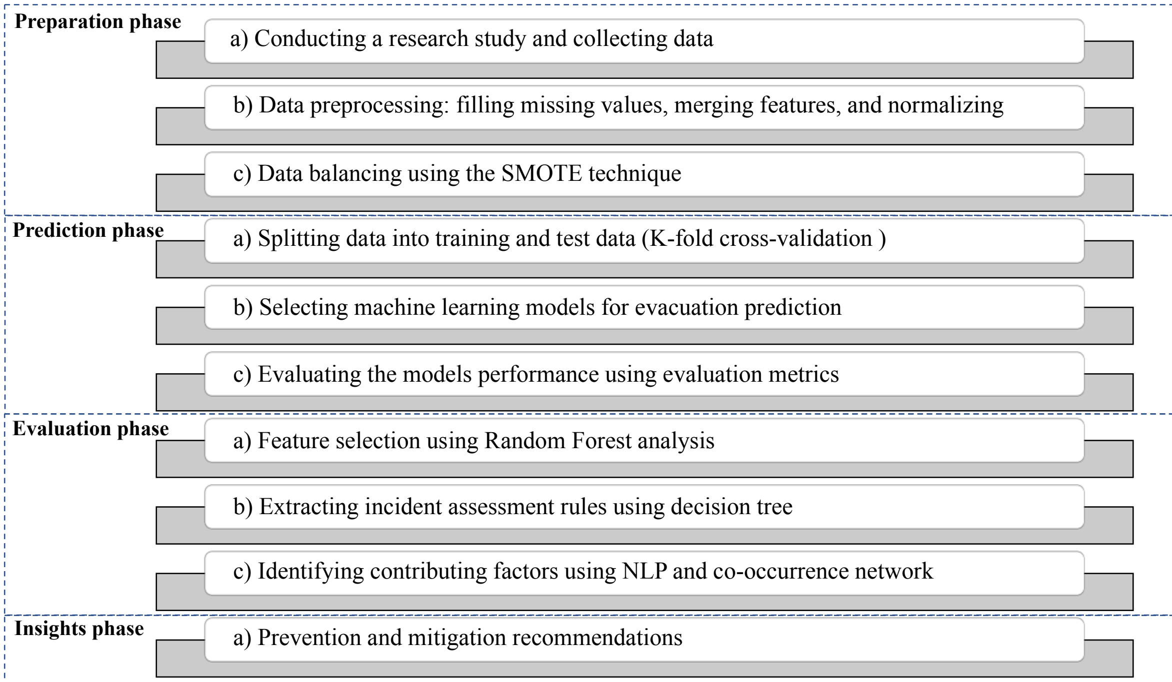


Fig. 4.1 A brief overview of the study's steps.

4.3.1 Data description

Fourteen years (2007-2020) of hazmat railway incident data for Canada were extracted from the Dangerous Goods Accident Information System (DGAIS) (Transport Canada, 2020). DGAIS is a federally run program in Canada that annually provides data on incidents related to the transportation of dangerous goods. The dataset contains 575 rows (incidents) along with 23 columns that describe the characteristics of the incidents. The characteristics of the incidents include information about the date and time of the incident, incident location, postal code, the closest city to the incident location, the province where the incident occurred, latitude and longitude, mileage traversed by train, transport mode, transport phase, type of incident, action on Means of Contaminant (MOC), hazmat released (yes/no), evacuation (yes/no), class of hazmat (hazmat are categorized into nine classes with some divisions, for instance, class 2 contains flammable gases and class 3 contains flammable liquids), hazmat UN number (numbers are four-digit numbers, used to identify the type of hazmat in the framework of international transport), the amount of hazmat released (by volume), and a brief description of the incident. Data analysis reveals that 82.14% of railway incidents released hazmat, while 17.87% did not. Fig. 4.2 is a visual of the current dataset, where the radius of the circle corresponds to the volume of hazmat released. The Lac-Mégantic railway derailment (Quebec, 2013) released the most hazmat (about 6 million liters of petroleum crude oil), followed by the Gogama railway derailment (Ontario, 2015) and Lanigan railway derailment (Saskatchewan, 2019) with 2.6 million and 1.5 million liters of petroleum crude release, respectively.

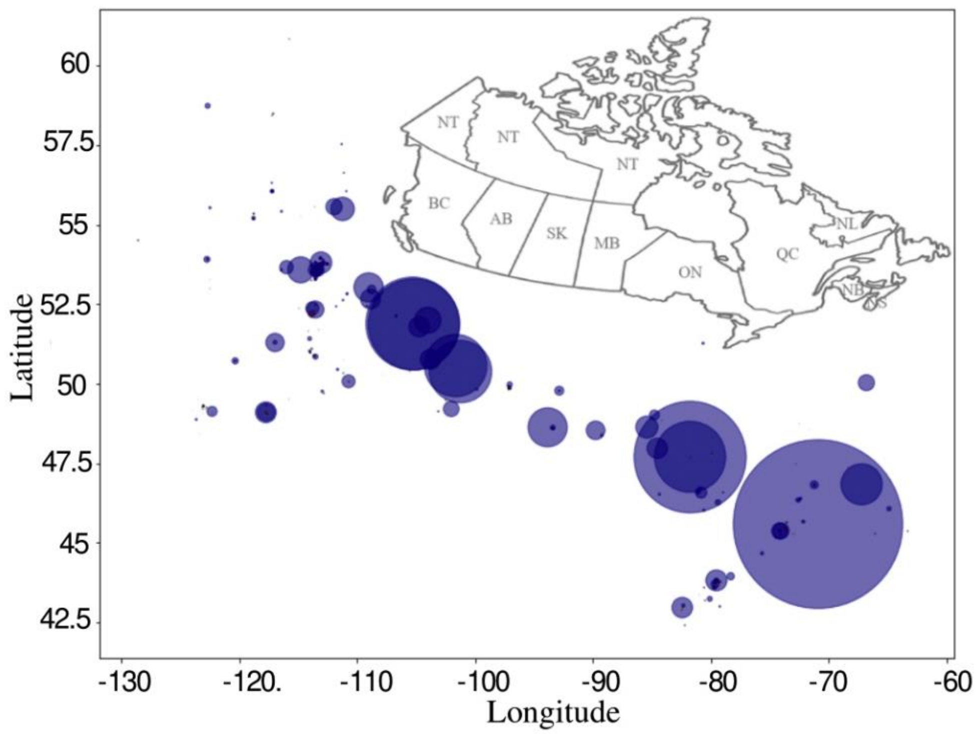


Fig. 4.2 Locations where hazmat was released (circle radii scaled to volume released).

In Fig. 4.3, locations, where railway incidents resulted in evacuation, are shown in blue circles, and locations that did not require evacuation are depicted in red circles. Fig. 4.3 shows the number of railway incidents involving evacuation is lower than those without. Incidents that led to evacuations have been more frequent in Alberta and then Ontario than in other regions of Canada.

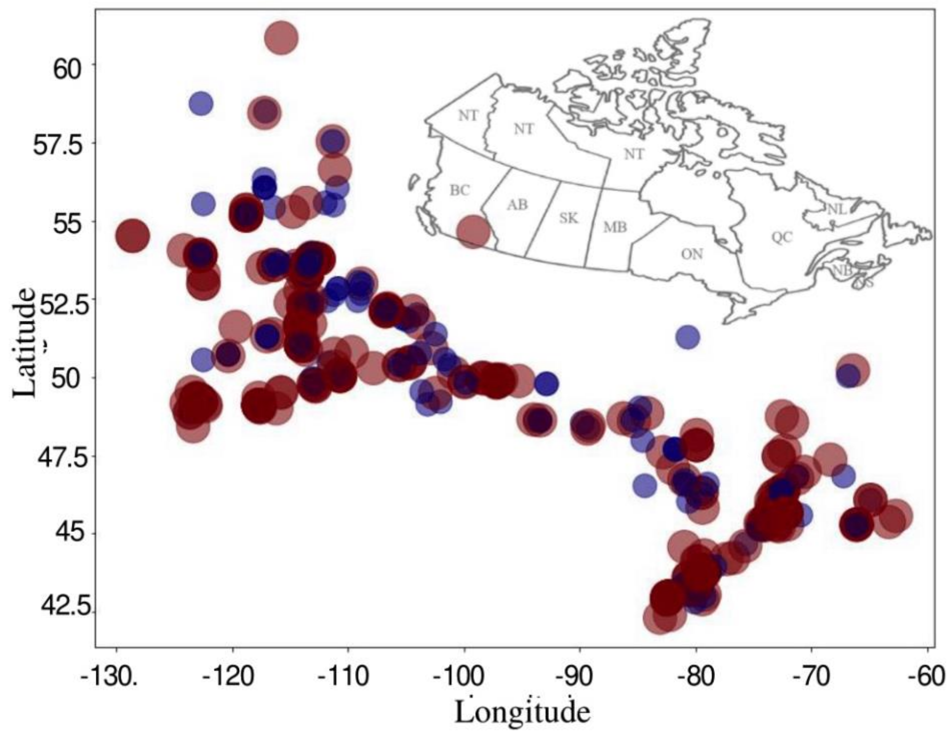


Fig. 4.3 Location of hazmat incidents resulting in evacuation (blue) and not resulting in evacuation (red).

4.3.2 Data preprocessing

Data provided by the DGAIS should be processed to meet the requirements for machine learning models. The postal code, nearest city to the incident location, amount of hazmat released, and latitude and longitude of the incident location were extracted from the database. As part of data processing, categorical variables were converted to numerical variables and normalized (Gao et al., 2021). The normalization technique converts numeric values into a standard scale without affecting the range of values or losing any information. In the normalization technique, duplicate data are minimized, and only related data within a range between zero and one are stored (Mehrani et al., 2022). Table 4-7 lists the input and output factors and their levels. All of these input factors are available at the time of the railway incident and can be used by risk managers to decide if evacuation is required. Data cleaning and processing resulted in 571 rows (incidents) with 13 columns (characteristics of the incidents) for investigation.

4.3.3 Data balancing

The range of variations of all factors is indicated in Fig. 4.4. The dataset is imbalanced due to the uneven distribution of factors (i.e., one class label has many observations and the other has a small number (Zhu et al., 2021)).

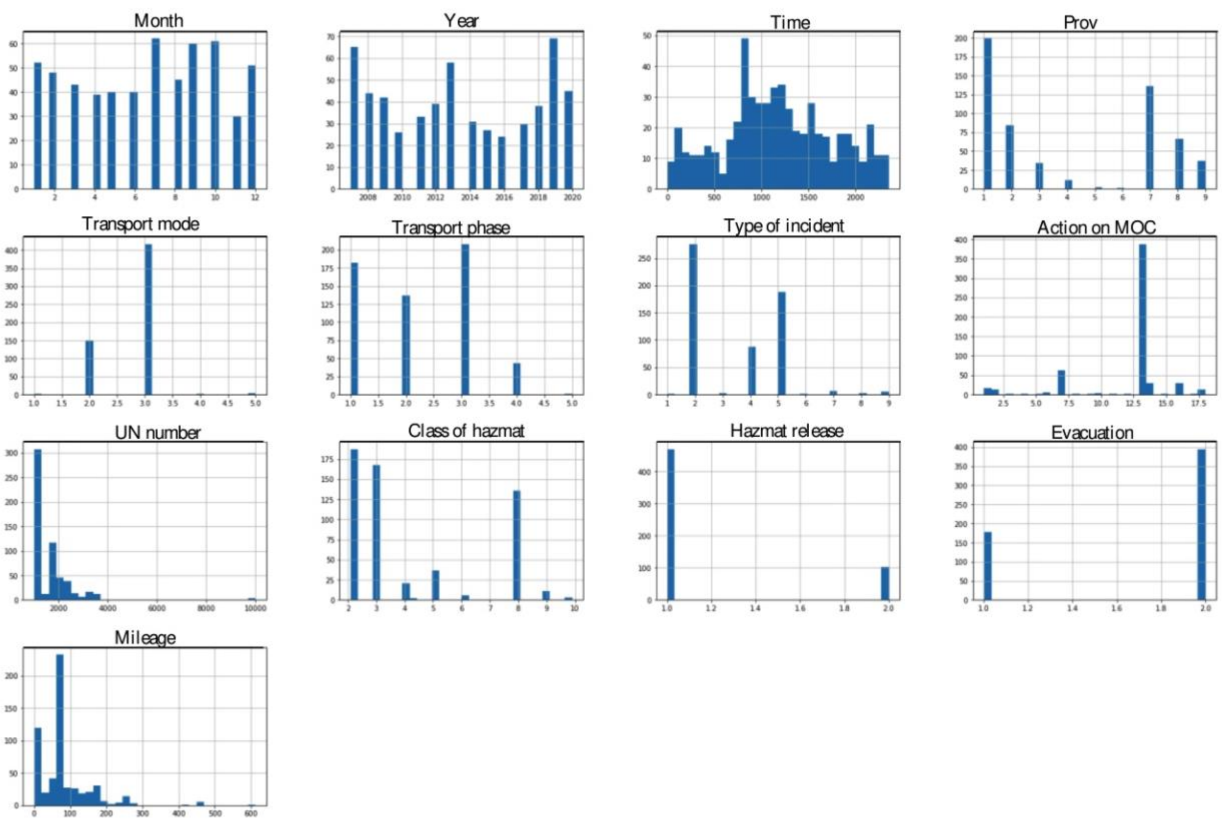


Fig. 4.4 An overview of the dataset as a histogram.

Undersampling and oversampling are the most common methods of dealing with imbalanced datasets (Ding et al., 2020). Undersampling is not recommended when the number of datasets is small, as it removes instances from data that may contain important information (Liu et al., 2020). Oversampling is another technique used for resampling and was applied in this study to adjust the class distribution of the dataset. A popular oversampling technique is SMOTE, which creates new synthetic samples for minorities (Zhu et al., 2021). The SMOTE technique relies on interpolation between positive instances to create new instances from the feature space. To increase the number of minority samples, SMOTE placed n synthesized minority samples between k adjacent samples (Y. Li et al., 2021). Although SMOTE does not significantly improve data distribution, it improves the performance of machine learning algorithms (Ding et al., 2020).

4.4 The selection of classification models

To find the most appropriate models for a study, numerous models should be applied (Bagheri et al., 2019). Various classification models are implemented in this study, including logistic regression, naïve Bayes, decision tree, random forest, support vector machine, k-nearest neighbor, and multi-layer perception, to predict the evacuation as a binary response (yes/no). The dataset is typically randomly divided into 80% for training and 20% for testing (Q. Li et al., 2021). In this study, 80% of the data are used for training the model and 20% for testing and predicting the outcome. The performance of the machine learning algorithms employed in this study is analyzed for the test dataset using evaluation metrics.

4.4.1 Classification models

A logistic regression model (LR) is a linear regression model. Linear regression uses a simple cost function, while LR uses a much more complex cost function. Rather than being a linear function, the cost function of LR has a sigmoid form called a logistic function. The cost function in LR is usually limited to a range between 0 and 1. Thus, linear functions cannot accurately represent this range, as they can have values greater or lesser than 1, which is not feasible based on the LR hypothesis (Ravi & Johnson, 2021).

Naïve Bayes (NB) classifier is one of the widely used classifiers in machine learning. For categorical output variables, Bayesian classifiers employ conditional probabilities based on Bayes' rules. By making a conditional independence assumption, the NB classifier reduces the number of parameters to predict from the original 2(2n-1) to just 2n when modeling P(X|Y), where X is the independent parameter, Y is the categorical parameter, and n is the number of independent parameters (Deng et al., 2022; Harinarayan & Shalinie, 2022).

Decision trees (DTs) are widely used for classification, as they are easy to interpret. DTs are used to find quantitative and qualitative patterns in data and to discover hidden information. Boosting is an ensemble method that merges many algorithms to perform predictions. Boosting is one of the most advanced algorithms among various classification DT algorithms, as it can transform an ensemble of weak classifiers into a robust classifier. Building a boosting DT involves a sequence of small trees that emphasize the features of the training set that were missed by the previous trees (Yang et al., 2022; Sohn & Lee, 2003).

Support vector machine (SVM) algorithms perform well in explaining small samples and non-linear problems with high-dimensional patterns. Algorithms are constructed using kernel functions that transform input data into the required format for processing. Different kinds of kernel functions are used in the SVM algorithms, including linear, radial basis functions and polynomials of degree d (Arshad et al., 2021; F. Li et al., 2019).

K-nearest neighbor (KNN) assumes that if most of the closest neighbors belong to a specific group, then the sample also belongs to that group and has its characteristics. Although KNN is used for classification, regression, and nonlinear classification, it requires a large amount of memory and tremendous calculations (P. Wu et al., 2021).

A random forest (RF) is an ensemble machine learning approach that produces many classifiers or regressors and combines them to make a more accurate prediction. Based on bagging or bootstrap aggregation with DTs, RF generates successive classification or regression trees from the data that do not depend on the earlier trees and then collects their outputs. In addition to handling high-dimensional data, RF is capable of handling imbalanced data. Therefore, even if some data are missed, RF can still predict the response well (Fu et al., 2022).

Multi-layer perceptron (MLP) is a classification model and an artificial neural network. MLP involves forward-structured machine learning and is represented by a directed graph with many nodes. In MLP, different activation functions are used, such as tanh, rectifier linear, maxout, and exponential rectifier linear, and then the one with the highest area under the Receiver Operating Characteristic (ROC) curve (AUC) is selected. The number of hidden layers is 70-90% of the number of input units in MLP according to a rule of thumb (Bagheri et al., 2015).

4.4.2 Performance assessment using evaluation metrics

The performance of classification models depends on the type of problem (Iranitalab & Khattak, 2020) and is evaluated and compared using various criteria, including accuracy, confusion matrix, precision, recall (sensitivity), F1 score, and AUC (Xu et al., 2018). In a confusion matrix, the results of the classification machine learning models are represented (Chicco et al., 2021). Four basic characteristics (numbers) are used to define the measurement metrics: True Positives, True Negatives, False Positives, and False Negatives (Chicco et al., 2021). If the model predicts a positive class correctly, it is called a True Positive (TP). Similarly, a True Negative (TN) indicates the model correctly predicted the negative class. False Positive (FP) occurs when a model predicts the positive class incorrectly. In contrast, a False Negative (FN) occurs when a model predicts a negative class incorrectly (Kopbayev et al., 2022). In this study, the terms negative and positive refer to classes with "no evacuation" and "evacuation," respectively. The confusion matrix for binary classification with positive and negative classes is shown in Table 4-1.

Table 4-1 Confusion matrix (Zhu et al., 2021).

	Actually positive (evacuation)	Actually negative (no evacuation)

Predicted positive (evacuation)	TP	FP
Predicted negative (no evacuation)	FN	TN

Confusion matrices are used to calculate precision, recall, F1-Score, and AUC-ROC curves (Zhu et al., 2021). A description of each performance evaluation metric can be found in Table 4-2.

Table 4-2 Metrics derived from the confusion matrix for the performance evaluation (Zhu et al., 2021).

Performance evaluation metric	Formula	Definition
Accuracy	$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$	Ratio of data correctly predicted.
Precision	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$	Ratio of true positives to all positive predictions.
Recall (sensitivity)	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$	Ratio of true positives to actual positives.
F1-Score	$2\frac{\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}$	Harmonic mean of precision and recall.

A ROC curve plots recall versus FP at different threshold settings (Iranitalab & Khattak, 2020). AUC is a measure of how well the model could distinguish between different classes, with 1 indicating the best prediction and 0 indicating the worst (Chen & Chen, 2022).

4.5 Natural language processing (NLP)

Text mining is the process of converting text data into numeric data. Human language is processed, understood, interpreted, and manipulated by computers through text mining or NLP (Macêdo et al., 2022). Data preprocessing and algorithm development are the two main phases of the NLP (Marie-Sainte et al., 2018).

In data preprocessing, text data are prepared and cleaned, and then the NLP algorithms may be used to analyze data and prepare a word cloud (Jing et al., 2022). Preprocessors convert data into usable forms and highlight those features that can be used by algorithms. This can be achieved through several steps, including tokenization (breaking down the text into smaller units for easier processing), stop word removal (removing common words and keeping unique words with the most useful information about the text), lemmatization and stemming (reducing words to their root forms), and part of speech tagging (classifying nouns, verbs, and adjectives according to their part of speech) (Kulkarni & Shivananda, 2019). The size of words in the word cloud is also determined by the accumulated Term frequency-inverse document frequency scores (TF-IDF). In a collection of documents, TF-IDF measures the relevance of a word to each document. TF-IDF is calculated by multiplying two metrics: how often a word appears within a document and its inverse document frequency (Ahadh et al., 2021). The word cloud only displays the words that are used most frequently, with larger words having a greater frequency (G. Liu et al., 2021).

An algorithm is developed for processing the data once they have been preprocessed (G. Liu et al., 2021). Algorithms for machine learning use statistical methods. Through training data, they learn to perform the analysis and modify their performance. By repeatedly processing, learning, and applying machine learning, deep learning, and neural networks, NLP algorithms develop their own rules (Willemink et al., 2020).

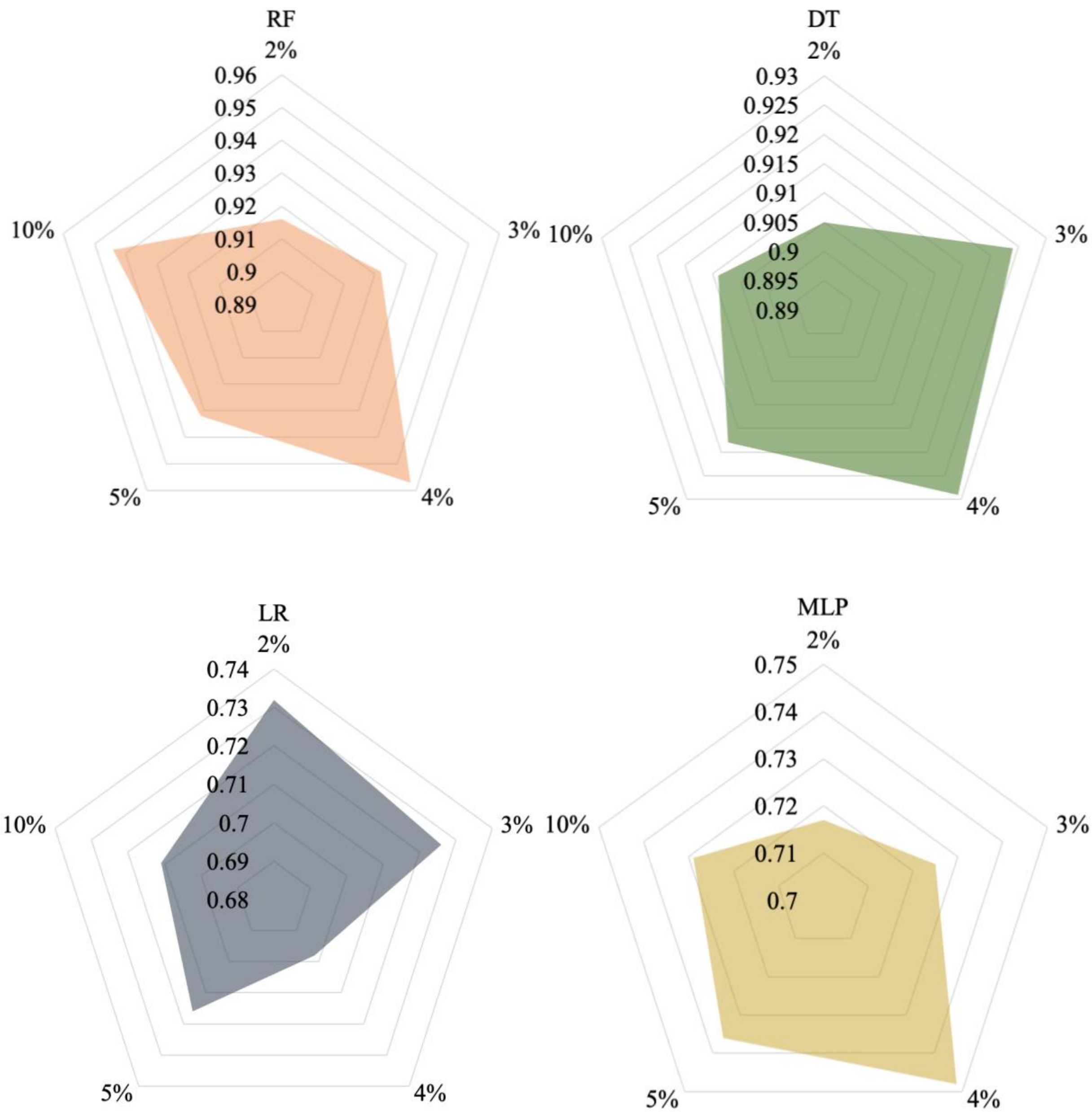
4.6 Co-occurrence network

In NLP, a co-occurrence network represents co-occurring patterns in text data and is commonly used for key object extraction and word sense discrimination (Grames et al., 2019). In addition to identifying causes and contributory factors, the co-occurrence network approach exhibits advantages in assessing their dependence (Qiu et al., 2021). Each unique word in the co-occurrence matrix is represented by a vector containing elements of its co-occurrences. A threshold value (coefficient) is set to only include those words with strong co-occurrences in the network diagram. The number of nodes represents the frequency of target words, while the strength of edges is determined by the coefficient between two co-occurring nodes. In the co-occurrence network, words with a close association are grouped into a community (or subgraph) marked by a particular color. Several communities can be seen in the co-occurrence network diagram, which indicates different types of events in the text. Also, a causal relationship might be observed between the words within the same community (X. Wu et al., 2021). In this study, Python (3.10.5) was used for programming and developing the methodology.

4.7 Results and discussion

4.7.1 Performance of classification models in evacuation prediction

In this study, two types of datasets (imbalanced and balanced) are used as inputs for machine learning. The prediction algorithms (LR, DT, SVM, NB, KNN, RF, MLP) are applied to predict evacuation. LR, DT, NB, and KNN do not require hyperparameter tuning, unlike SVM and RF. Grid search is used to tune the hyperparameters for SVM and RF (Babu et al., 2022). Then, a set of evaluation metrics is used to assess the performance of the algorithms on the test dataset. To avoid overfitting, k-fold cross-validation (k=10) is employed. For the percentage splitting option, different random seeds are used to verify the robustness of the algorithm based on a 10-fold crossover. The dataset is divided into training, validation, and test sets using random seeds, which ensure consistency every time the code is executed. The random seeds include 2, 3, 4, 5, and 10% (Sarkar et al., 2019). Figure 4.5 illustrates the high robustness of all algorithms and their potential for implementation in other scenarios.


RF
2%
3%
4%
5%
10%
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0.94
0.93
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DT
2%
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0.9
0.895
0.89
LR
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0.74
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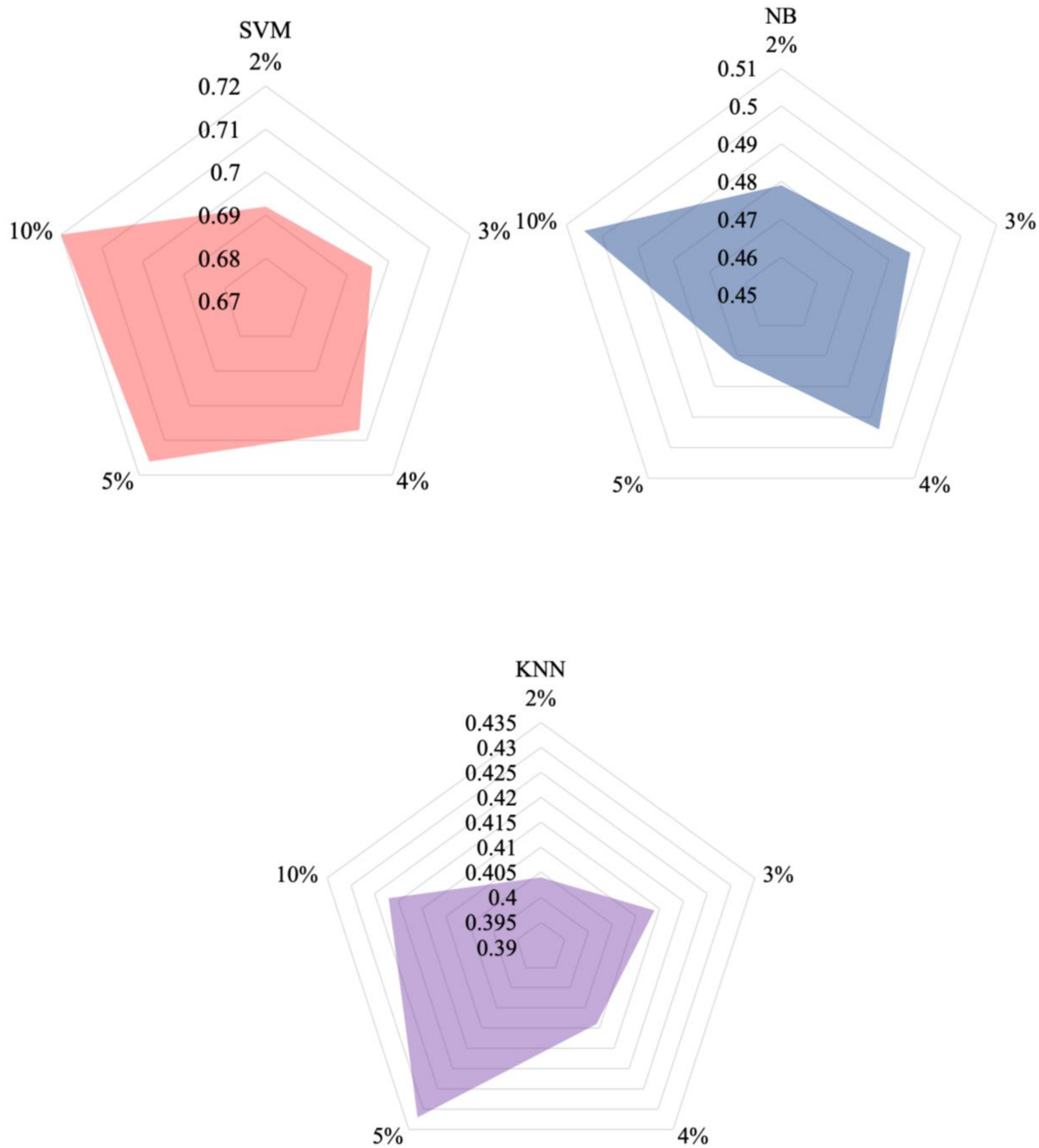

Fig. 4.5 A comparison of the F1-Scores for different random seeds.

Table 4-3 compares the results of all algorithms on two types of datasets. On the imbalanced dataset (test data), all of the indicators of RF are the highest. LR, DT, RF, and MLP show a high level of accuracy (LR: 0.70, DT: 0.91, RF: 0.92, MLP: 0.74) on the imbalanced dataset, which mostly contains incidents with "no evacuation" and neglects incidents with "evacuation." Using the SMOTE technique, the results confirm that oversampling techniques can improve model performance because all models have improved F1-Scores (a harmonic mean of precision and recall). On the balanced dataset (test data), the highest F1-Score (RF) is 95%, indicating the evacuation order did not occur at random, and machine learning models can be used to analyze potential patterns.

Table 4-3 Balanced and imbalanced dataset performance analysis.

Classification models	Precision (Imbalanced / balanced)	Recall (Imbalanced / balanced)	F1-Score (Imbalanced / balanced)	Accuracy (Imbalanced /balanced)
RF	0.92/0.95	0.92/0.95	0.92/0.95	0.92/0.95
DT	0.91/0.93	0.91/0.93	0.91/0.93	0.91/0.93
LR	0.76/0.77	0.77/0.78	0.76/0.77	0.70/0.72
MLP	0.71/0.76	0.75/0.77	0.72/0.76	0.74/0.75
SVM	0.68/0.75	0.69/0.72	0.68/0.73	0.67/0.72
NB	0.67/0.73	0.48/0.56	0.47/0.56	0.47/0.56
KNN	0.60/0.62	0.42/0.43	0.49/51	0.42/0.44

The high TP value (incidents correctly predicted as "evacuation") indicates all emergency situations with a high potential for causing severe consequences for people are correctly identified and evacuation orders are issued to protect them. The high FN value (incidents incorrectly predicted as "no evacuation") indicates people could suffer serious consequences, including death or injury, if evacuation is wrongly not ordered in emergency situations, such as toxic releases, fires, explosions, etc. As indicated in Table 4-3, the recall rate of RF and DT is high (RF: 0.92/0.95- DT: 0.91/0.93), which means the number of TP is high and FN is low. Models that are output-sensitive require a high recall (James et al., 2006). This study also needs high recall, and evacuation must be predicted accurately; otherwise, catastrophic consequences may result. The high FP value (incidents incorrectly predicted as “evacuation”) indicates evacuation orders wrongly issued in situations without serious threat to people can cost time and money. For example, if an evacuation order is issued, emergency personnel should attend to the site. Considerable resources should be prepared for people evacuating in an emergency, including shelters, which are costly and time-consuming to prepare. The best precision values (RF: 0.92/0.95-DT: 0.91/0.93) obtained by RF and DT indicate the number of TP is high and of FP is extremely low. If the cost of acting is high, precision will be more important (He et al., 2019). This study focuses on high precision because incorrect evacuation orders cost time and money. In an ideal system, all results would be correctly classified and returned and would have high precision and recall (Koklu & Ozkan, 2020). However, risk managers can select a model that has either high precision or recall, or both, depending on the problem (Iranitalab & Khattak, 2020). The high TN value (incidents correctly predicted as "no evacuation") indicates all incidents for which no significant threat to people is correctly identified, thus preventing an evacuation order, and leading to time and cost savings. The classifiers are more accurate when TP and TN are high, and FN and FP are low. The ROC curves for the five top models (RF, DT, LR, MLP, and SVM) with the highest F1-Score are shown in Fig. 4.6. The results indicate RF and DT have the highest AUC, followed by SVM, MLP, and LR (RF: 0.84, DT:0.76, SVM:0.73, MLP: 0.67, and LR:0.52).

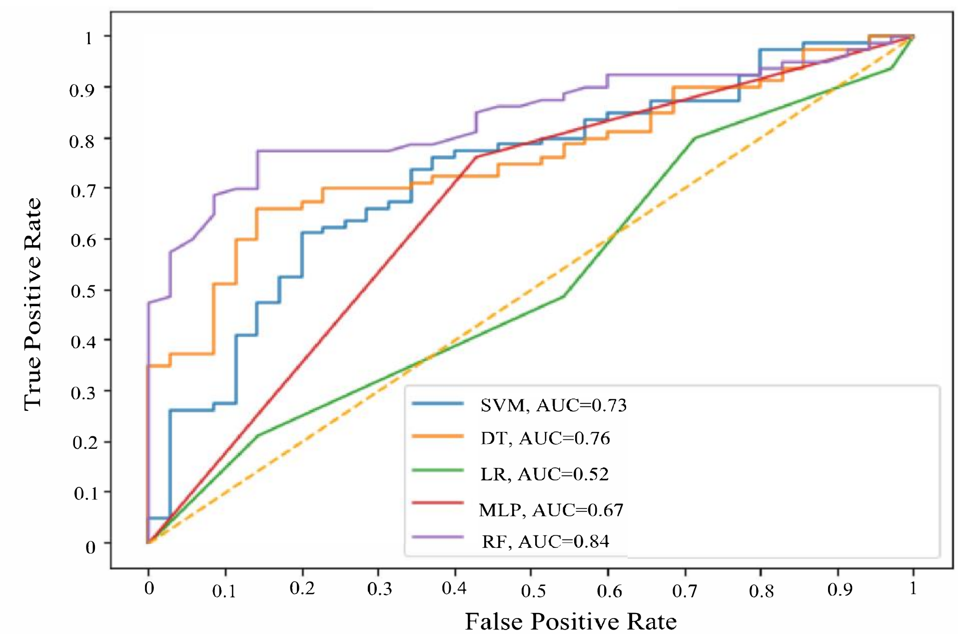

Fig. 4.6 ROC curve analysis.

4.7.2 Analysis of the confusion matrix

A confusion matrix analysis is performed to determine the cause of the algorithm's classification error. Using confusion matrices allows for an evaluation of how well a model performs in classification problems by determining how often it correctly predicts the response (Zermane et al., 2023). Table 4-4 shows the confusion matrix of RF, DT, LR, MLP, and SVM, which have the highest F1-Scores and AUCs on the balanced dataset (test data). The results indicate RF and DT can classify data correctly as TP and TN have high values and the errors (FP and FN) are relatively low and balanced. However, the results indicate some data cannot be correctly classified by LR, MLP, and SVM, and the errors (FP and FN) produced by these classifiers are substantial.

Table 4-4 Confusion matrix of the classification algorithms (Yes: Y NO: N).

Confusion matrix	RF		DT		LR		MLP		SVM	
Evacuation (%)	Y	N	Y	N	Y	N	Y	N	Y	N

Y	69.98	0	49.32	2.8	42.26	8.24	39.3	10.8	45.5	5.1
N	0	30.02	2.5	45.2	10.1	39.4	14.4	35.5	5.1	44.3

RF and DT show strong performance for predicting evacuation, as they have the highest F1-Scores, AUC values, and the lowest and most balanced errors in the confusion matrix. Also, the processing time of RF and DT is less than 1 minute on a MacBook Pro (8 GB of memory), which makes these models more applicable as the order for evacuation should be quickly predicted. Nevertheless, the MLP model, for example, requires approximately 12 minutes to run and thus may not be considered as a model with fast performance to predict evacuation. Risk managers may be able to use user-friendly applications to insert available information at the time of an incident to predict the necessity of evacuation.

4.7.3 Feature selection

4.7.3.1 Random Forest analysis

The importance of a factor can be determined by evaluating how much influence it has on predicting a response (Scavuzzo et al., 2022). It is possible to improve a prediction model by utilizing the importance of the factors (Zermane et al., 2023). Part of the random forest analysis assigns a score to each factor, with a higher score indicating a greater significance of that factor to the response (evacuation) (Bagherzadeh et al., 2021). Fig. 4.7 represents a ranking of the factors based on the random forest analysis.

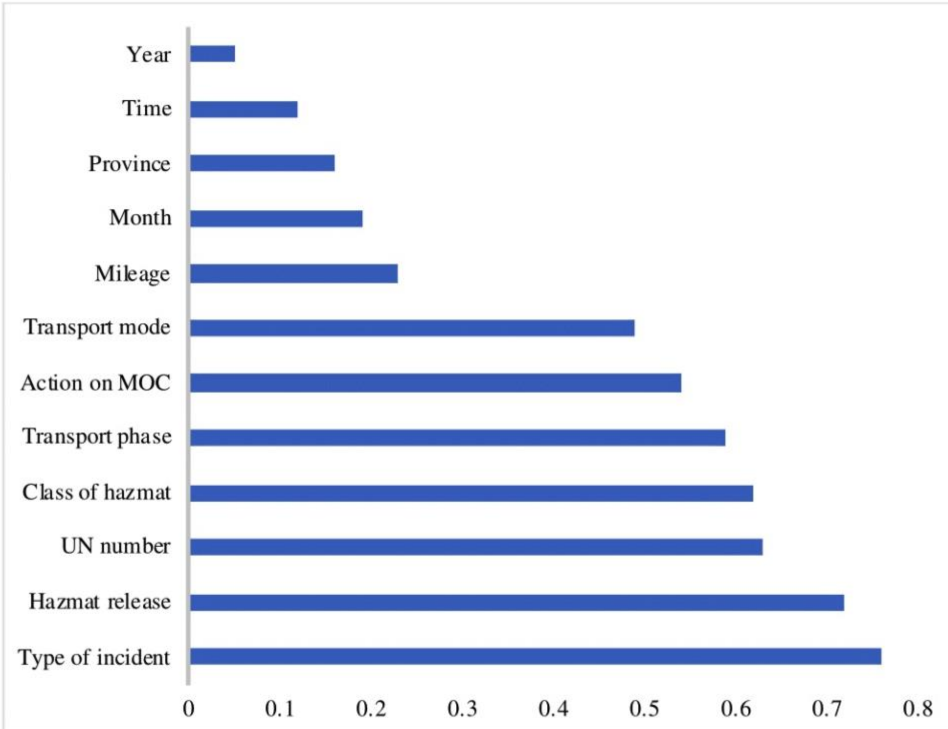

Fig. 4.7 The importance of the factors considered in this study.

As shown in Fig. 4.7, the type of incident (e.g., leak, spill, fire/smoke, explosion, etc.) is recognized as the most significant factor affecting evacuation. In case of an accident involving a toxic/flammable release, fire, or explosion, Halim et al. (2018) emphasize that one of the most important factors is the evacuation of people. Inspection and maintenance of tank cars and railway tracks (Garcia et al., 2009) and preventing human errors (Ebrahimi et al., 2021) could prevent railway incidents and the possible consequences. As depicted in Fig. 4.7, the occurrence of hazmat release is ranked second. In railway incidents, improper inspection and securing of tank cars by shippers (e.g., loose closures, open valves, defective gaskets) can result in the release of hazmat. Performing regular inspections of tank cars and avoiding operational errors (i.e., excessive speed) could prevent hazmat release during railway incidents (National Transportation Safety Board, 2022). The UN number and class of hazmat are the factors with the third greatest impact on evacuation. As flammable and combustible liquids have low flash points and high flammability, they are among the most hazardous hazmat (Alexeev et al., 2018). To prevent fires, explosions, injury, or death caused by flammable or combustible liquids release, evacuation is necessary. Integrated tank cars, such as the DOT-117R, could reduce the likelihood of hazmat release (Shultz et al., 2016). Appropriate instructions for handling and cleaning hazmat could also mitigate the consequences of hazmat release as quickly as possible (U.S. Department of Transportation, 2020). In future analysis, the factors with a less significant effect on evacuation (i.e., time and year) may be eliminated in data collection, with this modification possibly further improving the model accuracy.

4.7.3.2 Incident assessment rules extraction

Sarkar et al. (2019) employed the rules extraction method for incident analysis. Similarly, decision tree analysis is employed in this study to analyze incidents. By implementing the decision tree, the assessment rules can be extracted, revealing the underlying causes of evacuation. The rules are clear, and patterns are visualized in the form of a decision tree (de Oña et al., 2013). To generate rules, each path in the decision tree is followed, from the root node to the leaf node. The results of the test are recorded as antecedents and the classification of the leaf nodes as consequents (Griselda & Joaquín, 2012). A set of accident assessment rules could be provided to guide the supervisory department in analyzing the risk index. Table 4-5 represents seven rules determined by rules extraction using the decision tree model. There are three rules for railway incidents with "no evacuation" and four rules for railway incidents with "evacuation" listed in descending order based on the number of cases matched by each rule. According to the assessment rules, the type of incident significantly impacts evacuation, as it involves all evacuation paths. These results are in accordance with Fig. 4.7, which indicates the type of incident significantly contributes to evacuation.

Table 4-5 Incident assessment rules extraction using the decision tree.

Rule no.	Rules	Class evacuation= yes (1), no (2)	n or n/m
R1	Type of incident (1,2,3,4) +release (2) +action on MOC (12, 13, 14, 15, 16, 17, 18)	2	73/9
R2	Type of incident (5,6,7,8,9) +release (1) +class of hazmat (2.1, 2.2, 2.3, 3,4.1) + action on MOC (1,2,3,4,5,6,7,8,9,10,11,12,13)	1	62/10
R3	Type of incident (5,6,7,8,9) + class of hazmat (2.1, 2.2, 2.3, 3,4.1) +Transport phase (2,3,4,5) + action on MOC (15,16,17,18)	1	35/5
R4	Type of incident (1,2,3,4,5,6) + release (2) + class of hazmat (2.1, 2.2, 2.3, 3,4.1) + 00:00<=Time <= 7:40	2	32
R5	Type of incident (1,2,3,4) + release (1) + Transport phase (1,2) + transport mode (1,2,3,4)	2	23
R6	Type of incident+ (5,6,7,8,9) +class of hazmat (4.3, 5.1, 6.1, 8, 9, 9.9) + action on MOC (11,12,13,14,15,16,17,18) + Mileage (<=78.5)	1	18/3
R7	Type of incident (1,2,3,4) + release (1) + action on MOC (16,17,18) + Transport mode (1,2)	1	13

One way to validate the findings of this study is to compare the results with similar studies. However, validating the findings is difficult as similar studies in the railway industry are rare. Additionally, these rules should be considered with caution, as the dataset is small, and the oversampling technique (SMOTE technique) is used in this study. A larger and more balanced dataset, which includes a wide range of characteristics (e.g., train speed, tank car characteristics, population vulnerability characteristics), would be beneficial to meet these challenges.

4.7.4 Natural Language Processing analysis

The descriptions of railway incidents are gathered after the incident occurs and cannot be analyzed immediately. The brief descriptions of railway incidents are grouped into two categories: "evacuation" and "no evacuation." For a visual representation of the incidents that caused evacuation, a word cloud is built using a brief description of these incidents (Fig. 4.8).

Fig. 4.8 The word cloud developed by the top words of the incidents that led to the evacuation.

The most frequently used words in the descriptions of the incidents that led to the evacuation were extracted as depicted in Fig. 4.8. These words are categorized as shown in Fig. 4.9.

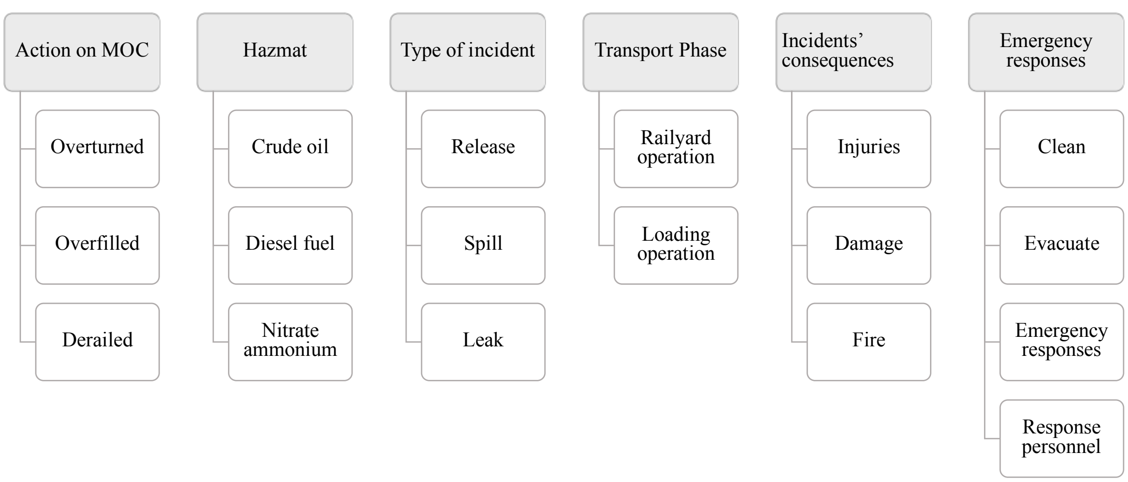

Fig. 4.9 The most frequent words acquired from the word cloud analysis.

Figure 4.8 illustrates that, based on the type of railway incident, the words ‘release,’ ‘spill,’ and ‘leak’ are frequently used in the word cloud and are likely to result in an evacuation. These results are consistent with Fig. 4.7, which indicates the type of incident has the greatest impact on evacuation. The word cloud illustrates the high frequency of ‘crude oil,’ ‘diesel fuel,’ and ‘nitrate ammonium’ in incidents that resulted in evacuation. Accordingly, these results are consistent with Fig. 4.7, which confirms that hazmat type is an important factor in incidents leading to evacuation. The overturning, overfilling, and derailment of trains categorized as action on MOC may occur during the railyard operation and loading operation, which are categorized as the transport phase. As these words are also the most frequent words in the word cloud, they have the potential to cause evacuation. Figure 4.7 also confirms the transport phase and action on MOC have significant effects on evacuation. According to the word cloud, injuries, damage, and fire, which are considered the consequences of railway accidents, are associated with evacuation. Railway incidents involving hazmat release are minimized by sending emergency response personnel to the site, evacuating the area, and cleaning up the site. This visualization could provide insights into the causes, contributing factors, and consequences of the incidents that led to the evacuation and possible improvement in the safety culture (Feng et al., 2021).

4.7.5 Co-occurrence network analysis

The co-occurrence network is employed to analyze the performance of NLP and text mining on safety (G. Liu et al., 2021). The co-occurrence network diagram (Fig. 4.10) is prepared using a brief description of the incidents that resulted in evacuations. The threshold value (Jaccard coefficient) is set to 0.2 (G. Liu et al., 2021) to consider strong associations (Libis et al., 2019). In the co-occurrence network, several nodes (words) with a strong co-occurrence create a subgraph of a particular color. The number of connections determines the size of each node. Co-occurrence between nodes is indicated by edges. Dashed lines indicate co-occurrences between nodes in different subgraphs. Each subgraph naturally exhibits a hierarchy of causes and consequences formed by its nodes and edges. Different scenarios can be described by subgraphs with an appropriate number of edges and nodes (Libis et al., 2019).

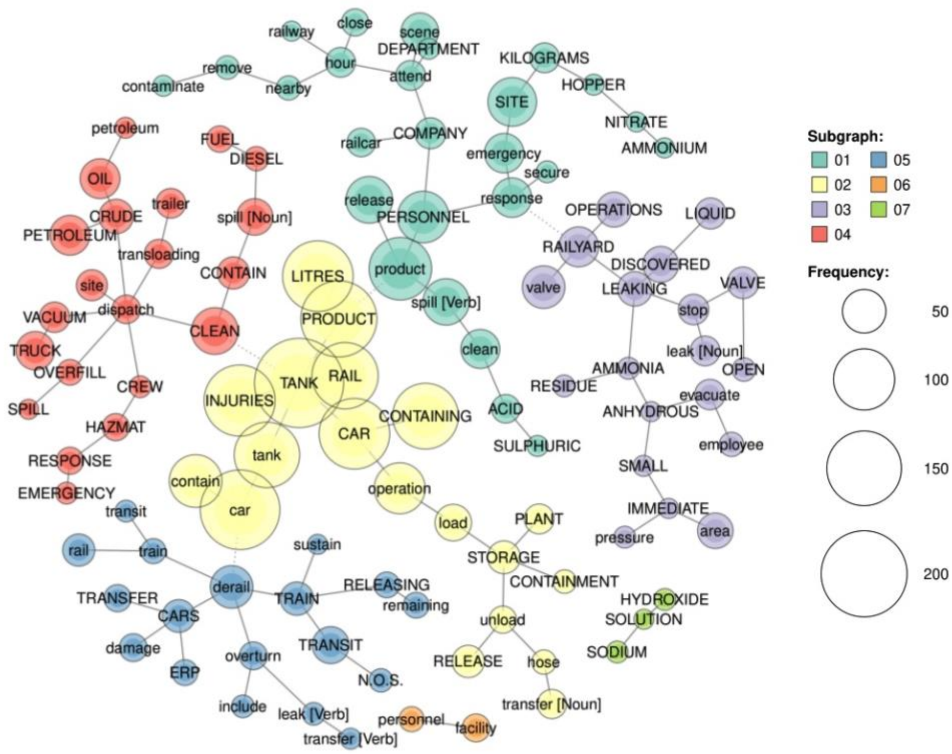

Fig. 4.10 The co-occurrence network developed by the significant words in the description of incidents that caused evacuations.

In subgraph number 1 (green color), the co-occurrence network describes an incident scenario as follows: two types of hazmat were transported on a train. “Sulphuric acid” was transported in a “tank” “car,” and “nitrate ammonium” was transported in a “hopper” “car.” A “tank” “car” “containing” “sulphuric acid” “spilled” the “product.” A certain number of “liters” of “product” was released and “cleaned up.” “Emergency” “response” “personnel” “attended” the “site” to “secure” the “hopper.” Moreover, the “fire” “department” “Company” “personnel” “attended” the “scene,” and the “nearby” “railway” was “closed” for a few “hours” to “remove” the “contaminant.” With the nodes "product" and "response," subgraph number 1 (green color) is connected to subgraph number 2 (yellow color) and subgraph number 3 (purple color). The link between subgraph number 1 (green color) and subgraph number 2 (yellow color) describes the following incident scenario: during “unloading” “operations” from a “rail” “tank” “car” “containing” “flammable liquid” into a “plant” “storage” “tank,” the “transfer” “hose” was “disconnected” before the “offloading” “operation” was completed. As a result, a certain number of “liters” of “product” was “released” from a “valve” on the “tank car.” There were no “injuries.” “Emergency” “personnel” were on “site” to “contain” and “clean up” the “spill” and “remove” the “contaminant.” An incident scenario when subgraph number 1 (green color) is connected to subgraph number 3 (purple color) could be as follows: a “residue” “rail” “tank car” “containing” “anhydrous ammonia” “leaked” a “small” “amount” of “product” from the “pressure” “relief” “valve” during “railyard” “operations.” “Emergency” “responder” tightened the “valve,” which “stopped” the “leak,” and “evacuated” “employees” and “area” “immediately.”

These scenarios are validated by the description of the incidents available in the dataset. As part of the validation process, the nodes with the highest frequency and connection (e.g., leak, spill, release, railyard operation, loading operation, petroleum crude oil, derailed, emergency response) are used to extract a brief description of the incidents that caused the evacuation (Table 4-8), Based on the analysis of the incidents reported in Table 4-8, the similarities between these incidents and the potential scenarios that have been derived from the co-occurrence network analysis are confirmed, which validates the results of this study.

Based on the connection and frequency of the nodes in the co-occurrence network, the main contributing factors that prompted the evacuation can be determined. The main contributing factors are leak and spill (categorized as different types of incidents); overturning and derailment (categorized as different types of action on MOC); railyard operations and loading operations (categorized as different types of transport phase); and petroleum crude oil, diesel fuel, sulphuric acid, nitrate ammonium, sodium hydroxide solution, and ammonia anhydrous (categorized as different types of hazmat). Table 4-6 presents a summary of the control measures for the factors contributing to the evacuations.

Table 4-6 An analysis of the factors contributing to evacuations and recommendations for controlling them.

Contributing factors	Measures to control the contributing factors
Leak and spill	Utilizing DOT-117R tank cars that are thicker than most cars in service, inspecting the tank head and shell regularly for defects such as dents, cracks, or leaks, and inspecting the pressure relief device to ensure that it does not leak (National Transportation Safety Board, 2022).
Overturning and derailment	Maintaining regular inspections of the tracks and equipment (e.g., rails and wheels), and avoiding operational errors (i.e., excessive speed (Shultz et al., 2016).
Railyard operations	Implementing measures to prevent accident causes (e.g., broken rail prevention), and improving tank car safety designs (X. Liu et al., 2013).
Loading operations	Training for safe loading/unloading, maintenance procedures (X. Liu, Saat, & Barkan, 2013), displaying safety signs like blue flags (commonly known as caution signs) prior to tank car loading and unloading (Otremba, 2016), locking the switch and/or derailer to prevent entry into the track during loading and unloading (ABELA, 2018), and checking hand brakes (Alexy, Jeong, & González III, 2013).

Petroleum crude oil, diesel fuel, sulphuric acid, nitrate ammonium, sodium hydroxide solution, and ammonia anhydrous	Using more robust tank cars to ship hazmat (National Transportation Safety Board, 2022), and reducing the operating speed (Shultz et al., 2016).

In practical applications, various industries may benefit from the use of the classification models identified in this study to retrain models according to the characteristics of their risk factors. The critical factors with the greatest influence on evacuation can also be emphasized. The method of rule extraction can be used to assess the risk level associated with other safety operations. Using NLP and the co-occurrence analysis in practical applications, risks can be communicated to various stakeholders, including regulators, host communities, shippers, and transloaders. Future efforts to collect data can be shaped using the co-occurrence network results. Researchers will be able to determine the latent causes more precisely by collecting additional information regarding the contributing factors identified by the co-occurrence analysis. The co-occurrence analysis can be combined with other approaches to provide a deeper understanding of incidents. A co-occurrence analysis, for example, may be compared to other reports (e.g., near-misses and car maintenance) to obtain additional information. Furthermore, the incident reports may also be incorporated into the user-friendly application and valuable results may be extracted and analyzed by safety experts.

4.8 Conclusion

Machine learning models could improve experts' approaches to decision-making problems. In the first part of this study, the DGAIS database was used to predict the need for evacuation using various supervised machine learning models (RF, DT, LR, SVM, MLP, KNN, NB). Based on the various performance metrics used (e.g., precision, recall, F1-score, AUC-ROC curve), RF was selected as the superior model for evacuation prediction. Based on the random forest analysis, the type of incident, hazmat released (yes/no), type of hazmat, and transport phase were determined to have the greatest effect on the decision to evacuate. The decision tree algorithm was applied to extract incident assessment rules that lead to an evacuation. Text data on incident narratives have been collected over the years and, if properly utilized, can be a valuable source of learning information. In the second part of this study, the descriptions of the incidents that led to evacuations were analyzed using NLP and co-occurrence network analysis to identify patterns in unstructured text data. The main contributors to evacuations were identified based on the frequency and connection of the nodes in the co-occurrence network. The contributing factors included leak and spill (categorized as different types of incidents), overturning and derailment (categorized as different types of actions on MOC), railyard operation and loading operation (categorized as different types of transport phase), and petroleum crude oil, diesel fuel, sulphuric acid, nitrate ammonium, sodium hydroxide solution, and ammonia anhydrous (categorized as different types of hazmat).

Despite the significant insights provided by this study, there are some limitations as follows:

- Railway incidents may occur under different circumstances and propagate differently, and the co-occurrence network can remove the significant information and latent causes.
- Other sources of information, such as the vulnerability of adjacent populations and their ability to respond to hazards, may be considered to develop evacuation plans.
- The input factors used have uncertainty, as they have been collected by risk managers and experts (type of incidents, action on MOC) and measuring equipment (mileage traversed by trains), and the uncertainties of these values are not reported in the dataset used in this study.

The following recommendations are provided to address these limitations in future studies:

- The contributing factors identified in this study can be used to extract only the reports that contain these contributing factors. This would enable a deeper probe into the latent causes of the incidents.
- A comprehensive dataset containing various information, including population vulnerability to predict evacuation, could be included in the analysis.
- The uncertainty of the input factors could be reported and used to improve the accuracy of the results.

Table 4-7 The input and output factors for evacuation prediction.

Input factors	Level	Output factor (response)	Level
Hazmat released	1= yes (82.14%) 2= no (17.86%)	Evacuation	1 =yes (30.99%) 2= no (69%)
Type of incident	1= fire/smoke (0.17%) 2= leak (48.34%) 3= leak and fire (0.52%) 4=no release/ anticipated release (15.41%) 5= spill (32.92%) 6= spill and explosion (0.17%) 7= spill and fire (1.05%) 8= spill and leak (0.52%) 9= spill, leak, fire, and explosion (0.87%)		
Action on MOC	1= collision (2.98%) 2= collision, derailment (2.28%) 3= collision, derailment, load shift (0.17%) 4= collision, derailment, other (0.17%) 5= collision, other (0.35%) 6= collision, overturn, derailment (0.87%) 7= derailment (10.85%) 8= derailment, other (0.17%) 9= derailment, struck (0.17%) 10= dropped (0.52%) 11= load shift (0.35%) 12= load shift, struck (0.17%)		

	13= no action (67.95%) 14= other (5.08%) 15= overturn (0.17%) 16= overturn, derailment (5.25%) 17= overturn, derailment, struck (0.35%) 18= struck (2.10%)
Province	1= Alberta (34.8%) 2= British Columbia (14.7%) 3= Manitoba (5.95%) 4= New Brunswick (2.1%) 5= Nova Scotia (0.35%) 6= Northwest Territories (0.17%) 7= Ontario (23.82%) 8= Quebec (11.56%) 9= Saskatchewan (6.48%)
Time	10:30= (2.8%) 13:00= (2.28%) 08:00= (2.10%) ……. 17:30= (0.17%) 19:25= (0.17%),
Month	1= January (9.11%) 2= February (8.4%) 3= March (7.53%) 4= April (6.83%) 5= May (7%) 6= June (7%) 7= July (10.85%) 8= August (7.88%) 9= September (10.5%) 10= October (10.68%) 11= November (5.25%) 12 = December (8.93%)
Transport phase	1= handling (31.87%) 2= in transit (23.99%) 3= rail yard operations (36.43%) 4= temporary storage (7.53%) 5= unknown (0.17%)
Transport mode	1= processing plant-chemical/gas manufacturer (0.17%) 2= rail (26.09%) 3= rail terminal (73.09%) 4= road terminal (0.17%) 5= warehouse (0.52%)

Class of hazmat	2.1= (18.39%) 2.2= (3.85%) 2.3= (10.5%) 3= (29.42%) 4.1 = (3.68%) 4.3= (0.35%) 5.1= (6.48%) 6.1= (1.05%) 8= (23.81%) 9= (1.92%) 9.9 = (0.52%)
UN number	1075= (16.81%) 1267= (8.93%) ………… 3266= (0.17%) 2923= (0.17%)
Year	2007= (11.38%) 2008= (7.7%) 2009= (7.35%) 2010= (4.55%) 2011= (5.78%) 2012= (6.83%) 2013= (10.15%) 2014= (5.43%) 2015= (4.73%) 2016= (4.2%) 2017= (5.25%) 2018= (6.65%) 2019= (12.08%) 2020= (7.88%)
Mileage	0= (41.5%) 72= (0.5%) ……. 174= (1.57%) 460= (1.05%)

Table 4-8 Sample incident descriptions of incidents that led to evacuation.

The date of the incident (month/ year)	Location (province)	Key nodes	Description
11/2020	Alberta	Railyard operation, leaking, emergency response personnel	During railyard operations, a tank car carrying liquefied petroleum gases

			un1075 residue was discovered to be leaking. An area of about 100 meters radius was cleared for 3 hours with the rail terminal being closed for 3 hours as well. Company personnel attended to the scene and found an open liquid line with the plug out. The plug was replaced, and the valve was closed.
05/2013	Alberta	Unloading operation, release, injuries, spill	During unloading operations from a rail tank car containing hydrochloric acid into a facility storage tank, a pipe burst causing a release of 800 litres of product. There were no injuries. The spilled product, which went into an on-site dump which flows into a containment pond, was immediately neutralized.
11/2014	New Brunswick	Railyard operation, release, derailed, petroleum crude oil, spill, emergency response personnel	During shoving operations in a railyard, a train derailed 16 cars, 10 of which were tank cars containing petroleum crude oil. All cars remained upright. One derailed tank car released 3785 litres of product from the bottom outlet valve. Emergency response personnel were on site to perform a product transfer from two derailed tank cars that

			had come off their trucks. The remaining tank cars were rerailed. The spilled product on the ground was then cleaned up with a vacuum truck.
01/2014	New Brunswick	Spill and fire, transit, derailed, damage, release, petroleum crude oil, fire, injuries	During transit, a train consisting of 122 rail cars derailed 12 tank cars containing dangerous goods after experiencing an unintentional emergency brake application due to a wheel failure. Six of the derailed tank cars were damaged in the derailment and released a combined total of 528,604 litres of dangerous goods. Of the derailed tank cars that released product, three contained petroleum crude oil and released a total of 174,859 litres of product and three tank cars contained liquified petroleum gas (butane) and were damaged and caught fire releasing 353,745 litres of product into the environment. There were no injuries.

Chapter 5

Chapter 5 of this thesis has been submitted as Hadiseh Ebrahimi, Fereshteh Sattari, Lianne Lefsrud, Renato Macciotta, "*An analytical approach to identifying the probability and contributing factors of hazmat release in Canadian railway incidents based on data-driven machine learning and text mining*". The contributions of the authors are listed below:

Hadiseh Ebrahimi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Fereshteh Sattari:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - review & editing, Supervision, Project administration**. Lianne Lefsrud:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Renato Macciotta:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

5.1 Introduction

Freight railways transport large quantities of hazmat, such as fertilizer, ethanol, crude oil, and chlorine, that impact people's health and quality of life in the event of hazmat release (Ebrahimi et al., 2021; Macciotta et al., 2018). Railway incidents, resulting in the release of hazmat can threaten people's lives and the environment (e.g., air and water). To minimize the negative consequences of railway incidents, risk assessment is critical to planning and improving the safety (Huang et al., 2020). The probability of hazmat release is one of the components of risk assessment, which needs to be considered to reduce the adverse consequences of the hazmat release (Iranitalab, 2018; Treichel et al., 2006).

The majority of railway hazmat releases are caused by train derailments (Liu et al., 2014). Many factors affect the number of tank cars released in a derailment, including the length of the train, the speed of the derailment, the cause of the incident, the point of derailment (the location of the first car that derailed), the position of the tank cars in the train, and the design of the tank car safety systems (Liu et al., 2014). Saccomanno et al., (1989) found that train derailment rates vary with traffic volume, track type (single track versus multiple tracks), train speed, region, and infrastructure and traffic characteristics. Anderson & Barkan., (2004) mentioned that a higher FRA track class has a lower derailment rate since higher operating speeds require higher track classes and more stringent maintenance and engineering safety standards. In addition, Liu., (2013) analyzed FRA track class, method of operation, and traffic density, and found that all three factors are strongly correlated with the rate of train derailments. Barkan et al., (2003) reported in their study that considering a number of derailed cars would be more appropriate for analyzing tank car safety and hazmat risks, as derailment energy is closely related to tank car safety and hazmat risk. Derailed cars are affected by the accident cause, the train speed, the train length, and the point of derailment (Liu et al., 2012; Liu et al., 2013; Liu et al., 2011). As derailed tank cars are related to the total number of cars (both tank and non-tank cars) and the number and placement of tank cars within a train (Liu et al., 2014), Glickman et al., (2007) found that the number of derailed tank cars followed a hypergeometric distribution when tank cars are randomly distributed in the train. In addition, Bagheri et al., (2014) mentioned that the total number of derailed tank cars is estimated based on their positions. Liu et al., (2014) identified that the point-of-derailment (POD) was located in the first 10 positions of the train in approximately 25% of train derailments. Treichel et al., (2006) developed regression models based on the Tank Car Accident Database, which were used to estimate the conditional probability of release for practically all common designs and new designs that incorporate existing features. Kawprasert & Barkan., (2010) found that speed had a significant effect on both derailment severity and release probability of cars, transporting hazmat. By considering different input variables (i.e., the type of incident, the cause of the incident, track class, the environmental condition, etc.), Iranitalab & Khattak, (2020) developed machine learning models to estimate the probability of hazmat release from railway mishaps occurred in Nebraska and Kansas (USA). Additionally, they provided recommendations regarding the application of machine learning models based on the analysis purpose.

The literature review revealed that different studies employed qualitative and quantitative methods to examine the effect of different factors (i.e., train speed, length, and derailment point) on the hazmat release occurrence. Due to the high speed of data processing and the high accuracy of the data prediction (Xuecai et al., 2022), machine learning models could be considered to examine the effect of the variables not previously considered in determining the probability of hazmat release. An analysis should be conducted to identify the relationship between these variables to identify the most significant factors responsible for the hazmat release. Although predicting the probability of hazmat release could minimize the casualties, a better understanding of the causes and contributing factors to hazmat release can lead to disaster risk reduction (Liu et al., 2021). To the best of the authors' knowledge, no study has identified the causes and contributing factors to the hazmat release using the reports of the incidents and text mining. In the first part of this study, the input variables not previously considered (i.e., the position of tank cars in trains, the last tank test year, the loading status of cars, and the type of rolling stock) are employed to predict the probability of hazmat release and classify hazmat release as a binary response (yes/no). The association between these factors is then analyzed and the factors with the greatest impact on the hazmat release are revealed. The second part of this study focuses on analyzing the brief descriptions of railway incidents reported after each incident using natural language processing (NLP) and co-occurrence network analysis to provide some insight into the causes and contributing factors, which lead to the hazmat release and strategies for mitigating the risk.

5.2 Materials and methods

This study used the following methodological approach, as shown in Fig 5.1.

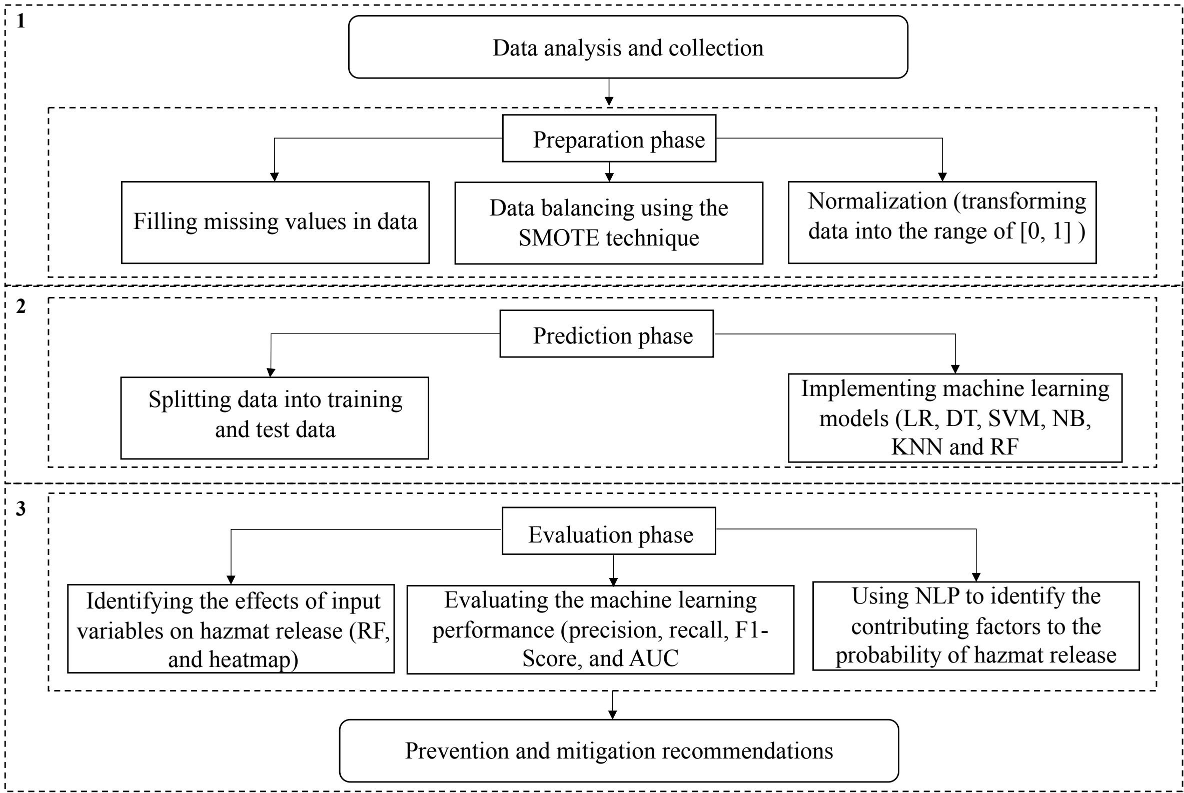

Fig. 5.1 Research methodology flowchart.

5.2.1 Data description

The data used in this study is collected from the Rail Occurrence Database System (RODS) between 2007 and 2020. The dataset contains information related to derailments, collisions, crossings, and other incidents involving hazmat-carrying trains. The dataset contains 15 columns (characteristics) describing the incidents. The factors recorded in each incident is train speed (mph), last tank test year, position in the train, rolling stock type, derailed cars (yes/no), hazmat cars involved (yes/no), carload status, number of cars, cause of the incident, locomotive derailed (yes/no), province, time, month, and year. Based on the analysis of the dataset, the highest number of rail incidents occurred in July followed by October and September. The most frequent railway incidents occurred in 2019, 2007, and 2013, and the railway incident peak time was around 8:30 a.m.

5.2.2 Data cleaning and data processing

RODS data should be processed so that machine learning models can be built from it. An important aspect of data processing is the identification and replacement of incomplete, inaccurate, or irrelevant values from a record set, table, or data (Hegde & Rokseth, 2020). To ensure that machine learning models perform effectively, data cleaning and processing are performed, including normalization (transforming data into the range of [0, 1] (Yang et al., 2019) and filling in missing values (Ma et al., 2020). Since the data are numerical and skewed, the median value is used to replace any missing values (Lei & Shiverdecker, 2020). According to the dataset, only 1.88% of railway incidents resulted in "hazmat release", while 98.12% resulted in "no hazmat release", indicating that the dataset is imbalanced. A method of oversampling, the Synthetic Minority Oversampling Technique (SMOTE), is used to solve this imbalanced dataset problem (Seo & Kim, 2018). The input and output variables and their respective levels used in this study are listed in Table 5-1.

Table 5-1 Variables used for predicting the probability of hazmat release in railway incidents.

Input and output variables	Variables' Value
Output variable (response)	
Hazmat released	1 = yes (1.88%)
	2 = no (98.12%)
Input variables	
Train speed (mph)	Mean= 10.25, standard deviation= 17.80
Last tank test year	Mean= 2014.23, standard deviation= 3.59
Position in a train	Mean= 22, standard deviation= 26.27
Rolling stock type	1=freight-covered hopper (0.1%)
	2= freight-non-press hazmat tank (59.77%)
	3= freight-press hazmat tank (39.82%)
	4= freight-press hazmat tank (cryogenic) (0.31%)
Tank car derailment	1=yes (28.94%), 2= no (71.05%)
Hazmat cars involved	1= yes (98%), 2= no (2%)
Carload status	1=empty (0.63%)
	2= loaded (54.65%)
	3=residue (44.72%)
Number cars	Mean= 23.36, standard deviation= 22.22
Locomotive derailed	1 = yes (7.5%)

	2 = no (92.5%)
Cause of incident	1 = non-main-track-derailment (39%)
	2 = non-main-track-collisions (6%)
	3 = trespasser accidents (6%)
	4 = crossing accidents (13%)
	5 = main-track-derailment (7%)
	6 = main-track-collisions (0.3%)
	7 =other (29%)
Province	1 = Alberta (34.8%)
	2 = British Columbia (14.7%)
	3 = Manitoba (5.95%)
	4 = New Brunswick (2.1%)
	5 = Nova scotia (0.35%)
	6 = Northwest Territories (0.17%)
	7 = Ontario (23.82%)
	8 = Quebec (11.56%)
	9 = Saskatchewan (6.48%)
Time	10:30= (2.8%)
	13:00= (2.28%)
	…….
	17:30= (0.17%)
	19:25= (0.17%),
Month	1= January (9.11%)
	2= February (8.4%)
	3= March (7.53%)
	4= April (6.83%)
	5= May (7%)
	6= June (7%)
	7= July (10.85%)
	8= August (7.88%)
	9= September (10.5%)
	10= October (10.68%)
	11= November (5.25%)
	12 = December (8.93%)
Year	2007= (11.38%)
	2008= (7.7%)
	2009= (7.35%)
	2010= (4.55%)
	2011= (5.78%)
	2012= (6.83%)
	2013= (10.15%)
	2014= (5.43%)
	2015= (4.73%)
	2016= (4.2%)
	2017= (5.25%)
	2018= (6.65%)

	2019= (12.08%) 2020= (7.88%)

The probability of hazmat release is classified into a binary response (yes/no) as listed in Table 5-1. Then, the classification methods are used to predict the probability of hazmat release.

5.2.3 Classification modeling

There are several classification methods used in this study, including Logistic Regression (LR), Naïve Bayes (NB), Decision Trees (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). These methods are explained in chapter 4.

5.2.4 Classification evaluation metrics

These methods are explained in chapter 4.

5.2.5 Natural language processing (NLP)

This method is explained in chapter 4.

5.2.6 Co-occurrence network

This. method is explained in chapter 4.

5.3 Results and discussion

5.3.1 Classification methods performance in predicting the probability of hazmat release

To predict the occurrence of hazmat release, machine learning algorithms are applied (RF, DT, KNN, SVM, LR, NB). Although LR, DT, NB, and KNN do not need hyperparameter tunning, SVM and RF need, tuning. The hyperparameters of SVM and RF are tuned using grid search and the k-fold cross-validation (Iranitalab & Khattak, 2020). The performance of the classification models used to predict the probability of hazmat release on the imbalanced dataset are listed in Table 5-2. The results indicate that RF are the most accurate classifiers followed by DT for predicting hazmat release due to their high precision (RF:0.88, DT: 0.86), recall (RF:0.88, DT:

0.86), and F1-scores (RF:0.88, DT: 0.86). The classification models listed in Table 5-2 have high accuracy rates (RF: 0.88, DT: 0.87, KNN: 0.83, SVM: 0.80, LR: 0.80, NB: 0.79), as the imbalanced dataset contains largely incidents with "no hazmat release" and neglects incidents with "hazmat release".

Table 5-2 Performance measure comparison for the imbalanced dataset.

Classification methods	Precision	Recall	F1-Score	Accuracy
RF	0.88	0.88	0.88	0.88
DT	0.86	0.86	0.86	0.87
KNN	0.77	0.77	0.78	0.83
SVM	0.76	0.78	0.77	0.80
LR	0.72	0.75	0.72	0.80
NB	0.74	0.76	0.67	0.79

The performance of classification models on the balanced dataset is also listed in Table 5-3. The results indicate that the SMOTE technique can improve the performance of the model, as F1-Scores (a harmonic mean of precision and recall) are improved in all the models.

Table 5-3 Performance measure comparison for the balanced dataset.

Classification methods	Precision	Recall	F1-Score	Accuracy
RF	0.90	0.90	0.90	0.90
DT	0.89	0.89	0.89	0.88
KNN	0.78	0.79	0.79	0.84
SVM	0.77	0.79	0.78	0.82
LR	0.76	0.78	0.76	0.80
NB	0.75	0.76	0.76	0.81

According to Table 5-3, the RF and DT classifiers perform better than other models due to their high precision (RF: 0.90, DT: 0.89), recall (RF: 0.90, DT: 0.89), and F1-Score (RF: 0.90, DT: 0.89) factors. The high recall rate of RF indicates that the number of TP is high, while FN is low. Output-sensitive predictions require high recall models (James et al., 2006). A high recall model is also required for this study, as hazmat release incidents may have catastrophic consequences if they are not accurately predicted. The high precision value obtained by RF indicates that the number of TP is considerable and the number of FP is extremely low. If the cost of acting is significant, precision will be more critical (He et al., 2019). As an incorrect prediction of hazmat release can result in a loss of time and money, the focus of this study is more on the precision of these models. An ideal system would produce most of the results, which are correctly classified with high precision and recall values (Koklu & Ozkan, 2020). Depending on the problem, risk managers can choose a model that has either high precision, recall or both (Iranitalab & Khattak, 2020).

The AUC values of all the classification models (LR, NB, SVM, RF, KNN, and DT) are shown in Fig. 5.2.

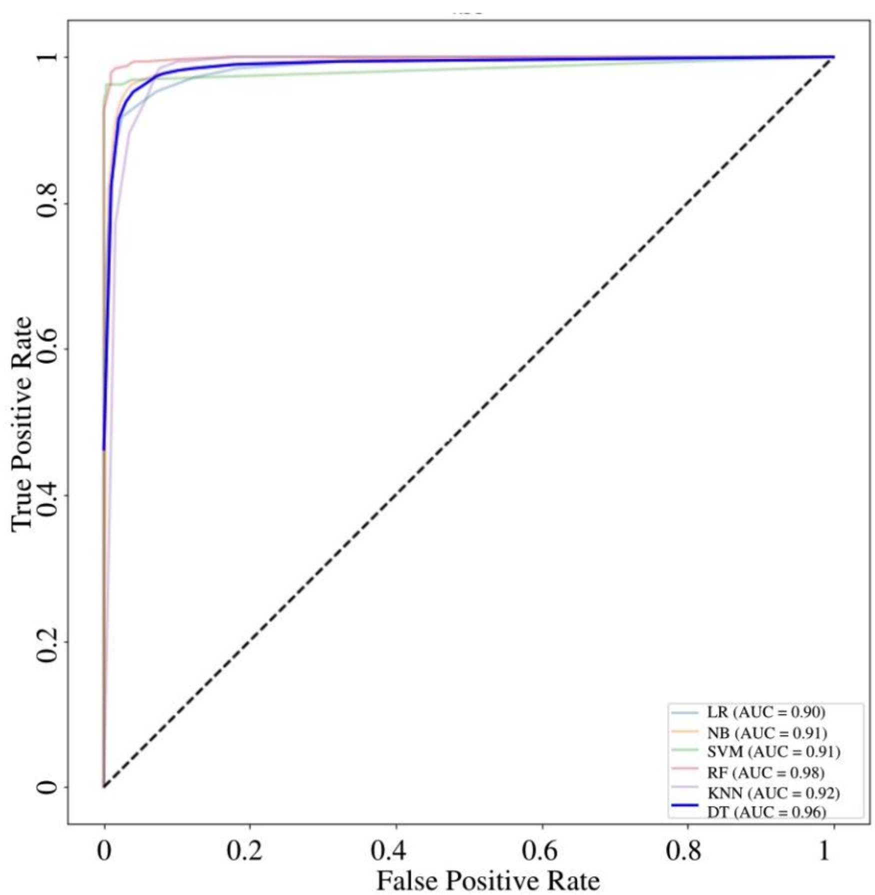

Fig. 5.2 ROC curves of the classification models.

As illustrated in Fig. 5.2, the highest AUC is found for RF followed by DT (RF: 0.98, DT: 0.96), demonstrating their capability to predict the probability of hazmat release.

5.3.2 Feature selection

5.3.2.1 Random Forest Analysis

The importance of an input variable could be determined by evaluating its influence on the prediction of the response (Scavuzzo et al., 2022). In this study, the RF method is used to identify the variables with the greatest influence on hazmat release. Each variable is assigned a score based on its relevance and importance to the response (hazmat release) (Zhu et al., 2021). The ranking of these variables on the prediction of hazmat release is indicated in Fig. 5.3.

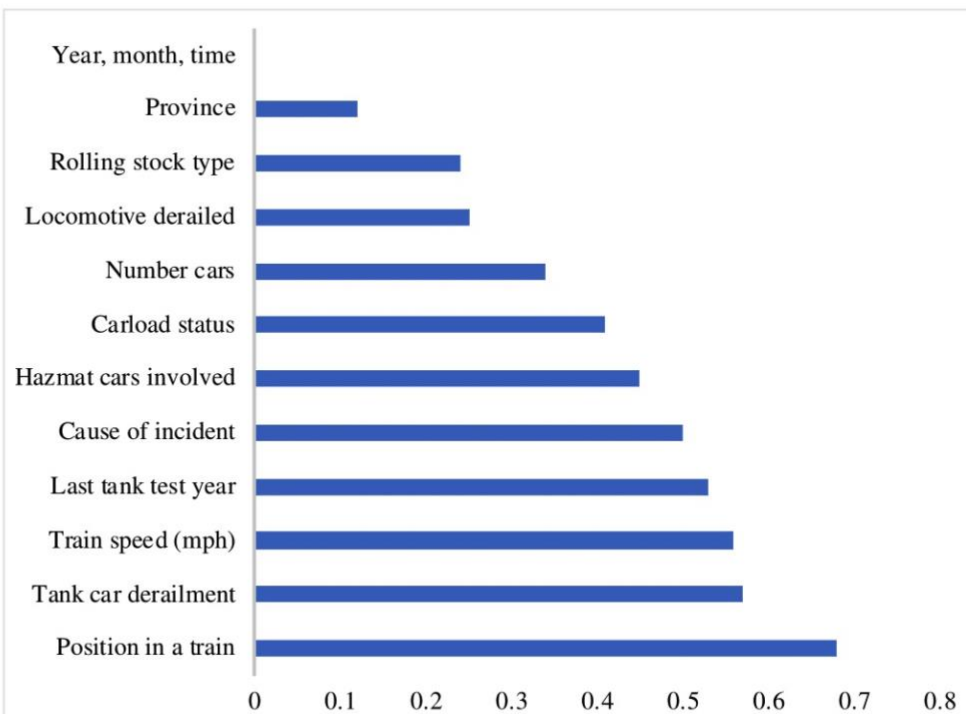

Fig. 5.3 Ranking of variables on the prediction of hazmat release.

As shown in Fig. 5.3, the position in a train, tank car derailment, train speed (mph), and last tank test year are the variables with the greatest impact on hazmat release. Analysis of these factors is necessary to minimize or avoid the probability of hazmat release. For instance, Liu et al., (2014) demonstrated that accidents may be less severe if tank cars are placed within the train at a location where they are less susceptible to derailment or damage. A number of factors must be considered for the safe placement of tank cars in a train, such as whether the tank car is empty or loaded and the number of hazmat cars in the train. Liu et al., (2014) also explained that train derailment could increase the probability of hazmat release from tank cars. Train derailment could be reduced by inspecting tracks, avoiding operational errors (i.e., excessive speed), and inspecting mechanical equipment (i.e., rails, wheels) (Shultz et al., 2016). According to Shultz et al., (2016), excessive speed can lead to a number of serious railway incidents and the release of hazmat. Using positive train control (PTC) train movements and speed can be monitored and controlled (Badugu & Movva, 2013). To prevent hazmat release from damaged tank cars during railway accidents, tank car damage assessment should frequently be carried out (Davis & Stone, 2002).

5.3.2.2 Correlation matrix with heatmap

The correlation heatmap describes how variables are related to each other or the response (DeBoer, 2015). The correlation ranges vary from -1 to +1. Values close to zero indicate no linear relationship exists between the two variables. Positive correlations indicate that the variables move in the same direction, while opposite scenarios happen for negative correlations (Bounova & De Weck, 2012). The correlation heat map is illustrated in Fig. 5.4 for the input variables with the greatest impact on the response obtained from Fig. 5.3. According to Fig. 5.4, tank car derailment and position in a train are highly correlated and they could contribute to each other's severity. Liu et al., (2014) examined the relationship between tank car derailment and train position and found that improperly assembled trains are more likely to derail. The railroad industry has also developed different guidelines for train makeup to increase an appropriate level of safety and reduce the probability of train derailment (Saccomanno & El-Hage, 1989).

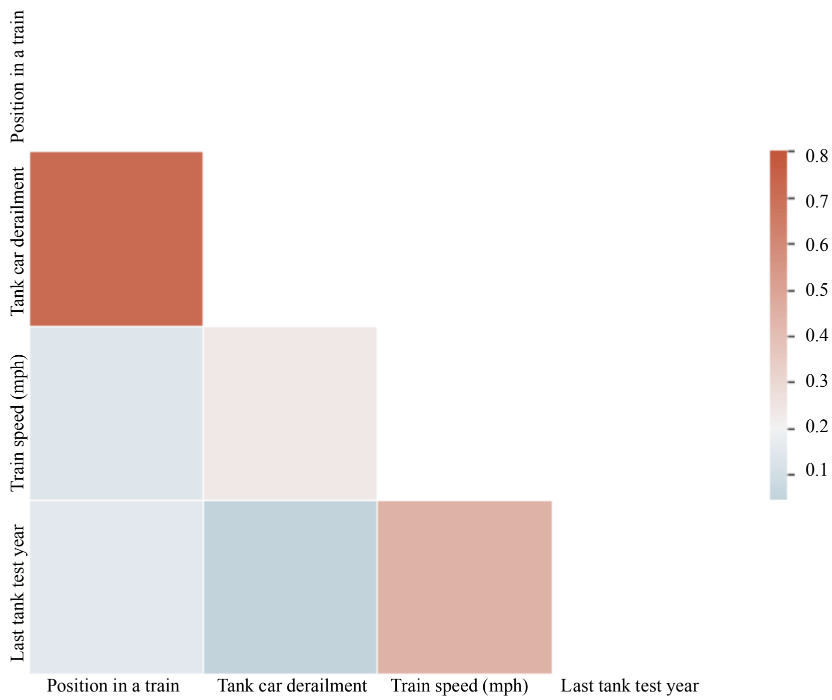

Fig. 5.4 The correlation heat map.

As depicted in Fig. 5.4, the tank car derailment is fairly correlated with the train speed, and the train speed is correlated with the last tank test year. Bagheri, (2010) in a study also confirmed that train speed is associated with train derailment. As these variables are correlated, controlling one variable will have a corresponding impact on the other variables, thereby reducing the probability of hazmat being released during transportation.

5.3.3 Natural Language Processing analysis

The reports prepared for describing the railway incidents, which are led to hazmat release, are used to build a word cloud (Fig. 5.5).

Fig. 5.5 The word cloud developed by the top words of the incidents that caused hazmat release.

The most frequent words in the word cloud are “tank car”, “injuries”, “CP (Canadian Pacific Railway) officials”, “CN (Canadian National Railway) officials”, “derailed”, “train crew”, “fire department”, “TSB” (Transport Safety Board of Canada), “leaking”, “dangerous goods”, “fuel oil”, “head office”, “investigator”, etc. Hazmat releases happened frequently by "product leaks" and "tank car derailments," as shown in Fig. 5.5. "Injuries" have occurred after hazmat release from "tank cars". As incidents that result in hazmat release could have significant consequences, further "investigation" was conducted by "TSB", "CN", and "CP" "officials" in association with "the head office". Moreover, "fuel oil" was one of the most frequent types of hazmat (or "dangerous goods") involved in the incidents that led to the release of hazmat. Using this visualization, different potential cause and consequence scenarios can be developed, and the most frequent causes and consequences can be identified. Co-occurrence analysis is employed to determine the relationships between these causes and consequences and understand their relationships.

5.3.4 Co-occurrence network analysis

To prepare the co-occurrence network diagram, a brief description of the incidents led to hazmat release is used, as shown in Fig. 5.6. As a result of setting the threshold value (Jaccard coefficient is set to 0.2 (Liu et al., 2021)), only strong associations are taken into account, while weak associations are ignored (Libis et al., 2019). Several nodes (words) form a co-occurrence network. Each network consists of several subgraphs. Each subgraph contains words with strong co-occurrence relationships in a specific color. Each node size is also determined by the number of connections. Co-occurrence is indicated between nodes by the edge between them. Co-occurrences between different subgraphs are indicated by dashed lines. As a result, each subgraph naturally exhibits a hierarchy of causes and consequences. To describe different scenarios, subgraphs with an appropriate number of edges and nodes could be formed (Sakuma et al., 2021; Libis et al., 2019).

Various subgraphs are presented in Fig. 5.6, and different hypothetical scenarios may be derived using these subgraphs. As illustrated in Fig. 5.6, a hypothetical incident scenario is described in subgraph number 4 (red color) as follows: a "train" loaded with X tank cars containing "aviation fuel" "derailed" in a "railyard" and "released" the product. "Emergency" "response" "responded" and "evacuated" the "nearby" neighborhood. Subgraph number 4 is connected to subgraph number 2 (yellow color) with the node emergency, resulting in the following scenario: Upon "inspection", it was revealed that X "loaded" "anhydrous ammonia" "tank" "cars" "derailed". As a result of the "derailment" "tank" "car" "PROX X", a "load" of "anhydrous ammonia" was "leaking". "Emergency" "services" were sent and "investigators", working from the "Toronto" "office" were called to take appropriate actions. The potential incident scenarios could be developed for all the subgraphs in the co-occurrence network to find the causes and consequences of the incidents that led to hazmat release.

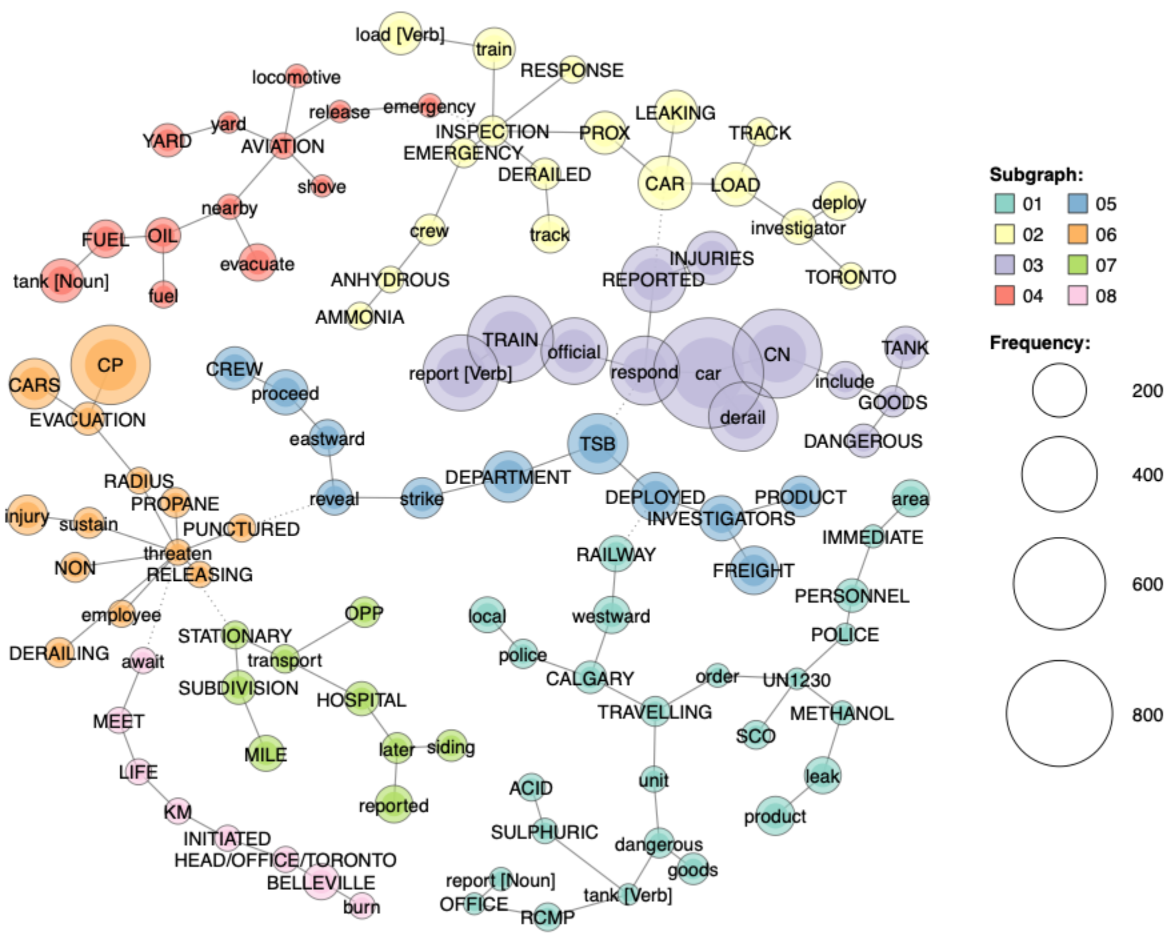

Fig. 5.6 The co-occurrence network derived from the incident reports with hazmat release.

The main contributing factors that prompted hazmat release can be identified through the analysis of the connection and frequency of the nodes in the co-occurrence network. The main contributing factors are derailment, strike, and puncture (categorized as different types of Action on Means of Contaminant (MOC)); release, leaking, burning, and BLEVE (categorized as different types of incidents); methanol, sulphuric acid, propane, aviation fuel, and anhydrous ammonia (categorized as different types of hazmat). Table 5-4 summarizes the contributing factors and control measures to prevent hazmat release.

Table 5-4 The contributing factors and recommendations for controlling these factors.

Contributing factors	Recommendations to prevent hazmat release
Derailment	Inspecting tracks, avoiding operational errors (i.e., excessive speed), and inspecting mechanical equipment (i.e., rails, wheels) (Shultz et al., 2016).
Puncture	Using the tank head shields, implementing thicker shell materials, installation of tank jackets and thermal protection systems, and enhancing the protection of bottom outlet valves and top fittings (National Transportation Safety Board, 2022).
strike	Installing active warning systems, such as boom gates, flashing lights, and warning bells (Occupational Health & Safety, 2022).
Release, leaking	Utilizing DOT-117R tank cars which are thicker than most cars currently being used, performing regular inspections of the tank head and shell for defects (National Transportation Safety Board, 2022).
BLEVE, burning	Incorporating a vent mechanism that allows vapors to escape directly into the atmosphere (National Transportation Safety Board, 2022).
Methanol, sulphuric acid, propane, aviation fuel, and anhydrous ammonia	Using more robust tank cars for hazmat transportation and reducing the speed of operation (Shultz et al., 2016).

Using the co-occurrence analysis, various stakeholders, such as regulators, host communities, shippers, and transloaders, may be able to investigate potential sources of needed resources, develop a plan for hazmat planning, and train and exercise this plan. The stakeholders must ensure that their resources are utilized in a manner that minimizes the consequences of a hazmat incident.

It is also critical to have a framework for responding, which can be used for directing resources in the right direction. Planning is essential to the effective management of resources. An essential component of hazmat planning is to respond effectively and efficiently to hazmat incidents, reduce the risk of injury and death, prevent or minimize property damage, and protect the environment. Using these results, we can gain insight into data analysis and data collection to learn more about the latent causes of hazmat releases. To determine the latent causes of hazmat releases more accurately, co-occurrence analyses could be performed on the reports of the incidents that contained contributing factors derived from Fig. 6. Also, supplementary information not included in the incident report could be obtained using the co-occurrence analysis in conjunction with other reports, such as near-misses and maintenance reports. As a result of this comparison, we can gain a deeper understanding of the incident. Although the co-occurrence analysis provides information concerning the causes and contributing factors to the hazmat release, the analysis is likely to eliminate significant information as each incident propagates differently (Liu et al., 2021). The contributing factors could be used to extract only those reports that contain these factors. Thus, more causes and contributing factors could be identified.

5.4 Conclusion

In this study, a machine learning-based risk assessment approach was developed to predict the probability of hazmat release in railway incidents. This study utilized the RODS dataset collected between 2007 and 2020 to develop different supervised machine learning models (i.e., RF, DT, LR, SVM, KNN, NB) to predict the probability of hazmat release. First, the dataset was balanced using the SMOTE technique, since only 2% of railway incidents resulted in hazmat release. Then, a performance evaluation was conducted, and RF was selected as the most accurate classifier based on recall, precision, F1-Score, and AUC values. The feature selection algorithms revealed that the position in a train, tank car derailment, approximate train speed (mph), and last tank test year are the variables with the most significant effect on the probability of hazmat release during railway incidents. Second, the short reports prepared for the incidents, resulting in hazmat release were examined to develop the potential cause and consequence scenarios and identified the contributing factors to the hazmat release using co-occurrence analysis. The results of this study indicated that several contributing factors exist, which can be categorized, namely action on MOC (i.e., derailment, strike, and puncture), type of incidents (i.e., release, leaking, burning, and BLEVE), and type of hazmat (i.e., methanol, sulphuric acid, propane, aviation fuel, and anhydrous ammonia). In this study, machine learning models were developed which were capable of predicting hazmat release probability and contributing factors. However, there are some limitations, which could be addressed. For example, the explanatory input variables were determined based on the literature review and the availability of data. Future studies may examine a more comprehensive dataset and analyze the impacts of a variety of factors, including the characteristics of the tank cars, the track, and weather conditions.

Chapter 6

6.1 Conclusions

To minimize the negative consequences of railway incidents, risk assessment is essential for improving safety and planning. Based on the components of the risk assessment (i.e., hazmat-related incident rates in the transportation infrastructure, the release consequences, and the probability of hazmat release), the objectives of this study are developed.

The first part of this study identified and analyzed the leading indicators (i.e., human factors) associated with railway incidents. This part can be summarized as follows:

- The data from 42 main track derailments and collisions involving the transport of dangerous goods in Canada between 2007 and 2018 was used to classify the causes of railway loss incidents using the SMS framework and identify system weaknesses. The role of human factors was further analyzed through the HFACS approach. Statistical techniques (i.e., the DEMATEL and the ANP methods) were used to identify causal relationships between different sub-categories of the HFACS framework and calculate the weighted influence of each sub-category on main track derailments and collisions.
- The results demonstrated that the most deficiencies were in the areas of organizational oversight, supervision, and the culture of the organization.
- The results highlighted the importance of supervisory and organizational factors in the prevention of railway loss incidents.

The second part of this study evaluated the consequences of railway incidents and the approaches taken to minimize such negative consequences (for example, developing risk maps). A summary of this part is as follows:

- A procedure was developed to estimate the risk of hazmat railway incidents with a focus on two parts. First, the most probable and the most dangerous meteorological variables were processed to simulate threat zones and prepare hazard maps. Second, sociodemographic characteristics of the affected population were used to create vulnerability maps. As risk is a function of hazard and vulnerability, risk maps were generated by superimposing the hazard and vulnerability maps using ArcGIS software.
- The risk maps revealed that hospitals, medical centers, route access, and emergency services should be considered in land-use planning to reduce and prevent future losses.
- Based on the risk maps generated in this study, some recommendations have been provided for improving the distribution of medical supplies and dredging paths in highly populated areas.

To minimize the negative consequences of railway incidents, emergency response systems, such as evacuation prediction models, are being developed. A summary of this study is as follows:

- In the first part, an accurate and reliable model was selected to predict evacuation by evaluating seven different supervised machine learning models. The variables with great influence on evacuation were identified, and the root causes of evacuation were determined. In the second part of this study, NLP and text mining were used to analyze the descriptions of incidents and to determine which factors are most likely to lead to evacuation. To build a network of causes and contributing factors and demonstrate a causal dependency between them, co-occurrence network analysis was applied.
- Over sampling technique (SMOTE) improved the accuracy of the models used in this study and Random Forest (RF) was selected as the most accurate model for predicting evacuations.

- Co-occurrence networks are very useful to extract simple patterns from complex datasets. The results indicated that leak and spill —categorized as the various types of incidents — are the most significant contributing factors to evacuation. In terms of types of action on MOC, overturning and derailment were found as the main factors. Railyard operation and loading operation (i.e., loading, unloading, transloading, storage, and handling) were selected as the leading causes of evacuation among the different transport phases. Moreover, petroleum crude oil, diesel fuel, sulphuric acid, nitrate ammonium, sodium hydroxide solution, and ammonia anhydrous were among the types of hazmat that led to the evacuation. Since these factors contribute most to evacuations, they must be considered when assessing risk and planning for emergencies.

The last part of this study examined the probability and contributing factors of hazmat release in railway incidents. A summary of this part is as follows:

- To predict the probability of hazmat release in railway incidents, supervised machine learning models were employed to identify the most reliable model. In addition, text mining and co-occurrence network analysis were used to determine the causes and contributing factors of hazmat release and their relationship.
- Feature selection revealed that tank car position in a train, tank car derailment, train speed, and last tank test year are among the most important factors, affecting hazmat release occurrences.
- Text mining identified the main contributing factors, such as the factors categorized as the type of incidents (i.e., release, leaking, burning, and BLEVE), the factors categorized as the action on MOC (i.e., derailment, strike, and puncture), the type of hazmat involved in

the incidents (i.e., methanol, sulphuric acid, propane, aviation fuel, and anhydrous ammonia), etc.

- It is possible to use co-occurrence analysis not only to provide insights that could assist in the collection of additional information about contributing factors that may help uncover latent causes of incidents, but also to communicate risk causes, consequences, and controls to a variety of stakeholders.

6.2 Recommendations for Future Studies

The following suggestions are provided for future work:

- A comprehensive dataset containing a variety of input variables, including tank car characteristics, track conditions, operator characteristics, and environmental conditions, may be used to develop machine learning models for hazmat release prediction and evacuation.
- Deep learning models could be employed for inference and prediction, and the results may be compared by this study to identify the most accurate model for predicting evacuation and the probability of hazmat release
- The methods developed in this study can be applied to other aspects of hazmat risk (i.e., incident rate and release consequences) to make recommendations for improving safety.
- Using the best machine learning model developed in this study, other incidents involving the transportation of hazmat (i.e., road incidents) may be analyzed.
- A variety of SMS frameworks that contain different elements can be utilized in conjunction with text mining in order to categorize incident reports. As a result of the text mining project, risk managers will be able to improve SMS frameworks as well as understand how to gather data more efficiently.

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