Machine Learning and Text Mining: A New Approach to Determine the Weather Effects on Construction Incidents

by

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Abstract

In the construction industry, safety standards are not only a priority but a necessity due to the dynamic nature of the field. Workplace safety is a complex issue influenced by a variety of factors that are constantly evolving. Each incident has the potential to impact the industry's intricate structure, causing project delays, and more importantly, direct impact on human lives. The adverse effects of workplace incidents reverberate not only within the construction companies themselves but also on a national and global scale. To enhance safety in the construction industry, this thesis explores two crucial aspects - the influence of weather conditions and the interplay of worker demographics. These factors are integral in fortifying this vital sector and contributing to a safer and more resilient industry

In the first study, there was a comprehensive examination of the influence of weather conditions on the frequency of incidents. By utilizing advanced machine learning methods, predictive models, including Random forest, Decision trees and K-Nearest Neighbors were constructed with high accuracy. Particularly, the Random Forest model demonstrated superior performance with an accuracy of 97%. In addition to model creation, an executable application was developed to enable stakeholders to conduct real-time risk assessment. This innovation has the potential to facilitate proactive incident management in situations where weather conditions are constantly evolving.

In the second study, a detailed analysis of the interaction between worker demographics and incident rates was examined. By employing root cause analysis, significant factors contributing to incidents, such as insufficient training, inadequate hazard identification, and ambiguous operating procedures, were identified. Additionally, the utilization of time series analysis further enhanced the understanding of incident rates by uncovering dynamic fluctuations among different age groups, occupational categories and experience levels. This comprehension of the influence of

demographic variables on workplace safety establishes a solid foundation for the development of effective strategies to mitigate risks in areas with high incident rates

Bringing these two studies together, we recognize the pivotal role that comprehensive safety management plays in addressing workplace incidents. While the first study emphasizes the significance of predictive models in managing incident risks related to weather conditions, the second underscores the intricate relationship between worker demographics and safety. Together, they forge a comprehensive approach to proactive safety management in high-incident zones, ultimately aiming to make such environments safer and more resilient.

This revised structure encapsulates both studies within a unified thesis, maintaining the distinctiveness of each while emphasizing the collective pursuit of enhanced workplace safety.

Preface

I was responsible for the data collection, data analysis as well as manuscript composition. Dr. Lianne Lefsrud was the supervisor for this project and contributed to the study design and manuscript edits. Dr. Fereshteh Sattari was involved in study design, providing research direction, editing manuscripts, and assisting with publishing procedures.

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I would like to extend my gratitude to my supervisors, Dr. Lianne Lefsrud and Dr. Fereshteh Sattari, whose unwavering guidance and expertise have been invaluable throughout this research journey.

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Finally, my heartfelt appreciation goes towards my loving parents for their unwavering love, support and encouragement throughout this academic endeavor.

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1. Introduction

1.1 Background

The Canadian construction industry is a dynamic sector, encompassing a wide array of projects ranging from residential and commercial developments to infrastructure improvements, plays a pivotal role in driving economic growth and the construction of vital infrastructure. However, within this foundation of growth and development lurk challenges of paramount importance, notably those pertaining to safety and risk management.

Incidents within the construction sector can have a profound and multifaceted impact, which extends far beyond mere statistics. The safety of its workforce and the reliability of structures are two fundamental concerns.

The first research study, explores the complex interplay between weather conditions and incident rates. In an environment where the safety of the workforce is paramount, the research delves into the intricate relationship between meteorological variables and incident occurrence. With the application of advanced machine learning techniques and the development of weather metrics, this study offers a predictive model to estimate incident likelihood and frequency under diverse weather conditions. This approach, which yielded commendable accuracy rates, endeavors to empower stakeholders in making informed decisions, proactively managing risks, and enhancing incident management within the variable and dynamic weather conditions faced by the industry.

The second research study, situated within high-incident zones where dynamic weather conditions prevail, extends its focus to the multifaceted realm of occupational safety. Root cause analysis and time series analysis converge to dissect and understand the temporal patterns of incidents. Notably, the study emphasizes the crucial examination of worker demographics, task attributes, and incident rates. By doing so, it reveals fundamental contributors to incidents, namely, inadequacies in training, hazard identification, and operating procedures. Simultaneously, a time series analysis unravels the nuanced patterns that underscore the variations in incident rates across different age groups, trade classifications, and experience levels.

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2.1 Introduction

The construction industry is one of the largest industries in the world. It is heavily influenced by factors of outdoor environmental quality (OEQ), such as temperature, humidity, wind speed, and precipitation which significantly affects the safety performance of construction workers (Lee et al., 2021). Therefore, accurate prediction and management of incidents are essential for mitigating risks and ensuring worker well-being.

Some other researchers have also emphasized the significance of weather conditions in safety incident prediction. These include the development of a machine learning model that incorporates weather data to predict safety incidents in construction sites and the utilization of machine learning techniques to predict safety incidents based on weather conditions, emphasizing the need for improved incident prevention strategies (Liu et al., 2020; Nguyen et al., 2020).

Weather conditions, including temperature, precipitation, and wind, have profound implications for construction activities and, in turn, worker safety. Understanding these impacts is essential for effective project planning and management. Temperature variations can affect construction materials and worker productivity. Extreme heat or cold can impact the workability of concrete, leading to structural issues and compromised durability. High temperatures pose significant risks to construction workers, particularly in hot climates or during summer months. Heat stress is a significant concern and can result in heat-related illnesses, such as heat exhaustion and heat stroke (Tang et al., 2017). Studies have shown a correlation between high temperatures and increased falls, slips, and trips, possibly due to fatigue, dehydration, and decreased alertness (Yi et al., 2017; Choi et al., 2019). Moreover, high temperatures can cause thermal discomfort, leading to decreased concentration, irritability, and distractions, contributing to errors and accidents (Wong et al., 2014). Combining high temperatures with other factors, such as high humidity, exacerbates the risks. High humidity reduces the body's ability to dissipate heat through sweating, impairs evaporative cooling, and increases the risk of heat-related illnesses (Kjellstrom et al., 2018).

On the other hand, low temperatures present unique hazards in construction environments and can increase the risk of incidents. Studies have identified several ways low temperatures contribute to accidents and injuries. For instance, cold temperatures can impair manual dexterity and decrease workers' ability to grip tools properly, increasing the likelihood of hand-held equipment accidents

(Liu et al., 2017). In addition, cold weather can cause surfaces to become icy or slippery, leading to slips, trips, and falls (Amin et al., 2016).

Precipitation, i.e., rain or snowfall, can cause delays in various construction operations. Heavy rainfall can hinder site preparation, excavation, and concrete pouring, leading to project delays and increased costs. It can also result in soil erosion and affect the stability of slopes and foundations. Additionally, rainwater infiltration can delay surface finishing activities such as painting and asphalt paving (Sacks et al., 2018). Similarly, snowfall can impede transportation, disrupt supply chains, and hinder worker mobility, causing setbacks in project schedules (Bouzidi et al., 2016). The effects of precipitation can also be seen to impact construction equipment significantly. Exposure to rain and excessive moisture can lead to corrosion, rust, and electrical system malfunctions (Hua et al., 2019). Construction equipment is particularly vulnerable to water ingress, damaging sensitive components, affecting electronics, and leading to equipment downtime. Snow and ice can also cause equipment malfunctions, reduce traction, and increase the risk of accidents (Liu et al., 2017). Therefore, developing a comprehensive and integrated framework that leverages weather information and real-time incident data for informed risk mitigation is essential.

Wind also adversely affects construction operations, particularly those involving work at height. Strong winds can compromise worker safety and require the temporary suspension of specific tasks, such as crane operations and exterior finishing works. Wind can also impact material handling, leading to increased risks of accidents and property damage. Furthermore, wind gusts can cause instability in temporary structures, scaffolding, and formwork systems (Kamat et al., 2020), which can also pose challenges to the safe operation of construction equipment, especially aerial and lifting machinery. Strong winds can cause instability, compromising the stability and balance of cranes, scaffolding, and other elevated equipment (Nguyen et al., 2020). Wind gusts can also affect material handling, leading to accidents and property damage. Construction sites in windy areas require careful monitoring of wind speeds and the implementation of wind-related safety protocols to prevent equipment failures and protect worker safety using ML techniques.

Machine learning (ML) techniques that use meteorological data as a predictor have gained popularity in the research community to improve incident rate predictions.

Several studies have employed machine learning (ML) and weather data to analyze and predict incidents in the construction industry, and these studies have highlighted the importance of incorporating weather data in predicting safety incidents, ultimately improving project planning and risk management (Chen et al., 2019; Fan et al., 2021). These studies collectively showcase the benefits of ML algorithms such as Random Forest (RF) to predict incidents using weather information. Random Forest (RF) is a supervised ensemble learning method that constructs multiple decision trees and combines their predictions to enhance accuracy and robustness. RF has demonstrated its capability in predicting occurrence and identifying relevant attributes contributing to incidents. The ensemble nature of RF mitigates bias and variance, yielding reliable predictions even in the presence of noisy or unbalanced data (Liaw et al., 2002).

Another ML technique is the K-nearest neighbors (k-NN) algorithm, a fundamental non-parametric classification and regression technique. It operates on the principle of proximity, where the classification or prediction for a data point is determined by the majority class of its k-nearest neighbors. The k-NN algorithm is known for its simplicity, adaptability, and applicability to various domains. The analysis forms descriptive statistics to ascertain whether the data consists of a set of distinct subgroups (Hastie et al, 2009).

Another supervised ML algorithm is the decision tree algorithm, which partitions the feature space into subsets, using hierarchical decision rules to guide classification or regression tasks. They offer transparency in decision-making processes and facilitate the interpretability of model results. By visually representing decision rules, decision trees allow practitioners to comprehend the criteria that influence risk categorization, enhancing the interpretability of the model (Géron et al., 2017). K-Means is a popular unsupervised clustering algorithm that partitions data into distinct groups by minimizing the sum of squared distances between data points and cluster centroids. It provides insights into data structures and assists in identifying natural groupings.

In this context, data normalization is critical in data analysis. It ensures that variables are consistently scaled, mitigating biases or distortions arising from differing units or magnitudes. This process is critical when dealing with diverse data types or integrating multiple datasets for analysis. By incorporating working hours as a normalization factor, the analysis accounted for variations in project durations and labor inputs, providing a standardized measure of incidents per hour worked.

While previous studies have explored the relationship between weather conditions and workplace incidents, a notable research gap exists in understanding how specific combinations of weather variables, particularly in regional variations, influence incident rates. Furthermore, the extent to which incident prevention strategies are adapted to these conditions remains underexplored. This research seeks to employ ML techniques to address these gaps by providing a comprehensive analysis of incident likelihood about specific weather thresholds, focusing on tailored risk mitigation measures.

2.2 Methodology

The data for this research consisted of an incident dataset of 113,551 records (2004 - 2023) obtained from an industrial construction company in Alberta, Canada and the weather information extracted from Environment Canada (Historical Climate Data, 2023) using the specific geolocation of incident. The incident dataset contained information about the incident date, incident description, work category, incident type, etc., while the weather information had fields related to hourly wind speed (km/h), temperature (^{o} C), precipitation (mm), and relative humidity (%). All the CSV files containing each monthly weather information were combined to create a comprehensive document containing the weather data for each incident record. The weather data now contained information describing the incident location, incident date and time, temperature, wind speed, relative humidity, and precipitation. The methodology adopted in this study is shown in Figure 2-1.

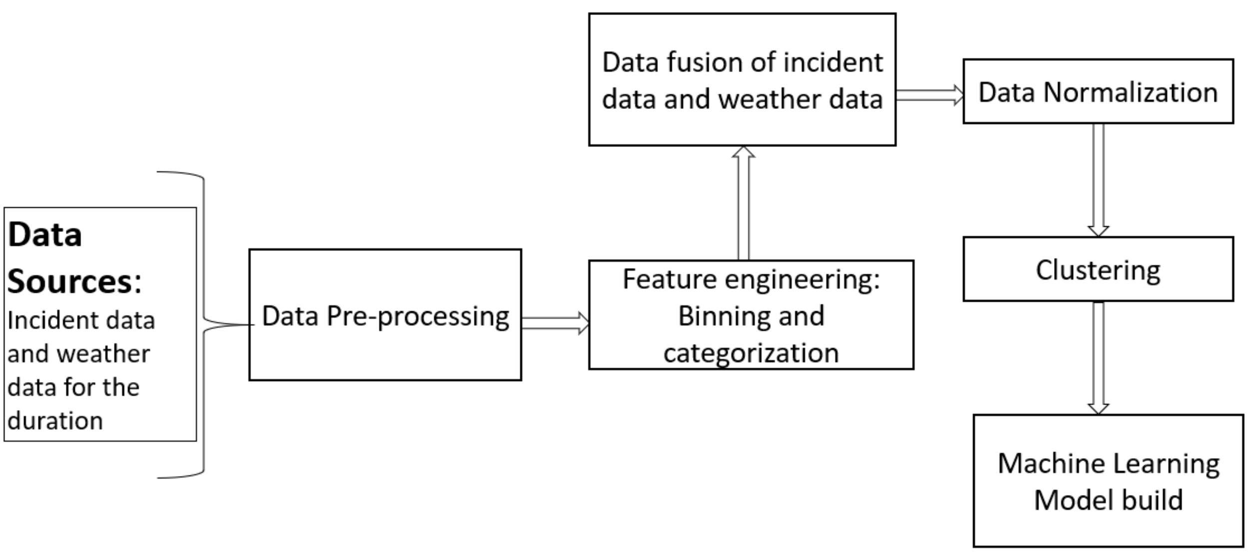

Figure 2-1. Research methodology adopted in this study

2.2.1 Data Pre-processing

The datasets were cleaned by handling missing and null values for each record. Within the weather data, this was handled by deleting the specific row with null values. The Pandas library in Python was utilized for the data pre-processing steps. After data pre-processing, keyword extraction was conducted to include incidents related to weather conditions.

The following keywords: "snow, wind, ice, sunny, hot, degree, visibility, freezing, fog, dark, heat, storm, lightning, temperature, sun, slip, rain, cold, sunny, wet" were identified from literature to be related to weather and a keyword extraction was done to limit the incident data to only records associated with these words.

2.2.2 Data Fusion

Next, the weather data was merged with the incident data for each project based on the project location, incident date, and time columns, which gave the weather information for each incident record. The weather information recorded was at the time each incident occurred.

2.2.3 Feature Engineering

Feature engineering was conducted to transform the raw data into meaningful and informative features that can enhance the predictive power of a model. This step allowed the analysis of the incidents based on temperature ranges and the identification of potential relationships between temperature and incident occurrences. A new feature representing temperature categories was created from -45^{o} C to 35^{o}C, in increments of 5^{o}C and also, for wind speed categories from 0km/hr to 60km/hr, in increments of 5km/hr.

For the relative humidity, the values were represented from 0% to 100%, in increments of 5%, and finally, the precipitation categories were from 0mm to 5.5mm, in increments of 0.5mm. Data Frame methods like between () and cut () were used to bin the weather values into various categories.

2.2.3.1 Aggregated Data Frame

An aggregated data frame was created to store the counts of each category. This step allows us to summarize and analyze the distribution of incidents across different temperature and wind speed categories.

2.2.3.2 Incidents Count per Category

The number of incidents with each category was counted to provide insights into the frequency of incidents in different temperature and wind speed ranges.

2.2.3.3 Incident Proportions

Next, the proportion of incidents in each category was calculated by dividing the count by the total number of incidents.

This crucial step in the analysis process aims to enhance the comprehension of the frequency and distribution of incidents across various temperature and wind speed categories.

2.2.4 Data Normalization

To analyze the relationship between incident occurrences and weather conditions, it is essential to normalize the data based on the working hours for each month. This helps to improve the performance and training stability of the ML model.

The steps for the normalization involved the incident dataset, which contains information about project incidents, merged with the working hours dataset, which includes the corresponding working hours for each month. This merger was performed based on the common date column. The incidents were normalized by dividing the incidents per month by the respective working hours, assuming that each row in the dataset represents all incidents that occurred for that specific month. The normalized incidents per hour worked were calculated as incident density.

A scatter plot was generated to visualize the relationship between temperature, wind speed, and incident density using the Plotly Express library in Python.

2.2.5 Calculating Incident Counts per Month

The incident data was grouped by month, and each month's incidents were counted using the group by () and size() functions. This step provided the total incident count for each month.

2.2.6 Normalization Using Working Hours

The incident counts were normalized by dividing them by the corresponding working hours for each month. This normalization process considered variations in the number of working hours in different months, ensuring an accurate comparison of incident occurrences. The incident counts were divided by the working hours using the element-wise division operation in the Pandas library.

2.2.7 Merging Normalized Data with Weather Information

The normalized incident counts were merged with the weather data using the month as the common key. This step ensured the normalized incident data was associated with each month's respective temperature and wind speed categories.

2.2.8 Grouping and Averaging

Weather categories further grouped the merged data for each month. The average value of the normalized incident counts was calculated for each temperature and wind speed category. This step summarized the average incident occurrences for different weather conditions.

2.2.9 Clustering

Clustering was done to identify distinct clusters of incidents with similar patterns, and similar data points were grouped based on their shared characteristics.

2.2.10 Feature Selection

Temperature, wind speed, humidity, and precipitation were selected as the attributes for clustering, as these were the four key weather variables identified. These features were used to create a 4-dimensional dataset for further analysis.

2.2.11 K-means Clustering

With the preprocessed data, K-means clustering algorithm was applied. The elbow method (which plots the cost function value produced by different k values) was used to determine the appropriate number of clusters (Dangeti, 2017). The optimal number of clusters was three, indicating low, medium, and high-risk regions based on the weather variables.

After clustering, the results were visualized using a 3D scatter plot. Each cluster was assigned a distinct color, allowing easy identification of the risk levels for different regions.

2.2.12 Prediction Model Development

The dataset was split into training and testing sets for the prediction models. This is useful in developing machine learning models that can accurately predict new, unseen data. Cross-validation was used in dividing the data into subsets (for training and testing). Three models, namely, DT, RF, and KNN were used for evaluation.

A Decision Tree classifier was built using the training data. The Decision Tree algorithm recursively splits the data based on the selected features, creating a tree-like structure.

Next, a Random Forest classifier, an ensemble learning method that combines multiple decision trees to improve prediction accuracy, was developed. This ensemble learning method combines multiple decision trees to provide robust and highly accurate predictions, and it excels in handling complex datasets and capturing intricate patterns.

The KNN algorithm predicts the class of a data point by considering its k-nearest neighbors. The KNN model was trained, and the optimal value of k was determined through cross-validation. This model relies on the proximity of data points for classification, making it sensitive to noise and outliers.

2.2.12.1 Model Evaluation

The performance evaluation of each model was conducted using accuracy as the chosen metric. In addition, confusion matrices were generated to give insight into true positive classifications, true negatives, false positives, and false negatives. These matrices depict how the models' classifications align with actual outcomes.

2.2.12.2 Model Comparison

After evaluating all three models, their performance was compared based on the prediction accuracy to select the best predictor for incident risk levels.

2.2.13 Application Build

Creating an executable application bridges the gap between technical and non-technical users. This process adheres to the following steps:

Tool Selection: The PyInstaller tool was chosen for its simplicity and effectiveness in packaging Python scripts into standalone executables.

Application Script: The heart of the application lies in a Python script that integrates the weather prediction model based on the meticulously crafted clustering and machine learning models developed during the research.

Executable Generation: By running the PyInstaller command, the Python script is transformed into an executable that includes all necessary dependencies, eliminating the need for users to install Python.

Usability Enhancement: The executable application features a user-friendly interface where users can input weather parameters, such as temperature, wind speed, humidity, and precipitation. The application then employs the pre-trained model to predict the low, medium, or high-risk severity level associated with the provided conditions.

The outcome of this process is a self-contained executable application that seamlessly integrates the prediction model. Users can execute the application without worrying about any technical prerequisites. This makes it accessible to a broader audience, including non-technical stakeholders and field experts who may lack Python expertise. In this research, Python version 3.10 and RapidMiner 10.1 were utilized.

2.3 Results and Discussions

2.3.1 Categorization and Proportions

Weather attributes, including temperature, wind speed, humidity, and precipitation, were categorized into suitable bins for analysis. The data was divided into intervals of 5°C for temperature and 5 km/h for wind speed, while humidity and precipitation were categorized into intervals of 5% and 0.5 mm, respectively. For example, incidents recorded at a temperature of -8.7ºC were grouped into the -10 to -5º C. Proportions of incidents within each weather category were then calculated, providing insights into the relative occurrence of incidents under different weather conditions.

2.3.2 Heatmap Visualization

A color scale ranging from cool shades (e.g., blue) for lower incident occurrences to warm shades (e.g., red) for higher incident occurrences was used. High-risk areas with increased incident risks were identified based on specific temperature and wind speed combinations, with darker color shades, while cooler shades indicated regions with lower incident occurrences. The heatmap was displayed in a two-dimensional plot, showing temperature vs. wind speed. Figure 2 shows that most incidents occurred between temperature values of -0.1ºC-10ºC and Wind speed values of 5-9km/hr., with an incident count of 42. This concentrated region highlights a critical area of interest, signifying that incidents will most likely occur within these specific weather conditions. The combination of lower temperatures and moderate wind speeds poses a heightened risk to workplace safety. Understanding this hotspot is pivotal for enhancing incident management and risk mitigation strategies.

In addition, Figure 2-2 underscores the dynamic nature of incident occurrence concerning varying weather conditions. The incident count notably decreases as the temperature and wind speed deviate from this hotspot. This suggests the importance of proactive measures and targeted interventions in conditions diverging from the identified high-risk zone, thereby minimizing the incident occurrence and its associated impact on worker safety.

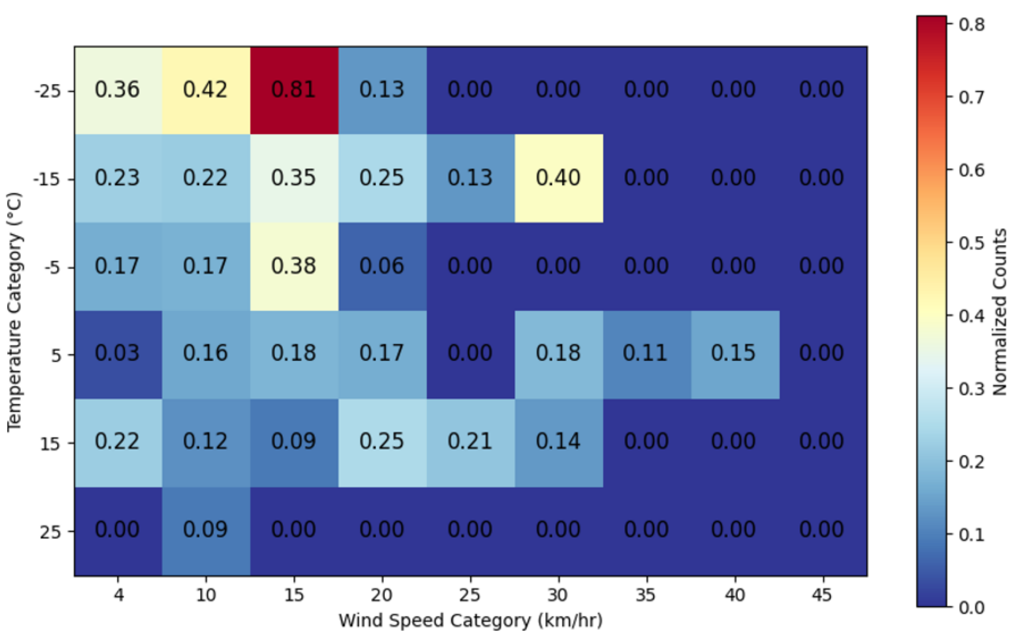

Figure 2-2. Two-dimensional heat map of Temperature vs. Wind speed.

2.3.3 Scatter Plot Visualization

A 4D scatter plot was developed to identify the relationship between weather attributes and incident occurrences (Figure 2-3). Each data point represents an incident record, with the point size indicating the severity of the incident and the color representing the frequency of incidents at that particular weather combination. The clustering of data points in the scatter plot revealed incident patterns and identified potential high-risk regions. These clusters signify that incidents tend to congregate under specific combinations of weather conditions.

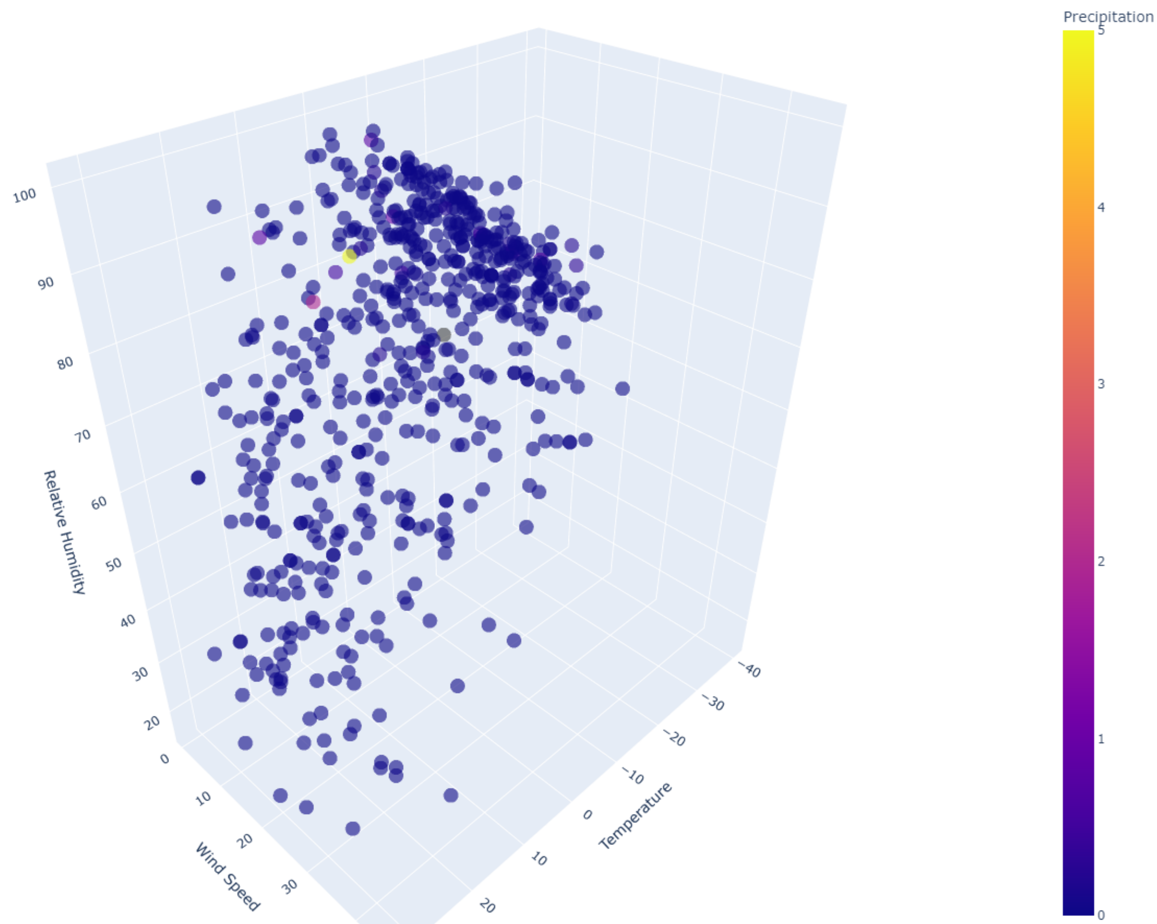

Figure 2-3. Four-dimensional scatter plot of four weather variables (temperature, wind speed, relative humidity and precipitation).

2.3.4 Clustering

K-means clustering was applied to group similar incidents based on weather attributes. The clustering analysis identified distinct incident risk areas with similar weather conditions. To determine the appropriate number of clusters, the elbow method was used. The optimal number of clusters was three, indicating low, medium, and high-risk regions based on the weather variables. Incidents within the same cluster were associated with similar weather patterns and incident risks, providing valuable insights for resource allocation and preparedness efforts. From the plot, cluster_2, cluster_1, and cluster_0 represent high, medium and low severity risk levels, respectively.

Risk level	Temperature (ºC)	Relative Humidity (%)	Precipitation (mm)	Wind Speed (km/hr)
Low severity	0.7	80	0	18
High severity	-11.8	77	0	24
Low severity	-2.4	96	0	8
High severity	-30.2	69	0	11
High severity	-11	70	0.023	11
High severity	-24.5	68	0	15
High severity	-24.3	69	0	17
High severity	-21.9	76	0.3	13
Medium severity	29.9	20.0	0.0	26.0

Table 2-1. Table showing clusters for different combinations of weather variables.

Table 2-1 presents insights derived from the K-means clustering analysis applied to the incidents based on weather attributes. This analysis aimed to identify patterns in incident occurrences influenced by weather conditions.

The table consists of the following columns:

1. Risk Severity Level: This column categorizes incidents into three distinct risk levels: high, medium, and low. These risk levels were determined through clustering, where incidents with similar weather attributes were grouped.
2. Temperature: This column represents the temperature associated with each incident cluster. It provides information about the temperature range for each risk severity level and indicates the average or representative temperature within the respective clusters.

3. Humidity: The humidity values corresponding to each incident cluster are provided in this column. Similar to temperature, humidity patterns are revealed for different risk severity levels, aiding in understanding how incidents relate to varying humidity conditions.
4. Precipitation: This column shows the precipitation data for each incident cluster. It illustrates the precipitation experienced within the clusters representing different risk severity levels.

High severity cluster (Cluster 2): Incidents falling under this cluster are associated with higher temperatures, specific humidity levels, and perhaps significant precipitation. This suggests that weather conditions in this cluster are conducive to incidents with higher severity levels.

Medium severity cluster (Cluster 1): This cluster might exhibit moderate temperature, humidity, and precipitation values, indicating conditions that lead to incidents of moderate severity.

Low severity cluster (Cluster 0): Incidents in this cluster correspond to relatively lower temperature, humidity, and precipitation levels. This cluster represents conditions less likely to result in incidents or incidents of lower severity.

	Temperature		**Wind Speed**		**Humidity**		**Precipitation**	
	min	max	min	max	min	max	min	max
Label								
Cluster 0	-10.4	23.2	0	45	57	100	0	5
Cluster 1	-12.5	31.3	0	46	16	67	0	0
Cluster 2	-40.2	-5.8	0	34	52	96	0	0.7

Table 2-2. Minimum and Maximum values for each cluster

Table 2-2 illustrates each variable's minimum and maximum clusters and depicts the variability in weather attributes across the identified clusters resulting from the K-means clustering analysis. Each cluster represents a distinct grouping of incidents characterized by similar weather conditions. The minimum and maximum values for each variable within these clusters provide an understanding of the range of conditions present within each cluster.

In the analysis:

- Minimum Value (Min): This refers to the lowest observed value of a specific weather attribute within a particular cluster. It indicates the extreme lower end of the range for that attribute within the cluster.
- Maximum Value (Max): This signifies the highest observed value of the same weather attribute within the cluster. It represents the upper range boundary for that attribute within the cluster.

The application of these minimum and maximum values lies in their ability to provide a quantitative description of the variability and diversity of weather conditions within each cluster. Specifically:

- Cluster Characterization: By examining the range between the minimum and maximum values for each variable in a cluster, analysts can discern the scope of weather conditions that contribute to incidents in that cluster (Tan, P., 2005).
- Intra-cluster Comparison: By comparing the minimum and maximum values across clusters for a given weather attribute, patterns of variation can be identified between clusters (Boomija, M., 2008).

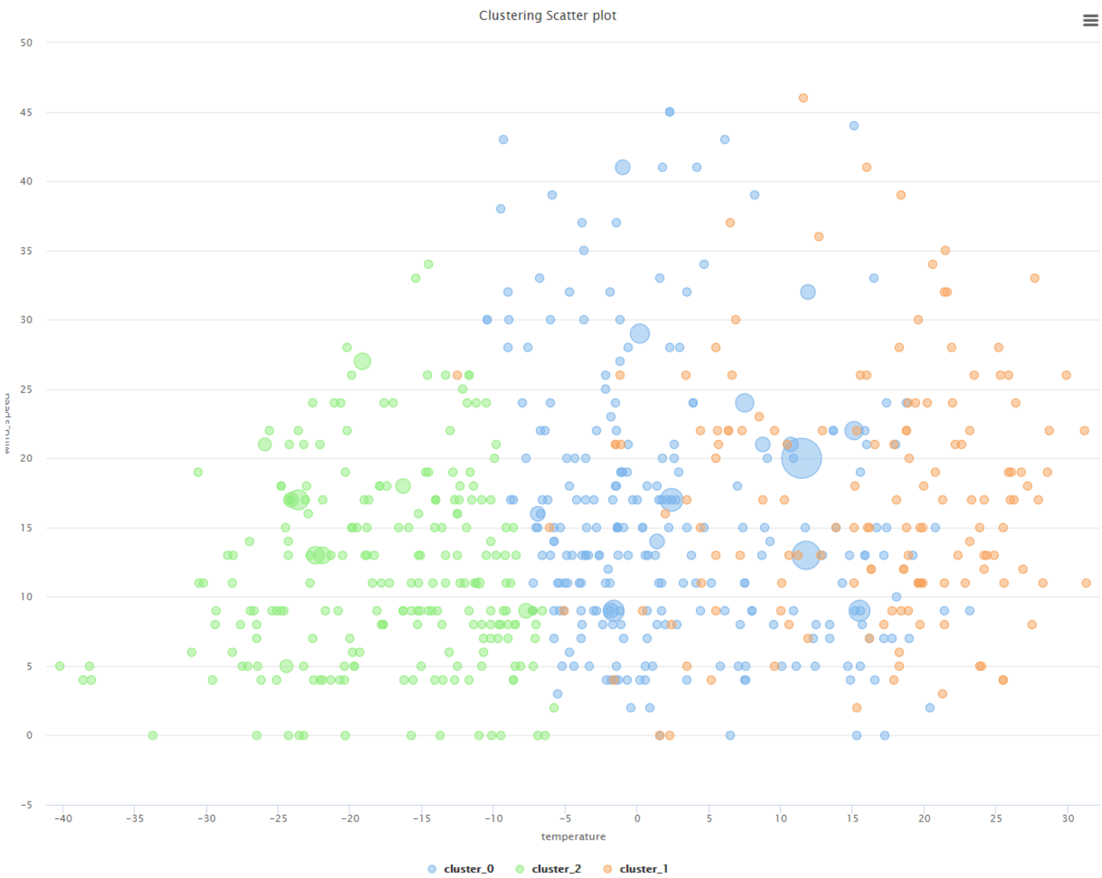

Figure 2-4. Scatter plot of K-means clustering

Figure 2-4 illustrates the scatter plot resulting from the K-means clustering. Each cluster captures a specific subset of incidents with similar attributes regarding the analyzed weather attributes. Each cluster resembles a unique "zone" where incidents exhibit comparable weather-driven behaviors. Cluster 0, Cluster 1, and Cluster 2 exhibit different arrangements of data points, which point to areas where the interplay of weather attributes leads to varying degrees of incident risk.

2.3.5 Performance of Prediction Models

For this study, KNN, Random Forest (RF) and Decision Tree (DT) models were developed to classify incidents into low, medium, and high-risk categories based on the weather conditions using RapidMiner software.

ML MODEL	ACCURACY
Random forest	97.0%
Decision tree	96.7%
K-nearest neighbors	85.2%

Table 2-3. Accuracy of different ML classifiers

The RF model performed best with an accuracy of 0.970, followed by DT with an accuracy of 0.967 and KNN with 0.852. While evaluating the three models, significant efforts were directed toward optimizing their predictive performance.

The RF achieved the highest accuracy of 97.0% through careful parameter tuning. By meticulously fine-tuning parameters like the number of trees and the maximum depth, a balance was struck between complexity and generalization.

Similarly, DT exhibited good performance with an accuracy of 96.7%. Detailed hyperparameter tuning, including controlling the tree's depth and applying pruning techniques, allowed for a more refined decision boundary. The emphasis on preventing overfitting while maintaining the model's inherent capacity for capturing intricate patterns resulted in the notable accuracy achieved.

On the other hand, k-Nearest Neighbors yielded an accuracy of 85.2%, relatively lower than the other two models. Despite careful parameter optimization, it's possible that k-Nearest Neighbors might not have been the optimal fit for predicting incidents based on the given weather attributes.

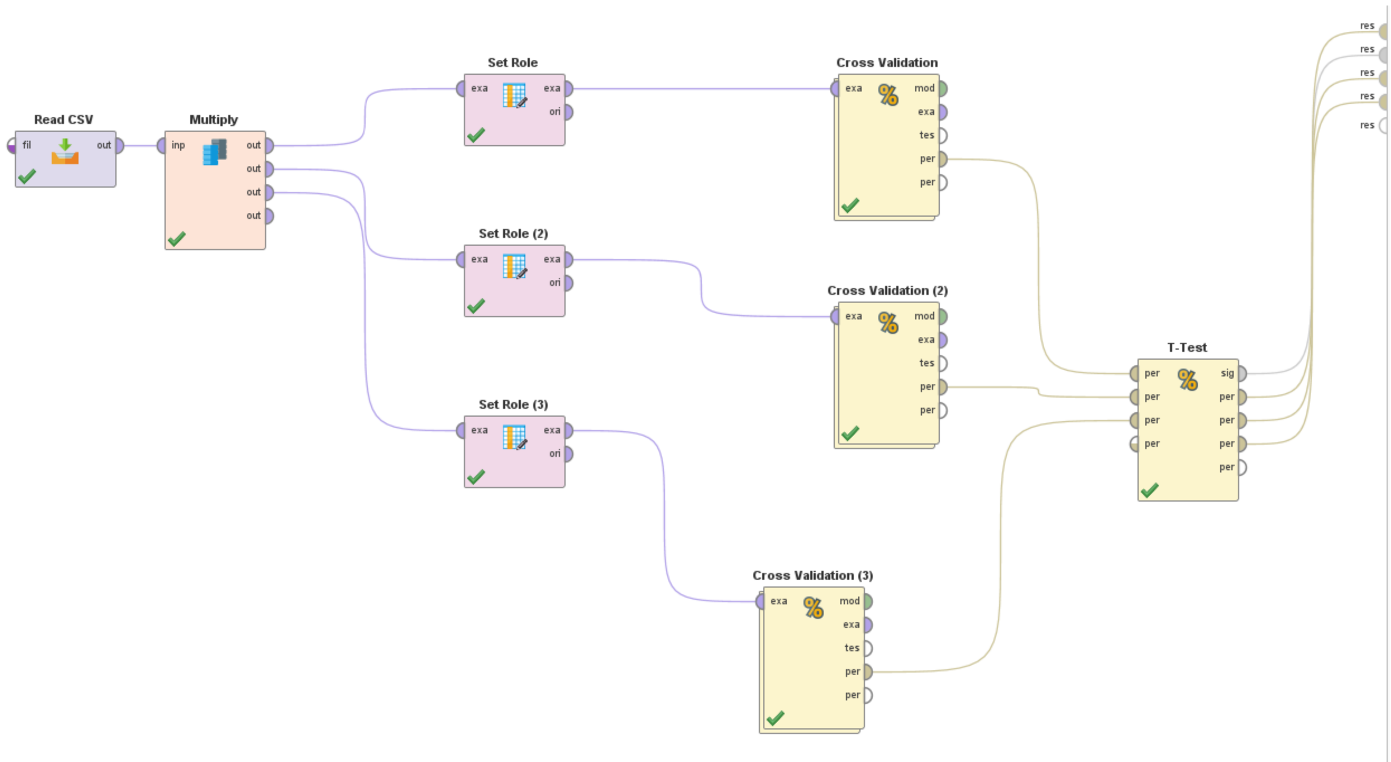

Figure 2-5. Machine learning model built in RapidMiner.

Figure 2-5 shows a visual representation of the machine learning model developed using RapidMiner, incorporating the three distinct algorithms (RF, DT and KNN). This model plays a pivotal role in the research by enabling the prediction of incident likelihood based on the interplays of weather attributes. To ensure the robustness and reliability of the machine learning model, a cross-validation technique was adopted for each of the three algorithms integrated within the RapidMiner-based model. Cross-validation enabled the assessment of the model's performance across multiple folds of data, effectively mitigating potential bias introduced by a single training-test split.

Furthermore, to establish the statistical significance of any observed differences among the algorithms, a t-test analysis was conducted, which allowed for the quantitative assessment of whether the model performance variations were statistically significant.

2.3.6 Risk Severity Predictor Application

As part of the broader research into weather-related incident prediction, a key challenge is ensuring that the developed tools are accessible and usable by a wider audience. However, sharing Python applications with non-technical users can be daunting due to the requirement of Python installation. To address this, an executable application has been developed (Figure 2-6), which leverages the PyInstaller tool that encapsulates the prediction model, allowing users to assess the risk severity associated with specific weather conditions easily.

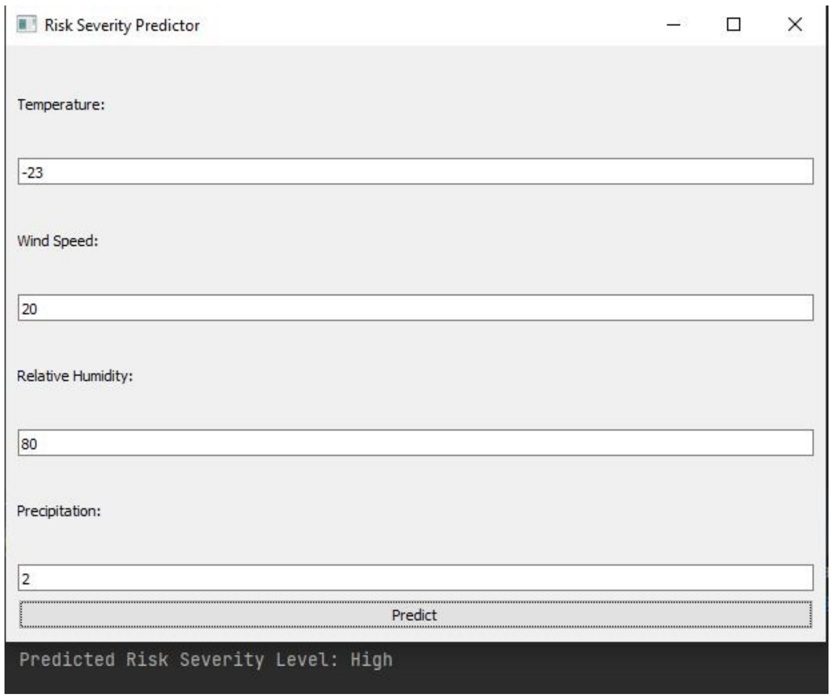

Figure 2-6. Risk Severity Predictor Application.

2.4 Recommendations

The culmination of the research into predicting incident likelihood based on weather variables yields valuable insights with great potential for enhancing incident management and risk assessment strategies. The predictive model stemmed from a comprehensive analysis of weather-related incidents and offers a tool to address potential incidents proactively. This research extends the work of other scholars by delving into the intricate interplay of temperature, wind speed, relative humidity, and precipitation in various regional contexts, elucidating their influence on incident rates. It presents an exhaustive analysis of the likelihood of incidents occurring under distinct weather thresholds, with a dedicated focus on devising tailored strategies to mitigate associated risks.

Building upon the findings, this study proposes the following recommendations:

2.4.1 Extreme Weather Precautions

Develop weather-specific safety protocols for extreme high and extreme low cases. For example, measures such as providing thermal insulation during cold spells and enforcing heat stress prevention strategies during hot weather can be implemented.

2.4.2 Real-time Incident Monitoring and Early Warning Systems

Integrate the predictive model into real-time monitoring systems to provide timely alerts and early warnings based on changing weather conditions. By identifying high-risk conditions through the predictive model, resources can be deployed effectively to implement preventive measures, thereby minimizing the impact of incidents (Jung et al., 2021).

2.4.3 Task-weather Compatibility

Assess the compatibility of tasks with prevailing weather conditions. Design work schedules that minimize exposure to adverse weather, rescheduling outdoor tasks during extreme conditions.

2.4.4 Planning and Maintenance

Incorporate predictive insights into infrastructure planning and maintenance strategies (Achouch et al., 2022). High-risk areas can be prioritized for enhanced infrastructure maintenance, reducing the vulnerability of critical systems to weather-related incidents and minimizing disruptions.

2.5 Limitations and Implications for Future Research

2.5.1 Data Quality and Generalizability

The accuracy, completeness, and generalizability of incident and weather data are crucial aspects that impact the reliability of research findings. Variations in data quality may introduce errors or omissions, potentially skewing the outcomes of safety assessments. Furthermore, findings derived from high-incident zones might not seamlessly translate to regions with different weather patterns or occupational practices. The limitations in data quality and generalizability can be attributed to:

- Diverse Data Sources: Incidents and weather data often come from diverse sources, leading to discrepancies in accuracy and completeness. Standardized reporting mechanisms are essential to enhance the consistency and reliability of the data.
- Regional Disparities: The applicability of research findings may be limited by regional variations in weather patterns and safety practices. Different geographic locations may have distinct occupational norms and diverse climates, rendering generalizations challenging.

2.6 Conclusion

In conclusion, the research has provided an approach to predicting incident likelihood using weather variables. The developed prediction models, decision tree, random forest, and k-nearest neighbors, accurately forecasted incident likelihood based on weather variables.

It also provides a pioneering solution that helps decision-makers (managers, supervisors, safety officers and high-level executives) mitigate risks and enhance incident management by effectively merging weather conditions with incident occurrences.

Integrating these predictive models into real-world project planning and management fosters resilience, preparedness, and efficient resource utilization. Creating an executable application enables translating complex data analysis and machine learning models into a practical tool that a diverse range of stakeholders can effortlessly use. This approach extends the research's impact, making its outcomes accessible and valuable to field personnel and other stakeholders in managing weather-related risks. The executable application harmonizes advanced data analysis with user-friendly accessibility, embodying the research's mission to bridge the gap between technical analysis and real-world application.

Finally, the work contributes to advancing the field of incident prediction and presents a tangible opportunity to create a safer and more resilient society while leaving a lasting and positive impact on incident management practices worldwide.

2.7 References

1. Acharya, P., Boggess, B., & Zhang, K. (2018). Assessing Heat Stress and Health among Construction Workers in a Changing Climate: A Review. International Journal of Environmental Research and Public Health, 15(2), 247. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ijerph15020247
2. Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. Applied Sciences, 12(16), 8081. MDPI AG. Retrieved from http://dx.doi.org/10.3390/app12168081
3. Anttonen, H., Pekkarinen, A., & Niskanen, J. (2009). Safety at work in cold environments and prevention of cold stress. Industrial health, 47(3), 254-261.
4. Awolusi, I., Marks, E., Hainen, A., & Alzarrad, A. (2022). Incident Analysis and Prediction of Safety Performance on Construction Sites. CivilEng, 3(3), 669–686. MDPI AG. Retrieved from http://dx.doi.org/10.3390/civileng3030039
5. Betz, T., El-Rayes, K., Johnson, M., Mehnert, B., & Grussing, M. (2023). Machine learning model to predict impact of climate change on facility equipment service life. Building and Environment, 234, 110192. https://doi.org/10.1016/j.buildenv.2023.110192

6. Bochenek, B., & Ustrnul, Z. (2022). Machine Learning in Weather Prediction and Climate Analyses—Applications and Perspectives. Atmosphere, 13(2). https://doi.org/10.3390/atmos13020180
7. Boomija, M., & Phil, M. (2008). Comparison of Partition Based Clustering Algorithms. Journal of Computer Applications, 1(4), 18-21.
8. Breiman, L. (1984). Classification and Regression Trees (1st ed.). Routledge. https://doi.org/10.1201/9781315139470
9. Chen, J., Tao, W. (2022). Traffic accident duration prediction using text mining and ensemble learning on expressways. Sci Rep 12, 21478 https://doi.org/10.1038/s41598-022-25988-4
10. Chen, J., Yu, J., Zhou, W., & Wu, M. (2019). A Machine Learning Approach for Predicting Accident Rates in Construction Projects considering Weather Conditions. Automation in Construction, 103, 239-251.
11. Chen, Z., Wang, D., & Yu, C. (2019). Predicting Construction Incident Rates using Machine Learning and Weather Data. Safety Science, 116, 320-329.
12. Choi, J., Gu, B., Chin, S., & Lee, J. (2020). Machine learning predictive model based on national data for fatal accidents of construction workers. Automation in Construction, 110, 102974.
13. Dangeti P. (2017). Statistics for Machine Learning. Packt Publishing Ltd. https://books.google.ca/books?id=C-dDDwAAQBAJ
14. Environment and Climate Change Canada Historical Climate Data website (https://climate.weather.gc.ca/index_e.html)

15. Fard, F. R., Kamardeen, I., & Newton, S. (2017). Impact of extreme weather conditions on construction labor productivity. Engineering, Construction and Architectural Management, 24(4), 689-707.

16. Fan, Y., Xu, X., & Wang, S. (2021). Predicting Construction Incident Rates using Machine Learning and Weather Factors. Journal of Construction Engineering and Management, 147(4), 04021001

17. Géron, A. (2017). Hands-On Machine Learning with Scikit-Learn and TensorFlow. O'Reilly Media

18. Hastie, T., Tibshirani, R., & Friedman J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition (Springer Series in Statistics).

19. Hua, J., Cao, S., Cao, Y., & Wang, L. (2019). Corrosion damage of construction machinery under different humidity conditions. Materials Science Forum, 954, 139-145.

20. Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: A review. ACM Computing Surveys (CSUR), 31(3), 264-323.

21. Jeong, J. R., Kim, H. E., & Rissanen, S. (2009). Research on winter working environment and working clothes at a construction site. Fashion & Textile Research Journal, 11(1), 174-179.

22. Jiang, Y., Pan, Y., Zhang, S., & Ye, W. (2015). Low-temperature adaptability analysis of construction machinery. In 2015 International Conference on Transportation Information and Safety (ICTIS) (pp. 41-45). IEEE.

23. Jung, K., Kashyap, S., Avati, A., Harman, S., Shaw, H., Li, R., Smith, M., Shum, K., Javitz, J., Vetteth, Y., Seto, T., Bagley, S. C., & Shah, N. H. (2021). A framework for making predictive models useful in practice. Journal of the American Medical Informatics Association : JAMIA, 28(6), 1149–1158. https://doi.org/10.1093/jamia/ocaa318

24. Kamat, V. R., Gupta, R., & Kaur, H. (2020). Wind-induced structural failures of tall buildings: A review. Structures, 27, 1183-1199.
25. Khosravi, Y., Asilian-Mahabadi, H., Hajizadeh, E., Hassanzadeh-Rangi, N., Bastani, H., & Behzadan, A. H. (2014). Factors influencing unsafe behaviors and accidents on construction sites: A review. International journal of occupational safety and ergonomics, 20(1), 111-125.
26. Lee, M., Jeong, J., Jeong, J., & Lee, J. (2021). Exploring Fatalities and Injuries in Construction by Considering Thermal Comfort Using Uncertainty and Relative Importance Analysis. International journal of environmental research and public health, 18(11), 5573. https://doi.org/10.3390/ijerph18115573
27. Lee, S. J., Chen, S. W., Wang, K., & Shen, L. (2019). Effect of low temperatures on the compressive strength and chloride resistance of concrete. Construction and Building Materials, 198, 609-617.
28. Liao, C. W. (2012). Pattern analysis of seasonal variation in occupational accidents in the construction industry. Procedia Engineering, 29, 3240-3244.
29. Liaw, A., & Wiener, M. (2002). Classification and regression by RandomForest. R News, 2(3), 18-22
30. Liu, Y., Ren, Z., Liu, H., & Zhang, M. (2017). Performance evaluation of construction machinery under extreme weather conditions. International Journal of Applied Mechanics, 9(1), 1750006.
31. Liu, Y., He, M., Yu, J., & Shi, L. (2021). Predicting Safety Incidents in Construction Projects considering Weather Factors: A Machine Learning Approach. Safety Science, 140, 105352.
32. Liu, J., Qiu, Y., & Sun, C. (2020). Predicting Safety Incidents in Construction Sites based on Weather Data using Machine Learning. Safety Science, 121, 403-413.

33. Lu, X., Guo, H., & Jiang, S. (2020). Prediction of Accident Rates in Construction Projects using Machine Learning and Weather Data. Safety Science, 124, 104574.

34. Luo, S., Cao, D., Li, Y., & Wu, Z. (2020). Predicting Construction Accident Rates using Machine Learning Models based on Weather Factors. International Journal of Environmental Research and Public Health, 17(13), 4689.

35. Mohammed, S. S., Kadhim, N. R., Abdulrasool, A. T., & al Shaikhli, H. I. (2022). The Use of Weather Website Data for Construction Project Decision-Making in the Short Term. IOP Conference Series: Earth and Environmental Science, 961(1). https://doi.org/10.1088/1755-1315/961/1/012038

36. Moohialdin, A., Trigunarsyah, B., Islam, M. S., & Siddiqui, M. K. (2022). Physiological impacts on construction workers under extremely hot and humid weather. International Archives of Occupational and Environmental Health, 95(2), 315–329. https://doi.org/10.1007/s00420-021-01785-w

37. Moohialdin, A. S. M., Lamari, F., Miska, M., & Trigunarsyah, B. (2019). Construction worker productivity in hot and humid weather conditions: A review of measurement methods at task, crew and project levels. Engineering, Construction and Architectural Management, 27(1), 83-108.

38. Papalexopoulos, T., Bertsimas, D., Cohen, I., Goff, R., Stewart, D. & Trichakis, N. (2022). Ethics-by-design: efficient, fair and inclusive resource allocation using machine learning. Journal of Law and the Biosciences. 9. 10.1093/jlb/lsac012.

39. Radevsky, R., Taylor, C., Stolfa, A., Generali, A., Uk, L., Cazzaniga, M., Wittowski, R., Re, S., Zurich, S., & Baltis, E. (n.d.). IMIA-WGP 78 (12) The effect of adverse weather on construction sites Working Group Executive Committee Sponsor.

40. Rameezdeen, R., Elmualim, A. (2017). The Impact of Heat Waves on Occurrence and Severity of Construction Accidents. International Journal of Environmental Research and Public health,14, 70. https://doi.org/10.3390/ijerph14010070

41. Rashid, H. A. (2015). Weather Effect on Workflow, and Labor Productivity of Construction Plant. 7(11). www.iiste.org

42. Rowlinson, S., YunyanJia, A., Li, B., & ChuanjingJu, C. (2014). Management of climatic heat stress risk in construction: a review of practices, methodologies, and future research. Accident Analysis & Prevention, 66, 187-198.

43. Sacks, R., Harel, R., & Qudah, E. (2018). Modeling the impact of rainfall events on construction labor productivity. Journal of Construction Engineering and Management, 144(5), 04018023.

44. Shahin, A., Eng, P., Abourizk; S M, Asce, M., & Mohamed, Y. (2011). Modeling Weather-Sensitive Construction Activity Using Simulation Overview of the Framework. Journal of Construction Engineering and Management, 137(3), 238–246. https://doi.org/10.1061/(ASCE)CO.1943-7862.

45. Srinavin, K., & Mohamed, S. (2003). Thermal environment and construction workers' productivity: some evidence from Thailand. Building and Environment, 38(2), 339-345.

46. Szer, I., Szer, J., Cyniak, P., Błazik-Borowa, E., Bernatik, A., Kocurkova, L., & Jørgensen, K. (2017). Influence of temperature and surroundings humidity on scaffolding work comfort. Prevention of accidents at work. Taylor & Francis Group, 19-23.

47. Tan, P., Steinbach, M., & Kumar, V. (2005). Cluster Analysis: Basic Concepts and Algorithms. Introduction to Data Mining. 487-568.

48. Thomas F. [and nine others], Working Group I Technical Support Unit. (2014). Climate change 2013 : the physical science basis : Working Group I contribution to the fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom Cambridge University Press

49. Varghese, B. M., Hansen, A., Bi, P., & Pisaniello, D. (2018). Are workers at risk of occupational injuries due to heat exposure? A comprehensive literature review. Safety science, 110, 380-392.

50. Vukadinovic, A., & Radosavljevic, J. (2020). Occupational safety and health of construction workers working in extreme temperature. In Proceedings of the 15th International Conference Risk and Safety Engineering, Kopaonik, Serbia (pp. 16-18).

51. Yi, W., & Chan, A. P. (2013). Optimizing work–rest schedule for construction rebar workers in hot and humid environment. Building and Environment, 61, 104-113.

3 Enhancing Risk Assessment for Occupational Safety: Discerning the relationship between worker attributes, weather variables and incident rates to develop effective risk mitigation strategies within high incident zones

3.1 Introduction

Occupational safety within high-incident zones is a paramount concern across various industries. These zones are characterized by their exposure to dynamic weather conditions, which can significantly influence worker safety. Worker vulnerability encompasses an array of factors that influence the safety of individuals in the workplace. Research conducted by Smith et al. (2019) underscores the importance of considering worker experience as a determinant of safety outcomes. Their findings indicate that less experienced workers tend to be more vulnerable to incidents, particularly those related to adverse weather conditions. This vulnerability is further exacerbated when workers lack appropriate training in coping with challenging weather circumstances. Understanding how worker vulnerability, task attributes, and weather variables interact is crucial for developing tailored risk mitigation strategies.

Task attributes, which encompass the nature and characteristics of tasks performed within high-incident zones, are another pivotal facet. Tasks vary significantly in complexity, duration, and susceptibility to weather elements. For instance, tasks involving work at heights or the operation of heavy machinery are often associated with higher risks (Johnson & Brown, 2018). These tasks are particularly vulnerable to weather-related incidents, necessitating a comprehensive analysis of their attributes.

Weather variables, such as temperature, wind speed, precipitation, and humidity, substantially influence occupational safety. Research has demonstrated that extreme temperatures can adversely affect worker productivity and heighten the risk of heat-related illnesses (García-Trabanino et al., 2020). Conversely, high wind speeds can jeopardize the stability of temporary structures and scaffolding (Li & Ng, 2017). Precipitation, in the form of rain or snow, can lead to slippery surfaces leading to incidents and project delays (Wang et al., 2019).

Incident severity classification is a fundamental aspect of occupational safety research, serving as a pivotal tool to categorize incidents based on their potential impact and consequences. In the research context, the aim is to enhance risk assessment in high-incident zones by understanding how incidents are classified.

Several studies have emphasized the significance of incident severity classification in occupational safety. Liu et al. (2020) and Nguyen et al. (2020) emphasized the need for improved incident prevention strategies, including considering weather conditions in incident severity classification.

In addition to weather conditions impacting incidents, task attributes and worker demographics also play an important role. Long working hours, often extending beyond the conventional 8-hour shift, can lead to fatigue and cause incidents. Research has shown a noteworthy correlation between extended work hours and incident rates within the construction sector (Lingard et al., 2013; Chen et al., 2019). It is crucial to recognize that the impact of long working hours on incident occurrence may vary based on several factors. The type of construction work, environmental conditions, and individual worker characteristics can all influence the degree to which extended work hours contribute to safety risks. Therefore, a nuanced understanding of these factors is essential for developing effective strategies to mitigate the impact of long working hours on incident occurrence in the construction industry.

Despite the extensive research on occupational safety and its correlation with weather variables, a notable research gap exists in understanding how specific combinations of weather variables, particularly in regional variations, influence incident rates within high-incident zones. Furthermore, there is a lack of comprehensive studies investigating how incident prevention strategies are adapted to these conditions. Existing studies have predominantly focused on individual aspects, such as worker vulnerability or the impact of specific weather variables, without considering their combined effects in high-incident zones. Therefore, there is a clear need for research that employs a holistic approach, incorporating data on worker demographics, task attributes, and various weather variables, as well as conducting thorough time series analyses. This comprehensive approach can lead to the development of more effective and tailored risk mitigation strategies, ultimately enhancing the safety of workers in construction sites.

3.2 Methodology

This study employs a multi-faceted approach, encompassing data analysis and modeling, to comprehensively investigate and address safety issues within high-incident zones. The data for this research consisted of an incident dataset of 113,551 records (2004 - 2023) and also workers' demographic information, including workers' age, trades and experience level obtained from an industrial construction company in Alberta, Canada. The methodology adopted in this study is shown in Figure 3- 1**Error! Reference source not found.**.

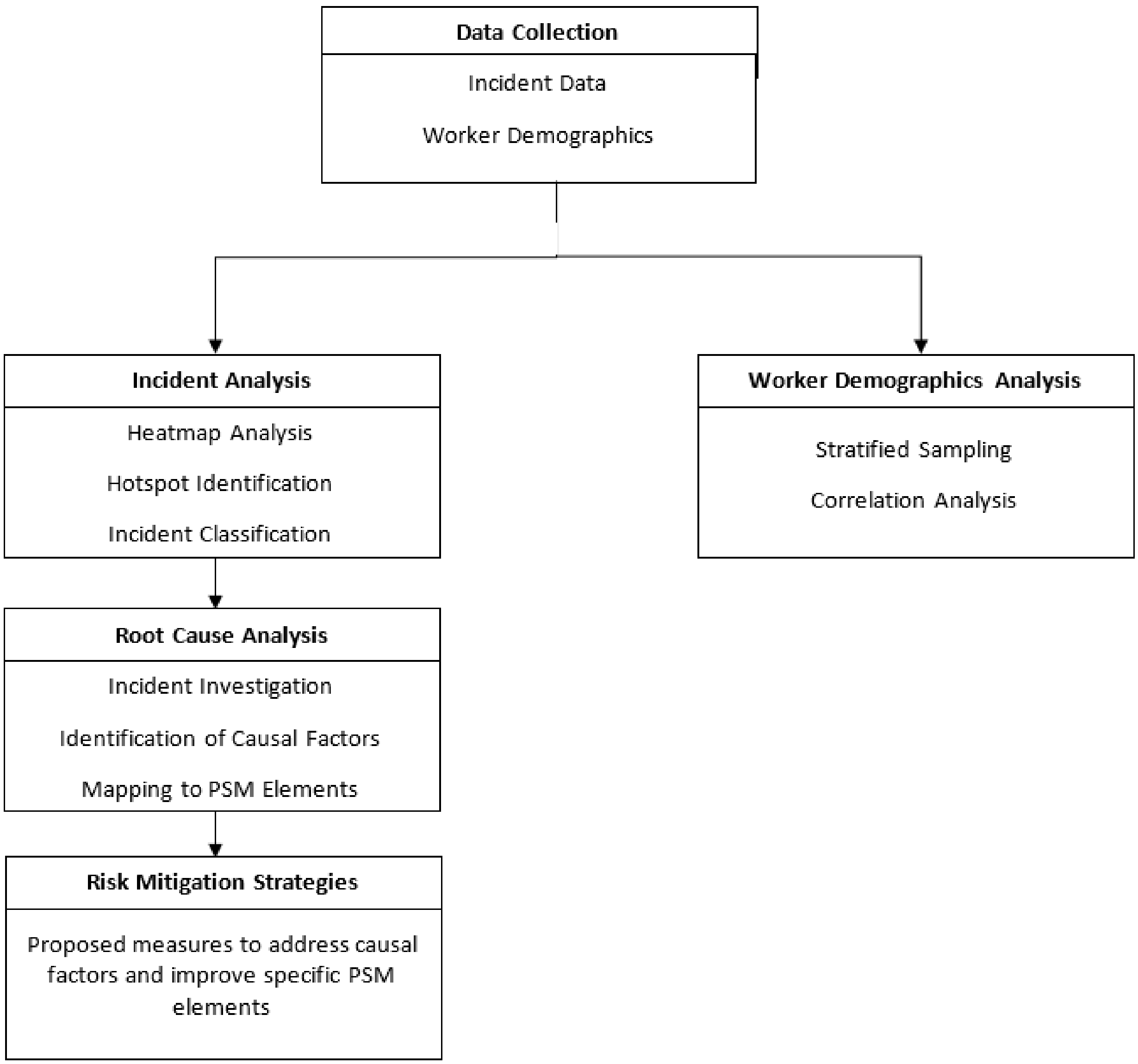

Figure 3- 1. Research methodology adopted in this study

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3.2.1 Data Pre-processing

In the initial phase, collection and preprocessing of the dataset took place, comprising incident reports from the high-incident regions.

Data Cleaning: This was done for the removal of several duplicate and irrelevant records and for handling missing data.

Data Integration: The incident reports were integrated with the worker demographic information, for a more comprehensive analysis.

Data Transformation: The incident date and time information were standardized to a common format, and additional features, such as grouping incidents by month/year, were created to facilitate time series analysis.

3.2.2 Data Analysis

Hotspot Identification: The first stage of data analysis involved identifying incident hotspots or clusters within high-incident regions. A heatmap generation approach proposed by Atsegbua et al. (2023) was utilized to achieve this. This technique enabled the pinpointing of areas with the highest number of incidents. Classification based on their impact and seriousness was conducted to gain a deeper insight into the severity of incidents. This classification was executed in alignment with a risk matrix, dividing incidents into categories such as A, B, and C, reflecting different levels of risk and impact.

3.2.3 Root Cause Analysis

Incident Investigation: For a deep dive into understanding the root causes of incidents, a comprehensive root cause analysis took place. This process involved meticulous examination of each incident within the dataset.

Identification of Causal Factors: During the root cause analysis, a number of causal factors contributing to each incident were identified and were mapped to the Process Safety Management (PSM) elements. The PSM framework is a systematic approach to managing hazardous processes and preventing incidents. It encompasses a set of principles and practices designed to enhance safety in various industries. This step provided a robust framework for understanding how deficiencies in specific PSM elements contributed to incidents.

3.2.4 Risk Mitigation Strategies

Enhancing Safety Measures: Proposed measures to enhance safety for vulnerable worker categories and high-risk tasks based on worker susceptibility and task analysis. These safety measures encompass targeted strategies aimed at improving the safety of worker categories particularly susceptible to incidents and tasks identified as high-risk.

3.2.5 Worker Demographic Analysis

3.2.5.1 Stratified Sampling

Acknowledging the potential for dataset imbalances, particularly with demographic categories, we implemented stratified sampling techniques, using the scikit-learn library in Python.
Using Python, specific age groups were created, enabling the categorization of workers into groups such as '18-30', '31-40', '41-50', and '51-60' and 61+ based on age. In contrast to the age classification, the trade classifications and experience levels were inherently structured in the original datasets, eliminating the necessity for further classification and enabling direct integration into the analysis.

3.2.5.2 Temporal Exploration

Preceding the time analysis, Python was utilized to intricately fuse incident data with worker demographic data using the date and time information.

3.2.5.3 Trade Classification

The trades were classified as follows within the dataset: 'Carpenter', 'EQ', 'Electrician', 'Instrument', 'Ironworker', 'LAB', 'Materials', 'Millwright', 'Other', 'Pipefitter', 'Scaffolder', 'Welder', 'Welder B Pressure', 'Welder CWB', 'Welder W/Rig'.

3.3 Results and Discussions

3.3.1 Temperature vs Wind Speed Heatmap

The heatmap (Figure 2) serves as a visual representation of the distribution of incidents across various combinations of temperature and wind speed categories and is an adaptation of the original figure used in a prior study (Atsegbua et al., 2023), where the relationships between weather conditions and incident severity were explored. Each cell in the heatmap corresponds to a specific range of temperature and wind speed, and the color intensity within each cell indicates the number of recorded incidents falling within that category. The heatmap is divided into multiple grids, each focusing on different severity levels of incidents, and the process of generating this heatmap was instrumental in uncovering patterns and insights related to occupational safety within high-incident zones. From Figure 3- 2**Error! Reference source not found.**, a high number of incidents were recorded in the temperature category of 0oC- 5 oC and wind category of 10 – 20km/hr.

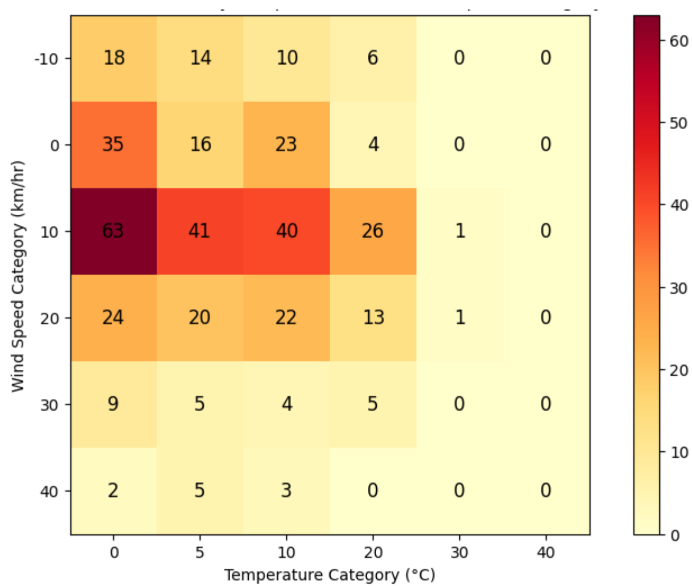

Figure 3- 2. illustrates the heatmap depicting the distribution of incidents based on temperature and wind speed

3.3.2 Analysis of Incidents by Severity Classification and Work Activity Category

In the dataset, the incidents have been categorized into three distinct classifications: A, B, and C, based on a rigorous risk matrix assessment, as seen in Table 3- 1**Error! Reference source not found.**. This classification system aids in identifying and prioritizing incidents according to their potential impact and severity. It is essential to note that within this classification, class A represents the most severe incidents, while B and C denote lower levels of severity.

The presence of category B incidents, numbering 12 within the work activity categories, is particularly noteworthy. These incidents serve as a focal point for the research, as they represent occurrences that possess a level of severity that demands attention but may not be as immediately critical as Category A incidents. Targeted risk mitigation strategies can be formulated by closely examining the characteristics, causes, and patterns associated with Category B incidents. The aim is to prevent these incidents from progressing to more severe categories and to enhance overall safety within high-incident zones.

Work Activity Category	Incident Classification		
	A	**B**	**C**
Equipment operator	0	2	9
Plumbing and Pipefitting	0	1	4
Scaffolding	0	1	4
Laborer	0	0	5
Millwright	0	4	1
Iron Worker	0	1	3
Specialty	0	1	2
Carpenter	0	1	2
Insulator	0	1	1
Equipment Maintenance	0	0	2

Table 3- 1. The distribution of Class A, B, and C incidents across the work activity categories

Identifying the top work activity categories provides insights into the types of tasks that are most frequently associated with incidents in these high-risk areas. This information is provided in Figure 3- 3.

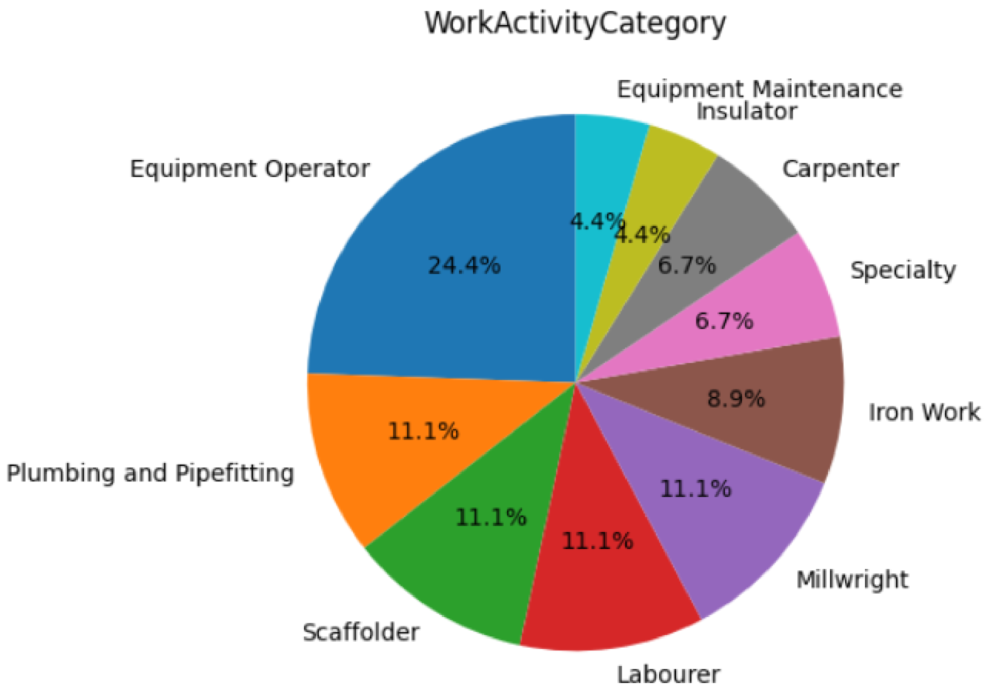

Figure 3- 3. Pie chart of the top 10 work activity categories involved in incidents.

From Figure 3- 1, "Equipment operator" has the highest count of incidents among all work activity categories. However, most of these incidents fall under the C classification (**Error! Reference source not found.**), signifying that they are less severe. This pattern is intriguing and aligns with findings from prior research on occupational safety (Wu et al., 2020).

Literature suggests that the work of equipment operators often involves repetitive tasks and routine operations. While these tasks can lead to a relatively higher number of incidents, they are typically less severe (Wu et al., 2020). Such incidents may include minor equipment malfunctions, near misses, or minor injuries that require minimal medical attention.

In the context of risk mitigation, it's crucial for organizations to recognize that while incidents involving equipment operators may be frequent, they tend to be less harmful. Therefore, safety strategies for this category should focus on preventing minor incidents, maintaining equipment properly, and providing adequate training to ensure operators are well-versed in equipment operation and safety protocols (Hallowell et al., 2015).

3.3.3 Incident Analysis and Root Causes Using the PSM Framework

To enhance safer workplaces and accident prevention, understanding the root causes of incidents becomes paramount. To this end, a comprehensive analysis of a series of incidents involving Equipment Operators was conducted, aiming to pinpoint their root causes by aligning each incident with specific elements of the Process Safety Management (PSM) framework, as defined by the Center for Chemical Process Safety (CCPS).

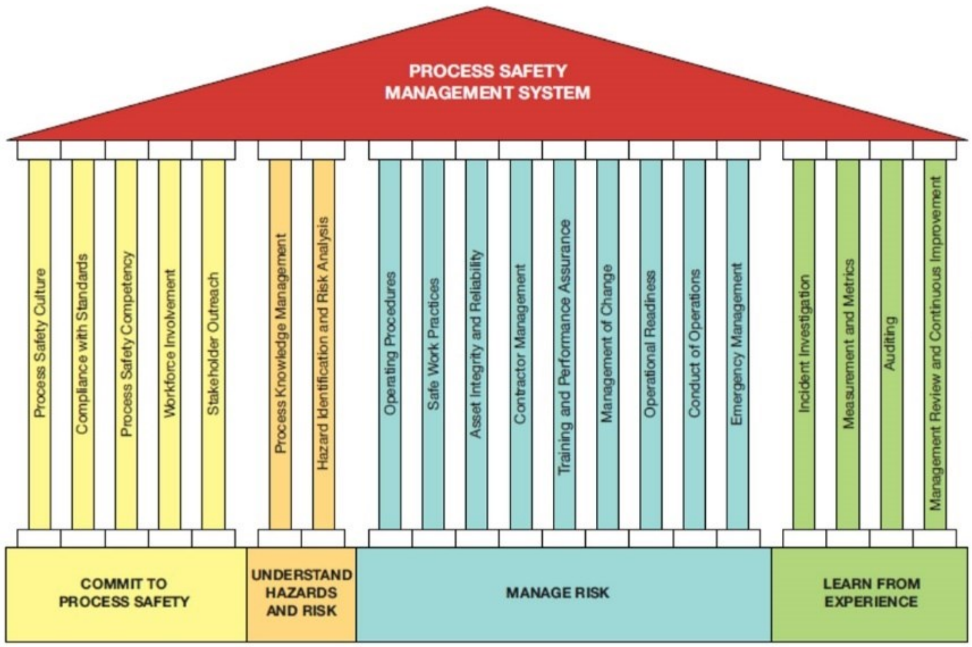

Figure 3- 4. CCPS Risk-based 20 PSM Elements (CCPS, 2011).

3.3.3.1 Incident 1:

"On Monday January 25, 2016, at approximately 2:20 pm, an Equipment Operator was operating a John Deere 744K loader in the Abalone stockpile area. The worker was tasked with loading material from the winter stockpile containment area into Rock Trucks to be transported into the battery limits for backfilling. This containment area is constructed of multiple 5 x 2½ concrete Lego blocks that weigh approximately 5000lbs. The containment area was 3 Lego blocks high thus making it approximately 7½ feet tall. This containment area was covered with tarps and was fed with Herman Nelson heaters at the front of the containment area in order to keep the material at optimal temperature for backfill. The containment area is also equipped with a conductor barrel (Steel Pipe) that runs under the material, fed with a 1 million BTU heater that is also in place to heat the soil to operational temperature. On this particular occasion, the operator had a spotter roll back the tarp and drove forward to pick up a load of dirt with his bucket. The material being scooped up was 6 feet away from the back end of the containment area. The operator then curled his bucket up and backed up the loader. While backing up the loader, the operator noticed that the top 2 levels of the Lego blocks at the back of the containment area had tipped over in a south direction. The operator froze the scene, notified Abalone Supervision and Safety immediately, and Supervision notified PCL Supervision immediately. The Canadian model was followed."

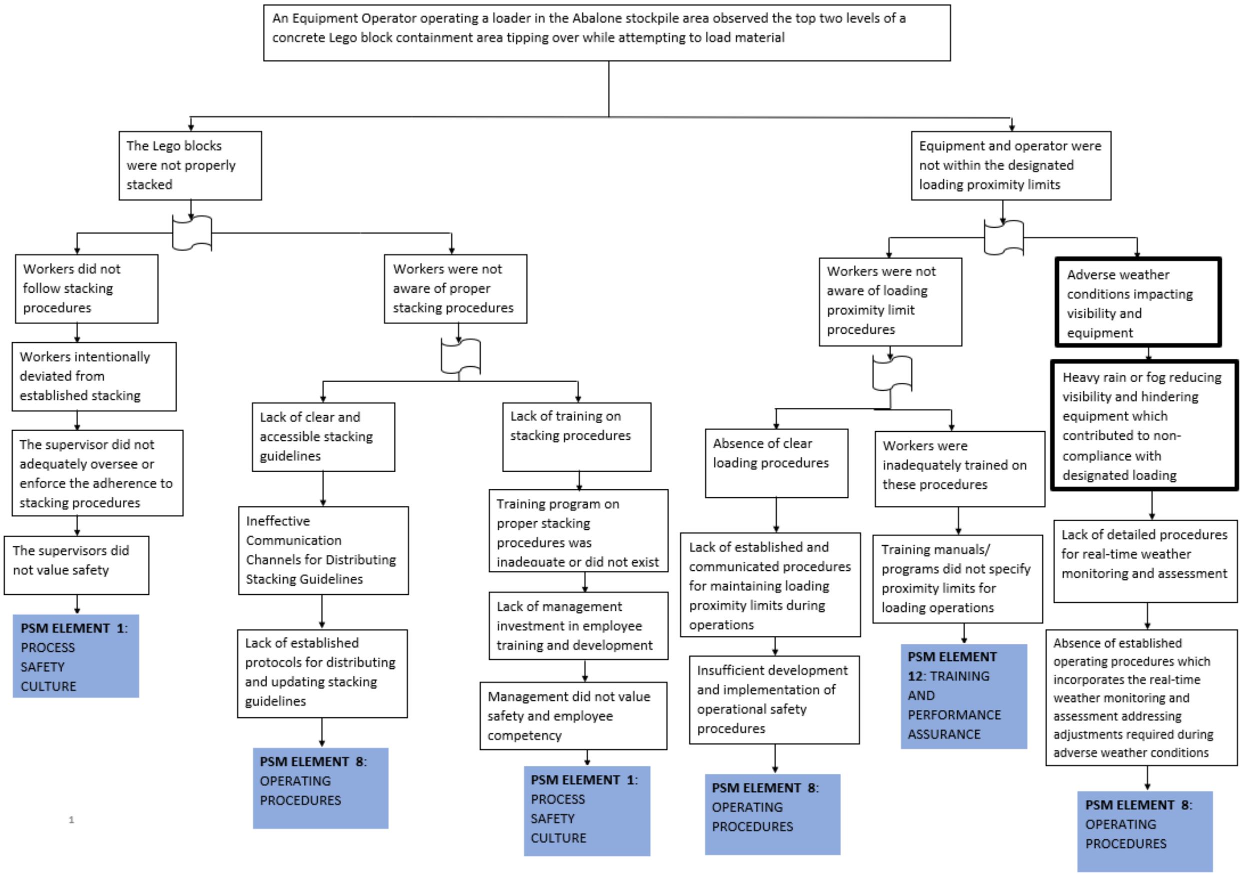

Figure 3- 5. Root cause analysis of first incident

Lack of adherence to these Process Safety Management (PSM) elements: Element 1 (Process Safety Culture), Element 8 (Operating Procedures), and Element 12 (Training and performance assurance).

3.3.3.2 Incident 2:

" Stones from sand being spread by a Bouchier sanding truck contacts the passenger window off the drive side of a shuttle van that had stopped at 4 way stop sign causing it to break. The drive states that he heard multiple stones contacting the vehicle as the sanding truck passed but did not realize the window that was directly behind him was shattered, until he felt a draft while making a right turn from the stop sign. He then pulled over then notified his supervisor, the drive was the only occupant of the vehicle at the time of the incident."

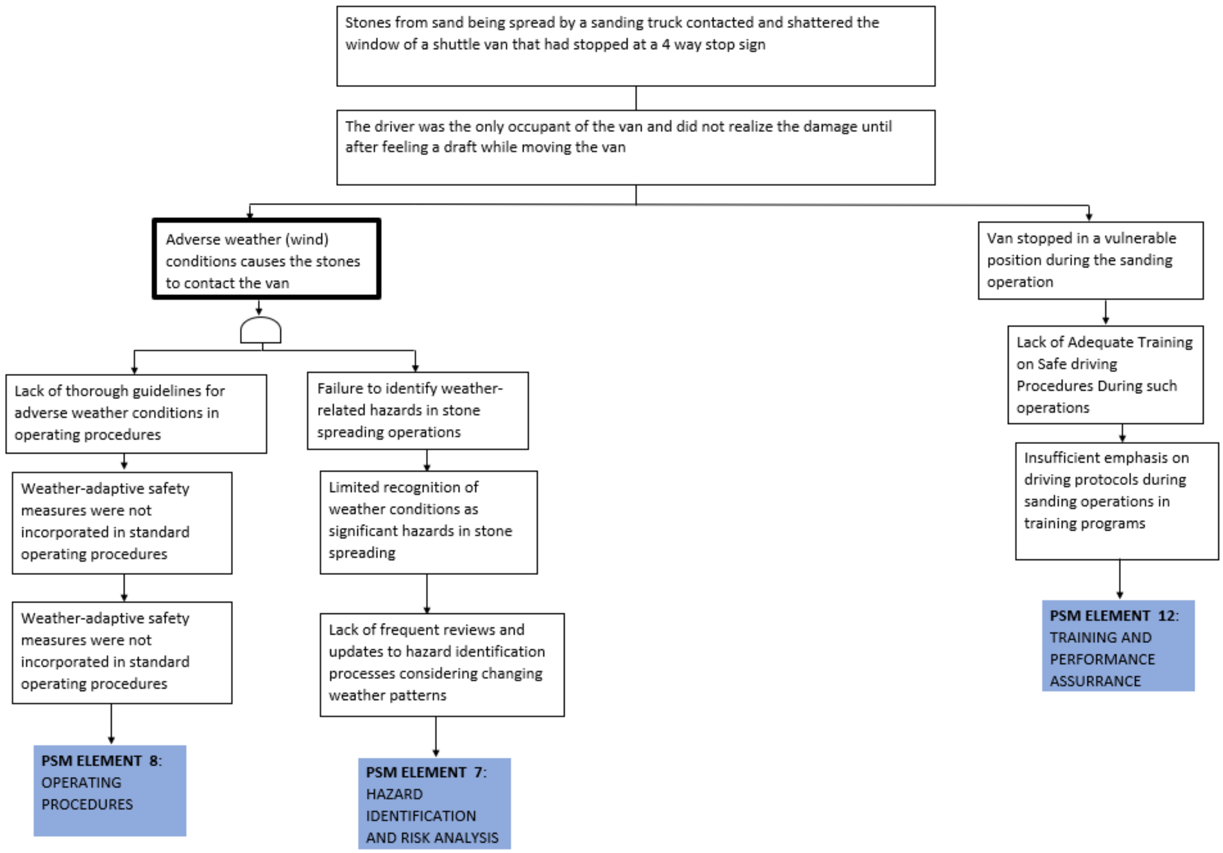

Figure 3- 6. Root cause analysis of second incident

Lack of adherence to these Process Safety Management (PSM) elements: Element 7 (Hazard Identification and Risk Analysis), Element 8 (Operating Procedures), and Element 12 (Training and Performance Assurance).

3.3.3.3 Incident 3:

"Operator was carrying a compressor with a loader-jib from hertz lay down to area 145. The compressor was 5 feet off the ground with a tagline attached. While transporting the compressor just west of the cold storage area, a KPCL SUV was parked on the road due to offloading material by another group. The Loader Operator did not see the SUV stopped in front of him due to his vision being obstructed by the compressor. As the loader progressed the front side of the compressor made contact with the SUV's back window resulting in extensive damage to window and surrounding window supports."

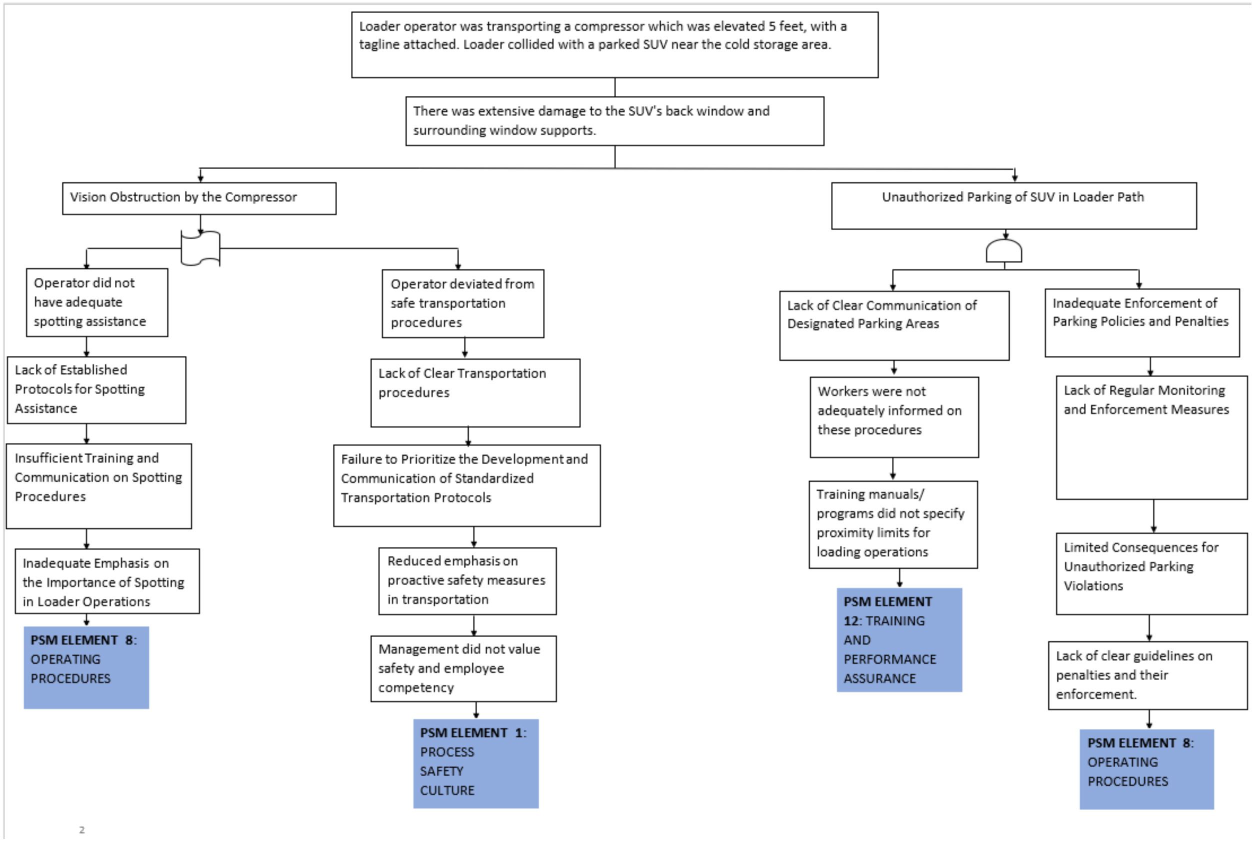

Figure 3- 7. Root cause analysis for third incident

Lack of adherence to these Process Safety Management (PSM) elements: Element 8 (Operating Procedures), Element 1 (Process Safety Culture), and Element 12 (Training and Performance Assurance).

3.3.3.4 Incident 4:

"A Monad worker transported a Herman Nelson Heater to the new water storage tank area, south of the power house using a Zoom Boom. When he pulled off the main road in front of the mill and started north towards the water tank, he encountered a change in elevation. The frontend of the heater made contact with the ground causing the opposite end of the heater to rise, making contact with the jib and caused minor damage to the top of the heater and cover on the built in containment compartment for the fuel tank. The operator immediately stopped and called his supervisor to the area."

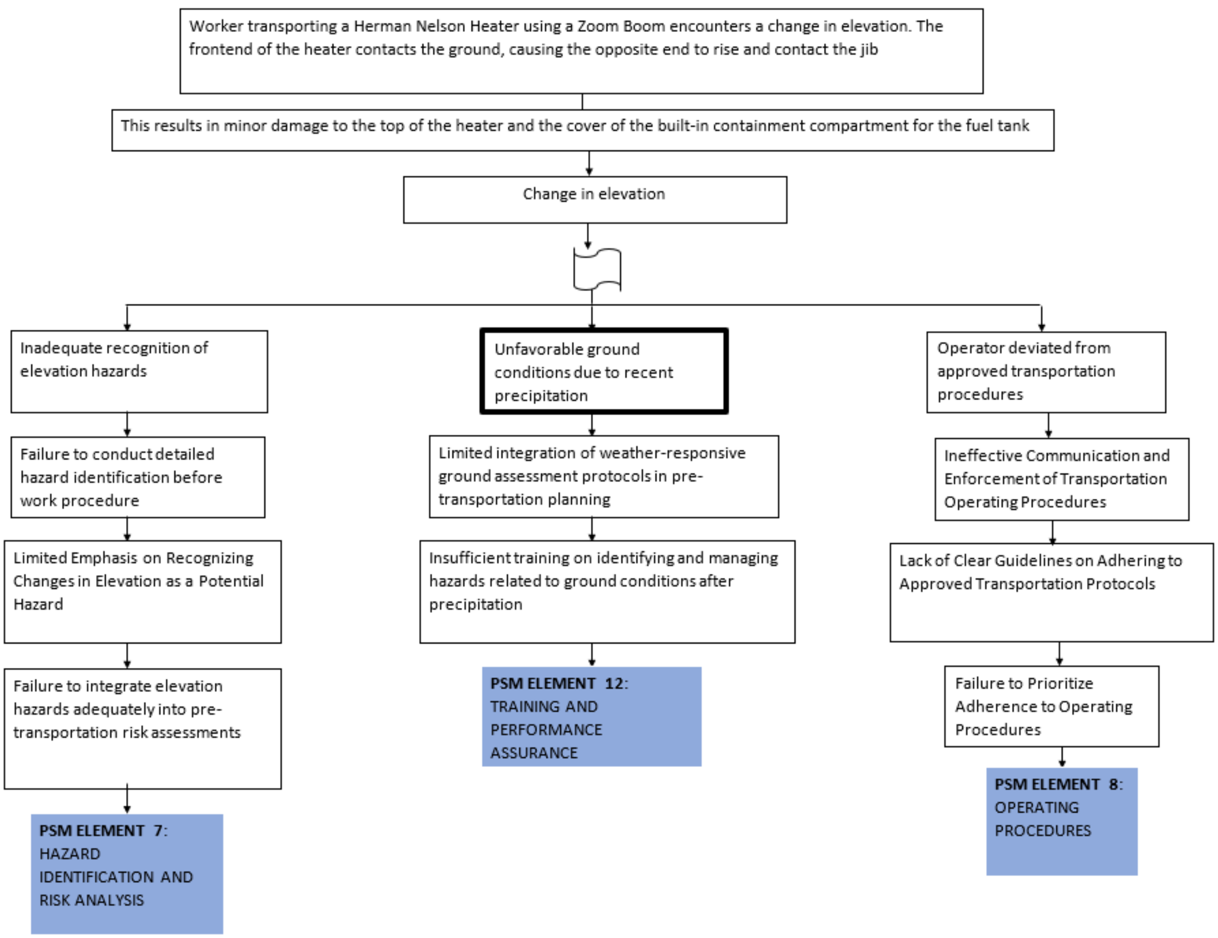

Figure 3- 8. Root cause analysis for fourth incident

Lack of adherence to these Process Safety Management (PSM) elements: Element 8 (Operating Procedures), and Element 12 (Training and Performance Assurance), Element 7 (Hazard Identification and Risk Analysis).

Building upon the detailed analysis of incidents and the identification of the key PSM elements associated with each, the next step involves ranking these elements to reveal the relative significance of each element in the occurrence of these incidents. Figure 3- 9 shows the prevalence of the PSM elements across the eleven incidents, highlighting the elements that emerged more frequently.

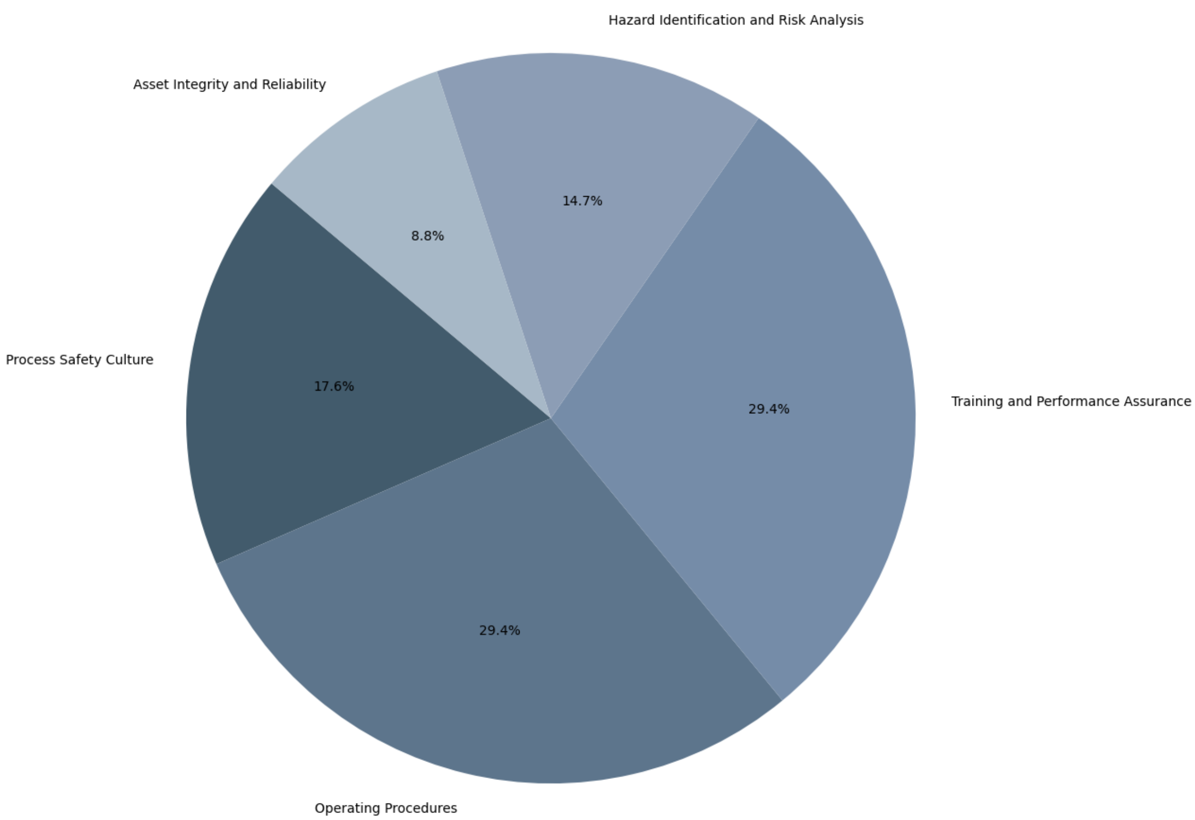

Figure 3- 9. Ranking of PSM Elements

Training and Performance Assurance (29.4%): Training and Performance Assurance takes the joint top spot in incident relevance, representing a significant portion of the incidents at 29.4%. This illustrates the importance of adequately training and maintaining the competence of personnel. A substantial number of incidents can be attributed to insufficient training or performance issues, highlighting the critical need for comprehensive training programs and ongoing performance monitoring. Robust training and performance assurance measures are crucial to reducing incidents and enhancing overall safety.

Operating Procedures (29.4%): Operating procedures also has a representation of 29.4%. This shows its critical importance in maintaining safe work practices. The significant percentage suggests that incidents often occur due to a lack of clear or effective procedures. Ensuring well-defined operating procedures is essential to providing workers with clear instructions and minimizing the risk of errors, accidents, and deviations from safe practices. Regular reviews and updates of procedures can address this gap and contribute to a safer work environment.

Process Safety Culture (17.6%): Process Safety Culture, with a representation of 17.6%, underscores its importance in building a safety-conscious work environment. While it ranks slightly lower than other elements, it remains a crucial factor in incident relevance. A positive process safety culture is essential for promoting a collective mindset focused on safety, where every individual prioritizes and contributes to the overall well-being of the workplace. Incidents associated with process safety culture highlight gaps in communication, awareness, or the overall commitment to safety principles. Organizations should emphasize building and maintaining a robust process safety culture, encouraging open communication, fostering a sense of responsibility, and reinforcing safe behaviors among all personnel.

3.3.4 Worker Demographics Analysis

To help understand the relationship between worker demographics and workplace incidents, an evaluation was conducted which focused on time series.

3.3.4.1 Correlation Analysis

In the correlation analysis, the heatmap visually represents the frequency distribution of incidents across different trade classifications and age groups within the construction workforce. Darker shades signify higher incident frequencies, revealing notable patterns of correlation between specific trades and age categories, as seen in Figure 3- 10 below.

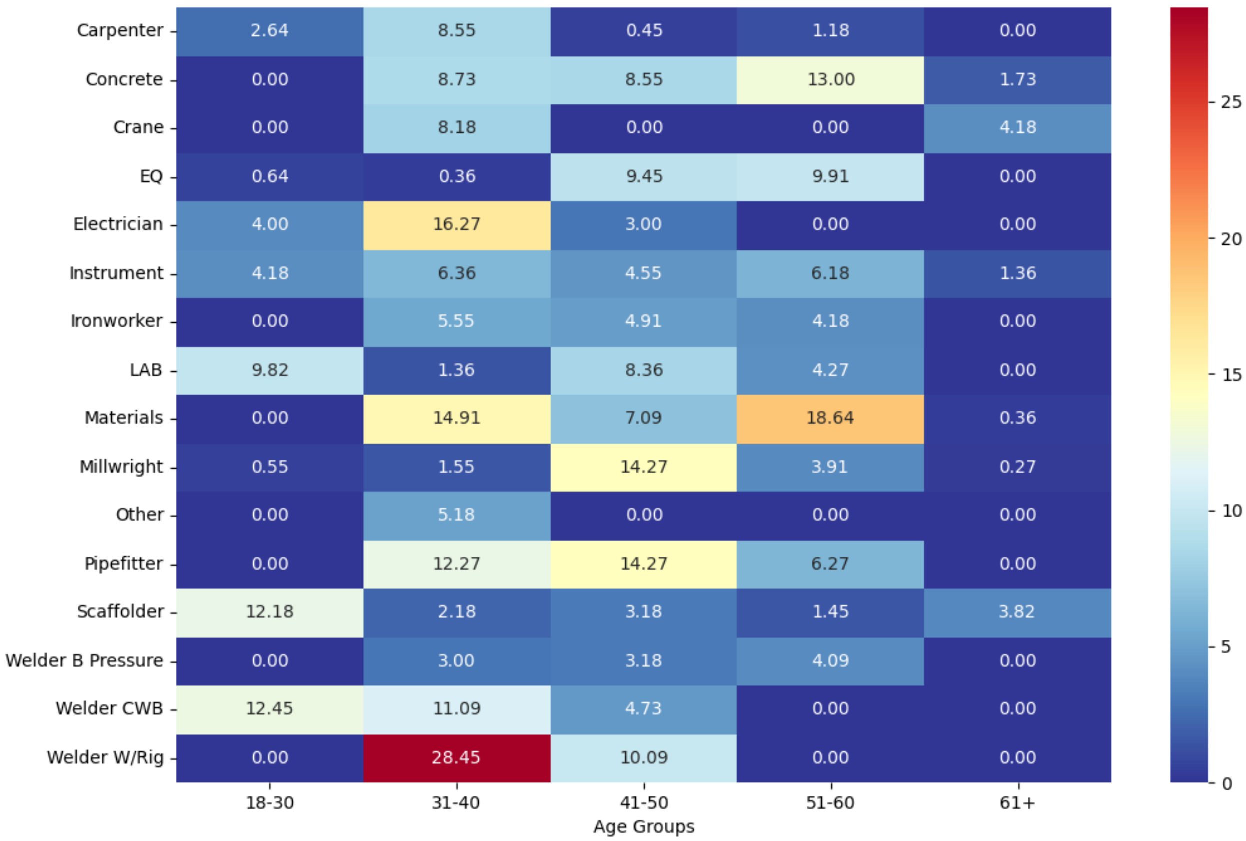

Figure 3- 10. Correlation of trade classifications across age groups

The heatmap was refined to spotlight the top 10 combinations of trade classifications and age groups, offering a concise visualization that prioritized the most impactful correlations within the dataset.

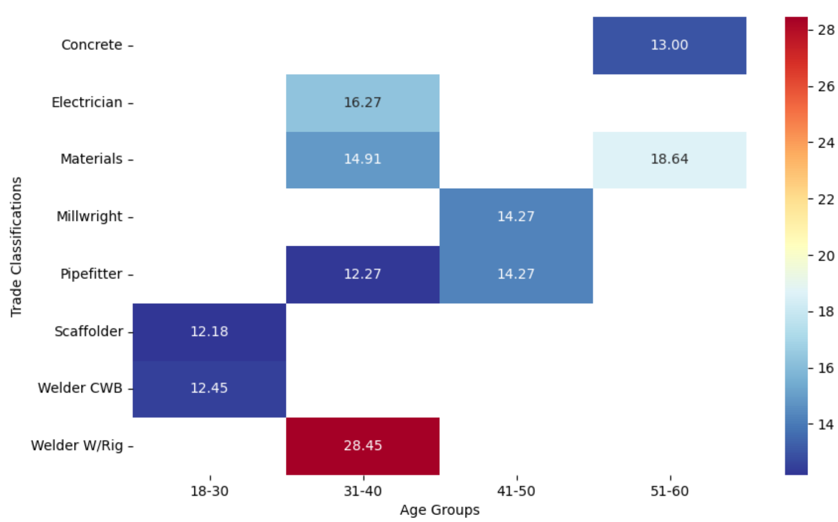

Figure 3- 11. Top 10 combinations of trade classifications across age groups

Examining the correlation analysis in Figure 3- 10 and Figure 3- 11 above, a clear and impactful trend emerges, highlighting the specific group: Rig welders within the 31-40 age bracket. This group exhibits an exceptionally high correlation rate of 28.45. This focused insight directs our focus squarely on the intersection of occupational role and age, pinpointing a critical area for targeted safety measures.

3.4 Recommendations

3.4.1 Data Quality

Implementing a standardized incident reporting template across multiple work categories is recommended to enhance data quality and facilitate more detailed incident breakdowns. In an effort to improve the current incident reporting framework, additional categories can be included to help facilitate a detailed root cause analysis. This enhanced framework, developed collaboratively with input from affected workers and supervisors, will ensure it is comprehensive, user-friendly, and applicable to various scenarios. The framework can include specific fields that guide the reporting parties in providing essential details about the incident, such as:

- Timeline of Events:
    - Sequential breakdown of events leading up to the incident to establish a chronological timeline.
- Environmental Factors:
    - Identification of relevant environmental conditions, including weather, lighting, and visibility.
- Equipment and Tools Involved:
    - Listing of equipment and tools used, specifying make, model, and condition.
- Human Factors:
    - Exploration of human elements involved, including worker actions, training, and potential stressors.
- Supervisory Response:
    - Assessment of the immediate response by supervisors and actions taken to mitigate the incident.

3.4.2 Training and Safety Awareness

3.4.2.1 Recruitment Requirements

It is crucial to prioritize safety in staff recruitment, ensuring that prospective employees not only express commitment to safety awareness but also demonstrate proficiency in safety protocols and operational competencies. This proficiency must be integrated in the organization's safety culture. To achieve this:

- Develop a comprehensive and standardized safety training program for all new employees, focusing on both theoretical knowledge and practical application.
- Incorporate safety assessments into the recruitment process to evaluate candidates' understanding of safety responsibilities.

3.4.2.2 Ongoing and Effective Safety Training:

Continuous training is vital to ensure that staff members maintain a thorough understanding of safety responsibilities. To achieve this:

- Establish a regular schedule for safety training sessions, incorporating updates on emerging safety trends.
- Utilize technology to facilitate flexible and accessible safety training for employees.

3.4.3 Proactive Monitoring System

3.4.3.1 Age-Specific Monitoring

Given the discovery that rig welders aged 31-40 were involved in the most incidents, implementing a proactive monitoring system specific to this age group is essential. This system should:

- Track and analyze incident data related to rig welders aged 31-40 to identify patterns and trends.
- Introduce targeted safety interventions, such as additional training programs or toolbox talks, based on the insights gained from monitoring.

3.4.4 Confidential Feedback System

3.4.4.1 Rig Welders (31-40)

In response to the high incident rates among rig welders aged 31-40, the introduction of a confidential feedback system within this specific field is recommended. This system should:

- Provide a secure platform for workers to report safety concerns anonymously, fostering open communication.
- Use the feedback received to address hazards proactively and enhance overall safety measures within the rig welding domain.

3.4.5 Job Rotation Opportunities

3.4.5.1 Diversifying Skill Sets

Introducing job rotation opportunities within the age group and trades can enhance workers' experience and skill sets, which helps to greatly mitigate the occurrence of incidents. To implement this:

- Design a structured job rotation program that exposes workers to different aspects of their job roles.
- Encourage cross-functional training to broaden employees' understanding of safety requirements in various work environments.

3.4.6 Process Safety Culture

3.4.6.1 Integration of Process Safety Culture

Recognizing the importance of process safety culture as one of the top three PSM elements, it is imperative to integrate this aspect into the overall safety improvement strategy:

- Conduct regular assessments of process safety culture, focusing on leadership commitment, employee involvement, and continuous improvement.
- Implement targeted training programs and initiatives to enhance process safety awareness and adherence to established protocols.

3.4.7 Risk Severity Predictor

3.4.7.1 Integrating into Operational Procedures

In an effort to enhance safety within high-incident zones, it is strongly recommended to integrate the developed Risk Severity Predictor into the standard operational procedures. This can be achieved by incorporating a comprehensive risk assessment checklist that includes weather-related considerations. The checklist should serve as a proactive tool, guiding workers through a systematic evaluation of potential risks associated with specific tasks before their initiation.

<table>
<tr><th></th><th>Latent Cause</th><th>PSM Element</th><th>Recommendation</th></tr>
<tr><td>1</td><td>Training programs did not specify proximity limits for loading operations</td><td>Training and Performance Assurance</td><td rowspan="2">Develop a comprehensive and standardized safety training program for all new employees, focusing on both theoretical knowledge and practical application</td></tr>
<tr><td>2</td><td>Inadequate training on the effects of weather on equipment components, resulting in corrosion and seal deterioration</td><td>Training and Performance Assurance</td></tr>
<tr><td>3</td><td>The supervisors did not value safety</td><td>Process Safety Culture</td><td>Incorporate safety assessments into the recruitment process to evaluate candidates' understanding of safety responsibilities</td></tr>
<tr><td>4</td><td>Weather-adaptive safety measures were not incorporated in standard operating procedures</td><td>Operating Procedures</td><td rowspan="2">Integrate the developed Risk Severity Predictor into the standard operational procedures.</td></tr>
<tr><td>5</td><td>Limited integration of weather-adaptive operating procedures in pile driving activities</td><td>Operating Procedures</td></tr>
</table>

Table 3- 2. Summary of Key Recommendations

3.5 Conclusion

In summary, this study examined the area of occupational safety within high-incident zones, with a specific focus on conducting a detailed Root Cause Analysis of incidents and analyzing the relationships between worker demographics. By utilizing incident records from 2015-2018 and worker demographic data for the same time period, the research discovered crucial insights into incident drivers and their correlation with worker attributes.

The root cause analysis identified three crucial elements of the Process Safety Management (PSM)—Training and Performance Assurance (29.4%), Operating Procedures (29.4%), and

Process Safety Culture (17.6%). These findings underlined the critical need for robust training programs, a positive process safety culture, and well-defined procedures to elevate overall safety.

Exploring worker demographics revealed a significant correlation between rig welders aged 31-40 and incident rates, emphasizing the necessity for targeted safety measures in this specific demographic.

In consideration of these insights, the study proposes recommendations to enhance data quality, fortify training and safety awareness, implement proactive monitoring, establish confidential feedback systems, introduce job rotation opportunities, and integrate process safety culture into safety improvement strategies.

3.6 Limitations and Implications for Future Research

3.6.1 Limitations

First, the study's scope was confined to a specific industry and a limited timeframe, potentially limiting the generalizability of its findings to other sectors and time periods. Additionally, the reliance on incident reports introduced variability in data quality and completeness, as some incidents may have been underreported or lacked comprehensive details. Moreover, the analysis primarily concentrated on organizational processes and PSM elements, overlooking the valuable perspectives and experiences of the workers directly involved in the incidents. Lastly, it's important to recognize that the study identified correlations between PSM elements and incidents but did not establish causation, leaving room for further exploration into the underlying causal factors.

3.6.2 Future Research

Given these constraints, future research in the field of workplace safety presents promising opportunities for advancement. Broadening the scope to encompass various industries and extended time periods can facilitate the identification of common trends and industry-specific challenges. Also, improving data quality through standardized incident reporting processes and conducting thorough incident investigations can enhance the accuracy and completeness of incident data. Additionally, future research should prioritize engaging with workers who have encountered incidents, gaining insights into their perspectives, challenges, and suggestions for safety improvement. Lastly, more in-depth investigations into causation, involving detailed analyses of incidents related to specific Process Safety Management (PSM) elements, can reveal the causal relationships between these elements and incidents, enabling more targeted safety improvements.

3.7 References

1. Atsegbua, J., Lefsrud, L., Sattari, F., & Gue, B. (2023). Machine learning and text mining: A new approach to determine the weather effects on construction incidents. Journal of Construction Engineering and Management (under preparation for review).
2. Bai, M., Qi, M., Shu, C. M., Reniers, G., Khan, F., Chen, C., & Liu, Y. (2023). Why do major chemical accidents still happen in China: Analysis from a process safety management perspective. Process Safety and Environmental Protection, 176, 411–420. https://doi.org/10.1016/j.psep.2023.06.040
3. Baker, M. R., & Moore, D. W. (2006). An analysis of wind-related construction accidents. Journal of Wind Engineering and Industrial Aerodynamics, 94(3), 181-194.
4. Bambra, C., Whitehead, M., Sowden, A., Akers, J., & Petticrew, M. (2008). Shifting schedules: The health effects of reorganizing shift work. American Journal of Preventive Medicine, 34(5), 427-434.
5. Brown, R. L., & Davis, C. E. (2019). Predictive modeling of weather-related construction incidents. Journal of Construction Engineering and Management, 145(7), 04019035.
6. Center for Chemical Process Safety (CCPS), 2011. Guidelines for Risk Based Process Safety. Wiley, New York
7. Chen, Y., Wu, P., & Peng, Y. (2019). Data-Driven Safety Management in Construction Projects: Framework and Case Study. Journal of Construction Engineering and Management, 145(9), 04019060.
8. Chen, W., Zhang, Y., & Lu, W. (2019). Investigation of construction worker fall incidents during non-standard working hours: A social network analysis. Construction Management and Economics, 37(4), 204-219.

9. Collins, P. T., & Hall, R. J. (2008). Weather-related delays in construction projects: A case study analysis. Journal of Construction Engineering and Management, 134(12), 1010-1020.

10. Davis, K. T., & Miller, H. J. (2014). Spatial analysis of construction incidents: Insights from geographic information systems. Automation in Construction, 39, 1-9.

11. Finogeev, A., Parygin, D., Schevchenko, S., Finogeev, A., Ather, D. (2021). Collection and Consolidation of Big Data for Proactive Monitoring of Critical Events at Infrastructure Facilities in an Urban Environment. Communications in Computer and Information Science, vol 1448. https://doi.org/10.1007/978-3-030-87034-8_25

12. Folkard, S., & Lombardi, D. A. (2006). Modeling the impact of the components of long work hours on injuries and "accidents". American Journal of Industrial Medicine, 49(11), 953-963.

13. Garcia, E. R., & Smith, L. P. (2015). Weather-related risks in construction: A case study analysis. International Journal of Occupational Safety and Ergonomics, 21(2), 221-231.

14. Garcia-Trabanino, R., Jarquin, E., Wesseling, C., Johnson, R. J., & Gonzalez-Quiroz, M. (2020). Heat stress, dehydration, and kidney function in sugarcane cutters in El Salvador—A cross-shift study of workers at risk of Mesoamerican nephropathy. Environmental Research, 182, 109086.

15. Hallowell, M., Mozel, M., & Gambatese, J. (2015). Safety Performance in Construction: An Empirical Study. Journal of Construction Engineering and Management, 141(8), 04015008.

16. Harris, A. B., & Robinson, C. S. (2011). Weather-induced risks in construction: A comprehensive review. Safety and Health at Work, 2(4), 305-315.

17. Johnson, A. F., & Brown, S. G. (2018). Identifying construction worker attributes for safer work environments. Journal of Construction Engineering and Management, 144(10), 04018102.

18. Johnson, P. A., & Williams, R. E. (2017). Exploring the impact of wind speed on construction site safety. Journal of Wind Engineering and Industrial Aerodynamics, 169, 160-169.

19. King, S. J., & Taylor, A. N. (2007). Temperature effects on construction worker performance: A field study. Building and Environment, 42(4), 1594-1603.

20. Lee, J., Cho, Y. S., & Moon, H. (2021). Environmental factors affecting the safety performance of construction workers. Journal of Construction Engineering and Management, 147(1), 04020129.

21. Lee, K. J., & Kim, Y. S. (2010). Assessment of temperature effects on construction site accidents using the spatial scan statistic. Safety Science, 48(6), 746-756.

22. Li, H., & Ng, S. T. (2017). Wind risk assessment for construction workers in high-rise building construction projects. Journal of Construction Engineering and Management, 143(10), 04017074.

23. Liu, J., Wang, Q., & Kim, Y. W. (2020). Predictive modeling of safety incidents at construction sites using weather data. Journal of Construction Engineering and Management, 146(6), 04020042.

24. Lingard, H., Cooke, T., Blismas, N., & Pegrum, M. (2013). Systems thinking and construction safety: The systemic accident model revisited. Safety Science, 51(1), 289-297.

25. Miller, V., Bates, G., & Schneider, J. D. (2021). The impact of heat stress on construction workers: Developing a heat stress management plan. Safety Science, 141, 105364.

26. Nguyen, T., Pham, A. D., & Thai, Q. V. (2020). Predicting construction safety risk using weather data and machine learning techniques. Automation in Construction, 117, 103238.

27. Patel, R. R., & Clark, M. J. (2013). Evaluating the impact of temperature on construction safety using Bayesian networks. Journal of Construction Engineering and Management, 139(9), 04013011.

28. Ricci, J. A., Chee, E., Lorandeau, A. L., & Berger, J. (2007). Fatigue in the US workforce: prevalence and implications for lost productive work time. Journal of Occupational and Environmental Medicine, 49(1), 1-10.

29. Rogers, N. L., Dorrian, J., & Dinges, D. F. (2010). Sleep, waking and neurobehavioural performance. Frontiers in Bioscience, E2, 768-793.

30. Smith, J. D., & Johnson, A. B. (2020). Weather-related incidents in construction: A comprehensive analysis. Construction Safety Journal, 36(2), 112-130.

31. Torkelson, A., Mullaney, S., & Lacey, S. (2016). Night work, long work hours, and the risk of work-related injury: implications for shift work research and practices. Accident Analysis & Prevention, 85, 8-14.

32. Turner, D. A., & Wright, J. M. (2009). Wind effects on construction crane stability: A case study analysis. Engineering Structures, 31(11), 2649-2658.

33. Wang, L., Sang, Y., Luo, X., & Zhai, X. (2019). Risk assessment of snowfall events for construction project management. Journal of Construction Engineering and Management, 145(8), 04019060.

34. Wu, P., Li, N., & Ruan, X. (2020). Safety Risk Assessment for Construction Equipment in China: A Hybrid Model. Sustainability, 12(16), 6540.

35. Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2019). Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models and Schedules. Automation in Construction, 97, 50-64.

4 Conclusion

This comprehensive research amalgamates findings from two distinct yet interconnected studies, offering a conclusion that shows the relevance of safety management in high-risk environments, particularly within the construction industry. These studies have been carried out to enhance our understanding of the intricate dynamics influencing safety and incidents.

In the First Study, the focus was on advancing incident prediction using a predictive model driven by weather variables. The research utilized the power of machine learning, with the development of three models: The Decision Tree, Random Forest, and K-Nearest Neighbors. The Random Forest model, boasting a high accuracy of 97%, emerged as the most accurate, offering precise incident likelihood forecasts based on weather conditions.

The creation of an executable application highlights an important step in this research, bridging the gap between complex data analysis and user-friendly accessibility. This practical tool offers invaluable support for proactively managing and mitigating incident risks associated with variable weather conditions. By bringing together the technical insights and real-world application, this work enriches the safety landscape, fostering resilience, preparedness, and efficient resource utilization.

The Second Study, on the other hand, takes a deep dive into the realm of occupational safety. Focused on high-incident zones, it unveils critical insights through root cause analysis and the examination of worker demographics. This study focused on two datasets: incident records and worker demographic data. Root cause analysis highlighted three primary Process Safety Management (PSM) elements driving incidents – Training and Performance Assurance (29.4%), Operating Procedures (29.4%), and Process Safety Culture (17.6%). These revelations underscore the need for robust training, a positive process safety culture, and clear operating procedures in enhancing safety.

The exploration of worker demographics provided a dynamic perspective, revealing how incident rates evolve across various age groups, trade classifications, and experience levels through time series analysis. This knowledge empowers organizations to tailor risk mitigation strategies and enhance safety management in high-incident zones.

In conclusion, these studies collectively inform practical applications, guide decision-makers, and bridge the chasm between technical analysis and real-world practices. The findings from the First Study empower the prediction and management of weather-related incident risks, while the insights from the Second Study enhance safety measures, offering a robust foundation for fortifying the workforce's safety within high-risk environments.

Works Cited

1. Acharya, P., Boggess, B., & Zhang, K. (2018). Assessing Heat Stress and Health among Construction Workers in a Changing Climate: A Review. International Journal of Environmental Research and Public Health, 15(2), 247. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ijerph15020247
2. Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. Applied Sciences, 12(16), 8081. MDPI AG. Retrieved from http://dx.doi.org/10.3390/app12168081
3. Anttonen, H., Pekkarinen, A., & Niskanen, J. (2009). Safety at work in cold environments and prevention of cold stress. Industrial health, 47(3), 254-261.
4. Awolusi, I., Marks, E., Hainen, A., & Alzarrad, A. (2022). Incident Analysis and Prediction of Safety Performance on Construction Sites. CivilEng, 3(3), 669–686. MDPI AG. Retrieved from http://dx.doi.org/10.3390/civileng3030039
5. Betz, T., El-Rayes, K., Johnson, M., Mehnert, B., & Grussing, M. (2023). Machine learning model to predict impact of climate change on facility equipment service life. Building and Environment, 234, 110192. https://doi.org/10.1016/j.buildenv.2023.110192
6. Bochenek, B., & Ustrnul, Z. (2022). Machine Learning in Weather Prediction and Climate Analyses—Applications and Perspectives. Atmosphere, 13(2). https://doi.org/10.3390/atmos13020180
7. Boomija, M., & Phil, M. (2008). Comparison of Partition Based Clustering Algorithms. Journal of Computer Applications, 1(4), 18-21.

8. Breiman, L. (1984). Classification and Regression Trees (1st ed.). Routledge. https://doi.org/10.1201/9781315139470
9. Chen, J., Tao, W. (2022). Traffic accident duration prediction using text mining and ensemble learning on expressways. Sci Rep 12, 21478 https://doi.org/10.1038/s41598-022-25988-4
10. Chen, J., Yu, J., Zhou, W., & Wu, M. (2019). A Machine Learning Approach for Predicting Accident Rates in Construction Projects considering Weather Conditions. Automation in Construction, 103, 239-251.
11. Chen, Z., Wang, D., & Yu, C. (2019). Predicting Construction Incident Rates using Machine Learning and Weather Data. Safety Science, 116, 320-329.
12. Choi, J., Gu, B., Chin, S., & Lee, J. (2020). Machine learning predictive model based on national data for fatal accidents of construction workers. Automation in Construction, 110, 102974.
13. Dangeti P. (2017). Statistics for Machine Learning. Packt Publishing Ltd. https://books.google.ca/books?id=C-dDDwAAQBAJ
14. Environment and Climate Change Canada Historical Climate Data website (https://climate.weather.gc.ca/index_e.html)
15. Fard, F. R., Kamardeen, I., & Newton, S. (2017). Impact of extreme weather conditions on construction labor productivity. Engineering, Construction and Architectural Management, 24(4), 689-707.
16. Fan, Y., Xu, X., & Wang, S. (2021). Predicting Construction Incident Rates using Machine Learning and Weather Factors. Journal of Construction Engineering and Management, 147(4), 04021001

17. Géron, A. (2017). Hands-On Machine Learning with Scikit-Learn and TensorFlow. O'Reilly Media

18. Hastie, T., Tibshirani, R., & Friedman J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition (Springer Series in Statistics).

19. Hua, J., Cao, S., Cao, Y., & Wang, L. (2019). Corrosion damage of construction machinery under different humidity conditions. Materials Science Forum, 954, 139-145.

20. Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: A review. ACM Computing Surveys (CSUR), 31(3), 264-323.

21. Jeong, J. R., Kim, H. E., & Rissanen, S. (2009). Research on winter working environment and working clothes at a construction site. Fashion & Textile Research Journal, 11(1), 174-179.

22. Jiang, Y., Pan, Y., Zhang, S., & Ye, W. (2015). Low-temperature adaptability analysis of construction machinery. In 2015 International Conference on Transportation Information and Safety (ICTIS) (pp. 41-45). IEEE.

23. Jung, K., Kashyap, S., Avati, A., Harman, S., Shaw, H., Li, R., Smith, M., Shum, K., Javitz, J., Vetteth, Y., Seto, T., Bagley, S. C., & Shah, N. H. (2021). A framework for making predictive models useful in practice. Journal of the American Medical Informatics Association : JAMIA, 28(6), 1149–1158. https://doi.org/10.1093/jamia/ocaa318

24. Kamat, V. R., Gupta, R., & Kaur, H. (2020). Wind-induced structural failures of tall buildings: A review. Structures, 27, 1183-1199.

25. Khosravi, Y., Asilian-Mahabadi, H., Hajizadeh, E., Hassanzadeh-Rangi, N., Bastani, H., & Behzadan, A. H. (2014). Factors influencing unsafe behaviors and accidents on construction sites: A review. International journal of occupational safety and ergonomics, 20(1), 111-125.

26. Lee, M., Jeong, J., Jeong, J., & Lee, J. (2021). Exploring Fatalities and Injuries in Construction by Considering Thermal Comfort Using Uncertainty and Relative Importance Analysis. International journal of environmental research and public health, 18(11), 5573. https://doi.org/10.3390/ijerph18115573
27. Lee, S. J., Chen, S. W., Wang, K., & Shen, L. (2019). Effect of low temperatures on the compressive strength and chloride resistance of concrete. Construction and Building Materials, 198, 609-617.
28. Liao, C. W. (2012). Pattern analysis of seasonal variation in occupational accidents in the construction industry. Procedia Engineering, 29, 3240-3244.
29. Liaw, A., & Wiener, M. (2002). Classification and regression by RandomForest. R News, 2(3), 18-22
30. Liu, Y., Ren, Z., Liu, H., & Zhang, M. (2017). Performance evaluation of construction machinery under extreme weather conditions. International Journal of Applied Mechanics, 9(1), 1750006.
31. Liu, Y., He, M., Yu, J., & Shi, L. (2021). Predicting Safety Incidents in Construction Projects considering Weather Factors: A Machine Learning Approach. Safety Science, 140, 105352.
32. Liu, J., Qiu, Y., & Sun, C. (2020). Predicting Safety Incidents in Construction Sites based on Weather Data using Machine Learning. Safety Science, 121, 403-413.
33. Lu, X., Guo, H., & Jiang, S. (2020). Prediction of Accident Rates in Construction Projects using Machine Learning and Weather Data. Safety Science, 124, 104574.
34. Luo, S., Cao, D., Li, Y., & Wu, Z. (2020). Predicting Construction Accident Rates using Machine Learning Models based on Weather Factors. International Journal of Environmental Research and Public Health, 17(13), 4689.

35. Mohammed, S. S., Kadhim, N. R., Abdulrasool, A. T., & al Shaikhli, H. I. (2022). The Use of Weather Website Data for Construction Project Decision-Making in the Short Term. IOP Conference Series: Earth and Environmental Science, 961(1). https://doi.org/10.1088/1755-1315/961/1/012038
36. Moohialdin, A., Trigunarsyah, B., Islam, M. S., & Siddiqui, M. K. (2022). Physiological impacts on construction workers under extremely hot and humid weather. International Archives of Occupational and Environmental Health, 95(2), 315–329. https://doi.org/10.1007/s00420-021-01785-w
37. Moohialdin, A. S. M., Lamari, F., Miska, M., & Trigunarsyah, B. (2019). Construction worker productivity in hot and humid weather conditions: A review of measurement methods at task, crew and project levels. Engineering, Construction and Architectural Management, 27(1), 83-108.
38. Papalexopoulos, T., Bertsimas, D., Cohen, I., Goff, R., Stewart, D. & Trichakis, N. (2022). Ethics-by-design: efficient, fair and inclusive resource allocation using machine learning. Journal of Law and the Biosciences. 9. 10.1093/jlb/lsac012.
39. Radevsky, R., Taylor, C., Stolfa, A., Generali, A., Uk, L., Cazzaniga, M., Wittowski, R., Re, S., Zurich, S., & Baltis, E. (n.d.). IMIA-WGP 78 (12) The effect of adverse weather on construction sites Working Group Executive Committee Sponsor.
40. Rameezdeen, R., Elmualim, A. (2017). The Impact of Heat Waves on Occurrence and Severity of Construction Accidents. International Journal of Environmental Research and Public health,14, 70. https://doi.org/10.3390/ijerph14010070
41. Rashid, H. A. (2015). Weather Effect on Workflow, and Labor Productivity of Construction Plant. 7(11). www.iiste.org

42. Rowlinson, S., YunyanJia, A., Li, B., & ChuanjingJu, C. (2014). Management of climatic heat stress risk in construction: a review of practices, methodologies, and future research. Accident Analysis & Prevention, 66, 187-198.

43. Sacks, R., Harel, R., & Qudah, E. (2018). Modeling the impact of rainfall events on construction labor productivity. Journal of Construction Engineering and Management, 144(5), 04018023.

44. Shahin, A., Eng, P., Abourizk; S M, Asce, M., & Mohamed, Y. (2011). Modeling Weather-Sensitive Construction Activity Using Simulation Overview of the Framework. Journal of Construction Engineering and Management, 137(3), 238–246. https://doi.org/10.1061/(ASCE)CO.1943-7862.

45. Srinavin, K., & Mohamed, S. (2003). Thermal environment and construction workers' productivity: some evidence from Thailand. Building and Environment, 38(2), 339-345.

46. Szer, I., Szer, J., Cyniak, P., Błazik-Borowa, E., Bernatik, A., Kocurkova, L., & Jørgensen, K. (2017). Influence of temperature and surroundings humidity on scaffolding work comfort. Prevention of accidents at work. Taylor & Francis Group, 19-23.

47. Tan, P., Steinbach, M., & Kumar, V. (2005). Cluster Analysis: Basic Concepts and Algorithms. Introduction to Data Mining. 487-568.

48. Thomas F. [and nine others], Working Group I Technical Support Unit. (2014). Climate change 2013 : the physical science basis : Working Group I contribution to the fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom Cambridge University Press

49. Varghese, B. M., Hansen, A., Bi, P., & Pisaniello, D. (2018). Are workers at risk of occupational injuries due to heat exposure? A comprehensive literature review. Safety science, 110, 380-392.

50. Vukadinovic, A., & Radosavljevic, J. (2020). Occupational safety and health of construction workers working in extreme temperature. In Proceedings of the 15th International Conference Risk and Safety Engineering, Kopaonik, Serbia (pp. 16-18).

51. Yi, W., & Chan, A. P. (2013). Optimizing work–rest schedule for construction rebar workers in hot and humid environment. Building and Environment, 61, 104-113.

52. Atsegbua, J., Lefsrud, L., Sattari, F., & Gue, B. (2023). Machine learning and text mining: A new approach to determine the weather effects on construction incidents. Journal of Construction Engineering and Management (under review).

53. Bai, M., Qi, M., Shu, C. M., Reniers, G., Khan, F., Chen, C., & Liu, Y. (2023). Why do major chemical accidents still happen in China: Analysis from a process safety management perspective. Process Safety and Environmental Protection, 176, 411–420. https://doi.org/10.1016/j.psep.2023.06.040

54. Baker, M. R., & Moore, D. W. (2006). An analysis of wind-related construction accidents. Journal of Wind Engineering and Industrial Aerodynamics, 94(3), 181-194.

55. Bambra, C., Whitehead, M., Sowden, A., Akers, J., & Petticrew, M. (2008). Shifting schedules: The health effects of reorganizing shift work. American Journal of Preventive Medicine, 34(5), 427-434.

56. Brown, R. L., & Davis, C. E. (2019). Predictive modeling of weather-related construction incidents. Journal of Construction Engineering and Management, 145(7), 04019035.

57. Center for Chemical Process Safety (CCPS), 2011. Guidelines for Risk Based Process Safety. Wiley, New York
58. Chen, Y., Wu, P., & Peng, Y. (2019). Data-Driven Safety Management in Construction Projects: Framework and Case Study. Journal of Construction Engineering and Management, 145(9), 04019060.
59. Chen, W., Zhang, Y., & Lu, W. (2019). Investigation of construction worker fall incidents during non-standard working hours: A social network analysis. Construction Management and Economics, 37(4), 204-219.
60. Collins, P. T., & Hall, R. J. (2008). Weather-related delays in construction projects: A case study analysis. Journal of Construction Engineering and Management, 134(12), 1010-1020.
61. Davis, K. T., & Miller, H. J. (2014). Spatial analysis of construction incidents: Insights from geographic information systems. Automation in Construction, 39, 1-9.
62. Finogeev, A., Parygin, D., Schevchenko, S., Finogeev, A., Ather, D. (2021). Collection and Consolidation of Big Data for Proactive Monitoring of Critical Events at Infrastructure Facilities in an Urban Environment. Communications in Computer and Information Science, vol 1448. https://doi.org/10.1007/978-3-030-87034-8_25
63. Folkard, S., & Lombardi, D. A. (2006). Modeling the impact of the components of long work hours on injuries and "accidents". American Journal of Industrial Medicine, 49(11), 953-963.
64. Garcia, E. R., & Smith, L. P. (2015). Weather-related risks in construction: A case study analysis. International Journal of Occupational Safety and Ergonomics, 21(2), 221-231.
65. Garcia-Trabanino, R., Jarquin, E., Wesseling, C., Johnson, R. J., & Gonzalez-Quiroz, M. (2020). Heat stress, dehydration, and kidney function in sugarcane cutters in El Salvador—A

cross-shift study of workers at risk of Mesoamerican nephropathy. Environmental Research, 182, 109086.

66. Hallowell, M., Mozel, M., & Gambatese, J. (2015). Safety Performance in Construction: An Empirical Study. Journal of Construction Engineering and Management, 141(8), 04015008.
67. Harris, A. B., & Robinson, C. S. (2011). Weather-induced risks in construction: A comprehensive review. Safety and Health at Work, 2(4), 305-315.
68. Johnson, A. F., & Brown, S. G. (2018). Identifying construction worker attributes for safer work environments. Journal of Construction Engineering and Management, 144(10), 04018102.
69. Johnson, P. A., & Williams, R. E. (2017). Exploring the impact of wind speed on construction site safety. Journal of Wind Engineering and Industrial Aerodynamics, 169, 160-169.
70. King, S. J., & Taylor, A. N. (2007). Temperature effects on construction worker performance: A field study. Building and Environment, 42(4), 1594-1603.
71. Lee, J., Cho, Y. S., & Moon, H. (2021). Environmental factors affecting the safety performance of construction workers. Journal of Construction Engineering and Management, 147(1), 04020129.
72. Lee, K. J., & Kim, Y. S. (2010). Assessment of temperature effects on construction site accidents using the spatial scan statistic. Safety Science, 48(6), 746-756.
73. Li, H., & Ng, S. T. (2017). Wind risk assessment for construction workers in high-rise building construction projects. Journal of Construction Engineering and Management, 143(10), 04017074.

74. Liu, J., Wang, Q., & Kim, Y. W. (2020). Predictive modeling of safety incidents at construction sites using weather data. Journal of Construction Engineering and Management, 146(6), 04020042.

75. Lingard, H., Cooke, T., Blismas, N., & Pegrum, M. (2013). Systems thinking and construction safety: The systemic accident model revisited. Safety Science, 51(1), 289-297.

76. Miller, V., Bates, G., & Schneider, J. D. (2021). The impact of heat stress on construction workers: Developing a heat stress management plan. Safety Science, 141, 105364.

77. Nguyen, T., Pham, A. D., & Thai, Q. V. (2020). Predicting construction safety risk using weather data and machine learning techniques. Automation in Construction, 117, 103238.

78. Patel, R. R., & Clark, M. J. (2013). Evaluating the impact of temperature on construction safety using Bayesian networks. Journal of Construction Engineering and Management, 139(9), 04013011.

79. Ricci, J. A., Chee, E., Lorandeau, A. L., & Berger, J. (2007). Fatigue in the US workforce: prevalence and implications for lost productive work time. Journal of Occupational and Environmental Medicine, 49(1), 1-10.

80. Rogers, N. L., Dorrian, J., & Dinges, D. F. (2010). Sleep, waking and neurobehavioural performance. Frontiers in Bioscience, E2, 768-793.

81. Smith, J. D., & Johnson, A. B. (2020). Weather-related incidents in construction: A comprehensive analysis. Construction Safety Journal, 36(2), 112-130.

82. Torkelson, A., Mullaney, S., & Lacey, S. (2016). Night work, long work hours, and the risk of work-related injury: implications for shift work research and practices. Accident Analysis & Prevention, 85, 8-14.

83. Turner, D. A., & Wright, J. M. (2009). Wind effects on construction crane stability: A case study analysis. Engineering Structures, 31(11), 2649-2658.
84. Wang, L., Sang, Y., Luo, X., & Zhai, X. (2019). Risk assessment of snowfall events for construction project management. Journal of Construction Engineering and Management, 145(8), 04019060.
85. Wu, P., Li, N., & Ruan, X. (2020). Safety Risk Assessment for Construction Equipment in China: A Hybrid Model. Sustainability, 12(16), 6540.
86. Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2019). Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models and Schedules. Automation in Construction, 97, 50-64.

Appendix A: Incident description of assigned PSM elements for 11 incidents

No	Incident Description	Task Division	PSM Elements
1	Operator was carrying a compressor with a loader-jib from hertz lay down to area 145.The compressor was 5 feet off the ground with a tagline attached. While transporting the compressor just west of the cold storage area, a KPCL SUV was parked on the road due to offloading material by another group. The Loader Operator did not see the SUV stopped in front of him due to his vision being obstructed by the compressor. As the loader progressed the front side of the compressor made contact with the SUV's back window resulting in extensive damage to window and surrounding window supports.	Operating loading equipment	Hazard Identification and Risk Analysis/ Operating Procedures/ Management of Change
2	Stones from sand being spread by a Bouchier sanding truck makes contact with the passenger window off the drive side of a PCL shuttle van that had stopped at 4 way stop sign causing it to break. The drive states that he heard multiple stones making contact with the vehicle as the sanding truck passed but did not realize the window that was directly behind him was shattered, until he felt a draft while making a right turn from the stop sign. He then pulled over then notified his supervisor, the drive was the only occupant of the vehicle at the time of the incident.	Driving site vehicles	Hazard Identification and Risk Analysis/ Operating Procedures/ Training and Performance Assurance
3	Approximately 03:50 am an OE operator was dropping off a cable reel with Zoom Boom. Worker stepped out of zoom boom to unstrap the load. Workers left foot slipped where crane mat transitions to the dirt. Worker felt no initial discomfort. Upon walking back to camp worker felt minor discomfort to left ankle and noticed slight swelling. Worker	Walking to/from job area	Safe Work Practices/ Training and Performance Assurance/ Hazard

	reported incident to foreman at following start of shift. Supervision was notified and worker taken to on-site Medical for assessment. Worker assessed for mild sprain occupational illness/injury. No treatment was provided & worker released â€œreturn to work regular. Worker to follow up with on-site medic at start of next shift.		Identification and Risk Analysis
4	A Monad worker transported a Herman Nelson Heater to the new water storage tank area, south of the power house using a Zoom Boom. When he pulled off the main road in front of the mill and started north towards the water tank, he encountered a change in elevation. The frontend of the heater made contact with the ground causing the opposite end of the heater to rise, making contact with the jib and caused minor damage to the top of the heater and cover on the built-in containment compartment for the fuel tank. The operator immediately stopped and called his supervisor to the area.	Handling material	Training and Performance Assurance/ Operating Procedures/ Management of Change
5	On Monday January 25, 2016, at approximately 2:20 pm, an Equipment Operator was operating a John Deere 744K loader in the Abalone stockpile area. The worker was tasked with loading material from the winter stockpile containment area into Rock Trucks to be transported into the battery limits for backfilling. This containment area is constructed of multiple 5 x 2½ concrete Lego blocks that weigh approximately 5000lbs. The containment area was 3 Lego blocks high thus making it approximately 7½ feet tall. This containment area was covered with tarps and was fed with Herman Nelson heaters at the front of the containment area in order to keep the material at optimal	Handling material	Hazard Identification and Risk Analysis/ Operating Procedures/ Training and Performance Assurance

	temperature for backfill. The containment area is also equipped with a conductor barrel (Steel Pipe) that runs under the material, fed with a 1 million BTU heater that is also in place to heat the soil to operational temperature. On this particular occasion, the operator had a spotter roll back the tarp and drove forward to pick up a load of dirt with his bucket. The material being scooped up was 6 feet away from the back end of the containment area. The operator then curled his bucket up and backed up the loader. While backing up the loader, the operator noticed that the top 2 levels of the Lego blocks at the back of the containment area had tipped over in a south direction. The operator froze the scene, notified Abalone Supervision and Safety immediately, and Supervision notified PCL Supervision immediately. The Canadian model was followed.		
6	While walking BH305 Excavator out of trench to go for coffee break, the front bottom window fell out and broke.	Digging trenches	Asset Integrity & Reliability/ Management of Change/ Training and Performance Assurance
7	On Saturday, April 15, 2017, at approximately 10:30 am, a worker was in the CWA-8 area along the 16-1 rack, when they noticed a fluid leak under a Wacker Neuson ground heater. The worker placed absorbent spill pads underneath the ground heater to contain the fluid. The worker notified supervision and PCL HSE attends the scene and obtains photographs. It was determined that approximately 50-75 liters of	Digging trenches	Hazard Identification and Risk Analysis/ Management of Change/ Training and Performance Assurance

	RECOFREEZE PG 50/50 glycol fluid had been released. Workers cleaned up the spilled fluid and dispose of contaminated soil in the appropriate bins.		
8	While driving the first battered pile at an angle of 14 degrees from vertical in area 125 the Hydraulic hammer fell off leads of an Enteco. E-7060 pile driver.	Operating piledriving equipment	Asset Integrity & Reliability/ Management of Change/ Training and Performance Assurance
9	Loading snow out; hit hidden manhole broke the collar of the manhole	Other	Hazard Identification and Risk Analysis/ Operating Procedures/ Training and Performance Assurance
10	Operator was using skid steer to back blade snow off of crane pad. Operator raised bucket above eye level to ensure no one in path of travel, causing a blind spot where the raised arms were. Operator drove forward towards edge of pad, when bucket came into contact with bottom edge of upper crane cab, pushing it from its travel position, further towards boom, causing damage to upper cab assembly.	Operating excavation equipment	Hazard Identification and Risk Analysis/ Operating Procedures/ Training and Performance Assurance

11	A crew was moving equipment out from between Boiler #3 and the Superdeheater building. While moving an EWP the rear wheel of the EWP made contact with a fixed scaffold ladder causing a slight bend in the beam or rail of the ladder. No one was in the line of fire.	Operating manlifts	Hazard Identification and Risk Analysis/ Operating Procedures/ Training and Performance Assurance

Table A- 1. Incident description of assigned PSM elements for 11 incidents

Appendix B - Root Cause Analysis

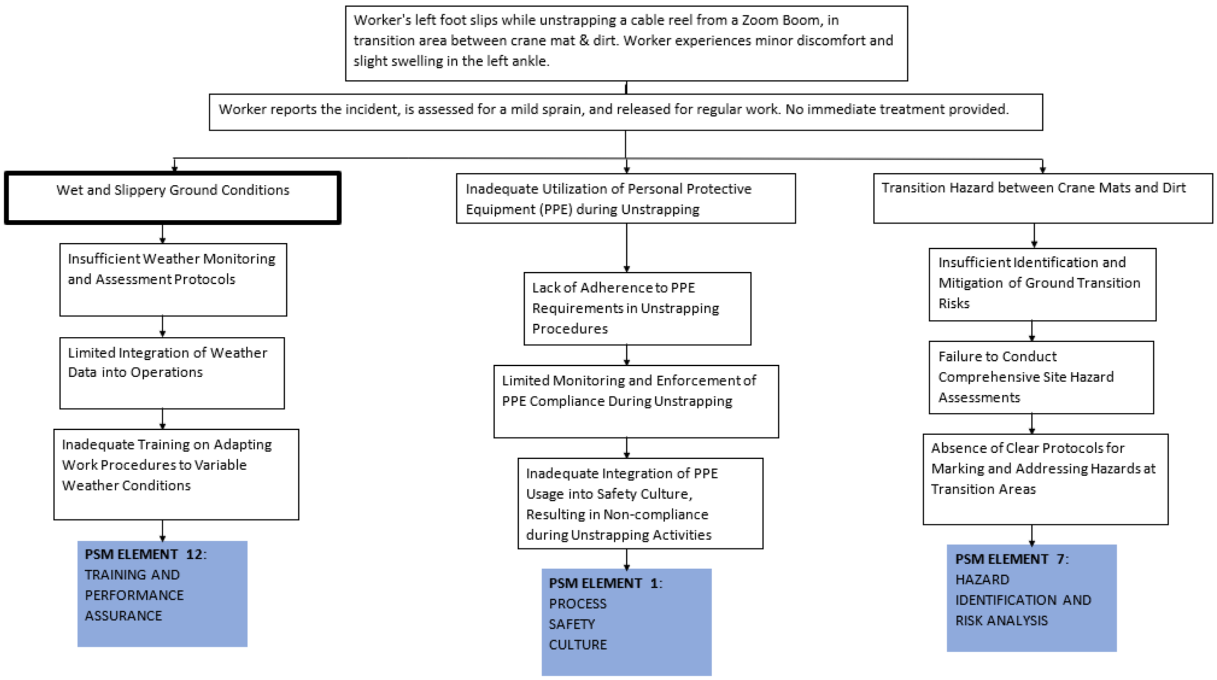

Figure B- 1. Root cause analysis for incident 5

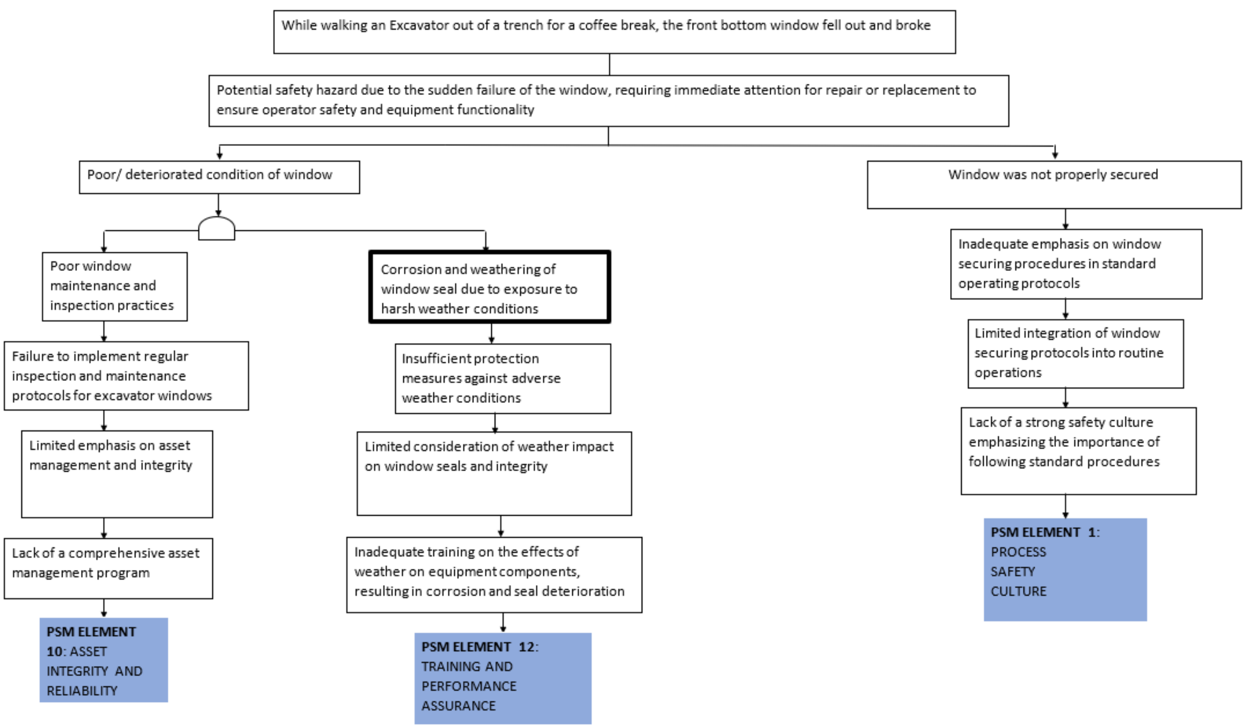

Figure B- 2. Root cause analysis for incident 6

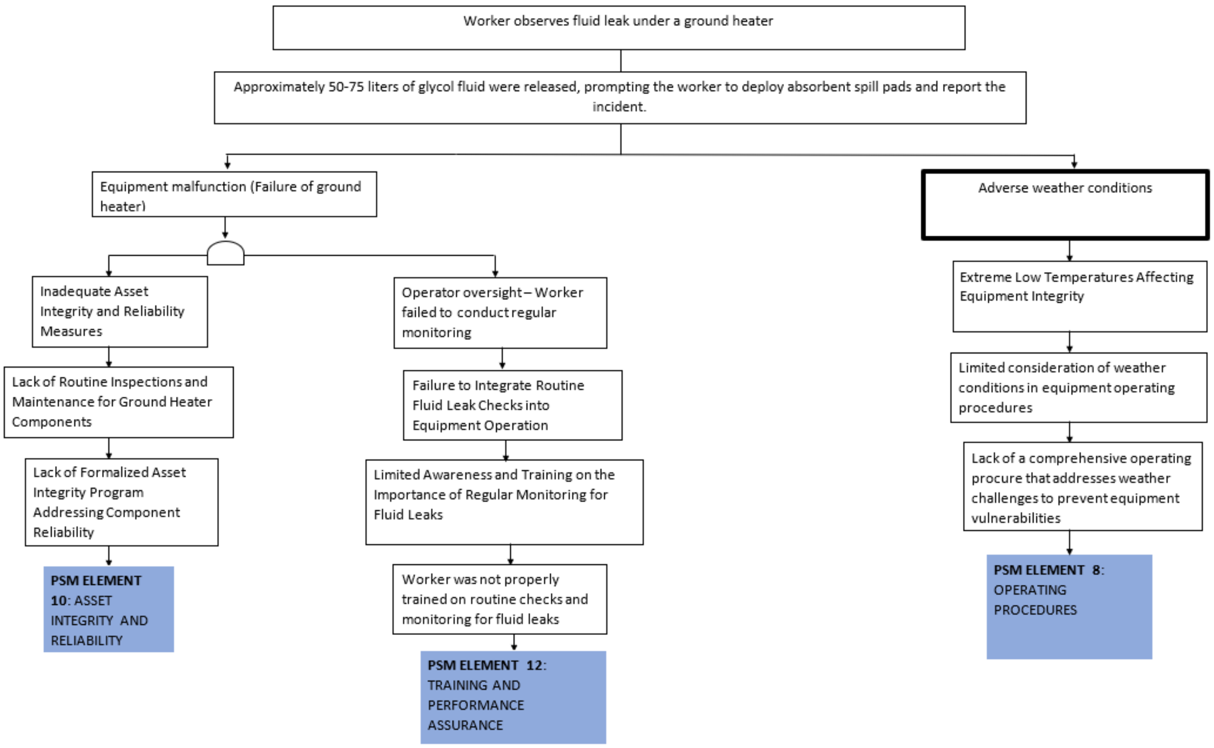

Figure B- 3. Root cause analysis for incident 7

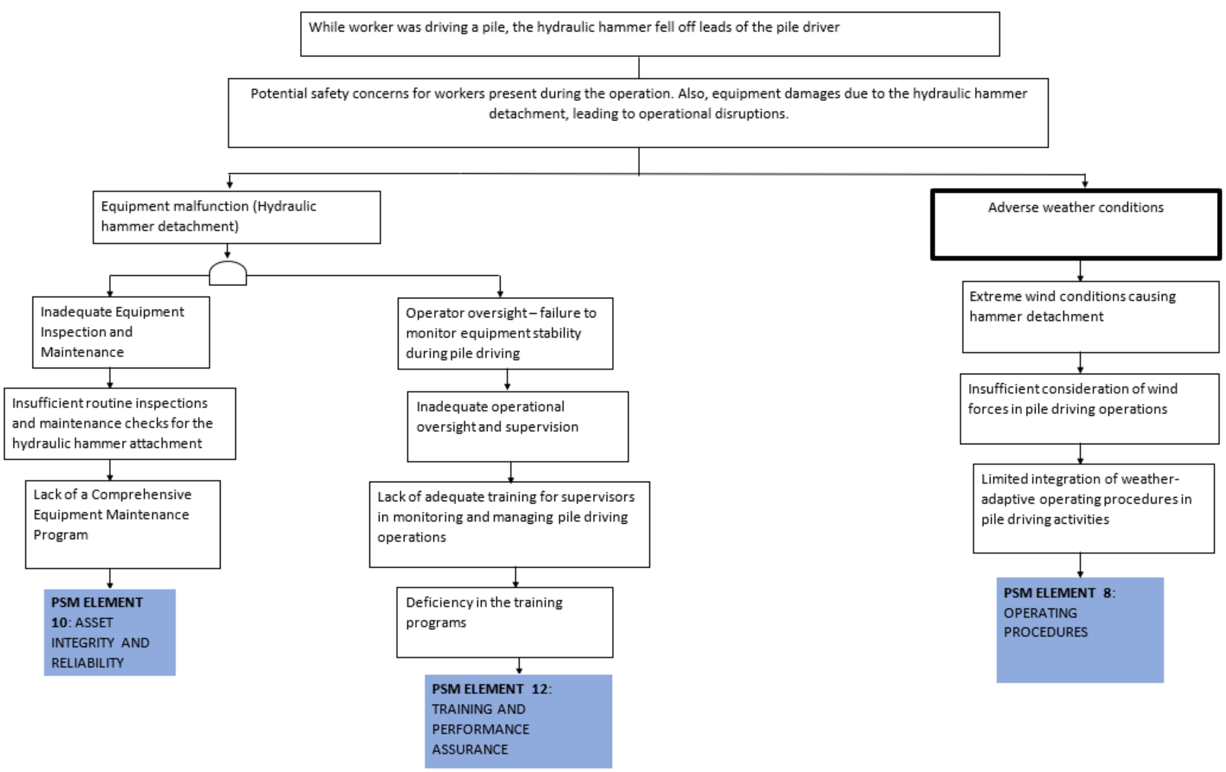

Figure B- 4. Root cause analysis for incident 8

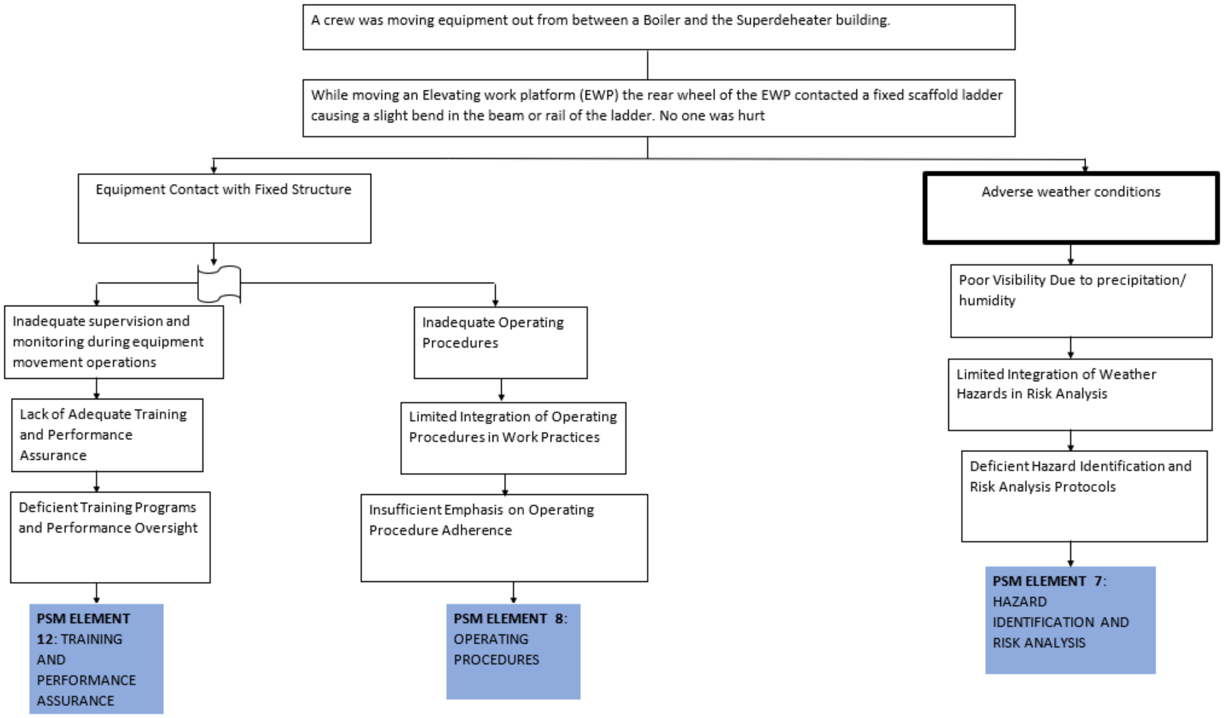

Figure B- 5. Root cause analysis for incident 9

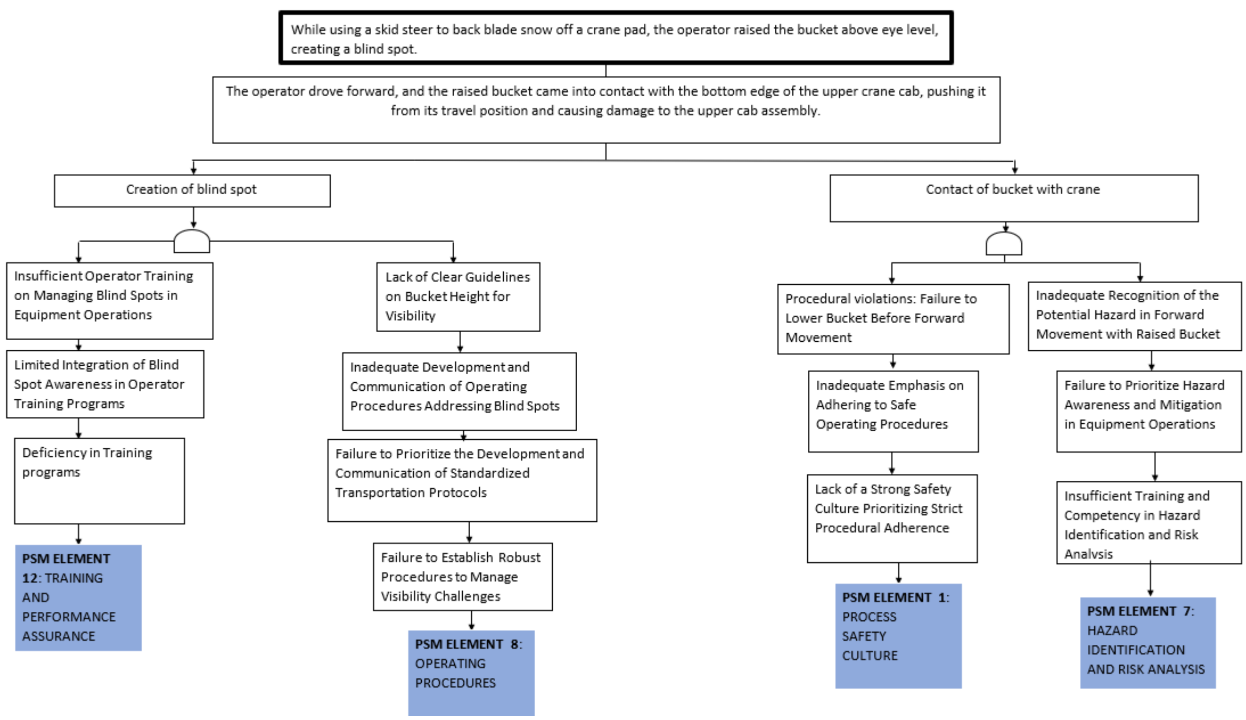

Figure B- 6. Root cause analysis for incident 10

Appendix C - Definition of ABC Incidents

ABC Incidents refer to a categorization system based on a risk classification matrix that assesses the severity and potential impact of incidents within a given context. In this classification:

1. A - Incidents (Most Severe): These incidents represent the highest level of severity and are characterized by their significant potential for adverse consequences. They demand immediate attention due to their potential to cause major disruptions, substantial harm, or severe financial, environmental, or human consequences. A - Incidents necessitate swift and comprehensive intervention and preventive measures to mitigate the risk.

2. B - Incidents (Moderate Severity): B Incidents denote a moderate level of severity. While they may not pose an immediate threat of extreme consequences, they still have the potential to cause notable disruptions, injuries, or financial impacts. B - Incidents require prompt action to prevent their escalation into more severe incidents. Timely intervention and management are essential.

3. C - Incidents (Least Severe): C Incidents are associated with a lower level of severity compared to A and B Incidents. While they may not pose an immediate risk of major disruptions or significant harm, they still warrant attention and monitoring. C - Incidents are typically less urgent and may be addressed through routine procedures and ongoing monitoring to prevent any potential escalation.