THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Toward Accident Prevention Through Machine Learning Analysis of Accident Reports

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Gothenburg, Sweden 2022

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Technical report no 2022:3 Lic /Architecture and Civil Engineering / Chalmers University of Technology

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Chalmers Reproservice
Gothenburg, Sweden 2022

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Abstract

Occupational safety remains of interest in the construction sector. The frequency of accidents has decreased in Sweden but only to a level that remains constant over the last ten years. Although Sweden shows to be performing better in comparison to other European countries, the construction industry continues to contribute to a fifth of fatal accidents in Europe. The latter situation pushes towards the need for reducing the frequency and fatalities of occupational accident occurrences in the construction sector. In the Swedish context, several initiatives have been established for prevention and accident frequency reduction. However, risk analysis models and causal links have been found to be rare in this context.

The continuous reporting of accidents and near-misses creates large datasets with potentially useful information about accidents and their causes. In addition to that, there has been an increased research interest in analysing this data through machine learning (ML). The state-of-art research efforts include applying ML to analyse the textual data within the accumulated accident reports, identifying contributing factors, and extracting accident information. However, solutions that are created by ML models can lead to changes for a company and the industry. ML modelling includes a prototype development that is accompanied by the industry's and domain experts' requirements. The aim of this thesis is to investigate how ML based methods and techniques could be used to develop a research-based prototype for occupational accident prevention in a contracting company. The thesis focus is on the exploration of a development processes that bridges ML data analysis technical part with the context of safety in a contracting company. The thesis builds on accident causation models (ACMs) and ML methods, utilising the Cross Industry Standard Process Development Method (CRISP-DM) as a method. These were employed to interpret and understand the empirical material of accident reports and interviews within the health and safety (H&S) unit.

The results of the thesis showed that analysing accident reports via ML can lead to the discovery of knowledge about accidents. However, there were several challenges that were found to hinder the extraction of knowledge and the application of ML. The identified challenges mainly related to the standardization of the development process and, the feasibility of implementation and evaluation. Moreover, the tendency of the ML-related literature to focus on predicting severity was found not compatible either with the function of ML analysis or the findings of accident causation literature which considers severity as a stochastic element. The analysis further concluded that ACMs seemed to have reached a mature stage, where a new approach is needed to understand the rules that govern the relationships between emergent new risks – rather than the systemization of risks themselves. The analysis of accident reports by ML needs further research in systemized methods for such analysis in the domain of construction and in the context of contracting companies – as only few research efforts have focused on this area regarding ML evaluation metrics and data pre-processing.

Key words: Accident report, accident causation models, construction, machine learning, prevention, health and safety.

List of Appended papers and authors' contributions

Paper I: A REVIEW OF MACHINE LEARNING FOR ANALYSING ACCIDENT REPORTS IN THE CONSTRUCTION INDUSTRY AND APPLICATION REQUIREMENTS (under review at The Journal of Information Technology in Construction (ITcon) submitted on 2022-02-10)

Shayboun, M, Kifokeris, D, and Koch, C (2022)

This paper is under review in The Journal of Information Technology in Construction (ITcon) submitted on 2022-02-10.

- May Shayboun contributed to formulating the research question, introduction, collecting the literature material, synthesising the literature and discussion and conclusion.
- Dimosthenis Kifokeris contributed to the development of the method and with feedback throughout the paper writing.
- Christian Koch contributed to the development of the method, development of the discussion and with feedback throughout the paper writing.

Paper II: A COMPARISON OF ACCIDENT CAUSATION MODELS (ACMS) AND MACHINE LEARNING (ML) FOR APPLIED ANALYSIS WITHIN ACCIDENT REPORTS

Shayboun, M, Koch, C, and Kifokeris, D (2021)

This paper was included in the proceedings of the 37th Annual ARCOM Conference, 6-7 September 2021, UK, Association of Researchers in Construction Management, 289-298

- May Shayboun contributed to writing the entire paper.
- Christian Koch contributed to the development of the method and with feedback and commentary throughout the paper writing.
- Dimosthenis Kifokeris contributed to the development of the method and with feedback and commentary throughout the paper writing.

Paper III: LEARNING FROM ACCIDENTS: MACHINE LEARNING PROTOTYPE DEVELOPMENT BASED ON THE CRISP-DM BUSINESS UNDERSTANDING

Shayboun, M, Koch, C, and Kifokeris, D (2021)

This paper appeared in the Proceedings of the Joint CIB W099 & W123 International Conference 2021: Changes and innovations for improved wellbeing in construction

- May Shayboun contributed to writing the introduction, conducting interviews, transcribing the interviews, writing of the method business understanding, empirical material, discussion and conclusion.
- Christian Koch contributed to writing the mapping of the context and with feedback and commentary throughout the paper writing.
- Dimosthenis Kifokeris contributed to writing the method and the status of ML development methods section and with feedback and commentary throughout the paper writing.

Acknowledgements

I want to thank everyone who had made this work possible and contributed with discussions, advice, and valuable insights. It had been a journey that involved much growth and development. I am very grateful that I had the opportunity to pursue my licentiate thesis. I want to start by recognizing the outstanding efforts of my main supervisor, Christian Koch and co-supervisor, Dimosthenis Kifokeris. Working with you has been a lifetime experience that I will always keep. I am incredibly thankful for the profound knowledge, the discussions, the guidance and the support that Christian Koch has provided throughout this work. I want to extend my gratitude to my co-supervisor, Dimosthenis Kifokeris, who has always contributed with learnings, continuous feedback, and close collaboration. I want to acknowledge the efforts of Christina- Claeson-jonsson for the engagement and for providing collaboration with the industry.

I would like to take the chance to thank all my colleagues within the division of Construction Management and the division of Building Design for contributing to the supportive academic dialogue. A special thanks go to my examiner Christine Räisänen for her valuable feedback, involvement, and support.

It was inspiring to meet the most impressive people in conferences, Ph.D. courses, and other academic activities during this journey. I am very thankful for that!

To all the respondents and reference group members and collaborators, thank you for sharing your experiences and taking the time to add insights and feedback.

Finally, I would like to acknowledge the support of my partner Ghaith and thank my mother, father and sisters. I would not have accomplished this journey without your continuous encouragement.

May Shayboun

Gothenburg, February 2022

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1. Introduction

This project focuses on identifying risks associated with occupational accidents within a Swedish Contracting Company, particularly those that result in injuries.

Contracting companies have improved their processes and registration of accident reports. These improvements have been parallel to developments in regulations and the available software for accident registration. There is, however, a desire and need to learn from failures by analysing the accidents that are now reported more consistently. Moreover, new opportunities to gain knowledge about the causes of accidents through the registration database have emerged, together with the increased interest in and the capabilities of machine learning (ML), both of which could potentially improve accident prevention.

1.1. Background

The health and safety (H&S) units within large contractor organisations continuously report their internal accidents and near-misses (incidents) that have occurred on construction sites. The accumulated reports form a database that details the different types of accidents. In addition, production personnel such as the site managers and safety engineers have practical knowledge of accidents and their causes. However, it is seldom that these accumulated accident reports are analysed. Nonetheless, there has been a recent increasing trend within publications in accident prevention to look at this data using ML (Xu et al. 2021). These include applying ML to analyse the textual data within the accumulated accident reports in contracting companies and national registries, identifying contributing factors, and extracting accident information (Hegde and Rokseth 2020, Sarkar and Maiti 2020, Khallaf and Khallaf 2021, Hou et al. 2021).

ML, designed to find underlying patterns in a dataset, can be used to predict situations that may pose the risk of accidents at construction sites (Baek et al. 2021, Vallmuur 2015). ML systems automatically improve their built-in functionality through experience (Jordan and Mitchell 2015). The use of ML – a subdivision within artificial intelligence (AI) - in a construction context is now being seen as a promising development (Vallmuur 2015, Kifokeris and Xenidis 2018, Pan and Zhang 2021). Another key tool in understanding the accumulated data is data mining, which is understood as "the process of discovering interesting patterns from large amounts of data" (Han et al. 2011).

Vallmuur (2015) reviewed eight ML system examples that analyse the database of registered occupational accidents. The ML systems use Bayesian networks (BN), decision trees (DT) and association rule mining. Examples of using ML in the prevention of occupational accidents are becoming more common within relevant published research studies (Hegde and Rokseth 2020). Algorithms such as DT, Random Forest (RF), Stochastic Gradient Tree Boosting (SGTB), artificial neural network (ANN), and natural language processing (NLP) for data pre-processing (Vallmuur 2015, Witten et al. 2016, Hegde and Rokseth 2020, Hou et al. 2021) can be used to analyse the data of injury cases. The purpose of the latter type of analysis includes the prediction of accident types, classification of causes, and information extraction. It is important to note that in this thesis, the author terms a "prototype" as the designed digital software that suggests a precise implementation for ML-based data analytics, i.e., that shows means of application and an interface that is ready for use.

Despite the attention being paid to the importance of safety in the workplace, the building industry has the highest frequency of fatalities (Arbetsmiljöverket 2021). Moreover, the rate of fatal injuries has not decreased since 2019 compared to other industries (such as transport and warehousing) (Arbetsmiljöverket 2021). The frequency of accidents (number of accidents / 1000 employees) has levelled out in the last decade, hanging roughly at around 11 (Byggforetagen 2021). The accident types show a rather complex and scattered pattern: body movement with physical overload (18%), injuries from tools and gear (16%), collapse, falls and rupture of material (12%), falls from a height (12%) and falls at the same level (tripping) (12%). Although Sweden's figures are better than other European countries (e.g., France, Portugal, and Germany), the construction industry accounts for one-fifth of all fatal accidents at work in the EU. Of these fatal accidents, 27 occurred within the construction sector (Eurostat 2018). There is a need to reduce the injury frequency and fatalities in the construction industry.

The construction industry is characterized by high complexity, uncertainty, and interdependence (Berglund et al. 2017). This situation creates difficulties in operational planning and creating a safe and disturbance-free workflow. An agenda for safer construction has been pursued by both practitioners and researchers alike. Multiple routines and approaches exist in Swedish projects and companies (Törner and Pousette 2009). Accident prevention research has developed several risk analyses and accident-related causal models (Behm and Schneller 2013, Berglund et al. 2017, Harms-Ringdahl 2013, Jørgensen 2002, Reason 2008). Some of these models systematically distribute different levels to different causes and systematize causes in a fault-tree analysis or a hierarchical analysis, assuming that multiple causes drive accidents. However, the use of such causal links is rare in the Swedish construction sector (Berglund et al. 2017). Safety in construction is affected and/or hindered by conditions such as the construction site's organization, management (Törner and Pousette 2009), equipment, and materials (Berglund et al. 2019). Those change from one workplace to another, making it more difficult to maintain sufficient, common safety routines (Albrechtsen and Hovden 2014, Lingard et al. 2012, Schwatka et al. 2016). In addition, safety and the safety culture are affected by several factors such as subcontractor and the main contractor cultures, organizational decision-making regarding safety considerations, and individual behaviour (Koch 2013, Zhou et al. 2015).

This thesis assumes that it is possible to prevent accidents by systematizing the learning and knowledge accumulated from registered accidents by investment in the latest digitization technology – in this case, ML (Berglund et al. 2017). However, IT research that implements ML data analysis can lead to changes not only for a company but for the entire industry (Bilal et al. 2016, Bilal and Oyedele 2020). Applying ML does not only include the development of a prototype, but also to address the industry requirements and collaborate with industry experts and ML analysts (Bilal and Oyedele 2020). Regardless, the current literature lacks concrete use cases and the required integration with domain and expert knowledge (Vallmuur 2015, Bilal et al. 2016). The aforementioned collaboration with domain experts needs an understanding of the context or the domain of the application and explaining the ML models to the humans involved (Gilpin et al. 2018). This thesis contributes to exploring development processes that bridge ML data analysis technical part with the context of safety in a contracting company. In understanding the context, the Cross Industry Standard Process Development Method (CRISP-DM) is of interest (Martínez-Plumed et al. 2019). CRISP-DM is a methodology consisting of six steps that catalogue and guide the process of data mining projects (Martínez-Plumed et al. 2019). Moreover, accident causation models (ACMs) are of interest in explaining ML models.

According to Kjellen and Albrechtsen (2017), ACMs are the "simplified representations of the processes in the real world that result in accidental loss" (p.25). ACMs are mature theoretical, conceptual models that have impacted the development of safety management methods and processes (Kjellen and Albrechtsen 2017).

1.2. Aim and research questions

This thesis aims to investigate how ML-based methods and techniques could be used to develop a research-based prototype for occupational accident prevention in a contracting company. The thesis focuses on exploring a development process that bridges ML data analysis technical part with the context of safety in a contracting company. The research context is accident prevention and H&S activities on-site, with the company being the case for the prototype development. The main (primary) data source is the registry of accident reports of the case company. Secondary data collection was undertaken through interviews with the company's H&S unit.

It is important for both business and academia to understand the use and the obstacles in introducing advanced technologies such as ML. Such understanding can benefit the construction industry through improved safety performance and better accident prevention strategies. As discussed earlier, this industry-wide interest in improving safety measures has been evident in the literature.

Therefore, this research project contributes to the development of ML for analysing accident reports and exploring methods for building a prototype to improve occupational accident prevention strategies while considering the context. The context of the contracting company and its safety processes are the targeted application domain for the digital system. The ML analysis is based on the data generated by different actors in the case company and is intended to be applied within its safety processes.

One overall research question and sub-questions were posed based on this research aim.

Overall research question: Does the application of ML on accident reports reveal new knowledge about accidents in the construction industry?

RQ1: What are the requirements for applied ML in the domain of accident prevention in a contracting company's occupational safety processes?

RQ2: What is the role of accident causation models (ACMs) as a theoretical framework for the ML results of analysed reported accidents in the construction industry – and what can be learned about ACMs through ML?

RQ3: What are the experiences and challenges of applying CRISP-DM's business understanding to assure a solid contextual embedding and an appreciation of local dynamics?

RQ4: What are the predictive attributes of accidents based on the application of ML to accident reports?

2. Theoretical framework

2.1. Accident causation models (ACMs)

ACMs may provide a foundation for accident investigation and feedback and, most importantly, highlight accidents' causal factors (Kjellen and Albrechtsen 2017). Moreover, ACMs were developed and adjusted over the last 100 years, resulting in different ACMs having their own characteristics (Pillay 2015, Fu et al. 2020). Thus, ACMs are different in causes representation and the logic behind the occurrence of accidents (Fu et al. 2020).

ACMs can be classified in different ways, such as linear and non-linear models according to the logical sequence of events that lead to accidents (Fu et al. 2020). Fu et al. (2020) further categorized the non-linear models into human-based, statistics-based, energy-based (e.g., the Bow-tie model, and the tripod beta model), and system-based (Systems Theoretic Accident Model and Processes (STAMP), AcciMap), while linear models included the Swiss cheese model (SCM), Heinrich domino theory, and the HFACS.

Kjellen and Albrechtsen (2017) distinguished between seven main ACMs categories. The categorization by Kjellen and Albrechtsen (2017) included causal-sequence models (the domino theory, the tripod model), process models (Occupational Accident Research Unit (OARU), Haddon's phase model), the energy model (the Swiss cheese model), logical tree models (fishbone diagram, Construction Accident Causation (ConAC)), system models (HFACS, MORT, AcciMap, STAMP).

The inclusion of models in Kjellen and Albrechtsen (2017) and Fu et al. (2020) demonstrates the complexity and diversity of ACMs, primarily evident in the difference in the typology of causes, levels of causes, the relationship between the levels, their application, and the mechanism within which events take place.

According to Woolley et al.'s (2019) categorization, accident causation models have three main categories based on their characteristics and their time of development:

- Simple linear models (1920s)
- Complex linear models (1950s–1990s)
- Complex non-linear models (1990s to present)

The simple linear models (e.g., the domino theory) represent the view on accidents as being predictable through a chain of events and that they could be prevented if one of the root causes was eliminated in the sequence of that chain of events (Woolley et al. 2019). This category usually concentrates on physical/mechanical and human error (Woolley et al. 2019). However, it is criticized for the lack of distinction of uncertain causal relationships at the personal, organizational, and management levels (Kjellen and Albrechtsen 2017).

Complex linear models (SCM, the Loughborough Construction Accident Causation Model, and the Causal Model of Construction Accident Causation) view the accident as being caused by the interaction between latent factors and unsafe human behaviour (Woolley et al. 2019). The SCM argues that accident causes can be traced back to the origins of organizational decision-making (Kjellen and Albrechtsen 2017). Although complex linear models introduce the organizational factors, they also retain the sequencing of events and do not include factors outside the organization (Woolley et al. 2019).

Complex non-linear models took a broader view of system-related factors (Woolley et al. 2019, Kjellen and Albrechtsen 2017) as a response to the growing complexity and tighter couplings in industrial domains. System-based models (Fu et al. 2020, Kjellen and Albrechtsen 2017) are now surpassing the previous ACMs through their systematic and thorough concentration on managerial and organizational factors and their interaction with individuals, technology, and behaviour. System-based models assume the responsibility of everyone within the system (including politicians and regulators), and accidents are claimed to have been caused by the dynamic and non-linear interaction among multiple factors within the entire system (Woolley et al. 2019).

The development of ACMs initially focused on human behaviour within sequences of events. More recently, ACMs have tended to explore the more dynamic approach and consider higher levels of causation (Pillay 2015). This development seems to be based on the assumption that higher levels of causation can explain accidents. Moreover, the different types of ACMs assume stochasticity in accident severity since the accident impact level is not differentiated within any of the reviewed models. ACMs break down to multiple causation levels that are primarily not assigned weights for their importance but portray the interplay of causation factors as either single-rooted and linear, multiple-linear, and having multiple and dynamic causes.

In construction research, applied causation models range from technological and behavioural models (e.g., the domino theory) to the more advanced socio-technical and cultural models (e.g., the Loughborough construction accident causation model, the fault tree analysis, and the Swiss cheese Model) (Pillay 2015). System-based models were, in contrast, hardly, if ever, used in the published literature dealing with accident causation analysis within the construction sector (Woolley et al. 2019). The scarcity of system-based models points to the limited inclusion of governance and regulatory factors in accident analysis (Woolley et al. 2019). When system-based models are applied to analyse accidents, regulatory and governance factors are often overlooked (Pillay 2015). For example, physical processes, actor activities, equipment and environment, unsafe acts, and management decision-making are more prominent in system-based accident analysis in multiple industrial contexts rather than regulatory and other governmental factors (Hulme et al. 2019).

The limited inclusion of higher levels of causation hampers the understanding of whether the predictability of accidents increases from the advanced growth in the interactions of causes and the inclusion of factors outside the organization and limit benefits in prevention (Grant et al. 2018). They also act to hinder identifying the relationship between factors (Woolley et al. 2019). Since accidents persist in the construction industry, there is a need to revisit theories and models of accidents' causation and critically reflect on applied ACMs in construction – especially set against the quantitative data that is now being derived from many registered accidents.

2.2. Machine learning (ML)

Machine learning is defined as the "computational methods using experience to improve performance or to make accurate predictions" (Mohri et al. 2018). Experience refers to existing information mostly available in a digital form of data (Mohri et al. 2018). ML is also defined as a set of methods that automatically detect patterns and use those to predict future data (Murphy 2012), while according to

Carbonell et al. (1983) "the study and computer modelling of learning processes in their multiple manifestations constitutes the subject matter of machine learning."

ML includes different types of learning: supervised and unsupervised learning are the main ones (shown in Figure. 1), but there is also semi-supervised learning, transductive inference, online learning, and reinforcement and active learning (Shalev-Shwartz and Ben-David 2014, Mohri et al. 2018, Murphy 2012).

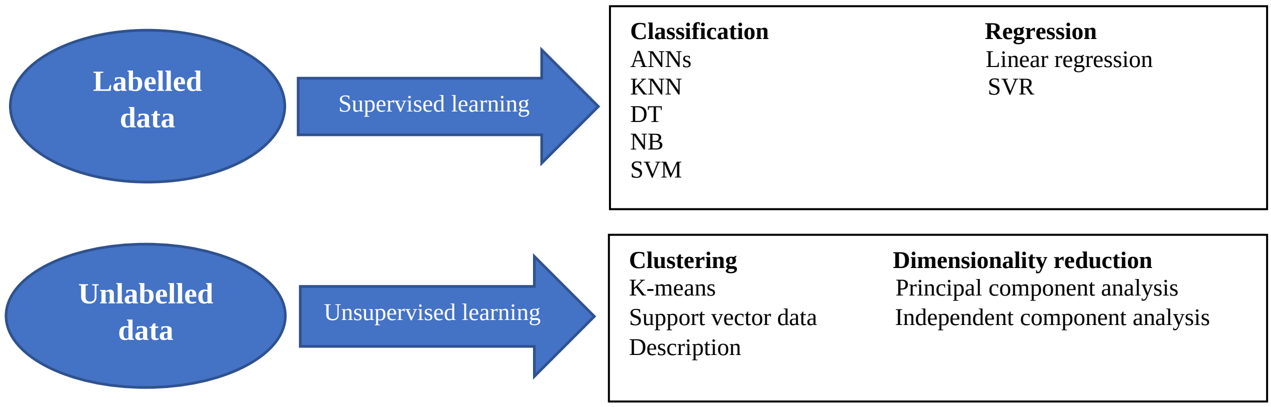

Figure 1. Machine learning summary.

- *Unsupervised learning* is a method of data exploration or description used for, among other things, clustering (Shalev-Shwartz and Ben-David 2014, Mohri et al. 2018, Murphy 2012). In unsupervised learning, there are no specific patterns to be followed or an error metric (Murphy 2012). Clustering can partition or group a set of objects into homogeneous subsets and is usually used in analysing large datasets (Mohri et al. 2018). The same sequence of objects can be clustered differently depending on the algorithm used; therefore, unsupervised learning does not always provide steady results (Shalev-Shwartz and Ben-David 2014). Another feature of unsupervised ML is that checking for accuracy and interpretation is subjective and requires expert knowledge for examining the results and inference (Shalev-Shwartz and Ben-David 2014).
- *Supervised learning* is an approach that learns a mapping from input to output and is used mainly for prediction (Murphy 2012). The input can be referred to as features, attributes, or covariates. At the same time, the output can be either categorical (a classification or a categorical problem) or numerical (a regression or ranking problem) (Murphy 2012). The data should be already labelled (input and output variables are known and identified through pre-assigned categorization). The purpose of using this type of learning is to predict or classify the labels of future examples as accurately as possible (Mohri et al. 2018). Moreover, supervised ML can be used in prediction or classification algorithms and assessed by calculating the potential loss in finding false instances (Shalev-Shwartz and Ben-David 2014).
- *Semi-supervised learning* is when the data is partially labelled and commonly when the unlabelled data is accessible but labelling the data unattainable (Mohri et al. 2018) or when the labelled part is used to infer the unlabelled part (El Naqa et al. 2019).

The ML model process

The ML process usually consists of multiple steps:

- Data exploration
- Data pre-processing
- Model training
- Model validation
- Model testing

It is important to note that the author of this thesis term an ML model as the specific mathematical or computational description that expresses the relationship between a set of input variables and one or more outcome variables studied or predicted.

Data exploration entails gaining knowledge into the attribute types (e.g., nominal or numerical), the entries contained in each attribute, and the distribution of the input and the output features (Han et al. 2011). Data pre-processing ensures data quality for a reliable ML analysis and consists of multiple tasks – including handling missing values, noise, and resolving inconsistencies and discrepancies (Han et al. 2011). Discrepancies might originate from the data entry form, human errors, system errors, and other reasons (Han et al. 2011). The data is then split into the training, validation, and testing datasets (Shalev-Shwartz and Ben-David 2014). The training data should not be used in testing the model to find out whether the ML model performs as well with data points that have not been used in its training (Han et al. 2011). The validation step is used to tune the model's parameters for the ML algorithms (Han et al. 2011).

The testing of ML performance depends on the type of ML problem and the employed algorithms. The Receiver operating characteristic (ROC) curves and the F1 measure are usually used in classification problems (Han et al. 2011). The F1 measure is based on the confusion matrix depicted in Table 1. TP, FP, FN, and TN stand for true positive, false positive, false negative, and true negative, respectively (Japkowicz and Shah 2015). In binary classification tasks, the class of interest is called the positive class while the other is the negative class (Gopal 2018). Accordingly, TP and TN are the accurate classifications that the algorithm achieves. FP and FN are referred to when the algorithm inaccurately classifies a positive when it is a negative in reality and a negative when it is positive, respectively (Gopal 2018). The latter can be variously combined to calculate specific performance metrics, as in the following (Japkowicz and Shah 2015, Han et al. 2011):

Accuracy=(TP+TN)/(P+N)

Precision=TP/(TP+FP)

Recall= TP/(TP+FN)

F1 measure= (2. Recall. Precision)/ (Recall + Precision)

It is common that accuracy does not sufficiently evaluate a model's performance, such as in cases of data imbalance (Japkowicz and Shah 2015). Precision and recall also have shortcomings in showing how a classifier behaves in terms of showing the detailed negative and positive recognition (Japkowicz and Shah 2015). Alternatively, the ROC curve is another method for testing the performance of an ML algorithm when accuracy, precision or recall fall short (Han et al. 2011, Japkowicz and Shah 2015, Gopal 2018) – e.g., when false-negative classifications are costly (such as in disease diagnostic applications). The ROC curve takes paired measurements of false-positive rates on the x-axis and the true-positive rates on the y-axis, with the highest value being 1 (Han et al. 2011).

Table 1. A generic confusion matrix

True class	Positive	Negative
True positive	TP	FP
True negative	FN	TN

Supervised and unsupervised learning have different algorithms characterized by different structures and application types (El Naqa *et al.* 2019). Supervised ML is more interpretable, testable and applicable when available data is labelled (Murphy 2012, Mohri et al. 2018). Furthermore, supervised ML algorithms can be organized into linear and non-linear models.

Linear Models

Linear regression (LR) and support vector machines (SVM) are linear algorithms that can be used for regression or classification (Shalev-Shwartz and Ben-David 2014). LR is a simple model without parameters to control model complexity (Ray 2019). However, if the data is not linearly separable, LR is not best to fit the data (Shalev-Shwartz and Ben-David 2014). Instead, a polynomial regression (which fits a non-linear function although being a statistical estimation problem) can be used (Shalev-Shwartz and Ben-David 2014), but the polynomial model is more complex than LR, and there is a risk for overfitting (Hawkins 2004). SVMs work by separating the dimension space into two classes in the case of a binary classification task (Shalev-Shwartz and Ben-David 2014). The margin of a hyperplane that separates the data is the smallest distance between a point in the training set and the hyperplane (Shalev-Shwartz and Ben-David 2014). This margin limits the performance of the linear SVM; if the margin is larger, the error decreases because the model becomes more tolerant to the disturbance in the data points. The SVM is regularized with using the parameter C – large values of C (smaller regularization) allow the model to fit the training data even in the case of a smaller margin, while larger regularization makes the model more tolerant to errors on individual data points (Bhavsar and Ganatra 2012, Singh et al. 2016).

Non-linear models

K-Nearest Neighbor (KNN) is one of the simplest ML algorithms used for regression and classification. It assumes that the close-by instances are likely to have the same labelling (Shalev-Shwartz and Ben-David 2014). The parameter K can take different values starting from 1, and then the algorithm looks at the single closest instance label to predict the label of another instance. The smaller K is, the more complex the model, and there is a risk of an overfitting decision boundary (Bhavsar and Ganatra 2012, Singh et al. 2016). The disadvantages of KNN models are the sensitivity to dimensionality (which can affect the algorithm's performance) (Shalev-Shwartz and Ben-David 2014) and the compromise of accuracy because the algorithm assigns equal weights for the features and the sensitivity to the local structure of the data and the value of K (Bhavsar and Ganatra 2012).

Kernelized support vector machines (KSVM) are a variation of SVM that transform the data into a high dimensional space to allow for a linear classification for a feature space that is not linearly separable (Shalev-Shwartz and Ben-David 2014). KSVM are highly sophisticated models and one of the most accurate models in binary classifications (Bhavsar and Ganatra 2012). On the other hand, DTs are characterized by the easy interpretation by simply visualizing the entire tree. However, feature importance rankings do not indicate which classes are predicted by a feature or the relationships between features (Singh et al. 2016). Moreover, the sample complexity of DTs might result in growing very large trees (deep trees) that are prone to overfitting (Shalev-Shwartz and Ben-David 2014). This situation, however, can be prevented by controlling the size of the tree by applying a reduced-error pruning method (Lee and El Naqa 2015). Random forest (RF) is a classifier consisting of a collection of DTs (Shalev-Shwartz and Ben-David 2014). The DTs within RF are built with random sample variations that are bootstrapped by a random feature split selection (Lee and El Naqa 2015). Although RFs are generally more accurate than simple DTs, they can be unstable, produce local optimal solutions instead of global ones, and have sampling errors (Ray 2019).

Artificial Neural Networks (ANNs) are computational models inspired by the structure of the brain's neurons and have recently reached high performance in different learning tasks (Shalev-Shwartz and Ben-David 2014). There are two main types of ANNs (feed-forward and back-propagation). Feed-forward networks – also called multi-layer perceptron (MLP) – take the idea of computing weighted sums of input features (like in logistic regression) but introduce a processing step that consists of several neurons as a hidden layer (hidden units) (Shalev-Shwartz and Ben-David 2014). The MLP complexity is affected by the number of units, layers, regularization and activation function (Lee and El Naqa 2015). Backpropagation has the same structure as an MLP but backwards learns the network's weights by employing a gradient descent to minimize the squared error between the network outputs and the target values of these outputs (Gopal 2018).

The characteristics of the previously presented ML algorithms are summarized in Table 2. The table characterizes the ML algorithms in strengths – represented in a plus sign – and weaknesses – represented in a minus sign. The table can be used to choose ML algorithms based on the task's requirements. This contributes to a systematic and informed choice of algorithms instead of the experimental approach.

Table 2. Summary of ML algorithms characteristics

Algorithm	NB	SVM	KSVM	DT	RF	KNN	LR	LogR
Interpretability	+	+	-	+	-	+	+	+
Parameters tuning	+	-	-	+	+	-	+	-
High dimensionality	+	+	+	+	-	-	-	-
Feature dependability	-	+	+	-	+	+	-	-
Generalization	-	+	+	-	+	+	-	-
Accuracy	-	+	+	-	+	+	-	+
Small data set	+	-	+	+	+	+	-	-
Large data set	+	+	+	-	+	-	+	+
Linearity	-	-	-	-	-	-	+	-
Low dimensionality	+	-	+	+	+	-	+	+

Dobbe et al. (2018) suggested that bias might originate from multiple sources when data is used in ML decision-making models. First, measurement bias can originate due to how the collected data is scaled, and the people registering their entries are represented. The modelling bias is affected by the engineering of features and the selection of the model classes. These processes include reconstructing a complex phenomenon in a finite data sample. The optimisation bias is related to the model builder choices of designing and optimising the parameters of the ML algorithms, which affect the outcomes or decisions the model produces (Dobbe et al. 2018).

Dobbe et al. (2018) explained that the origins of bias acknowledge the need for understanding the epistemology of the specific context, and the role played by the creator of the ML model. Also, when applying ML to research in social sciences, Radford and Joseph (2020) suggest a “theory in” and “theory out” approach. Theory in means that known theories about a phenomenon should be considered in the pipeline for research that uses ML in analysing social data. A problem and task definition should rely on the knowledge gap in what is already known about the social world, starting from the conception of an ML model. Thus, theory help in identifying which problems are worth solving and frame why a problem is important. Moreover, theory help to define the ML outcome that validly captures the construct sought to be measured (Radford and Joseph 2020). Theory out refers to considering the model’s interpretability, explainability and theory building beyond the model’s technical parameters – in other words, using theory to understand why the model learned what it did and what can be learned about the world based on its results (Radford and Joseph 2020). Theory building here refers to the new knowledge about the social world that can be discovered from the results of our model (Radford and Joseph 2020). The implication of the latter described approach is that an ML model needs to be developed by supporting the relevant theories throughout the ML development process.

One of the most famous models in ML industrial applications is the Cross Industry Standard Process Development Method (CRISP-DM) (Martínez-Plumed et al. 2019). CRISP-DM consists of multiple steps (business understanding, data understanding, data preparation, modelling, evaluation, and deployment) (Martínez-Plumed et al. 2019, Figure 2)

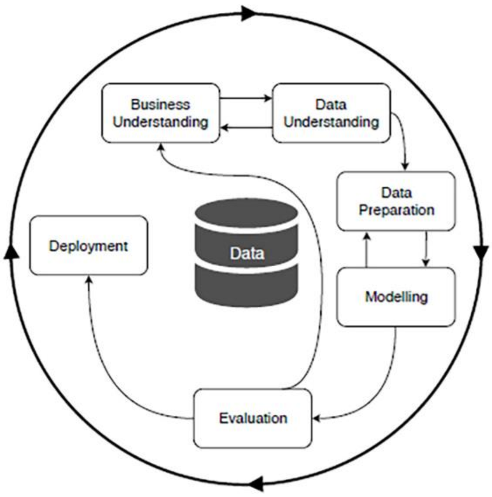

Figure 2. The CRISP-DM process model of data mining (Martínez-Plumed et al. 2019).

These steps can account for a contextualisation of the developmental process, starting with the initial step of business understanding. The business understanding plays a role in defining the business objective and offering a systemised process to mitigate the dependence only on data experimentation

(Chapman et al. 2000, Martínez-Plumed et al. 2019). The business understanding consists of four sub-tasks: determine business objectives, assess the situation, determine data mining goals, and produce a project plan (Chapman et al. 2000).

3. Research design

The approach chosen in this research is interpretive, where reality is deemed as the construction of the interaction between the researcher and the research (Alvesson and Sköldberg 2017). This approach assumes a reflexive research methodology that typically arises when different levels or elements of interpretation are played out against each other, and when none of the research components gains dominance throughout the entire research process (Alvesson and Sköldberg 2017). Reflexivity encourages creativity through the movement between different philosophical profundities and other empirical research elements (Alvesson and Sköldberg 2017). To follow a reflexive research methodology, multiple paradigms that are associated with this research were identified similar to mixed method approaches (Creswell and Clark 2017) – namely, the literature and texts, the empirical material, ACMs and the ML theory.

The research is mainly interested in understanding and interpreting ML methodologies and techniques as a process to develop ML models to be applied in existing practice. The research aim is motivated by the need to bridge the technical ML analysis and the context of the application that involves people. The focus here is on the H&S unit as both a generator of the accident reports dataset and the end-user of the ML intended prototype. The H&S unit consists of safety engineers, safety representatives, site supervisors, site managers, safety managers and safety strategists. The qualitative interpretive research is aligned with the research aim to cultivate interpretation and reflection as key elements of reflexive research (Alvesson and Sköldberg 2017). The premises of this research method is derived from the view that how researchers interpret phenomena is always perspectival and that facts are always theory-laden (Alvesson and Sköldberg 2017).

According to Alvesson and Sköldberg (2017) method, reflexive interpretation consists of four levels – namely, interaction with the empirical material, interpretation, critical interpretation, and reflection on text production and language use (p.331), also called the quadruple hermeneutics (p.122). ACMs, ML algorithms, and CRISP-DM provide the multiplicity needed in the interpretive approach - as illustrated in Figure 3.- each of these is used for interpreting the data analysis results. The formulated research questions are accordingly generated to support interaction across the aforementioned theoretical framework and the empirical material.

The primary data collection was done through the digital reporting system used by a contracting company: Synergi Life. Complementary data collection was done through twelve interviews with the H&S unit within the contracting company. Accident reports are highly dependent on the reporters, especially their interpretations of how accidents and their causes should be described (Dekker 2015). Thus, the challenges and opportunities of developing an ML-powered prototype and implementing it in the safety processes within the case company are ultimately dependent on the prevailing perceptual, theoretical and cultural assumptions within the case company. For the development and analysis of an applied ML model, the CRISP-DM (Cross Industry Standard Process Development Method) is chosen as a development process method. CRISP-DM is also used as a framework to understand the H&S objectives and identify ML utilisation propositions.

Mainly, primary data is analysed through the application of ML algorithms. ACMs is chosen as the theoretical framework for interpreting the ML model results. ACMs components that describe accident occurrences are used to contextualise and conceptualise the results of the ML analysis.

The critical interpretation level stems from the reflection on ACMs from the perspective of existing ML literature by a comparative analysis of the components and assumptions of ACMs against the components and assumptions of existing ML models. Moreover, the experience of conducting the CRISP-DM's business understanding analysis through the interviews was utilised to explore the fit of CRISP-DM to develop ML with the H&S unit.

The researcher finally reflects on their assumptions about the phenomenon and the limitation of the repertoire of interpretation.

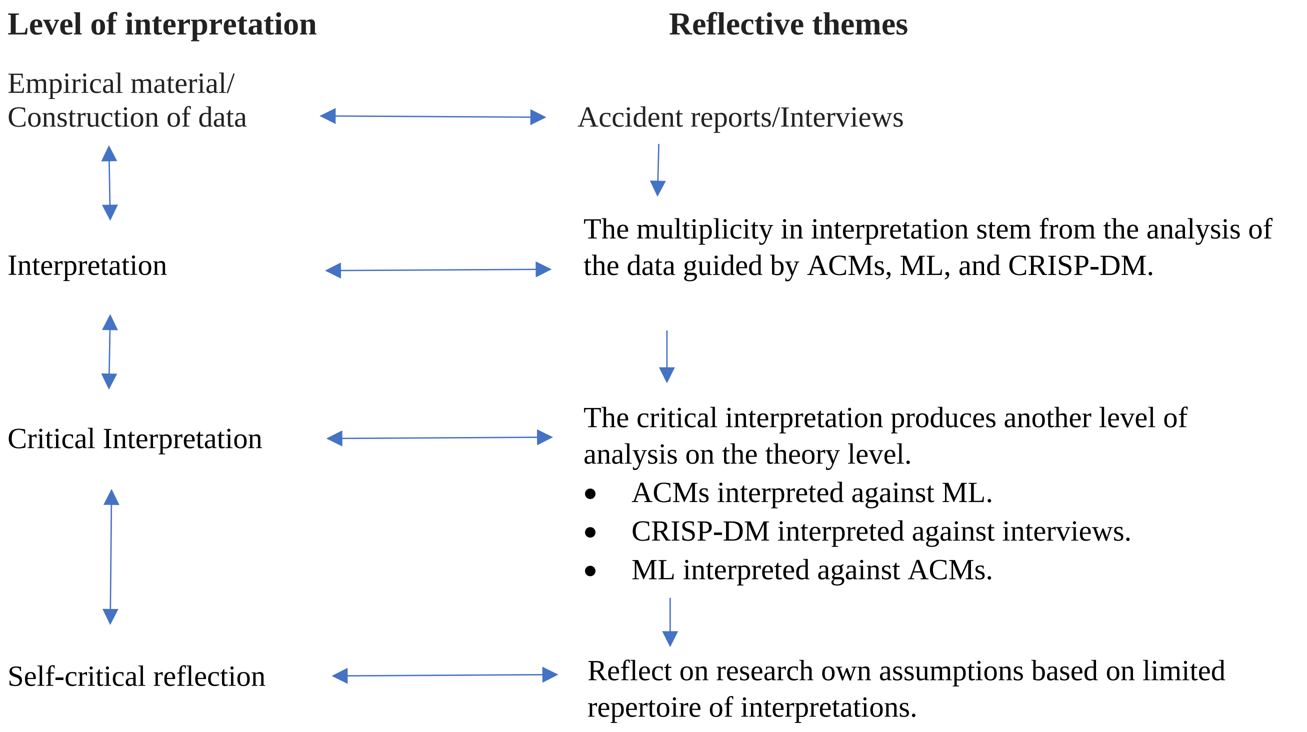

Figure 3. Illustration of reflexive methodology based on levels of interpretations (the quadruple hermeneutics, Alvesson & Sköldberg 2017).

3.1. Research process

The research process consists of the four steps described in paper I, paper II, and paper III summarised in section 4 and ML results described in section 5. The papers and data analysis were conducted sequentially, represented in a process graph shown in Figure 4. Each paper provided a background for the contribution and the development of the following paper.

The first step was to review the existing body of literature to identify the requirements for applied ML in occupational accident prevention within a construction company. This first step in paper I investigates the possible development requirements for an ML model to be implemented in occupational construction safety. The reviewed literature provides an in-depth and detailed exposition on the uses of ML in analysing accident reports, and is synthesised in terms of used algorithms, data characteristics, data processing, and purpose and scope of the ML models.

Consequently, paper II was designed to investigate the role of ACMs as a theoretical framework in ML application for analysing accident reports in the construction industry. A framework of understanding the ML results should be established to place causes in meaningful categories – and vice versa, to contribute to learnings about ACMs obtained through ML. The work is carried out in the form of a comparative desk study of the literature covering the application of ML to accident reports in the construction industry and ACMs. This contributed to providing a conceptualisation of ML models through the lens of ACMs' components.

After the means of understanding ML results through ACMs was established, the need for a systemised ML development method ensuring the contextual embedding led to the use of the CRISP-DM method for understanding the context of accident reporting in the case company, and analysing the experience and challenges in applying the "business understanding" stage (Martínez-Plumed et al. 2019). Paper III centres on five interviews with a safety strategist and four safety engineers at the case company in Sweden to answer this research question. Paper III contributed both to the identification of ML utilisation proposals that meet the needs of the H&S unit, and also adds value to accident prevention measures. Seven further interviews were conducted after paper III was published to gain further insights from different actors within the H&S unit of the case company.

The fourth step finally provides an ML analysis of accident reports from the case company based on an ML model design and interviews analysis. This work builds on the learnings and conclusions of papers I, II, and III. Furthermore, the continuation of the interviews contributed to decisions related to the purpose and design of the ML prototype. It is important to note that this thesis has not realised a prototype. However, paper I, paper II, paper III and the ML data analysis are all paving the path of the prototype development process.

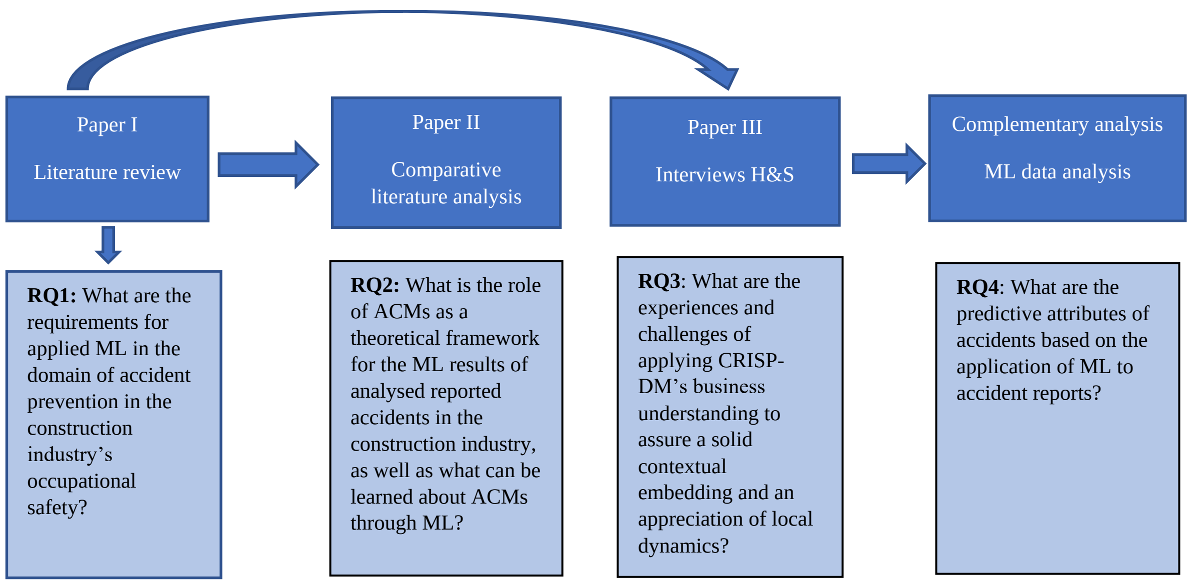

Figure 4. Research process.

3.2. Case description

This thesis's primary interest is in embedded accident prevention in the business setting. The contractor operates a project-based organisation. The building project is the most important value and turnover generator and cost transformer. The different building projects are produced in portfolios placed in divisions with slightly different business objectives, i.e., civil works, residential buildings, office buildings. The project commences with a contract with a client. The H&S work commences by documenting how H&S will be organised in the project in a bid for the customer. Typically, no risk analysis is carried out by the safety engineers (SEs) this early; however, this is done once a contract is obtained. A particular job role, called BAS P (educated in design safety), is part of this process. From the beginning of work planning, the SEs inspect the plans with an H&S perspective. During production, the safety representatives (the so-called BAS U personnel – basic education for production) are responsible for a particular part of the building project and the building process. They collaborate with the on-site H&S, Quality, and Environment (HES) manager and the SEs. Together, they constitute a horizontal element of the H&S organisation and support the similarly horizontal building processes. H&S work is thus organised close to the single building project. Apart from this horizontal element, the company also encompasses a vertical hierarchy, where H&S is attached to several organisational levels. A central H&S unit is part of a corporate management HR unit. HES units are adjacent to several organisational levels. This cross-organisational H&S apparatus works with behaviour issues, analysis and reporting, digitalisation, and developing directives. In it, it is a common perception that accidents are mostly due to behaviours, so efforts are targeting this issue. Another workstream is related to analysing and reporting, digitalisation, driving projects, and the way the company benefits from machines and innovation. The third workstream is related to developing directive processes and procedures.

3.3. Collection of empirical material

Below I elaborate first of the more quantitively oriented collection of date emanating from the accident reports, moving on to the rich knowledge and information in the interviews.

3.3.1. Accident reports

The accumulated accident data have a common method for registering and analysing single occurrences of accidents in the construction industry. The case company's data is mostly gathered by safety engineers, site managers, safety representatives, and workers. Accidents are registered through a digital software interface called Synergi Life, which is a complete quality, health, and safety risk management software package. Accident reports were extracted by the researcher into excel sheets and initially investigated in excel.

The software package offers the option of recording four types of reports:

- Accident: An event that led to personal injury.
- Incident: An unwanted, sudden event that could have led to a personal injury.
- Negative observation: An unwanted situation or risk that could have led to personal injury.
- Positive observation: A positive action or solution that has led to better health or safety.

The reporting process consists of four steps:

1. Registration, which is possible to be made by anyone working at the case company (either on the desktop or the mobile application software versions).
2. Appointment of a case handler.
3. Filling in the case with either investigations or a required action.
4. Closing of the case, which needs to be done by the health and safety unit.

The accident report consists of seven main sections (see Appendix).

- Where, what and who.
- General classification.

- Consequences.
- Potential loss.
- Causes.
- Prevention.
- Attached documents.

The data contains two forms of reporting: free text describing the accident, and pre-populated drop-down list options for causes, processes, consequences of severity, and personal injury-related information. The dataset contains 3,626 cases of accidents. The data status varies in terms of complete entries for every available case. Monetary loss information was only entered 109 times out of all cases, and prevention comments were only reported for 365 cases. Description of injury type was entered for only 139 cases. Moreover, there are usually two levels of entries: a general category and one that is more detailed- such as for the injured body part, the category of injury, Specific physical activity, and injury type.

The entered data shows that a number of entries did not belong to a known category, such as in injury type level 1 (310 cases) and specific physical activity level 1 (205 cases). Moreover, it is observed that the level of detail varies between the general level and the more detailed levels of the reported fields. The more detailed levels of "type of work in detail" contain 149 unique categories of entries, the "external factor that affected the incident" contains 159, and the "work process" contains 149.

Although these accidents report mainly describe the accident by pre-populated drop-down lists, the reporters select the causes and other information using their understandings. Dekker (2015) argues that the epistemology of accident descriptions implies that reporters can have different narratives for the same event, depending on multiple factors (such as the reporter's perspective and experience).

3.3.2. Interviews

The interviews were considered a secondary source of empirical material that was complementary to the accident reports. The semi-structured interviews were conducted in a thematic format to explore and gather information and knowledge about accident reporting. Thematic semi-structured interviews are useful in exploring a particular organizational issue, and are characterized by connecting a series of questions within a particular theme (Cassell 2015). The intention behind the interviews was to gain an insight into the perspectives of the H&S unit on the meaning of safety (in general), the accident response process, the quality of collected reports, and the expectations from an ML-based prototype.

Mainly, the ML-related questions and discussions were formulated based on the business understanding framework of CRISP-DM (Chapman et al. 2000) and the recommended practice (RP) framework (DVN GL AS 2020). The intention for this formulation concerns developing an ML prototype situated within the needs and perspectives of the H&S unit with the explicit purpose of improving awareness of accident prevention measures within the case contracting company.

Interviews were chosen to provide the actor's point of view on the needs of safety process and site accident prevention. The interviewees were selected based on the mapping of the H&S unit of the case company, as shown in case description section 3.2 and Table 3.

The interview guideline was organized into four thematic sections. The first focused on a background of position and experience, and the second on the meaning of safety and a description of daily safety processes. The third part included questions about the reporting regarding assigning causes, levels of causation, credibility, quality, and overall value of reporting accidents. The fourth part investigated the potential for improvement in relation to accident prevention, based on learnings from or the utilization of accident reports. The questions then targeted the anticipated added value of a potential ML application, potentially benefitted users, advised propositions, work-process constraints, risks, and ethical considerations.

Table 3. Interview respondents and position

Positions	Respondents
Safety engineer	4
Safety representative	4
Site manager	1
Site supervisor	1
Safety manager	1
Safety strategist	1

3.4. Analysis of empirical material

3.4.1. Interview's analysis

The interviews were analysed using a qualitative method combining Kvale & Brinkmann (2009) approach to analysing interviews with Alvesson and Sköldberg (2017) reflexive methodology. The themes of the interviews were organized based on the themes of the interview's questions.

- The meaning of safety at the contracting company
- A normal working day
- The response in the event of an accident
- The reporting of accidents
- Status of the data use and safety objectives
- The value of reporting of accidents and improvements
- Improvement in the safety process for accident prevention support
- Value proposition
- ML potential
- Proposals and ML risks
- Satisfaction with the reporting
- Success criteria for a prototype based on the reports' data

The analysis of the interviews was done in an iterative manner, where the interview questions were modified based on the gained insights from the previous interviews. The interviews continued until the responses began to be repeated and reached a state of saturation (Schutz 1972). Drawing on reflexive methodology in this context meant critically reflecting on the respondents' utterances, placing them in an organization and societal context and finally reflecting about the researcher own role and position - inspired by Alvesson and Sköldberg (2017) concept quadruple hermeneutics.

3.4.2. Machine learning design

3.4.2.1. Understanding the data structure

The dataset can be characterised as relational, namely a collection of records in tabular format (sometimes called "relations") with columns that denote data features, and rows that indicate individual observations of instances (Martyr and Rogers 2020). The dataset mainly consists of two types of features: structured and unstructured features. The data, in this case, might include a reference number that identifies the instances (Gopal 2018) – in this instance, the case unique number. This allows the features to be searched, filtered, and reorganised (Martyr and Rogers 2020). However, some features are labelled as accident title, description and health and safety category, cause description, comments, and prevention description, and are written by the reporter in free-text format (see Appendix). The free text data type is considered unstructured (Gopal 2018). Structured features can be handled differently than the free text, as the latter requires methods of data mining, NLP or unsupervised ML (Gopal 2018). In this thesis, the structured dataset acts as an investigative step for the predictability of accidents in building the information extraction on the first step of the prototype development and recommend prevention measures.

Another characteristic of the dataset is the definition of input and output features. In an application where an event happens at a specific point in time and in prediction models, data leakage must be prevented (Kaufman et al. 2012). Data leakage is defined as the introduction of information about the target of a data mining problem, from which it should not be legitimately available to mine (Kaufman et al. 2012). The input features chosen in the current case are listed in Table 4. The latter were chosen based on whether the features contained information that could be known before an accident occurred, since the data was generated as an occupational accident reporting. The downside is that most of the data described the event's outcome, which leaves only a few input attributes. Table 5 illustrates which existing feature could potentially be a target output for an ML analysis.

The data is generally nominal (which indicates that they are represented by symbols) – it can be represented numerically by coding the entries by a nominal encoding scheme (Han et al. 2011).

Table 4. Input features

	Input feature	Type of entries
1	Type of work in detail	Nominal
2	Involved substance / chemical	Nominal
3	Employment relationship	Nominal
4	Work environment	Nominal
5	Position	Nominal
6	Company name	Nominal
7	Specific physical activity level 1	Nominal
8	Specific physical activity level 2	Nominal
9	Shift or accident to / from work	Nominal
10	Experience in position (months)	Numerical
11	The last deviating event that preceded the injury	Nominal
12	Work Process	Nominal
13	External factor that affected the incident	Nominal

Table 5. Output features

	Output feature	Type of entries
1	Actual severity	Nominal
2	External factor that affected the incident	Nominal
3	Description of injury Type	Nominal
4	Description of damaged body part, Common	Nominal
5	The last deviating event that preceded the injury	Nominal
6	Injured body part	Nominal

7	Injury class	Nominal
8	Category of injury	Nominal
9	Injury type level 1	Nominal
10	Injury type level 2	Nominal
11	Cause category	Nominal
12	Circumstances of the accident	Nominal
13	Potential Severity - Most Severe	Nominal
14	Risk area	Nominal

3.4.2.2. Data pre-processing

Data pre-processing consists of several major tasks: data cleaning, data integration, data reduction, and data transformation (Han et al. 2011). Data cleaning is usually the first step in pre-processing the data and is done by handling missing values and noisy data (Han et al. 2011).

In the current case, the most interesting output feature was the actual severity. The distribution of the classes of this output was unbalanced and needed further data prepossessing. It is possible to combine the last three levels of injury in one category (called major injury) and the first two classes in another (called minor injury). This combination separates the severity into two categories, while the major injury class starts at the point where accidents result in the absence of a worker from the construction site.

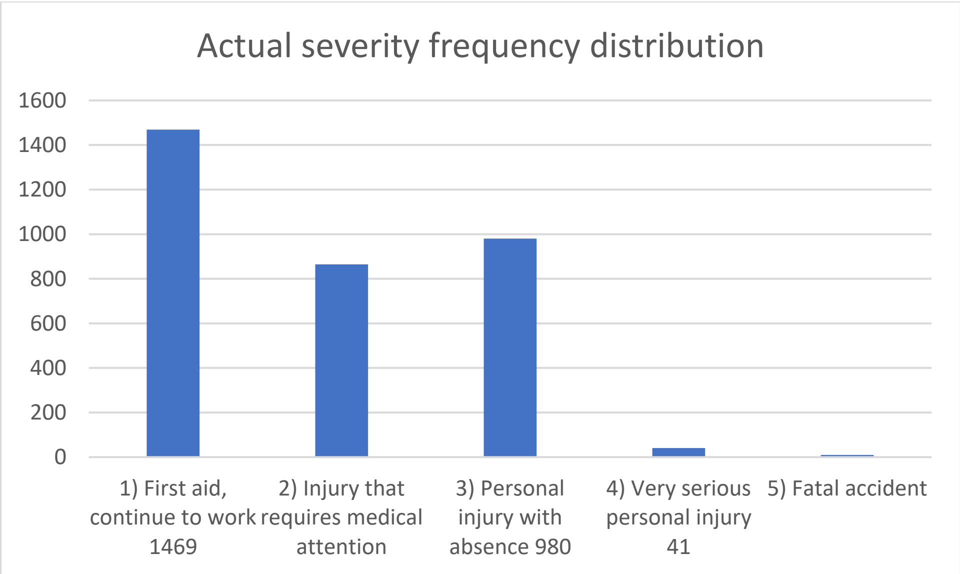

Figure 5. Actual severity frequency distribution

3.4.2.3. Algorithm choice

The goal of the first stage of the prototype is to predict the severity of construction processes. The following criteria influence the choice of algorithm for this first stage of the prototype (see Table 2), based on the purpose and the accident reports data structure:

- Interpretability: The algorithm must be interpretable, especially since there is a second step involving the prevention recommendation that is going to be connected to the prediction.
- Parameter tuning: A model that depends only on parameter tuning can be problematic because the model is then highly sensitive to the parameter's values – it is preferable that the chosen algorithm is less sensitive to parameter tuning, but it is deemed not as a strict requirement.

- High dimensionality: The high dimensionality criteria are not critical since our data structure is not high dimensional.
- Generalizability: Generalizability is one of the most essential features of ML algorithms, and there is a need for a model that generalizes well, especially for a relatively small dataset such as the one in this case.
- Accuracy: The model must produce high and accurate predictions, especially since safety is the application domain – and therefore, accuracy is crucial.
- Large dataset: The dataset is relatively small (fewer than 50000 instances), which is not a highly important criterion.
- Linearity: It is not known whether the data is linearly separable. Therefore, there is a need to experiment with linear and nonlinear algorithms to test which best classifies the severity level.
- Low dimensionality: The algorithm should perform well with low dimensional data since the dataset is relatively large compared to the number of input features.

Highly interpretable algorithms are NB, SVM, DT, KNN, LR and LogR (see Table 2). However, Only NB, DT, RF, LR and LogR perform well with low dimensional datasets. RF and KNN have very good generalization abilities. KNN, RF and LogR are usually good for this criterion in terms of accuracy. Only the LogR is suitable for building a linear model. Based on this breakdown of the algorithms and their characteristics, the chosen algorithms are KNN, DT, LogR and RF.

3.5. Researcher own role

In line with Alvesson and Sköldberg (2017)'s suggestions, all activities in this licentiate thesis were exposed to a critical reflection of my own role and identity vis a vis not only collaboration partners, literature, interview respondents and supervisors, but also in reflecting and analysing literature, developing analytical insights and discussion, even when arriving at the main results. Being a middle-class woman with a middle east background involves advantages and disadvantages. Particular Swedish construction industry traits are more visible for externals and can be identified comparing with the researcher own background. On the other hand, social group differences between university employees and building sector professionals would constitute more of a disadvantage, given the mutual stereotyping of academics and site professionals. In sum, these conditions are at a time enabling and constraining the research in characteristic ways.

3.6. Ethical considerations

There were a number of ethical considerations that shaped the research design. The use of the data by the licentiate team was governed by a non-disclosure agreement. The data transfer was only performed through secure channels managed by the data owner. The case company and respondents remain anonymous. Moreover, due to the sensitive nature of the data and the researchers' use of ML for generating solutions that target specific individuals, the author chose not to consider any personal or enterprise information in the ML data analysis.

4. Summary of the papers

This part presents a summary of the collection of papers included in this licentiate thesis.

4.1. Paper I: A REVIEW OF MACHINE LEARNING FOR ANALYSING ACCIDENT REPORTS IN THE CONSTRUCTION INDUSTRY AND APPLICATION REQUIREMENTS (under review at The Journal of Information Technology in Construction (ITcon) submitted on 2022-02-10)

Artificial intelligence (AI) and ML have become more popular in solving construction management problems (Pan & Zhang 2021). Applied ML reviews have shown advancements in safety management and knowledge extraction by examining accident records (Pan and Zhang 2021, Hon et al. 2021). However, the literature still lacks a comprehensive analysis of what developing and applying ML entails in the domain of accident reports analysis within the construction industry. It is not clear what the implantation of ML-based analysis in a contracting company might require. This paper aims to answer the research question: what are the requirements of an ML model based on accident reports data to be implemented in occupational safety in a contracting company?

This paper contributes to the identification of prerequisites of ML development that arise from the specific conditions and the processes associated with managing H&S in a contracting company in the construction industry. The research question was answered by a literature review conducted using the concept-centric framework augmented by units of analysis (Webster and Watson 2002). It was based on searches related to the application of ML to the analysis of accident registries in the construction sector. The organization of the review was done to synthesize the literature into appropriate units of analysis, namely data characteristics, data pre-processing, algorithm type and training the ML model, testing algorithm performance, and implementation of ML analysis. Three citation indexes were selected: Web of Science, Elsevier, and Scopus. The review was conducted iteratively within the three databases and within Google Scholar by using the search terms “accident report,” “construction industry,” “machine learning”, and “construction occupational safety.” Nineteen articles were finally selected, four of which were found in all the searched databases.

The analysis of the literature showed that multiple requirements are necessary. One of the most important requirements is a careful implementation strategy that considers existing safety processes and their relation to other in-place processes such as design and project planning. Thus, the implementation of ML-based models requires feasibility and implementation analysis - in a prototype format, for instance - and the involvement of practitioners. Another crucial requirement is ML performance measurement and evaluation to assess the performance metrics and accuracy threshold.

Risk critical application such as safety and, more importantly, accident analysis imposes higher requirements of accuracy and trustworthiness in applied ML solutions. Accidents have been shown to generate imbalanced data in terms of accident types, causes and severity. The ROC was proposed as an ML performance metric because of the visualization benefits for comparing different combinations of errors. The ML classifiers that have lower error rates for a specific class can then be chosen (Gholizadeh et al. 2018). This proposed approach was shown to be especially beneficial in maximizing the prediction accuracy of minority classes in unbalanced data sets in the construction accident reports data (Gholizadeh et al. 2018).

Overall, implementing ML in the construction industry, needs a standardized development method, notably due to the difficulty in assessing the best approaches in data pre-processing and applied algorithms. However, ML algorithms that are easily interpreted were found to fit the safety context because they allow for understanding ML results. The word embedding in the data pre-processing showed a pattern and potential improvement within the domain-specific corpus. Future research should experiment and conclude whether domain-specific dictionaries should be used in word embeddings in the pre-processing stage. Finally, there is a need for theoretical frameworks for guiding the contextualization of causal factors. This would assist when developing safety solutions and when they are being deployed further from centralized computing platforms for real-time decision-making support.

4.2. Paper II: A COMPARISON OF ACCIDENT CAUSATION MODELS (ACMS) AND MACHINE LEARNING (ML) FOR APPLIED ANALYSIS WITHIN ACCIDENT REPORTS

ACMs are theoretical frameworks and have had an impact on accident causation analysis. However, ACMs were not sufficiently addressed in the literature of applied ML in accident records analysis. ML-based analysis has been criticised for lacking interpretable recommendations, data quality issues, clear implementation cases, the integration with domain knowledge (Vallmuur 2015, Bilal et al. 2016), and generalizability (Xu et al. 2021, Sarkar and Maiti 2020). On the other side, ACMs can be categorised into many types characterised by different causation logic and focus of causation categories. The current literature on ML applications within the domain of accident analysis does not integrate ACMs as theoretical frameworks into the ML model development and analysis. The authors of this paper also assume that analysing accident reports using ML can contribute to learning about ACMs as well as occupational accidents. This research investigated the question of what ACMs can contribute to the ML results of analysed reported accidents in the construction industry, and what can be learned about ACMs from the application of ML in this domain. This paper contributes to conceptualising ML models through the lens of ACMs.

This paper is based on a desk study of the literature of applied ML in the analysis of construction accident reports and ACMs. The ML models are based on a literature review and the systemisation of the purpose of the ML, the included features, and the ranking of important factors. The themes are presented for an in-depth analysis. ACMs were selected based on crossing the models which were reviewed by Kjellen and Albrechtsen (2017), Fu et al. (2020) and Woolley et al. (2019). Three models were selected based on the types of ACMs and their common application in the construction industry.

ML analysis of accident reports usually results in components that are predictive of accident types or severity levels. The comparative study illustrated that the components extracted by ML could be compared to the typology of the BOW-Tie model and the SCM. However, one major difference was found in ML components in that they lack prevention measures which are a bottom-line building block in ACMs and, consequently, accident prevention. However, the levels of causations were found to be mostly those remaining close to the workplace and human behaviour factors. At the same time, ML results rarely included factors that are related to the higher levels of decision making within the organisation.

The lack of prevention measures or the inclusion of higher levels of causation factors is not necessarily a drawback of ML itself but the reporting that has repeatedly been missing the prevention measures suggestions. The more accident analysis considered factors further from the event, the harder it gets for further factors to become apparent in terms of their effect on the event. Furthermore, the mechanism causing accidents seem to differ between the representation of ML and the SCM. Nevertheless, such a comparison remains ambiguous and need visualisation to make more conclusive comparisons. Finally, ML models in the reviewed literature tend to highlight severity as an outcome that needs to be predicted. In contrast, ACMs focus on accidents as events that occur regardless of their level of severity.

The paper concluded that the ML analysis of accident reports needs to be guided by ACMs to be useful in real-life implementation. This combination contributes to making sense of ML-based recommendations of accident prevention measures. As much as a prediction of the event of an accident or the magnitude of the consequence might seem to be preventive, in the future, ML analysis might be better utilised in the modelling of risk factors. The integration with ACMs such as the BOW-Tie model and the SCM provides the backbone for ML-based accident analysis models to be tuned towards accident risks and any corresponding prevention measures. From an ML point of view, explainable algorithms should be used. The conclusions of this paper for approaching the ML-based accident analysis provides a possible recipe for better understanding causation factors and the mechanisms through which accidents happen.

4.3. Paper III: LEARNING FROM ACCIDENTS: MACHINE LEARNING PROTOTYPE DEVELOPMENT BASED ON THE CRISP-DM BUSINESS UNDERSTANDING

The increased interest in ML evident in the literature and the growing use of ML in accident statistical analysis has been shown to be valuable in analysing large volumes of data. However, it is not beneficial to reinvent existing methods, so in truth, no new knowledge is provided by such solutions. Moreover, the analysis of the literature contained in paper I have shown that there is a need to contextualise understandings of ML-based analysis and define clear ML tasks. This paper explored the local and corporate context for ML-based analysis and the ML development method known as CRISP-DM for conducting such studies.

The aim of this paper is to analyse experiences and challenges in using the “business understanding” phase of CRISP-DM as the first step towards ML prototype development with respect to the context and local dynamics of a Swedish contracting company. The investigation adopted a bottom-up approach, where knowledge of accident registration procedures was the point of departure.

The overall method is an interpretive approach. A concept-centric literature review was conducted (Webster and Watson 2002) to review the status of ML-based solutions for accidents report analyses. For the empirical context, five interviews were carried out: four with safety engineers and one with a safety strategist at a high level in a Swedish contractor company. The ML related interview questions and discussions were focused on gathering the safety requirements for developing a data-driven prototype, inspired by the business understanding framework of CRISP-DM and the recommended practice (RP) framework (DVN GL AS 2020).

The business understanding phase begins with defining the client’s goal and deciding on a value proposition for the ML application. The interviews showed a difference in safety priorities between top management and operational level, especially the focus on behaviour and fatal accidents, the planning of safety tasks, and communication. This leads to conflict between single versus multiple-goal orientation compared to the CRISP-DM model, which suggests that a single goal should be identified. In response to this obstacle, this paper suggested that at the end of the first step of the business understanding phase, there is a need for an intermediary step to agree on a common objective before proceeding to accident report analysis.

The second step of the business understanding phase requires a detailed analysis of the related resources, constraints, assumptions of the business objectives, risks of project failure, terminology, and cost-benefit analysis from a commercial perspective. The most important aspect of this application is to investigate the resources of the H&S unit and the characteristics of the data. The data incorporates valuable information, but the level of detail in reported accident causes is doubtable due to different experience levels among the personnel that do the reporting. Moreover, constraints can be found in the digital reporting system and the incorporation of safety planning between production's main objectives of meeting schedule and budget demands.

To sum up, following the recommendations of this business understanding phase reveals insights into possibilities and local constraints. However, it is not possible to cover all scenarios, especially if the first step of the business understanding phase was not concluded or aspects of the ethical consequences were very challenging to be identified through the interviews.

The following step would ideally be defining data-driven goals. These would include the ML prediction output and the model's acceptable accuracy. By the time the analysis arrived at this stage, this ideal had become more unattainable since the last two steps had not been completely closed. Moreover, the requirements of this step are highly dependent on the data condition. Thus, it is suggested that this step should be completed by adding an iteration as primary data analysis. This would then suggest realistic potentials and limitations to match the organisation's aspirations.

The previous analysis highlighted the application of CRISP-DM in the business understanding phase and the involvement of domain experts in a breakdown of daily processes and experiences. In project-based organisations such as the case contracting company, there is a need to investigate and analyse the business understanding phase on different organisational levels. The different organisational levels and their concentration on a very different set of priorities challenges the use of CRISP-DM. Moreover, the analysis showed that adding two intermediary steps was necessary to meet the challenges in defining ethical considerations, application design and data-driven goals.

5. Machine learning model design and analysis

This section describes a continuation of the thesis including the ML model design and analysis of accident reports. This section is organized after the summary of the papers (section 4) because the following analysis builds on the results of the previously described papers.

5.1. Model design

The following analysis encompasses a continuation of interviews based on the business understanding phase and a follow-up recapitulation of the proposed solutions. Seven further interviews were conducted by following the same main structure of the interview guide as in aper III. The conclusions of Paper III indicated the need to agree on a common organisational objective for the ML prototype design. The interviews which were conducted in paper III (section 4.3) were extended to include more actors from the H&S unit, including one site supervisor, four safety representatives, one safety manager and one site manager. The interviewees' collected ML application proposals are presented in Table 6.

Furthermore, a workshop was planned to discuss how the accumulated propositions identified by analysing the interviews could be integrated into the preliminary prototype development. The workshop included a presentation of the results of paper III and Table 6 as the intermediary step - suggested in paper III- of the business understanding phase.

The workshop included the following actors:

- Safety engineer from the contracting company (2)
- Trade union organiser
- Safety engineer contractor (1)
- Business Development Lead – Analytics contactor (3)
- Development leader Health and Safety contractor (3)
- Construction Workers' Union agent
- IT Solutions Manager contractor (3)
- Work environment manager contractor (2)

Table 6. Summary of interviews model propositions

Machine learning model propositions
To produce statistics on historical accident cases.
To pay attention to work steps where there are many accidents
To use Synergi more easily for safety work preparation and risk assessment
Tools for presenting information about safety risks to production people
Negative and positive observations to find the reasons behind workers not following the safety rules.
No safety improvement needs.

The workshop was organized in an online meeting and facilitated by the author of this thesis. The workshop resulted in a vote for the proposition that was considered the most value-adding for safety prevention, based on the ML analysis of the collected data from accident reports. Most of the workshop participants thought the proposition for work steps and safety risk assessment was the most value-adding use of ML (see Figure 6).

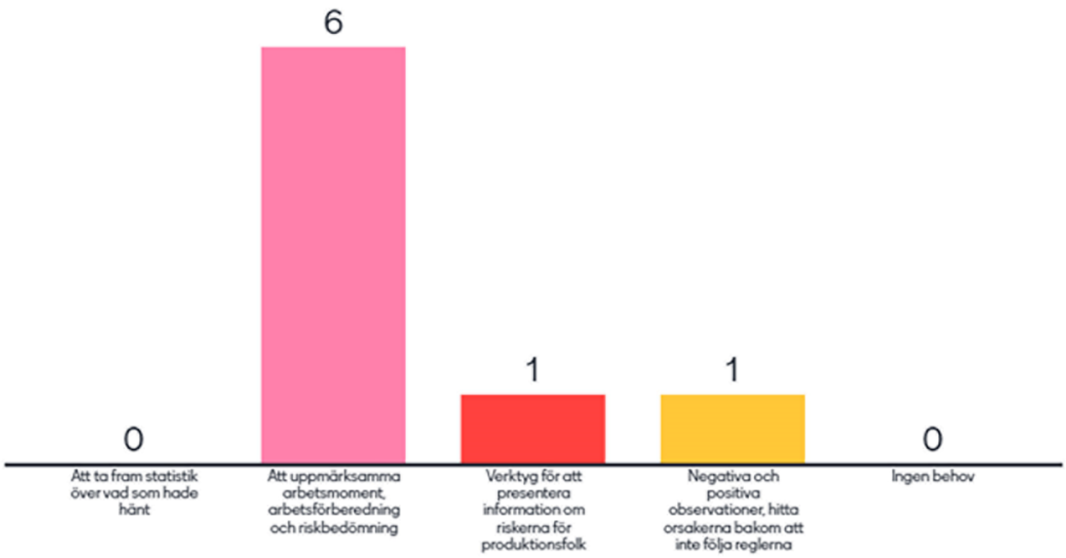

Figure 6. Workshop vote for ML model proposition.

The workshop then presented the preliminary data analysis of the case contractor's accident reports (section 3.4.2.1) and the corresponding prototype design (Figure 7). The prototype design consists of the input features, and the blue arrows represent a drop-list of predefined categories. The categories should be identical to those that constituted the accident reports for consistency. The prototype was designed to predict severity that is categorized as low risk and high risk. The high-risk category represents a prediction of a final outcome starting from the absence of workers towards outcomes of further severity.

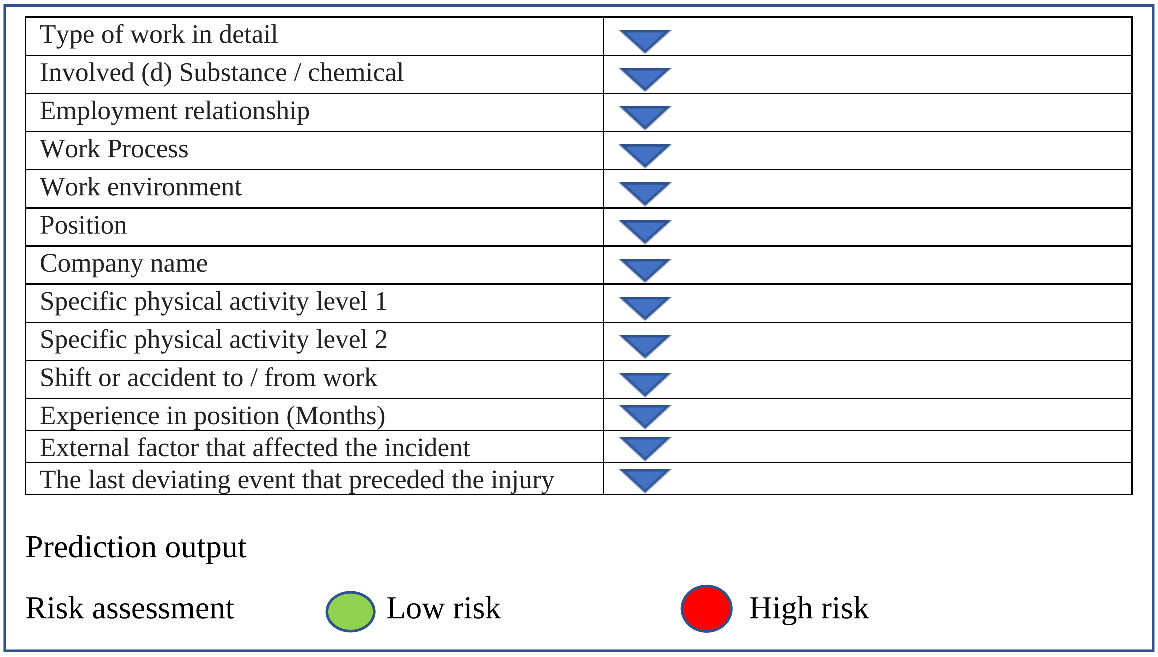

Figure 7. prototype design illustration.

5.2. Framework of understanding

In response to the conclusions of paper II (see section 4.2), the Bow-Tie model was chosen as a framework of understanding for the ML model. In this section, I will categorise the selected input features for the ML model into the components of the Bow-Tie model (see Table 7).

The BOW-Tie model (see Figure. 8) consists of multiple components characterising accidents. The model analysis starts by identifying a hazard in the organisation or the surrounding environment. I interpret that the input factors “Type of work in detail”, “Shift or accident to/from work”, “Experience in position (Months)”, Employment relationship”, “Work environment”, “Position” and “Company name” as representatives of the surrounding conditions of the work process. The hazard component is directly connected to the top event (see Figure 8), which I interpreted as the occurrence of an accident. The top event is at the centre of the BOW-Tie model and is caused by what the BOW-Tie model categorises as threats. The latter is represented by the input features “Specific physical activity level 1”, “Specific physical activity level 2”, “Involved (d) Substance / chemical”, and “The last deviating event that preceded the injury”. The “External factor that affected the incident” feature was interpreted as an escalation factor. Moreover, the consequences are interpreted as the level of severity of the accident. The input factors are summarised in Table 7.

Prevention barriers are very important components of the BOW-Tie model, and they are also reported in the accident reports. They are entered as free text, and the prototype design does take free-text data into consideration in this analysis (see section 5.1).

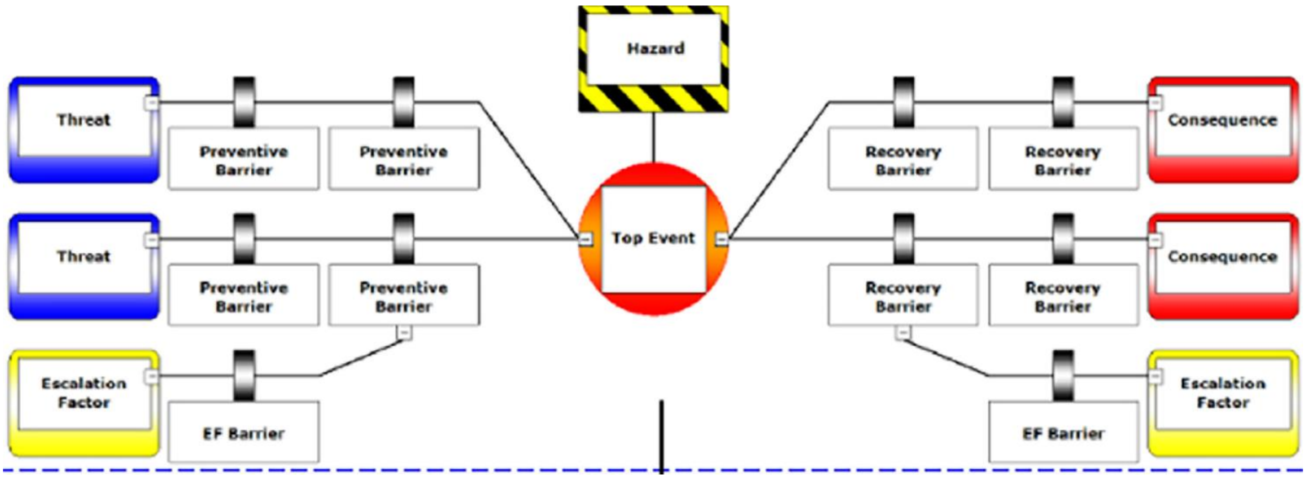

Figure 8. BOW-Tie, Fu et al. (2020)

Table 7. Input features categorization into the BOW-Tie framework.

	Input feature	
1	Type of work in detail	Hazards
2	Shift or accident to / from work	
3	Experience in position (Months)	
4	Employment relationship	
5	Work environment	
6	Position	

7	Company name	
8	Specific physical activity level 1	Threats
9	Specific physical activity level 2	
10	Involved (d) Substance / chemical	
11	The last deviating event that preceded the injury	
12	External factor that affected the incident	Escalating factor

5.3. ML analysis results

The input features represented in Table 8 were used to predict the level of accident severity in two different settings: the reported actual and potential severity. The actual and potential severity levels were reported and can be used as a prediction target. The potential severity represents the degree of severity of an accident that could have happened; for example, a minor accident requiring first aid medical attention could have resulted in a more severe injury and might have led to the worker having to take days off work. The ML model was performed by myself using the Pandas and Scikit-learn - Python 3.9.7 libraries version. Since almost all input features were nominal values, the data was encoded with the sklearn LabelEncoder function. The output features had five classes, which I then processed to make only two classes for binary classification. In particular, the first two initial severity levels "First aid, continue to work" and "Injury that requires medical attention" were merged into one category of low severity, and the highest three categories "Personal injury with absence", "Very serious personal injury", and "Fatal accident" into one high severity category. The results of the predictions are presented in Table 9.

The data analysis showed that the imbalanced state of the data had a considerable impact on the classification of severity. If we take the confusion matrix as a metric, the best prediction the DT algorithm can achieve is 383 true-positive cases of high severity, compared to 645 false-positive cases. However, if the accuracy is considered a metric, it was noted that it is not representative of how well the model classifies major and minor accidents. Since the interest here is to predict severity and the more critical one resulting in severe accident impact, accuracy alone is not enough as a metric. A good example here is the RF algorithm. The algorithm's accuracy is 69.29%, while the confusion matrix shows that the classifier almost always assigns minor severity to the case. The results of classifying the potential consequences showed the models' tendency to classify most cases as severe accidents – which is the most populated class in the potential severity case (see Table 9).

The unsuccessful prediction results can be attributed to the class imbalance, but they might also be attributed to the features. The features might be loosely correlated to the output, which explains the predictions. To test the features' predictability, I performed a random under-sampling for the high populated class to classify actual and potential severity. The random under-sampling reduced the frequency of the high severity class to match the frequency of the low severity class. This resulted in a slight reduction in accuracy but improved the ROC metric due to the more balanced confusion matrix. According to the confusion matrix metric, the predictions of the undersampled data showed slight improvement. This result indicates that the balanced data is not the only problem for classifying the target values, but also that the features are not correlated with the output.

The results of severity prediction illustrate that the proposed prototype design (Figure 7) can not be realised based on the ML model design and analysis of this thesis.

Table 9. The results of ML algorithms classification of severity.

Under sampling				
Actual severity prediction	RF	LogR	KNN	DT
Accuracy %	60.02	56.57	55.01	53.94
ROC	0.6002	56.57	0.5501	0.5394
Confusion matrix	[622 406] [416 612]	[569 459] [434 594]	[579 449] [476 552]	[560 468] [479 549]
Original data form				
Accuracy %	69.29	69.05	65.33	60.12
ROC	0.5549	0.5102	0.5324	0.5373
Confusion matrix	[2123 209] [823 205]	[2273 59] [981 47]	[1968 364] [801 227]	[1637 695] [645 383]
Under sampling				
Potential severity prediction	RF	LogR	KNN	DT
Accuracy %	55.68	51.9	51.65	52.75
ROC	0.5568	0.519	0.5165	0.5275
Confusion matrix	[758 607] [603 762]	[1086 279] [1034 331]	[696 669] [651 714]	[713 652] [638 727]
Original data form				
Accuracy %	60.69	62.26	57.08	54.26
ROC	0.5443	0.5034	0.5187	0.5177
Confusion matrix	[397 968] [457 1803]	[28 1337] [31 2229]	[420 945] [611 1649]	[569 796] [862 1398]

6. Results and discussion

The overall aim of this thesis is to investigate how ML-based methods and techniques could be used to develop a research-based prototype for occupational accident prevention in a contracting company. The thesis focuses on exploring development processes that bridge ML data analysis technical part with the context of safety in a contracting company. The overall research question was formulated with the focus on accident prevention and H&S activities on-site, with the company being the case for the prototype development. The following four sub-questions were sequentially investigated and critically reflected upon to answer this research question. The following discussion around the theoretical framework and the data analysis is structured with these research questions in mind.

RQ1: What are the requirements for applied ML in the domain of accident prevention in a contracting company's occupational safety processes??

The review of current ML literature found that when analysing accident reports, a number of challenges originated from the characteristics of the data in terms of data format, availability, and content. Accident reports, which were discussed in the reviewed literature, existed in textual format and lacked labels. In the case of high volumes of data, the accident description content and causes were therefore not easily understood. On the other hand, accident reports in predefined reporting categories clearly illustrated the reported features. However, they often had shortcomings on the level of causation, as they mainly reported the factors close to the physical work environment. Only a few datasets included distal causal factors, such as the type of construction and project size (Choi et al. 2020) and monthly project-related attributes (Poh et al. 2018). The shallow description of causes in the literature studied is one of the most disrupting challenges because it indicates that accident reports do not possess sufficient detailed causation capacity to explain why accidents occur.

Ultimately, the data characteristics determine a considerable part of the data pre-processing step. Accident reports are characterised by their use of language and domain-specific terminology. Although the literature review did not reach a definite conclusion about the application of domain-specific NLP, the critical literature analysis suggested that word-embedding algorithms trained with domain-specific corpus achieved good results in pre-processing accident reports (Zhang 2019, Zhang et al., 2020, Baker et al. 2020).

Moreover, accidents happen at different frequencies – particularly severe and fatal accidents which are rare compared to the high frequency of reported minor injuries. The reviewed literature mostly used a range of data resampling methods to counteract the less frequent accidents in the reported accident dataset, such as Random Over Sampling (ROS), Synthetic Minority Oversampling Technique (SMOTE), Random Under Sampling (RUS), inversed proportional weights, and manual labelling. However, the reviewed literature lacked a justification for the choice of methods, and the consequences of using such methods were not considered. This leads to difficulty understanding ML models' results for them to be applied in real-life situations.

One of the essential recommendations arising from the ML literature review is the need for a systemised method for accident analysis with ML. This originated from the technical aspects of ML modelling and the need to integrate the theoretical and domain knowledge of safety practices. Considering the development context is an applied ML development general requirement and not exclusive for ML accident analysis. Nevertheless, it is suggested that the context around the data and code systems, the data analysts, and the organisational expertise are the missing pieces of an ML modelling lifecycle (Garcia et al. 2018). Thus, in the construction safety domain, elements of digitalisation, change management, feasibility and implementation analysis depend heavily and necessarily on the involvement of domain experts.

The successful application of ML in the domain of safety requires reliable evaluation methods. More research is needed in the area of evaluating ML prediction models. The ROC was proposed as an efficient metric for maximising the prediction accuracy in construction accident reports, given the asymmetrical frequency of serious/non-serious accidents. Nevertheless, more research is needed in evaluating applied ML in construction safety, including external validation and implementation trials.

It is important to note that this literature analysis has been influenced by my thinking about the problem I intended to solve. I have been interested in finding the best way to conduct an ML model for analysing accident reports. It is not necessarily so that categorising the literature into main themes such as the data characteristics and the implementation of ML is original, but it has been shaped by my wish to find themes that could help my research. This probably explains my somewhat performative language use. Moreover, this observation also relies on being explicit about the fourth level in the reflective methodology, the researcher's role (Alvesson & Sköldberg 2017).

RQ2: What is the role of ACMs as a theoretical framework for the ML results of analysed reported accidents in the construction industry, as well as what can be learned about ACMs from ML?

The accident causation models (ACMs) (i.e., the BOW-Tie, the SCM, and the STAMP model) were compared to the literature that applied ML to analyse accident reports in the construction industry. This comparison considered their level of causes, the relationship between causes, and the predictability of severity. This contributed to a re-conceptualising of ML-based models through the lens of ACMs. The study in paper II concluded that ML could benefit from integrating accident report components into the components of ACMs. The benefit is derived from conceptualising extracted features from free text and providing a foundation for prevention measures. Rule-based data mining and feature extraction methods were found to have shortcomings due to features and rules being prepared by a human and the weak generalisation of results (Pan and Zhang 2021). The SCM, the Bow-tie model, and several ACMs categorise accident causes into predefined categories. These provide somewhat well-defined causes levels – I say somewhat here because I have a reservation on how well accident causes are defined in ACMs. Nevertheless, ACMs provided a reference point that partly alleviates confusion of interpreting free text data used in ML-based accident analysis. I would say the same about accident reports in pre-populated format. These might have their implicit theory, and to use ACMs components to recategorise reported accident causes may clarify that.

There is also a missed opportunity to reflect on ACMs from the perspective of ML analysis. Methods such as data mining (Zhong et al. 2020) and semantic roles and rules analysis of accident components (Kim and Chi 2019) have visualised the relationships between causal variables. Generally, this contributes to creating a link between accident types and accident consequences. However, further research is needed to understand the nature of the relationships between causal variables and investigate if the levels of causation contribute to accidents equally.

A major difference was found by comparing the analysed ML literature and the SCM and the BOW-Tie. It was found that the approach taken by ML modelling to predict the severity of accidents is contradictory with accident analysis and causation models that assume the outcome of accidents as involving an unpredictable stochastic element (Harms-Ringdahl 2013). Although the ML literature claimed success in severity predictions with internal validity (i.e., ML model accuracy and not in applied real-life situations), their results were not always consistent and did not show proof to counteract the assumptions of ACMs regarding the stochasticity of accident severity. I must say I would like that severity could be predicted. Maybe the academics who work in the same domain wish for that too. This might be a reflection of the desire to protect on-site personnel from a dangerous situation. One should be aware of such inclinations because they could lead to the opposite, such as increased exposure to the danger of minor accidents if predictions introduce overweight on instances leading to fatalities. This observation echoes Alvesson & Sköldberg's (2017) observations on the role of the researcher and the structural, societal distance between ML developers and the building site.

RQ3: What are the experiences and challenges of applying CRISP-DM "business understanding to assure a solid contextual embedding and an appreciation of local dynamics?

Based on the conducted literature review to answer RQ1, there was a recommendation to develop ML prototypes concerning the local context dynamics systematically. The CRISP-DM was investigated as a possible method. The application of this method by doing interviews, although posing relevant questions, was found too general to finalise a business understanding without adding multiple iterations. Nevertheless, the interviews revealed interesting insights into the safety processes and the perception of H&S personnel within the organisation. It is important to note that the description of the CRISP-DM method does not particularly advise doing interviews or a specific way for conducting the business understanding analysis. The decision to conduct interviews was my interpretation of using the CRSP-DM. It was somewhat challenging for me to start thinking about a prototype without understanding the existing safety processes and who would be using it.

While the respondents agreed on the meaning of safety ("everyone goes home injury-free"), it seems that ideas about achieving that goal were not as clearly a part of safety meaning. This indicated describing safety as the goal to be injury-free. There was much focus on the planning and preparing for safety measures on-site. Accordingly, processes were in place with a particular focus on fatal accidents and the behaviour of individuals. Individual risky behaviour was the shared major cause among top management and the safety engineers. However, another major cause mentioned by safety engineers and site managers was thought to be related to production time pressure and referring to contractual arrangements as an inevitable, unchangeable condition that produces safety risks.

There was also a prevailing assumption that effective accident prevention is achieved by systemically identifying the risks associated with accidents and taking measures to avoid their impact. Furthermore, the interviewees expressed conflicting views about risks associated with the prevailing safety assumptions about behaviour and the systemised risk analysis. These commonly held assumptions and associated risk evaluation techniques were often criticised in the literature for low inter-rater reliability, i.e., low degree of agreement among observers/raters/analysts in estimating frequencies and consequences (Harms-Ringdahl 2013). Analysts/raters tend to assume that a major consequence is automatically less probable (Harms-Ringdahl 2013).

The interviews showed a need and potential added value to accident prevention activities by improved safety planning and more accessible risk identification. It seems as if there is frustration with anticipating what would cause the next accident. It might be because some safety professionals have a perception that all that can be done to prevent accidents is known and well-established, but accidents still occur. Some of the respondents pointed to the need to know why allegedly workers do not follow the safety work packages. They attributed that alleged behaviour to the workers' tendency to prefer to do the work before thinking about safety. So, considering workers' behaviour as a significant cause of accidents makes much sense for those safety professionals who deem the rules known and sufficient.

Ultimately, the CRISP-DM is applied to collect and understand the context requirement and identity the business's expected advantage of using ML data analysis. However, the interviewees' experiences and views indicated complexity in defining a goal that solves an existing problem -from their perspective. This presented a difficulty in deciding on an ML utilisation goal and more so to analyse the implications and more specific ML prototype design requirements. Paper III concluded that CRISP-DM might benefit from adding two iterative steps to the existing ones in its process.

RQ4: **What are the predictive attributes of accidents based on ML application to accident reports?**

Based on the ML data analysis in this thesis (see section 5), the pr-populated categories of accident description were the point of departure for the ML model design. However, in the accident reports data of the case contractor, only a few reported features could represent knowledge before the accident took place (such as "work environment"). Compared to those features registering the consequences such as the description of the damaged body part and description of injury type and cause category.

In this thesis's accident reports analysis (section 5.3), the same phenomenon of the low frequency of severe accidents was encountered. The ML model classified most accidents into the low severity category, which was the most populated class. Random undersampling (RUS) was employed to test the impact of the uneven severity frequency. However, it was found that the difference in frequency did not explain the ML model's results since the use of RUS for the more populated class did not result in a considerable improvement in the classification performance.

This result indicated that the same features' entries that characterised the work environment for a high impact accident were the same for the low impact ones, according to other accident research. It is important to note that the prototype design and the choice of severity as an output for the ML model were impacted by the available features within the case accident reports and influenced by my own inclination to predict severity. This finding implies that research on analysing accident reports by ML needs new ways of thinking by approaching the analysis differently. More research is needed about this development phase, and only a little research can be found in response to the methodological limitations for handling severe accident reports data. A systemised data pre-processing approach that implements clustering, chi-square test and principal component analysis (PCA) has been proposed in earlier published studies (Lee et al. 2020).

In this thesis, the BOW-Tie model was used to understand the consequence prediction ML analysis. It was found that the data organised as hazards and threats did not differentiate between which work conditions, physical activities and deviating events explained the level of severity in the event of accidents. This result is in line with basic assumptions in the BOW-tie model. This result raises two critical questions. One involves safety planning and what, in fact, the H&S unit knows about the accidents that could be used in planning and prevention. This, in turn, relates to whether an overall prevention strategy is being implemented on-site.

The second important question involves the BOW-Tie model, or in general, whether the ACMs' assumption to prevent accidents by systematically analysing the risks is just an illusion. Building on the interviews with the staff of the H&S unit, this is probably true since general safety practices and accident analysis are more concerned with preventing the consequence/severity of an accident than the event itself. The ML analysis of accidents reports and the prediction model that was undertaken in this thesis supported this discussion. By using the reported potential accident consequence instead of the actual severity as a prediction target, there appears to be a stochastic element in accident outcomes. On a general note, there has been a change in the view of risk evaluation beyond probabilities and consequences and more towards a decision-making process that considers a broader view on the context of risk (Harms-Ringdahl 2013).

Intuitively, it could be assumed that the reported potential severity might alleviate some of the stochasticity in accident severity. However, the experimental ML analysis in this thesis (see Table 9) showed otherwise. This might be explained by the reported potential severity being overestimated. Most of the potential accident severities were estimated to be just in the next severity level above in the case accident reports. Although these results do not seem encouraging, accident reports and the application of ML could support other purposes instead of accident impact prediction. Such purposes could include causation modelling and extraction of unique accident cases that might present new knowledge. The case accident reports contained other data types such as causes and prevention measures and accident descriptions in free-text format (see Appendix). This type of data was not used in this thesis, but it can potentially be used in independent research that considers another ML model design.

Accident causation analysis of accident reports using ML provided an added value by giving means for efficient extraction of information. ML algorithms search for high frequency, often repeated patterns, and this approach is not compatible with finding new knowledge about all types of accident occurrences. The domain of accident prevention is mature, and much is known about accidents causation combined with developed ACMs that have evolved to include further levels of causes beyond the workplace and human behaviour. Therefore, expecting the next accident might not be associated with analysing frequent accidents cases but with discovering emergent risks. ACMs provide a stable foundation for putting emergent risks into perspective and support prevention strategies. However, ACMs seem to have reached a ceiling of causation levels and their representation. Thus, more development is needed in understanding the nature of the relationships between causes instead of adding further categorisations and levels of analysis.

Finally, according to my definition of a prototype" as the one suggesting a precise implementation for ML-based data analytics. One that shows means of application and a digital software interface that is ready for use". I can say that this thesis did not realise the aimed and designed prototype. Mainly, the results of the ML modelling of the case accident reports were not successful in being taken further to an implementation stage.

7. Conclusion

This thesis contributed to the exploration and understanding of ML development processes to bridge ML data analysis with the context of safety in a contracting company. The thesis has provided a method for choosing an ML algorithm based on the required criteria of the ML model. Moreover, the thesis discussion argued for the use of CRISP-DM as a method for understanding the context and gathering potential use of ML from the business perspective. ACMs were also essential in ML model interpretation, especially in identifying components of accident analysis and categories of causes.

ACMs provided a background for accident investigation and causation analysis for many years and developed over time. This has resulted in several classifications such as linear (e.g., SCM) and non-linear (e.g., Bow-tie model) models according to the assumed logical sequence of events that lead to accidents. Other classifications also exist, but ACMs have been divided into groups based on different stages and causations. The simple linear models attributed accidents to physical/mechanical and human errors. ACMs then became associated with complex linear models as they increasingly considered the interaction between latent organisational factors and unsafe behaviour. Complex non-linear models encouraged a broader view of system-related factors in response to the growing complexity and tighter couplings within industrial domains. They now explain accidents as being caused by the dynamic and non-linear interaction among multiple factors within the entire system, including political and regulatory factors.

ACMs evolved to include higher levels of causation. Moreover, ACMs assumed stochasticity in accident severity. Behaviour and advanced socio-technical and cultural models were used in the relevant domain literature in the construction research context, while the system-based models were hardly ever applied. Accidents continue to occur in the construction industry, and there is a need to investigate theories and models of accident causation against the quantitative data analysis that is now being derived from many registered accidents.

The ML-based approach to accident analysis includes supervised, unsupervised and semi-supervised learning. Unsupervised learning is a method of data exploration or description employed when there are no specific preassigned labels for the input or output features. In comparison, supervised machine-based learning depends on mapping an already labelled input to output. Semi-supervised machine-based learning consists of a combination of the latter two approaches. Supervised ML algorithms can be further categorised into linear and non-linear algorithms, each having different characteristics, strengths and weaknesses. The algorithms were organised based on their characteristics (e.g., interpretability, accuracy, generalizability).

This thesis has employed an overall qualitative-interpretive reflexive methodological approach. This approach combined different levels of interpretation. ACMs and ML accident analysis were chosen as the main theoretical frameworks for answering one overall research question and four related sub-questions. The associated empirical research included collecting accident reports and interviews conducted within the H&S unit in a contracting company. The CRISP-DM and ML algorithms were employed to develop and analyse an applied machine learning model. ACMs, ML algorithms, and CRISP-DM provided the desired multiplicity in interpreting the empirical material. The practical research method consisted of four sequential steps, including three papers and the ML-based analysis of accident data.

ML-based accident analysis can create knowledge about accidents in a contracting company or other organisations, such as objects and combinations of situations that cause accidents. The literature in this context showed various means by which the application of ML algorithms can enhance knowledge about accidents. ML models can be applied in severity estimation, accident type classification, information extraction and safety training scenario generation. However, the literature also showed that extracting new knowledge about accidents in a contracting company was hindered by an array of challenges. Mainly the systematisation of the ML process, the feasibility of implementation, and the focus on severity prediction.

The reviewed literature of applied ML in accident report analysis indicated the need for the standardisation of the development process regarding the feasibility of implementation and evaluation. However, implementing the CRISP-DM as a process did add essential components to understanding the context, such as context requirements, assumptions about safety processes and accident prevention. Although the CRISP-DM was found too general to provide specific guidelines for ML prototype development, it provided a backbone for the application domain. Further decisions on the ML system design can be established with a flexible-iterative model design process.

ACMs served as a theoretical framework for conceptualising reported accident features and understanding ML-based analysis and interpretation. It was concluded that the reported features that described the work environment do not explain severity. Although the domain produces less severe accidents that are not aligned with how the machine learning classification algorithms work, this was not the primary problem. The primary problem lies within the direction of the ML related literature to predict severity, which is stochastic.

Although ACMs have guided accident investigation and promoted successful prevention strategies, the promise of risk mitigation by systematically analysing accident risks has been undermined by the difficulties around the identification of unknown and emerging new types of risk. ACMs assume that the essence of prevention is by systemising risks and causes. However, in this mature field of study, what is needed is to understand better the rules that govern the relationships between emergent new risks. Accident report analysis using ML offers methods and means in this area. Data mining and unsupervised ML are proposed as a possible way forward to meet this ambition in that they are less explored in the ML models considered within the current literature.

This study suggests that there is a need for systemised machine learning modelling methods for analysing accident reports. Systemised methods should consider integrating an applied ML model within the context of domain experts responsible for implementing prevention measures and strategies. Moreover, there is a need for a development method that systemises the technical part of data pre-processing and the choice of algorithms along with the needed internal and external validation. Moreover, integrating a theoretical framework is essential for analysing accident reports, namely ACMs. The application of a theoretical framework proves to be particularly helpful in identifying components of accident prevention.

From a technical perspective, several methods in accident reports analysis in the construction industry were recommended. Specific NLP algorithms that consider the local domain language was recommended over ML algorithms trained with a general corpus. Moreover, data pre-processing and handling methods such as clustering and Chi-square were also recommended. These were explicitly suggested to justify and explain the consequences of the chosen methods. The same applies to the evaluation metrics, such as the ROC metric. A definitive consensus about the best use of algorithms was not evident in the existing literature. However, this thesis suggested a method for selecting the ML algorithm based on its preferences and task definition and strengths and weaknesses of the relevant ML algorithm.

The ML model that is built on accident reports from the contracting company did not explain accident outcomes. It was found that the entries of the features that described the accidents did not differentiate between high severity and low severity accidents. This result indicated that ML models that mainly focus on accident severity prediction are less successful than they seem. Instead, this thesis advised that the focus should shift from accident severity level and use ML to identify emergent risks. The latter direction should involve close collaboration with domain experts and organisational change.

8. Future work

Future work might take in consideration unsupervised-ML based analysis and data mining methods on the unstructured reported accidents. Such an ML based approach will be useful in discovering and understanding the relationships between causes. Moreover, an in-depth analysis of the ML development process could also be a useful direction for future research, where more case studies could be taken in consideration in order to explore the development of a more generalized process. Such a development would benefit from investigating the prevention strategies implemented on site because much can be learned about successful safety process. Such an empirical investigation could be of benefit in identifying the methods and principles of prevention measures that allow for safe production rather than merely focusing on accident occurrences that drive current thinking.

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List of abbreviations

Abbreviations	Explanation
ACMs	Accident causation models
AcciMap	accident map model
AI	Artificial intelligence
ANN	Artificial neural network
ConAC	Construction Accident Causation
CRISP-DM	Cross Industry Standard Process Development Method
DT	Decision tree
FN	False negative
FP	False positive
HSACS	Human Factor Analysis and Classification System
KNN	K-nearest neighbour
KSVM	Kernelized support vector machine
LogR	Logistic regression
LR	Linear regression
ML	Machine learning
MLP	Multi-layer perceptron
MORT	The Management Oversight and Risk Tree
NB	Naïve Bayesian
NLP	Natural language processing
OARU	Occupational Accident Research Unit
RF	Random forest
ROC	Receiver operating characteristic
ROS	Random over sampling
RUS	Random under sampling
SCM	Swiss cheese model
SMOTE	Synthetic Minority Oversampling Technique
STAMP	Systems Theoretic Accident Model and Processes
SVM	Support vector machine
SVR	Support vector regression
TN	True negative
TP	True positive

Appendix

Accident report dataset description.

<table>
<tr><th colspan="2">Where, what, who</th></tr>
<tr><td colspan="2">This section of the report consists of information about the date, time and notified authorities, followed by the health and safety category, and the company where the incident took place. A case title and description are asked for, as well as whether the accident involves in-house or subcontracted employees. Project information contains multiple levels of detail, indicating the project and divisions where the accident took place. The title of accident, its description, and the health and safety category are written by the reporter. The health and safety category report lists accident types such as machines and equipment, falling objects, walkways, access roads, lighting, etc.</td></tr>
<tr><th colspan="2">General classification</th></tr>
<tr><td colspan="2">The general classification section involves information about the detailed work process, material agent and the substance / chemical solution involved in the report and is listed in a pre-populated drop-down list. The work process concerns the general type of work, and the work process list concerns a more detailed process category. Both have multiple levels of detail, but despite being necessarily different from each other, they seem to be repeated in the data.</td></tr>
<tr><td>Type of work in detail</td><td>Reinforcement, Excavation, Concrete work, etc.</td></tr>
<tr><td>Involved substance / chemical solution</td><td>Gas, Cement, Bitumen, etc.</td></tr>
<tr><td>Work Process</td><td>Excavation, construction work, renovation, demolition
New construction – house
Etc.</td></tr>
<tr><td>External factor that affected the incident</td><td>Building and construction parts
Facilities
Etc.</td></tr>
<tr><th colspan="2">Consequences</th></tr>
<tr><td colspan="2">The consequences section indicates the severity of the accident, as well as details such as whether it resulted in personal injury, whether the worker was assigned alternative work, any financial losses, the units where the accident happened, and the work shift during which the accident occurred.</td></tr>
<tr><td>Actual severity</td><td>1) First aid, continue to work
2) Injury that requires medical attention
3) Personal injury with absence
4) Very serious personal injury
5) Fatal accident</td></tr>
<tr><td>Monetary loss</td><td>Monetary loss</td></tr>
<tr><td>Employment relationship</td><td>Part time employee, Own employee.</td></tr>
<tr><td>Work environment</td><td>Production site, factory, workshop
Underground – mine
Etc.</td></tr>
<tr><td>Position</td><td>Machine operator
Supervisor
Etc.</td></tr>
<tr><td>Description of damaged body part, Common</td><td>The leg / calf
Torso
Etc.</td></tr>
<tr><td>Description of injury type</td><td>Allergic reaction
Electricity injury
Etc.</td></tr>
<tr><td>The last deviating event that preceded the injury</td><td>Electrical problem due to defects in the installation - causes an indirect contact
Fire, ignition
Etc.</td></tr>
<tr><td>Number of registrations Personal injuries</td><td>The number of registered personal injuries.</td></tr>
</table>

Experience in position (Months)	The number of months of experience.
Actual number of days with Alternative work	The actual number of days with alternative work.
Actual number of days of absence (Absence damage), calendar days	The actual number of days of absence
Company name	Main contractor Subcontractor
Injured body part	Finger (fingers) Teeth Etc.
Injury class	1) First aid, continue to work 2) Injury that requires medical attention 3) Personal injury with absence 4) Very serious personal injury 5) Fatal accident
Category of injury	Hit by moving objects, collision with – no Squeezing, crushing, getting stuck in, etc. Not specified. Etc.
Injury type level 1	Wounds and superficial injuries Dislocation, sprains, and strain Etc.
Injury type level 2	Superficial injury Dislocation and subluxations Etc.
Specific physical activity level 1	Working with hand-held tools - Not spec. Driving / staying on board transport equipment / handling equipment - Not spec. Etc.
Specific physical activity level 2	Working with hand-held tools – motorized Driving a means of transport or handling equipment - mobile and not motorized Etc.
Shift or accident to / from work	Day shift Evening shift Etc.
Loss potential	
Possible further consequence	Material damage Personal injury
Potential Severity - Most Severe	1) First aid, continue to work 2) Injury that requires medical attention 3) Personal injury with absence 4) Very serious personal injury 5) Fatal accident
Risk area	Less serious area (green traffic light) Serious area (yellow traffic light) Critical area (red traffic light)
Causes	
Comments	Potential comments offered for a case.
Circumstances of the accident	During travel between the home and the workplace At work: During work At the workplace but not in work tasks: Other premises than those arranged by the employer Etc.
Cause level 1	Inadequate risk assessment and / or risk assessment not carried out

	Removal of safety devices Etc.
Cause level 2	Unconcentrated / distracted Insufficient safety assessment Etc.
Causes - Cause description	Free text
Cause category	Prerequisites (Direct cause) Person-dependent factors (underlying cause) Etc.
Prevention	
Expiration Status of Action	Ended after due date Completed before due date No deadline
Comments	Free text
Prevention status	Prevented Rejected
Prevention type	Temporary Prevention
Action - Created Date, Time Period = Day	Date format
Action - Fixed, Time period = Day	Date format
Action description	Free text
Case handling	
Case Management Time	Number of days
Registration delay (Established date - Case date)	Number of days
Case management and status	All cases in the data set are closed

Paper I

A REVIEW OF MACHINE LEARNING FOR ANALYSING ACCIDENT REPORTS AND APPLICATION REQUIREMENTS IN THE CONSTRUCTION INDUSTRY

REVISED: February 2022.

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SUMMARY: Recently, there has been a significant growth in the number of publications on applied machine learning (ML) in safety analysis within the construction industry. The increased application of ML-based analysis covers both workplace related risks and underlying accident patterns. However, ML based approaches to these concerns have been criticized for a lack of clarity around the description of methodologies, interpretation, and the context of the application. The construction industry tends to be complex with its project-based organization and the different collaborating disciplines. Therefore, this work aims to find the development requirements for a ML based model which can be applied in the area of occupational safety. A review of the published literature on applying ML based analysis to construction accident reports was carried out. The review included 19 selected articles from three main libraries: Web of Science, Elsevier, and Scopus. The analysis of the purposes for using ML based models, the ML methods, and the performance of ML based algorithms in the reviewed literature highlighted a need for a more thorough ML task definition. Moreover, differences in frequencies of accident severity and accident types make it difficult to articulate data pre-processing requirements and the criteria for the selection of ML algorithms. The use of ML based analysis in the construction industry, would benefit from incorporating a standardized development method. And interpretable ML algorithms are better suited to interpret safety recommendations. Moreover, future research should experiment and conclude whether domain specific dictionaries should be used in word embeddings in the pre-processing stage. Testing the performance of the ML models and implementation in the industry would require stakeholders to be more involved in setting up an accepted prediction accuracy threshold.

KEYWORDS: accident report; construction; implementation; machine learning; safety.

INTRODUCTION

The construction sector is well-known for being both risky and having a high frequency of occupational accidents (Hoła and Szóstak, 2015). Recently, there has been a notable increase in the literature on applying ML based analysis in the construction industry (Xu *et al*., 2021), including in the domain of safety (Hou *et al*., 2021). The accumulated accident reports in contracting companies and national registries are loaded with accident-related data, such as circumstances, processes, and the people involved. Moreover, the increased focus within the literature on ML based analysis has therefore also indicated risk assessment-related applications of ML that included learning from textual data in the context of accidents, identifying contributing factors, and the extraction of accident-related information (Hegde and Rokseth, 2020).

ML has increasingly been sought in finding underlying patterns within accident reports that has the potential to increase the predictability of risk at work, especially with large volumes of accident-related data that is available (Bilal *et al.,* 2016, Hegde and Rokseth 2020, Vallmuur 2015). Regardless, the current literature had been criticized for analysing textual injury records while lacking sufficient descriptions of the methodologies used in processing the data and training the ML models. This has made it harder to understand the potential impact of ML applications on safety processes (Vallmuur, 2015). Moreover, Bilal and Oyedele (2020) have suggested that the application of ML surpasses the development of a prototype. And that reliable ML models need to be developed in collaboration with the practitioners of the industry rather than just the ML expertise and intuition of data analysts that currently informs the design of ML models. Therefore, the development of ML learning prototypes requires understanding the context of application and interpretability (i.e., the ability to understandably explain predictions emanating from a ML model to a human) (Gilpin *et al*., 2018). As a domain of ML application, the construction industry is relatively complex by being mainly project-based and involving the collaboration between many disciplines. Added to which the management of safety is only one process among many other on-site production related processes (Milch and Laumann, 2016). Moreover, the current literature reviews include the application of ML in the construction industry and safety (Hegde and Rokseth 2020, Hou *et al.*, 2021, Xu *et al.*, 2021) and there is a need for more focused review on ML based analysis of accident reports. These sector specific complexities and the need for a narrow scope review lead to the research question: what are the requirements of a ML based analytical model using accident report data if it is to be implemented a representative contracting company?

This article aims to investigate the possible requirements for the development of a ML model that might be implemented in order to analyse occupational accidents data within the construction industry. Such an investigation would contribute to the identification of prerequisites of ML development that arise from the specific conditions and the processes associated with managing health and safety in a contracting company in the construction industry.

A literature review was carried out to answer the research question. The literature review focuses on the applications to accident reports regarding its use of algorithms, methods, data processing, and purpose and scope.

It should be noted that this literature review is part of a Licentiate thesis project that aims to apply ML based analysis to an archive of registered accidents from a large contracting company in Sweden. The reviewed articles are therefore arranged into the following themes: data characteristics, data pre-processing, algorithms and model training, algorithms and performance testing, model usage.

METHOD

The literature review was conducted using the concept-centric framework augmented by units of analysis (Webster and Watson 2002) and it was based on searches related to the application of ML to the analysis of accident registries in the construction sector. The subsequent review followed the concept centric review structure suggested by Webster and Watson (2002). Each article was organized by the identified concepts (see Table 1). The organization of the review was done to synthesize the literature into appropriate units of analysis; namely data characteristics, data pre-processing, algorithm type and training the ML model, testing algorithm performance, and implementation of ML analysis.

Three citation indexes were selected, namely Web of Science, Elsevier, and Scopus. The review was conducted iteratively within the three databases and within Google Scholar by using the search terms mentioned above. The relevant literature emerged from using the search terms “accident report,” “construction industry,” “machine learning” and “construction occupational safety.” The literature search was thus targeted whilst still being sufficiently comprehensive (MacLure 2005).

The selection of the literature was done based on Dundar and Fleeman’s (2017) exclusion and inclusion criteria steps. The included articles were ones that exclusively have the following criteria:

- Data source: Accident reports.
- Domain: Construction industry.
- Data analysis: Machine learning.

The selection of papers using these criteria yielded a narrowly-targeted list that is only related to the use of ML on reported accidents’ data in the construction industry. Any returned results in non-targeted contexts, e.g., the ones of chemical plants, steel plants, and car crashes were excluded. Articles analysing data from accident news, or the web-crawling technique were also deemed out of scope. One hundred thirty publications from Google scholar were also abstract scanned (70 within 2018-2019, 60 within 2020, and 60 within 2021). After scanning the abstracts against the inclusion criteria, the initial selection of full papers included 13 articles from Web of Science, 12 from Elsevier and 2 from Scopus.

The collected articles were compared across the four databases to identify the shared articles. Nineteen articles were finally selected, four of which were found in all the searched databases. The main reason for selecting these 19 papers was that they included in-depth studies within a cross-section of the concepts mentioned above, rather than the accumulation of references that might be peripheral. This work is also a preliminary part of a project aiming at applying ML based analysis to a dataset of registered accidents compiled by a large contracting company in Sweden. This impacts the review of literature by highlighting the implementational requirements that in turn guide the data analysis process within the larger research project.

The iterations of the literature review and the emergence of the themes mentioned above followed the abductive reasoning of qualitative research. Typically, observations and explanations of phenomena are developed by working iteratively between theory and data (which, in the present case, is the content of the references accumulated with each iteration). This facilitates the revision and refinement of earlier conceptions (Bell *et al.,* 2019).

LITERATURE REVIEW

Data characteristics

The following section presents the data source, format and structure, and content. This section lists the latter characteristics to make the connection with the following subsections about how the data was pre-processed, analysed, and utilized. The organization of the references in this section was based on common characteristics that have been used to define the data.

In Table 1, the reviewed references were organized in terms of the data source, the origin country, its type and balancing methods, the used accuracy metric and the respective achieved values, and the purpose for which the data were used.

Table 1. Literature review content in terms of data characteristics

Reference	**Data source**	**Country**	**Data type**	**Data balancing**	**Algorithms**	**Accuracy metric**	**Accuracy value**	**Purpose**
Choi *et al.,* (2020)	Ministry of Employment and Labour	Korea	Accident reports/137323 injuries and 2846 deaths	ROS	AdaBoost, LR, RF	AUROC	RF 0.9198	predict the fatality likelihood
Zhu *et al.,* 2021	Ministry of Emergency Management and the Work Safety Administrations	China	571 investigation reports	SMOTE	LR, DT, RF SVM, NB, KNN, MLP, AutoML	Precision/recall/ F1-score	AutoML 0.844	Predict severity of accident
Zhang *et al.,* 2020	OSHA	USA	18xx Accident reports	Manual labelling	BiLSTM, SVM, NB, and LR, CNN, LSTM	Weighted average F1	C-BiLSTM (BERT) 0.81	Classify accident categories
Zhang (2019)	OSHA	USA	1280	Manual labelling	KNN, NB, DT, LR, SVM, BiLSTM	Weighted average F1	BiLSTM 0,723	Classify accident categories
Kim and Chi (2019)	KOSHA, KISTEC	Korea	4,263 accident report	-	CRF	Weighted average F1	0.8	Information retrieval
Kang and Ryu, (2019)	KOSHA	Korea	6374 accident investigation	RUS	RF	ROC/ Weighted average F1	Weighted average F1 0.7	Predicting accident types

Cheng *et al.*, (2020)	OSHA	USA	1000 accident reports	-	SGRU, NLP KNN, LSTM, DT, GRU, SVM, LR, NB	Weighted average F1	SGRU 0.69	Causes classification
Fang *et al.*, (2020)	Wuhan Metro Safety Management System	China	3280 near miss report	-	BERT, Fast Text, TextCNN + BiGRU, TextCNN, BiGRU + Attention, TextRCNN	Accuracy	86,9%	Classification near miss type
Mo *et al.*, (2018)	National Institute for Occupational Safety and Health (NIOSH)	USA	246 Fatal Accident report	-	K-means	-	-	Clustering properties of accident related variables
Shrestha *et al.*, (2020)	OSHA	USA	1200 accident reports	-	SVM	F1 score	Injury Severity 0,85	Classification of upstream precursors, energy source, accident type, injury severity
Zhong *et al.*, (2020)	OSHA	USA	2000 accident reports	-	CNN, SVM, NB, KNN, LDA	Weighted average F1	CNN 0,63	classify accident causes/ correlations between causal variables
Baker *et al.*, (2020a)	Oil and gas company	International	90000 accident reports	Inversed proportional weights	RF, XGBoost, Linear SVM	Mean F1 score	SVM, severity classification 59.02	Classification of accident severity, incident type, injury type, body part
Baker *et al.*, (2020b)	Oil and gas company	International	90000 accident reports	Inversed proportional weights	Hierarchical Attention Network (HAN), CNN, Term Frequency - Inverse Document Frequency	Mean F1 score	HAN (Body part) 86. 97	Classification of accident severity, incident type, injury type, body part

					representation (TF-IDF) + (SVM)			
Poh *et al.*, (2018)	contracting company	Singapore	785 safety inspection records, 418 accident cases, monthly project attributes	SMOTE	SVM, LR, RF, DT, KNN	Accuracy	RF 0.78	accident severity classification
(Ayhan and Tokdemir 2019).	construction companies	Turkey	87 construction site/ 17,285 incidents records	-	ANNS, multiple regression	MAPE	70%	Predict severity
Zhang *et al.*, 2019	OSHA	USA	1000 accident reports	-	Optimized Ensemble, Ensemble, LR, SVM, NB, KNN, DT	Weighted average F1	Optimized Ensemble 0.68	Classification of accident causes
Xu *et al.*, 2021b	National and local websites	China	158 accident reports	-	LTP	-	-	Safety risk knowledge extraction
Ma *et al.*, 2021	OSHA	USA	150 accident reports	-	CNN, SVM, NB, KNN, Apriori algorithm T	F1 score	0.67-0.87	Safety risk assessment
Tang *et al.*, 2021	Ministry of Housing and Urban-Rural Development	China	157 accident reports	-	Apriori algorithm T	-	-	Safety risk knowledge extraction

The source of the data differs, either being single companies or national databases. Accident reports also differ in their format – e.g., free text or a template. The reviewed literature was organized in this section to group the references in common data sources to allow the comparison of how different bodies analysed the same data. The data was either collected from national sources, such as the Occupational Safety and Health Administration OSHA in the USA (Zhang *et al.*, 2019, Zhang 2019, Zhang *et al.*, 2020, Zhang 2019, Cheng *et al.*, 2020, Zhong *et al.*, 2020, Shrestha *et al.*, 2020, Fang *et al.*, 2020), accident reports from KOSHA (Korea Occupational Safety and Health Agency) (Kang and Ryu, 2019) and KISTEC (Korea Infrastructure Safety Technology Corporation) (Kim and Chi, 2019), the Ministry of Employment and Labor in the Republic of Korea (Choi *et al.*, 2020) and accident investigations from the national safety administration in China (Zhu *et al*., 2021).

The means of collection also differed. Xu *et al.*, (2021b) collected the data from national and local safety administration websites but only focused on the subway construction projects. Ayhan and Tokdemir (2019) collected data from multiple construction companies. Other collected accident reports were sourced by single companies, such as data collected from multiple construction sites involved in railway construction (Fang *et al*., 2020). Poh *et al.,* (2018) collected data covering 27 construction projects from a single contracting company in Singapore (consisting of nineteen building projects and eight infrastructure projects). Data was also acquired from an international oil and gas company operating globally (Baker *et al.,* 2020a, Baker *et al.,* 2020b).

Aside from differences in its origins, the collected accident reports can also be categorized by the structure or the format of the reports. The collected occupational accident reports which included data in the form of textual reports which were not labelled (i.e., the instances were not initially attributed into the sets of specific classes) (Kim and Chi 2019, Zhang *et al.,* 2019, Zhang 2019, Zhang *et al.,* 2020, Cheng *et al.,* 2020, Shrestha *et al.,* 2020, Baker *et al.,* 2020a, Baker *et al.,* 2020b, Xu *et al.,* 2021b, Ma *et al.,* 2021, and Tang *et al.,* 2021). The format of this type of data is mostly a continuous passage of text. Other efforts manually labelled free text reports such as labelling 2000 accident reports based on the Workplace Safety and Health Institute (Zhong *et al*., 2020). Mo *et al.,* (2018) used 246 fatal accidents reports which were later coded into 13 different variables, such as location, weekday, occupation project type, task, error origin, and causes.

Alternatively, the accident report data was labelled by other researchers who organized the reports by sub-systems, factors, and attributes – such as organization and behaviour, technical management, contract management, and safety training. The contract management subsystem included factors such as the contract agreement and tight schedule, while the safety training subsystem included factors like safety culture, training, and examination (Zhu *et al*., 2021). Unlike the data in other relevant studies (injury reports), Fang *et al.,* (2020) used near-misses reports, which consisted of 3280 reports and were categorized into 170 labels.

The other data flow consisted of structured or pre-categorized accident reports. This type showed better clarity in terms of held information. The organization of reports into certain features showed the reported relevant information about the accident. While reported accident in free text format require features to be extracted or assigned to each accident report. For example, information about the age, sex, length of service for each injured worker, the type of construction, employer scale, and the accident data were registered in a dataset consisting of 137323 injuries and 2846 deaths (Choi *et al*., 2020). Kang and Ryu (2019) included 55 input variables, such as age, occupational injury, work contents, unsafe states, unsafe behaviours, and accident type as an output variable. Also, safety monthly inspection records, accident cases, and their corresponding monthly project-related attributes were used (Poh *et al*., 2018).

Another approach was to collect data through a structured template (Ayhan and Tokdemir 2019); the templates consisted of six categories for accident causes: human factors, workplace factors, the course of an accident, and time of occurrence.

To sum up, the collected data can be different in its structure (i.e., labelled or unlabelled), the type of injury (fatality, near-misses, accidents), sources (single or multiple companies, national registries).

In terms of data volume, less data than what was available in national sources in most cases as manual labelling is challenging and time-consuming – but there were cases where the data was, indeed, manually labelled (Zhang 2019, Zhong *et al.,* 2020).

It will be seen that the use of pre-structured data provided for clearer definitions of the input features at the early stages of the development of the ML models, which in turn leads to a better understanding of the features that guide the accident analysis.

Data pre-processing

Many of the reviewed studies highlighted an essential step in the development, training, and utilization of the ML constructs, the pre-processing of data – i.e., trying to formulate and represent the data in a way that better fits the modelling and algorithmic structure of the ML system (Shehab *et al*., 2021). Data pre-processing can be therefore considered an important step when analysing data for its subsequent use in ML based analysis. It can help in terms of improving the time taken for the analysis, the utilization of resources, storage, efficiency, and even the output gained information (Shehab *et al*., 2021).

As such, challenges related to data characteristics (mentioned in the previous subsection) also tie with challenges in handling and pre-processing the data. Two main themes were found in the reviewed literature; the methods of textual data pre-processing and an element related to the difference in frequency of accident severity. In particular, the first theme considered the dominant pre-processing steps in textual data processing, including stop word removal, tokenization, and word embedding. However, the authors differ in using dictionaries and natural language processing (NLP) algorithms.

Word embedding uses different types of algorithms such as Word2Vec (Zhang 2019), Wikipedia Global Vector for Word Representation (GloVe) (Cheng *et al.,* (2020) and BERT (Zhang *et al.*, 2020). These types of word embedding algorithms are usually trained using generic corpus but can also be retained with domain-specific corpus (Zhang 2019, Zhang *et al.*, 2020). Other domain and language related dictionaries were used in the tokenization process Korean accident reports (Kim and Chi 2019) and lexical and syntactic data analysis using Chinese Language technology platform (LTP) (Xu *et al.*, 2021b).

Compared to the NLP toolkit, the LTP integrates the functions of text parsing and graph based syntactic dependencies (Xu *et al.*, 2021b). Zhang *et al.*, (2020) used BERT as a text pre-training algorithm instead of Word2vec algorithm for being more efficient in handling text multi-meaning. BERT as a method addresses the problems associated with word sequencing and multiple meanings. The method developed by Kim and chi (2019) consisted of developing a construction accident thesaurus in order to capture words and their synonyms or the unique representation words that are usually used in a construction-related context. In addition to that, the Word2vec algorithm was used to estimate the meaning of words in different contexts and find semantic relationships (Kim and chi 2019).

Alternatively, Baker *et al.,* (2020b) used parts of the data that were not used to train the ML model to pre-train the word embedding algorithm, which provides an advantage to use a word embedding that used domain-related vocabulary. Cheng *et al.,* (2020) performed the word embedding with a Wikipedia Global Vector for Word Representation (GloVe) algorithm. GloVe is an unsupervised ML step quantizing words into vectors (pre-trained databases in the GloVe website that is open for the public, such as the Wikipedia database, consist of 6.109 words and 100 dimensions).

The word embedding also exist in different modes such as the continuous bag of words (CBOW) and the skip-gram model. By testing both modes, the authors deemed the skip-gram model more suitable for accident report narratives because the latter may contain sparse text features (Zhong *et al*., 2020). The data pre-processing might also include text feature extraction (Fang *et al.,* 2020, Ma *et al.,* 20201, Tang et sl. 2021), or manually labelling the accident reports (Zhong *et al.*, 2020). The extraction of safety factors by the identifying the key words by using term frequency–inverse document frequency TF-IDF (Ma *et al.,* 20201) and manually assigning attributes to the identified risk factors (i.e., location, work type, accident causes, and results) (Ma *et al.*, 20201, Tang et sl. 2021). Feature extraction from textual reports was done by a ready NLP algorithm specially developed for industrial, infrastructure, and mining domains (Baker *et al.,* 2020a).

The second theme related to data pre-processing within the reviewed literature was found in the data. This featured classes with a considerable variation in the number of instances they include, most notably fatal accidents as opposed to other groups of accidents (so-called "unbalanced" classes). Such variation imposes a particular challenge in ML based analysis because the model's training tends to misclassify the sparsely populated class simply because it is harder to recognize than the more populated class. Frequency variation in the data has been found in classes including injury severity, energy type involved, causes, accident types, and body parts injured, which all affected the classification accuracy performance as described in section 3.4.

There had been multiple methods for managing the class imbalance for the ML model training step (see Table 1). One is to merge the serious and very serious accidents in one category and then apply SMOTE (Synthetic Minority Oversampling Technique) to the severity and all available factors in the data (Zhu *et al.*, 2021, Poh *et al.*, 2018). Zhu *et al.*, (2021) argued that SMOTE is better than random oversampling (ROS) as it adds artificially synthesized samples and does not risk overfitting. Another approach was to manually label additional reports of the less frequent class for obtaining a more balanced sample (Zhang *et al*., 2020, Zhang 2019). There is a need for clarity in additional labelling decisions as is not justified why these proportional additional cases were used or when classification categories frequencies are enough for a data set to be considered balanced.

Other suggested methods were random oversampling (ROS), random under-sampling (RUS), and SMOTE. ROS was chosen as the best method because it better fit with the categorical values in the dataset (Choi *et al*., 2020). Kang and Ryu (2019) used RUS, which is a method that reduces the major classes, which resulted in a reduction of the data sample from 9795 to 6374 accident reports. Finally, class imbalance can be handled by assigning weights to the minority classes in the training set (Baker *et al.,* 2020a, Baker *et al.,* 2020b). Few authors did not apply any resampling techniques (Fang *et al.,* 2020, Cheng *et al.,* 2020, Shrestha *et al.,* 2020, Zhong *et al.,* 2020). However, Cheng *et al.,* (2020) argue that balancing techniques are possible improvements to explore rebalancing together with Recurrent neural network algorithms (RNN).

Half of the reviewed articles used a type of data balancing method, which was almost equally distributed within the literature (ROS, SMOTE, RUS, Inversed proportional weights, and manual labelling). There are brief justifications for the choice of methods, but further exploration of the consequences of the method selection is needed. Moreover, word embedding algorithms (BERT, Word2vec, and GloVe, LTP) and word embedding pre-training with domain-related data (Baker *et al.,* 2020b) stand out as variations of the chosen methods. Extracting features that characterize the accident case and the risk factors from continuous text had been highlighted in the literature, which is mostly a manual process that needs the understanding of accidents and bounded by how accidents are described.

Algorithm type and training the ML model

The analysis of accident reports is mainly treated as a classification task in the reviewed literature – i.e., classification of accident type, severity, and causes. Given this observation, the literature can be classified based on the type of analytical algorithms used, namely deep learning, supervised, unsupervised, and data mining algorithms.

Deep learning was represented by using different variations of deep neural networks, including the convolutional bidirectional long short-term memory (C-BiLSTM) (Zhang *et al.,* 2020, Zhang 2019), Symbiotic Gated Recurrent Unit (SGRU) (Cheng *et al.,* 2020), Bidirectional Transformers of Language understanding (BERT) (Fang *et al*., 2020), feed-forward CNN (Baker *et al*., 2020b) and artificial neural networks (ANNs) (Ayhan and Tokdemir, 2019). The choice BiLSTM of was based on the superior performance in extracting information from the text and for examining information before and after the word and thus better understanding the context of the text (Zhang *et al.*, 2020). The SGRU is a variant of long short-term memory LSTM but more computationally-efficient and combined with an optimization algorithm for parameter optimization of the neural network (Cheng *et al*., 2020). The BERT algorithm used for better text classification and generalization than RNN and CNN and the unique attention mechanism, allowing for a single representation related to different text positions within the algorithm structure (Fang *et al.,* 2020). Baker *et al.,* (2020b) experimented with different algorithms, including feed-forward CNN, Hierarchical Attention Network (HAN), and Term Frequency - Inverse Document Frequency representation (TF-IDF) +Support Vector Machine (SVM). The HAN was explained as a state-of-the-art algorithm with two steps of self-attention mechanisms in which the most important words in a sentence are identified and then the most important sentences Baker *et al.,* (2020b).

A significant proportion of the reviewed literature revealed a preference for experimenting with multiple supervised ML algorithms to find the algorithm that provides the best accurate output for classifications or predictions. The most used algorithms are random forest (RF) (Poh *et al.*, 2018, Kang and Ryu 2019, Baker *et al.*, 2020a, Choi *et al.,* 2020) and support vector machine (SVM) (Poh *et al.,* 2018, Zhang *et al.*, 2019, Baker *et al.,* 2020a, Shrestha *et al.,* 2020, Zhu *et al.,* 2021). The SVM, XGBoost, and RF were used as state-of-the-art algorithms (Baker *et al*., 2020a). While linear (such as logistic regression (LR) and AdaBoost) or nonlinear (such as and RF) algorithms were considered interpretable or show feature importance (Choi *et al*., 2020). The conditional random fields (CRFs) algorithm was used for the effectiveness in labelling information from textual data and considering the sequence of a sentence (Kim and Chi, 2019).

Unsupervised ML algorithms were used to group accident reports by applying the K-means clustering algorithm (Mo *et al*., 2018). The algorithm application was paired with the theoretical framework of sociotechnical systems and game design elements. The Latent Dirichlet Allocation (LDA) as a topic mining and corresponding word occurrence method and was combined with CNN for processing unlabelled data (Zhong *et al*., 2020). Apriori rule association algorithm was used to mine safety risk factors (Ma *et al*., 2021) and accident-related attributes (Tang *et al*., 2021). The Apriori algorithm was deemed suitable for providing safety recommendations based on the association rule properties (Tang *et al*., 2021).

In summary, multiple algorithms were used to analyse accident reports which indicates that there is not universal agreement on the most suitable algorithms for accident analysis in construction. The choice of algorithm depends on the type of the data and the problem the ML model is expected to solve. Although there is no common criteria with which to determine the best choice of algorithm, it is worth noting that deep learning algorithms especially CNN and variations of LSTM were prominent and used in almost half of the reviewed studies. The second most used algorithm is the RF followed by SVM and finally data mining.

Testing algorithm performance

The generalization capability of a ML algorithm is usually evaluated using an unseen split of data (Riccio *et al.,* 2020). This split is referred to as the test split and is not used during model training or hyperparameter tuning and validation (Riccio *et al.*, 2020). The testing of a classification algorithm is used to evaluate how well the algorithm classifies the target after the training step and distinguishes which of the compared algorithms performs better against each other for performing the same task. In this section, algorithms performance is presented with the ML model purpose or the problem that it was designed to solve.

The measurements are variant for testing evaluations. The most frequently used is the weighted average F1 score (Kang and Ryu 2019, Kim and Chi 2019, Zhang *et al.,* 2019, Zhang 2019, Zhang *et al.,* 2020, Cheng *et al.*, 2020, Shrestha *et al.,* 2020, Zhong *et al.,* 2020, Zhu *et al.*, 2021, Ma *et al.*, 2021); mean F1 score (Baker *et al.,* 2020a, Baker *et al.,* 2020b); accuracy (Poh *et al.*, 2018, Fang *et al.*, 2020); Mean Absolute Average Percentage Errors (MAPE) (Ayhan and Tokdemir 2019); Area Under the Receiver Operating Characteristic Curve (AUROC) (Choi *et al.,* 2020, Kang and Ryu 2019), precision (Xu *et al.*, 20201b).

Almost always, the advanced deep learning algorithms outperformed other supervised ML algorithms (ex. SVM, NB, LR, KNN, DT) and simple deep learning ones (LSTM, GRU, CNN) (Zhang 2019, Cheng *et al.,* 2020, Zhang *et al.,* 2020, Zhong *et al.,* 2020). The weighted average F1 score is a better performance metric than a single F1 score, primarily when the data is characterized by class imbalance (Zhang *et al*., 2020). It is worth mentioning that the experiment depended on the parameter tuning of the word embedding step using unigrams, bigrams of two different dimensionalities, and the results showed that bigrams are constantly superior (Zhang, 2019). Moreover, testing BERT compared to other deep learning text classification algorithms for near-misses classification had the advantage of a pre-trained bi-directional network with an altered architecture and achieved 86.9% accuracy (Fang *et al*., 2020).

For the same data set as Baker *et al*'s. (2020a), HAN for body part classification had the best performance metric of 86.97 mean F1 score (Baker *et al.,* 2020b). Moreover, CNN was used and tested against other algorithms (see table 1) and combined with the Apriori algorithm as part of an integrated analysis framework to identify project safety risk factors (Ma *et al.*, 2021). With ANNs, 70% of the data was predicted with zero error. However, although the fatalities were predicted with 100% accuracy, the testing dropped by 50% in testing the algorithms (Ayhan and Tokdemir 2019).

NLP was applied to extract the causes of accidents and the objects which contributed to the accidents (Zhang *et al.,* 2019). Multiple classification algorithms were tested, and the best was an ensemble one with an average F1 score of 68%. This performance was considered low (Zhang *et al*., 2019), and the authors attributed that to natural language not being precise and to the difficulty of developing comprehensive rules to cover all meanings of different expressions (Zhang *et al.,* 2019, Xu *et al.,* 20201b). The CRF algorithm was used to classify accident reports and extract information from the reports with an average F1 score 0.8 (Kim and Chi, 2019).

The RF outperformed other classification algorithms, such as, indicatively, SVM, KNN, and AdaBoost (Poh *et al.,* 2018, Choi *et al.*, 2020). The classification by Poh *et al.*, (2018) into "No accident," "Minor accident" and "Major accident" achieved an accuracy of 78%, while in Choi *et al.,* (2020), the value of the Area Under the Receiver Operating Characteristic Curve (AUROCC) metric was 0.9198; this was considered as satisfactory, as the ideal value of AUROCC is 1. The RF algorithm was used and evaluated both with averaged F1 score and receiver operating characteristic (ROC) curve (Kang and Ryu 2019). On the other hand, compared with RF and XGboost, and among the different classification targets, the best performance was obtained in classifying the injury severity with the SVM (mean F1 score 59.02) (Baker *et al.,* 2020a). SVM was applied as a single algorithm to classify injury severity with a 0,85 F1 score (Shrestha *et al.,* 2020).

Zhu *et al.*, (2021) evaluated both the original and the adapted SMOTE data sets (see data pre-processing section) for comparing the evaluation metrics in accident severity prediction. The results showed that SMOTE demonstrated a slight improvement in the testing, but the authors found the SMOTE method prone to overfitting (Zhu *et al.*, 2021). The best F1-score was achieved by the AutoML, followed by LR and NB. The suitability of LR and NB explained this algorithm's performance in a binary classification (small and large accidents) (Zhu *et al*., 2021).

An observed pattern in the reviewed literature relates to the misclassification of the less populated classes. Although the averaged F1 scores might indicate acceptable performances for the tested algorithms, the low F1 scores of the single classes are as important. The misclassification of minority classes of accident severity, accident type, and accident causes was a challenge for few of the reviewed literature. For a single cause classification (collapse of an object), the model did not perform as well (66% F1 score) (Zhang *et al.*, 2020). These instances were found to have unique occurrences and characteristics and were manually sorted (Zhu *et al*., 2021).

The classification of accident categories of "caught in between objects" and "collapse of an object" had the lowest accuracy. The authors explain this because the "caught in between objects" was a relatively minor category than the other labels (Zhang, 2019). The CNN algorithm confused falling object type of accident as a moving object one because of the similarity in the word vectors of the two accidents, while the "electrocution" category had lower F1 score compared to other classes because of the less frequent accident data in this category (Ma *et al*., 2021). Compared to SGRU and for some of the classes, other algorithms had an F1 of zero (Cheng *et al*., 2020). The single F1 score for some accident labels in Zhong *et al.*, (2020) was low such as "Struck by falling object" (0.35 F1 score).

To sum up, there are variations in the used performance measures. The variations in the data, data pre-processing, training algorithms, and the testing measures, make a fair comparison challenging. In turn, it is harder to draw conclusions about which algorithms are better suited to apply in accident-related domains especially that there are not enough studies nor uniform methods. Furthermore, the difference in frequencies was found in severity, accident types, or causes is unique to the accident domain since it was found recurrent, and accidents happen stochastically. The variance in frequencies showed a high impact on the development and evaluation of ML models.

Implementation of ML based analysis

Model usage is one of the most central ML development processes (Bilal and Oyedele 2020). The reviewed literature presents two types of propositions to use ML based models in the analysis of accident reports. Models within the literature which suggested a possible use of the ML analysis results might be labelled as conceptual propositions, while those suggesting a precise implementation for ML based data analytics was termed a prototype.

One such prototype was proposed for information retrieval and knowledge extraction (Kim and chi, 2019). In this case, the authors assigned semantic roles for the elements that characterize the accident and defined the roles as predicates (i.e., "accident result," effector "hazard object," location "hazard position," and purpose "work process"). Another model was presented as an integrated framework of accident type classification, feature raking and calculating the cascading effect on project tasks based on the effect the risk factors have on the time of a task (Ma *et al*., 2021). A similar approach was implemented as a rule-based safety recommendation that was developed based on the safety management and known causes integrated with data mining of accident causes (Tang *et al*., 2021). The latter requires the interpretation of experts for the recommended safety instruction while an expert survey showed a positive response in terms of benefit to the management of safety (Tang *et al*., 2021). Accident reports and ML clustering were used together for virtual reality (VR) safety training scenario generation (Mo *et al*., 2018). The grouping of variables created potential accident scenarios that could be built into the VR training environment.

On the other hand, a decision-making scheme, based on the ANNs predictions and expert opinions fed to a fuzzy decision scheme qualifies as a conceptual implementation (Ayhan and Tokdemir, 2019). In this case, the decision categories depended on the predicted severity. If the decision-making scheme predicted a fatality, Ayhan and Tokdemir (2019) suggested that the construction should stop until an investigation is thoroughly done to eliminate the danger. Another implementation was suggested to predict risks for projects and individuals based on information about gender, age, experience, construction type, employment count, day of the week, and month (Choi *et al*., 2020). The proposition assumes that this information could be retrieved at the construction entrance terminal. Zhu *et al.,* (2021) recommended using the RF prediction rules for accident severity prediction to assess occupational risks and prevent injuries.

Another usage suggestion for a RF model prediction was as a leading indicator for high-risk projects in the company (Poh *et al*., 2018). Baker *et al.,* (2020a) and Baker *et al.,* (2020b) proposed using severity and accident type classification by practitioners who do safety planning. The model is argued to be suitable for safety planning by identifying the task, tools or equipment, and working circumstances (Baker *et al.*, 2020a, Baker *et al.*, 2020b). Another proposition was to use the classification of incident reports as part of a digital strategy to help managers extract information about near misses and increase awareness and learning on-site (Fang *et al*., 2020).

Kang and Ryu (2019) proposed the ML model as a prediction model for accident types but few ML models considered within the literature were developed to classify the accident reports with labels related to the accident causes (Zhang 2019, Zhang *et al.,* 2019, Zhang *et al.,* 2020, Zhong *et al.,* 2020). Shrestha *et al.,* (2020) formulated the ML classification into a framework of upstream precursors linked to accident type, energy source, and severity. The latter factors are supposed to be solved accident hazards at the design phase.

The literature showcases promising suggested implementation for applied ML in construction accident reports. However, it can be found that only a few propose a concise prototype. Moreover, the complexity and constraints of the context for implementing ML based analytical models should be considered given the domain specific complexities associated with the construction industry noted previously - but this is scarcely done in the existing literature. For example, solving hazards at the design stage would probably influence the design process and the involved professionals. Alternatively, extracting knowledge from the collected report text would first require a domain specific design for an information extraction application.

DISCUSSION

This section intends to analyse the previous layout of the literature specially to answer the research question: what are the requirements of a ML based analytical model using accident report data if it is to be implemented a representative contracting company? The analysis was designed backwards to respect the structure of the paper, first discussing the implementation of ML based analytical models and ending with the data characteristics.

By analysing the current literature on the application of ML based analysis of accident reports within the construction industry context, it is found that several purposes for ML based analysis were presented. ML based analytical models were suggested for prediction, classification, clustering, and information retrieval. Only four prototypes were presented (Kim and chi 2019, Mo *et al.,* 2018, Ma *et al*., 2021, Tang *et al*., 2021). The implementation of ML based analysis is best presented as a prototype because it makes room for spotting potential improvements or any functionality problems.

One of the examples that Kim and Chi (2019) presented showed that there is more than one consequence other than the injury - such as damage to infrastructure and material - while only one consequence was extracted from the accident report. This indicates that the labelling and classification of accident components are highly dependent on the labels that specialists assign to them. The same observation can be made in rule-based data mining examples (Tang *et al.,* 2021, Xu *et al.,* 2021b, Ma *et al* .2021). More risk factors and consequences could be hidden within the text but not extracted which is related to several factors such as the limitations in manual labelling (Zhong *et al*., 2020), defined extraction rules (Tang *et al.,* 2021, Xu *et al.,* 2021b), or the technology of NLP (Zhang *et al.,* 2019, Xu *et al.,* 2021b).

Other implementations and observations involve the utilization of safety recommendations that are extracted from the data. For example, the decision to stop construction to investigate a predicted accident (Ayhan and Tokdemir, 2019), or to make sure that the safety management-level is sufficient (Tang *et al*., 2021). To stop construction and investigate is worth it even if at a 50% chance that that would prevent a fatal accident but, in such case, an algorithm that allows for factors ranking and interpretability is better preferred to ANNs. Furthermore, predictions involving worker's information might raise ethical concerns that need to be taken in consideration (Choi *et al*., 2020). Generally, the recommendation provided by knowledge extraction of task-safety-risk-factors is one important ML contribution. But to expect that the ML based recommendations for safety as intuitive and easily implemented by practitioners, is not realistic. Elements of digitalization and change management research are options to evaluate the adoption of ML models.

Overall, the implementation of ML based models would benefit from feasibility and implementation analysis and the involvement of practitioners. Ideally, for applied ML models, task definition and its expected use, together with listing all assumptions are crucial to the successful implementation of ML based analytical models (Bilal and Oyedele 2020). On the theoretical level, there is a need for conceptual implementation frameworks such as ones that shift the focus from centralized computing platforms to overall systems of real time decision support (Chen, 2020).

Testing the performance of algorithms is particularly crucial for the successful implementation of ML in the field of occupational construction safety. The reviewed literature showed that mostly averaged F1 score was used in 11 out of 19 articles. However, the class imbalance appears on multiple occasions where even with a relatively high average F1 score, the algorithm misclassified single minority classes. This leads to the question as to whether the averaged F1 score is the best measure to measure classification performance in the applied ML to accident reports analysis. Gholizadeh *et al.,* (2018) proposed using the ROC as a ML performance measure to visualize different combinations of errors. Gholizadeh, suggested that choosing the ML classifiers that have lower error rates for a particular class is costly from a safety perspective (such as severe injuries). The experiment also highlighted the benefit of ROC in maximizing the prediction accuracy of minority classes in unbalanced data sets in the construction accident reports data (Gholizadeh *et al*., 2018).

The second question arising from the class imbalance then concerns the accepted level of accuracy to use the prediction models in real-life decision making. As mentioned earlier, a fair comparison for algorithm performance is not possible. This is the main reason for not making conclusions regarding which algorithm achieves the best performance. However, practitioners, safety experts, ML developers, and other stakeholders need to collaborate to set the requirements for ML implementation in terms of accepted performance levels.

In the reviewed literature, many different algorithms have been adopted in studies with broadly the same purpose. The stated purpose is mainly to enable improved prevention of accidents. More than 30 different algorithms were distributed across the 19 reviewed studies. The most used algorithms are SVM (10), LR (7), RF (5), DT (5), NB (6), KNN (6), and, followed by 12 others and variation of CNN and LSTM deep learning algorithms. Eleven studies used more than three algorithms. However, it is difficult to establish why and how specific algorithms were used. The series of adopted algorithms is not consistently accompanied with proper justification of the selected algorithm but appears to be a result of different experimental approaches. The different algorithms have been internally tested on the given dataset and, in many cases combining more than two algorithms. This experimental approach and using a combination of algorithms is a shared property with other machine learning studies (e.g., Portugal, 2018).

The review showed a promising application of deep learning algorithms (e.g., BERT, C-BiLSTM, SGRU, HAN). However, the benefit of applying deep learning as opposed to other ML algorithms is yet to be established. The word embedding theme in data pre-processing is to train word embedding algorithms with domain specific corpus capture domain specific terminology more efficiently. However, it is challenging to argue for a clear and consistent algorithm choice because a comparison would not reveal much about the ML models due to differences in the data sources, pre-processing, and applied algorithms' variations. This hinders the process of drawing conclusions about the performance of ML and the applicability of ML based analysis in safety processes.

As noted earlier, the data characteristics of the source, volume, and format differs considerably between the reviewed articles. Also, there are differences in the pre-processing stage, which is the step that sets the basis of the entire following analysis. By analysing the literature, it can be noted that the data can be different in the structure (i.e., labelled or unlabelled), the type of injury (fatality, near-misses, accidents), or the data source (single or multiple companies, national registries). There are brief justifications for choosing the pre-processing methods, but more these explanations need further elaboration in order to understand the consequences of the methods, especially if the final ML interpretation is to be valid and closer to practice.

The critique of the notion of “unbalanced” when resampling lies in the implicit assumption that a phenomenon should generate balanced datasets, but this is not the case in the causes, types, and consequences of accidents. The methods of ROS, RUS, SMOTE and labelling more instances to balance the dataset imply that the ML designer moves into an unknown ground by assuming similarities in different parts of the studied phenomenon. Future conceptual development of ML for accident analysis needs to investigate ways ML based analysis can understand accidents with the raw data. And reflecting on the consequences of using resampling methods. Zhu *et al.,* (2021) insight into the proneness of the SMOTE method to overfit indicate such consequences especially at the performance evaluation stage. The identified problems in data pre-processing are specific to the context of accidents in the construction industry and require further investigation.

CONCLUSION AND FUTURE RESEARCH

This article has endeavoured to explore the possible requirements for the development of a ML analytical model that might be implemented to improve occupational construction safety. The review and analysis of the literature on applied ML on accident reports show there are multiple purposes for using ML based models including the classification of accident causes, accident type and consequences, prediction of severity, and extracting information from textual accident reports.

The main limitation of this research is the narrowly targeted focus that resulted in only a limited number of papers to be reviewed. Four main prototypes were presented, the extraction of accident elements, risk assessment on the project schedule, rule-based safety recommendations, and VR safety training scenario generation. Few conceptual propositions were also presented as decision-making schemes when the ML based models predicted severe accidents. However, applying ML in the construction industry, would benefit from incorporating a standardized development method.

Most importantly, applying ML based analytical models in the construction industry for accident prevention purposes depends upon a clear definition of the ML task, its intended use and associated ethical concerns. Moreover, interpretable ML algorithms are better suited to interpret safety recommendations. Such developments might lead to a clarification of methodologies in terms of pre-processing and ML algorithm employment. As the literature on ML analysis demonstrates, developing ML based analytical models without careful feasibility studies and the involvement of relevant stakeholders has a noticeable negative impact on the methodological choices of data pre-processing, algorithm choice, ML performance evaluation, and context constraints. This is probably a general requirement that ML applied models in any domain should satisfy, but from a safety angle, this requirement is strictly necessary in the domain of construction.

Regarding accident reporting in construction industry, the differentiated frequencies relating to the severity, the accident type, and the causes stand out as problematic. This variation in frequency creates a need to use specific ML performance measurements such as ROC. This was found to maximize the prediction accuracy of minority classes while F1 score showed to be low for single class classification. Moreover, the review has suggested that future empirical research should consider whether domain specific dictionaries should be used in word embeddings in the pre-processing stage. Finally, the review suggests that a ML model performance threshold needs to be agreed amongst the industry-specific interests and stakeholders. Further research could usefully carry out implementation studies on safety processes and management in construction companies. Of particular interest in such studies would be frameworks of integrated centralized computing platforms that are constantly fed with real time accident report data. From a methodological point of view, more experimental studies are needed to in order to draw firmer conclusions about the best ML methods to fit the domain specific context.

ACKNOWLEDGMENT

This article and the research behind it are supervised by Christian Koch and Dimosthenis Kifokeris. I would like to thank my supervisors for their support and guidance in directing this paper. This research is part of a Ph.D. project aiming at applying machine learning to accident reports in Sweden. The project is funded by SBUF (Svenska Byggbranschens Utvecklingsfond).

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Paper II

A COMPARISON OF ACCIDENT CAUSATION MODELS (ACMS) AND MACHINE LEARNING (ML) FOR APPLIED ANALYSIS WITHIN ACCIDENT REPORTS

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Machine learning (ML)-supported accident prediction models appear as an alternative to the much older accident causation models (ACMs). ACMs represent a simplification of accident processes and resulted loss and play an important role in accident investigations and identifying potential risk factors. This effort investigates ACMs and ML results of accident reports analysis in relation to each other and aims at comparing the latter based on their level of causes, the relationship between causes, and the predictability of severity. A framework of understanding of these main processes and their challenges is provided, which is also used as a methodological framework for the comparison. The comparison is based on a desk study of literature and material on the two types of models. ACMs are different in typology, levels of causes, and the logic through which the analysis of the events that have taken place is conducted. Many ML prediction models in construction not only provide predictions but also result into structures of features which work as predictors, e.g., decision trees. ACMs and ML are different in the task they perform. ML models in the literature are focused on predicting the severity of an event while missing the identification of prevention measures. ACMs focus on the occurrence of unwanted events and lack the ranking of important features. Finally, ML analysis of accident reports need ACMs as a theory to shift focus to risks instead of severity, while interpretable ML algorithms (e.g., RF) appear more capable of complex representations of contributing factors. An unsolved issue is the random element involved in most accident processes.

Keywords: accident causation model; machine learning; occupational accident

INTRODUCTION

Recently, there has been a noticeable increase in the number of publications about the topic of ML in the construction industry, including occupational accidents and safety during construction (Xu *et al.,* 2021), and structural health monitoring and job safety management (Hou *et al.,* 2021). This trend was also observed in publications on applied ML for the analysis of archival data and surveys of work-related accidents (Sarkar and Maiti 2020). On the other hand, accident causation models have guided analysis and learning from accidents for many years. ACMs play an essential role in

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Shayboun, M, Koch, C and Kifokeris, D (2021) A Comparison of Accident Causation Models (ACMS) and Machine Learning (ML) for Applied Analysis Within Accident Reports *In:* Scott, L and Neilson, C J (Eds) *Proceedings of the 37th Annual ARCOM Conference,* 6-7 September 2021, UK, Association of Researchers in Construction Management, 289-298

identifying causes and processes in which events take place (Kjellen and Albrechtsen 2017, Fu *et al.,* 2020).

ML and ACMs have been equally criticized. ML was found to be shortcoming in interpretability, data quality concerns, the need for concrete use cases and the lack of required integration with domain and expert knowledge (Vallmuur 2015, Bilal *et al.,* 2016), as well as generalizability (Xu *et al.,* 2021, Sarkar and Maiti 2020). ACMs are different in typology and levels of analysis and have been questioned in terms of their components, accident path representation and their applicability (Fu *et al.,* 2020).

So far, the literature on ML applications within the domain of accidents reports has been focused on analysing and experimenting with algorithms without the perspective of ACMs as a theorical lens. The role of the theory of ACMs is not being adequately addressed in the current literature. The structure and components of ACMs provide attention to the important factors for prevention purposes and guide the process of ML analysis and use cases. Similarly, ACMs have not been examined in relation to the contribution of ML applications in understanding accidents. The availability of large volumes of data has the potential of not only unfolding causes behind accidents but also contributing to the development of added value to ACMs. Therefore, this research will investigate the role of ACMs as a theoretical framework for the ML results of analysed reported accidents in the construction industry, as well as what can be learned about ACMs from ML. We conduct a comparative desk study of the literature covering ML application to accident reports in the construction industry and ACMs in terms of their level of causes, the relationship between causes, and the predictability of severity. This will contribute to conceptualizing ML models in the lens of ACMs.

METHOD

The article is based on a desk study of the literature of applied ML in the analysis of construction accident reports and ACMs. The literature review and discussion were done in a synthesized problematization method (Alvesson and Sandberg 2011). The ML models are based on a literature review and the systemization of the purpose of the ML, the included features, and the ranking of important factors. ML has been applied for the prediction of severity, the classification of accident causes, and the extraction of information from textual data. The themes are presented for an in-depth analysis. ACMs were selected based on crossing the models which were reviewed by Kjellen and Albrechtsen (2017), Fu *et al.,* (2020) and Woolley *et al.,* (2019). Three models were selected, based on the types of ACMs and their common application in the construction industry.

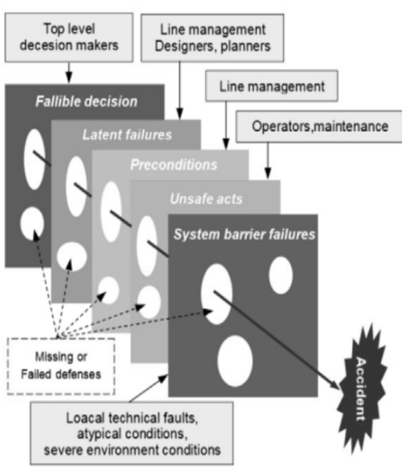
Accident Causation Models

ACMs are simplified representations of the process in which risk result in accidents and loss (Kjellen and Albrechtsen 2017). ACMs have been used in accident investigation and analysis to uncover how and why accidents happen. In the construction industry and in occupational accidents contexts, there are a few models that have been commonly applied. Woolley *et al.,* (2019) reviewed the most common accident causation theories in the building industry. The review revealed that linear models are more dominantly used in the construction context when compared to nonlinear system-based models. The linear models included ones such as the Domino Model. The models that the Woolley *et al.,* (2019) refer to as complex linear and organizational factors-related, include the Swiss Cheese Model (SCM), and the Systems Model of Causation.

Hopkins (2014) reviewed the paradox of major accident investigations. The author distinguished between two meanings of accident causes: sufficient causes and necessary ones. Necessary cause or the but-for one is the factor that without having existed, an accident would not have happened. Moreover, Hopkins (2014) illustrated that most ACMs are formulated within this logic (such as the SCM) and that the but-for logic works best with technical factors, but it becomes harder to assign a necessary cause with organizational distant factors because they are subject to expert judgement. Woolley *et al.,* (2019) also found that distant regulatory and association's related factors were not present in the construction context. Although accident analysis is done for the purpose of learning, they do not seem to be designed to make recommendation for future accident prevention, nor do they identify relationships between company, management, and staff levels as higher levels of causes. This article will focus on the SCM as a linear model, and the Bow-Tie model as energy-based model (Fu *et al.,* 2020).

The Swiss Cheese Model (SCM)

SCM (Reason 1997) is an energy-based model, according to the classification of Kjellen and Albrechtsen (2017), but categorized as a linear model in the review by Fu *et al.,* (2020). A linear model is one that consists of stages or levels of causes and corresponds to a chain of logical sequence that can be clearly examined. The paradigm of SCM (see Fig 1) explains accidents by giving an understanding of event occurrence through barrier failures all the way, starting from organizational factors to unsafe acts. Errors and violations function as active failures at the end of the system, while the latent conditions are the ones that exist but are undetected because the barrier had not been activated. The logic of the SCM is that accidents happen when a combination failure exists on all levels together at once. If a barrier was active at one of the levels, the accident could have been prevented. The first level starts with top level decision makers, followed by designers and planners, line management, operations and maintenance, and local faults (Fu *et al.,* 2020).



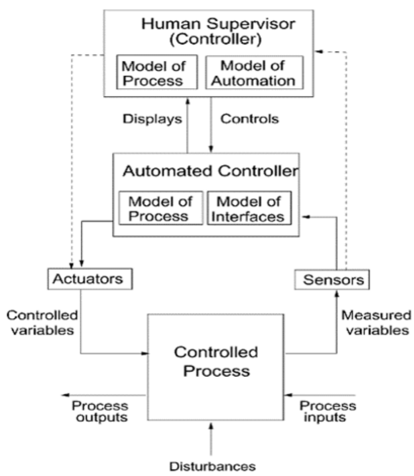


Fig 1: SCM, Fu et al., (2020) *Fig 2: STAMP, Fu et al., (2020)*

Systems-Theoretic Accident Model and Processes (STAMP)

The STAMP model (see Fig 2) is known to belong to the system-based causation models (Kjellen and Albrechtsen 2017), and is categorized as nonlinear (Fu *et al.,* 2020). This model's paradigm views accidents as being caused by dynamic equilibrium of system control that exist within an adaptive socio-technical system (Leveson 2004). The model consists of three key components (constrains, control loops and process models, and socio-technical levels of control) (Leveson 2004). Constraints are enforced throughout the interactions of the hierarchy of the system's operations and travel downwards for operation control. Moreover, the model is characterized by feedback loops that travel upward through the levels of the hierarchy of the system. The levels of system included are inspired by Rasmussen's (1997) socio-technical system models but with adding a parallel side that is concerned with system development beside the system operation. Accidents in the STAMP model are caused by failure at one of the main components of the models: either safety constraints are not adequately enforced (which might be influenced by a lack of proper control and process plan, or inadequate coordination), or accidents can be caused by inadequate control execution or feedback information (Fu *et al.,* 2020).

The BOW-Tie Model

The BOW-Tie model (see Fig 3) is a practical analysis model. The model analysis starts by identifying a hazard that exists in the organization or the surrounding environment. The hazard is in central connection to the second component of the model, which is the top event that is at the centre of the BOW-Tie. The model is built around this top event as threats and consequences should be identified. Accordingly, prevention barriers are then identified on the left side of the top event to combat their corresponding threats. In the same fashion, recovery barriers are placed after the top event. Threats are defined as whatever causes the top event to occur, and the more elaborate the analysis of threats, the more consequences are taken in consideration. The model suggests that barriers prevent the threat from causing the top event to happen, or in the case of that happening indeed, the consequences could still be prevented (Fu *et al.,* 2020). Interestingly, the model does not assume that prevention barriers always function, but there might be a failure that is caused by an escalation factor.

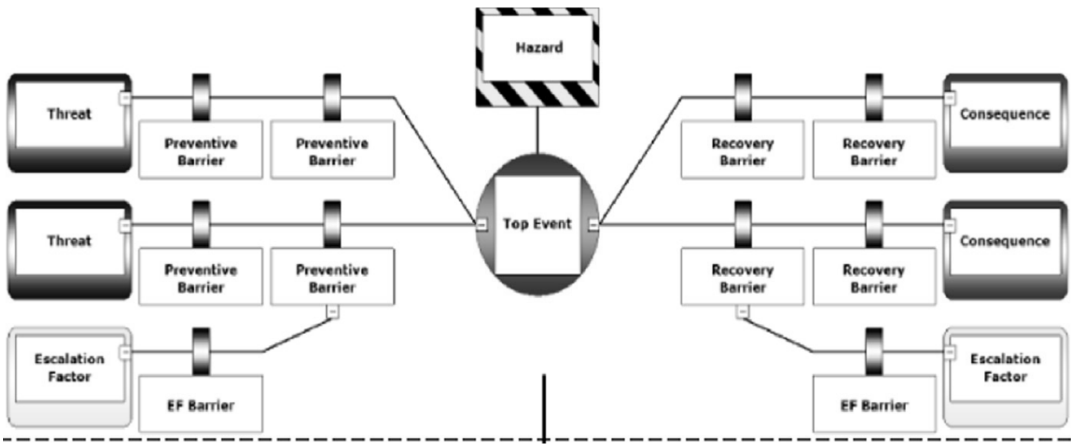


Fig 3: BOW-Tie, Fu et al., (2020)

The three chosen models represent a variety of common models in accident causation and understanding. The SCM is levelled and assumes failure on all levels to cause the accident. The BOW-Tie model assumes failure to prevent a particular threat to cause the accident. The STAMP model is more procedural and assumes that safety constraints and feedback loops are needed to be enforced to prevent hazardous events.

Machine Learning and Accident Data Analysis

The purposes of ML analysis within the domain of accident reports can (based on our conception) be divided in two different categories: A classification of accident severity, and a classification of accident type and information retrieval. The predictive ML models in both categories are further analysed below in terms of the purpose of the model, algorithms they utilized, the factors that were involved in the ML modelling, and their importance ranking compared to the output variables. The results of the review are summarily presented in Table 1.

Classification of Accident Severity

ML algorithms

Shrestha *et al.,* (2020), analysed the accident reports using ML as a method for the classification of severity and accident-related features. The multiclass support vector machines (SVM) and the results were organized into four different categories (upstream precursors, energy source, accident type and injury severity) (Shrestha *et al.,* 2020). Zhu *et al.,* (2021) used accident investigations which were organized into six subsystems, 16 factors, and 39 subfactors (see Table 1). Ayhan and Tokdemir (2019) used artificial neural networks (ANNs) and conventional multiple regression for accident outcome prediction using a total of 149 attributes which were discretised into the main causes' categories (see Table 1). The accident outcomes were categorized into 7 different classes (namely, At Risk Behaviour, Near Miss, The Incident with Partial Failure, The Incident requiring First Aid, The Incident requiring Medical Intervention, Lost Workday Cases, Fatalities) (Ayhan and Tokdemir 2019).

In terms of models' accuracy, considerable differences were found between training and testing accuracy; the testing accuracy dropped by 50% for the fatality class (Ayhan and Tokdemir 2019). Zhu et al.'s (2021) best accuracy results were achieved by the AutoML algorithm, with 70% accuracy. However, a misclassification problem was observed when the algorithm mistakenly classifies a large accident as a minor one Zhu et al.'s (2021). Choi *et al.,* (2020) used the value of the Area Under the Receiver Operating Characteristic Curve (AUROCC) metric; the RF achieved 0.9198 which is considered as excellent, as the ideal value of AUROCC is 1.

Factors and feature ranking

Shrestha *et al.,* (2020) coupled accident causes with accident severity. For example, pre-existing medical conditions were found to result in the most fatalities, although they happen in lower frequencies. Another approach was to rank features according to the level of importance and in relation to accident consequence severity, by using the Pearson correlation coefficient, Random Forest (RF) and principle component analysis (PCA) (Zhu *et al.,* 2021). Feature ranking resulted in three different rankings in each of the latter methods, however, the common features are the type of accident (i.e., fall, electrocution, etc), Accident reporting and handling, Training and examination, and Safety culture (Zhu *et al.,* 2021). Choi *et al.,* (2020)'s RF ranking of factors showed that the month in which accidents happen is the highest-ranking factor, followed by the employment size, age, day, and service length. However, the employment size was observed to be highly ranked in all algorithms. The latter factor was showing to be correlated to high accident rate in smaller projects while the level of fatality being increased in the project over 2000 employees (Choi *et al.,* 2020). Ayhan's and Tokdemir's (2019) choice of algorithm did not allow for feature importance demonstration. The prediction results of ANNs are less explainable compared to other algorithms that indicate feature importance. However, the conventional multiple regression (which is a more interpretable algorithm) was not successful compared to the ANNs, based on R-square and mean percentage errors as performance criteria.

Classification of Accident Causes and Information Retrieval

ML algorithms

Zhang *et al.,* (2019) used single and ensemble classification algorithms for the classification of 11 accident causes; the causes were extracted from accident reports by a natural language processing (NLP) algorithm. In addition, the objects mentioned in the passages of reported text were also extracted. However, it was found that the performance of the NLP was not satisfactory (Zhang *et al.,* 2019). Another approach was to classify accident causes in combination with relevance to accident severity (Zhong *et al.,* 2020, Kim and Chi 2019). Kim and Chi (2019) exhibited a prototype for extracting the cause of an accident (hazard object), location (hazard position), when the accident occurred (work process) and the result (accident result). They also identified the semantic roles and rules for the accident components in relation to the accident result and used the conditional random field (CRF) classification algorithm (Kim and Chi 2019). Kim and Chi (2019) exemplified their prototype by using a tower crane fall query. The information retrieval prototype was represented in terms of a statistical analysis of extracted information from the accident textual reports. Accident categories have also been analysed based on their causes and merged with weather related data and classified into four accident categories (Falls from height, Collision by objects, Rollover, Falling objects), (Kang and Ryu 2019).

Table 1: Summary of ML models, data source, algorithms, and purpose

Reference	Data source	Algorithms	Purpose
Shrestha *et al.,* (2020)	1200 accident reports	SVM	Classification (severity/accident type/energy source/ Upstream Measures)
Zhu *et al.,* (2021)	571 investigation reports	LR, DT, RF, SVM, NB, KNN, MLP, AutoML	Predict severity of accident
Ayhan and Tokdemir (2019)	17285 accident reports/ Construction sites	ANNs, Conventional multiple regression	Prediction of accident outcome
Choi *et al.,* (2020)	137323 injuries and 2846 deaths	RF, AdaBoost, LR, DT	Predict likelihood of fatality
Zhong *et al.,* (2020)	2000 accident reports	CNN, SVM, NB, KNN, data mining	Classification of accident type/Severity and causes
Zhang *et al.,* 2019	1000 accident reports	DT, KNN, NB, SVM, LR, Ensemble	Classify accident categories
Kim and Chi (2019)	4263 accident reports	CRF	Information retrieval
Kang and Ryu, (2019)	6374 accident investigation	RF	Classification of accident categories[2]

[1] Logistic regression (LR), Naïve Bayesian (NB), k-nearest neighbour (KNN), multilayer perceptron (MLP), Adaptive Boosting (AdaBoost)

Factors and feature ranking

The combination of a Convolutional Neural Network (CNN) and data mining provided deeper insights (see Table 1). Latent Dirichlet Allocation (LDA) and Word Co-occurrence Networks (WCN) data mining methods were used to identify correlations between retrieved causal variables and to visualize the information (Zhong *et al.,* 2020). The data mining methods provided the organization of the results as a main topic (ex. collapse of an object) and the corresponding actions (ex.

Collapse of object, Falls Work, Protect) and objects (ex. Subway, Construction, Fracture, Equipment, Scaffold, Crane). Furthermore, the WCN method showed insights into accidents and severity, for example scaffolding accidents are infrequent but tend to be sever and likely to result in a fatality (Zhong *et al.,* 2020).

The application of RF also revealed correlations thanks to the feature ranking possibilities (Kang and Ryu 2019). The assailing materials, original-cause materials, unsafe behaviours, protective equipment, unsafe states, work contents, and diagnosis names were ranked highest on the scale of feature importance, whereas weather related variables were not found influential in the classification of accident types. Kang and Ryu (2019) further examined feature importance for every accident type. For example, work activities before falling were installation or maintenance of mechanical equipment and facilities but most fall accidents were caused by workers not wearing safety protective equipment.

ANALYSIS

This research aimed at investigating the role of ACMs in the application of ML in the field of reported construction occupational accidents. At the same time, identify the relevant gained learnings from ML in relation to ACMs. The BOW-Tie model (see Fig 3) is useful in the analysis of threats, hazards, consequences, the top event and the prevention barrier. By comparing the BOW-tie typology to the ML model components, it can be observed that according to Shrestha et al.'s (2020) categorization, upstream precursors can be relative to threats while energy type to hazards, severity to the consequences and type of accident to the top event. Similarly, some components of the BOW-Tie model can be found in Zhang *et al.,* (2019) and Kang and Ryu (2019). Accident type can be categorized as a threat or a hazard. Zhong *et al.,* (2020) and Kim and Chi (2019) presented a linkage between accident types and the accident consequences. Furthermore, the application of data mining resulted in finding and visualising the relationships between causal variables (Zhong *et al.,* 2020). The main topic in Zhong et al.'s (2020) analysis can be considered like the typology of threats in the BOW-Tie model and the corresponding actions to the top event, and the objects (such as the scaffolding) like hazards. The latter features were linked to the consequences which is one step closer to the exhibited representation of the link between threats and consequences in the BOW-Tie model. Kim and Chi (2019) illustrated a more explicit setup for accidents' features, thanks to the semantic roles and rules of accident components. Simultaneously, it can be found that some factors and functions in the ML model are different from the structure of components and relationships within the BOW-Tie model. Zhu *et al.,* (2021) for example identified causes into categories related to the organization, safety training and contract management while the BOW-Tie model encompasses the immediate threats. Although the ML representation of causes and their relationships can identify a link to between the hazard and the consequence (Shrestha *et al.,* 2020, Zhu *et al.,* 2021, Choi *et al.,* 2020, Zhong *et al.,* 2020, Kang and Ryu 2019), which is similar to the structure of the BOW-Tie model. But a major difference can be found in the ranking of features importance that can only be found in the ML representation.

The SCM explains accidents by the concept of barrier failure that exists in multiple levels of the organization and influences human error down the chain. The SCM shows to be comprised of higher levels of causation compared to the ML illustrations of accident causes. The factors related to machinery, workspace, energy sources and weather (Shrestha *et al.,* 2020, Zhong *et al.,* 2020, Zhang *et al.,* 2019, Kim and Chi

2019, Kang and Ryu 2019) all exist within the first layer of the SCM (see Fig 1). Attributes of human factors, risky behaviour, occupation (Kang and Ryu, 2019, Choi *et al.,* 2020, Ayhan and Tokdemir 2019) can be categorized into the second layer of the SCM. Only one effort in the reviewed literature (Zhu *et al.,* 2021) has used variables related to the upper levels of the SCM. The contract management variable (Zhu *et al.,* 2021) belongs to the top-level decision-making layer. However, the results feature ranking showed that the type of accident, Accident reporting and handling, Training and examination, and Safety culture are the most influential factor in accident severity predictability. In terms of the mechanism in which accidents occur in the SCM logic, failure should happen on all the levels at once. The presented ML literature attempts to couple the accident-related features with the severity in some type of a direct relationship (Shrestha *et al.,* 2020, Zhu *et al.,* 2021, Choi *et al.,* 2020). However, the nature of this relationship remains ambiguous. The RF algorithm showed the biggest potential in understanding relationships between ranked features, but this will need visualization of the ML model structure and the features that result from using the algorithm. Moreover, the use of data mining methods (Zhong *et al.,* 2020) seems promising in visualizing relationships between causal variables, but the factors used in Zhong *et al.,* (2020) only cover the bottom level of causation, which does not reveal much about the SCM.

There are two major differences between the analysed ML literature and the SCM and the BOW-Tie. Both ACMs have defence barrier activation as a requirement for prevention. Secondly, a common feature in ACMs is that they do not differentiate the consequence of accident severity, but only focus on the occurrence of an accident. It is evident that all ML models do not consider neither the prevention barrier nor the barrier failure. Shortcomings in identifying prevention is not necessarily originating from ML but it could have been noticed if ACMs were used as a framework of the data analysis. It has been acknowledged that accident investigations might skip the preventive recommendations (Hopkins 2014). Suggesting measures that are further from the accident's technical circumstances becomes subjective and lacks concrete evidence - although Hopkins (2014) suggested recommendations can be reasonably made, even in the absence of evidence going beyond the particular case. This seems problematic because the consistency of the single report is then maybe compromised.

ACMs assume and promote severity as a stochastic element and impossible to be predicted. On the contrary to the reporting schemes that allow for reporting for the level of severity. Industrial reports sometimes encourage to report lost days which can have an impact on what the company reports. This tendency to focus on severity is reflected in the ML examples reviewed in this article (Shrestha *et al.,* 2020, Zhu *et al.,* 2021, Choi *et al.,* 2020, Ayhan and Tokdemir 2019). Although the ML literature claims success in predictions but the internal validity of 63% and 70% seems arbitrary and needs further proof of prediction success. Therefore, what should be focused on in the ML application is to find alternatives to severity classifications such as the modelling of risks, learning more about the prevention process, and most importantly, to prevent the accident from happening foremost by adopting the paradigms of ACMs.

ACMs had been constantly reviewed and more causation layers were introduced. More remote levels of causes which are further from the accident environment (e.g., regulations and governmental causes such in the STAMP model (see Fig 2)). The STAMP model is designed into feedback loops and constrains. Although Zhu *et al.,* (2021) featured higher levels of causation but the levels of causation of the STAMP model extend back to governmental and regulatory levels. In the construction industry, the STAMP model had not been detected (Woolley *et al.,* 2019). This might be due to that system thinking was not used in accident investigations and causation analysis. Furthermore, system models are diverse and lack the conceptual unity that would allow their use in qualitative accident predictions (Grant *et al.,* 2018). The causes of accidents in the STAMP model are procedural and they seem applicable since the model component are identifiable functions in almost every work situation. But the latter miss the definitions of simple measurement and a benchmark of comparison, especially for the personnel doing accident investigation.

CONCLUSIONS

By the review of ML and ACMs in relation to each other, it can be found that ML analysis of accident reports can learn from the components of ACMs to identify prevention measures. For further impact and concrete use cases, ML development needs to be guided by ACMs. Most importantly, the prevention component which is represented in the BOW-Tie and SCM models would have been detected if ACMs were used as a framework. The ML results appear to be more of a descriptive nature and especially useful in the classification of accident type and severity as well as information retrieval. However, a valuable contribution is found in defining the relationships between hazards, accident types and severity. Future ML analysis is suggested to be more focused towards the mapping of risks rather than classification of accident types and severity. The adaptation of ACMs such the BOW-Tie model could aid ML models to be developed further from severity and more towards the identification of risk and heir corresponding prevention barriers. Moreover, ACMs can be improved by the ranking of features and visualisation properties offered by data mining and the more explainable ML algorithms such as the RF. This conclusion would also mean that it is better deemed suitable to use more explainable ML algorithms rather than variations of ANNs. Knowledge about the importance of causation levels in ACMs would probably fill the gap of reporting distant factors. The more is known about the relationship of further factors from the construction site, the more these factors will be detectable by reporting personnel. The analysis points to a very important gap in the practice of the reporting of prevention measures, because unless the reporting include suggestions for how an accident can be prevented, less can be learnt from past experiences.

The paper is limited by the types of ACMs which were analysed. ACMs are within a developed field and different models could be analysed in a similar manner. The ML models are analysed in terms of algorithms, factors, and feature ranking only. Future research can highlight an in-depth analysis of the structure of algorithms to be compared with ACMs structure.

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Paper III

LEARNING FROM ACCIDENTS: MACHINE LEARNING PROTOTYPE DEVELOPMENT BASED ON THE CRISP-DM BUSINESS UNDERSTANDING

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ABSTRACT

Occupational accidents continue to be an unresolved problem in the Swedish construction industry, despite a whole range of routines, campaigns, education, management appraisals, authorities' enforcement, networks, and research in place. While registered accidents *are* less frequent, there is a widespread willingness to strive for better performance. A potential solution is to apply more robust data analytics to the large company occupational accident registers, complementing existing regular analysis. Machine learning (ML) can provide a promising solution for strengthening data analysis, and international prototypes of such systems are emerging. However, there is a need to appreciate local and corporate concerns, and the ML development method "Cross Industry Standard Process Development Method" (CRISP-DM) appears to offer just that. This paper aims to analyse experiences and challenges in using the first phase of CRISP-DM, i.e., "business understanding". The sociomaterial approach serves as the framework of understanding and is supplemented with accident research and ML development concepts. Methodologically, the paper draws on an ongoing research project to develop a ML prototype for occupational accident analysis. It quickly surfaced that CRISP-DM's "business understanding", while asking relevant questions in the company context (such as the goal for the model and the relative application), was too general to provide developmental guidelines. We, therefore, shifted from a top-down to a bottom-up approach, where knowledge on accident registration procedures and registered accidents became the starting point for iterative prototype development. Also, early challenges were to understand the registered data extracted from standard software with limited transparency, and tackle register entries of different quality. Apart from CRISP-DM's slightly idealistic approach to a company context, it is important to appreciate the classical decoupling between top management and (bottom) project levels in Swedish contractor companies.

Keywords: accidents, machine learning, Sweden, CRISP-DM, construction, accident register

INTRODUCTION

ML is receiving remarkable interest in safety research as a new approach to improve the prevention of occupational accidents (Goerlandt et al. 2020). The capability of analysing large amounts of accident reports appears to bolster this aspiration. However, preventing occupational accidents is a very mature discipline, which appears to function well alongside the continuing unsolved occurrence of accidents (Judson and Brown 1944, Hovden et al. 2010, Lingard and Wakefield 2019, Hasle et al. 2021). There is a risk of reinventing the wheel, repositioning the same prevention proposal repeatedly, disregarding central dynamics of the work environment context – as in Lingard and Wakefield (2019) and Hasle et al. (2021), proposing a better integration with design, project management, and operations management to lever accident prevention. Therefore, there is a need to appreciate the local and corporate context and their often-contradictory dynamics. ML software development appears as sufficiently malleable to meet exactly that requirement. In particular, the ML development method CRISP-DM is of interest, as it is one of the most used methods. The method of CRISP-DM starts with the "business understanding" stage for setting up developmental requirements and plan for the development and deployment stages.

Therefore, this paper aims to analyse experiences and challenges in using the "business understanding" phase of CRISP-DM to assure a solid contextual embedding and an appreciation of local dynamics. A sociomaterial approach serves as the framework of understanding, supplemented with accident research and ML development concepts. The context of a contractor company is indeed complex (Lingard and Wakefield 2019). Therefore, methodologically, the research adopts a bottom-up approach. The paper draws on an ongoing research project aiming at developing a ML prototype for occupational accident analysis.

Firstly, the paper contributes with an understanding that CRISP-DM's "business understanding" is too general to provide sufficient guidelines for ML development – even relevant general questions of the company context (e.g., the goal for the business and the relative application) are indeed asked. We, therefore, shifted from a top-down to a bottom-up approach, where knowledge on accident registration procedures and registered accidents became the point of departure for iterative prototype development. Secondly, it highlights the difficulties in understanding registered data extracted from standard database software with limited transparency, and tackling register entries of different quality – which echoes previous research on the importance of the reporter's interpretation (Dekker 2015, Jacinto et al. 2016). Thirdly, it appreciates the classical decoupling between top management and the building project level in Swedish contractors. Integrating accident prevention at the operational level is not a simple task (Hasle et al. 2021).

METHOD

The overall method is an interpretive approach (Alvesson and Kärreman 2007). A concept-centric literature review was conducted (Webster and Watson 2002) to review the status of ML-based solutions for accidents report analyses. The literature review was connected to the application of ML in analyzing reported accidents in the construction industry. For the empirical context, five interviews were carried out: four with safety engineers and one with a safety strategist at a high level in a Swedish contractor company. The questions for the interviews were developed towards the unfolding of the meaning of safety, accident response process, reporting process and quality, and the expectations from a ML-based prototype. Moreover, the ML questions and discussions were focused on developing a data-driven prototype, inspired by the business understanding framework of CRISP-DM and the recommended practice (RP) framework (DVN GL AS 2020).

THE STATUS OF ML DEVELOPMENT METHODS

ML is generally defined as the exploration of algorithms enabling computing systems to "learn" and make data-driven predictions by building a model from a sample dataset (Curtis and Scheinberg 2017). Computer systems that utilise ML automatically improve through experience (i.e., new domain data) (Witten et al. 2017, Portugal et al. 2018). ML is frequently classified into supervised, unsupervised, and hybrid (Kakarla et al. 2021). Supervised ML algorithms are "trained" and validated using labelled datasets with known reasoning of the application domain (Kakarla et al. 2021). Unsupervised ML analyses unlabelled data under assumptions about its properties (Jordan and Mitchell 2015) by finding hidden patterns in the data and developing models "on its own" (Portugal et al. 2018). Hybrid ML mixes several approaches (e.g., semi-supervised and reinforcement learning) (Gerard 2021).

There has been an increasing interest in developing ML models and prototypes for the analysis of occupational accident data within construction. Such recent prototypes can be largely categorized according to their purpose, i.e., classification, prediction, or information retrieval. For example, ML prototypes have been deployed for the classification of accident categories (Kang and Ryu 2019, Zhang et al. 2019), severity, type (Shrestha et al. 2020, Zhong et al. 2020), energy source, and related upstream measures (Zhong et al. 2020). When it comes to prediction, ML models have been developed to predict accident outcomes (Ayhan and Tokdemir 2019), the likelihood of fatality (Choi et al. 2020), and accident severity (Zhu et al. 2021). Finally, a ML prototype for information retrieval covers the hazard object and position, work process, and accident result (Kim and Chi 2019).

In all of the aforementioned (and other) cases, the developmental process (incl. the choice of algorithms, dataset preparation, and modelling) was mainly goal-informed. However, the contextualization of this developmental process and its constituents (e.g., the algorithms) emerges as a major issue. The conceptual matching of algorithms to a specific occupational accident-related problem and dataset is rarely carried out; their suitability is not contextually evaluated – the algorithms are rather selected on an experimental, trial-and-error process, lacking a systematic development method. Such an approach could lead to choices based solely on performance metrics (accuracy, error) prone to overfitting and not necessarily capturing contextual specificities. Moreover, "repairing" datasets (e.g., under- and oversampling) is sometimes employed without considering whether datasets maintaining their initial properties (such as sparsity) can represent reality and inform the algorithms more meaningfully. Things are even exacerbated by an overreliance on internal validity testing and a lack of external testing on performance metrics and prediction accuracy. In summary, the development of ML prototypes for the analysis of occupational accidents in construction largely lacks, in most cases, the framework of a specific methodology.

An exception to this rule can be the development of ML prototypes according to the CRISP-DM methodology; CRISP-DM dictates a series of six steps (business understanding, data understanding, data preparation, modelling, evaluation, and deployment) (Martínez-Plumed et al. 2019). These steps can account for a contextualization of the developmental process, starting with the initial step of business understanding – and thus offer a way to ameliorate the previously mentioned shortcomings. CRISP-DM can be considered to go beyond goal-directed development (Martínez-Plumed et al. 2019) by introducing systematic steps aiding in a conceptual systematization and mitigating the dependence on a solely experimental basis. Based on the organized steps of CRISP-DM, other industrial models have emerged, such as RP (DVN GL AS 2020). The latter claims to be differentiated from CRISP-DM by the usability in applications comprising data-driven models developed using other processes while focusing on risk assessment and quality assurance of data-driven applications (DVN GL AS 2020).

Business understanding

The business understanding aims to define the business objective (Chapman et al. 2000), including defining the client's goal and capturing the organization's business status. In more detail, this step corresponds to different subtasks: determine business objectives, assess the situation, determine data mining goals, and Produce project plan (Chapman et al. 2000). The same steps are followed in RP but add concrete documentation requirements, including commercial, safety, and social constraints anticipated in the deployment (DVN GL AS 2020).

Determine business objectives

In this step, the analyst uncovers what the business goal for the customer is and answers collateral business questions related to the primary goal. Objective or subjective success criteria are decided from the business point of view (Chapman et al. 2000). RP introduces a so-called value proposition statement, which documents the intended user and why and how the application would be used. The value proposition might be documented together with the business context in the form of use cases and users' stories (DVN GL AS 2020). The business context, objectives, and success criteria should be sufficiently and objectively defined at the end of this stage.

Assess the situation

Assessing the situation involves a detailed analysis of the resources, constraints, and assumptions related to the business objectives. This step should result in a series of outputs, including a list of all possible resources, a setup of project requirements, measurable and subjective expectations, risks of project failure, terminology, and cost-benefit analysis from a commercial perspective (Chapman et al. 2000). RP (DVN GL AS 2020) views this step as a risk assessment of the intended and unintended uses of a deployed application. It is suggested that this step can be done in two different iterations, also connected to the followed step (determine data-driven goals). Identifying and documenting stakeholders, available data resources, project requirements, project assumptions and constraints, suitable terminology, project risks, and the application design can be related to the modelling goals (high-level assessment). Defining the cost-benefit, failure modes, and legal and ethical consequences can be related to the modelling step from a technical-focused point of view (low-level assessment). All the deliverables of this step are required to be sufficiently identified and understood.

Determine data mining goals

This step must determine the objective of the data mining process in terms of data analytics linked to the business goal (Chapman et al. 2000). According to RP (DVN GL AS 2020), this stage requires close collaboration between domain experts and data analysis experts. At this point, the desired predicted target should be defined clearly together with the modelling success criteria – either objective, based on a low-level assessment, or subjective, based on a high-level assessment.

Produce project plan

A realization plan for the data mining goals is prepared to specify steps, resources, and possible iterations – while also developing a list of data analysis tools and techniques (Chapman et al. 2000, DVN GL AS 2020).

MAPPING OF THE CONTEXT

We are mainly interested in how accident prevention is embedded in the business setting when mapping the context. The contractor operates a project-based organisation. The building project is the most important value and turnover generator and cost transformer. The different building projects are produced in portfolios placed in divisions with slightly different business objectives, i.e., civil works, residential buildings, office buildings. The project commences with a contract with a client. The Health and Safety (H&S) work commences by documenting the way H&S will be organised in the project in a bid for the customer. Typically, no risk analysis is carried out by the safety engineers (SEs) this early; however, this is done once a contract is obtained. A particular job role, called BAS P (educated in design safety), is part of this process. From the beginning of work planning, the SEs inspect the plans with a H&S perspective. During production, the safety representatives (the so-called BAS U personnel – basic education for production) are responsible for a particular part of the building project and the building process. They collaborate with the on-site H&S, Quality, and Environment (HES) manager and the SEs. Together, they constitute a horizontal element of the H&S organisation and support the similarly horizontal building processes. H&S work is thus organised close to the single building project. Apart from this horizontal element, the company also encompasses a vertical hierarchy, where H&S is attached to several organizational levels. A central H&S unit is part of a corporate management HR unit. HES units are adjacent to several organizational levels. This cross-organizational H&S apparatus works with behaviour issues, analysis and reporting, digitalization, and developing directives. In it, it is a common perception that accidents are mostly due to behaviours, so efforts are targeting this issue. Another workstream is related to analysing and reporting, as well as digitalization, driving projects, and the way the company benefits from machines and innovation. The third workstream is related to developing directive processes and procedures.

The meaning of safety at the contracting company

At the case company, all four safety engineers (SEs) answered that safety in the organization means that everyone should go home safe and injury-free after a working day, and planning for that is the most important thing. One of the respondents indicated the difference between what safety means in the higher levels of the organization and on the site management level. On the higher levels, there is much talk about safety coming first, changing attitudes and behavior – while for site management, prioritizing different tasks and meanings affects many skilled workers.

A normal working day

A general remark regarded the respondents' thinking about the effect of COVID-19 on a "normal" working day. For some of them, working from home seemed abnormal. Before the pandemic, a normal working day involved the planning for project safety, safety support to site management and production personnel, follow-up on risk documentation, contact with site and project management, and discussing with the workers about the work environment and the reason protective equipment should be used. The project's risk assessment and work preparations must be ready, especially for those performing the work. There is a knowledge repository of tips and checklists of different subjects and tasks to help with planning. Often, if it is too cumbersome to search from the list, the site manager can ask the SE about the required information. Besides coordinating other tasks (such as the site economy), balancing what to take in and what to leave out is needed. It is better to use own knowledge first and then utilise the checklist to see if something was forgotten – the level of experience might determine how much of the checklist is needed.

The response of the event of an accident

The accident response routine is taken more seriously by the organization. There is a requirement for yearly training in the response process – although a respondent had not witnessed a severe accident in six years. The response depends highly on accident severity. In severe accidents, taking care of the injured comes first; people on-site also need attention to discuss the reasons and be involved in the investigation – for fact-checking, coming up with ideas for future prevention, and getting support in case of psychological shock.

The reporting of accidents

Accidents are reported internally through digital registering software. The responsible site manager initially does the registration, but the SE gets involved when needed. The reporter estimates what to fill in (e.g., a description of the event, information about the injured, prevention measures) and what to leave out. Most importantly, there is a list of fully defined accident causes, besides the possibility to comment in free text. In the portal, it is preferable to use the already defined options, as this allows one to look into the related statistics. The interviewee did not see the way free text can be used.

In severe accidents, the software allows for five causes and five prevention measures that need to be filled in (not needed in less serious accidents). The interviewees said that the reporters fill in what they think the cause is and, most importantly, relevant prevention measures. For deciding about those, one of the interviewees said that the first thing is thinking about the individual. The individual is responsible for planning and thinking; then, the company must provide safe work conditions and create a safety culture that emphasizes planning and knowledge sharing.

To decide on accident causes, the work environment plan helps check whether the work preparation was filled out properly and the risks were carefully estimated. However, there is a chance that all procedures were followed through properly, and the causes were person-related instead ("faulty acts"). The software can also guide on causes, but the filling in of information can differ according to the person doing it. Even if the causes and prevention measures are evident in the reporter's mind, this does not necessarily translate to a detailed enough description. One of the SEs describes their reporting as detailed so that anyone who reads the report can understand what happened – and added that it is crucial to go down to root causes and not stay at the surface level. The "5 whys analysis" is used as an easy and quick way to narrow down to root causes and come up with helpful prevention measures. Nevertheless, not all reporters are experts in root cause analysis; therefore, in very serious accidents, SEs come in and help with unfinished cases and more careful root cause analyses. Also, for many of the reporters in the portal (e.g., site managers), the human factor is the main cause – they thus do not what has caused the respective person to act this way.

Status of the data use and safety objectives

The accumulated accident reports are used in reporting key performance indicators by following statistics – but mostly on accidents that were severe or resulted in absence. In a recent use case, a sore card scheme was used to report the event type and find certain risk categories in different parts of the organization. Another use case to planning to purchase personal protective equipment (PPE) based on analysed accident reports. The company uses the Bowtie model for analysis, because it wanted to work with high-risk areas and detect where barriers can be set to prevent those risks from happening. As part of the reporting assurance, the reporting of severe cases is always secured by SEs. Otherwise, H&S managers keep track of their area and support the reports of single cases, besides following up with the safety function group. This indicates what needs improving, training, communicating, or developing IT tools. The focus for both severe and less severe cases is on the reduction of their frequency.

The value of reporting of accidents and improvements

The interviewees agreed about the value of learning from reporting and not experiencing the same accidents again – acknowledgement the importance of reporting and learning, taking out statistics, sharing the knowledge, identifying risks, and planning the resources for similar work steps. SEs also wish to report social-related issues, usually not part of the routine, such as harassment. There are risks when people do not feel good psychosocially. This is something that needs to be worked on within all workspaces across the sector. It is not easy to see and spot this type of situation, which is a risk for individuals and groups. However, another SE pointed out that reporting negative/positive observations, incidents, and accidents is a routine. In that way, the portal seems comprehensive for all categories – but it would be good to add safety rounds within the reporting software. Another comment about additional reporting was that people do not always want to report – e.g. when the accident is the person's fault.

Improvement in the safety process for accident prevention support

Registering more events (incl. observations) can improve the reporting status, by making reporting faster and better in handling registered cases and coupling that with feedback and prevention. With more reporting and feedback, the work becomes more proactive and safer – e.g., when handling machines and material.

One respondent mentioned that people on site should follow what was decided. There are prevention packages, but they are not always followed, mostly because people want to do the work first instead of taking more time for safety-related preparations. The respondent called this the "I will just do this first" syndrome. Another SE thought there is a need for better planning, but otherwise, all the tools and processes exist – just not fully used. The SE had a generally positive outlook, as in the last six years, the organization was more focused on safety, even resulting in zero accidents recently.

Value proposition

The safety strategist indicated that the company is quite advanced in collecting H&S data but still far from where it aims to be. The digital reporting software was introduced five years ago (a short period for a large company), but the company only started using the data and investigating its utilities, which creates more needs. Moreover, data quality and precision still need improvement, and only looking at the data and not reflecting on it can be suboptimal.

The company's top long-term priority is on behaviour, which according to the accident report statistics, is the most common cause of both minor and severe cases. Behaviour is hard to affect because the end-user is always a person, but the H&S organization, especially the SEs, can exert such an effect. Furthermore, fatalities are aimed to be at the level of zero.

ML potential

In this part, the SEs were asked about their view of ML potential in analysing accident reports and their tasks. At the beginning of this set of questions, ML was briefly described for the respondents.

One SE mentioned that there was potential in extracting statistics of what had occurred in incidents, observations, and accidents, grouping them according to the case or subject, and gathering all possible prevention measures instead of speculating on how to solve a problem. Double-checking whether something was forgotten can also be possible support. On the other hand, two respondents thought it was difficult to say what ML can offer for their work process – but one added that through all data across the whole company, it might be possible to pay attention to work steps or work tasks where there are many accidents or many people injured.

The question was then reformulated to be more general about what a needed area of support could be. One SE answered that, in general, a lot of the work is about attitude and the way of thinking. It will be good to have tools to present information about the risks to the production people, make it more relevant, and even visualize it (pictures, animation) and engage them in their own work's safety processes. Alternatively, there is much to be learned from negative and positive observations and finding the reasons behind not following the rules, even though they are known.

When SEs were asked whether they wish to see their proposals as digital applications. One answered that everything is already digital. Another mentioned that the most important thing about a digital tool is that it is practical, it functions fittingly with the activities, and it provides something new – not only being something that needs to be done because the system requires so.

Proposals and ML risks

From a safety strategy perspective, involving information about the individuals in the data registration should be avoided. However, this can be tricky if there are ethical concerns.

Understanding why people do not follow the rules is risky; it becomes a conflict if this information is handled as negative prevention towards the individual. The SE indicated that there is no answer for this concern. One of the perceived risks in creating new communicative meetings to show risks and narratives of accidents is workers and site management not having time for them or not finding them valuable.

Another interviewee did not see any risks, only opportunities, e.g., a knowledge bank helping in planning in the early stages. The respondent also did not find ethical concerns since the focus of the reporting is on the accident. Even for accident-prone people, it is information that only the site manager or the safety engineer knows about and maybe take a private discussion with the individual.

Satisfaction with the reporting

It would be better if one reports in a more detailed, informative, and descriptive manner, so that even if someone not involved in the event can understand. If investigations do not arrive at causes and prevention measures, then extracted conclusions cannot be made. One SE indicated dissatisfaction because much more could have been reported – reporting rates differ from site to site. Maybe site management did not want to catch attention, which causes reporting rates to drop – even though there are many more reports now; 1000 in one division while, some years ago, there were only 27.

As SEs support production and work with the portal, most of the reporting is done by site managers, site supervisors and maybe safety representatives. Many questions are very relevant for them, and they have another perspective of reporting and using the software.

Success criteria for a protype based on the reports' data

From the strategist's point of view, having the workers on board is the most important thing – maybe not every single worker, but at least a small group that had already tried a new tool and given feedback. Introducing new things in the construction industry is not very popular, and that is a risk but also a kind of attitude. Therefore, management needs to promote and try the new tools themselves and engage in communication.

COMPARATIVE DISCUSSION THAT CAPTURES THE CONCEPTUAL AND EMPIRICAL COMPARISON

The business objective includes defining the client's goal and deciding on the objective or subjective success criteria from a business point of view – or, according to RP (DVN GL AS 2020), a value proposition that defines users and use-cases. Based on the interviews, the safety strategist was chiefly interested in behaviour and fatal accidents, while the SEs' propositions included the planning of work tasks and prevention, communication, and behaviour. Moreover, one of the SEs defined acceptance criteria for a new digital application, namely practicality, functionality connected to activities, and giving the feeling of added value to users.

The first direct difference between CRISP-DM's concepts and the empirical context can be summarized as singular versus multiple-goal orientation. CRISP-DM and RP encourage the data analyst to look for and specify a single business objective and client goal, whereas the contractor's diversification on different products, different organizational levels, and the project-based organisation exhibits multiple goals and objectives. Notably, the project's typical goal constellation would involve costs, time, and quality as prime objectives, whereas H&S and prevention of occupational accidents might be present but still play a minor role. The latter setting introduced ambiguity into the objectives of using a ML model and has to be embedded into "goal contradictions" rather than just a single goal. At the end of the first step of the business understanding, there is probably a need for iteration to sum up objectives and re-evaluate to make decisions on a common objective. The CRISP-DM guideline of deciding on the objective or subjective success criteria from the business point of view of the ML model assumes the active participation of the managers and employees in the development of the ML model, which is a feature our project does not encompass.

The second step of business understanding requires a detailed analysis of the related resources, constraints, assumptions to the business objectives, risks of project failure, terminology, and cost-benefit analysis from a commercial perspective. The recommendation of this stage is related to the resources of the H&S organisation, its members and most importantly, the data. There are resources to a certain level, but a detailed analysis of accident causes is rare. It is the corporate registration system that sets the limits for the effort. The constraints of the prevention activity are due to the business objectives of production, where time and cost own prevalence. Moreover, assumptions in the field of accident prevention are related to several different safety cultures in the project organisation (Koch 2013). At least two competing assumptions prevail in the interviews: first, that accidents are due to human error and therefore should be prevented by campaigns and other behaviour-oriented efforts, and second, that accidents can be prevented when systemically analysing the risks and making barriers for their impact. Furthermore, the interviewees showed conflicting views about risks associated with the latter prevailing safety assumptions. To sum up, analysts can extract information related to assumptions, practices, and data validity constraints. However, more requirements at this step seem challenging to define (such as the application design and ethical concerns), especially since most requirements need a vivid project and commercial benefits.

The following step would be defining data-driven goals. At this stage, there must be a clear definition of the prediction target and an agreement about the model's acceptable accuracy in achieving such a target. Based on the interviews and the latter analysis, the goal and constraints need to be defined beforehand. The many projects, product types, management levels, and other factors, make the context challenging to handle, and such liability and weakly defined phenomena make applying ML difficult. Moreover, the data status might not allow for a clear definition of the prediction target. Another iteration could be proposed to overcome this difficulty. If the situation assessment step had required a primary data analysis (besides listing detailed available data resources), it might be easier for the analyst and the case company to make the connection to concrete targets.

One of the preconditions for a ML application is to make a critical difference in prevention work, i.e., that the system compiles a large amount of data and analyses it in an overview not offered in previous methods, practices, and systems. In this occupational accident context, this means coupling many building projects and units across time and space. The SEs function similarly across many project contexts, so their active use of a standard ML system might provide an additional critical contribution to prevention. The similar concerns and goals across time and space, rather than just the compiled database, create the critical mass for the system. It is likely that even other datasets in the contractor's system (e.g., quality data, production planning, and execution data) share this feature – a coexistence of a common database spread in space and time, but with similar goals.

The previous analysis shows that much can be uncovered by asking domain experts about daily processes and experiences. However, to define business understanding goals and expectations of data-driven (ML) applications requires working on multiple organizational levels, especially in project-based organizations. Adding an iterative step between the business understanding subtasks seems beneficial – otherwise, ethical, application design and data-driven goals, would remain ambiguous. Moreover, the current description of business understanding seems to target commercial gains at a strategic decision-making level. In contrast, in a large contracting company and on the operational level, the business understanding framework needs to and can be adapted to match the specific case.

CONCLUSIONS

This paper aimed at analysing experiences and challenges in using the "business understanding" phase of CRISP-DM; and as part of an ongoing endeavour to develop a ML-based system that utilises reported accidents for prevention. The interest in "business understanding" stems from intending to assure a solid contextual embedding and an appreciation of local dynamics (incl. variations in roles, competencies, and resources). Our sociomaterial framework of understanding was supplemented with accident research and ML development concepts, and the complex context of a contractor company was elected. Due to the contractor's differentiation in business units and areas and its project-based production, it can be (as the interviews also showed) compared to a loose constellation of many small companies. Therefore, the method adopted was a bottom-up approach.

The paper's first result evaluates CRISP-DM's "business understanding" as too general to provide sufficient guidelines for ML development. There are relevant questions to be asked in the company context, such as the goal for the business and the application domain, but little support can be found for more particular decisions on the ML system design. We, therefore, shifted from a top-down to a bottom-up approach, where the iterative system development drew directly on practical experience and knowledge on accident registration procedures and registered accidents. The second result was the difficulties in understanding registered data in the standard database software, with limited transparency and different quality – complementing other research on the importance of the reporters' interpretation. The third result is appreciating the classical decoupling between top management and the building project level in Swedish contractor companies. This hampers the integration of accident prevention in the operational level. ML systems should be designed to provide the coexistence of a common database and user experience spread in space and time, but with similar goals in large contractor organisations with many projects and job functions. The review of the "business understanding" in this case showed the need for two iterations within the process; one at the "determine business objective" step to agree on common goals, and the second at the "assess situation" stage to include primary data analysis for realistic data modelling goals and definitions.

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