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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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.

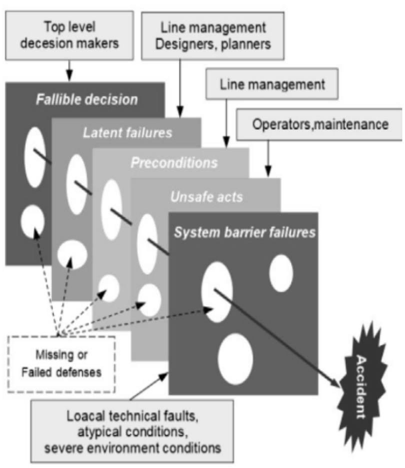
Accident Causation Models

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).



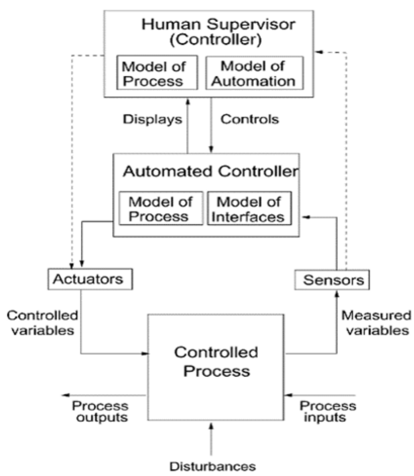


Fig 1: SCM, Fu et al., (2020) *Fig 2: STAMP, Fu et al., (2020)*

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.

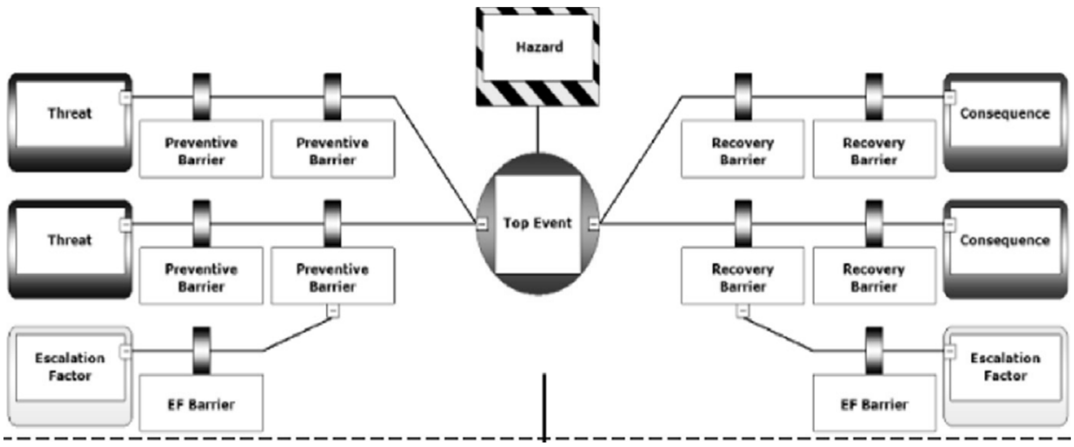


Fig 3: BOW-Tie, Fu et al., (2020)

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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