Applications of innovative accident analysis methods in railways: A review

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ABSTRACT

Accident analysis methods are used to determine the factors and their interrelationships that contributed to an accident. Various methods, including Fault Tree Analysis (FTA), Human Factors Analysis and Classification System (HFACS), and Systems Theoretic Accident Model and Processes (STAMP), were developed to model accident causation. However, the classical methods show weaknesses in accident modeling in sociotechnical systems that have complex dependencies of system components, and uncertainties in system behavior. To address the limitations, newer methods such as Bayesian networks (BNs), Petri nets (PNs), text mining (TM), and machine learning (ML) were used alone or with other techniques to model accidents. This article presents a review of publications in six databases (ScienceDirect, Scopus, Web of Science, SpringerLink, Google scholar, and IEEE Xplore) of these accident analysis methods for the railway industry. The publications are categorized into network-based and artificial intelligence (AI)-based accident analysis methods, and additional categories, such as the type of algorithms and techniques, data sources, and tools applied. The findings show that Bayesian networks and text mining are the most widely used network-based and AI-based methods for analyzing railway accidents.

1 INTRODUCTION

Risk management and accident analysis play a key role in understanding accidents' mechanisms and contributing factors and, thus, the most effective and efficient measures to prevent them. Heinrich (1931) presented the domino theory as the first accident analysis model to better learn from past events. Since then, various accident modeling methods have been developed to better represent our understanding of accidents and the complexity of sociotechnical systems. Traditional accident analysis models are classified into three categories: sequential (simple linear), epidemiological (complex linear), and systemic (complex non-linear) models based on their underlying assumptions (Underwood & Waterson 2013, Klockner 2015). Examples of the sequential accident models that describe an accident as the result of a chain of discrete events occurring in time-ordered sequences are fault tree analysis (FTA), failure modes and effects analysis (FMEA), and event tree analysis (ETA). Human factors analysis and classification system (HFACS) is the most popular epidemiological accident modeling (complex linear). Systemic (complex non-linear) models such as Accimap, systems theoretic analysis model and processes model (STAMP), and functional resonance analysis method (FRAM) are the best-fit methods to analyze accidents in complex systems.

These classical accident causation models usually make simplifying assumptions and ignore some characteristics of complex systems including dependencies among causes and contributory factors, complex relationships between humans and automation, organizational and human influencing factors, temporal and dynamic system behavior, and uncertainties (Huang et al. 2018, Kabir & Papadopoulos 2019). To address some limitations of these classical approaches, network-based methods such as Bayesian networks (BNs) and Petri nets (PNs) have recently achieved popularity for analyzing accidents and safety risks. Moreover, the advent of artificial intelligence (AI) technology, including machine learning (ML) and text mining (TM), offers more possibilities for automatically exploring occurrence databases and accident reports and discovering implicit, but not immediately obvious, relationships.

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Mkrtchyan et al. (2015) reviewed the use of BNs in human risk analysis (a.k.a., human reliability analysis (HRA)) and identified five main groups of BNs' usage involving: the modeling of organizational factors, analysis of the relationships among failure influencing factors, BN-based extensions of existing HRA methods, dependency assessment among human failure events, and assessment of situation awareness. The applications of BNs and PNs in system safety, reliability, and risk assessments were reviewed by Kabir & Papadopoulos (2019). They highlighted the efficacy of the BNs and PNs frameworks in comparison with the classical accident and safety analysis methods and illustrated their strengths and weaknesses as standalone or model-to-model transformation approaches in different practical application scenarios. Weber et al. (2012) also revealed the advantages of BNs over Markov chains (i.e., a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event) and fault trees techniques to model and assess the dependability in risk analysis. The main benefits of BNs were the capability to model complex systems, to make predictions as well as diagnostics, to compute the occurrence probability of an event, to update the calculations according to evidence, to represent multi-modal variables, and to help user-friendly modeling by a graphical and compact approach. Marcot & Penman (2019) showed that how the integration of BNs with other analytical frameworks such as management decision networks, structural equation modeling (SEM), and Bayesian neural networks can enhance Bayesian classifiers and machine learning algorithms, improve model structuring and parameterization, and facilitate the development of time-dynamic models.

Others such as Huang et al. (2018), Ghofrani et al. (2018), and Hegde & Rokseth (2020) put their efforts on reviewing the applications of Artificial Intelligence (AI)-based data analytics methods for incident analysis and their usefulness and gaps. Huang et al. (2018) emphasized a paradigm shift in accident investigation methodology in the era of big data and highlighted the advantages of the modern analysis methods over the classical ones. They concluded that data-driven accident analysis illustrates the circumstances of accidents more objectively, focuses on the relationships between a safety phenomenon and safety data, transforms accident analysis from qualitative to quantitative, recognizes the early warning and early intervention of an accident through real-time data, forecasts potential accidents, and are more congruent with new safety issues. The review conducted by Ghofrani et al. (2018) showed that descriptive analytics such as accident causes and influencing factors, accident frequency and severity, have higher popularity compared to predictive and prescriptive analytics in the data-driven rail safety analysis. They also proposed leveraging big data sources of rail infrastructure and train operations to merge smaller rail accident databases and trace the train accident occurrences based on a series of precursor events. Recently, Hegde & Rokseth (2020) presented a thorough review of publications using machine learning in engineering risk assessment. They illustrated that risk identification enjoyed the most popularity among three phases of risk assessment (i.e., risk identification, risk analysis, and risk evaluation) in using machine learning algorithms. They also uncovered that the railway industry is third, after automotive and construction industries, for adopting machine learning in risk assessment. The domain-specific applications of ML and TM techniques for accident and risk analysis were also reviewed by Halim et al. (2016) and Gutierrez-Osorio & Pedraza (2020) in road transportation, Ismail et al. (2021) in the mining industry, Yan et al. (2020) in the construction industry, and George & Renjith (2021) in process industries.

To the best of the authors' knowledge, the literature in this field of study suffers from the lack of a thorough review of the applications of these accident analysis methods to the railway industry. Therefore, in this paper, we review studies that use these state-of-the-art methods including Bayesian networks, Petri nets, machine learning, and text mining to delineate factors that contributed to the railway occurrences and how they are correlated. The remainder of our paper is organized as follows: Section 2 describes the fundamentals of Bayesian networks, Petri nets, and machine learning and text mining. Section 3 summarizes our bibliometric search methodology. Descriptive analysis and details review are discussed in Sections 4 and 5, respectively. Finally, our conclusions of this review are summarized in Section 6.

2 BACKGROUND

2.1 Bayesian Networks

Bayesian networks (BNs) are directed acyclic graphs that model a set of variables and their conditional dependencies as nodes and edges (Kabir & Papadopoulos 2019, Qiao et al. 2020). A graph-like representation is a qualitative part of the BNs model and prior and conditional probabilities are the quantitative parts. In the acyclic graph, the nodes, which are shown as circles, represent the random variables and directed arcs illustrate dependencies or cause-effect relations among the nodes (Kabir & Papadopoulos 2019).

Features such as the intuitive graphical representation, modeling uncertainty, developing interdependencies between factors, and the possibility to combine various sources of information (i.e., theoretical data, empirical data, and expert judgment) have made BNs an appropriate tool for accident and risk analysis (Weber et al. 2012, Mkrtchyan et al. 2015, Qiao et al. 2020). They have been deployed as a standalone approach and/or a model-to-model transformation approach (Al-Shanini et al. 2014, Kabir & Papadopoulos 2019). Constructing and using BNs compromise three steps of problem structuring (i.e., identifying variables and network structure and expressing as statistical variables), instantiation (i.e., specifying conditional probabilities), and inference (i.e., entering variables, propagating, and interpreting results) (Sigurdsson et al. 2001).

2.2 Petri Nets

Petri Nets (PNs) are mathematical and graphical tools that are appropriate for modeling and analyzing dynamic, distributed, parallel, and concurrent systems with time constraints (Vernez et al. 2003, Wu et al. 2015, Kabir & Papadopoulos 2019). They are described by a set of places, a set of transitions, a valuation function, and an initial marking. In a PN graph as a directed bipartite, a circle represents a place and a thin rectangle stands for a transition, and arrows and tokens respectively illustrate valuation functions and marking.

The required steps to create and analyze a PN model are problem structuring (i.e., identifying places and transitions based on system behavior and draw its PN model), instantiation (i.e., forming the initial marking by putting specified numbers of tokens in the specified places and specifying firing rates for the timed transitions), and analysis (i.e., executing/simulating the model using PN simulator and interpreting results) (Kabir & Papadopoulos 2019).

2.3 Machine Learning and Text Mining

Machine learning (ML) as a subset of artificial intelligence (AI) involves algorithms to create and adapt models which can automatically be improved through experience and by the use of data. The ML is a subset of artificial intelligence while deep learning and text mining are subsets of ML (Hegde & Rokseth 2020). There are three common types of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning contains classification and regression algorithms. Unsupervised learning mainly deals with unlabeled data and involves clustering and association techniques to discover similarities and differences. And reinforcement learning algorithms learn via feedback from their own actions and experiences and are good for developing an appropriate action model.

ML algorithms can analyze the various format of the input data, from numerical data to textual one, which can be historical, real-time, or a combination of both. Moreover, data mining and text mining are respectively referred to as applying ML itself or in association with other methods such as statistics and natural language processing (NLP) to analyze numerical data and textual data. Text mining contains everything from information retrieval to text classification and clustering, to entity, relation, and event extraction through exploring text corpora.

3 BIBLIOMETRIC SEARCH METHODOLOGY

We searched six databases (ScienceDirect, Scopus, Web of Science, SpringerLink, Google scholar, and IEEE Xplore) for published scholarly research in English, up to the date 1 August 2021. Our keyword search terms were: “accident modeling”, “accident analysis”, “accident causation”, “accident causal”, “accident models”, “accident prediction”, “safety”, “safety risk management” and “safety risk analysis”. Furthermore, our methods-related keywords are “Bayesian networks”, “Petri nets”, “Network theory”, “Artificial intelligence”, “Machine learning”, “Data mining”, “Text mining”, and “Deep learning”, which we used in conjunction with rail-related keywords “railroad” and “railway” to find published studies in the research subject. Then, we included those studies that have used these methods to analyze at least one railway occurrence. Thus, publications with the aims of safety risk assessment as well as accident prediction were included only if they investigated the railway accidents with such methods. This yielded 54 articles.

3 DESCRIPTIVE ANALYSIS

This section represents the statistical analysis of the 54 original research articles that have used these methods to analyze railway accidents and safety risks.

The distribution of published papers in different years is illustrated in Figure 1. In 2004, the first application of modern accident modeling was observed by the work of Marsh & Bearfield (2004). Years 2018 and 2019 with respectively 13 and 10 publications are the most significant periods for the deployment of this emerging field in rail transportation. The share of the two groups of methods is approximately equal, with 44% for the network-based methods and 56% for the AI-based techniques.

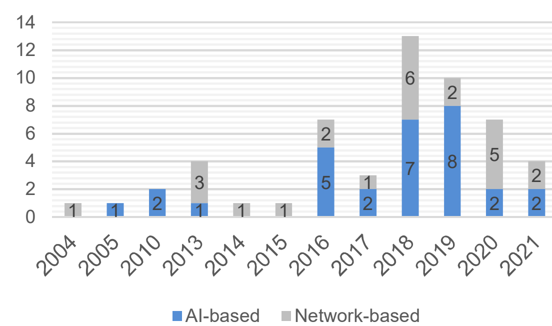

Figure 1. Yearly distribution of the reviewed articles based on the applied methods

As shown in Figure 2, the majority of the reviewed studies are journal articles (65%) with the remainder being conference papers.

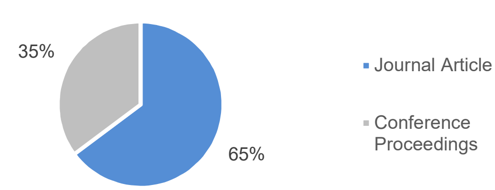

Figure 2. Distribution of the reviewed articles by type of publication

Table 1 reflects the distribution of articles published in journals. As can be seen, the Journal of Safety Science and the Journal of Reliability Engineering & System Safety are the two leading outlets, with a combined share of 37% of published papers.

Table 1. Distribution of the reviewed articles amongst the journal sources

Name of journal	No. of articles	% of articles
Safety science	7	20%
Reliability Engineering & System Safety	6	17%
Accident Analysis & Prevention	3	9%
AIMS Electronics and Electrical Engineering	2	6%
Other journals	17	48%

4 RESULTS AND DISCUSSION

The new accident and risk analysis frameworks can be classified into network-based and artificial intelligence (AI)-based methods, which can have further categorized by the type of algorithms and techniques, data sources, and tools applied.

4.1 Network-based Accident Analysis Methods

4.1.1 Bayesian Networks in Railway Accident and Safety Analysis

Bayesian networks (BNs) may be used alone or in combination with other analytical methods to analyze railway accidents and the associated safety risks.
Marsh & Bearfield (2004) used BNs to develop a casual model of signals passed at danger (SPAD) incidents in the UK by incorporating organizational factors. They later applied the same approach to model train boarding and alighting incidents and argued the advantages of BNs over fault and event trees for modeling events (Bearfield & Marsh 2010).

In a series of research, Liang and their colleagues developed BN-based frameworks for railway grade crossing occurrences to identify the important causal factors, their relationships, and their quantitative influence (Liang et al. 2017, Liang & Ghazel 2018, Liang et al. 2018, 2020). In 2017, they produced a causal statistic risk assessment based on hierarchical causal Bayesian networks (called CSRA-CBN) approach to explore the key contributing factors to accidents/incidents at grade crossings as well as their combined impacts on safety. The CBN model was created according to the statistical analysis of the accident and incident databases (Liang et al. 2017). Later, Liang et al. (2018) combined grade crossing accident/incident databases with expert knowledge data to construct a causal network structure and used forward and reverse inferences and Euclidean distance to identify the strength of factor interactions and the most important ones. Liang & Ghazel (2018) statistically analyzed grade crossing accident/incident database with respect to traffic moment (i.e., the combined traffic at the grade crossing, which is calculated by multiplying road traffic frequency by railway traffic frequency), different kinds of transport mode and different geographical regions and identified causalities between these factors and accident occurrence. Then, they established the BN risk model based on the outcomes of statistical analysis and predicted accident probability, and assessed risk level. To construct a BN structure for accident and safety risk analysis of railway level crossing, Liang et al. (2020) discovered preliminary causality through automatic structure learning including the Bayesian search (BS), naïve Bayes, and greedy thick thinning (GTT) algorithms, and optimized it by causality constraints derived from expert knowledge

Dindar and colleagues also conducted a series of BN studies on derailments. In the first study, Dindar et al. (2018) provided a Fuzzy Bayesian network (FBN) for weather-related derailments at railway switch systems. A causal relationship was built through analyzing 18,000 derailment reports across the U.S., which was quantified using Buckley's probability calculation and confidence intervals. In the second study, Dindar et al. (2019) adopted a new stochastic mathematical modeling technique based on a hierarchical Bayesian model (HBM) to investigate component failure-related derailments at railway switches. They integrated multiple specialized packages, such as MATLAB for image processing, R for statistical analysis, and ArcGIS for displaying and manipulating geospatial data, to better model and display complex solutions. Finally, in 2020, human factors related to derailments on switches and crossings were examined by Dindar et al. (2020) using a Fuzzy Bayesian network (FBN). They combined accident data and expert knowledge data to develop the BN model and employed fuzzy set theory to quantify the linguistic information and compute the human error likelihood of derailment.

A transformation of an event tree (ET) model to a BN model can be seen in Ye & Zheng (2016a). They first developed an event tree (ET) model for the failure of the component of the automatic train protection (ATP) system regarding the human cognitive process in the generic error modeling system (GEMS) (i.e., they considered perception, scenario analysis, decision making, and action-taking as a human cognitive process). They then transferred the ET model into hierarchical BN (HBN) considering rail-performance shaping factors (R-PSFs) and finally established a human-machine bow-tie model. Expert judgments which were aggregated by Dempster-Shafer (D-S) evidence theory were used for selecting appropriate R-PSFs for each cognitive phase, constructing causal relationships, and performing quantification. In another ET to BN model transformation for assessing human risks associated with using ATP, Ye & Zheng (2016b) utilized the fuzzy inference theory to improve conditional probability tables (CPT) building method for BN.

Zhang et al. (2018) defined and classified factors that contributed to high-speed railway accidents in China using the human factors analysis and classification system-railway accidents (HFACS-RAs) method. After that, they built a BN structure according to the HFACS-RAs classification and the results of interaction analysis by the Chi-square test and Odds ratios (OR). Finally, the D-S/AHP evidence fusion method relying on expert knowledge was adopted to infer the conditional probability tables (CPTs) in the BN. A hybrid approach of interpretive structural modeling (ISM) and BN was applied by Huang et al. (2020) to analyze the relationships and interaction strengths among the risk factors and accident causes of railway dangerous goods transportation system (RDGTS). The safety performance of five railways (i.e., Chinese, Japanese, Spanish, French, and South Korean railways) was compared through analyzing accident data sets and developing risk assessment models using Bayesian inference, decision tree, and Petri net techniques (Rungskunroch et al. 2021).

Table 2 provides a summary of the sources of data and software packages that were used to analyze and construct the BN models.

Table 2. Data sources for constructing the Bayesian network models

Author	Country	Software	Data sources	
			Expert judgments data	Occurrence data
Marsh & Bearfield (2004)	UK	-	♦	
Bearfield & Marsh (2010)	UK	-	♦	♦
Liang et al. (2017)	France	GeNIe		♦
Liang et al. (2018)	France	GeNIe	♦	♦
Liang & Ghazel (2018)	France	GeNIe		♦
Liang et al. (2020)	France	GeNIe	♦	♦
Dindar et al. (2018)	UK	MATLAB		♦
Dindar et al. (2019)	UK	MATLAB, R, ArcGIS		♦
Dindar et al. (2020)	UK	-	♦	♦
Ye & Zheng (2016a)	China	GeNIe	♦	
Ye & Zheng (2016b)	China	GeNIe	♦	
Zhang et al. (2018)	China	GeNIe	♦	♦
Huang et al. (2020)	China	GeNIe	♦	♦
Rungskunroch et al. (2021)	UK	Python	♦	♦

As can be seen in Table 2, occurrence data analysis is usually used in combination with expert judgments data to solve the data scarcity problem. In rich data situations such as level crossing incidents, the BN model development relies only on occurrence data. Furthermore, GeNIe is the widely used tool in the BN-based accident and safety analysis.

4.1.2 Petri Nets in Railway Accident and Safety Analysis

Similar to BNs, Petri nets (PNs) have been applied as standalone or as a part of model-to-model transformation approaches to assess railway accidents and risks.

Wu et al. (2015) deployed stochastic Petri nets (SPNs) to present a model of train rear-end collision accidents. The quantitative analysis and uncertainty modeling were respectively undertaken by the isomorphic Markov chain model and Fuzzy random method. Dirk et al. (2013)’s study is one of the proposed model-to-model transformation frameworks for PNs. They proposed formalSTAMP by integrating PNs with the systems theoretic accident model and processes (STAMP) method and employed it to scrutinize the Wenzhou 7.23 accident as the most serious rail accident in China. In 2018, Song & Schnieder (2018) extracted the fault tree (FT) of train head to tail collisions and then mapped it into colored Petri nets (CPNs) to address limitations of the FT method including modeling time-related attributions and non-linear relationships. The accuracy of the framework was verified by using Monte Carlo simulation and state-space analysis. Recently, Zhang et al. (2020) developed a Fuzzy Petri net-fault tree analysis (FPN-FTA) model for the stampede accident of Shijiazhuang high-speed railway station in China and simulated the FTA-FPN model with Stateflow of Matlab software. The accident was first represented in FTA and then converted to FPN through integrating dynamic weighting FPN and FTA. Finally, the optimal risk controls were determined after building a bi-objective risk control model and optimizing with the particle swarm optimization (PSO) algorithm.

4.1.2 Other Network-based Methods

Xin et al. (2013) believed that BNs and PNs methods suffer from having a local view in accident analysis as they focus on point-to-point or part-to-part analysis, which is not enough for complicated railway accidents. Therefore, they employed the complex network theory (CNT) to identify the causation of the Wenzhou 7.23 accident that occurred in China. They found that the inspection of signals and the checking of line conditions before trains run were the main reasons for this accident. The Wenzhou 7.23 accident was also investigated by the complex network theory integrated with the cascading failure theory by (Luo et al. 2014). They concluded that the equipment’s failure was the root cause of the accident while the control flaws of the train operation system in preventing or hindering the propagation of cascading failure played an important role. In another study, Li & Wang (2018) first identified the causes of railway accidents as well as their relationships by analyzing the Federal Railroad Administration (FRA) databases, and then, built the cause-effect network using complex network theory to depict how railway accidents occur.

Aguirre et al. (2013) presented a combined approach based on evidential networks (ENs) and fault tree analysis (FTA) to integrate the human, organizational and technical factors to risk analysis in railway accidents. They used the belief functions theory, also known as the Dempster-Shafer (D-F) or evidence theory, for quantification. Liu et al. (2019) provided a network theory-based accident model merged with topological analysis for understanding rail accidents. They delineated latent patterns of hazards and proposed a practical way to generate an accident causation network from accident reports. This model was later extended in Liu et al. (2021)'s study to better adapt to the heterogeneous characteristics produced by various causes of hazards and accident contributory factors. Recently, Lam & Tai (2020) presented a network analytical approach to clarify incident factors and how they affect each other in railway incident chains. The model was used to survey railway events in Japan from local view analysis, global view analysis, and contextual view analysis perspectives.

4.2 AI-BASED ACCIDENT ANALYSIS METHODS

This literature review illustrates that the applications of machine learning (ML) methods in accident and risk analysis are on the rise. The application of association rule mining to discover patterns among accident data can be seen in Mirabadi & Sharifian (2010)'s study. They utilized generalized rule induction (GRI) algorithm to recognize relationships between the accidents' causes by discovering repetitive patterns within the past accident data of the Iranian Railway (RAI). Ghomi et al. (2016) employed the ordered probit model (OPM), Apriori, and classification and regression tree (CART) algorithms to extract the factors affecting the severity of highway-railway grade crossings accidents. The results of the three algorithms showed that train speed has the highest impact on injury severity. 392 Chinese railway accident reports were collected and processed by Yu et al. (2018) and factors involved in accidents were identified and classified based on the cognitive reliability and error analysis method-railway accidents (CREAM-RAs) taxonomy framework. They called the categorized accident factors multi-attribute railway accidents dataset (MARA-D) which was later clustered and visualized adopting the self-organizing maps (SOM) algorithm. Alawad et al. (2019) employed machine learning, particularly the decision tree (DT) method to analyze accidents occurring at railway stations in the U.K. The significant causes, their interactions, and the traits of passengers influenced by accidents were extracted in order to improve safety at the railway stations. The application of 11 different types of ML algorithms to uncover patterns in the equipment accident database of the FRA and to predict derailments can be seen in Bridgelall & Tolliver (2021). The extreme gradient boosting (XGB) classifier showed the best prediction performance at predicting derailment accidents among other algorithms.

In another research stream, researchers analyzed semi-structured and/or unstructured textual descriptions of railway incidents and accidents, along with structured data. Williams et al. (2015)'s work focused on applying a topic modeling algorithm, called latent Dirichlet analysis (LDA), to uncover the themes of railway grade crossing accidents embedded in the text body of the FRA investigation reports. They find that additional training of conductors to make the leading freight car more conspicuous can reduce the accidents. In another study, Williams et al. (2016) adopted the LDA topic modeling and k-means clustering algorithms to analyze serious rail accidents in the U.S. and Canada to find key differences. Accidents involving bridges, for example, were more prominent in Canada, while it was not seen in the obtained clusters for the U.S. rail accident reports. Another distinction was the prevalence of accidents containing runaway cars in the Canadian railways.

Williams & Betak (2016) explored the FRA equipment accident reports from January 2010 to February 2015 using LDA as well as text clustering techniques and visually represented the text clusters. Both techniques concluded the main topics in the accident reports are grade crossings and trucks, shoving, and hump yards. They also discovered that major accidents themes are those related to lining switches and accidents involving the actions of railroad personnel. Brown (2016) investigated a role that text mining can play in a better understanding of accident characteristics and accident factors. They examined over 11 years of railway accident reports with and without incorporating text analytics. They concluded that the accuracy of prediction for accident severity can be improved by incorporating factors found by text mining and modern ensemble methods (i.e., random forests and gradient boosting).

Syeda et al. (2017) studied the rail accident investigation branch (RAIB) reports by exerting natural language processing (NLP) techniques. They first defined the entities of interests (EOIs) according to the traditional accident analysis approaches, e.g., human factors and organizational factors, and then determined the frequency, sequence, and co-occurrence of words and the EOIs to help accident investigators for surveying causal relationships.

Two textual analysis techniques, i.e., latent semantic analysis (LSA) and latent Dirichlet allocation (LDA) were used and compared in the study by Williams & Betak (2018). These methods uncovered the most frequent rail accidents (e.g., switching accidents and grade crossing accidents) but also uncovered the less frequent (e.g., accidents involving ballast maintenance equipment). Moreover, Williams & Betak (2018) showed that applying two methods for mining texts can identify more accident topics compared to applying only one text mining technique. Karthi & Priscilla (2018) offered using the ID3 algorithm to classify the semi-structured part of accident reports and to extract the causes of major rail accidents. Li et al. (2018) applied full-text retrieval and text classification techniques to analyze the accident and fault reports of the Taiyuan railway bureau. They first used the TF-IDF algorithm to identify the most important user input keywords in the given documents. They later made classification applying a special type of artificial recurrent neural network (RNN) algorithm called long short-term memory (LSTM). Kamerkar et al. (2018) proposed the utilization of the ID3 algorithm, the naïve Bayesian (NB) classifier, and the agglomerative hierarchical clustering (AHC) method to outline the factors that influenced the accidents of the Indian Railway industry.

Heidarysafa et al. (2018) examined if text mining is helpful to extract accident causes from accident narratives that include terminologies that are not easy to understand by non-expert readers. Moreover, to know whether the reported causes in the structured format are consistent with those explained in the narratives or not. To answer these questions, they adopted three main deep learning approaches, i.e., convolutional neural nets (CNN), recurrent neural nets (RNN), and deep neural nets (DNN), along with word embeddings such as Word2Vec (i.e., word to Vector) and GloVe (i.e., Global Vectors for Word Representation). The results indicated that applying deep learning techniques for exploring railway accident descriptions can accurately classify the causes of an accident and detect important inconsistencies in accident reporting.

In Hua et al. (2019)'s paper, 283 Chinese railway accident reports were classified into accident description and causal analysis classes using the multichannel convolutional neural network (M-CNN) model. After that, the accident factors were derived from the identified causal analysis sentences by using the conditional random field (CRF) model and summarized into the main categories of human factors, mechanical equipment factors, operating environment factors, and management factors. Soleimani et al. (2019a) investigated 48,080 highway-railway crossing incidents in the U.S. to discover the reasons for the incidents from the textual descriptions. The critical reasons for the incidents in every state were identified utilizing the TF and TF-IDF techniques. Furthermore, the incident similarities between all the states were assessed with the pairwise correlation calculation. Finally, machine learning methods (i.e., random forest and logistic regression) were employed to classify incidents into "car struck train" or "train struck car" categories, using both the fixed fields of the FRA reports and the narrative ones. The defined categories help understand whether the incidents were more related to the driver's behavior or warning devices. The model was later developed by incorporating decision tree (DT), random forest (RF), XGboost (XGB), and logistic regression (LR) machine learning algorithms as well as geospatial analysis (Soleimani et al. 2019b, Soleimani et al. 2021).

Table 3 summarizes the AI models and algorithms that were used to analyze railway safety databases. As can be ascertained, the applied methods are categorized into machine learning (ML) and text mining (TM). The latter involves those articles that utilized TM and/or ML algorithms to explore railway accident and incident narratives while the former only focuses on analyzing the structured occurrence data. Moreover, text mining studies usually contain two steps: first natural language processing (NLP) are applied to transform unstructured text into structured data and then machine learning (ML) algorithms are used to extract further information.

Table 3. Summary of the applied machine learning (ML) and text mining (TM) models and algorithms

Author	Method	Model	Algorithms	Data source
Mirabadi and Sharifian (2010)	ML	Association rule mining	GRI	RAI accident database
Ghomi et al. (2016)	ML	Association rule mining	Apriori, OPM	FRA database
Ghomi et al. (2016)	ML	Classification	CART	FRA database
Yu et al., (2018)	ML	Clustering	SOM	Chinese Railway accident reports
Alawad et al. (2019)	ML	Classification	DT	RAIB database
Soleimani et al. (2019b)	ML	Classification	DT, RF, XGB, LR	Rail Inventory Management System (RIMS) database
Bridgelall and Tolliver (2021)	ML	Classification	DT, RF, AB, XGB, GB, K-NN, NB, SVM, ANN, SGD	FRA database
Williams et al. (2015)	TM	Topic modeling	LDA	FRA database
Williams et al. (2016)	TM	Topic modeling	LDA	NTSB and TSB reports
Williams et al. (2016)	TM	Clustering	K-means	NTSB and TSB reports
Williams and Betak (2016)	TM	Topic modeling	LDA	FRA database
Williams and Betak (2016)	TM	Clustering	K-means	FRA database
Brown (2016)	TM	Topic modeling	LDA	NTSB reports
Brown (2016)	TM	Classification	OLS, PLS, RF, GB	NTSB reports
Syeda et al. (2017)	TM	Topic modeling	LDA	RAIB database
Syeda et al. (2017)	TM	Clustering	Ward's method	RAIB database

Author	Method	Model	Algorithms	Data source
Williams and Betak (2018)	TM	Topic modeling	LSA, LDA	FRA database
Li et al. (2018)	TM	Word importance	TF-IDF	Taiyuan Railway Bureau (TRB) accident reports
		Classification	LSTM	
Kamerkar et al. (2018)	TM	Classification	ID3, NB	Indian Railway accident database
		Clustering	AHC	
Karthi and Priscilla (2018)	TM	Classification	ID3	FRA database
Heidarysafa et al.(2018)	TM	Word importance	TF-IDF	FRA database
		Classification	CNN, RNN, DNN,	
Hua et al. (2019)	TM	Classification	NB, SVM, RF, M-CNN	Chinese Railway accident reports
		Pattern recognition	HMM, CRF	
Soleimani et al. (2019a)	TM	Word importance	TF, TF-IDF	FRA database
		Classification	RF, LR	
Soleimani et al. (2021)	TM	Word importance	TF, TF-IDF	FRA database
		Classification	XGB	

*Abbreviations: GRI (Generalized Rule Induction), OPM (Ordered Probit Model), CART (Classification and Regression Tree), SOM (Self-Organizing Maps), DT(Decision Tree), RF (Random Forest), XGB (Extreme Gradient Boost), LR (Logistic Regression), AB (Ada Boost), GB (Gradient Boost), k-NN (k-Nearest Neighbors), NB (Naïve Bayes), SVM (Support Vector Machine), ANN (Artificial Neural Network), SGD (Stochastic Gradient Descent), LDA (Latent Dirichlet Analysis), OLS (Ordinary Least Squares), PLS (Partial Least Squares), LSA (Latent Semantic Analysis), TF-IDF (Term Frequency-Inverse Document Frequency), LSTM (Long Short-Term Memory), ID3 (Iterative Dichotomiser 3), AHC (Agglomerative hierarchical clustering), CNN (Convolutional Neural Nets), RNN (Recurrent Neural Nets), DNN (Deep Neural Nets), M-CNN (Multichannel Convolutional Neural Network), HMM (Hidden Markov model), CRF (Conditional Random Field), TF (Term Frequency)

Table 3 also reveals that classification, clustering, and topic modeling were the common techniques to investigate railway accident databases. Furthermore, accident data associated with the US railways was investigated more than other railways using these new methods.

Overall, the AI-based accident analysis methods have some advantages over the classical methods. First, they can analyze high-volume data in a short time. Second, they provide an opportunity to automatically explore the narratives of railway accident reports that usually offer a much richer amount of information regarding accident characteristics and the potential reasons behind them. Third, they help understand similarities and differences between accidents, derive hidden relationships among factors and accidents, discover implicit information, and predict accidents, which are not easy to process manually. Finally, they can leverage rail infrastructure monitoring data, train operations data, human performance data, etc., for accident and safety analysis and acquire a deep understanding of their relationships.

5 CONCLUSIONS

This paper summarizes new approaches for analyzing railway accidents and safety risks, and categorizes them into network-based and artificial intelligence (AI)-based methods. Through this review, we have found that advances in computer technology have produced a paradigm shift in accident modeling and made Bayesian networks, Petri nets, machine learning, and text mining emerging fields of accident analysis studies. These newer methods have been employed standalone or in combination with the classical accident and risk analysis methods such as fault tree analysis (FTA) and HFACS.

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