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Benchmarking on Railway Safety Performance Using Bayesian Inference, Decision Tree and Petri-net Techniques Based on Long-term Accidental Data Sets.

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Abstract

Not only has the railway accidental prevention been a prime focus, but it has also become a key challenge for the industry in recent years. For many decades, rail authorities have attempted to significantly improve rail safety, whilst facing various passengers' risks and uncertainties. The overarching goal of this study is to develop a new posterior probability model to quantify uncertainties for benchmarking. This is the world's first to establish new insights from the benchmarking of risk and safety across different rail networks. The insights will point out the advantages and practicability of launching safety policies and reducing railway accidents for other rail networks. The new model has been developed using unparalleled long-term accidental data sets, including 'a trailer an accident' and 'causes of the accident'. The investigation adopts a Bayesian approach (via Python) to codify the novel model. The new findings lead to the better understanding into the uncertainty of railway accidents. Five notable rail networks have been selected as case studies. This study has also compared the effectiveness of the decision tree and Petri-net models using the posterior probability and number of injuries and fatalities. Based on the benchmarking outcomes, Chinese and Japanese railway systems denote the lowest risk over other networks, followed by Spanish, French and South Korean rail networks. The study also demonstrates that the novel benchmarking criteria can effectively measure and compare any rail networks' risk and uncertainties. Its adoption will lead to performance improvement in terms of safety, reliability and maintenance policies of railway networks globally.

Keywords: *Bayesian inference, risk and uncertainty, railway accident, decision tree, Petri-nets.*

Highlights

- The research is the world's first to establish a novel Bayesian model based on prior belief and probabilistic methods for railway operations.
- The unprecedented model is definitely capable of predicting the future railway accident rate.
- Model verifications against the long-term FRA's accident data sets clearly exhibit excellent accuracy above 95% confidential level.

- Both of DT (decision tree) and PT (Petri-nets) models are embedded to evaluate the risk level of railway networks. Those models can be practically applied to any railway authorities worldwide.
- Reducing the railway accident, saving passengers' lives, and increasing reliability can be achievable by adopting both models into railway companies' action plan.

1. Introduction

Railway networks are expected to cater exceptional travel services and safety to passengers and rail users. The railway sector has the lowest accidental rate compared with other transportation modes. The number of casualties had decreased approximately one-third across the EU during 2010 - 2018 (ERA, 2018, EC, 2020). Gradual reduction of the accidental number has pushed forward rail authorities' campaign to enable zero accident across rail networks globally.

It is well known that uncertainties play a key role in railway safety management and accidental prevention. In this study, the long-term accidental data sets, which include causes and consequences of an accident over 20 years, have been collected from railway authorities. The study examines the primary data sources to identify the impact of train accidents with respect to the number of injuries and fatalities. This study develops a novel Python-based model using a modified Bayesian approach for predicting railway accidental rate. One of the key benefits of this new model is the better understanding into the uncertainty propagation of accident, which indicates the future accident rate.

A primary issue about the unified measurement of safety performance is that rail authorities have developed their own safety policies and performance standards. Rail organisations usually claim that they are operating a low-risk network; however, it may contain systemic bias stemmed from the unbalanced safety performance standard used in a particular rail network or even within an operating company. An innovative solution to this problem is to establish a new framework catalyzed to benchmark balanced safety performance among railway networks, taking into account the uncertainties through the decision tree (DT) and Petri-nets (PT) models. The outcome offers a novel standardisation criterion with four groups of risk levels. The novel contribution of this study has a broad range of applications to benchmark risk performance for all HSR networks. This study also highlights the novel prediction and benchmarking risk models capable of quantifying uncertainties and balancing systems performance criteria. Both models will lead to the sustainable development on the upcoming rail networks that can help rail authorities to improve risk management strategies and assess the consequences of existing rail policies. This approach will enhance the public safety, which is paramount to social value, a pillar for sustainable development.

2. Literature review

2.1 Existing causes and effects of railway accidents

With the vast development of HSR technologies, the number of railway accidents has decreased during this decade. The EU-27 report reveals that the number of railway accidents in European countries was 666 in 2018, in which 748 passengers received severe injuries. However, the number of injured passengers showed a 30% decrease from 2010 (ERA, 2018). Similarly, London Underground states that the number of accidents had slightly decreased for five consecutive years during 2013-2018, while the number of accidents shows a 30.83% decrease (ORR, 2019).

Comparing by mode of transportation, research finds that railway services show the smallest number of passenger injuries and fatalities among all modes of transportation. The European Transport Safety Council's (ETSC) report reveals that the rate of fatalities due to railway services is only 0.035 persons per 100 million person-kilometres. In contrast, the overall fatality rate due to road accidents (motorcycle, foot, bike, car, bus and coach) is 0.95 persons per 100 million person-kilometres, as shown in Figure 1 (ETSC, 2003). Another study also mentions that three quarters of railway accidents across the EU occur due to trespass; accidents at level crossings are 15% of these (UIC, 2018; Schaefers and Hans, 2000).

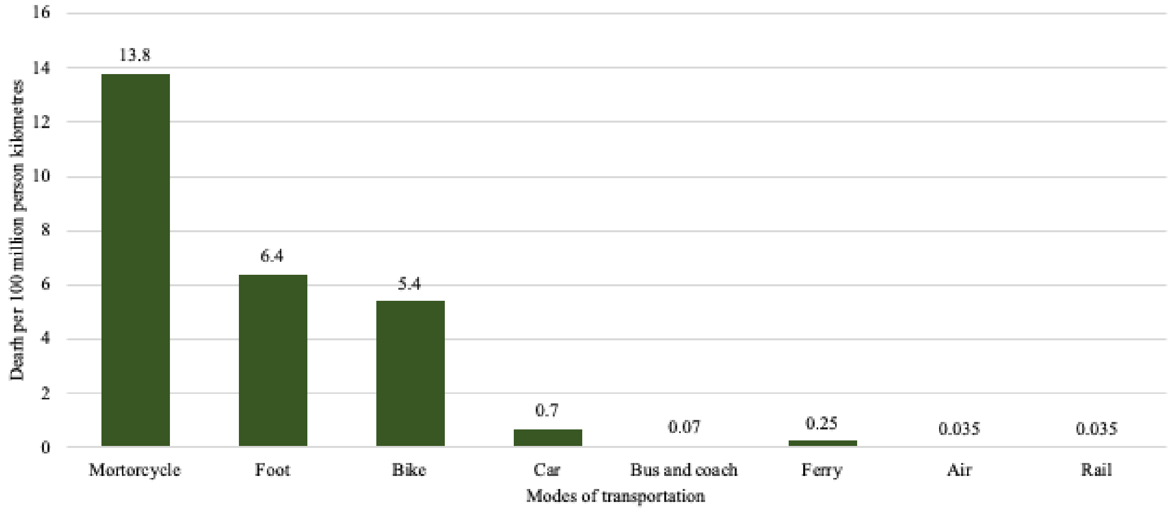


Fig. 1 Comparison of fatality rates for motorcycle, foot, bike, car, bus and coach, ferry, air and rail across the EU (unit: 100 million passenger-miles) (source: European Transport Safety Council, 2003)

Consequently, the US National Safety Council has found that railways have low injury and death rates. Figure 2 shows the fatality rate to be 0.01-0.12 per 100 million passenger-miles, whereas the rate for light duty vehicles is 0.46-0.66 per 100 million passenger-miles (USA National Safety Council, 2020).

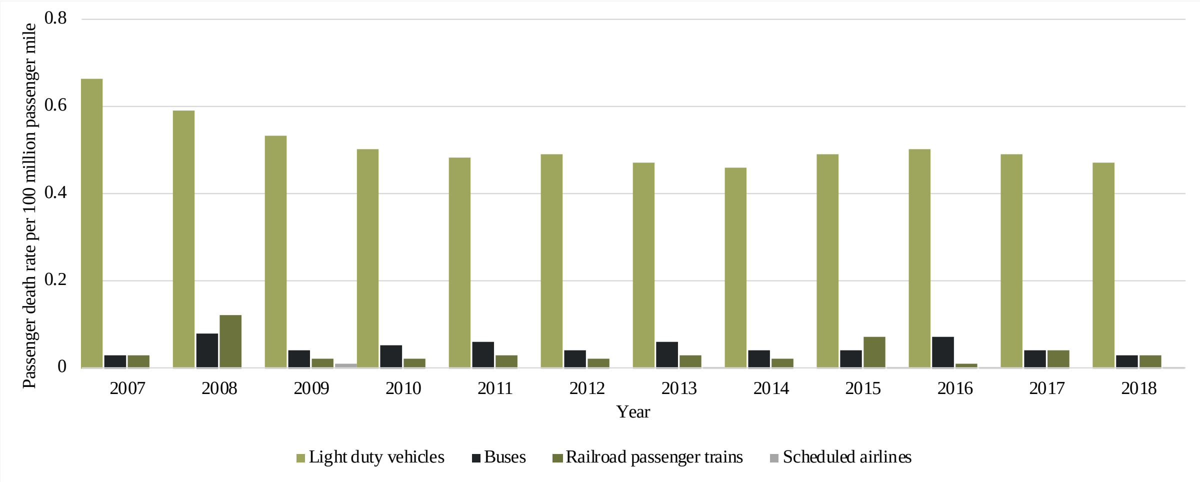


Fig. 2 Comparison of fatality rates between light vehicles, buses, railways and airlines across the USA (unit: 100 million passenger-miles) (source: National Safety Council, 2020)

In conclusion, the trend in railway accidents has been a gradual decrease, with railway services showing a small number of injuries and fatalities compared with other transportation modes. However, the challenge to achieve zero accidents and to reduce the level of damage are key drivers for rail organisations.

2.2 Application of Bayesian statistics to railway accidents

Bayesian statistics (Bayesian network, Bayes belief network, BN) was created to calculate conditional probability in complex models. Others probability-based methods, i.e. fault tree analysis (FTA), event tree analysis (ETA), and failure mode effect analysis (FMEA) could not solve this issue (Zhang *et al.*, 2014; Dindar *et al.*, 2018; Wang, Liu and Ni, 2018). The BN model has been widely applied in railway risk, safety analysis and other risk assessments. The BN model can be used to predict the probabilities for causes of accidents based on experience from working with existing data. BN allows the input of multiple hazards and uncertainties, which are suitable for complicated causes of railway accidents. The outcomes from BN applied to railway accidents show a higher degree of accuracy for risk assessment than from other models.

Marsh (2004) uses a Bayesian network, in relation to risk assessment, to model accidents in the UK railway industry. The research focuses on the issue of signals passed at danger (SPAD), when trains dangerously pass stop signals without authority. The outcome from the study has led changes in the UK railway industry’s driver training activities in order to reduce the number of rail accidents. Similarly, there is research concerning three types of level crossings in the UK, the railway-controlled, automatic and passive types. The findings show that, among the three different types of level crossing, automatic crossings have higher accident rates than the other crossing types (Evans, 2011; Igari and Hoshino, 2018).

Moreover, BN has been applied in the study of train derailments caused by severe weather conditions at railway turnouts (RTs), which are critical parts of railway infrastructure. This study's outcomes led to improved railway operation during uncertain climatic conditions (Dindar *et al.*, 2018; Zoeteman, 2020). Similarly, the failure prediction model for RTs, which is affected by weather conditions, was launched. The study also uses the BN model to evaluate the impact of extreme weather on the RTs. The results provide for suitable RT maintenance decisions, which can significantly save maintenance costs and improve safety performance (Wang *et al.*, 2016). The BN is also used to monitor the conditions of RTs, and the model can accurately account for track damage (Wang, Liu and Ni, 2018).

2.3 Uncertainties in railway risk assessment

Safety risk assessment is a key driver for railway operations, and that uncertainty analysis for railway systems plays a crucial role in rare cases. Uncertainties in railway systems can occur due to internal and external events. For example, internal events happen on trains or networks, whereas external events occur due to outside sources, such as disasters. Fukuoka (1999) mentions that railway risk assessment is challenging because accident frequency is low. This highlights the problem that lack of information (or data limitation) creates a considerable barrier for railway operators in assessing risk and uncertainty in railway systems.

On the other hand, various mathematical models have been developed to solve the issue of lack of reliable and sufficient information. In particular, de Miguel *et al.* (2019) use the output from a Monte Carlo simulation (MCS) to analyse uncertainty at railway turnouts. This method ultimately produces total sensitivity indices. A life cycle study on user value of rail and road level crossings in Austria was aimed at optimising maintenance costs (Grossberger, Mauler and Michelberger, 2017). The research faced complexity in terms of time and conditions of parameters; however, the MCS was applied to generate a probabilistic scenario and estimate uncertainties. Another rail life cycle study led to a decision to renew support infrastructure maintenance. This research mentions that rail track maintenance costs have increased dramatically; thus, the MCS is applied to find quantifications of uncertainty in track life cycle (Vandoorne and Gräbe, 2018). Similarly, a study of risk in railway tunnels included an MCS model to generate probability distributions. This research states that using probability distribution offers realistic descriptions that are influential in railway risk assessment (Vanorio and Mera, 2012).

2.4 Railway risk classification

To classify railway risk, this study groups all risks according to the root cause of accidents. It is necessary to understand the effects and root causes of accidents because this leads to developments in the sustainability of railway system safety policies. The data collected is classified into three groups based on the effects on the train after an accident, including (i) collision, (ii) derailment and (iii) other effects. The ‘other effects’ on trains mostly occur due to human failures, such as vandalism, passenger carelessness and objects on the track, as shown in Table 1.

Table 1. The classification of effect of accidents

Collision (A1)
Head-on collision
Rear-end collision
Slanting collision
Collision with buffer stop or obstruction on the track
Derailment (A2)
Any derailment at:
Plain
Curve
Junction
Other (A3)
Fire, explosion and the leak of the hazardous chemical (including sabotage)
Fall of the passenger on track
Collision with people on track

The causes of accidents can also be classified into seven groups, including (i) driver error, (ii) signal operator error, (iii) infrastructure failure, (iv) equipment failure, (v) human error, (vi) natural causes and (vii) contributory factors. With respect to the human error, this means the fault of staff other than drivers and signal operators. Moreover, the sub-causes of accidents can be classified into seven groups, as represented in Table 2.

Table 2. Summary of cause of accident and sub-causes of accidents.

Cause of accident	Sub-cause of accident
B1: Driver's error	Failure to release the hand brake Failure to control the speed of the car
B2: Signalmen's error	Signal equipment failure Loss of communication device
B3: Infrastructure failure	Track geometry Frogs, switches and track appliances Other ways and structure (bridge/design construction) Rail Joint bar Roadbed
B4: Equipment failure	Axles and journal bearings Coupler and draft system Doors General mechanical and electrical failures Locomotives Truck components Wheels Body Brake Trailer or container on flatcar
B5: Human error (Exclude Signalmen's and driver's error)	Cab signals Employee physical condition Flagging, fixed, hand and radio signals General Switching Rules Loading Procedures Main track authority - failure to stop the train in clear Miscellaneous Speed Switches Train handling or train make-up
B6: Natural causes	Snow, ice, mud, gravel, coal, sand, and others on track Heavy rain, tornado and landslide Flood, tsunami and landslide Dense fog or smog or things that make unclearly visible Extreme wind velocity
B7: Contribution factors	Trainload or overloaded car Highway Object on track Vandalism or track damage

However, table 2 points out only the frequency factors and prevailing conditions to affect railway accidents. This study excludes unobserved heterogeneity, which may influential and potentially by other possible circumstances (Saeed and et. al, 2017; Saeed and et. al, 2020; Waseem and et. al, 2019; Saeed T. U., 2019).

3. Risk assessment model

Risk assessment is the process of understanding risk characteristics in railway networks, and leads to the elimination or reduction of the risk of railway accidents. Research has developed various models of risk assessment in relation to railway accidents.

In Great Britain (GB), the RSSB's risk safety models are the standard used to measure safety and harm on the country's mainline. The measurement unit is known as 'fatalities and weighted injuries' (FWI), with one FWI being defined as one fatality, ten major injuries, 200 reportable minor injuries, or 1,000 non-reportable minor injuries (Gilmartin, 2010). Leitner (2017) also assesses railway-related risk by using the FWI unit on Slovakian railway systems. Such research focuses intensely on numbers of fatalities and injuries.

On the other hand, some research applies other factors in risk assessment equations, e.g. vulnerability, capacity to cope and frequency of hazards. For example, for Canadian railways, danger and vulnerability are combined in the assessment of risk corridors. Both factors play a primary role in evaluation without using numbers of injuries and fatalities. The reason is that most trains operating in these corridors are freight trains. Therefore, the risk to passengers and staff should be lower than for passenger trains. Business factors can also involve in risk on railway networks. Xue *et al.* (2020) studies the business factors involved in a risk coupling model of China's high-speed rail. This research focuses on the defects of technology, capital and management, and states that single risk categories can lead to accidents.

Moreover, big data analysis is applied to reveal failures and to assess infrastructure risks (Li *et al.*, 2010). Jamshidi *et al.* (2017) adopt risk models that use the MCS method in Bayesian data analysis to determine posterior distributions. This model can precisely estimate failure due to cracks in infrastructure enabling prevention of railway accidents in the long term.

Additionally, various risk assessment methods are applied in research, including DT, ETA, FTA, PT, risk evaluation, human factor analysis and others (Bayesian and fuzzy). A summary of risk analysis methodology in existing research is shown in Table 3.

Table 3. Summary of railway risk assessment models

Authors	Risk models / Risk assessment model	Gaps
Leitner (2017), Gilmartin (2010)	This research uses 'fatalities and weighted injuries' as a primary standard. The FWI measure is calculated as equal to one fatality, ten major injuries, 200 reportable minor injuries, or 1,000 non-reportable minor injuries.	Using the FWI measure may not be compatible with benchmarking between countries. For example, accidents with a lower number of injuries or fatalities cannot be measured.
Alexander (2012), Westerman (2020)	$R = \frac{H \times V}{C}$ where R = Risk, H = Hazards, V = Vulnerability, C = Capacity to cope with decreases.	The model suits natural events and human impacts. Although natural events are one cause of railway accidents, the model cannot fit all causes.
CsChe (2017)	Risk = Hazard x Vulnerability Hazard = likelihood of occurrence of derailment on a discrete mile segment based on incident history, infrastructure, and operating practices. Vulnerability = valuation of exposure to physical elements.	The model concerns only hazard and vulnerability factors. It is applied to freight train risk assessment. The model is not suited to benchmarking for passenger trains and for any impacts with passengers.
Xue *et al.* (2020)	$\varepsilon R = \frac{(LR \times WR)}{\sum(LR \times WR)}$ $\mathrm{CE(A-B)} = \frac{(X \parallel t = k - XCE(A-B) \parallel t = k)}{X \parallel t = k}$ CE(A − B) is the coupling effect of risk factors A and B X||t = k is the total risk level at the end of the k^{th} year, XCE(A − B) ||t = k represents the total risk level at the end of the k^{th} year after removing the coupling effect of risk factors A and B.	This research is deeply concerned with technical, capital and management issues in railway risk. Also, the study examines economic impacts and organisational problems in detail.
Jamshidi (2017)	$\pi\ (\theta\ \lvert\Delta L) = \frac{f\ (\Delta L\lvert\theta)\pi_0\ (\theta)}{f(\theta)} \propto f\ (\Delta L\lvert\theta)\pi_0\ (\theta)$ $\pi_0\ (\theta) = probability\ density\ function$ $f\ (\Delta L\lvert\theta)$ = likelihood from statistical observation $\pi = posterior\ distribution$	This research conducts posterior distribution methods to predict failure or cracks in railway infrastructure. Posterior distribution is a suitable method.

The literature review shows that studies are mostly intended to increase performance on railway networks. Dindar *et al.* (2018) provide suggestions to railway companies on how to operate under severe weather conditions. Their research uses fuzzy logic and Bayesian network to improve reliability for the railway industry (Dindar *et al.*, 2020). Some research uses the MCS, DT and ETA models to analyse risks from human errors, including rail employees, passengers and road users (Zhou and Lei, 2020; Khalid *et al.*, 2019; Vileiniskis and Remenyte-Prescott, 2017). Moreover, improvements in infrastructure and maintenance on rail networks is addressed using DT and other tools (Zhou *et al.*, 2020; Eisenberger and Fink, 2017; Jia *et al.*, 2011).

Regarding safety policies, some studies offer policies that include measurement to help avoid railway accidents. The analytical hierarchy process (AHP), along with the maximum absolute weighted residual (MAWR) and maximum entropy method (MEM) tools that calculate the dangerous failure rate for equipment, are provided to reduce the scale of accidents (Liu and *et al.*, 2020). Song and Schnieder

(2018) proposed to eliminate head to tail collisions using the FTA and PT methods. The driving model, which classifies drivers on a scale from excellent to poor, has been developed through the DT method (Ochiai and *et al.*, 2019). The result has led to decreased risk from human error. A similar result has been achieved from using subtree models with high demand rail. These outcomes have shown safety performance improvements of up to 48.05% (Chen *et al.*, 2018).

Several authors have addressed accident analysis. Fuzzy FTA has been applied in quantitative studies to predict railway accidents on HSR networks. The outcome shows that it is useful in making decisions when there is incompleteness and complexity (Liu *et al.*, 2015). Accidents due to signals passed danger have been focused on using risk factors to reduce the cost of accidents (Kyriakidis *et al.*, 2019). Similarly, Zheng *et al.* (2016) have collected previous accident data to make forecasts, in rare events, concerning profit decisions. Moreover, FT, fuzzy belief models and various other risk models have been adopted for risk assessments on freight trains. The outcomes can improve logistic performances in relation to dangerous products (Huang *et al.*, 2020; Huang *et al.*, 2021).

Previous studies have exclusively focused on the number of accidents, injuries, fatalities and other related factors (vulnerability, hazard level). Also, some models cannot be applied on other railway networks. Therefore, this study adopts new models to benchmark risk assessment across railway networks. These new models can be evaluated as tools to enhance safety performance without facing the issue of lack of information.

Table 4. Summary of risk analysis methodology in existing research

Author (s)	**Decision tree analysis**	**Event tree analysis**	**Fault tree analysis**	**Petri-nets**	**Risk evaluation**	**Human factor analysis**	**Others**
Jia, Xu and Wang, 2011					✓		
Khan *et al.*, 2014				✓			
Liu *et al.*, 2015			✓				
Boudi and et al, 2015				✓			
Zheng, Lu and Tolliver, 2016	✓						
Leitner, 2017	✓						
Eisenberger and Fink, 2017				✓			
Vileiniskis and Remenyte-Prescott, 2017				✓			✓
Chen, Dollevoet and Zhao, 2018		✓					
Song and Schnieder, 2018			✓	✓			
Dindar *et al.*, 2018							✓
Ochiai, Masuma and Tomii, 2019	✓						
Cheng and Yang, 2009				✓			✓
Consilvio *et al.*, 2019					✓		
Li *et al.*, 2019						✓	
Kyriakidis *et al.*, 2019							✓
Khalid *et al.*, 2019		✓					
Zhou *et al.*, 2020	✓						
Huang, Liu, *et al.*, 2020			✓				✓
Zhou and Lei, 2020						✓	
Liu *et al.*, 2020					✓		
Huang, Zhang, Xu, *et al.*, 2020					✓		✓
Huang, Zhang, Kou, *et al.*, 2020						✓	✓
Dindar, Kaewunruen and An, 2020						✓	✓
Huang *et al.*, 2021					✓		

4. Research framework

One approach to solving the information scarcity problem involves the use of Bayesian inferences. The research gathers long-term secondary passenger train accident data sets from railway companies' official reports. First of all, data collection and data cleansing processes are required, focusing in detail only on passenger train accidents. The data cleansing process for railway accidents includes stages to remove invalid data sets, match rail authorities' published documents, and recheck missing data sets. In this case, the invalid data sets mean that the data from unofficial records and the accidents under investigation.

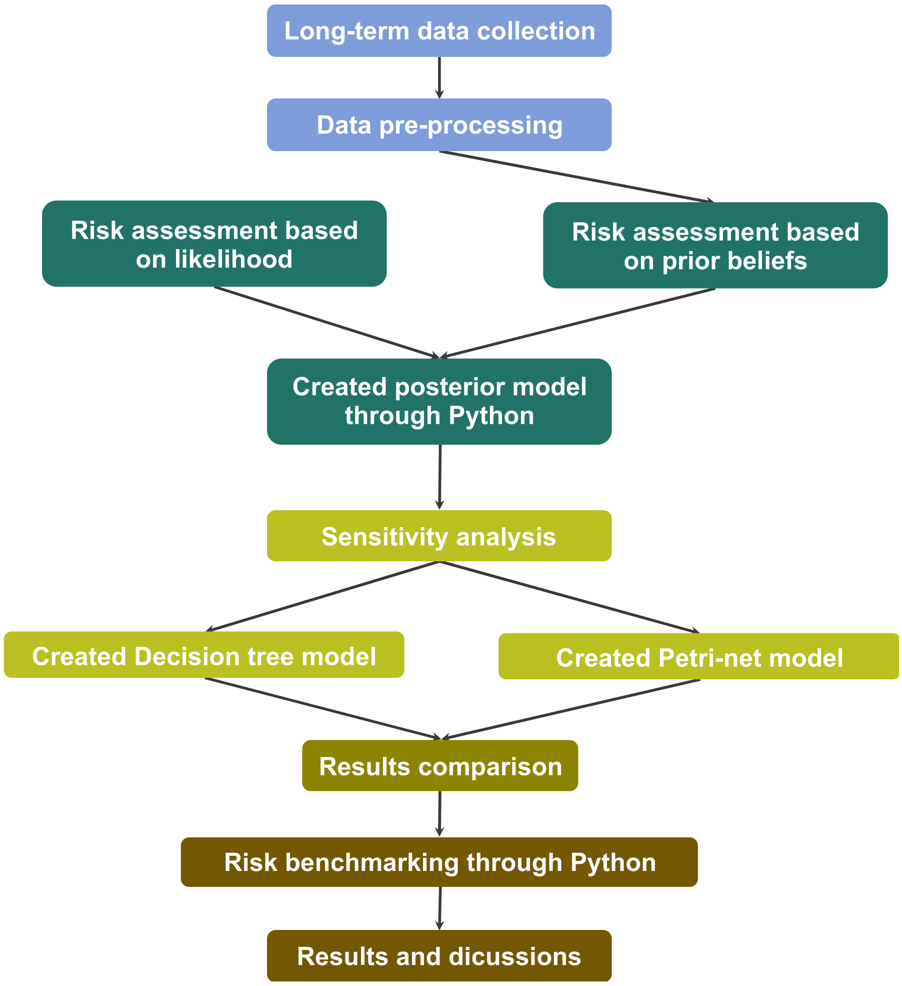


Fig. 3 The research framework

The risk assessment analysis is then provided by using Bayesian statistics. This stage plays a vital role in the estimated probabilities for railway accidents. One important key is to infer the posterior probability for each effect on a train after an accident. Uncertainties can be estimated from the data collected, based on experts' beliefs, due to the fact that such data usually contains uncertainty. As mentioned, some types of accident have an extremely low frequency and cannot be evaluated without using mathematical models. As a result, the research provides the outcomes from this stage as posterior probability values.

Following this, the analysis uses a non-uniform distribution ($\propto = 4{:}4{:}1$) to predict the posterior probabilities for A1, A2, and A3. This is because the research reveals that the likelihoods of effects after train accidents are not equal. The researchers have also placed the 'confidence interval' at 95%, leading to more precise predictions and more accurate interpretation outcomes than other publications. Lastly, benchmarking for risk levels is provided for five countries: China, France, Japan, South Korea and Spain. This study analyses data via Python and has developed the DT and PT models based on the posterior probability of effect after an accident, and the levels of severity of injuries and fatalities. Furthermore, understanding long-term risk and the uncertainties in data sets can ultimately enhance the safety levels on rail networks.

5. Methodology

5.1 Data availability

This study has collected railway accident data from official company, government and rail authority reports. The research focuses on passenger train accidents that occurred during 2000-2019. There are 650 appropriate data sets, which include injury and fatality numbers, are included in this study.

5.2 An application on the Bayesian network

In this study, a Bayesian network has been created to help readers clearly understand the causes and effects of railway accidents within conditions of uncertainty. This has led to the correct development of causes of railway accidents and the reduction of fatalities and injuries (Heckerman, Geiger and Chickering, 1995; Uusitalo, 2007).

By following the Bayesian network in this study, the list of all causes has been adopted from the FRA and other railway authorities (FRA, 2019), as illustrated in Tables 1 and 2. The basic model defines the relationship between (A) effects of accidents, (B) causes of accidents, and (C) sub-causes of accidents, as shown in Figure 4. It can be stated that 'C' is conditionally dependent upon 'B' and 'A' ($P(C \mid A, B)$), and that 'B' is conditionally dependent on A ($P(B \mid A)$). All variables 'A' denotes the effects of railway accidents, with A1, A2 and A3 referring to collisions, derailments and others, respectively.

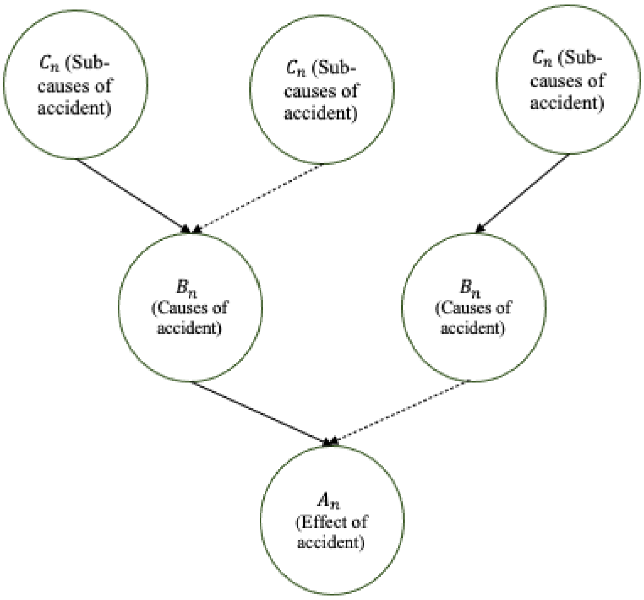


Fig. 4 Overall Bayesian network framework for railway accidents

5.3 Bayes' Theorem

Bayesian statistics can be explained as probabilities that express a degree of belief or information about an event called 'prior knowledge'. It involves the conditional probabilities of two events, A and B. Also, Bayes' theorem can be inverted to find the likelihood of a single event, as shown in equations 1 and 2 (Briggs, Ades and Price, 2003; Sobradelo, Bartolini and Martí, 2014).

$$P\ (A \mid B) = \frac{P\ (B \mid A)\ *\ P\ (A)}{P(B)} \tag{1}$$

$$P\ (B) = \frac{P\ (B \mid A)\ *\ P\ (A)}{P(A \mid B)} \tag{2}$$

Referring to the classification of the effects and causes of accidents in Tables 1 and 2, the conditional probability of the effects, A, given the causes, B, can be calculated from equation 1. Alternatively, the probability of the causes, B, can be attained from equation 2. Hence, the above equations can reveal the inherent relationship between Tables 1 and 2. For example, given the probability of train derailment, A1, due to driver error, B1, Bayes' theorem can be restated as the equations below.

$$P\ (Train\ derailment \mid Driver's\ error) = \frac{P\ (Driver's\ error \mid Train\ derailment)\ \times\ P\ (Train\ derailment)}{P(Driver's\ error)} \tag{3}$$

$$P\ (\ Driver's\ error) = \frac{P\ (Driver's\ error \mid Train\ derailment)\ \times\ P\ (Train\ derailment)}{P\ (Train\ derailment \mid Driver's\ error)} \tag{4}$$

By following the mathematical proofs for equations 3 and 4, the probability of the cause of an accident can be calculated. In addition to Bayes' theorem, Bayesian inference has been used; this is a statistical inference method in which the probability of a hypothesis is updated as more evidence or information becomes available (Payzan-Lenestour and Bossaerts, 2011; Dindar *et al.*, 2018). In general, Bayesian inference is carried out by (i) choosing the prior distribution, which is a probability density $p(\theta)$ expressing one's beliefs about a parameter θ before seeing any data, (ii) choosing a statistical model $p(x|\theta)$ that reveals one's beliefs about data x given parameter θ, and (iii) updating the beliefs and calculating the posterior distribution $p(\theta|D)$ after observing data D. By Bayes' theorem, the posterior distribution can be written as:

$$p\ (\theta|D) = \frac{p\ (D|\theta) * p(\theta)}{p(D)} \tag{5}$$

where $p\ (\theta|D)$ is the joint posterior distribution, which expresses uncertainty after taking both the prior distribution and data into account; $p\ (D|\theta)$ is the likelihood function; $p(\theta)$ is the set of prior distributions; and $p(D)$ is the normalising constant, which is also called the evidence. Figure 5 illustrates an overview of Bayesian inference.

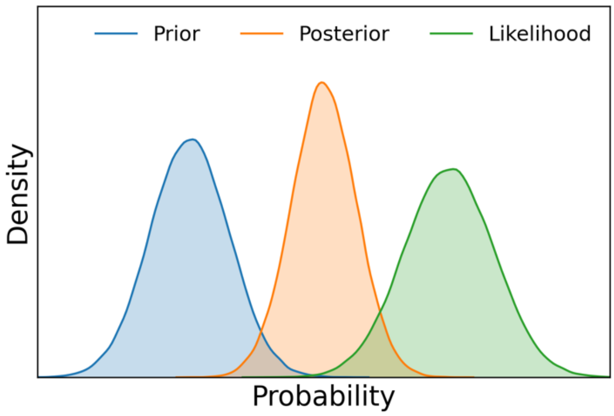


Fig. 5 An overview of Bayesian inference representing how one's beliefs are updated after observing the data

5.4 Bayesian statistics in Python and other computer programming languages

As posterior probability is expected to be the outcome from the research, the study adopts 'PyMC', a well-known Bayesian statistics package in Python. The research creates a novel model through Python to find the probabilities of railway accidents. Using this method, the outcome provides posterior distribution and statistical information, such as mean, variance, and confidence intervals. These can undoubtedly represent the uncertainty in the data collected for the research.

Various studies combine the Bayesian network model with computer programming (Pol, 2003; Patil, Huard and Fonnesbeck, 2010). Bayes' functionality has been created in computer programming languages because it can solve complicated conditional probability problems and offer visualised solutions. It can also be broadened and applied to other related fields such as statistics or mathematics. With respect to the Python language, PyMC is based on the Markov chain Monte Carlo (MCMC) method, which is a class of algorithm for sampling from probability distributions. The MCMC is a useful technique for attaining information about distributions, especially for estimating posterior distributions in Bayesian inference, which are often difficult to determine using analytical examination.

6. Data Analysis

In this study, Bayesian inference is used to examine uncertainty in collected data using proposed prior distributions. The Dirichlet distribution, which is a non-uniform distribution, is analysed and discussed. This is important for correctly interpreting the results obtained from experts' beliefs and data collection. Many scholars have widely applied the Dirichlet distribution into research for prediction, classification and match probabilities. This method suits the multinomial proportion analysis though the Bayesian model (Geiger and Heckerman, 1995; Bouguila and Ziou, 2008; Lange, 1995). In this study, the outcome is to enable the finding of probability density functions, in order to validly predict the probability of future accidents.

Dirichlet distributions, or multivariate beta distributions, are a family of continuous probability distributions for k categories. Let x form the probability of each parameter, $\theta = \{\theta_1, \theta_2, \dots, \theta_k\}$, where $0 \leq \theta_i \leq 1$ for $i \in [1, k]$ and, $\sum_{i=1}^{k} \theta_i = 1$. The probability density function of the Dirichlet distribution is given by:

$$Dir(\theta|\alpha) = \frac{1}{B(\alpha)} \prod_{i=1}^{k} {\theta_i}^{\alpha_i - 1} \tag{6}$$

where $B(\alpha)$ is the multinomial beta function, $B(\alpha) = \frac{\prod_{i=1}^{K} \Gamma(\alpha_i)}{\Gamma(\prod_{i=1}^{K} \alpha_i)}$; and α is a vector of positive real values called a hyperparameter, $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_k)$. The expected value of a Dirichlet distribution can be directly calculated from the vector α, which is $E[X_i] = \frac{\alpha_i}{\alpha_0}$; $\alpha_0 = \sum_{s=1}^{k} \alpha_s$.

In order to estimate posterior distribution (p) using Dirichlet distributions (α) as priors based on given observations (X) with a discrete distribution, this study uses the Dirichlet-multinomial model, which is a multinomial distribution with Dirichlet priors. Using Bayes' rule, the posterior distribution is:

$$P(p|X, \alpha) = Dir(N + \alpha) \tag{7}$$

This means that the posterior distribution is a Dirichlet distribution with parameters $N + \alpha$, where N is the occurrence count. Hence, the expected value can be analytically expressed as:

$$E[p_i|X, \alpha] = \frac{N_i + \alpha_i}{N + \sum_{s=1}^{k} \alpha_s} \tag{8}$$

where N_i is the observed count for each category, and α is the pseudo-observations for each type.

With regards to the long-term data collected, the Dirichlet distribution analysis is provided based on the assumption that the fractions for A1 and A2 are equal, and the fraction for A3 is less than for A1 and A2 (P(A3) < P(A1); P(A3) < P(A2)). This assumption is based on the collected data, which shows the fraction for A3 to be only 13%. Therefore, the Dirichlet models for non-uniform distribution are given as A1: A2: A3 = 4:4:1.

The research takes the long-term FRA data set and compares it with the actual rate of railway accidents to validate the created model. The 63,770 data sets are analysed within the developed Python model at a 95% confidential level. Many experts have mentioned that the probabilities for the effects of railway accidents are equal; in other words, the likelihoods of train collision, derailment and other effects should be given as $\propto = 1:1:1$. However, the model created proposes the fractions for prior belief to be $\propto = 4:4:1$ instead of $\propto = 1:1:1$.

Table 5. Comparison of the actual values: model 4:4:1 and model 1:1:1

Model/Type of accident	A1-Collision	A2-Derailment	A3-Others
Actual value	0.549	0.341	0.110
$\propto = 4:4:1$	0.546	0.352	0.102
$\propto = 1:1:1$	0.536	0.351	0.112

The results in Table 5 show that the model created with prior belief fractions of $\propto = 4:4:1$ has a high degree of efficiency, and more precisely predicts the actual A1, A2 and A3 values better than for prior belief fractions of $\propto = 1:1:1$. These findings imply that the probability of effects after accidents are not equal. For the current work, it is sufficient to point out that the non-uniform distribution type, '$\propto = 4:4:1$', is the best-fitting model.

7. Benchmarking levels of risk of railway accidents

In section 6, the research finds that a non-uniform distribution (4:4:1) is the most appropriate model for this study. This section aims at benchmarking the risk levels of railway accidents across five countries: China, Japan, South Korea, Spain and France. The research is conducted using accident datasets, which include the effects on trains, and the number of injuries and fatalities, during a time frame of 20 years.

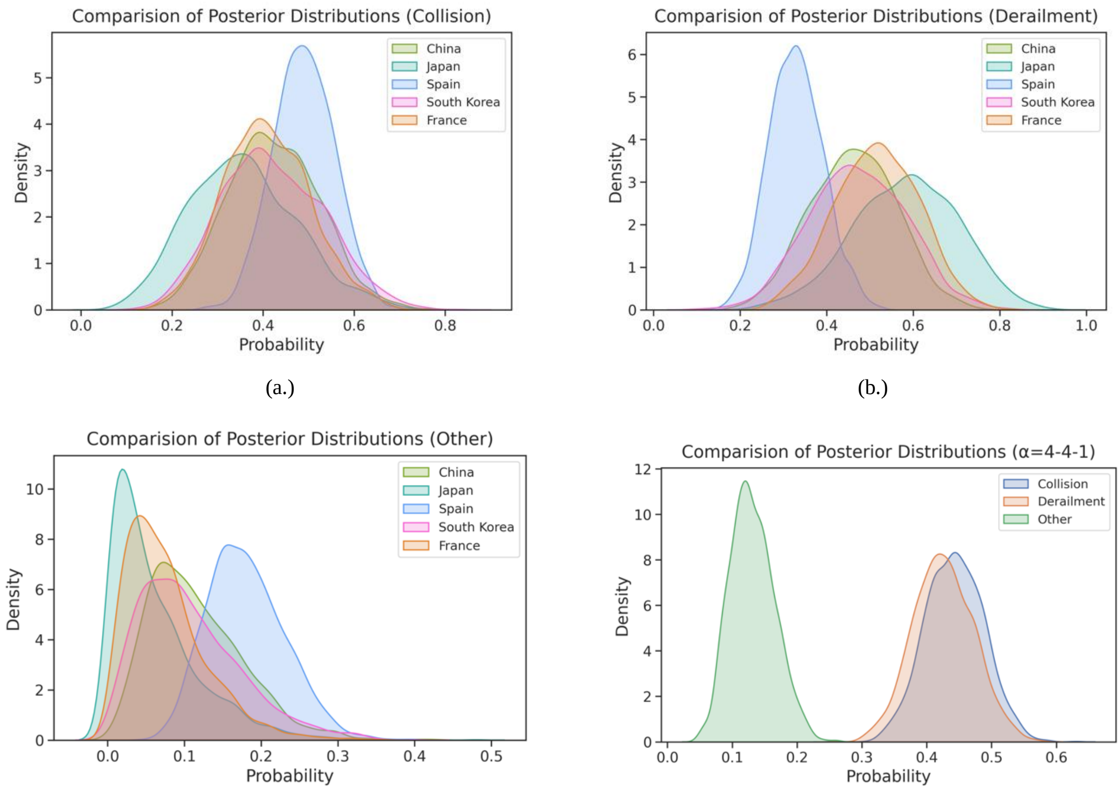
According to the classification of effects on trains after accidents, this study reveals that the effect type 'A3' is associated with a significantly higher number of injuries and fatalities than effect types 'A1' and 'A2'. The level of damage associated with A3 is approximately four times the usual level. The data collected on the five countries of interest illustrate that effect type 'A3' occurs only 14 times, with 2,354 injuries and 438 fatalities (ERA, 2018; ETSC, 2020; ORR, 2020; Statista, 2020; JR Central, 2021; CRRC, 2020; ARAIB, 2021). On the other hand, 'A1' and 'A2' occurred 47 and 45 times, respectively, with injury and death rates for 'A1 and A2' being close to the 'A3' figures. It can be concluded that 'A3' is associated with significantly more damage than other types of effect.

7.1 Posterior probability distribution results

The study uses the non-uniform distribution model (4:4:1) to find the posterior probabilities for collision, derailment and other effects. The analysed results are shown in Table 6, and are taken into account in the risk assessment process. The comparison of the posterior distributions for collision, derailment, other effects by country, and the overall posterior distributions, are shown in Figure 6.

Table 6. Comparison of the results of non-uniform distribution by country

		mean	sd	hpd_2.5%	hpd_97.5%	mcse_mean	mcse_sd	ess_mean	ess_sd	ess_bulk	ess_tail	r_hat
	A1	0.425	0.098	0.234	0.62	0.003	0.002	1447	1442	1443	1057	1
China	A2	0.462	0.098	0.281	0.656	0.002	0.002	1557	1546	1551	1299	1
	A3	0.113	0.06	0.023	0.24	0.001	0.001	1730	1562	1751	1219	1
	A1	0.407	0.095	0.225	0.588	0.003	0.002	1252	1252	1239	1144	1
France	A2	0.517	0.096	0.338	0.704	0.003	0.002	1406	1406	1396	1207	1
	A3	0.076	0.051	0.001	0.173	0.001	0.001	1571	1530	1449	974	1
	A1	0.357	0.118	0.154	0.603	0.003	0.002	1500	1495	1464	1033	1
Japan	A2	0.585	0.119	0.345	0.804	0.003	0.002	1548	1538	1534	1278	1
	A3	0.058	0.054	0	0.168	0.001	0.001	1629	1576	1483	884	1.01
	A1	0.424	0.113	0.203	0.629	0.003	0.002	1474	1392	1484	1144	1
South Korea	A2	0.473	0.115	0.267	0.702	0.003	0.002	1600	1600	1605	1333	1
	A3	0.103	0.067	0.004	0.235	0.002	0.001	1538	1437	1440	1042	1.02
	A1	0.492	0.063	0.374	0.619	0.002	0.001	1468	1461	1469	1444	1
Spain	A2	0.327	0.061	0.218	0.457	0.002	0.001	1609	1604	1607	1559	1
	A3	0.181	0.05	0.085	0.279	0.001	0.001	1507	1428	1533	1035	1
	A1	0.444	0.045	0.36	0.533	0.001	0.001	1830	1809	1843	1313	1
Overall	A2	0.426	0.045	0.335	0.511	0.001	0.001	1928	1918	1933	1326	1.01
	A3	0.129	0.031	0.072	0.189	0.001	0.001	1808	1781	1817	1416	1



(a.) (b.) (c.) (d.)

Fig. 6 Comparison of the posterior distributions for (a.) collision (b.) derailment (c.) other by country, and (d.) overall posterior distributions.

7.2 Risk assessment models

By analysing the existing risk models in Table 3, there is no previous research using posterior probability to benchmark railway network risk levels. Posterior probability offers highly accuracy prediction from the long-term data collected and expert beliefs. On the other hand, the existing models are mostly applied to vulnerability and hazard factors. This study concerns accident damage (numbers of fatalities and injuries) and posterior probabilities of the effects of train accidents (A1, A2, A3). With respect to benchmarking the risk levels among the five rail networks, the research combines the DT and PT models.

7.2.1 The design of the DT model

The DT model is a predictive structure flowchart used for classification after the input of attributes. In this study, the DT model is applied for the evaluation of the risk levels among rail networks. This research defines outcomes on each branch, which are either 'yes' or 'no'. The leaf nodes represent decision rules containing five conditions: fatality rate, injury rate, and the values of A1, A2 and A3. The model's end nodes break down into 32 outcomes to represent risk levels, in which the minimum score means the lowest risk and the maximum score means the highest risk.

7.2.2 The PT model

The PT model is a potential mathematical model that contains three elements: place, transition and arc. The model is mostly applied in the manufacturing process to explain the flow of elements in the system. In this study, the PT model is also used to evaluate risk level, as shown in equations 9-13.

Let *S* be an integer number representing the risk level, which is an expected outcome. *S* relies on two factors, as shown in equation 9.

$$S\ (\overline{e}\,,\overline{w}) \tag{9}$$

where; $\overline{e}$ *= events and* $\overline{w}$ *= weight*

The vector $\overline{e}$ represents events or model's conditions, which consist of fatalities rate, injuries rate, A3, A1 and A2 values.

$$\overline{e} = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \end{bmatrix} = \begin{bmatrix} death \\ injury \\ A3 \\ A1 \\ A2 \end{bmatrix} \tag{10}$$

where; $e_n = 1$ if $Input\ value > threshold$ and $e_n = 0$ if $Input\ value \leq threshol$

Given the vector $\overline{w}$ is the weight of vector $\overline{e}$, as shown in equation 11.

$$\bar{w} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \end{bmatrix} = \begin{bmatrix} 16 \\ 8 \\ 4 \\ 2 \\ 1 \end{bmatrix} \tag{11}$$

Then, the dot product of $\bar{w}$ and $\bar{e}$ vectors are a key operation in using vectors in geometry, as shown in equation 12. And, the risk level (S) can be evaluated by equation 13.

$$S = \bar{w} \cdot \bar{e} = \begin{bmatrix} 16 \\ 8 \\ 4 \\ 2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \end{bmatrix} \tag{12}$$

$$S = 16e_1 + 8e_2 + 4e_3 + 2e_4 + e_5 \tag{13}$$

The structure of the PT model, which is called ‘Synchronisation’, is designed as shown in Figure 9. The PT model has the advantage that it clearly represents the complex discrete events model. The model’s form can be shortened, but it remains a flow of information and outcomes. In this study, the PT model is used to evaluate risk levels. And, the DT and PT outcomes are then compared.

7.3 Sensitivity analysis

A sensitivity analysis is conducted in this study to find the optimal threshold for railway risks, which is used for decision-making. Additionally, it aims to determine the certainty of the DT and PT models created while new data sets are added to the models caused by changes in A1, A2 and A3. The preliminary analysis states that the model has a high level of certainty, which can be verified from the sharp edges in the graphs in Figure 5. Hence, the sensitivity analysis varies with the standard deviation in the ranges of ±1s.d. and ±2s.d., while the injury and fatality rates vary with the Q_1 (quartile 1), mode value, Q_3 (quartile 3) and mean values ($\bar{x}$).

Six analysis models have been created, all of which have been validated in the range ±1s.d. and ±2s.d. To evaluate and select the best model, the ‘total absolute error’ is used as a critical measurement. The model with the lowest total absolute error value can be interpreted as the model with the highest degree of certainty.

The total absolute error is calculated using the summation of the ‘percentage changed’ from the mean value, as shown in equation 14. Also, the absolute error and total absolute error are expressed in equations 15 and 16.

$$Percentage\ \text{changed (\%)} = \frac{X - \bar{x}}{31} \times 100 \tag{14}$$

$$Absolute\ error\ (\%)\ = \sum_{i=1} (\%\ changed\ _i) \tag{15}$$

$$Total\ absolute\ error\ (\%) = \sum_{j=1} (Absolute\ error\ _j) \tag{16}$$

where x is an outcome from the data analysed through the model, i is an index in the sensitivity analysis, $i \in \{-2s.d., -1s.d., 1s.d., 2s.d.\}$; and j is a country index, $j \in \{China, France, Japan, South\ Korea, Spain\}$.

In conclusion, the results from the models and for total absolute error are shown in Table 7. The research reveals that model 2, which uses Q_3 thresholding for both the injury and fatality rates, shows the minimum total absolute error at 61.29%. As a result, the sensitivity analysis for model 2 by country gives graphs with low levels of fluctuation, as illustrated in Figure 7. Lastly, the DT and PT models created in this research are shown in Figures 8 and 9, respectively.

Table 7. Summary of the model and the total absolute error

Model	Sensitivity analysis	Total absolute error (%)
1	Mean value thresholding with injury and fatality rates	112.90
2	Q_3 thresholding with injury and fatality rates	61.29
3	Mode thresholding with injury and fatality rates	64.52
4	Q_1 thresholding with injury and fatality rates	119.35
5	Q_3 thresholding with injury rate and Q_2 thresholding with a fatality rate	71.29
6	Q_2 thresholding with injury rate and Q_3 thresholding with a fatality rate	74.19

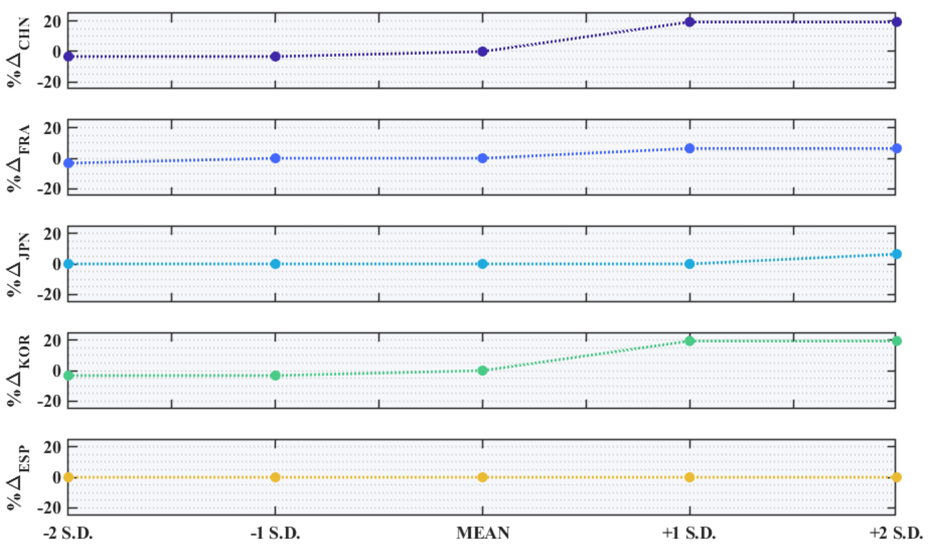


Fig. 7 Sensitivity analysis of Q_3 thresholding for injury and fatality rates

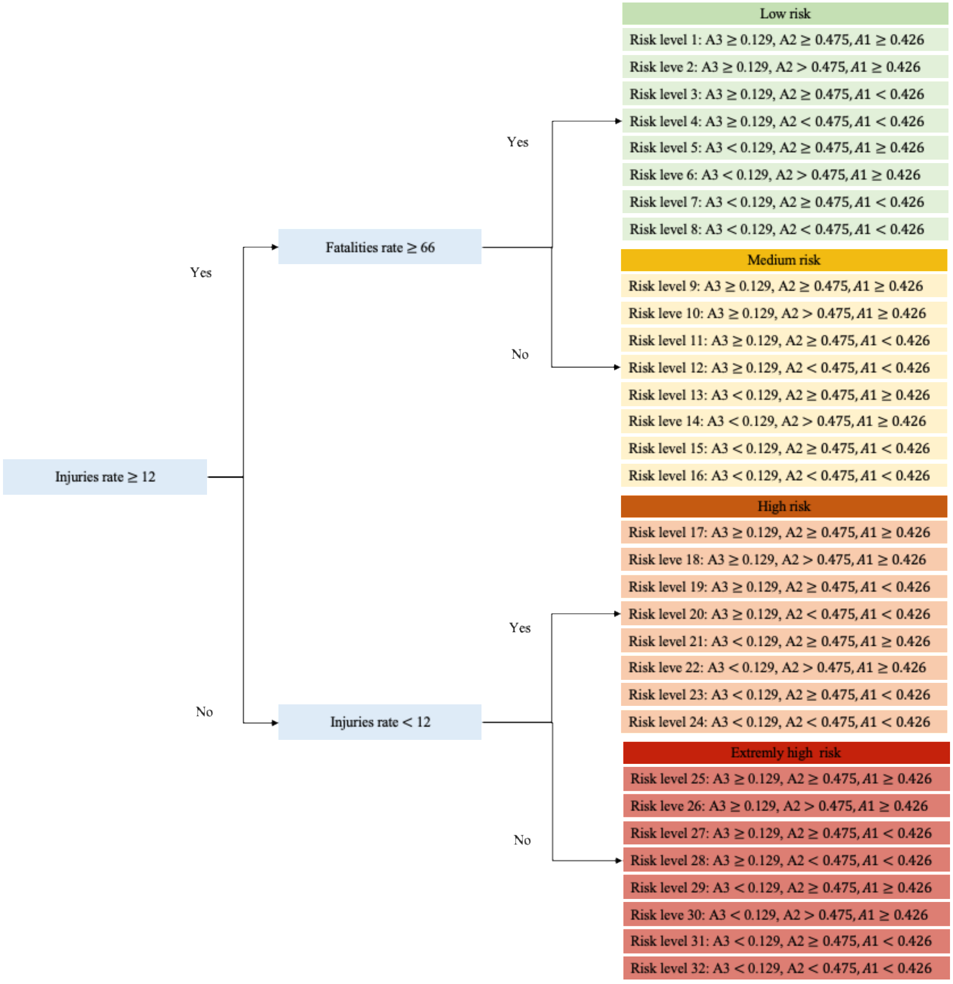


Fig. 8 Overall DT framework for evaluating risk score

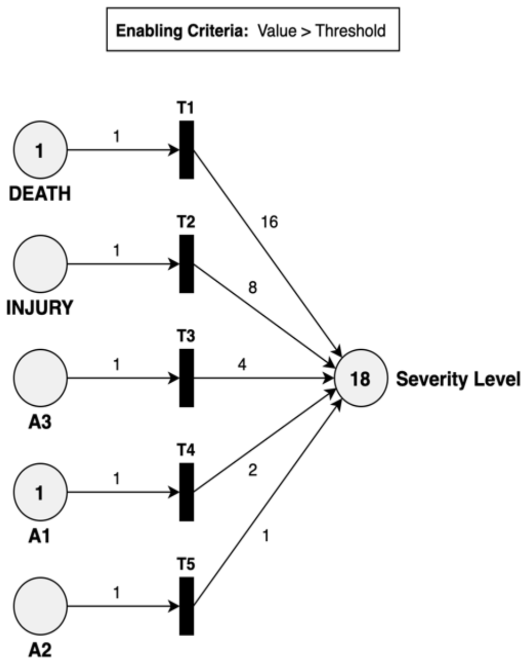


Fig. 9 Design of the PT model, containing five conditions: fatality rate, injury rate, and values for A1, A2 and A3

7.4 Result and discussion of benchmarking railway risk

The results from analysing the data sets via the DT and PT models produce discrete numbers in the range 1 to 32. The risk level can be classified into four groups based on the risk score. A score in the range 1-8 means low risk, 9-16 means moderate risk, 17-24 means high risk, and 25-32 means extremely high risk.

The benchmarking results across the five HSR networks are provided in Table 8. These outcomes give a significant advantage because safety policies can be adopted from those of 'low risk' networks for upcoming projects. The risk level analysis results show that South Korea's railway system has the greatest risk among these selected countries. The safety level of South Korea's network has score at 18 that classifies as 'high risk'; whereas, France's network has a score of 10, which is in the 'moderate risk' range. China's, Japan's and Spain's railway systems have scores of 2, 2 and 7, respectively, which are in the 'low risk' range.

Table 8. The result of risk level analysis

HSR networks	Risk score	Risk level	Ranked
China	2	Low	1st
France	10	Moderate	4th
Japan	2	Low	1st
South Korea	18	High	5th
Spain	7	Low	3rd

From the most in-depth analysis of China's and Japan's networks, both countries have a small number of accidents, and the injury and fatality rates per accident have been shown to be low. Therefore, the risk levels across these networks are 'low'. Moreover, advanced safety systems have been installed on these networks. For example, high magnitude earthquakes have affected train derailment in Japan, so the Japanese network has installed an urgent earthquake detection system on the track to cut off the power supply. This has led to a long-term improvement in passenger safety levels and prevention of damage to trains.

Similarly, Spain's network has a 'low' risk level, with a score of 7. Although Spain has the largest number of accidents, most accidents have not affected passengers or have caused few injuries. It is these low injury and fatality rates that lead to the Spanish network having a 'low' risk. France's network, meanwhile, shows a 'moderate' risk level of 10. The number of accidents is three times lower than in Spain. Nevertheless, the average fatality and injury rates are 15 and 96 persons per accident, respectively, which are more than the global average.

On the other hand, South Korea has a higher risk level than the other countries. Despite the low number of a train accidents, the severity of these accidents is 'high'. The data collected show average fatalities and injuries per accident of 18 and 41 persons. This brings South Korea's severity level above the global average, thereby causing the estimated risk score for South Korea's network to be ranked highest.

It is worth discussing these interesting facts revealed by the results of this risk benchmarking model. Extensive and overcrowded rail networks have high accident probabilities; therefore, this benchmarking model suggests that the levels of risk due to other related factors should be evaluated instead of the accident rate. The risk levels in the results can be standardly explained by case studies as above, and the model can be benchmarked with other networks.

In comprehensive detail, the causes in accident type 'A3' (other train-related causes) occur due to two primary reasons: mechanical failures and contributing factors. With respect to minimising risk level, the research highly recommends railway operators to provide adequate maintenance schemes for trains, tracks, and systems, and to enhance safety policies and staff training in coping with severe accidents.

8. Conclusions

With the growth of HSR and rail networks worldwide, safe rail services are a key driver for railway operators in supporting passenger journeys. Based on the long-term accident data sets, rail accidents can be classified into three groups: collisions, derailments and other effects. This study has found that the 'other effects' category caused four times more damage than collisions and derailments. Therefore, the research has analysed the accident data sets through novel models and has selected best practice. The results illustrate that the non-uniform distribution, with $\propto = 4{:}4{:}1$, offers the most accurate results.

This research aims at understanding the uncertainties of railway accidents to precisely reduce the impact of casualties. In terms of benchmarking risk levels, five countries have been selected: China, France, Japan, South Korea and Spain. The research has developed a 'benchmarking risk' model, which is a linear transform model based on posterior probability, and the severity levels of injuries and fatalities. Moreover, the analysis is conducted through the DT and PT methods. The benchmarking results illustrate that China's, Japan's and Spain's networks are in the 'low risk' category, while France's network is 'moderate risk' and South Korea's network is 'high risk'.

To improve safety on railway networks, this study recommends that 'other effects – A3' should be eliminated or minimised; because the severity level of A3 accident is extremely higher than A1 and A2. The causes of A3 are mechanical failure and contributory factors. Future studies should fruitfully explore this issue further by intensely discussing the root causes of accidents by using posterior distributions. Our findings on posterior probabilities can also be applied as a new form of measurement for policymakers or railway companies.

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