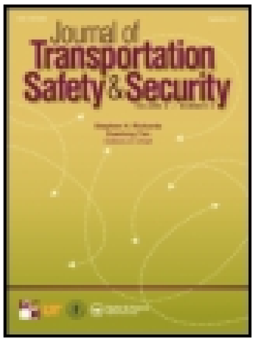

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Analysis of human-factor-caused freight train accidents in the United States

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ABSTRACT

Human factors are major causes of train accidents in the United States. Understanding the safety risk of these accidents can provide insights into safety evaluation and improvement. This paper focuses on analyzing the train derailments and collisions due to human factors using 2000–2016 accident data on mainlines from the US Federal Railroad Administration. This research methodology involves three main sections. First, we analyze the statistical trend of annual accident rates by accident type and year. Based on the cause-specific distribution of accident frequency, the major causes are determined for each common accident type such as derailments and collisions. Next, we calculate accident severity (e.g., derailed cars, casualties) due to each specific human-factor accident cause. Finally, we compute annual accident risk and cause-specific accident risk using mean and alternative risk measures. The detailed accident data analysis approach herein can also be adapted to other types of train accidents, in support of decisions for rail safety improvement. The analysis of human-factor-caused train accidents can provide key information for the development and evaluation of potential safety improvement strategies.

KEYWORDS

human-factor; train accidents; safety; risk; accident cause

1. Introduction

Railroads are a safe and reliable mode of transportation. Train accident rates have declined considerably over the past decade. However, a train accident may result in injuries or fatalities, infrastructure and rolling stock damages, and environmental impacts. The US freight rail network consists of nearly 140,000 miles with 1.74 trillion ton-miles of traffic annually (FRA, 2015; AAR, 2017a). This vast railroad network is crucial to the American economy, and consequently its safety is of great importance. Based on previous train accident analyses, derailments and collisions are common accident types (Barkan, Dick, & Anderson, 2003; Li, Cai, Liu, & Wang, 2018; Liu, Barkan, & Saat, 2011, Liu, Saat, & Barkan 2012, 2013, 2016a). Previous studies have

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analyzed the overall safety trends of derailments and collisions. In addition, there is quite a bit of work on grade crossing safety (Chadwick, Saat, & Barkan, 2012; Saccomanno, Park, & Fu, 2007). Furthermore, infrastructure or equipment failures as derailment causes have been studied (Liu et al., 2011, 2012) but there is no study specific to analyzing human-factor-caused accidents and we aim to fill this knowledge gap.

Human factors are major causes of freight-train accidents (derailments and collisions) on mainlines resulting in a total of 1,510 accidents with 551 casualties and 9,214 derailed cars in the period of 2000–2016 (FRA, 2007; Dhillon, 2007; Madigan, Golightly, & Madders, 2016). It is important to study the human-factor-caused accidents separately as they constitute for about 18% of the total freight train derailments and collisions on US mainlines. Human factor accidents occur due to a number of factors that degrade the operators' performance. The study of factors influencing human performance can be found in prior literature (Kyriakidis, Pak, & Majumdar, 2015; Zhang, Jiang, & Niu, 2014). Similar analyses have been performed in other industries like oil and gas (Theophilus et al., 2017), maritime transportation (Chen et al., 2013; Yildirum, Ugurlu, Basar, & Yuksekyildiz, 2017), aviation (Low & Yang, 2018), metro system (Chen, Zhang, Khasawneh, & Geng, 2018), etc. The human factors involving physical and organizational characteristics of a train operator have been studied to optimize and apply a human factor analysis and classification system (HFACS) to the railroad industry (Reinach & Viale, 2006; Madigan et al., 2016). The methodology of HFACS has also been used to study the potential root causes of railroad accidents in Indonesia (Iridiastadi & Ikatrinasari, 2012).

However, there has been very little prior work that uses statistical analysis to understand cause-specific human-error-caused train safety risk in the United States. The objective of this paper is to quantify the safety risk of human-error-caused train accidents on freight railroads in the United States. We focus on the historical safety data to quantitatively understand the frequency, severity, major causes, and safety risk of human-error-caused accidents on railway mainlines. This analytical approach could also be adapted to other types of train accidents. Using statistical approaches to determine accident rates will also enable the user to predict the potential risk in the future, based on the historical data.

2. Data sources

The data used for the analysis comes from the US FRA Rail Equipment Accident (REA) database, which is consistent with previous studies (Anderson & Barkan, 2004; Bagheri, Saccomanno, Chenouri, & Fu, 2011; Barkan et al., 2003; Liu, 2016a, 2016b; Liu, 2015). By regulation, each railroad operating in the United States must submit a detailed accident report to FRA if the damage cost of the accident to infrastructure and rolling stock exceeds a specified monetary threshold (e.g., the 2017 threshold was $10,700 (FRA, 2018). The FRA compiles these submitted accident reports into the Rail Equipment Accident (REA) database, which contains detailed information regarding the cause, severity, location, time, and other circumstances that are involved in the occurrence of each accident. However, FRA non-reportable accidents with damages less than the monetary threshold are excluded due to their unavailability.

There are four types of tracks included in the FRA REA database, which are main track, siding track, yard track, and industry track, respectively. These track types are used for different operational functions and consequently have different associated accident types, causes, and consequences. Train accidents are categorized into derailment, collision, highway-rail grade crossing accident, and other less frequent types in the FRA REA database. The type of accident recorded in the database is determined by the first reportable event in the accident sequence. Derailment, by definition in FRA guide (FRA, 2011), is the accident that occurs when on-track equipment leaves the rail. A collision is defined as the impact between on-track equipment consists while both are on rails and where one of the consists is operating under train movement rules. An accident at a highway-rail grade crossing with impact between on-track railroad equipment and a highway user is referred to as highway-rail grade crossing accident. Some instances where a derailment is induced due to the occurrence of a collision, is still considered as a collision based on the primary accident type. Similarly, if one grade-crossing collision accident leads to a train derailment, the accident is still identified as a grade crossing accident, instead of a derailment. In other words, the type of accident is identified per the first event in the accident (FRA, 2011). This study involves only derailments and collisions since the grade crossing accidents require separate analysis due to different accident characteristics. FRA train accident cause-codes are hierarchically organized and categorized into major cause groups—track, equipment, human factors, signal, and miscellaneous causes. Within each of these major cause groups, FRA has organized individual cause codes into subgroups of related causes, which were refined by Arthur D. Little (ADL, 1996). The accident data used in this study involves human-factor-caused freight derailments and collisions occurred on mainlines. The different cause codes in this cause-group are elaborated in Appendix 1.

In addition, the REA database also contains accident severity information in terms of damage cost to infrastructure and rolling stock, injuries, fatalities and hazardous material cars releasing contents (if any). Besides accident data, each railroad also reports their monthly train-mile data to the FRA through the Operational Safety Database. This research uses these data sources to analyze accident frequency and severity, to compute the risk, given traffic volumes.

3. Accident rate analysis

The train accident rate is defined as the number of train accidents normalized by traffic exposure. This rate helps to understand the extent of accidents occurring per certain traffic volume. Several previous studies adopted that the number of accidents can be approximated by Poisson distribution. The Poisson mean follows a gamma distribution to account for over-dispersion. The Gamma mean is a combination of input variables. A Negative Binomial (NB) regression model, which is also called Poisson-gamma regression, has been developed in this paper to analyze human-factor-caused freight-train accidents on mainlines. A similar NB model has been widely used in accident rate analysis for highway transportation rather than other models (Lord, 2006; Miaou, 1994; Mitra & Washington, 2007; Oh, Washington, & Nam, 2006) and its framework is given by equations 1–5. In this research, two predictor variables are considered, which are the year index and traffic volume for statistical analysis (Equation 4). The selection of these two variables is consistent with a prior study (Liu, 2016b). The year variable tests if there is a temporal change in the frequency of train accidents with a given traffic exposure. Similarly, the traffic exposure variable tests whether and how the number of train accidents may vary with the traffic volume in a given year. Traffic volume is measured in three metrics, namely gross ton-miles, car-miles and train-miles. Schafer and Barkan (2007) pointed out that most human errors are train-mile related causes for which the accident likelihood is proportional to the number of train miles. Thus, this study uses train-miles to normalize accident frequency. The three parameter coefficients, α, β, and γ, in the equation are estimated using the maximum likelihood method in a Negative Binomial (NB) model. This model can be used to develop cause-specific models for each of the major cause groups among derailments and collisions.

$$Y \sim Poisson(\lambda) \tag{1}$$

$$\lambda \sim Gamma\left(f, \frac{f}{m}\right) \tag{2}$$

$$m = \exp\left(\sum_{p=0}^{k} b_p X_p\right) M \tag{3}$$

Where,

Y = observed number of accidents

m = estimated number of accidents

b_p= p^{th} parameter coefficient
X_p= p^{th} explanatory variable
M= traffic exposure (e.g., train-miles).
f = inverse dispersion parameter

$$\mu_i = \exp(\alpha + \beta \times T_i + \theta \times M_i)M_i \tag{4}$$

Where,
μ_i= expected number of train accidents in i^{th} year
M_i= traffic exposure in i^{th} year (e.g., billion train-miles)
T_i= year index
α, β, θ = parameter coefficients

With respect to the accident rate definition, Equation 4 can be modified as follows.

$$Z_i = \frac{\mu_i}{M_i} = \exp(\alpha + \beta \times T_i + \theta \times M_i) \tag{5}$$

Where,
Z_i= expected train accident rate per billion train miles in i^{th} year

There are several types of freight train accidents due to human factors that occurred on US mainlines in the study period, 2000–2016: namely, derailments, collisions, grade crossing accidents, and other types such as obstruction, explosive-detonation, fire/violent rupture, and other impacts. This analysis focuses on two common human-factor-related accident types, specifically, derailments and collisions excluding grade-crossing accidents, which require a separate detailed analysis. Since passenger trains share most mainline tracks with freight trains in the US railroad industry, there exist both freight- and passenger-related human factor accidents. However, we focused only on freight accidents since those involving passenger trains are only about 4% of the total number of human-factor-caused derailments and collisions (59 out of 1569). Figure 1 shows the accident rate of human-factor-caused derailments and collisions in each year. This accident rate (Equation 5) is obtained by normalizing the annual frequency of accidents with the traffic exposure (e.g., train-miles). Given the traffic exposure for each year, the derailment rate is approximately 2–3 times that of the collision rate.

4. Major accident causes

In order to focus on the methods to prevent a significant proportion of accidents, it is necessary to understand the accident causes responsible for maximum number of accidents. This study focuses on three major causes among 12 subgroups with unique cause codes in the human factor cause group. According to the cause-specific frequency of derailment and

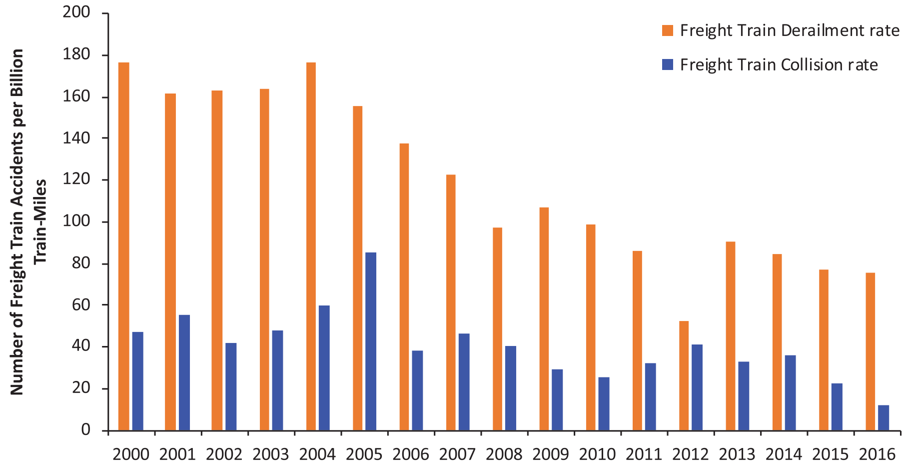

Figure 1. Human-factor-caused freight train accident rates by accident type and year, U.S. mainlines.

collisions combined, train handling (09 H), violation of train speed (10 H) and use of switches (11 H) are the major causes. For a more detailed study, we consider separate cause-specific analyses for derailments and collisions.

4.1. Human factor derailment frequency

The distribution of the number of derailments for each of the cause codes is shown in Figure 2. It indicates that improper train handling (09 H), use of switches (11 H), and brake operation (01 H) are the major human factor causes, resulting in more than 200 derailments over the 17-year study period. Train handling refers to the practices of manipulating the throttle and applying dynamic or automatic brakes, while the other two major causes are related to the improper operation of switches and brakes that may result in a derailment.

Using Equation 4, an NB model has been developed separately for the frequency of derailments caused due to human factors. Our model accounts for both traffic volume variable and year variable. Table 1 shows that the derailment rate, defined as the number of accidents normalized by traffic, is independent of traffic exposure ($p > 0.05$). However, as Equation 5 shows, accident frequency is linearly correlated with traffic volume given the same year. In addition, to test the correlation between train miles and year, a Pearson correlation test (Benesty et al., 2009) was used to test the correlation between train miles and year. Based upon the P-value (0.07, greater than the significance level alpha $= 0.05$), the test result indicates that there is no statistically significant correlation between the train mile and the year variable. However, the derailment frequency seems to have an annual decline of 6.1% from the parameter estimate of the year variable β.

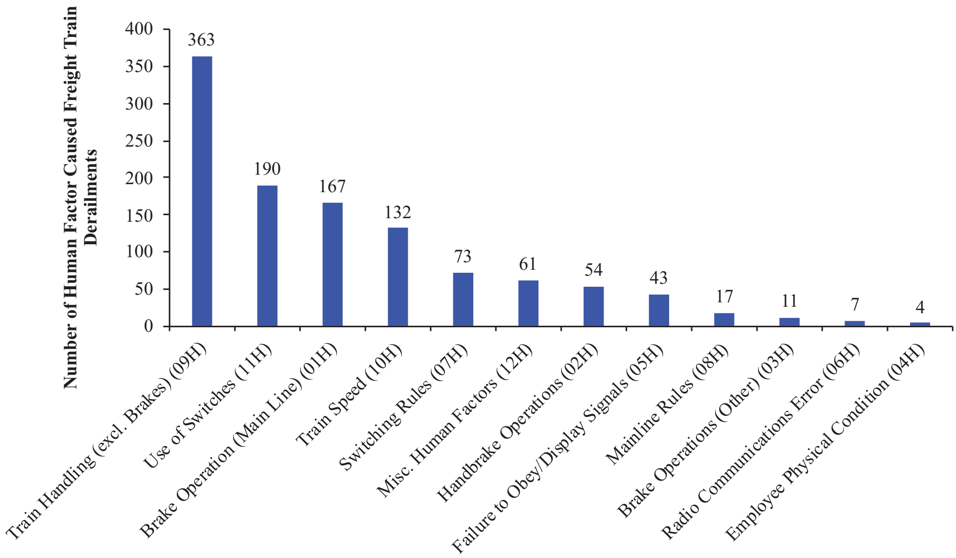

Figure 2. Cause-specific frequency of freight train derailments due to human factors, U.S. mainlines.

Table 1. Negative binomial regression for human-factor-caused freight train derailments (all causes combined).

Parameter	Estimate	Standard error	95% Confidence limits		p-value
α	127.277	18.367	87.883	166.671	6.99e-06
β	−0.061	0.009	−0.081	−0.042	8.45e-06
θ (insignificant)	1.021	1.202	−1.556	3.598	0.41

NOTE: Deviance= 33.69; degrees of freedom= 15; p-value > 0.1.

The model obtained from new parameters by excluding the traffic variable can be written as Equation 7. In order to evaluate the goodness of fit of these models, a statistical criterion called Deviance can be used. The Deviance approximately follows a chi-squared distribution and χ^2 test checks if the null hypothesis of independence is true. The acceptable significance level is usually 5%. If the test statistic is improbably large, then the null hypothesis can be rejected, making it a good-fit.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{6}$$

Where,
O_i = observed number of accidents in i^{th} year
E_i = estimated number of accidents in i^{th} year
n = sample size (number of years in the study period)

$$\mu_i = \exp(134.42 - 0.064 \times T_i) M_i \tag{7}$$

Table 2. Negative binomial model for cause-specific derailment frequency.

Accident cause	Derailment frequency (μ_i) by year (T_i) and traffic exposure measured by billion train-miles (M_i)	Deviance test
Train handling (09H)	$\mu_i = \exp(156.08 - 0.076 \times T_i)M_i$	p-value > 0.1
Use of Switches (11H)	$\mu_i = \exp(134.84 - 0.066 \times T_i)M_i$	p-value > 0.1
Brake Operations (01H)	$\mu_i = \exp(74.07 - 0.035 \times T_i)M_i$	p-value > 0.1

4.1.1. Cause-specific derailment frequency modeling

As we aim to understand the causal effect on the distribution of human-factor-caused train accidents, the earlier NB model for derailment frequency can be modified and adapted to each of the major causes in order to estimate the cause-specific derailment frequency (Table 2). The parameter for traffic exposure (θ) is insignificant for all major causes, which means that the cause-specific derailment rate does not vary much with the traffic (derailment frequency increases linearly with traffic exposure), similar to the model with all causes combined (Table 1). The derailment rates due to the train handling (09 H), use of switches (11 H) and brake operations (01 H) are found to decrease at the rate of 7.6%, 6.6% and 3.5% respectively. Since the p-value is greater than 0.05 for all three major causes in Table 3, the prediction reasonably reflects the empirical data according to the goodness of fit test. The empirical- and model-based estimated values are presented in Table 3.

4.2. Human factor collision frequency

In this analysis, train collisions involve the collisions between freight trains only and exclude the freight-to-passenger collisions or passenger-to-passenger collisions. The frequency of collisions is observed to be lower than that of derailments in the past 17 years. Among the 12 causes in the human factor cause group, it is observed that failure to obey or display signals (05 H), violation of train speed rules (10 H) and mainline rules (08 H) are the three major causes responsible for more than 60 human factor freight train collisions (Figure 3). Using the NB model discussed before, Table 4 gives the results of parameter coefficients obtained by analyzing the human-factor-caused collisions. Both the parameter estimates are significant, and the p-value of the estimated year variable indicates that the collisions are considerably decreasing at an annual rate of 4.6%.

4.2.1. Cause-specific collision frequency modeling

An approach similar to the above NB model for collision frequency is applied to develop models for each of the major causes (Table 5). The parameter for traffic exposure (θ) is insignificant for all major causes, which means that the cause-specific collision rate does not vary much with traffic. The collision rates due to failure to obey/display signals (05 H) and

Table 3. Observed and estimated frequency values for freight-train human-factor-caused derailments.

Year	Train Handling (09H)		Use of Switches (11H)		Brake Operation (01H)		All Causes	
	Observed	Estimated	Observed	Estimated	Observed	Estimated	Observed	Estimated
2000	39	35	21	17	11	13	97	104
2001	23	32	14	16	12	12	87	95
2002	34	30	13	15	13	12	89	91
2003	37	29	16	14	10	12	92	87
2004	37	28	18	14	14	12	103	85
2005	29	26	13	14	13	11	93	81
2006	21	25	15	13	14	12	86	80
2007	20	22	11	12	9	10	72	70
2008	16	20	9	11	7	10	55	64
2009	12	15	8	8	9	8	51	50
2010	17	15	8	8	9	8	50	50
2011	16	15	9	8	11	8	45	48
2012	9	14	3	8	5	8	28	46
2013	15	13	9	7	7	8	49	44
2014	12	12	10	7	9	8	47	42
2015	18	11	5	6	6	7	41	38
2016	8	9	8	5	8	6	37	33
Total	363	353	190	184	167	164	1122	1109
P-value (chi-squared test)		0.3358		0.9234		0.9893		0.3571

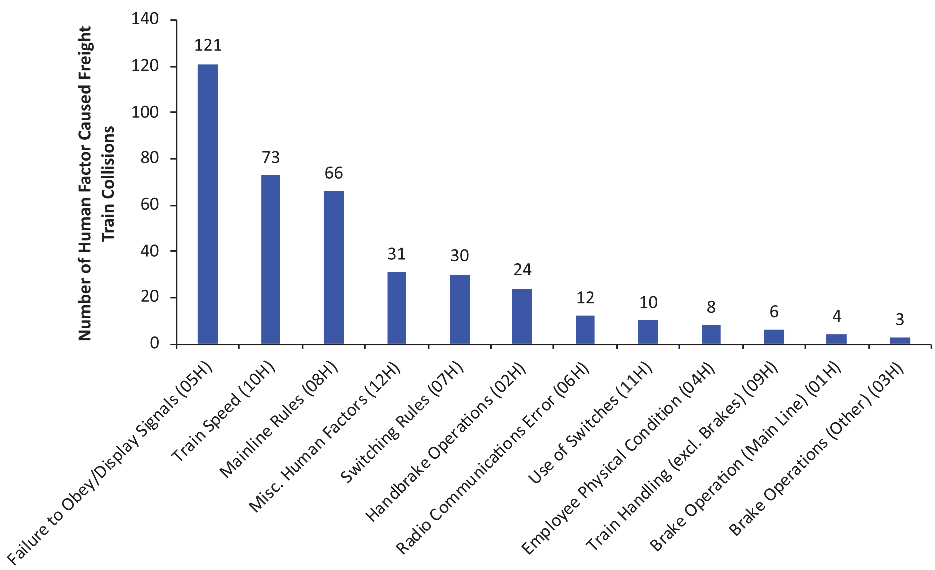

Figure 3. Cause-specific frequency of freight train collisions due to human factors, U.S. mainlines.

Table 4. Negative binomial regression for human-factor-caused freight train collisions (all causes combined).

Parameter	Estimate	Standard error	95% Confidence limits		p-value
α	94.680	28.610	33.318	156.042	0.0052
β	−0.046	0.014	−0.077	−0.017	0.0049
θ	5.012	1.872	0.998	9.027	0.0180

NOTE: Deviance= 37.16; degrees of freedom= 14; p-value > 0.1.

Table 5. Regression model for cause-specific collision frequency on mainlines.

Accident cause	Collision frequency (μ_i) by year (T_i) and traffic exposure measured by billion train-miles (M_i)	Deviance test
Failure to obey/display signals (05H)	$\mu_i = \exp(135.82 - 0.066 \times T_i)M_i$	p-value > 0.1
Train speed (10H)	$\mu_i = (7.633)M_i$	n/a
Mainline Rules (08H)	$\mu_i = \exp(137.62 - 0.067 \times T_i)M_i$	p-value > 0.1

NOTE: No deviance test for train speed (10 H), as NB model was not used.

Table 6. Observed and estimated frequency values for human-factor-caused collisions.

Year	Failure to Obey/ Display Signals (05H)		Train Speed (10H)		Mainline Rules (08H)		All Causes	
	Observed	Estimated	Observed	Estimated	Observed	Estimated	Observed	Estimated
2000	7	11	6	4	7	6	26	30
2001	10	10	6	4	6	5	30	27
2002	9	9	1	4	4	5	23	27
2003	8	9	3	4	2	5	27	29
2004	12	9	7	4	6	5	35	32
2005	15	8	12	5	8	4	51	33
2006	7	8	7	5	3	4	24	38
2007	8	7	3	4	5	4	27	28
2008	7	6	7	4	3	3	23	23
2009	5	5	2	4	3	3	14	12
2010	2	5	3	4	5	3	13	14
2011	11	5	3	4	1	3	17	15
2012	4	5	3	4	3	2	22	16
2013	6	4	2	4	4	2	18	16
2014	3	4	6	4	3	2	20	17
2015	4	4	2	4	2	2	12	14
2016	3	3	0	4	1	2	6	9
Total	121	113	73	70	66	61	388	380
P-value (chi-squared test)		0.3812		n/a		0.8856		0.1448

violation mainline rules (08 H) are estimated to decrease annually by 6.6%, and 6.7% respectively. On the other hand, neither β nor θ is significant for the cause of train speed (10 H); therefore, collision frequency for this cause exhibits a linear trend with respect to traffic exposure. The empirical- and model-based estimated values are presented in Table 6. Since the p-values in Table 6 are greater than 0.05, the prediction reasonably reflects the empirical data according to the goodness of fit test.

5. Severity analysis

In addition to analyzing the human factor accident frequency, train accident severity has to be analyzed to determine the magnitude of an incident. It can be measured using different metrics, such as the number of locomotives and cars derailed, infrastructure damage, casualties, or environmental impact. Since environmental impact is not reported to the FRA, we use derailed cars and casualties, as is consistent with prior work and due to the huge variation in the extent of casualties and derailed cars for derailments and collisions. The number of derailed cars includes all types of railcars (loaded freight cars and empty freight cars). but excludes locomotives. The category of casualties is the combination of all types of injuries from small to serious and deaths (fatalities). FRA defines an accountable casualty as a reportable death, injury, or illness arising from the operation of a railroad and may be classified as either fatal or nonfatal (FRA, 2011). In this study, injuries indicate the nonfatal casualties and fatalities mean the fatal casualties. Analyzing monetary damages is also important (Marty & Okine, 2018) but is out of the scope of this paper. This analysis can be adapted to other severity metrics as well. In order to check the randomness of a data set, a method called Wald–Wolfowitz runs test is used. Since the p-values for severity in casualties and derailed cars obtained by runs test are greater than 0.05, we conclude that there is no significant temporal trend of derailment and collision severity per accident in the study period. Therefore, we can use the average (mean) number of casualties and derailed cars to represent the overall accident severity. Though the derailed cars and casualties are to be measured in whole numbers, we considered decimals to show the minor variations in each year. This study shows that the average number of casualties per derailment in each year is fortunately low (Table 7). Although the frequency of derailments is high, most derailments result in zero casualties. In our dataset, a FRA-reportable collision has a relatively lower rate of occurrence but has a higher average number of casualties per accident. Accordingly, collisions exhibit a higher frequency of casualties than derailments and the average number of derailed cars per accident is higher for derailments than collisions. This is because most derailments have zero casualties and by definition, a derailment involves at least one derailed car.

Table 7. Different measures of severity per accident for each type of accident, 2000–2016.

Year	Derailments		Collisions	
	Derailed Cars per Accident	Casualties per Accident	Derailed Cars per Accident	Casualties per Accident
2000	7.73	0.05	2.04	1.68
2001	5.58	0.04	9.36	0.97
2002	6.02	0.02	6.43	0.99
2003	7.29	0.09	3.04	0.84
2004	8.31	0.12	6.97	3.45
2005	8.42	0.02	5.51	2.50
2006	7.63	0.03	2.00	0.69
2007	7.89	0.09	3.46	0.39
2008	4.00	0.03	5.06	0.90
2009	8.20	0.00	4.10	0.67
2010	5.92	0.04	3.84	1.40
2011	4.98	0.00	4.95	1.25
2012	2.50	0.00	5.07	0.83
2013	5.26	0.09	8.32	1.65
2014	7.02	0.07	4.64	0.96
2015	7.33	0.03	2.35	0.81
2016	6.13	0.06	5.28	0.63
Average	6.48	0.05	4.85	1.21
p-value (in runs test)	0.605	0.774	0.605	0.605

5.1. Cause-specific derailment severity

The severity values of each cause in Table 8 also exhibit a random trend because the p-value from runs test is greater than 0.05, thus average values can be considered as overall severity. Though use of switches (11 H) has slightly higher frequency than brake operation (10 H), it exhibits a relatively lower potential to derail the train cars. The casualty potential is extremely low even when all the causes are considered (Table 7).

5.2. Cause-specific collision severity

Table 9 gives the number of derailed cars and casualties per collision in each year. All the major collision causes also have a random temporal trend in derailed cars and casualties similar to derailment severity (p-value from runs test > 0.05). Failure to obey/display signals has the highest severity potential which can lead to almost 3 derailed cars and a casualty per collision.

6. Human factor accident risk

6.1. FN curves by accident type

The detailed differences between each of the severity measures caused by derailments and collisions can be illustrated through FN curves, which can visually compare alternative risks (Evans, 2011; Evans & Verlander, 1997). F (y-axis) represents the cumulative frequency of events that caused N or

Table 8. Different measures of severity per accident for major derailment causes.

Year	Train Handling (09H)		Use of Switches (11H)		Brake Operation (01H)	
	Derailed Cars per Accident	Casualties per Accident	Derailed Cars per Accident	Casualties per Accident	Derailed Cars per Accident	Casualties per Accident
2000	2.69	0.00	2.27	0.00	0.74	0.00
2001	1.58	0.00	0.41	0.00	1.28	0.00
2002	2.21	0.00	0.57	0.00	1.14	0.00
2003	3.03	0.02	0.54	0.01	1.14	0.02
2004	3.01	0.01	1.12	0.04	1.55	0.02
2005	3.17	0.00	0.48	0.00	1.50	0.00
2006	2.21	0.00	0.96	0.03	2.18	0.00
2007	2.54	0.00	0.61	0.00	0.81	0.00
2008	2.23	0.02	0.25	0.00	0.38	0.00
2009	2.24	0.00	0.86	0.00	1.68	0.00
2010	2.67	0.00	0.78	0.00	1.37	0.02
2011	1.65	0.00	0.68	0.00	2.11	0.00
2012	1.06	0.00	0.24	0.00	0.43	0.00
2013	2.22	0.00	0.84	0.00	1.02	0.00
2014	2.12	0.02	0.64	0.00	2.24	0.00
2015	2.91	0.00	0.26	0.00	2.23	0.00
2016	1.71	0.00	0.91	0.06	1.52	0.00
Average	2.31	0.00	0.73	0.01	1.37	0.00
p-value (in runs test)	0.605	n/a	0.301	n/a	0.121	n/a

NOTE: No significant results from runs test for casualties due to a large proportion of 0's.

Table 9. Different measures of severity per accident for major collision causes.

Year	Failure to Obey/Display Signals (05H)		Train Speed (10H)		Mainline Rules (08H)	
	Derailed Cars per Accident	Casualties per Accident	Derailed Cars per Accident	Casualties per Accident	Derailed Cars per Accident	Casualties per Accident
2000	0.56	0.30	0.59	1.15	0.62	0.23
2001	7.12	0.75	0.41	0.04	0.00	0.07
2002	3.97	0.44	0.07	0.04	1.51	0.29
2003	1.22	0.35	0.87	0.07	0.00	0.03
2004	3.05	3.05	1.26	0.03	1.54	0.31
2005	2.38	0.42	1.54	1.63	0.72	0.24
2006	1.08	0.32	0.45	0.13	0.03	0.13
2007	1.89	0.25	0.07	0.00	0.18	0.11
2008	3.30	0.30	0.90	0.26	0.13	0.30
2009	2.18	0.67	0.00	0.00	0.00	0.00
2010	0.98	0.21	0.35	0.00	2.44	0.98
2011	4.68	1.12	0.00	0.13	0.00	0.00
2012	1.22	0.06	2.95	0.38	0.19	0.26
2013	6.79	1.08	0.00	0.06	0.00	0.32
2014	0.96	0.30	2.41	0.30	0.00	0.06
2015	1.32	0.29	0.51	0.15	0.51	0.37
2016	1.90	0.63	0.00	0.00	3.38	0.00
Average	2.62	0.62	0.73	0.26	0.66	0.22
p-value (in runs test)	0.301	0.605	0.605	0.605	0.301	0.301

more (x-axis) casualties or derailed cars per accident. In this study, we focus on analyzing the derailments and collisions with at least one casualty or derailed car, since the logarithm of zero is undefined. No derailment caused more than 4 casualties per accident and over 97% of the human factor train derailments resulted in zero casualties. Train crew casualties are the majority of the casualties in freight-train collisions. Meanwhile, 3 freight-train collisions occurred with over 10 casualties due to the hazardous material releases as the accident narratives provided by the FRA REA database (FRA, 2018) show. The frequency of derailments with derailed cars is higher than collisions and the maximum number of derailed cars per accident is as high as 129 for derailments, compared to 66 for collisions. Therefore, unlike the risk in casualties, derailment risk measured by derailed cars is higher than that of collision risk.

6.2. Cause-specific risk profile

After studying the comparison between derailments and collisions with respect to different severity metrics, we now aim to analyze these accident types separately to evaluate their risk trends respective to major causes. Figure 5a presents the annual number of derailments, with N or more casualties per train derailment, by major causes, in 2000–2016. Despite different frequencies, the number of possible casualties per derailment is equally severe

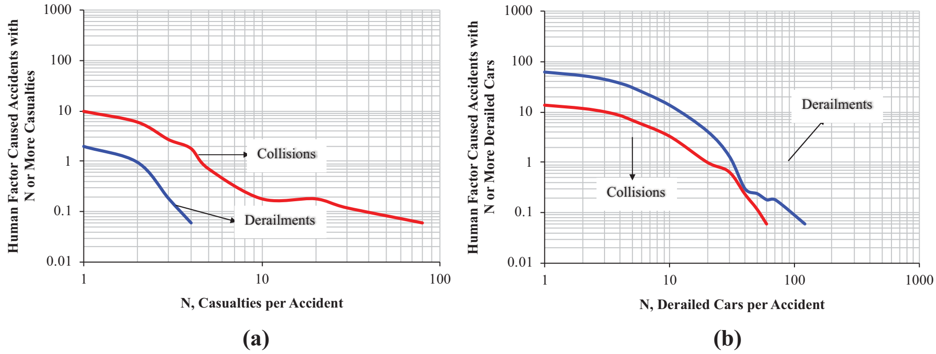

Figure 4. FN curves for derailments and collisions using different proxy measures of severity (all causes combined).

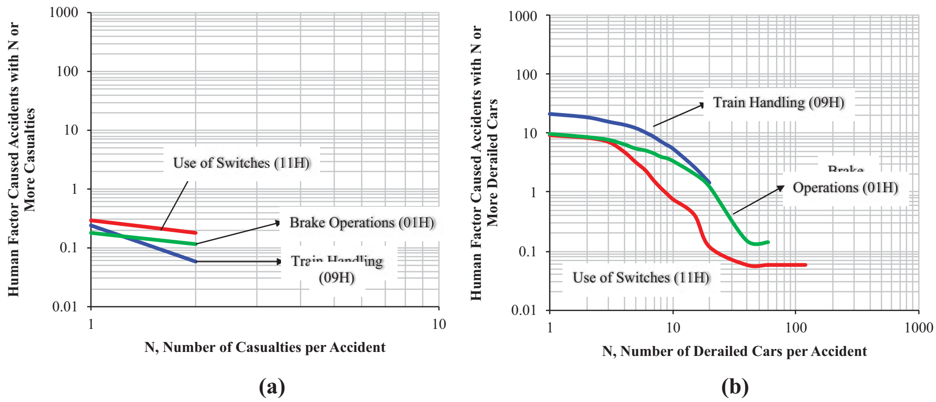

Figure 5. FN curves by major causes, with severity in terms of (a) casualties and (b) derailed cars, train derailments.

for all three major causes. Figure 5b shows the annual number of derailments, with N or more derailed cars per train derailment, by each of the major causes. It shows that though the train handling (09 H) has the highest number of derailments, use of switches (11 H) and brake operations (01 H) caused relatively higher numbers of derailed cars per accident.

The number of casualties per accident is observed to be higher in collisions than in derailments, whereas the severity in terms of derailed cars seems to have similar potential for both the accident types. The FN curves for each of the major collision causes in terms of casualties and derailed cars are shown in Figures 6a, b, respectively. By observing casualty risk, events related to mainline rules (08 H) exhibit relatively lower severity than the other two major causes. Among the three major causes, failure to obey or display signals shows the highest risk potential in terms of casualties as well as derailed cars due to the higher derailment frequency and severity.

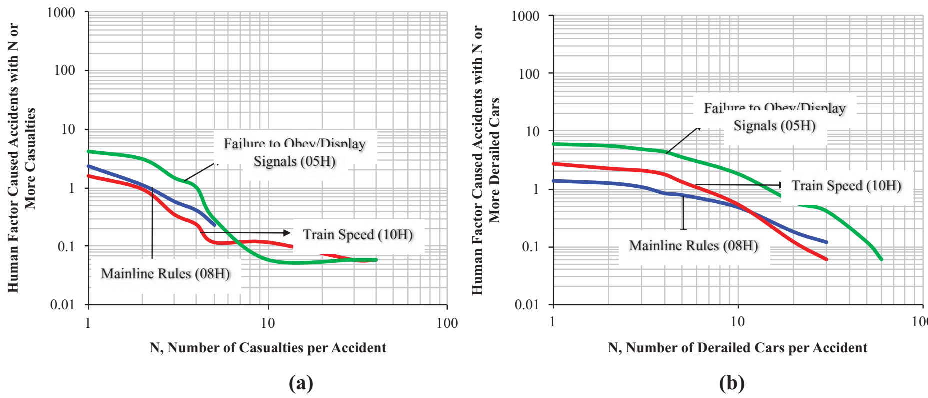

Figure 6. FN curves by major causes, with severity in terms of (a) casualties and (b) derailed cars, train collisions.

6.3. Annual train accident risk

Accident risk is defined as the expected number of casualties or derailed cars during a year, measured by the mean value (Equation 8). According to the Law of Total Expectation (LTE), if N is the total number of accidents with accident consequences X_{ij} with severity metric i in the j^{th} accident, then the risk can be estimated using the following equation, given that both N (accident frequency) and X_{ij} (accident severity) are random variables. The conditional expectation of the accident consequences given the occurrence of an accident is obtained as Equation 9. It shows that the annual risk can be expressed as a product of expected accident frequency and severity.

$$R_i = E\left[\sum_{j=1}^{N} X_{ij}\right] \tag{8}$$

$$E\left[\sum_{j=1}^{N} X_{ij}\right] = E\left[E\left[\sum_{j=1}^{N} X_{ij}|N\right]\right] = E[NE[X_{ij}]] = E[N]E[X] \tag{9}$$

Where,
i = severity metric, 1 for casualties and 2 for derailed cars
R_i = annual human factor accident risk for a specific severity metric i
X_{ij} = accident consequences of certain accident based on a specific severity metric

The expected accident frequency can be estimated using the negative binomial regression model described earlier, and the accident severity can be approximated by the sample mean. The 17-year average severity is used since there is no significant temporal trend of collision severity in the study period. Table 10 gives the estimated annual risk for each accident type,

Table 10. Annual accident risk by accident type.

Year	Derailments				Collisions			
	Total Number of Derailed Cars		Total Number of Casualties		Total Number of Derailed Cars		Total Number of Casualties	
	Empirical	Estimated	Empirical	Estimated	Empirical	Estimated	Empirical	Estimated
2000	615	657	4	4	124	145	31	36
2001	552	603	4	4	143	128	35	32
2002	564	574	4	4	110	130	27	32
2003	584	552	4	4	129	137	32	34
2004	653	539	4	4	167	152	41	38
2005	590	517	4	4	244	159	60	39
2006	545	506	4	3	115	181	28	45
2007	457	445	3	3	129	134	32	33
2008	349	403	2	3	110	111	27	27
2009	323	318	2	2	67	57	17	14
2010	317	318	2	2	62	69	15	17
2011	285	307	2	2	81	72	20	18
2012	178	294	1	2	105	75	26	18
2013	311	280	2	2	86	75	21	19
2014	298	269	2	2	96	79	24	20
2015	260	242	2	2	57	65	14	16
2016	235	208	2	1	29	45	7	11
Average	419	414	3	3	109	107	27	26

which is the product of their respective estimated frequency of all causes combined (Tables 3 and 6) and overall 17-year average severity because there is no temporal trend (Table 7). For example, the estimated frequency of derailments in 2006 is 80 and the overall average severity is 6.34 derailed cars and 0.04 casualties; thus, the estimated derailment risk in that year is 506 derailed cars (80×6.34) and 3 casualties (80×0.04). The derailment risk in terms of derailed cars is very high when compared to collision risk. This is because the total number of derailments (1122) is almost three times higher than collisions (388). However, the number of casualties due to derailments is extremely low. Therefore, the collision risk is higher than the derailment risk with respect to casualties.

6.4. Annual risk in alternative risk measure

The limitation of using mean as the risk measure is that it fails to account for the extreme characteristics of the accidents with low probabilities but high consequences. To address this "heavy-tail" effect, prior literature has used risk measures such as value at risk (VaR) or conditional value at risk (CVaR) as alternative risk measures (Soleimani, Seyyed-Esfahani, & Kannan, 2014; Spada, Paraschiv, & Burgherr, 2018; Zhang & Liu, 2019). This study considers CVaR rather than VaR as an alternative to mean risk, in accordance with the preference of many previous studies due to CVaR's coherency (Sarkaylin et al., 2008; Rockafellar & Uryasev, 2000). This is because VaR does not reveal anything about the magnitude of losses exceeding the VaR limit which can be addressed by CVaR. It is the weighted average of all outcomes exceeding the confidence

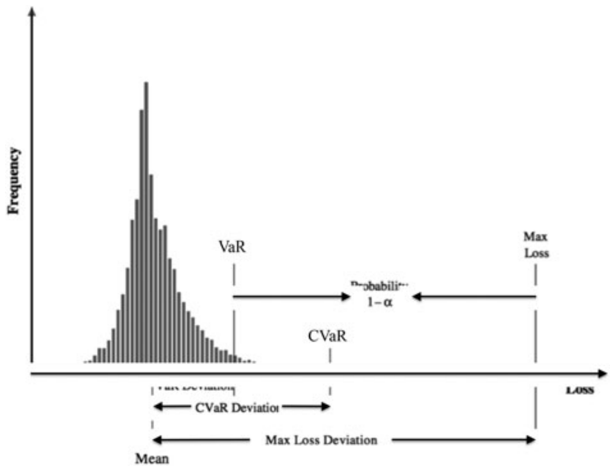

Figure 7. Graphical representation of alternative risk measures (Sarkaylin, Serraino, & Uryasev, 2008).

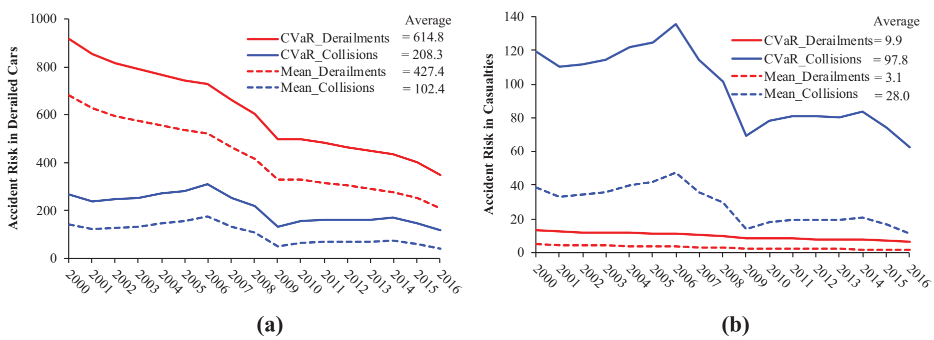

Figure 8. Annual freight train risk in terms of (a) derailed cars and (b) casualties.

interval of a data set sorted from worst to best. Simply put, the CVaR of the collision risk is the average of severity (number of casualties or derailed cars) of all the collisions that are more than $\alpha \in (0, 1)$ (Equation 10). Usually, a confidence interval of 95% is adopted ($\alpha = 0.95$). Figure 7 makes a lucid representation of these measures graphically. It shows that α is a chosen quantile, so the frequency at α is the VaR and the average of events exceeding it is CVaR.

$$CVaR_{\alpha}(X) = \frac{1}{1-\alpha}\int_{\alpha}^{1} q_u(X)du \tag{10}$$

Figure 8 presents the annual risk in mean and CVaR for both derailments and collisions using different severity metrics. The temporal trend of CVaR and mean risk in derailed cars is higher for derailments, but casualty risk is higher for collisions. The average $CVaR_{95\%}$ in the study period due to derailments is almost 615 derailed cars or 10 casualties, while the average $CVaR_{95\%}$ due to collisions is 208 derailed cars or 98 casualties. Since these CVaR values consider the risk associated with the worst 5% of accidents, they are higher than the mean risk values. The derailment risk in both metrics is clearly decreasing but the fluctuations in the collision risk measures is due to a sudden peak of frequency observed in 2005 which affected the estimated trend in the model.

7. Discussion on human factors and emerging mitigative measures

7.1. Train engineer education, training, and attentiveness

The analysis presented above helps to understand the primary causes and corresponding annual risk for each type of human factor accident. Besides, it is also important to understand and prevent causal factors. These major cause-groups are directly or indirectly associated with behavioral, psychological or organizational characteristics. Most incidents are linked to at least one organizational influence, which suggests that the improvement in resource management, organizational climate and organizational processes is important (Baysari, McIntosh, & Wilson, 2008). Train driving requires extensive knowledge of operation rules and vehicle behavior with ability to integrate different static and dynamic sources of information (Giesemann, 2012), failure of which result in accidents due to violation of operation or mainline or speed rules. Furthermore, heavy workload, fatigue, monotony and boredom are found to be the issues leading to human error accidents of train handling group (Dorrian, Roach, Fletcher, & Dawson, 2006). Fatigue is also responsible for lack of attentiveness which results in being negligent to obey signals or any rules. Therefore, the accidents caused with the major cause groups, may be reduced with periodic train operation education, well-established working schedule, and effective engineer fatigue monitoring program.

A variety of strategies and practices are being implemented in the railroads. For example, Rowe (2013) presented the development of train driver training simulator that has the ability to train multiple drivers simultaneously and to review performance in detail. In this effective simulator, essential tasks (e.g., being able to look around while driving, taking power/applying brakes) are included. Both normal and abnormal driving were documented in a full task list and analyzed with the task assessment observations. To mitigate train engineer fatigue risk, a real-time online prototype driver-fatigue monitor was proposed by Ji, Zhu, and Lan (2004). In this non-intrusive monitoring, it uses prototype computer vision system for real-time video images of the driver and monitors driver's vigilance. Similarly, cab alerters are designed and implemented to alert the train crew by emitting a flashing light and an alarm (Oman & Liu, 2007). For the

Positive Train Control (PTC) systems in the United States, the train could be automatically slowed down or stopped if the warning alarm in the cab is not acknowledged. The implementation of cab alerters or PTC system can potentially reduce the accidents due to certain human factor causes studied in this paper, such as failure of brake operation (01 H), excessive speed (10 H), or failure to obey/display signals cause group (05 H). This potentially can reduce the accidents due to the driver falling asleep under failure to obey/display signals cause group. A probabilistic framework is built to model fatigue, which systematically combines different visual cues and contextual information to produce a robust fatigue index. Another solution to driver inattentiveness addressed in literature is intelligent transportation systems (ITS) (Dong, Hu, Uchimura, & Murayama, 2011). Similar to the existing technology of intelligent brake assist and collision warnings in cars, its research in railroad industry is also evolving to detect any unsafe conditions on the tracks or right of way.

7.2. Near miss analysis

FRA initiated a partnership with National Aeronautics and Space Administration (NASA) and is working on a research project called Confidential Close Call Reporting System (C^3RS), to better understand the events called "close calls", which could have resulted in accidents but fortunately did not yet. This program facilitates anonymous reporting of unsafe railroad conditions. With this closed participation system, railroad employees will be able to report human-factor-related safety issues voluntarily and confidentially, which may have been ignored before. These reports involve incremental unsafe conditions and descriptions of human errors in railroad industry and then be analyzed by a Peer Review Team (PRT) comprising labor, management, and FRA representatives. The PRT faced challenges such as limited knowledge and lack of detailing in the reports (Multer, Ranney, Hile, & Raslear, 2013). The team collaborated with third parties to overcome the challenges and improve the quality of reports. Initial results shown that C^3RS was implemented successfully and achieved an initial improvement in safety culture through reviewing and implementing corrective actions (FRA, 2014). After the completion in 2017, its implementation in the railroad industry made it possible to disclose previously unknown safety risks and their causes (Morell, Davey, Ranney, Zuschlag, & Cantu, 2018). In addition to the identified frequent safety concerns and underlying contributing factors causing multiple types of safety issues, corrective actions could also be tracked and developed to ensure the implementation to be timely and effective. Figure 9 shows the reporting and corrective action process of C^3RS. Furthermore, C^3RS program focuses on company-level reporting and analytical results

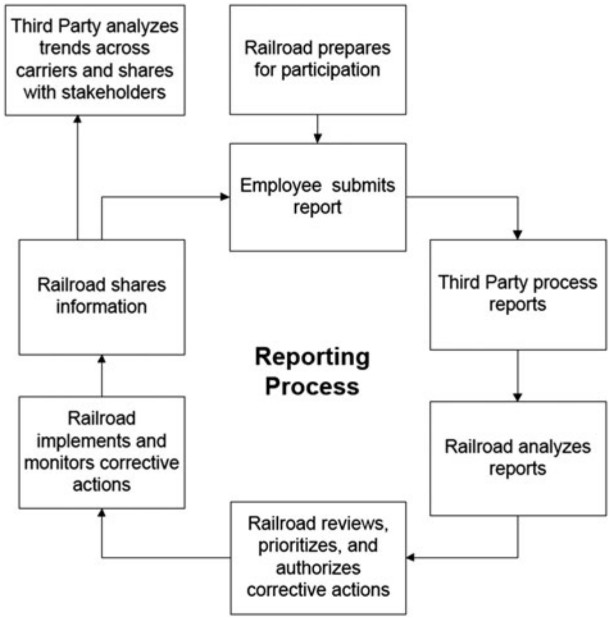

Figure 9. Reporting process of C^3RS (Multer et al., 2013).

which encourage the employees to reveal unsafe conditions confidentially. As a result, the mechanisms for specific companies reported that most human errors can be avoided. The system can provide understanding of the impacts of aforementioned company-level factors in human error accidents, such as periodic train operation education, working schedule, and engineer fatigue monitoring program, and could also promote the enhancement of these factors. Similarly, Rail Safety and Standards Board (RSSB) also maintains the "Close Calls" reported by railroad personnel in the accident database that is used in the analytics with Safety Risk Model (Van Gulijk, Hughes, Figueres-Esteban, Dacre, & Harrison, 2015). To achieve convenient user interfaces, the workers in Great Britain (GB) railroads can use mobile applications to make a close call report, which is freeform text report. Van Gulijk et al. (2015) disclosed that over a period of two years, approximately 150,000 entries were collected and saved into the GB's Close Call Database. The big data can be extracted and contribute to added value for safety and risk domain.

Besides, the surveillance camera videos in railroad yards, grade crossings, right of ways and cabs may provide information regarding near misses or unsafe behaviors. Issues such as knowledge-based errors were more frequently reported through this system (Wright & Schaaf, 2004). The causal factors of close calls involve not obeying signals, mainline and train speed rules which happen to be the major causes of train collisions and would result in severe consequences if not missed. The data from such near-miss accidents can be key in understanding deeper about the potential causes of an accident.

Moreover, the consideration of automation in the railroad industry reduces the human intervention and replaces the user tasks by technology and efficiency (Wackrow & Slamen, 2013; Woodland, 2015). The aim is to be effective in overcoming most of the aforementioned errors due to physical and mental inabilities. In the United States, Positive Train Control (PTC) is being implemented on a national scale and would have a significant impact on reducing human-factor-caused accidents.

7.3. Positive train control (PTC)

PTC is a communication-based/processor-based train control technology that has the potential to improve safety because it provides a layer of additional protection beyond that provided by the train crews and dispatchers (FRA., 2007b). More specifically, it can automatically prevent accidents attributable to human error by slowing or stopping trains and is designed to prevent four major types of accidents, namely train-to-train collisions, derailments caused by excessive speeds, unauthorized incursions into work zones, and movements through misaligned switches. The PTC system integrates the locomotive computer, wayside device, communication network, and back office to process collected movement authority and speed restrictions and then comparing these against the train's real conditions to ensure safety compliance (AAR, 2017b). If any noncompliant train operation occurred, the PTC system would automatically apply the brakes and bring the train to a positive stop. Figure 10 presents the network arrangement of various components integrated in PTC.

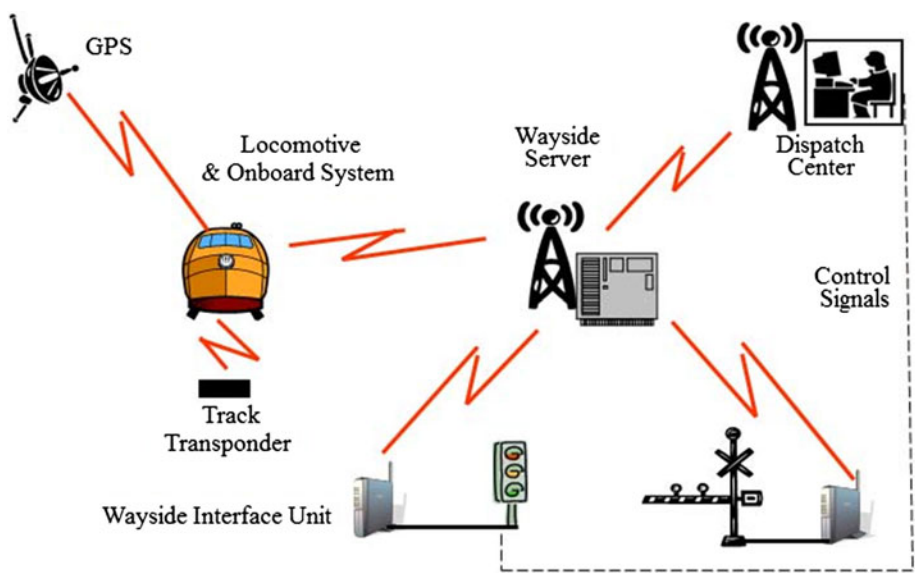

Figure 10. Architecture of PTC system (Bandara, Bondi, Goel, Pilapitiya, & Wijesekera, 2012).

It is acknowledged by FRA that not all the human-factor-related accident causes are PTC-preventable (FRA., 2007b). But based on the aforementioned PTC functions, it can still prevent a significant portion of human-factor-caused accidents with high-frequency causes that were identified in Figure 3. The PTC-preventable accidents include those caused by failure to obey/display signals (05 H), violation of train speed rules (10 H), and failures of switch uses (07 H). More specifically, to prevent accidents caused by the failure to obey/display signals and switch uses, the wayside device on the side of the track is capable of monitoring and reporting the switch position and signal status to locomotive computers and the back office, which is a centralized office for the communication and coordination of train orders, speed restrictions, train information, and track authorities (Zhang, Liu, & Holt, 2018). If a train fails to follow the signal indication, or the device reads switch use failure, then the PTC system would apply the brakes to slow and stop the train automatically. In terms of the violation of train speed rules, locomotive computers would accept the speed restriction information (e.g., maximum authorized speed, restricted speed indications) provided by the back office and compare it against the train's operating condition to ensure safe operations. Once the train speed rules are violated, a brake would be applied automatically to slow and stop the train to prevent any potential hazards.

The implementations of PTC systems are mandatorily required to be completed before December 31, 2018, which can be extended to December 31, 2020, with approval from the FRA (Congress, 2015). With the advancement in train control systems, it is essential to update risk analysis with the results of our current work. Since this paper is based on data prior to PTC implementation, it can act as the basis of safety analysis and compare with results from future technological developments, in particular for the annual risk analysis studied in Section 6. Subsequently, when PTC is fully implemented, an updated risk analysis should be developed in order to examine the safety benefits of this advanced systems in the prevention of human-factor-related accidents. For example, if the annual risk of accidents caused by the failure to obey/display signals (05 H) in a future period is reduced from 46 (the average number in the study period) to 10 cars derailed, it indicates that around 80% ($=1-10/46$) accidents within by this leading human-error-related cause group are effectively prevented and PTC system implementation would probably be one major strategy behind the significant accident prevention. Furthermore, based on the comparative analysis with the accident risk developed in this paper, the "residual risk" (such as the residual 10 cars derailed annually in the aforementioned example) related to human errors can be evaluated to provide practical insights for future research in the age of PTC.

As per current perspective, the "residual risk" involves but is not limited to three potential sources, such as PTC component failure, human-factor-caused accidents out of PTC territory, and cyber security. PTC failure modes consist of wayside system failure, loss of power, communications failure, and dispatcher error (Hartong, Goel, & Wijesekera, 2011) that may lead to the occurrence of human-factor-related accidents even though they are PTC preventable. In terms of accidents out of PTC territory, as mentioned before, not all the human-factor-related accident causes are PTC-preventable. For example, train accidents caused with failure to comply with restricted speed (H605 and H607 in FRA train accident cause-codes) cannot be prevented with functional PTC system due to the territory exemption (FRA, 2011). For PTC-related cyber security, the busy communications in PTC system may increase the risk of cyber-attacks, which can be catastrophic on commuter trains or freight trains with hazardous materials (Zhang et al., 2018). Bloomfield et al. (2016) studied cyber security issues in Britain's railway system involving European Rail Traffic Management System (ERTMS) but quite limited literature studied the cyber security directly related with PTC systems. Overall, these three probable sources of "residual risk" could be serious future research directions in the effective and adequate mitigation of train accidents caused by human errors.

7.4. Other alternative technologies

A train-handling technology called LEADER (Nickles, Hawthorne, & Haley, 2003) monitors the operating conditions of a train and analyzes the speed and dynamic braking. It has been proved to improve the fuel efficiency and is expected to be capable of improving the service of the locomotives by reducing repair and maintenance cost. Besides, this technology may potentially mitigate train-handling-related train accidents. In addition, distributed power system is able to improve the operational reliability with optimized redundancy and good traction performance (Hagiwara, Tanaka, & Ueno, 2001). The advantages of distributed power, such as efficient regenerative brake utility and good traction/braking performance, may help to reduce certain train accidents, such as the ones caused by train handling (09 H) and brake operation (01 H). Besides, the Association of American Railroads (AAR), (2019) pointed out that Advanced Technology Safety Initiative (ATSI) improves rail safety through reducing track and component related accidents. Stabler and Lauro (2005) pointed out that one of ATSI objectives is to keep switching and out-of-service time to a minimum. To this end, ATSI may also (indirectly) contribute to reducing train accidents caused by improper use of switches (11 H). However, to the authors' knowledge, the impact of ATSI on human factor accidents has not been well studied in the literature. Ultimately, in the future research, the impacts of these mentioned strategies would be quantitatively evaluated if the needed data is available.

8. Conclusion

This paper develops a statistical risk analysis of human-factor-caused freight train accidents in the United States based on FRA safety database from 2000 to 2016. Overall, the derailment and collision rate per train-mile has an average annual declining rate of approximately 6 and 5 percent respectively. Over the study period, there was no significant temporal trend of accident severity for either casualties or derailed cars. Each of the two major accident types has three different primary causes, namely the train handling (09 H), use of switches (11 H), and brake operation (01 H) for train derailments; failure to obey or display signals (05 H), violation of mainline rules (08 H), and train speed rules (10 H) for train collisions. Train handling (09 H) has the highest derailment frequency but has relatively lower risk potential than the other two causes as it led to more zero-casualty derailments. In cause-specific collision risk analysis, failure to obey/display signals (05 H) not only has the highest frequency among the three major causes but also has the greatest potential to result in high severity accidents. Nationwide, the average freight train derailment risk due to all human factor causes is almost 414 derailed cars or 3 casualties per year. Similarly, the average annual freight train collision risk is about 107 derailed cars or 27 casualties. In order to better understand the worst-case accidents, the mean-value-based risk measure can be bolstered by alternative risk measures such as the Conditional Value at Risk ($CVaR_{95\%}$), which represents the risk associated with the worst 5% of train accidents. For derailments, the $CVaR_{95\%}$ is 615 derailed cars or 10 casualties per year. By contrast, for collisions, the $CVaR_{95\%}$ in the study period is estimated to be 208 derailed cars or 98 casualties per year. While derailments tend to cause more cars to be derailed, collisions claimed more casualties. The implementations of C^3RS and the Positive Train Control (PTC) system, as well as well-developed train crew education and training program, in the United States will prevent a significant portion of human-factor-caused train accidents. The risk analysis results in this paper would act as the basis of safety analysis before the fully implementation of nation-wide PTC system and contribute to the comparative risk study with future technological developments. The statistical analysis presented herein can also be updated to calculate the “residual risk” after PTC implementation, which can provide incremental insights of future research directions in the age of PTC.

References

Anderson, R. T., & Barkan, C. P. L. (2004). Railroad accident rates for use in transportation risk analysis. In *Transportation research record: Journal of the transportation research board, No. 1863* (pp. 88–98). Washington, DC: Transportation Research Board of the National Academies. doi:10.3141/1863-12

Arthur D. Little, Inc. (ADL). (1996). *Risk assessment for the transportation of hazardous materials by rail. supplementary report: Railroad accident rate and risk reduction option effectiveness analysis and data*, 2nd rev. Cambridge, Mass: ADL.

Association of American Railroads (AAR). (2017a). Overview of America's Freight Railroads. Washington, DC.

Association of American Railroads (AAR). (2017b). *Positive train control.* Washington, DC.

Association of American Railroads (AAR). (2019). "ATSI Improves Rail Safety." https://www.aar.org/data/atsi-improves-rail-safety/

Bagheri, M., Saccomanno, F. F., Chenouri, S., & Fu, L. P. (2011). Reducing the threat of in-transit derailments involving dangerous goods through effective placement along the train consist. *Accident Analysis & Prevention*, *43*(3), 613–620. doi:10.1016/j.aap.2010.09.008

Bandara, D. S., Bondi, A. B., Goel, R., Pilapitiya, N., & Wijesekera, D. (2012). Developing a framework to address performance and security protocol concerns in identity management for interoperable positive train control systems. *In 2012 American Society of Mechanical Engineers Joint Rail Conference*, pp. 389–396.

Barkan, C. P. L., Dick, C. T., & Anderson, R. (2003). Railroad derailment factors affecting hazardous materials transportation risk. *Transportation Research Record: Journal of the Transportation Research Board*, *1825*(1), 64–74. doi:10.3141/1825-09

Baysari, M. T., McIntosh, A. S., & Wilson, J. R. (2008). Understanding the human factors contribution to railway accidents and incidents in Australia. *Accident Analysis & Prevention*, *40* (5), 1750–1757. doi:10.1016/j.aap.2008.06.013

Benesty, J., Chen, J., Huang, Y., & Cohen, I. (2009). Pearson correlation coefficient. In *Noise reduction in speech processing* (pp. 1–4). Berlin, Heidelberg: Springer.

Bloomfield, R., Bendele, M., Bishop, P., Stroud, R., & Tonks, S. (2016). The risk assessment of ERTMS-based railway systems from a cyber security perspective: Methodology and lessons learned. In International Conference on Reliability, Safety, and Security of Railway Systems (pp.-19) Springer, Cham.Chicago

Chadwick, S. G., Saat, M. R., & Barkan, C. P. L. (2012). Analysis of Factors Affecting Train Derailments at Highway–Rail Grade Crossings. *Presented at 91st Annual Meeting of the Transportation Research Board.*

Chen, S. T., Wall, A., Davies, P., Yang, Z., Wang, J., & Chou, Y. H. (2013). A human and organizational factors (HOFs) analysis method for marine casualties using HFACS-maritime accidents (HFACS-MA). *Safety Science*, *60*, 105–114. doi:10.1016/j.ssci.2013.06.009

Chen, W., Zhang, Y., Khasawneh, M. T., & Geng, Z. (2018). Risk analysis on Beijing metro operation initiated by human factors. *Journal of Transportation Safety & Security*, *10*, 1–17. doi:10.1080/19439962.2018.1470586

Congress of the United States of America. (2015). *Positive train control enforcement and implementation act of 2015 (PTCEI Act).* Washington DC: PTCEI. H.R. 3651.

Dhillon, B. S. (2007). Human reliability and error in transportation systems. *Springer Series in Reliability Engineering*, number 978-1-84628-812-8, April.

Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011). Driver inattention monitoring system for intelligent vehicles: A review. *IEEE Transactions on Intelligent Transportation Systems*, *12*(2), 596–614. doi:10.1109/TITS.2010.2092770

Dorrian, J., Roach, G. D., Fletcher, A., & Dawson, D. (2006). The effects of fatigue on train handling during speed restrictions. *Transportation Research Part F: Traffic Psychology and Behaviour*, *F9*, 243–257. doi:10.1016/j.trf.2006.01.003

Evans, A. W. (2011). Fatal train accident on Europe's railways: 1980-2009. *Accident Analysis & Prevention*, *43*(1), 391–401. doi:10.1016/j.aap.2010.09.009

Evans, A. W., & Verlander, N. Q. (1997). What is wrong with criterion FN-lines for judging the tolerability of risk? *Risk Analysis*, *17*(2), 157. doi:10.1111/j.1539-6924.1997.tb00855.x

Federal Railroad Administration (FRA). (2018). Railroad equipment accident/incident reporting threshold. Retrieved from https://safetydata.fra.dot.gov/OfficeofSafety/ProcessFile.aspx?doc=RAILROAD_REPORTING_THRESHOLD.doc

Federal Railroad Administration (FRA). Train accident cause codes. Retrieved from https://safetydata.fra.dot.gov/officeofsafety/publicsite/downloads/appendixC-TrainaccidentCauseCodes.aspx?State=0

Federal Railroad Administration. (2014). Update from C3RS Lessons Learned Team: Safety Culture and Trend Analysis, Research Results. FRA Office of Railroad Policy & Development, RR 14–18.

FRA. (2007a). *Development of a switch point monitoring system in non-signaled territory*. Washington, DC: FRA.

FRA. (2007b). *Human factors considerations in the evaluation of processor-based signal and train control systems*. Washington, DC: FRA.

Giesemann, S. (2012). *Automation effects in train driving with train protection systems – assessing person-and task-related factors*. Germany: German Airspace Centre.

Hagiwara, Y., Tanaka, M., & Ueno, M. (2001). Evaluation of advantages of high-speed EMU in the case of the Series 700 Shinkansen high-speed train with IGBT applied traction system. *In Proceedings of the World Congress on Railway Research* (Vol. 2001).

Hartong, M., Goel, R., & Wijesekera, D. (2011). Positive train control (PTC) failure modes. *Journal of King Saud University - Science*, *23*(3), 311–321. doi:10.1016/j.jksus.2010.12.003

Iridiastadi, H., & Ikatrinasari, Z. F. (2012). Indonesian railway accidents – utilizing human factors analysis and classification system in determining potential contributing factors. *Work*, *41*, 4246–4249.

Ji, Q., Zhu, Z., & Lan, P. (2004). Real-time nonintrusive monitoring and prediction of driver fatigue. *IEEE Transactions on Vehicular Technology*, *53*(4), 1052–1068. doi:10.1109/TVT.2004.830974

Kyriakidis, M., Pak, K. T., & Majumdar, A. (2015). Railway accidents caused by human error-historic analysis of UK railways. *Transportation Research Record: Journal of the Transportation Research Board*, *2476*, 126–136. doi:10.3141/2476-17

Li, S., Cai, B., Liu, J., & Wang, J. (2018). Collision risk analysis-based train collision early warning strategy. *Accident Analysis & Prevention*, *112*, 94–104. doi:10.1016/j.aap.2017.11.039

Liu, X. (2015). Statistical temporal analysis of freight train derailment rates in the United States: 2000 to 2012. *Transportation Research Record: Journal of the Transportation Research Board*, *2476*(1), 119–125. doi:10.3141/2476-16

Liu, X. (2016a). Analysis of collision risk for freight trains in the United States. *Transportation Research Record: Journal of the Transportation Research Board*, 121–128. doi:10.3141/2546-15

Liu, X. (2016b). Statistical causal analysis of freight train derailments in the United States. *Journal of Transportation Engineering Part A: Systems*, *143*(2), 04016001–04016007.

Liu, X., Barkan, C. P. L., & Saat, M. R. (2011). Analysis of derailments by accident cause: Evaluating railroad track upgrades to reduce transportation risk. *Transportation Research Record: Journal of the Transportation Research Board*, *2261*(1), 178–185. doi:10.3141/2261-21

Liu, X., Saat, M. R., & Barkan, C. P. L. (2012). Analysis of causes of major train derailment and their effect on accident rates. *Transportation Research Record: Journal of the Transportation Research Board*, *2289*(1), 154–163. doi:10.3141/2289-20

Lord, D. (2006). Modeling motor vehicle crashes using Poisson-gamma models: Examining the effects of low sample mean values and small sample size on the estimation of the fixed dispersion parameter. *Accident Analysis & Prevention*, *38*(4), 751–766. doi:10.1016/j.aap.2006.02.001

Low, J. M., & Yang, K. K. (2018). An exploratory study on the effects of human, technical and operating factors on aviation safety. *Journal of Transportation Safety & Security*, *10*, 1–34. doi:10.1080/19439962.2018.1458051

Madigan, R., Golightly, D., & Madders, R. (2016). Application of Human Factors Analysis and Classification System (HFACS) to UK rail safety of the line incidents. *Accident Analysis & Prevention*, *97*, 122–131. doi:10.1016/j.aap.2016.08.023

Marty, E. N., & Okine, N. A. (2018). Bivariate severity analysis of train derailments using copula-based regression models. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *4* (4), 1-11. doi: 10.1061/AJRUA6.0000982.

Miaou, S. P. (1994). The relationship between truck accidents and geometric design of road sections: Poisson versus negative binomial regressions. *Accident Analysis & Prevention*, *26*(4), 471–482. Vol. Issue doi:10.1016/0001-4575(94)90038-8

Mitra, S., & Washington, S. (2007). On the nature of over-dispersion in motor vehicle crash prediction models. *Accident Analysis & Prevention*, *39*(3), 459–568. Vol. Issue doi:10.1016/j.aap.2006.08.002

Morell, J. A., Davey, M., Ranney, J., Zuschlag, M., & Cantu, C. (2018). Transforming Railroad Safety with the Federal Railroad Administration Confidential Close Call Reporting System: Implementation, Impact, and Sustainability. Transportation Research Board, No. 18–01078.

Multer, J., Ranney, J., Hile, J., & Raslear, T. (2013). Developing an Effective Corrective Action Process: Lessons Learned from Operating A Confidential Close Call Reporting System. (No. DOT/FRA/ORD-13/12). US Department of Transportation, Federal Railroad Administration, Office of Research and Development.

Nickles, S. K., Hawthorne, M. J., & Haley, J. E. (2003). New York Air Brake LLC. Method of optimizing train operation and training. U.S. Patent 6,587,764.

Oh, J., Washington, S. P., & Nam, D. (2006). Accident prediction model for railway-highway interfaces. *Accident Analysis & Prevention*, *38*(4), 346–356. Issuedoi:10.1016/j.aap.2005.10.004

Oman, C. M., & Liu, A. M. (2007). *Locomotive in-cab alerter technology assessment*. MVL Publication, 7.

Reinach, S., & Viale, A. (2006). Application of a human error framework to conduct train accident/incident investigations. *Accident Analysis & Prevention*, *38*(2), 396–406. doi:10.1016/j.aap.2005.10.013

Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk*, *2*(3), 21–42. doi:10.21314/JOR.2000.038

Rowe, I. (2013). Developing a tram driver route learning training simulator for Manchester's metrolink trams. Rail human factors: Supporting reliability, safety and cost reduction. 262.

Saccomanno, F. F., Park, P. Y.-J., & Fu, L. P. (2007). Estimating countermeasure effects for reducing collisions at highway–railway grade crossings. *Accident Analysis & Prevention*, *39*(2), 406–416. doi:10.1016/j.aap.2006.08.016

Sarkaylin, S., Serraino, G., & Uryasev, S. (2008). Value-at-risk vs. conditional value-at-risk in risk management and optimization. *Tutorials in Operations Research*, 270–293.

Schafer, D., & Barkan, C. P. L. (2007). The relationship between train length and accident causes and rates. *Transportation Research Record: Journal of the Transportation Research Board*, *2043* (1), 73–82. doi:10.3141/2043-09

Soleimani, H., Seyyed-Esfahani, M., & Kannan, G. (2014). Incorporating risk measures in closed-loop supply chain network design. *International Journal of Production Research*, *52*(6), 1843–1867. doi:10.1080/00207543.2013.849823

Spada, M., Paraschiv, F., & Burgherr, P. (2018). A comparison of risk measures for accidents in the energy sector and their implications on decision-making strategies. *Energy*, *154*, 277–288. doi:10.1016/j.energy.2018.04.110

Stabler, L., & Lauro, D. (2005). Advanced technology safety initiative. http://www.marts-rail.org/wp-content/uploads/2018/02/ATSI-Update-for-MARTS-sep-05.pdf

Theophilus, S. C., Esenowo, V. N., Arewa, A. O., Ifelebuegu, A. O., Nnadi, E. O., & Mbanaso, F. U. (2017). Human factors analysis and classification system for the oil and gas industry (HFACS-OGI). *Reliability Engineering & System Safety*, *167*, 168–176. doi:10.1016/j.ress.2017.05.036

Van Gulijk, C., Hughes, P., Figueres-Esteban, M., Dacre, M., & Harrison, C. (2015). Big Data Risk Analysis for Rail Safety?. In *Proceedings of ESREL 2015. CRC/Balkema*.

Wackrow, J., & Slamen, A. (2013). The implications of automation on human intervention at London underground, 209–218. doi:10.1201/b13827-30.

Wright, L., & Schaaf, T. (2004). Accident versus near miss causation: A critical review of the literature, an empirical test in the UK railway domain, and their implications for other sectors. *Journal of Hazardous Materials*, *111*(1–3), 105–110. doi:10.1016/j.jhazmat.2004.02.049

Yildirum, U., Ugurlu, O., Basar, E., & Yuksekyildiz, E. (2017). Human factor analysis of container vessel's grounding accidents. *International Journal of Maritime Engineering*, *159*, 89–98. Vol. doi:10.3940/rina.ijme.2017.a1.395

Zhang, J., Jiang, P., & Niu, C. (2014). Human factor analysis of general accidents in railway passenger transportation. *Applied Mechanics and Materials*, 1723–1727. doi:10.4028/www.scientific.net/AMM.744-746.1723

Zhang, Z., & Liu, X. (2019). Safety risk analysis of restricted-speed train accidents in the United States. *Journal of Risk Research*, *7*, 1–19. doi:10.1080/13669877.2019.1617336

Zhang, Z. P., Liu, X., & Holt, K. (2018). Positive train control (PTC) for railway safety in the United States: Policy developments and critical issues. *Utilities Policy*, *51*, 33–40. Voldoi:10.1016/j.jup.2018.03.002

Appendix I. Major derailment and collision cause groups

Cause Group	Description	FRA Cause Codes	Code Description
01H	Brake operations (mainline)	H510	Automatic brake, insufficient (H001) – see note after cause H599
		H511	Automatic brake, excessive (H002)
		H512	Automatic brake, failure to use split reduction (H003)
		H513	Automatic brake, other improper use (H004)
		H514	Failure to allow air brakes to fully release before proceeding (H005)
		H515	Failure to properly cut-out brake valves on locomotives (H006)
		H516	Failure to properly cut-in brake valves on locomotives (H007)
		H517	Dynamic brake, insufficient (H009)
		H518	Dynamic brake, excessive (H010)
		H519	Dynamic brake, too rapid adjustment (H011)
		H520	Dynamic brake, excessive axles (H012)
		H521	Dynamic brake, other improper use (H013)
		H525	Independent (engine) brake, improper use (except actuation) (H023)
		H526	Failure to actuate off independent brake (H024)
05H	Failure to obey/ display signals	H201	Blue Signal, absence of
		H202	Blue Signal, imperfectly displayed
		H205	Flagging, improper or failure to flag
		H206	Flagging signal, failure to comply
		H207	Hand signal, failure to comply
		H208	Hand signal improper
		H209	Hand signal, failure to give/receive
		H217	Failure to observe hand signals given during a wayside inspection of moving train
		H218	Failure to comply with failed equipment detector warning or with applicable train inspection rules.
		H219	Fixed signal (other than automatic block or interlocking signal), improperly displayed.
		H220	Fixed signal (other than automatic block or interlocking signal), failure to comply.
		H221	Automatic block or interlocking signal displaying a stop indication - failure to comply.
		H222	Automatic block or interlocking signal displaying other than a stop indication - failure to comply.
		H299	Other signal causes (detailed description in narrative)
08H	Mainline rules	H401	Failure to stop train in clear
		H402	Motor car or on-track equipment rules, failure to comply
		H403	Movement of engine(s) or car(s) without authority (railroad employee)
		H404	Train order, track warrant, track bulletin, or timetable authority, failure to comply
		H405	Train orders, track warrants, direct traffic control, track bulletins, radio, error in preparation, transmission or delivery
		H406	Train orders, track warrants, direct traffic control, track bulletins, written, error in preparation, transmission or delivery
		H499	Other main track authority causes (Provide detailed description in narrative)
09H	Train handling	H501	Improper train make-up at initial terminal
		H502	Improper placement of cars in train between terminals
		H503	Buffing or slack action excessive, train handling
		H504	Buffing or slack action excessive, train make-up
		H505	Lateral drawbar force on curve excessive, train handling

(*continued*)

Continued.

Cause Group	Description	FRA Cause Codes	Code Description
		H506	Lateral drawbar force on curve excessive, train make-up
		H507	Lateral drawbar force on curve excessive, car geometry (short car/long car combination)
		H508	Improper train make-up
		H509	Improper train inspection
		H522	Throttle (power), improper use (H014)
		H523	Throttle (power), too rapid adjustment (H015)
		H524	Excessive horsepower (H016)
		H599	Other causes relating to train handling or makeup (detailed description in narrative)
10H	Train speed	H601	Coupling speed excessive
		H602	Switching movement, excessive speed
		H603	Train on main track inside yard limits, excessive speed
		H604	Train outside yard limits, in block signal or interlocking territory, excessive speed
		H605	Failure to comply with restricted speed in connection with the restrictive indication of a block or interlocking signal.
		H606	Train outside yard limits in non-block territory, excessive speed
		H607	Failure to comply with restricted speed or its equivalent not in connection with a block or interlocking signal.
		H699	Speed, other (detailed description in narrative)
11H	Use of switches	H701	Spring Switch not cleared before reversing
		H702	Switch improperly lined
		H703	Switch not latched or locked
		H704	Switch previously run through
		H705	Moveable point switch frog improperly lined
		H706	Switch improperly lined, radio controlled
		H707	Radio controlled switch not locked effectively
		H799	Use of switches, other (detailed description in narrative)