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Madigan, R orcid.org/0000-0002-9737-8012, Golightly, D and Madders, R (2016) Application of Human Factors Analysis and Classification System (HFACS) to UK rail safety-of-the-line incidents. Accident Analysis and Prevention, 97. pp. 122-131. ISSN 0001-4575

https://doi.org/10.1016/j.aap.2016.08.023

Application of Human Factors Analysis and Classification System (HFACS) to UK rail safety of the line incidents

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Abstract

Minor safety incidents on the railways cause disruption, and may be indicators of more serious safety risks. The following paper aimed to gain an understanding of the relationship between active and latent factors, and particular causal paths for these types of incidents by using the Human Factors Analysis and Classification System (HFACS) to examine rail industry incident reports investigating such events. 78 reports across 5 types of incident were reviewed by two authors and cross-referenced for interrater reliability using the index of concordance. The results indicate that the reports were strongly focused on active failures, particularly those associated with work-related distraction and environmental factors. Few latent factors were presented in the reports. Different causal pathways emerged for memory failures for events such a failure to call at stations, and attentional failures which were more often associated with signals passed at danger. The study highlights a need for the rail industry to look more closely at latent factors at the supervisory and organisational levels when investigating minor safety of the line incidents. The results also strongly suggest the importance of a new factor – operational environment – that captures unexpected and non-routine operating conditions which have a risk of distracting the driver. Finally, the study is further demonstration of the utility of HFACS to the rail industry, and of the usefulness of the index of concordance measure of interrater reliability.

Keywords: HFACS, System Analysis, Rail, Accident Investigation,

1. Introduction

In the period from 2001 to 2014 there were 803 fatalities (excluding suicides) and 5794 major injuries on the UK rail network (Department for Transport, 2014). Although, the rail industry has an excellent safety record in comparison to other forms of transport (Department for Transport, 2014), the Office of Road & Rail has put forward a safety vision for zero workforce and industry-caused passenger fatalities, and an ever-decreasing overall safety risk (ORR, 2014). If we are to move towards a realisation of this vision, it is important to gain a detailed understanding of all of the factors which contribute to accidents and incidents in order to put appropriate controls in place.

Recent analyses have argued that human error was a causal factor in the occurrence of many serious and fatal rail accidents, both in the UK (French & Cope, 2012) and across Europe (Kyriakidis, Pak, & Majumdar, 2015). On top of these more serious incidents, there are many hundreds of minor incidents within the UK rail industry, many of which are also attributed to driver error. These include speed exceedances and signals passed at danger (SPADs) that did not lead to any accidents, along with trains that stop short or overshoot their platform, or fail to call altogether. These types of incident are extremely costly for organisations due to fines and infrastructure costs, along with disruption leading to negative public opinion. The most recent National Rail Passenger Survey showed that punctuality/reliability was the factor with the biggest impact on overall customer satisfaction, and how a train company dealt with delays had the biggest impact on overall dissatisfaction (NRPS, 2016). Additional costs arise as these incidents often require a driver to be removed from duty for an investigation and possibly retraining. Furthermore, the concern is that a minor event is an indicator of the risk of a more serious incident in the future (Reason, 1997; Hollnagel, 2014).

The opportunity for minor safety of the line events to occur is huge. For example, the number of approaches to red signals annually in the UK may be in the region of 7.5m (Gibson, Mills, Basacik, & Harrison, 2015). Few of these result in actual SPADs, and error probability for SPADs or events such as wrong side door openings (Basacik and Gibson, 2015) suggests error rates may be approaching the limits of performance. Therefore, careful analysis of events is required if new levels of safety are to be achieved, and there is a need for rail companies to understand what causes these events, so that potential courses of remedial action can be identified including training, technical or procedural change.

Contemporary human factors approaches to system safety have been used to provide greater insights into the causes of accidents in many safety-critical domains (Lenné, Salmon, Liu, & Trotter, 2012). Much of this work has been based on Reason's (1990) Generic Error Modelling System (GEMS), which defines two broad categories of error: active and latent failures. Active errors are associated with the front-line operators of a system, and their effects usually become evident almost immediately. Latent (or hidden) errors refer to the errors of designers or managers, and their adverse consequences may lie dormant within the system for a long time, only becoming evident when they combine with other factors to breach the system's defences. Reason (1990) noted that latent errors may pose the greatest risk to system safety because unless they are identified they remain in a system despite attempts to resolve an issue through rectifying the immediate performance issue (e.g. through non-systemic equipment fixes or training). Thus, one of the most important aspects of Reason's model is the argument that human error is a consequence, not a cause, of latent failures; and that "it is only by understanding the context that provoked an error can we hope to limit its reoccurrence" (Reason, 1997, p.126). As a result of the issues outlined above, there is currently a strong emphasis on tackling human factors within the rail industry (e.g. Atkins, 2003; FRA, 2007; Lawton & Ward, 2005; RSSB, 2009), and as part of this process it is vital that both the active and latent failures which contribute to railway incidents are understood.

1.1 Human Factors Analysis & Classification System

A number of studies have used different frameworks to look at the factors contributing to specific types of railway incident i.e. SPADs (e.g. Edkins & Pollock, 1997; Lawton & Ward, 2005; Rjabovs and Palacin, 2016), and specific types of error e.g. communication errors (Murphy, 2001). Read, Lenné, and Moss (2012) used the Contributing Factors Framework to investigate the associations between factors involved in Australian rail accidents and found that task demand factors (e.g. high workload, distraction) were significantly associated with skill-based errors; knowledge and training deficiencies significantly associated with mistakes; and violations significantly linked to social environmental factors. Currently, the UK rail sector is working towards a database of trends and themes in human performance and incident underlying causes for a sample of high risk Great British (GB) rail incidents.

This database uses the Incident Factor Classification System (IFCS) of 10 factors that may shape human performance in rail incidents (Gibson et al., 2015). However, one of the most common frameworks for analysis, based on Reason's (1990) model, is the Human Factors Analysis and Classification System (HFACS; Wiegmann & Shappell, 2003). HFACS describes four levels of failure based on Reason's Swiss Cheese Model (Reason, Hollnagel, & Paries, 2006): unsafe acts, preconditions for unsafe acts, unsafe supervision, and organisational influences (see Figure 1). Critically, this model specifies that in order for an incident to occur, failures in defences at all levels of the system must line up, thus highlighting the importance of identifying the factors which contribute at each level. The unsafe acts level focuses on identifying any errors or violations made by front line workers that led to an accident or incident occurring. Within the error category there are three subcategories of skill-based error, decision error, and perceptual error. Decision errors can be further broken down into rule-based and choice-based decisions, and skill-based errors can be broken down to attentional and memory failures. Within the violations category there are two subcategories of routine and exceptional violations.

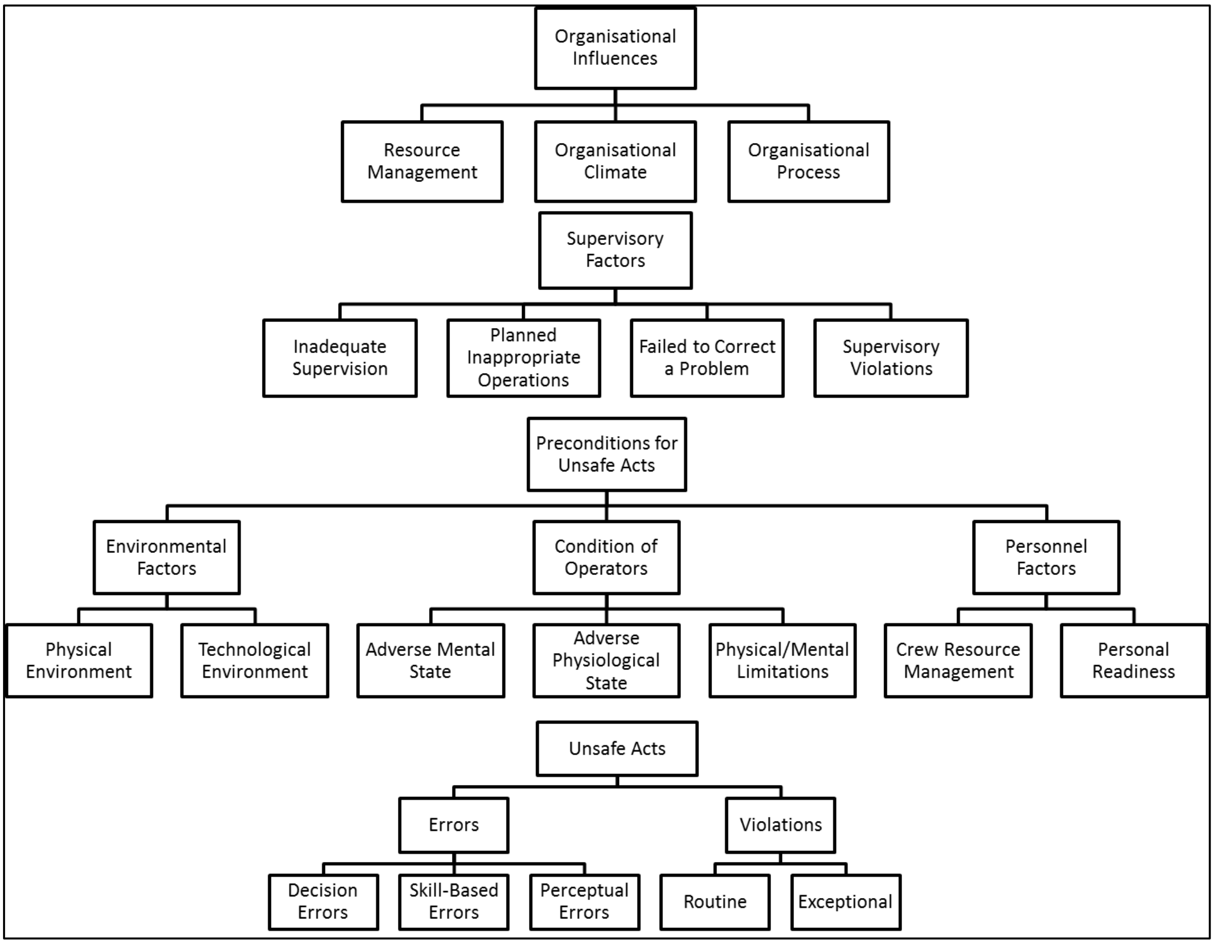

Figure 1: The HFACS framework (Wiegmann & Shappell, 2003)

The second level of the HFACS framework is "preconditions for unsafe acts". These refer to the immediate underlying conditions that contribute to the occurrence of unsafe acts. This level comprises three categories: condition of operators, environmental factors, and personnel factors. Each of these categories has a number of subcategories as shown in Figure 1. The third level within HFACS is "unsafe supervision". This considers the situations where supervision was either lacking or unsuitable and has four categories of inadequate supervision, planned inappropriate operations, failure to correct a problem, and supervisory violations. The fourth and final level within many applications of HFACS models is organisational influences. This level looks at the failures occurring at the higher managerial levels of the organisation which contributed to an accident, focusing on the subcategories of resource management, organisational climate and organisational process.

Typically, HFACS is used as a retrospective tool for analysing accident and incident reports, and the different failures which contributed to an accident at all four levels are identified. Although originally designed to classify aviation accidents (Wiegmann & Shappell, 2001; 2003), HFACS has now been applied successfully in numerous safety critical industries including maritime (Celik & Cebi, 2009), mining (Lenné et al., 2012; Patterson & Shappell, 2010), medicine (ElBardissi, Wiegmann, Dearani, Daly, & Sundt, 2007) and rail (Baysari, McIntosh, & Wilson, 2008; Reinach & Viale, 2006), with researchers making various adaptations to the model to make it more suitable in different contexts. One criticism of HFACS has been its failure to consider contributory factors outside of the organisation involved, such as government policy, or local authority oversights (Salmon, Cornelissen, & Trotter, 2012). For that reason, some versions have gone beyond the organisational level to include 'external influences' which take account of issues such as legislation gaps, administration oversights, and design flaws (e.g. Chen, Wall, Davies, Yang, Wang, & Chou, 2013; Reinach & Viale, 2006).

Overall, the results of previous studies provide strong support for the use of HFACS as a tool for understanding incidents in the rail industry. However, only two published studies have applied HFACS in this context. Reinach and Viale (2006) used an adapted version called HFACS-RR to examine six railyard switching incidents in the US and identified 36 probable contributing factors for these incidents. Baysari et al. (2008) investigated 40 publicly available railway incident and accident reports in Australia and identified 330 contributing factors. More than half of the incidents identified resulted from an equipment failure. In the remaining cases, skill-based errors (HFACS Level 1), adverse mental state (Level 2), and equipment/facility resources (Level 4) emerged as the most common contributory factors.

Both Baysari et al. (2008) and Read et al.'s (2012) studies focus on external inquiries into major accidents by relevant transport bodies (e.g. Australian Safety Transport Bureau), while the Reinach and Viale (2006) study focuses solely on switching yard incidents. However, to date, no published study has focused on the hundreds of minor incidents linked to train drivers every year, such as signals passed at danger or failure to call at stations. As previously noted, these incidents can have extremely damaging consequences in terms of both infrastructure costs and negative public opinion. In addition, the causal pattern of these incidents is often similar to that of more serious incidents (Wright & Van der Schaaf, 2004). Although human error is often identified as a causal factor within these incidents, there has been little effort to gain a systematic understanding of the latent factors which contribute, and whether or not these differ depending on the type of incident which occurs. Studies across other industries e.g. outdoor activity incidents, have shown the potential to identify multiple contributory factors, both active and latent, from similar minor events, thus emphasizing the potential explanatory power of these incidents (e.g. Salmon, Goode, Lenné, Finch & Cassell, 2014; Salmon, Goode, Taylor, Lenné, Dallat, & Finch, in press). Therefore, gaining an understanding of minor safety-of-the-line incidents is important to provide rail companies with the tools to prevent similar and more serious incidents occurring in the future.

HFACS was chosen as the tool for the purposes of this study into the analysis of safety of the line incidents. This was due to the number of studies generally that have used HFACS, its wide availability and research base that makes its application clear and results transferrable, and its prior use within the rail sector.

1.2 Reliability and Report Quality

Although a number of strengths of the HFACS model have been identified, including its detailed classification of the organisational context (Baysari, Caponecchia, McIntosh, & Wilson, 2009), and its ability to provide safety professionals with a theoretically based tool for accident investigations (Wiegmann & Shappell, 2001); a number of papers have identified some concerns with the reliability of the model. Beaubien and Baker (2002) and Olsen (2011) criticized the validation evidence supporting the usefulness of the HFACS system, as it was all collected and analysed by the developers of the framework. However, other authors have now successfully used and proven the system in a variety of industries (Baysari et al., 2008; Lenné et al., 2012, Li & Harris, 2006; Reinach & Viale, 2006).

Another concern raised by Olsen (2011) is the use of incorrect statistics for the reporting of HFACS reliability levels. It is argued that Cohen's Kappa is an inadequate measure of reliability, as it is based on the argument that coders who are coding randomly will agree by chance a certain percentage of the time, and that this should be deducted from the agreement that is not achieved by chance. However in incident classification systems, coders are not randomly assigning codes but are actually trying to identify the same causal factors, and therefore agreements are not chance events (Olsen, 2011). For this reason, Olsen argues that the correct method for calculating inter-coder consensus is to calculate the index of concordance which takes into account both the total number of agreements and the total number of disagreements of raters' codes. An additional issue is that a number of authors have highlighted difficulties with the clarity of error codes within HFACS, particularly in derivatives of HFACS such as HFACS-ADF (Olsen & Shorrock, 2010) and HFACS-DoD (O'Connor & Walker, 2011). Baysari et al. (2008) reported a large difference in the number of errors identified by the three raters in their study, with percentage agreement ranging from 40-75%, and as a result they only reported the ratings of the first author in their paper. Thus, in this paper the index of concordance is used to evaluate the reliability of HFACS as a tool for the categorisation of UK rail incident reports by two Human Factors experts.

As outlined in Section 1.1, one of the main benefits of HFACS is in identifying latent factors that can contribute to accident causation. However, this is dependent on the quality of investigation and subsequent reporting of accidents. While significant rail accidents are subject to extensive reporting, it was unclear whether it would be possible to identify latent features of accidents, at both organisational levels and beyond, in the type of reports generated for minor safety of the line incidents, or whether these investigations focus more on surface-level features relating to unsafe acts and their preconditions. Rjabovs and Palacin (2015) found that there was a tendancy not to attribute systemic, physical or design factors to the causation of SPADs in a metro environment, and it is likely that a similar issue might arise when looking at other types of rail transport. Therefore, this paper also aimed to measure the quality and depth of the information contained in minor incident investigation reports.

1.3 Purpose of current study

This paper presents an application of HFACS as an analysis tool to aid with the understanding of the factors that contribute to minor operational incidents in the UK rail. It aims to investigate the breakdown of causal factors for these incidents, and in doing so evaluate whether the patterns found in Baysari et al. (2008) are replicated in the UK rail industry. The study focuses on incidents which have previously been defined as being caused by Human Error and addresses five key questions:

1. Can HFACS help us to identify the precursors of minor operational incidents?
2. Are there any differences in the causation paths of different types of incident e.g. SPAD vs station overrun?
3. What is the breakdown of active and latent factors that contribute to this type of incident and does this vary across incident types?
4. What is the quality of reporting of minor incidents in the rail industry? Is report content sufficient to support the identification of latent factors of incident causation, including organisational and regulatory?
5. How reliably can two independent Human Factors experts' code investigation reports using HFACS?

2. Method

2.1 Data Sources

Incident investigation reports were collected from seven of the UK's Train Operating Companies (TOCs). These incidents had all been previously classified by the TOCs as involving some form of human error. A total of 74 investigation reports were included, all relating to minor safety-of-the-line incidents occurring between January 2012 and May 2014. None of the incidents included in this study had been investigated by the Rail Accident Investigation Branch (RAIB), who investigate any accidents causing death, serious injuries, or extensive damage, or incidents which had the potential to lead to these serious effects. 5 main types of incident were included:

- Signals passed at danger (SPADs, N=21)
- Fail to call incidents, where a train failed to stop at a booked station (N=15)
- Station Overruns, where a train overran the booked platform at a station (N=19)
- Stop Short incidents, where a train came to a stop at a station before all carriages were at the platform (N=10)
- TPWS Activations, where, for example, a train driver failed to acknowledge a speed restriction warning (N=9)

2.2 Data Coding & Analysis

Investigation reports were independently coded by two Human Factors researchers. Prior to commencing the HFACS coding, information about each incident was extracted, including a description of the incident type, the location, and date. Each coder also rated the quality of the investigation report as low, medium, or high depending on the amount of information included in the report and the evidence provided for any conclusions drawn. Each report was then read in its entirety and each contributing/safety factor identified in the incident narrative was mapped to a unique HFACS category following the procedure identified by Baysari et al. (2008) of using the definitions and tables provided in Wiegmann and Shappell (2003) and the flow-charts included in Viale and Reinach (2006). For example, in one report the investigator described a sign that was obscured by undergrowth. This was extracted as a contributory factor and coded under the Physical Environment HFACS code. The presence or the absence of each HFACS category was assessed in each accident report narrative. More than one category or sub-category could be identified at each level. However, to avoid over-representation from any single accident, each HFACS sub-category was counted a maximum of only once per accident (Li & Harris, 2006). To begin the analysis process, each analyst first independently coded 10 incidents. This coding was then discussed in detail to ensure a joint understanding prior to independently analysing the rest of the papers. Where disagreements in the final codes arose, these were discussed until a consensus was reached.

Once the initial analysis had begun, it became apparent that a total of 18 of the contributory factors identified as belonging in the Environmental Factors category did not fit into either the physical or technological environment, but rather could be described as arising from the operational environment. These factors related to unscheduled operational occurrences that were a departure from the operational norm, and examples included situations where there was a highly unusual signalling pattern, or a train was re-routed. Therefore, an additional subcategory of Operational Environment was included for this analysis (see Table 1 for examples).

Table 1: Examples of report elements that were included in the Operational Environment category

1. A signalling fault led to modified working on the train route, requiring the use of hand signals to communicate with the signaller.
2. A possession on a line led to the driver being directed onto a route that they were not familiar with.
3. An unusual signalling sequence led to a driver being directed to a different platform than usual.

Initial analysis of the incident characteristics and HFACS data were performed using frequency counts. Further analysis to evaluate the associations between HFACS levels and incident types were conducted using Chi Square analysis and adjusted standardized residuals (ASR). The ASR provides a measure of the strength of the difference between observed and expected values in situations when a cross-tabulation result is associated with more than one degree of freedom i.e. larger than a 2X2 contingency table. An ASR with a value of 2 or greater indicates a lack of fit of the null hypothesis in a given cell (Sharpe, 2015).

In order to evaluate interrater reliability the index of concordance was used to provide a percentage agreement, following the procedure set out in Olsen and Shorrock (2010). The proportion of agreeing pairs of codes out of all the possible pairs of codes is calculated as follows: (agreements) / (agreements + disagreements). Interrater consensus can then be reported as a figure between 0 and 1 or as a percentage. This method takes into account the cases where coders disagreed, along with providing a method for including situations where there was a difference in the number of codes assigned between coders. A criterion of 70% agreement between coders was adopted as a reasonable minimum, in accordance with Wallace and Ross (2006) and Olsen and Shorrock (2010).

3. Results

3.1 Inter-Rater Reliability & Quality of Reports

Prior to resolution of any discrepancies in coding between the two raters, the Index of Concordance was used to evaluate inter-rater reliability (Table 2). The results show that inter-coder consistency was well above the 70% threshold at both the descriptor and category levels for all variables other than Adverse Mental state where the consistency was 68.92%. This discrepancy will be discussed further in Section 3.2.

It should be noted that the quality of the incident reports for each of these incident types varied quite substantially across incident types (see Figure 2), leading to the identification of fewer contributory factors where the quality was low. Reports categorised as being of low quality generally contained only tick box information with no supporting data, medium quality reports contained a good description of the incident with support data and information, but generally did not have a systematic approach to evaluating human factors. High quality reports contained a good level of support data and an attempt to systematically evaluate contributory human factors. In general Category A SPADs, Station Overrun and Fail to Call reports tended to be of a high or medium quality, whereas TPWS Activation and Stop Short reports tended to have less detail.

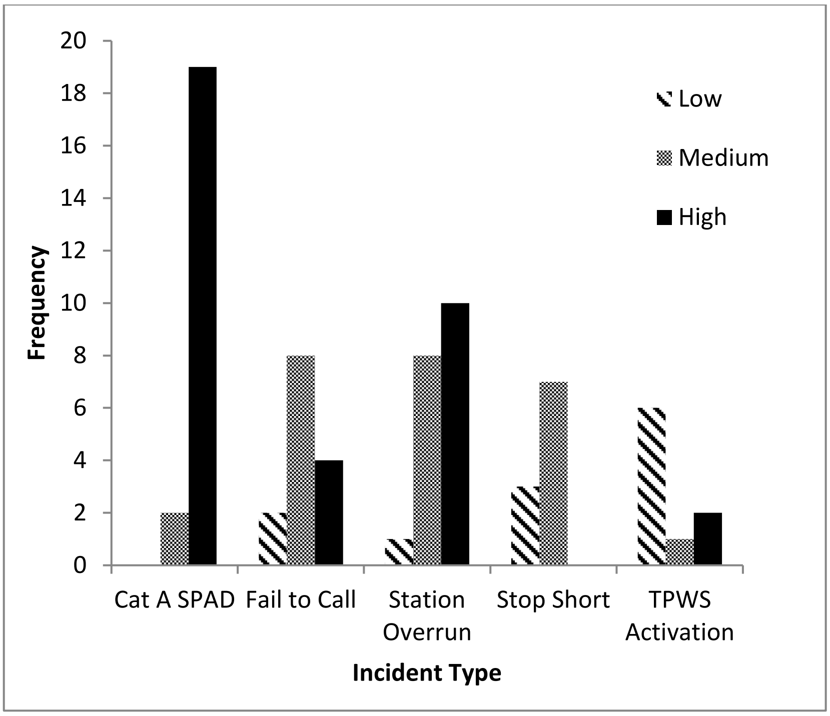

Figure 2: Quality of investigation reports across incident types

Table 2: Inter-rater reliability (prior to resolution) and Frequency counts (post-resolution for each HFACS category[a]

Error Categories	Error Subcategories	% Agreement	Frequency[a]	% Reports
Operator Acts				
Skill Based	Attention	77.03	42	56.76
	Memory	81.08	31	41.89
Decision Error	Poor Choice	86.49	9	12.16
Perceptual Error		98.65	1	1.35
Violation	Routine Violation	98.65	2	2.70
	Exceptional Violation	98.65	1	1.35
	Acts of Sabotage	100	0	0
Preconditions to Unsafe Acts				
Environmental Factor	Physical Environment	97.30	6	8.11
	Technological Environment	83.79	13	17.57
	Operational Environment	72.97	18	24.32
Personnel Factor	Crew Resource Management	97.30	6	8.11
	Personal Readiness	91.89	7	9.46
Condition of Operator	Adverse Mental State	68.92	63	85.14
	Adverse Physiological State	90.54	12	16.22
	Physical/Mental Limitations	90.54	10	13.51
Supervisory Factors				
Inadequate Supervision		97.30	2	2.70
Planned Inappropriate Operations		100.00	0	0
Failure to Correct Known Problem		91.89	6	8.11
Supervisory Violations		100.00	2	0
Organisational Factors				
Resource Management		94.59	2	2.70
Organisational Climate		100.00	2	2.70
Organisational Process		93.24	4	5.41

Organisational Violations	100.00	0	0

[a] More than one category could be identified at each of the HFACS levels

3.2 Can HFACS help us to identify the precursors of minor operational incidents which have the potential to lead to more serious events?

It was possible to code all of the contributing factors using our edited version of HFACS including Operational Environment. The presence of HFACS codes in the 74 incidents is presented in Table 2. A total of 228 contributory factors were identified, with an average of 4.05 factors (SD=1.07) per incident.

Unsafe acts were identified in all of the reports investigated. The most frequent Level 1 unsafe acts were skill-based errors (87.84%). Of these skill-based errors, the majority involved some type of attentional failure (56.76% incidents) such as failing to notice the status of a signal or getting distracted. 41.89% of the skill based errors involved an issue with memory e.g. forgetting a station stop. A decision error was identified in 12.16% of reports, all of which involved a poor choice e.g. not making any attempt to stop at a station because of weather conditions. Finally, only 4.05% of unsafe acts involved a violation, 2 of which were routine violations e.g. drivers always stopping at a certain incorrect part of a platform to avoid passengers having to walk out in the rain, and one of which was an exceptional violation involving a failure to clarify instructions.

One or more of the Level 2 preconditions for unsafe acts were evident in almost all incidents investigated, with one exception (a TPWS Activation). Adverse mental state was identified as a precondition in 85.16% incidents. Operational environment (24.32%), technological environment (17.57%), adverse physiological state (16.22%), and physical/mental limitations (13.51%) were all also identified as Level 2 contributory factors in 10 or more incidents. Unlike the pattern for other industries, crew resource management was not a pre-dominant causal factor, and only emerged in 8.11% incidents.

As adverse mental state was deemed to be quite a broad category, and was also the category where the inter-rater reliability was lowest, it was decided to explore the themes which emerged within this category further (see Figure 3). Five main themes emerged. The most commonly identified adverse mental state was work-related distraction, which occurred when drivers claimed to have been distracted by thinking about something which had occurred during work hours - including problems in the environment, time pressures, or previous driving patterns. Non-work related distraction occurred when the driver was distracted by thinking about non-work issues e.g. relationship problems. Lapses in concentration occurred when the driver claimed to have stopped concentrating on the task for no particular reason. A preconception refers to situations in which the driver had made an incorrect assumption about what would happen next. Finally, poor attitude – not following procedures correctly to avoid having a fault on record - was identified as contributory factor in one incident. As Figure 3 shows, drivers were considerably more likely to be distracted by work-related issues than non-work related ones. Of the 31 cases in which work-related distraction was identified, environmental issues were also identified in 18 of these reports (58.06%), suggesting a strong link between any unexpected changes to the driving environment and the propensity for the driver to lose focus. The weaker inter-rater reliability of adverse mental state can be accounted for by the fact that one rater was more inclined to only identify the environmental code in these cases, where the other rater selected both categories.

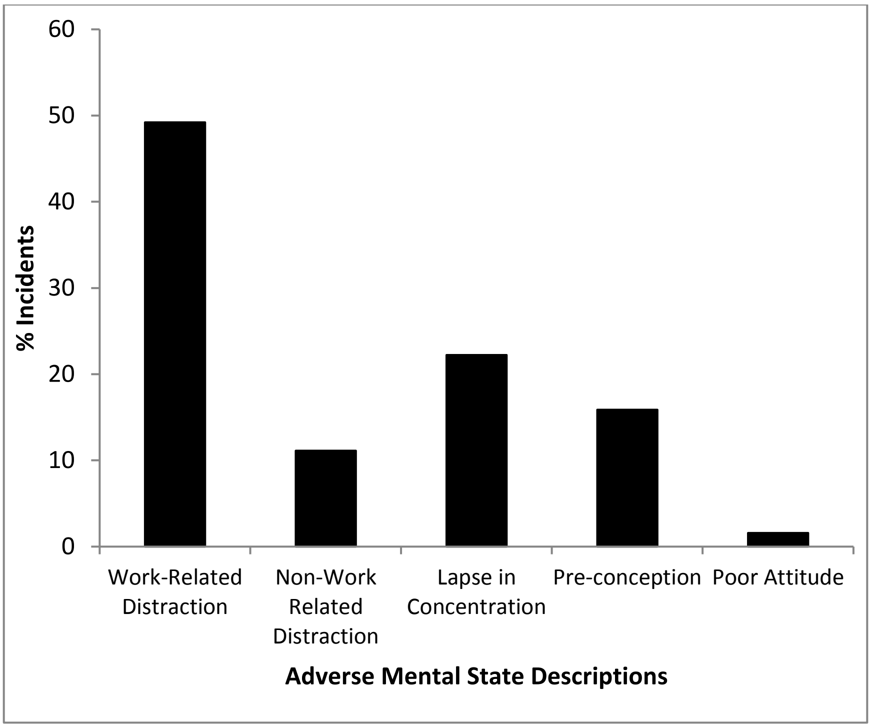

Figure 3: Breakdown of themes emerging in Adverse Mental State category

Finally, Level 3 supervisory factors and Level 4 organisational factors were both only identified in 10.81% investigations. Failure to correct a problem (8.11%) was the most common supervisory factor, usually resulting from a failure to implement development changes identified in previous incidents. The most common Organisational Factor was organisational process (5.41%), usually arising from poor practice and procedures.

3.3 Are there any differences in the causation paths of different types of incident?

Table 3: Frequency counts across Incident Types for each HFACS category

Error Categories	Error Subcategories	% Cat A SPAD	% Fail to Call	% Station Overrun	% Stop Short	% TPWS Activation
Operator Acts						
Skill Based	Attention	95.24	26.67	42.11	20.00	88.89
	Memory	9.52	86.67	63.16	30.00	0
Decision Error	Poor Choice	4.76	13.33	5.26	40.00	11.11
Perceptual Error		4.76	0	0	0	0
Violation	Routine Violation	4.76	0	0	10.00	0
	Exceptional Violation	4.76	0	0	0	0
Preconditions to Unsafe Acts						
Environmental Factor	Physical Environment	4.76	13.33	5.26	0	22.22
	Technological Environment	23.98	13.33	15.79	30.00	0
	Operational Environment	47.61	33.33	5.26	20.00	0
Personnel Factor	Crew Resource Management	14.29	13.33	5.26	0	0
	Personal Readiness	14.29	0	15.79	0	11.11
Condition of Operator	Adverse Mental State	85.71	93.33	94.74	70.00	66.67
	Adverse Physiological State	9.52	6.67	26.31	10.00	33.33
	Physical/Mental Limitations	19.05	6.67	5.26	30.00	11.11
Supervisory Factors						
Inadequate Supervision		4.76	0	0	0	11.11
Planned Inappropriate Operations		0	0	0	0	0
Failure to Correct Known Problem		19.05	0	0	20.00	0
Supervisory Violations		0	0	0	0	0
Organisational Factors						
Resource Management		9.52	0	0	0	0
Organisational Climate		0	0	10.52	0	0
Organisational Process		4.76	0	5.26	10.00	11.11
Organisational Violations		0	0	0	0	0

Table 3 shows that there was a difference in the pattern of contributory factors for each of the five incident types. In order to determine where significant differences between the groups emerged a series of chi-square analyses were conducted. Three of these relationships reached significance and these are explored further in Table 4 and Figure 4.

Table 4: Significant associations between HFACS categories and incident type

Incident Type		Attention Error	Memory Error	Operational Environment
		χ^2=28.26 (df=4) p<0.001	χ^2=31.05, df=4, p<0.001	χ^2=13.79 (df=4), p<0.01
Category A SPAD	Observed	20	2	10
	Expected	12.1	8.3	5.2
	ASR [a]	**4.1**	**-3.4**	**2.9**
Fail to Call	Observed	4	12	5
	Expected	8.1	5.6	3.5
	ASR [a]	**-2.4**	**3.9**	**1.1**
Station Overrun	Observed	8	12	1
	Expected	10.9	7.5	4.7
	ASR [a]	**-1.6**	**2.4**	**-2.3**
Stop Short	Observed	2	3	2
	Expected	5.8	4.0	2.5
	ASR [a]	**-2.6**	**-0.7**	**-0.4**
TPWS Activation	Observed	8	0	0
	Expected	5.2	3.6	2.2
	ASR [a]	**2.0**	**-2.6**	**-1.8**

[a]ASR = adjusted standardized residual

At level 1 of the HFACS framework, attention and memory errors were both significantly associated with incident type. For Category A SPADs (ASR=4.1) and TPWS Activations (ASR=2.0), attentional errors were over-represented. However for Fail to Call (ASR=3.9) and Station Overrun incidents (ASR=2.4), memory errors were over-represented. This suggests that attention and memory errors lead to different outcomes, and thus different initiatives will have to be taken to address each incident type.

At level 2 of the HFACS framework, operational environment was the only variable to be significantly associated with incident type. This category was significantly over-represented in Category A SPADs (ASR=2.9). This suggests that Category A SPADs are more likely to occur after some change in the operational environment.

There were no significant associations between Level 3 and Level 4 factors and incident type.

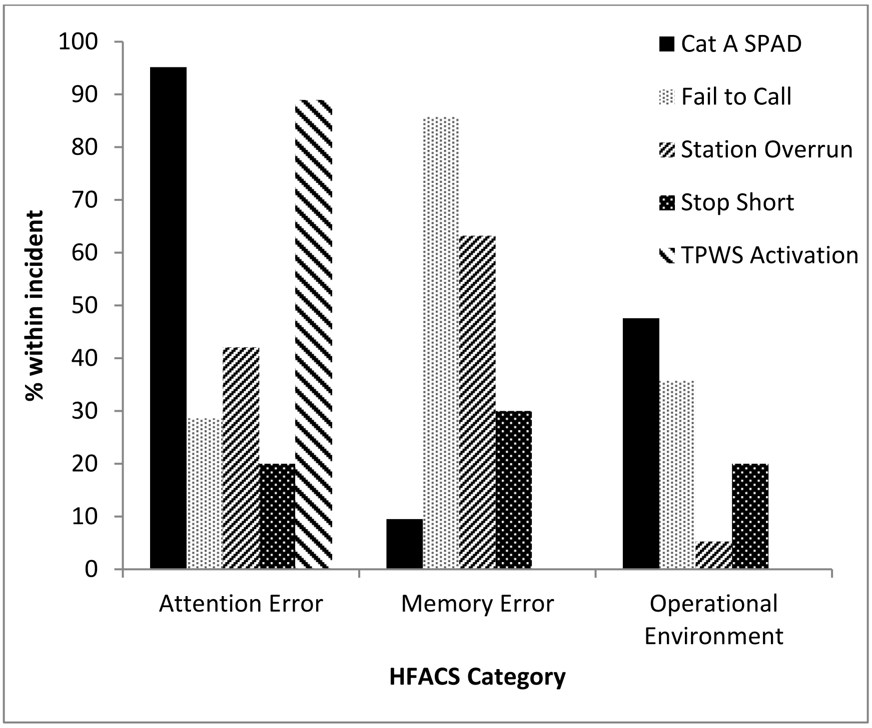

Figure 4. Percentages related to significant associations between HFACS categories and incident type

4. Discussion

The aim of the study was to examine the active and latent causal factors of minor safety of the line incidents, using the HFACS methodology, and one purpose of the research was to understand the utility of HFACS for the task at hand. A number of specific research questions were outlined, which are addressed below.

4.1 Can HFACS help us to identify the precursors of minor operational incidents?

74 minor incident investigations were analysed using HFACS to identify the factors which contribute to the occurrence of these types of events. In total, 228 contributory factors were identified and classified from the reports. The findings provide some initial evidence that the pattern of contributory factors for minor incidents is similar to that identified in more serious incidents (e.g. Baysari et al., 2008, Read et al., 2012), at least in terms of the Level 1 and Level 2 contributory factors.

Consistent with previous research in both rail (Baysari et al., 2008, Reinach & Viale, 2006) and other sectors (e.g. ElBardissi et al., 2007; Lenné et al., 2012; Li & Harris), skill-based errors emerged as the most common contributory factor at Level 1, with more attentional than memory errors arising. However, unlike previous studies, very few violations occurred, with only 2 routine violations and 1 exceptional violation identified. This suggests that minor incidents are more likely to be caused by an error or mistake than by a deliberate breach of rules. Adverse mental state was the most common Level 2 category, followed by operational environment, technological environment, and adverse physiological state. Baysari et al. (2008) also identified adverse mental state as the most common precondition and, indeed, adverse mental state and environmental factors consistently emerge as strong contributory factors across a range of sectors, although the order of importance may vary (e.g. Li & Harris, 2006; Shappell et al., 2007, Lenné et al., 2012). However, in both aviation and medicine, Crew Resource Management (CRM) also emerges as a common contributory factor (e.g. ElBardissi et al., 2007; Li et al., 2008; Shappell et al., 2007), which was not identified in this study. This is most likely a result of the more solitary nature of the train driver role compared to that of an airline pilot or medical surgeon.

Adverse mental state was the most commonly identified category across all of the incidents investigated. As it is quite a broad category, a deeper analysis was deemed necessary and it was, therefore, further broken down into 5 main themes. This analysis showed that distraction due to work-related issues was the single biggest contributory factor. Some caution should be taken in interpreting this result, as this finding arises from self-report aspects of the report and it is possible that drivers were unable to accurately remember, or chose to misrepresent what they had been thinking about prior to an incident. However, the fact that environmental factors, in particular operational environment, were also identified as a causal factor in over half of the reports suggests that work-related distraction is a real issue in incident causation.

Linked to this, one of the key findings of this study was the importance of the operational environment. The items in this category were environmental factors that were not overtly physical (e.g. weather) or technical (e.g. faulty equipment), but altered driving conditions based on operational circumstances - such as other late running trains in the area causing the incident-involved train to run on cautionary signals, or a temporary change to the station calling pattern. While these situations are well within the driver's required competency, they were a deviation from planned or routine action. Cognitively, changes to the operational environment create a situation where the driver moves from a skill-based, proactive feedforward mode of control (Rasmussen, 1983; Hollnagel and Woods, 2005), to a more rule-based, and cognitively effortful (and error prone), reactive mode of control. To amplify the risk, this change of mode takes place just at that point where the driver is likely to be late or trying to preserve tight performance allowances in the timetable. Thus, they have the paradox of needing to work faster at a time when the environment demands, cognitively, that they take longer. Baysari et al.'s (2008) analysis of Australian railway incidents identified a similar issue, and they advocated the creation of an extra category of Task Factors at the preconditions for unsafe acts level – many of the factors they identified could also be considered as part of the Operational Environment.

The problems identified in these analyses are not unique to the rail industry, and indeed similar incidents can easily be identified in other industries. For example, in aviation a flight path may have to be changed at short notice, or in medicine a routine operation may become more complex due to unforeseeable complications. Thus, the addition of the category of Operational Environment to HFACS would provide an additional opportunity to understand the impact of alterations to planned routine on the propensity for incidents to occur.

On the whole, these results highlight the potential power of minor incidents to provide valuable insights into common causal factors, at least at the unsafe acts and preconditions levels, and to reinforce some of the similarities (importance of skill-based error, and adverse mental state) and differences (few violations, increased emphasis on context including operational environment, reduced emphasis on CRM) between train driving and other domains. This highlights that a simple transfer of initiatives, such as training programmes, from other domains (e.g. aviation) into train driving is not always appropriate, and indicates where adaption (e.g. an emphasis on attentional over CRM-type support) is required.

4.2 Are there any differences in the causation paths of different types of incident e.g. SPAD vs station overrun.

Although Li et al. (2013) had compared contributory factors across aircraft type, pilot rank, and flight phase; this is the first study to investigate the causes of specific incident types within a single study. Our results indicate that different types of railway incidents appear to have different causal pathways, at least in terms of the factors immediately preceding the incident. Of particular interest is the fact that any change in the Operational Environment e.g. a change in diagrammed stops, an unusual sequence of restrictive aspects; was found to be significantly linked to the occurrence of a SPAD. Although the SPAD investigations included in this study were relatively minor events with no major repercussions, similar circumstances have been identified in more serious incidents. As far back as 1997, a study of over 100 Australian railway incidents identified that the expectation of a green signal was one of the most common skill-based errors contributing to drivers passing a red signal (Edkins & Pollock, 1997), and recent major incident investigations have re-iterated this finding (e.g. RAIB, 2014). Similarly, Rjabovs and Palacin (2016) found that unfamiliar tasks and locations may play a role in safety of the line incidents in a metro environment. In our paper it may not be that the location was unfamiliar as such, but that the conditions in which the location was experienced may be unfamiliar or, at least, a divergence from the norm. This highlights the importance of providing additional support to drivers in situations which are more cognitively effortful, suggesting that interventions which specifically address the methods of communicating and alerting drivers to areas of importance during changes to the operational environment could be successful in reducing the occurrence of SPADs.

In addition, it appears that Category A SPADs and TPWS activations (which have the capacity to escalate to become a SPAD) were both more likely to be caused by an attentional failure, while Fail to Call and Station Overrun incidents were more likely to be caused by a memory failure. The fact that different causal paths are emerging suggests that companies need to take different approaches to how they address these incidents and, in some cases, technical solutions will be required, similar to the ones reported by Basacik and Gibson (2015) for wrong side door openings. Read, Lenné, and Moss (2012) found that task demand factors (e.g. high workload, distraction) were significantly associated with skill-based errors in Australian rail accidents. We have further broken this down to show how the impacts of different types of skill-based error (i.e. memory versus attention) can vary, suggesting that safety interventions need to be carefully targeted to maximise their benefits. For example, technical systems to more clearly alert drivers of diagrammed station stops may be beneficial in preventing Fail to Call and Station Overrun incidents, whereas improving communication of the likely risk areas during non-routine running may reduce the risk of a SPAD.

4.3 What is the breakdown of active and latent factors that contribute to this type of incident, and does this vary across incident types?

Active factors dominated the causes identified from the incident analysis. Due to the small number of organisational and supervisory factors identified, it was impossible to identify any causal paths originating at these levels. In addition, some of the reports around TPWS activations, Stop Short, and Fail to Call incidents were of a low quality containing minimal information, which was usually related solely to driver error – no Supervisory or Organisational Factors were identified in any of the Fail to Call reports. In these reports it was often quite difficult to build a picture of the events which led up to the incident. Although, these incidents are often seen as quite minor, and companies have to make trade-offs in terms of the costs associated with detailed investigations; being able to address the causes of these minor incidents and eliminate them is likely to significantly reduce the risk of a more serious incident occurring (Wright & van der Schaaf, 2004), and result in greater savings in the long run. The fact that it was possible to identify differences in causal pathways from even basic quality minor investigations provides evidence of the importance of using minor events and near misses to further our understanding of how safety systems can be improved.

It is important to note, however, that even in reports with extensive data e.g. for SPADs or Station Overruns, there were still few references to organisational and supervisory issues, and many that were identified were cases where a driver had not yet completed relevant training after a prior incident (classified as 'Failure to correct known problem'). This indicates an issue with the focus of reporting, discussed next. Certainly, the perception of driver error as captured in the reports is that the issues lie in active factors, and this reinforced by train operating companies' interest in Non-Technical Skills programmes.

4.4 What is the quality of reporting of minor incidents in the rail industry?

Building on the point above, one of the questions entering into this study was whether reports contained enough detail to identify issues arising at the supervisory, organizational and regulatory levels. In practice the number of examples of this kind of factors in the data were few and far between. This is one of the major drawbacks of using HFACS as a tool to investigate more minor accidents, as several studies have found that systems approaches are hugely dependent on the quality of the data provided (e.g. Lenné et al., 2012). The majority of the investigations reported in this study were carried out by front-line supervisors rather than dedicated accident investigators, and thus it is perhaps unsurprising that these supervisors might be reluctant to find fault with themselves and, in many cases, their employers. Research shows that latent errors pose the greatest risk to system safety (Reason, 1990; 1997), and it is a key characteristic that these latent errors are the pre-conditions that enable active errors to occur. It is therefore important that organisations are able to identify these latent errors to mitigate against potentially serious accidents occurring in the future.

However, it is important not to appear too critical of reporting. Of all 74 reports identified by train operators as being related to human error, all did cover human error and presented issues that fitted naturally within HFACS. None presented information that suggested a significant misclassification of the report (e.g. that it was primarily a technical fault). This suggests a good level of understanding of basic human factors within the industry, and further work could help to refine or expand that understanding to seek out more latent factors. Further work to develop investigation and reporting around supervisory, organisation and external factors should not just look to support accident analysis using HFACS. This level of reporting would also help assist in the identification of causes of accident using systems-orientated approaches such as STAMP (Leveson, 2004) and Accimap (Rasmussen, 1997).

4.5 How reliably can two independent Human Factors experts code investigation reports using HFACS

On the whole, the research team found HFACS to be a straightforward tool to use, although it was not without its flaws. Previous research had identified problems with inter-rater reliability, and difficulties in identifying the level at which factors should be categorised (Olsen, 2011; Olsen & Shorrock, 2010; Baysari et al., 2008). Olsen (2011) investigated the success of air traffic controllers and human factors specialists in applying HFACS consistently and found that neither group achieved acceptable agreement levels between raters. However, this was not a problem in the current study, with inter-rater reliability reaching an acceptable level in all categories other than Adverse Mental State, where it was just below the 70% agreement level advocated. Prior to beginning the coding process, both raters had spent some time agreeing on their interpretation of each of the categories and this may have aided the coding process. Also, all incidents had already been classified by the train operating companies as relating to human error, which again may have reduced some of the scope for variance.

4.6 Limitations

A limitation of this study, particularly for TPWS activation and Stop Short events was the lack of data in the reports, and, as noted above, all of the reports lacked information on supervisory and organisational factors. This, coupled with a modest sample size of 74 investigation reports, limits the depth of conclusions that can be drawn from the reports regarding causal factors. As noted under data quality, a second factor is the potential bias in the reports through the reliance on the skills of the line managers and supervisors as investigators. These investigators could not be assumed to have extensive training or knowledge of Human Factors, and may have a personal relationship with the driver they were interviewing. Thirdly, putting aside the role of the investigator, the drivers were asked to recall their thoughts and mental states at the time of the incident. This is also likely to be biased, and caution must be taken when interpreting any self-report data. A final limitation is that HFACS was the only interpretation tool used in the study. While the aims of the study were practical, rather than a study of methodology, it might be useful to compare different tool outputs e.g. Accimap (Rasmussen, 1997), STAMP (Leveson, 2004), along with the Incident Factor Classification Study which is being adopted in the UK rail section (Gibson et al., 2015).

5. Conclusions

The current study successfully applies HFACS to provide a retrospective analysis of minor incident investigations in the rail industry. Such examination of minor incidents provides a much wider scope for us to interpret accident causal pathways, as these incidents occur much more frequently than more serious incidents. By highlighting the differences in the causes of different incident types, a greater level of understanding of the mechanisms required to prevent future incidents is achieved.

Active failures, specifically those related to attention and adverse mental state, dominate the results, suggesting that measures to reduce safety of the line incidents should be targeted at these areas. However, it is important to stress that training approaches should not be the only solution, and more systemic solutions are also required. Currently, supervisory and organisational issues are under-represented in the reports, and therefore more efforts should be made to identify latent factors that might be setting up the preconditions for active failures. Uncovering these latent errors may need rail companies to refine the current approach to minor incident investigation, in order to ensure that all factors can be identified, not only those relating to the competency or attitude of the driver.

Finally, this study has also identified the importance of the operational environment in shaping risk. Gibson et al (2015) put the case that as an aggregate, performance may be approaching a ceiling, and that further investigation is required to target specific locations or circumstances that might lead to error. From this analysis, we argue that operational environment may be one of those factors. To test this, one could compare the risk of SPAD for signals approached at red when operational conditions were out of the norm, from those approached in normal circumstances. If operational environment is a factor, then SPAD risk will be found to be higher. Also, it would also be interesting to investigate whether similar differences emerge in the causal factors of incidents on different types of routes (e.g. high-speed trains versus metro-links).

Acknowledgements

This project was co-funded by Innovate UK, ESRC and EPSRC as a Knowledge Transfer Partnership. We are also grateful to the UK Train Operating Companies who provided access to and information about their incident investigation processes, without whom this research would not have been possible.

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